HYSTAR: Hydrology and Sediment Transport Simulation using Time-Area Method

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Dissertation submitted to the faculty of the
Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Biological Systems Engineering

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January 28, 2011
Blacksburg, VA

Keywords: Time-area method, Distributed watershed modeling, Hydrology, Flow routing, Sediment transport, Uncertainty analysis, Calibration, Critical source area, Margin of safety

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Abstract

A distributed approach can improve functionality of H/WQ (Hydrology and Water Quality) modeling by facilitating a way to explicitly incorporate spatial characteristics of a watershed into the model. The time-area approach, with its intuitive and inherently distributed concept, provides a simple method to simulate runoff mechanisms. This study developed a distributed model based on the time-area approach with the goal of improved utility and efficiency in H/WQ modeling.

Uncertainty is always introduced into watershed modeling because of imperfect knowledge and scale dependent spatial heterogeneity and temporal variability. Uncertainty analysis can provide a modeler, policy maker, and stakeholder with reliability information, better understanding, and better communication about the modeling results. This study quantified uncertainty of the model parameter and output through uncertainty analysis in order to assess risk in watershed management. The main goal of this study was to develop a hydrology and sediment transport model capable of routing overland flow using a time-area concept and providing reliability of the modeling results in a probabilistic manner through uncertainty analysis.

The HYSTAR (HYdrology and Sediment transport simulation using Time-ARea method) model incorporates a modified Curve Number (CN) method and the newly devised time-area routing method to estimate runoff. HYSTAR is capable of simulating direct runoff, base flow, soil moisture, and sediment load in a distributed manner and in an hourly time step. In the model, the modified CN and a continuity equation are used to calculate infiltration of the routed runoff as well as rainfall on every overland cell. The effective direct runoff volume is distributed over downstream areas using the newly developed routing method. A direct runoff hydrograph is constructed directly through the discrete convolution of the time-area histogram and the effective direct runoff volume.
map without employing a unit hydrograph. In addition, sediment transport is simulated using the routing method and the sediment transport capacity approach without using a delivery ratio.

The sensitivity analysis found that the CN and root zone depth were the most critical parameters for runoff simulation with HYSTAR. The model provided acceptable performance in predicting runoff and sediment load of a subwatershed of the Owl Run Watershed (ORD) with the Nash-Sutcliffe efficiency coefficient and coefficient of determination greater than 0.5. However, it failed to reproduce runoff for a subwatershed of Polecat Creek Watershed (PCA), where data show that runoff is not immediately responsive to rainfall.

Uncertainty analysis revealed that the confidence intervals of the simulated monthly runoff and sediment load corresponded to 9.7 % and 10.2 % of their averages, respectively, at a significance level of 0.05. In addition, the average ranges of variation created by the Digital Elevation Model (DEM) and National Land Cover Data (NLCD) errors in the simulated monthly runoff and sediment load were equivalent to 7.5 % and 15.9 % of the average of their calibrated values, respectively. Based on the uncertainty analysis results, the Margin of Safety (MOS) of Total Maximum Daily Load (TMDL) were explicitly quantified as corresponding to 7.0 % and 21.3 % of the average of the simulated runoff and sediment load for ORD at significance level of 0.05.

In conclusion, the HYSTAR model provided a new way to explicitly simulate runoff and sediment load of a watershed in a distributed manner. The approach developed here retains the simplicity of a unit hydrograph approach without employing numerical methods. Uncertainty analysis found that parameter uncertainty had greater impact on the model output than did expected Geographic Information System (GIS) data errors. In addition, the impact of the topographic data error on the model output was greater than was that of the land cover data error. Finally, this study provided a proof that a 5 to 10 % MOS that many TMDL studies consider underestimates modeling uncertainty.
To Yunkyung, Yujune, and Yuchan
Acknowledgement

This study would not have been possible without support of the Department of Biological Systems Engineering, Virginia Polytechnic Institute and State University.

I would like to express my sincere appreciation to my advisor, Dr. Conrad Dean Heatwole, for his sharp advice, warm consideration, calm encouragement, and great patience. The main idea of this study was inspired by his teaching in the class.

I am grateful to my committee members, Dr. Saied Mostaghimi, Dr. Mary Leigh Wolfe, Dr. Brian Benham, and Dr. Stephen Prisley. Their advice and comments were very valuable for this study. In particular, the questions I received in the preliminary exam made me realize my own ignorance about the subjects on which I had studied and worked.

Thanks to Mr. Denton Yoder for his help. I am thankful to Sally, Javier, and Mike for their encouragement.

I appreciate all the people in BSE for their kind help.

Lastly, I believe that the knowledge acquired from the classes I took, the advice received from the people I met, and the experience gained from activities I participated in Virginia Tech built a solid foundation for my future work.
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1. INTRODUCTION

1.1 Overview

Watershed management is planned and implemented based on modeling and monitoring studies. Total maximum daily load (TMDL) development and best management practice (BMP) implementation are efforts to prevent and reduce pollution and subsequently improve water quality in the watershed. Field monitoring and hydrologic and water quality (H/WQ) modeling are used to track the fate of pollutants and to assess the effectiveness of BMPs. However, because field monitoring is expensive to implement and requires a long time to provide statistically useful information, it is usually utilized in evaluating the status of the watershed and in supporting H/WQ modeling. Thus, H/WQ modeling is a necessary complement to field monitoring because it is inexpensive and quick. In addition, H/WQ modeling allows what-if analysis of scenarios, which is not practical in field monitoring. Moreover, a model is reusable in other relevant cases and various functions of a model can be designed with respect to the modeler’s needs.

A H/WQ model uses a spatial element to represent the landscape as homogeneous areas in terms of soil, land use, and topography. The model can describe the whole watershed with only one unit, or as a group of small units to account for spatial variability of the watershed characteristics. The discretization level is defined with respect to the modeling objectives with consideration also to model efficiency and availability of required data. When using models to simulate detailed H/WQ processes, the corresponding number of equations, parameters, and amount of data to support the level of detail will be required. If a modeler is interested in the model output only at the outlet, discretization for distributed presentation may not be required. However, consideration of detailed H/WQ processes allows explicit simulation and potentially better modeling accuracy when the required amount and quality of data are available.

A distributed approach facilitates a way to reflect spatial heterogeneity of the landscape and variation of rainfall in H/WQ modeling, and to present the modeling results in a distributed manner. For instance, spatial characteristics of elevation, land use,
and soil of a watershed can be explicitly considered through parameterization in a distributed model. In addition, a distributed model is capable of simulating detailed movement of water and pollutants and their interaction with other pollutants over a watershed. Therefore, a distributed approach is expected to improve the utility of H/WQ modeling. However, many H/WQ processes are often considered and subsequently much input data and many parameters are required in a distributed approach. Thus, complexity and uncertainty of the model increase. These disadvantages present a challenge to widespread application of a distributed approach in H/WQ modeling.

In spite of the challenges, some distributed models such as Soil and Water Assessment Tool (SWAT), CASCade 2 Dimensional (CASC2D), Gridded Surface Subsurface Hydrologic Analysis (GSSHA), Distributed Hydrology Soils and Vegetation Model (DHSVM), Geographic Information System-based modeling system for Watershed Analysis (GISWA) are currently supported by the federal agencies like The United States Department of Agriculture Agricultural Research Service (USDA ARS), The United States Army Corps of Engineers (USACE), and The United States Department of Energy (USDOE) (Wigmosta et al., 1994; Neitsch et al., 2002; Ogden et al., 2003; USDOE, 2008; Texas A&M University, 2011; USACE, 2011). A distributed modeling approach seems to be the future direction of H/WQ modeling due to its utility and potential. In particular, it can incorporate the emerging Geographic Information System (GIS) / Remote Sensing (RS) data into H/WQ modeling in an explicit way. Thus, as quality of the data is improved with development of sensing technology and data processing, a distributed model is expected to provide more accurate simulation. In addition, reliability of a distributed H/WQ modeling can be assessed through uncertainty analysis. Therefore, it is desirable to develop a model capable of simulating detailed H/WQ processes efficiently for routine modeling practice while providing reliability information of the modeling results through built-in uncertainty analysis tools.

Although fully distributed models such as MIKE-SHE (System Hydrology European) and Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS2000) have been developed, they are too detailed to use as routine watershed-planning tools. Semi-distributed models, including SWAT, utilize homogeneous patches such as hydrologic response units (HRUs) for modeling efficiency,
but do not consider overland routing explicitly. CASC2D is a cell-based distributed, watershed-scale hydrology and sediment model, but it simulates only direct runoff. CASC2D was modified to enable groundwater and continuous simulation in GSSHA. DHSVM also can simulate detailed hydrologic processes in a distributed manner, and its functionality is enhanced in GISWA. However, they (CASC2D, GSSHA, DHSVM, and GIAWA) employ an explicit FDM (Finite Difference Method) solution, which requires satisfying the CFL (Courant-Friedrichs-Lewy) condition for convergence of the solution. Thus, the time step is restricted according to the spatial resolution of simulation, and this restriction may lead to inefficiency for long-term and fine spatial-scale modeling. None of these models has the functionality to provide information about its reliability and uncertainty.

The time-area approach provides a useful tool to understand runoff mechanisms and to construct hydrographs through its intuitive and inherently distributed concept. It does not require numerical methods to simulate hydrographs at the outlet in a distributed manner, thus the temporal and spatial steps for solution are not restricted. In addition, the time-area approach considers spatial variability of watershed characteristics in calculating travel time of runoff. Some researchers have applied this approach to develop unit hydrographs (UH) at outlets. However, the UH concept has limitations in application due to assumptions of a uniform distribution of excess rainfall and a constant base time of the direct runoff hydrograph regardless of excess rainfall intensity. Therefore, it may not be appropriate to use a UH for distributed hydrologic modeling of spatially varied excess rainfall.

In this study, therefore, a direct method to derive hydrographs based on the time-area approach without the assumptions of UH is presented. The method creates a direct runoff hydrograph using discrete convolution of the time-area histogram and the effective direct runoff map. Compared to the UH approach, the unit hydrograph ordinate and excess rainfall are replaced with the time-area histogram and the effective direct runoff map respectively in the discrete convolution. Thus, the newly proposed method can account for impact of intensity and spatial distribution of excess rainfall on a direct runoff hydrograph. The direct runoff hydrographs are created at all the time steps, and then they are merged to a single direct runoff hydrograph at the end of a storm event.
A new routing method is presented to simulate overlapping of excess rainfall volume along overland and channel flow paths. Thus, the term, “effective direct runoff”, rather than “excess rainfall” is preferred in this study. The CN method was modified in order to consider infiltration of the effective direct runoff using a continuity equation. In addition, the revised CN method was adapted from SWAT and EPIC to reflect variation of a curve number according to change in soil water content. The adapted methods are integrated to develop a new hydrology model. Thus, the newly developed model is capable of simulating runoff at the watershed outlet in a distributed and continuous way. In addition, the developed model was applied to identify critical areas of a watershed. Two different criteria were tested for identifying critical areas and the results compared.

In the model, the sediment transport capacity approach is used to decide a sediment transport process between detachment and deposition and to calculate amount of the transported sediment load. It is applied in a distributed manner so that the model can simulate the sediment transport processes on every cell within a watershed. The Yalin equation was selected based on sensitivity analysis, investigation on the conditions of the equations, and literature review. In the model, sediment load is routed using the same methods as the case of runoff. Thus, sediment routing can be explicitly simulated in the model. Then, the developed sedigraphs at all the time steps will be merged into a single sedigraph at the end of a storm event.

For distributed modeling, the use of GIS is important for efficiency in input data preparation and parameterization. It is now common to use digital data sets of elevation, land use, and soils in H/WQ modeling. In this trend, distributed modeling has been considered as a good way to precisely represent spatial watershed characteristics and to simulate H/WQ processes in detail. Many studies have examined the influence of the properties of GIS data such as accuracy and resolution on H/WQ modeling using uncertainty and sensitivity analysis. However, effects of uncertainty contained in GIS input data on the modeling results have been little studied even though errors in publicly available GIS data are officially reported. This negligence may be attributed to insufficient information about the errors and absence of an appropriate method to consider GIS data uncertainty in H/WQ modeling. Thus, this study identified methods for simulating the GIS data error in a statistically sound way without information about the
error. Then, variation of the model output caused by the simulated errors of GIS data was investigated to evaluate impact of the uncertainty on the output.

Uncertainty originates from scale dependant spatial heterogeneity and temporal variability of H/WQ processes and imperfect knowledge about the processes. Thus, uncertainty is always present in H/WQ modeling. A distributed modeling approach requires many parameters, much data, and more complicated model structures for detailed simulation of processes. The requirements may introduce additional uncertainty into the model. However, the effects on model results are often ignored due to difficulty in identifying sources and in quantifying the magnitude of uncertainty even though it has been a concern in H/WQ modeling for a long time. On the other hand, sometimes uncertainty is decided in a subjective way such as a margin of safety (MOS) used routinely in TMDL development.

Quantifying model uncertainty can provide a modeler, policy maker, and stakeholder with reliability information, better understanding, and better communication about the modeling results. If uncertainty is quantified through a formal uncertainty and error analysis instead of being selected in an arbitrary and unscientific way, the uncertainty measurements can be effectively utilized in many applications of H/WQ modeling such as TMDL development. Thus, this study tried to quantify uncertainty of the model parameters and output in order to assess reliability of the model and to evaluate MOS of sediment TMDL using a statistically formal uncertainty analysis method.

Many algorithms and frameworks have been developed for model output and parameter uncertainty analysis. In this study, the SCEM-UA algorithm was selected for quantifying uncertainty in model output because of its formality in a statistical sense. The quantified uncertainty in modeling output was converted into a MOS in a case study for a sediment TMDL. Then, the MOS was compared with that considered in routine TMDL studies.

The newly developed model is expected to facilitate an alternative way for distributed hydrology and sediment transport modeling while maintaining simplicity of the unit hydrograph approach. The uncertainty analysis may exhibit a way to quantify uncertainty in the parameters and output of a distributed hydrology and sediment
transport model and explicitly determine MOS of TMDL. In addition, comparison of the impact of uncertainty in model parameters and GIS input data on model output may show their relative importance for future improvement of H/WQ modeling.

1.2 Objectives

The goal of this study was to develop a hydrologic and sediment transport model capable of routing overland flow using a time-area concept and providing reliability of the modeling results in a probabilistic manner through uncertainty analysis. Specific objectives are the following.

1. Develop a distributed hydrology and sediment transport model based on a routing method using a time-area concept.
2. Evaluate performance of the newly developed model with observations from multiple watersheds.
3. Develop a framework to quantitatively assess uncertainty of a distributed model using statistical methods.
4. Evaluate impact of uncertainty in GIS input data on the output of spatially distributed modeling.
2. LITERATURE REVIEW

2.1 Hydrologic and Water Quality Modeling

2.1.1 Overview

Water is continuously circulating in the air and soil and on the ground surface. At the same time, it is transporting heat and matter. The circulation and transportation are driven by energy and force such as solar radiation and earth’s gravity at a global scale. On the ground surface and in the soil, quantity and velocity of the water movement are controlled by several forces like friction, capillary force, and external pressure, as well as gravitational force of the earth and thermal energy. At different spatial and temporal scales, some forces may control or predominate, or forces may interact equivalently in complicated ways. Thus, even though there are systems and phenomena whose governing mechanisms and laws of physics are known in detail, the implications are not understood because of the complexity of interactions (Winsberg, 2001).

A model helps us to study systems like a watershed in ways that would impractical or impossible by other means, and simulation is the process of conducting experiments with a model for understanding the system or evaluating strategies for the operation of the system (Nix, 1994). For better understanding about a complex system and phenomenon, a simulation model attempts to mimic the system or exhibit its key mechanisms by assuming, conceptualizing, and formalizing its features using logic and knowledge. Models use mathematical relationships to represent and simulate behavior of a system, and they can be as simple as one equation or be comprised of multiple individual equations (Nix, 1994). Modeling or simulation creates values of variables that emulate the characteristics of those we observe in the real world (Webster et al., 2007). Therefore, modeling is not simply a calculation or ‘number crunching’ technique (Winsberg, 2001), but integrated and sophisticated process to demonstrate, understand, and infer mechanisms governing a system and phenomena based on sound science.

A modeler employs models to understand a system, predict impact of any input on the system output, and provide input data for further research. Therefore, a model becomes a tool to study a complex system, a scientific base of prediction for the system,
and a collection of our knowledge about the system. Likewise, in H/WQ modeling, a modeler employs H/WQ models to understand mechanisms that govern H/WQ phenomena, to synthesize H/WQ events occurred in the past, and to predict future H/WQ events (Freeze et al., 1969). In addition, H/WQ models can be utilized to evaluate combinations of H/WQ events occurring rarely in nature for design purpose, evaluate the impact of natural change and/or anthropological activity on the environment, and provide input data for further social and environmental researches (Freeze et al., 1969). It should be noted before beginning discussion about H/WQ modeling that, in this study, the term ‘model’ means ‘mathematical model’ which uses mathematic algorithms and numbers to describe a system.

Despite this usefulness of a model, use of a model in conducting simulation experiments is limited by the model itself (Nix, 1994). Nix (1994) listed limitations of a mathematical model. First, every model is wrong to some degree in their representation of a system, thus it should be realized that any model is simply a tool and a modeler is responsible for the end product. In addition, a model can extract information from data but cannot overcome data inadequacies. Finally, the output produced by a computer model is no more accurate than numbers calculated by hands, just faster and efficient.

Since Sherman (1932) introduced the unit hydrograph method, H/WQ modeling has been advancing with the improvement of concepts, algorithms, and computing resources. In the 1930’s, the concept of physical hydrology was introduced and led to an understanding of the physics in the hydrologic cycle which laid the groundwork for most present developments (Dawdy, 1983). In addition, developments in sensing, monitoring, database technology, and of computing resources result in availability of extensive data for H/WQ modeling in a variety of forms and allowed H/WQ modeling to be done in a more sophisticated way. In spite of these advances, some issues and problems to overcome for better H/WQ modeling remain unsolved, and new viewpoints and accumulated modeling experience are introducing new issues and highlighting old questions.
O'Connell et al. (1996) listed contemporary issues and research themes in hydrologic modeling. Although the list is more than 15 years old, some of the points remain as major problems to be solved:

1) How to deal with heterogeneity in modeling at a coarser scale;
2) How to measure spatial and temporal variability in rainfall and incorporate them into modeling;
3) How to predict reliably the impacts of land use changes on hydrology of a watershed;
4) How to get a parsimonious physically-based distributed models;
5) How to locate the optimum parameter set, to validate the model, and to assess uncertainty.

Water shortages, distribution, pollution, and flooding are very important issues in many regions of the globe. The focus on sustainability has been making people think not only the present time but also the future of the earth for the next generations. It tries to incorporate environmental, economic, social, and ethical factors into the overall plan and processes in order to utilize and maintain the earth in better ways. In addition, it is believed that sustainability can best be achieved by an integrated approach in which professionals in relevant fields and all the stakeholders participate. Thus, H/WQ modeling is expected to play an important role, such as providing assessment of the present status and prediction of the future change in the environment, at fundamental steps in the whole plan and process. In this sense, accuracy, reliability, and uncertainty of H/WQ modeling might become a more critical concern in the integrated approach because they will be delivered and propagated into its next analyses and processes.

2.1.2 Classification and Selection of H/WQ Models

A model simplifies the reality with its own conceptualization scheme, scale, equations, parameters, and assumptions. Based on these features of a model, in this study, a classification of mathematical models was attempted and provided in Table 2.1. This
classification is made according to ‘items’ that compose a model, ‘factors’ that consist of the ‘items’, and ‘approaches’ that characterize the factors. The conceptualization schemes incorporate the randomness of process of the system, level of simplification, and method of model formulation. Some H/WQ processes in a model can be added or dropped depending on the purpose and spatial and temporal extents of the model.

In TMDL development, models are used to estimate source-loading inputs, evaluate receiving water quality, and determine load allocation to sources (Borah et al., 2006). Heatwole et al. (1991) distinguish water quality models from nonpoint source models based on the emphasis of transport and fate of pollutants in water bodies like streams and lakes in the model. Thus, nonpoint source and water quality models are called loading and receiving water models respectively (Heatwole et al., 1991; Novotny, 2003). A loading model estimates pollutant load entering to waterbody as a function of land use and pollutant discharge while a receiving water model predicts pollutant concentrations in the waterbody as a function of the pollutant load (NRC, 2001). Thus, loading and receiving water models are utilized to allocate TMDL among sources and to determine if TMDL meets the water quality standard respectively (NRC, 2001).

Mathematical modeling in TMDL development is also a way to “evaluate alternative pollutant loading scenarios” (USEPA, 1991; Munoz-Carpena et al., 2006).

The availability of data, modeling purpose, functionality, efficiency, and precision of a model determine the level of spatial and temporal details to be considered in a modeling application. Empirical, conceptual, and physically based models are classified based on level of physical meaning incorporated in parameters and equations and/or a way to introduce parameter into a model. Detail discussions are presented in 2.10. It is usually impossible to formulate the full set of mathematical equations of a H/WQ model in a closed-form (Winsberg, 2001) even though we can find and derive some laws that govern and describe the behavior of a system. Consequently, an analytical model is rarely found, and numerical simulation becomes a good way to integrate a set of equations in a manageable form.
<table>
<thead>
<tr>
<th>Item</th>
<th>Factor</th>
<th>Approach</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conceptualization Scheme</td>
<td>Random Process</td>
<td>Incorporated</td>
<td>Stochastic</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ignored</td>
<td>Deterministic</td>
</tr>
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<td></td>
<td>Simplification Level</td>
<td>Highly Simplified, Details Ignored</td>
<td>Black Box</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Little Simplified, Details Simulated</td>
<td>Process-based</td>
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<tr>
<td></td>
<td>Model Formulation</td>
<td>Continuous</td>
<td>Analytical</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Discrete</td>
<td>Numerical</td>
</tr>
<tr>
<td>Scale/Extent</td>
<td>Temporal</td>
<td>Short Term, Event- Driven</td>
<td>Event</td>
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<td></td>
<td></td>
<td>Long Term, Continuous-Process</td>
<td>Continuous</td>
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<tr>
<td></td>
<td>Spatial</td>
<td>Overland Process, Centered</td>
<td>Field/Small Watershed</td>
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<tr>
<td></td>
<td></td>
<td>Channel Routing, Incorporated</td>
<td>Watershed/Basin</td>
</tr>
<tr>
<td>Equation &amp; Parameter</td>
<td>Linearity</td>
<td>Linear Relationships between Processes</td>
<td>Linear</td>
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<tr>
<td></td>
<td></td>
<td>Nonlinear Relationships between Processes</td>
<td>Nonlinear</td>
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<tr>
<td></td>
<td>Spatial Details</td>
<td>Spatially Homogeneous Parameters</td>
<td>Lumped</td>
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<td></td>
<td></td>
<td>Spatially Heterogeneous Parameters</td>
<td>Distributed</td>
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<tr>
<td></td>
<td>Temporal Details</td>
<td>Temporally Constant Parameters</td>
<td>Time-invariant</td>
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<tr>
<td></td>
<td></td>
<td>Temporally Variable Parameters</td>
<td>Time-variant</td>
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<tr>
<td></td>
<td>Way to be Driven</td>
<td>Driven empirically with data</td>
<td>Empirical</td>
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<tr>
<td></td>
<td></td>
<td>Driven based on physical laws</td>
<td>Physically-based</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Driven based on logics and knowledge</td>
<td>Conceptual</td>
</tr>
</tbody>
</table>

In the classification of Table 2.1, some classes have opposite characteristics to each other. For instance, we can discriminate H/WQ models as stochastic and deterministic one in sense of incorporation of randomness. However, most of the classes
are not mutually exclusive to each other and sometimes one is a special case of another. Linear, event, and time-invariant models are special cases of nonlinear, continuous, and time-variant ones respectively. Moreover, boundaries of the classes are not distinct and rigid but rather gradual and flexible according to a viewpoint of scale. Process-base, watershed scale, and distributed models can be black box, field scale, and lumped models respectively at a more detailed, small-scale viewpoint. Although at the boundaries, the classification of models is sometimes subjective and unclear, the classification, nonetheless, will help to frame a better understanding of H/WQ models by providing a systematic and grand picture of them.

Dawdy (1983) traced the development and history of rainfall-runoff modeling from introduction of linear system in mathematical hydrology in 1930’s to tank models in the 1970’s. He anticipated a trend in hydrologic modeling toward physically-based and distributed-parameter models while emphasizing introducing rigorous error analysis to test if more complexity provides better prediction. EPA (1997) reviewed some loading and receiving water models for watershed and TMDL assessment and enumerated several considerations for model selection. They classified models for TMDL development as watershed-scale loading models, field-scale loading models, integrated modeling systems, and receiving water models. Then, they evaluated them in terms of types of land uses and pollution sources considered, degree of details in hydrology, pollutant loading, and routing incorporated in simulations, types of formats for model output, input data requirement, user interface, and applicability to BMP evaluation and design. The proposed model selection criteria includes availability of computing resources and trained modeler, in-house model experience, support of the model by a developer and/or community, and commitment to modeling as a tool.

The National Research Council (NRC, 2001) provided a comprehensive list of considerations desired to be made at selection of model for TMDL development. It includes compatibility of spatial and temporal scales and complexity of a model to those of the problem at hand, scientific basis, ability to give prediction error estimate, consistency with the amount of data available, interpretability for stakeholders, cost of annual model support and maintenance, and flexibility of model update and improvement (NRC, 2001). They also broadly discussed models’ utility, complexity, accuracy,
uncertainty, data requirements, incorporation of random process, and relationships among these characteristics.

Merritt et al. (2003) reviewed seventeen erosion and sediment transport models in terms of input, output, structure, fundamental mechanisms for runoff, sediment, and nutrient modeling, predictive accuracy, and limitations. They categorized the models into empirical or statistical, conceptual, and physics basis of the simulated physical processes, algorithms for describing the processes, and data dependence of the model. They listed considerations in determining an appropriate model for an application as suitability of a model to local conditions, data requirements, model complexity, accuracy and validity of the model, model assumptions, the spatial and temporal variations, components of the model, and objectives of the modeler. Finally, in the study, issues and recommendations were discussed for better erosion and sediment modeling: natural complexity, limitations in the understanding of sediment pathway, model complexity and accuracy, modeling in data poor environments, uncertainties in sediment generation and transport, and dependence on water quantity predictions.

Shoemaker et al. (2005) summarized features of currently available models for simulating watershed and receiving water conditions in TMDL development. The features included support for hydrodynamics and water quality of receiving water simulation at a watershed scale, capability of simulating BMP performance and treatment, linkage to another models, incorporation of statistical methods, and process-based or not. They evaluated the models in terms of receiving water simulation capabilities and watershed simulation capabilities and examined applicability, capabilities, and limitations of the models. They also represented factors that guide model selection for TMDL development including ability to simulate at temporal and spatial scales and appropriateness in evaluation of the endpoint’s magnitude, duration, and frequency.

Borah et al. (2003) reviewed eleven watershed-scale hydrologic and nonpoint-source pollution models in terms of mathematical basis and categorized the models by governing equations, temporal scale, and applicability. Borah et al. (2004) also evaluated performance of three models, SWAT, Hydrologic Simulation Program – Fortran (HSPF), and A Dynamic Watershed Simulation Model (DWSM), through investigation of
application studies of the models. Borah et al. (2006) reviewed over fifteen sediment and nutrient models for TMDL development. They categorized them by capabilities of the models and types of output variables the models provide, such as loading models, receiving water models, and watershed models, and by fundamental methods that the models employ to simulate excess rainfall, flow routing, subsurface flow, and sediment transport. Then, they gave brief introductions about capability, conceptual and theoretical basis, major equations and assumptions, limitations, and enhancements to the models since they were created. In addition, comparison studies about performance of the models, and TMDL studies applying the models were reviewed.

Munoz-Carpena et al. (2006) collected and reviewed articles of evaluating current water quality modeling technology for TMDL development and application in terms of proper selection and use of model, modeling uncertainty, and tools for economic assessment. From the literature review, they concluded that the current nutrient, sediment, and pathogen transport models were suitable for current modeling efforts in spite of their limitations, but many Dissolved Oxygen (DO) models were still not capable of simulating DO processes due to lack of understanding of the processes.

2.1.3 H/WQ Model Development Procedures

A H/WQ model is developed with consideration of the required functionality, efficiency, temporal and spatial precision, and the expected accuracy for its objectives. Considerations for the model functionality may include output types to be provided, ability to incorporate desired information and data, and capability to simulate special features and mechanisms the problem of interest has. The model efficiency might be evaluated in terms of quality and quantity of the needed input data, the required computing resources and time for a single run, ease of calibration, and ease of modification. Model precision can be determined by temporal and spatial calculations selected according to the objectives, functionality, and efficiency of a model. Accuracy is expected to be a function of the quality and completeness of input data, adequacy and accuracy of employed equations and algorithms, and soundness of utilized approaches.
Although H/WQ models employ different approaches, procedures of model development are common. A general procedure of deterministic H/WQ model development is represented in Figure 2.1 (Hall et al., 1977; Bloschl et al., 1995; Corwin, 1996; Refsgaard, 1997; Guisan et al., 2000; Beven, 2001; Jorgensen et al., 2001; EPA 2009). Model building steps of stochastic H/WQ model are somewhat different from those of the deterministic and the procedure Box et al. (1970) proposed is represented in Figure 2.2 (Salas et al., 1995).

![Diagram of model development process](image)

Figure 2.1. General procedure of deterministic H/WQ model development (Beven 2001).
2.2 Precipitation

Precipitation drives the hydrologic cycle and the resulting processes that generate diffuse pollution (Novotny, 2003). Evaporation and transpiration supply moisture to the atmosphere from open water and soil surface and vegetation, and then the water vapor forms clouds. As the atmosphere is saturated with water vapor, the moisture forms small water droplets that are then released back to earth as some form of precipitation (Ward et al., 2004). However, the atmosphere is not simply saturated by the supply of water vapor alone. When the air mass is lifted by some physical mechanism, it cools and condenses as its capacity to contain moisture decreases. The saturation vapor pressure decreases as the air cools and saturation is accelerated. Thus, the formation of precipitation is usually classified by the lifting mechanisms.
Precipitation varies not only temporally and spatially in local areas but also with geographic location and climate at a macroscopic viewpoint (Ponce, 1989). Climatic characteristics of a region: arid or humid, hot or cold, and the seasonal concentration of precipitation are critical information to consider when selecting or developing a H/WQ model because mechanisms that control water movement on the earth will vary according to those features. Classification of runoff generation mechanisms like Hortonian infiltration and variable source area concepts, or snow melt dominated runoff in some cold regions are examples of the importance of geographic location and climate in H/WQ modeling. After determining a regional extent and resulting approaches for modeling, a way for representing temporal and spatial variation of the precipitation in the model must be determined. If a lumped approach is selected, the spatial variation of precipitation may be averaged over a watershed of interest.

Wilson et al. (1979) investigated sensitivity of hydrographs simulated by hydrologic models to the number of rain gauges and correlation between data at adjacent rain gauges using synthesized rainfall from a weather generation model. Their study showed significant impact of the spatial distribution and accuracy of rainfall measurement on the simulated hydrograph for a watershed of 26.5 mi². Troutman (1983) tried to see factors causing bias in runoff prediction using a distributed rainfall-runoff routing model of Dawdy et al. (1972), with hypothetical rainfall. In their study, use of single point measurement or averaged over a small number of points resulted in the biggest variance in runoff prediction. Ogden et al. (1994) investigated sensitivity of a distributed model, CASC2D, to resolution of Next-Generation Radar (NEXRAD) and cell size of the model. They found that excess rainfall volume decreases as the resolution of rainfall data gets larger. Faures et al. (1995) examined variation in the simulated peak rate and runoff volume for a small watershed of 4.4 ha induced by change in the number of rain gages incorporated into the Kinematic Runoff and Erosion Model (KINEROS) model. In spite of the small dimensions of the watershed, they saw significant impact of the number of rain gages used for hydrologic modeling on predicted runoff.

There are several techniques to average point precipitations over an area. The simplest way is to take an arithmetic mean of the corresponding point precipitation values in the time interval of interest. If rain gages are evenly distributed over the area and
precipitation values of individual gages have an insignificant variance, the average method will be adequate (Chow et al., 1988). If these conditions are not satisfied, however, another simple technique, the Thiessen method, may be a good alternative. Thiessen et al. (1911) applied weights of the areas represented by individual gages in averaging point precipitations over the larger area. Based on this weighted average precipitation approach, assuming that precipitation at any point in the watershed is the same as that of the nearest gage, the depth recorded at a given gage can be applied to a distance halfway to the next station in any direction (Chow et al., 1988). Thus, the Thiessen polygon is constructed by using perpendicular bisectors to lines between gages and removing overlapping bisectors until an even spatial distribution is obtained (Wootton et al., 1996). Another way to get an average precipitation is the isohyetal method proposed by Linsley et al. (1949) (Wootton et al., 1996). The isohyetal map is constructed by plotting the gages and their precipitation amounts on a topographic base map, and then human judgment is used to determine the placement of isohyetal contours affected by topography (Wootton et al., 1996). After that, average precipitation for an area is calculated by the weighted average for the area (Wootton et al., 1996). The isohyetal method is known as more accurate than both the Thiessen and the simple arithmetic mean methods (Ponce, 1989).

Although advanced averaging and interpolation methods have been proposed, these approximations of rainfall certainly cause error and uncertainty in H/WQ modeling because “precipitation varies on the scale of kilometers while rain gages in the US are spaced 10’s to 100’s of kilometers apart” (DeBarry et al., 1999). For example, if rainfall is distributed over on upper parts of a watershed, most of the excess rainfall may be infiltrated into soil on lower parts while it is passing along its flow paths, and then runoff at the outlet may not be observed. Thus, an averaging technique with sparse rain gages may not appropriate in hydrologic modeling in particular for a large watershed. However, a recent development of rainfall measuring instrument, NEXRAD, is expected to provide a great advance in H/WQ modeling, especially for the distributed approach. The US National Weather Service (NWS) has deployed over 120 WSR-88D (Weather Surveillance Radar, 1988-Doppler) radars, also known as NEXRAD radars (DeBarry et al., 1999). The NEXRAD radars provide the 48 contiguous United States with continuous
radar coverage below 3000 m above sea level, except where rising terrain occludes low
elevation angle scans (DeBarry et al., 1999). This improvement of rainfall measuring
technique represents a significant advance in hydrology (Hudlow, 1988; DeBarry et al.,
1999). In this sense, studies for improvement and development of a distributed modeling
approach that can incorporate the detailed spatial variation into H/WQ modeling will be
valuable for providing more accurate assessment and prediction.

The temporal distribution of precipitation, especially rainfall, in a storm may
appear random (Ward et al., 2004). Typical rainfall patterns for a storm can be roughly
classified into four types: uniform, advanced, intermediate, and delayed (Schwab et al.,
1993). These patterns of rainfall may significantly affect temporal variation of runoff rate
in a storm. For example, if the rainfall amount is constant, the delayed rainfall may cause
higher peak runoff than the advanced. Relatively small rainfall amounts at low intensity
in the beginning of the delayed rainfall may mainly fill the soil’s moisture capacity by
infiltration, and then the larger amount of rainfall at high intensity in the end of the
rainfall will contribute to the generation of runoff. In the study with hypothetical rainfall
and a distributed watershed model, Krajewski et al. (1991) found that temporal resolution
of rainfall data considerably affected the simulated flow for a watershed of 7.5 Km² while
its spatial sampling density did not. Ogden et al. (1993) investigated sensitivity of the
CASC2D modeling outputs against rainfall spatial and temporal variability. In the
numerical experiment, they found that modeling output was more sensitive to spatial
variation of rainfall when rainfall duration was shorter than time to equilibrium of
watershed. On the other hand, it was more influenced by temporal variation of rainfall
when rainfall duration was longer than time to equilibrium.

Rainfall intensities of storm events in a short period, such as ten minutes or an
hour, are usually averaged into a more coarse time intervals like an hour or a day (Ponce,
1989). Alternatively, if rainfall is recorded in a coarser time interval than the temporal
resolution of modeling, rainfall may be interpolated by appropriate techniques. Several
authors such as Huff (1967), Pilgrim and Cordery (1975), Yen and Chow (1980), and
USDA SCS (1986) proposed methods to design hyetographs for storm events (Chow et
al., 1989).
Rainfall is also moving in a storm event and then amount of rainfall varies spatially and temporally. Yen et al. (1969) demonstrated the importance of the storm movement on the time distribution of surface runoff using an impervious hypothetical watershed of 1024 ft², 2 rainfall intensities, 4 slopes, and 14 velocities of storms. Singh (1998) derived analytical solutions to describe flow on an impervious plane using kinematic wave theory when a storm is moving downstream or upstream. From the derived equations, they concluded that a storm moving downstream produces a higher peak and a steeper hydrograph than does one moving upstream, and peak discharge and time to peak are a function of storm velocity. In the numerical experiments using one and two-dimensional distributed models, CASC and CASC2D, Ogden et al. (1995) observed considerable change in the simulated peak discharge when unique storms in size were moving in different directions. They also found that storm movement most significantly influenced on the peak runoff when the storm speed was close to a half of slope length divided by time to equilibrium.

De Lima et al. (2002) investigated impact of velocity and temporal distribution as well as direction of moving storm on peak discharge, time to peak, and base time using a non-linear kinematic wave model and hypothetical storms. They observed that storms moving upstream tended to produce early rise, low peak discharge, mild rising limb, and long base time, and storms moving downstream had the opposite effect. In addition, the numerical experiment showed that the way Ogden et al. (1995) synthesized equivalent moving storms provided significantly larger differences in the simulated time to peak and peak discharge than did the definition by Yen et al. (1969). De Lima et al. (2003) also conducted a laboratory experiment with a moving sprinkler and impermeable overland flow plane in order to assess impact of velocity and direction of moving storms on runoff response. Their laboratory experiment confirmed the conclusions De Lima et al. (2002) made from their numerical experiment and showed that variation in peak discharge were greatest when storm velocity was equal to the mean overland flow velocity.

Chaubey et al. (1999a; 1999b) investigated changes in the calibrated parameters values caused by spatial variability of rainfall using a distributed model and a network of 17 rain gauges. In the study, they found large variations of the calibrated CN, the retention parameter, land slope, and erodibility factor of Universal Soil Erosion Equation
(USLE) when different storms that have unique spatial variability were used for Agricultural Non-Point Source Pollution Model (AGNPS) modeling. From the results, they concluded that a larger range in the rainfall amount within a single event resulted in a higher uncertainty even in distributed modeling and suggested incorporation of spatial variability of rainfall for better accuracy of H/WQ modeling.

### 2.3 Evapotranspiration

Evapotranspiration (ET) is conversion of water to vapor and the movement of that vapor into the atmosphere (Haan et al., 1982). It is the process for returning water in the ground to the atmosphere and completes the hydrologic cycle (Ward et al., 2004). Thus, ET plays a crucial role in governing soil moisture, and together with infiltration must be considered in continuous hydrologic modeling to simulate surface and subsurface runoff correctly. ET is usually assumed to have a dominant effect on soil water content during events between rainfalls, while infiltration is controlling the soil water content during the events.

Two main factors in the evaporation process are the source of energy to supply the latent heat of vaporization, typically solar radiation, and a concentration gradient in the water vapor, which is measured by the difference of vapor pressures between the soil surface and air adjacent to the surface (Ward et al., 2004). Air movement removes the water vapor from the air layer adjacent to the surface so that the vapor pressure of the air is lower than that of the soil surface; therefore, the moisture usually moves from the soil surface to the atmosphere. However, because the soil moisture is finite, the evaporation will stop when the soil surface no longer has soil water that can evaporate into the air by the difference of the vapor pressures. Thus most of the developed equations for estimating ET or evaporation have terms related to these driving forces and limiting factors such as source of energy (solar radiation), air temperature, air movement (wind), vapor pressure (humidity), available soil moisture in the soil, and plant type.

Typical strategy to estimate ET is first to determine a potential ET based on meteorological factors and then adjust the potential ET into an actual ET with consideration for plant and soil characteristics (Haan et al., 1982). “The potential ET
(PET) is usually defined as an atmospheric determined quantity, which assumes that the ET flux will not exceed the available energy from both radiant and convection sources” (Haan et al., 1982). It also can be defined as the amount of ET that would occur when there is unlimited water available (Ward et al., 2004). Actual ET (AET) and PET can be measured by instruments such as evaporation pan and lysimeter. They can be estimated by equations based on physically driven concepts and equations like water and energy balance, mass transfer, aerodynamics, temperature based methods and their combinations.

In 1802, Dalton showed that the main driving force of evaporation is vapor pressure deficit (Ward et al., 2004) and expressed evaporation rate as multiplying vapor pressure deficit and wind function like the following equation (Equation 2.1) (Singh et al., 1997; Ward et al., 2004; Dodds et al., 2005).

\[ E = f(u)(e_s - e_a) \]  

where \( E \) is evaporation rate (in/mo), \( f(u) \) is a wind function, \( e_s \) is vapor pressure at the evaporating surface or saturation vapor pressure of air at the water temperature at 1ft deep, \( e_a \) is vapor pressure of the air (in of mercury)

Meyer (1915) developed an empirical equation (Equation 2.2) for estimating monthly evaporation from lakes or reservoir based on the Dalton equation (Ward et al., 2004). It is necessary to notice that these equations have been formulated for estimating evaporation from open water surface.

\[ E = C(e_s - e_a)\left(1 + \frac{u_{25}}{10}\right) \]  

where \( C \) is a wind coefficient, 11 for small lakes and reservoir, and 15 for shallow ponds, \( u_{25} \) is average wind speed at a height of 25 ft above the lake, or surrounding land areas.

An evaporation pan is one of the oldest and simplest ways for estimating the potential evaporation (Haan et al., 1982; Ward et al., 2004). The US Weather Bureau Class A pan, which is a metal pan 122cm in diameter, 25cm high, and mounted with its bottom about 10 cm above the ground surface, is well known (Haan et al., 1982). After measuring the water level deficit of the pan, PET is estimated by multiplying a pan coefficient because evaporation for a pan is generally more than that from a well-wetted
vegetated surface due to the pan’s excessive exposure and lower reflectance of solar radiation (Haan et al., 1982). The relationship between the pan evaporation and PET is represented in Equation 2.3.

\[ ET_{pt} = k_p E_{pan} \]  

where \( ET_{pt} \) is PET, \( k_p \) is a pan coefficient, and \( E_{pan} \) is evaporation from the pan.

The potential evapotranspiration was originally defined by Penman (1956) as “the amount of water transpired in unit time by a short green crop, completely shading the ground, of uniform height and never short of water” (Ward et al., 2004). In his definition for PET, the term “short green crop” seems vague. Some studies such as Wright et al. (1972) have used alfalfa and grasses to measure PET in practice (Wootton et al., 1996). This variation causes confusion; and even use of the term, “potential evapotranspiration” has been strongly discouraged due to its ambiguous definition and difficulty to measure and apply at the field (Wootton et al., 1996; Allen et al., 2004). In order to avoid this confusion, Jensen et al. (1990) introduced the term “reference crop evapotranspiration”, defined as “the rate at which water, if available, would be removed from the soil and plant surface of a specific crop” (Ward et al., 2004). Therefore, the equation for the relationship between pan evaporation and the PET can be transformed into Equation 2.4 (Allen et al., 2004). The pan coefficient, \( k_p \), is dependent on the pan type (Wootton et al., 1996) and Allen et al. (2004) provided various equations of \( k_p \) for different round cover, fetch, and climate condition. From here, the reference crop evapotranspiration is assumed a synonym of the PET in this study.

\[ ET_{tr} = k_p E_{pan} \]  

where \( ET_{tr} \) is reference evapotranspiration, \( k_p \) is a pan coefficient, and \( E_{pan} \) is evaporation from the pan (Allen et al., 2004).

Then actual ET (AET) is found by multiplying the reference crop ET by crop and soil coefficients like Equation 2.5.

\[ ET_a = k_c ET_{pt} = k_c ET_{tr} = k_c k_p E_{pan} \]  

where \( ET_a \) is AET, \( ET_{pt} \) is PET, \( k_c \) is a crop coefficient (0.2 \( \leq k_c \leq 1.3 \)).
The actual evapotranspiration can also be estimated by physical concepts and equations. One of the simple methods is the water balance approach (Wootton et al., 1996) and it is expressed in the equation below. In this method, the evaporation is calculated as a residual. Therefore if one measure or calculate precipitation, runoff, groundwater, and soil water change, actual evapotranspiration can be estimated from the water balance equation as:

\[ ET_a = P - Q \pm \Delta G \pm \Delta \theta \]  

where \( P \) is precipitation, \( Q \) is runoff, \( \Delta G \) is groundwater inflow or outflow, \( \Delta \theta \) is soil water change (all units are in depth).

Another basic method for estimating ET is the energy balance approach (Equation 2.7). It calculates PET based on the vertical energy budget of a vegetated surface under the assumption that energy is a limiting factor when soil water is sufficient (Haan et al., 1982). Thus, the horizontal components are usually neglected (Haan et al., 1982). While it is the most data intensive method, this procedure can be applied to wide range of problems (Wootton et al., 2004). The energy received from the sun is substituted as solar radiation in this approach (Haan et al., 1982; Wootton et al, 1996).

\[ R_n = R_s - \alpha R_s + R_{l,in} - R_{l,out} = H + LE + S + X \]  

where \( R_n \) is net radiation, \( R_s \) is incoming short wave radiation (solar radiation), \( \alpha \) is albedo, \( R_{l,in} \) is incoming long wave radiation, \( R_{l,out} \) is outgoing long wave radiation, \( H \) is energy convected from the water or vegetated ground surface as sensible heat, \( L \) is latent heat of vaporization (cal/cm\(^3\) or cal/g), \( E \) is a depth of evaporative water (cm\(^3\)/cm\(^2\)/min), \( LE \) is latent heat of water vapor, \( S \) is soil heat, \( X \) is miscellaneous heat sinks such as plant and air heat storage, and photosynthesis (all units are in MJ/m\(^2\)/d or cal/cm\(^2\)/min except for \( L \) and \( E \)).

The relation between the net radiation and PET is employed in several methods, such as the Jensen-Haise method to estimate PET (Haan et al., 1982). Jensen et al. (1963) developed an empirical equation (Equation 2.8) to estimate PET of a full cover crop like alfalfa based on radiation and temperature for a short period such as 5 days to 10 days (Jensen et al., 1963).
\[ PET = (0.025T + 0.078)R_s \]

where \( PET \) is potential ET (for 30-50 cm alfalfa, cm/d), \( T \) is mean air temperature, and \( R_s \) is solar radiation (cm/d).

Air temperature is one of the driving factors for evaporation and is readily available climate data (Haan et al., 1982). Although solar radiation is a main source of energy that vaporizes soil moisture, data is often limited because instruments are not available to measure solar radiation (Ward et al., 2004). Thus, alternative models use simplifications such as the Blaney-Criddle, which assumes that mean monthly air temperature and percentage of annual daytime hours can be used instead of solar radiation to provide an estimate of the energy received by the crop (Ward et al., 2004). A monthly consumptive use factor is defined and then actual ET (AET) for the season is calculated by multiplying the seasonal consumptive use coefficient for a crop with a normal growing season with the summation of the monthly consumptive use factors (Equations 2.9 and 2.10). Here the term “consumptive use” has the same meaning as the “evapotranspiration” for all practical purposes because the amount of water retained by plants is usually insignificant when compared to evapotranspiration (Jensen, 1968).

\[ U = K \sum_{i} f_i \]

where \( U \) is seasonal consumptive use (in/season), \( K \) is seasonal consumptive use coefficient for a crop with a normal growing season.

\[ f = \frac{tp}{100} \]

where \( t \) is mean monthly air temperature (Fahrenheit), \( p \) is mean percentage of annual daytime hours.

The Blaney-Criddle method has been widely applied for irrigation designs in the western US (Haan et al., 1982) and it can be used to obtain monthly estimates if monthly crop coefficients are locally available using Equation 2.11 (Haan et al., 1982; Ward et al., 2004).
\[ u = Kp \frac{45.7t + 813}{100} \]  
where \( u \) is consumptive use (mm/month), and \( t \) is monthly air temperature (°C).

The Blaney and Criddle method needs two types of meteorological data: air temperature and daytime hours. In the case hourly data are not available, an alternative can be the Thornthwaite method. Thornthwaite (1948) developed an empirical equation (Equation 2.12) to estimate monthly evapotranspiration from only mean temperature. Although the small amount of data needed is a beauty of this method, it should be used with caution because it was empirically derived based on temperature data that of course represents specific (Ward et al., 2004).

\[ E_{p} = 16 \left( \frac{10T}{I} \right)^a \]  
where \( E_{p} \) is monthly PET, \( T \) is mean monthly temperature (°C), \( a \) is a location dependant coefficient (\( a = 6.75 \times 10^{-7} I^3 - 7.71 \times 10^{-5} I^2 + 1.792 \times 10^{-2} I + 0.49239 \)), and \( I \) is a heat index (\( I = \sum_{j=1}^{12} \left( \frac{T_j}{5} \right)^{1.514} \)).

The methods previously reviewed do not consider the aerodynamic impact of removing the water vapor near the evaporating surface even though wind is one of the most crucial factors in the evapotranspiration mechanism. Penman (1948) first combined energy balance approach and aerodynamic mechanism into an equation (Equation 2.13) for estimating evaporation from open water surface (Wootton et al., 1996; Allen et al., 2004).

\[ LE = \frac{\Delta(R_n - G) + \gamma E_a}{\Delta + \gamma} \]  
where \( LE \) is latent heat of water vapor (MJ/m²/d), \( L \) is latent heat of vaporization, \( E \) is a depth of evaporated water, \( \Delta \) is slope of the saturation vapor pressure curve at temperature \( T_a \) (KPa/°C), \( R_n \) is net radiation, \( G \) is soil or water heat flux density (MJ/m²/d), \( \gamma \) is a psychometric constant (KPa/°C), \( E_a \) is bulk aerodynamic expression containing an empirical wind function.
\[ E_a = 6.43(a_w + b_w u_z)(e_a^0 - e_z) \]  \hspace{1cm} 2.14

where \( a_w \) and \( b_w \) are empirical wind function coefficients, \( u_z \) is wind speed at the \( z \) height (m/s), \( e_a^0 \) is saturation vapor pressure at temperature \( (T_a) \), \( e_z \) is vapor pressure at the height \( z \). Further,

\[ \Delta = 0.2(0.00738T + 0.8072)^2 - 0.000116 \]  \hspace{1cm} 2.15

where \( T \) is mean temperature (°C),

\[ \gamma = \frac{c_p P}{0.622 L} \]  \hspace{1cm} 2.16

where \( c_p \) is specific heat of the air at constant pressure (1.01 KJ/kg/°C),

\[ P = 101.3 - 0.01055H, \quad H \] is elevation above sea level (m), \( L = 2.501 - 2.361 \times 10^{-3}T \).

\[ G = 4.2 \frac{T_{i+1} - T_{i-1}}{\Delta t} \]  \hspace{1cm} 2.17

when the mean air temperature for the time period before and after the period of interest is known.

Although the Penman method was a great advance in evapotranspiration estimation methods in terms of combining radiation and wind mechanism, it did not take a surface resistance into account (Haan et al., 1996; Ward et al., 2004). Monteith (1965) added a term that accounts for vapor movement resistance from the evaporating surface (Haan et al., 1996). His modified equation is called the Penman-Monteith equation (Equation 2.18) (Ward et al., 2004; Allen et al., 2004; Sumner et al., 2005).

\[ LE = \frac{\Delta(R_n - G) + \rho_a c_p (e_a^0 - e_z)}{r_s + \gamma \left( 1 + \frac{r_z}{r_a} \right)} \]  \hspace{1cm} 2.18

where \( \rho_a \) is mean air density at constant pressure. The resistance terms, \( r_s \) is bulk surface resistance, \( r_a \) is bulk aerodynamic resistances, are further defined as
where \( z_w \) is height of wind measurements (m), \( z_h \) is height of humidity measurements (m), \( d \) is zero plane displacement height (m), \( z_{ow} \) is roughness length governing momentum transfer (m), \( z_{oh} \) is roughness length governing transfer of heat and vapor (m), \( K \) is Karman’s constant (0.41), \( u_z \) is wind speed at height \( a \), \( r_i \) is bulk stomatal resistance of the well-illuminated leaf (s/m), and \( \text{LAI}_{\text{active}} \) is an active leaf area index (m\(^2\)/m\(^2\)).

An open water surface has been proposed as a reference surface in the past even though differences between the open water and vegetated surfaces exist (Allen et al., 2004). Relating \( ET_p \) to a specific crop has the advantage of incorporating the biological and physical processes involved in \( ET \) from cropped surfaces (Allen et al., 2004). Thus, the FAO Expert Consultation on Revision of FAO Methodologies for Crop Water Requirements accepted the definition for the reference surface of “a hypothetical reference crop with an assumed crop height of 0.12m, a fixed surface resistance of 70 s/m and albedo of 0.23” (Allen et al., 2004). Based on this definition, the FAO Penman-Monteith method was developed to overcome shortcomings of the Penman method and to provide more consistent values with data of actual crop water use worldwide (Allen et al., 2004). The formulation of the FAO Penman-Monteith is,

\[
ET_{tr} = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_2 + 273} u_z (e_a^0 - e_z)}{\Delta + \gamma(1 + 0.34u_z)}
\]

where \( T_2 \) is mean daily air temperature at 2 m height, and \( u_z \) is wind speed at 2 m height.

Priestley and Taylor (1972) simplified the Penman-Monteith method by introducing a local parameter (Equation 2.22) (Castellvi et al., 2001). Thus, the Priestley-Taylor method does not require wind speed and humidity data to estimate evaporation from extensive wet surface under conditions of minimum advection (Sumner et al., 2005).
This method simulates conversion of about 90% of the net radiation into latent heat and 10% into sensible heat (Dodds et al., 2005).

\[ LE = \alpha \frac{\Delta(R_e - G)}{\Delta + \gamma} \]  \hspace{1cm} (2.22)

where \( \alpha \) is a location factor (1.26 for both water and wetland surfaces, 1.28 for crops in humid areas).

Hargreaves (1985) proposed an empirical equation that just employs temperature and extraterrestrial radiation data to estimate the potential evapotranspiration (Hargreaves et al., 1985; Hargreaves et al., 2003). Thus, this equation may be very useful in the cases of missing solar radiation, relative humidity, and/or wind speed data. However, it is reported that the equation has a tendency to underpredict in high wind conditions and to overpredict under conditions of high relative humidity (Allen, 2004; Trajkovic, 2007). The Hargreaves equation is expressed as:

\[ ET_{tp} = 0.0023(T_{mean} + 17.8)(T_{max} - T_{min})^{0.5} R_e \]  \hspace{1cm} (2.23)

where \( T_{mean} \) is mean daily temperature (°C), \( T_{max} \) is the maximum daily temperature (°C), \( T_{min} \) is the minimum daily temperature (°C), and \( R_e \) is extraterrestrial radiation with units of MJm\(^{-2}\)day\(^{-1}\) or MJm\(^{-2}\)hour\(^{-1}\), and is determined from,

\[ R_e = \frac{24(60)}{\pi} G_{SC} d_r \left[ \omega_s \sin(\varphi)\sin(\delta) + \cos(\varphi)\cos(\delta)\sin(\omega_s) \right] \]  \hspace{1cm} (2.24)

where \( R_e \) is daily extraterrestrial radiation (MJm\(^{-2}\)day\(^{-1}\)), \( G_{SC} \) is a solar constant (0.0820 MJm\(^{-2}\)min\(^{-1}\)), \( d_r \) is the inverse relative distance Earth-Sun, \( \omega_s \) is a sunset hour angle (rad), \( \varphi \) is latitude (rad), \( \delta \) is solar declination (rad)

\[ d_r = 1 + 0.033\cos\left(\frac{2\pi}{365} J\right) \]  \hspace{1cm} (2.25)

where \( J \) is the number of the day in the year between 1 for Jan 1\(^{st}\) and 365 or 366 for Dec 31\(^{st}\).

\[ \delta = 0.409\sin\left(\frac{2\pi}{365} J - 1.39\right) \]  \hspace{1cm} (2.26)
\[ \omega_s = \frac{\pi}{2} - \arctan\left(\frac{-\tan(\varphi)\tan(\delta)}{X^{0.5}}\right) \] 
\[ X = 1 - \tan^2(\varphi)\tan^2(\delta) \]

2hen \( X \leq 0 \), \( X = 0.00001 \).

For hourly periods, extraterrestrial radiation is calculated as,

\[ R_a = \frac{12(60)}{\pi} G_{sc} \left( \left( \omega_2 - \omega_1 \right) \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) \left( \sin(\omega_2) - \sin(\omega_1) \right) \right) \]

\[ \omega_1 = \omega - \frac{\pi_1}{24} \quad \omega_2 = \omega + \frac{\pi_1}{24} \]

where \( \omega \) is a solar time angle at midpoint of hourly period (rad), and \( t_1 \) is the length of the calculation period (hour), and

\[ \omega = \frac{\pi}{12} \left[ \left( t + 0.06667(L_c - L_m) + S_c \right) - 12 \right] \]

where \( t \) is standard clock time at the midpoint of the period (hour), \( L_c \) is longitude of the center of the local time zone (degrees west of Greenwich), \( L_m \) is longitude of the measurement site (degree of west of Greenwich), and \( S_c \) is seasonal correlation for solar time (hour), expressed as,

\[ S_c = 0.1645\sin(2b) - 0.1255\cos(b) - 0.025\sin(b) \]

where

\[ b = \frac{2\pi(J - 81)}{364} \]

All of these methods for estimating potential evapotranspiration consider evaporation and transpiration together at the same time so that the result represents the combined effects of transpiration from plants and evaporation from the soil surface. Allen et al. (1994; 1998; 2004) proposed the dual crop coefficient method for estimating actual evaporation and transpiration from soil and vegetation separately, which is also called FAO-56 method, to improve accuracy of the estimation. In the method, two new coefficients are introduced: the basal crop and the soil evaporation coefficient. The former represents the ratio of ET for a specific crop to the reference ET when the soil is
dry, where the average soil water content of the root zone is adequate to sustain full plant
transpiration so that small amounts of evaporation from the soil surface are included
(Allen et al., 2005). However, most of the evaporation from the soil surface followed by
rainfall or irrigation is considered separately in the soil evaporation coefficient. The
relationship among these coefficients is,

\[ k_{ca} = k_{cb} + k_e \]  

2.33

where \( k_{ca} \) is an actual crop coefficient that includes any effects of environmental stresses,
\( k_{cb} \) is a basal crop coefficient, \( k_e \) is a soil evaporation coefficient

\[ k_{cb} = k_{cb(std)} + (0.04(u_2 - 2) - 0.004(RH_{\text{min}} - 45))(h/3)^{0.3} \]  

2.34

where \( k_{cb(std)} \) is a basal crop coefficient (given in Table 17 of FAO-56 manual), \( u_2 \) is
mean daily wind speed at 2 m height (m/s), \( RH_{\text{min}} \) is mean daily minimum relative
humidity (%), \( h \) is mean plant height

\[ k_e = \min(k_r(k_{e,\text{max}} - k_{cb}), f_{ew} \cdot K_{c,\text{max}}) \]  

2.35

where \( k_e \) is a soil evaporation coefficient, \( k_{cb} \) is a basal crop coefficient, \( k_{c,\text{max}} \) is the
maximum value of \( k_e \) following rain or irrigation, \( k_r \) is a dimensionless evaporation
reduction coefficient dependent on the cumulative depth of water depleted or evaporated
from the topsoil, \( f_{ew} \) is a fraction of the soil that is both exposed and wetted or fraction of
soil surface from which most evaporation occurs.

\[ k_{e,\text{max}} = \max\left(1.2 + (0.04(u_2 - 2) - 0.004(RH_{\text{min}} - 45))(h/3)^{0.3}, K_{cb} + 0.05\right) \]  

2.36

\[ k_r = \frac{TEW - D_{e,\text{day}-1}}{TEW - REW} \]  

2.37

when \( D_{e,\text{day}-1} > REW \)

and when \( D_{e,\text{day}-1} = REW \), then \( k_r = 1 \).
**TEW** is the total evaporable water or maximum depth of water that can be evaporated from the soil when the topsoil has been initially completely wetted (mm), $D_{e,\text{day}-1}$ is a cumulative depletion of soil water from the soil surface at the previous day (mm, $0 \leq D_{e,\text{day}-1} \leq TEW$), **REW** is readily evaporable water (mm)

$$TEW = 1000(FC - WP)Z_e$$  \hspace{1cm} 2.38

where $FC$ is soil water content at field capacity (%), $WP$ is soil water content at wilting point (%), $Z_e$ is depth of the surface soil layer that is subject to drying by way of evaporation (0.10-0.15 m).

$$f_{ew} = \min(1 - f_c, f_w)$$  \hspace{1cm} 2.39

where $1 - f_c$ is average exposed soil fraction not covered by vegetation (0.01 – 1), $f_w$ is average fraction of soil surface wetted by rainfall (0.01 – 1), and when $f_c$ is not measured:

$$f_c = \left( \frac{k_{ch} - k_{c,\text{min}}}{k_{c,\text{max}} - k_{c,\text{min}}} \right)^{1+0.5h}$$  \hspace{1cm} 2.40

This approach was developed to estimate the actual evapotranspiration under the ideal or standard surface condition, where unlimited evaporable water is available such as an open water surface and/or a well-watered crop. However, in reality, the evaporation and transpiration are limited by the soil water content. Although the dual crop coefficient under the standard condition can consider soil moisture condition when estimating soil evaporation, it does not account for depletion of plant transpiration by soil water stress. For this, a water stress coefficient, $k_s$ was introduced in the dual crop coefficient method (Equations 2.41 to 2.43).

$$k_s = \frac{TAW - D_r}{TAW - RAW}$$  \hspace{1cm} 2.41

when $D_r > RAW$, and when $D_r = RAW$, then $k_s = 1$. 
Here, $TAW$ is the total available soil water in the root zone (mm), $D_r$ is soil water depletion in the root zone (mm, $1 \leq D_r \leq TAW$), $RAW$ is readily available soil water in the root zone (mm).

$$TAW = 1000(FC - WP)Z_r$$

where $Z_r$ is rooting depth (m)

$$RAW = p \times TAW$$

where $p$ is average fraction of total available soil water ($0 - 1$)

There are quick and simple approaches to estimate AET with consideration of soil moisture content for small watersheds. Jensen et al. (1971) proposed a method that incorporates soil moisture depletions after rain or irrigation in determining a crop coefficient such as,

$$tp_c E_k E = 2.44$$

where $c_k$ is a coefficient representing the combined effects of the resistance of water movement from the soil to the various evaporating surfaces, expressed as

$$k_c = k_{co} k_a + k_s$$

where $k_{co}$ is mean crop coefficient based on experiment data where soil moisture was not limiting, $k_a$ is a coefficient related to soil moisture which is equal to $\ln(AM + 1)/\ln(101)$, $AM$ is remaining available soil moisture, $k_s$ is coefficient for soil evaporation which increase when the soil surface is wetted and equals to $(0.9 - K_c)$ times 0.8, 0.5, and 0.3 for day 1, 2, and 3 after a rain.

Haan (1972) simulated daily AET with consideration of the maximum and available soil moisture (Equation 2.46).

$$E = E_{tp} \frac{M}{C}$$

where $E_{tp}$ is PET by the Thornthwaite method (mm/d), $M$ is available soil moisture (mm), $C$ is the maximum available soil moisture (mm). Ritchie (1972) composed a
series of equations to represent actual ET beginning with the Penman equation to define potential ET, then separately calculated soil and plant evaporation.

2.4 Infiltration

Infiltration is downward movement of water into the soil below the land surface driven by gravitational forces and tension in the soil matrix (Ponce, 1989; Ward et al. 2004). These tension forces are also known as suction or capillary force and are inversely proportional to the diameter of pores (Novotny, 2003). When sandy soil becomes saturated, gravitational forces are the primary cause of infiltration. On the other hand, infiltration for dry clay soils is primarily due to capillary suction force (Novotny, 2003). Infiltration rate is a function of permeability of soils, soil moisture content, vegetation cover, water viscosity, conditions of the soil surface, and possibly other factors (Novotny, 2003; Ward et al., 2004). These factors also depend on soil characteristics and conditions such as soil texture, soil structure, organic material content, soil fauna activity, soil profile, antecedent soil moisture, frozen soil, soil surface roughness, compaction, temperature (in terms of water viscosity), water quality, hydraulic depth, urbanization, and time (Haan et al., 1983; Ward et al., 2004). Darcy (1856) found that saturated flow rate in porous materials is directly proportional to the hydraulic gradient as in Equation 2.47 (Haan et al., 1982; Akan et al., 2003):

$$ q_z = -K \frac{\partial H}{\partial z} $$  \hspace{1cm} 2.47

where $q_z$ is flow or volume of water moving through the soil in the $z$ direction per unit area per unit time (m$^3$/m$^2$/s), $K$ is hydraulic conductivity (m/s), $H$ is total potential head ($H = h - z$, $h$: hydraulic pressure head (m), and $z$ is distance measured positively downward from the surface (m)).

The hydraulic conductivity is defined as soil’s ability of transmitting water under a unit hydraulic gradient (Ward et al., 2004). Although it is often called “permeability” (Ward et al., 2004), theoretically it is a function of the fluid itself such as dynamic viscosity and specific weight as well as characteristics of porous media (permeability) (Novotny, 2003).
If hydraulic pressure head is positive, a soil becomes saturated (water content is constant) and then the hydraulic conductivity will be constant regardless of magnitude of the hydraulic pressure head (Haan et al., 1982). However, if a soil is heterogeneous and/or unsaturated, the hydraulic conductivity will vary spatially depending on soil water content (Haan et al., 1983; Ward et al., 2004). In addition, since soil water content is a function of the hydraulic pressure head, hydraulic conductivity will be determined with the hydraulic pressure head and soil water content. Although soil water content also depends on the wetting and drying history as well as the hydraulic pressure head (Haan et al., 1983), the hysteresis effect is usually ignored when hydraulic conductivity is expressed as a function of the pressure head (Haan et al., 1983; Ward et al., 2004). By combining the Darcy equation with the principle of conservation of mass for the soil water system, the Richard equation, which explains water movement mechanism in the vertical direction for unsaturated flow, can be obtained (Richard, 1931; Haan et al., 1983; Ward et al., 2004). However, it is difficult to solve the Richard equation analytically due to the nonlinear relationship between the hydraulic conductivity, hydraulic pressure head, and soil water content (Haan et al., 1983; Celia et al., 1990; El-Hames et al., 1995; Akan et al., 2003; Ward et al., 2004). When soil is saturated with water, the Richard equation will reduce to the Laplace equation (Equations 2.48 to 50) because the gradient of soil water content will become zero (due to constant soil water content), the hydraulic conductivity will reach a constant, and the hydraulic pressure head will become positive (Haan et al., 1983; Ward et al., 2004). Then it can be solved by numerical techniques such as the finite difference or element methods (FDM or FEM) (Ward et al., 2004).

\[
\frac{\partial \theta}{\partial t} = -\frac{\partial q_z}{\partial z} \tag{2.48}
\]

where \( \theta \) is volumetric soil water content (m\(^3\)/m\(^3\)). Written as a function of \( h \)

\[
\frac{\partial \theta}{\partial t} = \frac{\partial \theta}{\partial h} \frac{\partial h}{\partial t} = -\frac{\partial q_z}{\partial z} = -\frac{\partial}{\partial z} \left( -K(h) \frac{\partial H}{\partial z} \right) = \frac{\partial}{\partial z} \left( K(h) \frac{\partial(h - z)}{\partial z} \right) = \frac{\partial}{\partial z} \left( K(h) \frac{\partial h}{\partial z} \right) - \frac{\partial K(h)}{\partial z}
\]

\[
\ldots \ldots \tag{2.49}
\]

or as a function of \( \theta \):
\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left( K(h) \frac{\partial h}{\partial z} \right) - \frac{\partial K(h)}{\partial z} = \frac{\partial}{\partial z} \left( K(h) \frac{\partial \theta}{\partial z} \frac{\partial \theta}{\partial z} \right) - \frac{\partial K(h)}{\partial z} = \frac{\partial}{\partial z} \left( D(\theta) \frac{\partial \theta}{\partial z} \right) - \frac{\partial K(h)}{\partial z}
\]

where \( D(\theta) \) is soil water diffusivity.

The Richard equation is formulated based on physical theories that describe the relationship between soil water content and combination of gravitation and capillary forces. As previously mentioned, however, it is difficult to apply the equation in calculating infiltration rate because of complicated nonlinear relationships among variables. Several scientists and engineers have developed simple empirical methods for estimating infiltration. Kostiakov (1932) proposed one of the simplest and oldest infiltration equations (Haan et al., 1983). It assumes that the infiltration rate is decreasing inversely with time. Holton (1939) presented a three-parameter equation to calculate infiltration rate (Haan et al., 1983; Wootton et al., 1996). In his method, infiltration rate exponentially decreases with time from the maximum infiltration rate at the beginning of rainfall to the final constant infiltration rate at the end.

Philip (1957) utilized the first two terms of his solution in a form of the Taylor expansion for calculating infiltration rate on the ponded surface into a deep homogeneous soil (Haan et al., 1983; Wootton et al., 1996). The ponding effect on infiltration is explicitly considered in his method. Holtan (1961, 1975) developed an infiltration equation under the assumption that soil moisture storage, surface connected porosity, and the effect of root paths are the dominant factors influencing infiltration capacity (Wootton et al., 1996). Thus, plant growth, soil surface condition, and available soil water storage are incorporated into estimating infiltration rate in his method.

Green-Ampt (1911) proposed an approximate model for estimating infiltration rate utilizing Darcy’s law (Haan et al., 1983; Wootton et al., 1996). In the method, water is assumed to infiltrate into the soil as piston flow and to result in a sharply defined wetting front (Haan et al., 1983; Wootton et al., 1996). Mein and Larson (1973) developed a way to apply the Green-Ampt method to rainfall condition (Wootton et al., 1996) under three assumptions: (1) prior to the time ponding begins, all the rainfall is infiltrated, (2) the potential infiltration rate is a function of the cumulative infiltration,
and (3) ponding occurs when the potential infiltration rate is less than or equal to the rainfall intensity (Chow et al., 1988). All the mentioned infiltration models are presented in Table 2.2.

Table 2.2. Infiltration models.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Equations</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kostiakov</td>
<td>$f = Kt^{-\alpha}$</td>
<td>$K$, $\alpha$: constant depending on the soil and initial conditions</td>
</tr>
<tr>
<td>Horton</td>
<td>$f = f_c + (f_0 - f_c)e^{-\beta}$</td>
<td>$f_c$: final constant infiltration rate, $f_0$: infiltration rate at the beginning, $\beta$: soil parameter that controls the rate of decrease of infiltration rate</td>
</tr>
<tr>
<td>Philip</td>
<td>$f = 0.5St^{0.5} + K$</td>
<td>$S$: sorptivity, $K$: conductivity parameter</td>
</tr>
<tr>
<td>Holtan</td>
<td>$f = GI \cdot a \cdot SA^{1.4} + f_c$</td>
<td>$GI$: growth index of crop in percent of maturity, $a$: an index of surface connected porosity, $SA$: available soil water storage, $f_c$: steady state infiltration rate</td>
</tr>
<tr>
<td>Green-Ampt</td>
<td>$f = K_s(H_0 + S_w + L_f)L_f$</td>
<td>$K_s$: hydraulic conductivity of the transmission zone, $H_0$: depth of water ponded on the surface, $S_w$: effective suction at the wetting front, $L_f$: distance from the surface to the wetting front</td>
</tr>
</tbody>
</table>

2.5 Curve Number (CN) Method

2.5.1 Overview

The curve number method was developed in 1954 by the USDA SCS (Ponce, 1996) to calculate runoff volume for agricultural fields in the Midwestern United States (Mishra et al., 2003) and to design hydrographs. The method was formulated based on a water balance equation and two hypothetical equations such as the proportional equality and linear relationship between the initial abstraction and potential maximum retention like Equations 2.51 to 2.55 (Mishra et al., 2003). The CN method assumes that the depth of excess precipitation, $P - I_a$ or $P_e$, is always less than or equal to the depth of precipitation, $P$ and the additional depth of water retained in the watershed, $F$, is less
than or equal to the potential maximum retention, $S$ (Chow et al., 1988). The first hypothetical equation, proportional equality, says that the ratios of the two actual quantities (excess rainfall and water retention) to the two potential quantities (rainfall and the maximum retention) are equal to each other (Equation 2.52 and Figure 2.3) (Mishra et al., 2003). A water balance is expressed:

$$P = I_a + F + Q \quad 2.51$$

and the proportional relationship defined:

$$\frac{Q}{P - I_a} = \frac{F}{S} \quad 2.52$$

and for simplification, the following condition defined,

$$I_a = \lambda S, \quad \lambda = 0.2 \quad 2.53$$

Potential maximum retention, $S$, is expressed in terms of a scale parameter, CN, which can vary between 0-100 representing zero storage or 100% runoff.

$$S = \frac{25400}{CN} - 254 \quad 2.54$$

Then direct runoff, $Q$, can be expressed as

$$Q = \frac{(P - I_a)^2}{P - I_a + S} = \frac{(P - 0.2S)^2}{P + 0.8S} \quad 2.55$$

where $P$ is total rainfall, $I_a$ is initial abstraction, $F$ is cumulative infiltration excluding $I_a$, $Q$ is excess rainfall or direct runoff volume, $S$ is potential maximum retention when runoff begins (all units are in depth, mm).
Some researchers (Hjelmfelt, 1991; Ponce, 1996; Fennessey et al., 2001; Mishra et al., 2003; Geetha et al., 2007) have pointed out limitations and cautions to use of the curve number method for estimating runoff. The concerns include the limited regional extent (midwestern) and landscape (agricultural) in which it was developed, weak physical basis, discontinuous and subjective Antecedent Moisture Condition (AMC), somewhat arbitrary selection of initial abstraction, applicable size of catchment is restrictive, ignores rainfall intensity and its temporal distribution, and does not consider temporal and spatial scale. It also does not consider runoff from snowmelt. Rallison et al. (1982) suggested that an alternative method be used to calculate runoff volume when a CN is less than 40 (Choi et al., 2002). In addition, Boughton (1989) stated, “the curve numbers were used as a proxy for the retention parameter $S$ in order to scale the curve to a convenient range between zero and one hundred.” Steenhuis et al. (1995) mentioned that the CN method does not require precipitation and infiltration rates to calculate runoff volume, as opposed to runoff rate. Hawkins (1979) found that the $I_a - S$ relationship, $I_a = 0.2S$ in the standard CN method did not provide good runoff estimation unless the retention parameter $S$ was dependent on rainfall amount (Steenhuis et al., 1995).
2.5.2 Runoff Generation Mechanisms and CN Method

There are two main approaches to describe runoff generation mechanisms in the overland flow: Hortonian and saturation overland flow (Dunne et al., 1970; Dune et al., 1983, 2002; Chow et al., 1988). Hortonian overland flow occurs when rainfall intensity exceeds infiltration rate, while saturation overland flow happens when soil moisture exceeds its holding capacity (Srinivasan et al., 2002). Thus, the Hortonian overland flow is common in arid and semi-arid landscapes where vegetation is not dense. On the other hand, the saturation overland flow is likely to occur in humid and healthily vegetated areas that have relatively high permeability and saturated hydraulic conductivity of soil (Fennessey et al., 2001) so that infiltration rate may be higher than rainfall intensity (O’Loughlin, 1981). Dune (1983) described characteristics and applicable situations of the runoff generation mechanisms as shown in Figure 2.4.

Figure 2.4. Runoff generation mechanisms (Dune, 1983).
Hewlett (1961) proposed a variable source area (VSA) concept based on runoff experiments implemented at hillslope-scale and, and Dunne and Black (1970) provided observation evidence supporting the concept from field studies (Dickinson et al., 1970; O’Loughlin, 1981). Its early history is well introduced by Dickinson et al. (1970). In the VSA concept, “storm runoff is generated by only a portion of the watershed and occurs first or most commonly around streams or areas where the water table and soil depth quickly cause saturation due to the lateral movement of soil water” (Fennessey, et al, 2001). In addition, it is recognized that for many storms the entire watershed is not contributing runoff, especially in humid regions like the North-Eastern USA (Engman, 1974; Fennessey et al., 2001; Walter et al., 2003; Agnew et al., 2006; Schneiderman et al., 2007). Walter et al. (2003) demonstrated a Hortonian approach is inadequate in representing runoff generation mechanism for undeveloped watersheds of New York City especially in winter using an empirical equation that describes fraction of the area with soil infiltration capacity greater than soil permeability.

Beven et al. (1979) developed a modeling framework to predict hydrographs at an outlet through simulating variable contributing areas within a watershed. In the study, they employed a topographic index, which Kirkby et al. (1975) proposed, in delineating saturated areas directly contributing to surface runoff at an outlet (Beven et al., 1979; Beven, 2001). Burt et al. (1985) compared the measurements of soil moisture distribution on hillslope with two topographic indices, the topographic or wetness index (Beven et al., 1979) and the plan curvature (Evans, 1980). He concluded that both indices are not satisfactory for predicting the changing pattern of soil moisture on the hill slope and a combined index is the most appropriate. Sivapalan et al. (1987) assumed that the water table is parallel to the soil surface to estimate downslope flow beneath a groundwater table in the method of Beven (1979). Franchini et al. (1996) examined validity of those assumptions in Topographic-based hydrological model (TOPMODEL) by analyzing the relationship between the output of the calibrated TOPMODEL and the topographic index curve. He found a certain correspondence of the topographic index with the variable contributing area. Agnew et al. (2006) tested applicability of indices such as a topographic index Kirkby et al. (1975) and Beven et al. (1979) proposed in describing hydrologically sensitive areas (HAS) by comparing spatial distribution of the calculated
indices with that of the averaged saturation probability map derived from distributed SMR (Soil Moisture Routing) modeling. They found better agreement of the topographic index with the simulated saturation probability map.

The CN method implicitly assumes the Hortonian mechanism (Schneiderman, et al, 2007). Garen et al. (2005) emphasized that the CN method was designed to predict direct runoff without consideration of which part of a watershed was contributing to generation of the runoff. However, Boughton (1987) speculated that the CN method has the ability to describe the spatially varied saturation overland flow because the initial abstraction, $I_a$, represents the minimum value of storage capacity of the watershed and the shape of the curves represent a pattern of variation in surface storage capacity. Steenhuis et al. (1995) incorporated the variable source area (VSA) concept into the CN method, and showed that the CN method can predict the contributing area correctly. He assumed that runoff occurs from areas that are saturated and the remainder does not contribute any runoff. Then he found that rate of runoff generation is proportional to fraction of the saturated watershed in two Australian and three U.S. watersheds. He also found that the modified CN method incorporated with the VSA concept did not provide good runoff estimations during high rainfall intensity over 4 cm/h during a thirty-minute interval because the high intensity might cause the Hortonian type runoff.

Schneiderman et al. (2007) reconceptualized the CN method for the VSA based on the study of Steenhuis et al. (1995) and incorporated it into the Generalized Watershed Loading Function (GWLF) model. The modified method did not consider spatial distribution of the variable saturated area in the watershed but only fraction of the saturated area according to a given rainfall amount. These two studies applied the reconceptualized CN method with the VSA concept in calculating runoff rate from the whole watershed in the lumped manner. Easton et al. (2008) tried to remodel the SWAT to simulate overland flow in ways consistent with the VSA concept by modifying methods to calculate CN and available water contents. He embedded the VSA concept into the SWAT model by redefining HRUs based on a soil topographic index (STI) class instead of slope with the Soil Survey Geographic Database (SSURGO) soil and land use
map. Then, runoff from a HRU can be calculated using the method Steenhuis et al. (1995) modified.

The Hortonian approach, in particular the CN method, is chosen in this research as a tool to describe runoff generation mechanism in the overland because this concept seems to be more suitable for simulating the overland flow and erosion usually caused by strong storm events. Only a few of the strongest storms in a year may cause very high discharge and severe erosion and produce most of the sediment in the watershed, so they should be a main concern in NPS modeling. On the other hand, the saturation overland flow looks more appropriate for simulating low stream flow (high frequency flow) and overland flow resulting from relatively small rainfall (Fennessey, 2001). Thus, the modified CN method Steenhuis et al. (1995) proposed will not be adopted in this study. The method is also not suitable for the distributed hydrologic modeling because it does not look reasonable to apply the method to an individual cell. Moreover, if a distributed model can simulate soil moisture variation and runoff processes reasonably and explicitly, the saturation overland flow over a watershed can be simulated correctly.

2.5.3 CN Method for Continuous H/WQ Modeling

Another issue arises when trying to apply the CN method in a continuous hydrologic modeling practice. Because the CN method was originally developed for computing excess rainfall from a storm (single rainfall event) (Chow et al., 1988), it does not account for temporal variability of CN according to variation in soil moisture. Thus, this limitation should be carefully considered when applying the CN method to a continuous hydrologic modeling practice that accounts for soil moisture redistribution. Some continuous models like Chemical, Runoff, and Erosion from Agricultural Management Systems (CREAMS) and SWAT adapted the CN method to calculate direct runoff volume. In the SWAT model, the retention parameter varies with temporal change of soil moisture as follows (Neitsch et al., 2002):

\[
S = S_{\text{max}} \left( 1 - \frac{SW}{SW + \exp(w_1 - w_2 \times SW)} \right)
\]  
2.56
where $S$ is the retention parameter for a given soil moisture content, $S_{\text{max}}$ is the maximum value the retention parameter can achieve on any given day, $SW$ is the soil moisture content of the entire soil profile excluding the amount of water held in the soil profile at wilting point, and $w_1$ and $w_2$ are shape coefficients.

The shape coefficients are determined by the following equation assuming that (1) the retention parameter for AMC1 corresponds to wilting point of soil profile water content, (2) the retention parameter for AMC3 corresponds to field capacity of soil profile water content, and (3) the soil has a CN of 99 ($S=25.4$ mm) when completely saturated.

\[
w_1 = \ln \left( \frac{FC}{S_3} - FC \right) \left( 1 - \frac{S_3}{S_{\text{max}}} \right) + w_2 \times FC \tag{2.57}
\]

\[
w_2 = \frac{\ln \left( \frac{FC}{S_3} - FC \right) - \ln \left( \frac{SAT}{S_{\text{max}}} - SAT \right)}{SAT - FC} \tag{2.58}
\]

where $FC$ is the amount of water in the soil profile at field capacity, $S_3$ is the retention parameter for a CN at AMC3, $S_{\text{max}}$ is the retention parameter for a CN at AMC1 (the maximum retention value), $SAT$ is the amount of water in the soil profile when completely saturated, and 2.54 is the retention value for a curve number of 99 (all units are in depth, mm).

After updating the retention parameter, a CN can be adjusted by the following equation.

\[
CN = \frac{25400}{S + 254} \tag{2.59}
\]

This formulation regards the retention parameter, $S$ as the available soil water storage capacity of the soil profile so that it may contain a physical meaning. Thus, the retention parameter can vary from the soil water storage capacity at wilting point (the maximum) to that at field capacity (the minimum). Then, a CN is inversely derived from
the adjusted retention parameter in the previous step. The description for variation of the retention parameter according to soil moisture content is represented in Figure 2.5.

Figure 2.5. Schematic diagram of the retention parameter and soil moisture content.

Choi et al. (2002) tried to simplify the nonlinear CN adjustment procedures used in the SWAT model by assuming that a CN varies linearly from a CN at AMC1 to a CN at AMC2 and a CN at AMC3. Geetha et al. (2007; 2008) modified the CN method to avoid sudden variation of a CN caused by the discrete AMC conditions so that a CN could be determined based on the antecedent moisture amount instead of the antecedent moisture condition. Williams et al. (1995) developed an equation to modify a CN for different slopes (Neitsch et al., 2002).

The CN method is popular because of several strengths like simple form, ease of application and understandability, small number of parameters (one or two parameters, CN and Ia), capability to consider the initial abstract (Ia), well-documented guide, and
many application experiences and data (Mishra et al., 2003). Another advantage of the CN method is that it can take account of antecedent moisture condition (AMC) and land use as well as soil characteristics (hydrologic soil group, HSG). Thus, the CN method enables the incorporation of land use change into H/WQ modeling explicitly. In this study, the CN method is selected as a method to calculate excess rainfall and the modification of the CN method in the SWAT model was adapted to take temporal variation of CN into account.

2.5.4 Distributed Modeling and CN Method

The CN method was developed to estimate direct runoff volume from not a field but a small agricultural watershed without consideration of path and source area of the flow. Thus, the CN implies direct deposition of rainfall on channel and quickly responding overland and subsurface flow (USDA-SCS, 1972; Garen et al., 2005). Garen et al. (2005) argued that validity of application of the CN method at a field scale, where channel and subsurface flow is not significant compared to overland runoff, must be questionable. However, contribution of the direct rainfall deposition and subsurface runoff to the runoff volume is usually insignificant in small size watersheds used in development of the CN method. Thus, some field-scale models such as CREAMS and the Environmental Policy Integrated Climate (EPIC) model employ the CN method in calculating direct runoff volume and many studies have applied the CN method to estimate excess rainfall volume of a hydrologic response unit or a cell in distributed hydrologic modeling.

Distributed modeling utilizes spatially distributed parameters over modeling units such as cells, hydrologic response units, or subwatersheds. When input data are provided at a finer scale than a unit of a distributed modeling, aggregation of the data would be necessary. Simple and area-weighted averaging are ways most commonly used for aggregation. However, if the relationship between input and output is nonlinear, then linear aggregation of the input data would result in output being over or under-estimated. A typical case is found in using linear aggregation to calculate direct runoff for a watershed based on a composite of the watershed where individual CNs represent the
multiple combinations of land cover and soil type. Because the CN method was formulated based on a concave nonlinear relationship between the CN and excess runoff, a weighted averaged CN always produces less excess runoff compared to an average where the individual excess runoff values are calculated for every CN (USDA-SCS, 1972; Grove et al., 1998).

Direct runoff volume is assumed equal to excess rainfall volume when the CN method is applied at a field scale or in grid-based distributed modeling. If it were used to calculate only excess rainfall contributing to direct runoff generated on an isolated field or cell, the assumption would be valid because rainfall is the only source of direct runoff there. However, a cell might have two sources of direct runoff, rainfall and routed runoff volume from upstream areas when distributed overland routing is utilized in distributed modeling. Thus, applicability of a traditional CN method should be limited when distributed overland routing is incorporated into a distributed modeling practice. Moglen (2000) reconceptualized the CN method so that it can account for not only direct deposition of rainfall on a cell of interest but also routed direct runoff volume from its upstream cells in calculating direct runoff volume generated on the cell in a grid-based distributed modeling. His modification of the CN method was not to provide a more reasonable way to calculate an areal average direct runoff volume at a point of interest within a watershed for distributed parameter modeling. However, the concept he proposed provided a clue about how to incorporate the CN method into distributed modeling with distributed overland routing.

2.6 Subsurface Flow

2.6.1 Overview

The study of surface water is incomplete without the knowledge of its interaction with subsurface water, including all water in both storage and flowing below the ground surface (Ponce, 1989). Usually two types of geological formulations, the vadose zone and aquifer, are considered in hydrologic modeling. The vadose zone, sometimes called the unsaturated zone, exists between the ground surface and the aquifer. The vadose zones
may vary in thickness from more than 100m on the upper slopes of alluvial fans that do not have faults to less than 1m along bands of effluent seepage bordering playas and deeply incised drainage channels (Wilson et al., 1994). The vadose zone plays several roles in terms of agriculture and water quality control, such as storage and a zone of transmission and filtering of water and substances (USGS, 2001). Thus, “the study of movement and distribution of water in unsaturated porous media is important as a naturally occurring process and in engineering design of soil barriers to the spreading of buried hazardous waste” (Gray et al., 1991).

The vadose zone consists of soil particles and pores filled with water and air. Thus, various forces such as capillary force, pressure, gravity, and vapor pressure gradient are factors in the movement of water in the vadose zone. In addition, interactions among them are known to be very complicated and nonlinear. Generally, the movement of water in the subsurface or vadose zone is subdivided into four categories according to the predominant forces involved and direction of movement: infiltration, percolation, capillary rise, and interflow (Eagleson et al., 1978; Varado et al., 2006).

In most of the studies of the unsaturated zone, the movement of water is assumed to obey the Richard equation (Zabra, 1990). As mentioned early, an analytical solution of the equation is difficult in complex cases due to the nonlinear relationship among variables so that it will be solved numerically (Haan et al., 1983; Celia et al., 1990; El-Hames et al., 1995; Akan et al., 2003; Ward et al., 2004). Thus, many approaches and schemes have been developed for solving the Richard equation.

Celia et al. (1990) investigated the numerical behavior of the Finite Element Method (FEM) and Finite Different Method (FDM) for unsaturated flow equations considering three standard forms -- the h- and θ-based equations, and mixed formulation. They concluded that the mixed form of the Richard equation is superior to the others and FEM that uses consistent formulations for the time matrix are generally inferior to FDM. El-Hames et al. (1995) tested the numerical difficulty in applying the Richard equation to determine infiltration and moisture redistribution in the unsaturated sandy and clay soils. In his research, the numerical difficulty was regarded as the required average number of iterations per time increment for the solution to converge. He found that it is relatively
difficult to simulate the soil that has more clay, deeper ponding on the surface, and less water content because of the nonlinear relationship between the absolute pressure head and soil moisture content.

Ross (2003) devised a fast and simple numerical method to solve the Richard equation for water transport based on the use of the Kirchhoff transformation that is used to convert a nonlinear equation to a linear one. He employed the soil hydraulic property description Brooks et al. (1964) proposed in order to relate soil moisture content to pressure head in the unsaturated soil, and then reformed time weightings in numerical iterative method to solve the Richard equation. Varado et al. (2006) compared the numerical solution Ross (2003) proposed with analytical solutions and another numerical solution of the SiSPAT model in a restricted condition. He found that the numerical method of Ross (2003) can provide an accurate solution of the one dimensional Richards equation even when soil moisture and surface ponding conditions quickly change, with any type of soil.

### 2.6.2 Unsaturated Hydraulic Conductivity

Soil properties like texture, structure, and organic matter content determine, in part, hydraulic conductivity. In a partially saturated soil, hydraulic conductivity is a function of soil water content as well as soil particle and pore size distribution. Thus, unsaturated hydraulic conductivity is usually regarded as being less than saturated hydraulic conductivity and more difficult to accurately measure (Durner, 1994). Many have proposed methods and models to estimate unsaturated hydraulic conductivity from saturated hydraulic conductivity and soil moisture content or an existing soil database. Gardner (1958) and Brooks et al. (1964) assumed that unsaturated hydraulic conductivity decreases exponentially and geometrically with the pressure head (Bransom, 1996; Zhu et al., 2004). Gardner (1958) expressed this as,

\[ K_{\text{unsat}} = K_{\text{sat}} \exp(\alpha \psi) \]
where $\alpha$ is a parameter dependent on the porous media, $\psi$ is pressure head (capillary pressure, suction head, or matric potential corresponding to height of capillary rise). The equation by Brooks et al. (1964) is

$$K_{\text{unsat}} = K_{\text{sat}} \left( \frac{\psi_a}{\psi} \right)^{\eta}$$

where $\psi_a$ is an air entry value, $\eta = 2 + 3 \lambda$ is a pore-size index, $\lambda$ is a another pore-size index (absolute value of the slope of the logarithmic plot of effective saturation vs. pressure head).

The Gardner method does not consider ability of the capillary fringe to conduct water at or near the saturated conductivity even though water is under tension in the vadose zone because unsaturated hydraulic conductivity drops below saturated hydraulic conductivity as soon as the pressure head becomes non-zero (Branson, 1996). Thus, a modification of the Gardner method was made to correct this drawback (Rijtema, 1965; Branson, 1996):

$$K_{\text{unsat}} = K_{\text{sat}} \exp(\alpha(\psi - \psi_a))$$

Verma et al. (1971) defined unsaturated hydraulic conductivity as proportional to effective or relative saturation of the soil moisture (Sloan et al., 1984; Nieber, 1984).

$$K_{\text{unsat}} = K_{\text{sat}} S_e^n$$

where $S_e$ is effective or relative saturation, $n$ is an empirical parameter related to the soil characteristics, and

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} = \left( \frac{1}{1+|\alpha\psi|^m} \right)^m$$

where $\theta_r$ is residual moisture content, $\theta_s$ is saturated moisture content, $\theta$ is current moisture content, $\alpha$ is a coefficient, and $n = 1/(1-m)$.

Brooks et al. (1964) introduced a relationship between soil water content and the ratio of air entry value to pressure head (Mualem, 1976). His method becomes another form of the Brooks-Corey method expressed as the soil water saturation instead of the pressure head.
\[ S_e = \left( \frac{\psi}{\psi_a} \right)^{-\lambda} \]  

where \( \lambda \) is a parameter related to soil.

Van Genuchten (1980) derived a closed-form equation for predicting the unsaturated hydraulic conductivity by combining his proposed S-shaped soil water retention function with a theoretical pore-size distribution model of Mualem (1976) (Mualem, 1976; van Genuchten, 1980; Zhu et al., 2004). He also proposed a supplementary relationship between pressure head, moisture content, and unsaturated hydraulic conductivity,

\[ K_{\text{unsat}} = K_{\text{sat}} S_e^{1/2} \left( 1 - \left( 1 - S_e^{1/m} \right)^m \right)^2 \]  

where \( K_{\text{unsat}} \) is unsaturated hydraulic conductivity, \( K_{\text{sat}} \) is saturated hydraulic conductivity, and \( m \) is a coefficient.

The air pressure required to force air through a porous cup, which has been thoroughly wetted with water, is called the bubbling pressure or air entry value (Collins et al., 1988). The concepts of entry or bubbling pressures are used in fluid mechanics to characterize the start of fluid-fluid (air-water) displacement in a porous medium (Wang et al., 2000). The equations Gardner (1958), Brooks et al. (1964), and Rijtema (1965) proposed are a function of the air entry value, \( \psi_a \). However, it is usually difficult to measure (Fredlund et al., 1993; Sun, 2007). In addition, the equation Verma (1971) proposed does not consider soil water retention. Thus, the van Genuchten method, Equation 2.66, has often been used in estimating unsaturated hydraulic conductivity from soil characteristics and water contents (Sunwoo, 2006).

Russo (1988) tested three models, Gardner, Brooks and Corey, and van Genuchten, in estimating unsaturated hydraulic conductivity of sandy loam and silt loam. In this test, the van Genuchten model was most accurate and consistent when compared to measured data. Russo et al. (1992) attempted to fit the van Genuchten model to data obtained from 417 undisturbed soil cores and document spatial variability of model parameters using the Akaike Information Criterion (AIC). His study showed high
variation of the parameters at the field local scale and in both horizontal and vertical
directions. Ross et al. (1993) and Durner (1994) proposed and evaluated a bimodal van
Genuchten model for an aggregated soil that had macropores and thus multimodal pore
size distribution. Carsel et al. (1998) also showed considerable variance and high
uncertainty in parameters of the van Genuchten model for 12 unique soil textures. Chen
et al. (2001) showed high sensitivity of the van Genuchten model results to different
sources of soil database.

Nearing et al. (1996) tried to relate the CN to the Green-Ampt effective
cconductivity parameters through WEPP model optimization and regression analysis. The
relationship they found was tested on approximately 350 plot-years of measured data
from 11 runoff and erosion stations, and it is adapted in the SWAT model. Zhu et al.
(2004) investigated correspondence of parameters used in some of the methods that
estimate unsaturated hydraulic conductivity and their applicability in upscaling of
hydraulic properties for steady-state flow in heterogeneous soils. They found that the
parameters corresponded very well so that the rule could be used for averaging the
parameters of different methods when predicting ensemble evaporation rates from
heterogeneous data. Leij et al. (1997) made a comprehensive summary of closed-form
expressions for water retention, relative hydraulic conductivity, and their combination to
estimate unsaturated hydraulic conductivity.

2.6.3 Interflow

“Hillslope hydrologists have long assumed that the downslope movement of water
and solute can best be described by surface topography since gravitational potential
largely dominates hydraulic gradients in steep terrain” (McDonnell et al., 1996). Woods
et al. (1996) investigated the spatial variability of subsurface flow through field
monitoring with trenches. In their study, subsurface flow was measured using thirty
troughs across the base of a steep forested hillside at several scales in Maimai, New
Zealand, for 110 days. From the field experiments, he found the spatial variability of
surface flow is associated with convergent and divergent topography and sharpened in a
case of small storm. McDonnell et al. (1996) measured subsurface flow of a hillslope in
the Panola catchment in Georgia based on the design of Woods et al. (1996). Unlike the catchment at Maimai, the Panola catchment is laid on bedrock. He compared the measured data with topographic and bedrock wetness indices and found that the bedrock index and the bedrock accumulated areas closely resemble the distribution of saturation on the hillslope and flow at the trench face.

Freer et al. (1997) analyzed results of the trench experiments of two catchments, Maimai in New Zealand and Panola in Georgia, and compared the subsurface flow measurements with the topographic and bedrock wetness index. From the study, he found that the correlation between each index and cumulative flow volume got weaker as the magnitudes of the events decreased at both catchments. It also was found that the bedrock surface has a considerable influence on local hydrological gradients and therefore the dominant flow path directions where bedrock topography is distinctly different from surface topography. Thus, he stressed the importance of understanding the dominant downslope hydraulic gradients at the hillslope scale, which may not necessarily be represented by surface topography.

2.6.4 Percolation

Percolation is defined as water flow in the vadose zone. It can follow all directions, even against gravity, because it is driven by both gravity and capillary gradients (Seiler et al., 2007). However, when focusing on rates of water movement on the border between the vadose zone and the aquifer, outgoing flow of soil water from the vadose zone to the aquifer can be assumed as percolation, and incoming flow from the aquifer may be presumed as capillary rise. In addition, the horizontal or lateral movement of soil water can be defined as interflow. In this study, percolation is defined as only the downward movement of water that eventually enters into the aquifer from the vadose zone by gravity.

Eagleson (1978) tried to model natural soil systems from the surface to a stationary groundwater table in one (vertical) dimension. In his modeling study, four hydrologic components, infiltration, exfiltration, percolation, and capillary rise were considered. Percolation was assumed to be controlled by only gravity and to be steady.
throughout the rainy season at a rate determined by the long-term space-time average soil moisture. He defined an apparent percolation rate as a steady gravitational seepage equal to the vertical unsaturated hydraulic conductivity. The conductivity was estimated by the Gardner model.

Wigmosta et al. (1994) developed a distributed hydrology-vegetation model that includes canopy interception, evaporation, transpiration, and snowmelt as well as runoff. In his model, percolation rate is also assumed as the vertical unsaturated hydraulic conductivity, but the Brooks-Corey method equation was used to calculate the conductivity. Famiglietti et al. (1994) examined modeling structures and equations of SWAT. Percolation rate was assumed equal to unsaturated hydraulic conductivity estimated by the Verma form of the Brooks-Corey method.

Wang et al. (1997) developed a physically-based and distributed model for simulating the water and energy transfer between soil, water, and atmosphere (WetSpa) at a basin scale. In the model conceptualization, a basin hydrological system was assumed composed of atmosphere, canopy, root zone, transmission zone, and saturation zone layers. In the model, percolation is also assumed as gravity-driven flow and then estimated in the same way as the WetSpa model. The approaches used in the above studies, which assume the rate of percolation as equal to the unsaturated hydraulic conductivity, can be regarded as a special case of the Darcy equation under a unit hydraulic gradient.

2.6.5 Capillary Rise

Soil water is redistributed from the aquifer to the vadose zone by capillary force, which is pulling soil water upward. This force forms capillary fringe immediately above the groundwater table, and height of saturated soil column from the table is called capillary rise. The rate of capillary rise is a function of soil pore characteristics and moisture content. When soil moisture is evaporated and depleted in the vadose zone, the suction head of the soil increases and the soil moisture is drawn up from the aquifer.
Calculations of capillary rise rate in soil are found in the literature for percolation. Gardner (1958) proposed the following analytical equation for the rate of capillary rise:

\[ w = C \frac{a}{z^b} \]

where \( C \), \( a \), and \( b \) are parameters related to soil type, and \( z_g \) is groundwater table depth (positive downward) (Eagleson, 1978; Famiglietti et al., 1994; Bogaart et al. 2008).

Eagleson (1978) formulated an equation to estimate capillary rise rate by simplifying the governing diffusion equation at a groundwater table under a steady-state assumption. The Gardner equation was used to derive an analytical form of the integration equation in terms of pressure head and unsaturated hydraulic conductivity. He expressed the parameters of the Gardner equation in terms of the Brooks-Corey soil parameters (Eagleson, 1978; Famiglietti et al., 1994; Bogaart et al. 2008). The equation is expressed as,

\[ w = k \alpha \left( \frac{\psi}{z_g} \right)^{\beta} \]

where \( w \) is rate of capillary rise, \( \alpha \) and \( \beta \) are parameters related to soil characteristics, \( \alpha \approx 1 + \frac{3/2}{\beta - 1} \), \( \beta = 2 + \frac{3}{b} \), \( b \) is a pore size distribution index.

This approach was used by modeling studies such as Famiglietti et al. (1994) and Wang et al. (1997). If rates of percolation and capillary rise are determined, the vertical flux of soil water between the vadose zone and the aquifer can be obtained by taking the net effect of the two-way interaction fluxes (Eagleson, 1978; Famiglietti et al., 1994; Bogaart et al., 2008). Bogaart et al. (2008) tested the approach of Eagleson (1978), estimating the net effect of a downward drainage flux and upward capillary rise flux under a steady-state assumption and then comparing it with calculation of the Darcy equation for quasi-steady-state conditions. Based on the test, they proposed a new closed-form parameterization of the Darcy equation-based fluxes that accounts for both root zone soil moisture and depth to the groundwater table. They found that differences between the computed net fluxes using the Eagleson (1978) method and a newly
developed formulation of the Darcy equation could be significant especially for high root zone moisture and/or a shallow groundwater level. Lu et al. (2004) derived a new closed-form analytical solution that calculates rate of capillary rise by combining two major assumptions of Terzaghi (1943) and the Gardner model (1958).

2.6.6 Pedotransfer Function

H/WQ models need information about soil characteristics such as hydraulic conductivity and water retention curve to calculate rates of the movement of soil water in the subsurface such as infiltration, interflow, percolation, and capillary rise. Usually, field and laboratory measurement of those characteristics and parameters is very difficult, laborious, costly, and often impractical for hydrologic analysis (Rawls et al. 1982; Saxton et al., 1986; Wosten et al. 2001; Saxton et al., 2006). Thus, modelers try to estimate those parameters from soil texture, which is more readily available in most of the soil database, using equations called pedotransfer functions. Bouma et al. (1987) first called methods used to obtain the required parameters from easily obtainable data “pedo-transfer functions” (Tietje et al., 1996).

Rawls et al. (1982) collected comprehensive literature and data sources for hydraulic conductivity and related soil water data for 1,323 soils with about 5,350 horizons of 32 states. Then, they developed water retention parameters of the Brooks-Corey method, total porosity, and saturated conductivity for the major USDA soil texture classes. Saxton et al. (1986) extended the work of Rawls et al. (1982) and provided mathematical equations for continuous estimates over broad ranges of soil texture, soil water potentials, and hydraulic conductivities using multiple nonlinear regression techniques. In their study, a set of equations for estimating unsaturated hydraulic conductivity were developed. More recently, Saxton and Rawls (2006) improved their previous research by including organic matter as a variable in the pedotransfer functions. The effects of density, gravel, and salinity are also considered to provide prediction of soil water characteristics more comprehensively. The results of their studies were incorporated in the SPAW model, which is a daily hydrologic budget model for agricultural fields (Saxton et al., 2006).
Tietje et al. (1996) compared performance of pedotransfer functions developed by six different researchers for estimating saturated hydraulic conductivity using laboratory soil data of the Lower Saxony Soil Information System (NIBIS), which contains information for soil samples of 1,067 in the northwestern part of Germany. In the study, the errors for clay and silt soils were bigger than for sandy soil. In addition, they found that the inaccuracy in the prediction of saturated hydraulic conductivity using the pedotransfer functions contributed to inherent variability of the conductivity. Then, they asserted that the saturated hydraulic conductivity should be interpreted as a log-normally distributed random variable.

Leij et al. (1996) developed UNSODA (Unsaturated Soil hydraulic Database) based on comprehensive search of closed form expressions for quantifying soil hydraulic characteristics. It was designed to provide properties of various soils such as unsaturated hydraulic conductivity in the vadose zone. Mathematical expressions that describe water retention and unsaturated hydraulic conductivity were evaluated (Leij et al., 1997). Nemes et al. (2001) reviewed database structures of UNSODA and developed UNSODA v.2.0 for providing more flexibility in data entry, manipulation, and retrieval as well as output and interfacing with other applications.

Schaap et al. (2000) tried to seek the best parameter set of the vanGenuchten model for a data set of 235 soil samples with retention and unsaturated hydraulic conductivity data using optimization techniques. They found that parameters providing the best fitting model often had negative values that are not theoretically correct. In addition, the default values of the parameters provided by the traditional vanGenuchten model resulted in relatively poor prediction of unsaturated hydraulic conductivity. In their studies, uncertainty analysis using a bootstrap technique showed that the prediction for the data set contains much uncertainty. Schaap et al. (2001) also developed a computer program that contains soil database, ROSETTA, which is capable of estimating soil hydraulic parameters using hierarchical pedotransfer functions. In the model, five different types of models can be chosen depending on available soil information. Calibration and uncertainty analysis are performed by neural network and bootstrap respectively to allow an assessment on reliability of the model prediction even when independent measurement and data for hydraulic characteristics of soil are not available.
Coppola (2000) tested applicability of bimodal van Genuchten models Ross et al. (1993) and Durner (1994) proposed in predicting unsaturated hydraulic conductivity of an aggregated soil with observations of soil moisture and hydraulic conductivity. In his study, bimodal models provided better agreement with the measurement than did single mode models especially when soil is wet. Wosten et al. (2001) reviewed methods to develop pedotransfer functions and to predict soil characteristics using the functions, and evaluated reliability and uncertainty.

Pedotransfer functions were exploited not only for estimating hydraulic characteristics of soil but also for deriving a particle-size distribution from information of soil texture. Skaggs et al. (2001) developed a generalized logistic regression equation to estimate the complete particle-size distribution from the fractions of clay, silt, and fine plus very fine sand mass. The accuracy of the equation was evaluated using 125-measured particle-size distributions of various soils, and the equation showed good performance excepting for 5 soils whose silt fraction was greater than about 0.7. For the cases that only fraction of all sand subclasses is available, Fooladmand et al. (2006) modified the equation Skaggs et al. (2001) proposed through applying radius of 999 µm instead of 125 µm for the extreme value of fine sand fraction. In the study, the modification provided better accuracy for 50 soils in the UNSODA soil database.

2.7 Groundwater

2.7.1 Overview

“Groundwater is found in aquifers, which have the capability of both storing and transmitting groundwater” (Schwartz et al., 2003). Precipitation that falls on the earth surface is a source of groundwater (Dunne et al., 2002). An aquifer is defined as a saturated permeable geologic formation that can yield significant quantities of water to wells and springs (Ponce, 1989). “A geological stratum through which water cannot move except at negligible rates in called an aquiclude” (Dune et al., 2002). The aquifer that directly contact with the atmosphere through open pores is called “unconfined”
On the other hand, a confined aquifer or artesian has its upper and lower boundaries marked by confining beds such as an aquiclude (Schwartz et al., 2003). Groundwater flows from a recharge area, through a groundwater reservoir, to a discharge area (Ponce, 1986). The recharge area is a unit of land surface where precipitation can infiltrate and fill the storage space or pores in the soil (Dunne et al., 2002). The discharge area is the area where the infiltrated water returns back to the surface like channel bottom (Ponce, 1986). Generally, groundwater in the unconfined aquifer is discharged in three ways: vapor diffusion and capillary rise upward through the soil, exfiltration into stream, and human-induced means (Ponce, 1986). Flow of water in the aquifer can be expressed by Darcy’s law, which relates velocity of soil water movement in a porous medium to the hydraulic gradient (Novotny, 2003). Darcy’s law indicates that groundwater flow occurs in response to a gradient of head and in a direction from high head to regions of low head (Dunne et al., 2002).

Groundwater represents the largest source of unfrozen fresh water in the world. It constitutes 21 percent of the entire world’s fresh water and 97 percent of all the unfrozen fresh water on earth (Dune et al., 2002). Nonetheless, “groundwater is a young science; Darcy’s experimental results were not published until 1856 and were not applied to groundwater until much later” (Zheng et al., 2002). In addition, “the role of groundwater in water resource planning frequently is neglected because many planners believe that groundwater cannot be adequately evaluated in terms of availability, quantity, cost of development, or the effect of development on the surface water supply” (Moore, 1979). Solute transport of groundwater was also considered only in a very limited way in early groundwater studies, and the problem where it arose most frequently was that of seawater intrusion (Zheng et al., 2002). However, the development of predictive groundwater and solute transport model since the middle 1950’s now provide a water planner and a researcher with techniques for planning groundwater development and simulation (Moore, 1979; Zheng et al., 2002).
2.7.2 Approaches for Groundwater Modeling

2.7.2.1 Recession Curve or Base Flow Modeling

Boussinesq (1877) presented a basic governing equation that describes flow in the aquifer (Hall, 1968). To simplify the solution, he linearized the equation by neglecting the vertical flow component and the effect of capillary rise above the water table (Hall, 1968; Nathan et al., 1990; Tallaksen, 1995). The resulting linearized equation (Equation 2.69) becomes a simple exponential equation (Hall, 1968; Tallaksen, 1995; Moore, 1997; Dewandel et al., 2003). This exponential decay function has been used for recession curve simulation and base flow separation (Brandes et al., 2005).

\[ Q_t = Q_0 \exp \left( -\frac{t}{k} \right) \quad 2.69 \]

where \( Q_t \) is the outflow at any time \( t \) (\( L^3 / T \)), \( Q_0 \) is the outflow at any time \( t_0 \) (\( L^3 / T \)), \( k \) is the recession coefficient (\( T \)), \( t \) is the time (\( T \)).

The equation implies that the aquifer reacts like a single linear reservoir where storage is proportional to outflow (Wittenberg, 1999a) and it can readily be shown that the exponential recession model corresponds to a linear reservoir model like Equations 2.70 to 2.78. Werner et al. (1951) also showed that the exponential equation is a linear solution of the one-dimensional differential equation governing transient flow in an artesian aquifer (Nathan et al., 1990). Singh et al. (1971) provided a method to determine the recession coefficient and found use of hydrograph recession after the inflection point gave consistent and stable estimates of the coefficient for 22 watersheds in Illinois.

Assuming the outflow is a function of the storage and characteristics of the aquifer, the outflow can be expressed as:

\[ Q = \frac{1}{k} S^m \quad 2.70 \]

where \( Q \) is the outflow (\( L^3 / T \)), \( k \) is the recession coefficient (\( T \)), \( S \) is the storage of the aquifer (\( L^3 \)), \( m \) is the coefficient.

In addition, from the continuity equation:
\[
\frac{dS}{dt} = I - Q \quad 2.71
\]

where \( I \) is the inflow (\( L^3/T \)). Here, the inflow \( I \) becomes zero because the recession curve is a portion of a hydrograph after contribution of direct runoff to the total runoff ceased. Therefore, we can write,

\[
\frac{dS}{dt} = -Q \quad 2.72
\]

Substituting Equation 2.72 into Equation 2.70, we can write Eq. 2.71 as:

\[
\frac{dS}{dt} = -\frac{1}{k}S'' \quad 2.73
\]

Here, if a linear reservoir or linear relationship between the outflow and the storage is assumed, \( m \) becomes 1, and then

\[
Q = \frac{1}{k}S \quad 2.74
\]

In addition,

\[
\frac{dS}{dt} = -\frac{1}{k}S \quad 2.75
\]

and integration gives

\[
S = \exp\left(-\frac{t}{k}\right) \quad 2.76
\]

Then, Equation 2.74 can be written as:

\[
Q = \frac{1}{k}\exp\left(-\frac{t}{k}\right) \quad 2.77
\]

Finally, a ratio of the outflow \((Q_t)\) for a time interval, \( t \), from \( t_0 \) to \( t_1 \), can be expressed as follows:

\[
Q_t = \frac{Q_{t_1}}{Q_{t_0}} = \frac{k_0 \exp(-kt_1)}{k_1 \exp(-kt_0)} \quad 2.78
\]

Assuming steady state of the aquifer, \( k_0 \) becomes equal to \( k_1 \), and then,
In hydrologic modeling, base flow or groundwater is often simulated by this linear reservoir model (Evans, 1972; Nathan et al., 1990; Wittenberg, 1994; Tallaksen, 1995). As Hall (1968) defined, however, base flow can come from delayed sources such as depression, detention, snow and ice, channel bank, and caverns including groundwater storage of the aquifer (Hall, 1968; Griffiths et al., 1997). In his context, therefore, the linear reservoir model does not just simulate groundwater flow but a recession curve of hydrograph. Riggs (1964) narrowed definition of base flow recession as a portion of the hydrograph of stream flow only when all the discharge comes from ‘ground-water sources’. Geological, climatological, and morphological features of a watershed as well as the sources of base flow affect a recession curve of a hydrograph, thus it shows wide spatial (within and between watersheds) and temporal (seasonal and chronological) variations (Singh, 1968; Tallaksen, 1995). In addition, differences in evapotranspiration, antecedent soil moisture, rainfall intensity and spatial distribution, and different combinations of drainage processes from multiple storage reservoirs influence recession curves (Riggs, 1964).

In this sense, Wittenberg (1994) claimed that recession curves could be approximated only section-wise by linear reservoirs with different retention constant values. Tallaksen (1995) also mentioned that a nonlinear reservoir model or a multiple linear reservoir model should be necessary in order to simulate base flow over a wide range of flows accurately. Wittenberg (1994; 1999a) derived various single nonlinear reservoir models from the measured flow in Germany and China using an iterative least square fitting method and applied them to separate base flow from hydrograph. Wittenberg et al. (1999b) considered evapotranspiration flux in base flow separation in order to account for seasonal variations of relationship between storage and discharge. Moore (1997) also found that the recession was nonlinear and a two-linear-reservoir model provided substantially better agreement with the measured data than did single linear and nonlinear reservoir models.

Griffiths et al. (1997) considered various sources of base flow such as depression, detention, snow and ice, channel bank, aquifer, cavern storages, and evapotranspiration
loss, in simulating recession curves through introducing independent terms for them into an equation. Although not all the possible combinations of the terms in a recession equation were explored due to efficiency of study and difficulty of calibration, the three-parameter models provided better performance in simulating streamflow recession than did the two-parameter models. Dewandel et al. (2003) examined suitability of models in an exponential and quadratic form in representing a recession curve by fitting the models to the simulated data using a two-dimensional cross-sectional finite difference model. In the numerical experiment, they found that the exponential and quadratic equations provided better agreement with the results of the numerical results when flow has a very significant vertical component or horizontal flow is dominant.

As the authors pointed out, base flow is not necessarily equal to groundwater flow. However, contribution of other sources besides groundwater to total runoff might be insignificant and thus neglected especially for a small watershed. Fenicia et al. (2006) examined a relationship between storage and discharge of groundwater using the results of the calibrated lumped model that has four reservoirs: interception, unsaturated soil, fast reacting, and slow reacting tanks. In their study, parameters relating to low flow of the model were calibrated first in order to avoid that the simulation of low flow is neglected in favor of a higher performance in simulating high flow and peak discharge, and then parameters for high flow were calibrated. The tank model was calibrated for each of eight watersheds ranging from 30 to 365 Km² in size and the storage-discharge relation was recalculated from the calibrated results. Based on the modeling results, they concluded that a linear model can well represent the groundwater behavior of the watersheds. They interpreted the nonlinearity as the result coming from a bias produced from groundwater recharge.

2.7.2.2 Groundwater Flow Modeling

A large number of models for simulating groundwater quantity and quality such as MODFLOW have been developed, and numerous modeling studies for applying the model and improving the numerical method in terms of accuracy and efficiency have been done. There are two different types of models for simulating groundwater flow:
analytical or numerical (Mandle, 2002). Once groundwater processes of interest are determined and the related governing equations are defined mathematically, they can be solved in an analytical or numerical way (Bear et al., 1992). Analytical models are an exact solution of a specific, often greatly simplified, groundwater equation while numerical models approximate the solution of the equation through discretization of the model domain and the simulation time (Mandle, 2002). Thus, numerical models produce errors and the accuracy of the model depends on that of the input data, resolution of the space and time discretization, and numerical schemes used to solve the equations (Mandle, 2002). Generally, an analytical model requires a number of assumptions such as one-dimensional flow, homogeneous and isotropic soil, sound professional judgments to simplify a problem at hand, and experience for field situations (Bear et al., 1992). On the other hand, numerical models are capable of solving complicated equations that account for heterogeneous and anisotropic features of soil in the multi-dimensions (Mandle, 2002).

There are several types of numerical methods: Finite Difference Method (FDM), Finite Element Method (FEM), boundary-element models, particle-tracking models, and integrated FDM. FDM is used in groundwater modeling because of its simplicity in discretizing the spatial domain and in solution procedures (Rozos et al., 2005). On the other hand, FEM is able to represent complex geometry with irregular spaced mesh (Mandle, 2002; Rozos et al., 2005), so that it may be the most widely used method for groundwater modeling (Narasimhan, et al., 1976). In order to take advantages of strengths of the two methods, the integrated finite difference method (IFDM) has been proposed based on the FDM (Narasimhan, et al., 1976). “Its mathematical structure combines the advantages of an integral formulation, which allows complex geometry problems to be solved more easily than classical FDM, with the simplicity of gradient evaluation, which can be regarded as an advantage over FEM” (Ferraresi, 1989).

In many groundwater models, excess water on the ground surface is incorporated as Neumann or Dirichlet boundary condition in the form of infiltration or ponding. It means that they do not simulate surface flow explicitly in groundwater modeling. However, surface water generated on the ground surface is dynamically infiltrated into the vadose zone and finally aquifer as a source of groundwater flow. In spite of their significant interaction, groundwater and surface water often have been considered
separately and simulated independently because groundwater movement has a much larger timescale than that of surface water (Liang et al., 2007). In particular, their interaction can be significant in modeling shallow groundwater, saturation runoff generation, inland waterbodies, and coastal regions. Winter et al. (1998) provided a good and concise introduction to the interaction and some research to integrate surface and subsurface modeling into a framework.

VanderKwaak (1999) developed the fully integrated numerical model capable of simulating surface-subsurface watershed flow and solute transport processes in a three-dimensional framework (VanderKwaak, 1999; Sudicky et al., 2008). In the model, overland and channel flow is simulated using the two-dimensional diffusion approximation of the Saint-Venant equation while a three-dimensional variably saturated form of the Richards equation governs subsurface flow (Sudicky et al., 2008). All the equations are solved by a control-volume FEM. Morita et al. (2002) coupled two-dimensional surface and three-dimensional subsurface flow models, which also use the diffusion approximation of the Saint-Venant equation for two-dimensional unsteady surface flow and a modified Richards equation for three-dimensional unsteady unsaturated and saturated subsurface flows. In the model, the equations are solved numerically and iteratively between the surface and subsurface components using infiltration as the internal boundary condition. In addition, they provide comprehensive summary for conjunctive surface-subsurface flow model.

Ogden et al. (2003) developed the GSSHA model based on the CASC2D model. They enforced the subsurface flow part and reformulated the surface flow part of CASC2D such as adding evapotranspiration so that GSSHA can simulate hydrologic processes continuously and non-Hortonian (saturation excess runoff) mechanism of generating excess runoff on the overland. In the model, overland flow and channel routing is implemented by FDM: alternating direction explicit (ADE) and up-gradient explicit schemes. In addition, lateral groundwater flow is vertically averaged and stream-groundwater interaction is simulated by Darcy’s law. Panday et al. (2004) proposed a physically based distributed model capable of simulating surface and subsurface flow and their interactions. The model consists of the three-dimensional Richards equation for saturated and unsaturated subsurface flow simulation and the diffusion wave equation for
overland flow simulation. The group of equations is discretized using a fully implicit procedure and solved with the Newton-Raphson method.

Zerihun et al. (2005) linked a one-dimensional zero-inertial model to a one-dimensional unsaturated zone water-flow model, HYDRUS-1D. In this model, depth of surface flow is used as Dirichlet boundary condition for the subsurface-flow model, and infiltration calculated by the subsurface model are used in the surface-flow mass balance equation. Then, the equations are solved with the Preissmann FDM scheme. Liang et al. (2007) coupled vertically integrated surface and subsurface flows by solving two sets of governing equations simultaneously in a two-dimensional numerical model. The Total Variation Diminishing (TVD) and standard MacCormack schemes of the FDM were used for the surface and subsurface flow respectively. Then, the modeling results were verified against the analytical solutions and experimental measurements.

Hall et al. (1972) attempted to simplify an equation that describes interaction between water in the stream and aquifer using a convolution relation. They formulated the instantaneous unit impulse response function, the unit step response function, and the derivative of the unit step response function for four highly hypothesized cases. Barlow et al. (1998) and Moench et al. (2000) derived analytical solutions to simulate hydraulic interaction between a stream and a confined, leaky, or water-table aquifer in frequency domain using the Laplace transform. Chen (2000) measured saturated hydraulic conductivity of streambed at a field and found that the hydraulic conductivity in the horizontal direction was four times faster than that in the vertical direction and those in other oblique directions were somewhere between them. Chen et al. (2003) utilized the MODFLOW model to investigate factors affecting stream-aquifer interaction and to quantify rates of stream infiltration and discharge of groundwater from bank storage to stream. They found that the regional hydraulic head gradients of groundwater significantly influenced stream water infiltration rate and storage zone extent in the aquifer but had little effect on flow rate and bank storage. In addition, the total effect of evapotranspiration for a long reach of the stream in a long dry season may significantly decrease water volume in storage zone and subsequently discharge rate of groundwater.
2.8 BMPs in H/WQ Modeling

2.8.1 Overview

Hydrology and water quality of a watershed are affected by the hydrologic characteristics of land use like roughness and permeability and its distribution such as distance to the stream, diversity, and fragmentation. Land use is one of the most crucial factors that determine the watershed’s hydrologic response, and the spatial distribution of land use is a hydrologically and ecologically important factor. However, its impact has not been addressed adequately and sufficiently in H/WQ modeling due to difficulties of consideration in lumped or semi-distributed modeling while the landscape has been rapidly changing since the mid 1980s (Li, 2004). Because BMPs introduce land use modifications like riparian buffers and cover crops, their location and spatial distribution should be incorporated into H/WQ modeling to get a better understanding of the effectiveness of BMPs and impact on the watershed response.

Modelers try to describe effectiveness of BMP through modeling its types or the fundamental processes that occur in a BMP (Huber, 2006). Thus, if simulating BMP by its type, a way to define parameters that describes performance of the BMP should be determined first. This may be done by investigating the reported effectiveness of the BMP from watershed monitoring or in literature such as International Stormwater BMP Database, ASCE National BMP Database, and CWP National Pollutant Removal Performance Database. However, because characteristics of a watershed or field in which BMPs were applied and dimensions of BMPs are very variable case-by-case, their effectiveness must be very site specific. Thus, use of the database can result in many questions about methods to measure performance of BMPs (Huber, 2006). In this sense, modeling the fundamental processes that happen in the BMP is an alternative to the coefficient approach for assessing BMP performance.

In order to simulate fundamental processes of a BMP, mechanisms that make the BMP work should be recognized and incorporated into a model appropriately. Typically, BMPs are installed to prevent pollutant from being generated at its source and/or from being transported along flow paths. For instance, BMPs protect source areas from raindrop splash and flowing energy of runoff, interrupt the flow paths, or capture
pollutants at a specific place. Models for simulating BMP performance can be classified as nonpoint source model and water quality model (Heatwole et al., 1991). The nonpoint source model focuses on generation of pollutants across the overland to stream and/or down through the soil profile to groundwater while the water quality model is more concerned with the transport and fate of pollutant during concentrated flows in waterbodies (Heatwole et al., 1991). Many H/WQ models such as SWAT and Storm Water Management Model (SWMM) have been employed in describing BMP effectiveness and simulating its impact on hydrology and water quality of watershed. In addition, the HSPF model is popularly used to establish TMDL using pollutant removal coefficient reported in literature.

### 2.8.2 Modeling for Evaluating BMP Effectiveness

Effectiveness of BMPs might be assessed through monitoring in the field or simulation with models. In a simulation study, functions of BMPs are usually considered and incorporated into modeling through adjusting or introducing parameters. The degree of the adjustment is usually determined based on literature and expert knowledge. Park et al. (1995) applied the CREAMS model in simulating impacts of BMPs that had been implemented in a small watershed, but they failed to describe the observed water quality phenomena adequately. Mostaghimi et al. (1997) applied an event-based nonpoint source model, AGNPS, in simulating impact of alternative BMPs for reducing NPS pollutant loadings. For long-term based evaluation of effectiveness of the BMPs, the event-based modeling results were converted to annual average values. In the modeling, several BMPs were incorporated into the AGNPS model through adjusting parameters relevant to describing processes that occur in the BMPs. The BMPs included conservation tillage, strip cropping, conservation reserve program (CRP), grassed waterway, animal-waster storage facility, vegetative filter strips (VFS), and fencing. For BMP simulation, they adjusted the curve number (CN), USLE management practice (C) factor, surface condition constant (SCC), and Manning’s roughness coefficient.

Huber et al. (2004) proposed ways to incorporate BMPs into EPA SWMM (Storm Water Management Model) for simulating effectiveness of various stormwater BMPs.
The methods include considerations of settling processes of sediment and flotation of pollutant in wetland and ponds, infiltration of water from trench and swale, more detailed overland routing for filter strips and vegetated buffers, and water quality routing through hydraulic devices. Houston (2006) applied EPA SWMM in evaluating effectiveness of individual BMPs at specific locations and tested the applicability of EPA SWMM 5.0. He found some shortcomings of the model in applying it at large scales and in simulating infiltration from conduits even though it performed well for most of the BMPs considered in the study.

Bracmort et al. (2006) examined the long-term impact of structural BMPs in two watersheds on sediment and phosphorus loads using SWAT. In the study, BMPs such as a grassed waterway, parallel terrace, field border, and grade-stabilized structure, were incorporated by modifying the associated parameters of SWAT based on literature. For instance, channel cover factor and channel Manning’s coefficient were increased but channel erodibility factor was decreased in order to simulate function of the grassed waterway. Arabi et al. (2008) also developed and evaluated methods for representing agricultural conservation practices in SWAT, such as contour farming, strip-cropping, parallel terraces, residue management, conservation crop rotation, cover crops, field borders, filter strips, grassed waterways, lined waterways, and grade stabilization structures. They utilized information about sensitivity of the output against change in parameter values in adjusting values of the associated parameters to reflect functions of BMPs in the modeling.

Ackerman et al. (2008) linked the low-impact development management practices evaluation computer module (BMP module) to the HSPF model to enable an evaluation of the BMP performance over a variety of storm types at a watershed scale. The calibrated and validated output of the HSPF modeling was used as input for the BMP module. In the study, runoff volume, sediment, and copper loads were simulated with bioretention basins and a dry swale were in a one-acre catchment. They found that the ranges of predicted effectiveness based on the modeling practice were a little bit larger than were those reported in literature and database. Shaw et al. (2006) coupled a watershed model, HSPF and a receiving water quality model, CE-QUAL-2E to link the
onsite BMP performance directly to receiving water quality benefits then to account the combined treatment effects of all the stormwater management practices in a watershed.

VT-BSE (2006) applied the GWLF (Generalized Watershed Loading Functions) for comparative modeling of the impaired and TMDL reference watersheds in developing sediment TMDL for a benthic impairment of Mill Creek in northern Virginia. Because the watershed does not have any measured data, the model was not calibrated and the parameters such as CN and USLE factors were determined based on the GWLF manual and professional judgment. Rao et al. (2009) tried to determine effectiveness of BMPs in reducing phosphorus load using the VSLF (Variable Source Loading Function) model, which is capable of simulating variable source area in the watershed. In the study, the effectiveness of BMPs was simulated by a BMP load reduction factor and it was calibrated for various BMPs.

A H/WQ model simulates effectiveness of BMPs in terms of reduction of pollutant load and/or improvement of water quality in a receiving water body. Although a BMP can reduce loading of pollutant at the site where it is placed, its effectiveness may not be preserved at the outlet of a watershed due to mixture with other untreated waterbody. Houston (2006) found that effectiveness of BMPs was quickly diminished as the treated flows mixed with other untreated flows when moving downstream in his SWMM modeling study. A lower effectiveness may be found at an outlet of a larger watershed. Thus, when evaluating BMP effectiveness, it will be important to determine and/or notice spatial context of the evaluation. Moreover, the goal of BMP implementation is to achieve the maximum pollutant reduction in the watershed (Maringanti et al., 2008). Therefore, evaluation of BMP effectiveness should be done at receiving waterbody of interest or at a watershed scale as well as at the site.

2.8.3 Optimal BMP Placement at a Watershed Scale

Shaw et al. (2001) compared relative effectiveness of BMPs at three different spatial placement levels like on-site, sub-regional, and regional levels in order to assist in the determination of BMP (stormwater and sediment detention basin) placement at a watershed scale. In the study, the AnnAGNPS model was employed to identify the
critical source areas that yield the most pollutant loads. Then, potential BMP sites were chosen with consideration of the spatial placement levels and sizes of the detention basin was calculated to retain runoff from a 10-yr 24-hr storm. After that, the AnnAGNPS model was used to simulate the long-term performance of the detention basin. Finally, the best BMP placement plan was selected by comparing the pollutant reduction effectiveness of the eight placement scenarios, their corresponding cost, and other constrains.

Veith et al. (2003) developed an optimization procedure to identify BMP placements at a watershed scale that meet specified pollutant reduction levels while minimizing costs. The genetic algorithm (GA) was employed to find the best BMP placement scenarios in terms of pollutant load and economic criteria in a heuristic manner. In the study, a nonpoint source component that consists of gross erosion and sediment routing modules was developed to save the required executing time of the optimization by GA. Shaw et al. (2006) proposed a Monte Carlo simulation technique to develop alternative BMP strategies at a watershed scale in his coupled watershed model study for BMP evaluation. The proposed approach was applied to a small watershed, and the Monte Carlo method generated 38 BMP placement scenarios that satisfy water quality.

Hsieh et al. (2007) developed a model for finding the optimum site of structural BMPs to treat stormwater runoff for Fei-Tsui reservoir in Taiwan. The model consists of discrete differential dynamic programming (DDDP) that finds the best combination of BMP type and placement that minimizes the total construction, operation, maintenance, and repair costs of the BMPs. The optimization results showed that building grass swales and buffer strips can achieve mesotrophic condition in a short time, and several detention ponds were needed to attain oligotrophic condition.

Lai et al. (2007) developed the SUSTAIN (System for Urban Stormwater Treatment and Analysis Integration) for helping develop, evaluate, select, and place BMP options in various watershed scales based on cost and effectiveness. It is comprised of watershed, BMP, and optimization modules. The watershed module adapted several features from SWMM5 and HSPF to simulate runoff and sediment processes on overland and in channel flow, and its results provided as input to the BMP module. Then,
effectiveness of the BMPs is estimated in the BMP module and the effectiveness and cost data of various BMP options are compared along their placement scenarios. In the study, optimization of the objective function was implemented using the genetic algorithm (GA).

Chang et al. (2007) investigated the relationship between spatial variability of rainfall and the optimal BMPs placements. In the study, three synthetic rainfall storms with varied spatial distribution, including uniform, downstream, and upstream rainfall, were simulated, and the WinVAST model was applied to simulate runoff and NPS pollution. Detention pond and swale were selected for the BMPs, and the genetic algorithm (GA) was used to find the optimal BMPs. The results showed that the optimal placement of BMPs could be different according to spatial distribution of rainfall. Chang et al. (2008) also tried to find an optimal number and location of BMPs using a similar methodology to their previous work. From the study, they found that the optimal location of BMP placement is in the downstream area near the outlet and on the main stream of the catchment.

Maringanti, et al (2008) pointed out that most of research done in the past tried to optimize the BMP selection and placement while considering two objectives (cost and performance) separately. Then, they applied a multi-objective optimization algorithm, non-dominated sorted genetic algorithm (NSGA-II) that can find the Pareto-optimum. Water quality simulation for BMPs was done by the SWAT model without in-stream processes, and the total cost for each BMP was estimated by incorporating maintenance, interest rate, and design life information. These simulation and estimation processes were repeated for possible BMP combinations to develop the database that consists of the BMP combinations, the corresponding effectiveness, and implementation costs, so the water quality model and the cost model did not have to be linked together dynamically.
2.9 Distributed H/WQ Modeling

2.9.1 Overview

A distributed model employs spatially distributed parameters in order to incorporate spatially distributed factors that influence output at points of interest within a watershed. Thus, it is often called as a distributed parameter model. Reed et al. (2004) defined it as “any model that explicitly accounts for spatial variability inside a basin and has the ability to produce simulations at interior points without explicit calibration at these points”. In other words, a distributed model should have a compatible flow and water quality generation and routing algorithms to the spatial distribution of parameters. Then, a distributed model can incorporate spatially variable input data and parameters into the model explicitly, simulate flow routing and water quality transport simulation in detail, and provide modeling output not only at the outlet of a watershed but also at any internal points. Especially, in TMDL development, it will be necessary to incorporate location of BMP or spatial heterogeneity of watershed characteristics as detailed as possible in order to simulate its influence on hydrology and water quality explicitly while considering the highly nonlinear relationships and complicated interactions between rainfall, discharge, and pollutant along the flow paths. Thus, it enables to maximize use of available data, facilitates opportunities to employ more physically and process based approaches, and provides the spatially detailed picture of the watershed response to input.

However, these strengths can be regarded as weaknesses from another point of view and some practical issues hinder its broad use. Bloschl et al. (1995) summarized two main difficulties in applying a distributed model: (1) the extreme heterogeneity of catchments that makes it hard to define element-to-element variations and subgird variability, and (2) the large number of model parameters to be calibrated or optimized. In addition, input data that contain the required detail for a distributed modeling is not always available and thus some techniques employed to derive more information from the original data will introduce additional uncertainty into the modeling. A distributed model also needs more knowledge and information about hydrology and water quality mechanisms in order to simulate detailed processes at every cell over a watershed.
Scaling is an extrapolation or transfer of information across temporal and spatial scales, and scaling issues introduce problems in distributed modeling (Bloschl et al., 1995). Most of concepts and equations for hydrology modeling were developed to be suitable at specific spatial and temporal scales and conditions generally assuming homogeneous and/or steady-state. However, the concepts and equations are often utilized at different scales and situations, generally longer temporal scale and/or bigger spatial scale than those at which they were devised. For instance, even though equations for calculating infiltration and potential evapotranspiration rates were developed for point estimation, they are also used for calculating areal rates commonly. In this case, usually assumption of homogeneity is made for the application unit such as a HRU (Hydrologic Response Unit) and a pixel. Thus, validity of the homogeneity assumption for a spatial unit can be an issue even in a distributed parameter model.

Bloschl et al. (1995) pointed out that the large number of equations and parameters incorporated in the model are subject to cause or deepen overparameterization and a subsequent the equifinality problem in calibration. In addition, Sivapalan et al. (2003b) pointed out the possibility of surplus in equations, parameters, and H/WQ processes in an upward approach such as a physically based distributed model because some of them are introduced to satisfy the perception of a modeler but they may not be supported by observation. Frequently, the level of observation is not enough to calibrate the large number of parameters or to obtain their best combination set, and thus the distributed model is calibrated only with data measured at the outlet. Consequently, not all the processes of the model that control outputs at internal points are optimized and verified.

Techniques and concepts were proposed to mitigate difficulties in applying a distributed model to a problem. In some distributed models, overland processes such as flow routing and water quality transport are simulated with numerical methods like finite difference method (FDM) and finite element method (FEM). However, a governing equation for the overland flow, the Saint-Venant equation or the shallow water equation is very complicated and computationally demanding, so thus some simplified forms of that such as diffusion and kinematic wave approximations are usually used to reduce computational cost in a distributed model. Another representative example to reduce
complexity of the distributed modeling is an introduction of hydrologic response unit (HRU) into a distributed model such as SWAT. Because model outputs are usually not required at all the internal points within a watershed and there are a limited number of unique combinations of topography, land use, and soil characteristics, HRUs can be used to represent seemingly homogeneous parcels that act differently with the others in terms of hydrology and water quality. For instance, in SWAT modeling, flow routing and water quality transport in the overland are simulated in a lumped way then outputs at subwatersheds are routed through defined channels. Thus, SWAT is sometimes called semi-distributed model because it ignores the detailed overland processes.

The US National Weather Service (NWS) formulated the distributed model intercomparison project (DMIP) to find the best way of distributed modeling approach for improving river and flash flood forecasting through comparison of existing distributed models as well as the NWS operational lumped models (Smith et al., 2004b). They compared characteristics of 12 lumped and distributed models and their application results (Reed et al., 2004). For effective comparison, the same observed streamflow data, the NEXRAD radar-based rainfall estimations for precipitation input, and the database for watershed characteristic were used (Reed et al., 2004). In the study, the uncalibrated modeling results at a watershed outlet are also examined to see how well physically based distributed parameter models perform with parameters derived from physical data. In addition, performances of various distributed modelings are compared at interior locations where the modeling is not calibrated deliberately.

They derived several interesting and notable conclusions such that “model formulation, parameterization, and the skill of the modeler can have a bigger impact on simulation accuracy than simply whether or not the model is lumped or distributed”. In addition, “models that combine techniques of conceptual rainfall-runoff and physically based distributed routing consistently showed the best performance in all but the smallest basin” and “the degraded performance was not simply a function of the fact that no explicit calibration at interior points was allowed (Reed et al., 2004)”. However, they did not answer the question of which spatial and temporal scale of an explicit distributed modeling can provide more useful products than can lumped modeling.


2.9.2 Lumped vs. Distributed

Loague et al. (1985) compared forecasting and prediction powers of a regression model, a unit hydrograph model, and a quasi-physically based model. From the comparison, they found that performance of the physically based model was inferior to those of the others, and they believed that lack of spatial variability of rainfall and soil hydraulic properties are responsible for its bad performance. Refsgaard et al. (1996) investigated performance of three different hydrologic models that have unique spatial representation of parameters such as lumped (NAM), distributed (MIKE SHE), and semi-distributed (WATBAL) through the split measured sample test. In their study, the three models showed similar performance when calibrated with measured data of 1 to 3 years, so thus the lumped model would be preferred in terms of efficiency. However, the proxy-basin test where calibration is not possible showed that uncertainty of the distributed model is significantly lower than that of the lumped even though the distributed performed marginally better than the lumped.

Boyle et al. (2001) examined performance gain of semi-distributed modeling over lumped modeling through comparing accuracy obtained from different lumped and distributed combinations of SAC-SMA model components, algorithms, and input data such as precipitation, soil moisture computation, flow routing algorithm, and parameters. In their study, performance was improved when the watershed is divided into three subwatersheds. However, any improvement was not observed when it is partitioned to eight subwatersheds. In addition, the spatially distributed parameter approach did not improve accuracy of the modeling output over the lumped. Ajami et al. (2004) also compared performance obtained from different levels of spatial discretization of the SAC-SMA (Sacramento Soil Moisture Accounting) modeling with the NEXRAD rainfall data. The modeling study showed that no improvement was identified in predictions at the watershed outlet when moving from the lumped approach to the semi-distributed approach of the SAC-SMA model. Their findings were similar to those of Boyle et al. (2001).
Michaud et al. (1994) compared accuracy of three hydrologic models that have different routing algorithms and levels of spatial discretization (a distributed KINEROS, a distributed CN method, and a lumped CN method) for a semiarid watershed of 150 Km\(^2\) using 24 storms. In their study, the distributed models provided better performance in predicting time to peak both before and after calibration, but the distributed CN was inferior in predicting peak flow and runoff volume comparing to the lumped SCS in the calibration. In validation, the distributed models were better in predicting time to peak but all the models provided poor accuracy. Meselhe et al. (2004) also compared prediction accuracy of lumped (HEC-HMS) and distributed (MIKE SHE) applications for a watershed of 21.2 Km\(^2\). In the study, the distributed model provided slightly better accuracy in predicting runoff volume and peak, but the lumped model showed a better prediction of time to peak, which is contrary to the findings of Michaud et al. (1994). In addition, they tested sensitivity of the models to temporal and spatial precision of rainfall data, and found that the modeling errors became greater as rainfall data were aggregated into longer temporal intervals and the number of rainfall gages used in the modeling got smaller. However, implication of this analysis is limited because the models were not calibrated when temporal and spatial precision of the rainfall data were changed.

2.9.3 Scale Dependency

Mathematical relationships describing a physical phenomena are scale dependent. Model parameters also should change as the degree of watershed disaggregation varies, and thus they are scale dependant (Fedak, 1999). Hydrology and water quality phenomena will be dominated by local physical features when the modeling scale is small but heterogeneity or spatial variability in the watershed will be ignored at a small scale (Fedak, 1999). For example, there has been a debate about validity of the Darcy model at a plot or smaller scale (Butts et al., 2004). As mentioned previously, physical equations that have been developed to describe a hydrologic process in a specific environment such as homogeneous landuse and soil will have its own spatial extent in an application. Consequently, their validity tested at a small-scale experimental condition is not guaranteed at a scale of distributed modeling like cell and HRU (Butts et al., 2004).
In addition, it will be difficult to appropriately and consistently scale up or down the spatial extents of all the physically based equations to a unit element like subwatershed, HRU, and cell when we attempt to build a physically based H/WQ model in the distributed manner.

Hassanizadeh et al. (1979a) defined the infinitesimal element of area (dA) used in integrating or averaging quantities over a multiphase system (flow and transport) as ‘representative element area’ (REA), which is borrowed from ‘representative element volume’ (REV, dV). Then, they suggested that a range for the characteristic length of the averaging region should be greater than the microscopic scale of the medium and less than the scale of the gross inhomogeneities in order to produce physically meaningful macroscopic quantities. They also derived conservation equations of macroscopic mass, momentum, energy, and entropy based on the averaging method (Hassanizadeh et al., 1979b). Wood et al. (1988; 1990) attempted to identify REA in hydrologic modeling at a watershed scale through investigating fluctuations of mean and standard deviation of the TOPMODEL outputs while increasing subcatchment areas. In the study, they found that REA existed in the context of the hydrologic response of catchments and its identification was mainly influenced by topography, but spatial variability of soil and rainfall played only a secondary role in determining the REA size. Thus, they suggested use of the REA as the fundamental scale or unit in watershed modeling.

Philip (1980) categorized spatial heterogeneity into two types: deterministic and stochastic. In his definition, the former means the known spatial variation but the latter comes from random process of the nature. Seyfried et al. (1995) proposed a conceptual measure of a specific range of scales, called ‘deterministic length scale’, which can be used to simulate hydrologic response with deterministic description of spatial variability. They suggested that spatial variability should be incorporated into a modeling because the hydrologic responses become sensitive to the distribution of characteristics when modeling is carried out at a scale within the deterministic length. On the other hand, homogeneous assumption or stochastic approach may suffice at larger scale and then reduce data requirement for modeling. Their study is an extension of Hassanizadeh et al. (1979a; 1979b) about the representative element area in a multiphase system. The ‘deterministic length scale’ emphasizes the scale dependency of a model and spatial
variability of parameters and input data. However, the requirement of detailed spatial information and subjectivity of its determination impede its practical use. In this sense, Beven (2000; 2001) pointed out “we have not developed the equivalent, scale consistent, process descriptions that would then take account implicitly of the effects of subgrid scale heterogeneity and nonlinearity because we have no measurement techniques that give information directly at the element grid scale.”

Prevailing mechanisms controlling hydrologic phenomena may be unique scale by scale. Generally, the impact of channel flow on the overall hydrograph is greater in a bigger watershed than in a smaller (Bloschl et al., 1995). Thus, a method developed for a small watershed may not be suitable for a large one or vice versa. The CN method is a good example of this issue. The CN method was developed to estimate excess rainfall from a rainfall event of a small agricultural watershed (Chow et al., 1988; Boughton, 1989; Allen, 1991; Ponce et al., 1996) where a channel is not well developed so that its storage effect is insignificant. Therefore, it is necessary to evaluate the storage effect on the hydrograph separately when applying the CN method to a large watershed having the dense channel network (Ponce, 1989). In addition, in a storm event, runoff is the predominant water movement, but evapotranspiration and groundwater hydrology are controlling the overall budget of water in a long-term aspect.

2.9.4 Number of Parameters and Complexity of Model

Another major issue in distributed modeling is the large number of parameters and related issues of overparameterization and complexity. Because distributed modeling deals with spatially distributed processes in a more complicated structure, it tends to have many parameters. However, when there are many parameters to be calibrated but only the measured data at a watershed outlet is available for calibration, it may not be easy to find the optimized or distinctly better parameter set (Beven, 1989, 2001; Bloschl et al., 1995; Senarath et al., 2000; Boyle et al., 2001; Ajami et al., 2004; Butts et al., 2004). As more parameters and processes are incorporated into a model, the response surface of the model in the parameter space may become very complicated and many local attractions may exist. Thus, overparameterization is associated with the uncertainty or equifinality
issue in calibration. Wagener et al. (2001) point out that parameter uncertainty can be reduced by incorporating only necessary level of model complexity that facilitates simulation of key processes and by increasing amount of information available in calibrating model parameters. An increase in the amount of information can be achieved by use of supplementary or auxiliary data such as stream salinity and groundwater level and by derivation of additional information from data already available (Wagener et al., 2001).

Hornberger et al. (1985) attempted to find the optimized set of 13 parameters for TOPMODEL using a method Rosenbrock (1960) proposed. Although they tried five randomly selected starting point sets and eight different objective functions for assuring calibration, it was failed to identify the best set for the 13 parameters. In order to solve the equifinality issue, the number of parameters was reduced to five through sensitivity analysis in their study. Hooper et al. (1988) assessed structure of a rainfall-runoff model, the Birkenes model, through calibration. In the study, only one parameter of six that represents the maximum head of the lower box was identifiable from the measured data. Thus, they concluded that the model was overparameterized in spite of its simple structure.

Costanza et al. (1985) examined eighty-seven mathematical models for freshwater wetlands and shallow water bodies and classified them by three indices such as articulation (or complexity), accuracy, and effectiveness. In the examination, they found that accuracy of the models decreased as articulation increased and effectiveness rose to the maximum at intermediate articulation. This reflected the fact that relatively complex or articulated models tended to be low in accuracy and vise versa.

Jakeman et al. (1993) investigated the required number of parameter and complexity of model structure to simulate the relationship between rainfall and runoff. They applied six statistical models at different levels of complexity to seven watersheds with various characteristics, and they compared accuracy of the applications. From the study, it was concluded that a model with two linear storages in parallel and four parameters was enough to reproduce responses of all the watersheds to rainfall. They
interpreted the two storages as being related to quick surface flow and slow base flow responses.

Moreda et al. (2006) attempted to reduce the number of parameters in a distributed modeling using knowledge about parameters gained in lumped modelings and information about physical properties of a watershed derived from GIS data. In the study, physical properties of 67 subwatersheds were related to the individually calibrated 11 parameters for the subwatersheds in independent lumped modelings using multiple linear regression. In their study, lumped modeling outperformed the distributed in predicting runoff volume but vise versa in the peak flow, and the lumped was superior to the distributed in overall accuracy of prediction for event modeling.

Carpenter et al. (2004; 2006) used information about the selected soil properties derived from the STATSGO database to represent spatial variation of parameters in a semi-distributed hydrologic modeling using the Hydrologic Research Center Distributed Hydrologic Model (HRCDHM). In the study of Carpenter et al. (2006), 21 and 19 subcatchments that have average sizes of 59 and 84 Km$^2$ respectively were delineated from two study watersheds, and they were used as a spatial element of HRCDHM. After defining subwatersheds, uniform parameter values were calibrated for an outlet of a main watershed and soil characteristics were averaged for every subwatershed. Then, parameters were scaled with the overall soil property for the main watershed and assigned to every subwatershed (Carpenter et al., 2004). Although their method employing other information derived from a public database is not explicitly validated with observation, it can be a simple but reasonable way to incorporate spatial variation of parameters into a distributed model if considering difficulty of measuring field data.

Overparameterization will lead to equifinality problems in H/WQ modeling as many researchers have pointed out. On the other hand, an insufficient number of parameters will also impede a model from achieving an optimum representation or describing the system accurately. Therefore, merely a simpler model will not assure accuracy and reliability. In this sense, a downward approach tries to reduce the number of parameters to as few as possible without deteriorating the prediction ability of a model. It systematically attempts to find the most suitable model structure as well as the best
parameter set through learning from measured data. Thus, the downward approach is a counterpoint and alternative to the reductionist (or upward, bottom-up, mechanistic) approach that dominates hydrological model development (Sivapalan et al., 2003a).

Sivapalan et al. (2003a) defined downward approach as “the attempt to predict overall catchment response and the catchment function based on an interpretation of the observed response at the catchment scale” and asserted, “the model structure is inferred from the data rather than being preconceived” in the upward approach. However, if determination of model structure or the entire modeling framework relies only or mostly on observed data, the opportunity for a modeler to intervene in the model is very limited, thus an opportunity to utilize the accumulated knowledge from past modeling studies will be restricted. In addition, he said that “since the downward approach attempts to identify processes directly at the scales of interest and interprets these in terms of properties and processes occurring at finer scales, it requires an ability to determine the net effect of small-scale interactions and feedback mechanisms” (Sivapalan et al., 2003a). However, this ability will require additional or auxiliary data that can directly describe or implicitly explain the internal processes occurring at finer scales, so thus its utility and reliability will be constrained by the amount of observed data.

Atkinson et al. (2002) tried to determine the minimum level of model complexity required to predict runoff in New Zealand watersheds using a simple bucket (tank) model. Based on a downward approach, they systematically added further process complexities, which provide better accuracy in prediction, to a bucket model in the simplest form at different timescales, from daily to annual. From the modeling experiments, they concluded that the required complexity increases as timescale decreases and a watershed get dry. Using a downward approach, Farmer et al. (2003) also attempted to find the most parsimonious structure of a simple bucket (tank) model that provides the results in the acceptable accuracy. Like the study of Atkinson et al. (2002), additional processes were added to the simplest form of the model when inadequacy in the prediction was found. Then, the simplest model formation was identified for 11 watersheds in Australia so that the important factors or processes controlling the water balance of the watersheds could be identified. They also found that drier watersheds were more sensitive to small-scale variation of climate and landscape than were humid watersheds.
Son et al. (2007) assessed adequacy of model structure complexity and numbers of parameters in predicting stream flow in terms of performance, predictive uncertainty, and physical realism. The model performance was evaluated by using a combination of multiple objective functions and by comparing the predicted and measured isotope concentration of deuterium. Then, predictive uncertainty was estimated through investigating variance of behavioral parameter sets. In their study, the most complicated model structure that represents the most detailed physical processes produced the best performance and the least predictive uncertainty.

Bai et al. (2009) proposed a way to choose a parsimony structure of a conceptual lumped model for multiple watersheds. It examines change in model performance using a fuzzy rule while model structure and the number of parameter are get larger and more complicated. Although these series of studies for the downward approach to hydrologic modeling have provided ways to build a parsimonious conceptual model inductively, they rely on measured data as statistical models do, thus it is hard to apply them to ungauged watersheds with different characteristics. In addition, the studies employed conceptual models because of its flexibility in model structure modification and parameterization. Thus, a downward approach may become no more than identification process of the best statistical model structure when it is hard to find or interpret the corresponding physical meanings and scientific bases of parameters in the conceptual model structure to quantities and processes in the reality. In this vein, a thesis of DBM (Data-Based Mechanistic) modeling Young (1998; 2003) emphasizes the importance of interpretability of parameters and equations in a downward approach using statistical models. He claimed that DBM models are considered credible only when “they can be interpreted in physically meaningful terms” and “this is a most important aspect of DBM modelling and differentiates it from more classical ‘black-box’ modelling methodologies” (Young, 1998; 2003).

In addition, the required complexity or the number of parameters and equations will increase as the number of processes H/WQ model considers and amount and detail of information we want to know from modeling increases. For instance, when outputs of interest extend from hydrology to sediment, the required model structure will become more complicated, so thus more data will be required to support the complex structure. If
the amount of data is not enough to support additional H/WQ processes of interest, knowledge about their mechanisms should be incorporated into development of a model. Therefore, even though the downward approach is providing a useful methodology to identify a well-posed model structure systematically with regard to the amount of available data, it is hard to say that it is a better approach in developing a H/WQ model than an upward approach. As Klemes (1983) noted, “a successful solution of a problem is more likely if it is approached from two opposite directions.”

### 2.9.5 Distributed H/WQ Modeling with GIS

It is now common to use GIS data of elevation, land use, and soils in H/WQ modeling because it is easy to acquire, manipulate, and visualize the data. In addition to this trend, distributed modeling in GIS environment has been considered as a good way to represent spatial watershed characteristics and simulate behavior of the H/WQ components in detail. A distributed model is a set of algorithms and equations that perform hydrologic and hydraulic simulation by considering subunits of the watershed (DeBarry et al., 1999). Thus, it will need spatially distributed information to consider and represent the characteristics of subunits. In this sense, GIS can provide a good environment and architecture to incorporate spatial variations of input data into a H/WQ model.

Many studies have incorporated exiting H/WQ models or developed new H/WQ models in GIS environment or with database of GIS, especially in raster format. Wolfe (1992) developed an automated procedure to assist in developing input data for a distributed parameter hydrologic model, FESHM (Finite Element Storm Hydrograph Model), using GRASS GIS (Geographic Resources Analysis Support System GIS). She also reviewed early attempts (1980’s) to utilize GIS in hydrologic modeling. Van Deursen (1995) categorized levels of integration between GIS and models as low, medium, and high level linkage. The low-level linkage employs some external software or procedures to convert spatial data in GIS into a format and information that a model recognize and utilize. In the medium-level linkage, a model can directly access the database in GIS with an automated and transparent procedure for exchanging data. On the
other hand, in the high-level integration, a model is embedded in a GIS environment, so thus a model will be an application that can be built using the generic functionality of a GIS toolbox.

Smith et al. (2007) also classified GIS-model relationships as loose, moderate, and tight coupling. Although the categorization scheme is similar to that of Van Deursen (1995), they focused on synchronism of operation of functions in GIS and a model. Thus, the tight connection is characterized by the simultaneous operation of systems allowing direct inter-system communication during the program execution, but the operation is asynchronous with data exchange between systems in the loose coupling. If a modeler tries to integrate a H/WQ model with GIS through processing data in a GIS manually or automatically using software to meet the required format and information of the model, the connection will be the low-level linkage or loose coupling. SWAT in the GIS software like AV-SWAT and ARC-SWAT (Luzio et al. 2004; Olivera et al., 2004) and r.water.fea or Vflow (Vieux et al., 1994: 2001) are typical examples of the medium-level and high-level linkage between GIS and a H/WQ model respectively. The characteristics of each type of linkage or coupling are well summarized in Van Deursen (1995) and Smith et al. (2007).

Sometimes, a spatial computing step for the distributed H/WQ modeling in the GIS environment is set to spatial resolution of the input data in order to avoid additional processes like interpolation and subsequent introduction of errors. An appropriate temporal computing step for a distributed H/WQ modeling in the GIS environment or with GIS data has not been reported yet. However, a criterion for determining a time step may follow the same as that of a numerical method like FDM if compatible equations and modeling framework are provided because they use the same calculation spatial unit called the cell in a grid format. Thus, a finer temporal computing step may provide the more accurate result when the spatial step is fixed at the resolution of input GIS data. However, a small time step can deteriorate efficiency of computation and a big one can degrade accuracy of a H/WQ modeling. Therefore, the temporal computing step should be determined with considering the given spatial resolution of the GIS input data, characteristics of equations used, and objectives of the modeling.
2.9.6 Determination of Spatial Resolution for Distributed H/WQ Modeling

In distributed modeling having a spatial calculating unit of a cell or a pixel, the size of a cell or spatial resolution of modeling should be determined with consideration of modeling goals and assumptions, heterogeneity and complexity of the study watershed, fundamental concepts and assumptions of algorithms and equations employed in a model, and the available input data. Determination of an appropriate spatial scale for hydrologic models may result from a trade-off between various considerations (Dehotin et al., 2007). Once requirements of model functionality for a certain application are satisfied, an appropriate level of modeling complexity may lead to better reliability and less uncertainty in the modeling results while a higher level of simplification may always bring more efficiency. Many authors have examined effects of grid cell size and tried to find the most appropriate resolution for distributed H/QW modeling (Goodrich, 1992; Zhang et al., 1994; Wolock et al., 1994; Molnar et al., 2000; Thompson et al., 2001; Cotter et al., 2003; Chaplot, 2005; Hessel, 2005; Bormann, 2006; Cho et al., 2010).

Goodrich (1992) reviewed the former research about geometric model complexity and scale issues. He also tried to define an acceptable level of watershed discretization or geometric complexity of the KINEROS modeling by assessing changes in model performance during simplification. Zhang et al. (1994) suggested that a grid size of 10 m would be sufficient for a DEM based hydrologic model based on examination of the effect of DEM resolution on the description of the land surface and hydrologic simulations using TOPMODEL. However, Wolock et al. (1994) concluded that coarse resolution of the DEM is not essentially inappropriate for estimating the water table configuration in TOPMODEL from implementing a similar study to Zhang et al (1994). The water table configuration may be smoother than the land surface even though the smaller resolution of DEM provided more details of land surface.

Thompson et al. (2001) found that slope becomes flatter on steeper slopes and steeper on shallower slopes as the resolution of DEM increase from 30 m to 10 m. In addition, ranges of curvatures become narrower, and specific catchment areas become
larger and smaller in upper and lower portions of the landscape, respectively. Bormann (2006) examined changes in the results of the regional scale water balance model, TOPLATS, as aggregating 25 m resolution DEM into from 50 m to 2000 m DEM. In the study, he found slight differences in the modeling results at the resolution of 50 m and 500 m but significant differences at the resolutions of 1000 and 2000 m in the simulated water balances.

Hessel (2005) analyzed the effect of temporal and spatial calculating steps on the prediction by LISEM (Limburg soil erosion model). In the study, they found that the predicted discharge and soil loss decreased as grid resolution and time step length increase due to decrease in slope and numerical dispersion of the kinematic wave solution. However, he did not clearly explain the behavior of the sediment prediction probably because mechanisms of sediment transport are too complex. He recommended that the grid size and time step length should not be larger than 20 m and 30 s respectively to accurately simulate hydrology and sediment transport by a storm event in the study watershed, Danangou of China, which is small (3.5 Km²) with steep slopes and a thick loess.

Molnar et al. (2000) tested several grid cell sizes from 127 to 914 m on the results of CASC2D. In his simulations for a small (Goodwin Creek, 21 Km²) and a large (Hickahala-Senatobia, 560 Km²) watershed, channel roughness coefficients are calibrated to higher values when the grid cell sizes were increased. He found that the distributions of drainage area of overland cells are the most sensitive to changes in grid cell size, whereas the grid cell size has little effect on those of channel cells. In addition, he concluded that coarse grid sizes are more appropriate when simulating events of high intensity or of long duration in terms of computational efficiency as long as parameters are appropriately calibrated.

Cotter et al. (2003) analyzed sensitivity of flow, sediment, NO₃-N, and TP of SWAT modeling to aggregating the resolutions of DEM, land use, and soil input data from 30 to 100, 150, 200, 300, 500, and 1000 m, and found that results were most sensitive to the DEM. In addition, they analyzed errors caused by the different resolutions of the input data and proposed the minimum GIS input data resolutions required to achieve less than 10 percent output error. However, usually some amount of error and
uncertainty is introduced in aggregating an original resolution to coarse ones, and they should affect the modeling results. It is particularly hard to aggregate or interpolate categorical data like land use into at another resolution without losing accuracy. Unless we quantify errors caused by changes in resolution and incorporate them in assessing error or uncertainty of modeling, a H/WQ model should be newly calibrated whenever any input data like DEM, soil, and land use map are changed. Then, we can fairly assess change in accuracy or error of the modeling results according to variation of the resolution. In SWAT modeling, for example, we have to recalibrate all the parameters if we change land use and soil percentage area thresholds in defining HRUs. In their study, nevertheless, the model has been calibrated once with the input data at the finest resolution of 30 m. Therefore, the result is questionable, and it can provide a little information in selecting a suitable resolution for a distributed H/WQ modeling. Chaplot (2005) did a similar research and represented an upper limit of DEM resolution of 50 m for watershed load simulation using SWAT. However, he also did not recalibrate the model when the resolution of the input data changed. Therefore, it can be said that what he showed in the study was sensitivity of the SWAT model to resolution of GIS data.

Shrestha et al. (2006; 2007) attempted to find the best spatial resolution of input data for a distributed hydrologic modeling with respect to area of a watershed of interest. A combined distributed parameter conceptual model, called MaScOD (Macro-Scale OHyMoS [Object-oriented Hydrologic Modelling System] assisted Distributed), using a runoff generation model (Xinanjiang) Zhao et al. (1980) developed and a lumped kinematic wave stream routing model was applied at simulating three macro scale watersheds ranging from 132,350 to 2,093 km². Every grid cell of the MaScOD model contained multiple runoff generation and routing models, so thus it could represent the hydrologic processes with single big size cell. In addition, they introduced an index, the IC-ratio, which divides the area of a cell by that of a watershed, to represent the sensitivity of modeling performance to the scale of input data. Then, performance of the model was evaluated with the observed discharge while changing spatial resolution of the input data.

The study showed that performances of the model for the three watersheds improved consistently as the IC-ratio increased and the rate of improvement was reduced.
significantly after a ratio reached 1:10. Therefore, they recommended use of an input data spatial resolution that satisfies at least the IC-ratio of 0.10. However, interestingly, the modeling performances were not deteriorated much at the IC-ratio of 1:5 or even 1:1 comparing to those at 1:10 or even smaller ratios, a result that should be attributed to the modeling framework. As mentioned early, every cell of the model can simulate runoff generation and routing independently and outflow of each cell was routed to downstream cells using the conceptual linear assumption between discharge and its contributing area that Shiiba et al. (1996) proposed. Thus, it should be noted that the recommended IC-ratio might not present the appropriate size of spatial discretization of a distributed hydrologic modeling but of spatially distributed input data resolution.

2.9.7 Application of Distributed Model at Macroscale Simulation

In the study of Shrestha et al. (2006; 2007) described above, a distributed model was used for large scale simulation that employs a larger grid cell for modeling efficiency and compatibility with existing database like GCMs. However, eligibility of equations and algorithms should be assessed for scale before starting modeling to avoid erroneous application. If applicable equations for the scale are not found or can not be derived, integration of individual field scale modelings at a macro scale can be a way to simulate H/WQ processes for a large region as shown by Shrestha et al. (2006; 2007). In addition, a certain assumption for simplification like the one that Shrestha et al. (2006; 2007) uses for flow routing may mitigate complexity of modeling and computational burden. Consequently, as its application scale gets larger, the degree of conceptualization of a model may become high because aggregation and averaging effect of spatially heterogeneous characteristics of geographical entities becomes significant.

Meanwhile, a macro scale model needs coarsely sampled input data or aggregation of data and information defined and derived at a finer scale. For instance, topography data like DEM are provided at a variety of scales ranging from 1/3 (about 10 m) to 30 arc-second (about 900 m but 1 km at the equator), so thus they or their derivatives such as slope and flow networks may become averaged and less precise at a macro scale than at a fine one. Thus, algorithms to calculate derivatives from DEM may
need to be refined with additional methods and knowledge to minimize information loss caused by aggregation and averaging for large scale modeling. Martz et al. (2008) examined change in topographic derivatives for a watershed as the resolution of DEM increases. Raina (2004) summarized cell-to-cell routing methods developed for a large-scale hydrologic modeling.

Oki et al. (1998) used a stream network obtained from DEM by automatic procedure as a first guess in determining flow directions and pathways (TRIP: total runoff integrating pathway) at the global scale of 1 degree. In the procedure, the lowest neighbor and steepest descent routines identified flow directions. Arora et al. (1998) considered amount of outflow of every cell in deriving flow directions at the resolutions of GCMs (General Circulation Models) such as 2.8 and 3.75 degrees. In the proposed method, a cell where the maximum outflow occurs is identified on the flow direction map created by Oki et al. (1998) at 1 degree first, then location of the cells determines a flow direction of a GCM cell of a larger size.

O’Donnell et al. (1999) proposed an algorithm, which utilizes stream networks generated from a fine scale DEM, to derive stream networks for hydrologic modeling at a macro scale. Although the final product needs adjustments, it provided 90% overall accuracy in comparison with manually derived stream networks. Wang et al. (2000) developed another algorithm that considers a division and merger of flow direction in a receiving low-resolution cell, which is acknowledged by the generated stream networks at a finer scale. They visually compared three flow networks derived from different resolutions, 30 m, 120 m, and 150 m and found consistency between them. Lear (2000) and Olivera et al. (2002) tried to improve the algorithm O’Donnell et al. (1999) developed through introducing the double maximum method (DMM). In the study, the method reduced the bias found in O’Donnell et al. (1999)’s algorithm such as predicting more flow on the sides than corners of a cell, but it showed poor performance in comparison of drainage area with that observed.

Reed (2003) attempted to improve the algorithm that O’Donnell et al. (1999) proposed by introducing ‘cell outlet tracing with an area threshold’ (COTAT). In their method, COTAT determines whether trace from an outlet subpixel of a cell of interest
toward subsequent outlet subpixels of the neighbor cells continues based on difference between drainage areas of the outlet subpixels of the cell and its neighbor cells. In comparing the sampled watershed areas and the detailed polygon boundaries, the COTAT algorithm reproduced boundaries and areas of watersheds whose areas are over 1,000 Km$^2$ at the relative error of 5%. Paz et al. (2006) tried to improve the COTAT algorithm by introducing another parameter, MUFP (minimum upstream flow path), to fix its wrong representation of flow directions of meandering river running in parallel and passing the same cell. In the method, if length of the flow path indentified by the COTAT algorithm is less than MUFP, another outlet subpixel that produces the longest path will be selected for the representative one in a coarse-resolution cell of interest. Then, the location will be used to define flow direction of the cell. Davies et al. (2009) evaluated several algorithms, such as MEM (Mean Elevation Method), COTAT with MUFP, NSA (Network Scaling Algorithm), and NTM (Network Tracing Method), to define flow directions of a coarse-resolution DEM from a high-resolution one. Their study showed that the COTAT with MUFP method provided the closest stream networks and watershed areas to those derived from a fine scale DTM.

### 2.9.8 Determination of Temporal Resolution for Distributed H/WQ Modeling

Objectives and efficiency of H/WQ modeling determine temporal and spatial scales for simulating flow and water quality. Bloschel et al. (1995) presented ranges of time-scales for types of problems at hand like Figure 2.6. As seen in the figure, hydrologic modeling for flood warning needs to be done in a relatively short time frame because usually flooding is advanced fast and caused by a sudden extreme storm event. On the other hand, change in watershed characteristic and its impact on the environment progress relatively slowly year-to-year, so only long term monitoring and modeling can evaluate that impact. In Figure 2.7 (Jorgensen et al., 2001) gives more systematic understanding about temporal scales of H/WQ modeling in terms of temporal order of the reactions. In the figure, modeling for purely physical natural phenomena that occurs in a second to several minutes gives hourly output to the next modeling. In addition, chemical
and biological modeling produces averaged output at daily and monthly scale to ecological modeling as input.

<table>
<thead>
<tr>
<th>Water Use</th>
<th>Management</th>
<th>Design</th>
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<tr>
<td>Irrigation &amp; Water Supply Reservoirs</td>
<td>Hydropower Optimization</td>
<td>Land Use &amp; Climate Change</td>
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<tr>
<td>Urban Drainage</td>
<td>Environmental Impact Assessment</td>
<td>Culvert</td>
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<td>Detention Basins</td>
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<td>Flood Warning</td>
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<td>Minor Dams</td>
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<td>Major Dams</td>
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Figure 2.6. Problem solutions required at a range of time-scales (Bloschl et al., 1995).
Bloschl et al. (1995) studied temporal and spatial scales of hydrological processes and concluded that those scales are interrelated to each other and there is “a roughly constant ratio of characteristic length and time scales for a given process over a range of scales”. The relation between them is rather natural because speed, which is the magnitude relates time with space in measuring system, is observable, recognizable and/or interested only within a certain range of its values. For example, in Figure 2.8, even though ‘infiltration excess overland flow’ occurs in a shorter temporal and spatial scale than does channel flow, their slopes and intercepts that represent speed of a phenomenon are similar to each other. On the other hand, channel flow usually moves faster than subsurface flow and groundwater at different temporal scale. Like this, hydrologic and water quality phenomena progress at their own temporal and spatial speeds and it should be accounted in choosing temporal and spatial calculation steps at

Figure 2.7. Space and time scale ranges for some typical submodels (Jorgensen et al., 2001).
the beginning stage of the H/WQ model development. However, as Klemes (1983) pointed out, the interconnectedness of temporal and spatial scales is often disregarded in scientific research and the levels of the two scales are chosen independently.

Figure 2.8. Hydrological processes at a range of characteristic space-time scales (Bloschl et al., 1995).

### 2.9.9 Approaches for Distributed H/WQ Modeling

Empirical models like a regression curve and Box-Jenkins type stochastic model attempt to describe and predict the natural phenomena inductively based on past observations of the specific location or region though statistical methods. Therefore, if a
H/WQ model is empirically developed only based on local measurements of flow and water quality, it should be applied to the area that has similar climate and landscape in order to get reliable results. In addition, it may have a relatively simple form because it ignores detailed causality between input and output. On the other hand, physically based models describe and predict the natural phenomena and their processes deductively using laws of nature and known physical processes like the law of conservation of mass and Newton’s law of gravitation. A physically based model is subject to have a relatively complicated form and easily associated with a process-based model because it attempts to simulate natural phenomena with detailed description about known relation between causes and effects. In general, simple models incorporate more approximations than do complex models. However, complex models often have many assumptions with undefined consequences even though their sophistication may provide more accuracy (DePinto et al., 2004).

A physically based H/WQ model also tries to scale up (upscaling or zooming out) the known physics about hydrologic and water quality phenomena at a laboratory scale to a catchment scale (Grayson et al., 1992b; Kuczera et al., 1998). Thus, temporal and spatial scaling becomes a key issue in developing a physically based model (Beven, 1989, 2001; Bloschl et al., 1995). If physical equations that depict hydrological processes are appropriately applied to a similar situation in which they were developed, they can be widely used for H/WQ modeling because it was developed based on a law of nature or a universal rule even though it may have a complicated form and/or many parameters, and scaling issues. A completely physically based H/WQ model seems not to exist due to limitation of knowledge and sensing technique and variability and heterogeneity of nature. Even the most advanced physically based model like WEPP contains many empirical parameters and equations calibrated to a specific condition to keep the calculation processes simple and derive relationship among variables from the limited data (Flanagan et al., 1995).

Klemes (1983) investigated scale issues on conceptualizing hydrologic phenomena in the development of a model. He argued that different forces and mechanisms tend to dominate at different scales so physical laws at the higher scale (lower resolution) are subject to express averages or integrals of those dominant at a
lower level (higher resolution). He also claimed, “Different sets of physical laws dominate at each level and seem to be anti-intuitive when viewed from a different level” and exemplified nonlinear hydraulic similarity between a model and prototype at a hydraulic scale model experiment. Consequently, validity of a routine application of physical relationships developed based on observations made at different levels of scale can be significantly deteriorated. In this sense, a distributed model provides a valuable measure for settling this scale problem by accommodating flexibility of simulation scale. Lastly, in spite of its triviality, it should be noted for better interpretation of his study that there are universal physical principles such as the laws of conservative and entropy, and these laws of thermodynamic are always valid at all the scales. Thus, the ‘physical laws’ he referred above may mean only phenomenological equations, which are widely used in a hydrologic modeling, such as Darcy’s and Manning’s equations developed based on empirical observations.

While the physically based approach can provide better understanding of hydrologic processes and behaviors of water quality materials, the empirical approach can give relatively quick overview and prediction for the system if sufficiently long and reliable data are provided. Tiwari et al. (2000) compared the results of a physical model, WEPP and empirical models, USLE and RUSLE, and the empirical exhibited better model efficiency than did the physical due to availability of more refined and site specific input parameters. However, only the physically based approach can be appropriately applied to simulate hydrographs and water quality for unmeasured watersheds unless the empirical approaches are extensively examined over wide temporal and spatial ranges. It has never been concluded that one is superior to the other in terms of accuracy. Therefore, it can be a crucial aspect in developing a simple but widely applicable H/WQ model to balance between well-defined empirical and sound physically based approaches.

Nonetheless, a physically based representation provides a critical strength over a lumped model in a spatially distributed modeling. A physically based model is not easily associated with a lumped parameter model because it is hard to get a suitable and correct single variable and parameter set for a physically based equation, which are normally developed for spatially homogeneous entities in the controlled environment at a watershed scale. Although the lumped or averaged variable and parameter for a
physically based equation could provide plausible results in a lumped modeling, it might be attributed to the offset effect of impact of different variables and parameters on the results. In addition, parameters of a lumped model are likely to be calibrated to values that are far from the original physical meanings because they contain averaged quantities about unknown effects caused by entities that have heterogeneous characteristics and interactions between them in order to get a better fit of the modeling results to the observed data.

Grayson et al. (1992b) emphasized physical bases of a distributed model in his definition; a model that depends on physically based equations is a method to simulate the spatial variability of flow and water quality materials in the watershed. When a physically based model is applied with spatially distributed parameters, it can describe H/WQ processes with variables and parameters whose meanings are close to their originals for a homogeneous entity. Thus, the physical base will benefit calibration of a distributed parameter model (which is subject to be overparameterized because of the large number of combinations of homogeneous entities to be simulated) by constraining the range of parameters and providing clues based on physical meaning and reasoning. Although parameters in a physically based distributed model are determined with the measured or measurable properties of a watershed, they may still need to be calibrated due to inability of model equations and parameters in representing the true watershed physics and heterogeneous, scaling effects, and error contained in the measured data (Smith et al., 2004b). For the same reason, parameters in a distributed model are usually derived from other variables (Moreda et al., 2006). Soil depth, stream network extent, and anisotropic ratio can be typical examples of conceptualization of watershed physical properties in a physically based distributed model. If watershed physics are described in detail with appropriate physical laws and equations and all the required input data are provided in the model, there might be little need to calibrate parameters in the physically based equations, so thus other empirical parameters may have more opportunity to be calibrated with more confidence and equifinality issue can be mitigated.

Beven et al. (1989) and Grayson et al. (1992b) concluded that the current generation of distributed physically based models like MIKE-SHE are distributed lumped conceptual models at the model grid scale based on examinations of the conceptual
nature of several models. In other words, hydrologic and water quality processes in and/or between computational units like a cell are usually simulated in the lumped manner in most distributed physically based model. Reggiani et al. (1998; 1999; 2000) tried to derive rigorous conservation (balance) equations for mass, momentum, energy, entropy, and the second law of thermodynamics for a watershed at representative elementary watersheds (REV) scale by integrating the point-scale conservation law over particular control volumes. However, the formulated balance equations should be converted in closed forms by parameterization according to a particular hydrologic situation at hand because his formulation is fully founded on universal balance laws (Reggiani et al., 1999; 2005). In addition, REV he proposed seems no more than a hydrologic response unit (HRU) that has already been employed in several existing H/WQ models. Reggiani et al. (2005) applied his methodology to a real watershed but did not get a good agreement of the results with observations. He concluded that the modeling errors are attributable to the chosen schematization, suboptimal parameter values, the spatial resolution, and simplified flux representation.

We try to simplify hydrologic and water quality processes by conceptualization in developing a H/WQ model because usually we do not know all the details but understand major mechanisms in the interaction among physical elements at the desired scale. Distributed H/WQ models can incorporate the hydrologic variability or heterogeneity that occurs at a range of scales by subdividing the watershed into a number of units such as HRUs, subcatchments, hillslopes, and individual grid cells (Bloschl et al., 1995). The presentation of process within the unit involves local scale descriptions and assumptions on the variability or heterogeneity in the unit (Bloschl et al., 1995). Therefore, distributed H/WQ models usually represent local phenomena in detail, while the heterogeneity within the unit is usually ignored or lumped by assumption, conceptualization, or parameterization (Bloschl et al., 1995).

The CN method is a good example of the physically based conceptualization for excess rainfall generation. Parameters, CN and initial abstraction are introduced to simplify the complicated physical processes deductively, and they contain physical meanings. Thus, they might be closely related to properties and characteristics of the processes. If parameters and equations of a conceptual model do not have any physical
meaning and subsequently their determination highly relies on calibration, the conceptual model will become a type of purely empirical or naïve model, and its determination becomes no more than statistical regression. Therefore, when we can conceptualize mechanisms of H/WQ processes at appropriate temporal and spatial scale based on the sound mathematical and physical fundamentals, conceptual approach may be much simpler and easier than the fully physical approach. However, interpretation of physical meaning of a parameter can become very complicated and unclear in the conceptual approach due to the intermingled impacts of factors that are not explicitly treated in the modeling. For example, the retention parameter of the CN method is interpreted as potential maximum retention, potential maximum infiltration, or potential post-initial abstraction retention (Singh, 2003). This unclear definition of a parameter in a conceptual approach may reduce benefit from using a physically based model in calibration.

Figure 2.9 displays the degree of participation of prior knowledge and observed data in development of empirical, conceptual, and physically based models, and the continuum between them. For example, observation is comprehensively involved in identification of model structure and parameter of an empirical model, but its participation is minimized in development of a physically based model. On the other hand, prior knowledge plays an important role in development of a physically based model. In addition, a physically based model may require observation for calibration and an empirical model may need prior knowledge for model selection. In the development of a conceptual model, levels of participation of prior knowledge and observation may be similar to each other. A conceptual model is between an empirical and a physically based model and there may not be a clear boundary between them.
2.10 Sensitivity Analysis

2.10.1 Overview

“Sensitivity is defined as the rate of change of one factor with respect to change in another factor (Wootton, 1996).” Sensitivity analysis is a study to examine how changes in a model’s input values affect its output (EPA, 2009) so that it can identify sensitive inputs to the modeling output. According to Saltelli (2002a), the sensitivity indices are related to decomposition of the variance of the model output into terms either due to each input taken singularly as well as into terms due to the cooperative effects of more than one input. The term, sensitivity analysis, is sometimes used in similar meaning of uncertainty analysis. Thus, some authors define it as the study of determining the contribution of individual input variables to the uncertainty in model predictions (Helton, 1993) and of how uncertainty in model predictions is determined by uncertainty in model inputs (Lilburne et al., 2009).

Jager et al. (2004) attempted to characterize similar methods, such as uncertainty analysis, sensitivity analysis, error analysis, error budget analysis, spatial decision analysis, and hypothesis testing using neutral model, which explore the relationship between variations in input and output of a model. In the study, they discriminated sensitivity and uncertainty analysis as seeking to rank input variables qualitatively by
their impact on modeling output versus to quantify the variation in the model output caused by parameter uncertainty. In addition, they pointed out that “if the parameter is measured very precisely, it may not generate much uncertainty, even though the model is sensitive to it.”

In H/WQ modeling, sensitivity analysis maps responses of the modeling output against change of input within the input space. The responses are usually expressed with absolute or standardized values and gradient of H/WQ modeling output of interest. One way to map the responses is to measure the impact of an input on the output while the other inputs are fixed. Thus, this approach is called the one-factor-at-a-time (OAT) methods (Saltelli et al., 2005), and it is the simplest method to screen sensitivity inputs and factors against the modeling output. However, in practice, parameters are interacting to each other in H/WQ modeling so that the OAT approach may over- or underestimate sensitivity of the model output. In addition, Beven (2000) pointed out that the OAT approach provides only local estimates of sensitivity in the parameter space. Thus, sensitivity by OAT is usually evaluated in the immediate region of the identified optimum parameter set after model calibration (Beven, 2000). He also argued that global sensitivity might provide more useful estimate of the importance of parameters in the given model structure.

2.10.2 Sensitivity Analysis Methods

Saltelli (2002b) argued the desirable properties of methods for sensitivity analysis should be global, model independent, and capable of coping with characteristics of input. Iman et al. (1990) also described an ideal sensitivity measurement as unconditional, easy to interpret and compute, and stable (Liu et al., 2009). Taylor series expansion is analytical method of sensitivity analysis. Once a model is represented with the Taylor series approximately, then variance propagation techniques are used to estimate the sensitivity of the modeling output against input (Helton, 1993). Although this method has capability of incorporating correlation of the input into the analysis, usually it is not possible to get a continuous and analytical form of a H/WQ model, which is differentiable, due to its complex structure (Xu et al, 2007). On the other hand, the Monte
Carlo method tries to map the model response against simultaneous changes of the all inputs through sampling the output within the entire input space so that it can provide global sensitivity. In addition, it does not need differentiation of the model and it is independent of a model.

However, usually sampling based methods like the Monte Carlo are less efficient than the differential ones such as the Taylor series expansion method because it needs a large number of model evaluations. Thus, some techniques like Latin Hypercube sampling and experiment design are used to explore the parameter space in ways that are more efficient. Helton et al. (2003; 2005) compared performances of simple random (Monte Carlo) and stratified (Latin Hypercube) sampling techniques with different sample sizes for sensitivity analysis of two-phase fluid flow model. Their study showed the simple Monte Carlo and the Latin Hypercube produced similar results. Cryer et al. (1999) applied the fractional factorial design technique of Plackett and Burman (PB) for sensitivity analysis of the GLEAMS model and showed the PB method can provide similar results as the simple Monte Carlo approach. However, the PB method showed different sensitivity ranks of the parameters with varied perturbation factors, and response surface methodology using an experiment design is obviously model dependent (Saltelli et al., 1999).

In the same vein, the LH-OAT (Latin Hypercube and One-factor-at-A-Time) method Griensven et al. (2006) proposed is an attempt to improve efficiency of sampling through introducing relatively efficient OAT techniques into sampling based method. The method samples \( L \) points for \( P \) parameters with the LH technique, and then calculates sensitivity of every parameter with the OAT. The final sensitivity is obtained by averaging the all partial sensitivities of \( L \) points. They applied this method to see sensitivity of the selected SWAT model’s parameters, and the study showed the curve number is the most sensitive parameter for the overall modeling and water quality highly depends on the groundwater parameter, \( ALPHA_{BF} \).

The Fourier Amplitude Sensitivity Test (FAST) approach was developed based on the idea that variance of the modeling output can be decomposed into variances of individual input variables. It transforms multidimensional integral over the input variable
space to a one-dimensional integral, and then the fractional contribution of the individual input variables to the variance of the modeling output is obtained through a decomposition of the Fourier series representation of the model (Helton, 1993). Sobol (1990; 1993) proposed another variance based sensitivity analysis method. The method decomposes the total unconditional variance of the modeling output into the number of combinations of parameters considering interaction and hierarchical structure of the parameters (Saltelli, 2000; Saltelli, 2002; Lilburne et al., 2009).

Some extended FAST approaches were also developed based on a decomposition of the modeling output variance into terms of increasing dimensionality as the Sobol method does (Saltelli, 2005). Xu et al. (2007) developed a technique to consider correlation of parameters with others in sensitivity analysis. The technique they introduced captures correlation structures of parameters through investigating the characteristic frequency of the parameter of interest based on the logic that the higher correlation of the parameter will present the more variations of the other parameters. Although the variance based methods relies on sound statistical basis, they have been little use in engineering and science community due to uncomfortness of moving away from the mathematical appeal of derivatives (Saltelli, 2002; 2005), very demanding computation of individual variations (Helton et al., 2003), and maybe too complex hierarchical structure of input and parameters to be unfolded.

As reviewed, the sampling based sensitivity analysis methods are global, model independent, and capable of considering features of input. In addition, techniques to impose correlation between parameters in sampling, such as the rank correlation Iman et al. (1982) proposed (Iman et al., 1982; Helton et al., 2002; 2003), have been developed. Thus, it becomes preferred as computing resources are improving and efficient sampling techniques are developing. Helton et al. (2006) reviewed issues in the utilization of sampling based methods for uncertainty and sensitivity analyses, such as sample generation methods, presentation of uncertainty analysis, and appropriate sensitivity analysis methods. They also pointed out that probability that sampling methods usually utilize may give the appearance of more knowledge than is really present.
Screening insensitive inputs of the modeling is another important task of sensitivity analysis. Hornberger et al. (1980) and Spear et al. (1980) proposed a way to classify sensitivities of parameters into ‘critical’, ‘sensitive’, and ‘insensitive’. They pointed out that a model can only simulate salient qualitative behavior of a system unless sufficient quantitative data and information for the study area are obtained. For assessing sensitivity of parameter, they first classified time series sets of the modeling output simulated within parameter spaces and with probability distributions defined by prior knowledge through a Monte Carlo technique into ‘behavior’ and ‘non behavior’ sets by comparing qualitative similarity of the simulated time series of interest with the measured. Then, difference of the cumulative probability distributions that belong to ‘behavior’ and ‘non behavior’ sets is calculated with Kolmogorov-Smirnov (KS) test. Finally, the parameters are divided into three classes, ‘critical’, ‘sensitive’, and ‘insensitive’, with different significance levels, 0.99, 0.90 to 0.99, and less than 0.90 respectively. Hence, a parameter, which is classified as ‘critical’, is regarded as very important in determining ‘behavior’ of the modeling output of interest.

2.10.3 Sensitivity Analysis Methods for Distributed H/WQ Models

A distributed H/WQ model normally requires the large number of parameters and amount of input data, and this may limit analyses of a distributed H/WQ model that requires relative long running time. In particular, the total operating time can be a critical concern in sensitivity analysis and calibration using a sampling based method. One of the methodologies proposed to solve this problem, is introducing scalar multiplier to fix spatial variability of spatially distributed parameters (Refsgaard, 1997; Madsen et al., 2003; Castaings et al., 2009). The spatial variability is redefined based on prior information and existing database, and then it is fixed using the scalar multiplier in an analysis like calibration. Thus, values of the parameters can be adjusted by only changing the scalar multiplier, and their relative magnitudes over a watershed are maintained.

Refsgaard (1997) tried to characterize methodologies for parameterization, calibration, and validation of distributed hydrological models through comparison with those of a lumped model. In the study, he also tried to reduce the number of the ‘free
parameters’ or ‘the degree of freedom’ in calibration of a MIKE SHE modeling through linking ratios to the ‘free parameters’. Use of the ratios, scalar multiplier, or scale factor allows reducing the number of parameters to be calibrated while still representing spatial patterns of the parameters and the available field data. Madsen (2003) applied the same technique as that Refsgaard (1997) used for automatic calibration of a distributed hydrologic model, MIKE SHE. However, Lilburne et al. (2009) argued that use of a scalar multiplier might severely constrain ability of a distributed model in presenting spatial variability of parameter and input data.

Shoemaker et al. (2003) and Benaman et al. (2004) proposed a methodology to reduce valid ranges of parameters in sensitivity analysis of a distributed watershed model, SWAT. They implemented a simple Monte Carlo simulation to identify biased parameters through comparing the cumulative frequency distributions of the evaluated outputs with the measured. After that, interval-spaced sensitivity analysis for the biased parameters is implemented, and then a threshold defining the maximum sensitivity of the modeling output was set to reduce parameter ranges. Finally, a Monte Carlo simulation was implemented over the reduced parameter space to confirm the range of the parameters through comparing the cumulative frequency distribution of the simulated output and the measurement. Although it can be used to reduce parameter space and help make calibration easier, the initial Monte Carlo simulation and arbitrary setting of threshold may constrain the parameter space so that the following calibration can fail to identify the best parameter set.

Yatheendradas et al. (2008) tried to see which uncertainty source, among radar rainfall estimate, initial soil moisture approximation, and model parameters, is the most influential to the semiarid flash flood forecasting. They applied the GLUE method in classifying behavioral simulations and parameter sets. Then they utilized the variance-based method Sobol (1990; 1993) proposed to identify dominant source of uncertainty. From the study, they found that uncertainty of radar rainfall estimation dominated the overall KINEROS modeling output uncertainty. In addition, the predictive uncertainty came from the given typical level of uncertainty in the three sources and often it was much higher than what would be considered acceptable for accurate flash flood forecasting.
Castaings et al. (2007; 2009) applied the automatic differentiation (AD) method for sensitivity analysis of a distributed hydrologic model, MARINE, which is formulated based on kinematic wave approximation. They analyzed sensitivity of flood peak to Manning’s roughness coefficient for every overland and channel cell and found that the sensitivity was characterized differently -- such as negative or positive and significant or slight -- according to spatial location within a watershed. Their finding means that parameters at different locations over a watershed are not equally controlled by the observations and compensation effects that counterbalance the overall effect usually occur (Castaings et al. 2009). Lilburne et al. (2009) reviewed sensitivity analysis approaches for spatially distributed models and demonstrated a way to apply the variance based method Sobol (1990; 1993) proposed to sensitivity analysis for input data layers of a simple spatial model. From a simple numerical experiment, they found that resolution and uncertainty range of the input layers critically influence sensitivity of the model.

Liu et al. (2009) developed a method to calculate the statistical index ($\delta_i$) Borgonovo (2007) proposed, which is known as global, model independent, and moment independent. They reformulated integral equations used to calculate the index in previous study to simple numerical summations by expanding equations in a form of the cumulative probability density function instead of the marginal. In the study, they found that the new method was easier to implement without the additional number of model evaluations. In addition, the statistical index approach that Chun et al. (2000) and Borgonovo (2007) proposed was relatively easy to interpret, understand, and compute, and it was capable of considering the output time series like hydrograph as well as a simple value like peak rates and time to peak. Thus, it would be a way to investigate sensitivity of the modeling output in a frequency domain rather than in a time domain. However, it should be noted that their methods are applicable only when model outputs are rearranged in forms of probability functions in frequency domain.
2.11 Calibration and Optimization

2.11.1 Overview

A H/WQ model is calibrated with observed data due to several reasons such as seasonal variation in hydrological features of the watershed, inconsistency in scales of equations and parameters with those at which they was developed and introduced, sometimes difficulty in measuring parameter values at field, and simplification of the reality. If a model is not built fully physically so that it should have some conceptual and empirical structures and/or parameters, the model must be calibrated to provide useful and satisfactory results. In addition, if the best parameter set was not obtained, “it is difficult to determine how sensitive the parameter estimates are to factors such as input and output data error, model error, quantity and quality of data, objective function used, and so on” (Duan et al., 1992). The scale problem of parameter in H/WQ modeling was discussed earlier and uncertainty associated with error in measured data will be examined later so only some issues associated with calibration methods will be discussed here.

Usually H/WQ models have multiple parameters so that an objective function or goodness-fit measure will be multidimensional. Therefore, calibration is no more than a job to find the global optimum in parameter space if assuming a H/WQ model has only one best parameter set in explaining the measured data in the given condition. However, calibration is an inverse problem or one-to-many mapping problem so that generally the solution is not unique (Moradkhani et al., 2008). This issue is usually called equifinality, nonuniqueness, or nonidentifiability.

Traditionally, calibration has been performed manually by trial-and-error. The process of manual calibration, however, may be a very tedious and time-consuming task, depending on the number of free model parameters and the degree of parameter interaction. Furthermore, because some level of subjectivity is usually involved, it is difficult to assess confidence of the modeling results explicitly. Thus, a great deal of research has been directed to development of more efficient and effective automatic calibration procedures (Madsen et al., 2002). Although there are many algorithms for automatic calibration proposed, implementation of an automatic calibration procedure commonly includes the selection of: 1) an objective function, 2) an algorithm to search
the parameter space, 3) a period of historical data against which to calibrate the model, and 4) termination criteria used to determine when to stop the search (Hogue et al., 2000).

Usually an objective function in parameter space of a H/WQ model cannot be expressed as a mathematical function in an analytical form due to the complexity of model structure. Therefore, if calibration cannot be done analytically, the simplest and most obvious but often tedious way to optimize parameters may be brute-force search or exhaustive enumerating. It tries to search or mapping objective function or goodness-fit surface for all the parameter value combinations in order to find the optimum. The elimination and random search methods are other types of the optimization techniques. Elimination method attempts to narrow the parameter space to be evaluated through focusing on a preselected part of the objective function surface (Verumi et al, 1970). Some algorithms were devised to explore parameter space in more efficient and sophisticated ways, and they are briefly introduced.

Yapo et al. (1996) investigated sensitivity and behavior of calibrated parameters in a conceptual rainfall-runoff model to the length of data used in calibration. From the study, they argued at least 8 years of measured data are required for stabilization of the Nash-Sutcliffe efficiency coefficient. Raat et al. (2004) tried to reduce uncertainty in calibration of the INCA (Integrated Nitrogen CAtchment) model through increasing the length or frequency of measured data. However, they found that the extending datasets did not significantly improve uncertainty caused by equifinality in model calibration.

2.11.2 Calibration and Optimization Methods

The simple random search method may be inefficient and computationally intensive because it does not use any knowledge-guided information can be acquired while searching. Thus, some modifications such as a bracketing approach were made to guide the random search adaptively toward the region of the global optimum (Duan et al., 1992; Chapra et al., 2002). These shortcomings may be a crucial weakness when computing environment was poor in the past. However, it provides a promising tool in finding a global optima rather than a local one.
A few more sophisticated iterative search techniques such as simulated annealing (SA) and genetic algorithm (GA) have been devised accompanying the rapid development of computing resources. Their convergence does not depend on the quality of the initial guess or seeding point. The SA and GA borrow ideas to find the global optimum from key mechanisms in annealing process of metallurgy and natural selection of evolutionism respectively. Unlike conventional Hill-Climbing methods, the SA allows descending of objective function in parameter space based on a probability controlled by a temperature, which represents level of optimization at each iteration step. (Kirkpatrick et al., 1983). The probability or acceptance rate of new state is determined by the Metropolis criterion, which was proposed to find the equilibrium configuration of a collection of atoms at a given temperature (Kirkpatrick et al., 1983; Metropolis et al., 1953).

In the GA, only parameter sets that give a good fitness value are chosen (selection) this iteration (generation) and delivered (inheritance) to the next iteration, then values of some parameters in two candidates parameter sets are exchanged (crossover) probabilistically and synchronously (Forrest, 1993). In addition, the GA flips values of some parameters in a parameter set that may provide a poor goodness-of-fit value in order to explore the parameter space comprehensively. After sufficient numbers of generations or iterations, only parameter sets that have good goodness-of-fit values will remain. These heuristic approaches can efficiently locate good global solutions if the algorithm is well designed for a specific problem at hand. In addition, they can “handle nonlinear and discontinuous problems that classical optimization methods cannot usually solve well” (Chapra et al., 2002). However, it may provide an approximated answer close to the exact global optimum. Nevertheless, the term, “global optimum” is generally used on behalf of “good global solution” in the heuristic approaches.

Hill-Climbing methods such as relaxation and gradient methods were proposed to improve efficiency in finding the optimum in the parameter space. For parameter calibration of H/WQ modeling, they have been an important research part since the start of computer modeling in the 1960 (Beven, 2000). Relaxation method searches for the optimum of one parameter at a time and repeats that as many times as the number of the parameters (Verumi et al, 1970). However, it may provide an optimum of each parameter
rather than an optimum parameter set because it does not consider interactions between parameters. Gradient methods such as steepest ascent method search along trial directions from the current state for improved objective function or goodness-of-fit value (Beven, 2000), and it explicitly uses derivative information to generate efficient algorithms to find optima (Chapra et al., 2002).

Duan et al. (1992) investigated objective function surfaces of a conceptual rainfall-runoff model (SIXPAR) that has six parameters using two different optimization methods: Uniform Random Sampling (URS) and Exhaustive Gridding (EG). In the study, they found that an objective function in a multi-parameter space is not smooth and it has discontinuous derivatives that vary in an unpredictable manner as well as the large number of minor optima. Therefore, the gradient methods cannot always get derivatives of the objective function at any point in a parameter space, so thus it may fail to find a global optimum at a discontinuous point.

Gupta et al. (1985) compared the performance of a derivative-based Newton-Raphson algorithm and the Simplex direct search method Nelder et al. (1965) proposed that needs no derivatives in calibrating conceptual catchment models. They found that the Newton algorithm converged faster than did the Simplex, but ability of the two algorithms to converge to the optimum point was similar to each other. Although the gradient methods provide an efficient way in terms of computing intensiveness, they are not always successful in locating global optima (Gupta et al., 1985) because termination of non-optimal regions depends on the initial guesses (Kavetski et al., 2006a). Thus, initial values are reseeded as many times as needed in the parameter space or algorithms are modified to allow further exploration in the parameter space for finding a global optimum (Kavetski et al., 2006b).

For example, a common software, PEST, adapts the gradient based optimization approach and employs a variant of the Gauss-Marquardt-Levenberg (GML) method in order to reduce the number of model runs in locating optima, but it is more subject to find one of the local optima rather than the global optimum (Gallagher et al., 2007). Attempts to overcome this shortcoming have been to try starting from different points in parameter space (Gallagher et al., 2007). However, sampling-based algorithms are known as more
efficient than multi-start local search procedures (Madsen et al., 2002). In addition, in order to prevent the algorithm being stuck in unreasonable local optima, regularization is applied to allow a user to supply a default system condition expressed in terms of preferred values of parameters or preferred values for mathematical relationships between parameters in PEST (Doherty et al., 2003). Skahill et al. (2006; 2009) tried to enhance the capability and efficiency of the gradient based method.

Duan et al. (1992; 1993; 1994) reviewed five major optimization issues we usually face when calibrating a conceptual rainfall-runoff model: (1) regions of attraction, (2) minor local optima, (3) roughness (not smooth and discontinuous objective function surface), (4) sensitivity (varying sensitivity of response surface in region of optimum and nonlinear parameter interaction), and (5) shape (non-convex response surface). As seen previously, probabilistic and exhaustive optimization methods that adapt a random search approach can be employed when an objective function is discontinuous and when it is difficult to obtain derivative information because they do not need restriction conditions such as continuity and differentiability (Duan et al., 1992). Moreover, it has been proven that many of them can provide a global optimum (Sorooshian et al., 1993; Luce et al., 1994; Gan et al., 1996; Cooper et al., 1997; Freedman et al., 1998; Thyer et al., 1999; Madsen et al., 2002; Tolson et al., 2005). Therefore (1), (2), (3), and (5) of the issues mentioned above can be resolved by using probabilistic and exhaustive methods in calibrating H/WQ models. In order to take advantages of robustness of genetic algorithm and simplicity of the direct search methods in optimizing a conceptual rainfall-runoff model, Duan et al. (1992) designed the Shuffled Complex Evolution (SCE-UA) method. It combines the strengths of the Simplex direct search method with the concepts of controlled random search developed by Price et al. (1987), competitive evolution by Holland et al. (1975), and complex shuffling based on competitive evolution (Duan et al., 1992; 1993).

Sorooshian et al. (1993) tested performances of the SCE-UA and the multistart simplex method (MSX) in finding the optimal parameter set for calibration of the Sacramento soil moisture accounting model (SAC-SMA) of the National Weather Service River Forecast System (NWSRFS). They also utilized two different types of objective function, daily root-mean square (DRMS) and heteroscedastic maximum
likelihood estimator (HMLE). From his tests, it was concluded that the SCE-UA algorithm provides more consistent, effective, and efficient way to locate the global optimum of a conceptual rainfall-runoff model, the SAC-SMA, than the MSX.

Luce et al. (1994) investigated the performance of the Simplex and the SCE-UA in calibrating a physically based storm runoff model, which is employing the Philip model and the kinematic wave approximation for infiltration and overland flow respectively. In his study, both algorithms could estimate physically reasonable parameter values reliably, and the performance of Simplex was little inferior to that of the SCE-UA because the objective functions did not have multiple attractions and local optima.

Gan et al. (1996) applied SCE-UA, MSX, and the Simplex optimization methods in calibrating four different conceptual rainfall-runoff models: SAC-SMA, the Nedbor-Aftromnings model (NAM), the Xinanjiang model (XNJ), and the soil moisture and accounting model (SMAR). They tested the algorithm with eight different catchments, and confirmed conclusions of Sorooshian et al. (1993) that the SCE-UA is more efficient than is the MSX and more effective than is the Simplex in terms of computational intensity and ability to find the global optimum.

Freedman et al. (1998) used the SCE-UA and the Simplex methods to identify the best erosion parameter set for a process-based model of runoff and sediment yield using the simple least-squares (SLS) and heteroscedastic maximum likelihood estimator (HMLE) as an objective function. In his research, contrary to the theoretical expectation, the Simplex method provided closer estimates of the parameters to the value considered as the optimum even though the SCE-UA algorithm also completely achieved to find the global optimum. He enumerated possible reasons for the unexpected outcome such as random features of the SCE-UA, use of the four-point finite difference scheme to solve the continuity equation for sediment transport, or errors in the formulation of the basic equations.

Some authors compared performance of the population-evolution-based optimization algorithms such as the SCE-UA, SA, and GA in calibrating conceptual rainfall-runoff models. Cooper et al. (1997) investigated robustness and efficiency of those three population-evolution-based methods in calibrating the 8-parameter TANK
model. He found that the SCE-UA was the most robust, followed by the GA, and then SA method. While the SCE-UA frequently located the optimum, the GA and SA could find only near optima, which is a typical characteristic of the heuristic methods. In addition, their efficiencies expressed by the required number of iterations for convergence were ranked at the same order as the robustness.

Franchini et al. (1998) and Thyer et al. (1999) compared performance of SCE-UA with those of three different optimization algorithms, the genetic algorithm coupled with sequential quadratic programming (GA-SQP), and the Pattern search with SQP (PS-SQP) and the three-phase simulated annealing algorithm respectively in calibrating conceptual rainfall-runoff models, A Distributed Model (ADM) and SFB model. Both authors concluded that the SCE-UA was superior to the others in terms of robustness and efficiency. Madsen et al. (2002) compared the overall performances of three different automated optimization methods, SCE-UA, clustering SA, and an expert system, for calibration of the MIKE11/NAM rainfall-runoff model. The results showed that none of the calibration methods was superior with respect to the performance measures considered such as the coefficient of determination, bias, and RMSE.

Tolson et al. (2005) tested performances of four optimization algorithms, the Simplex, simple Monte Carlo, SCE-UA, GA, and Global Greedy Search (GGS) in calibrating the SWAT model with two parameter sets that have six and fourteen parameters respectively. Although the numbers of model evaluation for two parameter sets were restricted to 2500 and 6000 respectively to avoid too long algorithm implementation time and ability to find the global optimum was out of interest, it was revealed that the SCE-UA and GGS have superior efficiency to the other.

As seen above, the population-evolution-based methods were mainly employed in calibrating conceptual rainfall-runoff models that do not need considerable executing time for single-run. In contrary to the direct search methods like the Simplex and MSX that usually provide quick solutions due to efficiency in term of computing resource, the population-evolution-based methods need a lot of tracers that will search better routes to the optimum in parameter space so that the processing time may be prolonged. In addition, distributed H/WQ models may need longer running time due to many numbers
of H/WQ processes considered (or modules) and many more parameters compared with lumped models. Moreover, if a modeler wants to implement further investigation such as uncertainty analysis after calibration, the required time for the whole modeling study would be greatly extended. Therefore, in practice, the efficiency of the optimization methods should be emphasized to get results in reasonable time especially when computing resources are restricted. In this sense, it must be very valuable to explore more efficient optimization algorithms in distributed H/WQ modeling.

Eckhardt et al., (2001) employed the SCE-UA algorithm to calibrate the SWAT-G. In the study, it took 6 days for the optimization procedure to be completed even though they constrained the number of parameters to be calibrated into eighteen by defining ratios among interrelated parameters. Ajami et al. (2004) compared the required time for a modeler to complete calibration using the SCE-UA algorithm and manually. They also tested three different formats of the SAC-SMA (Sacramento Soil Moisture Accounting) model, lumped, semi-lumped, and semi-distributed, in the calibration. He found that the semi-distributed format required computing time of over 2000 hours to complete the calibration while the lumped and semi-lumped approach required approximately 100 hours. The SCE-UA required only 3 hours to optimize the SAC-SMA model, but manual calibration required 20 hours to get the same results.

Lin et al. (2005) employed a two-stage strategy to calibrate SWAT model efficiently. At the first stage, spatial variation of parameters was ignored to reduce the dimension of the parameter space and possible region in the parameter space was narrowed so that a sampling based model could be employed efficiently. Then, the spatial variability of the original model parameters was restored and calibrated. Due to the increased number of parameters to be calibrated, a gradient-search algorithm, which is known much more efficient than is sampling based method, was employed. In addition, the regularization was adopted to avoid numerical instabilities and taking extreme values. This combined calibration strategy provided similar performance to the sampling based method, SCE-UA, in a less number of model evaluations. Tolson et al. (2007) proposed another stochastic and heuristic calibration algorithm, DDS (Dynamically Dimensioned Search), which attempts to improve efficiency of sampling based methods by probabilistically reduce the number of dimensions in a new search neighborhood. In their
comparison study, the algorithm showed better performance and efficiency than the SCE-UA algorithm in calibrating the SWAT model for the Cannonsville Reservoir watershed of 1,200 Km$^2$.

2.12 Uncertainty

2.12.1 Overview

A mathematical H/WQ model consists of equations, parameters, assumptions, initial, and boundary conditions and requires input data and information about a study watershed to provide outputs of interest. Input data and parameters essentially contain errors because they represent averaged characteristics of variables they try to depict at certain temporal and spatial scales. The possibility of including error arises when only the expected values are used to describe the solution of highly stochastic problems (Sohrabi et al. 2002). In addition, it is not possible for any model to mimic nature’s processes completely. Thus, assumptions are usually made to simplify a problem at hand so that known mechanisms and scientific logic expressed by equations and algorithms can be applicable. Consequently, input data, model algorithms, equations, data used for calibration, and temporal and spatial scale are usually considered as the sources of error in H/WQ modeling (Shirmohammadi et al, 2006).

Wagener et al. (2005) systematically discussed the conceptual nature of a hydrological model, types and sources of uncertainty, and methods to analyze the uncertainty. Schoups et al. (2006) describe well the relationship between errors of observation, input data, and model structure, and they provide a good framework for analysis of the errors. Bardossy et al. (2004) comprehensively discussed definitions, sources, characteristics of uncertainty, and methods and approaches for uncertainty analysis.

Modeling usually provides a point or series estimate or an expected value of the desired response variable, and this is often taken or understood as the best or even only answer. Such an understanding of the modeling result (as a single deterministic answer) may enable clear and easy communication between a modeler as a producer of the result
and end users such as researchers, stakeholders, and decision makers. On the other hand, when a model provides only point estimation, it may be difficult or even impossible to interpret the possibility of a failure of the predicted system due to lack of information about the reliability of the single result. Then, if the prediction is wrong, the design and management plan implemented based on the prediction can fail unexpectedly.

In order to account for the risk of failure, often a H/WQ modeling is implemented with conservative assumptions and/or a margin of safety is added to the results. However, usually it is hard to quantify a degree of the conservatism due to subjectivity, and thus a margin of safety is determined in a somewhat arbitrary way. If consideration of uncertainty is not incorporated into the prediction and design explicitly and quantitatively, countermeasures to deal with risk in management decisions or alternatives cannot be determined clearly and objectively. In this sense, uncertainty analysis provides a methodology for estimating reliability and confidence of the modeling results and in quantifying the probability of exceeding a certain threshold (Mowrer, 2000). Parasuraman et al. (2008) suggested uncertainty analysis should be a part of model development so that not only accuracy but also reliability can be considered in modeling practice.

Uncertainty analysis is useful as it provides a basis for the need of additional monitoring, experiments, or additional information in order to improve the scientific basis for decisions (Reckhow, 1994a; Vandenberghe et al., 2007). Uncertainty does not prevent management and decision making; rather, it provides a basis for selecting among alternative actions and for deciding if additional information is needed (Reckhow, 1994b). Quantification of uncertainty establishes the extent to which simulated results are reliable predictions of observed truth (Loague et al., 1998). Then, subsequent analysis like benefit-cost calculation (BC ratio) and decision-making procedures can be implemented with additional information and with more consideration about risk and reliability. However, there exist opinions that prefer ‘better safe than sorry’, and Finkel (1994) clearly describes the two opposite stands regarding conservatism in decision-making.

Warren-Hicks et al. (1998) enumerated potential benefits of quantitative uncertainty analysis in regulatory programs: 1) improving transparency, credibility, and
decision support, 2) avoiding worst-case assumptions, and 3) emphasizing data collection. In addition, they provided a comprehensive list of challenges for gaining acceptance of quantitative uncertainty analysis: 1) quantitative uncertainty analysis can be used inappropriately, 2) it cannot consider all sources of uncertainty, 3) it is difficult to do well, 4) it is not always practical, 5) it is not accepted by everyone, 6) it can make decision-making difficult, 7) it is not conservative, and 8) it can postpone decision-making. For a better uncertainty analysis, they also added some recommendations.

When H/WQ modeling is a part of the whole TMDL process, modeling should provide a decision support model for TMDL prescriptions (Chapra, 2003). However, the source and magnitude of H/WQ modeling uncertainty and its impact on TMDL assessment has not been studied in depth (Shirmohammadi et al, 2006). Although the uncertainty is implicitly considered with a margin of safety (MOS) in TMDL, qualitative and explicit assessment is rarely done (Reckhow, 2003). In practice, MOS is usually chosen implicitly and arbitrarily (Freedman et al., 2003). The National Research Council’s Committee assessed the scientific basis of TMDL approach and noted that parameters for the TMDL determination are probabilistic and a MOS is a measure of uncertainty (NRC, 2001). Thus, they recommended that a MOS of TMDL should be determined through a formal uncertainty and error analysis instead of being selected in an arbitrary and unscientific way (NRC, 2001).

Dilks et al. (2004) categorized the problems that inhibit the application of the margin of safety: 1) limited practical experience in defining the uncertainty in the TMDL development, 2) absence of information regarding the degree of protection provided by the MOS, and 3) possibility of that data-poor/high-uncertainty situations can results in the MOS values as large as to make implementation impractical. In addition, they proposed four attributes that a MOS should have in order to meet the statutory requirements of the TMDL rules as well as to address the problems: 1) account for uncertainty in TMDL calculations, 2) consider degree of protection, 3) address data limitation and implementation concerns, and 4) be feasible to conduct on a widespread basis.

Reckhow (2003) proposed two approaches to deal with uncertainty effectively in TMDL modeling and implementation: short-term and long term. Short-term approaches
include conducting an informative but incomplete error analysis. On the other hand, in the long-term approaches, he recommended restructuring models in such a way that complete error analysis becomes feasible (Reckhow, 2003). Chapra (2003) mentioned that our models are imperfect and these imperfections are best expressed probabilistically. This suggested that estimate of uncertainty and a margin of safety (MOS) should be formulated probabilistically. In the same sense, Shirmohammadi et al. (2006) asserted, “If considerations of uncertainty are included directly in the estimates of the waste load allocation (WLA) and the load allocation (LA), then the MOS is not necessary.”

Couclelis (2003) argued, “while much can and needs to be done to manage and resolve uncertainties where possible, accepting that uncertainty is an intrinsic property of complex knowledge and not just a flaw that needs to be excised.” She also insisted, “There are a surprising number of things that we cannot answer that are not the result of imperfect information” (Couclelis, 2003). Therefore, a MOS also plays an important role that incorporates our ignorance or things we cannot know beyond uncertainty into development of TMDL. “Including explicit quantification of uncertainty due to different sources in the TMDL process would provide more complete information for decision makers and other stakeholders” (Shirmohammadi et al., 2006). Walker (2003) tried to consider a confidence level and a compliance rate in estimating a MOS of TMDL under several normality assumptions of parameters. Langseth et al. (2004) proposed a simple methodology to calculate MOS of TMDL assuming the safety margin is normally distributed. Shirmohammadi et al. (2008) provided an example to incorporate uncertainty in parameters into determination of MOS in TMDL development using MFORM (Mean Value First Order Reliability Method).

In H/WQ modeling, uncertainty comes from variability and heterogeneity of nature and incomplete knowledge and limited ability of our understanding. In order to assess uncertainty and reliability of a model, many concepts, methods, and techniques have been devised and applied for variety of conditions. Methodologies for uncertainty analysis usually describe uncertainties of variables with probability distributions that have a measure of central tendency like mean, a dispersion of alternative outcomes such as variance (Mowrer, 2000). Then, they examine which uncertainty contained in the input propagates into output, and estimate the magnitude of its impact on the output.
Uncertainty of the modeling output is also usually expressed with probability distributions in the frequency domain, confidence limits in time domain, and contour lines in spatial domain.

Many statistical methods such as first-order approximation (FOA and MFORM) and Monte Carlo simulation type (LHS and GLUE) have been developed and applied to evaluate model uncertainty from input data, parameters, and equations in H/WQ models. However, it is very difficult to assess the benefits and limitations of different methods due to inconsistent definitions of uncertainty and complicated mix of various different techniques. In particular, it may not easy to select the optimum set of parameters for a distributed model that has many parameters to be calibrated because of the equifinality issue. Chapra (2003) asserted that adding unnecessary model complexity could make modeling results unreliable because of increased parameter uncertainty. In addition, it could make uncertainty analysis impossible to be done in a reasonable time period especially when calculation intensive techniques like a Monte Carlo simulation was employed in the analysis. Jakeman et al. (1993) showed only four or five parameters are enough to calibrate a rainfall-runoff model against runoff measurements if the model is designed in such a way as to ensure an appropriate level of sensitivity and the minimum correlation between parameters (Jakeman et al., 1993; Doherty et al., 2003). Thus, incorporation of only significant, necessary, and uncorrelated parameters in a parsimonious model structure can relieve the equifinality problem in H/WQ modeling.

Anderton et al. (2002) showed that even a physically based distributed model, SHETRAN (Systeme Hydrologique Europeen TRANsport), could have multiple optima in different parts of the parameter space when only outlet discharge data is available for calibration. They tried to locate the optimum parameter set in the parameter space and reduce uncertainty in parameters through evaluating model performance against not only discharge at the outlet but also watershed averaged soil water contents and phreatic surface levels at two internal points within the watershed. The use of complementary data which come from internal points or represent other responses of a watershed in model calibration and validation can reduce uncertainty in parameter identification (Anderton et al., 2002).
2.12.2 GIS and Remotely Sensed Input Data Uncertainty and Its Simulation

2.12.2.1 Overview

GIS and RS data is a product of processing and modeling. Uncertainty in geographic information comes from complexity and problems of processes used in conceptualization and measurement (Plewe, 2002). Once raw data are surveyed and sampled by basic or sophisticated devices such as level and photoelectric sensor, then it is manipulated and processed to derive meaningful and interpretable information. The manipulation includes radiometric and atmospheric corrections, georeferencing, and classification. Although various techniques and algorithms have been developed for them, none of them are perfect, and thus some level and types of errors are introduced through the process. In addition, GIS data itself is a product of spatial modeling that represents spatial variation in the variable of interest at a specific time frequently in a spatially averaged way. For example, a DEM is a model of topography, and the NLCD is one representation of land use and cover for a certain period. In this sense, Loague et al. (1996) listed concerns associated with use of GIS data in assessments of non-point source pollution.

In addition, many GIS and RS data are provided in a raster format, which uses tiny squares, so called pixels that represent individually sampled areas on a layer or map. Thus, information in a pixel is lumped or averaged and spatial features like boundaries are represented less precisely in a grid map than in a vector map. This approximated and lumped spatial representation of data may induce additional errors. However, usually minimal information about characteristics of error in GIS and RS data is provided to an end user like a H/WQ modeler. Nonetheless, the error should be accounted in a further analysis employing GIS and RS data like H/WQ modeling for better understanding on reliability of the result and identification of critical points to improve the reliability.

GIS and RS data are registered to a certain map projection in order to enable other geographic data to be used together and classified into predefined classes to enable users to interpret the data for some purposes (Janssen et al. 1994). When they are transformed into another form through registration and classification, errors are always introduced and
embedded in the data due to incompleteness of methodology employed in the processes. Thus, common GIS and remotely sensed data used in H/WQ modeling also contain some levels and kinds of errors because they are usually preprocessed to enable them to be used for the modeling as input data. Of course, the geographic data will contain some degree and kind of errors created at data acquisition step due to the natural variability, limitation of sensor and sensing methodology, and malfunction of device. However, human subjectivity in data processing, analysis, and interpretation is one of the most difficult sources of error to be quantified while geometric and radiometric error in data processing may be controlled (Lunetta et al., 1991).

Many studies examined the influence of the accuracy, error, and resolution of GIS data on H/WQ modeling through uncertainty and sensitivity analysis. In particular, vertical error of DEMs and classification error in land use data as well as their positional errors may add significant uncertainty in modeling results. In addition, a question about the best spatial scale or resolution in a raster based H/WQ modeling has been an issue of uncertainty. However, these GIS input data are usually regarded as correct, and uncertainty caused by their error has not been commonly addressed quantitatively. Lack of adequate techniques to deal with errors of spatially correlated variables and requirement for significant computing resource and time for analysis of two (or multi) dimensional data at a fine resolution seems to contribute to the indifference even though much GIS data contains officially reported error. A map generated from a GIS-based model or model employing GIS data may have no real utility without a corresponding map of associated uncertainties (Loague et al., 1998). Recently a few studies provided some ways to incorporate spatially correlated structure of the error into uncertainty analysis of spatial modeling with advancement in computing resources (Hunter et al., 1995). Hunter et al. (1996) discussed a variety ways to communicate uncertainty in spatial databases between producers and end users. They note that visual methods using colors, texture, size, shape, and pattern are inherently more communicative than are traditional approaches of employing cartographic symbolization, reliability diagrams, and positional accuracy statements.
2.12.2.2 DEM

The most commonly used DEMs, the NED and SRTM, are distributed by The U.S. Geological Survey (USGS), and the primary error information provided is the overall RMSE (Holmes et al., 2000). The USGS reported the overall absolute vertical RMSE of NED as 2.4 m and the errors range from -42.64 to 18.74 (USGS, 2009). In addition, Jet Propulsion Laboratory (JPL) estimated absolute height error of SRTM as ranging from 5.6m (Africa) to 9.0m (North America) depending on the Continent (Rodriguez et al. 2005). If error at any point occurs independently of that at any other point, RMSE can be a way to represent variance of the overall error in DEM appropriately. In addition, RMSE becomes equivalent to the standard deviation if the mean error is zero (Fisher et al., 2006).

When error is spatially variable and correlated, however, a single scalar index like RMSE neither distinguish areas that have more or less uncertainty nor assess spatial autocorrelation (Aerts et al., 2003). Detailed presentation of DEM accuracy will allow better understanding of DEM quality and of the consequent uncertainty with using DEM in applications (Carlisle, 2005). Few studies tried to find spatial structure of error, called spatial correlation, through comparing field data and DEMs. However, it has been difficult to identify spatial correlation of DEM due to inaccurate, sparse, and biased reference data even though there are strong intuition and indirect evidences concerning the correlation (Oksanen, 2006). Thus, an experiment of Bolstad et al. (1994) must be a valuable leading work for providing an approximate picture of the spatial autocorrelation of DEM despite of the limited regional extent of the study. Legendre (1993) reviewed and discussed methods to identify existence of autocorrelation, to measure its severity, and to incorporate it into modeling. Fisher et al. (2006) discussed the source, types, nature, and models of errors in DEM and in its derivatives.

Wechsler (2007) provided a comprehensive review and discussions about issues related to affect of uncertainty in DEM on its application to hydrologic analysis. They evaluated accuracy of elevations, slopes, and aspect of a USGS 7.5 minute quadrangle-based 30m DEM and a SPOT panchromatic stereopair DEM through comparing them with field-surveyed values. In their study, average vertical error of both DEMs were 6 meters, and the elevation errors of USGS and SPOT DEM were weakly correlated or not
spatially correlated with elevations respectively. Aspect errors were also not correlated with aspect for both DEMs. However, there were statistically significantly positive correlations between slope errors and slope, and the largest errors were distributed on the areas of the highest and lowest elevations. Kyriakidis et al. (1999) quantified cross-correlation between sparse field data and dense DEM and auto-correlation between themselves, and found very high auto and cross-correlations. On the other hand, Holmes et al. (2000) found weak isotropic spatial autocorrelation of DEM errors through examining semivariogram of a USGS 30 m DEM, GPS field data, and the corresponding errors or differences between them. Gorokhovich et al. (2006) assessed accuracy of CGIAR SRTM for New York and Thailand using GPS measurements of 255 points, and the results showed that elevation errors are strongly cross-correlated with slope and aspects. Thus, we see that the degree of spatial correlation of DEM varies depending on spatial extent of the experiment and type of application as well as quality of the reference data. In addition, the correlation may be scale (resolution) and methodology dependent.

Hunter et al. (1997) argued that a model of independent or uncorrelated disturbance is not acceptable because visual appearance alone does not look reasonable. In the thematic classification case, Canters et al. (2002) also mentioned that perturbed land cover maps with spatially independent random errors may be highly fragmented and not reflect the actual landscape structure. Therefore, positive correlations between adjacent errors should be assumed even though little information about spatial autocorrelation of errors is available. Once the spatial structure or correlation of error is known, the information can be incorporated into investigation of the potential impact of the error on a terrain analysis and H/WQ modeling. Goodchild (1980) proposed a way to embed a desired positive autocorrelation in simulating spatial data. In the method, the autocorrelation is calculated by the Moran’s I statistic, and swapping of a random pair of zones or pixels continues until the desired Moran’s I is obtained. Fisher (1991) applied the method Goodchild (1980) proposed into evaluating accuracy of the viewshed area, and he found the viewshed in the original DEM is consistently greater than that in the simulated DEM that contains autocorrelated errors. Fisher (1998) replaced the Moran’s I statistics with variogram in quantifying autocorrelation of DEM error while employing the same perturbation method: the pixel swapping. Although the concept of the swapping
technique or simulated annealing is easy to understand, it requires intensive computing (Oksanen, 2006) and it does not consider relationships between errors and terrain characteristics.

Hunter et al. (1997) tried to simulate auto-correlated DEM by generating spatially autoregressive random error, but their method also does not consider dependence of error on terrain characteristics. Thus, they pointed out that the method may be appropriate as the first approximation until more information about the real spatial structure of DEM errors is revealed. Holmes et al. (2000) employed the sequential Gaussian simulation (SGS), which was proposed by Goovaerts (1997) and Deutsch et al. (1998) to consider spatial variability of DEM error in examining its impact on terrain modeling. The parameters of the Gaussian local conditional cumulative distribution function (CCDF) are determined based on the isotropic semivariogram and then values are interpolated at each pixel by drawing from the CCDF (Holmes et al., 2000). In the method, the value of a variable at unmeasured points is estimated along the sequence of nodes based on the conditional distributions constructed using the lately simulated values as well as the observed values of the variable as a means of incorporating spatial autocorrelation of the variable (Goovaerts, 1997; Delbari et al., 2009). Aerts et al. (2003) applied the SGS in planning a ski run, and Pebesma (2004) developed a geostatistical package capable of implementing SGS in a statistical software, S-Plus. It accounts for terrain features when simulating DEM through employing Kriging technique in approximating spatial pattern of terrain. Recently, Delbari et al. (2009) applied SGS in approximating spatial distribution of soil water content and in evaluating its spatial uncertainty quantitatively.

Wechsler et al. (2006) generated random error layers with four different combinations of kernels and weights of spatial moving average. The error generating techniques included drawing independent random samples, applying a 3 by 3 low-pass filter to the unfiltered data, a mean D by D filter, and a weighted D by D filter. Once the errors were generated, they were rescaled to have a mean of zero and standard deviation of the known SRTM of DEM. His method is a typical example of the unconditional stochastic simulation in geostatistics, which does not consider the spatial dependency and autocorrelation structure of a variable and its error such as the swapping and autoregressive method (Webster et al., 2007). Carlisle (2005) developed regression
models to define a relationship between DEM error and morphometric characteristics of terrain like elevation, neighborhood, and gradient. The regression model can provide spatially non-stationary, correlated, and heteroscedastic error surface but it always needs field measurement and pre-analysis of the terrain like multivariate regression. Xu et al. (2005) applied the LU (Lower and Upper) decomposition algorithm to incorporate random components into geostatistical forest landscape model simulation.

There is a belief that a DEM error model without spatial correlation could be used to provide a worst-case scenario for spatial modeling (Oksanen 2005; 2006). However, Oksanen (2005; 2006) doubted that belief because the uncorrelated error model never produced the maximum variation of DEM derivatives such as slope, aspect, and drainage delineation in his research. Young et al. (2008) also evaluated impacts of vertical error in SRTM DEM on derivatives for hydrologic modeling. They used a spatial moving average technique to generate spatially autocorrelated DEM error and then compared slope, watershed boundary and area, flow network, travel time calculated from DEMs that contain autocorrelated and uncorrelated errors. The result showed that the maximum variances of slope, watershed boundary and area, and stream network were provided by autocorrelated or uncorrelated DEM error depending on assumed magnitude of the error. The autocorrelated DEM error produced shorter travel time than the uncorrelated due to less twisted flow path. Thus, their study partially supported the doubt.

Albani et al. (2004) presented a general analytical method of error propagation that accounts for the effects of window size for quadratic approximation of topographic surfaces and spatial autocorrelation of elevation errors. Their study showed that the propagation of elevation errors into the topographic derivatives, such as slope, aspect, and curvature, was reduced dramatically as the size of evaluation windows increased due to loss of information. Endreny et al. (2001) examined sensitivity of flow path algorithm and flow frequency and magnitude in NPS modeling to DEM vertical error. They generated a perturbed DEM with the swapping method Goodchild (1980) and Fisher (1991) proposed while varying RMSE from 0.5 to 6.0 m and spatial autocorrelation from 0.00 to 0.99. The results showed that the flow path algorithms were not sensitive to spatial distribution of the error but to magnitude of RMSE. Lindsay (2006) evaluated sensitivity of six channel network extraction methods to LIDAR DEM error. They also
used the pixel swapping method to generate autocorrelated DEM error layers. From the
discriminates, the four morphology-based (valley recognition) methods were more sensitive to
the degree of spatial autocorrelation of DEM error than were the two channelization-
based (channel initiation) methods because the morphology-based was based on local
surface morphology. In addition, the D8 algorithm was the least sensitive to the error so
that it could be suggested as the most robust of the tested channel mapping techniques.

2.12.2.3 Land Use/Cover Data (NLCD)

Errors are always introduced in classification of remotely sensed data due to
spectral overlap of classes, scale reduction from reality to the map, and discrete
approximation of vegetation continuums (Steele et al. 1998). Classification error of
remotely sensed scene is usually expressed by the overall percentage of correctly
classified pixels and/or an error matrix. Congalton (1991) reviewed techniques to assess
the accuracy of classifications of remotely sensed data, and suggested that the error
matrix is the most representative of the entire classification.

However, Cantor (1997) and Steele et al. (1998) pointed out that the error matrix
neither provide information on the spatial structure of error in a classification nor have
the ability to describe the variation of accuracy across a classified map. In addition,
Foody (2001; 2002) argued that widely used approaches for accuracy assessment and
reporting were often unsuitable for a specific application or purpose, and it might be
helpful for better assessment to provide information on sampling design to collect test
sets, confidence in ground truth, and classification protocol. Gopal et al. (1994) used the
fuzzy set method to assess thematic map error and provide more information on accuracy,
such as nature, frequency, magnitude, and source of error, than does confusion matrices.
In addition, the confusion matrix does not provide appropriate prediction or validation
accuracy unless external data are available that have not been involved in any part of
training for (supervised) classification or calibration. However, availability of post-
classification and external sampling data are usually constrained by cost due to the
requirement of a sufficient number of samples (Foody, 2002; Steele, 2005). Thus, some
methods, such as sample split and probability sampling (bootstrap and cross-validation),
were proposed so that the training data used in supervised classification can also be used for accuracy assessment (Steele, 2005).

Stehman et al. (2003) and Wickham et al. (2004) assessed the accuracy of 1992 National Land-Cover Data (NLCD) Level I and II of the western and eastern United States using an error matrix. They employed three stratification designs and two levels of selection for sampling ground truth points. In the study, they found that the accuracy varied regionally and the Level I data had better accuracy than did the Level II due to the fewer number of classes. Overall accuracy by region for Level I and II range from 70 to 85 % and from 38 to 70 % respectively, meaning that at least 15 % and 30 % of the overall errors are contained in the NLCD data. Moreover, the results error matrices revealed that variation of accuracy for a specific class was dramatically higher than that of the overall error, ranging from less than 10 % to over 90 % in the Level II. The classification methods employed for deriving NLCD from Landsat TM imagery are well described by Kelly et al. (1993) and Vogelmann et al. (1998).

Campbell (1981) found evidence supporting the conclusion that there is a tendency of classification errors towards spatially clustering. He pointed out that the clustered or spatially correlated errors might degrade the usefulness of a classification, especially supervised classification, because of possibility for the clustered error to be classified as genuine land covers. Congalton (1988) also indicated spatial autocorrelation of remotely sensed data could significantly affect the results of some analysis processes like smoothing, edge enhancement, and classification. He investigated the autocorrelation of the remotely sensed data by using the joint count statistics Moran (1948) proposed to test significance for the random distribution of the points in a lattice form. The study revealed that classification errors of Landsat MSS data for agriculture, range, and forest were clustered and they had different patterns because of land use complexity, pattern, and topography. Moisen et al. (1999) explored the relationship between errors in vegetation classification map, topographical factors, and a variable indicating membership in the road or off-road stratum using the generalized linear mixed model (GLMM). They found that classification errors tend to occur near roads in steep and heterogeneous areas, showing spatial autocorrelation structure of the error is controlled not only by topographical factors but also by vegetation distribution features.
Canters (1997) evaluated impact of different strategies to estimate the mean and covariance matrix in the maximum likelihood function, such as normal, fuzzy, robust, and fuzzy robust, on areas of classes. Then, they proposed a method to evaluate uncertainty of area estimation based on the fuzzy set theory. The fuzzy approach for estimating the statistics was adapted from Wang (1990) and Campbell (1980). Once the class membership probabilities were obtained from the maximum likelihood classification with one of the strategies, “fuzzy robust” in his study, Monte Carlo simulation generates the sufficient numbers of realizations or perturbed classification maps for evaluating sensitivity of class areas to the strategies based on the class membership probability. In the study, a random number was drawn not for an individual pixel, but for a field that contains several adjacent pixels having a similar probability vector. This technique was devised to avoid high fragmentation of classification and to account for spatial autocorrelation of land cover classes. The field was defined as a group of adjacent pixels that have the same two most likely classes regardless of which class has the highest probability.

Steele et al. (1998) developed a method to represent spatial distribution of classification errors for remotely sensed data so that perturbed land cover maps could be constructed with consideration of spatial autocorrelation of the errors. First, they proposed an approach that estimates misclassification probabilities at training data points using the leave-one-out bootstrap method based on the fuzzy set accuracy assessment Gopal et al. (1994) proposed. Then, they noticed that the misclassification probabilities were likely to be spatially autocorrelated especially when spatial dependency of error was not considered in classification. Thus, they employed a Kriging technique to incorporate spatial autocorrelation structure of classification error into interpolating the bootstrap estimates to every pixel in the map. Finally, an accuracy contour map was constructed with the estimates. In the same vein, Steele et al. (2005) proposed an approach to assess map accuracy based on maximum posterior probability estimators. It estimated the probability of correct classification for every map unit or pixel and calibrated the estimates with training data.

Canters et al. (2002) proposed a field-based instead of pixel-based approach to consider spatial autocorrelation of classes in simulating uncertainty of a land cover
classification. In addition, they employed a first-order autoregressive model to simulate spatial autocorrelation in the error field of DEM. Hines et al. (2005) introduced a method to account for class dependence of classification error in creating perturbed land cover classification maps. The method reassigns a class at a point to another through comparing a randomly drawn number within 0 and 1 with fractional commission error that describes probability that the class to be wrongly classified to another. The proportion of the reassigned pixels of the class to another is limited to the net of fractional producer and user’s accuracy (or omission and commission error) in the error matrix. Then, they applied this method in investigating sensitivity of habitat delineation for the California Spotted Owl in Southern California to the classification error. Although this method does not account for spatial correlation structure of classification errors, it effectively utilizes information in the error matrix in considering cross-correlation of the error over the classes.

2.12.2.4 Sequential Gaussian/Indicator Simulation

It is known that interpolation methods like kriging induce a smoothing effect and subsequent underestimation of overall variation in surface simulation (Goovaerts, 1997). In order to solve the issue in surface simulation using interpolation methods, stochastic simulation algorithms, such as sequential simulation, simulated annealing, LU (Lower-Upper) decomposition, and turning bands, introduce stochastic components into simulation (Goovaerts, 1997). Because kriging estimations present only the simplistic spatial pattern that possesses the minimum error-variance in a global perspective by smoothing the surface of an attribute, small and large values are over- and underestimated respectively and variances are likely to reduce (Wang et al., 2000; Juang et al., 2004). On the other hand, the stochastic simulation algorithms reproduce the local detail rather than the general pattern of variation as does interpolation method like kriging (Webster et al., 2007). In addition, the stochastic simulation can provide multiple possible event layers of an attribute map that have similar probabilities to be realized while estimation like interpolation produce only single output layer that is the most likely to happen based on deterministic logic and/or statistics. Thus, the stochastic simulation
enables spatial uncertainty analysis of data field and subsequent risk evaluation by providing a model of spatial uncertainty (Goovaerts, 2001).

Among the stochastic simulation algorithms, sequential simulation is known as a simple, fast, and the most straightforward technique, and thus it has been the most widely used in geostatistical applications (Emery, 2004). The SSA (Sequential Simulation Algorithm) draws random values from CCDFs (Conditional Cumulative Density Functions) derived in turn along a certain series of nodes and adds them to the original data set to preserve and simulate the overall variation of the data at a global viewpoint (Goovaerts, 1997). In the approach, level of conditioning information is increasing as simulation is progressing because the CCDFs are determined based on the simulated data as well as the original (Goovaerts, 1997; Deutsch et al., 1998). That is a way to generate spatially correlated random values. In addition, for screening influence of more distant data, only observed and simulated data within a certain semivariogram distance are utilized in constructing CCDFs (Goovaerts, 1997; Webster et al., 2007).

There are two ways to derive CCDFs in the sequential simulation: SGS (Sequential Gaussian Simulation) and SIS (Sequential Indicator Simulation). SGS assumes conditional density functions as a normal distribution, so thus CCDFs becomes a cumulative normal (Gaussian) distribution, and then simulates a multivariate Gaussian random fields based on a procedure of sequential simulation algorithm (SSA) (Goovaerts, 1997; Deutsch et al., 1998; Webster et al., 2007). However, if attributes of data or observations do not satisfy the normal assumption, the original data can be transformed into Gaussian space or SIS (Sequential Indicator Simulation) can be an alternative. SIS does not require any specific distribution model of the data, namely non-parametric and non-Gaussian, so thus it can be applied regardless of a type of data.

Goovaerts (1997) pointed out two critical properties of SGS: destructuration effect and symmetric spatial correlation to the median. The former means that “the Gaussian model does not allow for any significant spatial correlation of extremely large or small values” but the latter might not be found as a property of the actual data. Goovaerts (2001) verified the properties of SGS with numerical experiments using measured data of spatial soil characteristics such as cadmium and hydraulic conductivity.
From the study, Goovaerts (1997) warned, “the analytical simplicity of sequential Gaussian simulation is balanced by the risk of understanding the potential for critical features” such as high correlation of extreme values, and thus SIS is more preferred to a case that data observation does not follow the normal assumption than SGS (Juang et al., 2004).

SIS is the most widely used non-Gaussian and non-parametric simulation technique (Goovaerts, 1997). Unlike in SGS, CCDFs for individual locations are derived directly from the indicator kriging without a prior assumption about their shapes in SIS (Goovaerts, 1997; Machuca-Mory et al., 2008). The indicator has a value of zero or one when the value of the attribute is less or greater than a certain threshold respectively, but soft indicators such as probability also can be considered to account for the uncertainty in the classification of sampled points as fuzzy classification does (Goovaerts, 1999). Then, CCDFs represent the probability of an attribute being greater than a given threshold when classifying an unsampled location (Juang et al., 2004). Therefore, the indicator semivariogram of the indicator kriging measures the probability of transition between two classes of the attribute so thus the indicator kriging is used to estimate the probability for each state of the attribute to occur at the unsampled location (Deutsch et al., 1998; Goovaerts, 1999).

Bierkens et al. (1993a; 1993b) applied indicator kriging to classify and to map water table classes using a part of the observations, and validate the classification maps with the other part of the data. They also proposed a concept of ‘purity’, which represents the maximum probability of being classified as a class at every pixel. The study showed that accuracy of classification becomes better as the number of observations gets bigger and only 11% of the total observation (250 of 2259) provided accuracy of over 90% in mapping the water table. Wang et al. (2000) examined spatial variability of steepness and slope length factors of RUSLE (Revised Universal Soil Loss Equation) and generated probability maps of LS (topographic factor) factor exceeding a certain threshold using SIS. Juang et al. (2004) utilized multiple realizations generated from SIS to assess uncertainty in delineating heavy-metal contaminated soils.
Machuca-Mory et al. (2008) pointed out unfavorable features of SIS: uncontrolled transitions between classes and randomness within each class. In other words, simultaneous use of non-parametric CCDFs derived by indicator kriging and the Monte Carlo technique can lead to abrupt changes from one class to another, patches of uniform values near such samples, and/or lack of correlation within classes especially when a threshold is set to a nearby data value (Machuca-Mory et al., 2008). Therefore, they recommended use of SIS for only categorical variables. Bierkens et al. (1993a; 1993b) also claimed better suitability of the indicator approach against ordinal and nominal attributes because of their discrete and non-Gaussian probability distribution come from nominal or ordinal categories.

One interesting find in the literatures of Machuca-Mory et al. (2008) and Goovaerts (2001) is that histograms of multiple realizations for continuous attributes (copper deposit and hydraulic conductivity respectively) generated in SIS had a narrower range and smaller variance than those in SGS, and this result agree with that of Goovaerts (2001). From the results, Goovaerts (2001) concluded that SIS yielded better results than SGS because SIS provided a narrower response distribution of uncertainty while maintaining accuracy or including the true values. However, uncertainty is not a function of methods for assessing uncertainty but inherent properties of data and its observations. Thus, it cannot be said which one is better than the other merely based on features of the uncertainty distribution they provided. Therefore, observations and soft information including incomplete knowledge about the region of interest should be incorporated in conditioning a simulation in order to reflect the true conditions of the simulated region (Gotway et al., 1996).

Although the geostatistical stochastic simulation algorithms are useful to generate realizations that possess similar degrees of spatial variation to that of the original data field, they do not account for inherent statistics or characteristics of the original like a mean elevation and RMSE error for DEM and class proportions and an error matrix for land cover layer. This discrepancy between the realization and model statistics are referred to as ‘ergodic fluctuation’ (Goovaerts, 1997; Deutsch et al., 1998). Thus, Goovaerts (1996; 1997) suggested post-processing to improve agreement between the statistics or characteristics utilizing the simulated annealing simulation in the MAP
(Maximum A Posteriori) framework. In the study of Goovaerts (1996), the post-processing of SIS realizations using the simulated annealing algorithm reproduced better spatial continuity and covariance between classes for a categorical map.

2.12.3 Uncertainty caused by Parameters

2.12.3.1 Overview

Uncertainty contained in a parameter propagates through a model structure to the output of interest. Several methods have been proposed to quantify the amount of model uncertainty caused by parameter uncertainty. Similar strategies used in the optimization algorithms are applied to uncertainty analysis for parameters. If the value of a parameter is determined in a highly unsure manner and the model output is very sensitive the parameter, it will be classified as the important parameter to be investigated. Analysis of model uncertainty caused by parameter uncertainty is crucial in identifying the important parameters which we need to focus on to improve model performance and reduce overall uncertainty of the model (Haan, 2002). The parameter uncertainty and the resulting model uncertainty can be quantified through statistical methods.

2.12.3.2 First-order Approximation

The most popular ways to quantify uncertainty in H/WQ modeling are first-order approximation (FOA) and Monte Carlo simulation (Summer et al. 1993; Shirmohammadi, et al, 2006). The first-order approximation tries to estimate variance (or coefficient of variation) of dependant (or output) variables caused by variance of independent (or input) parameters. It does not assume normality of the input variable’s probability distribution in approximating variance of the model output. However, it presumes that the parameters are statistically independent and the assumption implies they are uncorrelated. The method may over or underestimate the model uncertainty caused by parameters because usually the calibrated parameters are correlated to each other. Although this method provides a simple way to quantify model uncertainty, it can account for only first (mean)
and second (variance or standard deviation) moments of the distributions as Summers et al. (1993) criticized.

The mean first-order reliability method (MFORM) was proposed to analyze reliability and risk of the system based on the FOA methodology. It incorporates the linear system performance function to deal with the failure point of the system where the load acting on the system exceeds the system’s capacity. However, it employs a single linear system performance function and assumes normality of its probability distribution. Melching (1992) examined theory and concept of MFORM and concluded that its shortcomings come from several factors: (1) the relative accuracy of the first-order Taylor expansion, (2) only focusing on the mean values rather than the extremes (by taking Taylor expansion at the mean of the input variable), (3) linear assumption of the system performance function, and (4) normality assumption of the probability distribution of the systems performance and input variable.

He proposed an advanced first-order reliability (analysis) method (AFORM) to make up for the weak points of MFORM while keeping its simplicity. AFORM takes a Taylor expansion at a point on the failure surface of the system performance function (Melching, 1992) so that MFORM weakness (2) above can be settled. In addition, it was recommended to transform the non-normally distributed input variables into equivalent normally distributed variables at the failure point in order to relax (4) of MFORM weaknesses. However, the other issues of MFORM remain unsolved (Beven, 2000). In his study, AFORM showed good performance for a non-linear model and close agreements with the results of the Monte Carlo simulation. However, the failure point for the Taylor expansion is determined iteratively so it may be a disadvantage of AFORM. In addition, the issue of the correlated input variables still remains unsolved in AFORM. Although the second order approximation (SOA) method and the second order reliability method (SORM) were developed in order to improve accuracy of the first order methods (FOA, MORM, and AFORM), they have been rarely used because of computational requirements and complicated procedures (Haan, 2002).
2.12.3.3 Monte Carlo Simulation

The Monte Carlo simulation (MCS) is a kind of sampling method. For uncertainty analysis in H/WQ modeling, MCS randomly and repeatedly generates input values according to their own probability distributions and the model is executed with the generated values as many times as the number of the input value combination sets. Then, we can evaluate modeling uncertainty based on the variance of the modeling results caused by the parameter uncertainty. MCS is widely used for different types of applications because it does not require knowledge of how input data or parameters are used in its operation (Aerts et al. 2003). In addition, MCS is regarded as the most robust method in evaluating uncertainty propagation through model structure caused by parameter uncertainty if a sufficiently large number of model runs is possible (Hammonds et al., 1994; Hession et al., 1996a; Beven, 2000).

In MCS, correlation among input parameters can be reflected in evaluating model uncertainty through generating correlated input parameter set (Haas, 1999; Pohlmann et al., 2002; Fu-Chun Wu et al., 2004). Especially when the correlation coefficient between input parameters exceeds 0.7, the correlation should be incorporated in MCS (Hass, 1999; Fu-Chun Wu et al., 2004). Pohlmann et al. (2002) found that the parameter correlation can reduce or enlarge the model uncertainty from his numerical modeling experiments for radionuclide transport at an underground unclear test site. Usually the probability distribution of an input parameter is not known, so thus it needs to be presumed. In addition, it is ambiguous how many samples are required to get results at a certain level of accuracy. As the required numbers of input value samples and model execution time increase, more computing resources and/or computing time will be required. Thus, many techniques such as Latin Hypercube sampling (LHS) and Markov Chain Monte Carlo (MCMC) have been invented to sample input parameter values more efficiently and to get results that are more accurate.

The Latin Hypercube sampling (LHS) was first proposed by Mckay et al. (1979) as a method to pick values of input variables efficiently (Swiler et al., 2004). It is an advanced sampling technique of the Monte Carlo simulation. This method makes sampling efficient by reducing sample values from low probability regions in the
probability distribution. Thus, extreme values of parameters are sampled with fewer iterations in LHS than in the simple Monte Carlo simulation (SMCS) technique. Iman et al. (1982) introduced a method to generate correlated Latin hypercube samples with a specified rank correlation matrix of the sample. Stein (1987) found that the larger number of samples comparing to that of variables produces an estimator with lower variance than does a simple Monte Carlo random sampling. Pebesma et al. (1999; 2000) showed a way to draw a Latin hypercube sample from a Gaussian random distribution. They found LHS distort the short distance spatial autocorrelation of zinc concentration in the topsoil along the River Meuse in the Netherlands, but its degree disappeared when sample size becomes large. Helton et al. (2003) compared performance of LHS and SMCS in evaluating output variances caused by input variability with monotonic and non-monotonic functions, and they found that LHS produced more stable estimates for the CDF than did SMCS.

Hession et al. (1996a; 1996b; 1996c) proposed ‘two-phase’ Monte Carlo simulation methodology to analyze uncertainty propagations for different types, knowledge and stochastic uncertain, of parameters in a model. They applied the procedure to a USLE equation application and EUTROMOD modeling. In the studies, they defined erodibility (K) and management practice (C) as the knowledge uncertainty parameter and rainfall erosivity as the stochastic uncertainty parameter. A large number of samples are drawn using LHS from the assumed probability distribution of the knowledge uncertain parameter then; another large number of random samplings for the stochastic uncertain parameter are implemented within each realization derived from the previous random sampling practice for knowledge uncertainty parameter. Their study showed utilities of quantitative uncertainty analysis in interpreting the modeling results in a probabilistic way.

Sohrabi et al. (2002; 2003) also utilized the Monte Carlo simulation based on LHS to investigate impacts of parameter uncertainty on the results of a water quality simulation using the MACRO and SWAT model. Like the study of Hession et al. (1996a; 1996b; 1996c), the probability distributions of parameters are assumed based on literature, experience and/or analysis of available field data. In early applications of the Monte Carlo simulation such as Smith et al. (1979) and Sharma et al. (1980), which investigated
impact of random spatial variability of soil hydraulic parameters on hydrologic response of a watershed, variability of saturated hydraulic conductivity was assumed to have normal or lognormal distribution. Because the shape of probability distribution of a parameter should reflect characteristics of the given input data, model structure, and the measured data for calibration, it must be site and case specific and its universal form applicable to any application of any model may not exist. Therefore, a simple Monte Carlo simulation that requires assumptions about the shape of parameter probability distribution may provide only approximative sensitivity measures of parameters.

Kumar (1995) tested sensitivity of the GLEAMS modeling outputs to probability distribution types of input parameters using the Monte Carlo simulation. He compared the interquartile ranges (IQRs) of the modeling outputs generated from the uniform and Beta distributions of the input parameters while the ranges of the parameters and IQRs for the Beta distribution are set to the same as those of the uniform. In the study, a sign test was employed to see impact of the distribution type on model predictions and statistical significance of difference between the two modeling results. In the test, only output variables related to the percolation process showed statistically significant differences between the results. Haan et al. (1998) also investigated the impact of parameter probability distribution on the AGNPS modeling outputs using a simple Monte Carlo simulation. In the study, only one cell in AGNPS was used to represent a study area so that the model could be implemented in a lumped manner. Seven scenarios with different shapes, means, and standard deviations of probability distributions for the eight parameters in AGNPS were tested. In the study, a nonparametric Kruskal-Wallis one-way analysis of variance test was utilized to see if all the output probability distributions have the identical shape. From the test results, they concluded that mean and variance estimations of a parameter affected modeling output more significantly than did shape of the probability distribution.

Benaman et al. (2004) proposed a procedure to identify feasible parameter ranges for the SWAT model by dropping some parts of parameter ranges that provide unrealistic model results. In the procedure, a Monte Carlo simulation was implemented within initial ranges of the uniform distributions for parameters first, and then it was checked if the measured data for variables of interest were located near the middle of the output
probability distribution. When a distribution of a variable did not contain the measured value near its middle, the associated parameter to the variable was investigated through interval-spaced sensitivity analysis. Then, a threshold was selected to reduce the ranges, and finally another Monte Carlo simulation was implemented to confirm the selection of the threshold. They suggested that this procedure might yield a more efficient calibration and uncertainty analysis.

### 2.12.3.4 Bayesian Approach and MCMC

Bayesian approach provides a theoretical framework in combining prior information based on historical data and expert knowledge with newly observed data (Bates et al., 2001). Relationship between output, input, parameters, and error can be expressed as

$$ M_t = f(x_t, \Theta) + \varepsilon_t $$

where $t$ is time, $M_t$ is model output at time $t$, $f(\cdot)$ is a model or function, $x_t$ is a set of inputs, $\Theta$ is a unknown parameter set, $\varepsilon_t$ is an error assumed to be normally distributed with mean of zero and variance of $\sigma^2$, $n$ is simulation duration.

The parameter vector $\Theta$ is treated as a random variable that has a probability density function, which expresses uncertainty or variability about $\Theta$ (Bates et al., 2001). The density function of the parameter is presumed based on the prior knowledge so called a prior density distribution and denoted by $P(\Theta)$. If one does not have any prior information about the parameter, a uniform distribution can be employed. Whenever data are collected, the prior density distribution of the parameter will be transformed into the posterior density through Bayes’ theorem.

$$ P(\Theta | O) = P(O | \Theta) P(\Theta) / P(O) \text{ or } P(\Theta | O) = \frac{L(O | \Theta) P(\Theta)}{P(O)} $$

where $\Theta$ is unknown parameter set, $O$ is observation, $P(\Theta)$ is the prior density distribution of the parameter, $P(O)$ is the scaling factor that ensures that the posterior density distribution integrates to 1, $P(O | \Theta)$ is the likelihood function that describes
chance to get the observed data on the given parameters and modeling set, $P(\Theta | O)$ is the posterior density distribution of the parameter.

The Bayesian method can incorporate prior expert knowledge about parameters using the assumed prior distribution in an analysis (Marshall et al., 2004) while frequentist method excludes any existing information due to concern of biasing the analysis (Malakoff, 1999). Especially when data are scarce, the subjective choice of a prior probability distribution can affect the posterior significantly, so thus uninformative (or noninformative, objective, flat) priors like uniform and Jeffrey’s prior are usually employed to minimize the influence of the prior (Malakoff, 1999; Robert et al., 2004). The likelihood function contains all the functional dependencies of the likelihood on the parameter set (Kavetski et al., 2002), and then the posterior density distribution contains all the available information about the parameters. Thus, Bayesian inference reduces to summarizing the posterior density (Bates et al., 2001).

In order to obtain the posterior probability of a parameter, the Bayesian inference combines modeler’s knowledge called a prior distribution of a parameter with a likelihood function that represents probability of observing the measured records when a parameter set is given. This framework of the Bayesian method, which tries to infer the most plausible parameter set in the given model structure based on the observed data, is very analogous to calibration in H/WQ modeling. However, a Bayesian framework provides not a single value but a selectable range as a posterior density distribution of a parameter for the given conditions in H/WQ model calibration. Gallagher et al. (2007) compared philosophies and statistical formulations for uncertainty analysis of the Bayesian framework with those of the frequentist approach.

One of the popular Bayesian approaches for uncertainty analysis is Markov Chain Monte Carlo (MCMC) technique. In MCMC methods, the exploration of the posterior distribution of a parameter is implemented within the Bayesian framework. The prior distribution is determined based on a modeler’s experience and reasoning. On the other hand, it is very difficult or even impossible to assess the likelihood function analytically because its form is very complicated depending on characteristics of the residuals.
However, when the residuals are assumed mutually independent and normally distributed with a constant variance, the likelihood can be reduced into a relatively simple form.

It is not always possible to summarize the posterior distribution by direct calculation or in the analytical manner especially for high dimensional modeling with correlated parameters (Bates et al., 2001). For this practical problem, MCMC provides an efficient way in accurately summarizing any desired feature of the posterior distribution through generating the enough numbers of samples from the posterior distribution using a carefully constructed Markov chain, which ensures that the parameter sequence converges in distribution to the posterior (Campbell et al., 1999; Bates et al., 2001; Marshall et al., 2004). Thus, the goal of MCMC is to sample parameter values from the posterior distribution by simulating a random process using a Markov chain that has the posterior distribution as its stationary distribution (Marshall et al., 2004). MCMC is known to provide a solution to a difficult problem of sampling from a high dimensional posterior distribution (Robert et al., 2004; Kanso et al., 2005). The required number of iteration for convergence of the Markov Chain is determined by some diagnoses measurements, and speed of convergence is controlled by efficiency of sampling strategy and proposal distribution (Haario et al., 1999). Harmon et al. (1997) well described fundamental theories for understanding a Bayesian framework, in particular MCMC (Markov chains and Monte Carlo) methods.

One of the popular MCMC methods is Metropolis-Hasting (MH) algorithm. It employs Metropolis algorithm, which is also used in the Simulated Annealing optimization method, to efficiently explore the posterior distribution of a parameter. The Metropolis-Hastings algorithm allows producing Markov chains that sample the posterior probability density function and recover the parameter means, variances, and standard deviations (Harmon et la., 1997). Usually, about ten thousand sample parameter sets and model evaluations are required to get a stationary Markov Chain posterior distribution. Thus, in spite of improvements of efficiency, the application in H/WQ modeling that usually has a large number of parameters has been obstructed by long executing time, and thus relatively simple conceptual models or a part of a model have been employed to examine parameter uncertainty and its propagation into the output. In this sense,
efficiency of methods used to assess uncertainty of H/WQ modeling is a critical consideration in practice.

One of the easiest ways to reduce operating time of massive computation is parallelization of the calculation. However, the Bayesian implementation is inherently sequential computing such that a posterior distribution becomes the next prior on evolvement of sampling. Thus, MCMC runs cannot be readily parallelized (Foglia et al., 2009). Haario et al. (1999; 2001) proposed an adaptive Metropolis algorithm to improve convergence speed of a MCMC. The new algorithm reduces the number of model evaluations by tuning the proposal distribution with information like covariance learned about the target (posterior) distribution at every stage. Marshall et al. (2004; 2005; 2007) applied the adaptive MCMC method Haario et al. (2001) proposed to improve efficiency of sampling and to incorporate interaction between parameters into assessing parameter and modeling uncertainty of AWBM. However, in the studies of Haario et al. (1999; 2000), the adaptive Metropolis algorithm showed slow convergence when the parameter dimension increased, and its convergence speed was sensitive to a choice of the initial covariance assumption.

In the study of Dilks et al. (1992), the posterior distributions of nine parameters in a simple dissolved oxygen model were obtained using uniform priors through the Bayesian Monte Carlo (BMC) method. Then, the posteriors were used to calculate the overall uncertainty of the model prediction. From the comparison of model output uncertainties resulted from two cases of considering covariance or not, they found that ignorance of covariance in between parameters overestimated the overall modeling uncertainty. Qian et al. (2003) compared efficiency and effectiveness of BMC and the Metropolis algorithm of MCMC in assessing uncertainty of parameters in a low-dimensional biochemical oxygen demand decay model. In their study, MCMC presented ability to exhibit correlation structure between parameters and clear convergence toward the most probable region in the posterior distribution. However, BMC skipped some samplings on important region of the posterior because it sampled from not the posterior distributions but the prior. Thus, sampling became inefficient and BMC was subject to failing to provide appropriate uncertainty estimation especially when parameters are highly correlated.
Kuczera et al. (1998) compared performance of the importance sampling in the GLUE framework with that of the Metropolis algorithm of MCMC in assessing parameter uncertainty of a simple water balance model. In the study, he tried to illustrate the insights the Metropolis algorithm could offer in the case of using a more complex catchment model. He found that the Metropolis algorithm was superior to the importance sampling technique when sufficiently large samples were not available. In addition, the Metropolis algorithm could provide parameter uncertainty even in the presence of bimodality. Arhonditsis et al. (2008) also compared efficiency and effectiveness of them using an eutrophication model for Lake Washington. In the study, MCMC provided stronger correlation structure of parameters and more consistent modeling uncertainty. In addition, MCMC made inference about uncertainty more efficiently than did GLUE because the results of GLUE were affected by ill-defined prior distributions significantly and use of only subjectively chosen ‘behavioral’ parameter subsets could cause difficulty in exploring parameter space comprehensively.

Campbell et al. (1999) established a Bayesian framework for parameter estimation in the quasi-distributed nonlinear flood event model, RORB (Runoff Routing). He found that the Metropolis-Hasting algorithm provided greater modeling flexibility than did a Gibbs sampler. Bates et al. (2001) developed a MCMC framework, especially Metropolis-Hasting algorithm, for analyzing uncertainty in eight parameters and the output of a simple eight-parameter conceptual rainfall-runoff model, AWBM (Australian Water Balance Model). In their study, it was found that the nonlinear conceptual structure and eight parameters of AWBM made convergence of the Markov chain slow. Thus, they concluded that the model structure was not adequate for their study watersheds due to too complicated model structure comparing to complexity of the data at hand. Kanso et al. (2005) tested the applicability and effectiveness of the MCMC sampling technique in sensitivity analysis, calibration, and validation of a simple urban runoff quality conceptual model. Reis et al. (2005) applied the Metropolis-Hasting algorithm of MCMC in 2 flood frequency distributions, log-normal and log-Pearson type 3, in Bulletin 17B (Guidelines for Determining Flood Frequency) of USWRC (United States Water Resources Council Hydrology Committee) to evaluate the posterior distribution of the flood magnitude.
2.12.3.5 GLUE

The Generalized Likelihood Uncertainty Estimation (GLUE) was invented to relieve the difficulty in obtaining the likelihood function for uncertainty analysis in the Bayesian framework. Unlike a formal Bayesian method, the likelihood function is defined as a fuzzy, belief, or possibilistic measure of how well the H/WQ model performs, and it is replaced with some measures of goodness of fit such as RMSE and Nash-Sutcliffe efficiency coefficient (Beven et al. 1992). Thus, the choice of a likelihood measure is inherently subjective. The GLUE is an extension of the sensitivity analysis method Hornberger et al. (1980) and Spear et al. (1980) proposed (Ratto et al., 2001; Stedinger et al. 2008). It adapted the main methodology from them such as grouping the model parameters into ‘behavioral’ and ‘nonbehavioral’ and employing the Monte Carlo technique to sample parameter sets based on prior information about features of the parameters. The parameter sets classified as ‘behavioral’ are used to rescale likelihood weights and the ‘nonbehavioral’ parameters are ignored in the inference processes (Mantovan et al., 2006; Stedinger et al., 2008). Beven (2006) suggested that models that do not fall within the multiple prior limits of acceptability should be rejected for many feasible models satisfying the limits of acceptability to be accepted as ‘behavioral’.

Beven et al. (1992) describes the GLUE procedure as a method to calibrate a distributed model and predict its uncertainty. Then, Beven et al. (1993) showed utilities of GLUE in estimating uncertainty of a rainfall-runoff modeling using TOPMODEL. Pappenberger et al. (2005) applied the GLUE in producing a probability map of flooding for an event with UNET module of HEC-RAS for unsteady flow, and they proposed a stopping criterion for the GLUE by analyzing the change of the cumulative probability density function of flooding for each cross section of the channel. Mugunthan et al. (2006) developed a tool for automatic calibration and uncertainty analysis, ACUARS (Automatic Calibration and Uncertainty Assessment using Response Surface). Although, comparing to GLUE, sampling efficiency was improved by incorporating a guided search algorithm in ACUARS, uncertainty assessment is implemented using only the selected behavior parameter subsets as does GLUE. Tolson et al. (2007) developed DDS optimization algorithm to improve sampling efficiency of GLUE and thereby to find more behavior parameter subsets. In the comparison study, DDS showed better efficiency.
and performance than GLUE (Tolson et al., 2008). Blasone et al. (2008) compared performance and efficiency of a simple Monte Carlo sampling algorithm with those of the Shuffled Complex Evolution Metropolis (SCEM-UA) global optimization algorithm, which is one of the guided or adaptive sampling strategies, in the GLUE methodology. From the comparison, they found that the GLUE method with the SCEM-US sampler provided better predictions of the model output more efficiently.

Although GLUE has been applied to uncertainty analysis of a H/WQ modeling widely, there are some criticisms about its subjectivity and informality. Beauties and criticisms of the GLUE methodology are well discussed by Blasone et al. (2008). One comment of them is about subjectivity in selection of the threshold value or limit of acceptability to separate ‘behavioral’ from ‘nonbehavioral’ parameter sets (Beven, 2006; Blasone et al. 2008; Winsemius et al., 2009; Liu et al., 2009). As Beven (2006) argued, the subjectivity can be useful for a ‘non-ideal’ condition of modeling such as lack or limitation of reliable observation because it can give some space for a modeler to intervene with a prior knowledge. However, the participation may lead to bias in an uncertainty analysis of a modeling, especially for an ‘ideal’ case.

Winsemius et al. (2009) attempted to build a method to set the threshold value less subjectively. They collected the slopes of the recession curves of hydrographs and calculated statistics like mean, standard deviation, and autoregressive coefficient of 1-lag of daily flows generated from Monte Carlo simulations of the HBV model. Then, the slopes were assumed to have the normal distribution and some of them within the 95% probability area were considered as ‘behavioral’. In addition, a parameter set was assumed ‘behavioral’ “if it produces a river discharge simulation of which these yearly statistics fall within the related limits of acceptability for each year of the model simulation” (Winsemius et al., 2009). They also introduced soft hydrological information, which is less formal and rigid than the hard information, and employed an auxiliary monthly discharges generated from the monthly HYMOD modeling in order to define another threshold for the seasonal discharge.

Liu et al. (2009) proposed a framework to account for discharge observation errors in determining the limits of acceptability or threshold. They evaluated the
generated discharges from Monte Carlo simulations of the Dynamic TOPMODEL using the normalized scores calculated from upper and lower limits of the rating curve prediction at every time step. Then, the distribution of the scores over all time steps in the calibration period was derived for every simulation. Finally, only runs that fall in the limits of acceptability were accepted as ‘behavioral’ and used for uncertainty analysis of the modeling.

Another comment on GLUE is use of informal likelihood functions in the Bayesian framework. Freer et al. (1996) pointed out that uncertainty bounds and the distribution of predicted discharges are affected by the choice of likelihood measure in a GLUE application. Zheng et al. (2007) examined variations of 90% uncertainty band while applying five different likelihood measures, four different numbers of the Monte Carlo runs, and five different behavior thresholds. Their experiment showed that the uncertainty band is very sensitive to selection of the behavior threshold and likelihood but not to the number of the samples.

Montanari (2005) investigated variations of the prediction limits and the Nash-Sutcliffe efficiency of the median GLUE output in validation while changing the number of Monte Carlo simulation runs, length of the calibration period, and likelihood measures, taking uncertainty of rainfall data into account, and adapting another model structure of the HYMOD model. The test showed that the prediction limits the GLUE provided did not cover the confidence level of the observed data and the GLUE underestimates the total uncertainty of the HYMOD modeling. In addition, Jia et al. (2008) investigated uncertainty in flow and fecal coliform modeling of the Hydrological Simulation Program – Fortran (HSPF) model. From the results, only 381 of 50,000 HSPH runs are accepted for ‘behavioral’ simulation in the GLUE, and it failed to find a unique parameter set for better modeling results.

Meanwhile, a few researchers indicated that use of the generalized likelihood functions such as Nash-Sutcliffe and RMSE functions rather than a likelihood function strictly defined in statistical sense might not provide reasonable assessment of uncertainty in H/WQ modeling. Christensen (2003) found that selection of likelihood function could significantly affect the accuracy of uncertainty bands in a groundwater flow modeling. In
his study, the GLUE uncertainty bands does not account for the uncertainty caused by small-scale error that occurs due to ignorance of variability at lower scale than the minimum of the modeling. Mantovan et al. (2006) pointed out possibility of providing biased results because of ignorance of ‘nonbehavioral’ parameters. He also verified that the use of the generalized likelihood functions in the GLUE instead of the statistically formal does not ensure the desired consistency property of a statistical inference process and lead to lose some properties of the statistical process for parameter inference. Montanari (2007) asserted that the GLUE is not a probabilistic method rather a weighted sensitivity analysis because the method used in rescaling likelihood measure does not provide a consistent estimate of the probability density function of the modeling output.

Finally, Stedinger et al. (2008) illustrated deficiencies of the GLUE methodology through examining behaviors of the uncertainty in a simple linear rainfall-runoff modeling output using GLUE. In their study, the linear model allowed calibration to become a linear regression where exact expressions for prediction precision and parameter uncertainty are known (Stedinger et al. 2008), so thus the illustration becomes more simple and clear. They examined the uncertainty bands and posterior probabilistic density functions of the modeling output and reaffirmed that the uncertainty results the GLUE provides are subject to change according to likelihood functions, shaping factor, sample size, and the threshold. In the study, even when the perfect fit of the simple model was found by the regression, the uncertainty interval generated using the informal likelihood functions did not collapse to zero contrary to the results the formal likelihood function provided. It must be an evidence to prove a critical defect of the GLUE methodology.

### 2.12.3.6 SCEM-UA

Vrugt et al. (2003c) introduced a more advanced MCMC method called Shuffled Complex Evolution Metropolis (SCEM-UA) algorithm to improve efficiency in updating a proposal distribution in the MCMC. This algorithm operates by merging the strengths of the Metropolis algorithm (or Simulated Annealing) and Shuffled Complex Evolution (SCE-UA) algorithm Duan et al. (1992) invented. The optimization algorithm is trying to
sample in a way as rapidly converging to the global optimum while maintaining sufficient occupation of the lower probability regions in the parameter space. However, the uncertainty analysis does not intend to find the single optimum but distributions of parameters at a feasible parameter space. Thus, the SCE-UA was modified to prevent the collapse of the algorithm into the relatively small region of a single best parameter set. For this, the SCEM-UA algorithm replaced the Simplex search method with the Metropolis method. Several researchers compared efficiencies of SCEM-UA and Metropolis-Hasting algorithms of MCMC methods and reported the SCEM-UA provided much better efficiency than did Metropolis-Hasting.

Vrugt et al. (2003a) applied the SCEM-UA algorithm to assess uncertainty of the parameters in three soil hydraulic models: Brook and Corey (1964), Mualem-van Genuchten (1980), and Kosugi (1999) models. In the study, coefficient of variance, which was calculated of each parameter from the sampled parameter sets by the algorithm, was interpreted as its uncertainty. Then, relationship between the variance statistics and the choice of a model structure was examined to assess impact of the model structure on the parameter uncertainty. The great values of coefficient of variance revealed that all the model were in need of further improvement. In addition, the study showed significant sensitivity of the parameter uncertainty to the model structure.

Vrugt et al. (2004) compared parameter uncertainty ranges and predictive capability of a physically based distributed and a lumped bucket model through examining the derived parameter uncertainty by the SCEM-UA algorithm. They found that the physically based distributed model provided consistent and unbiased forecasts of spatially distributed drainage area in the calibration and validation periods even though the significant CPU time was required.

Vrugt et al. (2006) utilized the SCEM-UA algorithm in calibrating 13 parameters of the Sacramento Soil Moisture Accounting (SAC-SMA) model. They investigated the relationship between the length and variability of the measured data used in the calibration and parameter uncertainty. In addition, they compared the derived uncertainty of the parameters by the SCEM-UA algorithm with the calibrated values of the parameters by the SCE-UA algorithm. In the study, the parameter uncertainty was not
affected by the length of the calibration period when it was over 3 years, but longer calibration period provided better average performance in validation. In addition, most the calibrated parameter values were located at vicinity of modes in the posterior distributions of the parameters, but the SCE-UA algorithm showed better efficiency in locating the optimum parameter sets.

Feyen et al. (2007) applied the SCEM-UA algorithm to calibrate five parameters of the LISFLOOD model, which is a cell-based distributed conceptual hydrology model, and assess their uncertainty. In the examination for ensuring adequacy of the derived posterior probability distribution of the parameters, they found a strong autocorrelation structure in the residual, which is a strong evidence to reject one of the fundamental assumptions of a likelihood function of the SCEM-UA algorithm. They expected the wrong assumption might lead to underestimation of the prediction limits.

2.12.4 Uncertainty caused by Measured Data for Calibration

2.12.4.1 Runoff Measurement

In a H/WQ modeling, measured data provide direct and/or indirect information in calibration of process-based or deductive modeling and basis in constructing model structure of some data-driven or inductive models such as statistical, stochastic, and regression models. Once a H/WQ model is set (calibrated, built, or even not calibrated), the data are also used in assessing the modeling prediction reliability through validation. All the measured data contain errors due to temporal and spatial variability of the nature, incomplete measuring technique, blunders, and malfunction of devices. Moreover, errors may be introduced into water quality data at the stage of storing water quality samples and analyzing them in laboratory (Harmel et al., 2006). These errors contained in the measured data affect accuracy and reliability of H/WQ modeling at calibration and validation.

Flow discharge data are usually obtained through interpolation and extrapolation from flow level measurement using a rating curve, and thus regression error is inevitably introduced in the flow discharge data. In this case, measured data itself is a product of a
regression modeling. In order to build a rating curve, the enough number of flow discharges should be estimated through summing velocity and area measurements for all the segments over a channel cross section, so-called velocity-area method. Thus, several factors, such as precision of the current meter, approximation of area measurement, and technique of velocity measurement, may induce error in the flow discharge estimation. When converting level measurement to discharge using a rating curve, errors in the level measurement are also propagated into the discharge data. Moreover, a rating curve is built based on the assumption that flow discharge is a function of only flow level, and thus it ignores other physical forces such as acceleration and diffusion that controls flow in the channel. Once flow discharge is estimated from flow level measurement, it is sometimes aggregated and averaged at coarser time interval for further analysis. At a long point of view, the geometry of the channel varies rather than stationary because of erosion (i.e. widening and cutting) and deposition of sediment, and friction of the perimeter of a channel cross section also alters due to change of seasonal vegetation and bottom material (i.e. channel armoring).

Dymond et al. (1982) proposed statistical ways to estimate error in flow discharge derived from a rating curve, which may be caused by rating curve error, flow level measurement error, and error comes from negligence of physical parameters other than flow level. Petersen-Overleir (2004) pointed out that traditional statistical methods for developing a rating curve do not consider possibility of heteroscedasticity in the model, and then proposed the heteroscedastic maximum likelihood method. Aronica et al. (2006) investigated sensitivity of a conceptual rainfall-runoff model prediction, IHACRES (Identification of Hydrographs And Components from Rainfall, Evapotranspiration and Streamflow data), to error in a rating curve using GLUE. Although their study showed impact of rating curve uncertainty on not accuracy of the prediction but prediction itself, it was found that overestimation in a rating curve had a greater effect on the model prediction than did the underestimation.

Baldassarre et al. (2009) attempted to quantify errors from different sources such as discharge measurement, interpolation, and extrapolation of a rating curve, unsteady flow, and seasonal changes of the roughness, in determining flow discharge using a rating curve. They built rating curves for the Po river reaches in Italy using the generated
discharges from the HEC-RAS modeling with different flow schemes (steady and unsteady) and unique Manning’s roughness coefficients. The study showed that the overall error of flow discharge observations averaged over the river reaches ranged 6.2 to 42.8 % at the 95 % confidence level. Although persuasive power of this study’s conclusion was lowered by using surrogate of the measured flow discharge as output of the calibrated one-dimensional hydraulic modeling, the estimation of error showed a close agreement with Slade (2004)’s study about error in a stage-discharge relationship (Harmel et al., 2006).

2.12.4.2 Sediment Load Measurement

Sediment load is usually estimated by multiplying sediment concentration measurement by flow discharge. Thus, errors in the estimated flow discharge data and in measurement of sediment concentration are propagated into the sediment load estimation. Sediment concentration is normally sampled not interpolated or extrapolated like flow discharge due to its very complicated spatial and temporal variability. However, sampling frequency of sediment concentration is limited by monitoring and analysis cost, accessibility when flooding, and rapid fluctuation of water quantity and sediment concentration even in a small watershed. In addition, there is no way to check balance of sediment like flow discharge (Walling, 1977) Moreover, there are different types of sediments such as bed and suspended load, so thus it might be difficult to separate them completely in sampling at field. Therefore, much higher uncertainty will be induced into sediment concentration and load data than flow discharge.

Campbell et al. (1940) developed a regression equation, so called sediment rating curve, to identify a relationship between daily suspended load and flow discharge, and then they employed the equation in calculating sediment load from discharge. They compared the estimated silt load from the sediment rating curve and field measurements for the Red river in Texas. In the study, they found that the differences between them ranged from -25.0 % to 14.8 % for seven sub-periods of 60 months and the error reduced to 1.5 % for the total period. Walling (1977) assessed accuracy of continuous long-term sediment load estimation using a rating curve through comparing with continuous
suspended sediment load measurement. In his study, turbidity was recorded continuously using photoelectric turbidity meter, and the data used to provide continuous suspended sediment concentration. Then, the concentration was combined with discharge records to produce continuous sediment load data. In order to examine impact of seasonal frictional variation and unsteady flow profiles on error of the sediment rating curve, continuous discharge and sediment load data were separated into two seasons (from October to March and from April to September) and stages (rising and falling limbs) in constructing the rating curves. Their study showed that use of stage distinguished rating curve reduced half of the total error but seasonal rating curves barely better the accuracy of annual load estimation. In addition, the rating curve overestimated sediment load from 30 to 60% than the estimation by turbidity.

Walling et al. (1981) also investigated error of continuous long-term sediment load estimation using interpolation (averaging) and extrapolation of rating curves derived from different sampling intervals or frequencies. They measured turbidity continuously using a light transmission sensor and transferred the turbidity into suspended sediment concentration using the defined relationship between them. Then, they could obtain continuous sediment load using the rating curve and the concentration data. In order to investigate impact of sampling frequency on long-term (annual) sediment load estimation based on interpolation (averaging), the load records were randomly selected for several sampling intervals. They also employed six sediment load interpolation (averaging) methods to see impact of types of interpolation on annual sediment load estimation. Different sampling strategies with respect to season, flow profiles (rising and falling), the minimum threshold discharge to sample, and temporal discharge averaging intervals are used in deriving sediment rating curves and extrapolating function. The results showed that sampling intervals did not significantly affect accuracy of annual sediment load estimation but interpolation (averaging) methods did. In addition, use of appropriately separated sediment rating curves regarding the season, profile, and threshold could improve accuracy of annual sediment load. Finally, in the study, even the best interpolation and extrapolation methods underestimated by 50% of the measured annual sediment loads.
Jansson (1985) found that a logarithmic regression equation produced bias but a power function did not in his study, which compared detransformed sediment concentrations from both forms with the original data. Miller (1984) statistically derived unbiased forms of detransformed estimators to remedy bias when calculating a mean from an equation transformed using the logarithm and positive or negative fractional power. Ferguson (1986) also revealed the reason why a sediment rating curve is subject to underestimate sediment load. He pointed out that a rating curve is normally derived on a log scale to employ the linear least square regression that has a closed form solution. Thus, the predicted sediment load for a specific discharge on the log scale is the geometric mean, which is always less than the arithmetic, of the conditional distribution of the true load value. In order to avoid this underestimation, he proposed to use a bias correction factor that accounts for the relationship between degrees of bias and scatter (variance of the residual). Finally, he argued that the degree of underestimation can reach 50%, and this result agreed well with the study of Walling et al. (1981).

Asselman (2000) did a similar research to that of Walling et al. (1977; 1981) with several different watersheds with respect to size and location to improve methodology and find physical interpretation of a rating curve. His study showed that the degrees of improvement of estimation accuracy of suspended sediment transport rate depended on consideration of seasonal effects (summer and winter), different flow profiles (rising and falling), and physical characteristics of watershed. In addition, he found that a rating curve in the form of a power function based on nonlinear least squares regression provided better accuracy than did a logarithmic form even when the bias correction factor Ferguson (1986) proposed was applied in detransforming the logarithmic data.

Harmel et al. (2005) compared errors of different sampling strategies with respect to temporal interval and composition in estimating suspended sediment, nitrate (NO$_3$-N), and phosphate (PO$_4$-P) for storms. From the study, they found cumulative errors of the water qualities for a storm were less than 10% for all the sampling strategies employing constant discharge interval rather than constant time interval. In addition, the composite sampling technique, which collects samples on equal discharge intervals and store them in a bottle for an individual storm, did not produce significant effect on sampling error. Harmel et al. (2006) also classified sources of water quality measurement errors: stream
measurement and sampling method at field, sample preservation and storage method, and laboratory analysis. Then, they examined error reports of the selected researches related to the errors and estimated probable error ranges for the source with respect to different QA/QC (Quality Assurance / Quality Control) scenarios. The study showed that sampling collection most significantly contributed to water quality measurement error at the typical QA/QC scenario but laboratory analysis did at the worst scenario. In addition, errors in stream flow and nutrient load were less and greater than that in suspended sediment respectively regardless of QA/QC scenarios.

2.12.5 Uncertainty caused by Model Structures

Shamseldin et al. (1997) proposed a way to incorporate model structure uncertainty into a hydrologic modeling. They applied five different conceptual rainfall-runoff models and three methods to combine the modeling results for obtaining ensemble hydrographs of 11 catchments. In the study, an averaged hydrograph of the ensemble showed better agreement with the measured and the neural network method provided better performance than the other, simple average and weighted average methods. In addition, when the modeling that provided the worst result was dropped from creating the ensemble hydrograph, the overall accuracy increased. It means that selection of candidate models is subjective, and the resulting ensemble hydrographs may be biased. Therefore, the simulated variation of hydrographs by five models is subject to underestimates model structure uncertainty or overestimate reliability.

Duan et al. (2007) and Ajami et al. (2007) used three hydrologic conceptual models, SAC-SMA (SACramento Soil Moisture Accounting), HYMOD (HYdrologic MODel), and SWB (Simple Water Balance), to generate ensemble hydrographs with BMA (Bayesian Model Averaging) and the combined BMA with SCEM-UA (Shuffled Complex Evolution Metropolis – University of Arizona) respectively. Vrugt et al. (2007) compared performance of BMA and EnKF (Ensemble Kalman Filtering) in probabilistic streamflow forecasting using eight conceptual hydrologic models at different levels of complexity. Georgakakos et al. (2004) used eight different hydrologic models ranging from spatially lumped, catchment-based, grid, to tin-based in characterizing the impact of
parameter and model structure uncertainty on flow simulation. The studies showed significant impact of model uncertainty on the modeling overall reliability even though the impact may be underestimated and biased due to the incomprehensive selection of model.

Butts et al. (2004) interpreted uncertainty of model structure as variations in modeling results provided by different possible model structures in the same modeling framework, and then compared the variation with impacts of uncertainties in rainfall input data and parameters. They explored 10 different combinations of the overland and routing methods incorporated in the MIKE SHE model and calibrated every combined structure with the same measured data using an automatic multiple objective calibration technique. Then, the 10 different calibrated models were used to generate model structure ensembles in order to estimate the modeling uncertainty caused by the model structure uncertainty. In the study, they found that model performance and behavior, especially peak runoff and time to peak, are very sensitive to model structure and distributed rainfall information. A spatially distributed parameter model structure provided the best calibration results; however, it was outperformed by other model structures in the validation probably due to overparameterization or equifinality. In addition, a more complex model did not always provide better performance. Finally, they recommended using the ensemble average of the possible combinations of model structures rather than single calibrated model for better predictive reliability of modeling. Although not all the possible combinations of the model structures were explored, and thus variation in modeling results of 10 different model structures might not represent total uncertainty of model structure, it showed a way to evaluate model structure uncertainty in a H/WQ modeling and provided some evidences to doubt a proportional relationship between model complexity and predictive accuracy.

Parasuraman et al. (2008) criticized bias of the former researches in selecting models to generate ensemble results and argued that the exhaustive search of possible model structures enables a more realistic quantification of model structure uncertainty. Thus, they proposed an ensemble based genetic programming framework, which combines genetic programming (GP) and nonparametric bootstrap method, to search plausible models comprehensively. In the framework, the bootstrap generates initial
realizations of the measured data and the GP explores the possible model structures and
the associated parameters. Thus, uncertainties in the measured data used in calibration,
parameter, and model structure will contribute to variation in the modeling output
explicitly and simultaneously. In addition, they employed fixed model structures in
calibration and compared their impacts while varying model structures in order to
identify pure contribution of model structure uncertainty to the overall modeling output
variation. In the study, they found that prediction accuracy became better but uncertainty
band became wider, and uncertainty of model structure became more significant as model
complexity increased. However, it should be noted that the model they used is conceptual
and empirical so that their findings may be different from when employing more physical
based model.

Chiang et al. (2005; 2007) categorized the entire H/WQ modeling uncertainty into
system, inherent, and structure uncertainties. They denoted the entire uncertainty as being
caused by all possible sources of uncertainty including the uncertainty of the measured
data used in calibration. The system uncertainty is defined as being caused by possible
errors of the calibrated models. In addition, they defined the inherent uncertainty as a
difference between modeling results come form the best parameter set and the other sets,
and thus it comes from parameter uncertainty. Then, the structure uncertainty is
quantified as the difference between the entire and inherent uncertainty. Although input
data is restricted to rainfall data and uncertainty of input data and parameter are
predefined arbitrarily, they tried to separate and quantify uncertainties of the overall
modeling results that come from different sources. Especially, the study proposed a way
to separate the model structure uncertainty from the overall modeling uncertainty.

2.13 Time-Area Method

2.13.1 Overview

A time-area histogram is a graph that explains which parts of a watershed
contribute to direct runoff at a point of interest within the watershed during a specific
period. It is constructed from a cumulative travel time map, which consists of isochrones
that join areas in the same travel time zone at a specific time. The time-area histogram can be used as a function to translate excess rainfall into a runoff hydrograph by considering characteristics of the watershed such as shape, roughness, and slope. A way to construct hydrographs using the time-area histogram is called ‘time-area method’. Since Clark (1945) applied the time-area method in developing a unit hydrograph with a linear reservoir at the outlet (Maidment et al., 1996), many other studies have tried to relate hydrologic responses to characteristics of a watershed using the time-area method (Rodriguez-Iturbe et al., 1979; Maidment et al., 1993, 1996; Muzik, 1996; Gyasi-Agyei et al., 1996; Ajward et al., 2000; Saghaifian et al., 2000, 2002; Martinez et al., 2002; Melesse et al., 2004; Lopez, 2005; Noto, 2007; Du et al., 2009). However, the method has not been employed widely in H/WQ modeling in spite of its simplicity and explicitness probably because it has, in the past, been regarded as a way to develop unit hydrographs.

Information about geographic characteristics of a watershed such as topography, land cover, soil, and stream networks is requisite to get a time-area histogram because those factors influence velocity and subsequently travel time of flow. Thus, GIS and its database might provide useful tools in constructing runoff hydrographs from relationships between the characteristics and hydrologic responses of a watershed in the time-area approach. Rodriguez-Iturbe et al. (1979a; 1979b) introduced geomorphologic instantaneous unit hydrograph (GIUH) approach that derives instantaneous unit hydrograph (IUH) from geomorphologic characteristics of a watershed such as the Holton’s stream order, bifurcation, length, and area ratios. The GIUH approach was devised to account for impact of temporal change of excess rainfall intensity in constructing a unit hydrograph by updating stream velocity for different time intervals during a storm (Rodriguez-Iturbe et al., 1979a; Ajward et al., 2000). Although they perceived strong relationships between geomorphologic features and runoff hydrograph of a watershed, they employed probabilistic arguments in order to simulate travel time due to absence of GIS and its database like DEM. Rodriguez-Iturbe et al. (1982a; 1982b) also attempted to relate intensity and duration of rainfall as well as geomorphologic characteristics of a watershed to hydrologic responses of the watershed.
Maidment et al. (1993) tried to employ the time-area diagram in developing the unit hydrograph. Unlike the GIUH study by Rodriguez-Iturbe et al. (1979a; 1979b), average travel time along a flow path was assumed constant, so runoff velocity field did not change with time, amount of excess rainfall, and discharge in their study. Simply, the velocity was a function of surface cell slope. This assumption was equivalent to those of the unit hydrograph approach such as constant base time and linearity of rainfall-runoff response so that it could make its application simple and easy, but unrealistic. They differentiated their approach from the GIUH method and called the ‘spatially distributed unit hydrograph’ because they utilized flow direction and stream network maps derived from DEM in constructing a time-area histogram. The GIS-based approach also relaxed the requirement for uniform excess rainfall over a watershed of the unit hydrograph method in their study.

Maidment et al. (1996) improved the spatially distributed unit hydrograph approach by introducing a lagged linear reservoir to account for storage effect that causes time delay of flow in a cell and watershed, so thus it could simulate attenuation of a hydrograph as well as translation in flow routing. In addition, they considered not only slope of a cell but also its upstream drainage area in calculating average velocity of flow on the cell. In spite of these reinforcements for the method, the assumption of spatially distributed but time-invariant velocity field of flow still limited application of the time-area approach into only developing a unit hydrograph.

Muzik (1996) modified the spatially distributed unit hydrograph (SDUH) approach proposed by Maidment et al. (1993; 1996) through distinguishing travel time calculations for overland and channel flow and accounting for channel storage. The travel times for overland and channel flows were calculated by the kinematic wave equation and Manning’s equation respectively, and travel times for channel reaches were increased based on length and geometry of the reach. He applied the method in deriving a one hour unit hydrograph for a watershed of 229 Km$^2$ in Alberta, Canada using 1 Km × 1 Km grid cells, and the developed unit hydrograph was used to construct a runoff hydrograph for the 21-hour storm. Unlike the result of Maidment et al. (1993), his modification of the method showed good agreement between the measured and simulated hydrographs. Saghafian et al. (2000; 2002) used the same kinematic wave equation as Muzik (1996)
did in calculating travel time of overland flow but a different equation, which was
developed by Saghaifian et al. (1995), in estimating time to equilibrium of channel flow.

Martinez et al. (2002) tested three approaches that distinguish types of flow in
building a time-area map: uniform flow assumption of using Kirpich’s formula,
discrimination of sheet and channeled flows using kinematic wave equation, and
distinction of sheet, shallow concentrated flow, and channeled flow using the equation of
USDA-SCS Technical Release 55 (USDA-SCS, 1986). In addition, only the second
approach considered influence of excess rainfall on flow velocity while the others did not.
In other words, velocity of flow on a cell was assumed constant during an event in the
first and third approaches. They applied three methods in constructing direct runoff
hydrographs from uniformly distributed theoretical excess rainfall with different
intensities over two small rural watersheds. Their study showed that the distinction of
overland and channel flows could provide time-area map that reflected the
geomorphologic features of the watershed more clearly.

Gyasi-Agyei et al. (1996) also calculated travel times of flow on the overland and
in the channel separately with a linear advection-dispersion routing model. For
considering the variable saturation excess rainfall production mechanism (or Dunne
saturation excess overland flow), their hillslope routing method, called a dynamic
hillslope instantaneous unit hydrograph determination, weighted the impulse response
function with the travel distance distribution of saturated cells to the main channel
network. The channel networks and the distribution of hillslope travel distance for
saturated cells were modeled using the topographic index proposed by Beven et al.
(1979). Once IUHs (Instantaneous Unit Hydrographs) for the hillslope and main channel
were constructed, a catchment IUH was developed by discrete convolution of them.
Lopez et al. (2005) compared performance of two methods, isochrones of the time-area
approach and subwatershed networks, in representing a watershed as a cascade of
reservoirs to develop a unit hydrograph. The methods were applied to an agricultural
watershed of 169 ha in Spain, and they did not produce significant differences in the
simulated hydrographs. Noto et al. (2007) tried to build travel time maps of flow on every
grid cells within GIS.
2.13.2 Unit Hydrograph and Time-Area Method

Rainfall amount is varied spatially over a watershed and temporally during a storm event. In addition, land use and soil characteristics over the watershed are not homogeneous. Therefore, excess rainfall amount must be not uniform in space and constant over time. Moreover, flow depth and velocity on the overland and in the stream are varied with rainfall intensity and discharge in a highly nonlinear manner. Thus, the base times of the direct runoff hydrograph resulting from different amount of effective rainfall for the given duration are not constant. Therefore, some assumptions of the unit hydrograph approach, such as the uniform excess rainfall and the constant base time of a direct runoff hydrograph, may not correspond with the reality even though it has been used widely in hydrologic modeling because of its simplicity and convenience. In particular, the unit hydrograph approach may not be appropriate for a relatively big watershed where channel routing plays an important role in surface water hydrology and spatial variation in rainfall and landscape tend to be great.

The time-area method was used to derive a unit hydrograph in a lumped manner. For instance, in the Clark’s unit hydrograph method of HEC-HMS, a typical time-area relationship that represents translation of excess rainfall to the watershed outlet is expressed as a power function of the ratio of travel time to time of concentration. As the former studies showed and Saghafian et al. (2002) pointed out, however, the time-area method can be performed in the distributed manner. If we figure out excess rainfall amount and flow velocity in the distributed manner, one can derive the time-area relationships and construct hydrographs at any point of interest in the watershed even without some of the unit hydrograph assumptions. In other word, one can construct runoff hydrographs directly from the time-area histogram in the distributed manner.

Melesse et al. (2004) proposed the spatially distributed direct hydrograph travel time technique (SDDH) to construct direct runoff hydrographs from travel time and excess rainfall maps straightforwardly. The SSDH approach constructs a direct runoff hydrograph through dividing every summation of excess rainfall volume within the corresponding isochrone in a travel time map by a time step of the hydrograph. They employed the SCS-CN method for estimating excess rainfall and a kinematic wave
approximation and the Manning’s equation for estimating travel time of flow in the overland and channel. The SDDH method predicted direct runoff hydrographs for the 16 storms at the outlet of the watershed of 114 Km$^2$ in Florida at an average efficiency of 0.65. They claimed that the SDDH approach might be preferred to the traditional time-area method when reliable spatially distributed rainfall data are available because it can directly use spatially distributed excess rainfall.

Du et al. (2009) tested the SDDH approach with the observed direct runoff hydrographs at the outlet of the watershed of 259 Km$^2$ in China and modified the approach by adding a parameter to adjust channel flow velocity in calibration. After calibrating with one storm, the newly proposed method predicted the hydrographs for the other seven storms at a efficient coefficient of over 0.9. Thus, we can notice a certain degree of improvement was made in performance of the SDDH approach comparing to that of the approach Melesse et al. (2004) proposed, and it might be contributed to introduction of the new parameter for adjusting channel flow velocity. In the study of Melesse et al. (2004), it could be found that the original SDDH generally overestimated the time to peak. This overestimation should be caused by ignorance of influx of routed flow to a cell from upstream cells. The both SDDH approaches consider only excess rainfall estimated by the CN method in calculating velocities of overland and channel flow whereas, in reality, the routed flow into a cell is added to excess rainfall of the cell and then increase total water volume to be routed downstream. Therefore, the travel time for flow to pass through a cell should be overestimated in the previous SDDH approach. However, the modified SDDH by Du et al. (2009) introduced a parameter to increase velocity of channel flow uniformly over a watershed so thus they could have better agreement of the time to peak with the measured data. Although Du et al. (2009) doubted physical basis of the parameter, it can be interpreted as ‘velocity compensation for influx of the routed water’ in the SDDH approach, but it should be calibrated with the measurement as they pointed out because it is a lumped parameter for the entire channel networks. In their study, the parameter was calibrated to a value of five, and it means the channel flow velocity should be increased to five times as much as the calculated from the equations with nominal parameter values.
2.13.3 Storage and Backwater Effects in Time-Area Method

The time-area method proposed by Maidment et al. (1993) did not account for attenuation of upstream hydrograph caused by storage and backwater effect of the watershed stream networks but only translation because the equilibrium condition or ‘stationarity’ was assumed (Ponce, 1989; Saghafian, 2002). However, a watershed may reach to its equilibrium condition only when pores in soil matrix of the overland and storage capacity of the channel are filled with water completely. Thus, it will take a certain amount of time for the watershed to reach to the equilibrium condition because it should take significant time for rainfall and channel flow volume to fill those rooms. When the watershed is at the equilibrium, channel flow volume at an outlet in a certain time interval will become equal to rainfall volume fallen on the contributing area of the outlet in the same time interval. In addition, if sufficient rainfall exceeding the infiltration rate is supplied after the watershed reached to its equilibrium condition, the equilibrium state will continue until rainfall rate is less than that of infiltration.

When Clark (1945) and Nash (1957) proposed their methods for synthesizing a unit hydrograph, they introduced a watershed or reservoir storage coefficient in order to take into account storage effect caused by the channel networks of a watershed. Thus, the methods could simulate attenuation as well as translation of upstream hydrograph while the flow is routed along the channel (Chow et al., 1988; Wootton et al., 1996). However, some of flow volume in the channel networks may stay in a channel segment while flow runs through the part due to backwater effect even when the overland flow reaches its equilibrium. This backwater effect will also cause attenuation and delay of the upstream hydrograph. Therefore, if these storage and backwater effects of the channel are ignored especially in a big watershed that has well developed stream networks, time to peak can be underestimated and peak discharge may be overestimated.

Only a few studies have considered the storage effect in developing direct runoff hydrographs using the time-area curve approach. Muzik (1996) incorporated the channel storage effect by increasing travel time empirically using the length and geometry of channel segment. Maidment et al. (1996) attenuated and delayed upstream hydrograph by introducing a lagged linear reservoir so that an average residence time of flow in the
storage of a watershed could be prolonged. Saghafian et al. (2000; 2002) employed the equation they developed to estimate time to equilibrium of a watershed in deriving a time-area diagram. However, any literature that devised or introduced a way to consider the backwater effect has not been found yet probably because all the variants of the time-area methods employed the kinematic assumption in order to make computation of travel time simple. Although the kinematic approximation is one of the variants of the full Saint-Venant equation, it cannot consider backwater effect. However, it has been used widely in hydrologic modeling because of very simplified form of the equation, requiring fewer initial and boundary conditions, and subsequently, requires less effort for solving (Tsai, 2005).

Kilgore (1997) developed a SDUH (Spatially Distributed Unit Hydrograph) method, which is similar to the method Muzik (1996) proposed but implemented in GIS, to construct unit hydrographs resulting from uniformly distributed excess rainfall using a time-area approach. In her method, the Muskingum method was used for reservoir routing, then its storage and weighting factors were assumed equal to the estimated average hydraulic residence time and 0.2 respectively. She applied the method in constructing hydrographs of 40 storms for an agricultural watershed of 1,153ha and compared its performance with those of three synthetic unit hydrograph methods: SCS, Snyder, and Clark. The results showed that the SDUH method did better in predicting the peak flow and shape of hydrograph than did the other methods, but it consistently underestimated time to peaks.

Al-Smadi (1998) improved the method Kilgore proposed by incorporating spatial variation of excess rainfall in the SDUH method. In his research, a curve number (CN) was calculated and assigned to each cell based on land use and soil information in GIS so that every cell within a watershed could have unique CN and subsequently produce different excess rainfall. He examined sensitivity of hydrograph against the representation type of spatial variations of excess rainfall such as distributed and uniform (or averaged) excess rainfall over the watershed. Then, he compared the simulated hydrograph using variants of the CN method with that from the Phi index method. For the same agricultural watershed Kilgore (1997) used, the distributed and uniform curve number models provided similar performance in predicting peak flow rate and time to
peak and better results than did the Phi index. However, the distributed curve number model gave better result for heavier storm in summer than did the uniform model. He also provided some ways to estimate velocity in cells with zero excess rainfall and non-zero inflow.

One interesting thing found in the studies of Kilgore (1997) and Al-Smadi (1998) is that their simulated hydrographs generally showed shorter time to peak and higher peak runoff comparing to the measured hydrographs in particular for short, small, and intermittent storm rainfalls. In their research, the channel storage effect was ignored and the equilibrium condition was assumed implicitly in order to make the procedures for developing a time-area diagram simple. This simplification may cause their underestimation in time to peak and overestimation in peak runoff. Another possible explanation for the results might be inappropriate selection of antecedent moisture conditions (AMC) in the CN method. In other words, an initial condition of soil moisture of the watershed might not be estimated correctly in their research. Because a storm event hydrologic model is very sensitive to the initial soil moisture condition (Senarath et al., 2000), if AMC is not appropriately determined or the number of the soil moisture classes does not adequately describe an initial soil moisture condition, use of the CN method in H/WQ modeling might fail to get the good simulation results. In addition, the results might be attributed to the erroneous base flow separation they did to extract direct runoff from the entire hydrograph measured at the outlet.

2.14 Sediment

2.14.1 Overview

Sediments originate from soil and other suspended matter carried in with the inflowing water or they are formed within the waterbody itself as a result of the growth, metabolism, and death of plants and animals (DiToro, 2001). The physical, chemical, and biological processes in water bodies are critically influenced by sediments (DiToro, 2001). Sediment is not only the major pollutant by weight and volume but it also serves as a catalyst, carrier, and storage agent of other forms of pollution (ASCE, 2006).
Sediment together with pathogens and habitat alterations were cited as the leading causes of impairment in rivers and streams of the USA (EPA, 2007). Sediments may reduce visibility, shorten the depth of the photic zone, and thereby alter the vertical stratification of heat in the water column by suspending in the water bodies (Wilber et al., 2001). In addition, sediment may lead to capacity loss of reservoir, channel, and wetland and efficiency loss of man-made structure such as intake of a dam and irrigation canal by filling their storage and blocking path (Morris et al., 1998).

At the same time, however, nutrients, detritus, and other organic matter that sediment transports are critical to the health of a waterbody (EPA, 2003). Sediment in natural quantities also replenish sediment bedloads and create micro-habitats such as pools and sand bars (EPA, 2003). Thus, in general, sediment may be considered a pollutant when it exceeds natural concentration and has a detrimental effect on water quality in its biologic and esthetic sense (Dunne et al., 2002). On the other hand, clear water with little sediment and high flow energy can cause excessive scour on the waterbody boundary such as streambed degradation, bank failure, channel armoring, and degradation of stream habitat (Morris et al., 1998).

Sediment can be classified as cohesive and noncohesive based on its stickiness. However, there is no clear boundary between them and their definition is usually site-specific (US Department of the Interior, 2006). Cohesive sediments are comprised primarily of clay and silt-sized fractions of clay-type minerals but may be mixed with a range of organic compounds and sometimes very fine sand (Raudkivi, 1998; Shrestha et al., 2005). Thus, in general, sediment whose size is smaller than 2 µm are considered cohesive sediment while sediment greater than 60 µm is coarse noncohesive sediment (US Department of the Interior, 2006). Silt whose size ranges from 2 to 60 µm is considered to be between cohesive and noncohesive sediment (US Department of the Interior, 2006). Mechanical behavior of cohesive sediment is strongly influenced by the interparticle cohesion caused by electrostatic and related surface forces, which may be several orders of magnitude larger than gravitational forces (Raudkivi, 1998; Morris et al., 1998). These attractive forces make cohesive sediments tend to be stuck together and to form agglomerates having much faster settling velocity than an individual particles like
sand (Raudkivi, 1998; Morris et al., 1998). The forces also provide the main resistance to erosion of cohesive sediment (Morris et al., 1998).

The current level of understanding on cohesive sediment transport is relatively primitive comparing with that of noncohesive sediment transport due to complicated interactions of the forces and wide specific surface area (US Department of the Interior, 2006). The attractive forces help cohesive sediments to aggregate toward large and low-intensity units and then agglomerates are deposited on the bottom by gravity (US Department of the Interior, 2006; Morris et al., 1998). The settled cohesive sediment units are consolidated or compacted by the self-weight and overlying sediment (US Department of the Interior, 2006; Morris et al., 1998). Because of these aggregation and consolidation, the critical flow conditions for erosion and deposition may not coincide for cohesive sediments (Novotny, 2003). The wide specific surface area makes cohesive sediment tends to absorb fine materials on its surface so that cohesive sediments have a high sorptive capacity and act as a carrier for pollutants (Novotny, 2003). Absorption and desorption are controlled by local equilibrium and thus the pollutants become absorbed or dissolved when a pollutant concentration in the water is greater or less than the equilibrium state respectively (US Department of the Interior, 2006; Novotny, 2003). These processes can be simulated using isotherm models such as Langmuir and Freundlich (Novotny, 2003).

On the other hand, gravitational forces predominate settling velocity and incipient motion of coarse noncohesive sediments so thus grain size, shape, and specific gravity that determine gravitational forces are important characteristics of soil particles for understanding of coarse noncohesive sediments (Morris et al., 1998; Sturm, ). Especially, the concept of incipient motion has been playing an important role in the study of sediment transport and the design of a stable channel for noncohesive sediment (Yang, 1973). However, it is difficult to precisely define a critical flow condition that initiates a sediment particle movement due to the stochastic nature of sediment movement and the continuous changes of sediment transport rate (US Department of the Interior, 2006; Morris et al., 1998). Therefore, the critical condition of initiation of motion has been defined differently by researchers using various physical measures such as shear stress, velocity, and stream power (Rhoads, 1987; Morris et al., 1998).
Transport of sediment by flowing water is usually described by suspended load and bedload (Leopold, 1994). Sometimes, sediments are grouped into three types of bedload, suspended load, or washload (Haan et al., 1994) or suspended load and washload are used without discrimination (Novotny, 2003). However, washload was introduced to define the size fractions of total sediment load, which is not present in significant amounts in the sediment bed and easily washed away by the flow (Woo et al., 1986). Therefore, washload may include suspended load and some parts of bedload. For example, sands and fine gravels can be considered as washload in the case of the sediment transport capacity remains larger than the availability of sediment (Woo et al., 1986). On the other hand, the bedload consists of fine silts in some channels having very slow flows (Haan et al., 1994). In general, the suspended sediment contains mostly fine sediment particles while normally bedload may be a composite of sand and gravel (Novotny, 2003).

Suspended sediment will settle through the waterbody eventually owing to gravity but it is caught in local turbulent eddies randomly and lifted into the flowing waterbody repeatedly so thus it tends to make the waterbody look muddy (Leopold, 1994). The concentration of the suspended sediment decreases exponentially from bed to water surface (Leopold, 1994). Suspensions of fine particles whose diameter is less than 1 micron are known as colloidal systems (Raudkivi, 1998). Even in the nonturbulent waterbody, settling of colloidal particles is hindered by large-scale thermal convection and small-scale thermal agitation of water, and the resulting motion is known as the Brownian movement (Raudkivi, 1998). On the other hand, bedload is the part of the sediment load, which is supported by the unmoving bed, by intermittent contact between the moving sediment, and by the layer of sediment grains at the unmoving surface of the bed (Leopold, 1994). Thus, bedload moves by saltation, rolling, or sliding in the flow layer just above the waterbody bed, which is generally considered to be a few particle diameters thick (Haan et al., 1994). Unlike suspended load, bedload are not swept up by turbulent eddies, thermal convection, or thermal agitation but are pushed along near the streambed (Leopold, 1994).

Due to the wide ranges of sediment properties, complexity of sediment transport mechanisms, and spatial variability of sediment distributions, most of the equations to
describe sediment behavior has been developed are empirical and even site-specific. In
general, sediment equations are grouped into equations for simulating bedload, suspended
load, and total load transport based on types of sediment transport (Haan et al., 1994;
Yang, 1996). In addition, different equations, concepts, and approaches have been
applied to describe sediment transports occurring on overland and in channel or on
interrill and in rill because they possess different topographic and hydraulic features and
thereby have unique composition of sediments. Graf (1971) classified the bedload
transport equations into the DuBoys-type using a shear stress relationship, the
Schoklitsch-type utilizing a discharge relationship, and the Einstein-type based on
statistical concept of lift forces (Haan et al., 1994). Of the approaches to describe bedload
transport, the Shields diagram based on shear stress is the most widely used criterion in
determining the condition of incipient motion despite of considerable dissatisfaction with
this criterion and misconceptions found in literature (Yang, 1973; Haan et al., 1994; Cao
et al., 2006).

On the other hand, the suspended sediment load is usually simulated based on a
sediment diffusion equation under a steady equilibrium assumption of balancing the
downward movement of sediment due to gravity by the net upward movement of
sediment due to turbulent fluctuations (Leopold et al., 1995; Yang, 1996). Since the
settling of sediment particles tends to offset the upward diffusion, it is reasonably
assumed that the sediment movement ultimately reaches a steady equilibrium condition
during a specific period (Leopold et al., 1995; Haan et al., 1994). Typically, movement of
suspended sediment particle is very complicated because it is influenced by local
turbulent eddies as well as average flow condition of a specific period. Therefore, it
seems sounder to regard sediment particles as a group by utilizing time-averaged
sediment concentration in a sediment diffusion equation than to try to figure out a critical
condition for initiate movement of individual particles.
2.14.2 Impact of Raindrop Energy on Sediment Detachment and Transport

Sediment detached from soil surface, transported through water, and deposited on overland and in channel. The detachment, transport, and deposition rates depend on local flow hydraulics, sediment concentration of flow, and sediment characteristics like cohesiveness and size. On the interrill, the flow is usually very thin because of relatively steep slope. Thus, the impact of falling raindrop energy can easily accelerate soil erosion and transport by generating turbulent in the flow and disturbing the soil structure. Therefore, overland flow is responsible for most of the transport of soil to rills while detachment is primarily from raindrop impact (Haan et al., 1994). Consequently, it is recommended to consider the raindrop energy (splash impact) in calculating sediment detachment on the interrill (Proffitt, 1991; Salles. 2000; Parson. 2000; Erpul. 2002; Beuselinck. 2002; Gabet et al., 2003).

In general, the Reynolds number is low due to relatively small hydraulic depth and large viscosity in the thin overland flow. Thus, Julien et al. (1985) asserted perturbations induced by raindrop impact and surface roughness are greatly attenuated due to the large magnitude of viscous forces at low Reynolds number in sheet flows. In addition, they expected that sheet flows over rough surface might remain laminar until a critical value of the Reynolds number like 500 or 2,000 is exceeded (Julien et al., 1985).

On the other hand, the flow is relatively fast and deep (flow momentum has high energy) in the rill and channel so that raindrop impact can be ignored (Hessel. 2007). Thus, equations for calculating erosion from the rill were developed considering only channel runoff while many equations for the interrill were developed considering both of rainfall splash and overland runoff. In addition, vegetation canopy may significantly reduce the rainfall impact on the interrill by changing the drop size distribution of rain (Brandt, 1989; 1990). Because usually the interrill is fully or partially covered by vegetation, incorporation of the canopy effect can allow more realistic simulation of sediment detachment for the interrill.
2.14.3 Sediment Transport Capacity

There are two main approaches in simulating mechanisms of sediment transport: supply-limited and capacity-limited. In the supply-limited approach, sediment transport is limited by the upstream supply of sediments (Julien, 1995) but transportation capacity is assumed to be unlimited or under a limitation. USLE (Universal Soil Loss Equation) is a typical for supply-limited approach. The supply of sediment is closely related to characteristics of soil on the bed, and it is usually estimated by physical measurement like shear stress or index like soil erodibility. On the other hand, the capacity-limited approach assumes that sediment transport is controlled by the flow capacity and sediment is supplied sufficiently or unlimitedly. The transport capacity concept is a type of this approach. The sediment transport capacity is associated with characteristics of flow and sediment like flow energy, sediment particle size, and concentration.

In the reality, the two approaches may control sediment transport reciprocally so that one approach alone may be not enough to simulate sediment transport phenomena completely except for some extreme cases such as the completely armored channel (supply-limited) and hyperconcentrated flow (capacity-limited). In general, however, capacity-limited and supply-limited conditions are assumed dominant on highly erodible soils and on less erodible soils respectively (Haan et al., 1994). On the overland, the shear stress is low due to much less flow rate per unit width even though slope of the overland is usually much steeper than that of the stream, so thus transport capacity is smaller than that in the channel. In addition, the shallow depth of overland flow may limit sediment transport by suspension and saltation (Julien et al., 1985). Therefore, the bedload may predominate in the overland flow and it is limited by the transport capacity of the flow (Julien et al., 1985; Haan et al., 1994).

On the other hand, it is often assumed that the washload travel by stream flow with little deposition and it is carried primarily in suspension (Haan et al., 1994). Thus, total sediment load of the stream flow consists of bedload and washload. In general, the finer sediment particle has less availability in the watershed (Haan et al., 1994). Fine sediment particles may show high spatial variability because they are detached and transported relatively easily due to lightweight and deposited in a calm waterbody having
slow flow velocity. Therefore, the washload or suspended load may be limited by the supply of the fine sediment. Julien (1995) used Figure 2.10 in explaining the concept of supply- and capacity-limited sediment erosion and transport mechanism (Julien, 1995; Rojas et al., 2003).

![Figure 2.10. Sediment transport capacity and supply curves (Julien, 1995).](image)

Many sediment transport models adapted the concept Meyer et al. (1969) proposed based on the capacity-limited approach in order to calculate detachment or deposition rate of sediment. In the method, the estimated transport capacity is used to determine which sediment transport process of between detachment and deposition would occur and its rate in the given condition (Figure 2.11).
Foster and Meyer (1972) proposed the continuity equation for sediment transport on the interrill and rill. The basic form of the equation is like below.

\[
\frac{dQ}{dx} = D_i + D_r
\]  \hspace{1cm} 2.82

where \( Q \) is sediment load, \( D_i \) is delivery rate of sediment detached on interrill to rill, \( D_r \) is rate of detachment or deposition of sediment in rill flow.

They expressed a continuity equation of sediment transport as a relationship between sediment detachment and deposition like below.

\[
\frac{D_f}{D_c} + \frac{G}{T_c} = 1
\]  \hspace{1cm} 2.83

where \( D_f \) is detachment rate \( (ML^2T^{-1}) \), \( D_c \) is detachment capacity \( (ML^2T^{-1}) \), \( G \) is sediment load \( (ML^1T^{-1}) \), and \( T_c \) is transport capacity \( (ML^{-1}T^{-1}) \).
In this relationship, “when hydraulic shear stress exceeds the critical shear stress of the soil and when sediment load is less than sediment transport capacity, net soil detachment in rills is calculated (Nearing et al., 1989)” using Equation 2.84.

\[
D_f = D_c \left(1 - \frac{G}{T_c}\right)
\]

2.84

Also “when hydraulic shear stress exceeds critical shear stress for the soil, detachment capacity (Nearing et al., 1989)” is calculated using Equation 2.85.

\[
D_c = K_r (\tau_f - \tau_c)
\]

2.85

where \( K_r \) is channel soil erodibility, \( \tau_f \) is flow shear stress, \( \tau_c \) is critical shear stress of the soil.

Finally, the detachment rate equation will become Equation 2.86, so thus the approach can consider supply-limited by channel soil erodibility and capacity-limited cases by transport capacity simultaneously.

\[
D_f = K_r (\tau_f - \tau_c) \left(1 - \frac{G}{T_c}\right)
\]

2.86

Julien et al. (1985) found a general form of equation for sediment transport capacity on the overland flow like Equation 2.87.

\[
T_c = \alpha S^\beta q^\gamma \left(1 - \frac{\tau_c}{\tau}\right)^\epsilon
\]

2.87

In the channel, this relationship between the sediment transport capacity and the other variables may be reduced to Equation 2.88 because rainfall impact on sediment detachment can be ignored and the critical shear stress may be much less than the flow shear stress. Julien et al. (1985), Prosser et al. (2000), and Hessel et al. (2007) comprehensively summarized the empirical sediment transport equations for the overland flow.

\[
T_c = \alpha S^\beta q^\gamma
\]

2.88

Various types and forms of the transport capacity relations are used in physically based sediment transport model such as CREAMS, WEPP, KINEROS, ANSWERS,
AGNPS, GUESS, EUROSEM, and LISEM. One of the widely used equations for the transport capacity is the Yalin sediment transport equation. CREAMS, WEPP, and ANSWERS adapt modifications of the Yalin equation to calculate the transport capacity. The equation compares the critical shear stress with shear stress of flow acting on the bed. In AGNPS and GUESS, the transport capacity is estimated by the stream power concept of Bagnold (1966) and its variation. The stream power concept emphasizes energy of flow rather than the forces or stresses applying to the bed, and the stream power per unit area of bed is calculated by multiplying all of the specific weight of water, discharge per unit width, and local energy gradient or surface slope together. In addition, the transport capacity is modeled as a function of the unit stream power Yang (1972) and Govers (1990) proposed in KINEROS, EUROSEM, and LISEM. The unit stream power concept is calculated as multiplying mean velocity of flow with local energy gradient or surface slope. The detail descriptions about the sediment transport capacity equation are provided in Julien et al. (1985), Prosser et al. (2000), and Hessel et al. (2007).

Polyakov et al. (2003) tested if sediment transport capacity is a function of only given soil, flow rate, and slope and if equilibrium sediment concentrations obtained in net detachment and net deposition are the same through the lab experiments. They measured sediment concentrations along the flume length after the detachment and deposition rates reached the equilibrium with and without adding extra sediment into the flow at unique combinational settings of flow rates and slopes. From the experiments, they found that equilibrium concentrations of sediment were different in sediment excess and deficit conditions. They hypothesized that selective deposition and detachment of sediment in the flow and subsequent changes in composition of source sediment and hydraulic roughness might cause the hysteresis phenomenon observed in the experiment. Sander et al. (2007) also pointed out physical inconsistency of the sediment transport capacity approach in simulating transition between net erosion and net deposition of sediment. From the numerical experiments, they noted that the model Hairsine et al. (1992a; 1992b) proposed is only one capable of reproducing and explaining the observation made by Ployakov et al. (2003).
2.14.4 Sediment Transport Simulation of Existing Models

2.14.4.1 General Approaches

Moore and Burch (1986) applied the concept of unit stream power and sediment transport equation of Yang (1973) in calculating sediment transport capacity of sheet and rill flow. Unlike most of the approaches such as shear stress and mean stream power for estimating sediment transport capacity of the flow, the unit stream power approach does not consider raindrop energy because it was developed for the stream flow. They ignore the rainfall impact based on the statement of Moss (1979), “basic mechanisms of erosion, transportation, and deposition vary little from rivers to overland flow” (Moore and Burch, 1986). Nord et al. (2007) quoted Ferro’s (1998) study that recalled “the rainfall contribution to total transport becomes negligible when the flow depth is greater than three times the rainfall diameter” from experiments of Sharma (1993). Because most of the sediment erosion in a year occurs in a few severe storms that can produce a relatively deep overland flow immediately, this simplification can be applied to event based storm water modeling. Nevertheless, the sediment erosion by rainfall can be dominant for the very shallow sheet flow on the overland especially for a little excess rainfall in the continuous hydrologic modeling.

Several physically based sediment transport models such as CREAMS, WEPP, KINEROS, ANSWERS, AGNPS, GUESS, EUROSEM, and LISEM simulate erosion from interrill and rill or by raindrop splash and runoff separately using physically based equations. Erosion from interrill and rill is not strictly distinguished from erosion by raindrop impact and runoff in most of the sediment transport equations. However, both of raindrop impact and runoff can affect detachment of soil particle on the interrill while only runoff can be an effective driving force on the rill. Thus, in this review, the original intentions of the equations are described based on the user manual and literature for the models.

CREAMS estimates interrill detachment rate using an empirical equation that contains terms related to some factors of the USLE equation such as soil erodibility, crop management, and practice factors, rainfall energy, slope, and characteristic of overland runoff. Some terms associated with energy of stream runoff were added in the equation.
for calculating sediment detachment in the rill and the term considering rainfall energy was excluded.

ANSWERS also discriminates detachments of soil particles by raindrop impact and overland flow. They are estimated using some factors of the USLE such as crop management and soil erodibility factors in similar equations CREAMS contains (Aksoy et al., 2005). It adapted the transport capacity approach to simulate overland sediment transport, and deposition and the sediment transport capacity is estimated by two-stage empirical equations in ANSWERS or a modified form of Yalin equation in ANSWERS-2000 (Beasley et al., 1981; Wes Byne. 2000).

Unlike CREAMS and ANSWERS, WEPP does not use any factor from the USLE equation in estimating interrill and rill erosion even though it uses the same continuity equation Foster et al. (1974) proposed as CREAMS does. The equation for the interrill erosion rate includes erodibility of soil, effective rainfall intensity, effect of the plant canopy and ground cover, and dimension of the interrill. The detachment of sediment in the rill is calculated by equation Foster et al. (1972) proposed to estimate rate of detachment. ANSWER employs similar empirical equations that contain crop management and soil erodibility factors but it discriminates detachments by raindrop impact and overland flow.

Unlike CREAMS and WEPP, KINEROS calculates rates of splash and hydraulic erosion instead of interrill and rill. In the equation for calculating splash erosion in KINEROS, a parameter that represent reduction in splash erosion caused by increased depth of water and another parameter related to soil and surface properties are included. The hydraulic erosion rate is assumed linearly dependent on the difference between the equilibrium concentration (transport capacity concentration) and the current concentration. The slope in the equation is called transfer rate coefficient and theoretically equal to the sediment settling velocity divided by the flow depth. Kalin (2003) provided a brief review about mathematical models for the TMDL developments, and compared fundamental algorithms and performance of KINEROS and GSSHA in simulating hydrology and sediment transport.
GUESS also distinguish detachment of soil particles by raindrop impact and runoff. The rate of detachment by raindrop splash is estimated with consideration of detachability of soil, the fraction of the soil surface exposed to raindrop, rainfall intensity, and particle size classes. The detachment by runoff is calculated as a function of stream power and the fraction of the soil surface exposed to runoff. The equation for detachment by runoff contains two parameters to be calibrated: the required unit stream power to detach a unit mass of soil and the required critical stream power to start erosion.

Like KINEROS, EUROSEM discriminates rates of erosion by rainfall impact and flow. Sediment detachment by rainfall impact is calculated by an equation that considers detachability of the soil, particle density, kinematic energy of the rainfall at the ground surface, depth of surface water, and fraction of non-erodible surface. The equation for erosion by flow is expressed in terms of the transport capacity, the current sediment concentration, and detachment efficiency expressed as settling velocity of sediment particle. LISEM employs a similar approach to that of EUROSEM in calculating erosion by flow, but the equation for splash detachment contains terms related to soil aggregate stability, kinetic energy of rainfall, and depth of surface flow.

### 2.14.4.2 Equations for Sediment Detachment and Deposition Simulation

Many sediment transport models adapt equations Meyer et al. (1969) proposed and the relationship between detachment and deposition Foster et al. (1972) proposed to determine detachment and/or deposition and estimate rates of them. ANSWERS simulates detachment and transportation of the various particle size classes. In addition, sediment is transported in two forms: bedload and suspended load. After calculating detachment and transport capacity, ANSWERS directly calculates rates of detachment and deposition by comparing the potential transport rate of sediment and detachment rate for every cell (Beasley et al., 1981). CREAMS classifies four possible cases for a slope segment, which are (1) deposition over the entire segment, (2) detachment by flow on the upper end and deposition in the lower end, (3) deposition on the upper end and detachment by flow on the lower end, (4) detachment over the entire slope. Then, it uses the closed-form of erosion equation Foster et al. (1972) introduced to estimate...
detachment and/or deposition rates along the slope on a field (Foster et al., 1980; Haan et al., 1994). Like CREAMS, WEPP calculates erosion from rill and interrill areas and uses the concept that detachment and deposition rates in rills are a function of the transport capacity (Foster et al., 1995). In the models, if sediment load is less than the transport capacity, all of the load will be transported and deposition will not occur. AGNPS estimates erosion from only upland using the modified USLE, and then the detached sediment is routed with runoff from a cell to another cell based on the steady-state continuity equation. CREAMS, WEPP, and AGNPS estimate rate of sediment deposition on a field using the same equations like below (Silburn et al., 1989; Young et al., 1989; Foster et al., 1995).

\[ D = \alpha (T_c - q_s) \]  
2.89

where \( D \) is deposition or detachment rate (mass per unit area per unit time), \( T_c \) is transport capacity, \( q_s \) is potential sediment load, \( \alpha = \frac{E_f V_s}{q_w} \) is first-order reaction coefficient, \( E_f \) is a coefficient and equal to 0.5 for overland flow and 1.0 for channel flow or furrow irrigation, \( V_s \) is particle fall velocity, \( q_w \) is flow discharge.

KINEROS employs a similar equation for calculating both of detachment and deposition rates like below.

\[ D = C_g (C_m - C_s) A \]  
2.90

where \( C_g = \frac{V_s}{h} \) is a transfer rate coefficient, \( h \) is flow depth, \( C_m \) is sediment concentration at equilibrium transport capacity, \( C_s \) is current local sediment concentration, \( A \) is area.

Like the other models, in GUESS, detachment of sediment is not particle-size selective. However, like ANSWERS, selectivity occurs in deposition. The rate of deposition of sediment of class is expressed like below.

\[ d_i = \alpha_i v_{si} C_i \]  
2.91
where \( \alpha_i \) is a dimensionless parameter with a value dependent on the depth of flow for sediment class \( i \), \( v_{si} \) is fall velocity of sediment particle class \( i \), \( C_i \) is concentration of sediment class \( i \) in the flow.

In EUROSEM and LISEM, efficiency of detachment is incorporated into the relationship between the deposition and the sediment transport capacity in order to account for that the detachment will be limited by the cohesion of the soil using Equation 2.92.

\[
D = Y(T_{c} - C)V_s
\]

Where \( D \) is deposition or detachment rate (mass per unit area per unit time), \( Y \) is dimensionless efficiency factor.

De Roo (1996) developed a physically based distributed hydrologic and soil erosion model, LISEM (Limburg Soil Erosion Model). The model can simulate splash detachment by rainfall kinematic energy, flow detachment by runoff, and deposition through transport capacity concept (De Roo, 1996). In the latest version, the splash detachment can be adjusted in order to consider raindrop energy reduction caused by vegetation canopy and ponding on the overland. The sediment transport capacity of flow is calculated by means of an equation proposed by Govers in 1990, and the detachment or deposition rate is a function of the transport capacity, sediment concentration, settling velocity of particle, and efficiency that takes account of soil cohesion. This approach is uniformly applied in sediment transport simulation for the interrill, rill, and channel flow.

Hessel (2007) applied LISEM in modeling soil erosion for a small steep Chinese catchment with several sediment transport equations. In the study, the Shield parameter was not suitable for the study catchment because its values become very high for the steep slopes, high-density flows, and small grain size of the catchment. Because the Shield diagram has been developed to study incipient motion of bed load particle in the channel, which usually has much shallower slope and greater grain size than them of the overland, his conclusion looks reasonable. In addition, as mentioned in the previous, Guy and Dickinson (1990) showed the Shield diagram approach might underpredict the overland erosion due to overpredicting the minimum threshold for erosion when rainfall
is significantly affecting flow hydraulics. Therefore, they concluded that the Shield diagram approach should be applied in estimating sediment transport only for the channel flow. In addition, most of the equations used in his research were very sensitive to slope so that “transport rates were overpredicted for steep slopes and underpredicted for gentle slopes.” Finally, “the Govers equation performed better than the other because it has lower slope dependency” so “Govers equation is recommended for erosion models that deal with small grain size and steep slopes.”
3. METHODOLOGY

3.1 Model Development

3.1.1 Hydrology

3.1.1.1 Overview

The time-area method plays a key role in simulating hydrograph with the proposed overland and channel routing methods in HYSTAR. The CN method is used in calculating excess rainfall volume for every individual overland cell, and then it becomes a part of the runoff volume of each cell. Thus, runoff volume of a cell is equal to a summation of excess rainfall volume and the difference between volumes of inflows and outflows on the cell. Then, discharge of an overland cell in a unit time interval is determined from the calculated runoff volume using the continuity equation and the Manning’s equation under the steady, uniform flow assumptions (Equations 3.1 to 3.11). On the overland flow plane, the velocity of flow is calculated using the Manning’s equation under an assumption of very thin sheet flow where hydraulic radius can be approximated to depth of flow. On the other hand, for the sake of simplicity, a rectangular cross section of the channel is assumed. Then, depth and velocity of channel flow at a point in the stream network are determined through iterative procedures of the Manning’s equation using the calculated discharge of the cell in every time interval (Equations 3.12 to 3.15).

A cell, which is a spatial calculation unit of a grid-based distributed hydrologic model, may have a series of upstream cells that contribute runoff volume to the cell on hillslope or in channel (Figure 3.5). In addition, the difference between volumes of inflows and outflows of a cell are calculated by routing overland and channel runoff volume along the flow path. For overland and channel routing, HYSTAR employs a simple routing algorithm that distributes runoff volume into cells within the next lower time zone or isochrone defined along a flow path. The isochrone map defined with the calculated flow velocity at the present time step (i.e. 2 hr travel time zone) cannot describe an exact next lower time zone (i.e. 1 hr travel time zone), which should be determined with the flow velocity obtained at the next time step. However, travel time of
flow on an isochrone map is determined based on flow volume estimated from routing, and flow volume distribution in the routing is calculated using the isochrone map. In other words, constructing isochrone maps and routing cannot be done at the same time because they simultaneously refer to each other to define themselves.

Thus, in HYSTAR, runoff volume is distributed within the next lower time zone (i.e. 1 hr travel time zone) defined at the present time step (i.e. 2 hr travel time zone) to avoid another iterative calculation in routing. Then, the distributed runoff and excess rainfall compose the runoff volume of the cells in the next lower time zone. In addition, runoff volume of every cell within a time zone (Ex. 2 hr) is assumed evenly redistributed on downstream cells within the next lower time zone (Ex. 1 hr) along the flow paths. Therefore, a cell on which many flow paths are passing may receive routed runoff volume as much as density of the flow path. HYSTAR has a simulation time step of 1 hour for modeling efficiency in contrast to a numerical method like Finite Difference Method (FDM) and Finite Element Method (FEM) that uses a fine time step for very detailed routing and/or stability of computation.

Once velocities and the corresponding travel time of runoff on the overland and in the channel cells are calculated for a time interval, then a time-area histogram for the time interval is constructed from the calculated travel time. In order to consider temporal variation of excess rainfall intensity, the same number of time-area histograms as that of the time intervals of excess rainfall duration will be constructed. In other words, because different excess rainfall intensity at every time interval of excess rainfall duration will change the time-area map, a new time-area map should be developed for the every time interval of a excess rainfall period to consider impact of change in excess rainfall intensity on runoff hydrograph. Then, a direct runoff volume diagram at a point of interest within a watershed can be constructed through discrete convolution using excess rainfall hyetograph and the developed time-area histograms (Figure 3.6). The overall procedure to calculate excess rainfall on overland and routing it along flow paths are presented in Figures 3.1 to 3.2.

Once inflow and outflow of surface runoff volume using the CN and routing methods is calculated for every cell within a watershed, soil water content of the soil root
zone on every cell in a watershed will be updated through the continuity equation (Equations 3.21 to 3.24). These equations describe the water budget from vertical movement of water in a control volume of soil and accounts for rainfall, runoff, evapotranspiration, percolation, and infiltration in a unit time interval. The rate of percolation is determined using the van Genuchten equation that calculates unsaturated hydraulic conductivity at the given soil water content. The modified CN method updates a CN map continuously with respect to variation in water content of the soil root zone. Then, water volume to be infiltrated into the soil root zone is determined by Equation 3.4. Thus, soil water content of the soil root zone directly controls percolation of soil water into the aquifer and influences infiltration of surface runoff into soil root zone through feedback in moisture-based CN adjustment (Figure 3.3).

In the model, soil water content can vary from wilting point to field capacity in the soil root zone. HYSTAR tracks water content only in the soil root zone and other parts of the vadose zone are ignored in subsurface water modeling. Thus, equilibrium condition is assumed for percolation in the rest of vadose zone and percolated water from the soil root zone is recharged to the aquifer immediately. In addition, horizontal flow of soil water in the vadose zone, interflow, and capillary rise are ignored due to its insignificant contribution to the total runoff volume.

For groundwater modeling in HYSTAR, an unconfined aquifer is assumed, and thus groundwater level is equal to hydraulic head of groundwater flow (free groundwater or phreatic surface). In addition, for the sake of simplicity, groundwater flow is assumed to be the sum of the recharged water within a watershed in a given time interval. Then, simulation of direction of groundwater flow becomes unnecessary in groundwater modeling. In addition, the Dupuit-Forchheimer assumptions are applied (Ritzema, et al., 1994). Thus, hydraulic head is not varied in the vertical direction and all groundwater velocity vectors are horizontal. Groundwater flow is also assumed steady and governed by Darcy’s equation. Subsequently, the governing differential equation for groundwater flow is simplified to a function of recharge to the aquifer or percolation from soil root zone (Equations 3.29 to 3.36). In summary, there is no horizontal flow in the vadose zone including soil root zone and no vertical flow in the aquifer.
In this study, the spatial resolution of 30 m was selected for modeling with respect to consistency with GIS input data resolutions. Many land use maps like NLCD, which were derived from the most common satellite imagery for the earth surface observation, LANDSAT TM imagery, has a resolution of 30m. Although there are finer DEMs like 10m NED, the resolution of 30 m is still common in many types of DEM data. In addition, aggregating or interpolating original input data into a finer resolution may introduce unavoidable additional error and uncertainty into a modeling. Considering modeling efficiency and precision, an hour time step was chosen in the model. The longer time step may provide less precise output but the smaller time step potentially leads to inefficiency of modeling, especially continuous modeling. Therefore, a trade off between efficiency and precision of modeling should be explored with consideration of computing resources and modeling objectives.

For hydrology simulation, HYSTAR employs six scalar multipliers or scale factors as parameters which are used to reduce the number of free parameter to be calibrated: CNF, MNO, MNC, BCC, EFS, and RZD (Tables 3.1 and 3.2). A distributed parameter model may have a large number of spatially distributed parameters depending on complexity of topography and heterogeneity of landscape and soil in a study watershed. In the Owl Run watershed, for example, 18 unique curve numbers were identified based on combinations of land use and soil type. In this case, introduction of a scale factor, which controls relative magnitude of the curve number as a whole, can decrease the number of unique curve number parameters to only one ratio. Thus, the spatial distribution of a parameter is determined by a modeler at the beginning of a modeling practice, and then modification of the fixed spatial variation is not allowed in calibration. In addition, because the scale factor will increase or decrease values of spatially distributed parameters at the same rate, nonlinear relationship between the parameter and output is not considered in calibration. For instance, 5% increase in CN of 85 will produce much larger excess runoff than does the same increase in CN of 65. In spite of these issues, it is expected for the introduced six scale factors to make calibration more efficient and practicable. Relationships between parameters and variables utilized in HYSTAR are described in Figure 3.3.
Figure 3.1. Flow chart of routing direct runoff on overland and updating soil water content.
Figure 3.2. Flow chart of routing runoff in channel.
### Table 3.1. Parameters of HYSTAR.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Type</th>
<th>Feature</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNF</td>
<td>Curve Number Factor</td>
<td>Ratio</td>
<td>Spatial Scale Factor</td>
<td>0.5-1.5</td>
</tr>
<tr>
<td>MNO</td>
<td>Manning’s roughness coefficient for overland</td>
<td>Ratio</td>
<td>Spatial Scale Factor</td>
<td>0.5-1.5</td>
</tr>
<tr>
<td>MNC</td>
<td>Manning’s roughness coefficient for channel</td>
<td>Ratio</td>
<td>Spatial Scale Factor</td>
<td>0.5-1.5</td>
</tr>
<tr>
<td>THA</td>
<td>Threshold area that defines initiation points of channel networks</td>
<td>Absolute</td>
<td>Unit: ha</td>
<td>1-100</td>
</tr>
<tr>
<td>GCL</td>
<td>Coefficient L of the van Genuchten equation</td>
<td>Absolute</td>
<td>-</td>
<td>0.25-0.75</td>
</tr>
<tr>
<td>GCM</td>
<td>Coefficient M of the van Genuchten equation</td>
<td>Absolute</td>
<td>-</td>
<td>0.25-0.75</td>
</tr>
<tr>
<td>BCC</td>
<td>Basal crop coefficient of the crop coefficient method</td>
<td>Ratio</td>
<td>Spatial Scale Factor</td>
<td>0.5-1.5</td>
</tr>
<tr>
<td>EFS</td>
<td>Effective fraction of soil surface covered by vegetation of the crop coefficient method</td>
<td>Ratio</td>
<td>Spatial Scale Factor</td>
<td>0.5-1.5</td>
</tr>
<tr>
<td>RZD</td>
<td>Root zone depth</td>
<td>Ratio</td>
<td>Spatial Scale Factor</td>
<td>0.1-2.0</td>
</tr>
<tr>
<td>SAR</td>
<td>Soil anisotropic ratio</td>
<td>Ratio</td>
<td>Spatial Scale Factor</td>
<td>0.1-2.0</td>
</tr>
<tr>
<td>GWC</td>
<td>Groundwater constant gain/loss coefficient</td>
<td>Absolute</td>
<td>Unit: m³/s</td>
<td>-</td>
</tr>
</tbody>
</table>
Table 3.2. Input data types and sources of HYSTAR.

<table>
<thead>
<tr>
<th>Types</th>
<th>Sources</th>
<th>Parameters</th>
<th>Variables</th>
<th>Format</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topography</td>
<td>DEM (NED)</td>
<td>THA</td>
<td>SLP, FD, FAC, CHWD, CHDP, CHNET</td>
<td>Raster/Value</td>
</tr>
<tr>
<td>Land Cover</td>
<td>NLCD 1992</td>
<td>CNF, MNO, BCC, EFS</td>
<td>AET</td>
<td>Raster/Code</td>
</tr>
<tr>
<td>Soil</td>
<td>SSURGO</td>
<td>CNF, GCL, GCM, RZD, SAR</td>
<td>FC, WP, POR, SD, RWC, SHC, HSG, THEAW</td>
<td>Vector/DB</td>
</tr>
<tr>
<td>Rainfall</td>
<td>VT-BSE HAS</td>
<td>-</td>
<td>RAIN</td>
<td>Time Series</td>
</tr>
<tr>
<td>Thiessen</td>
<td>VT-BSE HAS</td>
<td>-</td>
<td>RAIN, PET, TEMP, RH</td>
<td>Vector/Code</td>
</tr>
<tr>
<td>Temperature</td>
<td>VT-BSE HAS</td>
<td>-</td>
<td>TEMP, RH</td>
<td>Time Series</td>
</tr>
<tr>
<td>Growing States</td>
<td>Assumption</td>
<td>BCC, EFS</td>
<td>AET</td>
<td>Time Series</td>
</tr>
<tr>
<td>Runoff</td>
<td>VT-BSE HAS</td>
<td>-</td>
<td>RUNOFF</td>
<td>Time Series</td>
</tr>
</tbody>
</table>

Parameter: Related parameters to the corresponding input data; Variables: Related variables to the corresponding input data; SLP: Slope; FD: Flow Direction; FAC: Flow Accumulation; CHWD: Channel Width; CHDP: Channel Depth; CHNET: Channel Network; AET: Actual Evapotranspiration; FC: Field Capacity; WP: Wilting Point; POR: Porosity; SD: Soil Depth; RWC: Residual Water Content; SHC: Saturated Hydraulic Conductivity; HSG: Hydrologic Soil Group; THEAW: Soil water depletions of readily evaporable soil zone depth and the root zone depth by evapotranspiration; RAIN: Rainfall; PET: Potential Evapotranspiration; TEMP: Temperature; RH: Relative Humidity; RUNOFF: Runoff
Figure 3.3. Relationship between variables and parameters.
3.1.1.2 Hydrologic Components

There are two directional movements of water on a cell: vertical and horizontal. Usually the horizontal movement of water is described in two dimensions and the vertical movement is depicted in one dimension in H/WQ modeling, thus the water flow can be expressed in three-dimensional axes. Two opposite directions on a vertical axis are used to describe the vertical movement, upward and downward, while typically a vector on two perpendicular axes such as the Cartesian coordinate is employed in depicting the horizontal movement of water.

Rainfall is one of the downward movements of water by gravity at a point of view on the ground. Water provided by rainfall is moved into the earth by several driving forces such as gravity, tension (capillary force), osmotic pressure, and external pressure. Gravity is the most powerful driving force that lets water penetrate into the earth. It is always acting toward the center of the earth, thus water on the earth surface is always flowing downward along a flow path created by topography as long as the other forces are not acting significantly. Consequently, surface water passes through a cell along the path by gravity on the ground surface and its velocity including direction and speed is determined by characteristics of topography and land cover.

Water falling in the form of rainfall on the ground infiltrates into soil root zone of the vadose zone. In the vadose zone, tension as well as gravity is a major driving force that transports water through the soil matrix. The infiltration is purely downward movement of water by gravity and tension, and its rate depends on rainfall intensity, topography, land cover, and soil characteristics. Once water enters into the soil root zone, it can percolate through the rest of the vadose zone into an aquifer and/or move to a neighboring area by gravity and tension. The speed of percolation is determined based on soil hydraulic properties such as soil water content, hydraulic head, and saturated hydraulic conductivity. There are two mechanisms for upward movement of water in the vadose zone. In the soil root zone, soil water enters into plant through its root by osmotic pressure, and it is transported to its leaves by diffusion. In addition, water seeps up from the groundwater table by tension in the capillary fringe.
Even between storms, water keeps moving in the earth. However, stored water in the earth, especially the vadose zone and aquifer, begins to decrease after a storm event because significant amounts of water in the earth may be evaporated from the earth and open water surfaces into the air by vapor pressure gradients, and transpirated by plants. Once soil water in the vadose zone percolates or recharges the aquifer, it will be discharged into the stream or lost to the deep aquifer and another watershed. Groundwater flow is forced by gravity and external pressure, and its speed depends on soil hydraulic properties like hydraulic head and saturated hydraulic conductivity.

In order to model behaviors of these hydrologic components in a distributed manner, HYSTAR represents the ground surface with a grid consisting of cells, with assumed homogeneous topographic, land use, and soil characteristics. In addition, it employs two grid layers to represent the soil root zone and aquifer. However, HYSTAR does not account for any processes in the vadose zone excepting in the soil root zone, interflow, and capillary fringe. For continuous hydrologic modeling, soil moisture is updated considering vertical flux of soil water in the soil root zone at every time step. These movements of water can be evaluated by means of a water budget. The water budget consisting of the hydrologic components is expressed mathematically as the continuity equation. Hydrologic components considered by HYSTAR and the continuity equation are depicted in Figure 3.4.

Figure 3.4. Water flux in a control volume.
The continuity equation is usually used to describe the conservative movement of water in a control volume. On the earth surface, the continuity equation for each cell in a unit time interval can be expressed as:

\[ S = R - ET - I + \sum Q_{in} - Q_{out} \]  \hspace{1cm} 3.1

where \( S \) is stored water volume on a overland cell, \( R \) is rainfall, \( \sum Q_{in} \) is summation of the inflows to the cell, \( Q_{out} \) is outflow or runoff from the cell, \( I \) is infiltration, and \( ET \) is evapotranspiration (all units are a depth).

This equation assumes that each cell has outflow in only one direction determined by the predefined flow direction map using a DEM. In addition, in HYSTAR, volume of all the inward water flows into a cell such as excess rainfall and sum of the routed runoff from upstream cells is assumed equal to that of all the outward water flows such as evapotranspiration, infiltration, and the routed runoff into a downstream cell. In other words, all the inflows leave from a cell in a specific time interval and thus there is no storage or ponding of water on the overland cell. Thus, if \( S = 0 \), the continuity equation will become:

\[ R + \sum Q_{in} = Q_{out} + I + ET \]  \hspace{1cm} 3.2

and then:

\[ Q_{out} = R + \sum Q_{in} - I - ET \]  \hspace{1cm} 3.3

Usually evapotranspiration is assumed not to occur during a storm event. Thus, for a storm event, the equation can be reduced to:

\[ I = R + \sum Q_{in} - Q_{out} \]  \hspace{1cm} 3.4

In the equation, rainfall, \( R \) is given as input data and the outflow or runoff, \( Q_{out} \) will be estimated from the modified CN method. The sum of inflows \( \sum Q_{in} \) will be estimated from routing. The methods for calculating \( Q_{out} \) and \( \sum Q_{in} \) are explained in the following chapters, 3.1.1.3 and 3.1.1.4. Then, only the infiltration remains as an unknown variable in the equation. Thus, the derived continuity equation (Equation 3.4) will be used to calculate infiltration volume in every time interval during a storm. Another continuity
equation developed for soil water in the soil root zone will be applied in updating soil water contents for a period between storms. The methods for these are represented in 3.1.1.5 and 3.1.1.6.

3.1.1.3 Excess Rainfall and Runoff Volume

In the continuity equation, the runoff volume, $Q_{\text{out}}$, is calculated by the modified CN method (Moglen, 2000):

$$Q_{\text{out}} = \frac{(R + \sum Q_{\text{in}} - 0.2S)^2}{R + \sum Q_{\text{in}} + 0.8S} = \frac{\left( R + \sum Q_{\text{in}} - 0.2 \left( \frac{25400}{CN} - 254 \right) \right)^2}{R + \sum Q_{\text{in}} + 0.8 \left( \frac{25400}{CN} - 254 \right)}$$

where $S$ is the retention parameter, $CN$ is a curve number.

Because the CN method had been developed to calculate runoff volume for a storm event, it was modified to consider variation in soil moisture in continuous hydrologic modeling. HYSTAR employs the modified CN method proposed by Neitsch et al. (2002) in updating CN with respect to variation in soil water content of the soil root zone. In the modified CN method, the retention parameter is time dependant (Equations 3.6 to 3.8).

$$S_t = S_{\text{max}} \left( 1 - \frac{SW_t}{SW_t + \exp(w_1 - w_2 \times SW_t)} \right) \approx S_{\text{max}} \left( 1 - \frac{SW_{t-1}}{SW_{t-1} + \exp(w_1 - w_2 \times SW_{t-1})} \right)$$

where $S_t$ is the retention parameter at the present time $t$, $S_{\text{max}}$ is the maximum retention parameter value, $SW_t$ is the soil moisture at the present time $t$, $w_1$ is the first shape factor, $w_2$ is the second shape factor, $SW_{t-1}$ is the soil moisture at the previous time $t - 1$

$$w_1 = \ln\left( \frac{FC}{1 - S_t / S_1} - FC \right) + w_2 \cdot FC$$
where $FC$ is field capacity, $S_3$ is the retention parameter for the antecedent moisture condition 3, $S_1$ is the retention parameter for the antecedent moisture condition 1 or $S_{\text{max}}$, $SAT$ is the soil moisture amount in the soil profile when completely saturated.

### 3.1.1.4 Runoff and Routing

#### 3.1.1.4.1 Overland Flow in the Time-Area Method

The time-area histogram is constructed based on the calculated overland and channel runoff velocity and the corresponding travel time of the runoff along a flow path. Therefore, it is critical to calculate accurate velocity of overland and channel runoff in the time-area method. Julien et al. (1985) summarized equations for the overland flow hydraulics according to types of flow such as laminar and turbulent using bed slope and amount of discharge. Chow et al. (1988) provided one of the equation and procedure sets to calculate velocity for the overland flow when its volume is known, and they are presented below (Equation 3.9 to 3.11). Velocity and depth of channel runoff will be discussed in 3.1.1.4.4.

Velocity and depth of overland runoff are determined as follows.

a. Discharge per unit width of each overland cell is calculated using the continuity equation,

$$ q = \frac{y}{\Delta t} L_0 S_0 $$

where $q$ is discharge per unit width of a overland cell ($m^2/s$), $y$ is runoff volume of the cell in depth $m$, $\Delta t$ is a time step ($s$), $L_0$ is the length of the cell $m$, $S_0$ is slope of the cell.

Under an assumption of turbulent and uniform flow (the Reynolds number must be over 2,000 or 500 for open channel flow), the Manning’s equation is applied in
calculating the depth of flow. However, the overland runoff is assumed as turbulent flow regardless of the Reynolds number in HYSTAR.

\[
d = \left( \frac{nq}{S^{1/2}} \right)^{3/5}
\]

3.10

where \( d \) is depth of runoff (m), \( n \) is a Manning’s roughness coefficient (s/m\(^{1/3}\))

b. Finally, the velocity of flow on each cell can be calculated as,

\[
V = \frac{q}{d}
\]

3.11

where \( V \) is velocity of overland runoff (m/s).

3.1.1.4.2 Overland Routing in the Time-Area Method

In routing, the total runoff volume of a cell in an upper time zone is distributed onto cells in a lower time zone along its flow path. However, travel time map is changed at every time interval due to variation in runoff volume, thus the boundary of a lower time zone is also varying continuously. In addition, determinations of runoff volume and travel time map mutually depend on each other. For simplicity of calculation, therefore, runoff volume of each cell in an upper time zone in the present time interval, will be evenly distributed into all the cells in the next lower time zones in the next time interval. Thus, cells that have concentrated flow path downstream can be expected to receive the more routed runoff volume while cells in the upper most time zone will not receive any routed runoff. The general routing concept is depicted in Figure 3.5.

The isochrones are not necessarily continuous in a travel time map. When the difference between a time zone and its next lower time zone is greater than 1 hour, runoff volume in the time zone will be evenly distributed onto all the downstream cells in the same time zone along its flow path. For example, runoff volume on a cell in the 3 hour travel time zone is evenly distributed onto its downstream cells in the same 3 hour travel time zone when the travel time of the right next zone in its downstream is 1 hour. Thus, a cell located at the most downstream in the 3 hour travel time zone will receive more routed runoff than does any other cell in the same travel time zone.
3.1.1.4.3 Time-Area Method for Zero Excess Rainfall

The spatial distribution of rainfall and thus also of excess rainfall are not evenly distributed over a watershed due to variability of rainfall, soil and land use. Thus, some portions of the watershed may not have any excess rainfall at any given point in a rainfall event. If a cell does not have excess rainfall, it will not have runoff volume unless it is receiving routed runoff from any adjacent upstream cell in a specific time interval. In addition, when only the routed runoff from upstream cells contributes to runoff volume of a cell, travel time of the runoff should be prolonged along its flow path due to reduced runoff volume and velocity.

Figure 3.5. Routing of excess rainfall.
In HYSTAR, runoff volume rather than excess rainfall is estimated by the CN method. Thus, even when there is no excess rainfall on a cell, runoff volume can be generated on the cell by routing. However, if any runoff is not routed from upstream cells onto a cell as well as excess rainfall is not generated on the cell in a certain time interval, runoff volume will not be created in the time interval and travel time will be infinity due to ‘divide by zero’ calculation in Equations 3.10 to 3.11. In this case, a tiny velocity such as 0.00001 m/s will be assigned to the cell in order to avoid termination of the model program.

3.1.1.4.4 Channel Flow and Routing in the Time-Area Method

The total runoff volume of a channel cell during a certain time interval is obtained similarly to the procedure for overland cells, then velocity of the channel flow can be determined using the Manning’s equation (Equations 3.12 to 3.15). In HYSTAR, a rectangular channel is assumed for convenience of calculation and its width can be assigned based on observation. The extent of the channel network is defined from the flow accumulation map and a threshold area specifying the minimum contributing area for channel initiation. The threshold area can be determined based on observation and literature or calibrated. The channel is assumed to be located along the centerline of a channel cell, which is defined as a cell located on the stream network. When calculating evapotranspiration, percolation, excess rainfall, and infiltration on the cell, channel dimension is ignored and then the processes occur through the entire channel cell.

In HYSTAR, the relationship between discharge and flow depth in the channel is modeled by the Manning’s equation. However, there is no analytical solution of the Manning’s equations to calculate flow depth when discharge is known. Velocity and cross section area of flow are complicated functions of its depth, and the depth is significant enough not to be ignored in comparison of width of flow (Chow et al., 1988). Therefore, the flow depth must be determined iteratively. Detailed procedures for channel routing are presented below (Chow et al., 1988).
Velocity and depth of channel runoff are determined with the following steps:

a. Discharge per unit width of each channel cell is calculated using the continuity equation,

\[
Q_k = \frac{y}{\Delta t} A_0 S_0
\]  

where \( Q_k \) is discharge per unit width of a overland cell (m\(^2\)/s), \( y \) is runoff volume of the cell in depth (m), \( \Delta t \) is a time step (s), \( A_0 \) is area of the cell (m), and \( S_0 \) is slope of the cell.

b. An initial depth (\( d_0 \)) of channel runoff for the first time interval is assumed for every channel cell, and then a trial discharge of channel runoff is calculated using Equation 3.13 and 3.14.

\[
V_i = \frac{1}{n} S_0^{1/2} R_i^{2/3} = \frac{1}{n} S_0^{1/2} \frac{(w \cdot d_i)^{2/3}}{(w + 2d_i)^{2/3}}
\]  

\[
Q_i = AV_i = \frac{A}{n} S_0^{1/2} R_i^{2/3} = \frac{1}{n} S_0^{1/2} \frac{(w \cdot d_i)^{5/3}}{(w + 2d_i)^{2/3}}
\]  

where the index \( (i) \) is the number of iterative calculation step, \( V \) is velocity of channel flow (m/s), \( S_0 \) is slope of the channel bottom, \( w \) is width of channel flow (m), \( d \) is depth of channel flow (m), \( Q \) is discharge of channel flow (m\(^3\)/s), \( A \) is cross section area of channel (m\(^2\)), \( R \) is hydraulic depth of channel flow (m), \( n \) is the Manning’s roughness coefficient (s/m\(^{1/3}\)), and \( w \) is width of channel (m).

c. Using the discharges obtained at the step a. and b., a trial depth of channel runoff is calculated using Equation 3.15.

\[
d_{i+1} = d_i - \frac{1 - Q_j / Q_i}{\left( \frac{2}{3R dd} + \frac{1}{A dd} \right)} = d_i - \frac{1 - Q_j / Q_i}{\left( \frac{2}{3R dd} + \frac{1}{A dd} \right)} = d_i - \frac{1 - Q_k / Q_i}{\left( \frac{2}{3R dd} + \frac{1}{A dd} \right)}
\]  

where \( d_i \) is depth at the current step, and \( d_{i+1} \) is depth at the next iterative step.
d. If the difference between depths at the present and next iterative steps comes in the allowable range, take $d_{i+1}$ as the depth of the channel cell. If it does not, go back to step b. with the latest trial value of depth, and get another trial discharge of channel runoff. Then, to calculate a trial depth of channel runoff and compare it with the discharge obtained at the step a. again.

### 3.1.1.4.5 Discrete Convolution for Constructing Hydrograph

Once runoff velocity of all the overland and channel cells is determined for every time interval of the excess rainfall duration, the same number of time area histograms as the number of the excess rainfall intervals are obtained. Then, they are used to construct a hydrograph for a storm. Although this research employs the time-area concept rather than the unit hydrograph method in developing a hydrograph for a storm directly, the same discrete convolution calculation can be applied in constructing a direct runoff hydrograph using an excess rainfall hyetograph. In the discrete convolution equation of the time-area method, as seen in Figure 3.6, the ordinates of the unit hydrograph are replaced with time zone areas for every time interval in the travel time maps. Thus, the base time of the obtained hydrograph is calculated by the same way as that of the unit hydrograph.
Figure 3.6. Discrete convolution of excess rainfall hyetograph and time-area histogram for developing direct runoff hydrograph.

\[ Q_n = \sum_{m=1}^{n} A_m \times ER_{n-m+1} \quad n = \text{No. of time zones} - 1 + \text{Duration of ER} \]
3.1.1.5 Evapotranspiration and Soil Water Content

The FAO Penman-Monteith equation has been recommended as the standard method in estimating reference evapotranspiration because of its improved accuracy due to explicit incorporation of physiological and aerodynamic parameters (Allen, 2004). However, the equation requires significant data inputs, which often may not exist for a study area. When all the required data are not available, some simple empirical equations such as Hargreaves et al. (1985) can be used (Trajkovic, 2007). The Hargreaves equation requires only temperature and extraterrestrial radiation data to estimate reference evapotranspiration (Hargreaves et al., 1985; Hargreaves et al., 2003). Detailed procedures of estimating reference evapotranspiration are described earlier.

Once the potential or reference evapotranspiration (PET) is calculated, actual evapotranspiration (AET) can be estimated based on the PET and soil and vegetation conditions of interest areas. There are some methods to estimate AET without calculating PET, such as a water and energy balance approach, evaporation pan, or lysimeter. However, for the model, a method using hydrometeorological data and equations was desired. The crop coefficient method is one of the most common and simple approach to estimate AET from PET with consideration of vegetation growing stages. Allen (2004) proposed the dual crop coefficient method which estimates evaporation and transpiration from bare soil and vegetation separately. The details are described earlier is section 2.3.

Several sub-parameters should be defined considering characteristics of local soil in the dual crop coefficient Allen (2004) proposed. Because there is no established relationships between them, values of the sub-parameters should be assumed with the recommendation of the method. In this study, the readily evaporable soil zone depth was assumed as 10% of the root zone depth, and readily evaporable water (REW) is defined as 50% of the total evaporable water (TEW), which means the maximum depth of water that can be evaporated from the soil when the topsoil has been initially completely wetted. The total available water (TAW) for evaporation and transpiration was assumed as available soil water obtained by subtracting wilting point from field capacity, and the readily available soil water (RAW) was defined as 50% of the total available water (TAW). In addition, the TEW and TAW were adjusted in order to account for impervious
cover of each land cover. They were reduced by 50 %, 90 %, and 97 % for residential, commercial, and industrial land uses.

The crop coefficients for the method were developed at the standard climate condition of 45 % minimum relative humidity and 2.0 m/s average wind speed at height of 2 m from the ground. Thus, the crop coefficient should be adjusted using Equation 3.16 (Allen, 2004) to reflect conditions different from this standard. In this study, however, the crop height of 1m and the average wind speed of 2.0 m/s are assumed for simplicity, and then only the minimum relative humidity was considered in the adjustment.

\[
k_c = k_{c(st)} + \left[0.04(u_2 - 2) - 0.004(RH_{\text{min}} - 45)\right]\left(h \over 3\right)^{0.3}
\]

where \( k_c \) is an adjusted crop coefficient, \( k_{c(st)} \) is a crop coefficient for the standard condition or found in the published table, \( u_2 \) is average wind speed at height of 2 m from the ground (m/s), \( RH_{\text{min}} \) is the minimum relative humidity (%), and \( h \) is crop height.

The minimum relative humidity was estimated with an assumption that dew point temperature is close to the daily minimum temperature, so the equation for estimating the minimum relative humidity can be simplified to

\[
RH_{\text{min}} = 100 - \frac{e_a}{e^0(T_{\text{max}})} = 100 \frac{e^0(T_{\text{min}})}{e^0(T_{\text{max}})}
\]

where \( e_a \) is actual vapor pressure (kPa), \( e^0(T_{\text{max}}) \) is saturated vapor pressure at daily maximum temperature (kPa), and \( e^0(T_{\text{min}}) \) is saturated vapor pressure at daily minimum temperature (kPa).

\[
e_a = e^0(T_{\text{dew}}) = 0.6108 \exp\left[\frac{17.27 T_{\text{dew}}}{T_{\text{dew}} + 237.3}\right]
\]

\[
e^0(T_{\text{max}}) = 0.6108 \exp\left[\frac{17.27 T_{\text{max}}}{T_{\text{max}} + 237.3}\right]
\]

\[
e^0(T_{\text{min}}) = 0.6108 \exp\left[\frac{17.27 T_{\text{min}}}{T_{\text{min}} + 237.3}\right]
\]
3.1.1.6 Infiltration, Percolation, and Soil Water Content

Although there are many equations to calculate infiltration rate based on characteristics of soil and rainfall, HYSTAR estimates infiltration indirectly using the continuity equation (Equations 3.2 to 3.4). Runoff calculated as leaving a cell ($Q_{out}$) is subtracted from the total surface inflow and precipitation and runoff routed into the cell from the upstream cells ($\sum Q_{in}$) are obtained using the CN method and routing respectively, infiltrated runoff volume is the difference between inflow ($\sum Q_{in}$) and outflow ($Q_{out}$). This formulation of the continuity equation enables infiltration in a cell due to upstream runoff volume from upstream cells even when there is no rainfall.

Once amount of the infiltrated water volume is obtained, soil water content will be updated based on another continuity equation (Equation 3.22) for the soil root zone which states:

\[
\Delta SW = SW_t - SW_{t-1} = I_t - ET_t - PC_t
\]

3.21

\[
SW_t = SW_{t-1} + I_t - ET_t - PC_t
\]

3.22

where $SW$ is soil water content (mm or %), $t$ is time index, $ET$ is evapotranspiration (mm), and $PC$ is percolation (mm).

The rate of percolation is determined by unsaturated hydraulic conductivity, which is a function of soil water content when the root zone is not saturated with water. If the root zone is saturated with water, hydraulic conductivity will become equal to saturated hydraulic conductivity (Equations 3.23 and 3.24). In HYSTAR, the relationship between hydraulic conductivity and soil moisture is described by Equations 2.63, 2.64, and 2.66 in 2.6.2.

\[
k = k_{sat} \text{ when } SW \geq SAT
\]

3.23

\[
k = k_{unsat} \text{ when } SW < SAT
\]

3.24

where $SAT$ is soil water content when the root zone is saturated (%), $k$ is hydraulic conductivity, $k_{sat}$ is saturated hydraulic conductivity, and $k_{unsat}$ is unsaturated hydraulic conductivity.
Percolation is movement of soil water in vertically downward direction and its rate is different from that of horizontal movement in soil. Generally, vertical hydraulic conductivity is estimated by multiplying horizontal hydraulic conductivity by a coefficient called anisotropic ratio or relative hydraulic conductivity (Equation 3.25). In HYSTAR, rate of percolation is assumed equal to vertical unsaturated hydraulic conductivity.

\[ k_{unsat,ver} = AR \cdot k_{unsat,hor} \]  

3.25

where \( AR \) is anisotropic ratio, \( k_{unsat,ver} \) is vertical unsaturated hydraulic conductivity, \( k_{unsat,hor} \) is horizontal unsaturated hydraulic conductivity.

After rain stops, the overland surface and the root zone gets dry and the stream flow level gets low due to evapotranspiration from the ground and water surface as well as percolation. If the evapotranspiration occurs at a certain rate, for example at 5 mm/day, soil water content of the root zone will be lessened at the same rate. Then, this reduction in soil water content will decrease the unsaturated hydraulic conductivity and rate of percolation. In addition, percolation always occurs so that soil moisture in the root zone will keep decreasing unless it rains. The rate of the percolation is a function of soil water content of the root zone, and thus rate in decrease of soil moisture will decrease as soil gets dry, and percolation will stop at wilting point eventually.

When soil moisture of the root zone becomes low due to evapotranspiration and percolation, a watershed may be able to absorb much rainfall, and runoff may occur only on place where relatively high soil water content is held. Thus, only some portion, for example close to the stream in the watershed, may directly contribute to runoff at the outlet. Runoff generated on the upper parts of the watershed may not reach the outlet during a storm event. This mechanism of generating runoff, called saturation overland flow, is simulated naturally in HYSTAR through routing and updating soil water contents in a spatially distributed manner.
3.1.1.7 Groundwater

Amount and movement of groundwater are controlled by geological and geographical features such as soil texture and structure, lithologic formation, topography, climate, and vegetation as well as human activities like pumping, agricultural practice, and land use modification. Subsequently, groundwater flow is very complicated and site specific. Thus, for the sake of simplicity of groundwater flow modeling, the Dupuit-Forchheimer assumptions (Ritzema, et al., 1994) are applied in HYSTAR. Therefore, it is assumed that groundwater flow is steady, Darcy’s equation is applicable, and all the velocity vector of groundwater flow is horizontal (Ritzema, et al., 1994). Additionally, an unconfined aquifer, free groundwater surface, and horizontal surface of the impervious layer are hypothesized. However, capillary rise is ignored in HYSTAR. Consequently, the conservation of mass or continuity equation to describe groundwater flow can be reduced into two dimensions and then simplified with a recharge term.

\[-K \left\{ \frac{\partial}{\partial x} \left( h \frac{\partial h}{\partial x} \right) + \frac{\partial}{\partial y} \left( h \frac{\partial h}{\partial y} \right) \right\} (dx \cdot dy) = R \cdot dx \cdot dy\]

where \( K \) is hydraulic conductivity \((m/s)\), \( \partial x \) is an infinitely short distance in the x-direction \((m)\), \( \partial y \) is an infinitely short distance in the y-direction \((m)\), \( h \) is hydraulic head of groundwater \((m)\), and \( R \) is recharge or percolation rate from the root zone \((m/s)\).

For one-dimensional groundwater along a flow path, Equation 3.27 can be rewritten as:

\[-K \frac{d}{dx} \left( h \frac{dh}{dx} \right) + R = 0\]

In addition, from the Darcy’s equation,

\[ q_x = -Kh \frac{dh}{dx} \]

where \( q_x \) is the groundwater discharge per unit width along the x-direction in a unit time \((m^2/s)\).
If Equation 3.29 is substituted into Equation 3.28, Equation 3.28 becomes:

$$\frac{dq_x}{dx} = R$$

3.30

By integration, Equation 3.30 becomes:

$$q_x = Rx + q_0$$

3.31

where $q_x$ is the average groundwater discharge per unit width along the x-direction in a unit time ($m^2/s$), $x$ is the length of areas ($m$), recharge and $q_0$ is a constant determined by the boundary conditions ($m^2/s$).

Finally, from Equation 3.31, an equation describing the groundwater discharge per unit width along a flow path can be derived like Equation 3.32.

$$Q = R \cdot A + q_1$$

3.32

where $Q$ is the average total groundwater discharge along flow paths at an outlet of watershed in a unit time ($m^3/s$), $A$ is the recharge area ($m^2$), $q_1$ is a constant determined by the boundary conditions ($m^3/s$).

Because HYSTAR is a grid-based distributed model, Equation 3.32 can be rewritten as:

$$Q = A_{cell} \sum_{i=1}^{N} R_i + q_1$$

3.33

where $A_{cell}$ is the cell area ($m^2$), $N$ is the number of cells where percolation occurs, $i$ is an index, and $R_i$ is the recharge rate of individual cell ($m/s$).

Because the percolation rate is provided in simulation for soil water content, $q_1$ remains the only parameter to be estimated with any boundary condition in Equation 3.33 or to be calibrated with measured data. The term can be groundwater inflow from an area outside a watershed or loss of groundwater through deep percolation. In this study, it is assumed as zero. Although this approach cannot describe variation in groundwater level by recharge, discharge, and groundwater flow, it provides a simple way to simulate groundwater discharge at a watershed outlet.

205
3.1.1.7 Reservoir Routing

As runoff passes through a reservoir, some volume may be retained in the storage and the runoff peak is moderated. HYSTAR simulates reservoir runoff routing by allowing a cell that represent a reservoir to have a certain capacity to store runoff. Runoff will not leave the reservoir cell until the volume stored in the reservoir reaches its capacity. However, once it is filled with water, all the inflow volume will be discharged to a downstream cell in the same time interval immediately. For reservoir routing simulation, initial and boundary conditions, such as initial water level, the maximum capacity to store water, and a relationship between level and capacity, are required.

3.1.2 Sediment

3.1.2.1 Overview

Detachment, transportation, and deposition of sediment are controlled by characteristics of rainfall, flow, land cover, and soil, such as energy of rainfall impact and flowing runoff, canopy protection, resistance against flow, and size distribution of soil particle. Sediment erosion is driven by surface runoff and rainfall energy. Usually runoff is regarded as the most powerful driving force of erosion including sheet, rill, and channel erosion. For instance, in overland flow, when land cover on a cell is changed, hydraulics of runoff that controls the behavior of sediment also changes because roughness and amount of excess rainfall on the cell changes. In other words, runoff volume and velocity governs erosion rate in the given condition. Therefore, hydrologic variables such as runoff rate and depth are required to simulate erosion processes. In HYSTAR, sediment transport is simulated on all the overland and channel cells using the calculated runoff velocity and depth in the direct runoff simulation. Then, detachment and deposition on an individual cell are controlled by the predefined sediment transport capacity with flow conditions and sediment characteristics.

The USLE-type approach is an empirical way to estimate gross erosion of a small field especially when detailed hydrologic and erosion processes are not known or erosion
is estimated without calculation of runoff. In addition, changes in hydraulic features of a
field like cover crop and management practice can be easily incorporated into estimating
erosion by adjusting the corresponding factors in the USLE-type approach. For example,
when cover crop is changed, the crop management factor can be adjusted to reflect the
change in estimating gross erosion of a field. In the original USLE equation the
topographic factors, slope steepness and length factors, accounts for the impact of
hydrologic variables such as runoff velocity and volume on soil erosion. In other words,
they were defined together and empirically, so should not be defined and employed
independently in another sediment transport modeling framework unless roles of all the
factors and parameters are examined carefully. Thus, in this study, USLE-type
approaches or its factors are not utilized in calculating detachment of sediment in spite of
its simplicity and ease of use.

Many equations for estimating overland and channel erosion driven by rainfall
splash and runoff energy have been proposed. Each equation has its own applicable range
corresponding to the environment where it was developed. Usually the range of
applicable slopes, targeted sediment types, and available data for application of the
equations may be crucial considerations in choosing an equation for sediment transport
modeling. Because the overland usually has steeper slope than does the channel,
sensitivity of the equations against slope should be considered in the selection. Thus,
sensitivity of the erosion equations as a function of slope was examined in this study. In
addition, the required information and data for solving the equations must be considered.
After these examinations, suitable sediment erosion and transport equations were chosen
and the required assumptions for the equations were made.

In sediment transport modeling, the transport capacity concept is one of the most
popular methods in determining which process between detachment and deposition
occurs and how much they occur in a specific condition. It assumes that erosive energy is
independent of sediment concentration and is only a function of the power of flowing
runoff (Morgan et al., 1998a; 1998b). At the transport capacity concentration, detachment
and deposition rates of sediment are in balance. If the sediment load is greater than the
transport capacity, deposition will occur. On the other hand, if the flow is carrying less
material than its capacity, it will detach sediment and fill the carrying capacity (Morgan,
This concept is simple and intuitive so that several sediment transport models such as CREAMS, WEPP, KINEROS, AGNPS, GUESS, EUROSEM, and LISEM adapt this approach in simulating deposition and detachment processes. HYSTAR also utilizes the transport capacity concept in sediment transport modeling.

HYSTAR is a distributed H/WQ model. The detached sediment on an upstream cell may be transported or routed into a downstream cell with runoff. Field-scale models such as CREAMS and WEPP do not have to consider overland routing of runoff and sediment. Watershed-scale and semi-distributed models such as KINEROS and EUROSEM, which employ a plane to represent an independent overland unit, simulate interactions of runoff and sediment between overland units by a numerical method like FDM. Another watershed-scale fully distributed model, LISEM, also routes runoff and sediment on the overland by FDM. As described previously, HYSTAR employs the simple volume routing method instead of the numerical methods in routing runoff on the overland and in the channel for achieving simplicity of modeling. Thus, HYSTAR assumes that runoff volume of each cell in the upper time zone is evenly distributed onto cells in the lower time zone along its flow path. In the same vein, it is assumed that sediment that runoff carries is routed in the same way. Once sediment is routed onto a cell and transport capacity for the corresponding cell is calculated, the transport capacity concept will be applied in determining which process between detachment and deposition will occur.

### 3.1.2.2 Equations for Sediment Transport

#### 3.1.2.2.1 Equations for Erosion by Rainfall Splash and Runoff

Some equations used to calculate detachment rate by rainfall splash and runoff in other models, such as CREAMS, WEPP, KINEROS, ANSWERS, AGNPS, GUESS, CASC2D-SED, EUROSEM, LISEM, and SWAT, were examined. However, equations that contain any factor of USLE were excluded thus approaches of CREAMS, ANSWERS, AGNPS, CASC2D-SED, and SWAT were considered in this study. WEPP can simulate relatively concrete sediment transport processes based on physically based equations, but it was developed for field scale modeling. GUESS simulates detachment
and deposition of sediment size classes along a hillslope so that it requires detailed size distribution of sediment that sometimes may not available in practice.

EUROSEM and LISEM adapted the approach and equations from KINEROS. In the models, once boundary and initial sediment concentration is estimated by the continuity equation for kinematic water and sediment flow (Bennett et al., 1974), sediment concentration at every point on a slope plane will calculated by a four-point implicit scheme of FDM (Morgan et al., 1998a; 1998b). Then, the transport capacities estimated for interrill and rill are used to determine sediment processes for a specific location by comparing the capacity and the current sediment concentration or load. Although the approach is implemented by the numerical method in those models, it was selected as a method to simulate sediment transport in HYSTAR due to its simplicity and soundness.

In this study, the total erosion for overland is assumed to consist of soil detached by raindrop splash and runoff (Equation 3.34). However, shear stress of runoff is assumed as the only driving force for channel erosion. The detailed equations and procedures used in this study are as follows (Brandt, 1990; Morgan et al., 1998a; 1998b).

\[ e = DR + DF \]  

where \( e \) is net erosion rate of the bed per unit length of flow (\( g/m^2/s \) or \( m^3/s/m \)), \( DR \) is the detachment rate by impact of raindrop splash (\( g/m^2/s \) or \( m^3/s/m \)), \( DF \) is the balance between the rate of soil particle detachment by the flow and the particle deposition rate (\( g/m^2/s \) or \( m^3/s/m \)).

\[ DR = k(KE)e^{-bh} \quad \text{or} \quad DR = \frac{k}{\rho_s}(KE)e^{-bh} \]  

where \( k \) is an index of the detachability of the soil (\( g/J \)), \( \rho_s \) is soil particle density (\( g/cm^3 \)), \( KE \) is the total kinetic energy of the rain (\( J/m^3 \)), \( b \) is an exponent (between 0.9 and 3.1, 2.0 is recommended), and \( h \) is the depth of the surface water (\( mm \)).

\[ KE(Rain) = 8.95 + 8.44\log(R) \]  
\[ KE(Throughfall) = 15.8PH^{0.5} - 5.87 \]

where \( R \) is rainfall intensity (\( mm/h \)), and \( PH \) is height of the plants (\( m \)).
\[ DR_{pav} = (1 - FP)DR \]  

where \( FP \) is the fraction of the cell covered by non-erodible surfaces.

\[ DF = \beta w V_s (TC - C) \]  

where \( \beta \) is a flow erodibility efficiency coefficient (when \( DF \) is negative or deposition is occurring, \( \beta \) is equal to 1, and \( \beta \) is less than one for cohesive soils when \( DF \) is positive or detachment is happening), \( w \) is flow width (\( m \)), \( V_s \) is settling velocity of soil particles in the flow (\( m/s \)), \( TC \) is the volumetric sediment concentration of flow at the transport capacity (\( m^3/m^3 \)), \( C \) the current local sediment concentration (\( m^3/m^3 \)).

\[ \beta = 0.79e^{-0.85J} \text{ for } J \geq 1 \]  
\[ \beta = 0.335 \text{ for } J < 1 \]

where \( J \) is cohesion of the soil at saturation as measured with a torvane (kPa).

Deposition of sediment is assumed to occur at a particle settling velocity when current local sediment concentration is greater than the transport capacity. Settling velocity is calculated with the Stokes equation, which can be written:

\[ V_s = \frac{2gr^2(\rho_s - \rho_f)}{9\mu} = \frac{gD^2(\rho_s - \rho_f)}{18\rho_f\nu} = \frac{gD^2(SG - 1)}{18\nu} \]

where \( \mu \) is dynamic viscosity (\( kg/m/s \)), \( \nu \) is kinematic viscosity (\( m^2/s \)), \( \rho_s \) is soil density (\( kg/m^3 \)), \( \rho_f \) is fluid density (\( kg/m^3 \)), \( SG \) is specific gravity of sediment particle, \( g \) is gravitational acceleration (\( m/s^2 \)), \( r \) is radius of soil particle (\( m \)), and \( D \) is diameter of soil particle (\( m \)).

### 3.1.2.2.2 Equations for Transport Capacity

Hessel et al. (2007) classified eight different sediment transport equations by types of sediment load that they try to estimate (Table 3.3), and evaluated their applicability in estimating overland and channel transport capacity for gully catchments of the Chinese Loess Plateau. In their study, the equations were restated to derive equations for estimating transport capacity (Yalin, 1963; Yang, 1973; Bagnold, 1980;
Low, 1989; Rickenmann, 1990; Govers, 1990; Guy et al., 1992; Abrahams et al., 2001; US Department of the Interior, 2006; Hessel et al., 2007). Details of the equations are presented below.

Table 3.3. Sediment transport equations.

<table>
<thead>
<tr>
<th>Flow</th>
<th>Load</th>
<th>Equation</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overland</td>
<td>Total</td>
<td>Govers</td>
<td>1990</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Abrahams</td>
<td>2001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yang</td>
<td>1973</td>
</tr>
<tr>
<td>Channel</td>
<td>Bed</td>
<td>Schoklitsch</td>
<td>1962</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yalin</td>
<td>1963</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bagnold</td>
<td>1980</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Low</td>
<td>1989</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Rickenmann</td>
<td>1990</td>
</tr>
</tbody>
</table>

a. Govers estimated water transport capacity of sediment laden water as

\[ T_{cf} = c(S \cdot u - S \cdot u_{cr})^d \rho_s \]  

where \( u \) is mean velocity (cm/s), \( u_{cr} \) is critical mean velocity of flow (cm/s), \( \rho_s \) is density of particle; 2.65 g/cm\(^3\), \( c \) is a coefficient: \( c = \left( \frac{d_{50} + 5}{0.32} \right)^{-0.6} \), \( d_{50} \) is median grain size (\( \mu m \)), \( d \) is a coefficient: \( d = \left( \frac{d_{50} + 5}{300} \right)^{0.25} \), and \( S \) is sine of slope angle (dimensionless), \( S \cdot u_{cr} \) is critical unit stream power (cm/s), assumed to 0.4 cm/s.

Clear water transport capacity is expressed as

\[ T_c = \frac{\rho T_{cf}}{\rho_s - T_{cf}} \]  

b. Abrahams calculated the volumetric bedload transport per unit width (m\(^2\)/s) as:

\[ q_b = aD_{50}U_sY \left( 1 - \frac{Y_{cr}}{Y} \right)^b \left( \frac{V}{U_s} \right)^c \left( \frac{w_s}{U_s} \right)^d \]
where $V$ is mean velocity ($m/s$), $a$ is a coefficient: $\log(a) = -0.42 \left( \frac{C_r}{D_r} \right)^{0.2}$, $C_r$ is stone cover (dimensionless): assumed to 0.7 for channel, 0 otherwise, $D_r$ is stone size ($m$): assumed to 0.1 $m$, $b$ is a coefficient: $b = 3.4$, $c$ is a coefficient:

$$c = 1 + 0.42 \left( \frac{C_r}{D_r} \right)^{0.2}, \quad D_{50} \text{ is median grain size } (m), \quad w_i \text{ is inertia fall velocity } (m/s),$$

$$w_i = (g(s-1)D_{50})^{0.5}, \quad g \text{ is gravitational acceleration, } 9.8 \text{ m/s}^2, \quad s \text{ is a ratio between grain and fluid density: } s = \frac{\rho_s}{\rho_f}, \quad \rho_f \text{ is fluid density } (1.0 \text{ g/cm}^3), \quad Y_{cr} \text{ is critical Shield parameter } (0.06), \quad U_s \text{ is shear velocity } (m/s), \quad U_s = \sqrt{gRS}, \quad R \text{ is hydraulic radius } (m),$$

and $Y$ is a Shields parameter (dimensionless shear stress, $Y = \frac{RS}{D_{50}(s-1)}$).

Finally, clear water transport capacity ($g/l$) would be

$$T_c = \frac{q_b w \rho_s}{Q}$$

where $Q$ is clear water discharge ($m^3/s$ or $cms$), and $w$ is flow width ($m$).

c. Low expressed clear water transport capacity ($g/l$) as

$$q_b = \frac{6.42}{(s-1)^{0.5}} (Y - Y_{cr}) D_{50} V \cdot S^{0.6}$$

Then,

$$T_c = \frac{q_b w \rho_s}{Q}$$

d. Rickenmann defined the relationship

$$q_b = \frac{12.6}{(s-1)^{1.6}} \left( \frac{D_{90}}{D_{50}} \right)^{0.2} (q - q_{cr}) S^2$$

where $q$ is fluid discharge per unit width ($m^2/s$). The discharge threshold for sediment transport ($m^3/s$) is

$$q_{cr} = 0.065(s-1)^{1.67} g^{0.5} D_{50}^{1.5} S^{-1.12}$$
where, $D_{30}$ is characteristic grain size, 30% by weight finer (m), $D_{90}$ is characteristic grain size, 90% by weight finer (m). Then, the clear water transport capacity of the Rickenmann equation ($g/l$) is

$$T_c = \frac{q_b w \rho_s}{Q}$$ \hspace{1cm} (3.51)

e. Yalin proposed sediment transport rate (kg/ms) as

$$q_s = (\rho_s - \rho_f)D_{50}U_sP$$ \hspace{1cm} (3.52)

where

$$P = 0.635 \left[ \frac{Y}{Y_{cr}} - 1 \right] \left[ 1 - \ln(1 + as) \right] \frac{as}{as} \text{ (dimensionless coefficient), and}$$

$$as = \frac{2.45}{s^{0.4}} \sqrt{Y_{cr}} \left[ \frac{Y}{Y_{cr}} - 1 \right] \text{ (dimensionless coefficient)}$$

Then, the clear water transport capacity ($g/l$) is

$$T_c = \frac{q_s w}{Q}$$ \hspace{1cm} (3.53)

f. Yang defined the relationship with concentration (ppm)

$$\log(C_p) = I + J \log \left( \frac{V \cdot S}{\omega} - \frac{V_{cr} \cdot S}{\omega} \right)$$ \hspace{1cm} (3.54)

where $I = 5.435 - 0.286 \log \left( \frac{\omega D_{50}}{V} \right) - 0.457 \log \left( \frac{U_s}{\omega} \right)$ \hspace{1cm} (dimensionless),

$$J = 1.799 - 0.409 \log \left( \frac{\omega D_{50}}{V} \right) - 0.314 \log \left( \frac{U_s}{\omega} \right)$$ \hspace{1cm} (dimensionless),

$$\frac{V_{cr}}{\omega} = \max \left\{ \frac{2.5}{\log \left( \frac{U_s D_{50}}{V} \right) - 0.06} + 0.66, 2.05 \right\} \text{ (dimensionless),}$$

and $\omega$ is settling velocity (m/s).

Then, the clear water transport capacity ($g/l$) of the Yang equation is
\[ T_c = \frac{\rho_f C_p}{10^6} \left( \frac{C_p}{10^6} \right) \]

3.55

g. Bagnold expressed sediment transport rate \((kg/m/s)\) as

\[ q_s = q_{s,r} \left( \frac{\Omega - \Omega_{cr}}{\Omega - \Omega_{cr}} \right)^{3/2} \left( \frac{h}{h_r} \right)^{-2/3} \left( \frac{D}{D_r} \right)^{-1/2} \]

3.56

where \(q_{s,r} = 0.1\) (reference sediment transport rate, \(kg/m/s\)), \(\Omega = \rho_f \cdot h \cdot S \cdot V\) (stream power per unit bed area, \(kg/m/s\)), \(\Omega_{cr} = 290D_{50}^{1.5}\log\left(\frac{12h}{D_{50}}\right)\) (critical stream power per unit bed area, \(kg/m/s\)), \((\Omega - \Omega_{cr})_r\) is reference excess stream power (assumed to \(0.5 \, kg/m/s\)), \(h\) is water depth (m), \(h_r\) is reference water depth (assumed to \(0.1\) m), \(D\) is mode of grain size (m), and \(D_r\) is reference grain size (assumed to \(0.0011\) m). Then, the clear water transport capacity of the Bagnold equation \((g/l)\) is

\[ T_c = \frac{q_{s,w}}{Q} \]

3.57

h. Schoklitsch expressed sediment transport rate \((kg/m/s)\)

\[ q_s = 2.5\rho_f S^{1.5}(q - q_{cr}) \]

3.58

where \(q_{cr} = 0.26(s-1)^{5/3}D_{40}^{3/2}S^{-7/16}\) (critical sediment transport rate), \(D_{40}\) is characteristic grain size, 40\% by weight finer. Then, the clear water transport capacity \((g/l)\) is

\[ T_c = \frac{q_{s,w}}{Q} \]

3.59

Features of the equations including the environment where they were developed, sediment types, and concepts were investigated from the original literature in order to select a equation for the sediment transport simulation, and characteristics are summarized in Tables 3.4 and 3.5. Based on the investigation and the study of Hessel et al. (2007), the Yalin equation was chosen to estimate sediment transport capacity for both
overland and channel flow. The Yalin equation was theoretically driven using measurements from literature that represented a wide application range. In addition, the Yalin equation was recommend in estimating transport capacity for shallow overland and channel flow, and Foster et al. (1972) concluded that the Yalin equation was most appropriate for shallow flows associated with upland erosion (Meyer et al., 1969; Foster et al., 1972; Alonso et al., 1981; Frinkner et al., 1989).

On the other hand, the slope ranges, 1 to 12 degree, used for developing the Govers and Abrahams equations indicate that they can be better applied to overland rather than channel, and thus it is reasonably expected for them to provide significant underestimation in sediment transport capacity for channel. Although the general approach to sediment transport simulation for overland or upland is usually applicable to channel, the choice of transport capacity relation can be different for the two flow conditions (Woolhiser et al., 1990). However, for the sake of consistency in sediment transport simulation, the same equation was preferred for both overland and channel in this study. In the Low and Rickenmann equations, use of artificial material in a specific shape and commercially available clay may limit their application ranges. In the sensitivity analysis, the Yang’s equation provided negative concentration unrealistic, for small particles like clay and silt due to use of several logarithms. The Bagnold equation was developed based on monitoring data from natural streams in three regions, Israel, Alberta, and Utah, and thus the application ranges also might be limited. In the Schoklitsch equation, the sediment transport capacity is a function of only slope and particle size, and impact of dynamically varied hydraulic features like flow depth and velocity is ignored.
Table 3.4. Development environment of the Grovers, Abrahams, Low, and Rickenmann sediment transport capacity equations.

<table>
<thead>
<tr>
<th>Equations</th>
<th>Govers</th>
<th>Abrahams</th>
<th>Low</th>
<th>Rickenmann</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goal</td>
<td>Total load</td>
<td>Total load</td>
<td>Bed load</td>
<td>Bed load</td>
</tr>
<tr>
<td>Application</td>
<td>Overland</td>
<td>Overland</td>
<td>Channel</td>
<td>Channel</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Used Sed. Size</th>
<th>Max.</th>
<th>Min.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max.</td>
<td>Coarse sand</td>
<td>1.16 mm</td>
</tr>
<tr>
<td>Min.</td>
<td>Silt</td>
<td>0.098 mm</td>
</tr>
<tr>
<td>Used Coarse sand</td>
<td>3.5 mm, extruded cylinder shaped plastic particle, specific gravity of 1.17 to 2.46</td>
<td>commercially available clay</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Used Slope</th>
<th>Max.</th>
<th>Min.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max.</td>
<td>12 degree</td>
<td>0.0149</td>
</tr>
<tr>
<td>Min.</td>
<td>1 degree</td>
<td>0.0046</td>
</tr>
<tr>
<td>Used Slope</td>
<td>0.20</td>
<td>0.07</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Used Flow</th>
<th>Max.</th>
<th>Min.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max.</td>
<td>100 cm$^3$/s/cm</td>
<td>0.65 m/s</td>
</tr>
<tr>
<td>Min.</td>
<td>2 cm$^3$/s/cm</td>
<td>0.09 m/s</td>
</tr>
<tr>
<td>Used Flow</td>
<td>4.5 m$^3$/s/m</td>
<td>30 l/s (2.75m/s)</td>
</tr>
<tr>
<td>10 l/s (0.17m/s)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Used Devices</th>
<th>Flume of 12 m long and 0.117 m wide, 436 runs</th>
<th>Flume of 5.2 m long and 0.4 m wide, 1295 runs</th>
<th>Flume of 6.0 m long and 0.155 m wide, 187 runs</th>
<th>Flume of 5.0 m long and 20.1 cm wide</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Concept</th>
<th>Unit Stream Power</th>
<th>Shield Parameter</th>
<th>Shield Parameter</th>
<th>Shield Stress</th>
</tr>
</thead>
<tbody>
<tr>
<td>Particle Size</td>
<td>d50</td>
<td>D50</td>
<td>D50</td>
<td>D30, D50, D90</td>
</tr>
<tr>
<td>Flow Velocity</td>
<td>cm/s</td>
<td>m/s</td>
<td>m/s</td>
<td>-</td>
</tr>
<tr>
<td>Flow Depth</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Flow Rate</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>m$^3$/s/m</td>
</tr>
<tr>
<td>Shear Velocity</td>
<td>-</td>
<td>Incorporated</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Settling Velocity</td>
<td>-</td>
<td>Inertial Fall Velocity</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
Table 3.5. Development environment of the Yalin, Yang, Bagnold, and Schoklitsch sediment transport capacity equations.

<table>
<thead>
<tr>
<th>Equations</th>
<th>Yalin</th>
<th>Yang</th>
<th>Bagnold</th>
<th>Schoklitsch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>1963</td>
<td>1973</td>
<td>1980</td>
<td>1962</td>
</tr>
<tr>
<td>Goal</td>
<td>Total load</td>
<td>Total load</td>
<td>Bed load</td>
<td>Bed load</td>
</tr>
<tr>
<td>Application</td>
<td>Channel</td>
<td>Channel</td>
<td>Channel</td>
<td>Channel</td>
</tr>
<tr>
<td>Used Sed. Size</td>
<td>Max.</td>
<td>2.85 to 0.0315 cm (combined from different literatures)</td>
<td>7.01 to 0.102 mm (combined from different literatures)</td>
<td>Natural stream bed (Israel, Alberta of Canada, Wyoming and Utah of USA)</td>
</tr>
<tr>
<td></td>
<td>Min.</td>
<td>-</td>
<td>0.025 to 0.001 mm (combined from different literatures)</td>
<td>0.03 to 0.00056</td>
</tr>
<tr>
<td>Used Slope</td>
<td>Max.</td>
<td>-</td>
<td>0.025 to 0.001 mm (combined from different literatures)</td>
<td>0.03 to 0.00056</td>
</tr>
<tr>
<td></td>
<td>Min.</td>
<td>-</td>
<td>0.025 to 0.001 mm (combined from different literatures)</td>
<td>0.03 to 0.00056</td>
</tr>
<tr>
<td>Used Flow</td>
<td>Max.</td>
<td>-</td>
<td>-</td>
<td>300 cms</td>
</tr>
<tr>
<td></td>
<td>Min.</td>
<td>-</td>
<td>-</td>
<td>2.04 cms</td>
</tr>
<tr>
<td>Used Devices</td>
<td>Theoretically derived and compared with the measured data</td>
<td>Theoretically derived and compared with the measured data of 152 previously</td>
<td>Natural stream monitoring</td>
<td>Flume experiments of Gilbert (1914) with median sediment sizes ranging from 0.3 to 5 mm</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Concept</th>
<th>Shield</th>
<th>Parameter</th>
<th>Unit Stream Power</th>
<th>Stream Power</th>
<th>Discharge</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td>Particle Size</td>
<td>D50</td>
<td>D50</td>
<td>Dmode</td>
<td>D40</td>
</tr>
<tr>
<td>Flow Velocity</td>
<td>-</td>
<td>m/s</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Flow Depth</td>
<td>-</td>
<td>-</td>
<td>Incorporated</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Flow Rate</td>
<td>-</td>
<td>-</td>
<td>Incorporated</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Shear Velocity</td>
<td>Incorporated</td>
<td>Incorporated</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Settling Velocity</td>
<td>-</td>
<td>Incorporated</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Once the transport capacity is calculated, the process between detachment and deposition which occurs on a cell is determined through comparing the sediment concentration or load with the transport capacity. It should be noted that erosion rate by rainfall and flow is expressed by volumetric concentration, $m^3/m^3$, but transport capacity has an unit of concentration by mass, $kg/m^3$, in the equations presented in
Thus, the unit of transport capacity should be converted to the volumetric concentration with soil particle density as below (Hessel, 2002).

\[
C_m = \frac{\text{Mass of Sediment}}{\text{Volume of Dirty Water}} = \frac{\rho_s \cdot V_s}{V_w + V_s} \quad 3.60
\]

\[
C_v = \frac{\text{Volume of Sediment}}{\text{Volume of Dirty Water}} = \frac{V_s}{V_w + V_s} = \frac{C_m}{\rho_s} \quad 3.61
\]

or

\[
C_m = \rho_s \cdot C_v \quad 3.62
\]

where \(C_m\) is fluid concentration or dirty water concentration (kg/m\(^3\)), \(\rho_s\) is density of sediment (kg/m\(^3\)), \(V_s\) is volume of sediments (m\(^3\)), \(V_w\) is volume of water (m\(^3\)), and \(C_v\) is clear water concentration (kg/m\(^3\)).

The amount of sediment that water can carry is limited. Theoretically, for instance, the sediment concentration cannot be over 2650 kg/m\(^3\) when density of sediment particle is 2650 kg/m\(^3\) and all the sediment particles are uniform. Thus, the maximum possible transport capacity should be set to the corresponding maximum sediment concentration so that the model may not provide unrealistic sediment concentration. Then, if the summed sediment mass from erosion and sediment routing is over the predefined maximum concentration, the excessive sediment mass will be deposited and only sediment mass that flow can carry will be transported into downstream cells. Hessel et al. (2007) choose the maximum possible transport capacity of 1060 kg/m\(^3\) because it corresponded with the sediment concentration at the transition from streamflow to debris flow and it was close to the field observation reported from the rivers in a steep watershed. In this study, the maximum possible transport capacity was adapted from Hessel et al. (2007) instead of being parameterized.

### 3.2.2.2.3 Critical Shield Parameter

The Yalin equation employs a critical Shield parameter to determine flow condition that initiates movement of sediment particle. In the Shield diagram, critical shear stress for incipient motion of a particle is a function of the shear Reynolds number.
For channel flow where the shear Reynolds number is usually greater than 400 for turbulent open channel flow, it can be assumed equal to 0.056 to 0.060 (Equation 3.63) (Haan et al., 1994; Ferro, 1998; USACE, 2007). However, the shear Reynolds number of overland flow is generally much smaller than that of channel flow and then easily classified into laminar flow due to greater friction forces.

Mantz (1977) suggested a relationship between the critical Shield parameter and the shear Reynolds number when the shear Reynolds number is less than 1

\[
Y_c = \frac{0.1}{(R_e^{0.3})}
\]

Ferro (1998) tried to improve the relationship using additional experiment data and derived the expression,

\[
Y_c = \frac{0.1224}{(R_e^{0.1709})}
\]

(Haan et al., 1994; Ferro, 1998). In addition, engineers often assume that the sheet flow occurs when the critical Shield parameter reaches 0.8 (USACE, 2007). The literature showed a wider range of the critical Shield parameter for overland than that for channel flow. However, in the Shield’s diagram, the critical Shield parameter fluctuates as a shear Reynolds number increases even after it reaches 1. In this study, therefore, the critical Shield parameters for overland and channel flow were parameterized with CSO (Critical Shield parameter for Overland) and CSC (Critical Shield parameter for Channel), and then calibrated with the sediment load measurement (Equations 3.66 and 3.67).

\[
Y_c = \frac{CSO}{(R_e^{0.1709})}
\]

### 3.2.2.2.4 Soil Detachability and Soil Cohesion

Two parameters, soil detachability and soil cohesion coefficients, were adapted from EUROSEM to describe soil erodibility. Typical soil cohesion of bare saturated soils for different textures were provided by Morgan et al. (1998), and they recommended it be
adjusted according to changes in the soil and surface conditions such as the degree of compaction and types of vegetation cover. However, it is hard to quantitatively measure soil cohesion accurately unless measuring it in the field. In addition, kinetic energy of raindrop that causes splash also should be estimated to determine soil detachability, which is a function of soil and surface condition. Thus, in this study, the two parameters, soil detachability and cohesion, were calibrated with the measured sediment load. In the calibration, similar to the calibration for hydrologic simulation, only spatial scale factors, SDR (Soil Detachability Ratio) and SCR (Soil Cohesion Ratio), was optimized while the spatial distribution was fixed (Equations 3.68 and 3.69). Their typical values provided by Morgan et al. (1998) were implicitly assumed constant over time.

\[
DR = k(KE)e^{-bh} = SDR(KE)e^{-bh} \tag{3.68}
\]

\[
DF = \beta wV_s(TC - C) = SCR \cdot wV_s(TC - C) \tag{3.69}
\]

### 3.1.2.3 Estimation of Characteristic Sediment Particle Sizes

To employ the Yalin equation, measurement of characteristic sediment particle sizes of \( D_{so} \) is required. However, even very fine soil database like SSURGO does not provide a particle-size distribution for any soil. In addition, it is time-consuming and laborious to conduct sieving tests with field-sampled soil. Thus, in this study, a pedotransfer function, which was proposed by Skaggs et al. (2001) and Fooladmand et al. (2006), was utilized in estimating the characteristic sediment particle sizes through developing particle-size distributions for all the soils used in the modeling. The equations adopt the following form (Skaggs et al., 2001; Fooladmand et al., 2006)

\[
P(R) = \frac{1}{1 + \left(\frac{1}{clay} - 1\right)\exp\left(-u(R-1)^c\right)} \tag{3.70}
\]

where \( R \) is radius of soil particle, \( P(R) \) is the mass fraction of soil particle less than the radius \( R \), \( clay \) is the fraction of clay, \( u \) is a parameter, and \( c \) is a parameter.

\[
u = \frac{(-\nu)^{-\beta}}{(-\omega)^{-\beta}} \tag{3.71}
\]
where $\nu$ is a parameter, $\omega$ is a parameter, $\beta$ is a size coefficient, and

$$
\nu = \ln \left( \frac{1}{\frac{1}{\text{clay} + \text{silt}} - 1} \right), \quad \omega = \ln \left( \frac{1}{\frac{1}{\text{clay} + \text{silt} + \text{sand}} - 1} \right)
$$

where $\text{silt}$ is the fraction of silt, $\text{sand}$ is the fraction of fine and very fine sand,

$$
\beta = \alpha \ln \left( \frac{r_{\text{silt}} - r_{\text{clay}}}{r_{\text{clay}}} \right), \quad \alpha = \frac{1}{\ln \left( \frac{r_{\text{silt}} - r_{\text{clay}}}{r_{\text{sand}} - r_{\text{clay}}} \right)}, \quad c = \alpha \ln \left( \frac{\nu}{\omega} \right)
$$

where $\alpha$ is a size coefficient, $r_{\text{silt}}$ is the extreme radius of silt of 25 $\mu$m, $r_{\text{clay}}$ is the extreme radius of clay of 1 $\mu$m, and $r_{\text{sand}}$ is the extreme radius of fine sand 125 $\mu$m.

### 3.1.2.4 Sediment Routing

Once sediment is detached from the soil surface, it will be transported into the next time zone defined by time-area method in hydrology simulation. If the total sediment including the eroded soil from a cell and the transported soil from upstream cells exceeds the transport capacity of the cell, the excess sediment will be deposited on the cell. Then, the amount of sediment under the transport capacity on the cell will be evenly transported onto cells in the next time zone along its flow path. Thus, HYSTAR does not utilize a sediment delivery ratio to decide how much sediment on a cell is transported into another cell. In HYSTAR, the amount of sediment transported between cells is simulated using the developed time-area in the hydrologic simulation and the estimated transport capacity. In addition, HYSTAR does not distinguish types of sediment in sediment transport simulation while transport of sediment is particle-size selective in the reality. Therefore, even though the equations employed in HYSTAR were developed to model bed or total sediment load transport, what HYSTAR provides is only total sediment load or concentration.
3.1.3 Input GIS Data

Generally, a H/WQ model requires information about land use, soil, topography, and rainfall to simulate responses of a watershed to rainfall events and to any change in the watershed. A distributed H/WQ model usually needs several spatial data layers for land use, soil, topography, and rainfall to consider their spatial variability. Some of these layers are publicly available in a ready-to-use form or they can be generated from the other source layers by a modeler. In this research, only the publicly available spatial datasets for the US were utilized because of ease in acquisition. In addition, only vertical error in DEM and classification error in the land use map were addressed in examining sensitivity of the proposed model to error in GIS input data even though positional (horizontal) error may more significantly contribute to reliability of H/WQ modeling.

The digital elevation model (DEM) is generally stored in one of three data structures: grid, triangular irregular network (TIN), and digitized contour lines. The grid is the most typical form of elevation and topographic data layer for H/WQ modeling because of its simple structure to store and manipulate elevation data. The National Elevation Dataset (NED) was developed by merging the highest-resolution and best quality elevation data available across the US from the USGS 7.5-minutes DEMs into a seamless raster format (USGS, 2010). NLCD 1992 was the first land-cover mapping project with a national scope. NLCD 1992 provides 21 different land cover classes at the 30-meter resolution of Landsat TM for the lower 48 states. The acquisition date of the target scene is 1992, although cloud cover and other factors forced use of scenes from other years. The land cover classification was done by unsupervised clustering and logical modeling using a suite of ancillary data. It was prepared on a geographic projection with the NAD83 datum.

Natural Resources Conservation Service (NRCS) has established three soil geographic databases representing kinds of soil maps: SSURGO, STATSGO, and NATSGO. The maps were produced from different intensities and scales of mapping. Each database has a common link to an attribute data file for every map unit component. The soil survey geographic (SSURGO) database was designed primarily for farm, township, and county natural resource planning and management so that it can provide...
the most detailed level of information. Data in SSURGO were collected and archived in 7.5-minute topographic quadrangle units. Then, they were distributed as a complete coverage for a soil survey area usually consisting of 10 or more quadrangle units. Line vectors are digitized according to specifications and standards established by the NRCS for duplicating the original soil survey map. SSURGO dataset available through the Soil Data Mart can be obtained either in the UTM Zone (NAD83) or in the State Plane coordinate system. The SSURGO dataset contains many attribute data (ratio measurement, ordinal, and nominal scale) such as particle size distribution, bulk density, available water capacity, as well as map identification number.

3.2 Model Evaluation Method

3.2.1 Study Watersheds

The proposed model was applied in predicting runoff and sediment at a subwatershed outlet of the Owl Run watershed (1,153 ha) located in Fauquier County and at a subwatershed outlet of the Polecat Creek watershed (12,048 ha) located in Caroline County, Virginia (Figures 3.7 and 3.12). The average annual rainfall for the Owl Run watershed is about 1000 mm (Table 3.6 and Figure 3.8) (Mostaghimi et al., 1999). Although precipitation is well distributed throughout the year, runoff is concentrated in the winter (Table 3.7 and Figure 3.9), from Dec to Mar, because of relatively wet soil moisture condition of the watershed in that season. The topography of the Owl Run watershed consists of rolling to steep Piedmont Plateau, and soils within the watershed are mostly shallow silt loams (Brannan et al., 2000). Nearly 70 % of the watershed is used for agricultural production, including crop and livestock (Shukla et al., 2001). Based on NLCD 1992, land use of the watershed includes 62 % agricultural land, 31 % forest, and 7 % residential and commercial.

In this study, the measured runoff at the outlet of the QOD catchment in the Owl Run watershed was used in calibrating and validating the model. The watershed boundary of QOD was delineated and the area of QOD was estimated as 328.86 ha from the 30 m NED. The entire Owl Run watershed was covered by four raingages (POB, POD, POF,
and POH), which has available precipitation data for the simulation period, but QOD belongs to only one raingage, POF. The annual average and seasonal variation of rainfall of QOD are similar to those of the entire Owl Run watershed, and higher water yield was found in winter (Table 3.7 and Figure 3.9). There was no weather station measuring temperature in the Owl Run watershed, so the daily maximum and minimum temperature was taken from the National Weather Service (NWS) station, ‘THE PLAINS 2 NNE’, which is located 20 km north of QOD. Seasonal variation of the temperature data are presented in Figures 3.10 and 3.11.

Figure 3.7. Owl Run watershed and its monitoring points (Mostaghimi et al., 1999).
Table 3.6. Observed yearly rainfall, runoff, and water yield of the Owl Run watershed.

<table>
<thead>
<tr>
<th>Year</th>
<th>Runoff (QOD, mm)</th>
<th>Rainfall (POF, mm)</th>
<th>Water Yield (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>302.2</td>
<td>1023.2</td>
<td>29.5</td>
</tr>
<tr>
<td>1991</td>
<td>254.1</td>
<td>980.0</td>
<td>25.9</td>
</tr>
<tr>
<td>1992</td>
<td>439.1</td>
<td>1090.7</td>
<td>40.3</td>
</tr>
<tr>
<td>1993</td>
<td>484.7</td>
<td>1121.4</td>
<td>43.2</td>
</tr>
<tr>
<td>1994</td>
<td>437.1</td>
<td>1203.2</td>
<td>36.3</td>
</tr>
<tr>
<td>1995</td>
<td>287.5</td>
<td>1040.1</td>
<td>27.6</td>
</tr>
</tbody>
</table>

Figure 3.8. Variations in yearly rainfall, runoff, and water yield of the Owl Run watershed.

Table 3.7. Observed monthly, rainfall, runoff, and water yield of the Owl Run watershed.

<table>
<thead>
<tr>
<th>Month</th>
<th>Runoff (QOD, mm)</th>
<th>Rainfall (POF, mm)</th>
<th>Water Yield (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>370.3</td>
<td>481.8</td>
<td>76.9</td>
</tr>
<tr>
<td>2</td>
<td>212.5</td>
<td>317.3</td>
<td>67.0</td>
</tr>
<tr>
<td>3</td>
<td>462.1</td>
<td>669.5</td>
<td>69.0</td>
</tr>
<tr>
<td>4</td>
<td>199.1</td>
<td>423.5</td>
<td>47.0</td>
</tr>
<tr>
<td>5</td>
<td>111.4</td>
<td>518.6</td>
<td>21.5</td>
</tr>
<tr>
<td>6</td>
<td>37.3</td>
<td>602.3</td>
<td>6.2</td>
</tr>
<tr>
<td>7</td>
<td>112.4</td>
<td>716.4</td>
<td>15.7</td>
</tr>
<tr>
<td>8</td>
<td>72.3</td>
<td>574.9</td>
<td>12.6</td>
</tr>
<tr>
<td>9</td>
<td>45.6</td>
<td>583.5</td>
<td>7.8</td>
</tr>
<tr>
<td>10</td>
<td>66.8</td>
<td>471.9</td>
<td>14.2</td>
</tr>
<tr>
<td>11</td>
<td>170.7</td>
<td>500.9</td>
<td>34.1</td>
</tr>
<tr>
<td>12</td>
<td>344.1</td>
<td>598.1</td>
<td>57.5</td>
</tr>
</tbody>
</table>
Figure 3.9. Variations in monthly rainfall, runoff, and water yield of the Owl Run watershed.

Figure 3.10. Variations of daily temperature for the Owl Run watershed (The Plains NWS station).
The Polecat Creek watershed includes forest (73 %), pasture (13 %), cropland (2 %), developed area (10 %), and water (2 %) (Im et al., 2007). The majority of the watershed lies in the Coastal Plain, which tends to be mostly level to gently sloping and has sandy loam surface and sandy clay loam to clay loam subsurface soils of moderate to slow permeability. (Im et al., 2003). For calibration and validation of the model, the runoff measurement made at the outlet of the PCA catchment was used. Using 30 m NED data, the area of PCA was estimated to be 284.7 ha. Rainfall observation made at gauge PP7 was used for hydrologic simulation of PCA (Figure 3.12). The annual average rainfall from 1999 to 2002 was 821.7 mm (Table 3.8 and Figure 3.13), and rainfall was evenly distributed through the years (Table 3.9 and Figure 3.14). Seasonal water yields of PCA were similar to those of QOD, which were low in summer but high in winter by the same reason (Table 3.9 and Figure 3.14). The Polecat watershed did not have a weather station measuring temperature so the daily maximum and minimum temperature was taken from the National Weather Service (NWS) station at the Richmond International Airport (WBAN 13740), which is located 45 km south of PCA. Seasonal variation of the temperature data are presented in Figures 3.15 and 3.16.
Table 3.8. Observed yearly rainfall, runoff, and water yield of the Polecat Creek watershed.

<table>
<thead>
<tr>
<th>Year</th>
<th>Runoff(QPA, mm)</th>
<th>Rainfall (PP7, mm)</th>
<th>Water Yield (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>139.4</td>
<td>1003.2</td>
<td>13.9</td>
</tr>
<tr>
<td>1998</td>
<td>529.4</td>
<td>1105.8</td>
<td>47.9</td>
</tr>
<tr>
<td>1999</td>
<td>58.9</td>
<td>973.8</td>
<td>6.1</td>
</tr>
<tr>
<td>2000</td>
<td>143.2</td>
<td>856.6</td>
<td>16.7</td>
</tr>
<tr>
<td>2001</td>
<td>158.8</td>
<td>775.9</td>
<td>20.5</td>
</tr>
<tr>
<td>2002</td>
<td>78.5</td>
<td>680.6</td>
<td>11.5</td>
</tr>
</tbody>
</table>
Table 3.9. Observed monthly, rainfall, runoff, and water yield of the Polecat Creek watershed.

<table>
<thead>
<tr>
<th>Month</th>
<th>Runoff (QPA, mm)</th>
<th>Rainfall (PP7, mm)</th>
<th>Water Yield (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>37.7</td>
<td>328.6</td>
<td>11.5</td>
</tr>
<tr>
<td>2</td>
<td>55.6</td>
<td>186.0</td>
<td>29.9</td>
</tr>
<tr>
<td>3</td>
<td>103.8</td>
<td>381.6</td>
<td>27.2</td>
</tr>
<tr>
<td>4</td>
<td>70.1</td>
<td>271.4</td>
<td>25.8</td>
</tr>
<tr>
<td>5</td>
<td>21.6</td>
<td>236.6</td>
<td>9.1</td>
</tr>
<tr>
<td>6</td>
<td>21.9</td>
<td>374.5</td>
<td>5.9</td>
</tr>
<tr>
<td>7</td>
<td>4.0</td>
<td>235.6</td>
<td>1.7</td>
</tr>
<tr>
<td>8</td>
<td>2.6</td>
<td>244.7</td>
<td>1.1</td>
</tr>
<tr>
<td>9</td>
<td>13.2</td>
<td>459.4</td>
<td>2.9</td>
</tr>
<tr>
<td>10</td>
<td>7.7</td>
<td>137.0</td>
<td>5.7</td>
</tr>
<tr>
<td>11</td>
<td>41.5</td>
<td>211.7</td>
<td>19.6</td>
</tr>
<tr>
<td>12</td>
<td>59.6</td>
<td>219.6</td>
<td>27.2</td>
</tr>
</tbody>
</table>

Figure 3.13. Variation in the observed yearly rainfall, runoff, and water yield of the Polecat Creek watershed.
Figure 3.14. Variation in monthly, rainfall, runoff, and water yield of the Polecat Creek watershed.

Figure 3.15. Observed daily temperature at Richmond Airport (WBAN 13740) used in simulations of Polecat Creek watershed.
Channels of both QOD of the Owl Run watershed and PCA of the Polecat watershed were assumed as rectangular shaped. The minimum and maximum channel widths were set to 0.2 and 2.0 m for QOD and 0.1 and 1.0 m for PCA respectively based on field observation and literature. Then, channel widths were distributed along the predefined channel networks through upstream area weighted interpolation. In QOD, two reservoir were identified from field observation, land cover map (NLCD 1992), and soil map (SSURGO) while no reservoir was found in PCA. Hereafter, QOD is referred to as ORD (Owl Run watershed D).

### 3.2.2 Model Performance Evaluation and Measures

The goodness-of-fit or degree of agreement between simulation results of modeling and measurement is evaluated quantitatively using absolute statistics and relative indices as performance measures. These measures are also used as objective functions in calibration to find the best parameter set for the given observations. Different types of measures may provide unique evaluations of agreement and optima. Therefore, a
type of measure should be selected considering objectives of evaluation and characteristics of the subject to be evaluated. There are several measures proposed for evaluation of hydrologic model performance such as the relative error in runoff volume \( (RERV) \), average error in peak rates \( (AEPR) \), average error in peak time \( (AEPT) \), and root mean square error \( (RMSE) \). In addition, coefficient of determination \( (R^2) \) and coefficient of efficiency or Nash-Sutcliffe coefficient \( (E) \) are also commonly used in evaluation of H/WQ modeling performance. The characteristics of each measure are described in the literature (Legates et al., 1999; Krause et al., 2005; Moriasi et al., 2007; USACE, 2000; USACE, 2009).

The \( R^2 \) performance measure is criticized for the fact that it quantifies only dispersion from linear relationships between simulation and measurement, thus it cannot detect over- or underestimation of the prediction (Legates et al., 1999; Krause et al., 2005). In addition, it is known that \( RMSE \) and \( E \) are sensitive to a shift in the timing between the simulated and observed hydrographs (Meng et al., 2008) and more sensitive to extreme values than is \( R^2 \) (Legates et al., 1999). However, \( E \) tends to overestimate larger values but underestimate smaller ones because differences between the simulation and measurement are squared in calculation (Krause et al., 2005). Thus, similar to \( R^2 \), \( E \) it is not very sensitive to systematic model over- or underestimation during low flow periods. Unlike relative indices such as \( R^2 \) and \( E \), an absolute error measures such as \( RMSE \) provides an evaluation of error in the units of the variable, which can provide more information about model performance than can the relative measures (Legates et al., 1999). However, relative indices provide standardized measures, for example ranging from 0 to 1, which can allow easy comparison of model performance in different modeling conditions.

HYSTAR is designed to construct a continuous hydrograph for consecutive storms that have pauses between them so that it can predict low flows as well as peak rates. Thus, the entire simulated hydrograph including low flow will be compared with the measured flow for the simulation period. For diverse assessment of model performance, several measures, such as \( RERV \), \( AEPR \), \( AEPT \), \( RMSE \), \( R^2 \), and \( E \), will be utilized in this study. These measures are calculated with Equations 3.74 to 3.79.
\[ RERV = \frac{V_s - V_m \times 100}{V_m} \]  
\[ AEPR = \frac{\sum_{i=1}^{N} |Q_{\text{peak,s},i} - Q_{\text{peak,m},i}|}{N} \]  
\[ AEPT = \frac{\sum_{i=1}^{N} |T_{\text{peak,s},i} - T_{\text{peak,m},i}|}{N} \]  
\[ RMSE = \sqrt{\frac{\sum_{t=1}^{T} (Q_{s,t} - Q_{m,t})^2}{T}} \]  
\[ R^2 = \left( \frac{\sum_{t=1}^{T} (Q_{s,t} - \bar{Q}_s)(Q_{m,t} - \bar{Q}_m)}{\sqrt{\sum_{t=1}^{T} (Q_{s,t} - \bar{Q}_s)^2} \sqrt{\sum_{t=1}^{T} (Q_{m,t} - \bar{Q}_m)^2}} \right)^2 \]
where $R^2$ is the coefficient of determination, $\overline{Q}_s$ is the average of the simulated runoff rates over the simulation period ($m^3/s$), and $\overline{Q}_m$ is the average of the measured runoff rates over the simulation period ($m^3/s$).

$$E = 1.0 - \frac{\sum_{t=1}^{T} (Q_{s,t} - Q_{m,t})^2}{\sum_{t=1}^{T} (Q_{m,t} - \overline{Q}_m)^2}$$

where $E$ is the coefficient of efficiency, and other parameters as defined previously.

Performance of the model can be assessed statistically. There are some statistical methods, such as paired t-test (parametric) and the Wilcoxon signed rank test (non-parametric), that can be used in determining if differences between the simulated and measured data or errors are statistically significant or not. All of them assume the differences as independent. However, usually when continuous time series of measurements were derived from several independent and discrete measurements using a rating curve for flow and sediment, the time series are usually autocorrelated, and thus the differences and errors are likely to be autocorrelated as well. The measurements employed in this study were derived in the same way. In this case, the number of independent observations decrease and the time series are not random variable any more (Dawdy et al., 1964). Thus, chance of committing Type I error might increase if the number of effective samples is not incorporated in the test. Therefore, only relative indices and absolute statistics were utilized in model evaluation of this study in order to avoid additional treatment and analysis for data.

### 3.3 Sensitivity Analysis

The one-factor-at-a-time (OAT) method is a common and simple way to investigate the impact of each parameter on model output. It examines the amount of variation in model output according to a unit change in a parameter of interest while the other parameters are fixed to a base value. Thus, it ignores effect of interaction between other parameters. For the same reason, however, the OAT method is useful in
investigating if change in a parameter results in change in an output variable in the same or the opposite direction. Often, the OAT method focuses on the vicinity of a nominal or base point in the parameter space, and then it may be classified as a local sensitivity analysis. On the other hand, an AAT (all-factor-at-a-time) method investigates amount of variation in model output while all the parameters are being varied at the same time.

However, because it is not always guaranteed that the nominal value set of parameters is identical or close to the optimum set or a meaningful region in the parameter space for a specific application, a global analysis was undertaken to explore the response of HYSTAR through the entire parameter space. A sampling method based on the Monte Carlo simulation technique can be employed in order to incorporate a global exploration in sensitivity analysis.

In sensitivity analysis, variation of a model output, such as runoff volume, peak runoff rate, and time to peak, against change in each scale factor will be examined. In addition, both the OAT and AAT approaches will be tried. From a sensitivity analysis using the OAT method, relative sensitivity is calculated as in the following equation (McCuen, 1973; Haan et al., 1982; Haan et al., 1995).

\[
RS_{i,j,k} = \frac{\partial O_{i,j,k}}{\partial P_{j,k}} \frac{P_{j,N}}{O_{i,N}} = \frac{O_{i,j,N} - O_{i,j,k}}{P_{j,N} - P_{j,k}} \frac{P_{j,N}}{O_{i,j,N}}
\]

where \(RS_{i,j,k}\) is relative sensitivity of the model output \((O_i)\) of interest against the \(k^{th}\) change in parameter \((P_j)\), \(i\) in an index to represent types of model output, \(j\) is an index to represent types of parameter, \(k\) is an index to represent sequence of change in parameter value, and \(N\) is an index to represent a nominal value of the interested parameter.
3.4 Parameter Calibration

A distributed model may have many parameters because it incorporates spatially distributed parameters into modeling in order to consider spatial variability of input data and H/WQ processes. However, it is not common for a modeler to have enough measured data or observations that can be used in calibration. Thus, only measured flow at a watershed outlet is usually employed in calibrating model parameters. In this study, six scale factors were introduced reducing the number of parameters to be calibrated to 14 in HYSTAR. Those parameters were calibrated with the measured runoff at a watershed outlet using the SCE-UA algorithm (Duan et al., 1992, 1994), which is capable of locating the global optimum in the parameter space. The detailed procedures of SCE-UA are provided below and summarized in Figure 3.17.

SCE-UA algorithm (Duan et al., 1992, 1994)

a. Generate sample points in the parameter space: \( s \) samples (Each sample is a vector of parameter set. Ex., if we have two parameters like CN and Manning’s n, a sample, \( x_i \), may have a form of \( \begin{bmatrix} 78 \\ 0.03 \end{bmatrix} \) are randomly generated without any prior information in the feasible parameter space (The feasible space consists of theoretical possible ranges of parameter’s values. Ex., 0 to 100 for CN and 0.00001 to 1. However, any reasonable ranges of parameters may be applied to construct the feasible space) using a uniform probability distribution. The size of the sample, \( s \) is determined by \( s = p \times m \) where the number of complexes (\( p \)) and the number of samples (parameter vectors) (\( m \)) in each complex on the following step, c. By authors, the number of samples (\( m \)) was recommended to \( m = 2N + 1 \) where \( N \) is the number of dimensions or parameters, and the number of complexes (\( p \)) is only parameter that should be determined by a modeler in the SCE-UA algorithm.

\[
X = \{x_1, x_2, ..., x_s\} = \{x_i, i = 0, 1, ..., s\}
\]
b. Rank the generated sample points: The generated sample points in the step are sorted in order of increasing objective function (response or goodness-of-fit) value. If assuming that the goal is to minimize the objective function value, the first sample point will represent the smallest response value.

\[ X_{\text{sorted}} = \{(x_7, f(x_7)), (x_{11}, f(x_{11})), \ldots, (x_2, f(x_2))\} \]

\[ D = \{(x_1, f(x_1)), (x_2, f(x_2)), \ldots, (x_s, f(x_s))\} \]

c. Partition into complexes: Partition the \( s \) sample points into \( p \) complexes, each containing \( m \) sample points. The complexes are partitioned such that the first complex contains every \( p(k-1)+1 \) ranked point, the second complex contains every \( p(k-1)+2 \), and so on, where \( k = 1, 2, \ldots, m \).

\[ A^k = \left\{ x^k_j, f(x^k_j) \mid x^k_j = x_{k+p(j-1)}, f(x^k_j) = f(x_{k+p(j-1)}), j = 1, 2, \ldots, m \right\} \]

For example,

\[ A^1 = \{(x_1, f(x_1)), (x_{1+p}, f(x_{1+p})), (x_{1+p+2}, f(x_{1+p+2})), \ldots, (x_{1+p(m-1)}, f(x_{1+p(m-1)}))\} \]

\[ A^2 = \{(x_2, f(x_2)), (x_{2+p}, f(x_{2+p})), (x_{2+p+2}, f(x_{2+p+2})), \ldots, (x_{2+p(m-1)}, f(x_{2+p(m-1)}))\} \]

(So, \( D = \{A^1, A^2, A^3, \ldots, A^p\} \})

d. Evolve each complex: Evolve each complex according to the competitive complex evolution (CCE) algorithm. Repeat the following steps \( \beta \) times.

i. Construct a subcomplex by randomly selecting \( q \) sample points from \( m \) sample points in each complex based on a trapezoidal probability distribution (The weight of random sampling by the authors is proposed such as \( w_i = \frac{2(m+1-i)}{m(m+1)}, i = 1, 2, \ldots, m \)). Therefore, the sample point with the smallest or best response value will have the highest chance of being chosen to form the subcomplex, and the worst sample point will have the least chance. The number of sample points (parameter vectors) of a subcomplex, \( q \), should be equal to or less than \( m \). \( q = N + 1 \) is recommend
by the authors where $N$ is the number of dimensions or parameters (so that $q$ becomes less than $m$).

For example, from the above complex, $A^2$, randomly selecting $q$ sample points with weights, $w_i = \frac{2(3+1-1)}{3(3+1)} = \frac{1}{2}$ for the best sample point with the smallest response value and $w_3 = \frac{2(3+1-3)}{3(3+1)} = \frac{1}{6}$ for the worst sample point with the largest response value when $m = 3$.

\[
A^2 = \{(x_2, f(x_2)), (x_{2+p}, f(x_{2+p})), (x_{2+2p}, f(x_{2+2p})), ..., (x_{2+p(m-1)}, f(x_{2+p(m-1)}))\}
\]

Thus, the constructed subcomplex will have a form of

\[B^i = \{u_i^k, f(u_i^k), i = 1, 2, ..., q\}\]

where $u_i^k$ is a newly selected sample point by a trapezoidal probability distribution.

ii. Identify the worst point of the subcomplex and compute the centroid of the subcomplex excluding the worst point using the expression, $g = \frac{1}{q-1} \sum_{j=1}^{q-1} u_j$.  

iii. Attempt reflection or contraction steps in the Simplex direct method by moving the worst point through the centroid.

Shuffle complexes:

i. Combine the points in the evolved complexes (into a single sample population.

\[D = \{A^{i1}, A^{i2}, A^{i3}, ..., A^{ip}\}\]

where $A^*$ is an evolved complex.

ii. Sort the sample population in order of increasing response function values.

iii. Repartition (shuffle) the sorted sample population into $p$ complexes like the step c.
f. Check convergence by the pre-defined convergence criteria (acceptance threshold). If the criteria is satisfied, stop; otherwise, continue.

g. Check the reduction in the number of complexes. If the minimum number of complexes required in the population, \( p_{\text{min}} \) is less than \( p \), remove the complex with the lowest ranked sample points and set \( p = p - 1 \) and \( s = p \times m \), and then go to the step d. If \( p_{\text{min}} \) is equal to \( p \), also go to the step d.

![Flowchart Diagram](image)

Figure 3.17. General procedure of SCE-UA algorithm (Duan et al., 1992, 1994).

Direct runoff simulation of an event model is calibrated with observed flow, which has been separated from base flow. There are many techniques to separate direct
runoff and base flow from the total hydrograph (Tallaksen, 1995). Their accuracies are sensitive to mathematical techniques and assumptions and variability, length, and quality of data employed in the separation (Bates et al., 1988; Vogel et al., 1996), thus hydrograph separation would remain a subjective process (USGS, 1996). Therefore, in this study, parameters related to direct runoff simulation of HYSTAR were calibrated first with flow measured at the outlets of the study watersheds (ORD and PCA). To ensure insignificant contribution of base flow to the total runoff, the measured runoff hydrograph in a relatively dry period, when base flow was not observed, was used for calibration. Thus, base flow separation was not required to derive direct runoff data from the runoff measurement. Finally, rainfall events whose starting dates are far enough from the beginning of the simulation were selected to minimize impact of the initial soil moisture conditions on calibration.

In this study, RMSE was used as objective function for calibration. First, RMSE is sensitive to time shifting of the simulated hydrograph (Meng et al., 2008), thus it might be a good measure to assess accuracy of time to peak simulation. In addition, it is more sensitive to extreme values than are the coefficient of determination and the efficiency coefficient (Legates et al., 1999; Krause et al., 2005). In addition, because RMSE is an absolute error measures in the units of the variable, it can provide more information about model error than the relative measures (Legates et al., 1999).

Usually, sediment transport is modeled after when hydrologic simulation is completed because the simulated hydrologic variables are required for sediment simulation. In addition, groundwater or base flow can be simulated once infiltrated water volume into the root zone is calculated in direct runoff simulation of HYSTAR. Thus, calibration is a hierarchical process beginning with direct runoff, followed by base flow and sediment transport simulations (Donigian, 2002; Cho, 2007). Through the hierarchical process, not only variables but also their error and uncertainty are transferred into all the following components (Cho, 2007). In this study, therefore, parameters that control soil moisture and groundwater flow and parameters that control sediment transport were calibrated separately after calibration for direct runoff parameters was finished.
3.5 Uncertainty Analysis

3.5.1 Definition of Uncertainty

Error and uncertainty are sometimes used without discrimination in talking about accuracy and/or reliability of a model, and this confusion causes misunderstanding in communicating the result of analysis. Thus, they are defined and addressed in separate sections here to avoid the confusion. Here, error is defined as the numerical difference between the simulated and measured values, with the measured value taken as the true, correct, exact, reference value or a value assumed as true. Consequently, error can be calculated only when true, correct, and/or exact values are known or any reference value is set. On the other hand, uncertainty is expressed with a distribution of possible or expected values that a variable may possess. This indetermination or indefiniteness of the variable value is caused by incomplete knowledge and/or randomness in nature. In addition, when the true value is known or reference is determined, the distribution or uncertainty can describe frequency of potential errors in the variable.

In this sense, an error becomes a realization of one of the possible uncertainties. In other words, uncertainty describes a set of possible states or realizations of a variable or its error, and then an error is a measurement of difference between a possible state of a variable and the true or reference when uncertainty is simulated. For instance, when a calibrated parameter set provides a single output of interest, difference between the measured and simulated output in the calibration period may represent the ‘overall modeling error’. On the other hand, if multiple possible parameter sets identified through uncertainty analysis provide multiple outputs of interest, distribution of the differences may represent the ‘overall modeling uncertainty’ for the calibration period. In this sense, error is a sufficient condition for uncertainty. Thus, a big error always implies great uncertainty but big uncertainty does not necessarily produce a great error. It means that it is possible to have modeling results that have great uncertainty but a small error. This definition may be valid in this study while different definitions about error and uncertainty are found easily in other disciplines (Guare, 1991).

Usually, uncertainty is expressed with a distribution of probability or likelihood such as probability density or likelihood function that describes potential of a variable
value being true. Likelihood expresses the relative frequencies with which a parameter or a set of parameters would yield the observed sample (Fisher, 1922; Wolf, 1962). On the other hand, probability represents the relative frequencies with which an event of interest occurs. Thus, likelihood of being true is evaluated through calibration of uncertainty analysis with the measured data. In this sense, uncertainty is not determined subjectively based on a modeler’s personal impression and confidence about parameter and input data but estimated statistically through comparing the simulated results with measurements in a probabilistic way.

Accuracy of modeling is evaluated with error rather than uncertainty of the modeling result while reliability is assessed with not only accuracy or error but also uncertainty of the results. Thus, when a measured data set for calibration is not given, a model with uncertainty may produce an accurate result by chance. However, a model with low uncertainty may have more opportunity or probability of providing an accurate result. Consequently, a model with high reliability that may not need calibration to predict H/WQ processes at an acceptable accuracy will be the most desirable type of H/WQ models. Therefore, a modeler should try to reduce uncertainty of parameters through improving model structure and enhancing quality of input data for better reliability of H/WQ modeling.

### 3.5.2 Sources and Causes of Uncertainty

In H/WQ modeling, topography, land use and cover, soil, and weather used as input data are temporally variable. However, elevation and soil characteristics are usually assumed constant because of relatively short temporal extent of the simulation compared to geological time scale of topography and soil formation. However, soil is eroded and the eroded sediment is transported and deposited by flow of water. Thus, change can be significant in not only geological and sedimentological time scale but also within a single severe storm. Moreover, anthropological activities like construction and reclamation rapidly alter topography, land cover, and even soil characteristics. In addition, change of land use and cover usually occurs in a relatively short period, and it might be more
obvious than that of topography and soil feature. For example, vegetation and associated human activities change daily and seasonally.

The state variables for H/WQ modeling such as topography, land use and cover, soil, and weather are not spatially homogeneous. The degree of heterogeneity varies with location and scale as well. For simplicity and efficiency, H/WQ modeling employs concepts and tools like the hydrologic response unit (HRU) that assumes homogeneity in a specific spatial extent at a certain spatial scale. An HRU can contain several fields and even small catchments. Some H/WQ models also assume a field as an independent hydrologic response unit. However, even a field may have significant spatial variation in topography and soil at a finer scale. Therefore, definition or quantification of the heterogeneity also varies with spatial scale.

A modeler simplifies hydrologic and water quality processes through conceptualization and parameterization and ignores some processes known as minor factors to the output of interest for the sake of efficiency and/or due to insufficient knowledge about the processes. Thus, it may not be possible for a H/WQ model to consider all temporal variability and spatial heterogeneity. Therefore, the source of uncertainty will be the variability and heterogeneity of the nature, and the cause of uncertainty will be the incomplete knowledge and limited ability of the human (Figure 3.18). Consequently, if a modeler could incorporate all variability and heterogeneity into H/WQ modeling completely and accurately, there may be no uncertainty in the modeling results.
3.5.3 Comparison of Sensitivity and Uncertainty analysis

Sensitivity analysis is a procedure to examine how a model is organized (assembled or structured) with equations and parameters through mapping responses of the model against changes of parameters and input data. On the other hand, uncertainty analysis is an effort to figure out uncertainty contained in parameter, input data, and/or model structure and to evaluate its impact on the model output. Both are utilized to see how reliable a model is and how reasonable the modeling results are. Sometimes, they share similar techniques, so thus often the terms, sensitivity and uncertainty analysis, are used without discrimination. In addition, “uncertainty has been assessed by exploring the
sensitivity of predictions to parameter variations around some optimal model” (Beven, 2000a). Therefore, uncertainty analysis is often regarded as a special type of sensitivity analysis. In the literature, uncertainty analysis is frequently referred to as error propagation, error modeling, uncertainty modeling, geographical error analysis, determination of the reliability of the output, and analysis of uncertainty through sensitivity analysis. On the other hand, sensitivity analysis is often referred to as error analysis, quantification of the contribution made by different components to propagated error, geographical sensitivity analysis, and sensitivity analysis (Crosetto et al., 2001). However, they have different objectives and functions in H/WQ modeling.

Sensitivity analysis mainly focuses on testing how well a model represents the important hydrologic and water quality processes through checking the behavior of the model against changes in a parameter. On the other hand, uncertainty analysis examines how much uncertainty is contained in the model input and how it affects reliability as well as output of modeling. Thus, in order to see modeling uncertainty through uncertainty analysis, first we have to estimate or assume features of uncertainty in the modeling input like magnitude, variance, and distribution before implementing uncertainty analysis. In addition, in uncertainty analysis, observation is required to calculate probability that a model result is true.

In sensitivity analysis, the distribution of input data or parameter is often arbitrarily assumed uniform, while a variety of distributions could be assumed or quantified based on algorithms, observations, or professional judgment in uncertainty analysis (Figure 3.19). In addition, sensitivity analysis maps model output responses according to model input changes in the parameter space (Figure 3.19). Thus, values of contour lines on the maps represent values of model output. Therefore, it provides general description about characteristics of a model through examining modeling responses against change of modeling input. Saltelli et al. (2008) limited sensitivity analysis to work that identifies sources of prediction uncertainty (Foglia et al., 2009).

On the other hand, uncertainty analysis maps probability of finding the best parameter in the parameter space (Figure 3.19). In other words, uncertainty analysis is implemented with probabilistic basis while sensitivity analysis is not. Both sensitivity and
uncertainty analyses are case-dependent and model-dependent. It means that it is difficult to generalize results of the analyses conducted in a specific modeling practice.

![Figure 3.19. Comparison of sensitivity and uncertainty analysis.](image)

### 3.5.4 Uncertainty Components in H/WQ Modeling

In a H/WQ model, parameters and processes in its structure describe relationships between variables and between variable and input data. When model structure and input data are determined, usually parameters are adjusted to get the best fit of the model output to observation through calibration. At this point, a modeler usually assumes that input data and the measured data used in the calibration do not have any error. However, there is a certain amount of error and uncertainty. Subsequently, these uncertainties may affect parameters through calibration because parameters are determined empirically in order to relate input data, variables, and model structure that have been built, introduced, and developed at different scales and for unique purposes. In other words, the calibrated parameters will necessarily reflect the effects of errors in input, model structure, and the measured, and thus uncertainty of the estimated parameter is controlled by these other uncertainties. Therefore, the parameter uncertainty may come from three uncertainty sources: uncertainties in input data, the measured data for calibration, and model structure.
A quantitative investigation of uncertainty separately can reveal what portion of the overall modeling input and output uncertainty come from what kinds of components in H/WQ modeling, and consequently help to prioritize efforts to reduce uncertainty and improve reliability of modeling. For quantifying the contribution of individual uncertainty components to the overall modeling input and output uncertainty, it can be assumed that the overall modeling input and output uncertainty come from three uncertainty components such as input data, model structure, and the measured data. In this framework, parameter uncertainty becomes a surrogate that represents the overall modeling input uncertainty that consists of uncertainties of the three components. Then, the parameter space becomes the place where the uncertainties are presented with probability density functions. In addition, the overall input uncertainty is propagated and projected onto an output of interest through modeling, and then integration of the projected uncertainties will be the overall modeling output uncertainty. Therefore, individual output uncertainties partitioning the overall modeling output uncertainty also can be separated into proportions of the three components such as input data, model structure, and the measured data for calibration. Figure 3.20 describes this concept.

In Figure 3.20, uncertainty contained in the input data and measured data for calibration is propagated through the model structure into the parameter. Then, the integrated uncertainty of the input data, measurement, and model structure is projected on the parameter space by calibration. The projected uncertainty can be embodied and identified in form of the probability distribution of a parameter. Finally, the parameter uncertainty or the probability distributions that contain the integrated uncertainty is directly propagated into the modeling output when the model tries to predict. Therefore, parameter space is a place where uncertainty of input data, measured data, and model structure is presented and a parameter set is a media that contains the integrated uncertainty. Thus, parameter uncertainty is changed whenever input data, measurement for calibration, and model structure is varied.

It is usually assumed in routine H/WQ modeling that uncertainty does not exist in input data and the measured data or observation for calibration. In this case, the overall model input uncertainty or parameter uncertainty would consist of only model structure uncertainty so that parameter uncertainty will be equal to model structure uncertainty.
Model structure includes architecture of simulation and fundamental assumptions. Thus, the overall modeling output uncertainty solely comes from the model structure uncertainty in the case.

Calibration tries to find the optimum parameter set based on the given model structure, input data, and the measured data. It means that the calibrated parameter values may not necessarily represent their intended or designated conceptual or physical meanings. Refsgaard (1997) pointed out that a parameter can lose some of its direct physical interpretation through calibration because possible errors in an estimated
parameter have been compensated with effects of other processes and their interactions. Once calibration is done, there is nothing for parameters to do in order to improve accuracy of the modeling. If one chooses a set of parameter that does not provide the best fit to the measured data, proportions of the three components participating in production of the overall modeling output error may be changed, and amount of the error can be greater than that at the optimum case.

### 3.5.5 Uncertainty of Parameters

SCEM-UA is known as one of the most efficient and robust algorithm (Vrugt et al., 2003c; Feyen et al., 2007), thus it was selected as a tool to assess uncertainty in every parameter and the influence on the outputs of interest in this study. For assessing the uncertainty using the SCEM-UA method, feasible ranges of parameters used in the model will be specified first. For example, the feasible ranges of curve number (CN) for forest and Manning’s roughness coefficient (n) for natural stream can be found as 25 to 83 and 0.020 to 0.080 respectively based on literature. The SCEM-UA algorithm provides estimates of posterior probability distribution or probability density function (PDF) of a parameter as well as PDFs of the outputs of interest. The detailed procedures of SCEM-UA are described below and summarized in Figure 3.21.

For instance, if the first 100 parameter sets of the 1000 are discarded for ensuring a stationary Markov Chain distribution, the other 900 sets will be used to describe the posterior distributions of the parameters. Then, a distribution of the output of interest can be obtained from the model simulations using the selected 900 parameter sets. In addition, the 900 realizations of the model output will be used to analyze their statistical characteristics so that confidence intervals for the output such as 95% upper and lower limits can be calculated. The posterior distributions of the parameters will be examined to assess their uncertainties. A parameter that contains relatively high uncertainties or wide variances can be identified for further tuning of the model such as narrowing feasible ranges and finding better prior distribution of the parameters.
3.5.6 Uncertainty of GIS Input Data

3.5.6.1 Overview

H/WQ modeling requires data about topography, land use and cover, and soil features. Nowadays, the data are publicly available in forms of DEM, classified remotely sensed scene, and digitized maps. The developer and/or distributor usually provide accuracy and error statistics of the data in a certain form such as RMSE, error matrix, and scale used to digitize. Although the amount of information about error is limited, and thus often not sufficient to have a clear and detailed picture of its spatial characteristics, the information contains some clues about the most critical error type of the geographic data. For instance, DEM and land cover layer usually provide information for vertical error and classification error. In addition, soil data like SSURGO provide scale used in digitizing.
Amount of input data is a function of spatial and temporal coverage of a H/WQ model application even though the quality is model and case-independent. In addition, input data contains various errors in their measurement, boundary, classification, and attribute. Thus, uncertainty of input data may positively correlate to its amount and depend on spatial and temporal coverage of the modeling application. Uncertainty of input data is propagated through a model so that contribution of the uncertainty to the overall output uncertainty may depend on characteristics of the model. HYSTAR employs three GIS layers as input data: DEM, NLCD, and SSURGO. Of them, in this study, impact of uncertainty in the DEM and NLCD input data layers on modeling output was examined through sensitivity analysis. As mentioned earlier, vertical measurement error and classification error were assumed as a major uncertainty source of DEM and NLCD respectively.

In simulating errors in DEM and NLCD, spatial autocorrelation should be considered to make the realizations reasonable in geographic and hydrologic terms. Some techniques were invented to generate autocorrelated error using information about spatial distribution of data and/or the reported error statistics. Once the sufficient number of realizations for the spatial data is obtained using the techniques, the output will be simulated with the realization. Then, variance of the output of H/WQ modeling will be investigated to evaluate impact of the errors on the model output, and the variance and distribution of the modeling output of interest will be interpreted as uncertainty caused by error contained in the input DEM.

As mentioned earlier, the overall modeling output uncertainty caused by the GIS input data is investigated by sensitivity analysis. It means the model parameters are not calibrated in the uncertainty assessment. If they are not calibrated, a model may not exhibit its best performance, and thus quality of the input data may not be assessed reasonably in terms of modeling accuracy and uncertainty. However, it will be difficult and very laborious to calibrate parameters whenever a new realization of the GIS layers is applied to the modeling. In this study, therefore, only impact of simulated GIS error on the output value of a modeling was examined through sensitivity analysis.
3.5.6.2 DEM Error Simulation

Sequential Gaussian simulation (SGS) was utilized to simulate spatially correlated errors and produce multiple realizations of DEM in this study. The steps of the SGS algorithm are described below (Goovaerts, 1997).

1. Check the appropriateness of the Gaussian random field model, which may call for a prior transform of the original data into z-data with a standard normal cumulative density function (CDF) using the normal score transform.

2. Define a random path to visit every cell in a grid once.

3. At each cell, determine the parameters of the Gaussian conditional cumulative density function (CCDF) such as mean and variance using simple kriging with the normal score semivariogram model. Here, the conditioning information that defines the Gaussian CCDF consists of a specified number of both normal score data and values simulated at previously visited grid nodes.

4. Draw a simulated value from the Gaussian CCDF, and add it to the data set, and proceed to the next cell along the random path, and repeat from Step 3 to 4 until all cells are simulated.

5. Finally, transform the simulated normal scores into simulated values for the original variable, which amounts to applying the inverse of the normal score transforms to the simulated z-data.

In this study, elevation errors were simulated for the randomly selected cells, and their total area corresponded to 30% of the watershed, ORD. In other words, 70% of elevation data was assumed as correct, and then used as training data set. Once the disturbed DEMs were simulated, sinks in the DEM were removed through a filling process to make the DEM correct in a hydrologic sense. Then, runoff and sediment load hydrographs were simulated with the sink removed disturbed DEMs, and their variations were investigated to see sensitivity of the hydrographs against the DEM error.
3.5.6.3 Land Use and Cover Data Error Simulation

Sequential Indicator Simulation (SIS) was utilized to simulate spatially correlated errors and produce multiple realizations of NLCD in this study. The steps of the SIS algorithm are described below (Goovaerts, 1997).

1. Transform each land use categorical datum into a vector of $K$ hard indicator data. If a land use is equal to a specific category, its code is converted into one for every category; otherwise, zero.

2. Define a random path visiting each cell in a grid once.

3. Determine the conditional probability of occurrence of each land use categories using simple or ordinary indicator kriging. Here, the conditioning information that defines the conditional probability consists of transformed indicators of neighboring original data and previously simulated values.

4. Correct the probabilities for order relation deviations.

5. Define any ordering of the $K$ categories and build a cumulative density function by adding the corresponding probabilities of occurrences.

6. Draw a random number uniformly distributed between 0 and 1, and the simulated category at a specific location is the one that corresponds to the probability interval that includes the random number.

7. Add the simulated value to the conditioning data set.

8. Proceed to the next cell along the random path, and repeat steps 3 to 7.

In this study, classification errors were simulated for the randomly selected cells, and their total area corresponded to 50% of the watershed, ORD. In the case of that multiple different land cover classes were simulated for a cell, a class that possessed higher probability was assigned to the cell. Then, the area where land cover class was altered decreased to about 30%. The disturbed NLCDs with the errors were applied to hydrology and sediment transport simulations to see impact of the error on runoff and sediment load hydrographs.
4. RESULTS

4.1 Sensitivity Analysis

Sensitivity of some important equations and methods used in HYSTAR to their parameters and HYSTAR modeling output against the parameters (Table 3.2) were investigated to see how HYSTAR is organized with equations and parameters and which parameters are the most critical to hydrology and sediment transport simulation. The important equations and methods include the CN runoff equation, the Manning’s equation, Van Genuchten equation, the equation for estimating soil particle size distribution, and the equations for calculating sediment transport capacity. Response of model outputs - peak runoff, runoff volume, time to peak, and sediment load - to changes in parameter values was investigated using two different approaches: OAT (One at-a-time) and AAT (All at-a-time). OAT showed how much and which direction change in the model output occurred to a unit change of the parameter of interest. On the other hand, AAT shows the integrated impact of changes in parameters on the model output through considering interaction between parameters and the possible maximum output of the modeling output. The AAT and OAT sensitivity analyses were implemented for the Owl Run watershed, ORD.

4.1.1 Sensitivity Analysis for Some Equations used in HYSTAR

4.1.1.1 Sensitivity of Excess Rainfall to CN

Sensitivity of excess rainfall volume to rainfall volume was investigated with different CN. As seen in Figure 4.1, excess rainfall volume increased almost linearly as rainfall volume increased. However, as CN and rainfall volume decreased, the relationship between the rainfall and excess rainfall volume became nonlinear and its slope became shallower. It indicates that excess rainfall volume depends relatively highly on the retention parameter (S, soil capacity of storing water) than on rainfall volume (P), when CN is low in Equation 2.55. On the other hand, when rainfall volume is extremely large (i.e. over 254 mm), excess rainfall volume becomes proportional to rainfall volume.
regardless of CN because soil capacity of storing infiltrated water volume must be filled first and quickly especially for a high CN.

Figure 4.1. Relationship between excess rainfall and rainfall volume for different CNs.

Sensitivity of excess rainfall volume to CN was also examined. As seen in Figure 4.2, when rainfall volume was less than 254 mm, which means the theoretical maximum retention volume of soil (Beven, 2001), the relationship between CN and excess rainfall volume was in a concave-shape. However, it was in a convex-shape when rainfall volume was over 254 mm. It means that excess rainfall is more sensitive to larger CN when rainfall volume is less than 254 mm. On the other hand, it is less sensitive to larger CN when rainfall volume is greater than 254 mm. Rainfall volume for an event is usually less than 254 mm except for extreme events, thus the relationship between CN and excess rainfall volume has been regarded as a concave-shaped nonlinear function. From this concave-shaped relationship, it can be reasonably expected that a hydrology modeling using a distributed CN value will provide more excess rainfall volume than does using an area-weighted average CN when the same amount of rainfall is applied.
4.1.1.2 Sensitivity of Excess Rainfall to Temporal Distribution of Rainfall

Unique temporal pattern of rainfall may result in different excess rainfall volume in the CN method. When the CN method is used to calculate hourly excess rainfall volume for a storm event, cumulative rainfall volume is employed to consider reduction in infiltration rate as time goes. In this case, a delayed rainfall pattern may produce higher peak excess rainfall than does an advanced pattern because rainfall volume in low intensity at the beginning of the storm event will fill the soil capacity, and then the delayed intensive rainfall volume will contribute to generating excess rainfall. Thus, change in the temporal pattern of excess rainfall volume against the four SCS rainfall types was investigated using a 24-hour storm event of 100 mm. The SCS rainfall types are shown in Figure 4.3 and the calculated excess rainfall by the CN method is presented in Figure 4.4.
Figure 4.3. Temporal distributions of the SCS rainfall types.

Figure 4.4. Temporal distributions of the calculated excess rainfall using different curve numbers in the SCS rainfall types.

In Figure 4.4, the most advanced rainfall pattern, Type 1-A, produced the smallest peak excess rainfall consistently. On the other hand, the Type 2 rainfall pattern that has a
delayed and relatively high peak rainfall produced the highest peak excess rainfall for all the CN values used. The Type 3 pattern that has the most delayed but lower peak rainfall comparing to that of the Type 2 produced the highest peak excess rainfall when CN is 65. In particular, The Type 1 and Type 3 patterns had similar peak rainfall but different time to peak (Figure 4.3), but the Type 3 produced much higher peak excess rainfall than did the Type 1 (Figure 4.4). Thus, this sensitivity analysis shows that the temporal pattern of rainfall volume may significantly affect that of excess rainfall volume. In the CN method, the total excess rainfall volume is not affected by the temporal pattern of rainfall volume. However, unique temporal distributions of rainfall volume may result in different total direct runoff volume in a distributed overland routing because of their different time to peak rainfall as well as peak rainfall volume.

4.1.1.3 Sensitivity of CN to Soil Moisture

In order to facilitate variation in CN as a function of change in soil moisture for continuous modeling, several equations were adapted from SWAT (2.5.3). Once a CN is determined at the AMCII condition based on the land cover and hydraulic soil feature, the set of the equations allows CN to vary within a range predetermined based on soil texture and water content. Although the SWAT model has been used popularly and a lot of literature has been published, few studies investigated sensitivity and validity of the equations. In this study, thus, response of CN to soil moisture and texture was examined and is presented in Figures 4.5 and 4.6.

As seen in Figure 4.5, CNs for sandy soils (sand, sandy loam, and loamy sand) quickly approaches to a CN of 99 as soil gets wetter. On the other hand, CNs for soil (loam, silt loam, and sandy clay loam) is not sensitive to soil water content (percentage of total soil water content to porosity) lower than 60, but CNs quickly increase when soil water content is greater than 60. For clay soils (clay loam, silty clay loam, sandy clay, silty clay, and clay), CNs are not responsive to change in soil moisture.
Figure 4.5a. Sensitivity of curve number to soil water content in sand.

Figure 4.5b. Sensitivity of curve number to soil water content in loamy sand.
Figure 4.5c. Sensitivity of curve number to soil water content in sandy loam.

Figure 4.5d. Sensitivity of curve number to soil water content in loam.
Figure 4.5e. Sensitivity of curve number to soil water content in silt loam.

Figure 4.5f. Sensitivity of curve number to soil water content in sandy clay loam.
Figure 4.5g. Sensitivity of curve number to soil water content in clay loam.

Figure 4.5h. Sensitivity of curve number to soil water content in silty clay loam.
Figure 4.5i. Sensitivity of curve number to soil water content in sandy clay.

Figure 4.5j. Sensitivity of curve number to soil water content in silty clay.
As seen in Figure 4.6, CNs for the soils vary from their minima to maxima determined at dry and wet soil conditions respectively, and patterns of the changes depend on soil texture. For instance, although the CN of 65 at the AMC II condition was determined for sandy loam, it may vary from 46 to 97 according to soil moisture content at the beginning of a storm event. On the other hand, the same CN determined at the same AMC condition for clay loam may vary from 46 to 67. This approach allows the CN method to be utilized in a continuous modeling approach.
Figure 4.6a. Sensitivity of curve number to soil water content for different soil texture when the curve number is 35 at AMC II condition.

Figure 4.6b. Sensitivity of curve number to soil water content for different soil texture when the curve number is 50 at AMC II condition.
Figure 4.6c. Sensitivity of curve number to soil water content for different soil texture when the curve number is 65 at AMC II condition.

Figure 4.6d. Sensitivity of curve number to soil water content for different soil texture when the curve number is 80 at AMC II condition.
4.1.1.4 Sensitivity of Flow Velocity to Manning’s Equation Parameters

In a time-area method, travel time calculation of runoff may be the most critical component in deriving time-area histogram. In HYSTAR, the Manning’s equation was utilized in calculating runoff velocity and rate when runoff volume, topography, land cover, and channel geometry are given. Thus, sensitivity of runoff velocity to Manning’s roughness coefficient, slope, and channel width and depth was evaluated. The results (Table 4.1) show that runoff velocity is most sensitive to the Manning’s roughness coefficient (Manning’s n) and least sensitive to the channel width. Therefore, the roughness coefficient should be selected with care, but it can be expected that the assumptions about channel width for the two study watersheds will not affect the simulation results significantly.
Table 4.1. Sensitivity of runoff velocity to the Manning’s equation parameters.

<table>
<thead>
<tr>
<th>Man. n</th>
<th>Slope</th>
<th>Width (m)</th>
<th>Depth (m)</th>
<th>Velocity (m/s)</th>
<th>Differences in Man. n</th>
<th>Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.020</td>
<td>0.01</td>
<td>2.0</td>
<td>0.10</td>
<td>1.01</td>
<td>-0.202</td>
<td>-40.44</td>
</tr>
<tr>
<td>0.025</td>
<td>0.01</td>
<td>2.0</td>
<td>0.10</td>
<td>0.809</td>
<td>0.01</td>
<td>-0.135</td>
</tr>
<tr>
<td>0.030</td>
<td>0.01</td>
<td>2.0</td>
<td>0.10</td>
<td>0.674</td>
<td>0.01</td>
<td>-0.096</td>
</tr>
<tr>
<td>0.035</td>
<td>0.01</td>
<td>2.0</td>
<td>0.10</td>
<td>0.578</td>
<td>0.01</td>
<td>-19.26</td>
</tr>
<tr>
<td>0.040</td>
<td>0.01</td>
<td>2.0</td>
<td>0.10</td>
<td>0.505</td>
<td>0.01</td>
<td>-14.44</td>
</tr>
</tbody>
</table>

| 0.030  | 0.01  | 2.0       | 0.10      | 0.674          | Slope                |
|--------|-------|-----------|-----------|----------------|----------------------|----------|
| 0.030  | 0.02  | 2.0       | 0.10      | 0.953          | 0.01                 | 0.279    |
| 0.030  | 0.03  | 2.0       | 0.10      | 1.167          | 0.01                 | 0.214    |
| 0.030  | 0.04  | 2.0       | 0.10      | 1.348          | 0.01                 | 0.181    |
| 0.030  | 0.05  | 2.0       | 0.10      | 1.507          | 0.01                 | 0.159    |
| 0.030  | 0.01  | 0.5       | 0.10      | 0.574          | Width                |
| 0.030  | 0.01  | 1.0       | 0.10      | 0.636          | 0.50                 | 0.062    |
| 0.030  | 0.01  | 1.5       | 0.10      | 0.661          | 0.50                 | 0.025    |
| 0.030  | 0.01  | 2.0       | 0.10      | 0.674          | 0.50                 | 0.013    |
| 0.030  | 0.01  | 2.5       | 0.10      | 0.682          | 0.50                 | 0.008    |
| 0.030  | 0.01  | 2.0       | 0.05      | 0.438          | Depth                |
| 0.030  | 0.01  | 2.0       | 0.10      | 0.674          | 0.05                 | 0.236    |
| 0.030  | 0.01  | 2.0       | 0.15      | 0.857          | 0.05                 | 0.183    |
| 0.030  | 0.01  | 2.0       | 0.20      | 1.010          | 0.05                 | 0.152    |
| 0.030  | 0.01  | 2.0       | 0.25      | 1.140          | 0.05                 | 0.130    |

4.1.1.5 Sensitivity of Unsaturated Hydraulic Conductivity Ratio to the Coefficients and Soil Water Content in the Van Genuchten equation

In HYSTAR, percolation rate is calculated using the Van Genuchten equation. The equation employs two parameters, GCL and GCM, to estimate unsaturated hydraulic conductivity with consideration of soil moisture. Responses of the unsaturated hydraulic conductivity to change in the parameters were examined to indentify the significance of these parameters in estimating unsaturated hydraulic conductivity in the Van Genuchten equation. This evaluation was based on a silt loam soil with the following assumptions about soil characteristics: residual water content of 1.5 %, saturated water content (porosity) of 50.1 %, soil moisture content of 26 %, and soil water saturation of 50.4 %.
As seen in Figure 4.7, as GCM increases and GCL decreases, the ratio of unsaturated hydraulic conductivity to saturated hydraulic conductivity increases, and impact of GCM is much more significant than that of GCL. Thus, more care should be paid in determining GCM than GCL. Figure 4.8 shows sensitivity of the ratio against soil moisture content when the parameters are fixed to 0.50 respectively. As seen in the figure, unsaturated hydraulic conductivity is close to zero while soil moisture content is less than 40 % of the porosity, but it increases exponentially as soil moisture increases over 40 %. In the case of the Owl Run ORD sub-watershed, the average porosity is estimated as 47.4 % thus unsaturated hydraulic conductivity would be close to zero when soil moisture content is less than about 19 %.

![Figure 4.7. Sensitivity of the unsaturated / saturated hydraulic conductivity ratio to coefficients in the van Genuchten equation (L = GCL, M = GCM).](image_url)
4.1.1.6 Sensitivity of Soil Particle Distribution and Characteristic Soil Particle Size to Soil Texture

The empirical equation that Skaggs et al. (2001) proposed was utilized in estimating the cumulative particle size distribution of soil particles based on soil texture. The shear Reynolds number that controls a critical Shield parameter (Equation 3.45) is a function of the characteristic diameter (i.e. D50 or R50) of soil particle (Equation 3.67). Thus, sensitivity of the characteristic radius to soil texture was investigated and represented in Table 4.2 and Figure 4.9. The analysis showed that sandy loam had the widest characteristic radius range but silt has the narrowest. In the case of R50, sand and silt had the largest and smallest soil particle radius respectively. In addition, the cumulative mass fraction distributions of soil particle were distributed between those of sand and silt in an S shaped curve except for that of silt.
Table 4.2. Characteristic soil particle sizes for different soil texture in the empirical equation proposed by Skaggs et al. (2001).

<table>
<thead>
<tr>
<th>Characteristic Radius</th>
<th>Loam</th>
<th>Sand</th>
<th>Loamy Sand</th>
<th>Clay Loam</th>
<th>Sandy Loam</th>
<th>Sandy Clay Loam</th>
<th>Silt Loam</th>
<th>Silt</th>
</tr>
</thead>
<tbody>
<tr>
<td>R30</td>
<td>2</td>
<td>70</td>
<td>34</td>
<td>1</td>
<td>10</td>
<td>12</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>R40</td>
<td>9</td>
<td>86</td>
<td>41</td>
<td>1</td>
<td>20</td>
<td>22</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>R50</td>
<td>19</td>
<td>101</td>
<td>48</td>
<td>6</td>
<td>32</td>
<td>30</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>R90</td>
<td>127</td>
<td>187</td>
<td>87</td>
<td>44</td>
<td>182</td>
<td>67</td>
<td>43</td>
<td>13</td>
</tr>
</tbody>
</table>

Unit: µm; Rxx: radius of soil particles that by mass passes a sieve mesh with an opening equal to xx µm

Figure 4.9. Cumulative soil particle size distributions for different soil texture in the empirical equation proposed by Skaggs et al. (2001).

4.1.1.7 Sensitivity of Sediment Transport to Slope, Runoff, and Soil Type

For sediment transport simulation, eight equations used to calculate sediment transport capacity were investigated to identify the most appropriate one for HYSTAR based on the development environment surveyed from the original literature (Table 3.3) and sensitivity to slope, flow, and soil texture. For this sensitivity analysis, the Manning’s roughness coefficient and channel width were set to 0.03 and 30 m respectively. In
addition, characteristic soil particle sizes for D50 were assumed as 0.75, 0.05, and 0.002 mm for sand, silt, and clay respectively. The analysis showed that sediment transport capacity is most sensitive to slope and the least response to the soil particle size (Figure 4.10 and Table 4.3). Therefore, it can be reasonably expected that rough estimation of the characteristic soil particle size using the empirical equation of Skaggs et al. (2001) might not significantly affect accuracy of the sediment transport capacity calculation.

In Table 4.3, the Rickenmann, Bagnold, and Abrahams equations produced the greatest sediment transport capacity, while the Govers equation provided the smallest due to consideration of the theoretical maximum transport capacity of 1250 g/l. A maximum of 2500 g/l is applied in the Schoklitsch equation. On the other hand, the Yalin equation results in a lower sediment transport capacity without a specified maximum capacity. As seen in Figure 4.10, all the equations showed similar sensitivity to slope. However, the different intercepts in the figures indicate that they will provide different sediment transport capacity for the same soil.

Figure 4.10a. Sensitivity of transport capacity to slope in the equations in clay.
Figure 4.10b. Sensitivity of transport capacity to slope in the equations in silt.

Figure 4.10c. Sensitivity of transport capacity to slope in the equations in sand

Figure 4.10. Sensitivity of transport capacity to slope in the equations.
Table 4.3. Sensitivity of the transport capacity to soil texture, flow, and slope for several sediment transport equations.

<table>
<thead>
<tr>
<th>Soil</th>
<th>Clay Flow (cms)</th>
<th>0.01</th>
<th>1</th>
<th>100</th>
<th>0.01</th>
<th>1</th>
<th>100</th>
<th>0.01</th>
<th>1</th>
<th>100</th>
<th>0.01</th>
<th>1</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Equation</td>
<td>Slope</td>
<td>Transport Capacity (g/l)</td>
<td>0.0001</td>
<td>0.001</td>
<td>0.01</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
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</tr>
<tr>
<td></td>
<td>Govers</td>
<td></td>
<td>0.0001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.01</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>Abrahams (Overland)</td>
<td>0.0001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.01</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
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<td>0.1</td>
</tr>
<tr>
<td></td>
<td>Abrahams (Channel)</td>
<td>0.0001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.01</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
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<td>0.1</td>
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</tr>
<tr>
<td></td>
<td>Low</td>
<td>0.0001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.01</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
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<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>Rickenmann</td>
<td>0.0001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.01</td>
<td>0.1</td>
<td>0.1</td>
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<td>0.1</td>
</tr>
<tr>
<td></td>
<td>Yalin</td>
<td>0.0001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.01</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
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<td>0.1</td>
<td>0.1</td>
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</tr>
<tr>
<td></td>
<td>Bagnold</td>
<td>0.0001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.01</td>
<td>0.1</td>
<td>0.1</td>
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<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>Schoklitsch</td>
<td>0.0001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.01</td>
<td>0.1</td>
<td>0.1</td>
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<td>0.1</td>
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<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

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4.1.2 Sensitivity of Hydrology Simulation

4.1.2.1 Sensitivity of Direct Runoff

Sensitivity of direct runoff simulation of HYSTAR to the 10 parameters (CNF, MNO, MNC, THA, GCL, GCM, BCC, EFS, RZD, and SAR) was analyzed through a Monte Carlo simulation using Latin Hypercube sampling technique. Change in characteristics of the simulated direct runoff hydrographs, such as peak direct runoff, total direct runoff volume, and time to peak direct runoff, was investigated while values of a parameter were being varied. The four consecutive storms that occurred between 2 and 10 Sep 1992 in ORD (a subwatershed of the Owl Run watershed) were used in the analysis. Parameter value sets of 100 for each parameter were randomly sampled within their own ranges predetermined based on consideration of their physical meanings and literature (Table 4.4 and Figure 4.11). While values of a parameter were sampled, values of the other parameters were set to their calibrated values (4.2.2.1). Thus, total 1000 parameter sets were evaluated with the model, and then change in the characteristics of direct runoff hydrographs were investigated.

In addition, sensitivity of the direct hydrographs was examined separately for different storms because they have unique contribution of direct runoff to total runoff hydrograph, initial soil moisture condition, and temporal rainfall pattern. Therefore, it was expected to see unique sensitivity of the direct runoff hydrographs to the parameters for different storms. Statistics of the sampled parameter values for the sensitivity analysis are provided in Table 4.4 and Figure 4.11, and sensitivity analysis results are presented in Tables 4.5 to 4.7 and Figures 4.12 and 4.13. Sensitivity was examined qualitatively by plotting output values for each unique set of parameters and quantitatively using statistical measures such as IQR, standard deviation (Stdev), and coefficient of variation (CV) of the output.
Table 4.4. Statistics of the sampled parameters values for the Monte Carlo analysis (Hydrology simulation).

<table>
<thead>
<tr>
<th>Stat.</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>50.46</td>
<td>0.50</td>
<td>0.50</td>
<td>1.00</td>
<td>1.00</td>
<td>1.04</td>
<td>1.06</td>
</tr>
<tr>
<td>Q1</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>25.93</td>
<td>0.37</td>
<td>0.38</td>
<td>0.75</td>
<td>0.75</td>
<td>0.58</td>
<td>0.58</td>
</tr>
<tr>
<td>MIN</td>
<td>0.51</td>
<td>0.51</td>
<td>0.51</td>
<td>1.56</td>
<td>0.25</td>
<td>0.25</td>
<td>0.50</td>
<td>0.50</td>
<td>0.12</td>
<td>0.11</td>
</tr>
<tr>
<td>MAX</td>
<td>1.50</td>
<td>1.49</td>
<td>1.49</td>
<td>99.80</td>
<td>0.75</td>
<td>0.75</td>
<td>1.49</td>
<td>1.50</td>
<td>1.99</td>
<td>1.99</td>
</tr>
<tr>
<td>Q3</td>
<td>1.24</td>
<td>1.25</td>
<td>1.25</td>
<td>74.72</td>
<td>0.62</td>
<td>0.62</td>
<td>1.25</td>
<td>1.25</td>
<td>1.53</td>
<td>1.52</td>
</tr>
<tr>
<td>MEAN</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>50.49</td>
<td>0.50</td>
<td>0.50</td>
<td>1.00</td>
<td>1.00</td>
<td>1.05</td>
<td>1.05</td>
</tr>
<tr>
<td>Stdev</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>28.73</td>
<td>0.15</td>
<td>0.15</td>
<td>0.29</td>
<td>0.29</td>
<td>0.55</td>
<td>0.55</td>
</tr>
<tr>
<td>CV</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.57</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.52</td>
<td>0.52</td>
</tr>
</tbody>
</table>

Figure 4.11. Box-Whisker diagram for the statistics of the sample parameter values by the Monte Carlo sampling technique.
Figure 4.12a. Sensitivity of peak direct runoff and time to peak direct runoff to CNF.

Figure 4.12b. Sensitivity of direct runoff volume to CNF.
Figure 4.12c. Sensitivity of peak direct runoff and time to peak direct runoff to MNO.

Figure 4.12d. Sensitivity of direct runoff volume to MNO.
Figure 4.12e. Sensitivity of peak direct runoff and time to peak direct runoff to MNC.

Figure 4.12f. Sensitivity of direct runoff volume to MNC.
Figure 4.12g. Sensitivity of peak direct runoff and time to peak direct runoff to THA.

Figure 4.12h. Sensitivity of direct runoff volume to THA.
Figure 4.12i. Sensitivity of peak direct runoff and time to peak direct runoff to GCL.

Figure 4.12j. Sensitivity of direct runoff volume to GCL.
Figure 4.12k. Sensitivity of peak direct runoff and time to peak direct runoff to GCM.

Figure 4.12l. Sensitivity of direct runoff volume to GCM.
Figure 4.12m. Sensitivity of peak direct runoff and time to peak direct runoff to BCC.

Figure 4.12n. Sensitivity of direct runoff volume to BCC.
Figure 4.12o. Sensitivity of peak direct runoff and time to peak direct runoff to EFS.

Figure 4.12p. Sensitivity of direct runoff volume to EFS.
Figure 4.12q. Sensitivity of peak direct runoff and time to peak direct runoff to RZD.

Figure 4.12r. Sensitivity of direct runoff volume to RZD.
Figure 4.12s. Sensitivity of peak direct runoff and time to peak direct runoff to SAR.

Figure 4.12t. Sensitivity of direct runoff volume to SAR.

Figure 4.12. Sensitivity of runoff hydrograph to the parameters for storm events occurred on 2, 5, 8, and 10 Sep 1992 in Owl Run subwatershed D.
Variation in the characteristics of the direct runoff hydrograph developed using the 100 unique parameter value sets are plotted for each parameter in Figures 4.12. At the watershed outlet, direct runoff was generated when CNF is around 1.0 and 1.1 for the first and third storm events respectively (Figures 4.12a and 4.12b). It means that higher curve numbers are required to generate direct runoff in the third storm event than the first. Because evapotranspiration and percolation occurred between the two storm events would lower soil water content in the root zone depth, the soil moisture condition became drier at the beginning of the third storm event than the first in spite of soil moisture recharge by the second event.

Peak direct runoff occasionally dropped due to routing, whereas direct runoff volume rose monotonically as curve number increased (Figures 4.12a and 4.12b). Increased direct runoff volume in a certain area within the watershed might allow the direct runoff volume generated along its flow path to reach the outlet more quickly by increasing overall velocity of the direct runoff volume, thus the peak of the hydrograph will be flattened. In other words, sometimes the increased direct runoff volume can more evenly distribute contribution of this direct runoff volume generated along its flow path to a hydrograph at the outlet. In addition, in Figure 4.12b, as curve number increases, direct runoff volume passing the outlet increases in an S-shape contrary to the sensitivity analysis results (Figure 4.2) provided in 4.1.1.1 because the maximum curve number of 99 was set. Thus, as CNF got greater than even 1.5, the curve numbers of the watershed did not exceed the maximum.

When no direct runoff was generated at the outlet, time to peak direct runoff was assigned to one. However, when direct runoff volume was just created at the CNF of around 1.0 to 1.1, the time to peak direct runoff was maximized (Figure 4.12a). Then, as CNF increased from the threshold values, time to peak direct runoff decreased rapidly and converged into the minima of 5 to 7. In the Manning’s equation for calculating channel flow velocity, when flow width of a rectangular channel is fixed, flow depth becomes proportional to direct runoff volume, but channel flow velocity increases logarithmically as flow depth increases. Then, decrease in time to peak direct runoff is limited by the channel flow velocity because travel time is inversely proportional to flow velocity.
In Figure 4.12c, as MNO increased, peak direct runoff decreased slightly overall except in the third event that did not produce any direct runoff at the outlet. Time to peak direct runoff of the first and the fourth events also was not responsive to change in MNO.

In Figure 4.12d, direct runoff volume was just waved as MNO increased. On the other hand, in Figure 4.12e, as MNC increased, peak direct runoff of the first event decreased, but that of the fourth increased slightly overall with fluctuation. The fluctuation in peak direct runoff found in Figure 4.12c and 4.12e can be explained by the merge of two hydrographs oriented from two branches of a channel at a junction. For example, sometimes a certain Manning’s roughness coefficient for channel might allow hydrographs that had a similar time to peak direct runoff to be merged at a junction. Then, peak direct runoff could be higher even when the roughness coefficient increased.

In addition, the slight overall increase in the peak runoff of the fourth event (Figure 4.12e) can be explained by increased soil water content. A higher Manning’s roughness coefficient may result in greater infiltration and subsequent wetter soil water content for the following storm event. Direct runoff volume also increased slightly overall as MNC increased because its tail became thicker (Figure 4.12f). In the CN method, more rainfall contributes to excess rainfall at the end of a storm event than at the beginning. Thus, the delayed direct runoff might contribute to thickening tail of the direct runoff hydrograph. Finally, the abrupt change in time to peak direct runoff of the second event found in Figure 4.12c and 4.12e) is caused by shift of the maximum time to peak direct runoff over two peaks of its hydrograph (Figure 4.45).

Sensitivity of the hydrograph to THA looks more dynamic and complicated than the sensitivity to other parameters. In Figure 4.12g, peak runoff rapidly dropped as THA increased up to about 30 ha then became rather constant until THA reached to about 80 ha. Generally, as THA gets smaller, more areas will contribute to direct runoff hydrograph quickly at the outlet, so thus peak runoff may increase and time to peak direct runoff may decrease. In addition, when THA is small, channel networks get denser. Thus, when THA was less than 30 ha, the direct runoff hydrograph was mainly controlled by channel hydraulics. In addition, time to peak direct runoff was barely changed and rather constant because a constant Manning coefficient of 0.03, which is much smaller than that of the overland, was assigned to the flow network regardless of vegetation cover.
On the other hand, when THA is greater than 80 ha (about 25% of the watershed area), overland hydraulics may dominate the direct runoff hydrograph. Thus, time to peak direct runoff decreased rapidly due to large roughness coefficient and subsequent slow velocity of overland runoff. Abrupt rises of peak runoff near THA of 80 to 90 ha might be caused by merging of hydrographs that had higher parts in a similar time at a junction. Between THAs of 30 and 80 ha, overland and channel hydraulic looked balanced in control of peak direct runoff and time to peak direct runoff. In Figure 4.128), runoff volume fluctuated when THA was less than about 30 ha, and then became stable until THA reached 70 ha. When THA was over 80 ha, runoff volume increased with fluctuation.

No characteristics of hydrograph were significantly sensitive to GCL (Figure 4.12i). Only peak direct runoff and direct runoff volume of the fourth event slightly increased with wave as GCL increased (Figure 4.12j). Therefore, GCL can be regarded as an superfluous parameter for short-term direct runoff hydrology simulation of HYSTAR, and then it can be skipped to reduce the number of parameters to be calibrated. On the other hand, as GCM increased, peak direct runoff and direct runoff volume of the fourth event were decreased largely (Figures 4.12k and 4.12l). GCM is one of the coefficients in the van Genuchten equation that describes a ratio of unsaturated hydraulic conductivity to saturated hydraulic conductivity based on soil water content. A bigger GCM will produce higher unsaturated hydraulic conductivity and subsequently greater percolation volume, which is one of the soil water losses from the soil root zone. Thus, impact of change in GCM would be greater on direct runoff hydrograph generated by a following storm event that allows longer time for percolation to occur.

An abrupt change in time to peak direct runoff of the second event was observed as GCM varied from 0.52 to 0.53 (Figure 4.12k). The second storm event produced a hydrograph that had distinguished two runoff peaks, and the later peak became higher than the earlier as GCM increased. A similar pattern was found in Figures 4.12c and 4.12e. As seen in Figures 4.12i to 4.12l, any change in direct runoff hydrographs for the first event was not observed because it is not affected by change in the parameters for soil moisture simulation. In addition, the third event did not produce any direct runoff for any
combination of the parameters in the entire simulation when CNF is fixed to its calibrated value.

The sensitivity of direct runoff against BCC is similar to that for GCM (Figures 4.12m and 4.12n. As BCC increased, peak runoff and runoff volume decreased but time to peak direct runoff increased because a greater crop coefficient will remove more soil water from the root zone making the soil drier. In addition, the direct runoff hydrograph generated by a following rainfall event may be more affected by change in BCC because it may allow more time for evapotranspiration. On the other hand, as EFS increased, peak runoff and runoff volume increased but time to peak direct runoff decreased (Figures 4.12o and 4.12p). However, when EFS went over about 1.05, they became constant because the maximum ‘kfc’, fraction of cover area covered by vegetation, for all the land cover classes was set to 1. Thus, when EFS was greater than 1.05, all the ‘kfc’ values reached the maximum of 1. The runoff hydrograph of the second storm event has two peaks. Then, the abrupt changes in time to peak direct runoff for the second event were caused by movement of the highest direct runoff over the two peaks.

RZD describes a ratio of the root zone depth, where soil water content actively responds to inflow and outflow of water, to the predefined soil zone depth of about 150 cm for the watershed from SSURGO. A larger RZD means thicker root zone depth, the RZD of 1 implies that the root zone depth is equal to the soil zone depth. Thus, it controls level of change in soil water content when water in the root zone is recharged by infiltration and discharged by evapotranspiration and percolation. For example, a soil with a small RZD will respond to the water fluxes more quickly and significantly than does one with a large RZD. Subsequently, a smaller RZD may produce higher temporal variation of soil water content in simulation than does a larger RZD.

As seen in Figures 4.12q and 4.12r, peak direct runoff and direct runoff volume reached their maxima when RZD was around 0.15. Then, they decreased exponentially as RZD became greater. Rates of evapotranspiration and percolation are a function of soil water content, and they become limited when the soil gets dry. On the other hand, infiltration rate is not directly determined by soil water content but curve number. However, curve number is determined based on soil water content, and low soil water
content will result in less excess rainfall and subsequent more infiltration. In addition, the total amount of infiltrated water was much greater than that of evapotranspirated and percolated water within a relatively short period of 10 days, 2 to 10 Sep 1992. Thus, variation in the soil water content might be dominated by infiltration than evapotranspiration and percolation in the period. Then, as RZD increased, proportion of the infiltrated water volume to the root zone depth got smaller, and then increase in soil water content by the infiltrated water volume became smaller. Subsequently, as RZD increased, curve numbers for the following events were adjusted to lower values, and thus peak runoff and runoff volume decreased but time to peak direct runoff increased. At the RZD of about 0.15, the integrated effect of evapotranspiration, percolation, and infiltration might maximize the soil water contents of the following storm events, so thus curve numbers might be adjusted to higher values.

SAR describes a ratio of vertical unsaturated hydraulic conductivity to horizontal unsaturated conductivity calculated by the van Genuchten equation, and percolation rate is proportional to the vertical unsaturated hydraulic conductivity. Thus, a higher SAR will produce a greater percolation rate. Consequently, as SAR increases, soil moisture content drops more quickly by an increased percolation rate, and then curve number might be adjusted into lower values. As seen in Figures 4.12s and 4.12t, therefore, as SAR increased, peak runoff and runoff volume decreased but time to peak direct runoff increased. In addition, because the fourth event allowed more time for percolation to occur, its hydrograph was more sensitive to SAR.

Tables 4.5 to 4.8 and Figure 4.13 show quantitative measures for sensitivity of direct runoff hydrograph to the parameters using statistics such as IQR (Interquartile Range), Stdev (Standard Deviation), and CV (Coefficient of Variation). Although the statistics do not represent in which direction variation in an output of interest occurs as parameters changes, they allow quantitative comparison of the overall sensitivity to every parameter. These sensitivity measures were calculated from the results of the model evaluations using the same parameter set (Table 4.4 and Figure 4.11). In addition, the sampled parameter sets were also used to see impact of the interaction between the parameters on direct runoff hydrograph. It is denoted as ‘All’ in Tables 4.5 to 4.8 and Figure 4.13.
Table 4.5. Sensitivity of peak direct runoff (m³ s⁻¹) to the parameters for different storms.

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Table 4.6. Sensitivity of time to peak direct runoff (hr) to the parameters for four storms.

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Table 4.8. Sensitivity ranks of the parameters.

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<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
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</tr>
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<td>-</td>
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<td>7</td>
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<td>4</td>
<td>3</td>
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<td>6</td>
<td>2</td>
<td>5</td>
</tr>
</tbody>
</table>
Figure 4.13a. Sensitivity of peak direct runoff to the parameters in the first storm event.

Figure 4.13b. Sensitivity of time to peak direct runoff to the parameters in the first storm event.
Figure 4.13c. Sensitivity of direct runoff volume to the parameters in the first storm event.

Figure 4.13d. Sensitivity of peak direct runoff to the parameters in the second storm event.
Figure 4.13e. Sensitivity of time to peak direct runoff to the parameters in the second storm event.

Figure 4.13f. Sensitivity of direct runoff volume to the parameters in the second storm event.
Figure 4.13g. Sensitivity of peak direct runoff to the parameters in the third storm event.

Figure 4.13h. Sensitivity of time to peak direct runoff to the parameters in the third storm event.
Figure 4.13i. Sensitivity of direct runoff volume to the parameters in the third storm event.

Figure 4.13j. Sensitivity of peak direct runoff to the parameters in the fourth storm event.
Figure 4.13k. Sensitivity of time to peak direct runoff to the parameters in the fourth storm event.

Figure 4.13l. Sensitivity of direct runoff volume to the parameters in the fourth storm event.

Figure 4.13. Sensitivity of runoff hydrograph to the parameters for different individual storm events occurring on 2, 5, 8, and 10 Sep 1992.
All the three statistics provided in Tables 4.5 to 4.7, IQR, Stdev, and CV, represent degree of dispersion in the output of interest. Thus, they can show how much a direct runoff hydrograph is responsive to change in the parameter values for the same storm event. However, CV normalizes variance with an average so that it can used to compare sensitivities of direct runoff hydrographs developed for different storm events. Thus, the sensitivity ranks presented in Table 4.8 were analyzed based on CVs of the direct runoff hydrograph characteristics. No parameter sets except for CNF produced any runoff for the third event, and thus statistics for the storm event were zero or not defined. In addition, as mentioned earlier, a direct runoff hydrograph for the first storm event is not responsive to any parameter for soil moisture simulation such as GCL, GCM, BCC, EFS, RZD, and SAR.

As seen in Tables 4.5 to 4.8 and Figure 4.13, the simulated direct runoff hydrograph was most sensitive to CNF for all the storm events. In the case of peak runoff, CNF was followed by THA, MNC, and MNO for the first storm event, but a direct runoff hydrograph was more sensitive to the parameters for soil moisture simulation in the second and fourth storm events. In particular, CV of RZD was significantly greater than those of the others expect for CNF. GCM and BCC that control evapotranspiration rates of water from the root zone depth were also identified as very sensitive parameters for peak runoff of the second and fourth storm events, and their CVs were greater in the fourth than in the second. It proved that a direct runoff hydrograph of the following event is more sensitive to change in the parameters for soil moisture simulation. On the other hand, peak runoff was not responsive to MNO and MNC in the two events. GCL was recognized as the least sensitive parameter for peak direct runoff, time to peak direct runoff, and direct runoff volume consistently.

In the case of time to peak direct runoff, CVs of GCM and BCC became similar to or greater than that of RZD. Especially, variation in time to peak direct runoff became much greater in the second storm event due to switch of the maximum direct runoff between two peaks. Contrary to the cases of peak runoff and runoff volume, CVs of ‘All’ was smaller than those of CNF. This means that variation in the direct runoff hydrograph caused by changes in the parameter values was limited or enhanced by interaction between the parameters. However, the interaction did not appear strong because the direct
runoff hydrograph is very sensitive to one parameter, CNF. Direct runoff hydrographs were plotted in Figure 4.14 based on the AAT sensitivity analysis. It represents theoretically possible upper and lower boundaries of the direct runoff hydrograph that the model can provide within the predefined ranges of parameter values. The statistics in the figure were derived from the ‘All’ parameter sets.

Sensitivity of direct runoff volume to the parameters was very similar to that of peak runoff. RZD showed strong sensitivity for direct runoff volume, and it was followed by GCM and BCC. In addition, CVs of the parameters for soil moisture simulation became greater in the fourth than in the second storm event. In summary, CNF was the most sensitive parameter for direct runoff hydrograph in all the storm events, but the other three parameters for direct runoff simulation were not strongly sensitive for the second and fourth storm events. Three parameters, RZD, GCM, and BCC, of the parameters for soil moisture simulation were sensitive for a direct runoff hydrograph in all the storm events. Their impact became more significant in the fourth event because it allowed longer time for them to participate into controlling soil water content.

Figure 4.14. Possible upper and lower boundaries of the hydrograph used for sensitivity analysis.
4.1.2.2 Sensitivity of Base Flow

Sensitivity of base flow simulation of HYSTAR to the 10 parameters (CNF, MNO, MNC, THA, GCL, GCM, BCC, EFS, RZD, and SAR) was analyzed through the same method utilized in the sensitivity analysis for direct runoff simulation. However, only 10 parameter value sets for each parameter were randomly sampled for efficiency. Thus, 100 parameter sets were evaluated with the model, and changes in the simulated base flow volume were investigated. Sensitivity analysis results are presented in Tables 4.9 and 4.10 and Figures 4.15 and 4.16. In this study, sensitivity was examined qualitatively by plotting output values came from unique sets of parameter value and quantitatively with statistical measures such as IQR, standard deviation (Stdev), and coefficient of variation (CV) of the output.

Figure 4.15a. Sensitivity of base flow volume to CNF.
Figure 4.15b. Sensitivity of base flow volume to MNO.

Figure 4.15c. Sensitivity of base flow volume to MNC.
Figure 4.15d. Sensitivity of base flow volume to THA.

Figure 4.15e. Sensitivity of base flow volume to GCL.
Figure 4.15f. Sensitivity of base flow volume to GCM.

Figure 4.15g. Sensitivity of base flow volume to BCC.
Figure 4.15h. Sensitivity of base flow volume to EFS.

Figure 4.15i. Sensitivity of base flow volume to RZD.
As expected, base flow volume was insensitive to the parameters for direct runoff simulation (MNO, MNC, and THA) except CNF (Figure 4.15). CNF produced the maximum base flow volume at vicinity of its calibrated value, 1.094 (Table 4.20). Then, base flow volume decreased as CNF increased. A higher curve number will produce greater direct runoff volume and subsequently make runoff velocity faster. Thus, it may reduce overall time for runoff to be infiltrated into the soil, and then soil will become drier. Percolation rate is small in the dry soil and subsequently base flow volume becomes small. However, when CNF is less than about 0.9, base flow was not responsive to CNF because all the rainfall will be infiltrated into the soil and any direct runoff will not be generated. In addition, in Figure 4.15d, when THA is close to 100, base flow volume is a little higher because a bigger THA may decrease overall runoff velocity in the watershed.

As seen in the sensitivity analysis, unsaturated hydraulic conductivity is inversely proportional to GCL and exponentially proportional to GCM. These relationships are confirmed in Figures 4.15e and 4.15f. In Figure 4.15f, sensitivity of base flow volume to
GCM was the greatest in the first storm event and it gradually decreased in the following events. On the other hand, as BCC increased, base flow volume decreased because a higher BCC may take more moisture from the soil (Figure 4.15g). In addition, its impact on base flow volume is increasing in the following storm events because the later event will allow more time for soil moisture to be evapotranspirated. Definitely, base flow volume decreased as EFS increased (Figure 4.15h). However, it is not sensitive to EFS because EFS greater than about 1.10 may make all the ‘kfc’ values reach to the maximum of 1.

In Figure 4.15i, as RZD increased, base flow volume decreased exponentially. This relationship is also found in Figure 4.12r, and the same explanation can be applied. As RZD increasing, contribution of the infiltrated runoff on soil water content of the root zone depth becomes weaker while percolation continues until the soil water content reaches the residual water content. Finally, in Figure 4.15j, as SAR increased, base flow volume increased. Percolation rate is directly proportional to SAR but limited by decreased soil water content. Thus, the relationship between them is not completely linear in the figure.

Table 4.9 and Figure 4.16 show quantitative measures for sensitivity of base flow volume to the parameters using statistical measures such as IQR, Stdev, and CV that represent degree of dispersion in the output of interest. Table 4.10 shows the sensitivity ranks of the parameters, which were analyzed based on CVs of the simulated base flow volume. As seen in Tables 4.9 to 4.10, the simulated base flow volume was most sensitive to RZD for all the storm events, and then it was followed by GCM, BCC, SAR, and CNF (Table 4.10). While GCM produced higher variation of the simulated base flow volume, RZD provided higher normalized variation (Figures 4.15f and 4.15i, and Table 4.9). The simulated base flow volume was most insensitive to GCL among the parameters for soil moisture simulation.
Table 4.9. Sensitivity of base flow volume ($10^3$ m$^3$) to the parameters for four storms.

<table>
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<th>Event</th>
<th>Stat.</th>
<th>All</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
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<td>1,449</td>
<td>1,674</td>
<td>873</td>
<td>8,897</td>
<td></td>
</tr>
<tr>
<td></td>
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<td>8</td>
<td>6</td>
<td>234</td>
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<td>5</td>
<td>6</td>
<td>15</td>
<td>319</td>
<td>14,610</td>
<td>2,025</td>
<td>1,449</td>
<td>1,674</td>
<td>873</td>
</tr>
<tr>
<td></td>
<td>CV</td>
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<td>0.286</td>
<td>0.002</td>
<td>0.003</td>
<td>0.008</td>
<td>0.076</td>
<td>0.841</td>
<td>0.128</td>
<td>0.107</td>
<td>0.880</td>
<td>0.487</td>
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<td>3,566</td>
<td>3,601</td>
<td>3,775</td>
<td>14,456</td>
<td>1,007</td>
<td>1,251</td>
<td>901</td>
<td>5,807</td>
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<tr>
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<td>23</td>
<td>25</td>
<td>15</td>
<td>319</td>
<td>14,456</td>
<td>1,007</td>
<td>1,251</td>
<td>901</td>
<td>5,807</td>
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<td>17</td>
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<td>202</td>
<td>9,250</td>
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<td>1,251</td>
<td>901</td>
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<tr>
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<td>0.005</td>
<td>0.008</td>
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<td>3,468</td>
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<td>2,699</td>
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<tr>
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<td>0.005</td>
<td>0.008</td>
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<td>0.661</td>
<td>0.339</td>
<td>1.376</td>
<td>0.268</td>
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Table 4.10. Sensitivity ranks of the parameters.

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<th>Storm Event</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
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<td>4</td>
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<td>9</td>
<td>8</td>
<td>7</td>
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<td>1</td>
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<td>10</td>
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<td>5</td>
<td>1</td>
<td>6</td>
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<td>2</td>
<td>5</td>
<td>1</td>
<td>6</td>
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</table>

**4.1.3 Sensitivity of Sediment Transport Simulation**

Sensitivity of sediment transport simulation of HYSTAR to the 4 parameters (CSC, CSO, SCR, and SDR) was analyzed through a Monte Carlo simulation using Latin Hypercube sampling. Change in characteristics of the simulated sediment load, such as peak load, total load, and time to peak load, was investigated while values of a parameter were being varied. The storm that occurred on 5 Jan 1993 was used for the analysis. Parameter value sets of 100 for each parameter were randomly sampled within their own ranges determined based on consideration of their physical meanings and literature (Table 4.11 and Figure 4.16). While values of a parameter of interest were sampled, values of the other parameters were set to their base values. In addition, all the
parameters for hydrology simulation are set to their base values. Thus, 400 parameter sets were evaluated with the model, and then change in the characteristics of predicted sediment load hydrographs was investigated. Statistics of parameter values used for this sensitivity analysis are provided in Table 4.11 and Figure 4.16, and sensitivity analysis results are presented in Table 4.12 and Figures 4.17 and 4.18.

Table 4.11. Statistics of the parameter values sampled by the Monte Carlo technique (Sediment transport simulation).

<table>
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<th>Stat.</th>
<th>CSO</th>
<th>CSC</th>
<th>SCR</th>
<th>SDR</th>
</tr>
</thead>
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<td>1.04</td>
<td>1.05</td>
</tr>
<tr>
<td>Q1</td>
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<td>0.046</td>
<td>0.58</td>
<td>0.58</td>
</tr>
<tr>
<td>MIN</td>
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<td>0.10</td>
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<td>1.52</td>
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</tr>
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<td>0.013</td>
<td>0.55</td>
<td>0.55</td>
</tr>
<tr>
<td>CV</td>
<td>0.52</td>
<td>0.227</td>
<td>0.53</td>
<td>0.52</td>
</tr>
</tbody>
</table>

Figure 4.16. Box-Whisker diagram for the statistics of the parameter values sampled by the Monte Carlo sampling technique.
Variation in the characteristics of the sediment load developed using the 100 unique parameter value sets are plotted for every parameter in Figure 4.16. Time to peak load is not responsive to any change in values of the parameters, meaning that time to peak load is determined by time to peak direct runoff which is constant during this sensitivity analysis. In Figure 4.17a, as CSO (Critical Shield parameter for Overland) increases, total and peak sediment load decrease exponentially, showing great sensitivity to CSO when its value is less than about 0.4. On the other hand, total and peak sediment load decrease almost linearly as CSC (Critical Shield parameter for Channel) increases (Figure 4.17b). The inverse relationships between the critical Shield parameters and the sediment loads are attributed to the fact that sediment transport capacity is inversely proportional to a critical Shield parameter in the Yalin equation (Equations 3.52 and 3.53).

However, critical Shield parameters for overland and channel are a linear function of CSO and CSC respectively when hydraulic flow condition such as a shear Reynolds number remains the same (Equations 3.66 and 3.67). Thus, the difference in the decreasing patterns (exponential vs. linear) would be contributed to unique contribution of overland and channel sediment hydraulic to sediment load generation. Most sediment may be eroded and transported from overland that occupies most of the watershed area. Subsequently, impact of change in amount of sediment transport capacity on total and peak sediment load may be accumulated along overland flow paths. On the other hand, area of the channel is relative small compared to that of overland flow surface. Thus, the contribution on sediment load is limited even though runoff generally has a higher velocity and subsequently greater sediment transport capacity in channel than in overland flow.

In Figure 4.17c, total and peak sediment load stays constant as SCR (Soil Cohesion Ratio) decreases from 0.10 to around 0.33. Soil erodibility efficiency coefficient ($\beta$) becomes constant at 0.335 when soil cohesion is less than 1.0 in Equation 3.41, and the spatially averaged soil cohesion of the watershed is about 3.0. Therefore, when SCR value is less than 0.33, the spatially averaged soil cohesion become less than 1.0, and then soil erodibility became a constant of 0.335. Consequently, sediment load
did not change when SCR is less than 0.33. As SCR increases from 0.33, total and peak sediment load decreases almost linearly. Although SCR also controls the amount of sediment erosion on overland as does CSO, responses of sediment load to their changes are different: exponential vs. linear. Because soil erodibility efficiency coefficient (β) is an inverse exponential function of soil cohesion in Equation 3.42, accumulation of impact of change in SCR or soil cohesion may be nullified with the inverse exponential relationship.

Figure 4.17d shows the proportional relationship between sediment load and SDR (Sediment Detachability Ratio). SDR controls the rate of sediment detachment by raindrop impact on overland so that a higher SDR will provide greater sediment. However, sediment load increases logarithmically as SDR increases even though sediment detachment rate is a linear function of sediment detachability or SDR. Transportation of detached sediment by raindrop impact may be limited by the predefined transport capacity on overland. In addition, most sediment detachment by raindrop impact may occur at the beginning of a storm event because depth of overland runoff may get deeper as the event proceeds. Therefore, sensitivity of sediment load to SDR can be diminished as SDR increases.
Figure 4.17a. Sensitivity of total and peak load to CSO.

Figure 4.17b. Sensitivity of total and peak load to CSC.
Figure 4.17c. Sensitivity of total and peak load to SCR.

Figure 4.17d. Sensitivity of total and peak load to SDR.

Figure 4.17. Sensitivity of predicted sediment load to the selected parameters.

Table 4.12 and Figure 4.18 show quantitative measures for sensitivity of direct runoff hydrograph to the parameters using statistics such as IQR (Interquartile Range),
Stdev (Standard Deviation), and CV (Coefficient of Variation). In the table and figures, relative sensitivities of sediment load to the parameters can be examined. These sensitivity measures were calculated from the results of the model evaluations using the same parameter shown in Table 4.11 and Figure 4.16. However, 100 parameter sets that had been randomly sampled values for all the parameters simultaneously was also evaluated to see impact of the interaction between the parameters on direct runoff hydrograph. It is denoted as ‘All’ in Table 4.12 and Figure 4.18.

Table 4.12. Sensitivity of sediment load hydrograph to the parameters.

<table>
<thead>
<tr>
<th>Item</th>
<th>Stat.</th>
<th>All</th>
<th>CSO</th>
<th>CSC</th>
<th>SCR</th>
<th>SDR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Load</td>
<td>Mean</td>
<td>24.69</td>
<td>25.88</td>
<td>18.24</td>
<td>16.72</td>
<td>18.14</td>
</tr>
<tr>
<td></td>
<td>IQR</td>
<td>18.32</td>
<td>20.46</td>
<td>0.53</td>
<td>7.11</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>Stdev</td>
<td>40.44</td>
<td>37.86</td>
<td>0.32</td>
<td>3.75</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>CV</td>
<td>1.64</td>
<td>1.46</td>
<td>0.02</td>
<td>0.22</td>
<td>0.01</td>
</tr>
<tr>
<td>Peak Load</td>
<td>Mean</td>
<td>5.51</td>
<td>5.76</td>
<td>4.16</td>
<td>3.80</td>
<td>4.15</td>
</tr>
<tr>
<td></td>
<td>IQR</td>
<td>3.82</td>
<td>4.72</td>
<td>0.09</td>
<td>1.79</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>Stdev</td>
<td>9.03</td>
<td>8.27</td>
<td>0.06</td>
<td>1.02</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>CV</td>
<td>1.64</td>
<td>1.44</td>
<td>0.01</td>
<td>0.27</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Figure 4.18a. Sensitivity of total sediment load to parameters.
As seen in Table 4.12 and Figure 4.18, predicted sediment load was the most sensitive to CSO. Then, CSO was followed by SCR, CSC, and SDR. Thus, it is revealed that sediment load is more sensitive to the parameters for overland (CSO and SCR) than those for channel (CSC). As mentioned earlier, impact of SDR on sediment load is relatively very limited. Sensitivity of total sediment load to the parameters is similar to that of peak sediment load. In addition, IQRs (Interquartile Range) of ‘All’ and CSO in Table 4.12 shows sensitivity of sediment load to CSO can be limited by interaction of CSO with the other parameters. Figure 4.19 shows the theoretically possible upper and lower boundaries of the sediment load that the model can provide within the predefined ranges of parameter values. The statistics in the figure were derived from the ‘All’ parameter sets.
Figure 4.19. Possible upper and lower boundaries of the sediment load used for sensitivity analysis.

### 4.1.4 Sensitivity to GIS Data Error

GIS data may contain errors that may affect the model output. Sensitivity of the model output to GIS data error will show the importance of GIS input data quality on the model. For this, errors in elevation and land use map were simulated using the SGS (Sequential Gaussian Simulation) and SIS (Sequential Index Simulation) techniques. Variations in the simulated runoff and sediment load caused by the introduced errors were examined to quantify model sensitivity to the errors. In total, 30 realizations of each DEM and NLCD for the watershed, ORD, were generated, and runoff and sediment load for the entire simulation period were simulated with the disturbed data. The simulated runoff and sediment load using the disturbed data are compared with the simulated sediment load using the base (original) GIS data and base parameter sets.

#### 4.1.4.1 Sensitivity to DEM Error

HYSTAR requires flow direction to route runoff, flow accumulation to define stream network, and slope to calculate velocity of runoff, and that information is derived
from elevation data, DEM. Thus, errors in the elevation data will affect the information and then influence the modeling results. In order to see the impact of error in elevation data on the modeling results, artificial errors were generated using the SGS algorithm, and then variation in the simulated runoff and sediment load hydrographs was investigated. The original DEM used for simulation and average elevation of the disturbed DEMs are described in Figures 4.20 and 4.21 respectively. Figure 4.22 displays autocorrelated structure of the errors distributed along the channel network and ridge.

The SGS algorithm employs variogram and kriging technique to identify spatial autocorrelation structure of data and then simulates data at unknown points. Therefore, it can be applied to a case of having a small number of observations. However, when utilizing only 5% of the watershed area for training, the algorithm provided very different topography and channel network from those of the original data (Figure 4.23). It removed most of topographic characteristics like ridge and valley and changed stream network greatly. As it is hard to identify which size of training data is most appropriate in using this kind of algorithm, a training area of 70% of the watershed area was arbitrarily used for this study.

![Figure 4.20. Original DEM (Owl Run subwatershed D).](image)
Figure 4.21. Average elevations of the disturbed DEMs.

Figure 4.22. Differences between the original and average elevations of the disturbed DEMs.
Figure 4.23a. A disturbed DEM.

Figure 4.23b. Stream network of a disturbed DEM.

Figure 4.23. A disturbed DEM and its stream network generated using a small (5 \%) training data with the SGS algorithm.

The differences between the original and the average elevation of the disturbed DEM ranges -7.6 to 6.9 m (Figure 4.22) and the spatially averaged standard deviation of the errors is 1.0 m. In Table 4.13, the ranges of errors for every elevation class show that
variations of the errors are symmetric and greater in the mid classes of elevation, 90 to 120 m. On the other hand, the minimum, maximum, and mean statistics of the error for the classes indicate that the SGS algorithm produced biased errors for lower and higher areas. The errors tend to be positive and negative on higher and lower elevations respectively, while the overall average error, -0.01 m, is close to zero. In other words, the disturbed DEMs overestimated and underestimated elevation on low and high elevation areas respectively. It implies that correlation between error and elevation was considered in the algorithm.

Table 4.13. Statistics of differences (original – disturbed) between the original and the disturbed DEMs for the elevation classes.

<table>
<thead>
<tr>
<th>Class</th>
<th>Area (ha)</th>
<th>Min (m)</th>
<th>Max (m)</th>
<th>Range (m)</th>
<th>Mean (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>80-85</td>
<td>4.95</td>
<td>-3.46</td>
<td>1.69</td>
<td>5.15</td>
<td>-0.55</td>
</tr>
<tr>
<td>85-90</td>
<td>24.93</td>
<td>-3.55</td>
<td>3.73</td>
<td>7.28</td>
<td>-0.15</td>
</tr>
<tr>
<td>90-95</td>
<td>48.24</td>
<td>-7.53</td>
<td>3.03</td>
<td>10.57</td>
<td>-0.34</td>
</tr>
<tr>
<td>95-100</td>
<td>42.66</td>
<td>-6.73</td>
<td>4.99</td>
<td>11.71</td>
<td>0.00</td>
</tr>
<tr>
<td>100-105</td>
<td>52.29</td>
<td>-6.37</td>
<td>5.19</td>
<td>11.57</td>
<td>0.02</td>
</tr>
<tr>
<td>105-110</td>
<td>51.75</td>
<td>-4.73</td>
<td>6.87</td>
<td>11.60</td>
<td>0.16</td>
</tr>
<tr>
<td>110-115</td>
<td>35.46</td>
<td>-7.63</td>
<td>4.97</td>
<td>12.60</td>
<td>0.09</td>
</tr>
<tr>
<td>115-120</td>
<td>40.32</td>
<td>-5.59</td>
<td>3.54</td>
<td>9.13</td>
<td>-0.01</td>
</tr>
<tr>
<td>120-125</td>
<td>23.13</td>
<td>-2.35</td>
<td>4.32</td>
<td>6.67</td>
<td>0.30</td>
</tr>
<tr>
<td>125-130</td>
<td>5.13</td>
<td>-0.42</td>
<td>4.50</td>
<td>4.93</td>
<td>0.51</td>
</tr>
</tbody>
</table>

Figure 4.24 shows spatial variation in the channel network derived from the disturbed DEMs using the threshold area of 17.91 ha, which is the calibrated value of THA (4.2.2.4). The numbers in the figure represent frequency of being classified as a cell on the channel network among the total 30 realizations. Greater variations are found at vicinity of junctions because slopes are relatively shallow there. In particular, the tributaries located in the most northern and southern parts of the channel network show the biggest variations. Figure 4.25 exhibits variation in watershed boundary defined with the disturbed DEMs. Because errors were added to areas only within the original watershed in order to keep the same watershed outlet, areas of the simulated watershed became smaller than that of the original. Subsequently, only 11 realizations provided watershed areas greater than 95 % of the original. In addition, some realizations of DEM
produced much smaller watershed areas less than 85% of the original. The added errors altered relatively much elevation comparing to its vicinity on low elevation areas, then the changed flow direction defined watershed with very different boundary and excluded significant areas from the watershed.

Figure 4.24. Variation in stream network defined with the disturbed DEMs.

Figure 4.25. Variation in watershed boundaries and areas defined with the disturbed DEMs.
The original and the averaged simulated slope maps are compared in Figure 4.26 and 4.27. On the simulated slope map, spatial autocorrelation structure of slope is weakened and slopes are more fragmented. The overall average error (original – disturbed) of slope is 0.48 %, which indicates that overall slope was underestimated on the simulated slope maps. In addition, slope was underestimated for all the elevation classes (Table 4.14), and was overestimated and underestimated slopes on shallow and steep slopes areas respectively (Table 4.15).

Figure 4.26. Slope derived from the original DEM.

Figure 4.27. Slope derived from one of the disturbed DEMs.
Table 4.14. Statistics of differences (original – disturbed) between the original and the derived slopes from the disturbed DEMs by elevation classes.

<table>
<thead>
<tr>
<th>Elevation (m)</th>
<th>Area (ha)</th>
<th>Min (%)</th>
<th>Max (%)</th>
<th>Range (%)</th>
<th>Mean (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>80-85</td>
<td>4.95</td>
<td>-2.17</td>
<td>3.83</td>
<td>6.00</td>
<td>0.66</td>
</tr>
<tr>
<td>85-90</td>
<td>24.93</td>
<td>-5.62</td>
<td>4.40</td>
<td>10.02</td>
<td>0.49</td>
</tr>
<tr>
<td>90-95</td>
<td>48.24</td>
<td>-5.96</td>
<td>7.55</td>
<td>13.52</td>
<td>0.53</td>
</tr>
<tr>
<td>95-100</td>
<td>42.66</td>
<td>-10.62</td>
<td>6.90</td>
<td>17.52</td>
<td>0.65</td>
</tr>
<tr>
<td>100-105</td>
<td>52.29</td>
<td>-4.17</td>
<td>9.35</td>
<td>13.52</td>
<td>0.62</td>
</tr>
<tr>
<td>105-110</td>
<td>51.75</td>
<td>-6.46</td>
<td>8.42</td>
<td>14.88</td>
<td>0.28</td>
</tr>
<tr>
<td>110-115</td>
<td>35.46</td>
<td>-5.29</td>
<td>9.39</td>
<td>14.68</td>
<td>0.48</td>
</tr>
<tr>
<td>115-120</td>
<td>40.32</td>
<td>-3.33</td>
<td>7.71</td>
<td>11.03</td>
<td>0.40</td>
</tr>
<tr>
<td>120-125</td>
<td>23.13</td>
<td>-2.93</td>
<td>7.81</td>
<td>10.74</td>
<td>0.52</td>
</tr>
<tr>
<td>125-130</td>
<td>5.13</td>
<td>-0.42</td>
<td>4.50</td>
<td>4.93</td>
<td>0.51</td>
</tr>
</tbody>
</table>

Table 4.15. Statistics of the derived slopes disturbed DEMs to slope classes.

<table>
<thead>
<tr>
<th>Slope (%)</th>
<th>AREA (ha)</th>
<th>MIN (%)</th>
<th>MAX (%)</th>
<th>RANGE (%)</th>
<th>MEAN %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1.5</td>
<td>44.73</td>
<td>-7.14</td>
<td>0.68</td>
<td>7.82</td>
<td>-0.81</td>
</tr>
<tr>
<td>1.5-3.0</td>
<td>78.12</td>
<td>-10.62</td>
<td>1.84</td>
<td>12.45</td>
<td>-0.27</td>
</tr>
<tr>
<td>3.0-4.5</td>
<td>77.31</td>
<td>-6.46</td>
<td>3.18</td>
<td>9.64</td>
<td>0.29</td>
</tr>
<tr>
<td>4.5-6.0</td>
<td>59.67</td>
<td>-5.90</td>
<td>4.59</td>
<td>10.49</td>
<td>0.86</td>
</tr>
<tr>
<td>6.0-7.5</td>
<td>36.63</td>
<td>-4.17</td>
<td>5.90</td>
<td>10.06</td>
<td>1.46</td>
</tr>
<tr>
<td>7.5-10.0</td>
<td>24.57</td>
<td>-2.83</td>
<td>7.30</td>
<td>10.14</td>
<td>2.32</td>
</tr>
<tr>
<td>10.0-16.0</td>
<td>7.83</td>
<td>-0.48</td>
<td>9.39</td>
<td>9.87</td>
<td>3.88</td>
</tr>
</tbody>
</table>

Direct and total runoff hydrographs were simulated using the original and disturbed DEMs, and then were aggregated into monthly data. In Figure 4.28 and Table 4.16, the monthly direct runoff for the original DEM was located between the maximum and minimum of the monthly direct runoff for the disturbed DEMs for 40 months of the entire simulation period of 72 months (6 years). The maximum range (Max – Min) of the monthly direct runoff for the disturbed DEMs, 16.9 m$^3$/s, was in Mar 1994 when the model provided the highest monthly direct runoff of 194 m$^3$/s. The greater ranges and IQRs (Interquartile Range) were in the months that produced higher direct runoff. An average range and IQR of the monthly direct runoff for the disturbed DEMs are 2.45 m$^3$/s and 0.68 m$^3$/s, and they correspond to 12 % and 3.4 % of the average monthly direct runoff for the original DEM, 20.2 m$^3$/s respectively (Table 4.16).
Figure 4.28a. In an arithmetic scale.

Figure 4.28b. In a logarithmic scale.

Figure 4.28. Comparison of the monthly direct runoff for the original and disturbed DEMs.
The simulated monthly total runoff hydrographs using the original and disturbed DEMs are compared in Figures 4.29 and 4.30. The monthly total runoff for the original DEM was fell between the maximum and minimum of the monthly total runoff for the disturbed DEMs for 36 months of the entire. The maximum range of the monthly total runoff for the disturbed DEMs, 16.9 m³/s, was in Mar 1994. An average range and IQR of the monthly total runoff for the disturbed DEMs are 2.48 m³/s and 0.69 m³/s, and they respectively correspond to 7.4 % and 2.1 % of the average monthly total runoff for the original DEM, 33.3 m³/s (Table 4.16). As seen in Figure 4.29, the average monthly total runoff for the disturbed DEMs was a little overestimated than that for the original DEM. The minimum and average total runoffs for the disturbed DEMs in the entire simulation period, 2400 and 2461 m³/s respectively, are also greater than the total runoff for the original DEM, 2397 m³/s.

In the analysis, however, error in elevation were simulated only within the predefined boundary of ORD using the original DEM, so that some parts of the watershed could have their own outlets within the watershed boundary rather than the predefined one main outlet (Figures 4.24 and 4.25). Then, the fragmented small watersheds within the predefined entire watershed produced runoff more quickly than when they were included in the main watershed, and the quick response was reflected in the resulting hydrograph.
Figure 4.29a. In an arithmetic scale.

Figure 4.29b. In a logarithmic scale.

Figure 4.29. Comparison of the monthly total runoff for the original and disturbed DEMs.
Figure 4.30. Agreement of the average monthly total runoff for the original and disturbed DEMs.

Table 4.16. Statistics of variations in the monthly direct runoff, runoff, and sediment load simulated with the disturbed DEMs.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Direct Runoff</th>
<th>Runoff</th>
<th>Sediment Load</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>m^3/s</td>
<td>%</td>
<td>m^3/s</td>
</tr>
<tr>
<td>Max Range</td>
<td>16.9</td>
<td>-</td>
<td>16.9</td>
</tr>
<tr>
<td>Ave. Range</td>
<td>2.45</td>
<td>12.1</td>
<td>2.48</td>
</tr>
<tr>
<td>Ave. IQR</td>
<td>0.68</td>
<td>3.4</td>
<td>0.69</td>
</tr>
<tr>
<td>Ave. Original</td>
<td>20.2</td>
<td>100.0</td>
<td>33.3</td>
</tr>
</tbody>
</table>

Sediment load was simulated with the disturbed DEMs and aggregated into monthly data. The monthly sediment load for the original DEM was fell between the maximum and minimum of the monthly sediment load for the disturbed DEMs for 35 months of the entire simulation period of 48 months (4 years) (Figure 4.31). The maximum range of the monthly sediment load for the disturbed DEMs, 27.7 tons, was in Mar 1993 when the model provided the highest sediment load of 264 tons. The greater ranges and IQRs (Interquartile Range) were in the months that have higher sediment load. An average range and IQR of the monthly sediment load for the disturbed DEMs are 5.14
tons and 1.72 tons, and they correspond to 15% and 5.0% of the average monthly sediment load for the original DEM, 34.4 tons (Table 4.16).

Contrary to the case of runoff hydrograph, the monthly total sediment load for the original DEM, 1650 tons, is between the maximum and minimum of the monthly total sediment load for the disturbed DEMs. However, Figure 4.32 shows that the monthly sediment load for the disturbed DEMs was a little underestimated from that of the original DEM. In addition, the average monthly sediment load for the disturbed DEMs was less than that for the original DEM. The fragmented watersheds might have shallower overland runoff depth than when they are included in the main watershed due to their small contributing area. For the same reason, the main watershed might have shallower overland runoff depth. In addition, critical Shield parameter, which is the most sensitive parameter for sediment transport simulation, increases exponentially as the overland runoff depth decreased. Subsequently, the fragmentation resulted in overall underestimation in sediment load simulation using the disturbed DEM. In Figure 4.32, on the other hand, the overestimation for the sediment load less than 0.02 ton might be contributed to the relatively quick contribution of the fragmented watersheds on runoff and sediment.

![Figure 4.31a. In an arithmetic scale.](image-url)
Figure 4.31b. In a logarithmic scale.

Figure 4.31. Comparison of the monthly sediment load for the original and disturbed DEMs.

Figure 4.32. Agreement of the averaged monthly sediment load for the original and disturbed DEMs.
4.1.4.2 Sensitivity to Error in Land Cover

In the model, a land cover map provides necessary information in determining surface conditions like roughness, type of vegetation, and portion of pervious area. Thus, errors in a land cover map may directly affect the modeling results. In order to see impact of error in a land cover map on the modeling results, artificial errors were generated using the SIS algorithm, and then variation in the simulated runoff and sediment load with the errors was investigated. The original land cover map (NLCD 1992) used for simulation and spatial distribution of the errors are shown in Figures 4.33 and 4.34.

Figure 4.33. Original land cover (NLCD 1992).
Figure 4.34a. Disturbed NLCD 1.

Figure 4.34b. Disturbed NLCD 2.

Figure 4.34. Examples of the disturbed NLCDs.
In the error simulation, 50% of the watershed area participated in generating spatially autocorrelated land cover classification errors for the remaining 50%. The area of 50% for the training area was arbitrarily chosen for this study. However, the same land cover as the original was generated in 40% of the disturbed areas. Consequently, the land cover was altered in only 30% of the watershed area. As seen in Figure 4.34, land cover classes became more fragmented in the disturbed maps, and small patches surrounded by larger ones were shrunk or disappeared. Area statistics for land use classes of the disturbed land use map are provided and compared with the original in Table 4.17. The averaged areas of evergreen forest, pasture and hay, and row crop in the disturbed land cover maps are greater than those of the original whereas the others are smaller. The biggest change was found in the class of mixed forest.

<table>
<thead>
<tr>
<th>LULC</th>
<th>Original</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Stdev</th>
<th>COV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open Water</td>
<td>0.36</td>
<td>0.27</td>
<td>0.63</td>
<td>0.41</td>
<td>0.10</td>
<td>0.0211</td>
</tr>
<tr>
<td>Low Intensity Residential</td>
<td>18.99</td>
<td>17.01</td>
<td>18.99</td>
<td>18.09</td>
<td>0.49</td>
<td>0.0024</td>
</tr>
<tr>
<td>Commercial/Industrial</td>
<td>1.98</td>
<td>0.99</td>
<td>1.98</td>
<td>1.23</td>
<td>0.22</td>
<td>0.0157</td>
</tr>
<tr>
<td>Deciduous Forest</td>
<td>50.04</td>
<td>46.71</td>
<td>48.69</td>
<td>47.84</td>
<td>0.53</td>
<td>0.0010</td>
</tr>
<tr>
<td>Evergreen Forest</td>
<td>21.78</td>
<td>21.78</td>
<td>24.12</td>
<td>23.01</td>
<td>0.60</td>
<td>0.0024</td>
</tr>
<tr>
<td>Mixed Forest</td>
<td>14.31</td>
<td>9.27</td>
<td>11.25</td>
<td>9.99</td>
<td>0.50</td>
<td>0.0045</td>
</tr>
<tr>
<td>Pasture/Hay</td>
<td>192.24</td>
<td>195.84</td>
<td>198.99</td>
<td>197.61</td>
<td>0.79</td>
<td>0.0004</td>
</tr>
<tr>
<td>Row Crops</td>
<td>29.16</td>
<td>29.16</td>
<td>31.68</td>
<td>30.67</td>
<td>0.62</td>
<td>0.0018</td>
</tr>
</tbody>
</table>

The simulated direct and total runoff hydrographs using the original and disturbed NLCDs were aggregated into monthly data. The monthly direct runoff for the original NLCD was fell between the maximum and minimum of the monthly direct runoff for the disturbed NLCDs for 39 months of the entire simulation period of 72 months (Figure 4.35 and Table 4.18). The maximum range of the monthly direct runoff for the disturbed NLCDs, 3.43 m$^3$/s, was Jul 1994, which is one of the driest months. The greater ranges and IQRs (Interquartile Range) were in the months that have higher direct runoff. An average range and IQR of the monthly direct runoff for the disturbed NLCDs are 0.76 m$^3$/s and 0.19 m$^3$/s, and they correspond to 3.7% and 0.9% of the average monthly direct runoff for the original NLCD, 20.2 m$^3$/s (Table 4.18).
The simulated monthly total runoff hydrographs using the base and disturbed NLCDs are compared in Figures 4.35. The monthly total runoff for the original NLCD was fell between the maximum and minimum of the monthly total runoff for the disturbed NLCDs for 25 months of the entire (Table 4.18). The maximum range of the monthly total runoff for the disturbed NLCDs, 3.34 m³/s was in Jul 1994. An average range and IQR of the monthly total runoff for the disturbed NLCDs are 0.72 m³/s and 0.17 m³/s, and they respectively correspond to 2.2 % and 0.5 % of the monthly average runoff for the original NLCD, 33.3 m³/s (Table 4.18). In Figure 4.36, the average monthly total runoff for the disturbed NLCDs shows a good agreement with that for the original NLCD. However, bigger variation was found when monthly runoff is less than about 10 m³/s. It indicates that total runoff is more responsive to land use change when it is relatively small in drier season. The average of the total runoff for the disturbed NLCDs, 2397 m³/s, is very close to that for the original NLCD, 2397 m³/s. Although total area of forest decreased by 5.29 ha (1.6 % of the watershed) and area of pasture and row crop increased by 6.88 ha (2.1 %), the total runoff was not affected by the change. Overall, impact of the simulated error in the land use layer on runoff is not significant.

![Figure 4.35a](image_url) In an arithmetic scale.
Figure 4.35b. In a logarithmic scale.

Figure 4.35. Comparison of the monthly direct runoff for the original and disturbed NLCDs.

Figure 4.36a. In an arithmetic scale.
Figure 4.36b. In a logarithmic scale.
Figure 4.36. Comparison of the monthly runoff for the original and disturbed NLCDs.

Figure 4.37. Agreement of the averaged monthly runoff for the original and disturbed NLCDs.
Table 4.18. Statistics of variations in the monthly direct runoff, runoff, and sediment load simulated with the disturbed NLCDs.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Direct Runoff</th>
<th></th>
<th>Total Runoff</th>
<th></th>
<th>Sediment Load</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>m³/s</td>
<td>%</td>
<td>m³/s</td>
<td>%</td>
<td>m³/s</td>
<td>%</td>
</tr>
<tr>
<td>Max Range</td>
<td>3.43</td>
<td>-</td>
<td>3.34</td>
<td>-</td>
<td>10.1</td>
<td>-</td>
</tr>
<tr>
<td>Ave. Range</td>
<td>0.76</td>
<td>3.8</td>
<td>0.72</td>
<td>2.2</td>
<td>2.07</td>
<td>6.0</td>
</tr>
<tr>
<td>Ave. IQR</td>
<td>0.19</td>
<td>0.94</td>
<td>0.17</td>
<td>0.51</td>
<td>0.67</td>
<td>2.0</td>
</tr>
<tr>
<td>Ave. Calibrated</td>
<td>20.2</td>
<td>100.0</td>
<td>33.3</td>
<td>100.0</td>
<td>34.4</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Sediment load hydrographs were simulated with the disturbed NLCDs, and then they were aggregated into monthly data. The monthly sediment load for the original NLCD fell between the maximum and minimum of the monthly sediment load for the disturbed NLCDs for 22 months of the entire simulation period of 48 months (4 years) (Figure 4.38 and Table 4.18). The maximum range of the monthly sediment load for the disturbed NLCDs, 10.1 tons was in Mar 1993 when the model provided the highest sediment load of 264 tons. The greater ranges and IQRs (Interquartile Range) were in the months that produced higher sediment load. An average range and IQR of the monthly sediment load for the disturbed NLCDs are 2.07 tons and 0.67 tons, and they correspond to 6% and 2.0% of the average monthly sediment load for the original NLCD, 34.4 tons (Table 4.16). Figure 4.39 shows a good agreement between the average monthly sediment loads for the original and disturbed NLCDs.
Figure 4.38a. In an arithmetic scale.

Figure 4.38b. In a logarithmic scale.

Figure 4.38. Comparison of the monthly sediment load hydrographs for the original and disturbed NLCDs.
4.1.4.3 Sensitivity to Error in DEM and Land Cover

Using the disturbed DEMs and NLCDs, runoff and sediment load were simulated, and then they were aggregated into monthly data. For sake of the analysis efficiency, the 30 realizations for each DEM and NLCD were one-to-one combined to create 30 realizations that have errors in both DEM and NLCD. Then, direct and total runoff hydrograph were simulated with the disturbed DEMs and NLCDs, and then they were aggregated into monthly data. In Figure 4.40, the monthly direct runoff for the original DEM and NLCD was located between the maximum and minimum of the monthly direct runoff for the disturbed DEMs and NLCDs for 21 months of the entire simulation period of 72 months (6 years) (Table 4.19). The maximum range (Max – Min) of the monthly direct runoff for the disturbed DEMs and NLCDs, 15.8 m$^3$/s, was in Mar 1994 when the model provided the highest monthly direct runoff of 194 m$^3$/s. The greater ranges and IQRs (Interquartile Range) were found in the months that produced higher direct runoff. An average range and IQR of the monthly direct runoff for the disturbed DEMs and NLCDs are 2.46 m$^3$/s and 0.72 m$^3$/s, and they correspond to 12 % and 3.6 % of the average monthly direct runoff for the original DEM and NLCD, 20.2 m$^3$/s (Table 4.19).
Figure 4.40a. In an arithmetic scale.

Figure 4.40b. In a logarithmic scale.

Figure 4.40. Comparison of the monthly direct runoff for the original and disturbed DEMs and NLCDs.
The total monthly runoff for the original and disturbed DEMs and NLCDs were compared in Figure 4.41. The monthly total runoff for the original DEM and NLCD was located between the maximum and minimum of the monthly total runoff for the disturbed DEMs and NLCDs for 30 months of the entire. The maximum range of the monthly total runoff for the disturbed DEMs and NLCDs, 15.7 m$^3$/s, was in Mar 1994. An average range and IQR of the monthly total runoff for the disturbed DEMs and NLCDs are 2.49 m$^3$/s and 0.72 m$^3$/s, and they respectively correspond to 7.5 % and 2.2 % of the average monthly runoff for the original DEM and NLCD, 33.3 m$^3$/s (Table 4.19). As seen in Figure 4.42, the average monthly total runoff for the disturbed DEMs and NLCDs was a little overestimated than that for the original. The minimum and average monthly total runoffs for the disturbed DEMs and NLCDs are 2425 m$^3$/s and 2482 m$^3$/s respectively, and they are greater than the average monthly total runoff for the original DEM and NLCD, 2397 m$^3$/s. This overestimation also can be explained the fragmentation of the watershed.

![Figure 4.41a](image-url)  
Figure 4.41a. In an arithmetic scale.
Figure 4.41b. In a logarithmic scale.

Figure 4.41. Comparison of the monthly total runoff for the original and disturbed DEMs and NLCDs.

Figure 4.42. Agreement of the averaged monthly total runoff for the original and disturbed DEMs and NLCDs.
Table 4.19. Statistics of variations in the monthly direct runoff, runoff, and sediment load simulated with the disturbed DEMs and NLCDs.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Direct Runoff</th>
<th>Total Runoff</th>
<th>Sediment Load</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>m$^3$/s</td>
<td>%</td>
<td>m$^3$/s</td>
</tr>
<tr>
<td>Max Range</td>
<td>15.8</td>
<td>-</td>
<td>15.7</td>
</tr>
<tr>
<td>Ave. Range</td>
<td>2.46</td>
<td>12.2</td>
<td>2.49</td>
</tr>
<tr>
<td>Ave. IQR</td>
<td>0.72</td>
<td>3.6</td>
<td>0.72</td>
</tr>
<tr>
<td>Ave. Calibrated</td>
<td>20.2</td>
<td>100.0</td>
<td>33.3</td>
</tr>
</tbody>
</table>

Sediment load hydrographs were simulated with the 30 combinations of the disturbed DEMs and NLCDs, and then they were aggregated into monthly data. The monthly sediment load for the original DEM and NLCD was located between the maximum and minimum of the monthly sediment loads for the disturbed DEMs and NLCDs for 31 months of the entire simulation period of 4 years (Figure 4.43 and Table 4.19). The maximum range of the monthly sediment load for the disturbed DEMs and NLCDs, 30.7 tons, was in Mar 1993 when the calibrated model provided the highest sediment load of 264 tons. The greater ranges and IQRs were found in the months that produced higher sediment load. An average range and IQR of the monthly sediment load for the disturbed DEMs and NLCDs are 5.48 tons and 1.90 tons respectively, and they correspond to 16% and 5.5% of the average monthly sediment load for the original DEM and NLCD, 34.4 tons (Table 4.19).

The total sediment load for the original DEM and NLCD, 1650 tons, is between the maximum and minimum of the total sediment load for the original DEM and NLCD. However, Figure 4.44 shows that the monthly sediment load for the disturbed DEMs and NLCDs was a little underestimated than that of the original. In addition, the average monthly sediment load for the disturbed, 1580 tons, is less than that for the original, 1650 tons. Similar results were found in 4.1.4.1, and the same explanation could be applied.
Figure 4.43a. In an arithmetic scale.

Figure 4.43b. In a logarithmical scale.

Figure 4.43. Comparison of the monthly sediment load for the original and disturbed DEMs and NLCDs.
Figure 4.44. Agreement of the averaged monthly sediment load for the original and disturbed DEMs and NLCDs.

4.2 Calibration

4.2.1 Overview

Commonly, flow measurement at an outlet of a watershed is the only observation for calibration of a hydrologic model. Although groundwater level and soil moisture are sometimes measured at some locations within a watershed for providing complementary data to hydrology modeling, their utility can be restricted due to the insufficient number of samples in the limited spatial extent. The lack of observation may lead to overparameterization and equifinality issues in modeling. In order to derive more information and data from the observations already made, some techniques such as base flow separation and rating curve are frequently used. In particular, the base flow separation technique is used to derive direct runoff and base flow from total runoff. In a routine modeling practice, a measured hydrograph consists of direct runoff and base flow, so thus usually parameters for direct runoff simulation of a model are calibrated with the base flow separated hydrograph.
However, base flow separation is another modeling practice. In addition, contribution of base flow to total hydrograph changes based on the initial soil moisture condition at the beginning of a storm event. In other words, partition of direct runoff and base flow in total hydrograph is varied storm-by-storm with change in soil moisture condition and its spatial distribution within a watershed. Therefore, disregard of the temporal variation in their contribution may lead to bias and error in the separation and in further analysis. Thus, in order to avoid introduction of the error and bias in calibrating parameter, the parameters for direct runoff simulation of HYSTAR were calibrated with the total runoff measurements of a storm event made at an outlet of a small subwatershed where the contribution of base flow to the total hydrograph is relatively insignificant. In addition, a rainfall event, which occurred after long dry time and enough far from the beginning of the entire simulation period not to be affected by the initial soil moisture condition, was selected for calibration.

Consequently, the four rainfall events, which occurred in the Owl Run watershed from 2 to 10 Sep 1992 were selected for calibrating the parameters for direct runoff and soil moisture simulation in this study. The observed runoff of the first rainfall event was utilized to calibrate the parameters for direct runoff simulation, and then the other parameters for soil moisture and base flow simulation were calibrated with the observed runoff of the subsequent three storm events. Then, the parameter for base flow simulations of HYSTAR was calibrated with the 1-year total runoff measurements (from 2 Sep 1992 to 2 Sep 1993) while the parameters for direct runoff simulation are fixed to their calibrated values in the previous step. This separated calibration scheme are described in 4.2.1.1 (Case 1).

Although the storm event that has relatively dry soil condition at the beginning has been selected, degree of base flow contribution to the total runoff is still unsure. Therefore, several alternative calibration strategies are implemented for better calibration of HYSTAR to the rainfall events (Figure 4.45). In Case 2, only the last storm event of the four, which produced relatively high runoff peak, was employed in calibration of the parameters for soil moisture simulation. Because only parameter for base flow simulation, GWC, which represent a rate of base flow to the percolated water volume, is determined
after the other parameters for direct runoff and soil moisture simulation are calibrated, the base flow is not simulated in the calibration schemes (Case 1 to 4).

In Case 3, the parameters for direct runoff and soil moisture simulations were calibrated with the total runoff measurements of only the first and last rainfall events. On the other hand, in Case 4, all the four rainfall events were employed in calibration of the parameters for direct runoff and soil moisture simulations at the same time. In Case 5, the parameter for base flow simulation, GWC, was calibrated simultaneously with the parameters for soil moisture simulation. Finally, in Case 6, all the 11 parameters of HYSTAR were calibrated with the measured runoff of all the rainfall events at the same time. Detailed descriptions and results of the alternative calibrations are presents in
Appendix A. From these variations in calibration scheme, it was expected to get better calibration results using the short runoff measurements of the four rainfall events. Additionally, it may provide an opportunity to investigate dependency of calibration accuracy and parameter uncertainty on hydrologic feature of data used and the number of parameters to be calibrated together.

For calibration, the initial soil moisture condition for the storm event of 2 Sep 1992 was simulated using the nominal values of the parameters. The nominal values of the parameters (scale factors) were determined based on consideration of their physical meanings in the model (Tables 4.20 and 4.21). At the beginning of the entire simulation period, 1 Jan 1990, soil water content of 30% to the root zone depth is assumed uniformly distributed over the watershed.

In the definition of the initial soil moisture condition, if a different nominal value set for the parameters is applied, the simulation may produce a different initial soil moisture condition. Then, the different initial condition may lead to different calibration results. In this study, thus, a recursive calibration practice was tried to refine initial condition for calibration. It assumes that a better parameter value set will result in better identification of initial condition and subsequently lead to better calibration results. In addition, it is assumed that the calibrated parameter value set can be a better parameter value set in defining the initial condition for calibration. Thus, the calibrated parameter value set in the previous calibration practice can be used to refine the initial condition for the present calibration practice. Through this recursive calibration procedure, the updated initial soil moisture condition may get close to its true state in the context of this modeling practice, and thereby it is expected for calibration to be done more accurately. Based on this assumption, in this study, parameter calibrations were implemented in an iterative way (Figure 4.46), and improvement in agreement between the simulated and observed hydrographs was examined as the iterative calibration proceeded.

The eight parameters, CNF, MNO, MNC, BCC, EFS, RZD, SCR, and SDR are scale factors introduced to keep spatial distribution of the parameters while changing their values. Spatial distribution of the relating parameters to the scale factors are presented in Figure 4.47. The Manning’s roughness coefficient for channel was assumed
equal to 0.03 over the entire watershed. This approach may limit utility of calibration and subsequently result in additional error and uncertainty in parameter optimization and model output. On the other hand, it can improve efficiency of calibration and mitigate equifinality issue by reducing the number of parameters to be calibrated.

To reflect seasonal variation in development of vegetation, a relevant parameter, BCC, was assumed varied temporally, and its seasonal change was determined based on literature and the crop management practice provided by Cho et al. (2009). Finally, four parameters for sediment transport simulation, CSO (Critical Shield parameter for Overland), CSC (Critical Shield parameter for Channel), and SCR (Soil Cohesion Ratio), SDR (Soil Detachability Ratio) were calibrated with the observed sediment load at the watershed outlet.

![Recursive calibration strategy](image)

Figure 4.46. Recursive calibration strategy.
Figure 4.47a. Curve number for CNF.

Figure 4.47b. Manning’s roughness coefficient for MNO.
Figure 4.47c. Crop coefficient for BCC.

Figure 4.47d. Fraction of soil surface covered by vegetation for EFS.
Figure 4.47e. Soil depth for RZD.

Figure 4.47f. Soil erodibility efficiency for SCR.
4.2.2 Hydrology Simulation

4.2.2.1 Owl Run - Sep 1992 to Aug 1993

HYSTAR employs four parameters for direct runoff simulation: a scale factor for the Curve Number (CNF), scale factors for the Manning’s roughness coefficients for overland and channel (MNO and MNC), and a threshold area of defining channel networks (THA). They were calibrated with the measured runoff at the outlet of the most upper subwatershed of the Owl Run watershed, subwatershed D (ORD). The storm event that occurred on 2 Sep 1992 and produced rainfall amount of 35.6 mm was selected for the parameter calibration because its hydrograph has a distinguished and relatively high peak of 0.452 m³/s. In addition, it is far enough from the beginning of the entire simulation period, Jan 1 1990, not to be affected by the initial condition. The storm event was immediately followed by three independent storm events, which will be used in the next calibration procedure for soil moisture simulation, so thus the required time for the entire calibration practice can be reduced. Moreover, the storm event period well agrees with the acquisition year of the land cover data, NLCD 1992.
In the calibration, runoff hydrograph of the storm event was assumed not directly and significantly affected by frost in the winter and reservoir storage, and the initial condition for the beginning of the entire simulation, 1 Jan 1990. In addition, the contribution of base flow to runoff hydrograph of the storm event is assumed insignificant, so thus the parameters for only direct runoff simulation could be calibrated effectively using the runoff hydrograph. The insignificant contribution was ensured by the very little runoff (less than 0.01 m$^3$/s) observed for 15 days before the storm event. The initial soil moisture condition for the calibration was simulated using nominal values of the parameters (Tables 4.20 and 4.21). Then, the calibrated parameter values in the first iteration of calibration were used to generate a new initial soil moisture condition for the second iteration. The recursive calibration practice was continued as long as the simulated runoff hydrograph provided better RMSE in comparison with the observed runoff. However, the number of iterations did not exceed three in consideration of efficiency.

Calibration was implemented using the Shuffled Complex Evolution (SCE) algorithm (Duan et al., 1992; Duan et al., 1993; Duan et al., 1994). It was run with 25 complexes, a population size of 9 for each complex, and the total sample population of 225. The minimum number of complexes was set to 12. Root Mean Squared Error (RMSE) was used as an objective function to measure agreement of the simulated runoff with the measured. The predefined upper and lower limits of the parameters and the starting and calibrated values of the parameters are represented in Table 4.20. Figure 4.48 and 4.49 depict convergence of the objective function and parameter values in the last 100 explorations. In the calibration for direct runoff simulation, the SCE-UA algorithm was scheduled to stop when a RMSE value of the last exploration becomes less than 0.010 m$^3$/s. However, RMSE did not drop into the threshold value in spite of long explorations over 1000, so thus the SCE-UA algorithm was forced to stop. The calibrated direct runoff hydrograph are presented in Figure 4.50.
Table 4.20. Calibrated values of the four parameters for direct runoff simulation.

<table>
<thead>
<tr>
<th>Parameter a</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>RMSE d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ranges b</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
<td>1.00</td>
<td>-</td>
</tr>
<tr>
<td>Upper</td>
<td>1.500</td>
<td>1.500</td>
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<td>-</td>
</tr>
<tr>
<td>Starting Value c</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iter. 1</td>
<td>1.096</td>
<td>1.012</td>
<td>1.242</td>
<td>19.07</td>
<td>0.0111</td>
</tr>
<tr>
<td>Iter. 2</td>
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<td>0.779</td>
<td>1.370</td>
<td>18.17</td>
<td>0.0108</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>1.094</td>
<td>1.054</td>
<td>1.171</td>
<td>17.91</td>
<td>0.0102</td>
</tr>
</tbody>
</table>

a CNF: curve number scale factor; MNO: Manning’s roughness coefficient scale factor for overland; MNC: Manning’s roughness coefficient scale factor for channel; THA: threshold area to define the extent of stream networks (ha); RMSE: RMSE for the calibrated parameter set (m^3/s);
b Ranges were determined based on primary investigation of model sensitivity;
c Starting Value is equal to nominal value, and they were determined based on literature and personal experience; d Unit of RMSE is m^3/s

Figures 4.48 and 4.49 show convergence of the objective function and parameter values at every iteration step of calibrations as the SCE-UA algorithm explore in parameter space. In the figures, values of the parameter and the objective function started to converge and drop into their optima and minimum respectively from around the last 65 explorations (sequences). After the objective function became stable, sequences of the CNF values and the objective functions were constant while the others was fluctuating. This high cross correlation between values of CNF and the objective function reflects sensitivity of direct runoff hydrograph to CNF. In Figure 4.48, CNF escaped from a local optimum close to 60 at the last 85 sequences and converged to its optimum at the last 70 sequences. In addition, THA got out of a local attraction and converged to its optimum at the last 70 sequences. The calibrated direct runoff hydrograph for the storm event is presented with the measured in Figure 4.50.
Figure 4.48a. Iteration 1.

Figure 4.48b. Iteration 2.
Figure 4.48c. Iteration 3.

Figure 4.48. Convergence of CNF, MNO, MNC, and THA in the calibration.

Figure 4.49a. Iteration 1.
Figure 4.49b. Iteration 2.

Figure 4.49c. Iteration 3.

Figure 4.49. Convergence of the objective function value (RMSE) in the calibration.
Figure 4.50a. Iteration 1.

Figure 4.50b. Iteration 2.
Figure 4.50c. Iteration 3.

Figure 4.50. Calibrated direct runoff hydrograph for the 2 Sep 1992 storm event.

In Figure 4.50, the calibrated direct runoff hydrograph showed good overall agreement with the measured runoff. However, the calibrated direct runoff simulation provided abrupt rises at the beginning of the rising part (about 6 hours after the beginning) in the direct runoff hydrograph while the measured showed a smooth rise. This discrepancy between the simulated and measured hydrograph might be contributed to inaccurate initial soil moisture condition and/or the fixed spatial variations of the input data and parameters. In addition, for this calibration, insignificant contribution of base flow to total runoff was assumed. However, long and smoothly dropping tail of the observed hydrograph implies existence of base flow. Thus, the calibrated parameter set might provide a higher peak but lower tail than those of the observed hydrograph because the objective function, RMSE, tends to distribute errors over the length of data evenly. Therefore, there is a possibility of overestimating the parameters for direct runoff simulation in the calibration.

Once calibration for direct runoff simulation is completed, the parameters for soil moisture simulation would be calibrated with the measured runoff. Because the number of parameters to be calibrated is greater than that of the calibration for direct runoff
simulation, the SCE-UA algorithm was run with the different total population size of 325 and a population size of 13 for each complex to maintain the same number of complexes (25 complexes) that controls effectiveness of the algorithm. The minimum number of complexes was also set to 12, and Root Mean Squared Error (RMSE), which is the same as that used in the calibration for direct runoff simulation, was also utilized as an objective function.

The parameters to be calibrated in this calibration practice include two coefficients of the van Genuchten equation (GCL and GCM), basal crop coefficient and effective fraction of soil surface covered by vegetation of the dual crop coefficient method (BCC and EFS), root zone depth (RZD), and soil anisotropic ratio (SAR). The four consecutive storm events that occurred between 2 and 10 Sep 1992 were selected in the calibration for soil moisture modeling. They produced four distinguished peaks ranging from 0.075 to 0.685 m$^3$/s. The storm event set includes the event occurred on 2 Sep 1992, which was used for the direct runoff modeling in the previous step, and thus the same initial soil moisture condition could be employed. Then, only the parameter for base flow simulation, GWC, was calibrated using the one-year runoff measurement between 2 Sep 1992 and 1 Sep 1993 through matching the simulated total runoff volume to the measured. The starting and calibrated values of the parameters are shown in Table 4.21. Figures 4.51 and 4.52 describe convergence of the objective function and parameter values in the last 100 explorations.

As seen in Figure 4.51, contrary to the case of the direct runoff calibration, values of the parameters did not converge into their optima strongly. In Figure 4.52, values of the objective function did not become stable but kept dropping. It indicates the possibility of getting better optima of the parameters as explorations continue. However, additional long explorations did not produce better parameter sets for soil moisture and direct runoff simulations. Thus, in this study, the SCE-UA algorithm was forced stopped because the RMSE did not drop into the threshold value of 0.05, which was set in the calibration for soil moisture simulation, despite additional long explorations. Sequences of the RZD and GCM values were more stable than was the GCL in the last 100 explorations while values of the objective functions continued to decrease. This observation corresponds to the sensitivity analysis results. In the sensitivity analysis, RZD and GCM were the most
sensitive parameters for direct runoff hydrograph simulation. The calibrated direct runoff hydrographs for the storm events were compared with the measured in Figure 4.53.

Table 4.21. Calibrated values of the six parameters for soil moisture simulation.

<table>
<thead>
<tr>
<th>Parameter a</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
<th>GWC</th>
<th>RMSE d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ranges b</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td>0.250</td>
<td>0.250</td>
<td>0.500</td>
<td>0.500</td>
<td>0.100</td>
<td>0.100</td>
<td>0.000</td>
<td>-</td>
</tr>
<tr>
<td>Upper</td>
<td>0.750</td>
<td>0.750</td>
<td>1.500</td>
<td>1.500</td>
<td>2.000</td>
<td>2.000</td>
<td>1.000</td>
<td>-</td>
</tr>
<tr>
<td>Starting Value c</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iter. 1</td>
<td>0.508</td>
<td>0.254</td>
<td>0.588</td>
<td>1.420</td>
<td>0.177</td>
<td>0.267</td>
<td>0.584</td>
<td>0.0712</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>0.710</td>
<td>0.316</td>
<td>0.508</td>
<td>1.281</td>
<td>0.216</td>
<td>0.209</td>
<td>0.591</td>
<td>0.0685</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>0.662</td>
<td>0.325</td>
<td>0.512</td>
<td>1.187</td>
<td>0.339</td>
<td>0.164</td>
<td>0.502</td>
<td>0.0759</td>
</tr>
</tbody>
</table>

a GCL: Coefficient L of the Van Genuchten equation; GCM: Coefficient M of the Van Genuchten equation; BCC: Basal crop coefficient of the crop coefficient method; EFS: Effective fraction of soil surface covered by vegetation of the crop coefficient method; RZD: Root zone depth; SAR: Soil anisotropic ratio; RMSE for the calibrated parameter set (m³/s); b Ranges were determined based on primary investigation of model sensitivity; c Starting Value is equal to nominal value, and they were determined based on literature and personal experience; d Unit of RMSE is m³/s

Figure 4.51a. Iteration 1.
Figure 4.51b. Iteration 2.

Figure 4.51c. Iteration 3.

Figure 4.51. Convergence of GCL, GCM, BCC, EFS, RZD, and SAR in the calibration.
Figure 4.52a. Iteration 1.

Figure 4.52b. Iteration 2.
Figure 4.52c. Iteration 3.

Figure 4.52. Convergence of the objective function value (RMSE) in the calibration.

Figure 4.53a. Iteration 1.
Figure 4.53. Calibrated direct runoff hydrograph for the storms that occurred between 2 and 10 Sep 1992 using the calibrated parameter values for the direct runoff and soil moisture simulations (Case 1).
As seen in Figure 4.53, the calibrated direct runoff hydrograph showed significant differences with the observed runoff due to ignorance of base flow in the simulation. For the same reason, the RMSEs are relatively large comparing to the RMSEs of the calibration for direct runoff simulation (Tables 4.20 and 4.21). In addition, the calibrated simulation produced no direct runoff for the third hydrograph and relatively small peaks for the second and last storm events. This comparison implies that contribution of base flow to the total runoff for the three rainfall events (2nd, 3rd, and the last) can be significant. Subsequently, the parameters for soil moisture simulation might be overestimated theoretically. Thus, other calibration schemes were devised and tried to explore a way to avoid the issue resulting from calibrating the parameters without base flow separation. The results of the alternative calibration schemes are presented in Appendix A. However, all the alternatives provided inferior calibration results than did this calibration practice (Case 1), and it implies that the Case 1 approach is a better way to optimize parameters for direct runoff and base flow simulation without base flow separation.

In the recursive calibration practices, the calibrated direct runoff hydrographs were lowered, in particular for the last storm event, as the iterations proceeded. Even though contribution of base flow to the total hydrograph might become more significant as soil moisture got wetter in the following storm events, the calibrated direct runoff hydrograph looked underestimated. The model performances in predicting runoff at every iteration step are presented in Appendix B. Although the recursive procedures were implemented in order to refine the initial soil moisture condition for the calibration, representativity of the series of storm events can be questionable because only four storms that occurred during 10 days of the entire simulation period of 6 years were employed in the calibration. Thus, another set of storm events were tested in calibration for hydrology simulation of HYSTAR in order to compare and ensure the calibration results. The results are presented in 4.2.2.2.
**4.2.2.2 Owl Run - Oct 1990 to Sep 1991**

A storm event that occurs on 18 Oct 1990 was selected for an alternative calibration of the parameters for direct runoff simulation. The event produced rainfall amount of 48.0 mm and runoff peak of 0.502 m³/s. It was also assumed not directly and significantly affected by frost in the winter, reservoir storage, and the initial soil moisture condition for the beginning of the entire simulation, Jan 1 1990. The initial soil moisture condition for the calibration was generated using nominal values of the parameters (Table 4.22), and its spatial average was 16.6% in volumetric soil moisture content in the root zone layer. Calibration was implemented using the same optimization algorithm, number of complexes, population size for each complex, minimum number of complexes, objective function, upper and lower value limits of the parameters, and the starting values of the parameters as those used in the previous calibration. Figures 4.54 and 4.55 depict convergence of the objective function and parameter values in the last 100 explorations. The calibrated direct runoff hydrographs are presented in Figure 4.56.

**Table 4.22. Calibrated values of the four parameters for direct runoff simulation.**

<table>
<thead>
<tr>
<th>Parameter a</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>RMSE a</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ranges b</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
<td>1.000</td>
<td>-</td>
</tr>
<tr>
<td>Upper</td>
<td>1.500</td>
<td>1.500</td>
<td>1.500</td>
<td>100.00</td>
<td>-</td>
</tr>
<tr>
<td><strong>Starting Value c</strong></td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>10.00</td>
<td>-</td>
</tr>
<tr>
<td><strong>Calibrated Value</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iter. 1</td>
<td>1.030</td>
<td>0.554</td>
<td>0.530</td>
<td>17.00</td>
<td>0.0091</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>1.036</td>
<td>0.709</td>
<td>0.667</td>
<td>15.70</td>
<td>0.0225</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>1.036</td>
<td>0.618</td>
<td>0.504</td>
<td>18.16</td>
<td>0.0116</td>
</tr>
</tbody>
</table>

a CNF: curve number scale factor; MNO: Manning’s roughness coefficient scale factor for overland; MNC: Manning’s roughness coefficient scale factor for channel; THA: threshold area to define the extent of stream networks (ha); RMSE: RMSE for the calibrated parameter set (m³/s); b Ranges were determined based on primary investigation of model sensitivity; c Starting Value is equal to nominal value, and they were determined based on literature and personal experience; d Unit of RMSE is m³/s

In Table 4.22, as the iterations proceeded, the RMSEs were fluctuating. In particular, in the second iteration, it increased by 250% of the RMSE of the first iteration. Then, it decreased by half in the third iteration even though values of the most sensitive parameter, CNF, are similar in the last two iterations. In addition, in Figure 4.56, the
calibrated direct runoff hydrograph in the second iteration shows the worst agreement of the shape with that of the observed. It indicates that iterative calibration practices do not necessarily improve the agreement between the simulated and observed. This unfavorable result might be contributed to inaccurate definition of the initial soil moisture condition for the calibration. As seen in Figure 4.54, the sensitive parameters for soil moisture simulation such as GCM, BCC, EFS, and RZD are highly fluctuating due to the short calibration period while the objective function values are being minimized slowly. In addition, runoff hydrographs of only two storm events were utilized in the calibration of the parameters for soil moisture simulation (Figure 4.59). This uncertainty or equifinality arisen from the parameter calibration may deteriorate validity of the calibrated parameters in the other period than the calibration. Thus, the determined parameter values in the previous calibration iteration may provide a worse initial soil moisture condition to the next calibration iteration and subsequent worse calibration results.

Figures 4.54 and 4.55 show variations in values of the objective function and parameter in the last 100 explorations of the SCE-UA algorithm. In the figures, values of CNF and the objective function started to converge and drop into their optima and minimum respectively from around the last 70 explorations while values of the other three parameters were still fluctuating. In addition, in Figure 4.55a, the objective function converged before the last 100 explorations but the parameters were waving expect for CNF. Similar to the results of the previous calibration, the high correlation between values of CNF and the objective function indicates that direct runoff simulation of HYSTAR is the most sensitive to CNF. The calibrated direct runoff hydrograph for the rainfall event was presented with the measured in Figure 4.56.
Figure 4.54a. Iteration 1.

Figure 4.54b. Iteration 2.
Figure 4.54c. Iteration 3.

Figure 4.54. Convergence of CNF, MNO, MNC, and THA in the calibration using the storm event occurred on 18 Oct 1990.

Figure 4.55a. Iteration 1.
Figure 4.55b. Iteration 2.

Figure 4.55c. Iteration 3.

Figure 4.55. Convergence of the objective function value (RMSE) in the calibration using the storm event occurred on 18 Oct 1990.
Figure 4.56a. Iteration 1.

Figure 4.56b. Iteration 2.
In Figure 4.56, the calibrated direct runoff hydrograph showed good overall agreement with the measured total runoff. Contrary to the runoff hydrograph of the storm event that occurred on 2 Sep 1992, the observed runoff also showed an abrupt rise at the beginning of the hydrograph (about 5 hours after the beginning). It may mean the storm event that occurred on 18 Oct 1990 had wetter soil moisture condition at the beginning than the event on 2 Sep 1992 so that wider area could contribute to direct runoff quickly. In addition, similar to the previous calibration results, all the calibrated hydrograph provided a little higher peak runoff than that of the observed because RMSE tends to distribute errors over the entire data evenly.

Once the parameters for direct runoff simulation were calibrated, the parameters for soil moisture simulation, GCL, GCM, BCC, EFS, RZD, and SAR, would be calibrated with the measured flow. The two consecutive storm events that occurred between 18 and 22 Oct 1990 were chosen in the calibration for soil moisture simulation. The second storm event, which immediately followed the first, produced a distinguished peak of 0.520 m³/s. Finally, only the parameter for base flow simulation, GWC, was calibrated using the one-year runoff measurement between 18 Oct 1990 and 17 Oct 1991.
through matching the simulated total runoff volume to the measured. The same initial soil moisture condition, algorithm, and objective function as those of the direct runoff calibration were employed. In addition, the same setting of the SCE-UA algorithm as the previous calibration for soil moisture simulation was utilized. The starting and calibrated values of the parameters are represented in Table 4.23. Figures 4.57 and 4.58 depict convergence of the objective function and parameter values in the last 100 explorations.

Table 4.23. Calibrated values of the six parameters for soil moisture simulation for the 18 Oct to 22 Oct 1990 storm event.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
<th>GWC</th>
<th>RMSE (m$^3$/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ranges</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td>0.250</td>
<td>0.250</td>
<td>0.500</td>
<td>0.500</td>
<td>0.100</td>
<td>0.100</td>
<td>0.000</td>
<td>-</td>
</tr>
<tr>
<td>Upper</td>
<td>0.750</td>
<td>0.750</td>
<td>1.500</td>
<td>1.500</td>
<td>2.000</td>
<td>2.000</td>
<td>1.000</td>
<td>-</td>
</tr>
<tr>
<td><strong>Starting Value</strong></td>
<td>0.500</td>
<td>0.500</td>
<td>1.000</td>
<td>1.000</td>
<td>0.500</td>
<td>1.000</td>
<td>0.500</td>
<td>-</td>
</tr>
<tr>
<td><strong>Calibrated Value</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iter. 1</td>
<td>0.579</td>
<td>0.550</td>
<td>0.612</td>
<td>0.909</td>
<td>0.319</td>
<td>0.100</td>
<td>0.670</td>
<td>0.0316</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>0.534</td>
<td>0.290</td>
<td>0.928</td>
<td>0.562</td>
<td>0.356</td>
<td>0.186</td>
<td>5.018</td>
<td>0.0326</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>0.667</td>
<td>0.380</td>
<td>1.226</td>
<td>1.139</td>
<td>0.349</td>
<td>0.128</td>
<td>2.318</td>
<td>0.0308</td>
</tr>
</tbody>
</table>

$^a$ GCL: Coefficient L of the Van Genuchten equation; GCM: Coefficient M of the Van Genuchten equation; BCC: Basal crop coefficient of the crop coefficient method; EFS: Effective fraction of soil surface covered by vegetation of the crop coefficient method; RZD: Root zone depth; SAR: Soil anisotropic ratio; RMSE for the calibrated parameter set (m$^3$/s) ; $^b$ Ranges were determined based on primary investigation of model sensitivity; $^c$ Starting Value is equal to nominal value, and they were determined based on literature and personal experience; $^d$ Unit of RMSE is m$^3$/s
Figure 4.57a. Iteration 1.

Figure 4.57b. Iteration 2.
Figure 4.57c. Iteration 3.

Figure 4.57. Convergence of GCL, GCM, BCC, EFS, RZD, and SAR in the calibration using the storm event occurred on 18 to 22 Oct 1990.

Figure 4.58a. Iteration 1.
Figure 4.58b. Iteration 2.

Figure 4.58c. Iteration 3.

Figure 4.58. Convergence of the objective function value (RMSE) in the calibration using the storm event occurred on 18 to 22 Oct 1990.
Similar to the case of the previous calibration, values of the parameter waved in certain ranges, and values of the objective function was not stabilized. In the last 100 explorations, variations in GCM and RZD were smaller than were those in the others. However, GWC was calibrated into unrealistic values, which is greater than 1.0, in the second and third iterations. Contribution of the percolated water volume to base flow is proportional to GWC. Thus, GWC greater than 1.0 means that more soil water than the percolated water volume discharged to the aquifer and then contributed to base flow. Those unrealistic values were originated to compensate reduction in total runoff volume with base flow volume. Thus, it implies significant underestimation of direct runoff in the simulation. Therefore, the calibrated parameter values in the second and third iterations should be discarded in simulation and model evaluation.

The calibrated runoff hydrograph for the storm events was presented with the measured in Figure 4.59. In the figures, the calibrated direct runoff hydrographs show higher peak runoff but thinner tail in the second event due to ignorance of base flow in the calibration. This comparison implies that the contribution of the base flow to the total runoff becomes more significant in the following storm, and it was observed in the previous calibration as well. Contrary to the previous calibration, however, the predicted direct runoff hydrographs was not lowered for the following storm event as the iteration proceeded.

The CNF was calibrated to 1.094 and 1.036 for the storm event that occurred on 2 Sep 1992 and 18 Oct 1990 respectively. Considering sensitivity of the model to the parameters, even though the change in the calibrated values of CNF, 0.058 (= 1.094 – 1.036), appears very small, it may cause significant change in hydrology simulation. For instance, when CNF of 1.094 and 1.036 are applied in the simulation, average CNs for the watershed are calculated as 77.17 to 73.12 respectively at the AMC II condition. Then, the average CN of 73.12 produces excess rainfall of only 2.6 mm while the average CN of 77.17 produces 4.4 mm for the storm event occurred on 2 Sep 1992 (Table 4.24). Therefore, the change may lead to significant difference in the peak runoff as well as total runoff volume in the entire simulation period.
Figure 4.59a. Iteration 1.

Figure 4.59b. Iteration 2.
Figure 4.59c. Iteration 3.

Figure 4.59. Calibrated direct runoff hydrograph for the storms that occurred between Oct 18 and 22 Oct 1990 using the calibrated parameter values for the direct runoff and soil moisture simulations (Case 1).

Table 4.24. Example calculation of excess rainfall volume with different CNs (unit: mm).

<table>
<thead>
<tr>
<th>Rainfall</th>
<th>5.3</th>
<th>8.1</th>
<th>0.3</th>
<th>7.8</th>
<th>2.9</th>
<th>11.1</th>
<th>0.1</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acc. Rainfall</td>
<td>5.3</td>
<td>13.4</td>
<td>13.7</td>
<td>21.5</td>
<td>24.4</td>
<td>35.5</td>
<td>35.6</td>
<td></td>
</tr>
<tr>
<td>Acc. Ex. Rainfall</td>
<td>CN=77.17</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.5</td>
<td>1.0</td>
<td>4.4</td>
<td>4.4</td>
</tr>
<tr>
<td>CN=73.12</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.3</td>
<td>2.6</td>
<td>2.6</td>
<td>-</td>
</tr>
<tr>
<td>Ex. Rainfall</td>
<td>CN=77.17</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.5</td>
<td>0.5</td>
<td>3.3</td>
<td>0.0</td>
</tr>
<tr>
<td>CN=73.12</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.2</td>
<td>2.2</td>
<td>0.0</td>
<td>2.6</td>
</tr>
</tbody>
</table>

THA was calibrated to the value close to that in the previous calibration. THA was varied between 15.7 and 19.1 through the recursive procedures in the both calibrations. It may imply that the threshold area that defines stream network of a watershed is mainly determined by physical characteristics of the watershed. RZD was also calibrated to a value close to that of the previous calibration, and its calibrated values varied in a relatively narrow range of between 0.319 and 0.356. As the example shown in the previous calibration, when the calibrated RZD is applied, the depth of sensitive part of soil to the water flux becomes about 51 cm.
4.2.2.3 Polecat Creek – Sep 2000 to Aug 2001

The four parameters for direct runoff simulation were calibrated with the measured flow at the outlet of the most upper subwatershed of the Polecat watershed, subwatershed A (PCA). A rainfall event that occurred on 2 Sep 2000 was selected for calibration of the parameters. Based on the results of the previous applications of the multiple calibration approaches, only Case 1 was applied in the calibration. The event produced a distinguished peak of 0.28 m$^3$/s from rainfall amount of 51.0 mm. The event can be one of the representatives of the storm events for calibration in spite of its small runoff peaks considering only 15 storm events produced peak runoffs over 0.20 m$^3$/s and the highest peak was 1.27 m$^3$/s for 4 years from 1999 to 2002. In addition, the period was assumed not directly and significantly affected by frost in the winter, reservoir storage, and the initial soil moisture condition for the beginning of the entire simulation, 1 Jan 1999.

The initial soil moisture condition for calibration was determined using the same nominal values of parameters as those used in the Owl Run watershed modeling (Table 4.25). The generated initial soil moisture condition using the parameter’s nominal values for the calibration showed the spatially averaged soil moisture of about 14.0 % at the beginning of the rainfall event, 2 Sep 2000 while the spatially averaged wilting point was 13.9 % in volumetric soil moisture content in the root zone depth. Calibration was performed using the same algorithm, Shuffled Complex Evolution (SCE) (Duan et al., 1992; Duan et al., 1993; Duan et al., 1994), and the same measure, Root Mean Squared Error (RMSE), was used as an objective function. The starting and calibrated values of the parameters are represented in Table 4.25. Figures 4.60 and 4.61 describe convergence of the objective function and parameter values in the last 100 explorations.

As seen in Figures 4.60 and 4.61, the sequences of CNF and objective function values are relatively constant in the last 100 explorations of the second and third. It means the parameters were optimized more quickly in the iterations. On the other hand, variations of the other parameters’ values (MNO, MNC, and THA) are greater than are those of the previous calibration in all the iterations of this calibration. In addition, the RMSEs of the calibration are greater than are those of the calibration for ORD even
though total runoff volume and peak runoff of the storm are smaller. It indicates that more uncertainty is contained in the calibrated parameter values.

In Figure 4.62, the calibrated direct runoff hydrograph displays two peaks whereas the observed has only one. In addition, qualitative comparison of the agreements between the calibrated and observed direct runoff hydrographs in ORD and PCA (Figures 4.50, 4.56, and 4.62) implies that quality of the calibrated parameter values in PCA is inferior to those in ORD. In Table 4.25, THA was calibrated between 2.32 and 3.15, which are much smaller than those in ORD. Although sequences of the THA values were fluctuating overall in the calibration (Figure 4.60), they were converged into a small region in the last 10 explorations. The small THA means that the watershed, PCA, has denser channel network than does ORD in the context of this modeling.

Table 4.25. Calibrated values of the four parameters for direct runoff simulation (Polecat Watershed).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ranges b</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td>0.500</td>
<td>1.500</td>
<td>1.500</td>
<td>1.00</td>
<td>-</td>
</tr>
<tr>
<td>Upper</td>
<td>1.500</td>
<td>1.500</td>
<td>1.500</td>
<td>100.00</td>
<td>-</td>
</tr>
<tr>
<td>Starting Value c</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iter. 1</td>
<td>0.935</td>
<td>1.353</td>
<td>0.735</td>
<td>2.78</td>
<td>0.0330</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>0.997</td>
<td>0.837</td>
<td>0.575</td>
<td>3.15</td>
<td>0.0292</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>1.011</td>
<td>0.998</td>
<td>1.231</td>
<td>2.32</td>
<td>0.0249</td>
</tr>
</tbody>
</table>

a CNF: curve number scale factor; MNO: Manning’s roughness coefficient scale factor for overland; MNC: Manning’s roughness coefficient scale factor for channel; THA: threshold area to define the extent of stream networks (ha); RMSE: RMSE for the calibrated parameter set (m³/s); b Ranges were determined based on primary investigation of model sensitivity; c Starting Value is equal to nominal value, and they were determined based on literature and personal experience
Figure 4.60a. Iteration 1.

Figure 4.60b. Iteration 2.
Figure 4.60c. Iteration 3.

Figure 4.60. Convergence of CNF, MNO, MNC, and THA in the calibration using the storm event occurred on 2 Sep 2000 in the Polecat Creek watershed, PCA.

Figure 4.61a. Iteration 1.
Figure 4.61b. Iteration 2.

Figure 4.61c. Iteration 3.

Figure 4.61. Convergence of the objective function value (RMSE) in the calibration using the storm event occurred on 2 Sep 2000 in the Polecat Creek watershed, PCA.
Figure 4.62a. Iteration 1.

Figure 4.62b. Iteration 2.
After the parameters for direct runoff simulation were calibrated, the parameters for soil moisture simulation, GCL, GCM, BCC, EFS, RZD, and SAR, were calibrated with the measured flow. The three consecutive storm events that occurred between 2 and 24 Sep 2000 were chosen in the calibration for soil moisture simulation. Then, only the parameter for base flow simulation, GWC, was calibrated using the one-year runoff measurement between 2 Sep 2000 and 1 Sep 2001 through matching the simulated total runoff volume to the measured. The same initial soil moisture condition, algorithm, and objective function as those of the direct runoff calibration were employed. In addition, the same setting of the SCE-UA algorithm as the previous calibration for soil moisture simulation was utilized. The starting and calibrated values of the parameters are represented in Table 4.26. Figures 4.63 and 4.64 describe convergence of the objective function and parameter values in the last 100 explorations.
Table 4.26. Calibrated values of the six parameters for soil moisture simulation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
<th>GWC</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ranges b</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td>0.250</td>
<td>0.250</td>
<td>0.500</td>
<td>0.500</td>
<td>0.100</td>
<td>0.100</td>
<td>0.000</td>
<td>-</td>
</tr>
<tr>
<td>Upper</td>
<td>0.750</td>
<td>0.750</td>
<td>1.500</td>
<td>1.500</td>
<td>5.000</td>
<td>2.000</td>
<td>1.000</td>
<td>-</td>
</tr>
<tr>
<td>Starting Value c</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iter. 1</td>
<td>0.404</td>
<td>0.597</td>
<td>0.940</td>
<td>1.435</td>
<td>3.049</td>
<td>0.517</td>
<td>0.181</td>
<td>0.0235</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>0.266</td>
<td>0.730</td>
<td>0.553</td>
<td>1.235</td>
<td>3.375</td>
<td>0.555</td>
<td>0.047</td>
<td>0.0260</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>0.691</td>
<td>0.734</td>
<td>1.266</td>
<td>0.547</td>
<td>1.247</td>
<td>0.408</td>
<td>0.199</td>
<td>0.0291</td>
</tr>
</tbody>
</table>

Figure 4.63a. Iteration 1.
Figure 4.63b. Iteration 2.

Figure 4.63c. Iteration 3.

Figure 4.63. Convergence of GCL, GCM, BCC, EFS, RZD, and SAR in the calibration using the storm events occurred on 2 to 24 Sep 2000 in the Polecat Creek watershed, PCA.
Figure 4.64a. Iteration 1.

Figure 4.64b. Iteration 2.
Figure 4.64c. Iteration 3.

Figure 4.64. Convergence of the objective function value (RMSE) in the calibration using the storm events occurred between 2 and 24 Sep 2000 in the Polecat Creek watershed, PCA.

Contrary to the cases of the previous calibrations, values of the parameter waved in certain ranges except for RZD while values of the objective function were stabilized completely in the last 100 explorations. In particular, RZD highly fluctuated within the full range of 0.1 to 5 in the second and third iterations. The maximum limit of RZD was set to 5 instead of 2, which was used in the calibration for ORD, in order to reflect land cover characteristics of PCA. 76% of the watershed, PCA, is covered by forest that may have a well-developed layer of leaf litter, which can hold significant amount of water. Thus, temporal variation in the soil water content may be relatively small comparing to that of ORD. In fact, in all the iterations, RZD was calibrated between 1.508 and 3.661, which is much larger than the calibrated RZD of 0.339 in ORD.

As seen in Figure 4.65, the calibrated direct runoff hydrograph showed significant differences with the observed runoff. In particular, the simulation did not produce any runoff for the second storm event. The second storm event produced a peak runoff of 0.257 m$^3$/s from rainfall of 7.9 mm while the first storm produced a peak runoff of 0.28
m³/s from rainfall of 51.0 mm. In addition, the calibrated parameters greatly overestimated the hydrograph of the third storm event in the second and third iterations. In Table 4.24, RMSE is bigger in the higher iterations as well. In the calibration for hydrology simulation, as iteration proceeded, CNF increased and RMSE decreased. Then, the increased CNF might result in the overestimation.

Figure 4.65a. Iteration 1.
Figure 4.65b. Iteration 2.

Figure 4.65c. Iteration 3.

Figure 4.65. Calibrated direct runoff hydrograph for the storms that occurred between 2 and 24 Sep 1990 using the calibrated parameter values for the direct runoff and soil moisture simulations (Case 1).
4.2.3 Time Variant Parameters

Evapotranspiration rate of land cover is changing seasonally in accordance with vegetation development stages. Thus, temporally variable parameters of HYSTAR such as BCC, EFS, MNO, and MNC can be adjusted in order to reflect impact of seasonal change in vegetation cover on calibration for hydrology simulation. In this study, however, their temporal variations were ignored or assumed based on literature (Cho et al., 2009) and assumption like Tables 4.27 to 4.30 for the sake of efficiency. These assumptions may introduce error in the simulation and subsequently deteriorate performance of the model. However, detailed information about crop management practice is not sufficient to reflect seasonal change in land cover characteristics on the simulation. In addition, the land cover data, NLCD 1992, used in the modeling does not have detailed land cover classes for agricultural activities.

Table 4.27. Temporal variation of the time variant parameters for hydrology.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>BCC</th>
<th>EFS</th>
<th>MNO</th>
<th>MNC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan ~ Mar</td>
<td>Stage 1</td>
<td>Stage 1</td>
<td>Constant (Table 4.26)</td>
<td>Constant (0.03)</td>
</tr>
<tr>
<td>Apr ~ Sep</td>
<td>Stage 2</td>
<td>Stage 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sep ~ Dec</td>
<td>Stage 3</td>
<td>Stage 3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.28. Manning’s roughness coefficients for land cover classes of NLCD 1992.

<table>
<thead>
<tr>
<th>NLCD Code</th>
<th>Description</th>
<th>n</th>
<th>NLCD Code</th>
<th>Description</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Open Water</td>
<td>0.02</td>
<td>51</td>
<td>Shrubland</td>
<td>0.07</td>
</tr>
<tr>
<td>12</td>
<td>Perennial Ice/Snow</td>
<td>0.022</td>
<td>61</td>
<td>Orchards/Vineyards/Other</td>
<td>0.1</td>
</tr>
<tr>
<td>21</td>
<td>Low-Intensity Residential</td>
<td>0.12</td>
<td>71</td>
<td>Grasslands/Herbaceous</td>
<td>0.035</td>
</tr>
<tr>
<td>22</td>
<td>High-Intensity Residential</td>
<td>0.121</td>
<td>81</td>
<td>Pasture/Hay</td>
<td>0.033</td>
</tr>
<tr>
<td>23</td>
<td>Commercial/Industrial/Transportation</td>
<td>0.05</td>
<td>82</td>
<td>Row Crops</td>
<td>0.04</td>
</tr>
<tr>
<td>31</td>
<td>Bare Rock/Sand/Clay</td>
<td>0.04</td>
<td>83</td>
<td>Small Grains</td>
<td>0.035</td>
</tr>
<tr>
<td>32</td>
<td>Quarries/Strip Mines/Gravel Pits</td>
<td>0.06</td>
<td>84</td>
<td>Fallow</td>
<td>0.032</td>
</tr>
<tr>
<td>33</td>
<td>Transitional</td>
<td>0.1</td>
<td>85</td>
<td>Urban/Recreational Grasses</td>
<td>0.03</td>
</tr>
<tr>
<td>41</td>
<td>Deciduous Forest</td>
<td>0.16</td>
<td>91</td>
<td>Woody Wetlands</td>
<td>0.14</td>
</tr>
<tr>
<td>42</td>
<td>Evergreen Forest</td>
<td>0.18</td>
<td>92</td>
<td>Emergent Herbaceous Wetlands</td>
<td>0.035</td>
</tr>
<tr>
<td>43</td>
<td>Mixed Forest</td>
<td>0.17</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>
Table 4.29. Assumed temporal variation of the time variant parameters for hydrology (Part 1).

<table>
<thead>
<tr>
<th>NLCD 1992 Code</th>
<th>Description</th>
<th>Stage $^a$</th>
<th>Kcb $^b$</th>
<th>Kfc $^c$</th>
<th>Pav $^d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Open Water</td>
<td>1</td>
<td>1.05</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>1.05</td>
<td>0.15</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>1.05</td>
<td>0.15</td>
<td>0.05</td>
</tr>
<tr>
<td>12</td>
<td>Perennial Ice/Snow</td>
<td>1</td>
<td>0.00</td>
<td>0.00</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.00</td>
<td>0.00</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.00</td>
<td>0.00</td>
<td>0.95</td>
</tr>
<tr>
<td>21</td>
<td>Low-Intensity Residential</td>
<td>1</td>
<td>0.30</td>
<td>0.45</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.75</td>
<td>0.45</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.75</td>
<td>0.45</td>
<td>0.55</td>
</tr>
<tr>
<td>22</td>
<td>High-Intensity Residential</td>
<td>1</td>
<td>0.30</td>
<td>0.10</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.75</td>
<td>0.10</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.75</td>
<td>0.10</td>
<td>0.90</td>
</tr>
<tr>
<td>23</td>
<td>Commercial/Industrial/Transportation</td>
<td>1</td>
<td>0.30</td>
<td>0.05</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.75</td>
<td>0.05</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.75</td>
<td>0.05</td>
<td>0.90</td>
</tr>
<tr>
<td>31</td>
<td>Bare Rock/Sand/Clay</td>
<td>1</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td>3</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>32</td>
<td>Quarries/Strip Mines/Gravel Pits</td>
<td>1</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
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<td>1.00</td>
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<td></td>
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<td>0.00</td>
<td>1.00</td>
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<tr>
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<td>0.15</td>
<td>0.10</td>
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<td></td>
<td>3</td>
<td>0.75</td>
<td>0.15</td>
<td>0.10</td>
</tr>
<tr>
<td>41</td>
<td>Deciduous Forest</td>
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<td>0.30</td>
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<td></td>
<td>3</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>42</td>
<td>Evergreen Forest</td>
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<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>0.00</td>
</tr>
<tr>
<td>43</td>
<td>Mixed Forest</td>
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</tr>
<tr>
<td></td>
<td></td>
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<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
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<td></td>
<td>3</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Table 4.30. Assumed temporal variation of the time variant parameters for hydrology (part 2).

<table>
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<tr>
<th>NLCD 1992 Code</th>
<th>Description</th>
<th>Stage</th>
<th>Kcb</th>
<th>Kfc</th>
<th>Pav</th>
</tr>
</thead>
<tbody>
<tr>
<td>51</td>
<td>Shrub land</td>
<td>1</td>
<td>0.30</td>
<td>0.50</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>1.00</td>
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<td>3</td>
<td>1.00</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td>61</td>
<td>Orchards/Vineyards/Other</td>
<td>1</td>
<td>0.60</td>
<td>0.50</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>1.00</td>
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<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.80</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td>71</td>
<td>Grasslands/Herbaceous</td>
<td>1</td>
<td>0.30</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.75</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.75</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td>81</td>
<td>Pasture/Hay</td>
<td>1</td>
<td>0.40</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.85</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.85</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td>82</td>
<td>Row Crops</td>
<td>1</td>
<td>0.40</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>1.20</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.70</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td>83</td>
<td>Small Grains</td>
<td>1</td>
<td>0.40</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>1.15</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.55</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td>84</td>
<td>Fallow</td>
<td>1</td>
<td>0.40</td>
<td>0.75</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>1.15</td>
<td>0.75</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.55</td>
<td>0.75</td>
<td>0.00</td>
</tr>
<tr>
<td>85</td>
<td>Urban/Recreational Grasses</td>
<td>1</td>
<td>0.30</td>
<td>0.75</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.75</td>
<td>0.75</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.75</td>
<td>0.75</td>
<td>0.10</td>
</tr>
<tr>
<td>91</td>
<td>Woody Wetlands</td>
<td>1</td>
<td>0.60</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>1.20</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.60</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td>92</td>
<td>Emergent Herbaceous Wetlands</td>
<td>1</td>
<td>0.60</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.70</td>
<td>0.90</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.70</td>
<td>0.90</td>
<td>0.00</td>
</tr>
</tbody>
</table>

* Stage: Table 4.27; Kcb: Crop coefficient; Kfc: Average exposed soil fraction covered or shaded by vegetation; Pav: Average impervious or paved land cover fraction

Curve number was also assumed as constant over time although land use change may alter ground surface condition for the curve number method. The values of curve number for every land cover class in NLCD 1992 are presented in Table 4.31.
Table 4.31. Curve numbers for land cover classes of NLCD 1992 (Mishra et al., 2003).

<table>
<thead>
<tr>
<th>NLCD Code</th>
<th>Description</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Open Water</td>
<td>99</td>
<td>99</td>
<td>99</td>
<td>99</td>
<td>Water</td>
</tr>
<tr>
<td>12</td>
<td>Perennial Ice/Snow</td>
<td>98</td>
<td>98</td>
<td>98</td>
<td>98</td>
<td>Ice</td>
</tr>
<tr>
<td>21</td>
<td>Low-Intensity Residential</td>
<td>54</td>
<td>70</td>
<td>80</td>
<td>85</td>
<td>1/2 acre</td>
</tr>
<tr>
<td>22</td>
<td>High-Intensity Residential</td>
<td>77</td>
<td>85</td>
<td>90</td>
<td>92</td>
<td>1/8 acre</td>
</tr>
<tr>
<td>23</td>
<td>Commercial/Industrial/Transportation</td>
<td>89</td>
<td>92</td>
<td>94</td>
<td>95</td>
<td>Commercial</td>
</tr>
<tr>
<td>31</td>
<td>Bare Rock/Sand/Clay</td>
<td>77</td>
<td>86</td>
<td>91</td>
<td>94</td>
<td>Bare soil</td>
</tr>
<tr>
<td>32</td>
<td>Quarries/Strip Mines/Gravel Pits</td>
<td>98</td>
<td>98</td>
<td>98</td>
<td>98</td>
<td>Impervious</td>
</tr>
<tr>
<td>33</td>
<td>Transitional</td>
<td>68</td>
<td>79</td>
<td>86</td>
<td>89</td>
<td>Poor open space</td>
</tr>
<tr>
<td>41</td>
<td>Deciduous Forest</td>
<td>30</td>
<td>55</td>
<td>70</td>
<td>77</td>
<td>Good woods</td>
</tr>
<tr>
<td>42</td>
<td>Evergreen Forest</td>
<td>45</td>
<td>66</td>
<td>77</td>
<td>83</td>
<td>Poor woods</td>
</tr>
<tr>
<td>43</td>
<td>Mixed Forest</td>
<td>36</td>
<td>60</td>
<td>73</td>
<td>79</td>
<td>Fair woods</td>
</tr>
<tr>
<td>51</td>
<td>Shrubland</td>
<td>35</td>
<td>56</td>
<td>70</td>
<td>77</td>
<td>Fair brush</td>
</tr>
<tr>
<td>61</td>
<td>Orchards/Vineyards/Other</td>
<td>43</td>
<td>65</td>
<td>76</td>
<td>82</td>
<td>Fair orchard</td>
</tr>
<tr>
<td>71</td>
<td>Grasslands/Herbaceous</td>
<td>49</td>
<td>69</td>
<td>79</td>
<td>84</td>
<td>Fair grassland</td>
</tr>
<tr>
<td>81</td>
<td>Pasture/Hay</td>
<td>30</td>
<td>58</td>
<td>71</td>
<td>78</td>
<td>Meadow</td>
</tr>
<tr>
<td>82</td>
<td>Row Crops</td>
<td>67</td>
<td>78</td>
<td>85</td>
<td>89</td>
<td>Good straight row crops</td>
</tr>
<tr>
<td>83</td>
<td>Small Grains</td>
<td>63</td>
<td>75</td>
<td>83</td>
<td>87</td>
<td>Good small grain</td>
</tr>
<tr>
<td>84</td>
<td>Fallow</td>
<td>76</td>
<td>85</td>
<td>90</td>
<td>93</td>
<td>Poor fallow</td>
</tr>
<tr>
<td>85</td>
<td>Urban/Recreational Grasses</td>
<td>39</td>
<td>61</td>
<td>74</td>
<td>80</td>
<td>Good open space</td>
</tr>
<tr>
<td>91</td>
<td>Woody Wetlands</td>
<td>98</td>
<td>98</td>
<td>98</td>
<td>98</td>
<td>Wet soil</td>
</tr>
<tr>
<td>92</td>
<td>Emergent Herbaceous Wetlands</td>
<td>96</td>
<td>96</td>
<td>96</td>
<td>96</td>
<td>Wet soil</td>
</tr>
</tbody>
</table>

4.2.4 Reservoir Simulation

Three parameters were introduced to simulate function of reservoir: reservoir storage capacity, initial reservoir level, and constant seepage rate. Evaporation rate from reservoir water surface was assumed equal to potential evaporation rate (PET) calculated by the Hargreaves equation. However, seepage rate is highly dependent on groundwater hydrology and geological feature of the watershed. In particular, a reservoir may be receiving water from or contributing water to a stream based on groundwater level. Thus, the hydrologic interaction between a reservoir and groundwater may be site specific and seasonally dynamic, and a simple time-invariant constant may be not enough to simulate the complicated interaction. In addition, hydrographs or periods affected by the reservoir
operation should be identified through examining differences between the simulated flow by the calibrated model without reservoir and the measured flow.

However, there is no data about reservoir operation including initial reservoir level at a certain time and level-storage relationship in the study watersheds. Therefore, it was assumed that two reservoirs, which were identified by the NLCD 1992 and SSURGO maps (Figures 4.66 and 4.67), in the Owl Run watershed would receive all the routed water from upstream areas. This assumption has the effect of eliminating the upstream areas from the watershed in hydrology and sediment transport simulation. However, the effect will be limited to large storms where runoff comes from a wider contributing area including the upstream areas of the reservoir, which are located upstream relatively far from the outlet. The impact of the reservoir was evaluated through comparing the simulated runoff hydrographs with and without the reservoirs based on these assumptions (Table 4.32 and Figures 4.68 to 4.71).

Figure 4.66. Reservoir location in the SSURGO map.
Figure 4.67. Reservoir location in the NLCD 1992 map.

Table 4.32. Comparison of the simulated water and sediment load budget with/without the reservoirs.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>With Reservoir</th>
<th>Without Reservoir</th>
<th>Difference (mm or ton)</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Runoff (mm)</td>
<td>Monthly Mean</td>
<td>36.23</td>
<td>39.36</td>
<td>3.13</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>2608.5</td>
<td>2833.8</td>
<td>225.4</td>
</tr>
<tr>
<td>Sediment Load (ton)</td>
<td>Monthly Mean</td>
<td>34.38</td>
<td>37.21</td>
<td>2.82</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>1650.4</td>
<td>1786.0</td>
<td>135.6</td>
</tr>
</tbody>
</table>
Figure 4.68. Comparison of the simulated monthly runoff with/without the reservoirs.

Figure 4.69. Agreement between the simulated monthly runoff with reservoir and without reservoir.
Figure 4.70. Comparison of the simulated monthly sediment load with/without the reservoirs.

Figure 4.71. Agreement between the simulated monthly sediment load with reservoir and without reservoir.

As seen in Table 4.32, impact of the reservoir storage is similar on sediment load and on runoff. In Figure 4.68, the differences between the simulated monthly runoffs are overall larger in the months that produced greater runoff. The simulation with the
reservoirs produced a little more runoff volume in Aug and Oct 1992. Because the reservoirs prevented runoff to be routed from their upstream areas into the downstream, curve number is adjusted into lower values than the case of not having the reservoirs in the downstream areas. Thus, more water could be infiltrated into the root zone depth, and then soil got wetter. Subsequently, higher unsaturated hydraulic conductivity is calibrated in the van Genuchten equation, and then more water could contribute to base flow through percolation because the parameters of the van Genuchten equation are more sensitive to the high soil water content than is curve number in the modified method for a continuous simulation. Therefore, total runoff volume increased due to increase in base flow volume even though direct runoff volume decreased. Of course, it does not agree with reality.

Figure 4.70 indicates that the differences between simulated monthly sediment loads are overall larger in the months that produced greater sediment, which is similar to the situation with runoff. Figures 4.69 and 4.71 show that the simulation without the reservoirs produced more monthly runoff and sediment load than did the simulation with the reservoirs systematically (slope is greater than one and the coefficient of determination is close to one).

4.2.5 Sediment Transport Simulation

4.2.5.1 Calibration using Storm Event of 5 Jan 1993

For sediment transport simulation, four parameters were introduced: CSO (Critical Shield parameter for Overland), CSC (Critical Shield parameter for Channel), SCR (Soil Cohesion Ratio), and SDR (Soil Detachability Ratio). They were calibrated using the observed sediment load produced by the storm event that occurred on 5 Jan 1993 while the parameters for hydrology simulation were fixed to their calibrated values. In the calibration, absolute error of sediment load instead of RMSE was utilized as an objective function because total sediment load mass was the output of interest rather than temporal pattern of the sediment loading. The calibration results are represented in Table 4.33. Figures 4.72 and 4.73 show convergence of the objective function and parameter
values at every iteration of calibrations as the SCE-UA algorithm explore in the parameter space.

Table 4.33. Starting and calibrated values of the parameters for sediment transport simulation in the calibration using the storm event that occurred on 5 Jan 1993.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>CSO</th>
<th>CSC</th>
<th>SCR</th>
<th>SDR</th>
<th>Error (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting Value</td>
<td>0.800</td>
<td>0.060</td>
<td>1.000</td>
<td>1.000</td>
<td>-</td>
</tr>
<tr>
<td>Calibrated Value</td>
<td>0.744</td>
<td>0.057</td>
<td>0.891</td>
<td>1.066</td>
<td>0.0012</td>
</tr>
</tbody>
</table>

Figure 4.72. Convergence of CSO, CSC, SCR, and SAR in the calibration using the storm event that occurred on 5 Jan 1993.
All the parameters were calibrated into values close to their starting (or nominal) values determined based on literature and consideration of their physical meanings (Table 4.30). The CSC (critical Shield parameter for channel) values of 0.056 and 0.060 were found in literature (Haan et al., 1994; Ferro, 1998; Yang, 2003; Cao et al., 2006; Hessel et al., 2007). In addition, the values of SCR (soil cohesion ratio) and SDR (soil detachment ratio) were adapted from the EUROSEM model (Morgan et al., 1998), and the starting value of CSO, 0.80, was found in USACE (2007). The shear Reynolds number is a function of hydraulic characteristics of overland runoff and sediment particle such as shear velocity and median particle size, so thus its value is time-dependent. Subsequently, the critical Shield parameter for overland would be varied over time with shear Reynolds number even though CSO was calibrated into a constant (Equation 3.67).

As seen in Figures 4.72 and 4.73, values of the objective function were quickly converged into its minimum in the last 90 explorations while values of the parameters were still fluctuating around their averages. Although the sediment transport simulation was calibrated at an absolute error of 0.001 kg, the calibrated sediment load hydrograph
showed somewhat different temporal pattern with that of the observed (Figure 4.74). The use of an absolute error as objective function produced the discrepancy in the peak sediment load but good agreement in the overall load. In addition, sediment load of 320 to 400 kg were still found 12 hours after the peak load in the measurement, whereas the simulation provided sediment load less than 1 kg. In the model, it was assumed that erosion and sediment transport were driven by only direct runoff. Thus, sediment transportation by base flow in the channel is not simulated. Subsequently, it is expected for the model to underestimate the total sediment load over the entire simulation period.

Figure 4.74. Calibrated sediment load hydrograph for the storm event that occurred on 5 Jan 1993 using the calibrated parameter values for the hydrology simulation.

4.2.5.2 Comparison of the Calibration Results for Sediment Transport using Storm Events of 2 Sep and 22 Nov 1992.

In the previous calibration practice, the parameters for sediment transport simulation were calibrated with the observed sediment load produced by only one storm event that occurred on 5 Jan 1993. However, its representativity could be questionable when considering the length of the entire simulation period, 6 years. In fact, in the
calibration, three candidate storm events that occurred on 2 Sep 1992, 22 Nov 1992, and 5 Jan 1993 were selected upon examination on characteristics of the storm events and the corresponding observed sediment load. Then, the parameters for sediment transport simulation were calibrated using sediment load hydrographs of the storm events. Thereafter, sediment load hydrographs were simulated for the entire period using the calibrated parameters to identify the storm event that provides the best overall agreement with the observed. Thus, it can be said that the observation for the entire period was utilized in the calibration even though the parameters were calibrated for a specific storm event. Here, the calibration results for the other two storm events, 2 Sep 1992 and 22 Nov 1992, are presented to exhibit variability of sediment load.

Table 4.34 shows variation in the calibrated parameter values for the different storm events. The storm event that occurred on 5 Jan 1993 produced sediment load of 18.2 tons, which is in between those the other storms did. In addition, CSO was calibrated into the value in between those for the other storms. On the other hand, the calibrated values of the other parameters were not varied much for the different storm events. This comparison may imply that CSC, SCR, and SDR are constant over time while CSO, which is the most sensitive parameter for sediment transport simulation, is time-variant parameter.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall Depth (mm)</td>
<td>35.6</td>
<td>40.2</td>
<td>27.0</td>
</tr>
<tr>
<td>Runoff Volume (mm)</td>
<td>2.29</td>
<td>20.38</td>
<td>14.27</td>
</tr>
<tr>
<td>Peak Runoff (m3/s)</td>
<td>0.452</td>
<td>4.803</td>
<td>1.626</td>
</tr>
<tr>
<td>Sediment Load (ton/event)</td>
<td>2.2</td>
<td>72.8</td>
<td>18.2</td>
</tr>
<tr>
<td>Peak Sediment Load (ton/hr)</td>
<td>0.74</td>
<td>21.57</td>
<td>3.26</td>
</tr>
<tr>
<td>Parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CSO</td>
<td>1.263</td>
<td>0.303</td>
<td>0.744</td>
</tr>
<tr>
<td>CSC</td>
<td>0.059</td>
<td>0.056</td>
<td>0.057</td>
</tr>
<tr>
<td>SCR</td>
<td>0.923</td>
<td>0.861</td>
<td>0.891</td>
</tr>
<tr>
<td>SDR</td>
<td>1.054</td>
<td>0.943</td>
<td>1.066</td>
</tr>
</tbody>
</table>
The typical values provided by Morgan et al. (1998) were implicitly assumed as constant over time. However, soil moisture is one of the factors that control soil detachability and cohesion (Bullock et al., 1988; Matsushi et al., 2006), and thus they may be varied with change in soil moisture. In addition, the deposited sediment after being eroded in upstream area might have less cohesion than do native soil particles, so thus they might be more easily detached when another storm event was followed. Thus, it is expected for incorporation of these mechanisms into modeling to increase accuracy of sediment transport simulation. However, HYSTAR does not consider those mechanisms yet. Therefore, a selection of an appropriate storm event for calibration may be important in a modeling using HYSTAR especially when short-period data is utilized in calibration.

Figures 4.75 to 4.78 show the last 100 evolutions of samples and the objective function in the calibration for the two storm events. The simulated sediment load hydrograph for the storm events were compared with the observed in Figure 4.79 and 4.80. The values of CSC, which is most sensitive parameter, are more fluctuating in Figure 4.77 (22 Nov 1992) than in Figure 4.75 (2 Sep 1992), and convergence of the objective function values are slower in Figure 4.78 (22 Nov 1992) than in Figure 4.76 (2 Sep 1992). In addition, the sediment load hydrographs were calibrated at the absolute error of 26.7 for the storm event occurred on 22 Nov 1992 but of 0.0079 for the event occurred on 2 Sep 1992. Because the direct runoff that controls sediment transport hydraulic was calibrated using the storm event occurred on 2 Sep 1992, the sediment load for the event might be calibrated more accurately. In addition, the storm event that occurred on 22 Nov 1992 produced much greater peak direct runoff than did the other storm events.
Figure 4.75. Convergence of CSO, CSC, SCR, and SAR in the calibration for the sediment transport simulation using the storm event that occurred on 2 Sep 1992.

Figure 4.76. Convergence of the objective function value (absolute error) in the calibration for the sediment transport simulation using the storm event that occurred on 2 Sep 1992.
Figure 4.77. Convergence of CSO, CSC, SCR, and SAR in the calibration for the sediment transport simulation using the storm event that occurred on 22 Nov 1992.

Figure 4.78. Convergence of the objective function value (absolute error) in the calibration for the sediment transport simulation using the storm event that occurred on 22 Nov 1992.
Figure 4.79. Calibrated sediment load hydrograph for the storm that occurred on 2 Sep 1992 using the calibrated parameter values for the hydrology simulation.

Figure 4.80. Calibrated sediment load hydrograph for the storm that occurred on 22 Nov 1992 using the calibrated parameter values for the hydrology simulation.
In comparison of the simulated total sediment load hydrographs (Table 4.35), the simulation for the A and B storms greatly underestimated and overestimated the sediment load for the entire period respectively. The parameters calibrated for the A storm event produced only 30% of the observed. Even when considering that sediment in base flow was not taken into account in the sediment transport simulation contrary to the observed sediment load data, it looked too much underestimated. Subsequently, representativity of the storm event became questionable. On the other hand, the parameters calibrated for the B storm event produced twice as much as the observed sediment load for the entire period.

Table 4.35. Comparison of the observed and simulated total sediment load using the different storm events for the entire simulation period (Jan 1990 to Dec 1993).

<table>
<thead>
<tr>
<th>Item</th>
<th>Observed</th>
<th>2 Sep 1992 (A)</th>
<th>22 Nov 1992 (B)</th>
<th>5 Jan 1993 (C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sediment Load (ton)</td>
<td>2742</td>
<td>831</td>
<td>5622</td>
<td>1650</td>
</tr>
<tr>
<td>Percentage</td>
<td>-</td>
<td>30.3</td>
<td>205.0</td>
<td>60.2</td>
</tr>
</tbody>
</table>

4.3 Validation

4.3.1 Hydrology Simulation

4.3.1.1 Owl Run - Sep 1992 to Aug 1993

Summarizing the calibration procedures, four parameters for direct runoff simulation were calibrated simultaneously with the measured runoff hydrograph of the storm event that occurred on 2 Sep 1992. Then, the other six parameters for soil moisture simulation were calibrated simultaneously with the measured runoff hydrograph of the four storm events that occurred between 2 and 10 Sep 1992 while the four parameters were fixed to their previously calibrated values. Finally, only the parameter for base flow simulation, GWC, was calibrated using the one-year runoff measurement between 2 Sep 1992 and 1 Sep 1993 through matching the simulated total runoff volume to the measured.

For validation of the calibrated model, the split sample approach was employed, and thus the calibrated hydrology model was validated with the measurements made in
periods other than the calibration period. Performance of the model in predicting runoff was evaluated through comparing the simulated runoff with the measurements made between Jan 1990 and Dec 1995 excluding Sep 1992 to Aug 1993 used for the calibration. Because simulations for the period between Jan 1990 and Feb 1990 could be significantly affected by the crude assumption of initial soil moisture condition, they were not utilized for any model evaluation. In addition, because the calibration period was located in the middle of the entire simulation period, the periods for validation were separated into Mar 1990 to Aug 1992 (validation 1) and Sep 1993 to Dec 1995 (validation 2).

Several goodness-of-fit measures were employed to evaluate model performance in this study. The model performance in predicting runoff for calibration and validation periods was assessed with the Root Mean Squared Error (RMSE), the Nash-Sutcliffe efficiency coefficient ($E$), and the coefficient of determination ($R^2$). In addition, relative errors in runoff volume, peak runoff, and time to peak of a runoff hydrograph for an individual storm event were also evaluated. Figures 4.81 to 4.84 show strength of a linear relationship between the simulated and measured daily runoff. In Figures 4.85 and 4.86, the simulated and observed monthly runoff hydrographs are compared, and variations in the observed monthly runoff and water yield are examined in Figure 4.86 and Table 4.36. Figures 4.87 to 4.90 exhibit agreement between the simulated and measured hourly runoff in different scales. In Figures 4.91 to 4.96, the simulated and observed seasonal recession curves were compared. Figures 4.97 to 4.100 show strength of a linear relationship between the simulated and measured monthly runoff, and Table 4.37 provides detailed comparison of them. Performance of the model in predicting runoff is summarized in Tables 4.38 to 4.40. Finally, the simulated and observed runoff hydrographs for the selected storm events are compared in Table 4.38.

In Figure 4.81, the slope of linear regression equation indicates that the hydrology simulation overall overpredicted runoff for the entire simulation period. The plot in a log scale provides better view on the overestimations in low daily runoff less than 0.01 mm as well as in high daily runoff greater than 10 mm. In the calibration period (Figure 4.82), the linear relationship between the simulated and measured daily runoff becomes stronger, and the coefficient of determination increases from 0.71 to 0.90. The slope also indicates
overestimation of the simulation. The biggest discrepancy between them was found in the storm event occurred between 12 and 13 Mar 1993. Although there was precipitation of 39.4 mm in 21 hours, only runoff of 0.78 mm was observed at the outlet while the simulation provided runoff of 29.63 mm. When considering that the minimum temperature dropped to 21.9 F in those days, there must be snow instead of rainfall so that the precipitated water did not immediately contribute to the runoff hydrograph of the outlet.

In the first validation period (validation 1; Mar 1990 to Aug 1992, Figure 4.83), the coefficient of determination reduced to 0.63, and the biggest discrepancy was found in the storm event occurred on 18 Jan 1991. There was rainfall of 82.8 mm but only 3.4 mm runoff was observed at the outlet while the simulation produced runoff of 26.4 mm on the day. Before the event, zero runoff was observed, and there was only rainfall of 8.9 mm in the previous 30 days, thus the very dry soil did not produce much runoff, but absorbed most of them. Although curve numbers for every storm event are determined considering soil water content at the beginning of the event, the curve numbers must be overestimated for the event.

Another severe overestimation is found in the second validation period (Figure 4.84), raising the possibility that parameters and equations for soil moisture simulation or the curve number adjustment for dry soil water conditions are in need of improvement. When soil water content gets close to wilting point, evapotranspiration and percolation become very limited. Based on the SSURGO database, wilting points for ORD were estimated to range from 8.1 to 22.6 at an average of 14.8. Thus, the wilting points could be reduced to allow more evapotranspiration and percolation from soil so curve numbers would be adjusted to lower values at the wilting points.

In the second validation period (validation 2: Sep 1993 to Dec 1995, Figure 4.84), overestimation was frequently found over the entire range of the observed daily runoff, and the linear regression equation’s slope of 1.7 displays its severity. In the comparison of monthly runoff, it becomes clearer. As seen in Figure 4.84, for one year from Nov 1993 to Oct 1994, the simulated runoff volume by HYSTAR was about two times greater than the observed. However, Figure 4.86 and Table 4.36 show that the observed water
yield was close to zero in Jul to Oct 1993, which is the period just before the overestimated period (Nov 1993 to Oct 1994). In addition, even though there was more precipitation (634 mm) between Nov 1993 and Mar 1994 than (592 mm) between Nov 1992 and Mar 1993, the observed total runoff volume in the overestimated period is 89 mm less than that in the period between Nov 1992 and Mar 1993. Therefore, some kinds of change in watershed conditions were reasonably suspected. The land use statistics of the Owl Run watershed (Brannan et al., 2000) show that inactive agricultural area of 66.9 ha was converted to cropland (active agricultural area) in 1993. Agricultural management practices implemented in the new cropland might have lessened runoff volume from overland flow.
Figure 4.81a. In an arithmetic scale.

Figure 4.81b. In a logarithmic scale.

Figure 4.81. Agreement between the simulated and observed daily runoff for ORD in the entire simulation period (Jan 1990 to Dec 1995).
Figure 4.82a. In an arithmetic scale.

Figure 4.82b. In a logarithmic scale.

Figure 4.82. Agreement between the simulated and observed daily runoff for ORD in the calibration period (Sep 1992 to Aug 1993).
Figure 4.83a. In an arithmetic scale.

Figure 4.83b. In a logarithmic scale.

Figure 4.83. Agreement between the simulated and observed daily runoff for ORD in the first validation period (Jan 1990 to Aug 1992).
Figure 4.84a. In an arithmetic scale.

Figure 4.84b. In a logarithmic scale.

Figure 4.84. Agreement between the simulated and observed daily runoff for ORD in the second validation period (Sep 1993 to Dec 1995).
Figure 4.85. Comparison of the simulated and observed monthly runoff for ORD.

Figure 4.86. Variation in the observed monthly runoff and water yield for ORD.
Table 4.36. The observed monthly runoff and water yield for ORD.

<table>
<thead>
<tr>
<th>Month</th>
<th>Runoff (mm)</th>
<th>Precipitation (mm)</th>
<th>Water Yield (%)</th>
<th>Month</th>
<th>Runoff (mm)</th>
<th>Precipitation (mm)</th>
<th>Water Yield (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan-90</td>
<td>70.2</td>
<td>80.9</td>
<td>86.8</td>
<td>Jan-93</td>
<td>68.4</td>
<td>79.2</td>
<td>86.4</td>
</tr>
<tr>
<td>Feb-90</td>
<td>38.4</td>
<td>47.3</td>
<td>81.2</td>
<td>Feb-93</td>
<td>31.2</td>
<td>59.5</td>
<td>52.4</td>
</tr>
<tr>
<td>Mar-90</td>
<td>20.8</td>
<td>64.2</td>
<td>32.4</td>
<td>Mar-93</td>
<td>176.3</td>
<td>191.9</td>
<td>91.9</td>
</tr>
<tr>
<td>Apr-90</td>
<td>46.6</td>
<td>101.5</td>
<td>45.9</td>
<td>Apr-93</td>
<td>80.6</td>
<td>110.0</td>
<td>73.3</td>
</tr>
<tr>
<td>May-90</td>
<td>50.7</td>
<td>133.1</td>
<td>38.1</td>
<td>May-93</td>
<td>30.2</td>
<td>115.8</td>
<td>26.1</td>
</tr>
<tr>
<td>Jun-90</td>
<td>7.1</td>
<td>50.6</td>
<td>14.0</td>
<td>Jun-93</td>
<td>2.4</td>
<td>58.6</td>
<td>4.1</td>
</tr>
<tr>
<td>Jul-90</td>
<td>6.7</td>
<td>116.6</td>
<td>5.7</td>
<td>Jul-93</td>
<td>0.0</td>
<td>20.2</td>
<td>0.0</td>
</tr>
<tr>
<td>Aug-90</td>
<td>2.0</td>
<td>101.9</td>
<td>2.0</td>
<td>Aug-93</td>
<td>0.0</td>
<td>101.3</td>
<td>0.0</td>
</tr>
<tr>
<td>Sep-90</td>
<td>1.9</td>
<td>44.8</td>
<td>4.3</td>
<td>Sep-93</td>
<td>0.1</td>
<td>83.0</td>
<td>0.1</td>
</tr>
<tr>
<td>Oct-90</td>
<td>9.8</td>
<td>120.8</td>
<td>8.1</td>
<td>Oct-93</td>
<td>0.3</td>
<td>65.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Nov-90</td>
<td>11.2</td>
<td>55.9</td>
<td>19.9</td>
<td>Nov-93</td>
<td>52.8</td>
<td>145.2</td>
<td>36.3</td>
</tr>
<tr>
<td>Dec-90</td>
<td>36.7</td>
<td>105.5</td>
<td>34.8</td>
<td>Dec-93</td>
<td>42.4</td>
<td>91.1</td>
<td>46.6</td>
</tr>
<tr>
<td>Jan-91</td>
<td>76.3</td>
<td>75.4</td>
<td>101.1</td>
<td>Jan-94</td>
<td>67.7</td>
<td>105.9</td>
<td>63.9</td>
</tr>
<tr>
<td>Feb-91</td>
<td>6.9</td>
<td>14.3</td>
<td>48.5</td>
<td>Feb-94</td>
<td>82.2</td>
<td>102.9</td>
<td>79.9</td>
</tr>
<tr>
<td>Mar-91</td>
<td>32.5</td>
<td>98.3</td>
<td>33.1</td>
<td>Mar-94</td>
<td>144.0</td>
<td>189.2</td>
<td>76.1</td>
</tr>
<tr>
<td>Apr-91</td>
<td>17.7</td>
<td>51.2</td>
<td>34.6</td>
<td>Apr-94</td>
<td>19.3</td>
<td>48.8</td>
<td>39.5</td>
</tr>
<tr>
<td>May-91</td>
<td>2.8</td>
<td>31.8</td>
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* Shaded areas represent the period for calibration
The simulated and observed time series of daily runoff are plotted in Figures 4.87 to 4.90, and they were also plotted in a log scale to get a better view on lower flows. As seen in the previous figures, some major overestimations of peak runoff were found in 1991 and 1994. In the log scale plots, the simulated runoff shows good agreement with the observed data in the overall pattern of low flow less than 1 mm and in the recession parts of runoff hydrographs. For further examination, the recession parts of hydrographs whose peak runoffs were over 1.0 m$^3$/s were investigated and compared in Figures 4.91 to 4.96. Figure 4.91 shows agreement in the averaged recession curves of the simulated and observed runoff hydrographs. In addition, for considering seasonal effect, the recession curves were separated into two seasons, Apr to Sep (dry) and Oct to Mar (wet), and then their averaged curves were compared in Figures 4.91 to 4.95.
Figure 4.87a. In an arithmetic scale.

Figure 4.87b. In a logarithmic scale.

Figure 4.87. Comparison of the simulated and observed daily runoff for ORD in the entire simulation period (Jan 1990 to Dec 1995).
Figure 4.88a. In an arithmetic scale.

Figure 4.88b. In a logarithmic scale.

Figure 4.88. Comparison of the simulated and observed daily runoff for ORD in the calibration period (Sep 1992 to Aug 1993).
Figure 4.89a. In an arithmetic scale.

Figure 4.89b. In a logarithmic scale.

Figure 4.89. Comparison of the simulated and observed daily runoff for ORD in the first validation period (Jan 1990 to Aug 1992).
Figure 4.90a. In an arithmetic scale.

Figure 4.90b. In a logarithmic scale.

Figure 4.90. Comparison of the simulated and observed daily runoff for ORD in the second validation period (Sep 1993 to Dec 1995).
As seen in Figure 4.91, the simulation generally overestimated the recession parts of hydrographs in particular when runoff was over 0.1 m$^3$/s. Figure 4.92 shows that the two seasons have unique recession curves. Hydrographs of the wet season, Oct to Mar, had higher recession flows and thicker tails than did those of the dry season, Apr to Sep. In Figures 4.93 to 4.96, it can be noticed that the model provided better and more consistent prediction on recession parts of hydrographs in the wet seasons than in the dry seasons. In particular, the simulated low runoff showed good overall agreement with the observation: high values in coefficient of determination and slope close to one (Figures 4.94 and 4.96). In the validation period, however, the model overpredicted recession curves, and the high values of coefficient of determination indicate that the overestimation is systematic (Figures 4.94 and 4.96). As mentioned earlier, the model overpredicted runoff in dry soil water condition mainly due to overestimation of curve number, and thus the recession of the hydrograph was also overpredicted. This examination again demonstrated the need of improvement in the parts of the model that calculate evapotranspiration, percolation, and direct runoff volume in dry soil water conditions.

Figure 4.91. Comparison of the simulated and observed recession curves for ORD in the entire simulation period (Jan 1990 to Dec 1995).
Figure 4.92. Comparison of the simulated and observed seasonal recession curves for ORD in the entire simulation period (Jan 1990 to Dec 1995).

Figure 4.93. Comparison of the simulated and observed recession curves for ORD in the period from April to September (dry).
Figure 4.94. Comparison of the simulated and observed recession curves for ORD in the period from April to September (dry).

Figure 4.95. Comparison of the simulated and observed recession curves for ORD in the period from October to March (wet).
Agreement in between the simulated and observed monthly runoff was investigated and represented in Figures 4.97 to 4.100. As indentified in the comparison of daily runoff and recession curve, the simulation also overall overpredicted monthly runoff. While the simulated monthly runoff shows good agreement with observed in the calibration period, it a little underpredicted and greatly overpredicted in the first and second validation periods respectively. The simulated and observed monthly runoff time series are represented in Figure 4.85 and Table 4.37. In the first validation period, the biggest errors are found in Aug 1991, which is one of the driest months in a year (Figure 4.99 and Table 4.37). On the other hand, in the second validation (Figure 4.100), several large overpredictions occurred in winter wet seasons (Nov, Dec 1993, Mar 1994, and Oct 1995) as well as in dry summer seasons (Jul and Aug 1994).

Considering the good agreement in between the simulated and observed runoff in the other months (excepting Nov, Dec 1993, Mar 1994, and Oct 1995) of the second validation period, the overpredictions might be attributed to changes in agricultural management practice as well as the alteration in agricultural land use. In this modeling analysis, no BMPs were considered and only straight row was assumed in determining
curve numbers for row crops and small grains at the AMC II condition. In addition, parameter values for evapotranspiration were assumed in 4.2.1.3 based on coarse information about agricultural management schedules (Cho et al., 2009; FAO, 2004), and they have not been calibrated.

\[ y = 1.2192x \]

\[ R^2 = 0.8263 \]

Figure 4.97a. In an arithmetic scale.

Figure 4.97b. In a logarithmic scale.

Figure 4.97. Comparison of the simulated and observed monthly runoff for ORD in the entire simulation period (Jan 1990 to Dec 1995).
Figure 4.98a. In an arithmetic scale.

Figure 4.98b. In a logarithmic scale.

Figure 4.98. Comparison of the simulated and observed monthly runoff for ORD in the calibration period (Sep 1992 to Aug 1993).
Figure 4.99a. In an arithmetic scale.

Figure 4.99b. In a logarithmic scale.

Figure 4.99. Comparison of the simulated and observed monthly runoff for ORD in the first validation period (Jan 1990 to Aug 1992).
Figure 4.100a. In an arithmetic scale.

Figure 4.100b. In a logarithmic scale.

Figure 4.100. Comparison of the simulated and observed monthly runoff for ORD in the second validation period (Sep 1993 to Dec 1995).
### Table 4.37. Comparison of the simulated and observed monthly runoff for ORD.

<table>
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<th>Error (mm)</th>
<th>Month</th>
<th>Runoff (mm)</th>
<th>Error (mm)</th>
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<td></td>
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<td>45.9</td>
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* Shaded areas represent the period for calibration.
The quantitative performance measures are provided in Tables 4.38 and 4.39. The model produced a higher RMSE of daily runoff in the calibration period than in the first validation, but normalized RMSE (NRMSE) shows that its relative magnitude to the average observed runoff is lower (Table 4.39). The simulated monthly runoff shows lowered NRMSE and similar pattern to that of the daily results for the two periods. In terms of the Nash-Sutcliffe efficiency coefficient, the model failed to reproduce daily runoff in the second validation period while it provided good agreement with the observed data in the calibration period (Table 4.39). In addition, the low coefficient value indicates that prediction of the model is not satisfactory (less than 0.5) for the first validation (Moriasi et al., 2007). In the monthly scale, the model performance can be judged as satisfactory for all the periods except for the second validation period when the model prediction was as accurate as the average of the observed data (Table 4.39).

On the other hand, in Table 4.39, values of the coefficient of determination ($R^2$) over 0.5 indicates that the daily simulation results for all the periods can be considered as acceptable (Santhi et al., 2001; Moriasi et al., 2007). As Legates et al. (1999) pointed out; however, the coefficient is not sensitive to proportional differences between the simulated and observed data (Moriasi et al., 2007). Therefore, the errors for the second validation are regarded as systematic rather than random. In other words, the model produced greater errors in higher runoff. This error pattern might be mainly contributed to overestimation of curve number in the second validation period.

The parameters for direct runoff and soil moisture simulations were calibrated with the observed runoff of only one storm event and four consecutive events respectively. Then, one parameter for base flow simulation was optimized with the observed runoff of one year in order to match the total runoff volume. This short length of the calibration period was determined considering the number of parameters, the required time for overland routing to be implemented, and subsequent computing resource requirement. If a longer period is used in the calibration, errors will be increased in the calibration but decreased in the validation. Although an appropriate length of data for calibration may be dependant on variability of data, calibration using a longer data record may provide better agreement with the observed data in validation.
Table 4.38. Comparison of the simulated and observed total runoff for ORD in the entire simulation period (Jan 1990 to Dec 1995).

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Table 4.39. Performance measures of the simulated runoff for ORD.

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<tr>
<th>Scale</th>
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<th>Obs. Mean (mm, B)</th>
<th>NRMSE (A) / (B)</th>
<th>Nash-Sutcliffe R $^2$</th>
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<td>Monthly</td>
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<td>32.9</td>
<td>29.3</td>
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</tbody>
</table>

The forty-three individual runoff hydrographs whose peak runoffs are greater than 1.0 m$^3$/s were investigated to see performance of the hydrology simulation in predicting details of the runoff hydrograph. The simulated and observed peak runoff, time to peak, and runoff volume of individual storms were compared in Table 4.40. Percentage errors in peak runoff and runoff volume vary widely storm-by-storm while errors in time to peak are relatively constant except for two storm events in Feb and Mar 1994. Table 4.38 shows that the seventeen and twenty-six of the forty-three hydrographs can be considered as satisfactory (percent error is less than 25%, Moriasi et al., 2007) in terms of peak runoff and runoff volume respectively. In addition, the simulation was considered as satisfactory if an absolute error in time to peak is less than or equal to 1 hours in Table 4.41. From the investigation, it was revealed that the model predictions were more accurate in time to peak than in peak runoff and runoff volume.
All the simulated and observed individual runoff hydrographs of the forty-three storm events are compared in Appendix C. At the beginning of the simulation period (i.e. the 1st, 2nd, and 3rd storm events), the shape of the simulated runoff hydrographs is quite different from that of the observed, but it becomes more similar later in the simulation. The initial soil water content at the beginning of the entire simulation was roughly assumed equal to 0.30 (30% of the root zone depth) over the watershed. Unique spatial distributions of soil water content may result in different time-area histograms and subsequently different shapes of runoff hydrographs. Thus, the discrepancy in the shape might be contributed to the rough initial soil moisture assumption, and then its impact on the shape diminished as the simulation proceeded. The runoff hydrograph of the 4th storm event (28 May 1990) first showed similar hydrograph shape, so thus it can be said that memory of the hydrologic simulation of the model may last about 6 months.

In the hydrograph comparison for the second validation (from the 29th to 43rd), the simulation overestimated peak runoff and runoff volume but provided shape of hydrographs close to those of the observed. In several storm events such as 29th, 30th, 32nd, 35th, 36th, 37th, and 38th, which occurred in 1994, high similarity was found in shapes of the simulated and observed hydrographs in spite of relatively complicated temporal patterns of rainfall.
Table 4.40. Comparison of the simulated and observed runoff hydrograph for the selected
storm events of ORD.
Storm Information
Observed Runoff
Simulated Runoff
Error (%, hrs)
Time
Order R a D b P c Peak d Vol e TP f Peak Vol TP Peak g Vol h TP i
1990/1/29 13
1
20.4 12 111
1.0 14.5
11
0.9 11.4
11
-11
-21
0
1990/4/2 17
2
13.7
8
84
1.0
9.7
3
0.2
5.8
9
-77
-39
6
1990/5/9 22
3
39.2 21
63
1.9 10.4
14
1.0
8.5
15
-51
-17
1
1990/5/28 9
4
47.2 29 123
4.0 27.8
26
4.1 24.0
25
3
-14
-1
1990/7/13 21
5
37.1 21
16
1.4
3.7
22
0.9
3.2
22
-40
-14
0
1991/1/11 4
6
38.6 35
86
3.0 33.1
18
3.3 37.5
18
10
13
0
1991/1/16 5
7
17.0 15 489
1.8 23.0
5
0.6 20.6
6
-68
-11
1
1991/6/18 3
8
82.8
4
96
1.3
3.3
4 11.9 25.0
3
791
648
-1
1991/8/9 2
9
99.3 23 246
5.3 19.8
23 11.4 53.2
23
116
168
0
1991/9/4 17
10
49.8 14
21
1.7
4.5
7
1.7
6.1
7
3
34
0
1991/9/17 23
11
45.7
5 128
1.4
4.5
6
1.8
5.4
6
33
20
0
1991/12/2 13
12
35.7 32 140
1.7 22.5
24
2.6 24.8
23
47
11
-1
1991/12/9 17
13
27.5 10
81
1.6 13.4
7
1.6 13.3
9
0
-1
2
1992/2/25 21
14
21.1 10 222
1.4 17.4
7
0.5
9.6
9
-67
-45
2
1992/4/21 9
15
59.7 31
48
3.4 17.0
15
3.4 17.1
14
2
1
1
1992/6/30 16
16
36.8
4
21
1.0
3.0
4
0.8
3.4
4
-19
15
0
1992/7/27 3
17
49.8 15
80
4.9 17.5
14
6.3 21.7
14
28
25
0
1992/7/31 2
18
20.8 16
91
1.1
6.0
16
0.6
6.3
18
-48
5
2
1992/11/12 17 19
18.5
8 199
1.1
8.9
10
0.1
3.1
13
-89
-65
3
1992/11/22 4
20
40.2 24
41
4.8 18.6
24
4.0 13.3
24
-17
-29
0
1992/12/10 5
21 116.6 47 113 26.4 112.3
17 21.7 134.2
15
-18
19
-2
1993/1/5 1
22
27.0
6
67
1.6 13.0
4
1.7 12.8
7
4
-2
3
1993/3/3 21
23
70.1 45 111
5.0 67.3
15
6.4 82.6
15
28
23
0
1993/3/17 5
24
22.1 12
82
1.7 29.2
11
1.5 16.3
11
-15
-44
0
1993/3/27 10
25
32.9 22
33
4.3 23.3
15
4.0 22.9
15
-8
-1
0
1993/4/9 23
26
35.1 19 134
1.4 17.1
17
2.0 17.6
17
39
3
0
1993/4/16 8
27
53.3
6 114 10.1 37.2
4
9.3 37.8
5
-8
2
1
1993/5/4 18
28
57.2 27 164
5.2 20.7
27
5.8 21.4
27
13
4
0
1993/11/27 6
29 122.0 24 145
9.1 48.8
19 15.0 87.5
19
65
79
0
1993/12/4 7
30
51.0 31 233
1.6 25.3
26
3.8 56.3
28
133
122
2
1994/1/27 8
31
21.3 32 265
1.2 19.8
28
0.8 18.1
33
-31
-8
5
1994/2/23 3
32
43.4 32 123
3.2 38.3
9
3.4 43.6
31
6
14 22
1994/3/1 14
33
70.9 47 106
2.0 53.2
75
8.6 98.3
33
323
85 -42
1994/3/7 23
34
29.0 61 191
1.2 28.7
58
2.2 29.6
59
81
3
1
1994/3/27 4
35
75.7 56
53
1.8 41.5
27
4.7 106.0
28
167
156
1
1994/7/26 14
36
73.7
4
21 12.9 32.1
3 28.3 54.7
3
120
71
0
1994/7/27 15
37
46.2 25 170
4.4 25.3
5
5.8 66.1
5
32
162
0
1994/8/16 10
38
72.6 36
91
3.6 26.8
34
9.4 73.1
34
159
173
0
1994/9/26 1
39
49.0 23 305
2.1
6.8
5
1.4 12.4
5
-35
82
0
1995/1/15 7
40
36.8 10 104
3.9 20.5
10
3.6 15.6
10
-6
-24
0
1995/1/20 1
41
23.4
5 202
3.0 17.9
4
1.7 15.8
5
-43
-11
1
1995/3/8 10
42
39.1 14 456
3.4 29.2
12
3.2 29.1
12
-4
0
0
1995/10/20 17 43
82.3 16 152
5.6 32.8
11 12.5 67.3
11
125
105
0
a
b
c
* Shaded areas represent the period for calibration; R: Rainfall depth; D: Event Duration; P: Pause
d
e
f
Period after Event; Peak: Peak Runoff (m3/s); Vol: Runoff Volume (103 m3); TP: Time to Peak (hour);
g
h
i
Peak: Relative Error in Peak Runoff (%); Vol: Relative Error in Runoff Volume (%); TP: Error in
Time to Peak (hour)

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Table 4.41. Performance statistics of the simulation runoff hydrograph for the selected storm events of ORD.

<table>
<thead>
<tr>
<th>Items</th>
<th>Entire Period</th>
<th>Calibration</th>
<th>Validation 1</th>
<th>Validation 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No.</td>
<td>%</td>
<td>No.</td>
<td>%</td>
</tr>
<tr>
<td>No. of Total Storm</td>
<td>43</td>
<td>-</td>
<td>10</td>
<td>-</td>
</tr>
<tr>
<td>No. of Satisfied Storm</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peak Runoff</td>
<td>17</td>
<td>40</td>
<td>7</td>
<td>70</td>
</tr>
<tr>
<td>Runoff Volume</td>
<td>26</td>
<td>61</td>
<td>7</td>
<td>70</td>
</tr>
<tr>
<td>Time to Peak</td>
<td>33</td>
<td>77</td>
<td>7</td>
<td>70</td>
</tr>
</tbody>
</table>

4.3.1.2 Owl Run - Oct 1990 to Sep 1991

The parameters for hydrology simulation were calibrated using another series of storm events and its performance in predicting runoff hydrograph was assessed for the same watershed, ORD. The model was calibrated in the same way as that of the previous practice but using storm events that occurred between 18 Oct 1990 and 17 Oct 1991. Then, the simulated and observed runoff between 1 Jan 1990 and 17 Oct 1990 (validation 1) and between 18 Oct 1991 and 31 Dec 1995 (validation 2) was compared to validate the calibrated model. In the calibration, the second and third iterations provided worse RMSE than did the first. Thus, the calibrated parameters in the first iteration were validated here. The same goodness-of-fit measures such as $RMSE$, $E$, and $R^2$ were employed in the validation.

Figures 4.101 to 4.104 show strength of a linear relationship between the simulated and measured daily runoff. Figures 4.105 and 4.108 exhibit agreement between the simulated and measured daily runoff in different scales. In Figure 4.109, the simulated and observed monthly runoff hydrographs are compared. Figures 4.110 to 4.113 show strength of a linear relationship between the simulated and measured monthly runoff. Finally, performance of the model in predicting runoff is summarized in Tables 4.42 and 4.43.

As seen in Figures 4.101 to 4.104, the hydrology simulation underpredicted runoff in all the periods including the calibration period. In particular, the simulation significantly underpredicted daily runoff greater than 30 mm in the second validation period (Figure 4.104). The storm event used in the calibration for hydrology simulation is
in one of the driest seasons (Figure 4.86). As seen in Table 4.36, water yield of the month, Oct 1990, is 8.1 %, which is the half of that (15.5 %) of Sep 1992. Thus, curve numbers were calibrated to lower values than those of the calibration using the storm event that occurred on 2 Sep 1992 (Tables 4.20 and 4.22). On the contrary, the other sensitive parameters such as RZD, BCC, and GCM were calibrated to similar values to those of the previous calibration (Tables 4.21 and 4.23). It implies that validity of the model is responsive to hydrologic characteristics of the period used for calibration. However, use of a longer observation in calibration may mitigate the sensitivity. The simulated and observed daily runoff hydrographs are compared in Figures 4.105 to 4.108.

Figure 4.101a. In an arithmetic scale.
Figure 4.101 b. In a logarithmic scale.

Figure 4.101. Agreement between the simulated and observed daily runoff for ORD in the entire simulation period (Jan 1990 to Dec 1995).

Figure 4.102a. In an arithmetic scale.
Figure 4.102b. In a logarithmic scale.

Figure 4.102. Agreement between the simulated and observed daily runoff for ORD in the calibration period (Oct 1990 to Sep 1991).

Figure 4.103a. In an arithmetic scale.
Figure 4.103b. In a logarithmic scale.

Figure 4.103. Agreement between the simulated and observed daily runoff for ORD in the first validation period (Jan 1990 to Sep 1990).

Figure 4.104a. In an arithmetic scale.
Figure 4.104b. In a logarithmic scale.

Figure 4.104. Agreement between the simulated and observed daily runoff for ORD in the second validation period (Oct 1991 to Dec 1995).

The underprediction is also found in Figures 4.105 to 4.108. The tails of the simulated daily runoff hydrographs are thicker than are those of the observed in the calibration and the second validation periods. In order to compensate the effect of the lowered curve number on the total runoff volume, the parameter for base flow simulation, GWC, was calibrated to a higher value (0.670) than that (0.502) of the calibration for the period from Sep 1992 to Aug 1993. The increase of 33% (0.670 / 0.502) in the parameter means 33% increase in base flow when soil water content is the same. However, the base flow dropped more quickly than the observed data in the first validation period, which is one of the driest seasons (Figure 4.86 and Table 4.36). GWC determines what portion of the percolated water contributes to base flow and percolation rate is a function of soil moisture. Thus, the increased GWC leads to quicker discharge of soil water, and then base flow decreases more quickly as long as sufficient water is not supplied to the root zone depth.
Figure 4.105a. In an arithmetic scale.

Figure 4.105b. In a logarithmic scale.

Figure 4.105. Comparison of the simulated and observed daily runoff for ORD in the entire simulation period (Jan 1990 to Dec 1995).
Figure 4.106a. In an arithmetic scale.

Figure 4.106b. In a logarithmic scale.

Figure 4.106. Comparison of the simulated and observed daily runoff for ORD in the calibration period (Oct 1990 to Sep 1991).
Figure 4.107a. In an arithmetic scale.

Figure 4.107b. In a logarithmic scale.

Figure 4.107. Comparison of the simulated and observed daily runoff for ORD in the first validation period (Jan 1990 to Sep 1990).
Figure 4.108a. In an arithmetic scale.

Figure 4.108b. In a logarithmic scale.

Figure 4.108. Comparison of the simulated and observed daily runoff for ORD in the second validation period (Oct 1991 to Dec 1995).
As seen in Figure 4.109, the simulation underpredicted runoff in Dec 1992 and Mar 1993 but had good agreement with observed runoff in Dec 1993 to Mar 1994. In the previous validation, however, the simulation provided better agreement with the observed runoff in Dec 1992 and Mar 1993 but overpredicted runoff Dec 1993 to Mar 1994. In addition, comparison of goodness measures based on Tables 4.38, 4.39, 4.42, and 4.43 shows the improvement of model performance in the second validation period. This change is attributed to the lowered curve numbers in this calibration. Figures 4.110 to 4.113 show strength of the linear relationship between the simulated and observed monthly runoff. Contrary to the previous simulation results (Figures 4.97 to 4.100), the fitted lines have intercepts ranging from 3.5 to 11.1 in all the periods. This unfavorable result indicates consistent underprediction in the simulated runoff.

Figure 4.109. Agreement between the simulated and observed monthly runoff for ORD.
Figure 4.110. Agreement between the simulated and observed monthly runoff for ORD in the entire simulation period (Jan 1990 to Dec 1995).
Figure 4.111a. In an arithmetic scale

Figure 4.111b. In a logarithmic scale

Figure 4.111. Agreement between the simulated and observed monthly runoff for ORD in the calibration period (Oct 1990 to Sep 1991).
Figure 4.112a. In an arithmetic scale

Figure 4.112b. In a logarithmic scale

Figure 4.112. Agreement between the simulated and observed monthly runoff for ORD in the first validation period (Jan 1990 to Sep 1990).
Figure 4.113a. In an arithmetic scale

Figure 4.113b. In a logarithmic scale

Figure 4.113. Agreement between the simulated and observed monthly runoff for ORD in the second validation period (Oct 1991 to Dec 1995).
Tables 4.39 and 4.40 summarize performance of the calibrated hydrology simulation in all the periods. Although the simulation produced the lowest RMSE in the calibration period, the Nash-Sutcliffe efficiency coefficient and coefficient of determination were worse in the calibration period than in the second validation period. In terms of the efficiency coefficient, the simulation can be classified as satisfactory in the total period as well as in the second validation period (Moriasi et al., 2007).

Table 4.42. Comparison of the simulated and observed total runoff for ORD in the entire simulation period (Oct 1990 to Sep 1991).

<table>
<thead>
<tr>
<th>Period</th>
<th>Runoff (mm)</th>
<th>Error (mm)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Observed</td>
<td>Simulated</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>2203.9</td>
<td>1800.3</td>
<td>-403.6</td>
</tr>
<tr>
<td>Calibration</td>
<td>245.6</td>
<td>245.6</td>
<td>0.0</td>
</tr>
<tr>
<td>Validation 1</td>
<td>245.1</td>
<td>148.7</td>
<td>-96.4</td>
</tr>
<tr>
<td>Validation 2</td>
<td>1713.1</td>
<td>1405.9</td>
<td>-307.2</td>
</tr>
</tbody>
</table>

Table 4.43. Performance measures of the simulated runoff for ORD.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Period</th>
<th>RMSE (mm, A)</th>
<th>Obs. Mean (mm, B)</th>
<th>NRMSE (A) / (B)</th>
<th>Nash-Sutcliffe</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>Total</td>
<td>2.39</td>
<td>0.98</td>
<td>2.43</td>
<td>0.52</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>Calibration</td>
<td>1.46</td>
<td>0.67</td>
<td>2.17</td>
<td>0.27</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>Validation 1</td>
<td>1.48</td>
<td>0.59</td>
<td>2.50</td>
<td>0.28</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>Validation 2</td>
<td>2.66</td>
<td>1.12</td>
<td>2.38</td>
<td>0.53</td>
<td>0.58</td>
</tr>
<tr>
<td>Monthly</td>
<td>Total</td>
<td>16.8</td>
<td>29.9</td>
<td>0.56</td>
<td>0.78</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>Calibration</td>
<td>14.4</td>
<td>20.0</td>
<td>0.72</td>
<td>0.47</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>Validation 1</td>
<td>18.2</td>
<td>19.4</td>
<td>0.94</td>
<td>0.13</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>Validation 2</td>
<td>17.1</td>
<td>33.7</td>
<td>0.51</td>
<td>0.81</td>
<td>0.86</td>
</tr>
</tbody>
</table>

4.3.1.3 Polecat Creek – Sep 2000 to Aug 2001

The parameters for hydrology simulation were calibrated and its performance in predicting runoff hydrograph was assessed in a different watershed, PCA. The model was calibrated in the same way as that of the previous practice using the storm events that occurred between 2 Sep 2000 and 1 Sep 2001. Then, the simulated and observed runoff
between 1 Jan 1997 and 1 Sep 2000 (validation 1) and between 2 Sep 2001 and 31 Dec 2002 (validation 2) was compared to validate the calibrated model. In the calibration, the third iteration provided better RMSE than did the others, thus the calibrated parameters in the third iteration were used for the validation results presented in Table 4.44 and 4.45.

Table 4.44. Comparison of the simulated and observed total runoff for PCA in the entire simulation period (Jan 1997 to Dec 2002).

<table>
<thead>
<tr>
<th>Period</th>
<th>Runoff (mm)</th>
<th>Error (mm)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Observed</td>
<td>Simulated</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1172.0</td>
<td>1288.2</td>
<td>116.3</td>
</tr>
<tr>
<td>Calibration</td>
<td>162.4</td>
<td>162.4</td>
<td>0.0</td>
</tr>
<tr>
<td>Validation 1</td>
<td>882.4</td>
<td>972.1</td>
<td>89.6</td>
</tr>
<tr>
<td>Validation 2</td>
<td>88.2</td>
<td>111.3</td>
<td>23.1</td>
</tr>
</tbody>
</table>

Table 4.45. Performance measures of the simulated runoff for PCA.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Period</th>
<th>RMSE (mm, A)</th>
<th>Obs. Mean (mm, B)</th>
<th>NRMSE (A) / (B)</th>
<th>Nash-Sutcliffe</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>Total</td>
<td>2.20</td>
<td>0.55</td>
<td>4.00</td>
<td>0.06</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>Calibration</td>
<td>3.94</td>
<td>1.65</td>
<td>2.39</td>
<td>0.35</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>Validation 1</td>
<td>2.51</td>
<td>0.37</td>
<td>6.84</td>
<td>-1.53</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>Validation 2</td>
<td>1.44</td>
<td>0.32</td>
<td>4.54</td>
<td>-1.79</td>
<td>0.04</td>
</tr>
<tr>
<td>Monthly</td>
<td>Total</td>
<td>27.6</td>
<td>16.7</td>
<td>1.66</td>
<td>0.28</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>Calibration</td>
<td>37.9</td>
<td>50.1</td>
<td>0.76</td>
<td>0.63</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
<td>Validation 1</td>
<td>27.7</td>
<td>11.7</td>
<td>2.37</td>
<td>-2.49</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>Validation 2</td>
<td>24.6</td>
<td>9.5</td>
<td>2.58</td>
<td>-2.77</td>
<td>0.01</td>
</tr>
</tbody>
</table>

As seen in Table 4.44, the model predicted runoff volume of the Polecat Creek watershed at the overall relative error of 10 % in the entire simulation period. However, Figure 4.45 shows that performance of the model is not satisfactory in predicting daily and monthly runoff. In particular, the Nash-Sutcliffe efficiency coefficients are negative and the coefficients of determination are close to zero in the validation periods. The simulated and observed monthly runoffs are compared in Figure 4.114.
As seen in Figure 4.114, the simulation does not follow the overall temporal pattern of the observed monthly runoff, especially in 1992, 1993, and 1994. In addition, the model significantly underpredicted the largest events that occurred between Jan and Apr 1991, and overpredicted runoff in Sep 1992. Figure 4.115 shows characteristics of the simulated and observed daily runoffs. The simulated daily runoff hydrograph drops and rises quickly while the observed data fluctuates smoothly. This indicates that the observed runoff hydrograph mainly consisted of base flow and/or quick responding subsurface flow between Sep 2001 and Jun 2002, but the model did not simulate that processes.
This discrepancy might be attributed to wrong calibration of the model and/or limitation of the model. First, the calibrated value, 1.247, of RZD in PCA is much greater than that of ORD, 0.339 (Tables 4.21 and 4.25). In the sensitivity analysis (Figure 4.15i), it was seen that base flow volume was most sensitive to RZD, and base flow volume decreased exponentially as RZD increased. In addition, another sensitive parameter, GCM, was also calibrated into a high value of 0.734. The greater GCM might reduce base flow volume significantly as well (Figure 4.15f). Values of RZD and GCM were maintained greater than about 1.0 and 0.5 in all the iterations of the calibration. As seen in Figure 4.114, the simulated runoff decreased quickly in the second month (Feb 1997), and then the soil water content remained close to the wilting point in the entire simulation period. For parameter set comparison purpose, a parameter set that was not found in the calibration results was applied in simulating runoff for PCA. The parameter set produced significant error in the calibration, thus it has been never considered as a candidate of the optimum. The parameter values are presented in Table 4.46, and the simulated monthly runoff is displayed in Figure 4.116.
Table 4.46. Comparison of the calibrated and non-optimal parameter sets for PCA.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
<th>GWC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibrated</td>
<td>1.011</td>
<td>0.998</td>
<td>1.231</td>
<td>2.32</td>
<td>0.691</td>
<td>0.734</td>
<td>1.266</td>
<td>0.547</td>
<td>1.247</td>
<td>0.408</td>
<td>0.199</td>
</tr>
<tr>
<td>Non-optimal</td>
<td>0.947</td>
<td>1.365</td>
<td>1.465</td>
<td>74.94</td>
<td>0.680</td>
<td>0.342</td>
<td>1.051</td>
<td>1.392</td>
<td>0.389</td>
<td>0.822</td>
<td>0.734</td>
</tr>
</tbody>
</table>

Figure 4.116. Comparison of the simulated and observed monthly runoff for PCA in the entire simulation period (Jan 1997 to Dec 2002) using the non-optimal parameter set.

As seen in Table 4.46, values of RZD and GCM are decreased in the alternative parameter set. On the other hand, values of the parameters SAR and GWC, which also control percolation rate and a ratio of base flow to percolation volume, were increased. The alternative parameter set produced better agreement with the observed monthly runoff than did the calibrated (Figures 4.114 and 4.116) even though some over- and under-predictions are still maintained. In addition, the quick drop of runoff in the second month (Feb 1997) was disappeared. In Figure 4.117, the simulated daily runoff produces base flow and does not drop quickly. Thus, this comparison proves that the wrongly calibrated parameter values deteriorate performance of the model in the validation. The failure of the calibration might be contributed to wrong selection of the storm events and
the short calibration period. In addition, the expanded parameter range of RZD (from 2 to 5) might degrade efficiency and subsequently effectiveness of the calibration using the SCE-UA algorithm.

![Figure 4.117. Comparison of the simulated and observed daily runoff for PCA between Sep 2001 and Jun 2002 using the non-optimal parameter set.](image)

Finally, as seen in Figures 4.115 and 4.117, the observed daily runoff did not respond to precipitation immediately. For example, there was rainfall of 51.8 mm in Sep 2001 but the runoff increased in the middle of Oct 2001. In addition, the runoff did not have peaks in spite of several intensive rainfall events between Dec 2001 and Apr 2002, but high base flow is maintained at an average runoff of 0.15 m³/s. It implies that PCA has a storage that keeps precipitation, and then runoff is released from the storage slowly. Because PCA mainly consists of forest, its leaf litter layer may play a role to store and release water. Thus, it is suggested to incorporate a conceptual tank into every forest cell in order to simulate the hydrologic process. However, subsurface flow of the vadose zone may not participate in this process because average values of the soil hydraulic
conductivity for ORD and PCA are similar to each other, 11.44 and 12.26 µm/s respectively.

4.3.2 Sediment Transport Simulation

The calibrated sediment transport model was validated with the observed sediment load in the watershed, ORD. In the calibration, four parameters for sediment transport simulation were calibrated simultaneously with the measured sediment load hydrograph on 5 Jan 1993 while all the parameters for hydrology simulation were fixed to their calibrated values. Using the calibrated parameter values, performance of the model in predicting sediment load was evaluated through comparing the simulated sediment load with the measurements made between Jan 1990 and Dec 1993 excluding the period between 5 and 7 Jan 1993 used for the calibration. Because the period between Jan 1990 and Feb 1990 was used for warming up simulation, they were not considered in model evaluation. In addition, even though the calibration period was located in the middle of the entire simulation period, the model was validated for the entire simulation period, because the length of the calibration period, 3 days, is very short compared to the entire period of four years, Jan 1990 to Dec 1993.

The model performance in predicting sediment load was assessed with the Root Mean Squared Error (RMSE), the Nash-Sutcliffe efficiency coefficient (E), the coefficient of determination (R²). Figures 4.118 and 4.120 show strength of a linear relationship between the simulated and measured daily and monthly sediment load, and Figures 4.119 and 4.121 exhibit agreement between the simulated and measured daily and monthly sediment load in different scales. Table 4.47 provides detailed comparison of the simulated and observed monthly sediment load for the entire period. Finally, performance of the model in predicting sediment load is summarized in Tables 4.48 and 4.49.

In Figure 4.118, the slope of linear regression equation indicates that the sediment transport simulation overall underpredicted runoff in the entire simulation period. In addition, the simulation produced relatively larger errors in the smaller sediment loads. In
Figure 4.119, severe underpredictions of peak sediment load were found in 1992 and 1993. The log scale plots shows that the simulation frequently produced very low daily sediment load, which is under 0.01 kg. Because sediment detachment and transport are assumed to occur by rainfall and direct runoff, the model did not provide any sediment load between storm events. In other words, base flow was assumed not contributing to any sediment erosion and transport. Subsequently, the simulation tends to overall underpredict sediment load. The calibrated simulation produced 60% of the total observed sediment load for the entire simulation period (Table 4.48).

![Graph showing observed vs simulated sediment load](image_url)

Figure 4.118. Agreement between the simulated and observed daily sediment load for ORD in the validation period (Jan 1990 to Dec 1995).
Figure 4.119a. In an arithmetic scale.

Figure 4.119b. In a logarithmic scale.

Figure 4.119. Comparison of the simulated and observed daily sediment load for ORD in the validation period (Jan 1990 to Dec 1995).
Agreement between the simulated and observed monthly sediment load was investigated and represented in Figure 4.119 and Table 4.48. As identified in the previous comparison of daily sediment load, the simulation also overall underpredicted monthly sediment load even though overall agreement between the simulated and observed monthly sediment load ($R^2$) is better than that of the daily (Figures 4.118 and 4.120). In Figure 4.119 and Table 4.47, the biggest errors were found in Jul, Nov, and Dec 1992 and Mar, Apr, and Dec 1993, all with underprediction. On the other hand, the model provided much better agreement between the simulation and observed runoff in the months (Figure 4.85 and Table 4.36).

In fact, this result is rather unexpected. The parameters for sediment transport simulation were calibrated in one of the wettest seasons (Jan 1993, Table 4.36). A wet soil may have stronger cohesion than drier soil, but the model ignores the relationship between soil cohesion and water content. Thus, the simulation was expected to provide higher sediment load in the wet seasons such as Nov and Dec 1992 and Mar 1993. On the contrary, the sediment load was not underpredicted but overpredicted in the dry seasons such as Aug 1990, Jun, Jul, and Aug 1991. Therefore, this result suggests that the relationship between soil cohesion and water content is not significant in the ORD watershed.

The sediment transport simulation of the model employs an equation (Equation 3.65) Ferro et al. (1998) proposed to describe nonlinear relationship between critical Shield parameter and shear Reynolds number on overland. It was designed to provide a higher critical Shield parameter value for a lower Reynolds number. Thus, as overland flow depth gets deeper, the critical Shield parameter becomes smaller and then sediment transport capacity becomes larger. In the wet seasons when overland flow depth is deeper generally, for example, overall average of Reynolds number might be large so that overall average of critical Shield parameter value would be small. Therefore, the underestimation in wet seasons can be resolved to allow more sediment to be eroded and transported through reducing the critical Shield parameter value to a certain Reynolds number. In the same sense, less sediment would be detached and transported by increasing the value in dry seasons. Subsequently, for better performance of the model in this modeling practice, it is suggested that the exponent of 0.1709 in Equation 3.65
should be decreased so that sensitivity of the critical Shield parameter to a Reynolds number would be mitigated.

In addition, the storm event that occurred on 5 Jan 1993 was selected for the calibration because the calibrated sediment transport simulations using the other storm events occurred on 2 Sep and 22 Nov 1992 significantly underestimated and overestimated overall sediment load in the entire period respectively. Thus, the calibrated model using the storm event occurred on 22 Nov 1992 might provide better agreement between the simulated and observed sediment load in the wet seasons but much overprediction in the dry seasons. On the other hand, the calibrated model for the storm event occurred on 2 Sep 1992 might provide opposite results.

![Graph showing agreement between simulated and observed sediment load](image)

Figure 4.120. Agreement between the simulated and observed monthly sediment load for ORD in the validation period (Jan 1990 to Dec 1995).
Figure 4.121a. In an arithmetic scale.

Figure 4.121b. In a logarithmic scale.

Figure 4.121. Comparison of the simulated and observed monthly sediment load for ORD in the validation period (Jan 1990 to Dec 1995).
The quantitative performance measures are provided in Tables 4.48 and 4.49. Although the model was calibrated at absolute total sediment load error close to zero, it underpredicted total sediment load in the entire simulation period by 40%. The model provided a high Nash-Sutcliffe efficiency coefficient of 0.98 and a coefficient of determination of 0.99 in the calibration period because only one storm event was employed in the calibration. For the same reason, they dropped rapidly in the validation period. Nonetheless, the Nash-Sutcliffe efficient coefficients are greater than 0.5 in the daily and monthly simulations, and it indicates that the model performance in reproducing the sediment load is satisfactory in the entire simulation period (Moriasi et al., 2007). These quantitative measures are better than are those of the hydrology.
simulation (Table 4.36). However, sediment load measurements were available in only four years of Jan 1990 to Dec 1993 so that the period between Jan 1994 and Dec 1995, which showed the worst performance in predicting runoff, should be excluded from the evaluation of sediment transport modeling.

In addition, the coefficient of determination ($R^2$) values greater than 0.5 indicate that both daily and monthly sediment transport simulations can be considered as acceptable (Santhi et al., 2001; Moriasi et al., 2007). On the other hand, higher NRMSEs (Normalized RMSE) than those of the hydrology simulation (Table 4.39) implies that agreement in shape of the simulated and observed sediment load hydrograph is worse than that of the runoff hydrograph.

Table 4.48. Comparison of the simulated and observed sediment load for ORD in the entire simulation period (Jan 1990 to Dec 1995).

<table>
<thead>
<tr>
<th>Period</th>
<th>Sediment Load (ton)</th>
<th>Error (ton)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Observed</td>
<td>Simulated</td>
<td></td>
</tr>
<tr>
<td>Calibration</td>
<td>18.2</td>
<td>18.2</td>
<td>0.0</td>
</tr>
<tr>
<td>Validation</td>
<td>2742.3</td>
<td>1650.4</td>
<td>-1091.9</td>
</tr>
</tbody>
</table>

Table 4.49. Performance measures of sediment transport simulation for ORD.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Period</th>
<th>RMSE (ton, A)</th>
<th>Obs. Mean (ton, B)</th>
<th>NRMSE (A) / (B)</th>
<th>Nash-Sutcliffe</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>Calibration</td>
<td>0.99</td>
<td>6.06</td>
<td>0.165</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>Validation</td>
<td>9.63</td>
<td>1.88</td>
<td>5.132</td>
<td>0.50</td>
<td>0.52</td>
</tr>
<tr>
<td>Monthly</td>
<td>Calibration</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Validation</td>
<td>80.89</td>
<td>57.13</td>
<td>1.416</td>
<td>0.58</td>
<td>0.79</td>
</tr>
</tbody>
</table>

4.4 Parameter Uncertainty Analysis

4.4.1 Uncertainty of Parameter for Direct Runoff Simulation

A value vector of the eleven parameters for hydrology simulation of HYSTAR was found in the calibration practice. It provides the optimum (or minimum) objective function value in the parameter space but does not provide information about how strong
the optimum value is for the given model. Thus, in this study, the SCEM-UA algorithm (Vrugt et al., 2003c), which is one of the MCMC (Markov Chain Monte Carlo) methods that estimate parameter uncertainty based on a Bayesian framework, was employed for examining uncertainty of parameter and reliability of the modeling output.

The same rainfall events, conditions, and objective function as those used in the calibration were applied in the uncertainty analysis for the ten parameters of HYSTAR. Uncertainty of the six parameters for soil moisture simulation was analyzed after the four parameters for direct runoff simulation were fixed to their calibrated values. The German-Rubin statistic was used to assess convergence of the Markov chain into a stationary distribution. The SCEM-UA algorithm was run with the same numbers of complexes, population size for each complex, and total sample population as those of the SCE-UA algorithm used for calibration. Thus, the number of complexes, a population size for each complex, and the total sample population were set to 25, 9, and 225 respectively in the uncertainty analysis for the direct runoff simulation.

The formal likelihood function was utilized to assess posterior probability distribution of parameters (Equation 4.1, Vrugt et al., 2003c; Feyen et al., 2007). Thus, errors are assumed as distributed normally and independently (Bates et al., 2001; Vrugt et al., 2003c; Feyen et al., 2007). The sampled parameters by the Markov chain are plotted in Figure 4.130. Figure 4.131 depicts sequences of the German-Rubin statistic as the Markov chain evolved. The posterior distributions of the parameters, which are regarded as their uncertainty, are presented in Figure 4.132.

A formal likelihood function for the SCEM-UA algorithm is expressed as

\[
L(\theta, \psi \mid O) = \exp \left( -\frac{1}{2} \sum_{i=1}^{N} \frac{e_i^2}{\sigma_e^2} \right) \tag{4.1}
\]

where \( \theta \) is a parameter set, \( \psi \) is a parameter set of the assumed error model, \( O \) is the observed data set, \( N \) is the length of the data, and \( e \) is a vector of statistically independent errors with zero expectation and constant variance (\( \sigma_e \)).
The trace plots in Figure 4.122 indicate that the Markov chain moved around the parameter space well for CNF, MNO, and MNC. The sampled values of the parameters should be bouncing randomly around a common mean value and should look like random noise. However, the chain tends to be ‘stuck’ or ‘sticky’ in a certain region for a while after the number of explorations (or sequence of the chain) reached about 700. CNF, which is the most sensitive parameter of the model, started converging into a region of high probability (Figure 4.122 1)), thus the rejection rate of newly sampled points increased.

On the other hand, the trace plot of THA shows a periodic movement in Figure 4.122d, and it means that THA did not have good mixing. When a Markov chain is moving periodically, parameter sets can be sampled between certain values in a deterministic way, and then it may not converge to a stationary distribution. In spite of bad mixing found in the evolution of THA and ‘stickiness’ in the last sequences of the Markov chain for the other parameters, the German-Rubin statistic dropped below 1.2 quickly at the beginning of the sampling (Figure 4.123), which may indicate that the sampled parameter sets settled into stationary distributions (Vrugt et al., 2003).

The posterior distributions of the parameters were developed using the last 900 samples drawn by the algorithm after stationary distributions were achieved during the first 100 evolutions of the Markov chain. As seen in Figure 4.124, the posterior distribution of CNF has one distinguished mode while those of MNO and MNC have multi modes. The peak of CNF corresponds well with its optimized value, 1.094, in the calibration. On the other hand, the calibrated values of MNO and MNC, 1.054 and 1.171, are located at regions that do not have highest peaks in the posterior distribution.

In Figure 4.122a, values of CNF are bouncing only between 0.5 and 1.1 of its predefined range of 0.5 to 1.5 because CNF greater than 1.1 produced greater error than did small CNF values that did not produce any runoff regardless of the other parameter’s values. When the small CNF values were sampled more frequently by the Markov chain, any value set of the other parameters might be sampled with the same likelihood. Thus, the posterior distributions of the other parameters tend to be flat and subsequently their uncertainty would be increased. For example, the calibrated value of THA, 17.91, is not
located at the highest peak but at a region that has lowest frequency in its posterior distribution. Therefore, it is suggested to impose a penalty value on an objective function or on a likelihood function value of a parameter set that produces zero runoff in order to remove falsely created modes from the posterior distributions (Figure 4.124).

Figure 4.122a. Trace plot of CNF.

Figure 4.122b. Trace plot of MNO.
Figure 4.122c. Trace plot of MNC.

Figure 4.122d. Trace plot of THA.

Figure 4.122. Sequence of the sampled parameter values by the Markov chain (Direct runoff simulation for ORD).
Figure 4.123. Sequences of the German-Rubin statistic (Direct runoff simulation for ORD).

Figure 4.124a. Posterior distribution of CNF.
Figure 4.124b. Posterior distribution of MNO.

Figure 4.124c. Posterior distribution of MNC.
The likelihood function (Equation 4.1) of SCEM-UA algorithm used in this uncertainty analysis assumed that the residuals are normally distributed and independent. Thus, normality of the residuals was tested using Kolmogorov-Smirnov goodness of fit and its independence was examined using an autocorrelation function plot in order to assure the assumptions. Before implementation of the tests, the simulated and observed data were normalized using the Box-Cox transformation to alleviate heteroscedasticity of the residual (Feyen at al., 2007). Then, the residuals were obtained through subtracting the transformed simulated runoff by the transformed observed one. In this calculation, the last 225 parameter sets that provided the highest likelihood were employed to get the simulated runoff.

As seen in Figure 4.125, the residual does not follow a normal distribution, and the two-sided Kolmogorov-Smirnov test confirmed its non-normality at a 5 % significance level (p-value = 0.00644). In addition, Figure 4.126 shows strong dependency of the residual on the simulated runoff. It means that the bigger simulated runoff may produce greater error. Moreover, in Figure 4.127, the autocorrelation function
plot shows there is a strong autocorrelation structure at the first lag in the residual. Consequently, validity of the assumptions becomes questionable.

Figure 4.125. Normal Q-Q plot of the averaged residuals (Direct runoff simulation for ORD).

Figure 4.126. Plot of the averaged residuals to the transformed simulated runoff (Direct runoff simulation for ORD).
As mentioned earlier, when a value of CNF is small enough not to produce any runoff at the outlet, values of the other parameters would be falsely sampled by the Markov chain. Thus, a very tiny value, 1e-307, was assigned on likelihood of a parameter set that did not produce any runoff in the SCEM-UA algorithm. Then, the parameter set of producing no runoff will be sampled less frequently. Using this penalty rule, parameter value sets were resampled (Figures 4.128 and 4.129) and then the posterior distributions of the parameters were developed again (Figure 4.130). In the case of CNF, contrary to the previous practice, the trace plot (Figure 4.128a) quickly converged into about 1.10, which is close to its calibrated value. Then, the German-Rubin statistic was more quickly stabilized into 1.0 in Figure 4.129, and the posterior distribution of CNF shows a clearer peak in Figure 4.130a. However, trace plots of MNO, MNC, and THA show similar mixing patterns to those of the previous practice. Nonetheless, as seen in Figure 4.130, the newly developed posterior distributions for MNO and MNC have modes around their calibrated values. On the other hand, the calibrated value of THA is not located at one of the modes in the posterior distribution due to its poor mixing (drifting).
Figure 4.128a. Trace plot of CNF.

Figure 4.128b. Trace plot of MNO.
Figure 4.128c. Trace plot of MNO.

Figure 4.128d. Trace plot of THA.

Figure 4.128. Sequence of the sampled parameter values by the Markov chain (Direct runoff simulation for ORD with penalty on zero runoff).
Figure 4.129. Sequences of the German-Rubin statistic (Direct runoff simulation for ORD with penalty on zero runoff).

Figure 4.130a. Posterior distribution of CNF.
Figure 4.130b. Posterior distribution of MNO.

Figure 4.130c. Posterior distribution of MNC.
Figure 4.130d. Posterior distribution of THA.

Figure 4.130. Posterior distributions of the parameter (Direct runoff simulation for ORD with penalty on zero runoff).

### 4.4.2 Uncertainty of Parameters for Soil Moisture Simulation

Uncertainty of the six parameters for soil moisture simulation was explored in the same way. The SCEM-UA algorithm was run in the same setting as that used in the calibration. Thus, the number of complexes, a population size for each complex, and sample population were defined as 25, 13, and 325 respectively. Trace plots of the sampled parameter values and evolvement of the German-Rubin statistic are plotted in Figures 4.131 and 4.132. The posterior distributions of the parameters are presented in Figure 4.133.

In Figure 4.131, values of all the parameter are well sampled in reasonable mixing rates (Bates et al., 2001). There was no ‘stickiness’ and periodic movement in the evolvement of samples. In addition, the German-Rubin statistic dropped under 1.10 quickly just after the search began, and it did not go over 1.20 in the entire sequence (Figure 4.132). Therefore, the sampled parameter sets can reasonably be assumed to converge into the stationary distributions. As seen in Figure 4.133, however, the posterior distributions of the parameters have multiple modes, and none of their calibrated values
are located at a mode having the highest frequency. Although the trace plots and the German-Rubin statistics suggest that the algorithm was implemented well, the results did not well correspond to the calibration results.

As mentioned early, values of the parameters might be sampled falsely at regions that do not produce any runoff for the storm events. In the posterior distribution of RZD, for instance, frequencies of parameter values are higher at a region greater than 1.0, which tend to produce less runoff. Similar patterns are found in the posterior distributions of all the parameters (Figure 4.133). In addition, the posterior distributions of all the parameters are relatively uniform comparing to that of CNF. As seen in the sensitivity analysis, CNF dominates the characteristics of direct runoff hydrograph, and then direct runoff is relatively insensitive to the other parameters. Thus, degree of spread in the posterior distribution might be associated with sensitivity of a model to a parameter.

Figure 4.131a. Trace plot of GCL.
Figure 4.131b. Trace plot of GCM.

Figure 4.131c. Trace plot of BCC.
Figure 4.131d. Trace plot of EFS.

Figure 4.131e. Trace plot of RZD.
Figure 4.131f. Trace plot of SAR.

Figure 4.131. Sequence of the sampled parameter values by the Markov chain (Soil moisture simulation for ORD).

Figure 4.132. Sequences of the German-Rubin statistic (Soil moisture simulation for ORD).
Figure 4.133a. Posterior distribution of GCL.

Figure 4.133b. Posterior distribution of GCM.
Figure 4.133c. Posterior distribution of BCC.

Figure 4.133d. Posterior distribution of EFS.
Figure 4.133e. Posterior distribution of RZD.

Figure 4.133f. Posterior distribution of SAR.

Figure 4.133. Posterior distributions of the parameter (Soil moisture simulation for ORD).

Normality and independency of the residuals were also tested using the same statistical techniques as that used in the previous uncertainty analysis. In the tests, the last
325 parameter sets that provided the highest likelihood were employed to get the simulated runoff. Figure 4.134 shows that the residuals do not follow a normal distribution, and the two-sided Kolmogorov-Smirnov test confirms its non-normality at a 5% significance level (p-value = 7.105e-15). However, the residual does not appear to depend on the simulated runoff in Figure 4.135, indicating the residual is not heteroscedastic. The autocorrelation function plot in Figure 4.136 indicates strong autocorrelation structure of the residuals. Consequently, validity of the assumptions is also questionable in this uncertainty analysis.

![Normal Q-Q Plot](image)

Figure 4.134. Normal Q-Q plot of the averaged residuals (Soil moisture simulation for ORD).

![Plot of the averaged residuals against the transformed simulated runoff](image)

Figure 4.135. Plot of the averaged residuals against the transformed simulated runoff (Soil moisture simulation for ORD).
Figure 4.136. Autocorrelation function plot of the averaged residuals (Soil moisture simulation for ORD).

Due to the tendency of being sampled in parameter space that produces zero runoff, the same tiny value, $1e^{-307}$, was assigned on likelihood value of a parameter set that did not produce any runoff in the SCEM-UA algorithm. The mixing rates and sequences of the German-Rubin statistics are similar to those of the case without a penalty function (Figures 4.137 and 4.138). In Figure 4.139, the posterior distributions of the four parameters, GCL, GCM, EFS, and RZD, have modes at vicinity of the calibrated values. On the other hand, the calibrated values of BCC and RZD were not placed at any mode of their posterior distributions. Therefore, only posterior distribution of CNF was narrowed significantly through imposing the penalty on likelihood value of a parameter producing no runoff. Because CNF is the distinguishingly sensitive parameter, the impact of the penalty might be significant on the posterior distributions of only CNF.
Figure 4.137a. Trace plot of GCL.

Figure 4.137b. Trace plot of GCM.
Figure 4.137c. Trace plot of BCC.

Figure 4.137d. Trace plot of EFS.
Figure 4.137e. Trace plot of RZD.

Figure 4.137f. Trace plot of SAR.

Figure 4.137. Sequence of the sampled parameter values by the Markov chain (Soil moisture simulation for ORD with penalty on zero runoff).
Figure 4.138. Sequences of the German-Rubin statistic (Soil moisture simulation for ORD with penalty on zero runoff).

Figure 4.139a. Posterior distribution of GCL.
Figure 4.139b. Posterior distribution of GCM.

Figure 4.139c. Posterior distribution of BCC.
Figure 4.139d. Posterior distribution of EFS.

Figure 4.139e. Posterior distribution of RZD.
4.4.3 Uncertainty of Parameters for Sediment Transport Simulation

The SCEM-UA algorithm (Vrugt et al., 2003c) was employed to examine uncertainty of parameters and reliability of the sediment transport modeling. The same rainfall events, conditions, and objective function as those used in the calibration were applied for uncertainty analysis for the four parameters of HYSTAR. Uncertainty of the parameters for sediment transport simulation was analyzed while the eleven parameters for runoff simulation were fixed to their calibrated values. The German-Rubin statistic was utilized to check stationary of the Markov chain. The SCEM-UA algorithm was run with the same numbers of complexes, population size for each complex, and total sample population as those of the SCE-UA algorithm used for calibration. Thus, the number of complexes, a population size for each complex, and the total sample population were set to 25, 9, and 225 respectively in uncertainty analysis for sediment transport simulation. The formal likelihood function was utilized to assess posterior probability distribution of parameters (Equation 4.1), thus errors are assumed independent and distributed normally (Bates et al., 2001; Vrugt et al., 2003; Feyen et al., 2007).
Sequences of the sampled parameter values by the Markov chain are plotted in Figure 4.140. Figure 4.141 depicts sequences of the German-Rubin statistic for sediment transport simulation as the Markov chain evolves. The posterior distributions of the parameters are presented in Figure 4.142. All the trace plots in Figure 4.140 show ‘sticky’ movement of the Markov chain, which means high rejection rates of the proposed samples. It indicates that the Markov chain did not move around the parameter space well. Because CSO is the most sensitive parameter, when it is stuck in a certain region for a while, the others are also likely to stay at the same values (Figure 4.140). In addition, its periodic movement implies the sampled parameter sets may not be settled to a stationary posterior distribution. Despite of the apparently poor sampling, the German-Rubin statistic dropped below the threshold of 1.2 quickly at the beginning of the sampling (Figure 4.141), indicating the sampled parameter sets converged into a stationary distribution (Vrugt et al., 2003).

Posterior distributions of the parameters were developed using the last 900 samples drawn by the algorithm to ensure stationary distribution of the samples. The posterior distribution of CSO shows two modes, and the smaller one contains the calibrated value of 0.744. In addition, at the end of the search, values of CSO appear to be converging into a region where the calibrated value is located. In Figure 4.142, the calibrated values of CSC, SCR, and SDR, 0.057, 0.891, and 1.066, are located at vicinities of the modes in their own posterior distribution.

Figure 4.140a. Trace plot of CSO.
Figure 4.140b. Trace plot of CSC.

Figure 4.140c. Trace plot of SCR.
Figure 4.140d. Trace plot of SDR.

Figure 4.140. Sequence of the sampled parameter values by the Markov chain (Sediment transport simulation for ORD).

Figure 4.141. Sequences of the German-Rubin statistic (Sediment transport simulation for ORD).
Figure 4.142a. Posterior distribution of CSO.

Figure 4.142b. Posterior distribution of CSC.
Figure 4.142c. Posterior distribution of SCR.

Figure 4.142d. Posterior distribution of SDR.

Figure 4.142. Posterior distributions of the parameter (Sediment transport simulation for ORD).
4.5 Model Output Uncertainty

In the uncertainty analysis, the posterior distributions of the parameters were developed using the SCEM-UA algorithm. Then, uncertainty in runoff and sediment modeling was examined through quantifying variation in the simulated model output using the sampled parameter sets from the posterior distributions. In this practice, uncertainty was defined as a confidence interval of the output at every hour in the period. The confidence interval of the simulated runoff and sediment load was determined at a significance level of 0.05. However, other statistics such as range and IQR were compared in defining the uncertainty. The parameter samples were derived from the posterior distributions developed using the penalty. The estimated uncertainty in the simulated runoff and sediment load of the watershed, ORD, is presented in Figures 4.143 to 4.145. In addition, agreement between the calibrated and simulated model output using the parameter uncertainty was investigated in Figures 4.144 and 4.146. Finally, model output uncertainty is summarized in Tables 4.50 and 4.51.

In Figure 4.143, the uncertainty band (width of the confidence interval) does not cover the calibrated and observed runoff completely. Generally, the band is located under the calibrated monthly runoff hydrograph in the wet seasons, but it is over the hydrograph in the dry seasons. Figure 4.144 shows the underprediction of the uncertainty band clearly. It means that variation in the band is less than that of the calibrated and observed monthly runoff. In the uncertainty analysis (4.4.1), the SCEM-UA algorithm failed to identify the optima of the parameter values due to the false parameter sampling in the regions that produce zero runoff. Although the penalty was imposed on the regions, performance of the algorithm was not improved for the parameters excepting CNF. Thus, the discrepancy between the uncertainty band and the calibrated runoff is attributed to the inaccurately derived posterior distributions of the parameters.
Figure 4.143a. In an arithmetic scale.

Figure 4.143b. In a logarithmic scale.

Figure 4.143. Uncertainty of the simulated monthly runoff for ORD.
Figure 4.144. Agreement between the calibrated and average of the simulated monthly runoff for ORD using uncertainty in the parameters.

The discrepancy is also found between the calibrated monthly sediment load hydrograph and the uncertainty band (Figures 4.145 and 4.146). For the same reason, the uncertainty band overall underpredicted the monthly sediment load. In Table 4.50, the confidence interval includes the calibrated monthly runoff and sediment load during only 6 and 14 months respectively. While the range covers the calibrated monthly runoff in the entire simulation period, it covers the sediment load in only 48 months. In Table 4.51, the confidence interval produced the narrowest uncertainty band for the monthly runoff and sediment load, and the range provided the widest bands.
Figure 4.145a. In an arithmetic scale.

Figure 4.145b. In a logarithmic scale.

Figure 4.145. Uncertainty of the simulated monthly sediment load for ORD.
Figure 4.146. Agreement between the calibrated and average of the simulated monthly sediment load for ORD using uncertainty in the parameters.

Table 4.50. Statistics of uncertainty of the model output for ORD (part 1).

<table>
<thead>
<tr>
<th>Item</th>
<th>Uncertainty Measure</th>
<th>Monthly Runoff</th>
<th>Monthly Sediment Load</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(times)</td>
<td>(%) b</td>
</tr>
<tr>
<td>No. Months a</td>
<td>Range</td>
<td>72</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>IQR</td>
<td>25</td>
<td>34.7</td>
</tr>
<tr>
<td></td>
<td>C.I.</td>
<td>6</td>
<td>8.3</td>
</tr>
</tbody>
</table>

* a: The number of months that the bands of the uncertainty measures include the calibrated monthly runoff and sediment load; b: Percentage of the times to the number of the entire simulation period (72 months)

Table 4.51. Statistics of uncertainty of the model output for ORD (part 2).

<table>
<thead>
<tr>
<th>Item</th>
<th>Uncertainty Measure</th>
<th>Monthly Runoff</th>
<th>Monthly Sediment Load</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(mm)</td>
<td>(%) d</td>
</tr>
<tr>
<td>Max a</td>
<td>Range</td>
<td>324.9</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>IQR</td>
<td>103.2</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>C.I.</td>
<td>11.5</td>
<td>-</td>
</tr>
<tr>
<td>Average b</td>
<td>Range</td>
<td>110.3</td>
<td>290.1</td>
</tr>
<tr>
<td></td>
<td>IQR</td>
<td>26.2</td>
<td>68.4</td>
</tr>
<tr>
<td></td>
<td>C.I.</td>
<td>3.5</td>
<td>9.7</td>
</tr>
</tbody>
</table>

* a: The maximum width of the band of the uncertainty measure; b: Average width of the band of the uncertainty measure; c: Average of the calibrated monthly runoff and sediment load; d: Percentage of the times to the average of the calibrated monthly runoff and sediment load
When the confidence interval is applied, the average widths of the uncertainty band of 2.9 mm and 3.5 tons are estimated for the simulated monthly runoff and sediment load respectively in the entire simulation period (Table 4.51). They correspond to 8.0 % and 10.2 % of the average of the calibrated monthly runoff and sediment load respectively. On the other hand, the IQR and range provided much wider uncertainty bands. However, the level of significance is set to 5 % arbitrarily in this analysis. Thus, if a smaller significance level is applied, the width of uncertainty band will be increased. For example, an average width of the confidence interval for the monthly runoff increases to 3.9 mm at a level of significance of 0.01.

As seen above, the results of the uncertainty analysis do not correspond well to those of the calibration. The calibrated parameter values are not placed at the highest peaks in the posterior distributions of the parameters. The analysis of the residuals shows that the required assumptions, normal and independent errors, are not satisfied the SCEM-UA algorithm. In addition, the trace plots exhibit bad mixing in the Markov chain evolutions for some parameters even while the German-Rubin convergence statistics is maintained less than 1.2. Moreover, the mean and median of the simulated monthly hydrographs do not look better than the calibrated when roughly comparing their agreement with the observed. Subsequently, it can be concluded that the SCEM-UA failed to provide correct posterior distributions of the parameters. If the SCEM-UA algorithm worked well, the posterior distributions should have the highest mode at a place close to the calibrated value in the parameter space. This failure may be attributed to too short evolutions (1000 sequences) of the Markov chain, the wrong assumptions about the residual and the short length of the data used in the calibrating and uncertainty analysis. In addition, ‘sticky’ movement of the Markov chain, which implies the high rejection rates of the newly proposed parameter sets, suggested improvement was needed in prior distributions.
5. MODEL APPLICATIONS

5.1 Critical Area Identification

Areas of a watershed that contribute to surface and subsurface runoff are referred to as critical areas with respect to pollutant transport (Loganathan et al., 1989). Sometimes, the term ‘critical source area’ is used in the case of focusing on runoff and pollutants (Agnew et al., 2006). In addition, when runoff is the only consideration, the critical areas are sometime called ‘hydrologically sensitive areas (HSA)’ (Walter et al., 2000). A quantitative identification of the critical area may be required for developing water quality management practices for controlling nonpoint source pollution effectively (Frankenberger et al., 1999; Walter et al., 2000). Some studies have delineated critical areas using hydrologic models such as SWAT, or a topographic index approach (Loganathan et al., 1989; Srinivasan et al., 2005; Busteed et al., 2009; Qiu, 2009; White et al., 2009). In this study, methodologies for identifying the critical area are demonstrated based on the simulated travel time and runoff volume maps.

In this study, a critical area is defined as an area that significantly contributes to the generation and transport of direct runoff at the outlet. Thus, the flow path as well as the source of direct runoff can be considered simultaneously in the identification. Two different methodologies were used to define the critical area: the average direct runoff travel time and the accumulated direct runoff volume. The average direct runoff travel time map shows frequency of contribution of every cell to direct runoff at the outlet. On the other hand, the accumulated direct runoff volume map represents total volume of runoff being generated in a cell and passing through the cell. Efficacy of these two methodologies was assessed by comparing the identified critical area with the contributing area map and the locations of the two reservoirs in ORD.

Figure 5.1 shows average direct runoff travel time as time progresses in the simulation period. The contour lines represent the frequency of contributing to direct runoff of the watershed outlet in a certain travel time during the entire simulation period of 6 years. In Figure 5.1a, for example, the contour line of 600 means that a cell on the line contributed to the direct runoff in a 1-hr travel time for 600 hours of 6 years. Thus, a
higher number indicates that a cell contributed to the direct runoff more frequently, and the areas having high numbers become wider as time progresses from 1 to 10 hours. The maximum frequency of 5682 is found at the outlet. For comparison of the average direct runoff travel time maps with the topographic characteristics of the watershed, the contributing area map is presented in Figure 5.2.

As seen in Figure 5.1, higher frequencies are distributed along the channel network, and the distributions well agrees with the contributing area in Figure 5.2. Because the channel conveys concentrated runoff volume, velocity of channel flow is faster than that of overland flow. Thus, area in the vicinity of the channel can contribute runoff to the outlet quickly. In this method, consequently, the critical area becomes a function of contributing area.

Figure 5.1a. Distribution of the 1 hr travel time area.
Figure 5.1b. Distribution of the 2 hr travel time area.

Figure 5.1c. Distribution of the 5 hr travel time area.
Figure 5.1d. Distribution of the 10 hr travel time area.

Figure 5.1. Progression of travel time areas.

Figure 5.2. Contributing area.
Figure 5.3 shows the accumulated direct runoff volume, which is a sum of the generated and passed direct runoff on every cell within the watershed during the entire simulation period of 6 years. Interestingly, some channel segments in upstream areas, which are shown as dark blue in Figure 5.3, transported more direct runoff volume that did those in downstream areas. In addition, some overland areas, which are displayed as yellow, generated and transported more direct runoff than did the other overland areas. Because generally a channel cell has a greater contributing area, the accumulated direct runoff volume was normalized by dividing by the contributing area in order to compare contributions of channel and overland areas on direct runoff. The normalized direct runoff volume map is presented in Figure 5.4.

Figure 5.4 shows the opposite spatial distribution of direct runoff to Figure 5.3. It indicates that contribution of the channel areas to direct runoff of the outlet is less significant than that of the overland areas when considering their contributing areas. The normalized direct runoff is less than the average of 0.76 on all the channel cells. On the other hand, some overland areas, which are displayed as yellow in Figure 5.3, have high values (light green and blue) in Figure 5.4. In addition, interestingly, the two reservoirs of the watershed are located just downstream of the cells having high values in Figures 5.3 and 5.4, indicating that the reservoirs received relatively high direct runoff volume considering their contributing areas.

The two methodologies provided different critical areas. They can be applied effectively only when their characteristics are taken into consideration. For example, the average direct runoff contribution area focuses on travel time of runoff, so it can be useful in the case of interest in concentration time of runoff and soluble pollutants. On the other hand, the accumulated direct runoff volume concentrates on runoff volume generated and passing over an area. Thus, it can be useful in identifying a location for a BMP to effectively block or interrupt runoff and soluble pollutant volume routed from upstream areas. However, they both require subjective criteria in the identification. For instance, the standard travel time can be set to 1 or 2 hours in the average direct runoff travel time map. In addition, it may hard to decide which value of (normalized) direct runoff volume is more suitable for a certain practice.
Figure 5.3. Cumulative direct runoff volume map.

Figure 5.4. Normalized direct runoff volume map.
Critical areas also can be identified through sensitivity analysis of the impact of change in every area within a watershed on the runoff or pollutant of the outlet. In other words, the impact can be quantified by comparing the outlet runoff hydrographs derived with and without consideration of the change. For example, when a curve number of a cell is set to the minimum value (i.e. 35) and its regular value (i.e. 75), the calculated amount of the decrease in the outlet runoff volume can represent sensitivity of the runoff volume to the cell. This comparison can be conducted for every cell to identify critical areas within a watershed. The information derived from this sensitivity analysis can be useful in finding target areas for runoff and pollutant load reduction.

In the identification of critical areas, the newly developed model facilitated ways to consider not only runoff generation but also flow path and routing. In particular, the time-area approach employed in the model permits chronological examination of the relative contribution of overland and channel runoff to the direct runoff at the outlet through showing evolution of the critical area as time progressed. In addition, comparing to an arbitrarily determined distance to channel, the average direct runoff travel time map may provide a scientific basis for identifying critical areas. On the other hand, the routing of the model allowed an alternative investigation into the contribution of overland and channel flow to the direct runoff at the outlet. The integrated role of every cell in generating and passing direct runoff volume is represented in the accumulated direct runoff volume map. On the contrary, in the normalized accumulated direct runoff volume map, the role of every cell in generating direct runoff volume is emphasized. Thus, it is demonstrated that HYSTAR facilitates multiple ways to identify critical areas thus can addresses broader concerns in a water quality management plan.

5.2 Assessment of a Margin of Safety

Uncertainty analysis using the SCEM-UA algorithms provided probability density functions (PDFs) of the parameters and model output. The PDFs of parameters can be utilized to decide if the model is overparameterized and to see which parameters require further investigation. In addition, the PDFs of the model output provide information about reliability of the modeling by exhibiting probabilities and ranges of possible output.
Once a threshold is set, probability or risk of system failure can be estimated from the PDFs. This framework was applied in assessing an appropriate level of the margin of safety (MOS). Although it is difficult to generalize these uncertainty analysis results due to the case-dependent nature, this example demonstrated a way to explicitly incorporate a MOS into determination of a TMDL.

In this study, development of sediment TMDL was used to show a way to determine a MOS of TMDL. All the conditions including a numeric target of water quality for the sediment TMDL are assumed. The probability distribution of the predicted sediment load was adapted from the results of the previous uncertainty analysis. The objective of this demonstration is to show a way to incorporate the quantified model uncertainty into determining a margin of safety (MOS). Thus, the simulated uncertainty band was assumed coincident with the calibrated sediment load hydrograph.

The sediment load that meets the designated use of the waterbody was assumed equal to 70.5 tons/day, which corresponds to the maximum simulated daily sediment load that occurred on 28 Nov 1993. Then, the probability of exceeding the sediment load standard was calculated using the sediment load probability distribution of the day. Finally, the margin of safety for the sediment load TMDL was calculated using a confidence interval, which was determined at a certain level of significance. The concept is described in Figure 5.5. Because a MOS is considered to represent probability of failure of the model prediction, the lower part, which is not connected to the failure, can be neglected. Thus, only the upper part of the confidence interval was regarded as a MOS. In addition, sensitivity of the interval to different levels of significance was investigated.
The normality of the sediment loads probability distribution was checked first in order to estimate a confidence interval appropriately. The simulated sediment load of 28 Nov 1993 did not follow a normal distribution, and a Kolmogorov-Smirnov test confirmed its non-normality at a 5% significance level (p-value = 0.00848). Thus, the simulated sediment load was log transformed and its normality was checked again. Figure 5.6 shows good agreement between the transformed data and the normal distribution, and its normality was confirmed at a 5% significance level (p-value = 0.4367) by a Kolmogorov-Smirnov test.

A confidence interval for the log transformed sediment load was estimated using its probability distribution. Then, it was converted into arithmetic scale. At a significance level of 10%, for example, the upper part of the confidence interval was calculated as between 4.8480 and 4.9184 (Figure 5.8). It means that the sediment load may not exceed 82.9 tons (= \(10^{4.9184}\) kg) in nine cases out of ten on the day, 28 Nov 1992. The estimated confidence intervals for different significance levels and the corresponding MOS are presented in Table 5.1.
Figure 5.6. Normal Q-Q plot of the log transformed sediment load.

Figure 5.7. Probability distribution of the log transformed sediment load.
Table 5.1. Margin of safety for sediment load at different significance levels.

<table>
<thead>
<tr>
<th>Significance Level (%)</th>
<th>Average (ton, A)</th>
<th>Standard Deviation (ton)</th>
<th>No. Samples</th>
<th>Lower Limit (ton)</th>
<th>Upper Limit (ton, B)</th>
<th>MOS (ton, B-A)</th>
<th>MOS (%) (B-A) / A</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>70.5</td>
<td>78.4</td>
<td>100</td>
<td>58.1</td>
<td>85.5</td>
<td>15.0</td>
<td>21.3</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td>59.9</td>
<td>82.9</td>
<td>12.4</td>
<td>17.6</td>
</tr>
<tr>
<td>20</td>
<td></td>
<td></td>
<td></td>
<td>62.1</td>
<td>80.0</td>
<td>9.5</td>
<td>13.5</td>
</tr>
<tr>
<td>50</td>
<td></td>
<td></td>
<td></td>
<td>65.9</td>
<td>75.3</td>
<td>4.8</td>
<td>6.9</td>
</tr>
</tbody>
</table>

In Table 5.1, as a significance level increases, the confidence interval and a MOS become narrower. At a significance level of 10% (90% confidence), for example, a MOS is 12.4 tons which corresponds to 17.6% of the average sediment load (70.5 tons). On the other hand, at a significance level of 50%, a MOS decreased to 6.9%. It means that the sediment load may exceed the standard in five cases out of ten on the day. In other words, the narrowed confidence interval and MOS were estimated at a higher significance level. Therefore, impact of prediction failure on the designated water use should be considered in determining a level of significance.

For comparison of a MOS, a confidence interval of the runoff prediction was estimated with the same methodology. Contrary to the sediment load, the simulated runoff was normally distributed on 28 Nov 1993 (Figure 5.9), and a Kolmogorov-Smirnov test confirmed the normality at 5% significance level (p-value = 0.699). The estimated confidence interval of the simulated runoff and the corresponding MOS are presented in Table 5.2. At a significance level of 10%, for instance, the MOS is 3.5 mm, which corresponds to 5.9% of the average runoff (59.7 mm) (Figure 5.10). The confidence intervals and MOS for runoff are narrower than were those of the sediment load. Because four more parameters were introduced into the model in order to simulate sediment transport than hydrology, the simulated sediment load is expected to have greater variance and uncertainty.
Figure 5.8. Normal Q-Q plot of the runoff.

Table 5.2. Margin of safety for runoff at different significance levels.

<table>
<thead>
<tr>
<th>Significance Level (%)</th>
<th>Average (mm, A)</th>
<th>Standard Deviation (mm)</th>
<th>No. Samples</th>
<th>Lower Limit (mm)</th>
<th>Upper Limit (mm, B)</th>
<th>MOS (mm, B-A)</th>
<th>MOS (%) (B-A) / A</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>59.7</td>
<td>21.3</td>
<td>100</td>
<td>55.5</td>
<td>63.9</td>
<td>4.2</td>
<td>7.0</td>
</tr>
<tr>
<td>10</td>
<td>56.2</td>
<td>63.2</td>
<td></td>
<td></td>
<td></td>
<td>3.5</td>
<td>5.9</td>
</tr>
<tr>
<td>20</td>
<td>57.0</td>
<td>62.4</td>
<td></td>
<td></td>
<td></td>
<td>2.7</td>
<td>4.6</td>
</tr>
<tr>
<td>50</td>
<td>58.3</td>
<td>61.1</td>
<td></td>
<td></td>
<td></td>
<td>1.4</td>
<td>2.4</td>
</tr>
</tbody>
</table>
Figure 5.9. Probability distribution of runoff.

Freedman et al. (2003) found that a MOS ranged from 5 to 90 % of a TMDL for 17 cases in which the MOS was considered explicitly of 176 TMDL studies reviewed. Thus, the MOS estimated for the sediment load, 6.9 to 21.3 %, is smaller than an average of the explicit MOS cases. In addition, the MOS of runoff, 2.4 to 7.4 %, is close to the minimum of the cases. The size of the MOS must be proportional to uncertainty in modeling. Then, lower parameter uncertainty may lead to lower model output uncertainty and subsequently smaller MOS. However, it also depends on the sample size because the confidence interval is a function of sample size. Thus, the greater the sample size, potentially the narrower the confidence interval and MOS. In the case of sediment load, for example, when only 10 samples were employed to estimate the confidence interval, the MOS for a significance level of 10 % increased to 32.7 % (Table 5.3). Therefore, a MOS will decrease as number of simulated samples used in the assessment of a MOS increases.
Table 5.3. Sensitivity of MOS for a significance level of 10 % to a size of sample.

<table>
<thead>
<tr>
<th>No. Sample</th>
<th>Lower Limit (mm)</th>
<th>Upper Limit (mm, B)</th>
<th>MOS (mm, B-A)</th>
<th>(% , (B-A) / A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>59.9</td>
<td>82.9</td>
<td>12.4</td>
<td>17.6</td>
</tr>
<tr>
<td>50</td>
<td>56.6</td>
<td>87.8</td>
<td>17.3</td>
<td>24.6</td>
</tr>
<tr>
<td>30</td>
<td>53.9</td>
<td>92.2</td>
<td>21.7</td>
<td>30.8</td>
</tr>
<tr>
<td>10</td>
<td>53.1</td>
<td>93.5</td>
<td>23.0</td>
<td>32.7</td>
</tr>
</tbody>
</table>

In this example, utility of the uncertainty analysis was exhibited in explicitly quantifying a MOS for a TMDL. A MOS was defined as an upper part of the estimated confidence interval for a storm event that produced the greatest runoff and sediment load. The estimated MOS for a sediment TMDL was smaller than the average of MOSs in the literature Freedman et al. (2003) investigated, but it was greater than a 5 to 10 % MOS that most TMDL studies consider (Mostaghimi et al., 2000). Thus, this result could be a proof that the typical assumptions about MOS underestimate modeling uncertainty. Of course, MOS varies with accuracy of modeling, the algorithm utilized in uncertainty analysis, level of significance, and sample size. Thus, some guidelines for methodologies of explicitly defining MOS may be required for widespread application and objectivity of MOS quantification.
6. SUMMARY

6.1 Model Development

The main goal of this study was to develop a distributed, continuous hydrology and sediment transport model that incorporates uncertainty analysis. The newly developed model, HYSTAR (HYdrology and Sediment transport simulation using Time-ARea method) is capable of simulating direct runoff, base flow, and sediment load of a watershed. In the model, a square cell represents a homogeneous unit with spatially distributed parameter for input data such as rainfall, topography, land cover and use, and soil in a grid format. The model simulates runoff, soil moisture, and sediment transport in an hourly time step. The uncertainty analysis algorithm, SCEM-AU, is integrated into the model so that the model can provide its parameter and output uncertainty in a probabilistic way.

In the model, a direct runoff hydrograph is calculated through discrete convolution of an effective direct runoff volume map and a time-area histogram. The effective direct runoff volume of a cell consists of excess rainfall volume and the routed direct runoff volume from its upstream areas along the flow path. The velocity of direct runoff is calculated using the Manning’s equation in an iterative way. Then, a time-area histogram is created based on the direct runoff velocity map at every time step. The newly devised routing method evenly distributes effective direct runoff volume of a cell into cells within the next time area zone of the time-area map. In a case of having discontinuity in travel times of the time-area zones sharing a border, it evenly distributes effective direct runoff volume into downstream cells within the current time area zone.

The infiltrated volume of the effective runoff volume is calculated using the modified CN method and a continuity equation on every cell at every time step. For continuous modeling, the model is based on the revised CN method from the SWAT model, thus a curve number of every cell is updated based on the simulated soil water content at the beginning of a storm event. The revised CN method was modified to consider effective runoff volume instead of excess rainfall volume so that the routed direct runoff volume as well as rainfall volume can be reflected in calculating effective
direct runoff and infiltration volume. The curve number, Manning’s roughness coefficient, and crop coefficient are determined based on information about land cover, land use, and soils.

The soil water content of every cell is updated through summing up the infiltration, evapotranspiration, and percolation using a continuity equation in a root zone layer at every time step. For calculating evapotranspiration rate, potential evapotranspiration is calculated using the Hargreaves equation, and then actual evapotranspiration is estimated by the dual crop coefficient method. Percolation rate is calculated using the unsaturated hydraulic conductivity and anisotropic ratio. The unsaturated hydraulic conductivity is estimated using the saturated hydraulic conductivity identified in SSURGO and van Genuchten equation, and then the anisotropic ratio is applied to estimate vertical unsaturated hydraulic conductivity. Lateral flow is ignored in the model. The base flow is assumed directly proportional to a summation of the percolated volume in the entire watershed at every time step. Soil characteristics such as field capacity and soil depth are adapted from SSURGO or derived from soil texture using pedotransfer functions.

In the sediment transport simulation, sediment transport capacity of every cell is calculated using the Yalin equation. Then, the integrated concentration of the detached and routed sediment is compared with the sediment transport capacity to determine sediment deposition and transportation rates. In the application of the Yalin equation, the characteristic soil particle diameter is estimated from soil texture using a pedotransfer function. The different equations are applied to calculate critical Shield parameters for overland and channel flow separately. The shear Reynolds number is employed to consider characteristics of the overland flow. The soil particle is detached by raindrop splash and runoff in the simulation, and then impact of the raindrop becomes diminished, as overland runoff depth gets deeper. The sediment is routed in the same way as the runoff. The maximum sediment concentration of 1060 g/l is applied in the sediment transport simulation to avoid unrealistic results of the simulation.
6.2 Model Evaluation

To calibrate the model, 15 parameters were selected of which 8 were scale factors, which allowed efficient calibration for the corresponding parameters while keeping their spatial variation. In the sensitivity analysis, the CNF (curve number scale factor) was identified as the most sensitive parameter for direct runoff, and it was followed by RZD (root zone depth), GCM (a coefficient of the van Genuchten equation), and BCC (crop coefficient). However, the simulated runoff was insensitive to GCL (the other coefficient of the van Genuchten equation). On the other hand, the base flow volume was most sensitive to RZD, and responsive to GCM, BCC, SAR (anisotropic coefficient), and CNF. The sensitivity analysis showed unique sensitivity of the simulated direct runoff and base flow volume to the parameters in different storm events. The AAT (all at a time) practice of the sensitivity analysis showed that the variation of the simulated direct runoff and base flow volume was limited by interaction between the parameters.

While the 11 parameters for hydrology simulation were fixed to their calibrated values, sensitivity of sediment load to the 4 parameters for sediment transport simulation was investigated. The sediment load and peak sediment load rate were most sensitive to CSO (one coefficient of the equation for calculating critical Shield parameter of overland runoff), and it was followed by SCR (soil cohesion coefficient for overland runoff). CSC (critical Shield parameter for channel runoff) and SDR (soil detachability efficiency coefficient) were not sensitive for the sediment transport simulation. Contrary to the hydrology simulation, in the AAT (all at a time) practice, the variation of the simulated sediment load was amplified by interaction between the parameters.

The model was applied in two subwatersheds (ORD and PCA) of the Owl Run and Polecat Creek watersheds to assess its applicability. The RMSE was used as an objective function in the calibration of the parameters for hydrology simulation. The SCE-UA algorithm was employed to find the optimum parameter set that minimizes the objective function value. The calibrated model was validated using a split sample approach. For calibration without base flow separation, several calibration schemes were tested, and the 3-step split-storm scheme was selected for the parameter calibration because of its best performance. The initial soil moisture condition for calibration was
refined through recursive processes, which updates the initial soil moisture condition using the latest calibrated parameter values in every iteration step.

In the 3-step split-storm calibration scheme, the 4 parameters for direct runoff simulation were optimized using the observed runoff hydrograph of one storm event. Then, the 6 parameters for soil moisture simulation were calibrated using the observed hydrographs of the storm event and the following three storm events. The observed runoff hydrograph was assumed consisting of only direct runoff. Finally, one parameter that controls the proportion of base flow to the percolated water volume was calibrated to match the simulated runoff volume to the observed in the total calibration period of 1 year. In the calibration, temporal variations of some time-variant parameters were not calibrated but were defined based on the literature. In addition, the two small reservoirs in upstream areas of ORD were assumed be capable of storing all the routed direct runoff volume from their upstream area.

The parameters for hydrology simulation were optimized using the observed runoff hydrograph of the storm events that occurred between 2 Sep 1992 and 1 Sep 1993. The calibrated model predicted daily and monthly runoff with Nash-Sutcliffe efficiency coefficients of 0.25 and 0.60 and coefficients of determination of 0.71 and 0.83 respectively in the entire simulation period. The model overpredicted runoff in the second validation period. On the other hand, using the storm events that occurred between 18 Oct 1990 and 17 Oct 1991, the calibrated model performed better in predicting daily and monthly runoff of ORD with the efficiency coefficients of 0.52 and 0.78 and coefficients of determination of 0.55 and 0.82 respectively. It did not overpredict runoff in the second validation period but underpredicted that in the calibration and first validation periods. The model showed the poor performance in predicting daily and monthly runoff in application to the Polecat Creek watershed (PCA), where runoff is not immediately responsive to rainfall, with the efficiency coefficients of 0.06 and 0.28 and determination coefficients of 0.16 and 0.33 respectively.

The observed hourly runoff hydrographs of 43 storm events, which produced peak runoff greater than 1.0 m$^3$/s, was compared with the simulated for ORD. The comparison showed good agreement between the observed and simulated recession curve in
particular wet seasons, Oct to Mar. However, the model overall overpredicted the recession parts of the runoff hydrograph in particular dry seasons, Apr to Sep. In the comparison of the peak runoff, time to peak, and runoff volume of the storm events, the model performed well in predicting time to peak with the 77% satisfactory predictions (equal to or less than 1 hour difference) of the 43 storm events. In the prediction of peak runoff and runoff volume, the percentages of the satisfactory predictions (relative error is less than 25%) were decreased to 40 and 60% respectively. Most of the poor performances were found in the second validation period.

The 4 parameters for sediment simulation were calibrated with the observed sediment load hydrograph of the single storm event that occurred on 5 Jan 1993 while the parameters for hydrology simulation were fixed to their calibrated values. The absolute error was used as an objective function and the SCE-UA algorithm was employed to find the optimum in the calibration of the parameters for sediment transport simulation. The model predicted daily and monthly sediment load with Nash-Sutcliffe efficiency coefficients of 0.50 and 0.58 and the coefficients of determination of 0.52 and 0.79 respectively. The storm events that occurred on 2 Sep and 22 Nov 1992 were also used for calibration, and the performance of the calibrated model in predicting sediment load was evaluated. The comparison revealed that model performance is sensitive to the selection of the storm events for the calibration.

6.3 Model Uncertainty

Uncertainty of the model parameters and output was investigated using the SCEM-UA algorithm, which is one of the MCMC (Markov Chain Monte Carlo) samplers. A formal likelihood function was employed to describe the characteristics of the modeling errors. While the Markov Chain explored the parameter space, sequences of the sampled parameter values and the Rubin-German statistics were monitored to assess quality of the samples and to identify convergence of the sampled parameter sets into a stable posterior distribution. The derived posterior distribution of CNF, which is the most sensitive parameter of the model, showed a single mode whereas the other parameters did not. In particular, the calibrated values of some parameters such as THA, EFS, and SAR
were not located at one of the modes in their posterior distributions due to the false sampling of the SCEM-UA algorithm. Thus, it is recommended that a more sophisticated penalty function and rule be implemented for better identification of the uncertainty. The normality check and autocorrelation function of the modeling errors indicated that the assumptions of the formal likelihood function were violated in the uncertainty analysis. Thus, the posterior distributions of the parameters can be erroneous and biased. The formal likelihood function proposed by Schoups et al. (2010) is recommended for future study to correct the statistical description of the model errors.

The model output uncertainty was estimated using the posterior distributions of the parameters derived in the parameter uncertainty analysis. The 100 parameter sets were sampled from their posterior distributions, and then runoff and sediment load were simulated with the sampled parameter sets. The ranges of the model output provided the widest uncertainty bands while the confidence interval defined at 5% significance level produced the narrowest band. The ranges corresponded to 290% and 438% of the average of the calibrated monthly runoff and sediment load respectively. On the other hand, the confidence intervals were equivalent to 9.7% and 10.8% of the average respectively.

Sensitivity of the model output to errors of GIS data was investigated to approximate the impact of these errors on model uncertainty. In the analysis, only elevation and land use classification errors were considered and other errors such as positional error were ignored. SGS (Sequential Gaussian Simulation) and SIS (Sequential Indicator Simulation) were used to induce error in the DEM and NLCD datasets, and 30 disturbed DEM and NLCD maps were generated. In the disturbed maps, elevation and land cover classification were altered in 30% of the watershed. Then, runoff and sediment load were simulated using the disturbed maps and variation in the simulated output were examined. The average ranges of variation created by the DEM errors in the simulated monthly runoff and sediment load corresponded to 7.4% and 14.9% of the average of their calibrated values respectively. On the other hand, the average ranges created by the NLCD errors were equivalent to 2.2% and 6.0% of the averages of the calibrated runoff and sediment load respectively. This indicated that the DEM errors had a greater impact on the model output than did the NLCD errors. Comparing to the
average ranges of variation created by the parameter uncertainty and the GIS data error, the impact of the GIS data errors on the model output was much less than that of the parameter uncertainty.

6.4 Model Application

The model was utilized in identifying critical areas, defined as an area that contributes significantly to direct runoff at the outlet. The critical area maps defined by two different criteria, the average direct runoff travel time and the accumulated direct runoff volume, were compared. The areas close to the stream network, which tends to have channelized flow, was identified as the critical area on the average direct runoff travel time map. On the other hand, the critical areas were distributed over overland areas as well as channel areas on the accumulated direct runoff volume map. The normalized accumulated direct runoff volume map by the contributing areas showed significantly different spatial distributions of the critical areas. In addition, critical areas were identified through examining sensitivity of model output to change in each cell in a watershed. In the case study, efficiency of a reservoir in reducing outlet runoff volume was not significantly affected by its location. However, a reservoir located at a downstream location covered greater upstream areas at a similar efficiency.

The uncertainty analysis results were used to demonstrate a way to assess a MOS (margin of safety) of sediment load TMDL. In the case study, the sediment load standard for ORD was assumed equal to the maximum simulated daily sediment load of 70.5 tons/day occurred on 28 Nov 1993. Then, the MOS was defined as the upper part of the confidence interval which was calculated using the 100 simulated sediment load realizations for the day. The sediment load realizations were log transformed for appropriate application of a confidence interval. At significance levels of 5 % and 10 %, the MOS corresponded to 21.3 % and 17.6 % of the average of the simulated sediment load or the assumed standard. In the case of runoff, the MOS was estimated as 7.0 % and 5.9 % of the average of the simulated runoff. The MOS was affected by the number of model output realizations used for the analysis.
7. CONCLUSIONS and RECOMMENDATIONS

7.1 Conclusions

The performance of the newly developed model, HYSTAR, in predicting runoff and sediment load was acceptable with the Nash-Sutcliffe efficiency coefficient and coefficient of determination greater than 0.5 at both daily and monthly time scales. Therefore, it can be concluded that the newly devised routing and modified CN methods were successfully incorporated into the time-area approach to route direct runoff on overland and in channel flow. At the same time, it was demonstrated that discrete convolution of the time-area histogram and the effective direct runoff volume could be used to develop direct runoff hydrograph without employing a unit hydrograph. In addition, the newly devised routing method and the sediment transport capacity approach were successfully incorporated into HYSTAR to route sediment load on overland and in channel flow. The newly developed model facilitates ways to explicitly identify the spatial distributions of critical areas.

The uncertainty analysis showed that the SCEM-UA algorithm could be applied to derive the uncertainty distributions of the parameter and model output and to explicitly quantify a margin of safety (MOS). This study is the first known attempt to apply the SCEM-UA algorithm in quantifying the uncertainty of a distributed hydrology and sediment transport model. In this study, the MOS of a sediment TMDL was explicitly quantified as corresponding to 7.0 % and 21.3 % of the average of the simulated runoff and sediment load at a significance level of 5 %. This result could be a proof that a 5 to 10 % MOS that most TMDL studies consider actually underestimates modeling uncertainty. However, the reliability and utility of the results were limited by the violation of the assumptions employed in the formal likelihood function. In addition, the posterior distributions of the parameters derived by the SCEM-UA algorithm did not completely match the calibrated parameter values by the SCE-UA algorithm due to the false sampling of the SCEM-UA algorithm.

In the comparison of modeling output uncertainty created by the parameter uncertainty and the GIS data error, the impact of the parameter uncertainty on the model output was much greater than that of the GIS data errors. Therefore, accuracy and
reliability of a distributed model will be more efficiently improved by refining the parameters and the associated model structure than by exploring better quality of the GIS input data. In addition, the impact of the topographic data error on the model output was greater than was that of the land cover data error. Thus, accuracy of the topographic data is more important than that of the land cover data for improving accuracy of distributed modeling.

7.2 Limitations and Recommendations

HYSTAR simplifies the known hydrology and sediment transport processes with several assumptions for efficient simulation. First, the model does not consider spatial variation of groundwater discharge. Although the model simulates water movement including percolation (groundwater recharge) in a distributed manner, it assumes that base flow (groundwater discharge) at a watershed outlet is proportional to a summation of the percolated water volume within a watershed in every time interval. In addition, the equilibrium condition is assumed in the vadose zone, thus the percolated water should contribute to base flow immediately. On the other hand, lateral flow, preferential flow, and capillary rise are not considered in the model. The validation results suggested that parameters and equations of the curve number method were in need of improvement for better performance of the model in dry soil water conditions.

The model does not simulate snow and ice melting processes. All the precipitation is regarded as rainfall. Thus, the delayed contribution of snow and ice to runoff is not considered in the model. The model simulates only runoff and sediment load. Other pollutants such as nutrients, bacteria, pesticide, and heavy metal should be incorporated into the model in the future to enhance its applicability. In the model, sediment is assumed transported only by direct runoff and deposited when direct runoff ceases, thus base flow does not contain any sediment between storm events. In addition, bank erosion is ignored. The validation results suggested that an improvement of the model performance in predicting sediment load could be achieved through mitigating sensitivity of the critical Shield parameter to the shear Reynolds number.
The model performed poorly in predicting runoff in PCA (a subwatershed of the Polecat Creek watershed) where runoff is not immediately responsive to rainfall. Thus, it is suggested to incorporate one more soil layer into the model, which can store significant amount of runoff and release it slowly. The sensitivity analysis and calibration experience suggested that the parameter, GCL, could be omitted from the model without significant deterioration in the model performance. In the model applications for ORD and PCA, temporal variations of the crop coefficients and the Manning’s roughness coefficients were fixed to their predetermined values based on the literature. Thus, detailed variations in agricultural management practices were not incorporated into the modeling.

Although HYSTAR employs a simple scheme in routing runoff volume, it still requires considerable computing time in particular for the sampling based calibration and uncertainty analysis methods. For example, when using a single thread on 3.00 GHz processor and watershed with 3654 cells at a cell size of 30×30 m, it took about 2 hours to complete a 6-year hydrology and sediment transport simulation. Thus, when 100 samples are required for uncertainty analysis, it would require around 8 days for the model runs. In addition, it took about 1 minute for the model to simulate hourly runoff and sediment load hydrographs of the four storm events. Thus, that it may take 17 hours to optimize the parameters and to derive their posterior distributions in the calibration and parameter uncertainty analysis when 1000 model runs are required. Some computational techniques such as parallelizing code may mitigate the excessive time requirements of the sampling based methods.
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Appendix A. Alternative Calibration Schemes and their Validation

A.1 Overview

In this study, the parameters for hydrology simulation were calibrated separately with the measured runoff data in order to avoid base flow separation procedures (Figure 4.45). Thus, the four parameters for direct runoff simulation were calibrated first with the measured runoff whose antecedent runoff is zero and soil water content is low at the beginning of the corresponding storm event (i.e. 2 Sep 1992). Then, the other six parameters for soil moisture simulation were calibrated with the measured runoff for the following storm events that occurred in ten days or a month (i.e. 2 Sep 1992 to 10 Sep 1992). Finally, only parameter for base flow simulation was calibration with the measured runoff for the entire calibration period of a year (i.e. 2 Sep 1992 to 31 Aug 1993 for ORD).

In the calibration for direct runoff simulation, contribution of base flow to runoff is assumed insignificant based on the zero antecedent runoff and dry soil water condition. However, this assumption may be not satisfied completely unless the soil water content becomes equal to wilting point that barely allows percolation from the soil root zone into the aquifer. In addition, the contribution may be increased in the following storm events because the soil may get wetter. For these reasons, the calibration may overestimate the parameters for direct runoff simulation. Thus, six different calibration schemes were introduced and tried to ensure better calibration results in this study (Figure 4.45). The calibration results presented in 4.2.2 was derived based on Calibration Scheme 1 (Case 1). The parameters were calibrated using the other schemes and the results are presented here.

Explaining briefly, in Case 2, the parameters for direct runoff are calibrated with the measured runoff of the first storm event, which is assumed having low soil water content at its beginning. However, the parameters for soil moisture simulation are calibrated with the measured runoff of the last storm event that produced the highest peak runoff. Then, the parameter for base flow is calibrated finally. In Case 3, the parameters for direct runoff and soil moisture simulation are calibrated with the measured runoff of the first and last storm events at the same time. In Case 4, the parameters are calibrated
with all the measured runoff of the four storm events. In Case 5, once the parameters for direct runoff simulation are calibrated with the measured runoff of the first storm event, the parameters for soil moisture and base flow simulation are calibrated with all the measured runoff at the same time. Finally, in Case 6, all the parameters for hydrology simulation are calibrated with the all the runoff data at the same time.

A.2 Calibration Scheme 2 (Case 2)

Table A.1. Calibrated values of the six parameters for soil moisture simulation (Case 2).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
<th>GWC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting</td>
<td>0.500</td>
<td>0.500</td>
<td>1.000</td>
<td>1.000</td>
<td>0.500</td>
<td>1.000</td>
<td>0.500</td>
</tr>
<tr>
<td>Iter. 1</td>
<td>0.443</td>
<td>0.283</td>
<td>0.527</td>
<td>1.049</td>
<td>0.190</td>
<td>0.406</td>
<td>0.417</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>0.459</td>
<td>0.353</td>
<td>0.529</td>
<td>1.478</td>
<td>0.239</td>
<td>0.163</td>
<td>0.564</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>0.713</td>
<td>0.269</td>
<td>0.503</td>
<td>1.215</td>
<td>0.201</td>
<td>0.504</td>
<td>0.612</td>
</tr>
</tbody>
</table>

a GCL: Coefficient L of the Van Genuchten equation; GCM: Coefficient M of the Van Genuchten equation; BCC: Basal crop coefficient of the crop coefficient method; EFS: Effective fraction of soil surface covered by vegetation of the crop coefficient method; RZD: Root zone depth; SAR: Soil anisotropic ratio; RMSE for the calibrated parameter set (m³/s)
Figure A.1a. Iteration 1.

Figure A.1b. Iteration 2.
Figure A.1c. Iteration 3.

Figure A.1. Convergence of GCL, GCM, BCC, EFS, RZD, and SAR in the calibration (Case 2).

Figure A.2a. Iteration 1.
Figure A.2b. Iteration 2.

Figure A.2c. Iteration 3.

Figure A.2. Convergence of the objective function value (RMSE) in the calibration (Case2).
Figure A.3a. Iteration 1.

Figure A.3b. Iteration 2.
Figure A.3c. Iteration 3.

Figure A.3. Calibrated direct runoff hydrograph (Case 2).

**A.3 Calibration Scheme 3 (Case 3)**

Table A.2. Calibrated values of the six parameters for soil moisture simulation (Case 3).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
<th>GWC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>10.0</td>
<td>0.500</td>
<td>0.500</td>
<td>1.000</td>
<td>0.500</td>
<td>1.000</td>
<td>0.500</td>
<td>0.500</td>
</tr>
<tr>
<td>Iter. 1</td>
<td>1.109</td>
<td>1.385</td>
<td>0.917</td>
<td>20.2</td>
<td>0.616</td>
<td>0.306</td>
<td>0.602</td>
<td>1.478</td>
<td>0.152</td>
<td>0.287</td>
<td>0.547</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>1.104</td>
<td>0.501</td>
<td>1.431</td>
<td>48.9</td>
<td>0.597</td>
<td>0.292</td>
<td>0.569</td>
<td>1.498</td>
<td>0.773</td>
<td>0.731</td>
<td>0.474</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>1.092</td>
<td>1.190</td>
<td>0.875</td>
<td>82.7</td>
<td>0.273</td>
<td>0.342</td>
<td>0.868</td>
<td>1.354</td>
<td>0.379</td>
<td>0.642</td>
<td>1.107</td>
</tr>
</tbody>
</table>

*CNF: curve number scale factor; MNO: Manning’s roughness coefficient scale factor for overland; MNC: Manning’s roughness coefficient scale factor for channel; THA: threshold area to define the extent of stream networks (ha); RMSE: RMSE for the calibrated parameter set (m^3/s); GCL: Coefficient L of the Van Genuchten equation; GCM: Coefficient M of the Van Genuchten equation; BCC: Basal crop coefficient of the crop coefficient method; EFS: Effective fraction of soil surface covered by vegetation of the crop coefficient method; RZD: Root zone depth; SAR: Soil anisotropic ratio; RMSE for the calibrated parameter set (m^3/s)*
Figure A.4a. Iteration 1.

Figure A.4b. Iteration 2.
Figure A.4c. Iteration 3.

Figure A.4. Convergence of all the parameters in the calibration (Case 3).

Figure A.5a. Iteration 1.
Figure A.5b. Iteration 2.

Figure A.5c. Iteration 3.

Figure A.5. Convergence of the objective function value (RMSE) in the calibration (Case3).
Figure A.6a. Iteration 1.

Figure A.6b. Iteration 2.
Figure A.6c. Iteration 3.

Figure A.6. Calibrated direct runoff hydrograph (Case 3).

A.4 Calibration Scheme 4 (Case 4)

Table A.3. Calibrated values of the six parameters for soil moisture simulation (Case 4).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Iter. 1</th>
<th>Iter. 2</th>
<th>Iter. 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNF</td>
<td>1.105</td>
<td>1.103</td>
<td>1.116</td>
</tr>
<tr>
<td>MNO</td>
<td>0.507</td>
<td>1.021</td>
<td>1.290</td>
</tr>
<tr>
<td>MNC</td>
<td>1.345</td>
<td>1.161</td>
<td>1.058</td>
</tr>
<tr>
<td>THA</td>
<td>78.4</td>
<td>83.2</td>
<td>80.9</td>
</tr>
<tr>
<td>GCL</td>
<td>0.584</td>
<td>0.283</td>
<td>0.547</td>
</tr>
<tr>
<td>GCM</td>
<td>0.340</td>
<td>0.328</td>
<td>0.443</td>
</tr>
<tr>
<td>BCC</td>
<td>0.615</td>
<td>0.995</td>
<td>0.618</td>
</tr>
<tr>
<td>EFS</td>
<td>1.447</td>
<td>1.426</td>
<td>1.105</td>
</tr>
<tr>
<td>RZD</td>
<td>0.247</td>
<td>0.464</td>
<td>0.700</td>
</tr>
<tr>
<td>SAR</td>
<td>0.247</td>
<td>0.771</td>
<td>0.949</td>
</tr>
<tr>
<td>GWC</td>
<td>0.461</td>
<td>0.863</td>
<td>0.578</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Starting Value</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
<th>GWC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iter. 1</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>10.0</td>
<td>0.500</td>
<td>0.500</td>
<td>1.000</td>
<td>1.000</td>
<td>0.500</td>
<td>1.000</td>
<td>0.500</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>1.105</td>
<td>0.507</td>
<td>1.345</td>
<td>78.4</td>
<td>0.584</td>
<td>0.340</td>
<td>0.615</td>
<td>1.447</td>
<td>0.247</td>
<td>0.247</td>
<td>0.461</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>1.103</td>
<td>1.021</td>
<td>1.161</td>
<td>83.2</td>
<td>0.283</td>
<td>0.328</td>
<td>0.995</td>
<td>1.426</td>
<td>0.464</td>
<td>0.771</td>
<td>0.863</td>
</tr>
</tbody>
</table>

a CNF: curve number scale factor; MNO: Manning’s roughness coefficient scale factor for overland; MNC: Manning’s roughness coefficient scale factor for channel; THA: threshold area to define the extent of stream networks (ha); RMSE: RMSE for the calibrated parameter set (m³/s); GCL: Coefficient L of the Van Genuchten equation; GCM: Coefficient M of the Van Genuchten equation; BCC: Basal crop coefficient of the crop coefficient method; EFS: Effective fraction of soil surface covered by vegetation of the crop coefficient method; RZD: Root zone depth; SAR: Soil anisotropic ratio; RMSE for the calibrated parameter set (m³/s)
Figure A.7a. Iteration 1.

Figure A.7b. Iteration 2.
Figure A.7c. Iteration 3.

Figure A.7. Convergence of all the parameters in the calibration (Case 4).

Figure A.8a. Iteration 1.
Figure A.8b. Iteration 2.

Figure A.8c. Iteration 3.

Figure A.8. Convergence of the objective function value (RMSE) in the calibration (Case4).
Figure A.9a. Iteration 1.

Figure A.9b. Iteration 2.
A.5 Calibration Scheme 5 (Case 5)

Table A.4. Calibrated values of the six parameters for soil moisture simulation (Case 5).

<table>
<thead>
<tr>
<th>Parameter a</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
<th>GWC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting Value</td>
<td>0.500</td>
<td>0.500</td>
<td>1.000</td>
<td>1.000</td>
<td>0.500</td>
<td>1.000</td>
<td>0.500</td>
</tr>
<tr>
<td>Calibrated Value</td>
<td>0.512</td>
<td>0.290</td>
<td>0.665</td>
<td>1.170</td>
<td>0.145</td>
<td>0.229</td>
<td>0.193</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>0.303</td>
<td>0.332</td>
<td>0.597</td>
<td>1.282</td>
<td>0.148</td>
<td>0.120</td>
<td>0.225</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>0.508</td>
<td>0.275</td>
<td>0.623</td>
<td>1.052</td>
<td>0.144</td>
<td>0.234</td>
<td>2.182</td>
</tr>
</tbody>
</table>

a GCL: Coefficient L of the Van Genuchten equation; GCM: Coefficient M of the Van Genuchten equation; BCC: Basal crop coefficient of the crop coefficient method; EFS: Effective fraction of soil surface covered by vegetation of the crop coefficient method; RZD: Root zone depth; SAR: Soil anisotropic ratio; RMSE for the calibrated parameter set (m³/s)
Figure A.10a. Iteration 1.

Figure A.10b. Iteration 2.
Figure A.10c. Iteration 3.

Figure A.10. Convergence of all the parameters in the calibration (Case 5).

Figure A.11a. Iteration 1.
Figure A.11b. Iteration 2.

Figure A.11c. Iteration 3.

Figure A.11. Convergence of the objective function value (RMSE) in the calibration (Case 5).
Figure A.12a. Iteration 1.

Figure A.12b. Iteration 2.
Figure A.12c. Iteration 3.

Figure A.12. Calibrated direct runoff hydrograph (Case 5).

A.6 Calibration Scheme 6 (Case 6)

Table A.5. Calibrated values of the six parameters for soil moisture simulation (Case 6).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>CNF</th>
<th>MNO</th>
<th>MNC</th>
<th>THA</th>
<th>GCL</th>
<th>GCM</th>
<th>BCC</th>
<th>EFS</th>
<th>RZD</th>
<th>SAR</th>
<th>GWC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting Value</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>10.0</td>
<td>0.500</td>
<td>0.500</td>
<td>1.000</td>
<td>1.000</td>
<td>0.500</td>
<td>1.000</td>
<td>0.500</td>
</tr>
<tr>
<td>Iter. 1</td>
<td>0.800</td>
<td>0.638</td>
<td>1.081</td>
<td>38.9</td>
<td>0.389</td>
<td>0.584</td>
<td>1.424</td>
<td>0.828</td>
<td>0.148</td>
<td>1.608</td>
<td>5.683</td>
</tr>
<tr>
<td>Iter. 2</td>
<td>1.116</td>
<td>0.941</td>
<td>1.337</td>
<td>65.4</td>
<td>0.506</td>
<td>0.276</td>
<td>0.573</td>
<td>1.376</td>
<td>0.237</td>
<td>1.007</td>
<td>0.642</td>
</tr>
<tr>
<td>Iter. 3</td>
<td>0.831</td>
<td>0.570</td>
<td>0.694</td>
<td>72.1</td>
<td>0.552</td>
<td>0.252</td>
<td>0.559</td>
<td>1.490</td>
<td>0.108</td>
<td>1.357</td>
<td>3.175</td>
</tr>
</tbody>
</table>

*CNF: curve number scale factor; MNO: Manning’s roughness coefficient scale factor for overland; MNC: Manning’s roughness coefficient scale factor for channel; THA: threshold area to define the extent of stream networks (ha); RMSE: RMSE for the calibrated parameter set (m³/s); GCL: Coefficient L of the Van Genuchten equation; GCM: Coefficient M of the Van Genuchten equation; BCC: Basal crop coefficient of the crop coefficient method; EFS: Effective fraction of soil surface covered by vegetation of the crop coefficient method; RZD: Root zone depth; SAR: Soil anisotropic ratio; RMSE for the calibrated...
Figure A.13a. Iteration 1.

Figure A.13b. Iteration 2.
Figure A.13c. Iteration 3.

Figure A.13. Convergence of all the parameters in the calibration (Case 5).

Figure A.14a. Iteration 1.
Figure A.14b. Iteration 2.

Figure A.14c. Iteration 3.

Figure A.14. Convergence of the objective function value (RMSE) in the calibration (Case6).
Figure A.15a. Iteration 1.

Figure A.15b. Iteration 2.
A.7 Comparison of Validation Results

The calibrated models using the different schemes were validated. The performances of the calibrated model at the last iteration are represented in Table A.6 to A.8. As seen in the tables, the calibrated model by the scheme, Case 1, provided the overall best validation results. On the other hand, performance of Case 3 was superior to that of Case 1 in the entire and second validation period. However, GWC was calibrated to a value greater than 1.0, which is unrealistic, in Case 3. Overall, Case 2, 4, and 5 provided poor performance in predicting runoff. Contrary to expectation, Case 6, which calibrated all the parameters at the same time, provided better performance than did Case 2, 4, and 5. It was hard to identify a clear relationship between the number of storms used in the calibration and performance. Thus, approaches that are more systematic should be incorporated in the future to clarify the dependency of calibration quality on the length of data used and the number of parameters calibrated at the same time in the calibration.
Table A.6. Comparison of the calibrated and observed total runoff for the entire simulation period using the different schemes

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Period</th>
<th>Runoff (mm)</th>
<th>Error (mm)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>Simulated</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Total</td>
<td>2203.9</td>
<td>2608.5</td>
</tr>
<tr>
<td></td>
<td>Calibration</td>
<td>613.4</td>
<td>613.4</td>
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<tr>
<td></td>
<td>Validation 1</td>
<td>770.6</td>
<td>779.9</td>
<td>9.3</td>
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<td></td>
<td>Validation 2</td>
<td>819.8</td>
<td>1215.2</td>
<td>395.3</td>
</tr>
<tr>
<td>Case1</td>
<td></td>
<td>The same as</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>2918.9</td>
<td>715.0</td>
<td>32.4</td>
</tr>
<tr>
<td></td>
<td>Calibration</td>
<td>613.4</td>
<td>0.0</td>
<td>0.0</td>
</tr>
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<td>166.1</td>
<td>21.6</td>
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<td>Validation 2</td>
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<td>548.9</td>
<td>67.0</td>
</tr>
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<td>Case2</td>
<td></td>
<td>The same as</td>
<td></td>
<td></td>
</tr>
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<td>Total</td>
<td>2622.6</td>
<td>418.8</td>
<td>19.0</td>
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<td>Calibration</td>
<td>613.4</td>
<td>0.0</td>
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<td>68.0</td>
<td>8.8</td>
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<td>Validation 2</td>
<td>1170.7</td>
<td>350.8</td>
<td>42.8</td>
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<td>The same as</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
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<td>796.5</td>
<td>36.1</td>
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<td>1332.4</td>
<td>512.6</td>
<td>62.5</td>
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<tr>
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<td></td>
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<td>Total</td>
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<td>683.1</td>
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<td>19.4</td>
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<td>44.4</td>
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<td>447.7</td>
<td>58.1</td>
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<td>Validation 2</td>
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<td>529.8</td>
<td>64.6</td>
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<td>Case6</td>
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<td>The same as</td>
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<td></td>
</tr>
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</table>
Table A.7. Performance measures for the calibrated daily runoff using the different scheme

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Period</th>
<th>RMSE (mm, A)</th>
<th>Obs. Mean (mm, B)</th>
<th>NRMSE (A) / (B)</th>
<th>Nash-Sutcliffe</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>Total</td>
<td>2.98</td>
<td>0.98</td>
<td>3.03</td>
<td>0.25</td>
<td>0.71</td>
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<tr>
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<td>1.68</td>
<td>1.33</td>
<td>0.87</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>Validation 1</td>
<td>1.56</td>
<td>0.72</td>
<td>2.16</td>
<td>0.15</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>Validation 2</td>
<td>4.17</td>
<td>0.96</td>
<td>4.33</td>
<td>-0.86</td>
<td>0.69</td>
</tr>
<tr>
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<td>Total</td>
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<td>3.44</td>
<td>-0.03</td>
<td>0.69</td>
<td></td>
</tr>
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<td>0.88</td>
<td>0.90</td>
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<td>2.80</td>
<td>-0.43</td>
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<td></td>
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<td>Validation 2</td>
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<td>-1.36</td>
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<td>2.24</td>
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<td>0.63</td>
<td></td>
</tr>
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<td>1.81</td>
<td>0.76</td>
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</tr>
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<td>Validation 1</td>
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<td>0.24</td>
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<td>0.37</td>
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<td>The same as the above</td>
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<td>0.52</td>
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<td>1.79</td>
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<td>3.51</td>
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</tr>
<tr>
<td></td>
<td>Validation 2</td>
<td>3.81</td>
<td></td>
<td>3.96</td>
<td>-0.55</td>
<td>0.59</td>
</tr>
<tr>
<td>Case 5</td>
<td>Total</td>
<td>3.52</td>
<td>3.58</td>
<td>-0.05</td>
<td>0.68</td>
<td></td>
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<td>Calibration</td>
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<td>0.84</td>
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</tr>
<tr>
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<td>Validation 1</td>
<td>2.34</td>
<td>3.23</td>
<td>-0.90</td>
<td>0.59</td>
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</tr>
<tr>
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<td>-1.39</td>
<td>0.73</td>
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</tr>
<tr>
<td>Case 6</td>
<td>Total</td>
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<td>2.69</td>
<td>0.41</td>
<td>0.58</td>
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<tr>
<td></td>
<td>Calibration</td>
<td>3.65</td>
<td>2.17</td>
<td>0.66</td>
<td>0.69</td>
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</tr>
<tr>
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<td>Validation 1</td>
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<td>2.91</td>
<td>-0.54</td>
<td>0.63</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Validation 2</td>
<td>2.65</td>
<td>2.75</td>
<td>0.25</td>
<td>0.72</td>
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</tr>
</tbody>
</table>
Table A.8. Performance measures for the calibrated monthly runoff using the different scheme

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Period</th>
<th>RMSE (mm, A)</th>
<th>Obs. Mean (mm, B)</th>
<th>NRMSE (A) / (B)</th>
<th>Nash-Sutcliffe R²</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>22.4</td>
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<td>0.75</td>
<td>0.60</td>
<td>0.83</td>
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<td>Calibration</td>
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<td>51.1</td>
<td>0.17</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>Validation 1</td>
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<td>0.51</td>
<td>0.65</td>
<td>0.68</td>
</tr>
<tr>
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<td>1.13</td>
<td>0.00</td>
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<tr>
<td></td>
<td>Total</td>
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<td>0.91</td>
<td>0.41</td>
<td>0.77</td>
</tr>
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<td>Case 2</td>
<td>Calibration</td>
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<td>0.17</td>
<td>0.98</td>
<td>0.98</td>
</tr>
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<td>Validation 1</td>
<td>16.9</td>
<td></td>
<td>0.77</td>
<td>0.20</td>
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<td>Validation 2</td>
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<td></td>
<td>Total</td>
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<td>0.66</td>
<td>0.69</td>
<td>0.85</td>
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<td>0.95</td>
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<td>0.92</td>
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<td>0.96</td>
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<td>1.04</td>
<td>-0.46</td>
<td>0.53</td>
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<td>0.87</td>
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Appendix B. Recursive Calibration Scheme and its Validation

The model performance in predicting runoff was investigated at every iteration step and presented in Tables B.1 to B.3. As the iteration proceeded, the performance got better overall. However, the more iteration steps did not always produce better calibration results and model performance in the validation period. RMSE was minimized and the Nash-Sutcliffe efficiency coefficient was maximized at the fourth iteration step in the calibration for daily and monthly runoff simulation. On the other hand, the performance measures were deteriorated at the fifth iteration step. At every iteration steps, the worst performance was found in the second validation period consistently.

### Table B.1. Comparison of the calibrated and observed total runoff for the entire simulation period at every iteration step.

<table>
<thead>
<tr>
<th>Iteration Step</th>
<th>Period</th>
<th>Runoff (mm)</th>
<th>Error (mm)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Observed</td>
<td>Simulated</td>
<td></td>
</tr>
<tr>
<td>Iteration 1</td>
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<td>2203.9</td>
<td>2782.3</td>
<td>578.4</td>
</tr>
<tr>
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<td>Calibration</td>
<td>613.4</td>
<td>613.4</td>
<td>0.0</td>
</tr>
<tr>
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<td></td>
<td>Validation 2</td>
<td>819.8</td>
<td>1328.8</td>
<td>509.0</td>
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<td>Validation 2</td>
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<td>525.9</td>
<td>64.2</td>
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Table B.2. Performance measures for the calibrated daily runoff at every iteration step

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<th>Obs. Mean (mm, B)</th>
<th>NRMSE (A) / (B)</th>
<th>Nash-Sutcliffe R²</th>
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Table B.3. Performance measures for the calibrated monthly runoff at every iteration step

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<th>Obs. Mean (mm, B)</th>
<th>NRMSE (A) / (B)</th>
<th>Nash-Sutcliffe R²</th>
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Appendix C. Comparison of the Simulated and Observed Runoff Hydrographs

Figure C.1. 1990/01/29 (the warming up period)

Figure C.2. 1990/04/02 (the first validation period)
Figure C.3. 1990/05/09 (the first validation period)

Figure C.4. 1990/05/28 (the first validation period)
Figure C.5. 1990/07/13 (the first validation period)

Figure C.6. 1991/01/11 (the first validation period)
Figure C.7. 1991/01/16 (the first validation period)

Figure C.8. 1991/06/18 (the first validation period)
Figure C.9. 1991/08/09 (the first validation period)

Figure C.10. 1991/09/04 (the first validation period)
Figure C.11. 1991/09/17 (the first validation period)

Figure C.12. 1991/12/02 (the first validation period)
Figure C.13. 1991/12/09 (the first validation period)

Figure C.14. 1992/02/25 (the first validation period)
Figure C.15. 1992/04/21 (the first validation period)

Figure C.16. 1992/06/30 (the first validation period)
Figure C.17. 1992/07/27 (the first validation period)

Figure C.18. 1992/07/31 (the first validation period)
Figure C.19. 1992/11/12 (the calibration period)

Figure C.20. 1992/11/22 (the calibration period)
Figure C.21. 1992/12/10 (the calibration period)

Figure C.22. 1993/01/05 (the calibration period)
Figure C.23. 1993/03/03 (the calibration period)

Figure C.24. 1993/03/17 (the calibration period)
Figure C.25. 1993/03/27 (the calibration period)

Figure C.26. 1993/04/09 (the calibration period)
Figure C.27. 1993/04/16 (the calibration period)

Figure C.28. 1993/05/04 (the calibration period)
Figure C.29. 1993/11/27 (the second validation period)

Figure C.30. 1993/12/04 (the second validation period)
Figure C.31. 1994/01/27 (the second validation period)

Figure C.32. 1994/02/23 (the second validation period)
Figure C.33. 1994/03/01 (the second validation period)

Figure C.34. 1994/03/07 (the second validation period)
Figure C.35. 1994/03/27 (the second validation period)

Figure C.36. 1994/07/26 (the second validation period)
Figure C.37. 1994/07/27 (the second validation period)

Figure C.38. 1994/08/16 (the second validation period)
Figure C.39. 1994/09/26 (the second validation period)

Figure C.40. 1995/01/15 (the second validation period)
Figure C.41. 1995/01/20 (the second validation period)

Figure C.42. 1995/03/08 (the second validation period)
Figure C.43. 1995/10/20 (the second validation period)