Development of Guidelines for TMDLs with Nonpoint Source Components Using SWAT

FINAL REPORT

NONPOINT SOURCE PROJECT FY1999 319(h) TASK 900

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INTRODUCTION

The State of Oklahoma is required to develop TMDLs for waters listed in Category 5 (303(d) list) of its Integrated Report. The Category 5 of the 2002 integrated report includes 436 water body segments listed as threatened or impaired and in need of TMDLs. Developing appropriate load allocations in waters that are impaired solely or primarily by nonpoint sources is essential if state water quality standards are to be met. To accurately and efficiently quantify current and future pollutant loads from watershed with significant nonpoint sources, observed water quality data in combination with hydrologic/water quality (H/WQ) models must be utilized. USEPA has developed protocols for developing TMDLs for nutrients and sediments (US EPA 1999a, 1999b). However, to date a detailed protocol designed specifically for applying comprehensive HWQ models has not been developed.

In this report we present a guidance manual for using a comprehensive hydrologic/water quality model, SWAT (Soil and Water Assessment Tool) (Arnold et al., 1998; Srinivasan et al., 1998), to estimate background and anthropogenic nonpoint source pollutant loads that can be used in the TMDL process for watersheds containing significant nonpoint sources of pollution. These guidelines focus on runoff volume, and nutrient (nitrogen and phosphorus) and sediment loading to streams, rivers and lakes in Oklahoma.

SWAT is a distributed hydrologic model. Distributed hydrologic models allow a basin to be broken into many smaller subbasins to incorporate spatial detail. Water yield and loading are calculated for each subbasin, and then routed through a stream network to the basin outlet. SWAT goes a step further with the concept of Hydraulic Response Units (HRUs). A single subbasin can be further divided into areas with the same soils and land use. Areas inside a subbasin with the same soil and land use combination are defined as HRUs. Processes within a HRU are calculated independently, and the total yield for a subbasin is the sum of all the HRUs it contains. HRUs allow more spatial detail to be included by allowing more land use and soil classifications to be represented. SWAT is a physically based continuous simulation model that operates on a daily time step. Long-term simulations can be performed using simulated or observed weather data. Relative impacts of different management scenarios can be quantified. Management is set as a series of individual operations (e.g. planting, tillage, harvesting, or fertilization).

SWAT is the combination of ROTO (Routing Outputs to Outlets) (Arnold et al., 1995) and SWRRB (Simulator for Water Resources in Rural Basins) (Williams et al., 1985; Arnold et al., 1990). SWAT was created to overcome maximum area limitations of SWRRB. SWRRB can only be used on watersheds a few hundred square kilometers in area and has a limitation of 10 subbasins. SWAT can be used for much larger areas. The HUMAS (Hydrologic Unit Model for the United States), (Srinivasan et al., 1997) project used SWAT to model 350 USGS 6-digit watersheds in the 18 major river basins in the US. Several models contributed to SWRRB and SWAT. CREAMS (Chemicals, Runoff, and Erosion from Agricultural Management Systems) (Knisel, 1980) , GLEAMS (Groundwater Loading Effects on Agricultural Management Systems) (Leonard et al.,1987), and EPIC (Erosion-Productivity and Impact Calculator) (Williams et al., 1984) all contributed to the development of SWRRB and SWAT. An extensive list of peer review articles related to the SWAT model is given in Appendix A.

HYDROLOGIC/WATER QUALITY MODEL APPLICATION PROTOCOL

Introduction

Planning for modeling projects is just as important as planning traditional environmental measurements for data collection projects. To use model predictions for anything from regulatory purposes, research, to design, the modeling effort should be scientifically sound, robust, and defensible. To ensure this and to lead to confidence in results, the US EPA (2002) recommends a planning process that incorporates the following elements:

- a systematic planning process including identification of assessments and related performance criteria;
- peer reviewed theory and equations;
- carefully designed life-cycle development processes that minimize errors;
- documentation of changes from the original plan;
- clear documentation of assumptions, theory, and parameterization that is detailed enough so others can fully understand the model predictions;
- input data and parameters that are accurate and appropriate for the application;
- model prediction data that can be used to help inform decision making.

A Quality Assurance Project Plan and good project management in modeling projects are closely linked. A good Quality Assurance Project Plan documents all criteria and assumptions in one place for easy review and reference. The plan can be used to guide project personnel through the model development or application process and helps ensure that choices are consistent with project objectives and requirements. However, it should be noted that many assumptions and decisions can not be made until the modeling effort is underway. A well prepared plan can be helpful in providing guidance. Assumptions and decisions made during the modeling process should be documented.

Quality assurance in hydrologic modeling is the procedural and operational framework put in place by the organization managing the modeling study to ensure adequate execution of all project tasks, and to ensure that all modeling-based analyses are verifiable and defensible (Taylor, 1985). The two major elements of quality assurance are quality control and quality assessment. Quality control addresses the procedures that ensure the quality of the final product. The procedures include use of appropriate methodology in developing and applying computer models, suitable verification, calibration, and validation procedures, and proper use of the methods and model. Quality assessment is applied to monitor the quality control procedures (van der Heijde, 1987).

Use of a modeling protocol provide several potential benefits to projects that include a significant modeling component. These include:

- Reduces potential modeler bias
- Provides a roadmap to be followed
- Allows others to assess decisions made in modeling the system of interest
- Allows others to repeat the study
- Improves acceptance of model results

A modeling protocol, preferably written, should be established prior to conducting a modeling study. To date, most hydrologic/water quality modeling projects and studies have not utilized formal modeling protocols, rather ad hoc approaches are typically employed. The goal of this paper is to define the contents of a modeling protocol or a modeling quality assurance plan that can be used to help hydrologic/water quality modelers establish such protocols for their modeling projects.

Literature Review

In following the scientific method, steps should be taken to minimize the potential influence of scientists' bias. The use of a modeling protocol or a quality assurance plan in modeling projects can provide the documentation needed to assess the project and can be helpful in reducing potential bias. By definition, the scientific method is impartial and the results from the application the scientific method must be reproducible. Therefore, the modeling protocol and associated documentation must provide enough detail to allow the modeling project to be repeated. It should be noted that models are not hypothesis, but are simply tools that are used to evaluate a hypothesis. As applied to hydrologic modeling, the steps in the scientific method may be given as:

1. Based on existing theory and data, develop a hypothesis that is consistent with the current understanding of the system being modeled
2. Based on the hypothesis, make predictions by applying an appropriate hydrologic model
3. Test the hypothesis by comparing model predictions with observed data
4. Accept or reject the hypothesis based on an appropriate criteria
5. If needed, modify the hypothesis and repeat steps 2-5

Refsgaard (1997) defined a modeling protocol as depicted in Figure 1. Refsgaard makes a distinction between a model and a model code; a model is any hydrologic model established for a particular watershed. Others might refer to Refsgaard's definition of a model as a model "setup" or a "parameterized" model. Refsgaard (1997) defined a model code as a generalized software package, which without changes, can be used to establish a model with the same basic types of equations (but allowing different parameter values) for different watersheds. Refsgaard (1997) defined model validation as the process of demonstrating that a given site-specific model is capable of making "sufficiently accurate" predictions, where "sufficiently accurate" will vary by application and project needs. A model is considered validated if its accuracy and predictive capability in the validation period have been proven to lie within acceptable limits. Again, acceptable limits will vary by application and project requirements. Interestingly, Refsgaard (1997) does not include a model sensitivity analysis in his steps. Sensitivity analyses, discussed in more detail later in the paper, can be helpful for a variety of purposes in modeling projects.

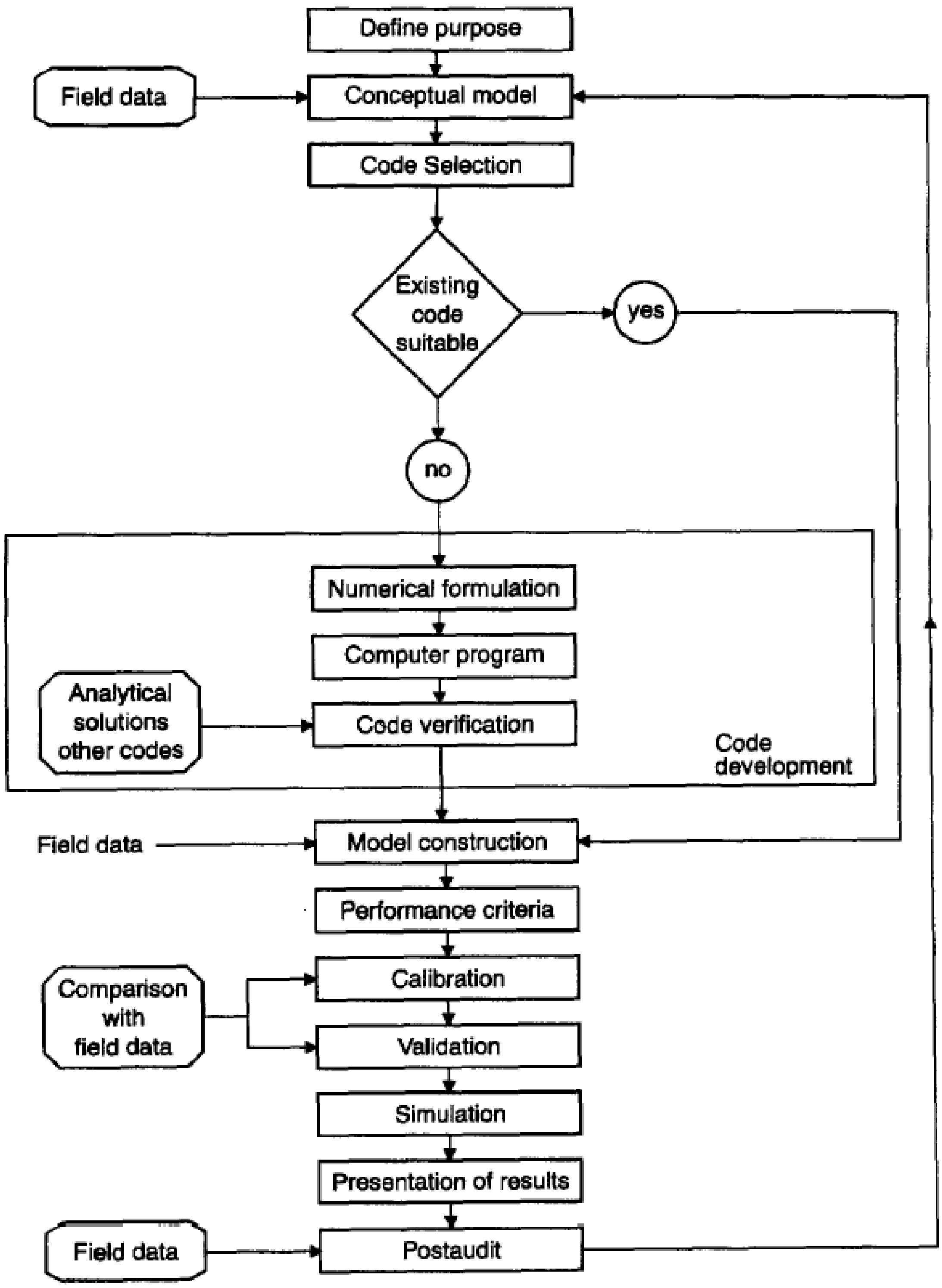


Figure 1. A hydrological model protocol as proposed by Refsgaard (1997).

Developing efficient and reliable hydrologic/water quality models and applying them requires numerous steps, each of which should be taken conscientiously and reviewed carefully. Taking a systematic, well-defined and controlled approach to all steps of the model development and application process is essential for successful implementation of the model. Quality Assurance provides the mechanisms and framework to ensure that decisions made during this process are based on the best available data and analyses.

EPA Quality Assurance

The US Environmental Protection Agency (EPA) uses the Quality Assurance Project Plan to help project managers and planners document the type and quality of data and information needed for making environmental decisions. The US EPA (2002) has developed a document, *Guidance for Quality Assurance Project Plans for Modeling (EPA QA/G-5M),* to provide recommendations on how to develop a Quality Assurance Project Plan for projects involving modeling (e.g., model development, model application, as well as large projects with a modeling component). A "model" is defined by US EPA as something that creates a prediction. The guidance regarding modeling is based on recommendations and policies from US EPA Quality Assurance Project Plan protocols, but is written specifically for modeling projects, which have different quality assurance concerns than traditional environmental monitoring data collection projects. The structure for the Quality Assurance Project Plan for modeling is consistent with the US *EPA Requirements for Quality Assurance Project Plans (QA/R-5)* (US EPA, 2001) and US *EPA Guidance for Quality Assurance Project Plans (QA/G-5)* (US EPA, 1998), though for modeling not all elements are included because not all are relevant.

The US EPA Quality System defined in US EPA Order 5360.1 A2 (US EPA, 2000), *Policy and Program Requirements for the Mandatory Agency-wide Quality System*, includes environmental data produced from models. Environmental data includes any measurements or information that describes environmental processes, location, or conditions, ecological or health effects and consequences, or the performance of environmental technology. As defined by US EPA, environmental data includes information collected directly from measurements, produced from models, or compiled from other sources such as databases or literature. The US EPA Quality System is based on the American National Standard ANSI/ASQC E4-1994.

Graded Approach to QA Project Plans

US EPA defines the graded approach as "the process of basing the level of application of managerial controls applied to an item or work according to the intended use of the results and degree of confidence needed in the quality of the results" (US EPA, 1998). This allows the application of quality assurance and quality control activities to be adapted to meet project specific needs. Models that provide an initial "ballpark" estimate or non-regulatory priorities, for example, would likely not require the same level of quality assurance and planning as would models that will be used to set regulatory requirements. However, US EPA provides no explicit categorizations or other specific guidelines for applying the graded approach (US EPA, 2002).

In applying the graded approach, US EPA suggests two aspects that are important for defining the level of quality assurance that a modeling project needs: (1) intended use of the model and (2) the project scope and magnitude (US EPA, 2002). The intended use of the model is a determining factor because it is an indication of the potential consequences or impacts that might occur due to quality control problems. For example, higher standards might be set for projects that involve potentially large consequences, such as Congressional testimony, development of new laws and regulations, the development of a TMDL, or the support of litigation. More modest levels of defensibility and rigor would often be acceptable for data used for technology assessment or "proof of principle," where no litigation or regulatory action are expected, such as cost-share water quality programs that require targeting critical source areas to focus Best Management Practices implementation efforts. Still lower levels of defensibility would likely apply to basic exploratory research requiring extremely fast turn-around, or high flexibility and adaptability. In such cases, the work may have to be replicated under more stringent controls or the results carefully reviewed prior to publication. The US EPA (2002) suggests peer review may be substituted, to some extent, for the level of quality assurance. By analyzing the end-use needs, appropriate quality assurance criteria can be established to guide the program or project. The examples presented are for illustration only, and the degree of rigor needed for any particular project should be determined based on an evaluation of the project needs and resources.

Other aspects of the quality assurance effort can be established by considering the scope and magnitude of the project. The scope of the model development and application determines the complexity of the project; more complex models or modeling projects likely need more quality assurance effort. The magnitude of the project defines the resources at risk if quality problems lead to rework and delays.

The QA Project Plan Elements for a Model Application Project

The US EPA (2002) defined the nine following model application tasks and mapped them into Quality Assurance Project Plan elements.

1. Needs assessment
2. Purpose, objectives, and output specifications
3. Define quality objectives, desired performance criteria, and documentation needs for model output
4. Select the most appropriate model
5. Data development, model parameterization, and model calibration
6. Determine whether data, models, and parameters for the application meet desired performance criteria
7. Run the computer code
8. Model output testing and peer review
9. Summarize results and document

Further details on how these modeling tasks fit within a potential modeling quality assurance plan are described in detail in *Guidance for Quality Assurance Project Plans for Modeling* (US EPA, 2002).

Model Application Protocol Steps

A hydrologic/water quality model application protocol is proposed based on the authors' experiences and review of the literature including the US EPA (2002) *Guidance for Quality Assurance Project Plans for Modeling* document. The authors recognize that a "graded" approach in implementing a modeling protocol will be required, and thus not all modeling quality assurance plans will include all sections or issues suggested. The US EPA (2002) suggests a graded approach can be used to define the level of quality assurance effort that a modeling project needs based on the intended use of the model and the project scope and magnitude (Table 1).

Table 1. Examples of Modeling Projects with Differing Intended Uses (adapted from US EPA, 2002)

Purpose for Obtaining Model-Generated Information (Intended Use)	Typical Quality Assurance Issues	Level of QA
• Regulatory compliance • Litigation • Congressional testimony	• Legal defensibility of data sources • Compliance with laws and regulatory mandates applicable to data gathering	
∫		
• Regulatory development • State Implementation Plan (SIP) attainment • Verification of Model	• Compliance with regulatory guidelines • Existing data obtained under suitable QA program • Audits and data reviews	
∫		
• Trends monitoring (non-regulatory) • Technology development • "Proof of principle"	• Use of accepted data-gathering methods • Use of widely accepted models • Audits and data reviews	
∫		
• Basic research • Bench-scale testing	• QA planning and documentation at the facility level • Peer review of novel theories and methodology	

The following items or sections should be included in a hydrologic/water quality modeling protocol:

1. Problem definition/background
2. Model application goals, objectives and hypothesis
3. Model selection
4. Model sensitivity analysis
5. Available data
6. Data to be collected
7. Model representation issues – data, BMPs, etc

8. Model calibration
9. Model validation
10. Model scenario prediction
11. Model output uncertainty analysis
12. Results interpretation/hypothesis testing

The proposed modeling protocol steps may be iterative. For example, the scientific literature and a preliminary sensitivity analysis using general data may initially be used to identify the model parameters that are the most sensitive. A more comprehensive sensitivity analysis assessment may be performed later once more detailed location specific data have been collected or obtained.

Decisions made throughout the modeling effort and the rationale for these decisions should be documented. In most instances, it will be necessary to make various assumptions and decisions throughout the modeling project. Many of these assumptions are best made during the modeling project rather than before the modeling starts, since information from prior steps may impact decisions. The amount of documentation that should be created depends on the project goals and the consequences of decisions that will be made as a result of the project findings. Each of the modeling protocol steps is discussed in more detail in the sections that follow.

Problem Definition/Background

Background information and preliminary data for the study area should be obtained to help initially define the overall problem that will be addressed by the study. The background information and data collected in this step will be useful to determine whether modeling will be necessary, assist in defining the modeling objectives (if modeling is required) and to select the model or models to be used. More detailed objectives or hypotheses to be examined within the project are defined in the subsequent step. This initial step is similar to the initial observation phase commonly employed within the scientific method.

Questions that may be addressed when defining the problem include:

- What is the specific problem?
- What are the overall goals and objectives of this project that will address this problem?
- Why should a modeling approach be used to address the problem?

It is also important to place the problem in context to provide a sense of the project's purpose relative to other project and program phases and initiatives. Questions that might be addressed include:

1. What information, previous work, or previous data may currently exist that this project can use?
2. Given that the problem is best solved by a modeling approach, what models currently exist (if any) that can be used to achieve this project's goals and objectives?

3. What are the advantages and disadvantages for these models?

The presentation of background information may also include a discussion of initial ideas or potential approaches for model application.

Model application goals, objectives and hypothesis

The specific objectives and/or hypotheses to be accomplished or tested by the modeling effort are defined based on the background information and data collected in the first step. The objectives or hypotheses should be stated in a manner that they can be tested or evaluated using the model predictions.

In setting the objectives or hypotheses to be tested, one should keep in mind that models are more accurate when making relative comparisons rather than making absolute predictions. Thus, an objective or hypothesis might be written to compare expected pollutant losses for different tillage systems rather than examining whether a particular tillage system results in pollutant losses below a given magnitude. Calibration of models can help improve absolute predictions, but data for calibration to represent the range of conditions of interest for the location of interest are not always available.

A summary of the work to be performed and the "products" to be created by the model application effort should be identified. These will be described in more detail in subsequent sections.

Model selection

An appropriate model should be selected based on the project goals, objectives or hypotheses, how model results will be used; the characteristics of the hydrologic/water quality system that are important to the problem, and various other factors including:

- Appropriate level of detail (space and time)
- Important processes
- Data requirements and availability
- Calibration requirements
- Previous model applications and acceptance in the scientific and regulatory communities
- Ease of use
- Sensitivity to processes of interest
- Available resources and time

Model sensitivity analysis

A model sensitivity analysis can be helpful in understanding which model inputs are most important or sensitive and to understand potential limitations of the model. Additional care should be taken when estimating model parameters that are the most sensitive. Data collection efforts that support the modeling study may focus on obtaining better data for the most sensitive parameters.

The sensitivity analysis can also identify potential limitations of the model. If a model is not sensitive to parameters that are to be varied in testing the project objectives or hypotheses, a different model may need to be selected. Models are abstractions of the systems they simulate and therefore typically represent system components with varying levels of detail. For example, the scientific literature may indicate that differences in tillage practices influence pesticide losses in surface runoff. In such a case, the use of a model that is not sensitive to tillage to examine the impact of switching from conventional tillage to conservation tillage on pesticide losses in surface runoff is likely inappropriate.

The literature and model documentation are often excellent sources of information on model sensitivity. For example, Muttiah and Wurbs (2002) identified the sensitivity of SWAT to various parameters. However, it may be necessary to conduct a sensitivity analysis for the study watershed if its conditions are significantly different than those for model sensitivity analyses reported in the literature, since model sensitivity may be somewhat specific to the model setup. Thus, limited data for parameterizing the model may need to be collected prior to conducting a sensitivity analysis. Generally, the sensitivity analysis should be completed using an uncalibrated model setup, since the sensitive parameters and those with the greatest uncertainty are typically used for model calibration. For example, Spruill et al. (2000) conducted a SWAT sensitivity analysis to evaluate parameters that were thought to influence stream discharge predictions. Then during calibration, minimization of the average absolute deviation between observed and simulated stream flows was used to identify optimum values or ranges for each parameter.

Available Data

The goal of this step is to select the most appropriate data for the modeling effort. Data available for the modeling effort will likely come from numerous sources. An assessment of available data, its quality, and the time period it covers should be made. The amount of data available for a watershed can vary greatly, as can the quality of the data. For example, flow and water quality data may be available for 1983 through 1988 while land use data might have been developed for conditions in 1995. This may result in a misrepresentation of the land uses that were present during the observed water quality data period, especially for areas experiencing rapid urbanization. In other instances, differences in data collected at different dates may be negligible. For example, soil property data used in modeling runoff from a watershed would not typically change significantly over time, even over periods of tens of years. In instances where data, such as land use, may have changed significantly, it may be necessary to estimate data for the period of interest by interpolating between data sets for different time periods or by adjusting the data from the available time period using other sources of data and information.

The US EPA (2002) indicates that a Quality Assurance Project Plan for modeling should address the following issues regarding information on how non-direct measurements (data and other information that have been previously collected or generated under some effort outside the specific project being addressed by the Quality Assurance Project Plan) are acquired and used in the project:

- the need and intended use of each type of data or information to be acquired;
- how the data will be identified or acquired, and expected sources of these data;

- the method of determining the underlying quality of the data; and
- the criteria established for determining whether the level of quality for a given set of data is acceptable for use in the project.

Water quality and runoff data for the study watershed may be available from federal, state or local government agencies. For example, the USGS is often an excellent source of stream flow data and the EPA STORET database may provide useful water quality data. Data sets may also be available from past studies. Such data sets may be documented in project reports. In many instances, these data will not be identified by simply conducting a literature search, rather contacts with local universities, state and local agencies, and local watershed groups will likely be necessary.

Well documented and widely used datasets, such as soil properties from the USDA NRCS, often have well understood properties and uncertainty. It is useful to understand this uncertainty and the assumptions in the data and how these will likely impact the model results. Spatial or geographic information systems (GIS) data may be available from federal, state and local government agencies. Increasingly, county and local governments are developing detailed spatial data sets. For example, many county governments with urban areas have developed detailed elevation data sets that provide more detail than state and national elevation datasets. Spatial data from these sources should have metadata available that describe the accuracy and other properties of the data that will be helpful in understanding data quality and limitations.

Remotely sensed datasets from satellites and aerial photography can potentially provide land use and other data needed in hydrologic/water quality modeling studies. In addition, archived satellite data and aerial photography may be useful in creating land use information for the past. Remotely sensed datasets will require interpretation to create the land use or other data that are needed. Accuracy assessments of the interpreted results should be performed to provide information regarding the quality of the land use products created.

The scientific literature may contain some information about the study area. Project reports, however, are more likely to contain the detailed data typically required for a model application project. Scientific papers may also provide insight into transformation of various data into the data required by the model. In most cases, these data must be transformed into values and formats required by the model.

After identifying the data available and its various properties, including quality and temporal aspects, an assessment of the suitability of the data for use in the model that has been selected must be made. The model data requirements and the sensitivity of the model to various parameters should be considered when evaluating and selecting the data to use. The rationale for the data selected for use in the model should be well documented, as should any required data transformation.

The scientific literature contains numerous studies on the impacts that various data sources and data errors can have on model results. Chaubey et al. (1999) explored the assumption of spatial homogeneity of rainfall when parameterizing models and concluded large uncertainty in estimated model parameters can be expected if detailed variations in the input rainfall are not considered. Nandakumar and Mein (1997) examined the levels of uncertainty in rainfall-runoff model predictions due to errors in hydrological and climatic data, and considered the implications for prediction of the hydrologic effect of land-use changes. Studies such as this highlight the importance of understanding the consequences of the data used in the project on the model results and their interpretation.

Additional data to be collected

The project objectives and hypotheses, available data and model sensitivity should be considered in deciding what, if any, additional data should be collected. After assessing these issues, the modeler may conclude that additional data should be collected. Following calibration or validation, the modeler may also decide that additional data should be collected in an attempt to improve model performance. The collection of additional data can be expensive as well as require a significant amount of time. An appropriate quality assurance plan for the collection of additional data should be prepared and followed (US EPA, 1998).

Model representation issues – data, BMPs, etc

Models are abstractions of the systems they are simulating. Therefore, the modeler will be required to make decisions on how to represent the various components of the system being modeled. This may include decisions on representation of components within the model and in the transformation of available data into the formats needed by the model. These decisions should be documented. The expected effect of these assumptions on the results, relative to alternative assumptions that could have been made should also be documented.

One of the data representation issues typically faced is related to pollutant sources. It is typically impossible to include all pollutant sources in the modeling effort. For example, if the amount of phosphorus leaving a watershed is of interest, the modeler may decide not to include phosphorus losses from septic systems, if they are small relative to other sources. Criteria should be established to determine which pollutant sources to include in the model and/or overall analysis. A simple mass balance for water and pollutants of interest may be helpful to identify the most important components of the hydrologic cycle and system to model and the most important sources of pollutants to consider. Another option is to use the selected model to perform a simple preliminary model simulation using limited data. Based on such a model, criteria to exclude pollutant sources that represent less than 1% (or other levels deemed appropriate) of the pollutant might be established. It should be noted, however, that pollutant sources less than this threshold may be included if these data are readily available and easy to incorporate into the model. When potential pollutant sources are not incorporated into the model, care in the interpretation of the final model results is required.

An understanding of the model sensitivity to various parameters and model representations can be useful in making decisions regarding representation issues within the model and in understanding how uncertainty in data will affect the model results.

The representation of BMPs within the model may not be well defined. Model documentation and the scientific literature can often provide guidance in BMP representation (Bracmort et al., 2003). However, in most instances, these sources do not fully describe how a specific BMP, such as a grassed waterway, should be represented within a particular model; rather the modeler must exercise judgment in the BMP representation decision. Therefore, the modeler will need to determine how BMPs will be represented in the application of a model to a given location.

The accuracy of hydrology/water quality models also depends in part on how well model input parameters describe the relevant characteristics of the watershed. Data that are obtained for a watershed will typically require some transformation and interpretation to create the inputs required by the model. For example, soil properties in the SSURGO database are often reported with a range of values, while the model will require a single value for each soil property. The model documentation and scientific literature can often provide guidance in transforming commonly available data into the inputs required by the model. These data used and the decisions made in data transformations should be documented.

Input parameter aggregation may have a substantial impact on model output. For example, Fitzhugh and MacKay (2000) used SWAT to determine how the size or number of subwatersheds used to partition the watershed affect model output, and the processes responsible for model behavior. Mankin et al. (2002) explored the errors introduced when translating GIS data into model–input data. Watershed modelers using GIS data should be aware of the issues related to appropriate grid cell sizes, generation of land–management practice GIS coverages, accuracy of GIS data, and accuracy of interface algorithms.

Refsgaard and Storm (1996) indicated that a rigorous model parameterization procedure is crucial to avoid methodological problems in subsequent phases of model calibration and validation. They suggest the following points are important to consider in model parameterization:

1. Parameter classes (soil types, vegetation types, etc) should be selected so it is easy in an objective way to associate parameter values. Thus, when possible parameter values in the classes should be determined based on available field data.
2. Determine which parameters can be assessed from field data or the literature and which will require calibration. For parameters subject to calibration, the physically acceptable intervals for the parameter values should be estimated and documented.
3. The number of calibration parameters should be minimized both from practical and methodological points of view. Fixing a pattern for a spatially varying parameter but allowing its value to be modified uniformly throughout the watershed can help minimize the number of calibrated parameters.

Model Calibration

The US EPA (2002) indicates that if no nationally recognized calibration standards exist, the basis for the calibration should be documented. Quality Assurance Project Plan guidance indicates that calibration for data collection efforts address calibration of the analytical instruments that will be utilized to generate analytical data. In modeling projects by analogy, the “instrument” is the predictive tool (the model) that is to be applied (US EPA, 2002). All models, by definition, are a simplification of the processes they are intended to represent. When formulating the mathematical representations of these processes, there are relationships and parameters that need to be defined. Estimating parameters for these relationships is called *calibration*. Some model parameters may need to be estimated for every application of the model using site-specific data. Similar to an analytical instrument, models are calibrated by comparing the predictions (output) for a given set of assumed conditions to observed data for the same conditions. This comparison allows the modeler to evaluate whether the model and its parameters reasonably represent the environment of interest. Statistical methods typically applied when performing model calibrations include regression analyses and goodness-of-fit methods. An acceptable level of model performance should be defined prior to the initiation of model calibration. The details of the model calibration procedure, including statistical analyses that are involved, should be documented.

Calibration Procedures

Model calibration is often important in hydrologic modeling studies, since uncertainty in model predictions can be increased if models are not properly calibrated. Factors contributing to difficulties in model calibration include calibration data with limited metadata, data with measurement errors, and spatial variability of rainfall or watershed properties poorly represented by point measurements. Model calibration can be done manually or by a combination of manual and automatic procedures. Manual calibration can be subjective and time-consuming (Eckhardt and Arnold, 2001). Initial values can be assigned to parameters which are then optimized by an automatic procedure (Gan et al., 1997). Chanasyk et al. (2002) calibrated SWAT until the predicted and observed results were visibly close. Many studies use comparable ad hoc approaches in calibration. However, approaches that use only visual comparison should be avoided. One of the advantages of an automated approach to calibration is that it uses a systematic approach in adjusting the model parameters, thereby removing potential modeler bias. With an ad hoc calibration approach, the modeler could potentially adjust model parameters during calibration that would create a model setup or parameterization that would be more likely to provide desired results when testing the project objectives or hypotheses.

Santhi et al. (2001a) presented a flow chart with the decision criteria used during the calibration of SWAT. This flowchart has been adapted by Bracmort et al. (2003) and others for calibration of SWAT, and an adapted version is presented in Figure 2. In some instances, this approach is too rigid to be strictly followed due to interactions between model parameters, and thus the modeler may need to deviate from strictly following such an approach.

The approach that will be followed in calibrating the model should be identified prior to beginning calibration. Performance criteria should also be established prior to beginning model calibration so that the modeler knows when the model has been successfully calibrated. The scientific literature can often provide an idea of the likely performance of the model following calibration. Statistical measures can be used to identify performance criteria for determining whether the model has been calibrated successfully. For some efforts, an ad hoc calibration approach may be acceptable, while in other instances it will be desirable to have a specific calibration protocol..

For projects supporting regulatory decision making, the US EPA (2002) suggests the level of detail on model calibration in the Quality Assurance Project Plan should be sufficient to allow another modeler to duplicate the calibration method, if the modeler is given access to the model and to the data being used in the calibration process. For other projects (e.g., some basic research projects), it may be acceptable to provide less detail on this issue for the Quality Assurance Project Plan. In some instances, projects may use procedures that are somewhat different from standard calibration techniques, such as “benchmarking” procedures, and therefore the level of detail may differ from what is generally portrayed for calibration.

Examples of features that the model calibration portion of the Quality Assurance Project Plan may address include the following:

- objectives of model calibration activities, including acceptance criteria;
- details on the model calibration procedure;
- method of acquiring the input data;
- types of output generated during model calibration;
- method of assessing the goodness-of-fit of the model calibration equation to calibration data;
- method of quantifying variability and uncertainty in the model calibration results;
- corrective action to be taken if acceptance criteria are not met.

The calibration plan should identify the parameters that will be adjusted, the order in which they will be adjusted, and ranges in which the adjusted parameters must fall. The ranges of parameters used in calibration and the calibration results obtained should be documented during calibration.

Not all models must be calibrated prior to use of the model to test the project objectives or hypothesis. However, in most cases calibration of the model for the study watershed(s) conditions can reduce the uncertainty in model predictions. If models are not calibrated, they should still be validated for the study watershed if possible.

For hydrologic/water quality models, the hydrology components are usually calibrated first. In the calibration of the hydrology components of the model, it may be necessary to separate stream flow into direct or surface runoff and base flow. The model is typically calibrated first to obtain acceptable performance in the hydrology components, then for erosion, and finally for nutrients and pesticides.

<u>Calibration Data</u>
Data that will be used for calibration should be identified. One common method is to split observed data into a dataset for calibration and one for validation. A common practice is to split data sets equally or approximately equally into calibration and validation data sets. It is important that the calibration and validation data sets each have observed data of approximately the same magnitudes. For example, both calibration and validation data sets

should have periods with high and low flows when the hydrologic portion of the model is being calibrated.

Yapo et al. (1996) used varying lengths of calibration data and found that approximately eight years of data were needed to obtain calibrations that were insensitive to the calibration period selected for their watershed. Gan et al. (1997) indicate that ideally, calibration should use 3 to 5 years of data that include average, wet, and dry years so that the data encompass a sufficient range of hydrologic events to activate all the model components during calibration. However, the required amount of calibration data is project specific.

<u>Calibration Statistics</u>
The goodness-of-fit statistics to be used in describing the model's performance relative to the observed data should be selected prior to calibration and validation. The ASCE Task Committee (1993) recommended graphical and statistical methods useful for evaluating model performance. In most instances, both visual comparisons of predicted and observed data as well as goodness-of-fit statistics should be used. Plotting of predicted results and observed results along with the 1:1 line can be helpful in identifying model bias. The percent deviation of predicted values from observed values is one numerical goodness-of-fit criterion. A second basic goodness-of-fit criterion recommended by the ASCE Task Committee (1993) is the Nash–Sutcliffe coefficient or coefficient of simulation efficiency. Legates and McCabe (1999) evaluated various goodness-of-fit measures for hydrologic model validation and suggested that correlation and correlation-based measures (e.g., the coefficient of determination) are oversensitive to extreme values and are insensitive to additive and proportional differences between model estimates and observed values. Thus, correlation-based measures can indicate that a model is a good predictor, even when it is not. Legates and McCabe (1999) concluded that measures such as the Nash-Sutcliffe coefficient of efficiency and the index of agreement are better measures for hydrologic model assessment than correlation-based measures. Legates and McCabe (1999) suggested a modified Nash-Sutcliffe coefficient that is less sensitive to extreme values may be appropriate in some instances. They also suggested additional evaluation measures such as summary statistics and absolute error measures (observed and modeled means and standard deviations, MAE and RMSE) should be reported for model results.

There are no standards or a range of values for goodness-of-fit statistical parameters that will adjudge the model performance as acceptable (Loague and Green, 1991). Ramanarayanan et al. (1997) suggested values of goodness-of-fit statistics for determining the acceptable performance of the APEX model. They indicated that values close to zero for the correlation coefficient and/or the Nash-Sutcliffe coefficient indicated the model performance was unacceptable or poor. They judged the model performance as satisfactory if the correlation coefficient was greater than 0.5 and the Nash-Sutcliffe coefficient was greater than 0.4. Santhi et al. (2001a) assumed a Nash-Sutcliffe coefficient greater than 0.5 and a goodness of fit (R^2) greater than 0.6 indicated acceptable model performance when calibrating SWAT. However, acceptable statistical measures are project specific.

The literature can provide typical ranges of goodness-of-fit statistics for models. For example, Saleh et al. (2000) obtained Nash-Sutcliffe coefficients for average monthly flow, sediment, and nutrient loading at 11 locations with values ranging from 0.65 to 0.99, indicating reasonable SWAT predicted values. SWAT also adequately predicted monthly trends in average daily flow, sediment, and nutrient loading over the validation period with Nash-Sutcliffe coefficients ranging from 0.54 to 0.94, except for NO3-N which had a value of 0.27. Fernandez et al. (2002) developed a GIS–based, lumped parameter water quality model to estimate the spatial and temporal nitrogen–loading patterns for lower coastal plain watersheds in eastern North Carolina. Predicted nitrogen loads were highly correlated with observed loads (correlation coefficients of 0.99, 0.90, and 0.96 for nitrate–nitrogen, TKN, and total nitrogen, respectively). However, note the limitations of correlation coefficients as discussed previously. Spruill et al. (2000) evaluated SWAT and its parameter sensitivities for streamflow from a small central Kentucky watershed and concluded the model adequately predicted the trends in daily streamflow, although Nash-Sutcliffe coefficient values were –0.04 and 0.19 for validation and calibration, respectively. The Nash-Sutcliffe coefficients for monthly total flows were 0.58 for validation and 0.89 for calibration.

In some instances, model calibration may not yield results that are acceptable based on the predefined model performance criteria. If this occurs, the observed flow and pollutant data as well as the model input data should be examined for potential errors. The poor model performance may be an indication that more detailed model inputs are required. In other cases, this may be an indication that the model is unable to adequately represent the processes of interest for this watershed.

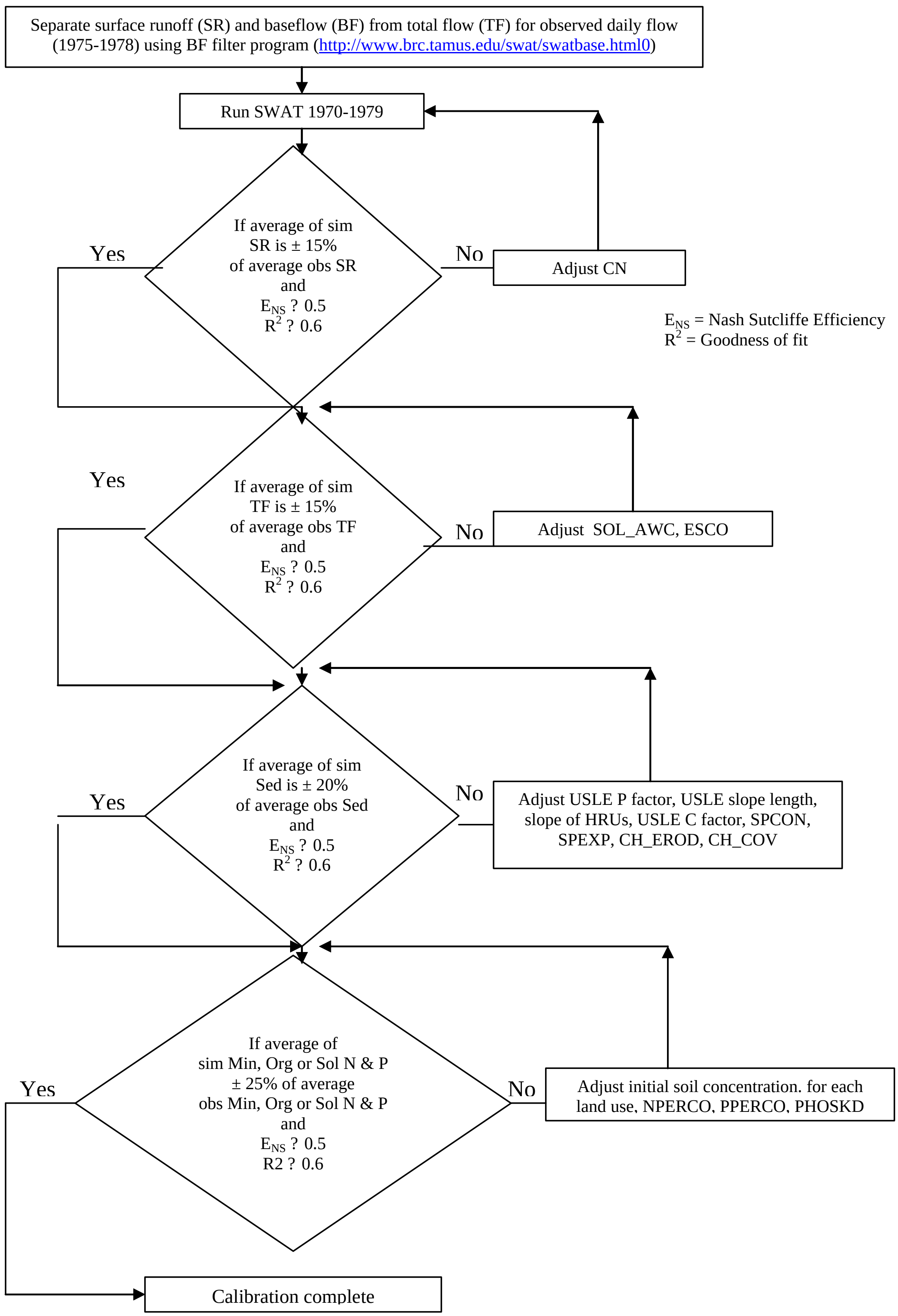


Figure 2. Example SWAT Calibration Flowchart (adapted from Santhi et al. (2001a) and Bracmort et al. (2003)).

Model Validation

When possible, it is important to reserve some observed data (e.g., flow and water quality data) for model validation. Additional discussion of the data for validation and calibration can be found in the Model Calibration section. Prior to beginning model validation, the criteria used to validate, that is, accept, reject, or qualify, the model results should be documented (US EPA, 2002). The same statistics used and reported for model calibration should be used in model validation. Typically, the values of these statistics are lower for validation than calibration. Acceptable levels of performance may be difficult to identify. Acceptable model performance levels that have been proposed are discussed in the Model Calibration section. The scientific literature can provide suggestions for levels of performance that might be anticipated for a given model. The specific purpose of the study, the available data and other factors should be considered when establishing the performance criteria. For example, the time period considered can impact model performance. Typically, model performance is poorer for shorter periods than for longer periods (e.g., daily versus monthly or yearly). For example, Yuan et al. (2001) found that AnnAGNPS provided an R^2 of 0.5 for event comparison of predicted and observed sediment yields while the agreement between monthly data had an R^2 of 0.7.

In some instances, acceptable model performance may not be obtained during the validation step. Note that the utility of the model may not depend on a single performance indicator and therefore some judgment will be required by the modeler. The uncertainty associated with models and model setups that do not attain the desired level of performance during validation will be greater than those for which model performance is deemed acceptable. Unacceptable model performance for validation can be an indication that the validation period data ranges or conditions are significantly different than those for the calibration period. Therefore, care in the selection of the data for calibration and validation periods is needed. In other cases, poor performance during validation may be an indication that the model has not been adequately or properly calibrated. It is possible that numerous model setups or parameterizations can provide acceptable model results for calibration. However, during validation such setups may provide poor results. In such cases, the model should be re-calibrated and then validation attempted again. In addition, in some cases the lack of acceptable validation may be the result of inaccurate validation data.

If data are unavailable for validation,, other approaches might be used to evaluate the potential performance of the model. The literature on the model may provide an indication of the model's expected performance. However, care should be taken in inferring the model's likely performance for the study watershed based on validation results found in the literature. These data used and model parameterization for studies reported in the literature are not often described with enough detail to allow a good assessment of the model's likely performance in other watersheds. Further, if the model study reported in the literature included calibration, assessment of the model's likely performance in the study watershed will be even more difficult since the model will not be calibrated for the study watershed.

Observed runoff and water quality data from a similar watershed could potentially be used to determine the likely performance of the model for the study watershed. Sogbedji and McIsaac (2002) demonstrated the expected performance of the ADAPT model through calibration of the model using data from a comparable watershed and then applying it to similar watersheds. However, it may be desirable not to calibrate the model for the similar watershed but rather simply validate the model for such watersheds, since data are unavailable for calibration of the model in the study watershed.

The US EPA (2002) indicates that a model can be evaluated by comparing model predictions of current conditions with similar field or laboratory data not used in the model calibration process, or with comparable predictions from accepted models or by other methods (uncertainty and sensitivity analyses). The results of a simple mass balance model could be compared with those of the model used in the study to see how well results match. Multiple comprehensive models might also be applied to the study watershed if data are unavailable for calibration and validation. If multiple models provide similar results, confidence in the results that are obtained may be increased. One must be cautious though with the interpretation of results in such a case, especially if the models use similar modeling components or approaches.

If validation is not possible, varying ranges of model inputs might be used in later stages of the modeling effort to determine the sensitivity of the model results to the model inputs. The use of Monte Carlo techniques and other approaches can also be used to identify confidence limits on outputs. “Biasing” the model inputs may also be used in later stages of the modeling effort to determine the sensitivity of the results to assumptions in model inputs. In such a situation, the model inputs would be set to extreme values in their expected ranges. If the same conclusions are reached with these inputs, the confidence in the conclusions reached would be increased since the conclusions are not sensitive to model input assumptions.

Model scenario prediction

Once the model has been validated and the results are deemed acceptable, the model is ready to be parameterized to the conditions of interest (e.g., a land use change, implementation of BMPs, etc.). The parameterization of the model and the rationalization for decisions regarding data and representations within the model should be documented to allow others to recreate the model setup (see Model representation issues section). These data and representation decisions should be consistent with those used in setting up the model for calibration and validation.

The uncertainty in model predictions when parameterized for the condition(s) of interest should be explored. The results from the validation stage provide some basis for expected model performance and level of uncertainty. Monte Carlo and other techniques can also be used to place confidence intervals on the expected results. For example, Kuczera and Parent (1998) used two Monte Carlo-based approaches for assessing parameter uncertainty in complex hydrologic models.

An approach that can be helpful in exploring the extremes in the uncertainty of model predictions is to bias model inputs in a direction that would be expected to represent the “worst case.” If the model results for such a case result in the same conclusion being reached, the confidence in the conclusion should be high.

Results interpretation/hypothesis testing

The model results should be interpreted accounting for the expected uncertainty in the modeled results. Typically, the uncertainty in models cannot be quantified due to complexity of interactions, and thus it will be necessary to qualitatively assess the objectives or hypotheses taking into account the expected uncertainty in the results. The approach to be utilized in testing the objectives or hypotheses should be identified and documented prior to initiating the modeling.

The literature contains numerous examples of interpretation of model results. For example, Kirsch et al. (2002) tested the SWAT model within pilot watersheds and then applied it throughout a larger watershed in Wisconsin and quantify impacts from the application of basin–wide BMPs. Modeling results indicated that implementation of improved tillage practices (predominantly conservation tillage) could reduce sediment yields by almost 20%. They deemed this a significant reduction relative to current conditions. Santhi et al. (2001b) applied SWAT, which had been validated for flow and sediment and nutrient transport, to a watershed to quantify the effects of BMPs related to dairy manure management and municipal wastewater treatment plant effluent. King and Balogh (2001) used SWAT running 99–year simulations for three locations for continuous corn, a forested environment, a golf course built in a previously agricultural setting, and a golf course constructed in a previously forested setting. Differences in hydrologic, nitrate–nitrogen, and pesticide impacts were examined using Tukey’s pairwise comparison to determine whether differences were statistically different.

Summary

Data collection for environmental projects typically follows a quality assurance/quality control plan. Quality assurance planning for environmental modeling projects is just as important as planning traditional environmental measurements for data collection projects. A modeling protocol, preferably written, should be established prior to conducting a modeling study. Twelve issues that should be addressed in hydrologic/water quality model application plans were identified based on the authors’ experience and the literature, including recent guidance from the US EPA. The issues that should be addressed in a modeling plan include:

1. Problem definition/background
2. Model application goals, objectives and hypothesis
3. Model selection
4. Model sensitivity analysis
5. Available data
6. Data to be collected
7. Model representation issues – data, BMPs, etc
8. Model calibration
9. Model validation

10. Model scenario prediction
11. Model output uncertainty analysis
12. Results interpretation/hypothesis testing

The extent of documentation that should be prepared for each of these items depends on various factors, including the purpose of the modeling study.

GIS DATA SOURCES

Several sources and resolutions of GIS data may be used for a particular modeling project.

Soils

There is currently only one GIS coverage for soils nationwide, STATSGO (State Soil Geographic Database), which were compiled by the NRCS (Natural Resource Conservation Service). These data are most commonly used with SWAT, and are available in the BASINS database. STATSGO was created from generalizations of other soil surveys. The minimum mapping area is 625 ha. No soil group smaller than 625 ha is included. Each map unit consists of several soils. An associated MUIR (Map Unit Interpretations Record) database contains the properties and distribution of soils in each map unit.

Other more detailed soil data may be available depending on the study area. The NRCS is currently working on SSURGO (Soil Survey Geographic Database). SSURGO is far more detailed, but not available for all areas. SSURGO is a digitized version of the NRCS county-level soil survey, and is the most accurate soil data available. Other soil data also available are a 200-meter resolution MIADS (Map Information Assembly and Display System) data from the Oklahoma NRCS, and other digitized soil surveys similar to SSURGO.

Topography

Digital Elevation Model (DEM) are used to define topography for SWAT. The US Geographic Survey (USGS) provide DEMs at a variety of scales. DEMs are available in a raster format at resolutions of 30, 60, 120, and in very limited areas at 10 meters. Topographic data included in BASINS have a resolution of 300 meters.

Land Cover

Land cover is more complicated to compare than soils or topography. Land cover can change over a relatively short time frame. Soils and topography take much longer to change significantly. Land cover is perhaps the most important GIS data used in SWAT. Several choices are available. The least detailed and easiest data to use with SWAT is USGS LULC (Land Use Land Cover) data. These data are available nationwide. The scale of these data is 1:250,000 and 1:100,000 for limited areas. Dates range from the late 70's to the early 80's. These data are available in the BASINS data set and are readily used by SWAT.

Several other sources of land cover data are available. The USGS and the EPA recently released the NLCD (National Land Cover Database) using early 1990's imagery, which have a 30 meter resolution. Another land cover data set is from GAP (Gap Analysis Project). The GAP project maps vegetation based on 30 meter Landsat Thematic Mapper satellite imagery. The primary purpose of this information is to predict the range of native vertebrate species. However, the categorical information between these two data sets is quite different. Project specific land cover data can also be developed using satellite imagery and/or areal photography. If historical land cover data are used, we recommend comparing the data to recent aerial photography to determine if significant changes may have occurred.

EFFECT OF DATA DETAIL ON SWAT MODEL PREDICTIONS

The Lake Eucha and Great Salt Plains Basins were used to evaluate the effect of data detail on the SWAT model. The contrast between these two basins makes them a good combination. Both are located at a similar latitude, but have radically different precipitation, land cover, topography, and soils (Figure 3).

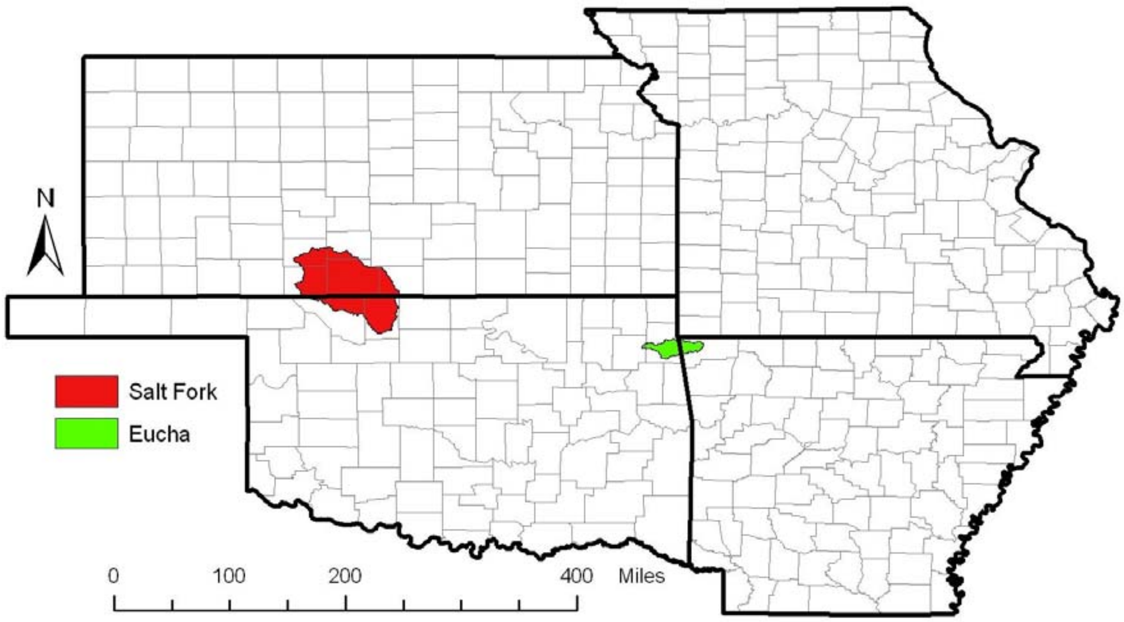
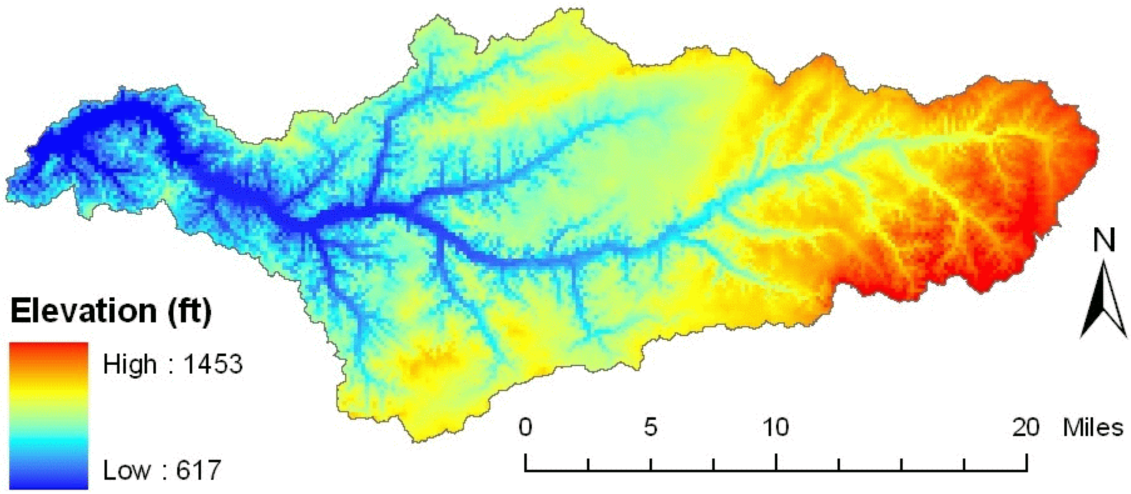


Figure 3. Study basin locations.

Data Types

Topography

DEMs (Digital Elevation Models) are used to define topography for SWAT (Figure 4). DEMs are available in a raster format at resolutions of 30, 60, 120, and in very limited areas at 10 meters. Thirty meter data are the most detailed that is addressed by this study. Thirty-meter data developed for use in SWAT BMP simulations were resampled to 60, 120 and 300 meters. These four levels of DEM resolution were included in the study. Individual 1:24,000 thirty meter DEMS were stitched together to construct a DEM for the entire basin. When tiled, 1:24,000 DEMS often have missing data at the seams. These missing data must be replaced. A 3x3 convolution filter was applied to the DEM to produce a seamless filtered DEM. Any missing data at the seams of the original DEM were replaced with data from the filtered DEM. The resulting seamless DEM retains as much non-filtered data as possible. Filtering tends to remove both peaks and valleys from a DEM thereby reducing the perceived slope. For this reason the use of filtered data were kept to a minimum.



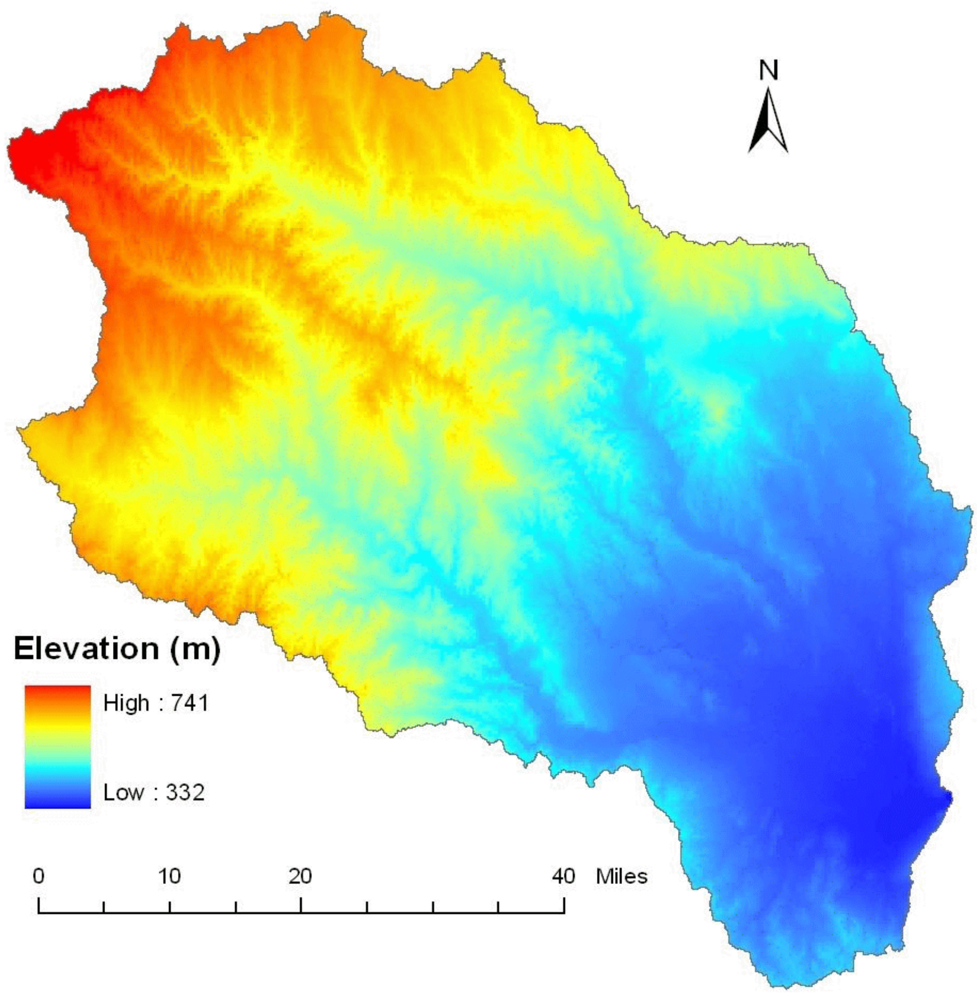


Figure 4. Lake Eucha Basin and Salt Fork Basin elevation derived from 30 meter Digital Elevation Models

Soils

STATSGO was created from generalizations of other soil surveys. The minimum mapping area is 625 ha and thus each map unit consists of several soils. An associated MUIR (Map Unit Interpretations Record) database contains the properties and distribution of soils in each map unit. Both low detail soils coverage were classified by MUID (Map Unit IDentification) (Figures 5 and 6).

High detailed soils for both basins were developed using a combination of sources. The soils layer for the Eucha basin was derived from the Oklahoma portion is 200-meter resolution MIADS data from the Oklahoma NRCS and the Arkansas portion is a 1:20,000 order II soil survey digitized by the University of Arkansas.

The soils layer for the Salt Fork basin was derived from three separate GIS coverages. The Alfalfa County, Oklahoma portion is 200-meter resolution MIADS (Map Information Assembly and Display System) data from the Oklahoma NRCS. The Woods County, Oklahoma portion is certified SSURGO (Soil Survey Geographic) soils data from the Oklahoma NRCS. The Kansas portion is 1:24,000 detailed soils digitized by Kansas State University. These highly detailed soils data are difficult to use with the SWAT model. The SWAT model has an internal database of soil properties based on STATSGO data. SSURGO data contains soils that are not available in this database. The most similar soils listed in the SWAT database were substituted for these unavailable soils. Similarity was based on soil properties weighted by their relative importance. Only soils with the same hydrologic soil group were considered for substitution. A score from zero to 1000 was given based on the formula:

$$\text{Score} = 1000 - \sum(\text{Relative difference at parameter} * \text{Parameter importance})$$

Parameter importance is given in Table 2. A score of 1000 is a perfect match but any score above 800 was assumed to be a reasonable match (Figure 7). Any soils with matching S5IDs are automatically assigned a score of 1000. A program was written to search all soils in the STATSGO database for Oklahoma, Texas, and Kansas. The ten highest ranking soils were recorded and the best among them were manually selected.

Soil GIS data are required by SWAT to define soil types. SWAT uses STATSGO (State Soil Geographic Database) data to define soil attributes for any given soil. The GIS data must contain the S5ID (Soils5id number for USDA soil series), or STMUID (State STATSGO polygon number) to link an area to the STATSGO database. Soils of the Eucha Basin were linked to SWAT by S5ID (Soils 5 IDentifier) (Figure 8). Soils of the Salt Fork Basin were linked using a modified MUID know as STMUID (STate Map Unit IDentification) which simply substitutes a two digit number for each state abbreviation and a sequence number (Figure 9). The addition of a soil sequence specifies a particular soil in each MUID.

Table 2. Parameter importance used to match SSURGO (Soil Survey Geographic) Soils to the STATSGO (State Soil Geographic) database included with SWAT.

Parameter	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
Fine earth fraction	15	10	8	5	2
Permeability low	10	7	5	4	2
Permeability high	10	7	5	4	2
Clay content low	8	6	4	3	2
Clay content high	8	6	4	3	2
Organic matter content low	8	6	4	3	2
Organic matter content high	5	6	4	3	2
Layer depth	8	4	4	3	2
Available water low	8	6	4	3	2
Available water high	8	6	4	3	2
Bulk density low	7	6	4	3	2
Bulk density high	7	6	4	3	2
% passing #4 sieve low	5	4	4	3	2
% passing #4 sieve low	5	4	4	3	2
% passing #200 sieve low	5	4	4	3	2
% passing #200 sieve low	5	4	4	3	2

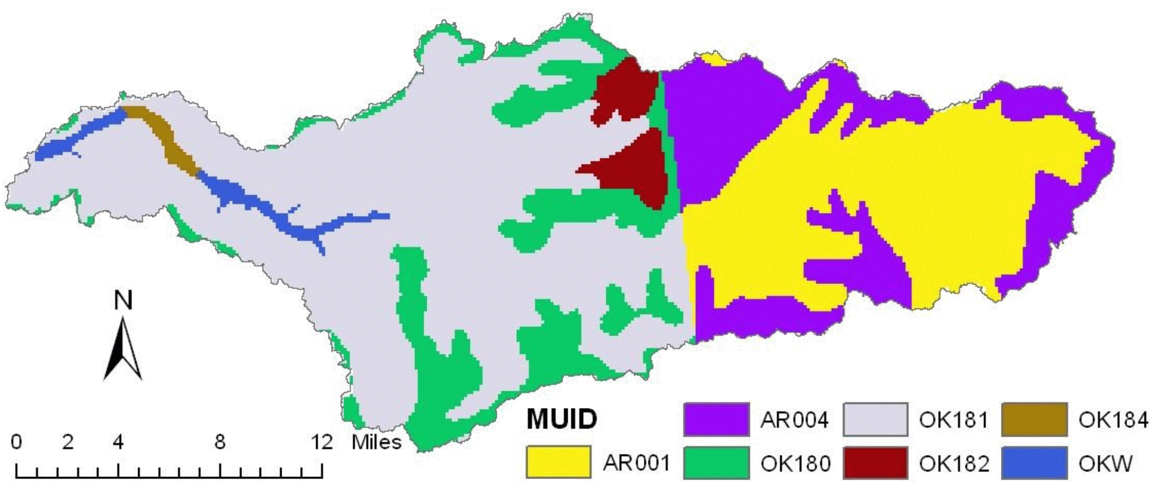


Figure 5. STATSGO (State Soil Geographic) derived soil data for the Lake Eucha Basin.

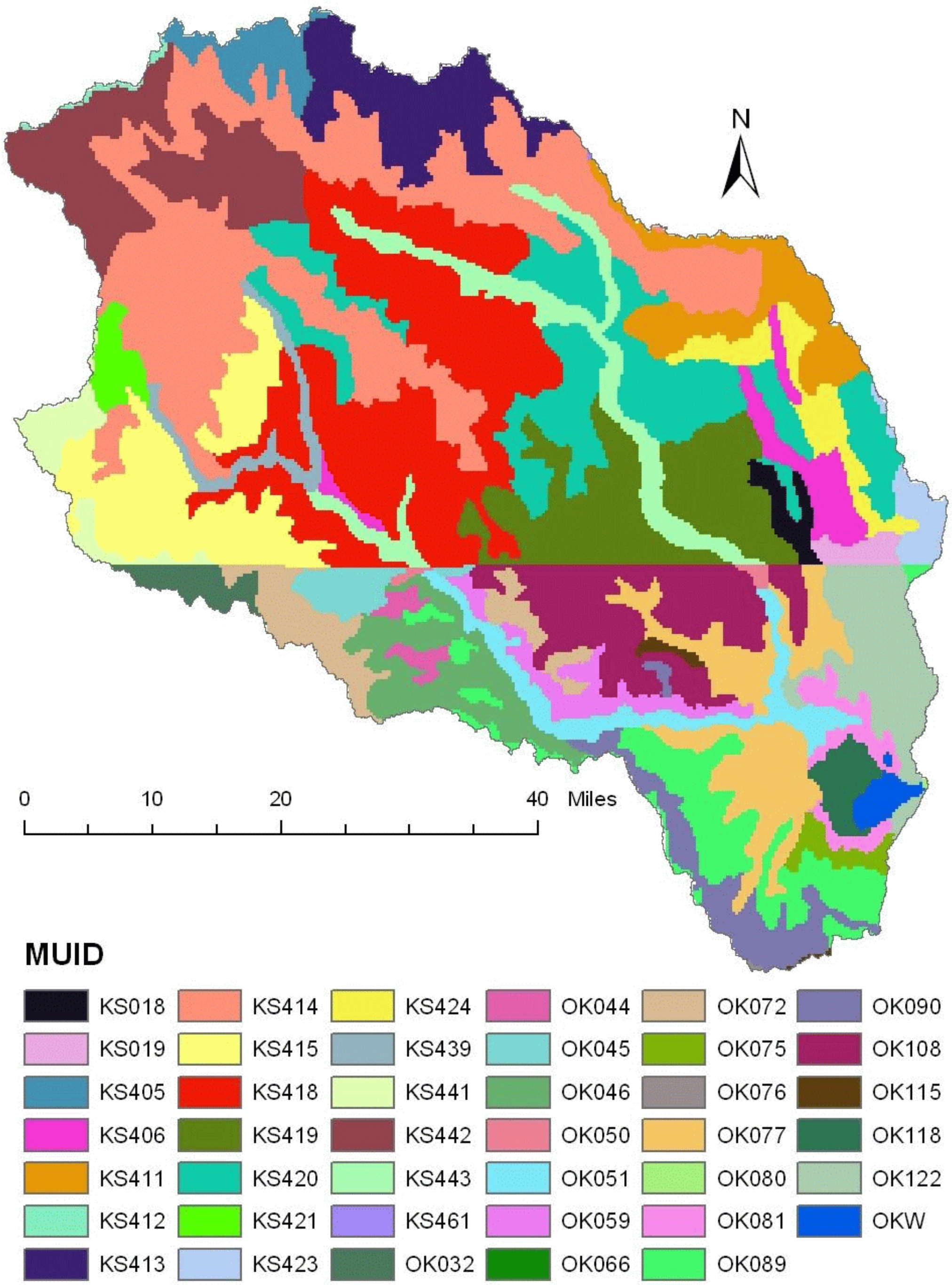


Figure 6. Low resolution STATSGO (State Soil Geographic) derived soil data for the Salt Fork Basin.

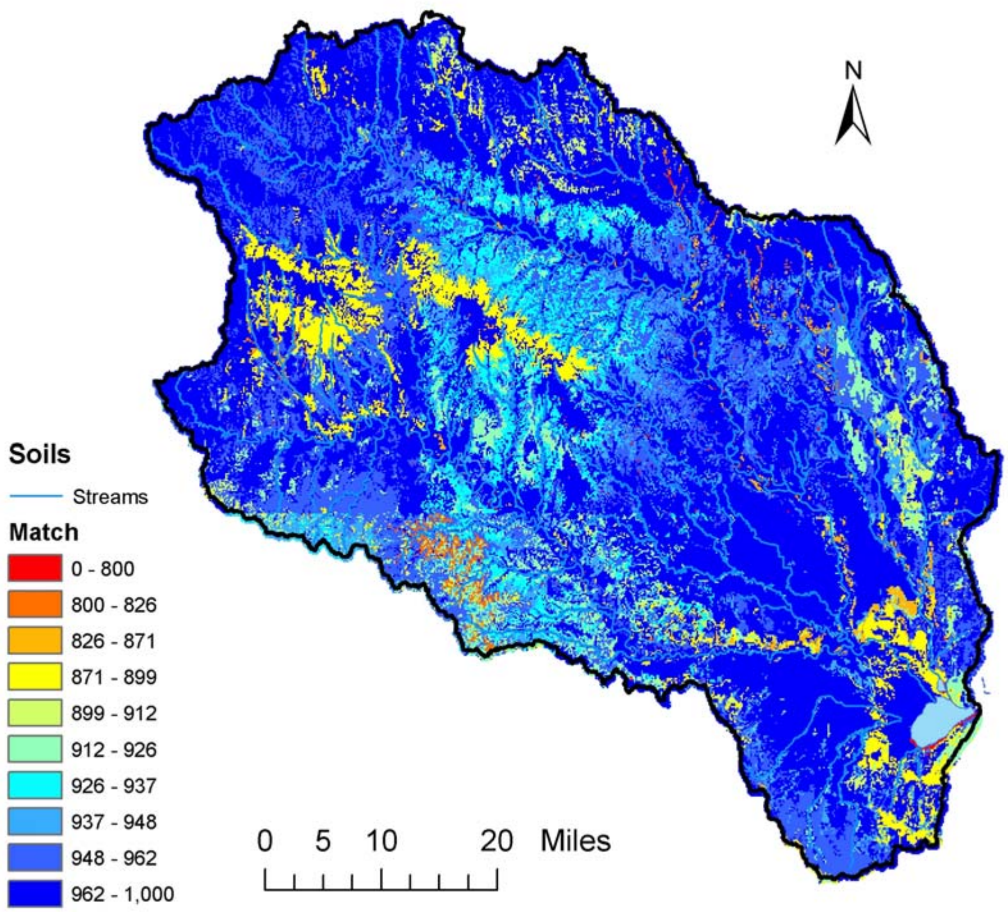


Figure 7. Results of high detail soils to SWAT soils matching algorithm.

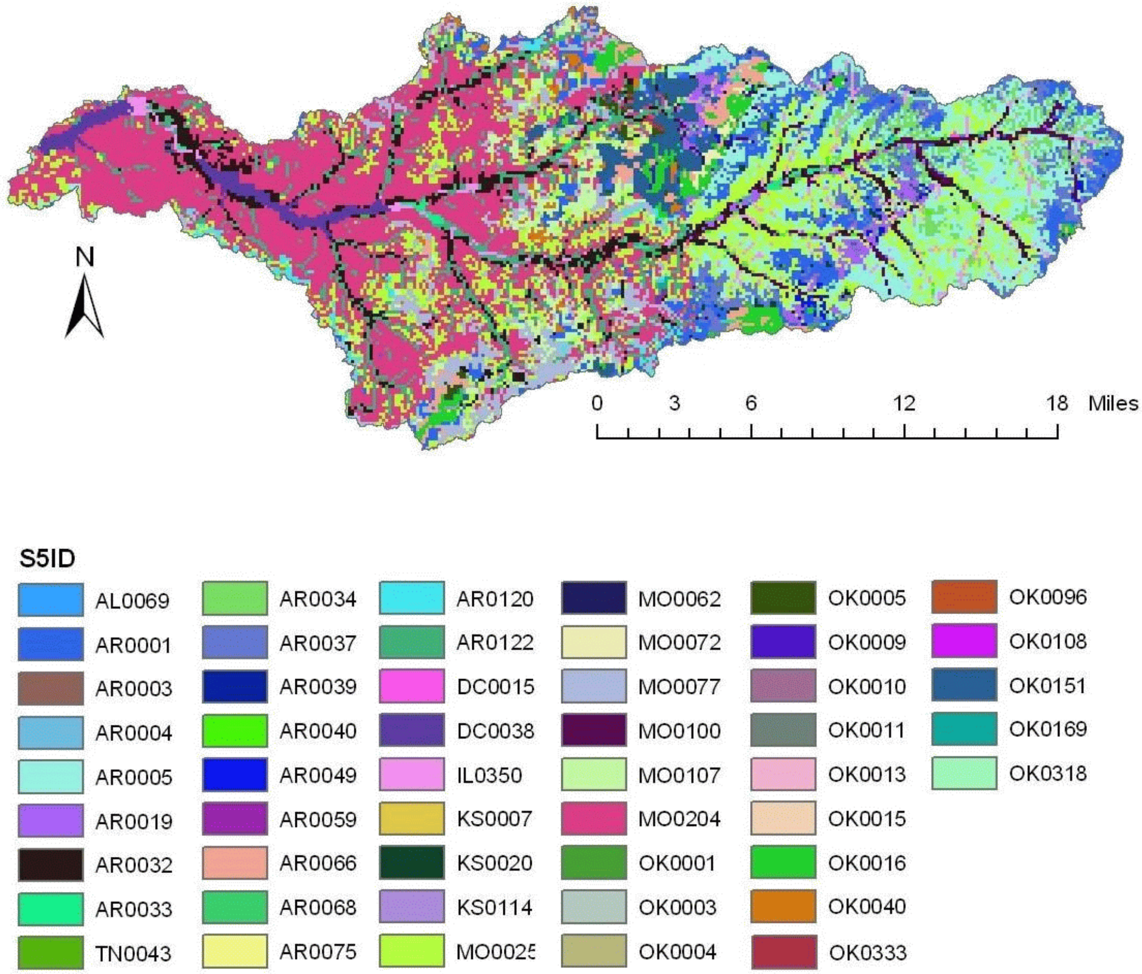


Figure 8. High resolution soils data for the Lake Eucha Basin**.**

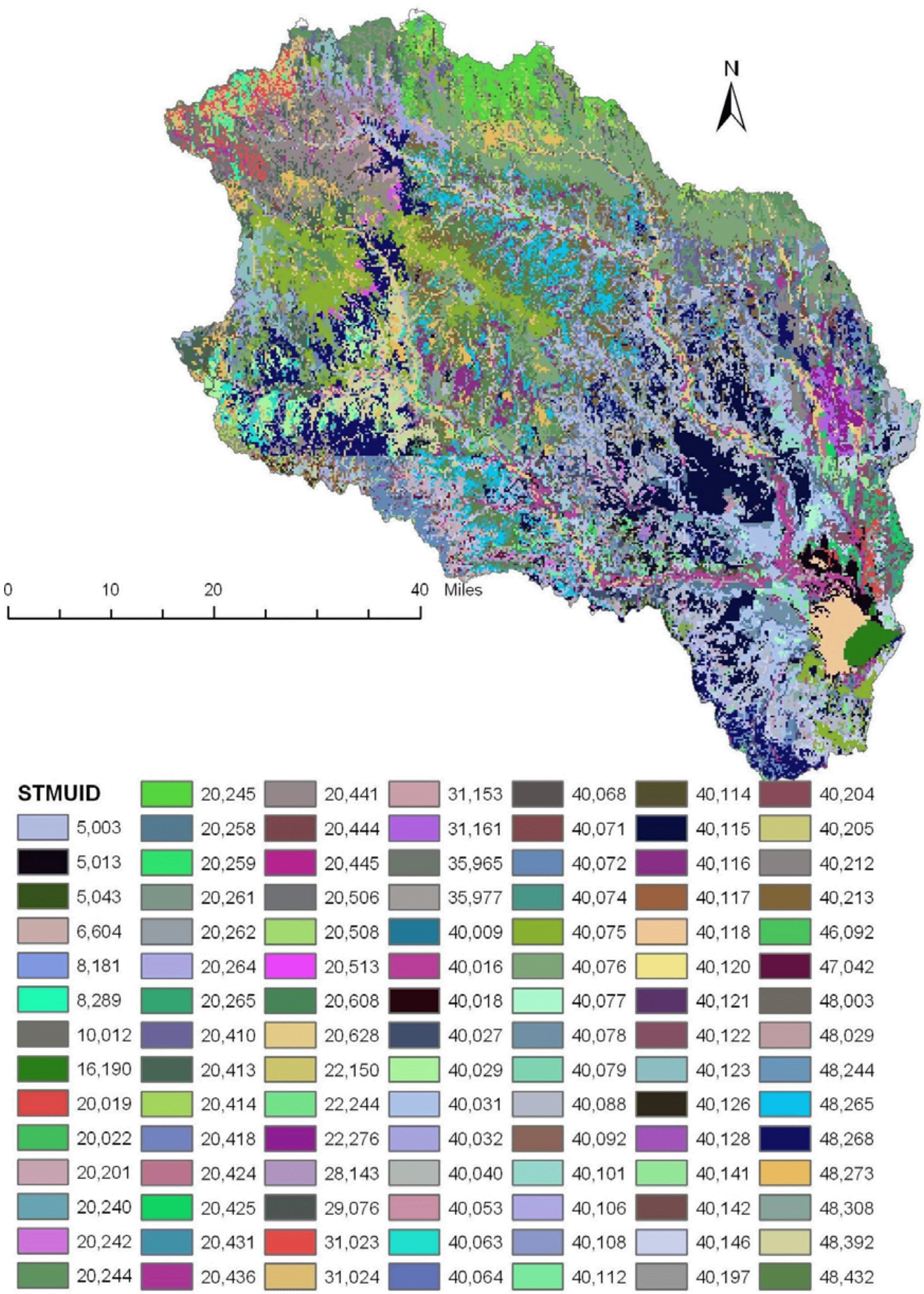


Figure 9. High resolution soils data of the Salt Fork Basin.

Land Cover

Land cover is more complicated to compare than soils or topography. Land cover can change over a relatively short time frame. Soils and topography take much longer to change significantly. Land cover is perhaps the most important GIS data used in SWAT. Several choices are available. The least detailed, easiest data to use with SWAT is USGS LULC (Land Use Land Cover) data. These data are available nationwide. The scale of these data is 1:250,000 and 1:100,000 for limited areas. Dates range from the late 70's to the early 80's. These data are available in the BASINS data set and are readily used by SWAT. LULC data were used to define the land cover for low detail simulations of both basins (Figures 10 and 11).

Several other sources of land cover data are available. The USGS and the EPA recently released NLCD (National Land Cover Database) using early 1990's imagery, which have a 30 meter resolution. These data were used to define land cover for the Salt Fork Basin (Figure 12). Land cover for the Eucha basin was derived from Oklahoma and Arkansas GAP (Gap Analysis Program) data (Figure 13). The GAP project mapped vegetation based on 30 meter Landsat Thematic Mapper satellite imagery. The 19 primary purpose of this information was to predict the range of native vertebrate species. GAP land cover defines many native vegetation categories, but very few agricultural categories. We simplified GAP categories to pasture, forest, urban, and water. The basin is composed of 43.2% pasture, 55.0% forest, 1.7% water, and 0.1% urban. These data were then combined to produce a seamless coverage of the entire area.

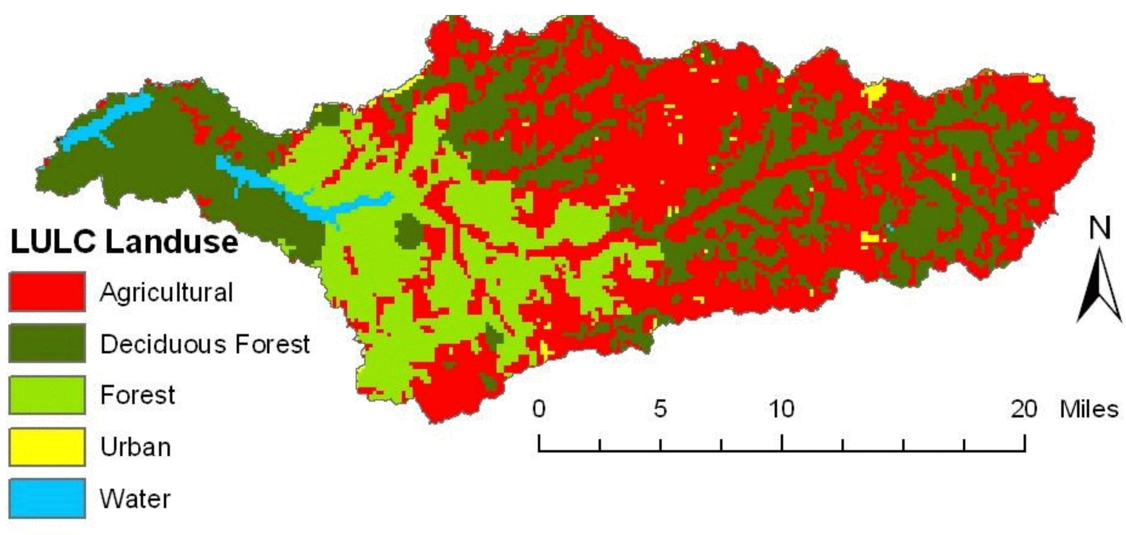


Figure 10. USGS LULC (Land Use Land Cover) derived land cover data for the Lake Eucha Basin.

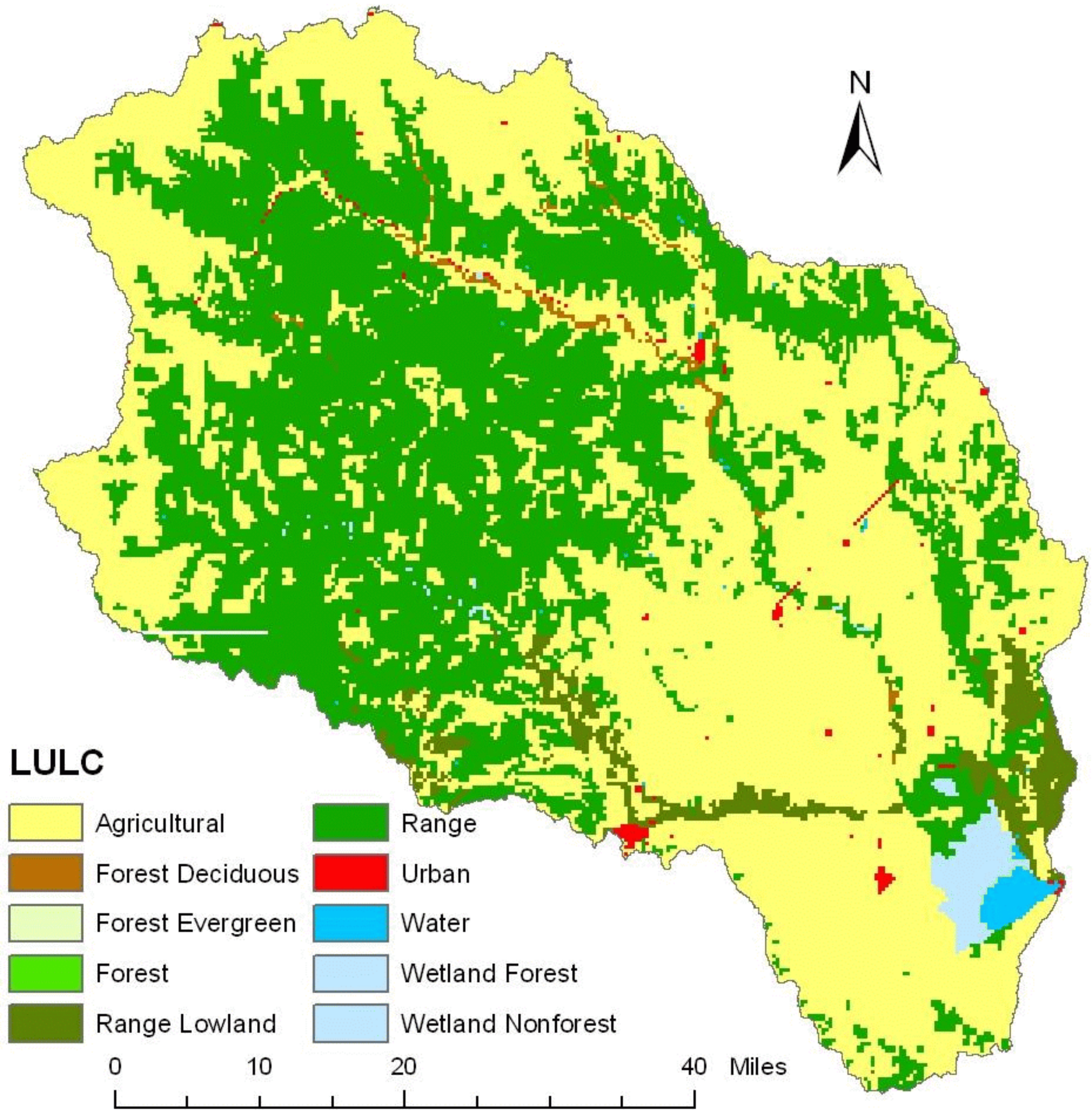


Figure 11. USGS LULC (Land Use Land Cover) derived land cover data for the Salt Fork Basin

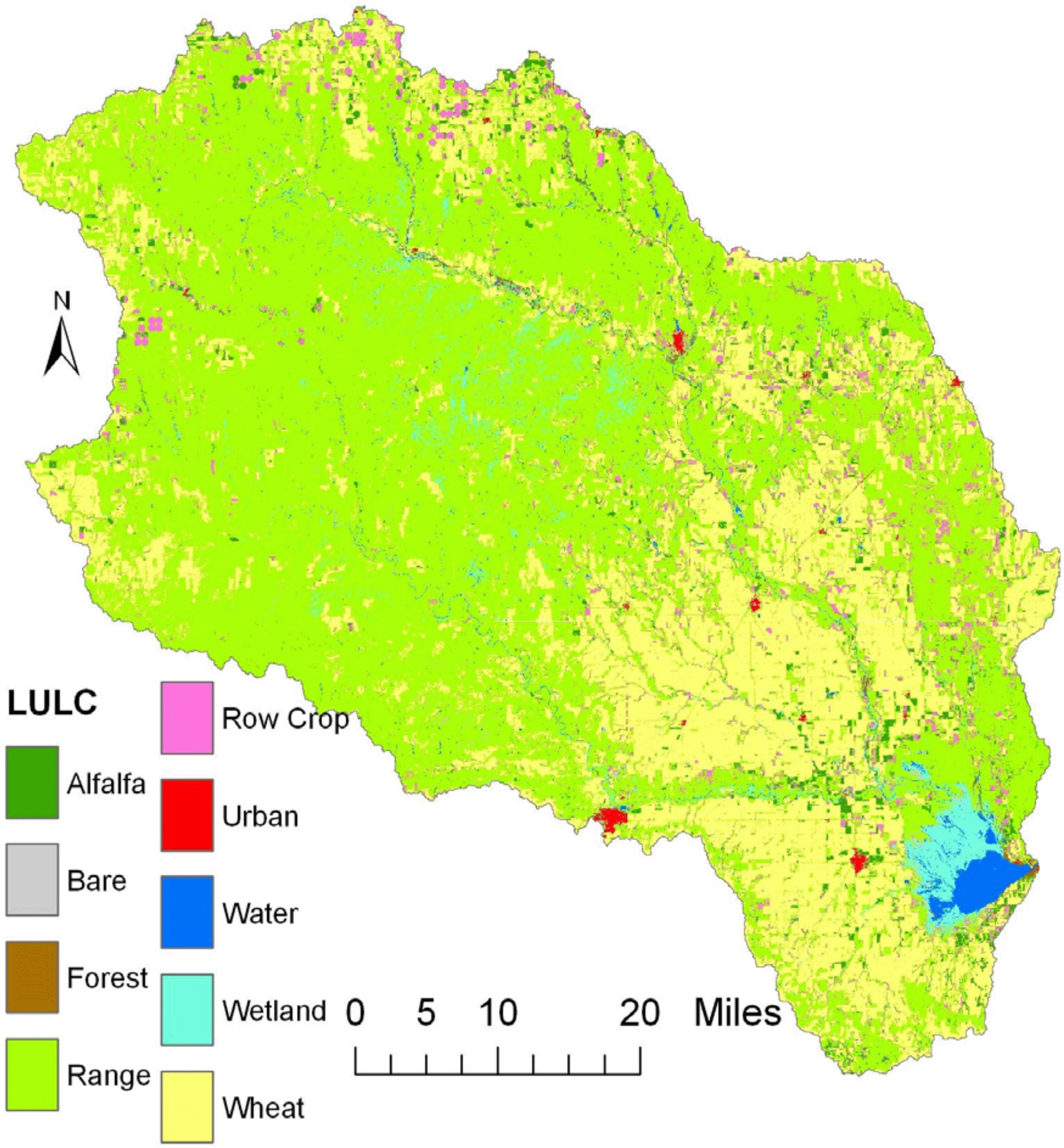


Figure 12. Thirty-meter resolution USGS NLCD (National Land Cover Data) derived data for the Salt Fork Basin.

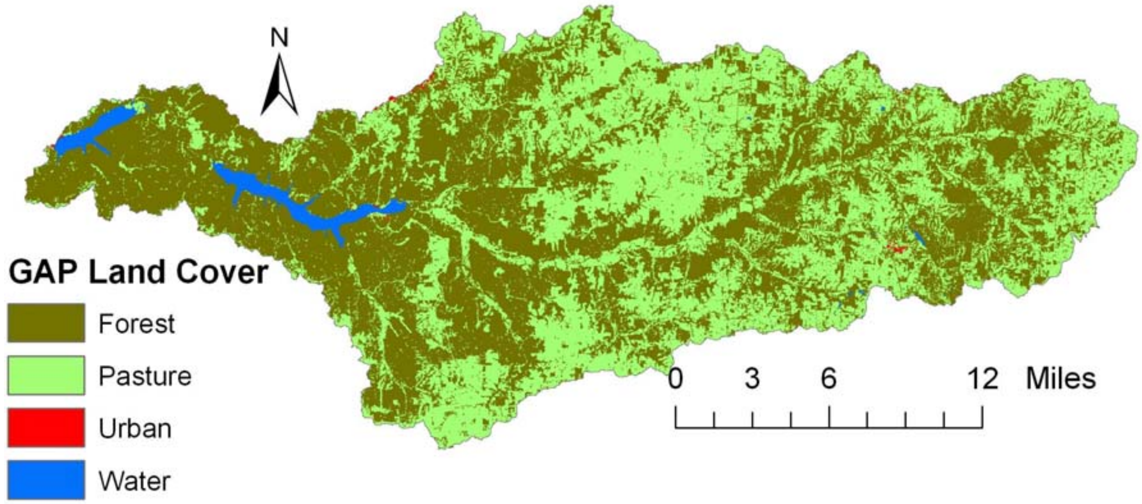


Figure 13. GAP (Gap Analysis Project) derived land cover data for the Lake Eucha Basin.

Methods

Each basin was examined separately with a model run for each combination of GIS data. A factorial experimental design was used (Table 3). Twenty average annual data points were taken from 25 year simulations, with the first 5 years removed to allow the model to "warm up". The following parameters were examined:

- Water yield
- Surface Runoff
- Baseflow
- Sediment yield
- Soluble Phosphorous yield
- Sediment-bound Phosphorous
- Nitrate in surface runoff
- Evapo-Transpiration
- Sediment-bound Nitrogen

The model was not calibrated since the calibration would tend to make all results similar regardless of the included data. Comparisons between model runs were made relative to the baseline or most detailed model run. Relative results across multiple parameters are more easily compared than absolute results because they are more similar in magnitude. The number of subbasins and HRUs remain nearly constant for all simulations of a particular basin. It is not possible to use the same number of subbasins and HRUs for each simulation. These are based partly on the input data which vary by simulation. This level of subdivision was selected based more on practicality than the recommendations of previous research (Binger et al., 1997). The approximate number of subbasins for each basin is 50. A stream threshold area of 1,000 ha was used for Lake Eucha Basin, and 10,000 ha for the Salt Fork Basin. HRU threshold settings were set as close to 10% land use over subbasins area and 9% soil over subbasin area as possible for both basins. Two simulations for the Salt Fork Basin required the soil over subbasin threshold to be reduced to 8% from the default value of 20%.

Table 3. Combinations of DEM resolution, soils, and land cover compared.

DEM Resolution (m)	Soils Detail	Land Cover Detail
30	High	High
30	High	Low
30	Low	High
30	Low	Low
60	High	High
60	High	Low
60	Low	High
60	Low	Low
120	High	High
120	High	Low
120	Low	High
120	Low	Low
300	High	High
300	High	Low
300	Low	High
300	Low	Low

Results were derived from non-routed model outputs obtained using a custom VBA (Visual Basic for Applications) program. Annual subbasin data were summarized on a per unit area basis to determine a basin average for each output studied. This program was also used in the Salt Fork Basin BMP study.

Results

Data from each of the 32 simulations were analyzed to determine the effect of changing data types or resolutions. Table 4 contains the mean from each simulation and averages across each level of GIS data type. Model predictions were analyzed using SAS (Statistical Analysis Software). The SAS programs are available in Appendix B. A factorial design was chosen to enable a comprehensive statistical analysis. Interaction between the different data types prohibited the analysis of main effects. One way to overcome this problem is to analyze only the simple effects. Because there are two basins, each with a 4x2x2 factorial experimental design and nine study parameters, analysis of simple effects is a prohibitively difficult task. In addition, all these simple effects would be very difficult to display in any meaningful manner in the context of this report. To overcome these difficulties only a select few simple effects were included in the statistical analysis.

At a DEM resolution of 30 meters land cover detail has a significant impact on more parameters than soils detail. Table 5 contains soils and land cover low detail simulations compared to the baseline condition. The effect of land cover detail is the result of more than simple detail differences. Each land cover type in the original GIS data must be matched to a corresponding category in SWAT by a conversion table. SWAT is able to incorporate LULC data directly using a conversion table, which is included in the interface. This table may not be accurate for all areas. A large portion of the Eucha basin was determined to be AGRL (Generic Agriculture) when the LULC data were imported. In reality, these areas are improved pastures which have dramatically different characteristics. This results in the dramatic changes when low detail land cover was included in the simulation. This problem is far less evident in the Salt Fork Basin, the LULC conversion table is more suited to this type of area.

Statistical comparison for DEM resolution levels are displayed in Table 6. These are simple effects calculated from only a fraction of the entire data set. DEM resolution has the greatest effect on sediment and sediment-bound nutrients. Presumably because slope is derived from the DEM. The resolution of the DEM also has other affects in the SWAT model. All additional GIS data included in the model are resampled to the same resolution as the DEM by the interface. This is thought to contribute to the interaction that prevented statistical analysis of main effects.

Figures 14 to 21 display graphical representation of some of the information displayed in Table 4. Figure 14 to 17 show how DEM resolution affects both basins. Figures 14 and 16 were constructed using the entire data set without concern for land cover and soils. Very large sediment yields in Figure 15 were the result of the incorporation of low detail land cover data. These spikes are not seen in Figure 17, which does not include the LULC data for the Lake Eucha Basin; however, the overall treads of reduced sediment with decreased resolution are similar.

Figures 15 and 17 are the simple effects, which have corresponding statistical tests in Table 6. Only high resolution soils and land cover were considered in these figures. Figures 18 to 21 contain comparison between soils and land cover combinations. Figures 18 and 20 contain averages across all levels of DEM. Figures 19 and 21 display only simple effects. The effect of adding LULC data to the Eucha Basin is illustrated in Figure 21, which resulted in a 94 fold increase in sediment. The addition of low detail soils data had the opposite effect on sediment and sediment-bound nutrients.

Table 4. The effect of data detail on several SWAT output parameters. All values are fractions relative to the most detailed simulation (30m DEM with high soils and land cover). "X" indicates averages across all categories.

Basin	DEM	Soils	Land Cover	Runoff	Water Yield	ET	Sediment	Organic N	Sed-Bound P	Nitrate in runoff	Soluble P	Ground water
Salt Fork	30	High	High	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	30	High	Low	1.39	1.35	0.97	2.10	1.49	1.21	0.85	0.82	1.01
	30	Low	High	0.94	1.02	0.99	0.91	0.93	0.95	1.04	0.95	2.41
	30	Low	Low	1.35	1.37	0.95	2.07	1.44	1.24	0.92	0.84	1.96
	60	High	High	1.01	0.99	1.00	0.73	0.82	0.84	1.02	1.02	0.79
	60	High	Low	1.37	1.33	0.97	1.55	1.29	1.11	0.84	0.82	1.11
	60	Low	High	0.94	1.01	0.99	0.69	0.79	0.83	1.05	0.95	2.53
	60	Low	Low	1.35	1.36	0.96	1.55	1.24	1.14	0.93	0.86	2.06
	120	High	High	1.01	0.99	1.00	0.52	0.64	0.66	1.03	1.02	0.98
	120	High	Low	1.40	1.34	0.97	1.12	1.05	0.97	0.85	0.82	1.14
	120	Low	High	0.94	1.01	0.99	0.50	0.63	0.67	1.06	0.96	2.57
	120	Low	Low	1.36	1.36	0.96	1.08	0.99	0.96	0.94	0.86	2.11
	300	High	High	1.17	1.11	0.99	0.47	0.60	0.59	1.06	1.06	0.65
	300	High	Low	1.38	1.32	0.97	0.75	0.79	0.79	0.84	0.81	1.18
	300	Low	High	0.93	0.99	0.99	0.34	0.46	0.49	1.04	0.94	2.63
	300	Low	Low	1.35	1.34	0.96	0.76	0.79	0.79	0.93	0.85	2.12
	30	X	X	1.17	1.19	0.98	1.52	1.22	1.10	0.95	0.90	1.59
	60	X	X	1.17	1.17	0.98	1.13	1.03	0.98	0.96	0.91	1.62
	120	X	X	1.18	1.17	0.98	0.80	0.83	0.81	0.97	0.91	1.70
	300	X	X	1.21	1.19	0.98	0.58	0.66	0.66	0.97	0.92	1.65
	X	High	X	1.22	1.18	0.98	1.03	0.96	0.90	0.94	0.92	0.98
	X	Low	X	1.15	1.18	0.97	0.99	0.91	0.88	0.99	0.90	2.30
	X	X	High	0.99	1.02	0.99	0.64	0.73	0.75	1.04	0.99	1.70
	X	X	Low	1.37	1.34	0.96	1.37	1.14	1.03	0.89	0.84	1.59
Eucha	30	High	High	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	30	High	Low	1.36	1.13	0.92	94.19	10.99	3.82	0.76	0.32	0.90
	30	Low	High	1.07	0.98	1.00	0.23	0.13	0.12	1.14	1.08	0.92
	30	Low	Low	1.42	1.11	0.93	18.06	7.40	3.79	0.83	0.33	0.79
	60	High	High	1.00	0.99	1.01	0.72	0.46	0.46	0.99	1.00	1.01
	60	High	Low	1.36	1.13	0.93	69.12	10.03	3.73	0.76	0.32	0.90
	60	Low	High	1.07	0.98	1.00	0.17	0.08	0.07	1.13	1.08	0.93
	60	Low	Low	1.42	1.11	0.93	13.26	6.11	3.74	0.83	0.33	0.79
	120	High	High	1.00	1.00	1.00	0.44	0.14	0.14	1.01	1.01	1.02
	120	High	Low	1.36	1.12	0.93	43.22	8.79	3.62	0.76	0.32	0.91
	120	Low	High	1.07	0.98	1.00	0.15	0.12	0.08	1.15	1.09	0.94
	120	Low	Low	1.42	1.10	0.93	8.55	4.58	3.56	0.83	0.33	0.79
	300	High	High	1.00	0.98	1.01	0.24	0.04	0.03	1.00	1.01	1.01
	300	High	Low	1.36	1.12	0.93	23.12	6.62	3.28	0.76	0.32	0.91
	300	Low	High	1.07	0.98	1.00	0.06	0.05	0.05	1.14	1.08	0.93
	300	Low	Low	1.42	1.10	0.93	4.58	2.68	2.30	0.83	0.33	0.79
	30	X	X	1.21	1.05	0.96	28.37	4.88	2.18	0.93	0.68	0.90
	60	X	X	1.21	1.05	0.97	20.82	4.17	2.00	0.93	0.68	0.91
	120	X	X	1.22	1.05	0.96	13.09	3.41	1.85	0.94	0.69	0.91
	300	X	X	1.21	1.04	0.97	7.00	2.35	1.42	0.93	0.69	0.91
	X	High	X	1.18	1.06	0.97	29.00	4.76	2.01	0.88	0.66	0.96
	X	Low	X	1.25	1.04	0.97	5.63	2.64	1.71	0.99	0.71	0.86
	X	X	High	1.04	0.99	1.00	0.37	0.25	0.24	1.07	1.04	0.97
	X	X	Low	1.39	1.11	0.93	34.26	7.15	3.48	0.80	0.33	0.85

Table 5. Parameters which show a significant difference when compared to the 30m high detail soils and land cover simulation.

Basin	Coverage	Runoff	Water Yield	ET	Sediment	Organic N	Sed-Bound P	Nitrate in runoff	Soluble P	Groundwater
Salt Fork	Land Cover	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	0.962
	Soils	0.103	0.505	**0.003**	0.350	0.255	0.220	0.099	**0.016**	**<.001**
Eucha	Land Cover	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**
	Soils	**<.001**	0.052	0.696	0.813	**0.010**	**<.001**	**<.001**	0.177	**<.001**

Table 6. Means and multiple comparison tests of simple effects for levels of DEM. Soils and land cover detail are high for all tests. Main effects cannot be analyzed due to interaction. Values in a column with the same letter are not significantly different from each other at α=0.05.

Basin	DEM	Runoff	Water Yield	ET	Sediment	Organic N	Sed-Bound P	Nitrate in runoff	Soluble P	Groundwater
Salt Fork	30	1.01 a	0.99 a	1.00 a	0.73 a	0.82 a	0.84 a	1.02 a	1.02 a	0.79 a
	60	1.01 a	0.99 a	1.00 ab	0.73 a	0.82 b	0.84 b	1.02 ab	1.02 a	0.79 a
	120	1.01 a	0.99 a	1.00 b	0.52 b	0.64 c	0.66 c	1.03 ab	1.02 a	0.98 a
	300	1.17 b	1.11 b	0.99 a	0.47 b	0.6 d	0.59 c	1.06 b	1.06 a	0.65 a
Eucha	30	1.00 a	1.00 a	1.00 a	1.00 a	1.00 a	1.00 a	1.00 a	1.00 a	1.00 a
	60	1.00 a	0.99 ab	1.01 a	0.72 a	0.46 ab	0.46 b	0.99 a	1.00 a	1.01 a
	120	1.00 a	1.00 a	1.00 a	0.44 a	0.14 b	0.14 c	1.01 a	1.01 a	1.02 a
	300	1.00 a	0.98 b	1.01 b	0.24 a	0.04 b	0.03 c	1.00 a	1.01 a	1.01 a

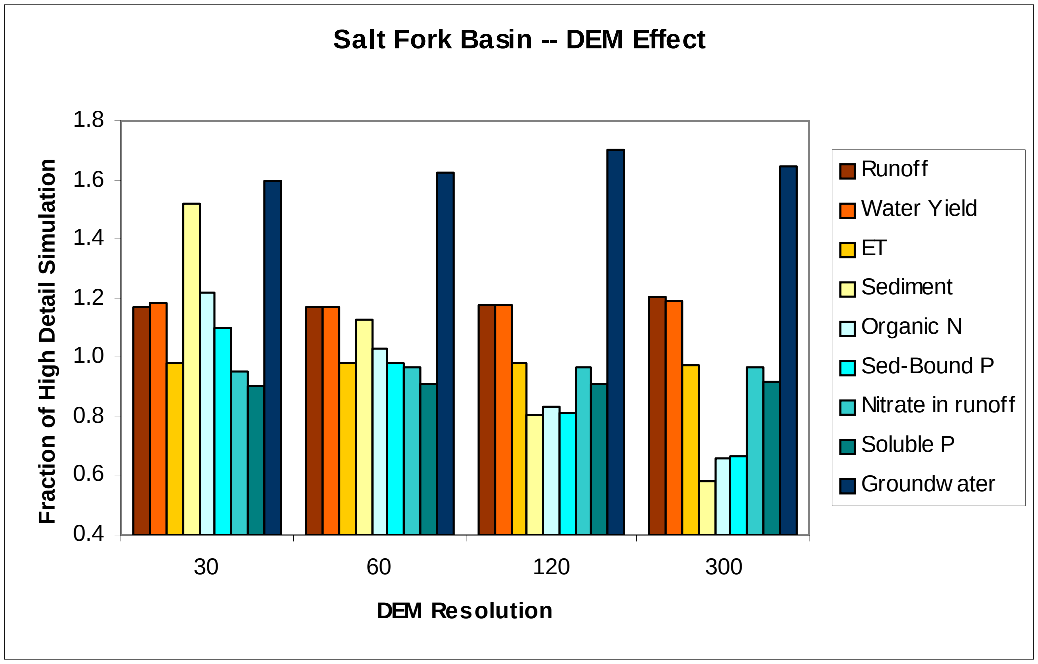


Figure 14. The effect of DEM resolution on the Salt Fork Basin averaged across all levels of soils and land cover. Displayed as a fraction of the 30m high detail soils and land cover simulation.

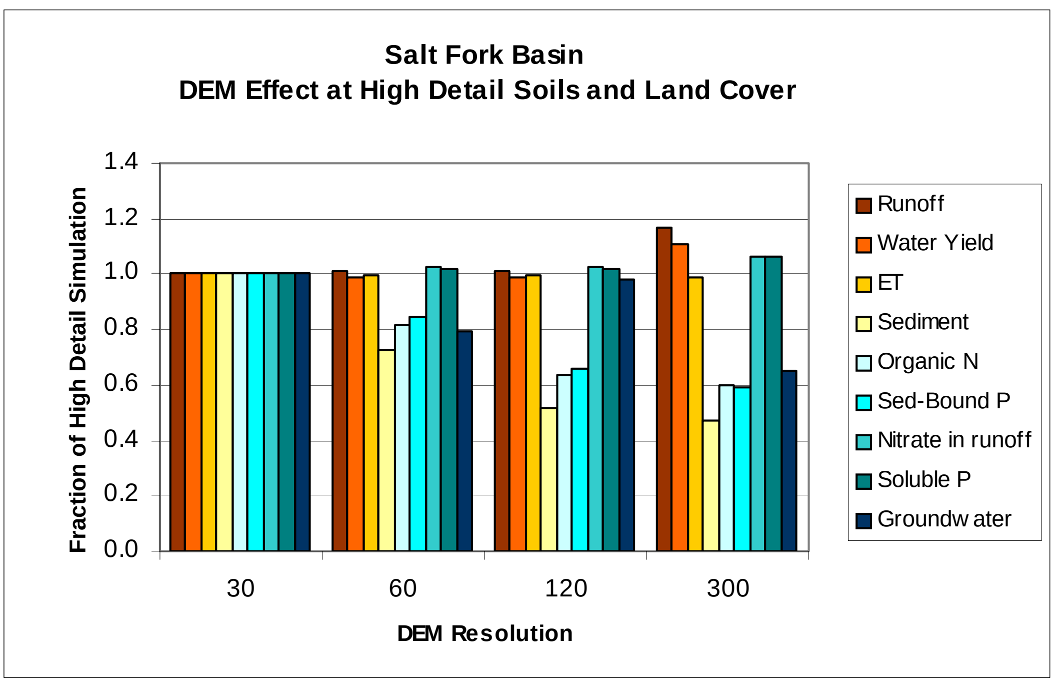


Figure 15. The effect of DEM resolution on the Salt Fork Basin at high detail soils and land cover. Displayed as a fraction of the 30m high detail soils and land cover simulation.

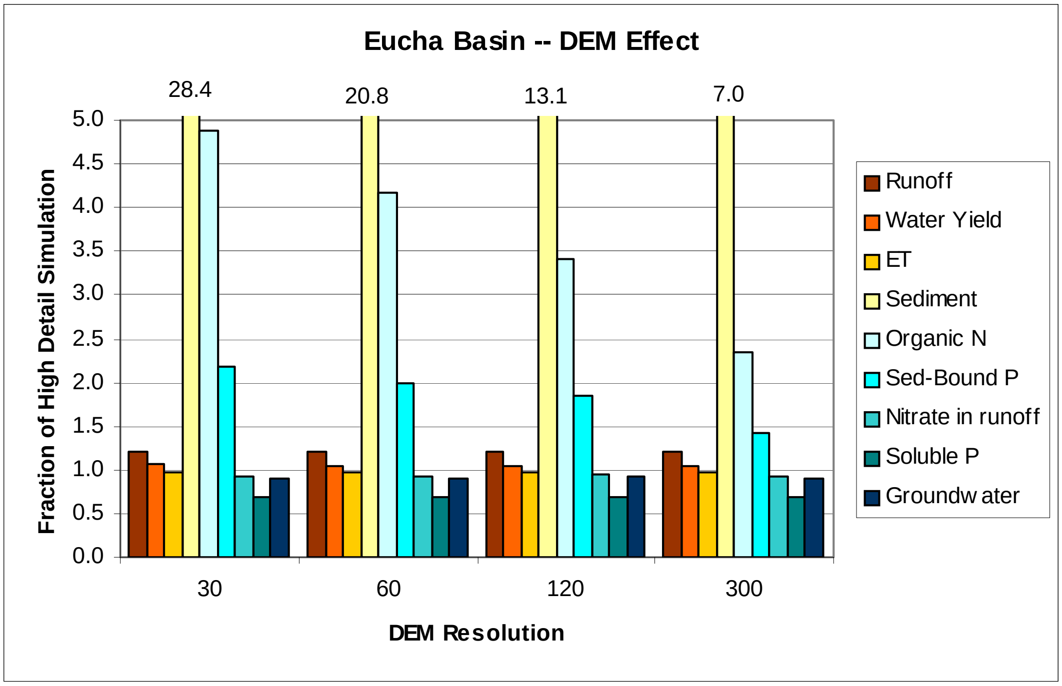


Figure 16. The effect of DEM resolution on the Lake Eucha Basin averaged across all levels of soils and land cover. Displayed as a fraction of the 30m high detail soils and land cover simulation.

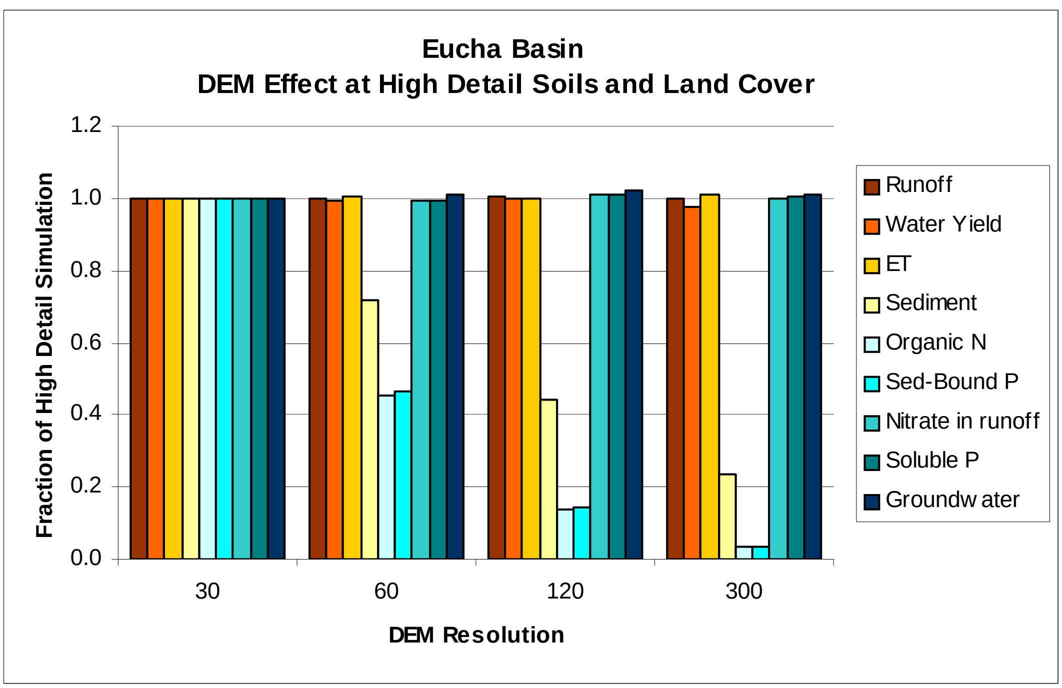


Figure 17. The effect of DEM resolution on the Lake Eucha Basin at high detail soils and land cover. Displayed as a fraction of the 30m high detail soils and land cover simulation.

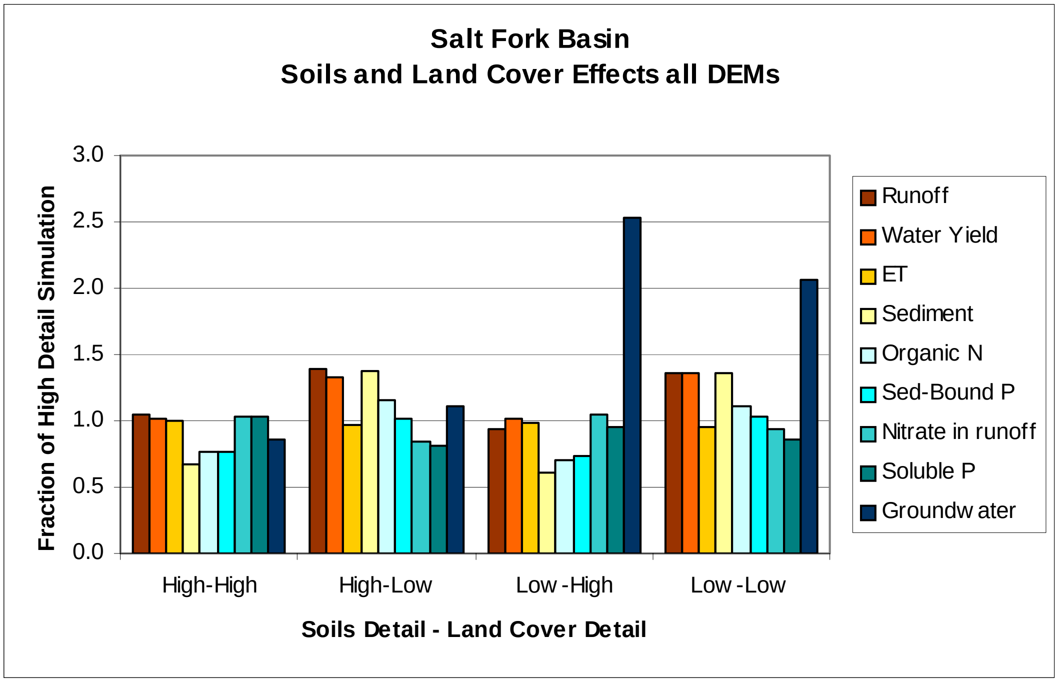


Figure 18. The effect of soils and land cover detail across all levels of DEMs for the Salt Fork Basin. Displayed as a fraction of the 30m high detail soils and land cover simulation.

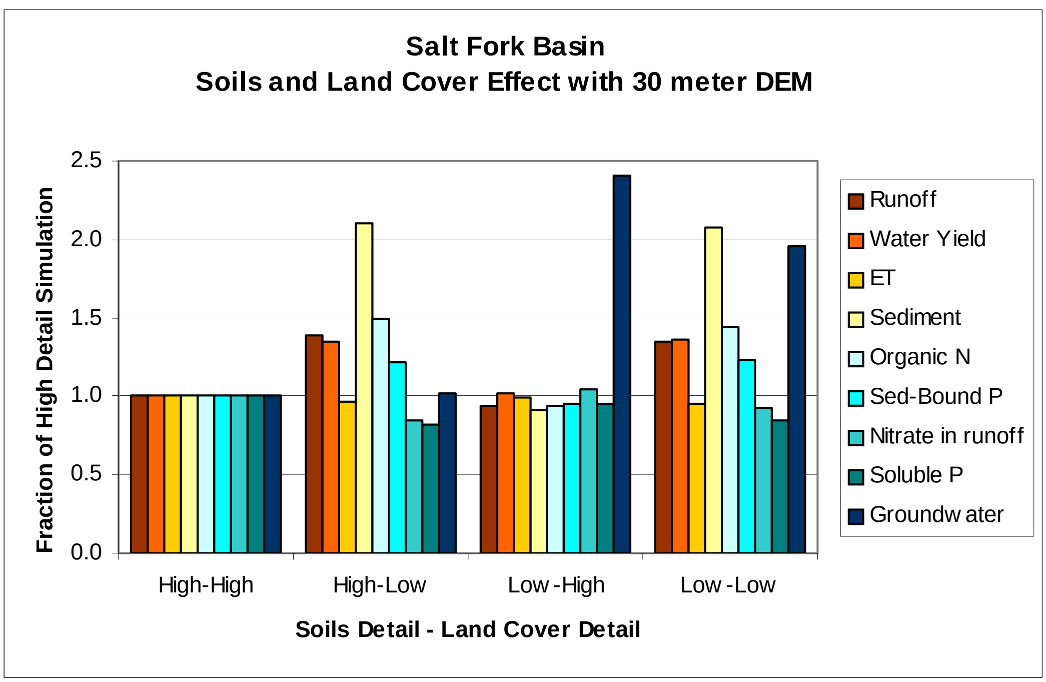


Figure 19. The effect of soils and land cover detail across 30 meter DEMs for the Salt Fork Basin. Displayed as a fraction of the 30m high detail soils and land cover simulation.

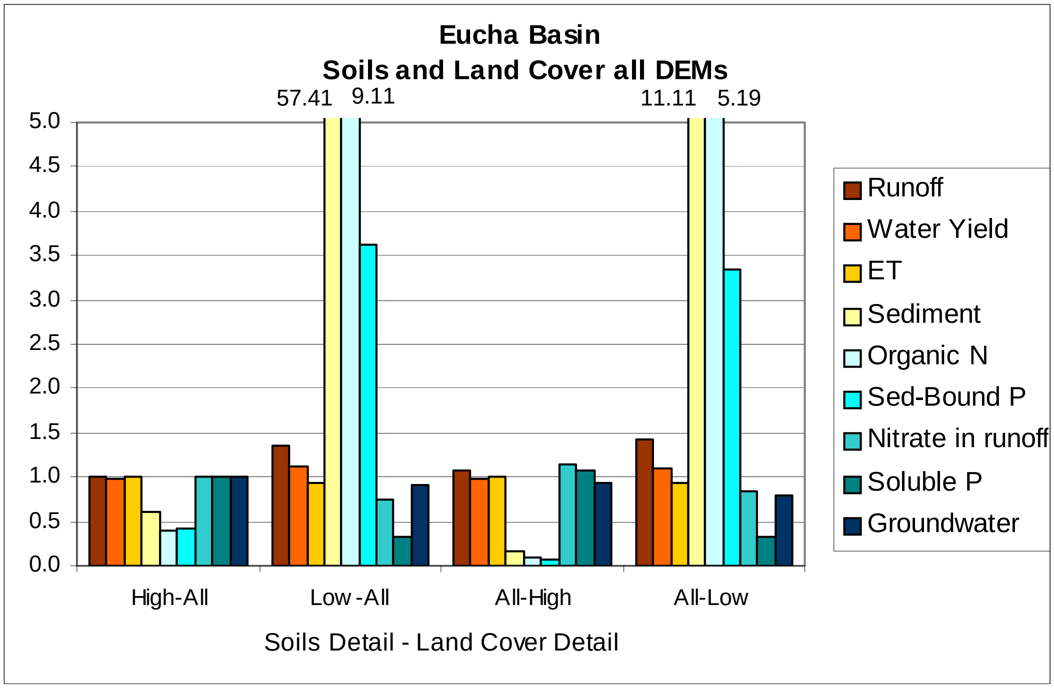


Figure 20. The effect of soils and land cover detail across all levels of DEMs for the Lake Eucha Basin. Displayed as a fraction of the 30 m high detail soils and land cover simulation.

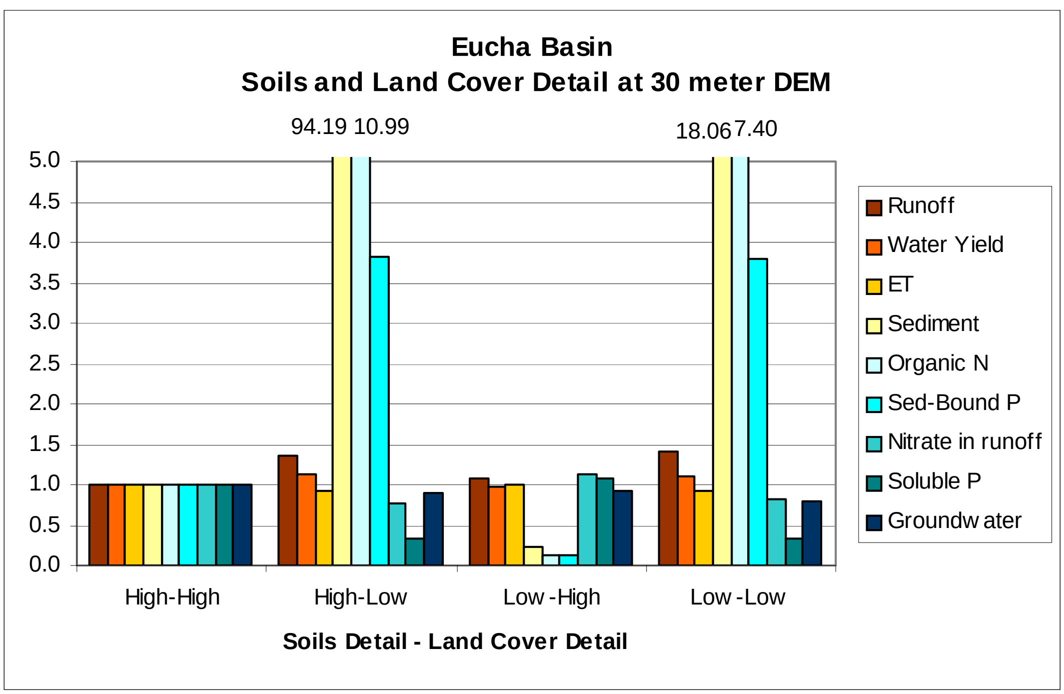


Figure 21. The effect of soils and land cover detail across 30 meter DEMs for the Salt Fork Basin. Displayed as a fraction of the 30 m high detail soils and land cover simulation.

Conclusions

The goal of this study was to evaluate the following hypotheses:

1) Soil data source has a significant effect on model output.

H0: SWAT simulations using SSURGO (or high resolution equivalent) soils are significantly different as compared to simulations using STATSGO soils.

H1: Choice of soil data source has no significant effect on SWAT predictions. STATSGO data are adequate.

H0 was not rejected.

Soils data type had little effect for the majority of outputs for both basins, but there were significant differences between basins. For instance, sediment and sediment-bound nutrients showed much greater differences for the Eucha Basin than for Salt Fork Basin. The importance of soils data is largely a function of how the model is to be used. In some situations, soil detail effects would not be significant, i.e. you are interested only in total water yields. Typically, it would be very advantageous to use low detail soils data due to the difficulty incorporating highly detailed soils data.

2) DEM resolution has a significant effect on model output.

H0: SWAT simulations at DEM resolutions of 30, 60, 120, and 300 meters are significantly different.

H1: SWAT simulations at various DEM resolutions are not significantly different.

H0 was not rejected.

Sediment and sediment-bound nutrients decreased as DEM resolution increases. This trend was apparent in both basins. If sediment and sediment-bound nutrients were of no interest, there would be little benefit in using very high resolution DEMs. Only the 300 meter Salt Fork simulations showed any significant difference in runoff.

3) Land cover data source has a significant effect on model output.

H0: SWAT simulations using LULC, GAP, and NLCD are significantly different.

H1: Land cover data source is not important. LULC land cover data are adequate.

H0 was not rejected.

Land cover was the single most influential data type tested. Land cover exhibited a significant effect at almost ever parameter of both basins. Land cover variations produced the largest departure from the baseline outputs for both basins. All SWAT simulations should use the most detailed and recent land cover available.

An additional goal of this research was to rate the difficulty of manipulating and including the various data types discussed into the SWAT model (Table 7). The purpose was to provide additional information to SWAT users to help them choose which data to include. These measurements are subjective in nature, but are the product of significant experience both using and teaching SWAT.

Table 7. Subjective relative difficulty developing and including selected GIS data types and resolution into SWAT (10 = high level of difficulty; 1 = minimal difficulty).

Data type	Coverage	Relative Difficulty 1-10
Land Cover	LULC	2
	GAP	4
	NDLC	3
Soils	SSURGO	10
	MIADS	5
	STATSGO	4
Topography	30 m DEM	6
	60 m DEM	5
	120 m DEM	4
	300 m DEM	2

Summary

The purpose of this study to determine how the inclusion of low detail data effects the SWAT model. SWAT was recently included in the release of the EPA hydrologic modeling suite BASINS 3.0 (Better Assessment Science Integrating Point and Nonpoint Sources). Along with BASINS, a data set of all necessary GIS data was compiled. The data set released with BASINS is far less detailed than that currently available from other sources, but is very easy to use. More detailed data may significantly improve results, or may not be worth the additional effort.

GIS layers of soils, land cover, and topography were examined in the SWAT model. Each basin was examined separately with a model run for each combination of GIS data. Comparisons between model runs were made relative to the baseline or most detailed model run. The number of subbasins and HRUs remain nearly constant for all simulations of a particular basin. Results were derived from non-routed model outputs obtained using a custom VBA (Visual Basic for Applications) program.
The following are conclusions drawn from this study:

1. Soils data detail had little effect for the majority of outputs for both basins.
2. Sediment and sediment-bound nutrients decreased as DEM resolution increases.
3. Land cover was the single most influential data type tested. Land cover exhibited a significant effect at almost ever parameter for both basins.

RECOMMENDED METHODS TO COMPARE SWAT MODEL OUTPUT

SWAT is a distributed model with both routed and unrouted outputs. SWAT provides output at the HRU, subbasin, and stream reach levels, thus there are many ways to evaluate model output. Model output must be evaluated during model calibration and validation, and to make predictions when testing scenarios or BMPs. Calibration is the process by which a model is adjusted to make its predictions agree with observed data. Validation is similar to calibration except the model is not modified. Validation tests the model with observed data that is not used in the calibration. How the model will be compared should be considered during the initial stages of modeling. Points of interest must be added as subbasin outlets so that SWAT will generate output at that location. All data that will be used should be in hand before the final model is constructed.

Acceptable Comparisons for Uncalibrated Models

The calibration of a model significantly improves the reliability of the model predictions. Although the calibration of a model is preferred, it is not always possible. Model calibration requires a significant amount of data, both water quality and stream flow measurements, and generally takes from several days to weeks to complete. Depending on the objectives of a particular project, calibration may not be necessary. SWAT does not require calibration or validation to evaluate scenarios or BMPs, however the lack of calibration does limit the predictive accuracy of the model due to high uncertainty. Model results may be compared on an absolute or relative basis. Absolute predictions describe a quality of a particular parameter, i.e. "the sediment load under the new BMPs changed from 750 to 500 Mg/yr". Relative comparisons typically evaluate results from a scenario or BMP to a baseline condition as a fraction or percent change, i.e "the sediment load under the new BMPs reduced by 33 %". Relative comparisons are more robust than absolute predictions because they reduce systematic errors common in uncalibrated models. Absolute comparisons from uncalibrated models contain far more uncertainty and should be presented in that context. Sometimes the objectives of a project permit results with high uncertainty and an uncalibrated model is easier.

Acceptable Comparisons for Calibrated Models

Calibration and validation require that model output be compared with measured data. It can be difficult to determine the best comparison, because SWAT's numerous outputs allow so many ways to make comparisons. The types of comparisons acceptable for calibrated models depends greatly on how the model was calibrated and the quality and detail of the data used in the model and its calibration.

Selecting the Output Time Step

SWAT provides output on an annual, monthly, or daily basis. The proper time step on which to make comparisons depends on the objectives of the project and the data used in the SWAT model. Annual predictions are in general more reliable and require less detailed data to be incorporated into SWAT than monthly or daily predictions. To get reliable daily predictions, significantly more accurate and detailed model input and calibration data are required than what is generally available. Monthly predictions are an excellent compromise, allowing the objectives of most projects to be met with readily available model input datasets.

Average Annual Comparisons

Average annual comparisons are the most basic of model comparisons requiring the least sophisticated or detailed model inputs. Weather data for simulations using average annual comparisons may be simulated using SWATs internal weather generator provided the comparison will be made over many years (at least 10 to 20 years). The weather generator uses statistics from local stations provided by an internal database. Most model calibrations begin by comparing average annual conditions before proceeding to other comparisons where the calibration if further refined. These are typically displayed in a table (Table 8).

Table 8. Example comparison of average annual model output.

Gage	Observed			Predicted			Relative Error
	Total Flow	Surface Runoff	Baseflow	Total Flow	Surface Runoff	Baseflow	Total Flow
Blackhollow	0.109	36% - 22%	78% - 64%	0.094	53%	47%	-13.7%
Beaty Creek	1.33	59% - 52%	48% - 41%	1.37	52%	48%	2.9%
Spavinaw Creek	3.3	60% - 43%	57% - 39%	3.45	48%	52%	4.4%

Annual Comparisons

Annual comparisons are performed year by year. Observed weather data are required due to the annual weather variability. These comparison can be made either in a table or graphically (Figure 22).

Monthly Comparisons

Monthly comparisons are typically the limit for most modeling endeavors using SWAT. Refining the model further to daily would typically require vastly more detailed weather and management information. Monthly comparisons capture the seasonal trends that are often important in many analyses (Figure 23). Average monthly comparison, i.e. average of all Januaries, average of all Februaries, etc., is particularly useful to identify systematic errors associated with baseflow and surface runoff. These seasonal trends are often lost in the noise of monthly variations due to weather (Figure 24).

Daily Comparisons

Daily data are common in observed datasets (i.e. streamflow and water quality measurements), thus it is tempting to view model results on a daily basis (Figure 25). However, that may not be the best approach. Weather is the driving force for any hydrologic model and thus uncertainty in the rainfall or the rainfall distribution across the watershed is important. Highly detailed rainfall data such as NEXRAD Weather Surveillance Radar 88D (WSR-88D), day by day management, and point source discharge data are preferred. The inclusion of NEXRAD derived weather data should improve the accuracy of the model and reduce this limitation. Rainfall can be quite variable in Oklahoma, especially in the spring and summer when convective thunderstorms produce precipitation with a high degree of spatial variability. It may rain heavily at one location, but be dry a short distance away. Instream processes become important when making daily predictions for monthly and annual predictions these are generally ignored. On an average annual or average monthly basis, these kinds of errors have less influence since they are typically not additive.

Comparing Modeled to Observed Data - Objective Functions

There are may ways to determine how well a model is performing by comparing predictions to observed data. These comparisons may be subjective visual comparisons using graphs or objective functions that calculate a “goodness of fit”. The most common include R^2 (Figure 26), Relative Error (Table 8), and Nash Sutcliffe Efficiency. Most modelers will use a combination of visual comparisons and objective functions. Visual comparisons and relative error calculations are typical relied upon during calibration when a modeler needs to know not only how good the fit is, but what should be changed to improve it.

Comparing Streamflow

Stream flow has two primary sources, surface runoff and ground water. Ground water contributions to stream flow are known as baseflow. When possible, the SWAT model should be calibrated on both surface runoff and baseflow. These fractions are not treated separately by the model once they enter a reach. It is possible to determine the amount of surface runoff and baseflow before they enter the reach. These data are in the Basins.BSB file. However, these data do not account for direct stream precipitation, evaporation, transmission losses, and other in-stream processes. An area weighted average of these data must be combined with the total routed flow to estimate the amount of surface runoff and baseflow. This problem is discussed further in Chapter 33 of the SWAT2000 User's Manual.

Comparing Model Predictions to Observed Water Quality Data

Direct comparisons of water quality sample values to SWAT model predictions requires daily model output. Daily model output should only be generated when input data are of sufficient quality, which is seldom the case. To circumvent this limitation water quality data are combined with stream flow to generate monthly or annual pollutant loads, which can be compared directly to the SWAT predictions. Estimating pollutant loads can be as simple as taking the flow weighted average concentration multiplied by the stream flow, depending on the required accuracy. More accurate methods develop relationships between concentration and flow, and these may be simple linear relationships or complex multi-variate relationships requiring eight or more parameters to be estimated.

There are several computer programs available to aid in the development of nutrient loads. Currently the most user friendly program is the USGS DOS program LOADEST2 (Crawford, 1996). This program was developed by Charles Crawford (USGS Supervisory Hydrologist) to estimate loading using the rating curve method. The software has ten models from which to choose, and will develop both seasonal and daily load estimates. A far more comprehensive discussion of load estimation methods can be found in *Estimation of Pollutant loads in Rivers and Streams: A guidance Document for NPS Programs* (P. Richards 1999).

Routed vs Unrouted Comparisons

SWAT contains two distinctly separate models, an upland model and an instream model. The upland model predicts how much water, sediment, nutrients, etc. reach the stream system from each subbasin. The instream model routes the water, sediment, and nutrients from each subbasin to the watershed outlet. Instream processes define the difference between routed and unrouted model predictions. Routed data are subject to these processes as simulated by SWAT, unrouted are not. During the routing process SWAT simulates evaporation and seepage, sediment deposition and reentrainment, and nutrient transformations. In most stream systems the routed and unrouted water yield will be similar at the month and year time scales. However, instream water storage and transportation lags become important when making daily stream flow predictions.

SWAT nutrient instream processes are based on the Enhanced Stream Water Quality Model QUAL2E (Brown and Barnwell 1987). There are limitations in SWAT's instream model with regard to nutrients, although work is progressing in that area (White et al., 2003; Wade et al., 2001; Viney et al., 2000; Santhi et al., 2001). We currently recommend that SWAT's built in instream nutrient processes be disabled. This presents a problem because when we measure water quality parameters by collecting a sample, it has been subjected to these processes. When we develop loads from these water quality data, the loads have been subject to these instream processes as well. We seldom have observed data to predict upland loads directly, but plot and field scale studies can sometime provide guidance to ensure that our loads are reasonable (Beaulac and Reckhow 1982). The extent to which the instream processes have modified nutrients depends on the particular stream system and where the sample was collected. In general the lower the stream order the less modification occurs by instream processes.

Instream nutrient processes cannot destroy nutrients, they are simply converted to other forms or detained in biota and sediments. Some nutrient transport by wildlife and domestic animals certainly occurs. Wildlife transport is likely negligible, however cattle can directly deposit significant quantities of nutrients into streams. In dimensionally stable streams total phosphorus can often be treated as conservative in the long term. Nitrogen, however, can leave the stream system as N_2 or NH_3 and may not be treated as conservative under all conditions. Both phosphorus and nitrogen may be converted from one form to another many times as they are transported downstream in a process refereed to as nutrient spiraling (House 2003).

In order to calibrate the model we must make some assumptions.

- Assume that the instream processes are insignificant, and calibrate using our loads derived from observed water quality data.

- Assume that over long periods (greater than one year) nutrients are conservative and restrict nutrient calibration to total phosphorus and total nitrogen.

Honesty in Predictions (Dealing with Uncertainly)

We can predict nutrient loads from a watershed next year only as accurately as we can predict the weather for the next year. Rainfall is the driving force behind nutrient transport. Because rainfall is so important, it represents a major source of uncertainty. The uncertainty associated with water quality models is difficult to fully quantify. According to MacIntosh et al. (1984), there are two major types of uncertainty, knowledge uncertainty and stochastic uncertainty. Knowledge uncertainly stems from measurement errors and the inability of the model to accurately simulate the physical, chemical, and biological processes. Stochastic uncertainty is due to the random nature of natural systems, like rainfall. One method to quantify this uncertainty is to perform many simulations of the same scenario using different rainfall records. In this manner we can quantify the stochastic uncertainty associated with natural temporal variability in rainfall. The uncertainly due to rainfall is generally larger than the benefit from most BMPs. Thus the impact of a BMP can be masked by natural variations in rainfall form year to year. We currently lack the science to quantify knowledge uncertainty, however we can make some qualitative statements about uncertainty that apply to all SWAT simulations.

- Scenarios involving radical departures from calibration conditions result in greater uncertainty. Although calibration assures the user that the results reflect the range of conditions encountered at the watershed, they do not assure the model will be accurate for drastic changes in land use or management.

- There is uncertainty associated with specifying uniform management for a land cover category. It is not practical to specify management for every field in a large basin, and thus a typical management is selected and applied basin-wide for each land cover type. Management operations include grazing, fertilization, tillage, planting, and harvesting.

Each watershed is unique and the model built to represent it will have it’s own sources of uncertainty. Hydrologic models will always have limitations, because the science behind the model is not perfect nor complete, and a model by definition is a simplification of the real world. Understanding the limitations helps assure that accurate inferences are drawn from model predictions.

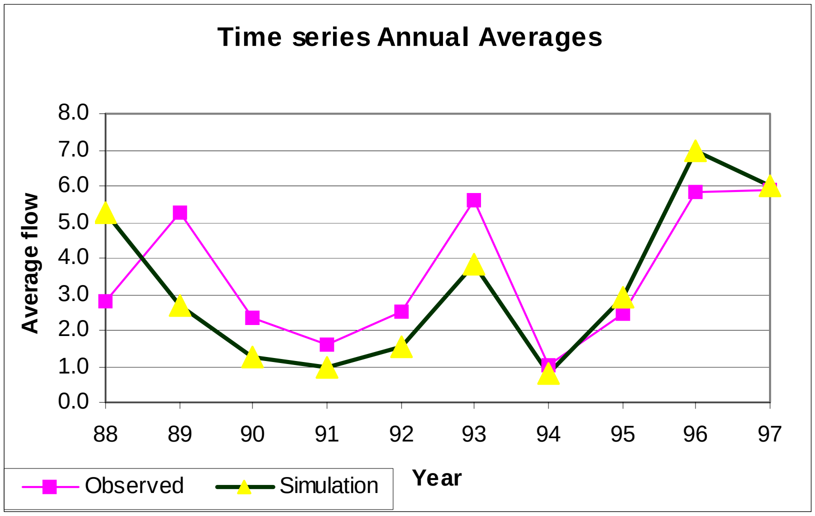


Figure 22. Example of annual comparison.

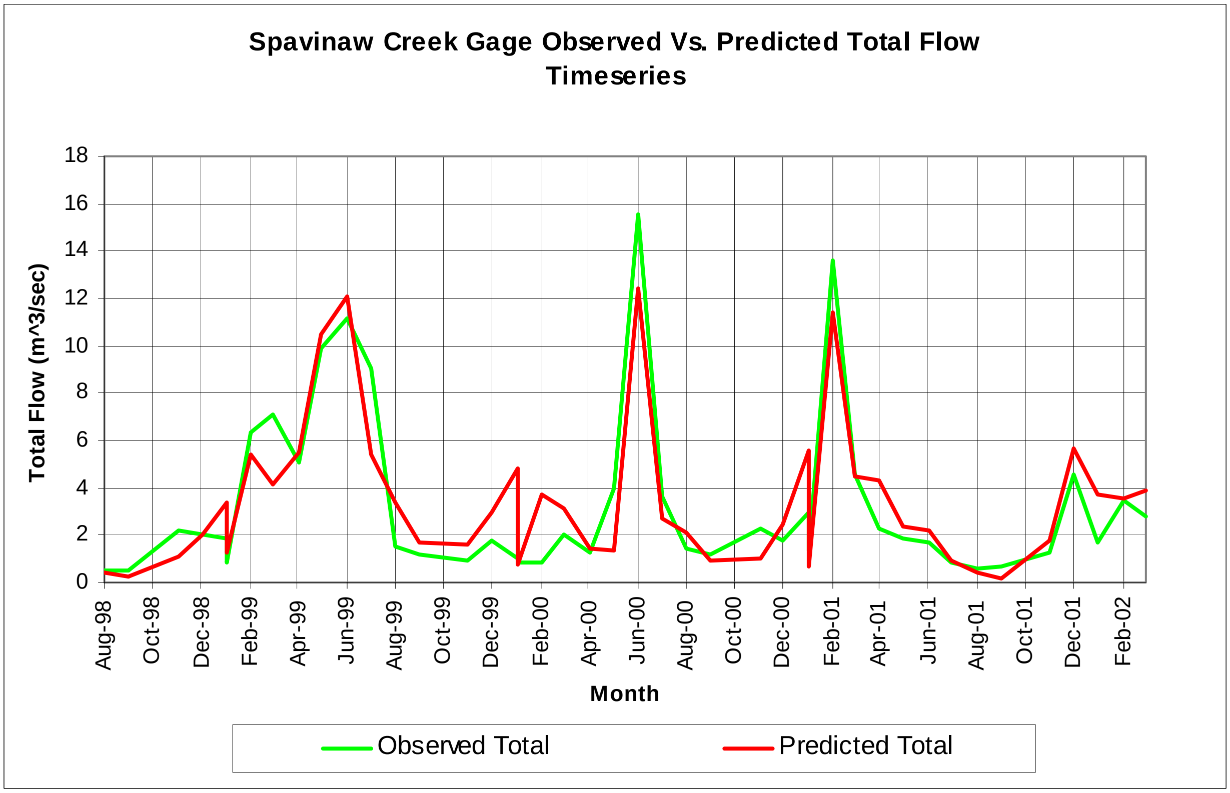


Figure 23. Example of monthly comparison.

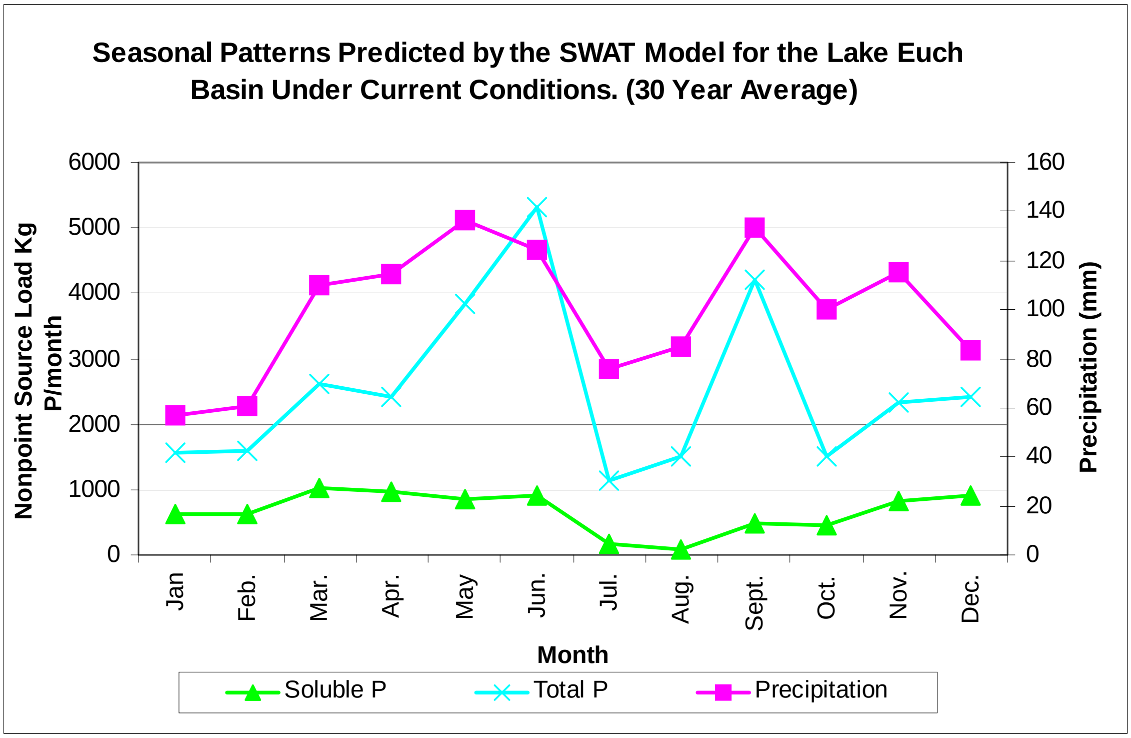


Figure 24. Example of average monthly comparison.

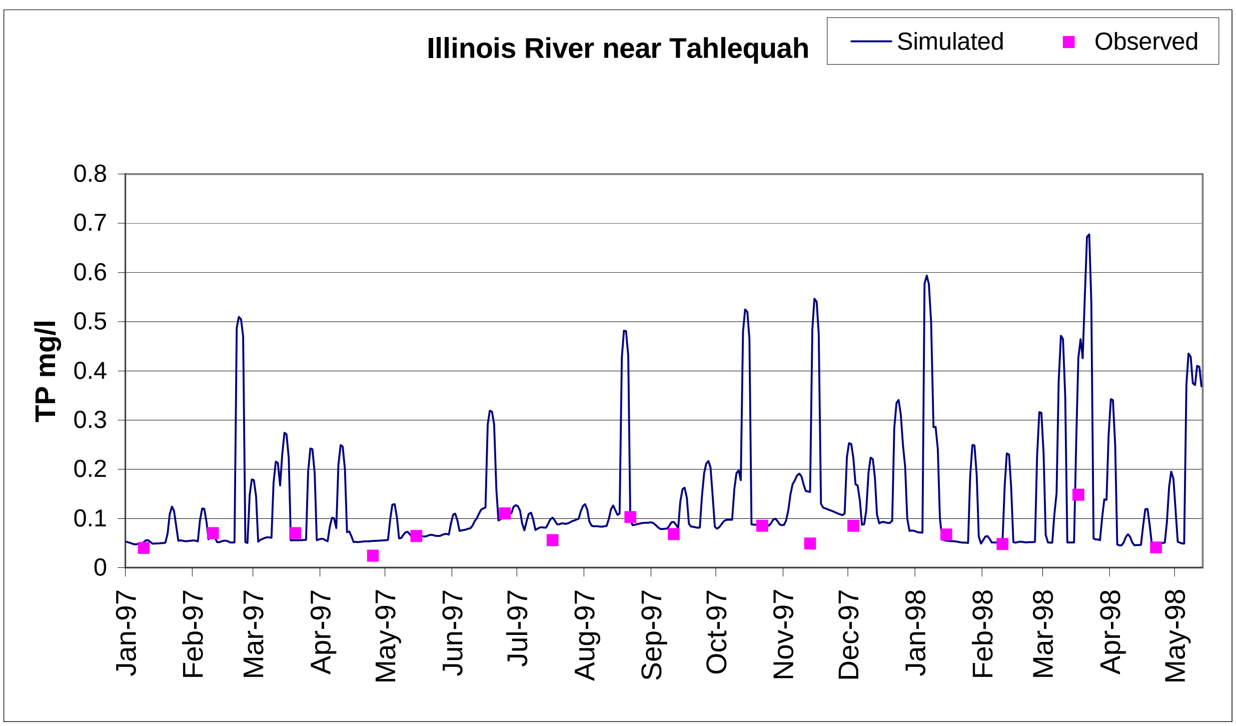


Figure 25. Example of daily predictions compared to water quality observations.

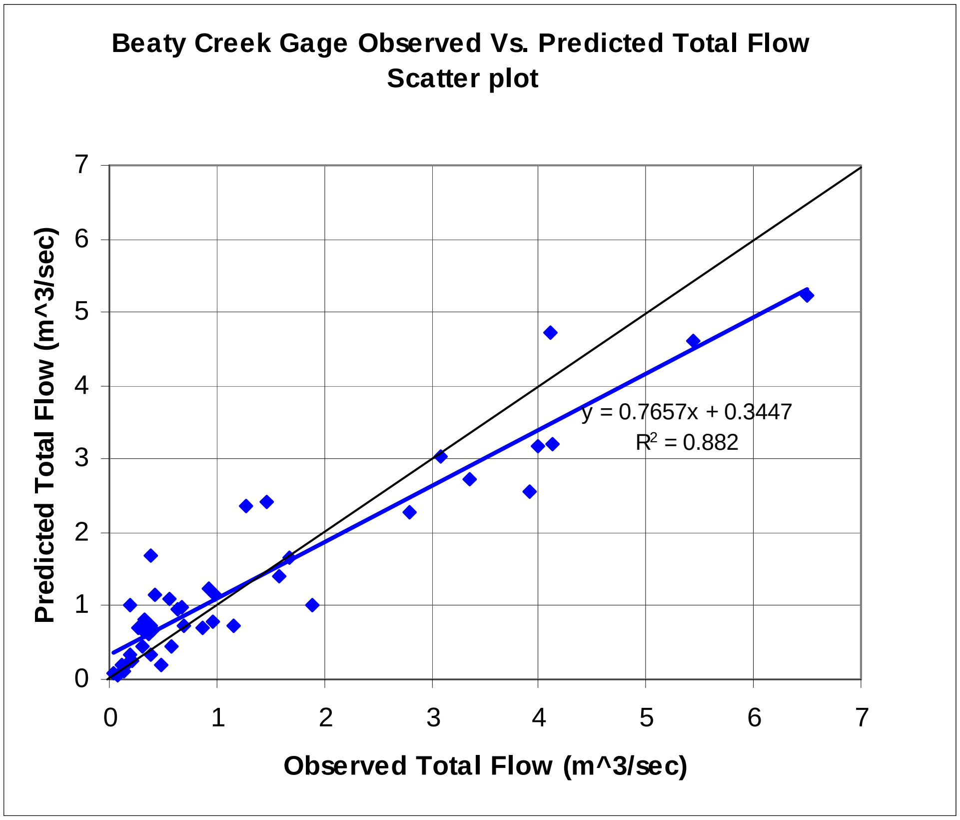


Figure 26. Example of Monthly scatter plot with regression R^2 and 1:1 line.

ADDITIONAL SWAT RESEARCH NEEDS

There are limitations to any hydrologic/water quality model, including SWAT. A good hydrologic/water quality model is continually being tested and updated as new data, modeling approaches, and processes are identified and quantified. The following are suggested areas for additional research and improvements for the SWAT model. Please note that some of these item may be in the new SWAT 2003 release.

Model

1. Detailed riparian model
2. Alternative instream model
3. Improvement to the current instream model
4. Improved vegetated buffer strip model
5. Surface application of animal wastes algorithm
6. Improvement in soil phosphorus pools and parameters
7. Alternative erosion algorithms
8. More robust ground water model
9. Improved nitrogen and phosphorus subsurface transport model
10. Carbon transport model
11. Supplemental cattle feed option
12. More accurate and detailed Curve Numbers for cattle grazing
13. Multiple/competing plant growth model

Interface

1. Grid-cell interface
2. Slope and distance to stream by HRU
3. Autocalibration routines
4. Grid-cell based weather input
5. Improve management editor
6. More flexibility in output options

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APPENDIX A

SWAT Peer Reviewed Publications
Journal Publications and Book Chapters

Updated June 2, 2004
Provided by Dr. Manuel R. Reyes
(Source: http://www.brc.tamus.edu/swat/pubs_peerreview.html)

Allen, P.M., J.G. Arnold, and E. Jakubowski. 1999. Prediction of stream channel erosion potential. *Environmental and Engineering Geoscience* V(3):339-351.

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APPENDIX B
SAS Programs

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*FILENAME STATS.SAS;
DATA ONE;
INFILE 'A:STATS.PRN';
INPUT year Tillage$ grazing$ PRCP SURQ GWQ ET SYLD SEDP NSURQ SOLP NO3L
Orgn LATN;
*PROC PRINT;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
MODEL PRCP = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
MODEL SURQ = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
MODEL GWQ = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
MODEL ET = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
MODEL SYLD = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
MODEL NSURQ = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
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MODEL SOLP = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
MODEL NO3L = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
MODEL Orgn = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
PROC MIXED;
CLASS YEAR TILLAGE GRAZING;
MODEL LATN = TILLAGE|GRAZING/DDFM=SATTERTH;
RANDOM YEAR;
LSMEANS TILLAGE*GRAZING/SLICE=(TILLAGE GRAZING) DIFF;
LSMEANS TILLAGE GRAZING/DIFF;
RUN;
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APPENDIX C

Application of SWAT 2000 to Basins with Significant NPS Components
Training Session/Short Course

December 9-13, 2002
Department of Biosystems and Agricultural Engineering
Oklahoma State University, Stillwater, Oklahoma

Precourse Reading Assignment

To make the best use of our limited classroom time, we have assembled a list of materials for review prior to the short course. These materials fall into two categories, ArcView review and SWAT theory. You may not need to review both depending on your experience.

ArcView Review:

The University of South Carolina has an excellent set of ArcView materials. We cannot provide copies due to copyright restrictions, but you may download them via the web. We recommend the following be reviewed prior to the course:

Introduction to GIS Concepts	ftp://ellie.cla.sc.edu/pub/gis_webdocs/concepts.pdf
Introduction to ArcView	ftp://ellie.cla.sc.edu/pub/gis_webdocs/av_intro.pdf
Raster GIS	ftp://ellie.cla.sc.edu/pub/gis_webdocs/av_raster.pdf
Other Sections:	http://wagda.lib.washington.edu/help/tools.html

SWAT Theory:

We have included a link to SWAT2000 manuals and some pertinent journal articles for review (30 MB). We will provide hard copies of the manuals at the time of the short course. If you wish to have your hard copy sent to you before the course, please contact Mike White at mjwhite@okstate.edu. Please review the following articles and sections of the manuals prior to the short course.

Articles:
Large Area Hydrologic Modeling and Assessment Part 1: Model Development
Large Area Hydrologic Modeling and Assessment Part 2: Model Application

Manuals:
Introduction (Chapter 1) - S.W.A.T. Theoretical Documentation

ArcView Interface for SWAT 2000 User's Guide - A detailed review of the manual is not required, but skimming it will help you get a feel for how the interface functions. A step-by-step tutorial is given in Section 15 if you wish to get a head start.

Course Outline

Instructors:

Dr. Dan Storm	Mike White
Professor	Research Engineer
dstorm@okstae.edu	mjwhite@okstate.edu
(405) 744-8422	(405) 744-8429

Description:

This is an applied modeling course that will be conducted in a computer laboratory in a "hands on" fashion. The materials are geared toward professionals with working knowledge of ArcView and a background in hydrology. A set of precourse materials will be given to allow students to review and prepare for the course. Upon completion of the course, you will be able to create and calibrate a basic SWAT model for any basin in the USA.

The course will consist of 14 sections, each increasing in complexity and building on the knowledge gained in the previous section. Sections are shown below:

Section	*Description*
Introduction	Soil and Water Assessment Tool (SWAT): Background and Theory
1	Introduction to SWAT
2	ArcView Review
3	Spavinaw Creek - Step by Step Modeling
4	Battle Branch - GIS Data Layers
5	Battle Branch - Tabular Data
6	Battle Branch - Baseline Model
7	Battle Branch - Flow Calibration
8	Illinois River - Baseline model
9	Illinois River - Model Refinement
10	Illinois River - Hydrologic Calibration
11	Illinois River - Nutrient Calibration
12	Illinois River - Scenarios
13	Estimating Loads using Loadest2

Location:

The course will be held at the Biosystems and Agriculture Engineering Department Laboratory. Temporary parking permits will be provided.

Section Descriptions

Section 1 Introduction to SWAT

The purpose of this section is to introduce some of the more important concepts related to the SWAT model. It is not intended as a theoretical guide and presents only simplified explanations. More detailed explanations are available in the SWAT User's Manual and theoretical documentation.

Section 2 ArcView Review

A working knowledge of ArcView is a prerequisite for this training. We will however, review some basic ArcView concepts, and install some extensions that we will need later on. ArcView 3.x is a powerful GIS software package distributed by Environmental Systems Research Institute, Inc (ESRI). The versatility of ArcView stems from the use of an object oriented programming language called Avenue, which makes ArcView fully customizable. ArcView was also designed to utilize modules called extensions to increase its capabilities. The SWAT interface is an ArcView extension. There are a great number of extensions written by ESRI, third party organizations, and individuals. Some are freely available and may be downloaded via the Internet.

Section 3 Spavinaw Creek - Step by Step Modeling

In this exercise we will set up the SWAT model for the Spavinaw Creek Watershed. The intent is to introduce you to SWAT using a very detailed step by step methodology. No calibration will be performed for this basin, however we will look at model output and the SWAT Calibration Tool. Spavinaw creek is located on the Arkansas/Oklahoma border. Note: All page numbers reference the SWAT ArcView manual.

Section 4 Battle Branch - GIS Data Preparation

The purpose of this exercise is to develop data layers required for SWAT. The following data layers will be created. Much of these data are available from the EPA BASINS 3 dataset. All the GIS used in SWAT will be converted into the projection UTM27 Zone 15.

Section 5 Battle Branch Watershed – Tabular Data

Weather Data

SWAT2000 can use a variety of observed weather data. In this exercise we will incorporate the most important two, daily precipitation and temperature. SWAT can also utilize solar radiation, wind speed, and relative humidity. All climate data used in this exercise will come from COOP stations. A COOP (Cooperative) weather station is a station at which observations are taken or other services are rendered by volunteers. NOAA has a database of 19,000 stations across the US.

Baseflow Separation

With the Battle Branch watershed, digital daily flow data are available. These data are located at C:\shtcrs\data\battle\Battle_flow.xls. Before calibration we must estimate the surface runoff and baseflow fractions. There are a number of methods to perform baseflow separation. The USGS HYSEP Method was selected because it is easy to use and works well with daily stream flow data.

Section 6 Battle Branch – Baseline Model

The goal of this exercise is to set up the SWAT model for Battle Branch. Data layers developed in sections 4 and 5 will be used in the SWAT model.

Section 7 Battle Branch - Flow Calibration

The purpose of this section is to calibrate the SWAT model for surface runoff and baseflow during our simulation period. Calibration is a trial and error process. The section is setup accordingly.

Section 8 Illinois River Baseline Model

The Illinois River Basin is located in eastern Oklahoma and western Arkansas. Because the basin contains scenic rivers, the basin is a hotbed of activity and policy. The remainder of this course will be dedicated to this basin.

Section 9 Illinois River - Model Refinement

Putting data into the ArcView SWAT interface and running the model is only part of modeling. The model needs to be refined to bypass limitations in the interface or to accommodate special circumstances particular to the basin. A major issue in the Illinois River Basin is the application of poultry manure to pastures in the basin. Over time it is thought that this practice has led to the high levels of STP observed in the area. We will include both the application of litter and the elevated STP in the model. In addition we will improve the estimates of slope by defining different slopes for land covers in each subbasin. SWAT normally uses the same slope for all land covers in a subbasin.

Section 10 - Illinois River – Calibration Hydrologic and Nutrient Calibration

We will perform the hydrologic and nutrient calibration by comparing model predictions with observed USGS stream gage and water quality data.

Section 11 - Illinois River – Scenarios

In this section we will alter the calibrated model to simulate a variety of scenarios. These scenarios are listed below:

1. ½ litter export
2. Pasture STP levels of 120 lb/acre with ½ litter export
3. All forested basin

Section 12 Estimating Nutrient Loads Using Loadest2

Loadest2 is a USGS program developed to compute loads using the rating-curve method. Loadest2 outputs several estimates of load calculated using different methods. Of primary concern are the Maximum Likelihood and Linear Attribution methods.