ABSTRACT

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                                       APPLICABILITY FOR WATERBODY
                                       IMPAIRMENT IDENTIFICATION AND
                                       TMDL ANALYSIS

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The U.S. EPA's Total Maximum Daily Load (TMDL) program has encountered

hindrances in its implementation partly because of its strong dependence on

mathematical models to set limitations on the release of impairing substances. The

uncertainty associated with predictions of such models is often not formally

quantified and typically assigned as an arbitrary safety factor to the margin of safety

(MOS) portion of TMDL allocations.

AVSWAT-X, a semi-distributed, watershed-scale model, was evaluated to determine

its applicability to identify the impairment status and tabulate a nutrient TMDL for a

waterbody located in the Piedmont physiographic region of Maryland. The

methodology for tabulating the nutrient TMDL is an enhancement over current

methods used in Maryland. The mean-value first-order reliability method (MFORM)

was used to calculate variance in output variables with respect to input parameter variance and the MOS value was derived based on the level confidence in meeting the water quality standard.

A calibration, validation and an uncertainty analysis was conducted on the AVSWAT-X model. Monthly results indicated that AVSWAT-X is a good predictor of streamflow, a moderate (at best) predictor of nutrient loading and a poor predictor of sediment loading. Improved performance was observed on an annual basis for nitrate and sediment loadings, indicating the most appropriate use of SWAT for long-term simulations. The most pronounced reason for discrepancies in model performance was the use of the SCS curve number method to tabulate surface runoff.

Uncertainty results indicated that input parameters that are highly sensitive may not necessarily contribute the largest amount of uncertainty to model output. The largest amount of variance in output variables occurred during wet periods. Predicted sediment output had the largest amount of variability around its mean, followed by nitrate, phosphate, and streamflow as indicated by average annual coefficients of variation of 28%, 19%, 17%, and 15%, respectively.

The methodology used in this study to quantify the nitrate TMDL and the MOS associated with it, was a useful tool and an improvement over current methods of nutrient TMDL analysis in Maryland. Overall, AVSWAT-X is a moderate to good

model for estimating waterbody impairment and conducting TMDL analysis of

waterbodies impaired by nutrients.

EVALUATION OF SWAT MODEL APPLICABILITY FOR WATERBODY
IMPAIRMENT IDENTIFICATION AND TMDL ANALYSIS

By

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Dedication

To those who exercise patience, care and understanding; those who build up and not
tear down; and those who operate in wisdom

In memory of the late Pastor Wayne D. Jackson
Your love will never be forgotten

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To my loving parents, Jacob and Dianna Sexton, you exemplify all of the traits listed on the dedication page, especially that of patience. Thank you for being by my side through thick and thin, for believing in me, encouraging me, and trusting me to make my own decisions in life. You have laid the foundation for my life's journey through your love, nurturing, and guidance. I am a product of you.

Finally, I give glory and honor to God my Savior, who has been my help and my strength through this entire process.

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Chapter 1: Introduction

Statement of the Issue

Uncertainties present in different aspects of water quality monitoring and modeling have been a major barrier impeding implementation of the most important water quality program to date. This program has the potential to bring U.S. waters to a level of wellness that has not been achieved over the last century. First enacted in 1972 as amendments to the Clean Water Act (CWA), the Total Maximum Daily Load (TMDL) program is the key legislative mandate to improve ambient water quality conditions. A TMDL is the maximum allowable load of a contaminant that a waterbody can receive while still meeting its water quality standard. A water quality standard consists of the designated use assigned to the water body (e.g., swimming, fishing, drinking, etc.), the water quality criteria (either numeric or narrative statement) to meet that use, and an anti-degradation policy to protect the existing use. Section 303(d) of the act says that States must identify all water quality limited segments (WQLS) (impaired waters), prioritize them, establish TMDLs for them, and submit them to the U.S. Environmental Protection Agency (EPA) for approval (U.S.Congress, 1972). States must determine the stressors (pollutants) and sources of impairment for WQLSs, as well as allocate TMDLs among contributing sources. The numerical endpoints that must be obtained to make TMDL decisions involve a great deal of natural, measurement and computational uncertainty that must be addressed in a scientifically defensible manner in order for the TMDL program to move forward.

History of the TMDL Program

Both Congress and EPA have halted revisions to TMDL regulations because of the many stakeholder concerns surrounding the scientific basis of the program. The TMDL program is currently operating under the 1992 amendments to the enacted TMDL regulations of 1985. Revisions to those regulations (called the "TMDL Rule") were released on July 13, 2000. Some two-dozen parties challenged the rule in August 2000. Those parties consisted mainly of farming and forestry groups who felt that non-point sources of pollution should not be regulated, but should continue to be handled on a voluntary basis (Christen, 2001). This prompted Congress, in October 2000, to suspend EPA's implementation of the 2000 rule until further information could be gathered on the program. This suspension was carried out through a rider to EPA's fiscal year 2001 budget. At the same time, Congress charged the National Research Council (NRC) to examine the scientific basis of the TMDL program (1992 regulations). The NRC conducted a four month study (January through April, 2001) that concluded, there is enough science to support the ambient water quality goals of the TMDL program, and in the face of uncertainties which will always exist, the program should still move forward (NRC, 2001).

In July 2001, EPA filed a motion asking the court to hold action on lawsuits over the rule for 18 months to allow the agency to review and revise the rule to achieve a workable program that meets the goals of the CWA. This decision, EPA claims, was based on the NRC report and numerous court challenges; however, the NRC felt that the hold on the TMDL rule should not have been based on their report (Christen,

2001). On December 20, 2002, EPA announced its proposal to withdraw the July

2000 final rule. EPA Administrator, Christine Todd Whitman, claimed that the rule

was "unworkable" (Anon., 2003). The 2000 final rule ("TMDL Rule") was

withdrawn on March 13, 2003. A new TMDL rule ("Watershed Rule") was expected

to be released in March 2003 (Shabman and Reckhow, 2002), however, it is currently

pending (September, 2007).

Numerical Endpoints in TMDL Tabulation

Decisions made within the TMDL program are based on essentially three numerical

endpoints. The first endpoint involves determining whether or not a waterbody is

impaired. As part of each State's water quality standards program, all waterbodies

within a State must be assigned a designated use and water quality criteria in order to

meet that use. When the amount of pollutant or pollutant indicator in a waterbody is

found to exceed the criteria to which it is assigned, that waterbody is considered to be

impaired. The second numerical endpoint upon which decisions are based is the

TMDL of a WQLS. A TMDL can be expressed as follows:

$$TMDL \leq LC \qquad\qquad\qquad\qquad\qquad (1)$$

where, LC is the loading capacity or the largest amount of contaminant load that can

be received by a waterbody without causing that waterbody to violate water quality

standards. A TMDL can be stated in a number of different ways, e.g. by reduction of

a pollutant in units of mass per unit time, or by a percentage reduction of the current

pollution load to meet water quality standards (NRC, 2001). The third numerical

endpoint is the portion of TMDL allocated to each individual source of contamination

as:

TMDL=∑WLA+∑LA+FG+MOS   (2)

where, WLA represents waste load allocation for point sources, LA corresponds to load allocation for non-point sources and natural background contributions, FG represents future growth estimates of WLA and LA, and margin of safety (MOS) accounts for uncertainty about pollutant loadings and waterbody response (USEPA, 1999a). Most of the controversy associated with the TMDL program lies within the quantification of all three of the previously mentioned numerical endpoints.

The values of the aforementioned numerical endpoints are obtained using both water quality monitoring and mathematical modeling strategies. Although some modeling is used, water quality monitoring is the preferred method of determining impairment within a State's water quality standards program (NRC, 2001; USEPA, 1999a). Monitoring is also important when measuring the effectiveness of TMDLs after treatment practices have been implemented. Mathematical models, however, play a central role in the TMDL program because they are used to determine the TMDL of a waterbody, as well as allocate that TMDL among sources. Models represent our knowledge, however limited, about the processes governing ecosystem response to stressors. They are one of the main tools used to make management decisions within the TMDL program. A recent review has found that the status of TMDL modeling tools for the most common stream impairments is inconsistent (Munoz-Carpena et al., 2006). Therefore, there is a need to address the existing problems in the modeling process.

Mathematical models are mainly used in the TMDL program because of the scarcity and limitations of monitored data. Non-point source pollution monitoring studies seldom have the ability to pinpoint sources of pollution and determine the best strategic plan to minimize pollution from different sources. On the other hand, models are able to estimate the amount of reduction necessary to meet water quality standards using different treatment scenarios as well as simulate the effect that different treatment strategies (e.g., National Pollutant Discharge Elimination System [NPDES] reductions, Best Management Practice [BMP] reductions) have on water quality after implementation.

One of the main problems associated with using mathematical models for TMDL assessment lies in the quantification of uncertainties (NRC, 2001; USEPA, 2002a). Stakeholders would like to have some sense of reliability in model predictions, especially when decisions based on model results can potentially impose both legal and financial responsibility upon point and non-point source contributors. Uncertainties in mathematical modeling are accounted for in the margin of safety (MOS) portion of TMDL allocations (see equation 2). MOS is typically expressed in implicit or explicit terms (USEPA, 1999a). Implicit considerations involve making some type of conservative assumption when tabulating a TMDL, e.g. increasing the threshold of a water quality criterion above that which is necessary. Explicit considerations involve assigning a numeric safety factor to the value of MOS, e.g. 5%

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of the point and non-point source allocations. Both terms represent a highly subjective means of accounting for uncertainty (NRC, 2001).

EPA guidance and report documents (USEPA, 1999a; USEPA, 1999b; USEPA, 2002a) have suggested that MOS be calculated based on scientific information rather than subjectively assigned, however, it is only recently that scientists have begun to devise and study formal uncertainty and error propagation strategies to determine MOS. As a result of the collective effort of a multidisciplinary panel of experts to evaluate the current status of TMDL modeling technology, Shirmohammadi et al. (2006) proposed that the explicit quantification of uncertainty be made an integral part of the TMDL process. Hence, there is a need for further study and development of formal methods to calculate MOS. The impact of the knowledge gained from these methods could allow the TMDL program to overcome a huge hurdle that has held back the program for some time. With more scientifically defensible measures of uncertainty, decision processes within the TMDL program can be accomplished with greater ease. This knowledge should also instill a greater sense of reliability for stakeholders who have opposed the program because of unknown measures of uncertainty.

Land Use and Contaminant of Interest

Non-point sources of pollution are the largest remaining unregulated source of water pollution (DNR, 2000). According to EPA's National Water Quality Inventory 2000 Report, agricultural activities are the leading source of impairment in lakes, ponds, reservoirs, rivers, and streams (USEPA, 2002b). Nutrients (mainly nitrogen and

phosphorus), one of the main types of pollutants emanating from agricultural lands, are the leading cause of impairment in lakes, ponds, and reservoirs; the fifth leading cause of impairment in rivers and streams (USEPA, 2002b).

Over the past two decades, major efforts have been underway to combat these issues across the nation. For example, the Chesapeake Bay Agreement of 1987, renewed in the year 2000, set a goal to reduce nutrient loads to the Bay by 40 percent (CBP, 2000). All indications show that this goal will not be met by the year 2010, its targeted year of completion (Blankenship, 2006). However, the goal will potentially be met in the future by improving the water quality of segments of the Bay and its tributaries that are currently listed as impaired waters in the TMDL program such that they are removed from the list (Blankenship, 2006; CBP, 2000).

Goal of Project

To address the TMDL problems highlighted above, this project evaluated the applicability of using the SWAT model to support waterbody impairment identification and TMDL analysis of nutrients in an agricultural watershed located in the tributary basin of the Chesapeake Bay. An uncertainty analysis approach was developed to quantify uncertainty in SWAT model output to support margin of safety (MOS) tabulation in the TMDL assessment process. We then conclude with a discussion and assessment of the impact of scientifically derived uncertainty values on the progression of the TMDL program.

Chapter 2: Literature Review

Use of Mathematical Models for TMDL Assessment: Description and Performance of

Models

Mathematical models play a central role in TMDL assessment. They have been used

to help determine whether or not a waterbody is impaired, to calculate TMDLs

(loading capacity) of contaminants originating from various sources, and to allocate

portions of the TMDL among contributing sources, thereby simulating practices

capable of alleviating large pollution problems. There are numerous types of models

that can be used for TMDL assessment, therefore we will discuss those models that

are widely used, readily available, capable of modeling nutrients emanating from

agricultural watersheds, and/or highly endorsed by the EPA. This assessment was

done for the purpose of identifying the most suitable model to use for the present

watershed/non-point source modeling project. The TMDL program emphasizes the

use of watershed-scale analysis (USEPA, 1997a) because it is able to capture the

cause-effect behavior of stressors and management practices on physical, chemical,

and biological response.

Loading and receiving water models are the most common types of mathematical

models used for watershed and ambient water quality assessment. Less common

ecological assessment models have also been developed and applied. However, in

recent years ecological models have begun to receive considerably more attention in

watershed assessment studies. These three types of models can further be

distinguished by their levels of complexity. Watershed loading models can be categorized into simple methods (mostly empirical approach), mid-range models (combining empirical and mechanistic approaches), and detailed models (mostly mechanistic approach). These models may also be described as lumped (physical, chemical, and biological characteristics of watershed assumed to be spatially homogeneous), distributed (spatial heterogeneities are included), or semi-distributed (partially represents spatial heterogeneities). Receiving water models can be grouped into hydrodynamic models (model the time-varying features of water transport) and water quality models (model the chemical and biological processes occurring within a waterbody). Water quality models can perform steady-state (no variation in time) or dynamic (accounting for time variation) analyses. Ecological assessment models may be statistically based or mechanistic in structure; the majority of those used in TMDL analysis being statistical because of the complexity of ecosystem processes.

Integrated modeling systems link different types of models into a single modeling framework. These systems are coming into wider use because of the need to apply more than one model in watershed assessment studies. Decision support systems (DSSs) have also been developed for TMDL assessment; these are a form of integrated modeling that generates automatic decisions based on a set of knowledge-based rules. Web-based modeling is also an emerging method to conduct watershed management studies. This type of modeling facilitates a wide user base, access to modeling software in the public domain , more data resources, better visualization of model inputs and outputs, and remote operation of modeling systems. Further

information regarding the different types of models used in TMDL assessment can be found in the EPA manuscript entitled, *Compendium of Tools for Watershed Assessment and TMDL Development* (USEPA, 1997a).

Watershed Loading Models

Watershed loading models are tools used to determine the amount of contamination emanating from different sources on the land surface. Within the TMDL program they have been used to determine the source of contaminants, to estimate the amount of pollution contributed by each source, and to determine the optimal allocation or management scenario for pollution reduction. Information from loading models can be placed into receiving water models to determine TMDLs. The loading models that will be discussed in this section are AGNPS (mid-range, distributed parameter), ANSWERS (detailed, distributed parameter), GWLF (mid-range, lumped parameter), HSPF (detailed, lumped parameter), and SWAT (detailed, semi-distributed parameter).

Agricultural Non-point Source Pollution Model (AGNPS) is a watershed-scale loading model that was originally developed to produce storm-event simulations of runoff, sediment, and transport of nitrogen, phosphorus, and chemical oxygen demand from agricultural lands (Young et al., 1986). An updated version of AGNPS is called AnnAGNPS, Annualized Agricultural Non-point Source Pollution model (Bingner and Theurer, 2001). This version is capable of continuous simulation of hydrology, soil erosion, and transport of sediment, nutrients and pesticides. With

continuous simulation capabilities, AnnAGNPS is able to produce long-term

chemical loadings making it more suitable for use in TMDL assessment compared to

AGNPS. Long-term simulations are necessary in order to determine the effects of

changes in management scenarios (Santhi et al., 2001a). AnnAGNPS is a fairly new

model in terms of its continuous simulation abilities and could use more validation

studies to test its watershed components (Yuan et al., 2001).

Yuan et al. (2002) tested the prediction capability of AnnAGNPS 2.0. Their study

was an analysis of nitrogen loading from a small agricultural watershed in the

Mississippi Delta. A sensitivity analysis revealed that soil initial nitrogen

concentration and crop nitrogen uptake had the most significant effect on nitrogen

loadings. In terms of predictability, AnnAGNPS estimated long-term monthly and

annual nitrogen loadings within 127% of the monitored data; a proportion at which

the authors deemed to be reasonable.

Areal Non-point Source Watershed Environment Response Simulation (ANSWERS)

is another model that was designed to evaluate agricultural watersheds using storm

event simulations (Beasley et al., 1980). ANSWERS-2000 is the updated version of

ANSWERS that was developed to simulate long-term average annual runoff and

sediment yield from agricultural watersheds (Bouraoui and Dillaha, 1996). The

developers of ANSWERS-2000 chose to develop ANSWERS over AGNPS for NPS

planning because AGNPS was shown to have problems with describing the physical

processes that determine BMP effectiveness (Bouraoui and Dillaha, 1996). Those

problems were attributed to AGNPS's reliance on the SCS curve number method and the modified Universal Soil Loss Equation (Dillaha, 1990). ANSWERS relied on a distributed storage model for overland flow prediction and detachment transport equations for erosion/sediment processes (USEPA, 1997a). Cumulative runoff volume was predicted within the range of 3-35% of the observed values, and cumulative sediment yield was predicted within the range of 12-68% of the observed values. The authors considered the ANSWERS-2000 predictions to be adequate for planning purposes because the model predictions were within 100% of the observed values. Borah and Bera (2003) pointed out that the continuous version of ANSWERS does not simulate channel sediment. Therefore channel sediments are not routed through the watershed making the sediment and chemical components non-applicable to watersheds.

The General Watershed Loading Function (GWLF) was developed to estimate streamflow and nutrient loads from ungauged watersheds (Haith and Shoemaker, 1987). Along with the other watershed loading models mentioned in this project, GWLF is one of the tools identified by EPA as having the necessary functionality for use in TMDL development (USEPA, 1997a). An updated version of GWLF was used to model nutrient export in the Choptank River Basin on the coastal plain of the Chesapeake drainage basin (Lee et al., 2000). At the decadal time scale (11-year period), GWLF made both accurate and precise predictions of streamflow, and TN and TP export. Cumulative errors were less than 1%. Model performance began to degrade with decreasing time scale from annual to monthly. However, with model

prediction accuracy ranging from 10-50% of observed values at the annual time scale, the GWLF model was deemed to be a useful model for estimation of fluxes of water, nitrogen, and phosphorus over long time periods. Predictions of total phosphorus were poor especially during wet years. The authors pointed out that because GWLF is a lumped-parameter model, it was not able to account for the effects of the spatial structure of land use, continuity of riparian zones, and thickness of buffer zones along streams which are all important factors in nutrient losses. Also, additional processes such as fertilizer application rates and land use change should be added to GWLF functionality.

The Soil Water Assessment Tool (SWAT) model (Arnold et al., 1998) is a watershed loading, water quality model that was developed by the U.S. Department of Agriculture- Agricultural Research Service (USDA-ARS) to estimate the impact of different management scenarios on water, sediment, and agricultural chemical yields in large ungauged basins. It is a physically-based model that has been widely tested in different physiographic regions and in various parts of the world (Boorman, 2003; Santhi et al., 2001a; Vandenberghe et al., 2001; White and Chaubey, 2005). SWAT does have receiving water modeling capabilities, however, it has primarily been used to predict loads emanating from the land surface. It is one of the more recent models added to the integrated BASINS modeling framework (DiLuzio et al., 2002) for use in TMDL assessment.

Chu (2003) tested the performance of the SWAT model in predicting hydrologic/water quality response in a mixed land use watershed (340 ha) in the Piedmont physiographic region of Maryland. Results showed that the SWAT model only handled subsurface flow bounded by the surface topography, not taking into account the possible subsurface flow contributed from outside the watershed. To address the problem, the author adjusted the measured base flow and stream flow to exclude groundwater recharge from outside the watershed, which improved model prediction. Results also indicated that SWAT makes more accurate predictions for long-term simulations (e.g., annual) than short-term simulations (e.g., daily or monthly) for hydrology, sediment, nitrate, and phosphorus loadings (Chu and Shirmohammadi, 2004; Chu et al., 2004). The model made poor predictions of extremely wet hydrologic conditions.

Uncertainty analysis of model output is a vital step in the use of models for environmental risk assessment. Uncertainty analysis for the SWAT model revealed that there was significant uncertainty associated with stream flow predictions due to input parameter uncertainty (Sohrabi et al., 2003). It was concluded that SWAT is a reasonable watershed-scale model for long-term simulation of hydrologic and water quality response in a mixed land use watershed (Chu and Shirmohammadi, 2004; Chu et al., 2004).

In a study conducted in the North Bosque River Watershed, Texas, SWAT was evaluated to determine management effects on point and non-point source pollution

(Santhi et al., 2001a). BMPs for both agricultural land (dairy manure management) and wastewater treatment plants (WWTPs) were employed to reduce in-stream soluble phosphorus concentrations in two locations; Hico and Valley Mills, Texas. Streamflow was predicted well in both locations with Nash-Sutcliffe coefficient of efficiencies (E) ranging from 0.62 to 0.87 during monthly calibration (1993-97) and validation (1998) periods. Predictions of sediment and nutrient loads in Hico were all at satisfactory levels with E ranging between 0.53 and 0.80. Mineral N and Soluble P were predicted well in Valley Mills; however, validation results were not satisfactory for sediment (E=0.23), organic N (E=0.43), and organic P (E=0.39). Overall, the SWAT model was shown to be a useful tool to study the effects of different BMPs on reducing contamination from point and non-point sources in a large watershed.

In-stream kinetics of the Enhanced Stream Water Quality (QUAL2E) model (Brown and Barnwell, 1987) were incorporated into SWAT. This component of SWAT has experienced some scrutiny because it has made significantly different output results embedded in SWAT compared to stand alone QUAL2E and it has made poor nutrient predictions (Houser and Hauck, 2002; Ramanarayanan et al., 1996). White et al. (2004) found the in-stream component of SWAT sufficient to predict total phosphorus yields. Further testing and improvement efforts should be made to strengthen this component of SWAT.

Kang et al.(2006) used SWAT to develop TMDLs for suspended sediments, total nitrogen, and total phosphorus in a small watershed (385 ha) in Korea containing

irrigated rice paddy fields. Their total maximum daily load system (TOLOS) consisted of AVSWAT using geographic information system (GIS) and remote sensing (RS). The TMDL was allocated amongst 23 sub-areas. Results indicated that simulated runoff and water quality values were acceptably close to observed data. The urbanized sub-watershed #2 required the largest allocation of load reduction, mainly because it was largest in area and was most concentrated in terms of residences and other community activities. TOLOS was found to be a useful tool for planning TMDLs for a small watershed including rice paddies in Korea.

Hydrological Simulation Program-Fortran (HSPF) (Johansen et al., 1984) is a watershed loading model that was developed by the USEPA for simulating water quantity and quality in a watershed. It also has the capability to simulate receiving water quality, adding to its modeling complexity. HSPF is a lumped parameter model but it does separate the watershed into pervious and impervious layers. This adds to its ability to model complex watersheds including mixed land uses. Before the SWAT model was integrated into BASINS, HSPF was the primary non-point source model used in the BASINS modeling framework. Despite several criticisms that HSPF is difficult to understand and use (NCASI, 2001; Saleh and Du, 2004; Whittemore and Beebe, 2000), it is still being used in TMDL assessments.

Neumiller (2001) conducted a calibration study on the HSPF model for Mica Creek, Idaho. The objective was to test the applicability of using HSPF in forestry management studies and to determine its utility within the BASINS GIS modeling

framework. Results of the study showed that simulated hydrographs compared well with observed hydrographs. However, many problems were reported. One problem was the setting of key parameter values to make the model work. For example, there was a gross overestimate of the deep seepage loss. The author also reported the problem of extensive input data requirements for HSPF. These problems led to a negative outlook on the usefulness of this model for assessing the impact of alternative management scenarios.

Receiving Water Models

While watershed loading models provide information about the source and amount of pollutants located on and emanating from the land surface, receiving water models simulate the chemical, physical and biological interactions of those pollutants within the waterbody. Hence, the collective and systematic use of both modeling processes to support decisions made within the TMDL program. Receiving water models (specifically, water quality models) are tools used to determine the impact of pollutant loads on water quality of surface waterbodies. Advective, dispersive, and reactive processes are used to model the transport and transformation of contaminants within the waterbody. In the TMDL program, receiving water models have been used to estimate the response of the waterbody to pollutant loads for determining impairment, to test different loading scenarios, and to determine TMDLs (loading capacities). The receiving water models that will be discussed in this section are CE-QUAL-W2 (dynamic, coupled hydrodynamic/water quality model), EUTROMOD (steady-state, water quality model), QUAL2E (steady-state, water quality model) and

WASP5 (dynamic, water quality model). HSPF is a dynamic water quality model with watershed loading capabilities as well. Therefore, it was discussed in the previous section under watershed loading models.

CE-QUAL-W2 (Cole and Buchak, 1995) is a laterally averaged, two-dimensional, mechanistic model with coupled hydrodynamic and water quality functionality. It was developed to predict the effects of nutrient load changes on phytoplankton growth. Bowen (2000) conducted a calibration performance study on CE-QUAL-W2. Salinity, nitrate-nitrite, and dissolved oxygen concentration predictions compared well with observations. Predictions of chlorophyll-a, however, did not compare well with observations producing a correlation coefficient of 0.39. This was explained to be a result of the model's inaccuracy in predicting the time and location of algal blooms. The predicted cumulative frequency distribution of chlorophyll-a did have better correlation with observed distributions, but peak observed values were much higher than peak predicted values. A sensitivity analysis revealed that predicted peak values of chlorophyll-a appeared to be limited by residence time. Peak chlorophyll-a is an important variable because it is used as an indicator of water quality impairment. Two-dimensional models such as CE-QUAL-W2 can be favored over three-dimensional models such as WASP5 (to be discussed later) because of their relative simplicity (Bowen and Hieronymus, 2000).

EUTROMOD (Reckhow et al., 1992) is a spreadsheet-based collection of nutrient loading and lake response models used for watershed scale analysis of eutrophication

in lakes and reservoirs. Annual loads of runoff, erosion, and nutrients (nitrogen and phosphorus) are used to predict average lake response conditions in terms of nutrient levels, chlorophyll a, Secchi Disk depth, and trophic state. Uncertainty analysis is built into the model to account for model error and hydrologic variability. Hession et al. (1995) compared the results of EUTROMOD and water quality monitoring data. They found that predictions of EUTROMOD agreed well with monitoring data.

Hession et al. (1996) used EUTROMOD in a watershed-level ecological risk assessment in Wister Lake, Oklahoma. The model estimated annual watershed phosphorus loads from point and non-point sources, as well as lake response in terms of chlorophyll-a concentration. Instead of relying on the uncertainty analysis methods within EUTROMOD, the authors incorporated what they felt to be a more robust uncertainty analysis estimation using Monte Carlo techniques. A two-phase Monte Carlo approach was used in order to determine parameter knowledge uncertainty and stochastic variability. Alternate management scenarios were tested within this modeling framework. Results indicated that this methodology of ecological risk assessment is a useful tool for making decisions on the management level.

Hession et al. (1998) summarized the EUTROMOD model in an assessment and suitability analysis. They described the structure and functions of the model concluding that the model performs at an acceptable level. However, during the time of their evaluation, only a few field tests had been conducted on the model's performance.

The Enhanced Stream Water Quality Model (QUAL2E) (Brown and Barnwell, 1987) is a one-dimensional stream water quality model that is widely used for stream wasteload allocations and discharge permit determinations. It represents a stream as a number of reaches depicting finite difference elements. An implicit backward difference numerical scheme is used to solve the advective-dispersive mass transport equation. The model contains built-in uncertainty analysis tools for determining the effect of parameter uncertainty on model prediction uncertainty. Chaudhury et al. (1998) calibrated and validated QUAL2E in a study on the Blackstone River located in the Northeastern United States. The model was found to predict DO and ammonia concentrations very well compared to observed conditions before and after wasteload allocations to the river. It was therefore able to successfully determine the impaired status of the waterbody before wasteload allocations and the impact of those allocations on the initial conditions of the river. QUAL2E was not built to address stormwater flow events, non-point source pollution, and transient stream flow (Shanahan et al., 1998). Therefore, caution should be used for application of this model to rivers experiencing temporal variations in streamflow or fluctuating discharges over short periods of time.

Water Quality Analysis Simulation Program (WASP5) (Ambrose et al., 1993) is a three-dimensional water quality model that was designed for linkage to hydrodynamic models. It consists of three sub-models, one for water quality/eutrophication simulation (EURO5), another for simulation of toxics (TOXI5), and the last one for

hydrodynamic simulations (DYNHYD). Jia and Cheng (2002) used WASP5 in an integrated system for water quality management in the Miyun reservoir in Beijing, China. Validation of the hydrodynamic portion of the model indicated that WASP5 could represent the hydrodynamic behavior of the Miyun reservoir. Water quality model verification indicated that predicted values of dissolved oxygen were fairly close to observed measurements. After testing the model under different scenarios, the study found that water quality was improved by banning cage fishery in the reservoir.

The State of Maryland has often used WASP5 to develop nutrient TMDLs (MDE, 2001a; MDE, 2001b). They have used field observations to determine impairment. Those field observations are used to calibrate the water quality model, and simulate base (current) conditions to which simulated reductions can be compared. The best simulated reduction scenarios are then used to assign TMDL allocations of wasteload, load, and margin of safety.

Ecological Assessment Models

Ecological assessment models simulate the effect of stressors on ecological endpoints such as species and biological communities. These models are being used more often in TMDL analysis to express modeling outputs in a form that is more useful to stakeholders and those involved in the TMDL decision making process. Ecological models that will be discussed in this section include Neu-BERN and AQUATOX. Borsuk and Reckhow (2000) developed the probabilistic model called Neuse Estuary

Bayesian Ecological Response Network (Neu-BERN) to support the formulation of a nutrient TMDL for the Neuse River estuary in North Carolina. Neu-BERN is a Bayesian probability network. As stated by the authors, "Probability networks are graphical models for the evaluation and presentation of scientific relationships for policy and analysis." These simple models seek to link predicted values of contaminants to ecological endpoints or responses while accounting for model uncertainty and natural variability. This undoubtedly helps to foster better understanding of the problems at hand and their effect on endpoints of interest to stakeholders. By considering uncertainties, this model is able to provide an explicit means of representing the reliability of model predictions. In their report, Borsuk and Reckhow (2000) describe a Bayesian probability network model that links the effect of algal growth (phytoplankton) on endpoints that are of concern to stakeholders, i.e., fish population health, fish kills, and shellfish abundance. The effect of nutrient load changes on algal growth was simulated using the mechanistic CE-QUAL-W2 model. The algal growth information (annual algal productivity) from CE-QUAL-W2 was then fed into the Bayesian network. This type of modeling approach is a valuable aid to the decision-making process.

AQUATOX (USEPA, 2000) is an ecosystem fate and effects model developed for EPA to predict the effects of chemical (nutrient and toxic) loadings on ecological endpoints from their point of entry to the top of the aquatic food chain. The effects are measured by estimating the amount of chemical per unit biomass over time. AQUATOX has been validated for estimating PCB bioaccumulation factors in Lake

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Ontario (Park, 1999). In that study, the model provided acceptable results considering it had never been applied to such a large system. In comparison to two other mechanistic, steady-state models (Gobas, 1993; Thomann, 1989), AQUATOX provided better fits to observed data for phytoplankton and mysids (shrimp-like animal). AQUATOX also showed a lower degree of uncertainty compared to the two models.

Integrated Modeling Systems

As previously mentioned, a number of different types of models (e.g., watershed loading models and receiving water type models) are often used collectively in watershed management studies. For this reason, integrated modeling systems link models together (e.g., loading and receiving water models) with a user interface to form a complete system. These modeling frameworks provide a system that is easy to use, capable of linking models to databases (e.g., Geographic Information Systems [GISs]), and allow user flexibility in choosing the type of analysis to conduct (USEPA, 1997a). The integrated modeling systems that will be discussed in this section are BASINS and GIBSI.

Better Assessment Science Integrating Point and Non-point Sources (BASINS) (USEPA, 1996) is an integrated modeling system that was developed by the EPA primarily to link point and non-point source modeling together for TMDL development. It contains several different components including databases (e.g., DEMs, soils data), GIS tools (e.g., automatic watershed delineation, definition of

Hydrologic Response Units [HRUs]), mathematical models (e.g., WINHSPF, SWAT, QUAL2E), and output analysis tools (e.g., GenScn and Export).

Although BASINS appears to be a widely accepted model and highly endorsed by the EPA, there have not been many published papers on its use and performance. In their evaluation of BASINS, Whittemore and Beebe (2000) stated that, "in EPA's rush to provide a new and useful tool for TMDL development, they have sacrificed good science and modeling practice in exchange for speed." They also noted the lack of published reports on BASINS and the importance of such material to describe experiences and solutions to problems encountered during modeling. That information is necessary for scientific advancement.

Di Luzio et al. (2002a) described the integration of watershed tools and the SWAT model into BASINS. In a simple application of the new tools, the use of SWAT within the BASINS framework was determined to be reliable and efficient.

Saleh and Du (2002) conducted a study in the North Bosque River Watershed in north central Texas, where dairy operations are the primary cause of impairment, to compare SWAT and HSPF performance within the BASINS framework. They found HSPF made more accurate predictions of flow and sediment, however, SWAT was more user friendly and made more accurate predictions of nutrient loading during calibration and validation.

Another integrated modeling framework that has been used for TMDL assessment is GIBSI (Mailhot et al., 1997). This modeling framework is composed of a database, a relational database management system, physically based simulation models, management modules, and a GIS platform. Rousseau et al. (2002) conducted a case study in the Chaudiere River watershed in Quebec, Canada where untreated municipal wastewaters and agricultural non-point source contamination were considered the cause of impairment. Their objective was to determine the applicability of using the GIBSI risk-based approach to determine probability of exceedance of water quality standards for recreational uses. Five different treatment scenarios were modeled for reducing both point sources (aerated lagoons for wastewater treatment plant effluents) and non-point sources (different fertilization rates for agricultural contributions) in order to meet phosphorus and fecal coliform water quality criteria. Probability of exceedance was determined for each scenario. The authors concluded that GIBSI is well suited to link contaminant loads to the probability of exceeding water quality standards, it is a good tool for independently evaluating the TMDL components (LA, WLA, and MOS), and it provides information that can be used to facilitate discussions with stakeholders. In comparison to BASINS, the authors pointed out that GIBSI uses a water quality model that simulates transient flows while BASINS utilizes a water quality model (QUAL2E) restricted to steady flows. This may add to the speed of prediction for BASINS, however, the GIBSI approach is a better representation of reality. This may lead to more accurate results in GIBSI calculations, or the added complexity may lead to less accurate results than BASINS.

Decision support systems (DSSs) are a form of integrated modeling system that generates automated decisions. They are provided with user specified prescriptions for making appropriate decisions. Prescriptions are mainly comprised of "if then" statements that are systematically examined to generate final output. WARMF is a DSS that was developed by Chen et al. (1999) to calculate TMDLs of a number of different pollutants for WQLSs within a river basin. The system is composed of five modules including data, engineering (dynamic watershed simulation model), knowledge (prescriptions for constraints), TMDL (a Windows graphical user interface, GUI, to guide stakeholders through the decision making process), and a consensus module. These modules work together to formulate different combinations of point and non-point source load allocations to meet water quality standards for WQLSs. By considering the interests of regulatory agencies and various stakeholders, the system is able to provide solutions with possible agreement from all parties. The authors suggest that this system goes beyond the functionality of the BASINS modeling framework because it considers the interests of all concerned parties.

A GIS/web-based DSS was developed to help identify areas within watersheds that might be priority areas for TMDL development (Choi et al., 2002). This system is composed of three main parts; a Long –Term Hydrological Impact Assessment (L-THIA) web application that estimates direct runoff and non-point source loading, a watershed delineation web application for hydrological input data preparation and an HTML based user interface. Advantages of such a system include more data

resources, potential users, and more visualization and remote operation (Choi et al., 2001). However, some disadvantages include complicated TMDL development procedures and implementation, as well as the restrictions on which the DSS is applied because of the web environment (e.g., network speed, security and over simplifications) (Choi et al., 2002).

The Chesapeake Online Assessment Support Tool (COAST) is a web-GIS-based interface that was created to allow the Phase 5 version of the Chesapeake Bay watershed model to be accessible to multiple users (Burgholzer and Sweeney, 2007). Users of different levels of expertise are able to access and collaborate on single projects that may range across several jurisdictions. It is an easy to use interface that includes 100% open source software. Only a web browser and internet connection are needed. COAST is made up of five major functional modules: land use/ river segmentation, source assessment and definition, source distribution, BMP design and application, and model input file generation and model output visualization. The authors (Burgholzer and Sweeney, 2007) claim that this modeling framework is capable of being used in watersheds of any size and composition whether inside or outside of the Chesapeake Bay watershed.

Literature Synthesis and Criteria for Model Selection

The watershed in which this study was conducted is a small agricultural watershed that has had a number of non-structural BMPs implemented within its boundaries. To determine the most suitable model for use in this project, we listed the most important criteria along with a ranking of each candidate model (see Table 1). Criteria were

chosen based on the necessity and/or benefit they provide to properly represent the present watershed characteristics and to meet the goals of this project. A continuous simulation model was needed to predict long-term effects of pollutant stressors and agricultural management practices. A model capable of properly representing the operations (e.g., cropping, animal feeding) found in agricultural watersheds was necessary especially when making nutrient loading predictions from non-point sources. HSPF is suitable for use in mixed land use watersheds, but it was not built to handle primarily agricultural management scenarios as the comparable models were.

Acceptable chemical simulation ability was needed to identify the status of the waterbody in terms of water quality standards.   The spatial extent of model parameters is important for locating pollutant sources in a watershed with mostly non-point sources of pollution. A model containing some level of parameter distribution would also be useful for implementing certain BMPs (e.g., riparian buffer zones) that are location specific. AGNPs and ANSWERS are distributed parameter models that represent spatial variability by subdividing the watershed into many cells (grid pattern). SWAT is semi-distributed in that each sub-watershed contains hydrologic response units (HRUs), which are areas containing uniform land use and soil type.

Several watershed loading models, such as HSPF and SWAT, contain in-stream modeling capability. This is useful for comparing in-stream pollutant concentrations with water quality standards which are normally expressed as threshold concentrations. Ideally, we would have wanted to utilize the in-stream modeling

capabilities of the chosen model; however, due to lack of monitored data for in-stream input parameters (e.g., dissolved oxygen, chlorophyll-a) we did not use the in-stream component of the chosen model.

In TMDL studies, models must be run several times in order to test different management scenarios to find the best solution for pollutant reduction. Therefore, it would be most useful to use models that do not require a long computational time frame.   In an effort to have modeling efficiency we sought to use a model not requiring extensive operational training and expertise; neither requiring long computational time. In the same instance, we sought a robust model that has been proven to perform well under the given watershed conditions. Our research group has done prior studies using previous versions of SWAT. Therefore, modeling issues could be discussed and solved, at times without having to consult outside parties. Also, HSPF has been criticized for being difficult to understand and use (NCASI, 2001; Saleh and Du, 2002; Whittemore and Beebe, 2000). All of the models seem to perform satisfactorily for streamflow prediction, but some of them lack the proper algorithms or spatial extent to predict sediment and nutrient loadings in an acceptable manner. ANSWERS, for example, does not model channel erosion and sediment transport which are important to tabulate sediment and nutrient loading in a watershed (Borah and Bera, 2003). Chemical loading using GWLF was poor due to lumped parameterization (Lee et al., 2000). Model inclusion within the BASINS modeling framework speaks to the worth of the model for wide use by the government and other agencies.

AVSWATX and HSPF were the two most suitable models for this project with ratings of 11.5 and 9.0, respectively. The main reasons for choosing AVSWATX over HSPF were its reputation for best use in agricultural watersheds, its prior use by our watershed modeling team, and its computational efficiency considering it is a detailed model. Not many studies have been conducted using AVSWATX as a separate entity for TMDL analysis, therefore we chose not to use SWAT as part of an integrated modeling system. We were planning to utilize the in-stream components of SWAT for nutrient assessment. However, there was not enough in-stream monitoring data to properly determine in-stream input parameter values.

Web-based models are good for allowing access to multiple users for a single project, remote access, and use of software in the public domain. The watershed of this study is small and did not require access to multiple users. The necessary software packages for modeling were available; therefore, there was no need to use a web-based model for this project. Web-based modeling was an extremely new concept in water resource modeling at the inception of this project. Its functionality has still not been widely tested.

Table 1 Criteria rating for each model considered for use in Warner Creek watershed study.

Criterion	AnnAGNPS	ANSWERS-Continuous	GWLF	HSPF	AVSWAT-X
Continuous Simulation	●	●	●	●	●
Agricultural Management	●	●	●	◘	●
Chemical Simulation	◘	◘	◘	●	●
Spatial Extent	●	●	○	○	◘
In-stream Component	○	○	○	●	●
Robustness/Accuracy	●●◘◘ HSNP	●◘◘◘ HSNP	●◘◘◘ HSNP	●●●● HSNP	●●●● HSNP
Mid-level to Low Operational Training	●	●	●	○	●
Computational Efficiency	●	●	●	◘	●
In BASINS Framework	○	○	○	●	●
Totals	8.5	8.0	7.0	9.0	11.5

●- full point, ○-no point, ◘- partial/half point, H- Hydrology, S- Sediment, N- Nitrogen, P- Phosphorus

Based on the literature synthesis and characteristics of the watershed in our study, the AVSWATX model was chosen over other comparable models. The main reasons for this selection were its predominant use in agricultural watersheds, low need for operational training, and its computational efficiency. There have not been many published studies in which AVSWATX was used for TMDL analysis, and no studies have been done to tabulate the uncertainty in AVSWATX output for MOS

determination. Therefore, AVSWATX was a good candidate for testing these capabilities.

The second goal of this research project involved determining an uncertainty analysis approach to quantify the level of SWAT output uncertainty. The following describes a brief review of the different approaches that have been used to quantify uncertainties in mathematical models used in water resources engineering. It is intended to address the specific need of tabulating a scientifically derived MOS value for TMDL development.

Measuring Model Uncertainties to Support TMDL Development: A Review of Strategies

One of the main driving forces for studying model uncertainty in water quality assessment is to aid the decision making process. The U.S. Environmental Protection Agency's (USEPA) Total Maximum Daily Load (TMDL) program is one of the leading and most controversial federally mandated programs rooted in the use of mathematical models to make policy decisions. Uncertainties in mathematical modeling are normally accounted for in the margin of safety (MOS), a component of TMDL allocations. MOS is typically expressed in implicit or explicit terms. Implicit considerations involve making conservative assumptions, e.g. increasing the threshold of a water quality criterion above that which is necessary. Explicit considerations involve assigning a numeric safety factor to MOS, e.g. 5% of the point and non-point source allocations. Both terms represent a highly subjective means of accounting for uncertainty (NRC, 2001). EPA guidance (USEPA, 1999a) has

suggested that the calculation of MOS be based on scientific information rather than subjectively assigned. However, it is only recently that scientists have begun to devise and study formal uncertainty and error propagation analyses to determine MOS. Hence, there is a need for further study and development of formal methods to calculate MOS.

The fact that uncertainties in modeling will always exist, leaves science with the primary mission of studying the sources and propagation of uncertainty in order to determine the reliability of model results that are used to assess risk levels. Several types of methods have been used for error propagation in mathematical models; the main two methods being first order error (FOE) analysis and Monte Carlo (MC) simulation. Some approaches (Borsuk and Stow, 2000; Borsuk et al., 2002; Cryer and Applequist, 2003a; Cryer and Applequist, 2003b) have skewed away from the main methods; however, the majority of approaches (Mailhot and Villeneuve, 2003; Portielje et al., 2000; Sohrabi et al., 2002) are simply derivations of FOE and MC.

The following section seeks to provide a general review of the most common and newly introduced methods of prediction uncertainty analysis applicable to models developed for water quality assessment. These approaches may have the capability to be used as scientifically defensible methods to quantify uncertainty, which would be an advancement in the modeling needs of programs (such as TMDL and pesticide registration) that make policy decisions based on model predictions.

Types of Uncertainties in Modeling

There are a number of different types of uncertainties involved in mathematical modeling. Beck (1987) discussed four problem areas of uncertainty in a review of the analysis of uncertainty in water quality modeling. The problems examined were: (1) uncertainty about model structure (the method used by the model to describe the dynamic behavior of the system), (2) uncertainty in the values used for each input parameter, (3) uncertainty in model predictions resulting from numerous error sources (e.g., measurement error of input and output variables, initial state of the system), and (4) the role of experimental design in reducing uncertainties associated with models. As discussed by Beck (1987), uncertainties in model structure (problem 1 above) should be perceived more as a science that will perhaps improve slowly as we piece together the actual behavior of modeled systems over some unforeseen and most likely distant amount of time. Problem 4 (above) should be addressed in the context of experimental studies or modeling/monitoring studies, but not in terms of modeling approaches per se.

Most of the studies examining uncertainty in mathematical models focus on quantifying the effects of residual variability and parameter uncertainty on prediction error, which are typified by problems 2 and 3 above. For example, Eckhardt et al. (2003) quantified uncertainty in model predictions due to parameters associated with land-cover. Muttiah and Wurbs (2002) and Cotter et al. (2002) considered the effect of spatial scale of input parameters on model output uncertainties. Chaubey et al. (1999) considered output uncertainty due to spatial variability of rainfall. Sohrabi et

al. (2003) examined the uncertainty in model output due to variability in input parameter values.

Strategies for Quantifying Uncertainty

The most common strategies for quantifying uncertainty in mathematical models used in watershed-scale water quality analysis are Monte Carlo (MC) simulation (Benjamin and Cornell, 1970), and first order error (FOE) analysis (Beck, 1987). The majority of other types of approaches have been derived from these initial methods. Examples of these derivations include Latin Hypercube Sampling (LHS) method (McKay et al., 1979), mean-value first order reliability method (MFORM) or mean-value first-order second-moment (MFOSM) method (Madsen et al., 1986; Yen et al., 1986), advanced mean-value first-order reliability method (AFORM) or advanced mean-value first-order second-moment (AFOSM) method (Hasofer and Lind, 1974), and the mean-value second-order (MSO) method (Mailhot and Villeneuve, 2003). First and second order methods can jointly be referred to as statistical moment estimation methods. They both involve approximating the first and second moment of the output function. Newly introduced methods, whether they have resurfaced after many years or are newly developed include Bayesian analysis (Borsuk and Stow, 2000), a probabilistic approach by Borsuk et al. (2002), and the Deterministic Equivalent Modeling Method (DEMM) (Cryer and Applequist, 2003a; Cryer and Applequist, 2003b; Tantang et al., 1997).

In reference to the type of approaches used, the majority of approaches have been probabilistic in structure. This is most likely due to studies (Dubus and Brown, 2002; Kirchsteiger, 1999; Shirmohammadi et al., 2001; Wu et al., 1997) that have found probabilistic methods of analysis to reveal more information. Reckhow and Chapra (1999) discuss the deterministic method of model validation as an alternative approach to estimating prediction error. The applicability of this method however depends on the rigor of the validation test. In other words, it depends on the amount of tuning done to the data. Several researchers (Beck, 1987; Melching and Bauwens, 2001; Wallace, 2000) have pointed out the inadequacy of conventional sensitivity analysis (referred to as parameter perturbation or one-at-a- time method) to determine the sources of uncertainty for predicted outcomes. This type of deterministic analysis is useful for addressing variations in parameters, but provides no information about the effect of collective parameter uncertainty on model predictions. Probabilistic methods of sensitivity analysis, however, have been found to be of much greater use for uncertainty analysis (Dubus and Brown, 2002).

The following sections describe the different approaches that have been used to propagate error in hydrologic/water quality models including examples of implementation.

Monte Carlo Approaches
Monte Carlo (MC) simulation involves the initial determination of a probability density function (pdf) to characterize the distribution of each uncertain input parameter for the model. Values from each parameter distribution are randomly

chosen to create multiple sets of input parameters that are used to create distributions

for model output variables (Sohrabi et al., 2002; Zhang and Haan, 1996). Random

samples of input parameters can be generated by using the integral of their pdfs

(called cumulative distribution function, cdf), a technique referred to as the CDF-

inverse method (Tung, 1996). This is done by randomly sampling numbers in the

probability range of 0 to 1, then feeding those numbers into the cdf of a given

parameter to obtain a value located on the input parameter pdf. Hundreds or

thousands of parameter substitutions and model runs are usually necessary in order

for the solution to converge. After the necessary number of solutions is obtained, the

combined effect of all uncertain terms is represented by a distribution of the

generated responses (cdf) of the output variable.

The accuracy of this approach depends on the number of model runs; however there

are no defined rules for choosing the number of simulations. Computational time and

the cost of repeated model runs can become problematic. Determining input

parameter pdfs can also be an issue when there is lack of sufficient data about

parameters. Advantages of the MC method include its ability to account for parameter

covariance, it is not limited by model non-linearity, and stratified sampling

techniques can be used to sample from input parameter distributions more efficiently.

Parameter covariance can be considered by allowing correlated sampling between

distributions. It is important for approaches of prediction uncertainty to consider

covariance between parameters especially since uncertainty has been found to

decrease when taking covariance among parameters into account (Di Toro and

vanStraten, 1979; Reckhow and Chapra, 1999). Many studies, however, assume that parameters are not correlated because there is not enough information to determine their relationships (Melching and Bauwens, 2001; Sohrabi et al., 2002; Zhang and Haan, 1996).

The procedure for drawing samples from each parameter distribution can be aided by a stratified approach such as Latin Hypercube Sampling (LHS), which can cut down on the number of iterations needed to obtain samples (McKay et al., 1979; Sohrabi et al., 2003; Wyss and Jorgensen, 1998). In other words, the solutions will converge much quicker. The LHS approach divides the range of each variable into equal probability intervals. Samples are then randomly chosen from each interval to be run in the computer model.

Dubus and Brown (2002) used two approaches to carry out sensitivity analyses for the preferential flow model MACRO for the purpose of determining the most influential parameters for the prediction of pesticide losses and percolated water volumes. The two approaches used were one-at-a-time and Monte Carlo with LHS scheme. For the one-at-a-time method, the Maximum Absolute Ratio of Variation (MAROV) was used to determine the magnitude of parameter sensitivity. In the Monte Carlo analysis, the Standardized Rank Regression Coefficient (SRRC) was used to determine the magnitude of parameter sensitivity. Results between the two approaches were said to be in fairly good agreement. Differences in ranking by the two different approaches may have been due to the conceptual differences in the

methodologies. For example, input pdfs in the MC approach may not match the variation of input parameters in the one-at-a-time method. Also, in the MC approach parameters were varied at once, while one-at-a-time method used single parameter variation. The results of the MC sensitivity analysis approach were used to do a first step assessment of uncertainty in modeling. Uncertainty was observed by expressing the variation of output predictions as confidence intervals. Uncertainties were found to be large in some input parameters, which led the authors to highlight the importance of uncertainty analysis in models such as MACRO that are used for pesticide registration.

van Griensven et al. (2006) combined both latin-hypercube (LHS) and one-factor-at-a-time (OAT) sampling methods to create a global sensitivity analysis tool that can be used with multi-variable catchment models. Global techniques differ from local types in that the entire input parameter space is sampled at once instead of only evaluating changes at one point in parameter hyperspace, e.g., mean, default, or optimum value. LHS was used to cover the entire parameter space, while OAT was used to identify the importance of individual parameters.

Results indicated that hydrologic parameters dominated the highest parameter sensitivity ranks. Curve number (CN2) and the groundwater parameter (ALPHA-BF) caused the most sensitivity in water quality variables. Also, sensitivity on one catchment is not directly transferable to another catchment due to differences in climate and physical characteristics. The same is true for subbasins located in a

common watershed where differences in land use, topography, and soil types are important.

This global type of method appears to be more robust than using local sensitivity schemes that represent a partial effect of input parameters. Therefore, it may be useful to apply such techniques to determine the sensitivity coefficient that is often used in uncertainty methodologies such as MFORM (Melching and Yoon, 1996), which often use local sensitivity methods to tabulate uncertainty.

Sohrabi et al. (2002) evaluated the effects of input parameter uncertainty on prediction uncertainty in the MACRO model. The approach used to propagate uncertainty was MC using the LHS scheme. This study was conducted for simulating atrazine leaching in the Coastal Plain physiographic region of Maryland. Results of the assessment determined that consideration of input parameter uncertainties by appropriate probability density functions (pdf) produced a 20% higher mean flow rate and two to three times larger atrazine loadings than the results predicted by mean input parameters. These results further demonstrated the need for quantification of prediction error in models used for environmental management and decision-making processes.

Uncertainty analysis was conducted on the SWAT 2000 model using the MC/LHS scheme (Sohrabi et al., 2003). Output distributions of interest were those associated with nutrient and sediment losses. The technique was applied to Warner Creek

watershed located in the Piedmont physiographic region of Maryland. Results

indicated that consideration of input parameter uncertainty by appropriate pdfs

produced 64% less mean stream flow and 8.2% greater sediment loads, while nutrient

output obtained using input pdfs showed very little difference from predicted outputs

using mean input parameters. This study demonstrated the value of using probabilistic

techniques to consider prediction errors as opposed to using mean value input

parameters.

Arabi et al. (2007) used a computational framework including the SWAT model,

One-At-a-Time (OAT) sensitivity analysis, and Generalized Likelihood Uncertainty

Estimation (GLUE) to analyze uncertainty associated with hydrologic and water

quality prediction, as well as the uncertainty associated with estimated benefits of

BMPs. Uncertainties in sediment and nutrient model outputs were too large.

However, the uncertainty in model output measuring the estimated effectiveness of

implemented BMPs was not nearly as large. This suggested that the effectiveness

BMPs can be determined with good confidence using the SWAT model. Therefore,

SWAT was determined to be a suitable model for use in watershed management

planning such as in the TMDL program.

Statistical Moment Estimation Methods
MFORM is an uncertainty analysis approach that allows the user to express

uncertainty in terms of variance. Variance is an indication of the closeness of the

values of a sample or population to the mean. MFORM allows the user to determine

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the variance of the dependent variable as well as the variance contributed by each

input parameter (basic variable). Each basic variable should be standardized to

receive equal consideration. By determining the parameters contributing to the most

uncertainty, one can go back and re-evaluate those parameters to determine their

values with greater certainty. This would provide updated model calibration and less

output uncertainty. The model can then be run to determine the uncertainty of results

based on validation data. Results are usually expressed in terms of variance,

probability (of failure), confidence intervals, or other descriptive statistics (e.g.,

coefficient of variation).

MFORM is derived by performing a Taylor series expansion of the model output

function as follows:

$$Y = g(X_e) + \sum_{i=1}^{n} (x_i - x_{ie}) \left(\frac{\partial g}{\partial x_i} \right)_{X_e} \tag{3}$$

where Y is the dependent variable or model output of interest; g ( ) is the function

representing the simulation process (algorithms, set of equations) to obtain Y; X_e is

the vector of basic variables at the expansion point; n is the number of basic variables

x_i; and $\partial g/\partial x_i$ represents the rate of change of the model output with respect to a unit

change in each basic variable, usually referred to as the sensitivity coefficient. In

MFORM, the expansion point is at the mean value of the basic variables. Therefore,

the mean and variance of the dependent variable can be approximated as:

$$E(Y) \approx g(X_m) \tag{4}$$

$$Var(Y) = \sigma_Y^2 \approx \sum_{i=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)_{X_m}^2 \sigma_i^2 + 2\sum_{i=1}^{n}\sum_{j=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)_{X_m} \left(\frac{\partial g}{\partial x_j} \right)_{X_m} \cdot C_v(x_i, x_j) \qquad (5)$$

where E(Y) is the expected value (mean) of random variable Y; X_m is the vector of

basic variables at the mean values; σ_i^2 is the variance of basic variable i; $C_v(x_i, x_j)$ is

the covariance of basic variables i and j; and all other variables are previously

defined. The first term represents the variance of statistically independent parameters,

while the second term is used to tabulate the variance of correlated parameters. $C_v(x_i,$

$x_j)$ can be tabulated by using the identity,

$$C_v(x_i, x_j) = E\left[(x_i - x_{mi})(x_j - x_{mj}) \right] \qquad (6)$$

where, x_{mi} is the mean value of all x_is and x_{mj} is the mean value of all x_js. If basic

variables are not correlated, $C_v(x_i, x_j)$ is equal to zero. In this case, the variance of

output can be written as:

$$Var(Y) = \sigma_Y^2 \approx \sum_{i=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)_{X_m}^2 \sigma_i^2 \qquad (7)$$

This term represents the fraction of model output variance (FOV) contributed by each

basic variable. When using complex models, the best way to solve for $\partial g / \partial x_i$ is by

using numerical methods. Melching and Bauwens (2001) tabulated $\partial g / \partial x_i$ using

forward difference with change in x_i equal to 0.01. The unit change of x_i depends on

the sensitivity of the model to change in parameters.

The FOE method of analysis has the advantage of being very efficient in that it only

requires calculation of the first two statistical moments (mean and variance) of the

basic variables. It also allows for consideration of parameter covariance. Another

advantage is that is does not require parameter pdfs, however, this could be a disadvantage because the method is insensitive to the distribution of parameters. The main shortcoming of this method is its linear approximation of the model, which may not be representative of some nonlinear models. Approximating to higher order derivatives may increase the accuracy of this method; however the level of complexity also increases. In comparison to MC methods, FOE requires much less computational time.

Melching and Bauwens (2001) evaluated uncertainty in coupled non-point source and stream water-quality models applied to a suburban watershed. They used LHS and mean value first-order reliability methods (MFORM) to determine prediction uncertainty of dissolved oxygen (DO) concentrations. LHS was used to identify the basic variables that significantly contribute to output uncertainty, while MFORM was used to provide estimates of the percentage contribution of the variables to output uncertainty. In LHS, input parameters were ranked in terms of their correlation with output values to determine their importance. General conclusions could not be made about the overall uncertainty of the system because of the limitations inherent in each individual model. However, the study was able to help identify key sources of uncertainty, i.e., the main parameters that significantly affect the uncertainty in simulated DO concentrations and the percent contribution of each parameter. The two uncertainty methods, LHS and MFORM, agreed well in determining key sources of uncertainty.

Two stochastic reliability methods were compared with MC simulations to determine the efficiency of these approaches to predict exceedance probabilities for extreme events using deterministic water quality models (Portielje et al., 2000). Both methods used the first order reliability method—one using LHS (FORM/LHS) and the other using Directional Simulation with Importance Sampling (DIS) (FORM/DIS). In DIS, individual parameters are not sampled, but directions are sampled within the u-space (independent standard normal distributed parameters). Sampling density is imposed in such a way that the number of simulations needed to obtain a desired accuracy is decreased. In the case using a simple numerical lake model, both FORM/LHS and FORM/DIS provided more accurate results than MC at exceedance probabilities less than 0.1. In the second case where a more complex non-linear stream model Dissolved Oxygen Stream Model (DOSMO) was used, results indicated that FORM/LHS was more efficient than FORM/DIS and MC in estimating very small probabilities. This study demonstrated the applicability of using stochastic reliability methods to determine prediction uncertainty in deterministic water quality models, which are the main types of models endorsed by EPA for making policy decisions.

Mailhot and Villeneuve (2003) presented a mean-value second order (MSO) method of uncertainty analysis to be applied in water quality modeling. This method was compared to two other methods—mean-value first-order second-moment (MFOSM) and advanced mean-value first-order second-moment (AFOSM). The MSO method involves computing the mean value point, and then taking the first- and second-order derivatives at the mean value point. Standard numerical packages can then be used to

diagonalize the matrix of second-order derivatives. Finally, the exceedance

probability function is found using numerical integration.   The authors used a

Streeter-Phelps prototype model (simple model) to predict exceedance probabilities

of dissolved oxygen (DO). Results showed that the MSO method predicted more

accurate estimates of exceedance probability. Also, the use of MSO was found to be

more appropriate for highly non-linear models and cases where MC methods lead to

extended computational time. However, the authors did point out the need to consider

covariance terms within the MSO approach, which could lead to even more

satisfactory results. MSO has not been applied to complex hydrologic or water quality

models.

Melching and Yoon (1996) used First-Order Reliability Analysis (FORA) to

determine the parameters contributing to the most uncertainty in model prediction of

dissolved oxygen (DO), carbonaceous biochemical oxygen demand (CBOD),

ammonia, and chlorophyll a. The study was conducted on the Passaic River in New

Jersey using the complex water quality model, QUAL2E. Results indicated that the

reaeration-rate coefficient and the algal maximum-specific-growth rate were the two

input parameters having significant effect on prediction uncertainty of DO and

chlorophyll a. The uncertainty in output values of CBOD and ammonia were not

significantly affected by input parameter uncertainty. A more detailed study as well

as more efficiently planned sampling of the significant input parameters would lead to

a reduction in prediction uncertainty of output parameters.

Zhang and Haan (1996) conducted a study on the effect of uncertainty in input parameters on output parameter uncertainty using the Field Hydrologic and Nutrient Transport Model (FHANTM). Parameters associated with flow and phosphorus outputs were examined. Both the First Order Analysis (FOA) and Monte Carlo Simulation (MCS) were used to quantify model parameter uncertainties. The authors used two different approaches because as they stated, "there was no clear guidance as to when FOA provided satisfactory results." The two different approaches produced different, but reasonably close results in indicating which parameters contributed to the most uncertainty in output values. FOA estimates of standard deviation for runoff (RO), subsurface lateral flow (LF), P concentration in runoff (Pcon_RO), and P concentration in lateral flow (Pcon_LF) were 8.17, 1.72, 0.085, and 0.063, respectively. While the corresponding standard deviations for MCS were 7.03, 1.80, 0.085, and 0.188.

The monthly potential evapotranspiration factor (FACTOR) and the horizontal hydraulic conductivity of the transmissive layer (HORTK) were the parameters contributing to the most variability in flow output. For phosphorus output, the mass of P added by animals each day (PADD) and the average daily potential yield of green matter (POTYLD) contributed the most variability. In order to reduce the level of uncertainty in output parameters, uncertainty in input parameters must be reduced. This type of study is useful in determining the most important input parameters to be considered for more careful value selection.

Other Approaches
Cryer and Applequist (2003a, 2003b) studied the use of Deterministic Equivalent

Modeling Method (DEMM) to propagate input parameter uncertainty on prediction

uncertainty. This method uses orthogonal polynomial chaos expansions and stochastic

weighted residual methods to propagate parameter uncertainty through complex

models. The polynomial expansions represent the uncertainty in parameter values like

as pdfs represent uncertainty in MC methods. Stochastic weighted residual methods

(e.g., Collocation method or Galerkin's method) are used to provide sample

coefficients to be placed in the input polynomial expansions to yield the polynomial

expansion of the dependent variable. Coefficients of dependent variable equations

can be determined using a linear solver package (e.g., MATLAB, Mathmatica).

Probability of occurrence is obtained in the form of a cdf for each output variable. An

advantage of this method over the Monte Carlo method is its computational

efficiency. DEMM carries representation of each uncertain parameter distribution

throughout calculation of the dependent variable.

In one study (Cryer and Applequist, 2003a) the authors used DEMM on two simple

models, one algebraic system (to determine pesticide risk quotients for invertebrates)

and the other a coupled ordinary differential equation system (modeling pesticide

degradation and metabolite formation/degradation in soil). The environmental fate

and risk for aquatic invertebrates of chlorpyrifos were examined. Uncertainties in

output predictions of the pesticide chlorpyrifos were determined by DEMM. This

paper mainly discussed the method for using DEMM on problems of environmental

fate and risk assessment. In a companion study (Cryer and Applequist, 2003b) the

authors compared DEMM and MC simulation for achieving estimated cumulative probability functions for pesticide fate predicted by PRZM3 (Carsel et al., 1988) and AGDRIFT (Bird et al., 2002). DEMM was found to be capable of achieving those estimates with an order of magnitude less iteration than MC. However, DEMM did not perform as well as MC at higher percentiles (>90%). DEMM can be easily applied to deterministic models with input/output file structure not requiring source code modifications. It has been introduced as an alternative to Monte Carlo methods for use with models with uncertainties in continuous parameters, when quick analysis of uncertainty and sensitivity of parameters is desired and when CPU time is an issue.

Borsuk et al. (2002) developed a probabilistic modeling approach to account for residual variability and parameter uncertainty that can be used with any type of model. This study was one of the few studies that directly tabulated a value for MOS for TMDL development. The approach was demonstrated using an empirical eutrophication model (simple model) built for the Neuse River estuary in North Carolina. The estuary contains several WQLSs found to be impaired by nutrients. Chlorophyll a (40μg/L) is the standard that the waters were found to exceed. That standard is expressed as a percentile, where a waterbody is determined to be impaired if more than 10% of samples from that waterbody violate the 40μg/L limit. The authors discussed the importance of percentile-based standards which attempt to accommodate occasional standard violations resulting from natural variability and measurement error.

In order to account for residual variability (e.g., imperfect system representation, intrinsic randomness, measurement error) within the process of predicting pollutant concentration, the response variable was considered to be normally distributed. The distribution of the response variable was used to determine the probability of exceeding the numerical criterion. Variability over a period of time was accounted for by choosing multiple sets of predictor variables (input variables), for example, daily values to represent an annual time period.

The uncertainty in predicted exceedance probability resulting from parameter uncertainty was tabulated using a Monte Carlo procedure to form a distribution of exceedance probabilities over 1000 sets of input parameters. That distribution was then expressed as a 90% confidence interval on the exceedance frequency and also as a "confidence of [standard] compliance" (CC).

CC was defined as the degree of confidence that the true value of the exceedance frequency is below the specified value (e.g. 10% as called for by EPA guidance). CC could then be used to determine MOS by calculating the difference of reduction percentage necessary to meet a CC where water quality standards are obtained and some higher level of CC specified by a decision maker. Advantages of this method are its simplicity; uncertainty is expressed in terms of exceedance frequency to meet percentile-based standards, as opposed to only determining uncertainty in the predicted pollutant concentration; parameter covariance can be considered; and it can be applied to non-linear models. This method was specifically crafted for MOS

determination in TMDL analysis; however it has not been applied to the complex type of models that are currently being used in TMDL analysis. The disadvantage of this method is the potentially large amount of computational time involved with Monte Carlo procedures.

Walker (2003) used a probabilistic method of uncertainty analysis on a simple empirical P loading model. They stressed the importance of accounting for both variability and uncertainty in margin of safety tabulation. Variability represents both temporal and spatial changes in a system that usually cannot be reduced. Uncertainty represents imperfection or errors in e.g., model structure, or input parameter estimation that can possibly be reduced by further study, additional sampling, and/or adaptive management practices. Model uncertainty was expressed as the coefficient of variation for predicted average P concentration. It was derived by adding coefficient of variations from lake model error and forecasted load error. Variability was expressed as the year-to-year coefficient of variation of Lake P concentration, derived from variance component analysis of large lake and reservoir datasets.

Borsuk and Stow (2000) used Bayesian analysis for a parameter estimation study. The basic premise of this technique is to use new information (observed data) to update the earlier assumed data. Each data set is expressed in the form of probability density functions. Bayes theorem puts this information into perspective as follows:

$$p(\theta \mid x) = \frac{p(x \mid \theta) \times p(\theta)}{p(x)} \qquad (8)$$

where $p(\theta \,|\, x)$ expresses the probability of the parameter values given the observed

data (posterior distribution), p(x|θ) is the likelihood function [the dependence of x

(new observations of parameters) on θ (prior belief parameters)], p(θ) is the pdf of

prior beliefs, and p(x) is the expected value of the likelihood function over the

parameter distribution.

The Bayesian approach to quantify prediction uncertainty computes a predictive

probability distribution for a given set of data by integrating the product of the

likelihood and prior over the parameter values as such:

$$p(x) = \int p(x \,|\, \theta) p(\theta) d\theta \qquad\qquad (9)$$

where each term has been defined above. Borsuk and Stow (2000) found that the use

of a mixed-order model for BOD decay as opposed to a first or second order model

resulted in a better fit of predictions to observed data. The use of the Bayesian model

facilitated the explicit consideration of uncertainty in model predictions by using pdfs

to describe parameters and their effect on overall predictions. This approach has not

been tested on complex models. Also, it has not been widely used possibly because of

the subjective information contained in the prior distribution (Reckhow and Chapra,

1999).

Wagner et al. (2007) conducted a study on uncertainties in the development of

TMDLs for biologically impaired waters using the reference watershed approach. The

variability in pollutant reduction requirements was analyzed by using different

combinations of land use data, alternative water quality models, and different non-

impaired reference watersheds. The study found that those alternative scenarios introduced considerable uncertainty into required pollutant reductions; so much so that they suggested that explicit margins of safety during the tabulation of sediment TMDLs may need to be substantially greater than 20% when using the reference watershed approach.

Synthesis of Uncertainty Methods and Criteria for Most Suitable Selection

The review of literature in the previous section describes a number of uncertainty analysis methods that have been used in hydrologic and water quality modeling. The purpose of this section was to select the most suitable technique for use in the current project. A list of the most important criteria used for evaluating these methods along with the ranking of each method is found in Table 2. Criteria were chosen based on the necessity and/or benefit they provide in meeting the goals and constraints of this study.

First, we wanted to select a method that could be used with ease on a complex, black-box model such as AVSWATX. Many of the reviewed methods have only been tested on simple, empirical models. A technique proven to give accurate predictions of uncertainty due to parameter uncertainty as well as provide the amount of uncertainty contributed by each parameter was also needed. This is useful for determining the parameters needing special attention during field measurement and model calibration to reduce their contribution to overall uncertainty. Computational efficiency was a

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major determinant in choosing a method. Uncertainty has been shown to be watershed condition specific (Eckhardt et al., 2003). In other words, parameters have different levels of importance depending on management scenarios and project purpose. In watershed assessments where numerous BMP's must be tested, it would be useful to use methodologies that do not require a long computational time frame. Most complex models have a certain level of non-linearity, which may be important when considering uncertainty; however methods that assume linearity have produced similar results as those that do not (Melching and Bauwens, 2001; Zhang and Haan, 1996). Consideration of parameter covariance is another attribute of an uncertainty analysis method, but the relationship between model parameters is often unknown. Therefore, most uncertainty studies of complex, black –box models assume parameters are not correlated.

MFORM was chosen as the most suitable uncertainty analysis method for this study. Its computational efficiency and provision of fraction of uncertainty contributed by each input parameter caused it to be chosen over methods that closely fit the criteria. The next section of literature review discusses the methods that have been used to tabulate MOS for TMDL analysis.

Table 2 Criteria rating of uncertainty analysis methods for use in Warner Creek watershed study.

Criterion	MCS	LHS	DEMM	Statistical Moment Estimation Methods			Baysian Analysis
				MFORM	AFORM	MSO	
Use on Complex Models	●	●	●	●	○	○	○
Accuracy	●	●	▫	▫	▫	●	▫
Parameter Uncertainty Contribution	○	○	○	●	●	●	○
Computational Efficiency	○	▫	▫	●	▫	▫	▫
Non-linear Model Performance	●	●	●	▫	▫	●	●
Simplicity	●	●	○	●	▫	○	●
Parameter Covariance Consideration	●	●	●	●	●	○	●
Totals	5	5.5	4	6	4	3.5	4

●- full point, ○-no point, ▫- partial/half point

Use of Formal Uncertainty Methods to Tabulate Margin of Safety for TMDLs

The majority of TMDL analyses conducted across the nation are using highly

subjective and arbitrary methods of assigning the MOS value (Dilks and Freedman,

2004). There has been no clear, widespread guidance as to how MOS should be

tabulated for the different parameters of concern. Therefore, many site specific

assessments are made. Few researchers have attempted to translate the uncertainty in

complex models used for TMDL analysis into MOS.

Walker (2003) developed a framework to tabulate margin of safety for lake phosphorus TMDLs by including stochastic terms in the phosphorus balance equation to reflect variability and uncertainty. The method is not easily applicable to complex models but the study made some interesting observations about MOS tabulation. When both variability and uncertainty are considered, the result is often a large margin of safety value (MOS). A large MOS means that a larger load reduction must be met by contaminant sources. This leads to higher costs for reduction measures and larger risk of not meeting water quality goals because of the uncertain performance level of most non-point source control measures.

The Walker (2003) study demonstrated the benefit of using an adaptive management approach to implement TMDLs. In this approach, a TMDL would first be implemented without considering an MOS, allowing an initial reduction in point and non-point source loads. Then after a period of time, in which further measurements and model adjustments can be made, the TMDL would then be adjusted to include an MOS. That MOS would presumably be smaller in value than what it would originally have been in the initial TMDL, that is, before measurement and model adjustments. The adaptive implementation approach has been suggested by a number of agencies (NRC, 2001; USEPA, 2002a).

Borsuk et al. (2002) tabulated uncertainty based on the exceedance frequency of a given output. Confidence of compliance (CC) was defined as the degree of confidence that the true value of the exceedance frequency is below a specified limit

(e.g. EPA guidance has suggested using a probability-based standard, for some contaminants, which states that a contaminant should not exceed its water quality standard more than 10 % of a specified time duration). CC could then be used to determine MOS by calculating the difference of reduction percentage necessary to meet a CC where water quality standards are obtained and some higher level of CC specified by a decision maker. This is a good approach assuming a normal distribution of exceedance frequencies. Also obtaining such a distribution would require obtaining a large number of exceedance frequencies implying a long computational time.

The MOS approaches discussed above by Walker (2003) and Borsuk et al. (2002) are similar in that MOS is determined based on the level of confidence that the water quality standard will be met. This level of confidence can be a policy decision or determined by regulation but it is a subjective quantity. Clearly there must be some level of subjectivity in determining MOS and the extent to which MOS will be implemented but the decisions should be based on proper scientific or deductive reasoning.

Zhang and Yu (2004) is the only current study that has applied first-order error analysis (MFORM) to a complex model (HSPF) to determine MOS for TMDL analysis. Based on the output of MFORM, one standard deviation of the output variable was assigned to MOS. It was then determined that the probability of the concentration being greater than the mean plus one standard deviation was

approximately 16%. Therefore, it was concluded that one standard deviation of the model output was reasonable and practical in that application. This method was pointed out to be subjective and then lead to the discussion of an upper limit of MOS. However, no further discussion of standard deviation measures was examined. The authors then suggested that the estimated MOS can be determined based on the variability in the most sensitive parameter. This however reverts to assigning an MOS based on sensitivity as opposed to uncertainty.

As the literature indicates, the number of studies that have tested models for their use in TMDL assessment has been lacking. Even fewer studies have developed methodologies for tabulating the MOS value of TMDLs using a formal method of uncertainty analysis. In this study we will determine MOS based on the confidence of compliance of a percentage-based water quality standard for nitrate concentration. Our method combines MFORM results with the procedure used by Borsuk et al. (2002) to tabulate MOS. This method addresses the use of percentage-based standards which attempt to account for measurement error and natural variability (USEPA, 2003a).

Chapter 3: Objectives

The overall goal of this project was to devise a modeling tool that can help enhance TMDL assessments for any given body of water. Such a tool may help stakeholders (e.g., State and Federal agencies) to fulfill the objectives of the Clean Water Act regarding improvement of impaired water bodies. To achieve such a goal, the following specific objectives were set to be achieved in this study:

1) Calibrate and validate the hydrology, sediment, and nutrient components of AVSWAT-X to evaluate its prediction capabilities,

2) Develop and evaluate a formal uncertainty analysis approach using mean-value first-order reliability method (MFORM) to support margin of safety (MOS) tabulation, and

3) Evaluate the applicability of using AVSWAT-X to support waterbody impairment identification and TMDL development for waterbodies impaired by nutrients.

Chapter 4: Methodology

Site Description and Monitoring Design

Warner Creek watershed is located in Frederick County, Maryland within the
piedmont physiographic region. The watershed area is approximately 840 acres and
drains into Little Pipe Creek, a tributary of the Monocacy River (Figure 1). The
Monocacy river basin is known to contribute high levels of nutrients to the
Chesapeake Bay (Blankenship, 2007; USDA-SCS, 1990). Nutrient loads in the study
watershed can be attributed to non-point sources including grazing cattle, and excess
nutrients from cropland.

There are two main types of soils in Warner Creek watershed, Manor-Edgemont-
Brandywine soils (~1/3 of watershed) and Penn-Reading-Croton soils (~2/3 of
watershed). Most of the upland agricultural soils belong to the Penn silt loam series
with slopes ranging from three to eight percent. The land uses consist of mixed
agriculture (~76%), urban (~13%), forest (~11%), and water (<1%) (based on land
use maps from Searing and Shirmohammadi (1994)).

The water quality monitoring design consists of upstream/downstream and paired
watershed schemes (Figure 2). Upstream/downstream studies have one monitoring
station upstream from the area where BMP implementation occurs (station 1C) and a
second monitoring station downstream from that area (station 2A). This design is

most useful for determining the magnitude of a non-point source (USEPA, 1993).

Paired watershed studies include one watershed where BMPs are not implemented (station 1A, control) and a second watershed with similar characteristics where BMPs are implemented (station 1B, study). This design is useful to demonstrate the effectiveness of BMP implementation (USEPA, 1993).

An automated flowmeter and sampler were installed at station 2A to record continuous streamflow hydrographs and collect water quality samples. A rain gauge was also installed at station 2A to collect rainfall data. Staff gauges were used at stations 1A, 1B, and 1C to estimate flow volume. In addition to automated samples taken during storm events, grab samples were taken on a weekly basis from February through June, and biweekly during the remainder of the year.
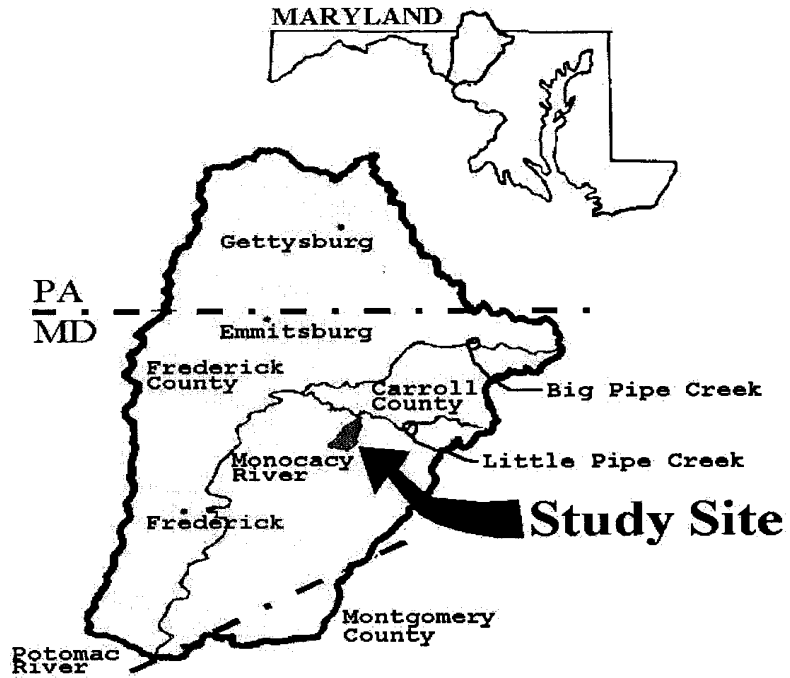
Figure 1 Location of Warner Creek watershed in Maryland.
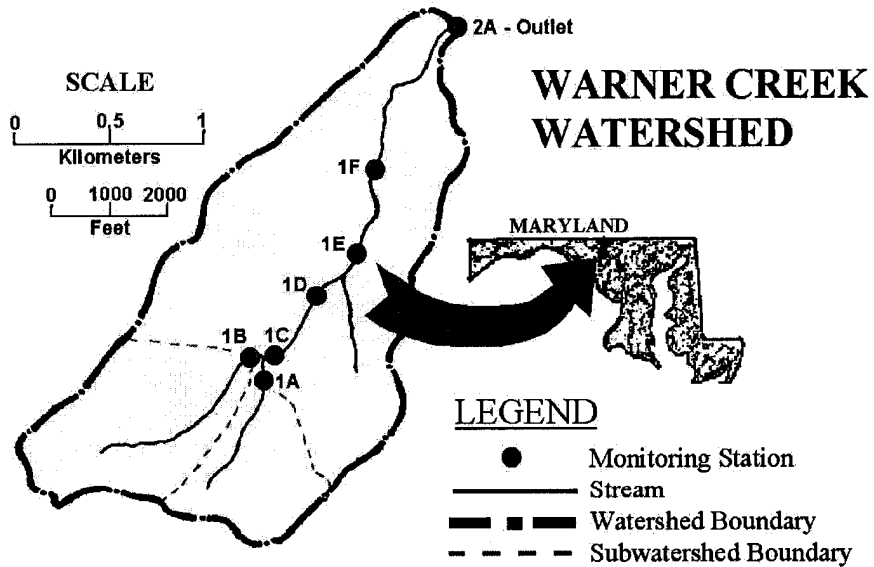
Figure 2 Watershed boundary and monitoring stations.

Model Description and Data Acquisition

The Soil Water Assessment Tool (SWAT) model (Arnold et al., 1998) is a watershed

loading/water quality model that was developed by the U.S. Department of

Agriculture- Agricultural Research Service (USDA-ARS) to estimate the impact of

different management scenarios on water, sediment, and agricultural chemical yields

in large ungauged basins. It is a complex, physically-based, semi-distributed model

that operates in continuous time on a daily time step. The main components of SWAT

include: climate, hydrology, land cover/plant growth, erosion, nutrients, pesticides,

land management, channel routing, and reservoir routing. Algorithms from the

QUAL2E model were incorporated into SWAT to give it in-stream water quality

modeling capabilities (Ramanarayanan et al., 1996). SWAT is one of the more recent

models added to the U.S. EPA Bettter Assessment Science Integrating Point and

Nonpoint Sources (BASINS) modeling framework for use in TMDL assessment (Di

Luzio et al., 2002a).

The version of SWAT used in this study was AVSWATX-2003, which operates in

the ArcView GIS interface. Site-measured daily precipitation data were used during

the entire simulation period (Appendix A-1). Missing rainfall data were filled in using

daily measurements from a nearby monitoring station in Emmitsburg, MD. Daily

maximum and minimum temperature data were also obtained from the Emmitsburg

monitoring station. Daily solar radiation, wind speed, and relative humidity data

were generated using AVSWATX's weather generator. The GIS maps required to run

SWAT include digital elevation model (DEM), land cover/land use, and soil data. A

U.S. Geological Survey (USGS) National Elevation Dataset (NED) DEM (30m resolution) was obtained from GISHydro2000 software (Moglen, 2004), a tool used to conduct hydrologic analyses in the State of Maryland. Two 7.5 minute quadrangle maps (Woodsboro and Union Bridge) were merged together to create the Warner Creek watershed DEM. The watershed was delineated in SWAT by specifying the outlet coordinates (212,887m North and 379,202m East, Maryland State Plane Coordinates). Land use data were collected for each field identified by aerial photos obtained from the U.S. Department of Agriculture's Agricultural Stabilization and Conservation Service (USDA-ASCS) office. The land use map was created in the ERDAS IMAGINE GIS system. A SSURGO soil map of Frederick County, MD (NAD83 coordinate system) was downloaded from USDA's Natural Resources Conservation Service (USDA-NRCS) Soil Data Mart server.

The delineated watershed was separated into 8 subbasins based on the configuration of stream segments (Figure 3). A threshold value of 15% was chosen for both soil and land use types. Therefore, soils and land uses making up less than 15% of a subbasin were not assigned to an HRU. That threshold was reasonable considering the small size of Warner Creek watershed compared to larger watersheds that would likely have more variability and require higher thresholds to create a reasonable number of HRU's for an efficient evaluation. As result of the 15% threshold assignment, the AVSWAT-X interface identified 53 HRUs in the Warner Creek watershed.
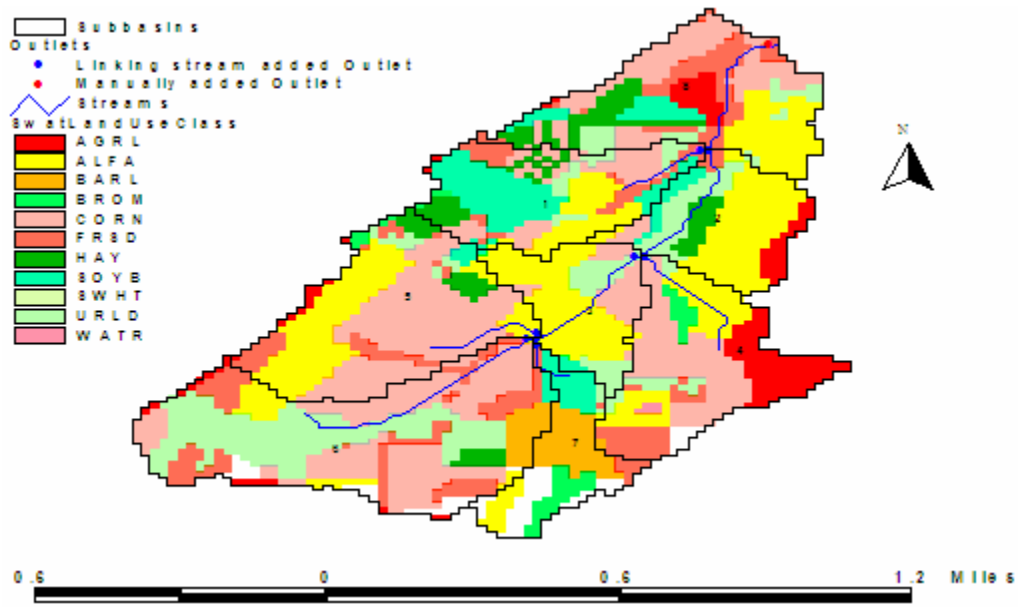
Figure 3 Location of subbasins and land use configuration.

Once the watershed was delineated and all subbasins and HRU's were assigned, the

SWAT view was created. This view allows you to create/edit input files on an HRU,

subbasin or watershed basis. The eleven files located in the edit subbasin menu of the

SWAT view are described below:

- Soil Physical Data (.sol)

  o Input of physical characteristics of the soil for up to 10 layers.

    Includes parameters such as hydrologic soil group, maximum rooting

    depth, percent sand, silt, and clay, soil bulk density, available water

    capacity, and saturated hydraulic conductivity. These properties are

    important to the movement of air, water, and chemicals through the

    soil profile.

- Weather Generator Input Data (.wgn)

- This subbasin level file contains the statistical data needed to generate representative daily climate data. Climatic data is generated when the user specifies that simulated weather will be used or when measured data is missing. Example parameters include weather station location and elevation, average daily maximum and minimum temperature for the month, average total monthly precipitation, and probability of a wet day following a wet or dry day in the month.

- General Subbasin Input Data (.sub)

  - General input data contained in this file include: properties of tributary channels within the subbasin, amount of topographic relief within the subbasin and its impact on climate, variables related to climate change, the number of HRUs in the subbasin and the names of HRU input files.

- General HRU Input Data (.hru)

  - General HRU data contained in this file include: area contained in HRU, parameters affecting surface and subsurface water flow, parameters affecting erosion and management inputs related to the simulation of urban areas, irrigation, tile drains and potholes.

- Main Channel Input Data (.rte)

  - This file contains parameters associated with the physical characteristics of the main channel, which affect water flow, and transport of sediment, nutrients and pesticides. These parameters

include: length, width, and depth of the main channel, Mannings roughness coefficient in main channel, effective hydraulic conductivity in main channel alluvium, and channel cover and erodibility factors.

- Groundwater Input Data (.gw)

    o The properties governing water movement into and out of the shallow and deep aquifers are initialized in this file. Parameters include, for example, groundwater delay time, baseflow alpha factor, groundwater revap coefficient, and deep aquifer percolation fraction.

- Consumptive Water Use Input Data (.wus)

    o This file is used to simulate removal of water from the basin for irrigation outside the watershed or urban/industrial use. Sources of removal can be from the shallow aquifer, deep aquifer, reach, pond or reservoir in any subbasin in the watershed. This water is considered to be lost from the system.

- Management Input Data (.mgt)

    o This HRU level file is used to describe the management practices taking place throughout the watershed. The first few lines of this file contain general management parameters and initial values. The remainder of the file lists the timing of operations such as planting, harvesting, irrigation application, nutrient applications, pesticide applications, and tillage.

- Soil Chemical Input Data (.chm)

    o Input of chemical characteristics of the soil by layer. Used to set the initial levels of different chemicals in the soil. Input of these properties is optional. Input parameters include: initial NO3, organic N, soluble P, organic P concentrations. Pesticide data may also be entered.

- Pond/Wetland Input Data (.pnd)

    o This file contains parameter information used to model the water, sediment, and nutrient balance for ponds and wetlands. Inputs into this file include: fraction of subbasin area draining into ponds/wetlands, initial water volume in ponds/wetlands, phosphorus settling rate in pond/wetland for month, and nitrogen settling rate in pond/wetland for month.

- Stream Water Quality Input Data (.swq)

    o Data governing in-stream water quality processes are contained in this file. Nutrient settling rates, rate coefficients and rate constants are included as well as pesticide reaction coefficient, volatilization coefficient, and partition coefficient.

Model Calibration and Validation

Calibration can be defined as the process by which optimal parameter values are determined by the model user in order to produce the most accurate model predictions

in comparison to measured data. Validation is the process by which a model is tested

by the model user to determine whether or not it can produce acceptable prediction

results according to a specified criteria or purpose. Model calibration and validation

were conducted on streamflow (FLOW_OUT), sediment (SED_OUT), nitrate

(NO3_OUT), and phosphate (MINP_OUT) output. Streamflow was calibrated first,

followed by sediment and then nutrients. There are several output files where

simulation results can be evaluated. Simulated output from the rch.dbf file was

compared to measured data for model performance evaluation. After each model run,

the rch.dbf file automatically stores routed flow and constituent input to the main

channel from each subbasin including the outlet of the watershed located at subbasin

#8. Another file that was used to examine the general water balance of output was the

summary output.std file located in the simulation txtinout directory. The output.std

file provides weighted average loadings from HRUs to streams not routed through the

watershed.

Manual calibration was performed by changing input parameters by percentage or

absolute value from within the tables menu of the ArcView GIS interface. Input

parameters used in calibration were chosen based on sensitivity analyses found in the

literature (Chu and Shirmohammadi, 2004; Chu et al., 2004; Sohrabi et al., 2003;

White and Chaubey, 2005), and the physical meaning of parameters as they relate to

output tabulation (model algorithms). The perturbed input parameters and the relative

predicted output response to changes in parameters are listed in Table 3.

Other parameters not included in Table 3 were adjusted during calibration; however the effects were less systematic. Lateral flow travel time (LAT_TIME in .hru input file) and groundwater delay time (GW_DELAY in .gw input file) were used to adjust the timing of flow in the subsurface. There was no direct change in magnitude of flow. Surface runoff lag coefficient (SURLAG in .bsn input file) was adjusted when trying to match hydrograph peaks. Baseflow alpha factor (ALPHA_BF in .gw file) was changed to fine-tune hydrograph recession curves. The higher this value, the less steep the baseflow recession curves. Melt factor for snow on June 21 (SMFMX in .bsn file) was not changed because there is no snow in the study watershed in June. Snow pack temperature lag factor (Timp in .bsn file) was adjusted to properly simulate the influence of the previous day's snow pack temperature on the current day. The previous parameters all relate to storm sequences (lag times and shapes).

Fraction of porosity from which anions are excluded (Anion_Excl in .sol file) was varied to adjust the transport of nitrate in the soil. Only slight changes were observed. Effective hydraulic conductivity in tributary channel alluvium (CH_K1 in .sub file) was lowered to reduce transmission losses. To get more evapotranspiration and less surface runoff we changed the potential evapotranspiration method of calculation (IPET in .bsn file) from the Priestly-Taylor Method (option 0) to the Hargreaves method (option 2).

A second, more detailed calibration approach was used in an attempt to obtain better calibration results. This method involves assigning one HRU at a time to the entire

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watershed in order to more closely calibrate parameters associated with specific land uses and soil types (Arnold and Sammons, 2006). This type of methodology is most useful in studies where a large portion of a watershed is made up of the same land use and soil type. First the SWAT executable file (e.g., swat2003.exe) should be placed in the **txtinout** folder located in the default directory of SWAT. Then changes should be made to the files listed below as follows:

1. Select the **fig.fig** file in txtinout: Move the subbasin containing the HRU that you want to use, to the top of the file (e.g., subbasin 5 would be 00005000000.sub). Change the last two digits in the first row of the subbasin to the number 1. Add a blank line after that subbasin entry to end the string of commands.

2. Select the **subbasin** file (e.g., 000050000.sub) in txtinout: Change the total number of HRUs modeled in the subbasin (HRUTOT) to 1. Choose the HRU (e.g., 000050003) that you want to assign to the entire watershed and bring it to the top of the list of HRUs. Add a blank line after that HRU entry to end the string of commands.

3. Select the **HRU** file (e.g., 000050003.hru) in txtinout: Change the fraction of subbasin area in HRU (HRU_FR) to 1.0.

The SWAT model should then be run using the executable file in the txtinout folder. Output from that execution can be found in the **output.std** file located in the txtinout folder, which can then be compared to measured data.

Streamflow measured at the outlet of the watershed (station 2A) was separated into

surface flow and baseflow using the streamflow partitioning method by Linsley et al.

(1982). This method involves observing streamflow hydrographs and terminating

surface runoff after a fixed time (e.g., days) after the peak of the hydrograph. Due to

equipment malfunction, flow data was incomplete during 1998. In order to correct

this problem, Chu and Shirmohammadi (2004) employed artificial neural network

(ANN) models (ASCE, 2000a; ASCE, 2000b) to estimate the monthly surface runoff

and baseflow during March through December 1998 using flow and rainfall data from

years 1994 through 1997 and 1999. Average sediment and nutrient concentrations

measured at the outlet of the watershed (station 2A) were used to calculate loadings

of these constituents leaving the watershed. Monthly collections of all measurements

were used to calibrate and validate the model (Appendix B). ANN generated flow

data for 1998 are noted by asterisks in Table B1 of Appendix B-1.

In a previous study done on this watershed using an earlier version of SWAT, Chu

(2003) found that subsurface contributions of flow and chemicals were not being

properly accounted for by the model. This was due to the fact that the model only

considered the watershed area delineated by surface topography, as is the case in most

if not all watershed-scale models. Warner Creek watershed's small size and large

baseflow contribution to total streamflow (~76%) makes it especially sensitive to this

occurrence. In order to conduct a fair evaluation of SWAT's performance in this

watershed, Chu (2003) performed a water budget analysis to remove measured

subsurface flow contribution from outside of the watershed. Once the baseflow

adjustments were made, measured chemical contributions were adjusted as well. The adjusted measured baseflow and chemical loads from Chu and Shirmohammadi (2004) and Chu et al. (2004)were used in the present study (see Appendix B).

Flow was calibrated using approximately three years of measured data (April-Dec. 1994, 1995, and 1997), and validated using four years of measured data (1998-2001). It should be noted that 1996 data were not used in hydrologic simulations because it was an unusually wet year with annual precipitation being almost double the normal annual values for Maryland. Since sediment measurements were not available after 1997, sediment yield was calibrated using measured data from two years (April-Dec. 1994 through 1995) and validated using 1996 and 1997 measured data. Nutrient loading was calibrated using approximately four years of data (April-Dec. 1994-1997) and validated using four years of data (1998-2001).

Table 3 Relative predicted output response to parameter perturbation in Warner Creek watershed.

Perturbed Parameters	Change in Input Parameter	Surface Runoff	Baseflow	Streamflow	Evapotranspiration	Sediment Yield	Nitrate Load	Phosphate Load
CNOP(.mgt2)	I	I	D			I		
	D	D	I			D		
ESCO(.hru)	I	D			D			
	D	I			I			
GW_REVAP(.gw)	I		D					
	D		I					
RCHRG_DP(.gw)	I		D					
	D		I					
SMFMN(.bsn)	I	I(w)						
	D	D(w)						
HRU_SLP(.hru)	I					I		
	D					D		
SOL_AWC(.sol)	I	D	D	D				
	D	I	I	I				
SOL_K1(.sol)	I	I	I	I				
	D	D	D	D				
SLSUBBSN(.hru)	I					I		
	D					D		
USLE P(.mgt1)	I					I		
	D					D		
ADJ_PKR(.bsn)	I					I		
	D					D		

Table 3 Cont.

	Change in Input Parameter	Surface Runoff	Baseflow	Streamflow	Evapotranspiration	Sediment Yield	Nitrate Load	Phosphate Load
	I					I	D	D
BIOMIX(.mgt1)	D					D	I	I
	I					I		
CH_EROD(.rte)	D					D		
	I					I		
CH_COV(.rte)	D					D		
	I					I		
SPCON(.bsn)	D					D		
	I					I		
SPEXP(.bsn)	D					D		
	I						I	
NPERCO(.bsn)	D						D	
Initial N03(.chm)	I						I	
	D						D	
	I						I	
CMN(.bsn)	D						D	
	I						D	
Frt_Surf(.mgt)	D						I(hwt)	
	I						I	
Anion_Excl(.sol)	D						D	
	I							D
PPERCO(.bsn)	D							I
	I							I
Sol_labp1(.chm)	D							D

I- increase, D- decrease, hwt- high water table, w- winter

Model performance was evaluated using several different criteria. In an effort to formulate guidelines to evaluate watershed models in a systematic and universal manner, Moriasi et al. (2007) conducted an extensive study on reported ranges of values and performance ratings for several criteria. The recommended model evaluation criteria from their study (Table 4) and some additional criteria were used in the present study.

Time Series and Scatter Plots (Graphical Analysis)

Visual inspection of graphical data is an important step in evaluating the relative closeness of predicted data to measured data. Time series plots reveal both the systematic (e.g., over- or under-prediction) and dynamic (e.g., timing, rising limb, falling limb and baseflow) behavior of the model (Krause et al., 2005). Scatter plots show how well the best-fit regression line matches up with the 1:1 line of equal values. This plot, along with the quantitative information in its regression equation (i.e., slope and intercept), can be used to describe the relationship between predicted and measured data assuming a linear relationship. Slope provides information about the systematic rate of over- or under-predictions, while intercept describes differences in magnitude. In order to represent good agreement, the y–intercept should be close to zero and the slope should be close to one. An intercept close to zero means that a measured data value of zero would also result in a prediction near zero. A slope close to one indicates a regression line nearly matching the slope of the 1:1 line of equal values.

Coefficient of Determination, r^2

The coefficient of determination (r^2) describes the degree of collinearity between two variates (e.g., predicted and measured data) (Legates and McCabe, 1999). Its value is based on the dispersion of variates around the regression line, not the line of equal values. It describes the total variance in the measured data that can be explained by the model. The expression for r^2 is:

$$r^2 = \left(\frac{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)\left(P_i - \overline{P}\right)}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2}\sqrt{\sum_{i=1}^{n}\left(P_i - \overline{P}\right)^2}} \right)^2 \qquad (10)$$

where O_i are observed and P_i are predicted data, $\overline{O}$ and $\overline{P}$ are observed and predicted mean values respectively, and n is the number of samples. The value of r^2 ranges from 0 (poor model) to 1 (perfect model). An r^2 value of 0.5 usually means an average or moderate model performance. Several studies (Legates and Davis, 1997; Legates and McCabe, 1999; Moore, 1991; Willmott, 1984) have shown that r^2 is insensitive to additive and proportional differences between measured and predicted data and it is more sensitive to outliers than to observations near the mean. In view of these limitations, an r^2 value close to 1 can still be attained, which would result in misrepresentation of model performance. Therefore, it is important to observe additional information such as slope and intercept of the regression line to get more detailed information about the measured vs. predicted relationship.

Nash Sutcliffe Coefficient of Efficiency, NSE

The coefficient of efficiency (NSE) by Nash and Sutcliffe (1970) is a measure that compares model predictions to the mean of observed values to determine the better predictor of observed values. Its value is based on the dispersion of variates around the line of equal values. The equation for NSE can be written as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \qquad (11)$$

where all terms are defined above. Unlike r^2 above, this criterion is sensitive to additive and proportional differences; however like r^2 it is oversensitive to extreme values because of squared differences (Legates and McCabe, 1999). The value of NSE ranges from negative infinity (poor model) to 1.0 (perfect model). If NSE<0, the observed mean is a better predictor than the model; NSE=0, the observed mean is as good a predictor as the model; NSE>0, the model is a better predictor of observed data than the observed mean (Legates and McCabe, 1999; Wilcox et al., 1990). According to Moriasi et al. (2007), very good to satisfactory values of NSE fall in the range of 1 to 0.5 respectively (see Table 4).

RMSE-Observations Standard Deviation Ratio, RSR

The root mean square error (RMSE) – Observations' Standard Deviation Ratio (SR) collectively called RSR, was developed by Moriasi et al. (2007) based on the recommendation of Singh et al. (2004). This error index criterion is used to quantify error in units of the variable being evaluated. In order to develop a performance rating for RMSE, it was divided by the standard deviation of observed values to create RSR:

$$RSR = \frac{RMSE}{STDEV_{O_i}} = \frac{\sqrt{\sum_{i=1}^{n}(O_i - P_i)^2}}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}} \qquad (12)$$

where $STDEV_{O_i}$ is the standard deviation of observed values and all other terms are

defined above. The resulting criterion and expected values can then apply to various

constituents. The value of RSR ranges from 0 (perfect model) to a large positive

value (poor model). According to Moriasi et al. (2007), very good to satisfactory

values of RSR fall in the range of 0.0 to 0.7 respectively (see Table 4).

Percent Bias, PBIAS

Percent bias (PBIAS) is a measure of over- and under-estimation bias of predicted

versus measured values, expressed as a percentage (Gupta et al., 1999):

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(O_i - P_i)*100}{\sum_{i=1}^{n}O_i} \right](\%) \qquad (13)$$

where all terms are described above. The optimal value of PBIAS is 0, indicating

accurate model prediction. Positive values indicate model bias towards under-

prediction, while negative values indicate model bias towards over-prediction.

Moriasi et al. (2007) developed a constituent specific performance rating for PBIAS

based on the known uncertainty of measured data (Harmel et al., 2006) (see Table 4).

Table 4 General performance ratings for recommended quantitative criteria, assuming typical uncertainty in measured data based on Harmel et al. (2006) (from Moriasi et al., 2007).

	RSR	NSE	PBIAS (%)		
			Streamflow	Sediment	N,P
Very Good	0.00≤RSR≤0.50	0.75<NSE≤1.00	PBIAS≤±10	PBIAS≤±15	PBIAS≤±25
Good	0.50<RSR≤0.60	0.65<NSE≤0.75	±10≤PBIAS<±15	±15≤PBIAS<±30	±25≤PBIAS<±40
Satisfactory	0.60<RSR≤0.70	0.50<NSE≤0.65	±15≤PBIAS<±25	±30≤PBIAS<±55	±40≤PBIAS<±70
Unsatisfactory	RSR>0.70	NSE≤0.50	PBIAS≥±25	PBIAS≥±55	PBIAS≥±70

RSR- RMSE-Observations Standard Deviation, NSE- Nash-Sutcliffe Coefficient of Efficiency, PBIAS- Percent Bias

Uncertainty Analysis Method

The Mean-Value First-Order Reliability Method (MFORM) was chosen to quantify uncertainties in the model prediction of streamflow, sediment yield, nitrate load and concentration, and phosphate load. This approach allows the user to determine the variance in the output variable as well as the variance contributed by each important input parameter, otherwise known as basic variable. These basic variables were determined to be important based on sensitivity analyses found in the literature (Sohrabi et al., 2003; White and Chaubey, 2005), the physical meaning of variables as they relate to output tabulation (model algorithms) , and the level of variable importance during model calibration. Depth into the soil layer and seasonal variation of curve number were also considered in the choice of parameters. A description of each basic variable considered in this study is listed in Table 5.

Table 5 Description of AVSWATX input parameters selected for evaluation in the uncertainty analysis.

Parameter	Description
Streamflow	
CNOPwgs	SCS runoff curve number for moisture condition II- during winter growing season
CNOPskp	SCS runoff curve number for moisture condition II- during spring kill planting season
CNOPsgs	SCS runoff curve number for moisture condition II- during spring growing season
ESCO	Soil evaporation compensation factor
GW_REVAP	Groundwater "revap" coefficient. Movement of water from shallow aquifer into unsaturated zone or taken up by plants
HRUSLP	Average slope steepness (m/m)
RCHRG_DP	Deep aquifer percolation factor. Fraction of percolation from root zone to deep aquifer
SMFMN	Melt factor for snow on December 21 (mm $H_2O/°C$-day). Varies the rate of snow melt. Accounts for impact of snow pack density on snow melt
SOL_AWC1	Available water capacity of soil layer 1(mm H_2O/mm soil); plant available water content, AWC=FC-WP
SOL_AWC2	Available water capacity of soil layer 2(mm H_2O/mm soil); plant available water content, AWC=FC-WP
SOL_K1	Saturated hydraulic conductivity of soil layer 1(mm/hr)
SOL_K2	Saturated hydraulic conductivity of soil layer 2(mm/hr)
Sediment	
ADJ_PKR	Peak rate adjustment factor for sediment routing in the subbasin. Impacts the amount of erosion generated in HRUs
BIOMIX	Biological mixing efficiency; redistribution of soil constituents due to activity of biota in the soil (e.g., earthworms)
CH_COV	Channel cover factor
CH_EROD	Channel erodibility factor
SLSUBBSN	Average slope length (m)
SPCON	Linear parameter in calculating maximum amount of sediment that can be reentrained during channel sediment routing
SPEXP	Exponent parameter in calculating maximum amount of sediment that can be reentrained during channel sediment routing
USLE_P	USLE equation support practice factor; ratio of soil loss with a specific support practice to the corresponding loss with up-and-down slope culture
Nitrate	
ANION_EXCL	Fraction of porosity from which anions are excluded. Important in transport of anions (e.g., nitrate) away from soil particle surface
CMN	Rate factor for humus mineralization of active organic nutrients (N and P)
FRT_SURF	Fraction of fertilizer applied to the top 10mm of soil
SOL_NO3_1	Initial NO3 concentration in soil layer 1 (mg/kg)
SOL_NO3_2	Initial NO3 concentration in soil layer 2 (mg/kg)
NPERCO	Nitrate percolation coefficient. Amount of nitrate removed in surface runoff relative to that removed via percolation
Phosphate	
PPERCO	Phosphorus percolation coefficient ($10m^3$/Mg). Ratio of solution phosphorus conc. in surface 10mm of soil to conc. in percolate
SOL_LABP1	Initial soluble P concentration in soil layer 1 (mg/kg)

MFORM is derived by performing a Taylor series expansion of the model output function as follows (equation 3):

$$Y = g(X_e) + \sum_{i=1}^{n} (x_i - x_{ie}) \left(\frac{\partial g}{\partial x_i} \right)_{X_e} \qquad (14)$$

where Y is the dependent variable or model output of interest; g ( ) is the function representing the simulation process (algorithms, set of equations) to obtain Y; X_e is the vector of basic variables at the expansion point; n is the number of basic variables x_i; and $\partial g/\partial x_i$ represents the rate of change of the model output with respect to a unit change in each basic variable, usually referred to as the sensitivity coefficient. In MFORM, the expansion point is at the mean value of basic variables. Therefore, the mean and variance of the dependent variable can be approximated as (equations 4 and 5):

$$E(Y) \approx g(X_m) \qquad (15)$$

$$Var(Y) = \sigma_Y^2 \approx \sum_{i=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)_{X_m}^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)_{X_m} \left(\frac{\partial g}{\partial x_j} \right)_{X_m} \cdot C_v(x_i, x_j) \qquad (16)$$

where E(Y) is the expected value (mean) of random variable Y; X_m is the vector of basic variables at the mean values; σ_i^2 is the variance of basic variable i; $C_v(x_i, x_j)$ is the covariance of basic variables i and j; and all other variables are previously defined. The first term represents the variance of statistically independent parameters, while the second term is used to tabulate the variance of correlated parameters. $C_v(x_i, x_j)$ can be tabulated by using the identity (equation 6),

$$C_v(x_i, x_j) = E[(x_i - x_{mi})(x_j - x_{mj})] \qquad (17)$$

where, x_{mi} is the mean value of all x_is and x_{mj} is the mean value of all x_js. If basic variables (e.g., soil hydraulic conductivity, curve number, slope steepness, etc.) are not correlated, $C_v(x_i, x_j)$ is equal to zero. In this case, the variance of output can be written as (equation 7):

$$Var(Y) = \sigma_Y^2 \approx \sum_{i=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)_{X_m}^2 \sigma_i^2 \qquad (18)$$

This term represents the fraction of model output variance (FOV) contributed by each basic variable (x_i). In this equation the squared sensitivity coefficient ($\partial g/\partial x_i$) serves as a way to assign a measure of importance to the variance of each basic variable. When using complex models, the best way to solve for $\partial g/\partial x_i$ is by using numerical methods.

Tomovic (1963) defined the sensitivity coefficient in its simplest form using one basic variable as:

$$\frac{\partial g}{\partial x} = \frac{g(x_0 + \Delta x) - g(x_0)}{\Delta x} \qquad (19)$$

where x_0 is the initial value of the basic variable, Δx is the change in the basic variable and all other symbols are defined above. Melching and Bauwens (2001) used the same forward difference scheme to tabulate $\partial g/\partial x_i$ in an MFORM analysis with change in x_i equal to 1%. They originally increased x_i by 10%, but that was too large for pollutant removal efficiency parameters. Their study was conducted using coupled

models; a non-point pollution load model (KOSIM), and a river water-quality model (SALMON-Q). Melching and Yoon (1996) increased parameter values in the QUAL2E model by 5% based on Brown and Barnwell's (1987) recommendation when calculating uncertainty in QUAL2E_UNCAS. That percentage of increase was effectively used. The unit change of x_i depends on the sensitivity of the model to change in parameters. We know that models such as SWAT are not linear, but for small perturbations it can be assumed linear. Numerous studies using this method have changed parameters between 1% and 10% because similar results for the sensitivity coefficient have been obtained within this range (Melching and Yoon, 1996; Melching and Bauwens, 2001; Zhang and Yu, 2004; Zhang and Haan, 1996). Changes beyond 10% would likely cause improbable estimates of sensitivity due to model nonlinearity. In modeling, there is always a balancing act between efficiency and accuracy. In this study, the forward difference numerical method was chosen to tabulate the sensitivity coefficient over a central difference scheme because it is a suitable method that gives valid results and it requires less model runs. This efficiency is very beneficial especially for studies requiring a large number of repeated simulations to test and compare different scenarios (e.g., BMP's in TMDL analysis).

The sensitivity coefficient is often normalized to get a dimensionless index which provides a more unbiased ranking of basic parameters for sensitivity analysis (Lenhart et al., 2002; Melching and Yoon, 1996; Shirmohammadi et al., 2006). Dubus and Brown (2002) refer to the absolute value of the normalized sensitivity as the

maximum absolute ratio of variation (MAROV) index. The absolute value allows for better comparison between parameters. Using only one parameter, x, for simplification purposes, the normalized sensitivity can be expressed as:

$$S = \left| \frac{g(x_0 + \Delta x) - g(x_0)}{\Delta x} \times \frac{x_0}{g(x_0)} \right| \qquad (20)$$

where all symbols are defined above. As S increases, the output variable has an increasing sensitivity to changes in the given input parameter. Sensitivity analysis was conducted on all output variables (streamflow, sediment, nitrate, and phosphate) over annual and monthly timeframes using the associated important input parameters.

MFORM has been an attractive method to use over other uncertainty techniques because of its simplicity only requiring the mean and variance of basic variables. Descriptive statistics for each basic variable (Table 6) were determined by assigning a range and probability distribution to each variable. The assigned range of each variable was determined based on the suggested range in the AVSWATX user's manual, the range of realistic perturbation values observed during calibration, and also ranges specified in the literature. The column labeled as "Range" in Table 6 represents the difference between the maximum and minimum values selected from the assigned range during the LHS random sampling scheme.

Probability distributions were chosen for each variable based on information synthesized from the literature. In all cases, a bounded distribution was necessary

because each parameter has an upper and lower limit. The uniform distribution was

assigned to those variables for which a range was determined, but not enough

information about the behavior or shape of the distribution was available. A log-

uniform distribution was assigned to such variables if the range was within a factor of

10 or greater. McCuen (2002) found the gamma distribution to be representative for

curve numbers used in designs built for annual maximum design storms in watersheds

composed mostly of rural lands. Gamma distributions require scale and shape factors

to identify its moments. The range is from zero to infinity (unbounded) and sample

mean and standard deviation are needed to quantify scale and shape factors (Brighton

Webs Ltd., 2007). That information was not readily available for this study; therefore

a similar and equally representative distribution was sought.

Soil hydraulic conductivity was shown to be log-normally distributed (Coelho, 1974;

Jensen and Refsgaard, 1991); however, the log-normal distribution is unbounded and

estimates of mean and standard deviation are necessary to determine its distribution.

That information again, was not readily available. The beta distribution is often used

when there is not enough information about the distribution (Wyss and Jorgensen,

1998) and for events that take place between a maximum and minimum value

(Brighton Webs Ltd., 2007). It is based on two shape factors which are assigned

according to the likely shape of the distribution. Therefore, a beta distribution was

used for those variables such as curve number and soil hydraulic conductivity for

which a range was determined and there was some information about the shape of

their distributions (Table 6). Variables in this study assigned to the beta distribution were considered to have a shape similar to that of the log-normal distribution.

The mean and standard deviation of a random variable considered to have a beta distribution can be obtained using the following equations:

$$\mu_X = A + \frac{p}{(p+q)}(B-A) \tag{21}$$

$$\sigma_X = \sqrt{\frac{pq}{(p+q)^2(p+q+1)}(B-A)^2} \tag{22}$$

where A and B are the lower and upper limits of the range respectively, p and q are the shape factors, and μ_x and σ_x are the respective mean and standard deviation of the random variable. The shape factors, p and q, can normally be determined using the method of least squares on data points obtained from the histogram of a data set (Ricciardi et al., 2005). However, data sets were not available for the input parameters in this study. Therefore, p and q were assigned values of 2 and 4, respectively based on typical shape factors for distributions fitting the profile of the lognormal distribution presented in Wyss and Jorgensen (1998).

The mean and standard deviation of a random variable of uniform distribution can be obtained using the equations:

$$\mu_X = \frac{1}{2}(A+B)$$ (23)

$$\sigma_X = \sqrt{\frac{1}{12}(B-A)^2}$$ (24)

where all symbols are defined above.

The mean and standard deviation of a random variable having a log-uniform distribution can be obtained using equations:

$$\mu_X = \frac{B-A}{\ln B - \ln A}$$ (25)

$$\sigma_X = \sqrt{(B-A)\frac{(\ln B - \ln A)(B+A) - 2(B-A)}{2(\ln B - \ln A)^2}}$$ (26)

where all symbols are defined above.

A Latin Hypercube Sampling (LHS) scheme (McKay et al., 1979) was used to confirm the descriptive statistics of each variable. Using the range and distribution of each variable, 250 samples of each variable were produced; the descriptive statistics were then tabulated for each parameter (Table 6). Descriptive statistic results using LHS verified those obtained using the equations for the distributions (beta, uniform, and log-uniform) listed above. Mean values of all variables were then used as input

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into AVSWATX to perform each model run (1 run using all mean values and 1 run for 5% change of each input parameter). Both mean and standard deviation values for all variables were used as input for MFORM tabulation of model output uncertainty.

A program was written to tabulate MFORM using the MATLAB® mathematical computation tool. Output files (rch.dbf) from AVSWATX representing each model run were read into the program and used to tabulate monthly and annual variances for streamflow, sediment, nitrate, and phosphate loadings. Daily variances were also quantified for constituent concentrations, which were used to demonstrate the methodology for margin of safety (MOS) tabulation (see programming code in Appendix C).

Table 6 Watershed averaged minimum, maximum, range, mean, median, standard deviation and coefficient of determination of basic variables.

Number	Parameter	Units	File Location	Distribution	Assigned Range	Minimum	Maximum	Range	Mean	Median	Standard Deviation	Coefficient of variation
1	ADJ_PKR	-	bsn	Uniform	0.0-1.0	0.0011	0.999	0.9979	0.5001	0.5	0.2893	0.5785
2	ANION_EXCL	-	sol	Uniform	0.0-1.0	0.0032	0.997	0.9938	0.4999	0.4995	0.2892	0.5784
3	BIOMIX	-	mgt1	Uniform	0.0-1.0	0.0006	0.998	0.9974	0.5001	0.5	0.2893	0.5784
4	CH_COV	-	rte	Uniform	0.0-1.0	0.0024	0.997	0.9946	0.4998	0.5	0.2892	0.5787
5	CH_EROD	-	rte	Uniform	0.0-1.0	0.0004	0.998	0.9976	0.5000	0.5	0.2892	0.5784
6	CMN	-	bsn	Uniform	0.00015-0.00045	0.0002	0.00045	0.0003	0.0003	0.0003	0.0001	0.2893
7	CNOPwgs	-	mgt2	Beta	67.0-85.0	68.2	83.4	15.2	75.9988	76	3.01087	0.03962
8	CNOPskp	-	mgt2	Beta	56.0-71.0	57.6	69.5	11.9	63.4996	63.5	2.49791	0.03934
9	CNOPsgs	-	mgt2	Beta	61.0-71.0	61.8	70.2	8.4	66.0004	66	1.67050	0.02531
10	ESCO	-	hru	Log-uniform	0.01-1.0	0.0100	0.986	0.9760	0.2151	0.0993	0.2505	1.1645
11	FRT_SURF	-	mgt2	Log-uniform	0.01-1.0	0.0102	0.986	0.9759	0.2149	0.1002	0.2501	1.1637
12	GW_REVAP	-	gw	Uniform	0.02-0.2	0.0200	0.2	0.1800	0.1100	0.11	0.0521	0.4735
13	HRUSLP	m/m	hru	Uniform	0.0-0.08	0.0003	0.07963	0.0794	0.0392	0.0401	0.0230	0.5867
14	NPERCO	-	bsn	Log-uniform	0.01-1.0	0.0100	0.99	0.9800	0.2151	0.10047	0.2503	1.1635
15	PPERCO	-	bsn	Uniform	10.0-17.5	10	17.5	7.5	13.7464	13.75	2.1687	0.1578
16	RCHRG_DP	-	gw	Uniform	0.0-1.0	0.0014	0.9990	0.9976	0.5000	0.4980	0.2893	0.5785
17	SLSUBBSN	m	hru	Beta	0.0-30.0	2.55	27.5	24.95	14.9992	15	5.0103	0.3340
18	SMFMN	mm H2O/°C-day	bsn	Uniform	1.4-8.5	1.43	8.49	7.06	4.94924	4.945	2.0541	0.4150
19	SOL_AWC1	mm H2O/mm soil	sol	Uniform	0.09-0.27	0.09043	0.269	0.17857	0.1800	0.18	0.05205	0.28920
20	SOL_AWC2	mm H2O/mm soil	sol	Uniform	0.06-0.18	0.06005	0.18	0.11995	0.1200	0.12	0.03470	0.28918
21	SOL_K1	mm/hr	sol	Beta	22.18-80.64	23	77.9	54.9	41.6868	40.55	10.51184	0.25216
22	SOL_K2	mm/hr	sol	Beta	9.64-100.0	11.1	85.5	74.4	39.7616	38.05	16.08984	0.40466
23	SOL_LABP1	mg/kg	chm	Uniform	100.0-250.0	111	241	130	175.004	175	25.1376	0.1436
24	SOL_NO3_1	mg/kg	chm	Uniform	0.0-3.0	0.0027	2.99	2.9873	1.5006	1.495	0.8678	0.5783
25	SOL_NO3_2	mg/kg	chm	Uniform	0.0-5.0	0.0162	4.98	4.9638	2.5004	2.5	1.4459	0.5783
26	SPCON	-	bsn	Log-uniform	0.0001-0.01	0.0001	0.0099	0.0098	0.0021	0.0010	0.0025	1.1635
27	SPEXP	-	bsn	Uniform	1.0-2.0	1	2	1	1.4999	1.5000	0.2890	0.1927
28	USLE_P	-	mgt1	Uniform	0.25-0.75	0.251	0.75	0.499	0.5001	0.5005	0.1445	0.2891

In Maryland, nutrient TMDLs are generally determined using the following steps (MDE, 2006):

1. A water quality model is calibrated to represent "baseline" conditions which are the observed conditions of the waterbody that match measured data taken during a given time period. These conditions also represent the impairment of the waterbody. Loads from both point and non-point sources are included in the modeling scheme.

2. The model scenario depicting baseline conditions is then used to create different nutrient loading reduction scenarios that will cause the waterbody to meet its water quality standard. Both urban and agricultural Best Management Practices (BMPs) are used to reduce pollutant loads. Load reductions are quantified based on nutrient removal efficiency ratings that have been developed for various BMPs. The future condition scenario represents the loading reductions used to estimate TMDLs. Both growing season and annual flow TMDLs are quantified.

3. Margin of safety is quantified explicitly. It is typically assigned as 5 to 10 percent of non-point source (NPS) load allocations (at times, specifically referred to as reduced agricultural loads) defined under the future condition scenario. For example, if the NPS allocation for nitrogen is tabulated as 100,000 lbs/year by a future condition model scenario, MOS

for that TMDL is 5,000 lbs/year assuming a 5% explicit assignment of

MOS. The NPS allocation for nitrogen then becomes 95,000 lbs/yr.

This methodology is missing two components that current efforts of TMDL

advancement consider important. EPA guidance has suggested making probability–

based water quality impairment decisions for conventional pollutants (USEPA,

1997b). The purpose of such guidance was to account for measurement error and

potentially small data sets not properly representing the conditions of a waterbody

(USEPA, 2003a). EPA guidance and recommendations from other agencies and

scientists have also stressed the importance of using formal uncertainty analysis

methods to tabulate MOS as opposed to arbitrarily assigning its value (NRC, 2001;

Shirmohammadi et al., 2006; USEPA, 2002a).

Current methods of nutrient TMDL assessment in Maryland are not probability-based

and do not account for MOS using a formal uncertainty analysis scheme. This study

suggests an alternative method of nutrient TMDL assessment in Maryland, which

uses a probability-based approach and MFORM, a formal method of uncertainty

tabulation, to determine a TMDL along with its MOS value.

The designated use of the study waterbody is aquatic life support (Shirmohammadi

and Montas, 2003). That is interpreted here as Maryland's Use I designation (Code of

Maryland Regulations [COMAR] 26.08.02.02); water contact recreation, and

protection of non-tidal warm water aquatic life. In Maryland, a waterbody of this use

would normally be evaluated for nutrient contamination using indicators such as chlorophyll-a and DO, however data containing that information were not collected in Warner Creek watershed. We therefore assumed a Use I-P designated use which is the same as Use I but contains an additional use as a public water supply. This justifies the employment of NO_3-N concentration (a drinking water contaminant) as an indicator of waterbody impairment in the current study.

According to EPA's *National Recommended Water Quality Criteria* the water quality criterion for nitrate concentration measured as nitrogen is 10 mg/l for a waterbody designated for drinking water use (USEPA, 2003b). EPA guidance has recommended listing a waterbody as impaired if greater than 10% of conventional chemical samples exceed the assigned water quality criterion (USEPA, 1997b; USEPA, 2002c). This type of probability-based standard is meant to account for natural variability and measurement error (Borsuk et al., 2002; USEPA, 2003a). The number of samples to be taken and the time duration of sampling were not specified; therefore daily samples from 1994 to 2001 were used in this study. Daily nitrate concentrations were derived from SWAT output by dividing nitrate load by flow rate as shown in the MATLAB program for daily MFORM calculations labeled calc29Daily.m in Appendix C-2.

After examining the number of daily nitrate concentrations that exceeded the maximum contaminant level (MCL) of 10 mg/L in Warner Creek watershed, we determined that the waterbody was not impaired. Less than 10% of daily nitrate

samples exceeded the 10 mg/L MCL over the entire time period (1994-2001),

therefore EPA guidelines were met. BMPs implemented in this watershed prior to

sampling efforts may be attributed to the unimpaired status of the waterbody. In order

to create a scenario in which the waterbody was impaired, we lowered the MCL to 6

mg/L. This increased the probability of exceedance so that the methodology to

tabulate a nutrient TMDL including MOS could be properly demonstrated.

Daily nitrate concentrations computed by the calibrated SWAT model (base-line

conditions representing current conditions of the waterbody) and the associated daily

standard deviations tabulated with MFORM were used to calculate daily exceedance

probabilities as (Borsuk et al., 2002):

$$p = P(c > c* \mid \beta, \sigma, X) = 1 - F\left(\frac{c* - g(X, \beta)}{\sigma}\right) \qquad (27)$$

where p is the exceedance probability, c is the chemical concentration, c* is the

numerical criterion of c (6 mg/L), β represents the set of all model parameters (e.g.

curve number, and hydraulic conductivity), σ is the standard deviation of chemical

concentration (found using MFORM), X represents model input variables (e.g.,

precipitation and temperature), g(X, β) is the output chemical concentration generated

by the model also known as c, and the function F depicts the cumulative standard

normal distribution.

Figures D1 through D8 in Appendix D show the trends of daily nitrate concentration

for each year of the study period (1994-2001). Notice that the scales on the y-axes

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differ for some years, but it is still quite clear that critical periods of nitrate

concentration and variance in model output (shown by standard deviation) occur

during wet seasons from January to May and from October to December, 8 months

out of the year. This is especially evident in years 1994-1997 (Figures D1-D4) which

include average (1994, 1995, and 1997) to wet years (1996). That trend is not as clear

in dry years (2001; Figure D8) or years that experienced partial periods of drought

during normally wet seasons (1998, 2000; Figures D5 and D7, respectively).

Therefore, the days within the previously mentioned wet season months were

considered the critical period in each year. The likelihood of exceeding the water

quality standard was larger during that time frame which represented the worst-case

scenario. The critical period of each year was then used to tabulate the exceedance

frequency. Exceedance frequency is defined as the number of days that the

exceedance probability is greater than 10% divided by the total number of days in the

critical time period of each year. A probability distribution of annual exceedance

frequencies was formulated to describe the uncertainty in the exceedance frequency

resulting from parameter uncertainty. The expected exceedance is defined as the

mean of the distribution of annual frequency values.

The portion of the probability distribution of exceedance frequencies less than or

equal to 10% represents the probability that the true exceedance frequency will meet

the 10% frequency standard. Borsuk et al. (2002) referred to that portion of the

distribution as the confidence of compliance (CC). CC is a measure by which water

quality goals can be expressed. For example, if a water quality manager wanted to be

40% confident that the exceedance frequency in a waterbody is 10% or less, the

manager would then reduce the load until the CC goal of 40% was met.

Once CC was determined for the baseline nitrate load (no reductions), several other

CCs were obtained by reducing the percentage of load flowing into the waterbody by

5% up to 40%. At the 40% load reduction in Warner Creek, the CC reached 100%.

Therefore, no further reductions were considered. The nitrate load associated with the

desired CC to meet the water quality *goal* was then compared to the load required to

meet the *water quality standard*. The difference between the load required to meet the

water quality standard and the load required to meet the water quality goal was

assigned to the margin of safety value. Therefore, the load reduction required to meet

the desired CC is the TMDL for the waterbody of interest.

Chapter 5: Results and Discussion

Model Performance

The performance of AVSWATX in predicting hydrology (surface flow, baseflow, and total streamflow), sediment, and nutrient (nitrate and phosphate) loads was examined over the course of eight years (1994-2001). Both graphical and statistical methods of evaluation were utilized. To get a general idea of climatic behavior at the study site, we examined annual precipitation amounts over the entire period of study (1994-2001) shown in Figure 4. The year 1996 was an unusually wet year with the State of Maryland receiving an average of 38% more rainfall than normal (USEPA, 2007). Although annual yields do not reflect it, Maryland experienced drought conditions during 1998 through 1999 (MD State Climatologist Office, 2007). Also, a drought period began in May, 2001 that lasted until December 2002.
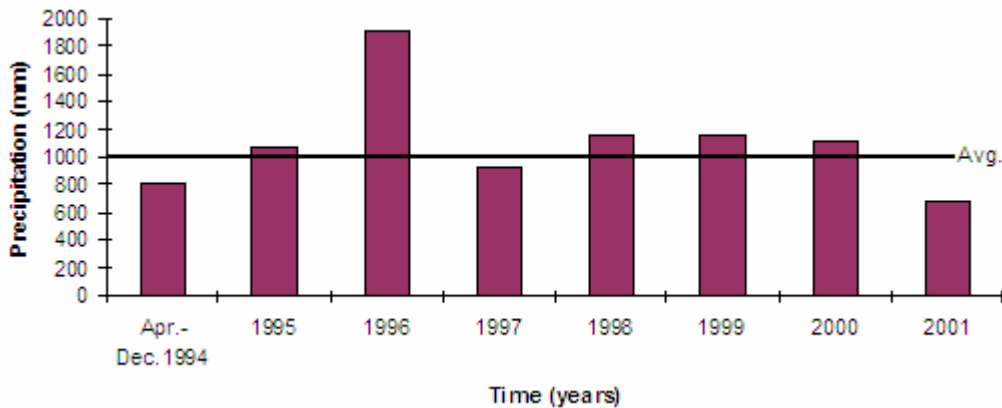
Figure 4 Annual precipitation and line of annual average precipitation in Warner Creek watershed.

Surface Runoff Results and Discussion
Figure 5 shows the time series and scattergram plots of measured and simulated

monthly surface runoff during the calibration period. The plots show that the model is

able to follow the dynamic monthly trends of flow well. However, systematic

discrepancies are quite evident especially during high flow periods (e.g., January

1995 and 1997, July 1995, and November 1997) where the model is under-predicting.

The same behavior is seen during the validation period in January 1998 and 1999

(Figure 6). Inconsistencies in surface runoff prediction may be attributed to use of the

SCS curve number method. The SCS method depends on empirical information to

tabulate surface runoff, which is often not flexible enough to capture natural

variability especially during major storm events. For instance, table information (land

use type, treatment or practice, hydrologic condition, and hydrologic soil group) is

used to determine curve number. In this study, calibrated curve numbers were

generally higher or lower than table values by 5-12 units.

The Green and Ampt (1911) method, modified by Mein and Larson (1973), was

added to AVSWAT-X as an alternative to tabulate surface runoff. This method is a

physically-based infiltration model that is sensitive to variations of rainfall intensity

during storm events. It uses effective hydraulic conductivity (Ke) as its infiltration

parameter as opposed to saturated hydraulic conductivity (Ks) because the soil is not

completely saturated during rainfall infiltration. Sub-daily precipitation data are

needed to use the Green-Ampt Mein-Larson excess rainfall method. We did not use

this method in our study because sub-daily rainfall measurements were irregular due to equipment malfunctioning which led to missing data.

Summary statistics and model evaluation criteria results for measured and simulated monthly surface runoff, baseflow, and streamflow during calibration and validation periods are listed in Table 7. The model appears to have performed better in predicting surface runoff during validation with NSE and RSR values of 0.67 and 0.57, respectively, both values indicating good agreement; while calibration results were slightly lower with NSE and RSR values of 0.62 and 0.61, respectively both values indicating satisfactory agreement. A slight under-prediction was observed during calibration indicated by a positive PBIAS value of 3%. Surface runoff was mostly over-predicted during validation shown by a negative PBIAS value of -5.5%.
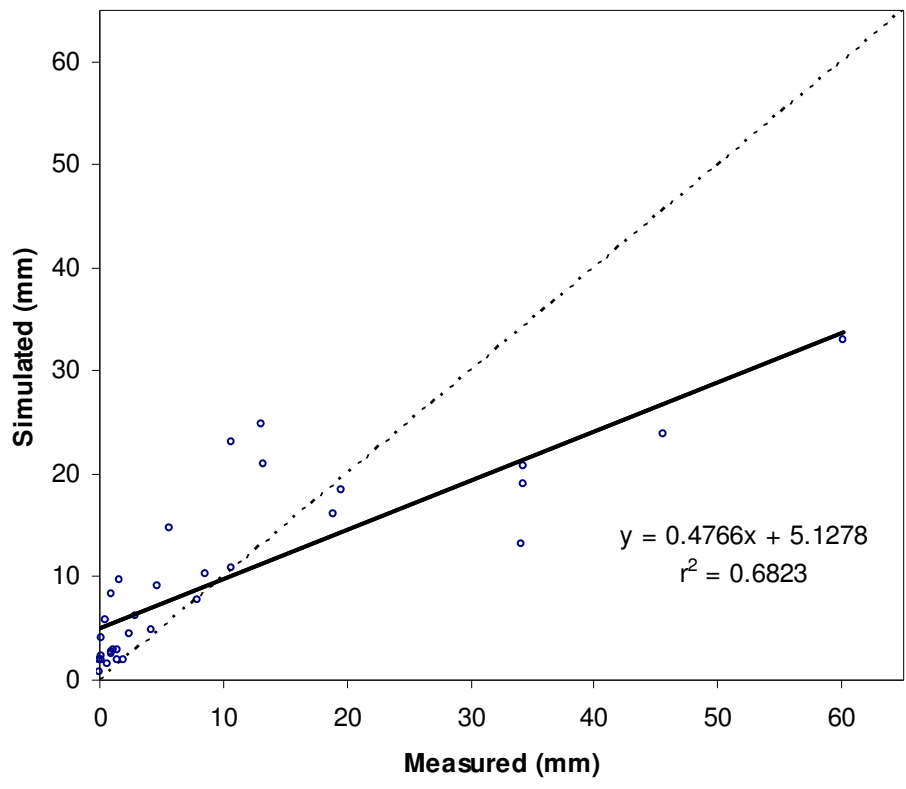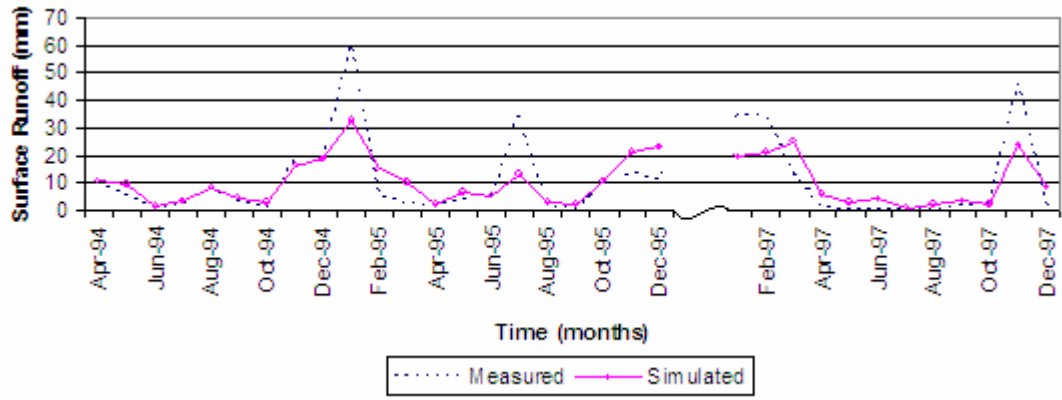
Figure 5 Time series and scattergram of measured and simulated monthly surface runoff (mm) data during the calibration period (April, 1994-1995 and 1997).
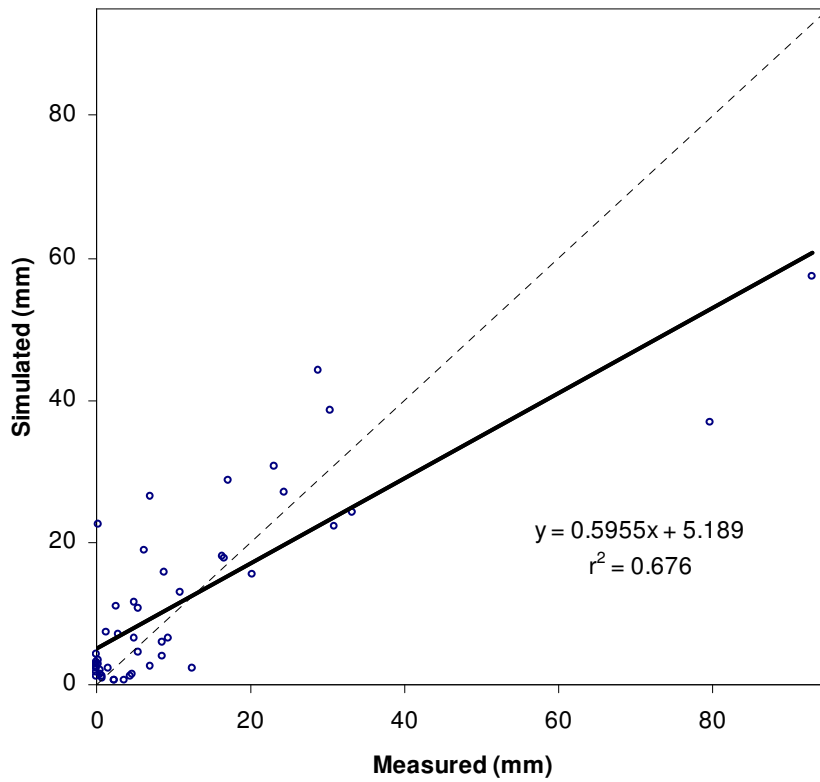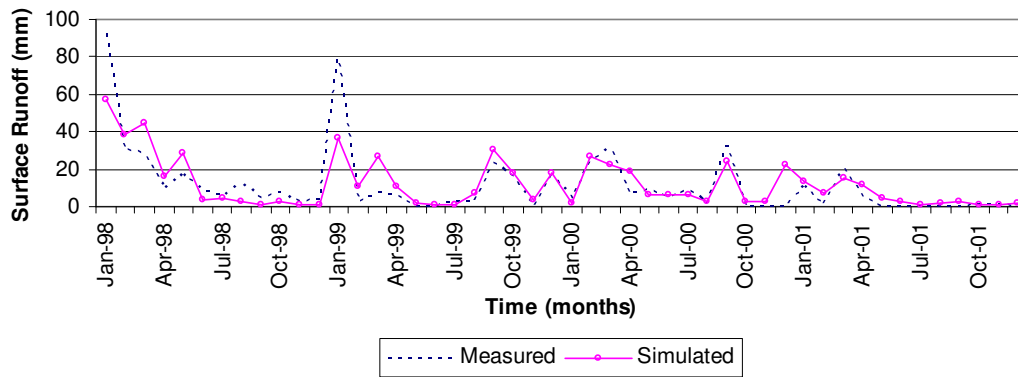
Figure 6 Time series and scattergram of measured and simulated monthly surface runoff (mm) data during the validation period (1998-2001).

Baseflow Results and Discussion

Baseflow was mostly over-predicted during calibration and validation periods as indicated by time series plots (Figures 7 and 8) and negative PBIAS values (Table 7). Model performance was clearly worst during baseflow calibration compared to surface runoff calibration. One reason for this is because errors associated with high streamflow values tend to be larger than those associated with low streamflow values, especially when squared terms (e.g., the term $\left(O_i - \overline{O}\right)^2$) are used in optimization/evaluation criteria such as r^2 (equation # 10) and NSE (equation # 11). Therefore trying to minimize high flow errors often leads to fitting the higher portion of the hydrograph (i.e., peak surface flows) at the expense of lower portions (i.e., baseflow) (Krause et al., 2005). All model evaluation criteria for monthly baseflow during the validation period were unsatisfactory (Table 7).

As mentioned earlier, adjustments to measured baseflow amounts were made to remove subsurface contributions of baseflow from outside the watershed boundary that were likely unaccounted for by the model (Chu and Shirmohammadi, 2004). Therefore, adjusted measured baseflow and streamflow amounts (signified in Table 7) were used in this study to provide a fair comparison between measured and model simulated values. The water budget analysis corresponding to baseflow adjustment may have contributed to errors already present at the time of field sampling. Other sources of error in this study be attributed to equipment failure, errors in sampling, measurement, and data handling, especially with instantaneous grab sampling being part of the monitoring scheme.
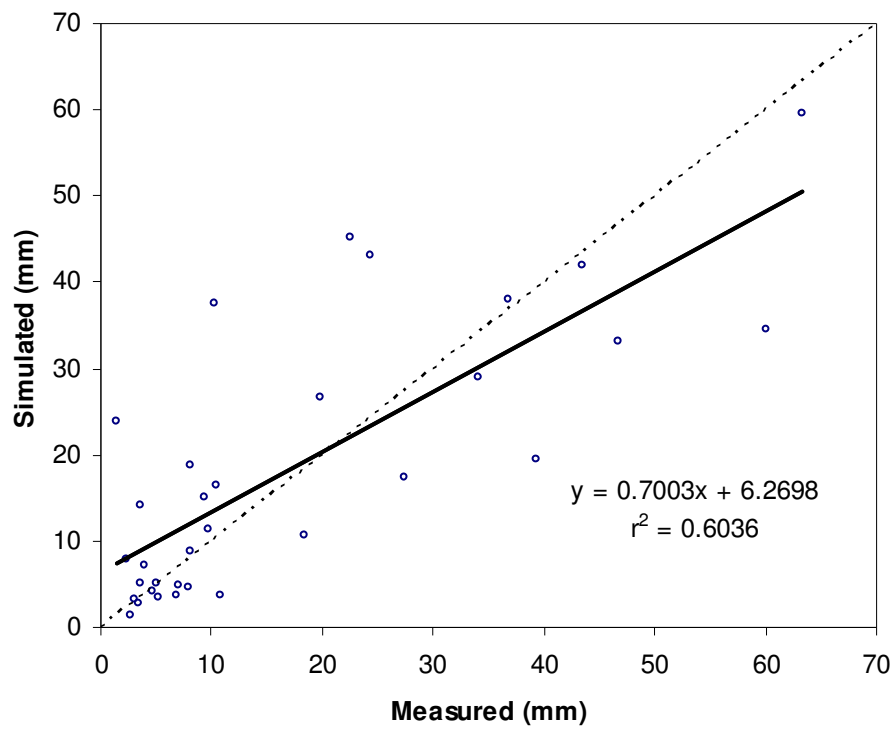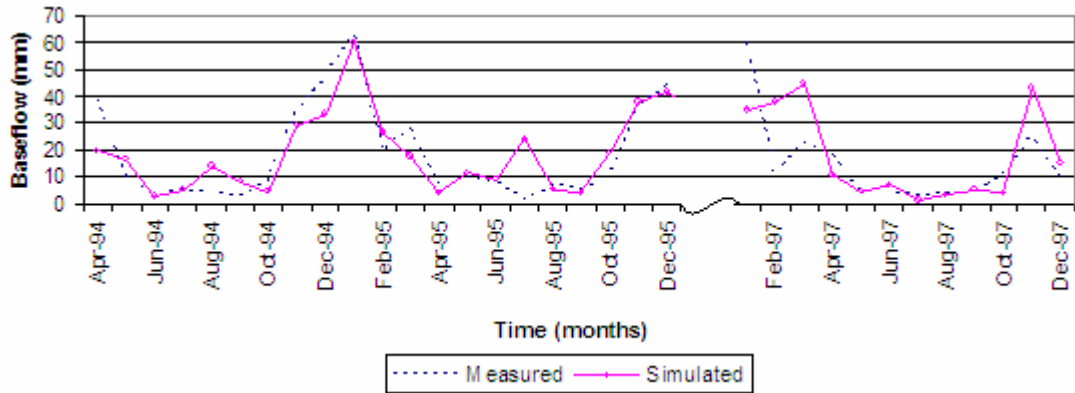
Figure 7 Time series and scattergram of measured and simulated monthly baseflow (mm) data during the calibration period (April, 1994-1995 and 1997)
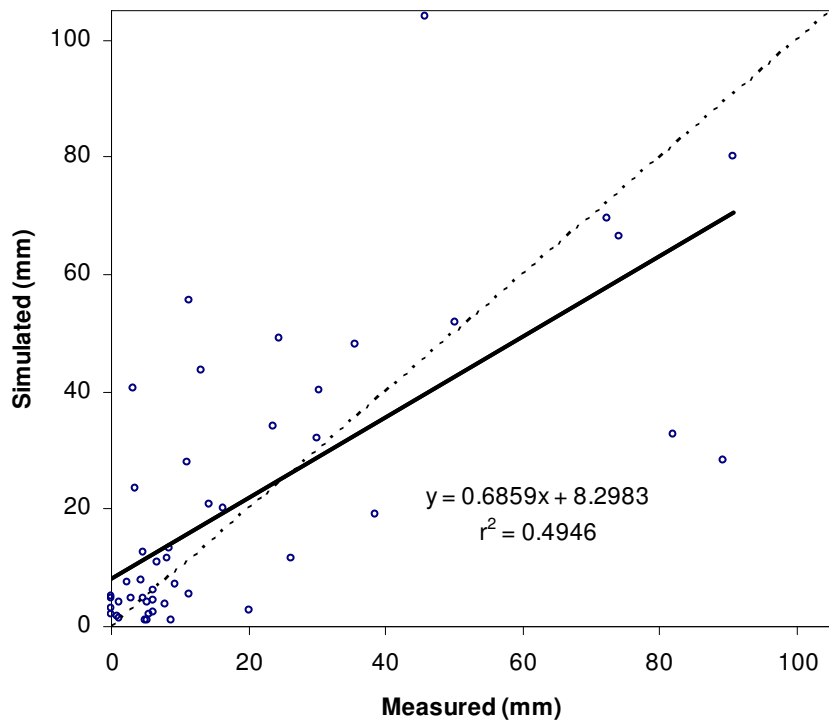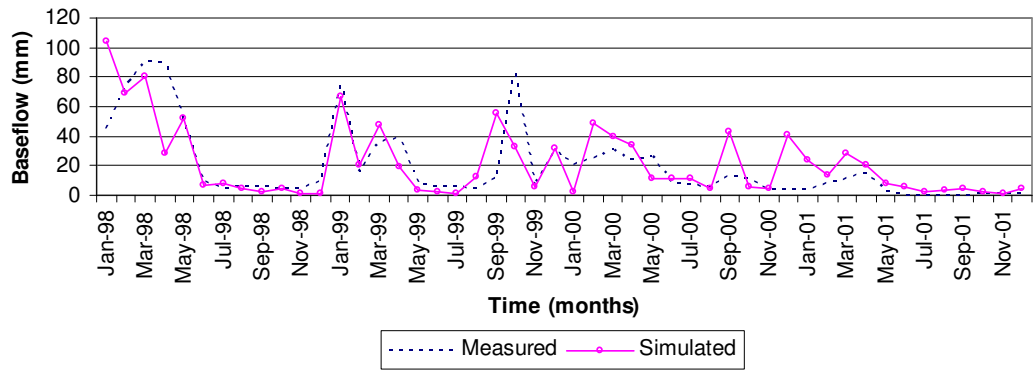
Figure 8 Time series and scattergram of monthly baseflow (mm) during the validation period (1998-2001).

Streamflow Results and Discussion

Graphical comparisons of measured and simulated streamflow during calibration and validation periods show major improvement over surface and baseflow results with timing and magnitudes matching up in time series plots and regression lines more closely meeting the 1:1 line of equal values in scattergram plots (Figures 9 and 10). Model performance was very good during calibration showing NSE, RSR, and PBIAS results of 0.78, 0.46, and -3%, respectively (Table 7).

Validated model performance was slightly lower than during the calibration period, but still categorized as good with NSE, and RSR values of 0.70 and 0.54, respectively. Although streamflow during the validation period was mostly over-predicted, model performance considering systematic deviations was very good because PBIAS was within the range of ± 10%. Total streamflow measurements are a combination of surface and baseflow values. Poor baseflow prediction is likely the reason for decreased model performance during streamflow validation compared to the calibration period.
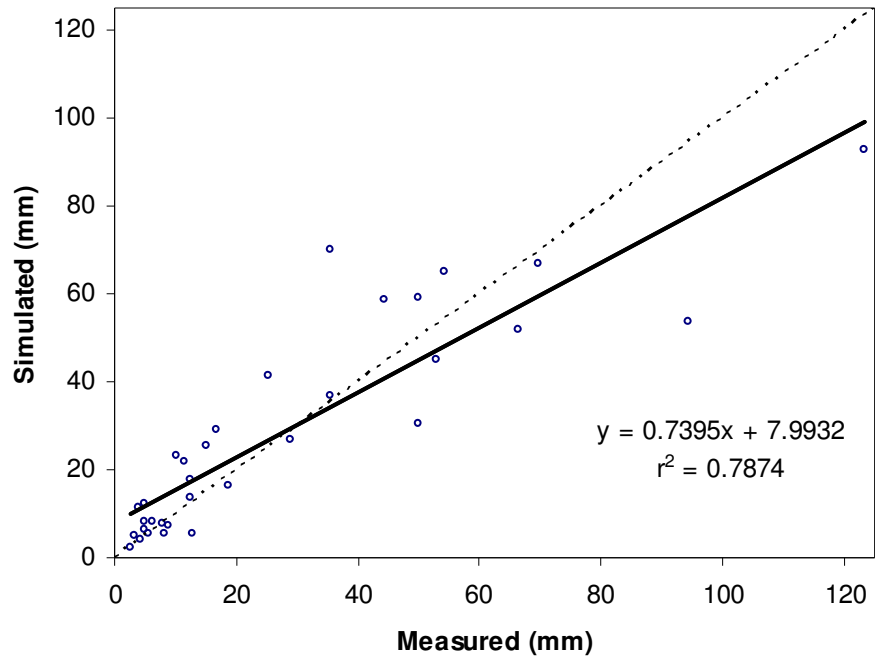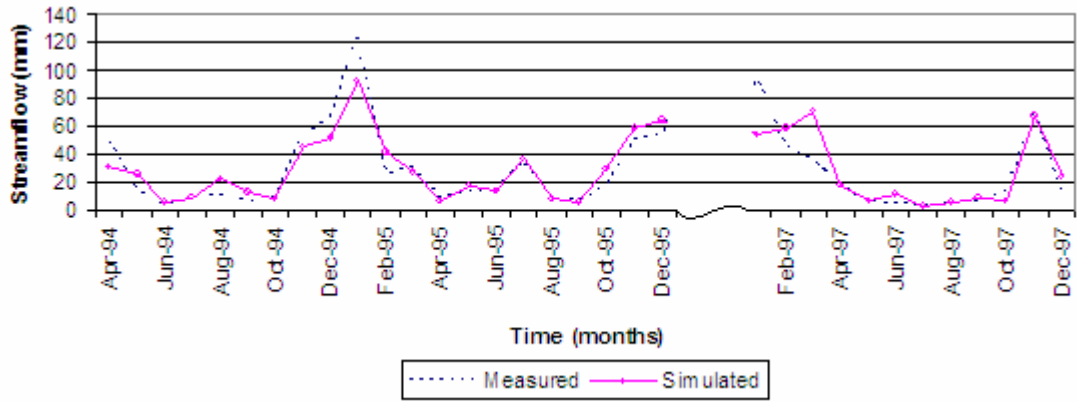
Figure 9 Time series and scattergram of measured and simulated monthly streamflow (mm) data during the calibration period (April, 1994-1995 and 1997).
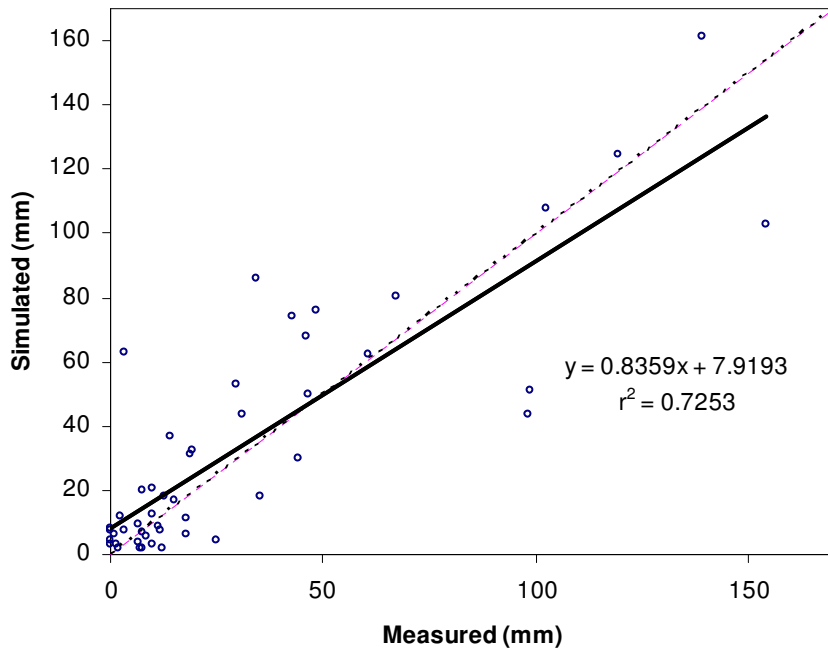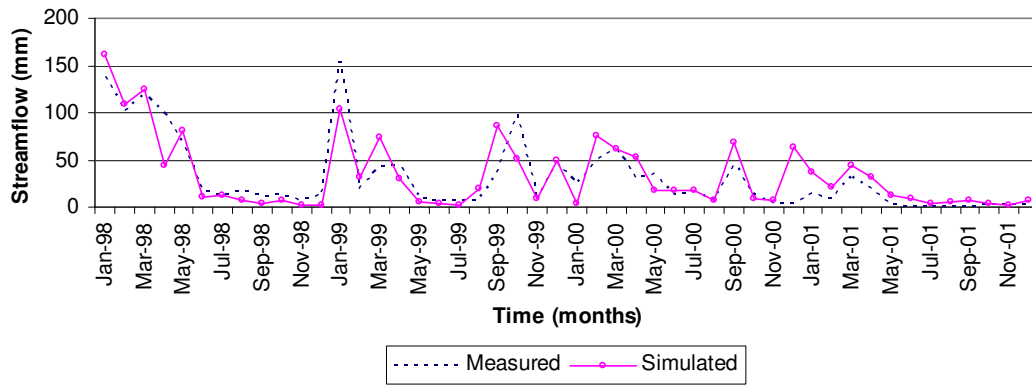
Figure 10 Time series and scattergram of measured and simulated monthly streamflow (mm) data during the validation period (1998-2001)

Table 7 Summary statistics and model evaluation criteria results for measured and simulated monthly hydrology results during the calibration and validation periods.

Hydrologic Measurement		Mean (mm)	StDev (mm)	No. of Samples	r2	b	RMSE (mm)	NSE	RSR	PBIAS (%)
Calibration Period (April, 1994-1995 and 1997)										
Monthly Surface Runoff	Measured	10.40	14.99	33						
	Simulated	10.08	8.65	33	0.68	0.48	9.10	0.62	0.61	3.00
Monthly Baseflow	Adjusted Measured	17.09	17.36	33						
	Simulated	18.24	15.65	33	0.60	0.70	11.03	0.58	0.64	-6.70
Monthly Streamflow	Adjusted Measured	27.49	29.16	33						
	Simulated	28.32	24.30	33	0.79	0.74	13.35	0.78	0.46	-3.00
Validation Period (1998-2001)										
Monthly Surface Runoff	Measured	11.30	18.45	48						
	Simulated	11.92	13.37	48	0.68	0.60	10.57	0.67	0.57	-5.50
Monthly Baseflow	Adjusted Measured	19.34	24.79	48						
	Simulated	21.56	24.18	48	0.49	0.69	18.80	0.41	0.76	-11.50
Monthly Streamflow	Adjusted Measured	30.58	38.25	48						
	Simulated	33.48	37.54	48	0.73	0.84	20.64	0.70	0.54	-9.50

StDev= standard deviation, r^2= coefficient of determination, b=slope, RMSE= root mean square error, NSE= Nash-Sutcliffe coefficient of efficiency, RSR= RMSE-observation's standard deviation ratio, PBIAS= percent bias

Evaluation of Sediment Predictions

Results for sediment prediction were acceptable except for high peak events. Observation of monthly trends during the calibration period shows a large amount of under-prediction, particularly in April 1994 and January 1995 (Figure 11). Part of the reason for this misrepresentation could be the fact that streamflow was also under-predicted during those time periods. Unforeseen occurrences in watershed management may have caused spikes in measured data. High measured sediment yield in April 1994 can be attributed to cows being allowed to wander through the stream. The measured spike in January 1995 may be due to application of ammonium based deicer to county roads, which would have caused higher flows and therefore increased erosion. Measured data for sediment concentration were quite poor as well.

Sediment yield during the validation period was mostly over-predicted as shown by the PBIAS of -22.3 (Table 8). Although NSE values for monthly results during calibration and validation periods are poor at 0.2, an NSE value greater than zero means that the model is a better predictor of measured data than using the mean of observed values. Trends during 1996 were unsatisfactory, mainly because 1996 was an extremely wet year. The SWAT model does not seem to perform well in predicting streamflow and sediment yield under extremely wet conditions. This again, can be attributed to use of the empirically based SCS curve number method to calculate surface runoff. Similarly poor predictions of monthly sediment yield using SWAT were observed in the literature (Kirsch et al., 2002; Santhi et al., 2001b). Annual results of sediment yield over the entire four year period show good results based on

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RSR and PBIAS results of 0.57 and 15.7%, respectively (Table 8). Based on the

efficiency coefficient value of 0.57, annual results are considered to be satisfactory.

Annual predictions were expected to be an improvement over monthly predictions

since SWAT was designed for long-term simulation.
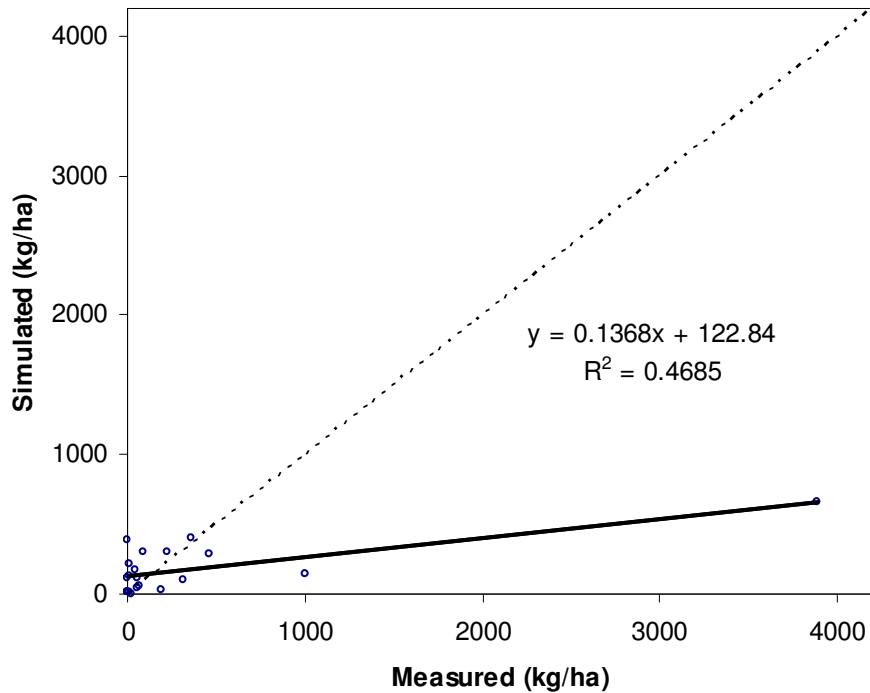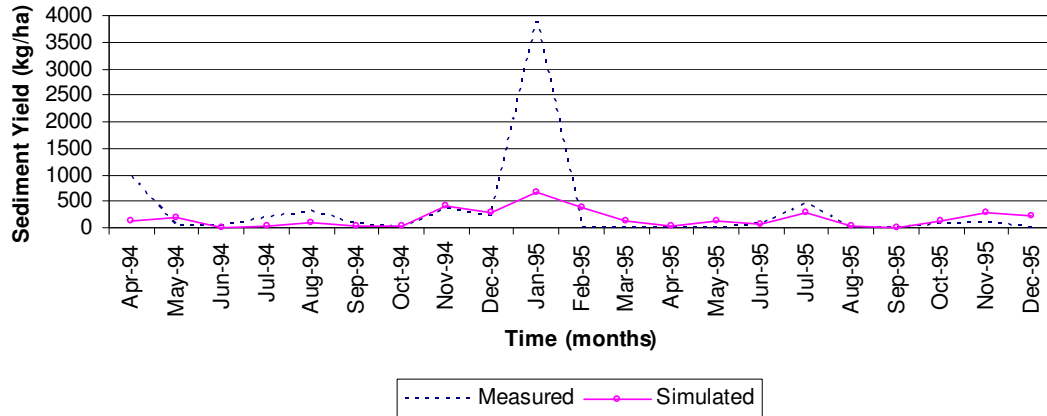
Figure 11 Time series and scattergram of measured and simulated monthly sediment loading (kg/ha) during the calibration period (April, 1994-1995).
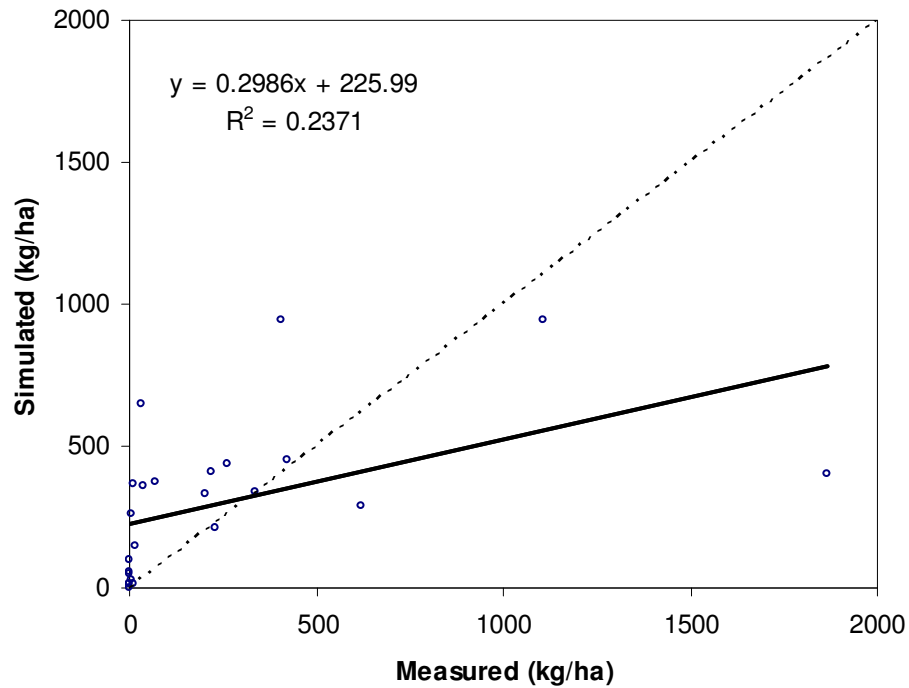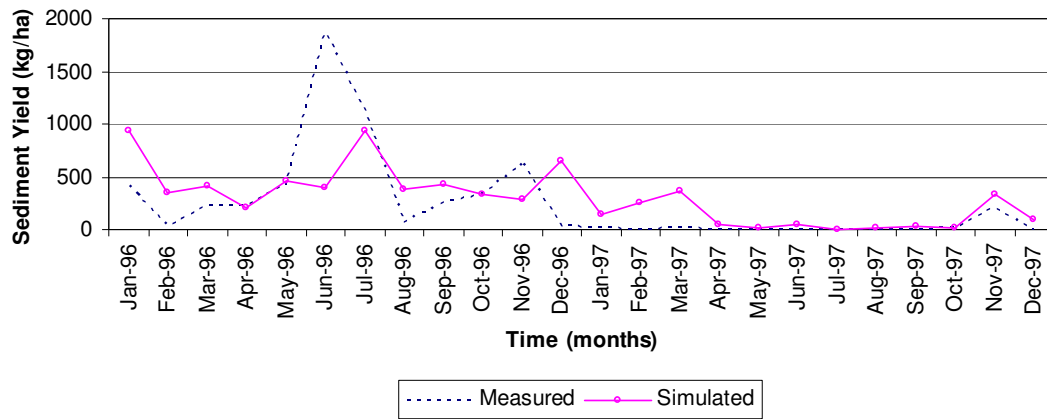
Figure 12 Time series and scattergram of measured and simulated monthly sediment loading (kg/ha) during the validation period (1996-1997).

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Table 8 Summary statistics and model evaluation criteria results for measured and simulated monthly sediment loading results during calibration and validation periods; also annual yields over the entire time period.

Sediment Measurement		Mean (kg/ha)	StDev (kg/ha)	No. of Samples	r^2	b	RMSE (kg/ha)	NSE	RSR	PBIAS (%)
Calibration Period (April 1994-1995)										
Monthly Sediment Yield	Measured	324.40	850.38	21						
	Simulated	167.21	167.92	21	0.47	0.14	743.33	0.20	0.87	48.5
Validation Period (1996-1997)										
Monthly Sediment Yield	Measured	244.38	434.30	24						
	Simulated	298.96	266.31	24	0.24	0.3	379.15	0.21	0.87	-22.3
Entire Period (April 1994-1997)										
Annual Sediment Yield	Measured	3169.36	2409.34	4						
	Simulated	2671.58	2139.43	4	0.63	0.71	1374.59	0.57	0.57	15.7

StDev= standard deviation, r^2= coefficient of determination, b=slope, RMSE= root mean square error, NSE= Nash-Sutcliffe coefficient of efficiency, RSR= RMSE-observation's standard deviation ratio, PBIAS= percent bias

Nitrate Results and Discussion

Nitrate calibration trends were fairly good with the exception of 1996 loadings

(Figure 13). The high nitrate loading event of January 1996 can be attributed to

unusually high flow events as well as ammonium based deicer placed on county roads

during that time frame. The ammonium based deicers eventually oxidize to nitrate

(Dixon, 2001). Nitrate load was under-estimated in areas where streamflow was also

under-estimated pointing to shortcomings of the SCS curve number method. This is

true during the validation period as well, e.g., the large under-estimation during

October 1999 (Figure 14).The r^2 value during nitrate validation was 0.5, which

represents moderate model performance. However, the NSE and RSR performance

criteria can both be interpreted as unsatisfactory with values of 0.35 and 0.80,

respectively during calibration and 0.44 and 0.74, respectively during validation

(Table 9).

Discrepancies in baseflow measurement could also have contributed to poor nitrate

prediction. Measured nutrient loadings were adjusted to remove the chemical

contribution transported by subsurface flow from outside of the watershed (Chu and

Shirmohammadi, 2004). Similar performance of the SWAT model for monthly nitrate

prediction was observed in the literature (Saleh et al., 2000; Santhi et al., 2001b).

Annual results of nitrate loading over the entire eight year period show good results

based on NSE and RSR values of 0.67 and 0.54, respectively. A PBIAS for annual

results of +20.6 means very good model performance in terms of the average

tendency of the simulated data to be larger or smaller than the observed data.
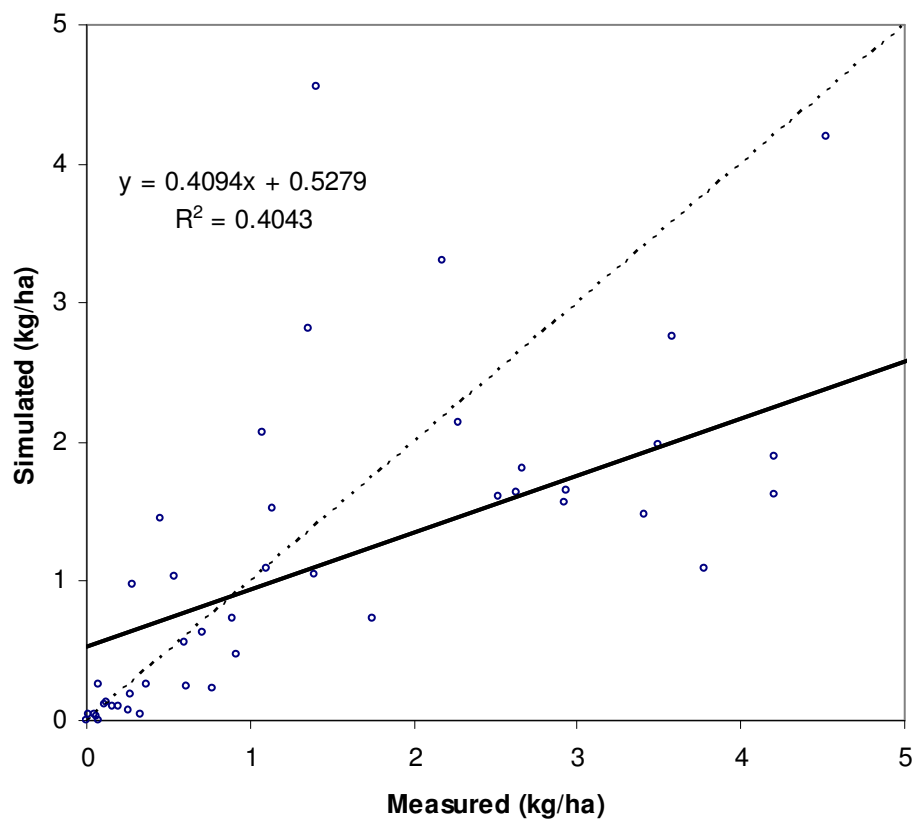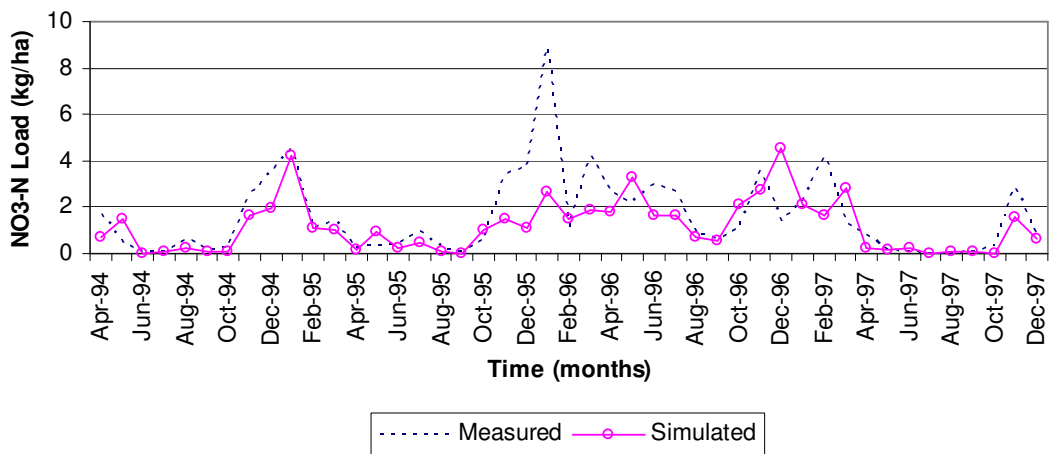
Figure 13 Time series and scattergram of measured and simulated monthly nitrate during the calibration period (April, 1994-1997).
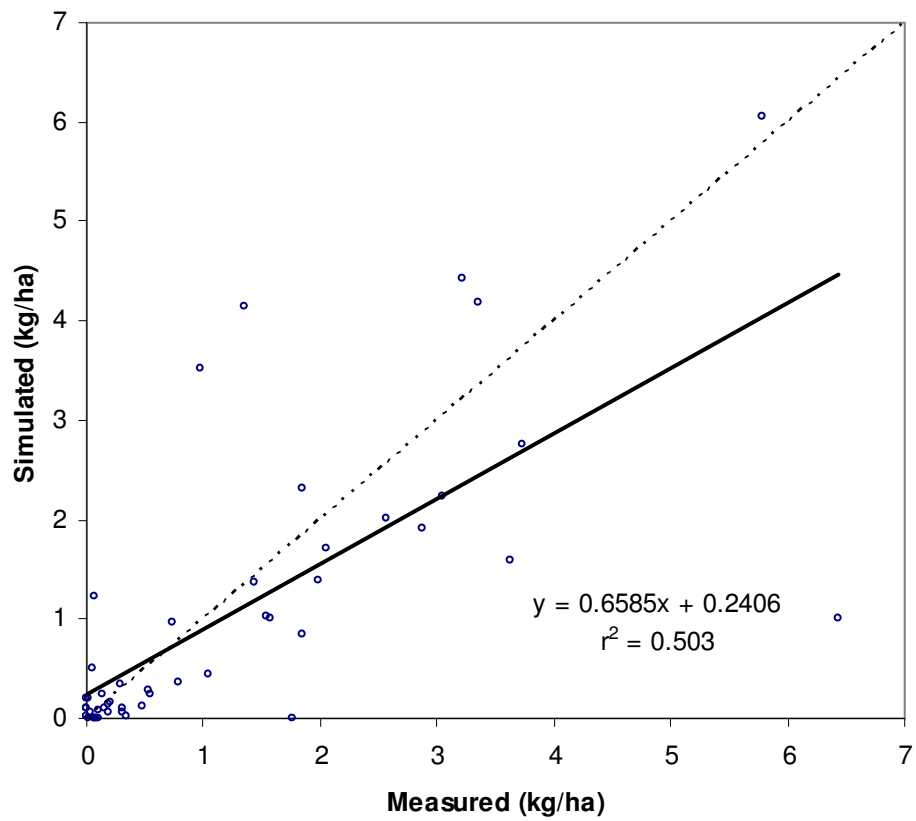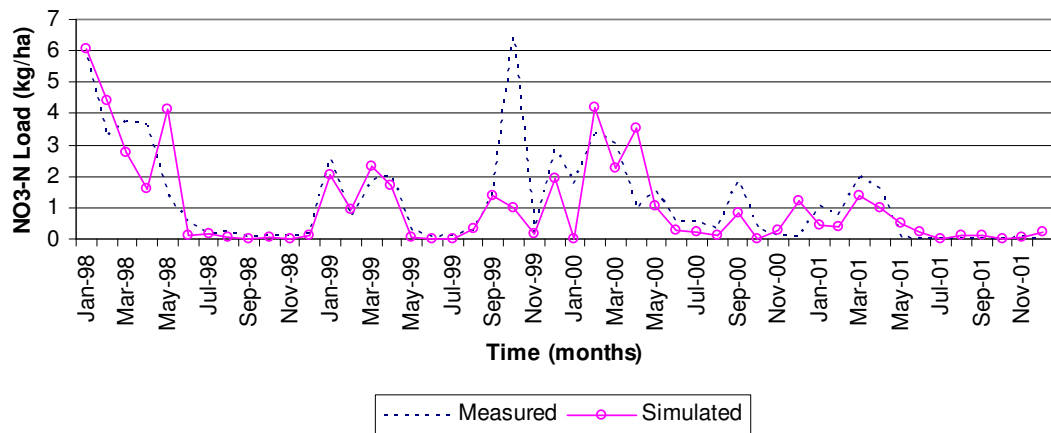
Figure 14 Time series and scattergram of measured and simulated monthly nitrate during the validation period (1998-2001).

Table 9 Summary statistics and model evaluation criteria results for measured and simulated monthly nitrate loading results during calibration and validation periods; also annual loads over the entire time period.

Nitrate Measurement		Mean (kg/ha)	StDev (kg/ha)	No. of Samples	r^2	b	RMSE (kg/ha)	NSE	RSR	PBIAS (%)
Calibration Period (April 1994-1997)										
Monthly Nitrate Load	Adjusted Measured	1.58	1.77	45						
	Simulated	1.18	1.14	45	0.40	0.41	1.41	0.35	0.80	25.7
Validation Period (1998-2001)										
Monthly Nitrate Load	Adjusted Measured	1.21	1.53	48						
	Simulated	1.03	1.42	48	0.50	0.66	1.13	0.44	0.74	14.2
Entire Period (April 1994-2001)										
Annual Nitrate Load	Adjusted Measured	16.14	7.97	8						
	Simulated	12.82	6.80	8	0.88	0.80	4.27	0.67	0.54	20.6

StDev= standard deviation, r^2= coefficient of determination, b=slope, RMSE= root mean square error, NSE= Nash-Sutcliffe coefficient of efficiency, RSR= RMSE-observation's standard deviation ratio, PBIAS= percent bias

Phosphate Results and Discussion

Phosphate was predicted very poorly during the calibration period. January 1996 shows a large over-prediction of phosphate (Figure 15). Although an extremely large amount of streamflow (mostly surface flow) was produced during that month, the measured phosphate load did not reflect such and occurrence. Then in November 1997 an abnormally high phosphate load was observed. As stated earlier, measured data for sediment concentration was very poor. Since phosphate mostly travels

attached to sediment and our samples were not filtered, this may have lead to inconsistencies in phosphate measurement.

Monthly predictions during the validation period were much better than during calibration. Model evaluation criteria reflect this difference with NSE and RSR values of -0.47 and 1.2, respectively during the calibration period and 0.41 and 0.76, respectively during the validation period (Table 10). This is mostly likely due to the poor model performance during 1996, the wettest year that was simulated in the calibration period. Although NSE and RSR values during validation on a monthly basis are unsatisfactory, the r^2 value of 0.59 indicates moderate model performance. The slope of 0.91 and intercept of 0.04 (nearly zero) uphold that positive rating. Similar performance of the SWAT model for monthly phosphate prediction was observed in the literature (Chu et al., 2004). Annual results over the eight year period were an improvement over calibrated monthly results, but not over the validated monthly results (Table 10).
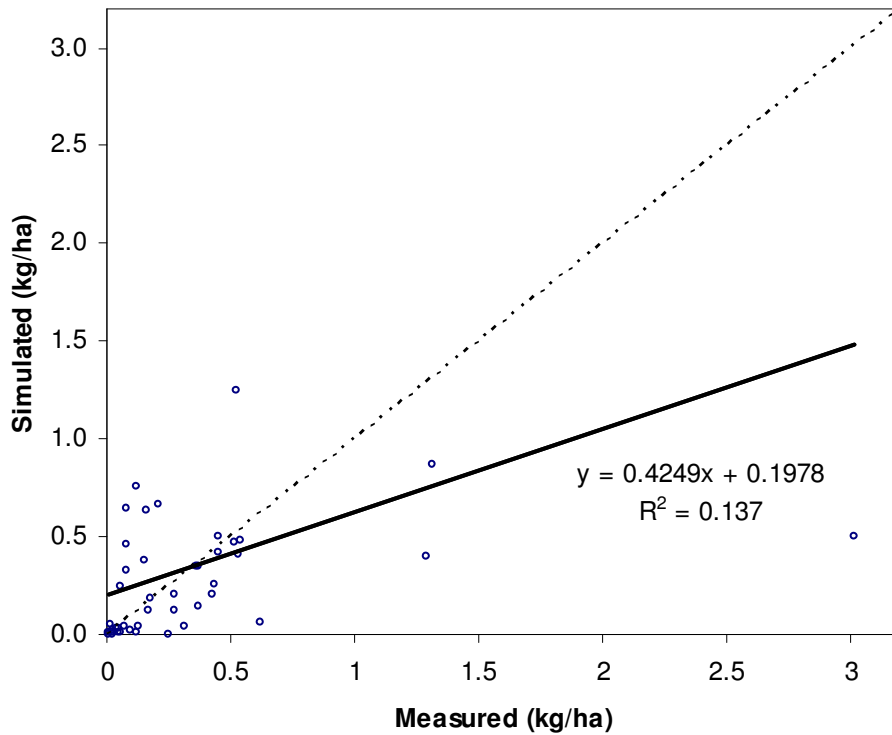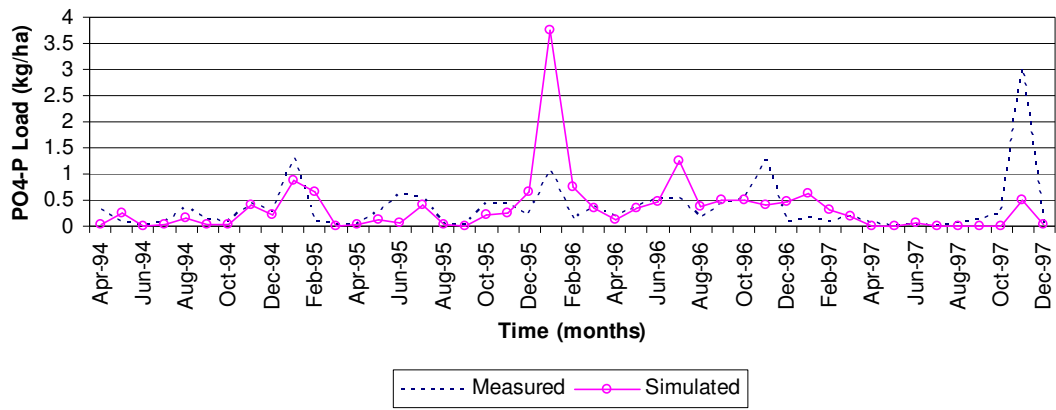
Figure 15 Time series and scattergram of measured and simulated monthly phosphate during the calibration period (April, 1994-1997).
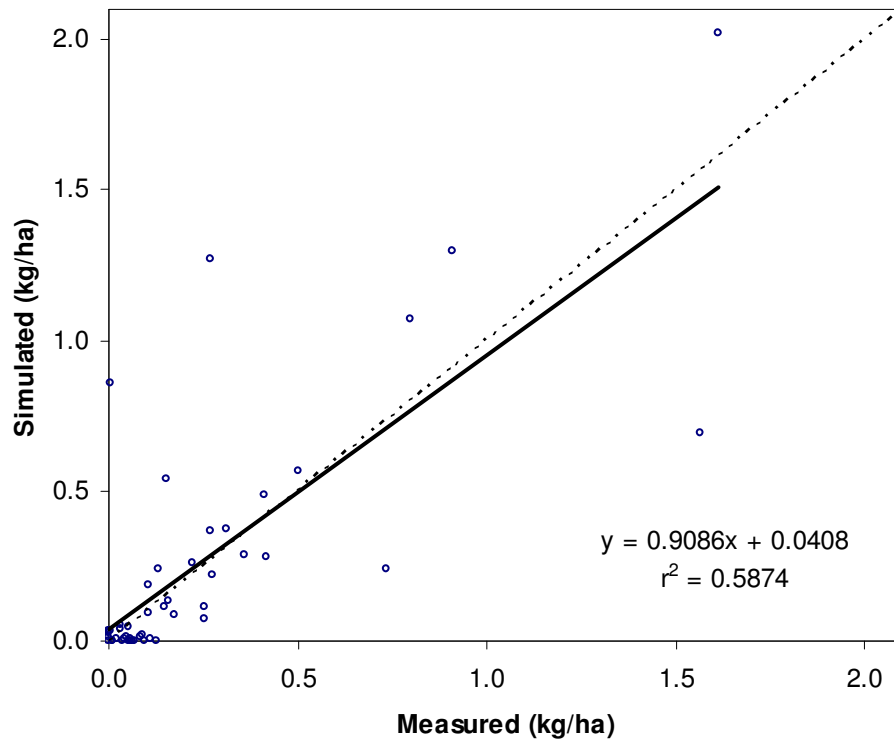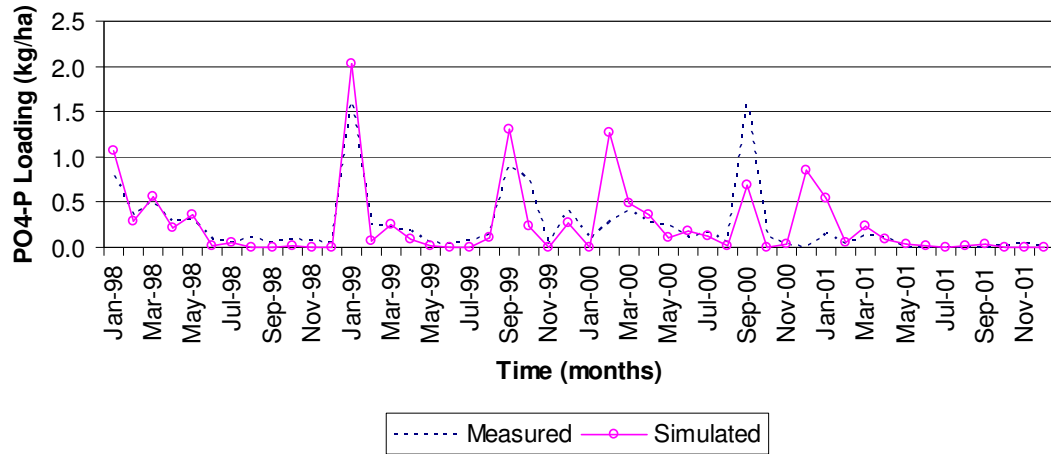
Figure 16 Time series and scattergram of measured and simulated monthly phosphate during the validation period (1998-2001).

Table 10 Summary statistics and model evaluation criteria results for measured and simulated monthly phosphate loading results during calibration and validation periods; also annual loads over the entire time period.

Phosphate Measurement		Mean (kg/ha)	StDev (kg/ha)	No. of Samples	r^2	b	RMSE (kg/ha)	NSE	RSR	PBIAS (%)
Calibration Period (April 1994-1997)										
Monthly Phosphate Load	Adjusted Measured	0.34	0.51	45						
	Simulated	0.34	0.59	45	0.14	0.42	0.61	-0.47	1.20	0.0
Validation Period (1998-2001)										
Monthly Phosphate Load	Adjusted Measured	0.23	0.35	48						
	Simulated	0.25	0.42	48	0.59	0.91	0.27	0.41	0.76	-8.2
Entire Period (April 1994-2001)										
Annual Phosphate Load	Adjusted Measured	3.34	1.64	8						
	Simulated	3.46	2.67	8	0.64	1.30	1.58	-0.06	0.96	-3.5

StDev= standard deviation, r^2= coefficient of determination, b=slope, RMSE= root mean square error, NSE= Nash-Sutcliffe coefficient of efficiency, RSR= RMSE-observation's standard deviation ratio, PBIAS= percent bias

Summary of Model Performance

- Performance ratings using AVSWATX-2003 to simulate monthly hydrology and water quality constituents in Warner Creek watershed are as follows:

  o Surface Runoff- Good

  o Baseflow- Unsatisfactory

  o Total Streamflow- Good

- - Sediment- Poor

  - Nitrate- Unsatisfactory to Moderate

  - Phosphate- Unsatisfactory to Moderate

- Although surface runoff and total streamflow predictions were good, problems during extreme storm events did have an effect on model performance, which carried over to sediment and nutrient prediction performance. Under-estimations of streamflow often led to under-estimation of the latter constituents. Use of the SCS curve number method in SWAT to tabulate surface runoff is likely the reason that severe storm events were not represented well. The SCS method depends on empirical information to tabulate surface runoff, which is often not flexible enough to capture natural variability especially during major storm events. The infiltration-based Green and Ampt (1911) modified by Mein and Larson (1973) excess rainfall method may be a plausible alternative to the SCS method to improve streamflow prediction during severe storm events.

- During streamflow calibration, special care should be taken to observe baseflow behavior while minimizing high flow errors to prevent fitting the higher portion of the hydrograph (i.e., peak surface flows) at the expense of lower portions.

- Subsurface contributions of flow and chemicals from outside of the watershed are important to consider, especially in small watersheds where the impact may be greater. Regions with abundant groundwater should also be examined

for this occurrence. This problem arises because we delineate watersheds based on surface topography, thus models should be extended to include the subsurface boundary. Groundwater flow often does not follow surface topography, thus there is a high potential for contributions of groundwater flow to the watershed streamflow from outside the watershed boundary.

- Poor data (due to e.g., equipment failure, improper sampling, handling or analytical methods) and unforeseen occurrences in watershed management (e.g., animal stream crossings, deicing) are added sources of error in model simulations. Therefore, great care should be taken to reduce errors and closely examine the surrounding environment for these instances.

- Annual sediment yields over the entire four year period of observation revealed satisfactory to good model performance, a tremendous improvement over poor model performance during the monthly validation period. The same observation was made for nitrate loading, which showed good model performance for annual observations. Model performance for phosphate load on an annual basis, however, remained at the unsatisfactory to moderate performance rating.

- Overall, AVSWATX is a moderate to good model for estimating the hydrologic and water quality response of mixed land use watersheds in the Piedmont physiographic region. The next segment of results and discussion will examine the uncertainties in SWAT model output based on input parameter uncertainties.

Uncertainty Analysis

Several different analyses were conducted based on the information gathered using MFORM. Analyses were conducted on model output sensitivity to input parameters, fraction of model output variance contributed by each input parameter, and total variance in model output based on all important input parameters. Each analysis is discussed below.

Sensitivity Analysis

In view of the previous sensitivity analysis conducted using the SWAT model on Warner Creek watershed (Chu, 2003), we used the sensitivity coefficient tabulated from the MFORM methodology to conduct a "rough" sensitivity analysis. It is considered "rough" here because it is a local sensitivity scheme that represents a partial effect of input parameters. Parameters were perturbed from their mean value points by five percent, in the positive direction. This method has been used effectively to determine the most sensitive parameters in watershed modeling (Dubus and Brown, 2002; Melching and Yoon, 1996). Computational efficiency is a large benefit to using this type of sensitivity method. Results were compared to other sensitivity studies and the importance of sensitive parameters to uncertainty analysis was examined.

Input parameters were ranked by comparing the magnitude of sensitivity displayed in output parameters using the normalized sensitivity coefficient, S (see equation 20). Based on average annual S values, Table 11 lists the rank of important parameters

associated with each output variable. Streamflow was most sensitive to CNOPwgs, the parameter representing curve number for moisture condition II during the winter growing season. Curve number determines the volume of surface runoff contributing to total streamflow. The impact of changing this value, especially during the wettest part of the year (winter growing season) should largely affect streamflow volume. However, the reason that streamflow is not as strongly affected by the other two seasonal curve numbers (CNOPskp [ranked #7], and CNOPsgs [ranked #11]) is likely because of their occurrence during the drier and warmer part of the year. Curve number during the spring kill/planting season takes place over a shorter duration of time, which may also have led to changes in that parameter having less of an affect on changes in streamflow output. Several studies have found the SCS curve number to be one of the most sensitive input parameter for streamflow prediction (Chu and Shirmohammadi, 2004; White and Chaubey, 2005). Compared to CNOPwgs, average slope steepness (HRU_SLP), saturated hydraulic conductivity of soil layer 1 (SOL_K1), available water capacity of soil layers 1 and 2 (SOL_AWC1 and AWC2), and recharge to the deep aquifer (RCHRG_DP) were moderately sensitive. Snow melt factor on December 21, SMFMN, had the least affect on changes in streamflow. Since this parameter depends on the occurrence of snowmelt and mostly influences the rate of snowmelt, its affects were not as significant on total streamflow volume.

Figures E1-E5 in Appendix E, show the monthly normalized sensitivity coefficients for each input parameter. There is a discrepancy in the sensitivity value recorded in June for SMFMN (Figure E2). Although sensitivity is small, the SMFMN parameter

should not produce any changes in streamflow especially in summer when there is no snowfall. Temperatures in June were checked to see if there were any incorrect or low temperatures recorded that would produce snowfall in June. All temperatures were normal in June. SMFMN is related to melt factor for snow on June 21 (SMFMX) in that the two parameters work together to balance out the rate of snowmelt through the year. In the northern hemisphere, SMFMX would normally be greater than SMFMN. However, in our study SMFMX was left at its default value of 4.5 mm H_2O/day-°C under the assumption that no adjustment was needed because there is no snowfall in Maryland in June. The mean value used for SMFMN was 4.95 mm H_2O/day-°C, a value larger than SMFMX. This may have offset the snowmelt calculations in AVSWATX. Other parameters seemed to have spikes of sensitivity in June as well, but for parameters such as ESCO (Figure E1) high sensitivity in June makes sense. ESCO is the soil evaporation compensation factor; therefore during dry periods this parameter modifies the depth distribution necessary to meet the soil evaporative demand.

The most sensitive parameter for sediment prediction was SPEXP, a parameter representing an exponent in calculating the maximum amount of sediment that can be re-entrained during channel sediment routing (Table 11). Average slope steepness (HRU_SLP) and average slope length (SLSUBBSN) were next in importance to sensitivity of sediment prediction. Channel cover (CH_COV) and erodibility (CH_EROD) had the same moderate level of sensitivity.

Nitrate prediction was most sensitive to the fraction of porosity from which anions are excluded (ANION_EXCL) (Table 11). This parameter determines the portion of anions, such as nitrate, that is transported away from the surface of soil particles. Biological mixing efficiency (BIOMIX) is another moderately sensitive parameter for both nitrate and phosphate prediction. As BIOMIX increases, nitrate and phosphate loads decrease (see Table 3) due to redistribution of nutrients by biological mixing (Neitsch et al., 2001).Initial soluble phosphorus concentration in soil layer 1 (SOL_LABP1) was the most sensitive parameter in phosphate prediction (Table 11). Percolation coefficients for both phosphate (PPERCO) and nitrate (NPERCO) had no effect on phosphate and nitrate predictions, respectively. As stated earlier, these sensitivity results are considered a rough estimate of sensitivity. Larger changes in input parameters (e.g., by 10% or 20%) and also changes in the negative direction may result in higher levels of sensitivity. However, these results are sufficient for the purpose of this study which was to examine the importance of sensitive parameters in the study of uncertainty analysis.

Table 11 Rank of important input parameters for average annual streamflow, sediment, nitrate, and phosphate output variables. S represents the normalized sensitivity coefficient.

Rank	Streamflow Input Parameter	S*	% Total S	Sediment Input Parameter	S	% Total S	Nitrate Input Parameter	S	% Total S	Phosphate Input Parameter	S	% Total S
1	CNwgs	2.39	62	SPEXP	1.67	55	ANION_EXCL	0.32	70	SOL_LABP1	0.72	79
2	HRU_SLP	0.35	9	HRUSLP	0.42	14	BIOMIX	0.10	22	BIOMIX	0.19	21
3	SOL_K1	0.30	8	SLSUBBSN	0.39	13	FRT_SURF	0.03	7	PPERCO	0.00	0
4	SOL_AWC1	0.23	6	CH_COV	0.20	6	SOL_NO3_2	0.00	1			
5	SOL_AWC2	0.21	5	CH_EROD	0.20	6	SOL_NO3_1	0.00	0			
6	RCHG_DP	0.16	4	ADJ_PKR	0.09	3	CMN	0.00	0			
7	CNskp	0.06	2	USLE_P	0.04	1	NPERCO	0.00	0			
8	ESCO	0.05	1	BIOMIX	0.03	1						
9	SOL_K2	0.04	1	SPCON	0.00	0						
10	GW_REVAP	0.04	1									
11	CNsgs	0.03	1									
12	SMFMN	0.01	0									

$* \; S = \left| \frac{g(x_0 + \Delta x) - g(x_0)}{\Delta x} \times \frac{x_0}{g(x_0)} \right|$ where x_0 and Δx are the initial value and change in input parameter, respectively, and $g(x_0)$ and $g(x_{0+}\Delta x)$ represent the initial value

and 5% change in output variable.

Fraction of Variance

The fraction of variance (FOV) was tabulated for input parameters important to streamflow, sediment, nitrate, and phosphate output loads on an annual and monthly basis. Table 12 shows the ranking of important input parameters for each output variable using annual loads. Recharge to the deep aquifer (RCHRG_DP) contributed 76% of the total variance in streamflow output. This parameter represents the fraction of water that percolates from the root zone to the deep aquifer. Water traveling to the deep aquifer is not redistributed into the system but is removed from the system. Hence, this parameter is important to the total volume of streamflow modeled in the hydrologic cycle. Note that RCHRG_DP was not a highly sensitive parameter in the sensitivity analysis (Table 11). The variance in this parameter makes a difference in its ranking. Monthly FOVs reflect the same ranking of importance for the first three input parameters, RCHRG_DP, CNOPwgs, and SOL_AWC2 (Table 13). HRU_SLP, ESCO, and SOL_AWC1 follow in level of importance making up the top five parameters in monthly and annual FOVs. Similar parameters are in the top five ranking of sensitive parameters (Table 11), however, parameters affecting flow through the soil layers appear to be more significant in sensitivity analysis.

CH_COV and CH_EROD were the leading contributors to uncertainty in sediment output with annual and monthly percentage totals of 40% and 34%, respectively (Tables 12 and 13). SPEXP and HRU_SLP are also ranked within the top five parameters having the highest FOVs in sediment yield simulation. BIOMIX and peak

rate adjustment factor for sediment routing in the subbasin (ADJ_PKR), exchange significance between annual and monthly observations of FOV.

Input parameters that have significance in the uncertainty of nitrate and phosphate simulation are ranked similarly between annual and monthly FOV results (Tables 12 and 13). ANION_EXCL and BIOMIX are ranked #1 and #2, respectively for variance contributed to nitrate output. SOL_LABP1 and BIOMIX are ranked #1 and #2, respectively in annual results and equally in monthly results. Sensitivity rankings of these parameters follow the same pattern (Table 11).

Researchers often consider sensitive parameters (input parameters that cause a large change in output with respect to changes in input) to be the most important parameters contributing to model output uncertainty. This study shows that other parameters not deemed as sensitive (e.g., RCHRG_DP, ESCO) are important contributors to model output uncertainty. The reason that such parameters can surpass highly sensitive parameters in their level of importance to uncertainty is explained by their variance. When the value of a parameter is known with little certainty, its potential to cause variability in output simulation is larger. The further away a parameter is from its true value (often considered mean value), the more likely it will cause variance in simulated output.

Table 12 Ranking of important input parameters to streamflow, sediment, and nutrient prediction uncertainty based on average annual fraction of variance (FOV) contribution.

	Streamflow			Sediment			Nitrate			Phosphate		
	Average Annual			**Average Annual**			**Average Annual**			**Average Annual**		
Rank	**Input Parameters**	**FOV* mm^2**	**% of Total Variance**	**Input Parameters**	**FOV $(kg/ha)^2$**	**% of Total Variance**	**Input Parameters**	**FOV $(kg/ha)^2$**	**% of Total Variance**	**Input Parameters**	**FOV $(kg/ha)^2$**	**% of Total Variance**
1	RCHRG_DP	2252.79	76	CH_COV	220616.13	40	ANION_EXCL	1.37	96	SOL_LABP1	0.16	60
2	CNOPwgs	314.22	11	CH_EROD	220616.13	40	BIOMIX	0.05	3	BIOMIX	0.11	40
3	SOL_AWC2	130.93	4	SPEXP	83172.86	15	FRT_SURF	0.00	0	PPERCO	0.00	0
4	HRUSLP	92.34	3	HRUSLP	18864.99	3	SOL_NO3_2	0.00	0			
5	ESCO	78.15	3	ADJ_PKR	4604.70	1	SOL_NO3_1	0.00	0			
6	SOL_AWC1	57.27	2	BIOMIX	1681.70	0	CMN	0.00	0			
7	SOL_K1	13.43	0	USLE_P	1322.35	0	NPERCO	0.00	0			
8	GW_REVAP	5.07	0	SLSUBBSN	753.55	0						
9	SOL_K2	1.78	0	SPCON	0.00	0						
10	CNOPskp	0.48	0									
11	SMFMN	0.27	0									
12	CNOPsgs	0.06	0									

$$* FOV = \left(\frac{\partial g}{\partial x_i}\right)^2_{x_m} \sigma_i^2$$

where ∂g is the change in output variable, ∂x_i represents the change in input parameter, and σ_i^2 is the variance of the input parameter.

Table 13 Ranking of important input parameters to streamflow, sediment, and nutrient prediction uncertainty based on average monthly fraction of variance (FOV) contribution (equation 18).

	Streamflow			Sediment			Nitrate			Phosphate		
Rank	Input Parameters	Average Monthly FOV mm^2	% Total Variance	Input Parameters	Average Monthly FOV (kg/ha)^2	% Total Variance	Input Parameters	Average Monthly FOV (kg/ha)^2	% Total Variance	Input Parameters	Average Monthly FOV (kg/ha)^2	% Total Variance
1	RCHRG_DP	39.73	76	CH_COV	618.01	34	ANION_EXCL	0.01	73	BIOMIX	0.0002	50
2	CNOPwgs	4.65	9	CH_EROD	618.01	34	BIOMIX	0.00	27	SOL_LABP1	0.0002	50
3	SOL_AWC2	3.26	6	HRUSLP	397.81	22	CMN	0.00	0	PPERCO	0.00	0
4	SOL_AWC1	1.78	3	BIOMIX	143.96	8	FRT_SURF	0.00	0			
5	ESCO	1.38	3	SPEXP	41.30	2	SOL_NO3_1	0.00	0			
6	HRUSLP	0.89	2	USLE_P	10.35	1	SOL_NO3_2	0.00	0			
7	GW_REVAP	0.13	0	SLSUBBSN	9.47	1	NPERCO	0.00	0			
8	SOL_K1	0.13	0	ADJ_PKR	5.24	0						
9	SOL_K2	0.04	0	SPCON	0.00	0						
10	SMFMN	0.02	0									
11	CNOPskp	0.01	0									
12	CNOPsgs	0.00	0									

$$* \; FOV = \left(\frac{\partial g}{\partial x_i} \right)^2_{x_m} \sigma_i^2$$

where ∂g is the change in output variable, ∂x_i represents the change in input parameter, and σ_i^2 is the variance of the input parameter.

Output Variance

Table 14 shows predicted annual loads simulated using mean values (MV) of input

parameters, standard deviations (StDev) and variances (tabulated using MFORM),

and coefficients of variation (CV) of streamflow, sediment, nitrate, and phosphate.

For all four output variables, the largest amount of variance in output value occurred

in 1996. Variances were 8510 mm^2, 2847800 $(kg/ha)^2$, 5.1 $(kg/ha)^2$, and 1.2 $(kg/ha)^2$,

for streamflow, sediment, nitrate, and phosphate, respectively, in 1996 (Table 14).

Record amounts of rainfall occurred in 1996 as shown in Figure 4. The second largest

amount of variance in streamflow output took place in 1998, the second wettest year

of simulation. The lowest amounts of variance in output were observed in 2001,

which was the driest year in the study period (Figure 4). These results show that

larger amounts of uncertainty occur during extremely wet years.

Table 14 Predicted annual loads simulated using mean values (MV) of input parameters, standard deviations (StDev) and variances tabulated using MFORM, and coefficient of variation (CV) of streamflow, sediment, nitrate, and phosphate.

Output Variable		1994(Jan-Dec)	1995	1996	1997	1998	1999	2000	2001	Average
Streamflow	MV Pred. Annual (mm)	311.0	277.0	817.0	218.0	360.0	308.0	227.0	98.0	**327.0**
	StDev (mm)	37.0	40.0	92.0	33.0	84.0	53.0	31.0	14.0	**48.0**
	Variance (mm2)	1377.0	1581.0	8510.0	1117.0	7059.0	2762.0	969.0	199.0	**2947.0**
	CV (%)	11.9	14.4	11.3	15.4	23.3	17.0	13.7	14.4	**15.2**
Sediment	MV Pred. Annual (kg/ha)	2158.0	1815.0	5997.0	1204.0	2187.0	1931.0	1485.0	558.0	**2167.0**
	StDev (kg/ha)	743.0	526.0	1688.0	392.0	493.0	452.0	312.0	197.0	**600.0**
	Variance (kg/ha)2	551350.0	277050.0	2847800.0	153810.0	242790.0	203990.0	97469.0	38909.0	**551646.0**
	CV (%)	34.4	29.0	28.1	32.6	22.5	23.4	21.0	35.3	**28.3**
Nitrate	MV Pred. Annual (kg/ha)	4.9	5.1	11.4	3.3	11.2	5.3	3.4	1.3	**5.7**
	StDev (kg/ha)	0.8	1.3	2.3	0.3	0.9	1.6	0.6	0.4	**1.0**
	Variance (kg/ha)2	0.6	1.8	5.1	0.1	0.8	2.4	0.3	0.2	**1.4**
	CV (%)	16.1	26.2	19.8	9.3	8.0	29.6	16.7	29.7	**19.4**
Phosphate	MV Pred. Annual (kg/ha)	3.2	2.4	6.3	1.3	1.8	2.2	1.7	0.6	**2.4**
	StDev (kg/ha)	0.5	0.4	1.1	0.2	0.3	0.5	0.3	0.1	**0.4**
	Variance (kg/ha)2	0.2	0.2	1.2	0.0	0.1	0.2	0.1	0.0	**0.3**
	CV (%)	14.1	18.1	17.8	15.3	15.0	21.0	19.6	18.6	**17.4**

Monthly observations of total output variance give further credence to the fact that the amount of variance in output variables is larger during wet periods. Tables 15 through 18 list monthly variances and monthly average variances for steamflow, sediment, nitrate, and phosphate output. Figures 17 thru 20 show the trend of monthly average variance for each output. Highest trends of streamflow variance occur during wet periods from November to March (Figure 17). Sediment variance shows a trend similar to streamflow variance; however there is a spike of variance in July (Figure 18) which is the result of an extremely high variance in July of 1996 (Table 15). As mentioned previously in the discussion of annual observations, 1996 was the wettest and most problematic year in this study, contributing extremely large amounts of variance to output variables.

Monthly average variance in nitrate output was largest in May (Figure 19). This was due to unusually high variances in 1998 [2.36 $(kg/ha)^2$] and 1996 [0.18 $(kg/ha)^2$], the two wettest years (Table 17). Although there was little variance detected in monthly phosphate results, the month producing the largest amount of variance in phosphate output was January (Figure 20). Early snowmelt in January 1996 is likely the reason for this (Table 18). Problems with model output during wet periods were evident in the results of model performance discussed previously and in output variance results. The use of the SCS curve number method to calculate surface runoff was highlighted as one of the main reasons for such poor performance. The SCS curve number method uses empirical data composed in a chart to determine surface runoff volume.

As a result, extreme variabilities in nature are not properly accounted for in the distribution of rainfall. An infiltration-based method such as the Green and Ampt Mein-Larson excess rainfall method may prove to be a better approach to account for surface runoff.

Comparison of average coefficients of variation in Table 14 show that sediment output has the largest amount of variability around its mean value (CV= 28%). Nitrate and phosphate have the next largest total amount of variability with average CVs of 19% and 17%, respectively. Streamflow output has the least amount of variability around its mean value (CV= 15%). These results are comparable to calibration and validation results because model performance was poorest during sediment simulation and best during streamflow simulation. Greater knowledge or certainty about the values of input parameters will lead to better model performance and less output uncertainties.

Table 15 Monthly and monthly average variances for streamflow output.

Output Variable		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1994	9.24	8.85	168.81	15.48	10.60	1.10	1.27	33.06	2.75	1.48	51.03	66.62
	1995	115.54	14.08	30.88	0.96	3.69	2.75	41.91	1.61	0.83	34.18	71.99	25.74
	1996	13.05	91.90	171.59	19.32	30.58	39.40	146.69	74.09	27.46	27.79	37.47	588.84
Streamflow	1997	18.34	44.36	120.77	3.83	1.44	39.89	0.44	1.06	0.91	0.73	136.97	14.10
mm^2	1998	557.89	578.22	430.65	17.22	178.97	4.43	3.92	2.05	0.97	1.41	0.29	0.14
	1999	125.13	27.26	165.38	7.22	1.30	0.76	0.30	24.33	124.73	66.78	2.50	34.34
	2000	0.98	35.07	35.91	20.16	3.20	3.19	7.24	2.21	67.83	3.15	1.13	38.61
	2001	15.50	5.84	21.32	6.24	1.04	0.90	0.68	0.85	2.29	0.53	0.20	0.42
	Average	**106.96**	**100.70**	**143.16**	**11.30**	**28.85**	**11.55**	**25.31**	**17.41**	**28.47**	**17.01**	**37.70**	**96.10**
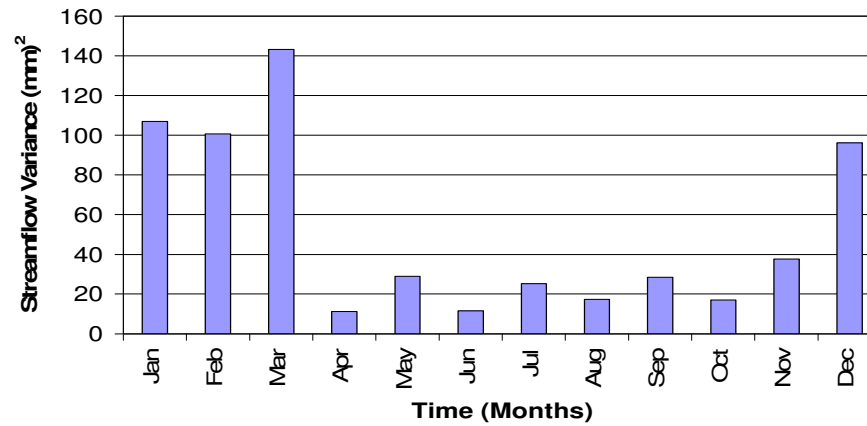
Figure 17 Monthly average variances for streamflow.

Table 16 Monthly and monthly average variances for sediment output.

Output Variable		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1994	39509	52508	80084	85	106	0.55	2.36	253.99	8.39	1.19	1427	1225
	1995	29612	6622	182	2	7	8.21	2346.30	2.35	0.85	2704	7518	9628
	1996	278300	18812	11318	638	975	2915	90505	10240	5039	3251	23349	50231
Sediment	**1997**	39318	15185	3109	18	2	2.63	0.08	1.10	0.99	0.34	4558	95
(kg/ha)^2	**1998**	28242	9502	35387	519	3274	5.66	11.99	1.03	0.67	1.53	0.04	0.01
	1999	41704	261	3541	94	1.48	0.44	0.06	397.86	13287	1433	1.08	610
	2000	0.43	15418	9107	805	12	30.43	35.36	1.27	1695	5.43	3.56	4210
	2001	19391	46	2477	199	2	1.34	0.26	0.80	11.19	0.10	0.09	0.06
	Average	**59510**	**14794**	**18151**	**295**	**548**	**371**	**11613**	**1362**	**2505**	**925**	**4607**	**8250**
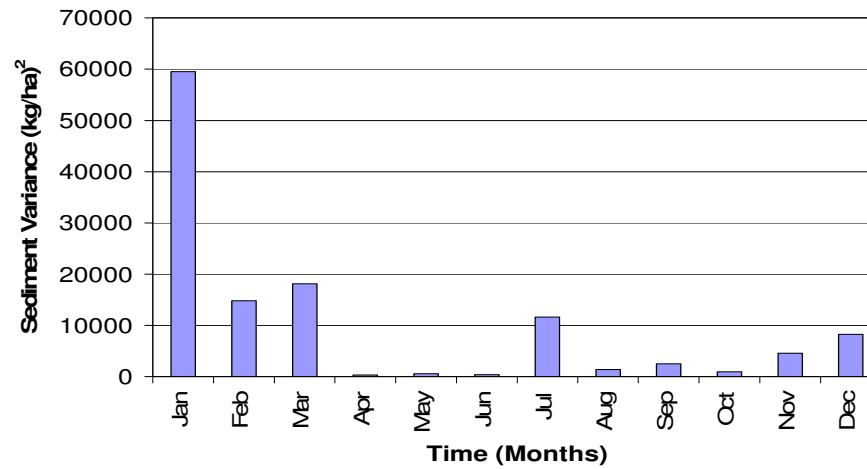
Figure 18 Monthly average variances for sediment.

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Table 17 Monthly and monthly average variances for nitrate output.

Output Variable	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1994	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.23
	1995	0.48	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.10	0.02
	1996	0.00	0.05	0.04	0.00	0.18	0.00	0.00	0.00	0.00	0.06	0.10	1.08
Nitrate	1997	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.02
(kg/ha)^2	1998	0.74	0.74	0.46	0.00	2.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	1999	0.10	0.06	0.05	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.00	0.29
	2000	0.00	0.08	0.01	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	2001	0.00	0.02	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Average	**0.17**	**0.12**	**0.09**	**0.00**	**0.32**	**0.00**	**0.00**	**0.00**	**0.00**	**0.02**	**0.03**	**0.20**
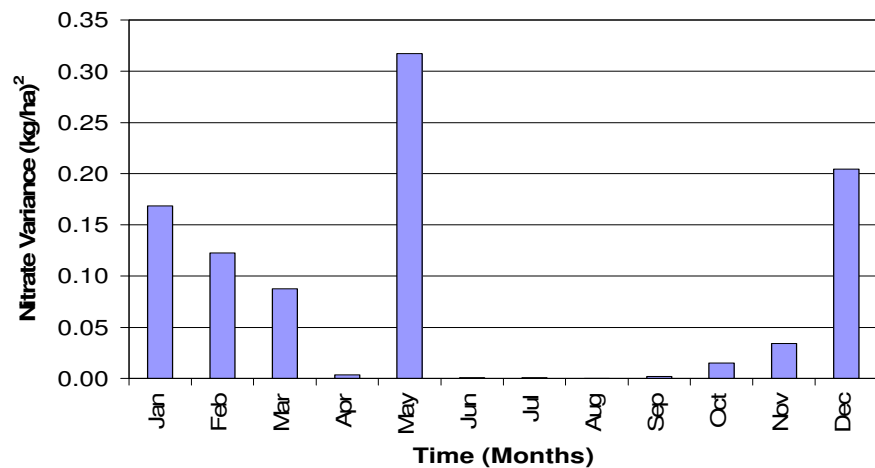
Figure 19 Monthly average variances for nitrate.

Table 18 Monthly and monthly average variances for phosphate output.

Output Variable	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1994	0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	1995	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
	1996	0.17	0.01	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.01	0.00	0.01
Phosphate	1997	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(kg/ha)^2	1998	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	1999	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	2000	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
	2001	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Average	**0.03**	**0.01**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
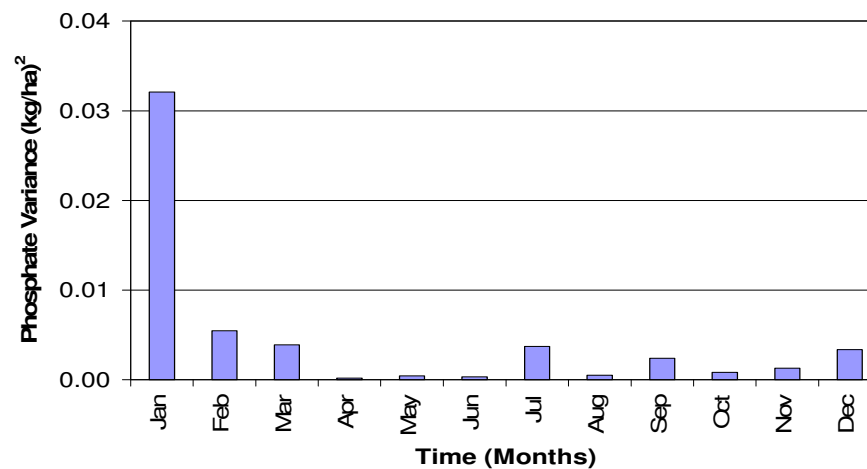
Figure 20 Monthly average variances for phosphate.

NO3-N Concentration

In the previous discussions of uncertainty, variance was calculated and discussed in
terms of loading. The water quality criterion for nitrate is expressed as a
concentration. Nitrate concentration is not to exceed 10 mg/L for waters being used
for drinking water purposes (USEPA, 2003b). Therefore, in order to calculate the
probability of exceeding the criterion, variances or standard deviations (as in equation
27) were expressed in terms of concentration. The behavior and importance of input
parameters, and the overall uncertainty in each output variable have already been
discussed in terms of load on an annual and monthly basis. Therefore, the same
evaluation is not necessary for results in terms of concentration. SWAT's
performance on a daily basis has been found to be poor in a number of studies (Saleh
and Du, 2004; Spruill et al., 2000). Therefore, daily evaluations of input parameter
sensitivity and contribution of FOV were not examined in this study. However, they
may be examined in a future study once the SWAT model algorithms are improved
for such simulations. In the next section of results we discuss the use of nitrate
concentrations predicted by SWAT and MFORM tabulated daily nitrate standard
deviations to quantify an MOS value for a nitrate TMDL.

TMDL and Margin of Safety (MOS)

As stated in the methodology section, based on the calibrated nitrate output from
AVSWAT-X, the waterbody at the outlet of the Warner Creek watershed was not
impaired under the 10 mg/L water quality criterion for nitrate. In order to demonstrate

impaired conditions, we assumed a criterion of 6 mg/L. The daily exceedance

probabilities seemed to exhibit a specific kind of statistical distribution (Figure 21)

that we felt would be useful to describe for future reference. Therefore, a

methodology by Karl Pearson (1895) (Kendall and Stuart, 1958) and modified by

Andreev et al. (2005), was used to characterize the type of Pearson distribution that

the daily exceedance probability data fit. The steps used to fit the distribution were as

follows (Andreev et al., 2005):

1. Estimate the first four moments of the observed data (mean [μ_1], variance [μ_2], skewness [μ_3], and kurtosis [μ_4]).

2. Calculate the Pearson parameters a, b_0, b_1, and b_2.

3. Use the parameters to compute the selection criteria D and λ.

4. Select an appropriate distribution from Tables 19 and 20 based on the criteria.

The Pearson parameters can be estimated using:

$$
\begin{aligned}
b_1 = a &= -\frac{\mu_3\left(\mu_4 + 3\mu_2^2\right)}{A} = -\frac{\mu_2^{1/2}\beta_1\left(\beta_2 + 3\right)}{A'} \\
b_0 &= -\frac{\mu_2\left(4\mu_2\mu_4 - 3\mu_3^2\right)}{A} = -\frac{\mu_2\left(4\beta_2 - 3\beta_1^2\right)}{A'} \\
b_2 &= -\frac{\left(2\mu_2\mu_4 - 3\mu_3^2 - 6\mu_2^3\right)}{A} = -\frac{\left(2\beta_2 - 3\beta_1^2 - 6\right)}{A'}
\end{aligned}
\tag{28}
$$

where $\beta_1 = \mu_3^2 / \mu_2^3$ and $\beta_2 = \mu_4 / \mu_2^2$ are measures of skewness, and scaling

parameters A and A' can be determined using:

$$
\begin{aligned}
A &= 10\mu_4\mu_2 - 18\mu_2^3 - 12\mu_3^2 \\
A' &= 10\beta_2 - 18 - 12\beta_1^2
\end{aligned}
\tag{29}
$$

Selection criteria D and λ can be calculated using:

$$D = b_0 b_2 - b_1^2$$

$$\lambda = \frac{b_1^2}{b_0 b_2} \tag{30}$$
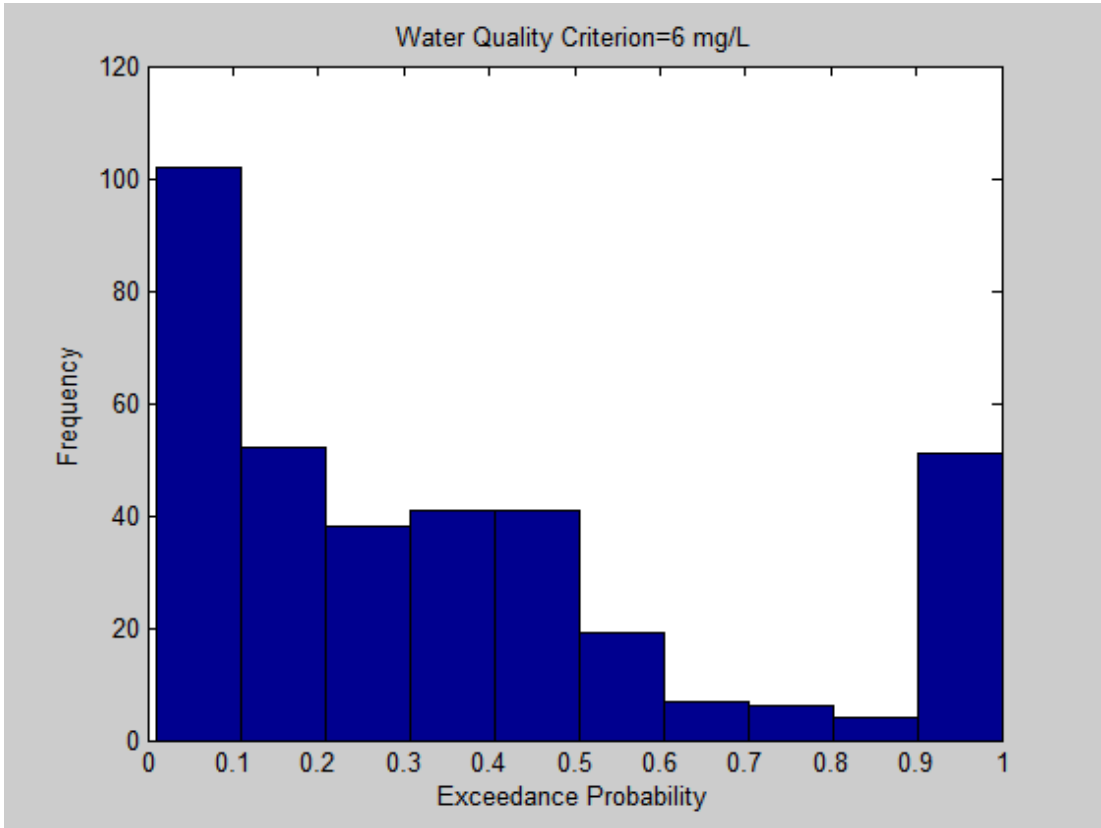
Figure 21 Frequency distribution of exceedance probabilities for water quality criterion of 6 mg/L.

Results of the Pearson distribution characterization are shown in Table 21. Based on the selection criteria in columns three and four where D<0 and λ<0, the daily exceedance probability distribution falls into either class 4 or class 8 Pearson distributions in Tables 19 and 20. According to Andreev et al. (2005), the

distributions that best describe those classes are Beta I and Beta II type distributions. The shape of the beta distribution is determined by two shape factors and occurs over a finite range.

Table 19 Pearson distributions. The table provides a classification of the Pearson distributions f(x) satisfying the differential equation (1/f)df/dx=P(x)/Q(x):=(a$_0$+a$_1$x)/(b$_0$+b$_1$x+b$_2$x^2). The signs and values for selection criteria, D :=b$_0$b$_2$-b$_1{}^2$ and λ :=b$_1{}^2$/(b$_0$b$_2$), are given in columns three and four (from Andeev et al. 2005).

$$P(x) = a_0,\ Q(x) = 1$$

	Restrictions	D	λ	Support	Density
1.	$a_0 < 0$	0	$0/0$	$\mathbb{R}^+$	$\gamma e^{-\gamma x}$ $\gamma > 0$

$$P(x) = a_0,\ Q(x) = b_2 x(x + \alpha)$$

	Restrictions	D	λ	Support	Density
2(a).	$\alpha > 0$	< 0	∞	$[-\alpha, 0]$	$\frac{m+1}{\alpha^{m+1}}(x+\alpha)^m$ $m < -1$
2(b).	$\alpha > 0$	< 0	∞	$[-\alpha, 0]$	$\frac{m+1}{\alpha^{m+1}}(x+\alpha)^m$ $-1 < m < 0$

$$P(x) = a_0,\ Q(x) = b_0 + 2b_1 x + x^2 = (x - \alpha)(x - \beta),\ \alpha < \beta$$

	Restrictions	D	λ	Support	Density
3(a).	$a_0 \neq 0$ $0 < \alpha < \beta$	< 0	> 1	$[\beta, \infty]$	$\frac{(\beta-\alpha)^{-(m+n+1)}}{B(-m-n-1,n+1)}(x-\alpha)^m(x-\beta)^n$ $m > -1,\ n > -1,\ m \neq 0,\ n \neq 0,\ m = -n$
3(b).	$a_0 \neq 0$ $\alpha < \beta < 0$	< 0	> 1	$[-\infty, \alpha]$	$\frac{(\beta-\alpha)^{-(m+n+1)}}{B(-m-n-1,m+1)}(x-\alpha)^m(x-\beta)^n$ $m > -1,\ n > -1,\ m \neq 0,\ n \neq 0,\ m = -n$
4.	$a_0 \neq 0$ $\alpha < 0 < \beta$	< 0	< 0	$[\alpha, \beta]$	$\frac{\alpha^{2m}\beta^{2n}}{(\alpha+\beta)^{m+n+1}B(m+1,n+1)}(x-\alpha)^m(x-\beta)^n$ $m > -1,\ n > -1,\ m \neq 0,\ n \neq 0,\ m = -n$

$$P(x) = a_0 + a_1 x,\ Q(x) = 1$$

	Restrictions	D	λ	Support	Density
5.	$a_1 \neq 0$	0	$0/0$	$\mathbb{R}$	$\frac{1}{\sqrt{2\pi}\sigma}e^{-(x-\mu)^2/2\sigma^2}$

$$P(x) = a_0 + a_1 x,\ Q(x) = x - \alpha$$

	Restrictions	D	λ	Support	Density
6.	$a_1 \neq 0$	< 0	∞	$[\alpha, \infty]$	$\frac{k^{m+1}}{\Gamma(m+1)}(x-\alpha)^{-m}e^{-k(x-\alpha)}$ $k > 0$

Table 20 Pearson distributions continued from Table 19 (Andeev et al. 2005).

$P(x) = a_0 + a_1 x,\ Q(x) = b_0 + 2b_1 x + x^2 = (x - \alpha)(x - \beta),\ \alpha \neq \beta$					
	Restrictions	D	λ	Support	Density
7(a).	$a_1 \neq 0$ $0 < \alpha < \beta$	< 0	> 1	$[\beta, \infty]$	$\frac{(\beta - \alpha)^{-(m+n+1)}}{B(-m-n-1, n+1)}(x - \alpha)^m (x - \beta)^n$ $m > -1,\ n > -1,\ m \neq 0,\ n \neq 0, m \neq -n$
7(b).	$a_1 \neq 0$ $\alpha < \beta < 0$	< 0	> 1	$[-\infty, \alpha]$	$\frac{(\beta - \alpha)^{-(m+n+1)}}{B(-m-n-1, m+1)}(x - \alpha)^m (x - \beta)^n$ $m > -1,\ n > -1,\ m \neq 0,\ n \neq 0, m \neq -n$
8.	$a_1 \neq 0$ $\alpha < 0 < \beta$	< 0	< 0	$[\alpha, \beta]$	$\frac{\alpha^{2m}\beta^{2n}}{(\alpha + \beta)^{m+n+1} B(m+1, n+1)}(x - \alpha)^m (x - \beta)^n$ $m > -1,\ n > -1,\ m \neq 0,\ n \neq 0, m \neq -n$
$P(x) = a_0 + a_1 x,\ Q(x) = b_0 + 2b_1 x + x^2 = (x - \alpha)(x - \beta),\ \alpha = \beta$					
	Restrictions	D	λ	Support	Density
9.	$a_1 > 0$ $\alpha = \beta$	0	1	$[\alpha, \infty]$	$\frac{\gamma^{m-1}}{\Gamma(m-1)}(x - \alpha)^{-m} e^{-\gamma/x}$ $\gamma > 0,\ m > 1$
$P(x) = a_0 + a_1 x,\ Q(x) = b_0 + 2b_1 x + x^2,\ \text{complex roots}$					
	Restrictions	D	λ	Support	Density
10.	$a_0 = 0,\ a_1 < 0$ $b_1 = 0,\ b_0 = \beta^2$ $\beta \neq 0$	> 0	0	$\mathbb{R}$	$\frac{\alpha^{2m-1}}{B(m-1/2, 1/2)}(x^2 + \beta^2)^{-m}$ $m > 1/2$
11.	$a_0 \neq 0,\ a_1 < 0$ $b_1 \neq a_0/a_1$	> 0	$0 >$ < 1	$\mathbb{R}$	$c(b_0 + 2b_1 x + x^2)^{-m} e^{-\nu \arctan((x+b_1)/\beta)}$ $m > 1/2,\ \beta = \sqrt{b_0 - b_1^2}$

Table 21 Results of Pearson distribution characterization including the first four moments, Pearson parameters, skewness coefficients, scaling parameters, and selection criteria.

First Four Momemts	Pearson Parameters	Skewness Coefficients	Scaling Parameters	Selection Criteria
$\mu_1 = 0.1377$	$b_1 = a = 0.7719$	$\beta_1 = 21.1143$	$A = 2.509 \times 10^{-4}$	$D = -0.6218$
$\mu_2 = 0.0215$	$b_0 = 0.0316$	$\beta_2 = 24.7178$	$A' = -24.1936$	$\lambda = -22.9154$
$\mu_3 = 0.0145$	$b_2 = -0.8228$			
$\mu_4 = 0.0114$				

Table 22 shows the average daily model predictions of nitrate load and concentration, the expected exceedance frequency, and the confidence of compliance for each load reduction of nitrate from 0% to 40% over the entire study period (1994-2001). Nitrate

load reductions greater than 40% resulted in a confidence of compliance equal to 100%, therefore those load reductions were not listed. The expected exceedance of 14% at 0% load reduction indicates impaired waterbody conditions. The confidence of compliance further indicates that there is only a 12.5% confidence that the 10% frequency standard will be met. At a load reduction of 20%, the mean exceedance frequency is expected to be 10% with a confidence of compliance equal to 37.5%. That is the load reduction necessary to meet the nitrate water quality standard. MOS was then determined based on the desired level of confidence. Therefore, at a desired level of confidence of 75%, the MOS load was equal to the difference between the load at 20% reduction (9.9 kg N/d) and the load at 30% reduction (8.6 kg N/d), which was 1.3 kg N/d. The TMDL for this waterbody is therefore 8.6 kg N/d, a 30% reduction from baseline conditions.

Table 22 Average daily model predictions of nitrate load and concentration, the expected exceedance frequency, and the confidence of compliance for each load reduction of nitrate from 0% to 40% over the entire study period (1994-2001).

NO3-N Reduction (%)	Average NO3-N Load (kg N/d)	Average NO3-N Concentration (mg/L)	Expected Exceedances (%)	Confidence of Compliance (%)
0	12.3	1.25	14	12.5
5	11.7	1.19	12	25
10	11.1	1.12	11	25
15	10.5	1.06	11	37.5
20	9.9	1.00	10	37.5
25	9.3	0.94	9	37.5
30	8.6	0.87	8	75
35	8.0	0.81	8	75
40	7.4	0.75	7	100

The probability that the true exceedance frequency will be below 10% is 100% at the nitrate reduction level of 40%. Using a water quality criterion of 6 mg/L did not make the water body at the outlet of the Warner Creek watershed extremely impaired. However, in other cases when a water body is highly impaired it may not be as feasible to set a water quality goal to 75% confidence; especially when the effectiveness and efficiency of improvement strategies are not well known. In that case, many researchers have suggested an adaptive management approach where an

initial set of improvement strategies are implemented, monitored and evaluated to determine their efficacy, and then further measures can be taken (Dilks and Freedman, 2004; Walker, 2003).

In summary, this study suggests the following steps for using the SWAT model for TMDL assessment:

1.   Calibrate the model to represent observed conditions of the impaired waterbody. In the absence of measured data for the watershed of interest, data from a reference watershed sharing the same physiographic region, land use, and climatic conditions may be used to calibrate the model. This is the baseline scenario.

2.   Perform MFORM methodology using mean values and standard deviations of input parameters to determine daily average standard deviations of the output variable concentrations.

3.   Use daily average standard deviations obtained from the MFORM method in step 2, and calibrated SWAT model's output concentrations to calculate daily exceedance probabilities. The following equation represents this step: $p = P(c > c* \mid \beta, \sigma, X) = 1 - F\left(\dfrac{c* - g(X, \beta)}{\sigma}\right)$

4.   Calculate the annual exceedance frequencies (EFs) (# of days with exceedances over 10% divided by the total # of days in the critical period).

5.   Determine the percent of annual EFs that are less than or equal to 10% (confidence of compliance).

6.   Repeat steps 3 through 5 for each incremental reduction of nutrient load until confidence of compliance level reaches 100%. It should be noted that different reduction levels may be needed for different watersheds based on their level of impairment.

7.   Evaluate each level of confidence with its corresponding nutrient reduction to set a feasible water quality goal (WQG). The difference in load between the nutrient reduction that meets water quality standards (WQS) (an expected exceedance less than or equal to 10%) and the nutrient reduction that meets the water quality goal (desired level of confidence) should be assigned to the MOS value.

These steps are presented as a flow chart depicted in figure 22.
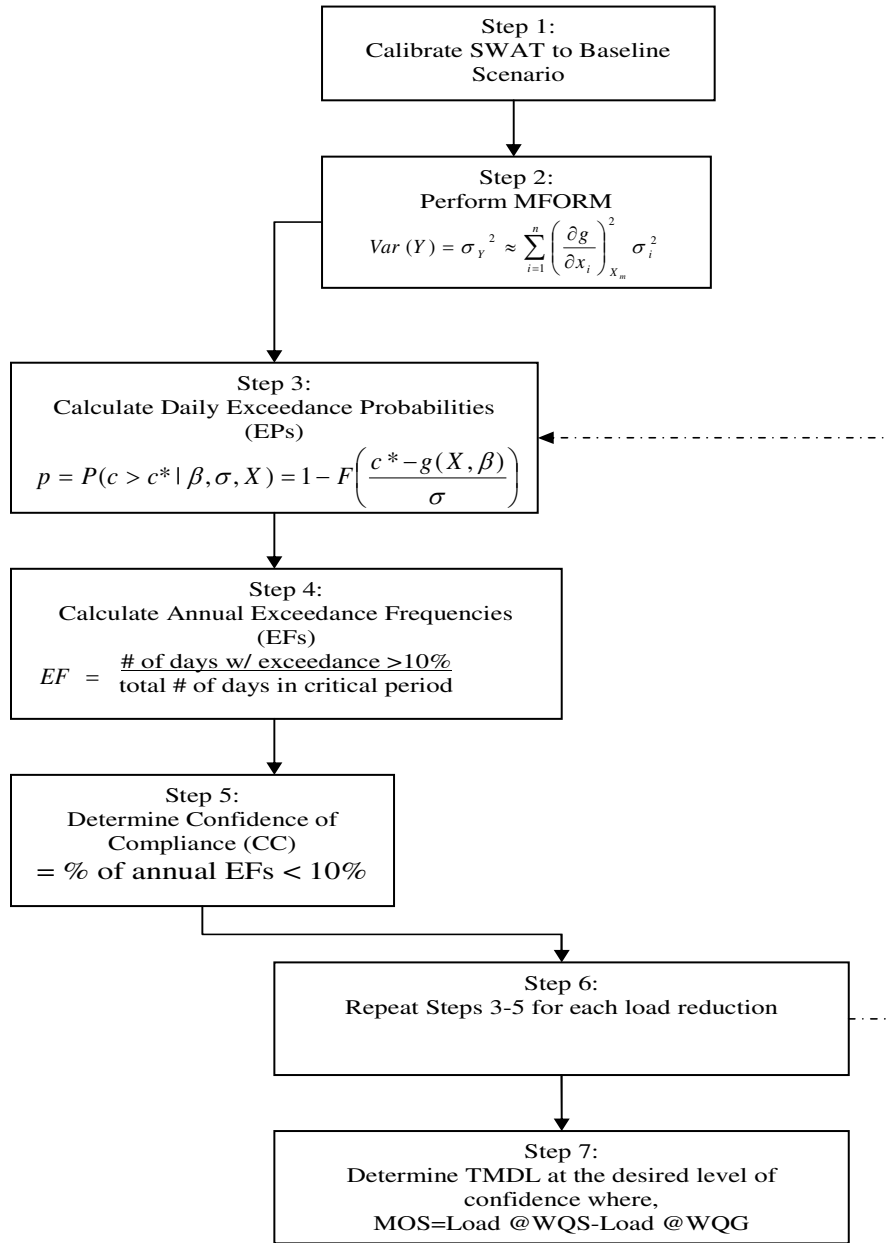
Figure 22 Flow chart of steps for using the SWAT model and uncertainty analysis in TMDL assessment.

Chapter 6: Summary and Conclusions

Watershed-scale hydrologic and water quality monitoring is often limited by the constraints of time and resources, therefore leading to scarcity of monitored data. Non-point source pollution monitoring studies seldom have the ability to pinpoint sources of pollution and determine the best strategic plan to minimize pollution from different sources. Mathematical modeling has become a useful tool to supplement monitored data, and in some cases substitute for monitored data in ungauged basins, in order to determine the best management scenarios to improve hydrologic and water quality conditions in a watershed. For this reason, EPA's Total Maximum Daily Load (TMDL) program leans heavily on the utility of models to set limitations on the amount of impairing substances that can be released from both point and non-point sources.

To insure that certain models are appropriate for use in programs such as TMDL, they must be properly tested to determine their strengths, weaknesses and most optimal scenarios for use. There has been much controversy over the utility of such models in the TMDL program because of unaccounted for uncertainty in model predictions. Stakeholders would like to have some sense of reliability in model predictions, especially when decisions based on model results can potentially impose both legal and financial responsibility upon point and non-point source contributors. The margin of safety (MOS) value in TMDL analysis is meant to represent the uncertainty about pollutant loadings and waterbody response that is accrued in establishing a TMDL.

MOS is typically assigned through subjective means although EPA guidance and report documents (USEPA, 1999a; USEPA, 2002a) have suggested that MOS be calculated based on scientific information. It is only recently that scientists have begun to devise formal uncertainty strategies to determine MOS. Hence, there is a need for further study and development of formal methods to quantify MOS.

In this study we have evaluated the applicability of using AVSWAT-X to identify the impairment status of a waterbody and to tabulate a nutrient TMDL. A formal method of uncertainty analysis was also developed to account for the MOS value in TMDL analysis. This effort was met by conducting a calibration, validation, and an uncertainty analysis (MFORM) on the AVSWAT-X model for Warner Creek watershed, which is located in the Piedmont physiographic region of Maryland. The conclusions of this study are as follows:

1. In order to rate the performance of AVSWATX-2003 in predicting surface runoff, baseflow, total streamflow, nitrate, and phosphate loadings we used the general performance ratings for recommended quantitative criteria compiled by Moriasi et al. (2007) (see Table 4). Performance ratings for AVSWATX-2003 prediction of monthly hydrology and water quality constituents in Warner Creek watershed were as follows:

   o Surface Runoff- Good

   o Baseflow- Unsatisfactory

   o Total Streamflow- Good

- Sediment- Poor

- Nitrate- Unsatisfactory to Moderate

- Phosphate- Unsatisfactory to Moderate

2. Annual sediment yields over the four year period of observation revealed satisfactory to good model performance, a large improvement over poor model performance during the monthly validation period. The same observation was made for nitrate loading, which showed good model performance for annual observations. Model performance for phosphate load on an annual basis, however, remained at the unsatisfactory to moderate performance rating. The fact that model performance level improved from the monthly time frame to the annual prediction time frame is an indication that AVSWATX-2003 performs better during long-term simulation studies.

3. Although monthly surface runoff and total streamflow predictions were good, problems during extreme storm events did have an effect on model performance, which carried over to sediment and nutrient prediction performance. Under-estimations of streamflow often led to under-estimation of the latter constituents. Use of the SCS curve number method in SWAT to tabulate surface runoff is likely the reason that severe storm events were not represented well. The SCS method depends on empirical information to tabulate surface runoff, which is often not flexible enough to capture natural variability especially during major storm events. The infiltration-based Green and Ampt (1911) modified by Mein and Larson (1973) excess rainfall method

may be a plausible alternative to the SCS method to improve streamflow

prediction during severe storm events.

4. During streamflow calibration, special care should be taken to observe

   baseflow behavior while minimizing high flow errors to prevent fitting the

   higher portion of the hydrograph (i.e., peak surface flows) at the expense of

   lower portions.

5. Researchers often consider sensitive parameters (input parameters that cause a

   large change in output with respect to changes in input) to be the parameters

   with highest potential to contribute to model output uncertainty. Through a

   comparison of the ranking of parameters by sensitivity and fraction of

   variance (FOV) that contribute to output variable, this study shows that other

   parameters not highly deemed as sensitive (e.g., RCHRG_DP, ESCO) are

   important contributors to model output uncertainty. The reason that such

   parameters can surpass highly sensitive parameters in their level of

   importance to uncertainty is explained by their variance. When the value of a

   parameter is known with little certainty, its potential to cause variability in

   output simulation is larger. The further away a parameter is from its true value

   (often considered mean value), the more likely it will cause variance in

   simulated output.

6. Results of annual and monthly total output variances indicated that the largest

   amount of variance in output variables occurred during wet periods. During

   the wettest year of the study period (1996), variances were orders of

   magnitude larger than other years. Monthly observations of streamflow

variance revealed higher trends of variance during wet periods between January to March and November to December. Increased levels of variance occurring in summer months were a result of wet periods during extremely wet years. As stated earlier, the poor performance of the model during wet periods is likely the result of the limitation of the model to properly account for extreme events through the use of the SCS curve number method.

7. Comparison of average coefficients of variation showed that sediment output had the largest amount of variability around its mean value (CV= 28%). Nitrate and phosphate had the next largest total amount of variability with average CVs of 19% and 17%, respectively. Streamflow output had the least amount of variability around its mean value (CV= 15%). These results are comparable to calibration and validation results because model performance was poorest during sediment simulation and best during streamflow simulation based on the statistical parameters computed in this study. Greater knowledge or certainty about the values of input parameters will lead to better model performance and less output uncertainties.

8. In this study, the distribution of exceedance probabilities closely resembled Pearson's Beta I and Beta II type distributions. It would be interesting to observe exceedance probability distributions of other watersheds to determine if there is any commonality of distribution types.

9. The methodology used to determine the margin of safety (MOS) value associated with the nitrate TMDL included the determination of waterbody impairment at 0% load reduction as well as tabulation of the level of load

reduction necessary to meet the nitrate water quality standard. The methodology was a useful tool to help determine the nitrate TMDL as well as the margin of safety associated with tabulating that TMDL.

10. Although a confidence of compliance of 100% was reached at a nitrate load reduction of 40% for Warner Creek watershed, this level of confidence may not be as feasible for highly impaired waterbodies. In that case, an adaptive management strategy could prove to be more effective by identifying and implementing the most useful management practices in a stepwise process as opposed to spending a lot of money to implement a large slate of BMPs to no effect.

11. Overall, this study shows that for monthly and longer timeframes, AVSWATX is a moderate to good model for estimating waterbody impairment and conducting TMDL analysis of waterbodies impaired by nutrients. No model can perfectly simulate or predict the behavior of either natural or anthropogenic land management practices in the environment, whether because of natural variability or insufficient knowledge about the processes. However, as we continue to increase our knowledge and understanding of environmental processes and consider the causes of variability and misrepresentation, we are constantly improving our abilities to simulate and predict these phenomena. The following section discusses some suggestions for future model application and research.

Suggestions for Future Model Application and Research

1. In this study, AVSWATX-2003 was found to perform poorly during sediment calibration and validation using monthly data. Unsatisfactory to moderate performance was observed for nutrients on a monthly basis. A major reason for this behavior was highlighted in this study as being due to inability of the model to properly account for extreme climate events as a result of using the empirically-based SCS method to calculate surface runoff volume. Therefore, it is suggested to conduct comparative studies using SCS curve number method and the infiltration-based Green and Ampt Mein-Larson excess rainfall method to determine if there is an improvement upon model predictions.

2. Sensitivity and uncertainty of output variables to important input parameters were evaluated in this study. Ranking of important input parameters revealed those parameters that should be considered with more care during the determination of their values, whether through field measurements or other methods of derivation. The importance of considering the variance of input parameters and not just the sensitivity effects as it relates to their potential to cause uncertainty in output variables was also revealed. More studies should be conducted to determine true values of input parameters as well as the variability associated with their values.

Appendices

Appendix A

AVSWAT-X Input Data for Warner Creek Watershed

The format of AVSWAT-X input data is given in the Arc View Interface for SWAT2000 User's Guide (Di Luzio et al., 2002b).

Appendix A-1

Daily precipitation for Warner Creek watershed from 1993 to 2001

Table A1 Daily precipitation for Warner Creek watershed from 1993 to 2001.

DATE	1993	1994	1995	1996	1997	1998	1999	2000	2001
	Daily Precipitation (mm)								
1-Jan	0.0	0.0	18.0	0.8	0.0	0.0	0.0	0.0	0.0
2-Jan	0.0	0.8	0.0	28.2	0.3	0.0	5.1	0.0	0.0
3-Jan	0.0	0.0	0.0	14.2	0.0	0.0	53.3	0.0	0.0
4-Jan	0.0	2.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5-Jan	12.7	0.0	0.0	0.0	1.7	0.0	0.0	0.1	3.8
6-Jan	0.0	5.8	0.0	0.0	0.0	3.0	0.0	0.0	0.0
7-Jan	0.0	0.0	26.4	66.0	0.0	1.3	0.0	0.0	0.0
8-Jan	3.6	2.5	0.0	68.6	0.0	81.3	30.5	0.0	3.0
9-Jan	11.4	0.0	0.0	0.0	20.8	3.8	12.7	0.0	0.0
10-Jan	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11-Jan	0.8	0.0	0.0	0.0	5.6	0.0	0.0	0.0	0.0
12-Jan	6.3	10.4	2.3	61.0	0.0	0.0	0.0	0.0	0.0
13-Jan	4.6	0.0	1.3	0.0	0.0	0.5	0.0	0.0	0.0
14-Jan	0.0	0.5	0.0	0.0	0.0	0.0	3.8	0.0	0.0
15-Jan	0.0	0.0	27.7	0.0	0.0	2.5	21.6	0.0	0.0
16-Jan	0.0	0.0	0.0	0.0	11.4	30.5	0.0	0.0	0.0
17-Jan	0.0	25.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18-Jan	0.0	10.2	0.0	11.9	0.0	0.0	15.0	0.0	0.0
19-Jan	0.0	0.0	0.8	19.6	0.0	0.0	0.0	6.9	29.2
20-Jan	0.0	5.1	44.5	0.0	0.0	0.0	1.3	0.0	0.0
21-Jan	3.6	0.0	0.0	0.0	0.0	0.0	5.1	0.0	11.9
22-Jan	11.4	0.0	0.0	0.0	0.8	0.0	2.5	0.0	0.0
23-Jan	1.5	0.0	0.0	1.0	3.0	40.6	3.8	0.3	0.0
24-Jan	0.0	0.0	0.0	12.8	2.3	1.3	26.9	0.0	0.0
25-Jan	0.0	0.0	0.0	0.0	16.1	4.6	1.3	0.0	0.0
26-Jan	0.0	8.9	0.0	12.7	0.0	0.0	0.0	15.7	0.0
27-Jan	0.0	0.0	0.0	4.3	0.0	0.0	0.0	0.0	0.0
28-Jan	0.0	2.5	0.0	0.0	17.2	30.5	0.0	0.0	0.0
29-Jan	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30-Jan	0.0	0.0	0.0	0.0	0.0	0.0	0.0	42.4	18.8
31-Jan	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1-Feb	1.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2-Feb	0.0	0.0	0.0	0.0	0.0	0.0	15.7	0.0	0.0
3-Feb	0.0	0.0	0.0	14.2	0.0	1.3	0.0	0.0	0.0
4-Feb	0.0	0.0	35.6	0.0	15.1	8.9	1.3	0.0	0.0
5-Feb	0.0	0.0	0.0	0.0	0.0	27.2	0.0	0.0	7.9
6-Feb	0.0	0.0	2.8	0.0	0.0	0.0	10.2	0.0	0.0
7-Feb	0.0	0.0	0.0	0.0	0.0	0.0	7.6	0.0	0.0
8-Feb	0.0	0.0	0.0	14.7	20.3	0.0	5.1	0.0	0.0
9-Feb	0.0	19.8	0.0	2.5	9.7	0.0	0.0	0.0	0.0
10-Feb	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11-Feb	0.0	34.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12-Feb	31.8	0.0	0.0	0.0	0.0	15.2	3.0	0.0	1.0

Table A1 Continued.

DATE	Daily Precipitation (mm)								
	1993	**1994**	**199**5	1996	1997	1998	1999	2000	2001
13-Feb	1.5	0.0	0.0	0.0	0.0	0.0	0.0	8.9	3.0
14-Feb	0.0	0.0	0.0	0.0	18.8	0.0	0.0	0.0	1.3
15-Feb	0.0	0.0	6.3	2.8	1.3	0.0	0.0	0.0	0.0
16-Feb	24.1	0.0	3.9	12.7	0.0	0.0	0.0	0.0	8.9
17-Feb	0.0	0.0	0.0	0.0	0.0	16.5	6.3	0.0	0.0
18-Feb	0.0	0.0	0.0	0.0	0.0	24.1	10.2	21.3	0.0
19-Feb	0.0	0.0	0.0	0.0	0.0	2.5	0.0	0.0	0.0
20-Feb	0.0	0.0	0.0	23.9	0.0	3.0	0.0	10.7	0.0
21-Feb	30.5	10.2	0.0	2.0	0.0	0.0	0.0	0.0	0.0
22-Feb	0.0	0.0	0.5	0.0	1.8	0.0	0.0	0.0	6.1
23-Feb	0.0	22.9	5.3	0.0	0.0	20.3	0.0	0.0	0.0
24-Feb	0.0	0.0	0.0	0.0	0.0	22.6	3.8	0.0	0.0
25-Feb	0.0	0.0	0.0	0.5	0.0	0.0	0.5	0.0	4.3
26-Feb	25.4	0.0	5.3	1.3	3.6	0.0	2.5	0.0	0.0
27-Feb	0.0	0.0	17.8	1.3	4.8	0.0	0.0	22.1	0.0
28-Feb	0.0	0.0	0.5	3.6	0.0	0.0	10.2	0.0	0.0
29-Feb				0.0				0.0	
1-Mar	0.0	1.0	0.0	0.0	11.8	2.5	0.0	0.0	0.0
2-Mar	0.0	20.3	0.0	0.0	0.5	0.0	0.0	0.0	0.0
3-Mar	0.0	22.9	0.0	0.0	24.3	27.2	0.0	0.0	0.0
4-Mar	39.4	1.8	0.0	0.0	6.1	0.0	20.3	0.0	19.8
5-Mar	11.7	0.0	1.3	1.8	0.5	0.0	0.0	0.0	0.0
6-Mar	1.0	0.0	5.1	8.6	6.7	0.0	12.7	0.0	0.0
7-Mar	0.0	0.0	0.0	21.1	0.0	0.0	0.0	0.0	0.0
8-Mar	0.0	0.2	9.1	1.3	0.3	25.4	0.0	0.0	0.3
9-Mar	0.0	25.7	11.2	0.0	0.0	18.5	7.6	0.0	0.0
10-Mar	3.6	0.0	0.0	0.0	1.8	0.0	3.8	0.0	0.0
11-Mar	1.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12-Mar	0.0	0.1	1.0	0.0	0.0	0.0	0.0	0.0	13.0
13-Mar	45.7	0.0	0.0	0.0	0.0	0.0	0.0	23.6	0.6
14-Mar	128.3	0.0	0.0	0.0	30.1	0.0	27.9	0.0	0.0
15-Mar	0.0	0.1	0.0	9.4	0.0	0.0	22.9	0.0	3.8
16-Mar	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.8
17-Mar	23.4	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0
18-Mar	0.0	2.0	0.0	0.0	13.1	7.6	0.0	18.5	0.0
19-Mar	0.0	0.0	0.0	27.9	6.1	21.1	0.0	0.0	0.3
20-Mar	0.0	0.0	0.0	33.0	0.0	2.5	0.0	0.0	0.0
21-Mar	7.4	15.5	2.8	0.0	0.0	52.1	20.3	51.6	18.3
22-Mar	0.0	0.0	1.0	0.0	0.0	6.3	2.5	0.5	0.0
23-Mar	8.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
24-Mar	17.8	4.8	0.0	0.0	0.0	2.5	1.3	0.0	0.0
25-Mar	0.0	0.0	0.0	0.6	0.0	0.0	0.3	0.5	0.0
26-Mar	0.0	0.0	0.0	0.0	14.8	0.0	0.0	0.0	0.3
27-Mar	8.1	43.4	0.0	0.0	0.0	0.0	0.0	10.4	0.0

Table A1 Continued.

DATE	Daily Precipitation (mm)								
	1993	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
28-Mar	8.6	21.8	1.0	32.8	0.0	0.0	0.0	0.0	0.0
29-Mar	2.5	2.8	2.5	0.3	7.7	0.0	0.0	2.0	38.4
30-Mar	1.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
31-Mar	0.0	0.0	0.0	0.0	20.0	0.0	0.0	0.0	0.0
1-Apr	23.4	0.0	0.0	20.8	0.0	15.2	0.0	0.0	0.0
2-Apr	17.8	0.0	0.5	0.0	0.0	0.0	0.0	0.3	3.3
3-Apr	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4-Apr	0.0	2.0	0.0	0.0	0.0	1.3	0.0	12.4	0.0
5-Apr	0.0	0.0	0.0	0.8	1.0	0.0	29.2	0.0	0.0
6-Apr	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7-Apr	0.0	14.5	0.0	0.0	8.0	0.0	0.0	0.0	0.0
8-Apr	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	27.4
9-Apr	0.0	0.0	0.0	16.5	0.0	38.1	12.7	27.9	6.3
10-Apr	27.9	9.1	6.9	8.9	0.0	2.5	10.2	0.0	0.0
11-Apr	6.1	0.0	0.9	0.0	0.0	0.0	12.7	0.0	12.2
12-Apr	3.6	1.8	0.0	0.0	0.0	0.0	3.8	0.8	0.3
13-Apr	0.0	17.3	21.8	0.0	14.6	0.0	0.0	0.0	0.0
14-Apr	0.0	7.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15-Apr	0.0	0.0	0.0	27.4	0.0	0.5	3.8	0.0	0.0
16-Apr	26.2	8.1	0.0	0.8	0.0	0.0	5.1	0.0	15.2
17-Apr	11.7	0.0	0.8	0.0	1.2	0.0	0.0	0.0	1.5
18-Apr	0.0	0.0	0.3	0.0	0.0	0.0	0.0	40.6	0.0
19-Apr	0.0	0.0	0.0	0.0	0.0	22.9	0.0	0.0	0.0
20-Apr	0.0	0.0	0.0	0.0	0.0	11.9	2.5	0.0	0.0
21-Apr	3.3	0.0	0.0	0.0	2.5	0.0	3.8	17.5	0.0
22-Apr	38.1	0.0	0.0	0.0	2.0	0.0	0.0	9.4	2.0
23-Apr	0.5	0.0	1.3	11.4	0.0	0.0	6.3	2.5	0.0
24-Apr	0.0	0.0	4.3	0.0	0.0	0.0	0.0	0.0	0.0
25-Apr	0.0	0.0	0.0	0.0	5.6	0.0	0.0	0.3	0.0
26-Apr	6.3	0.0	0.0	0.0	0.0	1.8	0.0	0.0	0.0
27-Apr	0.0	11.9	0.0	0.0	0.0	5.6	0.0	0.0	0.0
28-Apr	0.0	0.0	0.0	3.8	13.1	0.0	0.0	0.0	0.0
29-Apr	0.0	1.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30-Apr	0.0	5.8	9.4	17.3	0.0	2.5	0.0	0.0	0.0
1-May	0.0	0.0	8.1	2.3	1.5	10.2	0.0	0.0	0.0
2-May	0.0	0.0	0.0	0.0	0.0	10.7	0.0	3.3	0.0
3-May	0.0	0.0	0.0	3.3	0.0	5.1	1.3	0.0	0.0
4-May	0.0	9.4	0.0	0.3	17.4	20.8	0.0	0.0	0.0
5-May	0.0	0.5	2.3	22.4	0.0	22.9	0.0	0.0	0.0
6-May	15.2	0.0	0.0	0.0	0.0	3.8	0.0	0.0	0.0
7-May	0.0	0.0	0.0	8.6	0.5	2.5	1.3	0.0	0.0
8-May	0.0	31.8	0.0	30.7	4.6	27.9	19.0	0.0	0.0
9-May	0.0	0.5	0.0	0.0	2.3	1.3	0.0	0.0	1.3
10-May	0.0	0.0	3.0	0.0	0.0	2.5	0.0	28.4	0.0

Table A1 Continued.

DATE	Daily Precipitation (mm)								
	1993	**1994**	**1995**	1996	1997	1998	1999	2000	2001
11-May	0.0	0.0	16.0	25.9	0.0	12.7	0.0	0.0	0.0
12-May	20.3	3.8	1.8	5.8	0.0	20.3	0.0	0.0	0.0
13-May	0.0	0.0	0.0	0.0	0.0	3.8	1.3	8.9	0.0
14-May	0.0	0.0	18.5	0.0	0.0	0.0	0.0	0.0	0.0
15-May	0.0	11.7	0.0	0.0	1.5	0.0	0.0	1.0	0.0
16-May	2.5	0.0	0.0	8.6	0.0	0.0	0.0	0.0	0.0
17-May	0.0	0.0	6.9	0.3	0.0	0.0	0.0	0.0	1.3
18-May	0.0	0.3	7.1	2.0	0.0	0.0	0.0	0.0	2.8
19-May	10.2	0.5	0.0	0.0	4.6	0.0	0.0	0.0	0.0
20-May	0.0	0.0	0.0	0.0	1.5	0.0	0.0	0.0	13.7
21-May	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	24.6
22-May	0.0	0.0	2.0	4.6	0.0	0.0	0.0	18.3	14.5
23-May	0.0	0.0	0.0	0.0	0.0	0.0	15.2	13.2	0.0
24-May	0.0	0.0	0.0	0.0	0.0	0.0	5.1	4.1	0.0
25-May	0.0	2.8	0.0	0.0	2.3	2.5	0.0	0.0	10.9
26-May	0.0	30.6	29.0	8.9	14.3	0.0	0.0	0.0	0.0
27-May	0.0	0.0	0.0	12.4	0.0	0.0	0.0	0.0	0.0
28-May	0.0	0.0	7.1	10.9	0.0	0.0	0.0	0.0	4.6
29-May	0.0	0.0	17.8	17.0	0.0	0.0	0.0	19.8	0.5
30-May	0.0	5.8	0.3	0.0	3.1	1.3	0.0	0.0	0.0
31-May	62.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1-Jun	0.0	0.0	0.0	0.0	27.4	10.7	0.0	0.0	0.0
2-Jun	1.3	0.0	7.1	0.0	12.8	0.0	7.6	0.0	16.8
3-Jun	0.0	0.0	0.0	2.0	1.3	0.5	12.7	0.0	0.3
4-Jun	1.5	0.0	1.5	14.7	0.0	2.5	0.0	0.0	0.5
5-Jun	3.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6-Jun	0.0	0.0	0.5	0.0	0.0	0.5	0.0	11.9	0.0
7-Jun	0.0	0.0	0.0	0.0	0.0	3.6	0.0	0.0	15.0
8-Jun	9.4	0.0	0.0	0.0	1.5	0.0	0.0	0.0	0.0
9-Jun	17.8	0.6	0.0	12.2	0.0	1.3	0.0	0.0	0.0
10-Jun	0.0	0.0	3.3	1.5	0.0	7.6	0.0	0.0	0.0
11-Jun	3.8	0.0	5.1	3.3	0.8	2.5	1.3	0.0	0.0
12-Jun	0.0	0.0	4.3	1.5	0.3	18.8	0.0	0.0	0.0
13-Jun	0.0	0.0	0.3	0.3	1.8	13.7	2.0	3.3	0.0
14-Jun	0.0	0.0	0.0	24.4	0.0	0.0	14.0	0.0	0.0
15-Jun	0.0	0.0	0.0	0.0	0.0	3.8	0.0	17.0	0.0
16-Jun	0.0	7.6	0.0	0.0	0.0	1.0	0.0	0.0	20.3
17-Jun	0.0	0.0	0.0	21.6	0.0	11.9	10.2	0.0	0.0
18-Jun	0.0	0.0	0.0	45.2	6.7	0.0	0.0	5.3	0.0
19-Jun	0.0	0.0	0.0	7.1	0.0	3.8	0.0	0.0	0.0
20-Jun	7.1	0.0	0.0	9.7	0.0	3.8	0.0	0.0	0.0
21-Jun	20.3	2.2	0.0	0.0	0.0	0.0	2.5	44.2	0.0
22-Jun	0.0	0.0	3.0	0.0	1.3	0.0	0.0	0.0	11.9
23-Jun	0.0	5.6	37.1	0.0	0.0	0.0	0.0	0.0	13.5

Table A1 Continued.

DATE	Daily Precipitation (mm)								
	1993	1994	1995	1996	1997	1998	1999	2000	2001
24-Jun	0.0	11.4	1.3	15.0	0.0	1.3	0.0	0.0	0.0
25-Jun	0.0	6.3	4.8	0.0	0.0	0.0	0.0	15.2	0.0
26-Jun	3.0	2.5	22.6	0.0	0.0	7.6	0.0	0.0	0.0
27-Jun	0.0	7.6	1.3	0.0	3.1	0.0	0.0	0.0	0.0
28-Jun	1.5	0.0	0.0	0.0	0.0	1.3	1.8	12.7	0.0
29-Jun	0.0	1.7	0.0	15.2	0.0	0.0	0.0	0.0	0.0
30-Jun	0.0	0.0	0.9	21.8	0.0	5.1	0.0	0.0	1.0
1-Jul	7.1	0.0	45.0	0.5	4.4	3.8	0.0	0.0	0.0
2-Jul	14.7	0.0	0.0	10.7	0.3	0.0	1.0	0.0	0.0
3-Jul	0.0	0.8	1.5	1.8	0.0	0.0	7.6	1.5	0.0
4-Jul	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5-Jul	0.0	0.0	40.4	0.0	0.0	1.3	0.0	0.0	9.9
6-Jul	27.9	13.7	6.3	0.0	0.0	0.0	0.0	0.0	0.0
7-Jul	0.0	0.0	0.0	0.5	0.8	0.0	0.0	0.0	0.0
8-Jul	0.0	0.0	0.0	10.9	0.0	41.4	0.0	0.0	2.8
9-Jul	0.0	6.1	0.3	45.0	0.0	0.0	0.0	5.8	0.0
10-Jul	0.0	0.0	3.0	0.0	11.2	0.0	0.8	0.5	17.8
11-Jul	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12-Jul	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
13-Jul	0.0	0.0	0.0	59.2	0.0	0.0	2.5	5.8	0.0
14-Jul	0.0	3.3	0.0	0.0	0.0	0.0	0.0	28.7	0.0
15-Jul	1.0	0.0	0.0	1.8	0.0	0.0	0.0	0.0	0.0
16-Jul	0.0	0.0	5.1	0.0	0.0	21.6	0.0	17.3	0.0
17-Jul	0.0	10.2	11.4	0.0	0.0	3.8	0.0	0.0	0.0
18-Jul	0.0	12.7	0.0	2.3	2.0	6.1	0.5	0.0	1.0
19-Jul	29.2	0.0	0.0	42.9	0.0	0.0	0.0	39.1	0.0
20-Jul	0.0	0.0	3.6	26.8	0.0	0.0	0.3	0.0	0.0
21-Jul	0.0	25.7	0.0	0.0	5.9	0.0	0.0	0.0	0.0
22-Jul	0.0	5.6	0.0	6.3	0.0	0.0	10.2	0.0	0.0
23-Jul	0.0	0.0	0.0	0.0	7.9	2.5	0.0	0.0	0.0
24-Jul	0.0	0.0	2.3	0.0	6.7	0.0	0.8	4.1	0.0
25-Jul	0.0	0.5	0.0	9.1	0.0	0.0	0.0	0.0	0.01
26-Jul	0.3	29.5	0.0	0.0	0.0	0.0	0.0	4.3	0.3
27-Jul	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0
28-Jul	0.0	0.0	14.7	3.0	0.0	0.0	0.0	0.0	0.0
29-Jul	17.8	0.0	0.0	33.0	6.1	0.0	10.2	31.2	8.6
30-Jul	0.0	0.0	0.0	15.0	0.0	0.0	0.0	0.0	0.0
31-Jul	0.0	0.8	0.0	33.5	0.0	40.6	0.0	11.7	0.0
1-Aug	0.0	0.0	0.0	0.0	0.0	0.0	18.3	1.8	0.0
2-Aug	0.0	2.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0
3-Aug	0.0	0.0	0.0	41.4	0.0	0.0	0.0	5.6	0.0
4-Aug	0.0	0.0	0.0	0.0	12.8	0.0	0.0	0.0	0.0
5-Aug	0.5	6.9	16.0	0.0	0.8	0.0	0.0	0.3	0.0
6-Aug	22.4	0.0	32.3	0.0	0.0	0.0	0.0	12.7	0.0

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Table A1 Continued.

DATE	Daily Precipitation (mm)								
	1993	1994	1995	1996	1997	1998	1999	2000	2001
7-Aug	5.3	0.0	3.3	0.0	0.0	0.0	0.0	0.3	0.0
8-Aug	7.6	0.0	0.0	0.0	0.0	0.0	1.5	0.4	0.0
9-Aug	0.0	0.0	0.0	4.8	0.0	0.0	0.0	6.3	0.0
10-Aug	0.0	0.0	0.0	0.0	0.0	26.7	0.0	0.3	0.0
11-Aug	0.0	1.3	1.3	0.0	0.0	1.3	0.0	0.0	0.6
12-Aug	18.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	43.9
13-Aug	0.0	0.0	0.0	47.2	10.0	0.0	0.0	20.3	0.0
14-Aug	0.0	9.4	0.0	0.0	0.0	2.5	3.8	0.3	9.1
15-Aug	0.0	0.0	0.0	0.0	0.0	5.1	0.0	4.3	0.0
16-Aug	0.0	1.3	0.0	3.6	0.0	0.0	0.0	0.3	0.0
17-Aug	31.8	47.5	0.0	0.3	19.7	17.8	0.0	0.0	0.4
18-Aug	0.3	0.0	0.0	0.0	6.7	0.5	0.0	0.0	0.0
19-Aug	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20-Aug	6.6	0.0	0.0	0.0	34.3	0.0	1.0	0.0	0.3
21-Aug	0.0	15.5	0.0	1.5	0.0	0.0	77.5	0.8	0.0
22-Aug	0.0	36.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0
23-Aug	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.8
24-Aug	0.0	0.0	0.0	0.0	0.0	0.0	10.2	0.0	0.0
25-Aug	0.0	0.0	0.0	0.0	0.0	0.0	25.4	0.0	0.8
26-Aug	0.0	25.1	0.0	0.0	0.5	0.0	12.7	0.0	0.0
27-Aug	0.0	0.0	0.0	2.8	0.3	0.0	1.0	0.0	0.0
28-Aug	0.0	0.0	0.0	0.0	2.3	0.0	0.0	14.7	7.4
29-Aug	0.0	3.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30-Aug	0.0	0.0	0.0	0.5	0.0	0.0	0.0	10.7	0.0
31-Aug	0.0	1.8	0.0	0.0	0.0	0.0	0.0	2.3	2.0
1-Sep	0.0	0.0	0.0	0.0	0.0	0.0	0.0	18.0	0.0
2-Sep	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.1	0.0
3-Sep	0.0	0.0	0.0	0.0	0.5	7.6	0.0	19.8	0.0
4-Sep	81.3	0.0	0.0	14.2	0.0	0.0	0.0	1.0	0.0
5-Sep	0.0	0.0	0.0	1.3	0.0	0.0	19.6	0.0	0.0
6-Sep	0.0	0.0	0.0	63.8	0.0	0.0	2.5	0.0	0.0
7-Sep	0.0	0.0	0.0	0.0	0.5	0.0	16.5	0.0	0.0
8-Sep	0.0	0.0	2.5	0.0	0.0	4.6	1.3	0.0	0.0
9-Sep	63.5	0.0	0.0	0.4	0.0	0.0	0.0	0.0	1.3
10-Sep	0.0	0.0	0.0	0.0	32.5	0.0	6.3	0.8	0.5
11-Sep	0.0	0.0	0.0	0.0	10.5	0.0	0.0	0.0	0.0
12-Sep	0.0	0.0	0.0	0.0	17.4	0.0	0.0	18.0	0.0
13-Sep	0.0	0.0	0.0	10.9	0.0	0.0	0.0	0.0	0.0
14-Sep	0.0	0.0	0.0	0.0	0.0	0.0	0.0	42.9	2.3
15-Sep	0.0	16.3	0.0	0.0	0.0	0.0	5.1	0.0	0.0
16-Sep	17.8	0.8	33.8	33.5	0.0	0.0	81.3	0.0	0.0
17-Sep	5.1	0.0	0.5	1.7	0.0	0.0	0.0	0.0	0.0
18-Sep	2.8	32.8	0.0	0.0	2.6	0.0	0.0	0.0	0.0
19-Sep	0.0	0.0	0.0	0.0	0.0	0.0	0.0	32.8	0.0

DATE	Daily Precipitation (mm)								
	1993	1994	1995	1996	1997	1998	1999	2000	2001
20-Sep	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.3
21-Sep	2.5	0.0	0.0	0.0	0.5	1.3	14.0	0.0	0.0
22-Sep	14.2	14.7	0.0	16.0	0.0	22.9	7.6	0.0	0.0
23-Sep	0.0	4.1	13.7	3.4	0.0	0.0	0.0	0.0	0.0
24-Sep	0.0	0.0	7.9	0.0	0.0	0.0	0.0	6.1	0.0
25-Sep	0.0	9.7	6.1	0.0	0.0	5.1	0.0	0.0	55.9
26-Sep	17.8	2.3	1.0	0.0	0.0	0.0	0.0	0.0	0.0
27-Sep	6.6	0.0	0.0	0.0	0.0	0.0	0.3	34.5	0.0
28-Sep	0.0	1.5	0.0	0.0	17.2	0.5	22.9	0.0	0.0
29-Sep	0.0	0.0	0.0	16.3	0.3	0.0	0.3	0.0	0.0
30-Sep	1.3	0.0	0.0	0.0	0.0	0.0	45.7	0.0	0.0
1-Oct	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0
2-Oct	0.0	12.4	0.0	3.3	0.0	0.0	0.0	0.0	0.0
3-Oct	4.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4-Oct	0.0	0.0	3.0	0.0	0.0	24.1	11.4	0.0	0.0
5-Oct	0.0	0.0	22.9	0.0	0.0	0.5	10.2	0.5	0.0
6-Oct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.5
7-Oct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8-Oct	0.0	0.0	0.0	24.6	0.0	25.4	0.0	0.0	0.0
9-Oct	0.0	0.0	0.0	2.5	0.0	1.3	0.0	1.5	0.0
10-Oct	0.0	1.3	0.0	0.0	5.4	2.5	35.6	0.0	0.0
11-Oct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12-Oct	18.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
13-Oct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14-Oct	0.0	0.0	22.1	0.0	0.0	0.0	1.3	0.0	13.6
15-Oct	0.0	0.0	11.7	0.0	6.3	0.0	0.0	0.0	0.0
16-Oct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.9	6.6
17-Oct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18-Oct	0.0	0.0	0.0	0.0	7.4	0.0	1.3	0.0	0.0
19-Oct	0.0	0.0	0.0	67.8	0.0	0.0	6.3	0.0	0.0
20-Oct	12.4	1.5	0.0	5.1	0.0	0.0	0.0	0.0	0.0
21-Oct	4.8	0.0	52.6	3.8	0.0	0.0	0.0	0.0	0.0
22-Oct	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0
23-Oct	0.0	23.6	0.0	1.0	0.0	0.0	0.0	0.0	0.0
24-Oct	0.0	0.0	0.0	0.0	2.1	0.0	0.0	0.0	0.0
25-Oct	0.0	0.0	0.0	0.0	12.4	0.0	0.0	0.0	0.0
26-Oct	0.0	0.0	0.0	0.0	15.9	0.0	0.0	0.0	0.0
27-Oct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0
28-Oct	0.0	0.0	13.0	3.0	0.0	0.0	0.0	0.0	0.0
29-Oct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30-Oct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
31-Oct	20.8	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0
1-Nov	4.1	38.9	7.9	0.0	30.2	0.0	0.0	0.0	0.0
2-Nov	0.0	0.0	0.5	0.0	8.6	0.0	7.6	0.0	0.6

Table A1 Continued.

DATE	Daily Precipitation (mm)								
	1993	1994	1995	1996	1997	1998	1999	2000	2001
3-Nov	0.0	0.0	0.0	0.0	0.0	0.0	3.8	0.0	0.0
4-Nov	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.0
5-Nov	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6-Nov	0.0	3.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7-Nov	0.0	0.0	9.9	0.0	74.0	0.0	0.0	0.0	0.0
8-Nov	0.0	0.0	0.0	53.3	0.0	0.0	0.0	0.0	0.0
9-Nov	0.0	6.3	0.0	0.0	3.1	0.0	0.0	14.0	0.0
10-Nov	0.0	0.0	0.0	6.1	0.0	1.3	0.0	0.0	0.0
11-Nov	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12-Nov	0.0	0.0	23.6	0.0	0.0	0.0	0.0	0.0	0.0
13-Nov	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0
14-Nov	4.6	0.0	23.1	1.5	14.0	0.0	0.0	2.8	0.0
15-Nov	0.0	9.4	23.4	0.0	0.0	0.0	0.0	0.0	0.0
16-Nov	0.0	16.3	0.0	0.0	0.8	0.0	0.0	0.0	0.0
17-Nov	6.3	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18-Nov	0.0	0.6	0.0	1.0	0.0	0.0	0.0	0.0	0.0
19-Nov	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20-Nov	0.0	0.0	0.0	0.0	0.0	2.5	0.0	1.5	0.5
21-Nov	0.0	19.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
22-Nov	0.0	0.0	0.0	0.0	17.4	0.0	0.0	0.0	0.0
23-Nov	0.0	0.0	7.4	0.0	0.3	0.0	2.5	0.0	0.0
24-Nov	0.0	0.0	0.0	0.0	0.0	0.0	2.5	0.0	0.0
25-Nov	0.0	0.0	0.0	0.0	0.0	0.0	2.5	0.0	25.1
26-Nov	0.0	0.0	0.0	38.1	0.5	12.7	12.2	24.9	0.0
27-Nov	0.0	0.0	0.0	0.0	0.0	0.0	12.2	0.0	0.0
28-Nov	86.6	31.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
29-Nov	0.0	0.0	13.7	0.0	0.0	0.0	0.0	5.1	1.3
30-Nov	0.0	0.0	0.0	1.8	7.9	0.0	0.0	0.0	0.0
1-Dec	0.0	0.0	0.0	38.1	0.0	0.0	0.0	0.0	0.0
2-Dec	0.0	0.0	0.0	12.1	1.0	0.0	0.0	0.0	0.0
3-Dec	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4-Dec	3.6	31.5	0.0	0.0	0.0	0.0	0.0	0.3	0.0
5-Dec	79.0	0.8	1.3	0.0	0.0	0.0	0.0	0.0	0.0
6-Dec	0.0	0.0	0.0	24.9	0.0	0.0	10.9	0.0	0.3
7-Dec	0.0	0.0	0.0	11.7	0.0	0.0	0.0	0.0	14.2
8-Dec	0.0	0.0	5.3	0.0	1.5	7.6	0.0	0.0	0.0
9-Dec	0.0	3.6	19.6	0.0	0.0	0.0	0.0	0.0	0.0
10-Dec	0.0	21.3	0.0	0.0	8.4	0.0	13.2	0.0	0.0
11-Dec	5.3	0.0	0.0	0.0	1.0	0.0	0.0	0.0	6.1
12-Dec	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.3	0.0
13-Dec	0.0	0.0	0.0	44.7	0.0	0.0	6.3	0.0	0.0
14-Dec	0.0	0.5	6.9	3.6	0.0	0.0	35.1	32.3	0.0
15-Dec	0.0	1.0	2.5	0.0	0.0	0.0	0.8	0.0	0.0
16-Dec	4.8	0.0	19.6	0.0	0.0	0.0	0.0	0.0	9.7

Table A1 Continued.

DATE	Daily Precipitation (mm)								
	1993	1994	1995	1996	1997	1998	1999	2000	2001
17-Dec	0.3	4.8	0.0	2.3	0.0	0.0	0.0	51.8	9.9
18-Dec	3.8	4.8	0.0	10.4	0.0	0.0	0.0	0.0	0.0
19-Dec	0.0	0.0	15.2	0.0	0.0	0.0	0.0	6.3	0.0
20-Dec	0.0	0.0	20.1	0.0	0.0	0.0	6.3	0.0	0.0
21-Dec	17.3	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0
22-Dec	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
23-Dec	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
24-Dec	0.0	2.5	0.0	2.0	9.7	2.5	0.0	0.0	5.3
25-Dec	0.0	0.0	0.0	0.0	17.9	0.0	0.0	0.0	0.0
26-Dec	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
27-Dec	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
28-Dec	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0
29-Dec	0.0	0.0	0.0	2.8	5.1	3.8	0.0	0.0	0.0
30-Dec	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
31-Dec	0.0	0.0	0.0	0.0	5.1	0.0	0.0	0.0	0.0

Appendix A-2

**Daily maximum and minimum temperature in ℃ for Warner Creek watershed
from 1993 to 2001**

Table A2 Daily maximum and minimum temperatures for Warner Creek watershed from 1993 to 1997.

	Daily Maximum and Minimum Temperature (°C)									
	1993		1994		1995		1996		1997	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
1-Jan	18.0	0.0	1.0	-11.0	13.0	-1.0	4.0	1.0	3.0	-6.0
2-Jan	2.0	-5.0	7.0	-3.0	9.0	-3.0	2.0	1.0	8.0	-6.0
3-Jan	3.0	-4.0	2.0	-4.0	-1.0	-7.0	3.0	-3.0	18.0	7.0
4-Jan	18.0	1.0	-2.0	-4.0	-1.0	-5.0	-2.0	-8.0	19.0	8.0
5-Jan	18.0	7.0	-2.0	-6.0	-5.0	-12.0	-2.0	-8.0	19.0	8.0
6-Jan	7.0	-1.0	-4.0	-10.0	2.0	-12.0	-4.0	-11.0	18.0	5.0
7-Jan	7.0	1.0	-2.0	-6.0	6.0	-2.0	-7.0	-11.0	10.0	-3.0
8-Jan	5.0	2.0	-2.0	-8.0	4.0	-2.0	-5.0	-9.0	3.0	-6.0
9-Jan	3.0	-2.0	-2.0	-13.0	7.0	-2.0	-6.0	-11.0	1.0	-4.0
10-Jan	-1.0	-3.0	-5.0	-17.0	3.0	-4.0	-3.0	-11.0	3.0	-3.0
11-Jan	-1.0	-4.0	-3.0	-13.0	-1.0	-3.0	-6.0	-17.0	3.0	-8.0
12-Jan	1.0	-2.0	-2.0	-4.0	7.0	-1.0	-2.0	-12.0	-4.0	-11.0
13-Jan	7.0	1.0	-1.0	-4.0	11.0	0.0	3.0	-12.0	-3.0	-11.0
14-Jan	7.0	2.0	0.0	-4.0	21.0	1.0	4.0	-12.0	0.0	-11.0
15-Jan	7.0	0.0	-4.0	-17.0	18.0	16.0	7.0	-7.0	3.0	-14.0
16-Jan	3.0	-2.0	-12.0	-20.0	16.0	7.0	2.0	-14.0	6.0	-2.0
17-Jan	7.0	-3.0	-7.0	-14.0	8.0	4.0	4.0	-4.0	2.0	-14.0
18-Jan	7.0	-2.0	-2.0	-17.0	8.0	3.0	4.0	-3.0	-9.0	-14.0
19-Jan	3.0	-7.0	-17.0	-28.0	7.0	4.0	13.0	-3.0	-6.0	-18.0
20-Jan	7.0	-9.0	-14.0	-27.0	8.0	4.0	-3.0	-11.0	4.0	-12.0
21-Jan	1.0	-7.0	-9.0	-33.0	5.0	2.0	-1.0	-12.0	6.0	-7.0
22-Jan	9.0	0.0	-1.0	-18.0	2.0	-3.0	3.0	-12.0	7.0	-4.0
23-Jan	9.0	0.0	1.0	-13.0	3.0	-5.0	1.0	-6.0	11.0	4.0
24-Jan	10.0	-3.0	8.0	-2.0	3.0	-4.0	9.0	0.0	5.0	-6.0
25-Jan	9.0	-2.0	6.0	1.0	1.0	-1.0	9.0	-3.0	8.0	-1.0
26-Jan	1.0	-8.0	2.0	-7.0	3.0	-4.0	3.0	-9.0	3.0	-6.0
27-Jan	6.0	-8.0	-7.0	-12.0	3.0	-7.0	12.0	1.0	3.0	-5.0
28-Jan	3.0	-7.0	-1.0	-13.0	2.0	-2.0	3.0	-3.0	6.0	0.0
29-Jan	3.0	-5.0	6.0	-1.0	2.0	-8.0	1.0	-7.0	6.0	-7.0
30-Jan	7.0	-6.0	1.0	-7.0	2.0	-6.0	8.0	-3.0	2.0	-8.0
31-Jan	13.0	3.0	-1.0	-9.0	7.0	-8.0	6.0	-6.0	4.0	-3.0
1-Feb	10.0	-4.0	-2.0	-9.0	7.0	2.0	-4.0	-11.0	10.0	-1.0
2-Feb	1.0	-12.0	-4.0	-16.0	6.0	0.0	-4.0	-6.0	8.0	-3.0
3-Feb	13.0	-9.0	-1.0	-14.0	6.0	-9.0	-6.0	-12.0	12.0	1.0
4-Feb	9.0	1.0	2.0	-13.0	1.0	-6.0	-9.0	-16.0	8.0	-3.0
5-Feb	14.0	-1.0	3.0	-8.0	0.0	-11.0	-9.0	-24.0	9.0	1.0
6-Feb	11.0	-7.0	5.0	-9.0	-7.0	-18.0	-1.0	-25.0	7.0	2.0
7-Feb	-3.0	-13.0	7.0	-8.0	-4.0	-14.0	1.0	-16.0	5.0	-4.0
8-Feb	4.0	-10.0	7.0	-9.0	-4.0	-17.0	4.0	-1.0	8.0	-2.0
9-Feb	6.0	-8.0	-3.0	-10.0	-2.0	-11.0	8.0	1.0	3.0	-9.0

Table A2 Continued.

	Daily Maximum and Minimum Temperature (°C)									
	1993		**1994**		**1995**		**1996**		**1997**	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
10-Feb	13.0	-6.0	-5.0	-12.0	3.0	-6.0	9.0	-2.0	1.0	-8.0
11-Feb	9.0	-3.0	-7.0	-12.0	6.0	-8.0	11.0	0.0	2.0	-7.0
12-Feb	8.0	-2.0	-2.0	-7.0	6.0	-13.0	4.0	-4.0	2.0	-6.0
13-Feb	4.0	-1.0	3.0	-3.0	-2.0	-12.0	-1.0	-10.0	4.0	-11.0
14-Feb	3.0	-2.0	2.0	-3.0	2.0	-8.0	7.0	-5.0	9.0	-5.0
15-Feb	4.0	-8.0	5.0	-16.0	1.0	-9.0	4.0	-3.0	6.0	1.0
16-Feb	3.0	-1.0	7.0	-2.0	6.0	-1.0	2.0	-4.0	4.0	-7.0
17-Feb	6.0	-1.0	6.0	-11.0	8.0	-3.0	-2.0	-10.0	5.0	-4.0
18-Feb	1.0	-8.0	10.0	-11.0	9.0	-7.0	1.0	-6.0	14.0	-3.0
19-Feb	-6.0	-16.0	12.0	-9.0	10.0	-7.0	3.0	-10.0	19.0	5.0
20-Feb	1.0	-15.0	13.0	-4.0	14.0	-4.0	6.0	1.0	19.0	-1.0
21-Feb	0.0	-7.0	11.0	1.0	12.0	1.0	11.0	3.0	20.0	2.0
22-Feb	8.0	-6.0	6.0	-2.0	5.0	-6.0	12.0	4.0	14.0	6.0
23-Feb	5.0	-3.0	6.0	-3.0	7.0	-3.0	11.0	6.0	11.0	-2.0
24-Feb	-2.0	-8.0	6.0	-2.0	8.0	1.0	14.0	9.0	9.0	-2.0
25-Feb	-2.0	-13.0	3.0	-5.0	8.0	-8.0	20.0	9.0	8.0	-8.0
26-Feb	-2.0	-7.0	1.0	-7.0	6.0	-2.0	19.0	-1.0	12.0	-4.0
27-Feb	-1.0	-7.0	-4.0	-14.0	-1.0	-3.0	12.0	2.0	25.0	7.0
28-Feb	2.0	-18.0	-3.0	-16.0	7.0	-1.0	16.0	6.0	26.0	5.0
29-Feb							8.0	-4.0		
1-Mar	6.0	-7.0	-3.0	-7.0	7.0	1.0	3.0	-10.0	11.0	5.0
2-Mar	11.0	-6.0	-3.0	-5.0	4.0	-4.0	4.0	-4.0	18.0	9.0
3-Mar	9.0	1.0	2.0	-5.0	4.0	-3.0	2.0	-7.0	18.0	0.0
4-Mar	6.0	1.0	8.0	2.0	6.0	0.0	5.0	-12.0	7.0	0.0
5-Mar	2.0	0.0	6.0	2.0	7.0	2.0	12.0	-4.0	8.0	4.0
6-Mar	6.0	0.0	5.0	-6.0	13.0	4.0	12.0	5.0	10.0	4.0
7-Mar	11.0	-2.0	7.0	-6.0	13.0	4.0	9.0	-4.0	6.0	-2.0
8-Mar	11.0	-2.0	7.0	0.0	17.0	5.0	-3.0	-9.0	17.0	-4.0
9-Mar	9.0	3.0	4.0	-5.0	5.0	-6.0	-5.0	-11.0	14.0	-6.0
10-Mar	7.0	-2.0	4.0	-2.0	2.0	-9.0	1.0	-14.0	13.0	0.0
11-Mar	4.0	-1.0	4.0	-4.0	13.0	-7.0	6.0	-11.0	14.0	-2.0
12-Mar	5.0	-7.0	5.0	-9.0	20.0	-3.0	12.0	-7.0	9.0	-3.0
13-Mar	4.0	-4.0	9.0	-6.0	21.0	-1.0	15.0	-7.0	8.0	-3.0
14-Mar	-4.0	-9.0	9.0	-1.0	22.0	0.0	19.0	-3.0	6.0	1.0
15-Mar	-2.0	-16.0	13.0	-1.0	22.0	0.0	18.0	5.0	7.0	-1.0
16-Mar	7.0	-13.0	13.0	-3.0	24.0	0.0	16.0	-1.0	3.0	-4.0
17-Mar	6.0	2.0	1.0	-8.0	21.0	4.0	11.0	0.0	9.0	-7.0
18-Mar	4.0	-11.0	1.0	-4.0	16.0	-1.0	14.0	0.0	12.0	5.0
19-Mar	-1.0	-15.0	4.0	-2.0	16.0	-2.0	14.0	-1.0	6.0	-1.0
20-Mar	3.0	-6.0	11.0	-1.0	16.0	4.0	9.0	2.0	9.0	1.0

Table A2 Continued.

	1993		1994		1995		1996		1997	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
21-Mar	9.0	1.0	10.0	-4.0	16.0	8.0	9.0	1.0	17.0	-1.0
22-Mar	10.0	-2.0	13.0	-1.0	14.0	4.0	4.0	-3.0	16.0	6.0
23-Mar	7.0	1.0	24.0	1.0	14.0	-2.0	8.0	-1.0	8.0	-4.0
24-Mar	9.0	2.0	22.0	0.0	12.0	3.0	13.0	-3.0	7.0	-4.0
25-Mar	9.0	3.0	20.0	6.0	14.0	-4.0	20.0	-3.0	12.0	-1.0
26-Mar	13.0	-3.0	7.0	-3.0	17.0	4.0	18.0	4.0	13.0	7.0
27-Mar	13.0	2.0	6.0	2.0	14.0	2.0	10.0	-3.0	23.0	2.0
28-Mar	14.0	9.0	8.0	4.0	12.0	5.0	6.0	-3.0	23.0	2.0
29-Mar	13.0	11.0	8.0	-1.0	13.0	-5.0	4.0	0.0	21.0	10.0
30-Mar	19.0	9.0	8.0	2.0	11.0	5.0	13.0	1.0	19.0	10.0
31-Mar	19.0	3.0	11.0	-4.0	13.0	1.0	17.0	0.0	18.0	1.0
1-Apr	16.0	8.0	14.0	1.0	13.0	-4.0	17.0	0.0	14.0	-1.0
2-Apr	13.0	8.0	18.0	1.0	13.0	-4.0	11.0	2.0	20.0	5.0
3-Apr	10.0	3.0	20.0	1.0	17.0	-5.0	21.0	-2.0	22.0	3.0
4-Apr	10.0	-3.0	20.0	-1.0	18.0	3.0	21.0	2.0	24.0	6.0
5-Apr	10.0	-3.0	19.0	-2.0	18.0	-4.0	20.0	2.0	24.0	10.0
6-Apr	12.0	3.0	19.0	9.0	16.0	-3.0	9.0	1.0	18.0	8.0
7-Apr	14.0	-2.0	17.0	3.0	18.0	-1.0	10.0	1.0	19.0	7.0
8-Apr	18.0	-2.0	11.0	-4.0	18.0	1.0	10.0	-3.0	18.0	2.0
9-Apr	18.0	3.0	17.0	-3.0	25.0	3.0	8.0	1.0	14.0	-2.0
10-Apr	14.0	11.0	17.0	5.0	26.0	3.0	8.0	-1.0	14.0	-4.0
11-Apr	17.0	4.0	14.0	1.0	13.0	3.0	21.0	2.0	11.0	-1.0
12-Apr	17.0	6.0	14.0	1.0	17.0	9.0	29.0	13.0	11.0	-1.0
13-Apr	17.0	2.0	12.0	7.0	17.0	5.0	29.0	7.0	15.0	3.0
14-Apr	17.0	2.0	22.0	4.0	11.0	4.0	18.0	8.0	13.0	1.0
15-Apr	24.0	3.0	27.0	7.0	15.0	1.0	14.0	0.0	15.0	-2.0
16-Apr	25.0	13.0	25.0	9.0	18.0	1.0	13.0	6.0	19.0	-1.0
17-Apr	17.0	7.0	16.0	5.0	18.0	4.0	12.0	3.0	19.0	5.0
18-Apr	18.0	1.0	21.0	2.0	17.0	2.0	21.0	-2.0	11.0	3.0
19-Apr	23.0	4.0	25.0	8.0	30.0	12.0	23.0	3.0	15.0	3.0
20-Apr	24.0	9.0	23.0	7.0	29.0	7.0	25.0	12.0	17.0	-2.0
21-Apr	24.0	12.0	17.0	7.0	22.0	11.0	24.0	11.0	17.0	-1.0
22-Apr	16.0	1.0	15.0	2.0	23.0	8.0	29.0	8.0	17.0	-1.0
23-Apr	17.0	5.0	16.0	-2.0	17.0	2.0	27.0	14.0	19.0	6.0
24-Apr	17.0	-1.0	25.0	1.0	13.0	6.0	26.0	5.0	16.0	7.0
25-Apr	25.0	4.0	27.0	8.0	18.0	4.0	23.0	6.0	17.0	4.0
26-Apr	25.0	9.0	27.0	10.0	18.0	2.0	23.0	14.0	19.0	6.0
27-Apr	16.0	1.0	28.0	12.0	24.0	2.0	20.0	5.0	19.0	3.0
28-Apr	19.0	-1.0	26.0	12.0	23.0	8.0	21.0	2.0	17.0	8.0
29-Apr	22.0	3.0	21.0	11.0	20.0	1.0	28.0	11.0	19.0	4.0

Table A2 Continued.

	| 1993		| 1994		| 1995		| 1996		| 1997	
DATE	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**
30-Apr	22.0	7.0	23.0	12.0	19.0	4.0	28.0	12.0	23.0	3.0
1-May	25.0	7.0	22.0	13.0	15.0	4.0	18.0	2.0	25.0	3.0
2-May	26.0	11.0	14.0	1.0	14.0	7.0	21.0	6.0	26.0	6.0
3-May	25.0	13.0	14.0	1.0	19.0	4.0	21.0	9.0	23.0	10.0
4-May	22.0	14.0	9.0	6.0	19.0	5.0	24.0	10.0	23.0	8.0
5-May	23.0	17.0	18.0	8.0	19.0	11.0	24.0	10.0	20.0	0.0
6-May	26.0	13.0	17.0	8.0	20.0	9.0	20.0	12.0	20.0	12.0
7-May	26.0	12.0	17.0	1.0	21.0	4.0	16.0	6.0	18.0	1.0
8-May	24.0	8.0	13.0	6.0	21.0	1.0	13.0	8.0	18.0	-2.0
9-May	26.0	11.0	19.0	4.0	21.0	4.0	16.0	12.0	19.0	8.0
10-May	28.0	13.0	19.0	6.0	19.0	11.0	21.0	12.0	18.0	9.0
11-May	31.0	14.0	20.0	1.0	21.0	11.0	28.0	12.0	20.0	6.0
12-May	31.0	14.0	20.0	11.0	22.0	7.0	18.0	7.0	24.0	8.0
13-May	19.0	17.0	18.0	3.0	23.0	6.0	13.0	-1.0	22.0	11.0
14-May	20.0	7.0	18.0	-1.0	22.0	11.0	15.0	-2.0	19.0	2.0
15-May	26.0	8.0	24.0	7.0	23.0	10.0	15.0	6.0	21.0	11.0
16-May	26.0	15.0	23.0	14.0	23.0	4.0	14.0	8.0	21.0	8.0
17-May	19.0	11.0	14.0	7.0	23.0	13.0	17.0	9.0	21.0	7.0
18-May	20.0	8.0	14.0	3.0	24.0	18.0	29.0	16.0	23.0	7.0
19-May	17.0	11.0	13.0	7.0	23.0	12.0	33.0	18.0	31.0	13.0
20-May	17.0	10.0	16.0	8.0	26.0	11.0	33.0	18.0	31.0	18.0
21-May	18.0	5.0	23.0	2.0	26.0	8.0	33.0	19.0	21.0	6.0
22-May	19.0	9.0	26.0	6.0	23.0	8.0	27.0	13.0	18.0	7.0
23-May	21.0	4.0	29.0	9.0	26.0	6.0	27.0	8.0	22.0	4.0
24-May	26.0	10.0	28.0	11.0	29.0	16.0	27.0	17.0	25.0	8.0
25-May	27.0	17.0	26.0	11.0	28.0	16.0	23.0	12.0	25.0	9.0
26-May	27.0	11.0	22.0	13.0	23.0	17.0	19.0	9.0	22.0	7.0
27-May	26.0	9.0	22.0	7.0	23.0	15.0	12.0	10.0	19.0	6.0
28-May	29.0	11.0	22.0	1.0	23.0	13.0	13.0	10.0	21.0	4.0
29-May	30.0	19.0	22.0	3.0	26.0	13.0	13.0	12.0	22.0	4.0
30-May	22.0	4.0	26.0	8.0	25.0	16.0	19.0	2.0	22.0	13.0
31-May	23.0	10.0	26.0	11.0	26.0	8.0	22.0	2.0	24.0	8.0
1-Jun	22.0	8.0	27.0	11.0	26.0	9.0	25.0	6.0	24.0	11.0
2-Jun	22.0	4.0	27.0	9.0	28.0	16.0	24.0	9.0	23.0	6.0
3-Jun	22.0	10.0	22.0	4.0	27.0	19.0	24.0	9.0	15.0	2.0
4-Jun	22.0	10.0	25.0	6.0	26.0	16.0	25.0	11.0	21.0	10.0
5-Jun	22.0	13.0	24.0	11.0	27.0	10.0	24.0	12.0	22.0	6.0
6-Jun	23.0	13.0	27.0	13.0	26.0	12.0	27.0	11.0	22.0	7.0
7-Jun	24.0	8.0	29.0	18.0	29.0	17.0	29.0	13.0	18.0	6.0
8-Jun	24.0	16.0	28.0	17.0	30.0	19.0	31.0	16.0	22.0	4.0

Table A2 Continued.

	Daily Maximum and Minimum Temperature (°C)									
	1993		**1994**		**1995**		**1996**		**1997**	
DATE	**Max.**	**Min.**	**Max.**	**Min.**	Max.	Min.	Max.	Min.	Max.	Min.
9-Jun	33.0	17.0	23.0	6.0	29.0	14.0	29.0	17.0	26.0	7.0
10-Jun	32.0	21.0	26.0	5.0	23.0	19.0	31.0	21.0	29.0	7.0
11-Jun	30.0	20.0	26.0	13.0	29.0	20.0	27.0	18.0	29.0	12.0
12-Jun	28.0	13.0	28.0	17.0	30.0	16.0	27.0	18.0	29.0	12.0
13-Jun	24.0	12.0	31.0	15.0	21.0	10.0	27.0	16.0	27.0	18.0
14-Jun	26.0	10.0	32.0	18.0	26.0	10.0	29.0	19.0	26.0	18.0
15-Jun	27.0	16.0	34.0	18.0	26.0	10.0	29.0	18.0	24.0	13.0
16-Jun	27.0	13.0	34.0	21.0	26.0	13.0	30.0	14.0	26.0	12.0
17-Jun	29.0	11.0	28.0	17.0	27.0	11.0	31.0	19.0	28.0	17.0
18-Jun	32.0	17.0	31.0	17.0	29.0	11.0	31.0	19.0	31.0	13.0
19-Jun	33.0	21.0	33.0	18.0	31.0	13.0	27.0	20.0	28.0	13.0
20-Jun	32.0	19.0	30.0	18.0	33.0	18.0	28.0	21.0	32.0	13.0
21-Jun	29.0	20.0	31.0	18.0	32.0	19.0	28.0	18.0	32.0	14.0
22-Jun	29.0	19.0	29.0	17.0	26.0	18.0	31.0	18.0	32.0	16.0
23-Jun	29.0	14.0	30.0	13.0	25.0	18.0	31.0	18.0	31.0	13.0
24-Jun	27.0	9.0	31.0	13.0	23.0	17.0	28.0	16.0	33.0	14.0
25-Jun	29.0	11.0	27.0	19.0	28.0	21.0	28.0	19.0	36.0	18.0
26-Jun	30.0	16.0	29.0	13.0	27.0	21.0	28.0	12.0	36.0	24.0
27-Jun	30.0	17.0	28.0	17.0	24.0	21.0	27.0	13.0	36.0	16.0
28-Jun	31.0	17.0	26.0	17.0	21.0	16.0	28.0	14.0	30.0	12.0
29-Jun	31.0	19.0	27.0	17.0	22.0	16.0	27.0	18.0	30.0	13.0
30-Jun	28.0	17.0	27.0	16.0	28.0	16.0	31.0	18.0	27.0	13.0
1-Jul	27.0	18.0	27.0	14.0	28.0	16.0	32.0	22.0	29.0	19.0
2-Jul	23.0	19.0	30.0	14.0	27.0	18.0	28.0	19.0	26.0	21.0
3-Jul	30.0	19.0	29.0	18.0	26.0	12.0	28.0	17.0	33.0	22.0
4-Jul	32.0	18.0	28.0	17.0	28.0	16.0	23.0	13.0	33.0	23.0
5-Jul	33.0	21.0	29.0	21.0	28.0	22.0	26.0	13.0	28.0	16.0
6-Jul	33.0	23.0	33.0	19.0	31.0	21.0	28.0	12.0	28.0	12.0
7-Jul	33.0	22.0	31.0	17.0	28.0	20.0	29.0	14.0	29.0	15.0
8-Jul	34.0	21.0	32.0	21.0	26.0	16.0	31.0	21.0	31.0	14.0
9-Jul	34.0	20.0	31.0	21.0	24.0	12.0	29.0	19.0	32.0	18.0
10-Jul	34.0	22.0	28.0	19.0	27.0	17.0	29.0	17.0	27.0	15.0
11-Jul	33.0	22.0	28.0	13.0	28.0	16.0	25.0	11.0	28.0	13.0
12-Jul	31.0	21.0	28.0	12.0	29.0	16.0	25.0	16.0	31.0	12.0
13-Jul	31.0	19.0	31.0	15.0	32.0	18.0	28.0	20.0	33.0	14.0
14-Jul	33.0	19.0	31.0	19.0	34.0	18.0	29.0	21.0	33.0	12.0
15-Jul	29.0	22.0	29.0	20.0	36.0	24.0	28.0	22.0	35.0	14.0
16-Jul	29.0	13.0	28.0	19.0	35.0	22.0	29.0	19.0	34.0	21.0
17-Jul	29.0	12.0	28.0	17.0	31.0	22.0	31.0	21.0	34.0	18.0
18-Jul	28.0	13.0	28.0	19.0	31.0	20.0	29.0	19.0	36.0	18.0

Table A2 Continued.

		Daily Maximum and Minimum Temperature (°C)								
	1993		1994		1995		1996		1997	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
19-Jul	28.0	20.0	30.0	17.0	30.0	17.0	28.0	21.0	36.0	14.0
20-Jul	31.0	20.0	31.0	19.0	29.0	17.0	28.0	17.0	32.0	12.0
21-Jul	30.0	17.0	30.0	21.0	29.0	19.0	27.0	14.0	33.0	18.0
22-Jul	27.0	13.0	28.0	21.0	29.0	19.0	27.0	18.0	33.0	21.0
23-Jul	29.0	11.0	27.0	21.0	31.0	20.0	27.0	17.0	26.0	17.0
24-Jul	28.0	12.0	29.0	17.0	31.0	18.0	28.0	16.0	17.0	16.0
25-Jul	28.0	18.0	28.0	17.0	31.0	19.0	29.0	18.0	24.0	16.0
26-Jul	28.0	21.0	25.0	18.0	31.0	19.0	27.0	18.0	29.0	14.0
27-Jul	33.0	21.0	26.0	16.0	33.0	19.0	26.0	14.0	33.0	20.0
28-Jul	35.0	18.0	23.0	16.0	31.0	22.0	26.0	14.0	33.0	19.0
29-Jul	34.0	21.0	25.0	16.0	32.0	23.0	26.0	19.0	29.0	19.0
30-Jul	30.0	19.0	27.0	16.0	32.0	18.0	26.0	17.0	27.0	9.0
31-Jul	32.0	17.0	27.0	18.0	32.0	16.0	26.0	19.0	29.0	9.0
1-Aug	31.0	16.0	27.0	19.0	32.0	18.0	27.0	17.0	32.0	12.0
2-Aug	29.0	15.0	27.0	19.0	33.0	21.0	27.0	16.0	31.0	12.0
3-Aug	31.0	17.0	28.0	16.0	33.0	21.0	27.0	19.0	32.0	21.0
4-Aug	31.0	17.0	29.0	17.0	34.0	21.0	27.0	17.0	32.0	18.0
5-Aug	26.0	14.0	28.0	17.0	34.0	22.0	28.0	17.0	26.0	13.0
6-Aug	19.0	15.0	23.0	8.0	28.0	21.0	28.0	17.0	26.0	11.0
7-Aug	25.0	16.0	23.0	6.0	24.0	18.0	29.0	17.0	26.0	8.0
8-Aug	26.0	19.0	25.0	9.0	24.0	19.0	28.0	17.0	29.0	6.0
9-Aug	27.0	13.0	28.0	12.0	25.0	16.0	28.0	20.0	29.0	7.0
10-Aug	27.0	15.0	27.0	18.0	28.0	19.0	26.0	15.0	31.0	17.0
11-Aug	27.0	18.0	25.0	12.0	29.0	18.0	26.0	13.0	32.0	13.0
12-Aug	27.0	14.0	28.0	19.0	31.0	18.0	24.0	16.0	32.0	19.0
13-Aug	28.0	18.0	30.0	19.0	31.0	21.0	23.0	16.0	30.0	18.0
14-Aug	31.0	17.0	24.0	19.0	33.0	21.0	28.0	13.0	29.0	21.0
15-Aug	31.0	16.0	22.0	10.0	33.0	22.0	28.0	17.0	32.0	18.0
16-Aug	29.0	18.0	21.0	12.0	32.0	21.0	28.0	17.0	37.0	20.0
17-Aug	29.0	20.0	21.0	16.0	32.0	23.0	27.0	16.0	34.0	23.0
18-Aug	28.0	18.0	22.0	19.0	33.0	19.0	28.0	17.0	33.0	17.0
19-Aug	28.0	17.0	26.0	14.0	32.0	19.0	28.0	14.0	26.0	14.0
20-Aug	29.0	19.0	28.0	16.0	29.0	12.0	27.0	15.0	23.0	14.0
21-Aug	27.0	18.0	26.0	19.0	33.0	13.0	28.0	18.0	27.0	14.0
22-Aug	26.0	10.0	26.0	18.0	32.0	14.0	29.0	19.0	27.0	14.0
23-Aug	29.0	12.0	24.0	8.0	29.0	11.0	31.0	16.0	24.0	13.0
24-Aug	30.0	18.0	24.0	8.0	32.0	12.0	29.0	13.0	26.0	8.0
25-Aug	33.0	20.0	27.0	18.0	32.0	16.0	29.0	14.0	26.0	14.0
26-Aug	32.0	18.0	29.0	16.0	28.0	9.0	28.0	13.0	26.0	14.0
27-Aug	33.0	18.0	29.0	18.0	29.0	13.0	27.0	16.0	28.0	14.0

Table A2 Continued.

	Daily Maximum and Minimum Temperature (°C)									
	1993		1994		1995		1996		1997	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
28-Aug	35.0	19.0	29.0	16.0	28.0	20.0	27.0	14.0	28.0	17.0
29-Aug	35.0	17.0	28.0	16.0	30.0	14.0	27.0	14.0	26.0	16.0
30-Aug	35.0	16.0	25.0	9.0	31.0	18.0	26.0	15.0	26.0	12.0
31-Aug	32.0	18.0	26.0	13.0	33.0	15.0	28.0	13.0	29.0	13.0
1-Sep	31.0	19.0	25.0	18.0	32.0	22.0	28.0	14.0	30.0	16.0
2-Sep	32.0	20.0	22.0	10.0	28.0	13.0	29.0	13.0	32.0	16.0
3-Sep	34.0	23.0	22.0	10.0	28.0	11.0	28.0	14.0	31.0	18.0
4-Sep	24.0	19.0	22.0	12.0	29.0	9.0	25.0	18.0	21.0	9.0
5-Sep	25.0	15.0	26.0	8.0	30.0	12.0	28.0	20.0	26.0	6.0
6-Sep	27.0	12.0	24.0	8.0	32.0	9.0	28.0	19.0	27.0	8.0
7-Sep	26.0	14.0	26.0	16.0	31.0	13.0	28.0	21.0	30.0	10.0
8-Sep	25.0	16.0	24.0	8.0	29.0	14.0	28.0	17.0	26.0	16.0
9-Sep	23.0	16.0	27.0	8.0	29.0	19.0	28.0	17.0	24.0	18.0
10-Sep	24.0	17.0	25.0	9.0	29.0	14.0	28.0	17.0	23.0	17.0
11-Sep	22.0	7.0	24.0	8.0	23.0	4.0	28.0	19.0	24.0	18.0
12-Sep	23.0	4.0	24.0	6.0	23.0	4.0	24.0	17.0	25.0	15.0
13-Sep	26.0	12.0	27.0	8.0	28.0	16.0	24.0	16.0	24.0	11.0
14-Sep	28.0	13.0	30.0	16.0	31.0	19.0	21.0	9.0	24.0	14.0
15-Sep	29.0	17.0	29.0	21.0	29.0	8.0	21.0	8.0	25.0	13.0
16-Sep	26.0	13.0	28.0	20.0	23.0	12.0	22.0	12.0	27.0	10.0
17-Sep	15.0	13.0	28.0	17.0	22.0	14.0	18.0	14.0	27.0	14.0
18-Sep	21.0	13.0	26.0	16.0	22.0	14.0	21.0	14.0	26.0	19.0
19-Sep	21.0	8.0	23.0	7.0	23.0	9.0	23.0	13.0	27.0	9.0
20-Sep	19.0	6.0	23.0	6.0	22.0	16.0	23.0	7.0	28.0	18.0
21-Sep	18.0	10.0	23.0	7.0	27.0	18.0	24.0	8.0	28.0	5.0
22-Sep	18.0	12.0	23.0	13.0	27.0	17.0	23.0	13.0	20.0	2.0
23-Sep	21.0	9.0	20.0	14.0	17.0	9.0	21.0	13.0	20.0	9.0
24-Sep	21.0	9.0	23.0	11.0	17.0	3.0	19.0	9.0	18.0	9.0
25-Sep	18.0	6.0	25.0	16.0	14.0	12.0	21.0	7.0	21.0	4.0
26-Sep	22.0	11.0	25.0	18.0	19.0	13.0	20.0	7.0	22.0	12.0
27-Sep	22.0	14.0	24.0	19.0	24.0	7.0	24.0	14.0	21.0	8.0
28-Sep	17.0	9.0	22.0	12.0	25.0	9.0	22.0	18.0	21.0	11.0
29-Sep	17.0	6.0	19.0	8.0	22.0	9.0	22.0	9.0	23.0	16.0
30-Sep	14.0	4.0	21.0	6.0	21.0	6.0	23.0	6.0	23.0	15.0
1-Oct	14.0	-2.0	25.0	8.0	22.0	6.0	23.0	6.0	19.0	11.0
2-Oct	21.0	4.0	19.0	13.0	27.0	9.0	22.0	13.0	17.0	0.0
3-Oct	19.0	9.0	18.0	5.0	27.0	9.0	22.0	12.0	21.0	2.0
4-Oct	19.0	2.0	16.0	3.0	25.0	18.0	13.0	1.0	26.0	11.0
5-Oct	19.0	8.0	15.0	7.0	23.0	18.0	14.0	1.0	27.0	11.0
6-Oct	17.0	-1.0	17.0	1.0	28.0	19.0	16.0	3.0	29.0	13.0

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Table A2 Continued.

	|	1993	1994		1995		1996		1997	

		1993		1994		1995		1996		1997	
DATE		Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
7-Oct		21.0	3.0	20.0	2.0	28.0	17.0	18.0	2.0	29.0	13.0
8-Oct		21.0	7.0	22.0	4.0	23.0	9.0	18.0	11.0	28.0	12.0
9-Oct		23.0	8.0	24.0	8.0	23.0	3.0	20.0	7.0	31.0	12.0
10-Oct		21.0	4.0	19.0	7.0	22.0	8.0	16.0	11.0	27.0	18.0
11-Oct		11.0	-2.0	19.0	-1.0	24.0	8.0	13.0	3.0	26.0	2.0
12-Oct		12.0	5.0	17.0	-1.0	26.0	6.0	15.0	-2.0	21.0	1.0
13-Oct		12.0	4.0	16.0	1.0	26.0	10.0	21.0	4.0	23.0	6.0
14-Oct		11.0	4.0	17.0	10.0	24.0	14.0	24.0	12.0	23.0	12.0
15-Oct		11.0	3.0	18.0	7.0	23.0	9.0	23.0	2.0	18.0	9.0
16-Oct		17.0	3.0	19.0	2.0	14.0	7.0	24.0	6.0	17.0	4.0
17-Oct		16.0	9.0	19.0	-1.0	17.0	-1.0	25.0	8.0	15.0	4.0
18-Oct		19.0	9.0	22.0	1.0	19.0	0.0	23.0	10.0	16.0	7.0
19-Oct		18.0	7.0	21.0	3.0	22.0	4.0	16.0	5.0	15.0	7.0
20-Oct		15.0	11.0	22.0	14.0	23.0	5.0	11.0	7.0	18.0	2.0
21-Oct		19.0	12.0	21.0	5.0	20.0	8.0	14.0	5.0	17.0	-1.0
22-Oct		14.0	4.0	21.0	3.0	20.0	2.0	13.0	9.0	12.0	2.0
23-Oct		14.0	-2.0	19.0	11.0	22.0	2.0	19.0	9.0	11.0	-4.0
24-Oct		17.0	-2.0	19.0	2.0	23.0	3.0	19.0	7.0	12.0	-3.0
25-Oct		21.0	-1.0	19.0	3.0	22.0	5.0	19.0	4.0	12.0	7.0
26-Oct		19.0	4.0	15.0	0.0	13.0	-1.0	21.0	8.0	10.0	6.0
27-Oct		16.0	8.0	15.0	1.0	18.0	4.0	20.0	12.0	13.0	6.0
28-Oct		16.0	2.0	16.0	-3.0	18.0	14.0	20.0	14.0	13.0	3.0
29-Oct		16.0	-1.0	18.0	-2.0	14.0	8.0	16.0	3.0	14.0	-3.0
30-Oct		14.0	4.0	22.0	-2.0	15.0	-1.0	26.0	7.0	17.0	-2.0
31-Oct		6.0	3.0	19.0	5.0	13.0	6.0	24.0	10.0	17.0	-1.0
1-Nov		6.0	1.0	19.0	9.0	12.0	8.0	16.0	6.0	16.0	8.0
2-Nov		9.0	-2.0	19.0	7.0	21.0	12.0	7.0	3.0	16.0	9.0
3-Nov		6.0	-2.0	18.0	-1.0	21.0	12.0	8.0	-2.0	16.0	-1.0
4-Nov		12.0	-3.0	25.0	8.0	12.0	-1.0	11.0	-5.0	10.0	5.0
5-Nov		15.0	4.0	23.0	9.0	7.0	-2.0	15.0	-1.0	12.0	-4.0
6-Nov		14.0	5.0	24.0	10.0	9.0	-6.0	16.0	3.0	11.0	-2.0
7-Nov		6.0	-4.0	19.0	7.0	7.0	-4.0	21.0	12.0	11.0	6.0
8-Nov		7.0	-8.0	21.0	0.0	8.0	-4.0	21.0	12.0	8.0	6.0
9-Nov		9.0	-7.0	23.0	8.0	4.0	-3.0	12.0	6.0	12.0	7.0
10-Nov		11.0	-6.0	19.0	5.0	12.0	-6.0	9.0	0.0	11.0	4.0
11-Nov		13.0	-7.0	10.0	-3.0	18.0	2.0	4.0	-2.0	11.0	4.0
12-Nov		16.0	2.0	12.0	-6.0	16.0	0.0	5.0	-3.0	8.0	1.0
13-Nov		8.0	1.0	19.0	4.0	1.0	-4.0	4.0	-4.0	3.0	-3.0
14-Nov		20.0	1.0	19.0	2.0	2.0	0.0	3.0	-4.0	2.0	0.0
15-Nov		24.0	15.0	21.0	6.0	5.0	1.0	3.0	-7.0	6.0	1.0

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Table A2 Continued.

	Daily Maximum and Minimum Temperature (°C)									
	1993		**1994**		**1995**		**1996**		**1997**	
DATE	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**
16-Nov	19.0	3.0	17.0	6.0	6.0	-3.0	6.0	-8.0	4.0	-1.0
17-Nov	12.0	3.0	10.0	3.0	7.0	-4.0	8.0	-7.0	9.0	-3.0
18-Nov	14.0	4.0	13.0	8.0	7.0	-2.0	7.0	-1.0	6.0	-8.0
19-Nov	8.0	-3.0	17.0	6.0	9.0	3.0	11.0	-1.0	11.0	-8.0
20-Nov	9.0	1.0	17.0	-1.0	8.0	-3.0	7.0	2.0	13.0	-4.0
21-Nov	8.0	-7.0	13.0	2.0	11.0	1.0	6.0	-6.0	12.0	-2.0
22-Nov	13.0	-5.0	13.0	6.0	5.0	-2.0	6.0	-1.0	10.0	6.0
23-Nov	13.0	-6.0	8.0	0.0	5.0	-6.0	8.0	-5.0	11.0	2.0
24-Nov	11.0	-3.0	6.0	-5.0	3.0	0.0	8.0	-1.0	8.0	-1.0
25-Nov	8.0	1.0	12.0	-2.0	6.0	-7.0	15.0	-1.0	7.0	-6.0
26-Nov	4.0	-6.0	9.0	-4.0	7.0	-7.0	10.0	4.0	10.0	2.0
27-Nov	11.0	1.0	4.0	-3.0	12.0	-1.0	10.0	-2.0	12.0	6.0
28-Nov	14.0	4.0	13.0	-1.0	14.0	4.0	-1.0	-8.0	11.0	-1.0
29-Nov	7.0	-2.0	13.0	-1.0	4.0	-2.0	5.0	-7.0	11.0	9.0
30-Nov	4.0	-6.0	11.0	-2.0	3.0	-7.0	3.0	-6.0	9.0	7.0
1-Dec	4.0	-8.0	8.0	-3.0	16.0	-3.0	16.0	3.0	8.0	2.0
2-Dec	7.0	-3.0	12.0	-6.0	14.0	1.0	11.0	3.0	8.0	-1.0
3-Dec	13.0	-2.0	11.0	-4.0	11.0	-4.0	8.0	-5.0	8.0	-5.0
4-Dec	9.0	2.0	14.0	3.0	13.0	6.0	8.0	2.0	12.0	1.0
5-Dec	10.0	6.0	16.0	3.0	6.0	-4.0	5.0	-6.0	9.0	2.0
6-Dec	7.0	-4.0	18.0	3.0	4.0	-4.0	6.0	0.0	2.0	-2.0
7-Dec	7.0	3.0	17.0	7.0	6.0	2.0	6.0	-3.0	6.0	-2.0
8-Dec	7.0	-4.0	17.0	-2.0	6.0	-8.0	8.0	-4.0	6.0	2.0
9-Dec	7.0	-6.0	3.0	-5.0	3.0	-3.0	6.0	-1.0	3.0	-4.0
10-Dec	7.0	-3.0	4.0	2.0	1.0	-12.0	4.0	-2.0	4.0	2.0
11-Dec	7.0	-3.0	6.0	2.0	-6.0	-11.0	4.0	1.0	5.0	2.0
12-Dec	1.0	-7.0	2.0	-7.0	2.0	-14.0	7.0	2.0	6.0	2.0
13-Dec	9.0	-5.0	2.0	-7.0	-3.0	-6.0	8.0	6.0	7.0	-5.0
14-Dec	9.0	-6.0	2.0	-4.0	0.0	-5.0	7.0	3.0	6.0	-2.0
15-Dec	4.0	-2.0	6.0	1.0	7.0	-5.0	7.0	-2.0	7.0	-8.0
16-Dec	7.0	4.0	6.0	1.0	7.0	1.0	6.0	4.0	15.0	-6.0
17-Dec	6.0	-8.0	7.0	2.0	3.0	-4.0	8.0	4.0	13.0	-6.0
18-Dec	3.0	-6.0	9.0	1.0	2.0	-6.0	8.0	4.0	9.0	-8.0
19-Dec	7.0	-1.0	7.0	-1.0	1.0	-4.0	6.0	-1.0	15.0	-3.0
20-Dec	7.0	-3.0	7.0	-3.0	-3.0	-7.0	6.0	-8.0	14.0	-2.0
21-Dec	3.0	-2.0	10.0	-7.0	-1.0	-8.0	-1.0	-12.0	9.0	-6.0
22-Dec	2.0	-2.0	7.0	-6.0	-1.0	-6.0	2.0	-9.0	0.0	-5.0
23-Dec	2.0	-4.0	12.0	-2.0	1.0	-5.0	7.0	-3.0	7.0	-1.0
24-Dec	2.0	-7.0	9.0	5.0	1.0	-4.0	11.0	0.0	7.0	1.0

Table A2 Continued.

	Daily Maximum and Minimum Temperature (°C)									
	1993		1994		1995		1996		1997	
DATE	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**
25-Dec	-2.0	-9.0	13.0	6.0	-1.0	-3.0	5.0	-3.0	12.0	3.0
26-Dec	-2.0	-11.0	11.0	-4.0	-2.0	-5.0	1.0	-6.0	10.0	6.0
27-Dec	-7.0	-11.0	11.0	-8.0	-1.0	-7.0	9.0	-3.0	6.0	-2.0
28-Dec	-7.0	-9.0	14.0	-7.0	2.0	-4.0	9.0	-2.0	3.0	-4.0
29-Dec	-7.0	-14.0	13.0	1.0	4.0	-4.0	13.0	6.0	2.0	-7.0
30-Dec	-4.0	-10.0	4.0	-8.0	7.0	-9.0	13.0	8.0	2.0	-1.0
31-Dec	-2.0	-13.0	0.0	-9.0	8.0	-4.0	9.0	0.0	2.0	-6.0

Table A3 Daily maximum and minimum temperatures for Warner Creek watershed from 1998 to 2001.

	Daily Maximum and Minimum Temperature (°C)							
	1998		1999		2000		2001	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
1-Jan	-2.0	-12.0	-2.0	-11.0	10.0	-7.0	1.0	-5.0
2-Jan	11.0	-3.0	-5.0	-12.0	18.0	0.0	-1.0	-7.0
3-Jan	13.0	2.0	9.0	-9.0	17.0	10.0	0.0	-9.0
4-Jan	19.0	6.0	4.0	-7.0	19.0	8.0	1.0	-8.0
5-Jan	16.0	-2.0	-4.0	-11.0	12.0	0.0	-2.0	-10.0
6-Jan	18.0	7.0	-3.0	-17.0	6.0	-9.0	2.0	-6.0
7-Jan	18.0	14.0	2.0	-4.0	9.0	-9.0	4.0	-9.0
8-Jan	20.0	17.0	-4.0	-10.0	6.0	-6.0	3.0	-4.0
9-Jan	19.0	11.0	4.0	-10.0	6.0	1.0	1.0	-6.0
10-Jan	12.0	-1.0	0.0	-10.0	8.0	1.0	6.0	-5.0
11-Jan	9.0	-1.0	-3.0	-8.0	11.0	3.0	12.0	2.0
12-Jan	7.0	-4.0	11.0	-8.0	11.0	1.0	10.0	-3.0
13-Jan	8.0	1.0	9.0	4.0	12.0	-1.0	6.0	-9.0
14-Jan	3.0	-7.0	6.0	-9.0	1.0	-8.0	6.0	-7.0
15-Jan	3.0	-6.0	0.0	-9.0	1.0	-9.0	4.0	1.0
16-Jan	4.0	0.0	-2.0	-7.0	15.0	-4.0	5.0	-1.0
17-Jan	6.0	1.0	12.0	-2.0	4.0	-11.0	3.0	2.0
18-Jan	5.0	-1.0	12.0	2.0	-7.0	-13.0	3.0	-4.0
19-Jan	3.0	1.0	9.0	-1.0	3.0	-9.0	2.0	0.0
20-Jan	3.0	-2.0	9.0	2.0	-1.0	-9.0	2.0	0.0
21-Jan	2.0	-6.0	8.0	-4.0	-1.0	-11.0	0.0	-6.0
22-Jan	4.0	-5.0	5.0	3.0	-7.0	-17.0	-1.0	-18.0
23-Jan	3.0	-1.0	10.0	4.0	-3.0	-8.0	1.0	-19.0
24-Jan	7.0	-1.0	15.0	6.0	2.0	-8.0	6.0	-13.0
25-Jan	4.0	-2.0	8.0	-1.0	1.0	-7.0	3.0	-6.0
26-Jan	6.0	-5.0	9.0	-1.0	-1.0	-7.0	3.0	-13.0
27-Jan	4.0	-3.0	12.0	-6.0	-2.0	-11.0	5.0	-3.0
28-Jan	3.0	1.0	19.0	-1.0	-1.0	-11.0	4.0	-7.0
29-Jan	12.0	-1.0	17.0	3.0	1.0	-18.0	3.0	-8.0
30-Jan	11.0	3.0	7.0	-8.0	-1.0	-16.0	11.0	-1.0
31-Jan	6.0	0.0	4.0	-8.0	2.0	-14.0	8.0	-2.0
1-Feb	8.0	-7.0	4.0	-10.0	1.0	-7.0	8.0	1.0
2-Feb	8.0	-7.0	6.0	0.0	-1.0	-6.0	8.0	-3.0
3-Feb	6.0	2.0	12.0	2.0	-1.0	-14.0	2.0	-6.0
4-Feb	3.0	1.0	13.0	-2.0	3.0	-7.0	7.0	-8.0
5-Feb	5.0	1.0	9.0	0.0	3.0	-4.0	4.0	-2.0
6-Feb	8.0	3.0	14.0	0.0	3.0	-3.0	8.0	-1.0
7-Feb	7.0	-2.0	12.0	-2.0	6.0	-8.0	9.0	-3.0
8-Feb	5.0	-4.0	12.0	0.0	5.0	-13.0	9.0	-6.0
9-Feb	9.0	-7.0	7.0	-5.0	7.0	-14.0	17.0	-2.0

Table A3 Continued.

	1998		1999		2000		2001	
					Daily Maximum and Minimum Temperature (°C)			
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
10-Feb	12.0	-6.0	14.0	-1.0	11.0	-7.0	17.0	-2.0
11-Feb	11.0	-4.0	15.0	-5.0	12.0	2.0	5.0	-7.0
12-Feb	11.0	6.0	22.0	2.0	7.0	-4.0	4.0	-8.0
13-Feb	8.0	-1.0	5.0	-4.0	-1.0	-11.0	12.0	-1.0
14-Feb	8.0	-1.0	5.0	-5.0	11.0	-1.0	9.0	1.0
15-Feb	5.0	-8.0	11.0	-9.0	12.0	-1.0	11.0	4.0
16-Feb	5.0	-7.0	18.0	-7.0	16.0	-4.0	7.0	3.0
17-Feb	7.0	0.0	15.0	1.0	12.0	-4.0	5.0	-1.0
18-Feb	13.0	0.0	10.0	4.0	3.0	-3.0	2.0	-9.0
19-Feb	10.0	8.0	6.0	-5.0	6.0	-1.0	8.0	-9.0
20-Feb	9.0	3.0	4.0	-4.0	5.0	0.0	16.0	1.0
21-Feb	9.0	6.0	4.0	-5.0	8.0	-1.0	16.0	2.0
22-Feb	9.0	-2.0	0.0	-10.0	13.0	-4.0	2.0	-10.0
23-Feb	8.0	0.0	-2.0	-12.0	13.0	-4.0	7.0	-8.0
24-Feb	6.0	2.0	2.0	-10.0	21.0	1.0	6.0	-6.0
25-Feb	11.0	4.0	2.0	-9.0	26.0	4.0	10.0	-2.0
26-Feb	14.0	0.0	8.0	-4.0	17.0	6.0	14.0	4.0
27-Feb	15.0	-2.0	10.0	-7.0	14.0	6.0	13.0	-2.0
28-Feb	14.0	2.0	8.0	3.0	14.0	3.0	12.0	-1.0
29-Feb					16	-3		
1-Mar	13.0	1.0	8.0	3.0	16.0	-2.0	7.0	-9.0
2-Mar	12.0	1.0	12.0	0.0	12.0	4.0	12.0	0.0
3-Mar	11.0	1.0	19.0	-2.0	13.0	-1.0	12.0	6.0
4-Mar	8.0	0.0	16.0	-2.0	14.0	-4.0	11.0	1.0
5-Mar	7.0	-1.0	16.0	-6.0	18.0	2.0	2.0	-2.0
6-Mar	9.0	-6.0	8.0	-6.0	15.0	-3.0	2.0	-7.0
7-Mar	14.0	-1.0	9.0	-7.0	21.0	-4.0	8.0	-1.0
8-Mar	13.0	7.0	2.0	-10.0	28.0	-4.0	8.0	-6.0
9-Mar	18.0	6.0	-1.0	-7.0	28.0	6.0	8.0	0.0
10-Mar	17.0	1.0	4.0	-5.0	24.0	8.0	7.0	-2.0
11-Mar	1.0	-6.0	5.0	-5.0	17.0	7.0	12.0	-6.0
12-Mar	1.0	-8.0	7.0	-3.0	8.0	3.0	11.0	-6.0
13-Mar	3.0	-7.0	8.0	-3.0	9.0	-3.0	16.0	2.0
14-Mar	9.0	-1.0	7.0	-1.0	14.0	-2.0	16.0	4.0
15-Mar	6.0	-2.0	7.0	1.0	21.0	0.0	12.0	-3.0
16-Mar	6.0	-4.0	10.0	-2.0	19.0	7.0	7.0	2.0
17-Mar	7.0	-6.0	21.0	3.0	19.0	4.0	9.0	5.0
18-Mar	6.0	2.0	19.0	9.0	7.0	-7.0	9.0	-1.0
19-Mar	14.0	4.0	11.0	4.0	6.0	-1.0	12.0	-6.0
20-Mar	13.0	6.0	12.0	-5.0	9.0	-1.0	12.0	-6.0

Table A3 Continued.

	Daily Maximum and Minimum Temperature (°C)							
	1998		**1999**		**2000**		**2001**	
DATE	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**
21-Mar	8.0	2.0	12.0	-7.0	8.0	3.0	8.0	3.0
22-Mar	4.0	0.0	7.0	1.0	8.0	3.0	11.0	4.0
23-Mar	9.0	-2.0	12.0	-3.0	15.0	0.0	14.0	4.0
24-Mar	8.0	-4.0	12.0	5.0	19.0	2.0	12.0	-2.0
25-Mar	11.0	-6.0	11.0	2.0	22.0	6.0	8.0	-4.0
26-Mar	21.0	4.0	10.0	-4.0	17.0	8.0	7.0	-3.0
27-Mar	29.0	12.0	12.0	-2.0	18.0	-2.0	4.0	-8.0
28-Mar	26.0	16.0	14.0	5.0	18.0	-2.0	9.0	-9.0
29-Mar	28.0	13.0	19.0	-1.0	12.0	5.0	8.0	-3.0
30-Mar	29.0	8.0	18.0	0.0	17.0	-3.0	10.0	3.0
31-Mar	28.0	12.0	22.0	-3.0	16.0	-3.0	11.0	4.0
1-Apr	27.0	16.0	19.0	8.0	19.0	-2.0	11.0	6.0
2-Apr	21.0	11.0	21.0	11.0	20.0	3.0	11.0	3.0
3-Apr	19.0	2.0	22.0	10.0	23.0	12.0	17.0	-3.0
4-Apr	15.0	6.0	24.0	16.0	22.0	12.0	16.0	2.0
5-Apr	14.0	3.0	20.0	5.0	14.0	2.0	17.0	-2.0
6-Apr	16.0	1.0	17.0	-1.0	24.0	3.0	17.0	3.0
7-Apr	18.0	-3.0	22.0	6.0	24.0	5.0	20.0	13.0
8-Apr	19.0	7.0	28.0	4.0	23.0	6.0	17.0	6.0
9-Apr	20.0	8.0	28.0	9.0	11.0	-1.0	31.0	8.0
10-Apr	13.0	4.0	15.0	4.0	16.0	0.0	31.0	11.0
11-Apr	16.0	-2.0	15.0	0.0	16.0	4.0	15.0	9.0
12-Apr	18.0	1.0	13.0	4.0	12.0	6.0	18.0	11.0
13-Apr	20.0	-1.0	16.0	4.0	12.0	-3.0	23.0	14.0
14-Apr	20.0	7.0	20.0	0.0	15.0	-2.0	22.0	7.0
15-Apr	22.0	8.0	20.0	-5.0	17.0	6.0	21.0	8.0
16-Apr	24.0	11.0	17.0	7.0	26.0	6.0	18.0	7.0
17-Apr	24.0	16.0	17.0	5.0	26.0	8.0	12.0	-1.0
18-Apr	22.0	4.0	14.0	6.0	9.0	4.0	8.0	2.0
19-Apr	16.0	8.0	14.0	1.0	19.0	6.0	14.0	-4.0
20-Apr	16.0	8.0	13.0	4.0	19.0	7.0	17.0	0.0
21-Apr	18.0	3.0	13.0	1.0	18.0	11.0	18.0	9.0
22-Apr	19.0	6.0	24.0	-1.0	14.0	8.0	27.0	13.0
23-Apr	19.0	7.0	24.0	12.0	13.0	7.0	30.0	13.0
24-Apr	22.0	7.0	24.0	-3.0	18.0	5.0	29.0	15.0
25-Apr	22.0	8.0	16.0	-1.0	17.0	8.0	18.0	6.0
26-Apr	22.0	9.0	24.0	2.0	14.0	4.0	17.0	-1.0
27-Apr	14.0	4.0	24.0	1.0	14.0	6.0	24.0	0.0
28-Apr	16.0	1.0	18.0	1.0	17.0	7.0	24.0	6.0
29-Apr	22.0	1.0	19.0	0.0	20.0	3.0	17.0	0.0

Table A3. Continued.

	Daily Maximum and Minimum Temperature (°C)							
	1998		1999		2000		2001	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
30-Apr	22.0	12.0	19.0	1.0	21.0	9.0	23.0	1.0
1-May	21.0	11.0	20.0	-1.0	23.0	1.0	28.0	5.0
2-May	19.0	14.0	21.0	0.0	23.0	12.0	29.0	8.0
3-May	22.0	11.0	21.0	2.0	22.0	4.0	30.0	9.0
4-May	22.0	14.0	23.0	6.0	24.0	8.0	31.0	12.0
5-May	19.0	14.0	25.0	8.0	29.0	12.0	30.0	17.0
6-May	20.0	11.0	25.0	12.0	31.0	13.0	20.0	8.0
7-May	22.0	9.0	21.0	14.0	32.0	13.0	20.0	2.0
8-May	18.0	15.0	24.0	14.0	31.0	16.0	21.0	2.0
9-May	21.0	13.0	24.0	11.0	31.0	16.0	23.0	11.0
10-May	19.0	13.0	24.0	2.0	31.0	16.0	27.0	7.0
11-May	16.0	12.0	24.0	4.0	24.0	8.0	28.0	8.0
12-May	13.0	11.0	24.0	4.0	30.0	13.0	28.0	11.0
13-May	20.0	10.0	25.0	9.0	30.0	17.0	22.0	8.0
14-May	24.0	4.0	19.0	11.0	30.0	12.0	20.0	2.0
15-May	28.0	8.0	21.0	4.0	22.0	4.0	21.0	2.0
16-May	31.0	12.0	22.0	7.0	21.0	2.0	22.0	3.0
17-May	30.0	18.0	23.0	6.0	23.0	2.0	21.0	11.0
18-May	29.0	11.0	21.0	5.0	28.0	13.0	21.0	11.0
19-May	31.0	16.0	21.0	11.0	26.0	16.0	24.0	14.0
20-May	31.0	13.0	22.0	10.0	21.0	10.0	25.0	11.0
21-May	31.0	18.0	26.0	10.0	20.0	12.0	18.0	12.0
22-May	30.0	8.0	28.0	9.0	19.0	14.0	22.0	13.0
23-May	22.0	9.0	27.0	17.0	19.0	14.0	22.0	10.0
24-May	23.0	7.0	24.0	14.0	26.0	12.0	24.0	7.0
25-May	28.0	14.0	21.0	10.0	27.0	13.0	24.0	13.0
26-May	27.0	16.0	24.0	8.0	24.0	9.0	19.0	16.0
27-May	24.0	14.0	23.0	12.0	24.0	12.0	21.0	13.0
28-May	27.0	13.0	29.0	6.0	14.0	11.0	22.0	11.0
29-May	31.0	14.0	29.0	9.0	18.0	11.0	23.0	7.0
30-May	31.0	16.0	32.0	10.0	19.0	6.0	26.0	7.0
31-May	31.0	18.0	31.0	12.0	22.0	6.0	21.0	3.0
1-Jun	30.0	19.0	30.0	13.0	30.0	13.0	21.0	4.0
2-Jun	27.0	9.0	29.0	18.0	32.0	16.0	23.0	13.0
3-Jun	27.0	16.0	31.0	16.0	31.0	16.0	23.0	15.0
4-Jun	23.0	8.0	25.0	11.0	22.0	9.0	23.0	11.0
5-Jun	23.0	10.0	26.0	8.0	21.0	14.0	26.0	14.0
6-Jun	21.0	12.0	29.0	14.0	21.0	13.0	26.0	17.0
7-Jun	19.0	8.0	34.0	16.0	24.0	11.0	23.0	15.0
8-Jun	22.0	11.0	34.0	22.0	26.0	11.0	26.0	12.0

Table A3 Continued.

	1998		1999		2000		2001	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
9-Jun	22.0	5.0	33.0	16.0	29.0	15.0	27.0	8.0
10-Jun	16.0	13.0	32.0	17.0	31.0	15.0	27.0	8.0
11-Jun	18.0	14.0	26.0	13.0	33.0	17.0	29.0	12.0
12-Jun	22.0	17.0	26.0	9.0	32.0	21.0	30.0	15.0
13-Jun	26.0	17.0	28.0	18.0	28.0	17.0	31.0	18.0
14-Jun	26.0	18.0	28.0	18.0	21.0	17.0	31.0	19.0
15-Jun	25.0	14.0	27.0	13.0	26.0	17.0	29.0	18.0
16-Jun	29.0	14.0	26.0	13.0	29.0	19.0	29.0	21.0
17-Jun	29.0	17.0	22.0	14.0	29.0	22.0	30.0	18.0
18-Jun	29.0	17.0	23.0	9.0	28.0	21.0	29.0	15.0
19-Jun	29.0	16.0	26.0	7.0	27.0	17.0	31.0	13.0
20-Jun	31.0	19.0	23.0	13.0	27.0	10.0	33.0	16.0
21-Jun	31.0	18.0	22.0	14.0	28.0	17.0	29.0	16.0
22-Jun	29.0	19.0	28.0	9.0	29.0	21.0	29.0	19.0
23-Jun	28.0	21.0	29.0	10.0	28.0	16.0	26.0	18.0
24-Jun	30.0	19.0	28.0	10.0	30.0	15.0	26.0	13.0
25-Jun	32.0	18.0	29.0	13.0	32.0	21.0	28.0	12.0
26-Jun	33.0	18.0	33.0	20.0	31.0	21.0	30.0	13.0
27-Jun	31.0	24.0	32.0	19.0	31.0	21.0	33.0	15.0
28-Jun	31.0	19.0	31.0	22.0	23.0	18.0	33.0	18.0
29-Jun	31.0	19.0	33.0	22.0	27.0	18.0	33.0	18.0
30-Jun	28.0	21.0	31.0	17.0	27.0	12.0	33.0	21.0
1-Jul	28.0	18.0	31.0	22.0	26.0	13.0	32.0	21.0
2-Jul	28.0	12.0	29.0	23.0	28.0	12.0	29.0	9.0
3-Jul	29.0	12.0	34.0	21.0	28.0	15.0	26.0	7.0
4-Jul	29.0	16.0	36.0	22.0	29.0	21.0	29.0	18.0
5-Jul	27.0	16.0	36.0	21.0	29.0	19.0	28.0	16.0
6-Jul	28.0	13.0	37.0	21.0	28.0	14.0	28.0	10.0
7-Jul	28.0	16.0	37.0	21.0	26.0	16.0	28.0	8.0
8-Jul	28.0	17.0	33.0	13.0	26.0	10.0	28.0	19.0
9-Jul	29.0	17.0	35.0	13.0	29.0	14.0	32.0	17.0
10-Jul	29.0	17.0	33.0	23.0	31.0	21.0	32.0	16.0
11-Jul	28.0	11.0	28.0	10.0	27.0	21.0	28.0	18.0
12-Jul	27.0	11.0	28.0	11.0	27.0	13.0	27.0	11.0
13-Jul	29.0	12.0	28.0	14.0	26.0	13.0	27.0	10.0
14-Jul	30.0	17.0	27.0	17.0	28.0	13.0	28.0	12.0
15-Jul	30.0	17.0	32.0	11.0	26.0	17.0	29.0	11.0
16-Jul	30.0	21.0	35.0	17.0	27.0	16.0	31.0	13.0
17-Jul	31.0	22.0	37.0	13.0	27.0	14.0	33.0	15.0
18-Jul	31.0	19.0	36.0	18.0	29.0	17.0	32.0	20.0

Table A3 Continued.

DATE	Daily Maximum and Minimum Temperature (°C)							
	1998		1999		2000		2001	
	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
19-Jul	31.0	17.0	36.0	18.0	29.0	16.0	28.0	17.0
20-Jul	31.0	21.0	35.0	21.0	23.0	16.0	28.0	13.0
21-Jul	33.0	19.0	29.0	18.0	26.0	13.0	28.0	9.0
22-Jul	35.0	22.0	33.0	21.0	26.0	14.0	29.0	10.0
23-Jul	33.0	21.0	35.0	20.0	25.0	13.0	33.0	11.0
24-Jul	31.0	18.0	35.0	20.0	24.0	18.0	34.0	19.0
25-Jul	28.0	14.0	34.0	20.0	26.0	17.0	35.0	23.0
26-Jul	28.0	18.0	35.0	18.0	26.0	16.0	33.0	20.0
27-Jul	29.0	14.0	34.0	17.0	26.0	16.0	26.0	13.0
28-Jul	31.0	17.0	34.0	17.0	28.0	15.0	27.0	11.0
29-Jul	32.0	17.0	33.0	17.0	27.0	18.0	26.0	16.0
30-Jul	31.0	18.0	35.0	20.0	29.0	21.0	26.0	17.0
31-Jul	29.0	18.0	37.0	18.0	29.0	21.0	28.0	12.0
1-Aug	27.0	13.0	33.0	21.0	29.0	22.0	31.0	14.0
2-Aug	27.0	11.0	29.0	17.0	29.0	20.0	32.0	14.0
3-Aug	28.0	11.0	31.0	15.0	28.0	22.0	32.0	17.0
4-Aug	29.0	13.0	31.0	13.0	28.0	19.0	30.0	21.0
5-Aug	29.0	14.0	31.0	16.0	26.0	16.0	32.0	20.0
6-Aug	29.0	12.0	31.0	13.0	26.0	14.0	36.0	19.0
7-Aug	29.0	14.0	31.0	17.0	32.0	21.0	36.0	19.0
8-Aug	29.0	20.0	31.0	21.0	32.0	21.0	37.0	23.0
9-Aug	29.0	18.0	28.0	16.0	30.0	22.0	38.0	22.0
10-Aug	31.0	22.0	28.0	10.0	29.0	19.0	36.0	24.0
11-Aug	31.0	21.0	33.0	14.0	29.0	18.0	32.0	22.0
12-Aug	28.0	17.0	33.0	15.0	27.0	16.0	27.0	22.0
13-Aug	27.0	16.0	35.0	18.0	25.0	16.0	29.0	21.0
14-Aug	28.0	16.0	32.0	21.0	26.0	16.0	31.0	18.0
15-Aug	27.0	20.0	28.0	18.0	29.0	15.0	31.0	14.0
16-Aug	28.0	19.0	31.0	13.0	28.0	22.0	30.0	16.0
17-Aug	27.0	20.0	37.0	18.0	27.0	13.0	32.0	23.0
18-Aug	28.0	17.0	36.0	18.0	22.0	17.0	30.0	13.0
19-Aug	28.0	12.0	31.0	12.0	24.0	12.0	29.0	16.0
20-Aug	25.0	8.0	29.0	18.0	23.0	12.0	28.0	18.0
21-Aug	28.0	10.0	28.0	18.0	23.0	8.0	28.0	13.0
22-Aug	31.0	17.0	27.0	17.0	26.0	10.0	29.0	12.0
23-Aug	32.0	19.0	29.0	11.0	26.0	16.0	29.0	18.0
24-Aug	32.0	19.0	26.0	17.0	27.0	17.0	29.0	17.0
25-Aug	30.0	19.0	25.0	18.0	27.0	14.0	28.0	13.0
26-Aug	31.0	21.0	27.0	19.0	28.0	12.0	28.0	14.0
27-Aug	31.0	17.0	27.0	18.0	25.0	16.0	30.0	19.0

Table A3 Continued.

Daily Maximum and Minimum Temperature (°C)							
	1998		**1999**		**2000**		**2001**	
DATE	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**	**Min.**
28-Aug	31.0	22.0	29.0	17.0	26.0	19.0	32.0	16.0
29-Aug	31.0	18.0	29.0	17.0	24.0	17.0	32.0	16.0
30-Aug	32.0	17.0	29.0	12.0	26.0	19.0	30.0	18.0
31-Aug	31.0	18.0	23.0	12.0	27.0	20.0	31.0	18.0
1-Sep	29.0	14.0	27.0	13.0	29.0	22.0	31.0	20.0
2-Sep	29.0	16.0	28.0	11.0	28.0	21.0	27.0	10.0
3-Sep	30.0	16.0	29.0	15.0	28.0	22.0	27.0	9.0
4-Sep	30.0	12.0	28.0	18.0	29.0	20.0	31.0	18.0
5-Sep	29.0	12.0	26.0	22.0	28.0	12.0	31.0	13.0
6-Sep	34.0	10.0	28.0	22.0	21.0	7.0	31.0	7.0
7-Sep	34.0	22.0	29.0	21.0	22.0	7.0	29.0	9.0
8-Sep	30.0	13.0	29.0	16.0	23.0	8.0	30.0	9.0
9-Sep	22.0	11.0	28.0	16.0	28.0	16.0	30.0	14.0
10-Sep	24.0	12.0	27.0	19.0	29.0	16.0	29.0	22.0
11-Sep	28.0	8.0	26.0	9.0	28.0	18.0	28.0	9.0
12-Sep	33.0	12.0	27.0	9.0	28.0	21.0	28.0	8.0
13-Sep	33.0	19.0	26.0	9.0	27.0	18.0	31.0	9.0
14-Sep	33.0	14.0	25.0	15.0	26.0	10.0	31.0	12.0
15-Sep	32.0	18.0	26.0	15.0	24.0	16.0	21.0	6.0
16-Sep	33.0	21.0	17.0	15.0	18.0	8.0	24.0	3.0
17-Sep	32.0	19.0	22.0	13.0	21.0	6.0	27.0	4.0
18-Sep	29.0	17.0	22.0	6.0	23.0	8.0	27.0	8.0
19-Sep	28.0	17.0	23.0	6.0	22.0	13.0	27.0	8.0
20-Sep	28.0	16.0	24.0	10.0	28.0	11.0	25.0	17.0
21-Sep	28.0	17.0	22.0	11.0	28.0	18.0	26.0	14.0
22-Sep	28.0	20.0	17.0	6.0	21.0	8.0	28.0	17.0
23-Sep	23.0	11.0	22.0	4.0	21.0	8.0	27.0	12.0
24-Sep	22.0	4.0	24.0	7.0	26.0	19.0	27.0	12.0
25-Sep	22.0	12.0	25.0	9.0	19.0	11.0	22.0	13.0
26-Sep	31.0	11.0	25.0	10.0	11.0	8.0	18.0	7.0
27-Sep	32.0	17.0	24.0	18.0	19.0	3.0	17.0	8.0
28-Sep	32.0	18.0	22.0	18.0	20.0	6.0	17.0	6.0
29-Sep	24.0	7.0	21.0	18.0	16.0	3.0	18.0	8.0
30-Sep	28.0	7.0	21.0	13.0	18.0	2.0	17.0	6.0
1-Oct	29.0	18.0	22.0	4.0	20.0	3.0	23.0	7.0
2-Oct	20.0	1.0	23.0	6.0	23.0	8.0	24.0	11.0
3-Oct	18.0	3.0	24.0	9.0	27.0	11.0	28.0	9.0
4-Oct	15.0	9.0	23.0	13.0	28.0	12.0	27.0	8.0
5-Oct	16.0	9.0	18.0	7.0	28.0	14.0	26.0	7.0
6-Oct	18.0	13.0	19.0	2.0	23.0	16.0	25.0	12.0

Table A3 Continued.

	1998		1999		2000		2001	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
7-Oct	19.0	15.0	19.0	2.0	18.0	5.0	16.0	2.0
8-Oct	22.0	16.0	16.0	1.0	18.0	0.0	13.0	-2.0
9-Oct	20.0	13.0	20.0	10.0	10.0	1.0	16.0	-6.0
10-Oct	20.0	13.0	21.0	16.0	13.0	3.0	21.0	-1.0
11-Oct	22.0	11.0	22.0	14.0	21.0	1.0	24.0	3.0
12-Oct	22.0	11.0	20.0	3.0	22.0	1.0	24.0	6.0
13-Oct	19.0	10.0	21.0	6.0	22.0	1.0	26.0	11.0
14-Oct	18.0	7.0	20.0	10.0	23.0	2.0	26.0	11.0
15-Oct	17.0	2.0	16.0	-6.0	24.0	8.0	22.0	7.0
16-Oct	18.0	1.0	20.0	2.0	22.0	8.0	22.0	3.0
17-Oct	21.0	1.0	19.0	8.0	17.0	13.0	13.0	8.0
18-Oct	24.0	6.0	19.0	8.0	20.0	14.0	14.0	2.0
19-Oct	24.0	16.0	15.0	2.0	20.0	9.0	18.0	-2.0
20-Oct	21.0	8.0	13.0	8.0	21.0	3.0	22.0	4.0
21-Oct	19.0	6.0	15.0	2.0	24.0	4.0	24.0	4.0
22-Oct	15.0	4.0	15.0	2.0	24.0	4.0	25.0	4.0
23-Oct	17.0	-1.0	13.0	5.0	17.0	-1.0	24.0	9.0
24-Oct	21.0	4.0	13.0	5.0	17.0	4.0	27.0	11.0
25-Oct	21.0	-1.0	15.0	1.0	22.0	9.0	26.0	14.0
26-Oct	21.0	4.0	19.0	3.0	21.0	9.0	19.0	8.0
27-Oct	16.0	9.0	19.0	0.0	21.0	8.0	10.0	4.0
28-Oct	21.0	8.0	14.0	-2.0	21.0	11.0	10.0	1.0
29-Oct	20.0	11.0	22.0	0.0	14.0	-1.0	16.0	-6.0
30-Oct	20.0	-2.0	21.0	2.0	16.0	1.0	17.0	3.0
31-Oct	18.0	-2.0	25.0	4.0	15.0	1.0	17.0	1.0
1-Nov	18.0	0.0	24.0	4.0	17.0	-3.0	23.0	3.0
2-Nov	16.0	3.0	19.0	9.0	20.0	-2.0	26.0	11.0
3-Nov	12.0	3.0	19.0	5.0	21.0	0.0	23.0	15.0
4-Nov	9.0	1.0	14.0	2.0	19.0	6.0	20.0	2.0
5-Nov	7.0	-7.0	18.0	-2.0	14.0	2.0	18.0	3.0
6-Nov	9.0	-4.0	22.0	6.0	14.0	-5.0	14.0	-4.0
7-Nov	12.0	4.0	21.0	3.0	16.0	-2.0	21.0	8.0
8-Nov	10.0	2.0	13.0	-2.0	18.0	4.0	19.0	1.0
9-Nov	12.0	-1.0	21.0	-2.0	18.0	4.0	19.0	7.0
10-Nov	9.0	-1.0	21.0	13.0	18.0	11.0	19.0	-4.0
11-Nov	18.0	9.0	19.0	7.0	13.0	10.0	16.0	8.0
12-Nov	18.0	1.0	9.0	3.0	11.0	6.0	11.0	-6.0
13-Nov	18.0	-1.0	16.0	3.0	10.0	-1.0	13.0	-7.0
14-Nov	18.0	-3.0	21.0	4.0	12.0	4.0	18.0	-6.0
15-Nov	16.0	7.0	16.0	6.0	8.0	3.0	20.0	1.0

The table above is titled: **Daily Maximum and Minimum Temperature (°C)**

Table A3 Continued.

	1998		1999		2000		2001	
DATE	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
16-Nov	14.0	-3.0	16.0	1.0	8.0	-6.0	22.0	2.0
17-Nov	15.0	3.0	7.0	-2.0	11.0	1.0	21.0	6.0
18-Nov	12.0	2.0	11.0	-7.0	7.0	-2.0	21.0	-3.0
19-Nov	14.0	-4.0	14.0	-2.0	3.0	-2.0	17.0	-3.0
20-Nov	14.0	7.0	16.0	-1.0	6.0	-8.0	16.0	4.0
21-Nov	14.0	3.0	21.0	-1.0	3.0	-2.0	9.0	-8.0
22-Nov	9.0	-4.0	16.0	6.0	2.0	-6.0	16.0	-7.0
23-Nov	17.0	-4.0	15.0	12.0	2.0	-7.0	16.0	-4.0
24-Nov	18.0	8.0	16.0	12.0	4.0	-9.0	12.0	-2.0
25-Nov	13.0	-5.0	15.0	9.0	2.0	-7.0	18.0	11.0
26-Nov	16.0	3.0	18.0	8.0	13.0	1.0	16.0	6.0
27-Nov	13.0	8.0	18.0	7.0	11.0	4.0	16.0	2.0
28-Nov	21.0	-2.0	11.0	1.0	13.0	4.0	16.0	2.0
29-Nov	23.0	-1.0	8.0	-4.0	9.0	-3.0	14.0	11.0
30-Nov	23.0	-1.0	8.0	-4.0	7.0	4.0	20.0	13.0
1-Dec	17.0	6.0	8.0	-7.0	7.0	-3.0	20.0	11.0
2-Dec	18.0	-3.0	11.0	-8.0	3.0	-6.0	11.0	1.0
3-Dec	23.0	3.0	17.0	-3.0	2.0	-9.0	13.0	-4.0
4-Dec	23.0	8.0	18.0	3.0	7.0	-12.0	19.0	-2.0
5-Dec	23.0	13.0	18.0	2.0	7.0	-6.0	24.0	5.0
6-Dec	24.0	7.0	18.0	2.0	4.0	-7.0	20.0	8.0
7-Dec	24.0	12.0	13.0	4.0	2.0	-8.0	16.0	7.0
8-Dec	19.0	8.0	9.0	-7.0	6.0	-4.0	13.0	2.0
9-Dec	10.0	3.0	12.0	-4.0	4.0	-4.0	9.0	3.0
10-Dec	11.0	-6.0	14.0	-1.0	1.0	-9.0	6.0	-6.0
11-Dec	9.0	1.0	12.0	2.0	4.0	-4.0	12.0	2.0
12-Dec	8.0	-4.0	12.0	-4.0	9.0	0.0	12.0	-1.0
13-Dec	9.0	4.0	12.0	-4.0	0.0	-10.0	11.0	6.0
14-Dec	7.0	-1.0	6.0	3.0	4.0	-3.0	14.0	6.0
15-Dec	11.0	-9.0	6.0	1.0	4.0	-3.0	17.0	6.0
16-Dec	12.0	-3.0	7.0	3.0	1.0	-4.0	7.0	-4.0
17-Dec	8.0	-2.0	8.0	-3.0	10.0	1.0	8.0	1.0
18-Dec	6.0	0.0	7.0	0.0	3.0	-6.0	12.0	6.0
19-Dec	10.0	-4.0	4.0	-1.0	-2.0	-8.0	11.0	-2.0
20-Dec	11.0	4.0	4.0	-1.0	-2.0	-10.0	8.0	-1.0
21-Dec	13.0	3.0	5.0	1.0	-2.0	-17.0	6.0	-1.0
22-Dec	16.0	-1.0	3.0	-2.0	-2.0	-9.0	6.0	-7.0
23-Dec	-1.0	-11.0	6.0	-8.0	-2.0	-14.0	7.0	-7.0
24-Dec	0.0	-6.0	6.0	-9.0	1.0	-14.0	6.0	-2.0

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Table A3 Continued.

DATE	1998		1999		2000		2001	
	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
25-Dec	2.0	-11.0	-1.0	-9.0	2.0	-9.0	3.0	-4.0
26-Dec	1.0	-13.0	5.0	-7.0	-4.0	-12.0	2.0	-7.0
27-Dec	4.0	-12.0	2.0	-2.0	-2.0	-9.0	2.0	-9.0
28-Dec	3.0	-3.0	-1.0	-10.0	-3.0	-8.0	3.0	-6.0
29-Dec	3.0	-2.0	3.0	-10.0	-4.0	-13.0	5.0	-5.0
30-Dec	2.0	-6.0	10.0	-4.0	-2.0	-11.0	5.0	-7.0
31-Dec	-4.0	-8.0	11.0	1.0	1.0	-7.0	-1.0	-9.0

The table title "Daily Maximum and Minimum Temperature (℃)" spans all data columns.

Appendix B

Measured and SWAT Model Simulated Flow, Sediment, and Nutrient Data at the Outlet of the Watershed

Appendix B-1

Measured and SWAT Model Simulated Flow Data at the Outlet of the Watershed from 1994 to 2001

Table B1 Measured and SWAT simulated monthly hydrology at the outlet of the watershed from 1994-2001.

Month	Precipitation (mm)	Measured Hydrologic Data (mm)			Simulated Hydrologic Data (mm)		
		Surface Runoff	Adjusted Baseflow	Adjusted Streamflow	Surface Runoff	Baseflow	Streamflow
Apr-94	79.1	10.61	39.24	49.85	10.79	19.51	30.30
May-94	97.7	4.75	10.4	15.15	9.11	16.49	25.60
Jun-94	45.5	0.7	3.42	4.12	1.52	2.76	4.28
Jul-94	108.9	1.4	5.01	6.41	2.87	5.19	8.05
Aug-94	151.2	7.98	3.53	11.51	7.80	14.11	21.91
Sep-94	82.2	2.43	2.36	4.79	4.38	7.93	12.31
Oct-94	38.8	0.92	7.93	8.85	2.53	4.58	7.12
Nov-94	125.8	18.98	34.07	53.05	16.04	29.02	45.07
Dec-94	71.3	19.51	46.78	66.29	18.37	33.23	51.59
Jan-95	121	60.09	63.32	123.41	32.99	59.67	92.66
Feb-95	78	5.64	19.81	25.45	14.77	26.72	41.49
Mar-95	35	1.61	27.47	29.08	9.62	17.40	27.02
Apr-95	46.2	1.38	6.83	8.21	2.00	3.61	5.60
May-95	119.9	2.86	9.72	12.58	6.23	11.27	17.50
Jun-95	93.1	4.22	8.18	12.4	4.85	8.77	13.62
Jul-95	133.6	34.19	1.49	35.68	13.17	23.82	36.98
Aug-95	52.9	1.03	7.02	8.05	2.73	4.94	7.67
Sep-95	65.5	0.24	5.23	5.47	1.94	3.51	5.45
Oct-95	126.1	8.62	8.11	16.73	10.34	18.70	29.04
Nov-95	110.3	13.33	36.79	50.12	21.01	38.00	59.01
Dec-95	90.5	10.74	43.41	54.15	23.18	41.94	65.12
Jan-97	79.2	34.22	60.11	94.33	19.04	34.45	53.49
Feb-97	75.4	34.22	10.26	44.48	20.81	37.65	58.46
Mar-97	143.8	13.1	22.47	35.57	24.93	45.09	70.02
Apr-97	48	0.46	18.38	18.84	5.88	10.63	16.50
May-97	53.6	0.14	4.68	4.82	2.32	4.20	6.52
Jun-97	57	0.1	3.99	4.09	3.98	7.20	11.19
Jul-97	45.3	0.05	2.7	2.75	0.75	1.36	2.12
Aug-97	87.7	0.02	3.14	3.16	1.85	3.35	5.21
Sep-97	82	1.09	3.69	4.78	2.88	5.21	8.09
Oct-97	49.5	1.97	10.81	12.78	2.00	3.62	5.62
Nov-97	157.3	45.62	24.28	69.9	23.78	43.02	66.80
Dec-97	49.7	0.9	9.46	10.36	8.28	14.98	23.25
Jan-98	199.9	93.05	45.83	138.88	57.47	103.97	161.44
Feb-98	141.6	30.31	72.25	102.56	38.45	69.56	108.01
Mar-98	165.7	*28.84	*90.61	*119.45	44.25	80.05	124.29
Apr-98	102.3	*8.77	*89.15	*97.93	15.63	28.27	43.90
May-98	148.3	*17.23	*50.15	*67.38	28.58	51.70	80.28
Jun-98	101.3	*8.61	*9.32	*17.93	3.98	7.20	11.18
Jul-98	121.1	*5.48	*4.30	*9.78	4.38	7.92	12.29

Table B1 Continued.

Month	Precipitation (mm)	Measured Hydrologic Data (mm)			Simulated Hydrologic Data (mm)		
		Surface Runoff	Adjusted Baseflow	Adjusted Streamflow	Surface Runoff	Baseflow	Streamflow
Aug-98	53.9	*12.54	*5.24	*17.78	2.33	4.21	6.53
Sep-98	42	*4.4	*5.41	*9.80	1.13	2.04	3.17
Oct-98	53.8	*6.97	*4.81	*11.78	2.66	4.82	7.48
Nov-98	16.5	*2.41	*4.85	*7.26	0.62	1.13	1.75
Dec-98	16.9	*3.63	*8.74	*12.38	0.58	1.04	1.62
Jan-99	182.9	79.78	74.21	153.99	36.68	66.36	103.05
Feb-99	76.4	2.48	16.30	18.78	11.03	19.96	30.99
Mar-99	119.6	7.09	35.69	42.78	26.48	47.91	74.39
Apr-99	90.1	5.57	38.50	44.07	10.62	19.22	29.84
May-99	43.2	0.44	7.90	8.35	2.09	3.78	5.87
Jun-99	52.1	0.44	6.00	6.44	1.28	2.31	3.59
Jul-99	33.9	2.4	5.13	7.52	0.65	1.18	1.84
Aug-99	152.4	2.74	4.76	7.49	7.03	12.72	19.75
Sep-99	223.4	23.14	11.28	34.42	30.63	55.41	86.04
Oct-99	66.1	16.37	82.08	98.45	18.08	32.71	50.79
Nov-99	43.3	0.34	6.21	6.54	3.36	6.07	9.43
Dec-99	73.4	16.54	30.17	46.71	17.70	32.01	49.71
Jan-00	65.4	4.77	20.24	24.93	1.47	2.65	4.12
Feb-00	63	24.41	24.56	48.53	27.05	48.93	75.97
Mar-00	107.1	30.96	30.24	60.66	22.17	40.10	62.27
Apr-00	111.7	6.12	23.58	29.59	18.79	33.99	52.78
May-00	97	9.22	26.32	35.38	6.35	11.48	17.83
Jun-00	109.6	4.90	8.05	12.86	6.43	11.64	18.07
Jul-00	150.8	8.52	6.72	15.09	6.03	10.91	16.94
Aug-00	82.4	1.47	6.12	7.56	2.37	4.29	6.65
Sep-00	182	33.35	13.05	45.81	24.06	43.53	67.59
Oct-00	11.8	0.01	11.44	11.45	3.10	5.61	8.71
Nov-00	48.3	0.15	3.03	3.18	2.72	4.93	7.65
Dec-00	91	0.18	3.33	3.51	22.48	40.67	63.15
Jan-01	66.7	11.00	3.51	14.31	12.97	23.47	36.44
Feb-01	32.5	1.23	8.42	9.63	7.26	13.13	20.39
Mar-01	100.6	20.16	11.10	30.90	15.51	28.06	43.57
Apr-01	68.2	4.94	14.39	19.24	11.45	20.71	32.16
May-01	74.2	0.0	2.23	2.23	4.13	7.47	11.60
Jun-01	79.3	0.0	0.00	0.00	2.82	5.11	7.93
Jul-01	40.4	0.0	0.00	0.00	1.07	1.93	3.00
Aug-01	65.3	0.0	0.00	0.00	1.66	3.00	4.67
Sep-01	66.3	0.0	0.00	0.00	2.59	4.68	7.27
Oct-01	20.7	0.81	0.82	1.61	1.04	1.87	2.91
Nov-01	28.5	0.76	1.11	1.85	0.70	1.27	1.98
Dec-01	45.5	0.03	1.10	1.13	2.21	4.00	6.21

*Values in italics were generated using ANN models.

Appendix B-2

Measured and Simulated Sediment Loads at the Outlet of the Watershed from 1994 to 1997

Table B2 Measured and SWAT simulated monthly sediment loads at the outlet of the watershed from 1994 to 1997.

Month	Measured Sediment Loading (kg/ha) in Streamflow	SWAT Simulated Sediment Loading (kg/ha) in Streamflow
Apr-94	999.02	138.44
May-94	40.95	175.96
Jun-94	25.95	3.19
Jul-94	188.37	23.07
Aug-94	318.28	96.48
Sep-94	59.35	37.55
Oct-94	9.1	20.26
Nov-94	355.79	407.10
Dec-94	219.93	300.33
Jan-95	3889.64	655.23
Feb-95	1.13	391.59
Mar-95	7.58	126.57
Apr-95	5.22	17.63
May-95	0.48	114.49
Jun-95	70.39	62.33
Jul-95	459.97	290.46
Aug-95	4.32	16.56
Sep-95	0.53	10.46
Oct-95	60.62	116.79
Nov-95	87.07	298.24
Dec-95	8.7	208.59
Jan-96	407.89	942.44
Feb-96	38.13	356.40
Mar-96	217.33	409.48
Apr-96	229.26	209.25
May-96	422.97	453.33
Jun-96	1866.81	400.54
Jul-96	1106.93	944.23
Aug-96	70.94	374.29
Sep-96	261.13	434.83
Oct-96	337.18	335.22
Nov-96	621.05	291.29
Dec-96	32.54	645.69

Table B2 Continued.

Month	Measured Sediment Loading (kg/ha) in Streamflow	SWAT Simulated Sediment Loading (kg/ha) in Streamflow
Jan-97	14.11	146.79
Feb-97	3.63	258.04
Mar-97	11.86	367.43
Apr-97	2.55	54.88
May-97	0.72	16.99
Jun-97	0.63	50.55
Jul-97	0.12	0.44
Aug-97	0.59	14.36
Sep-97	5.07	25.78
Oct-97	12.6	13.00
Nov-97	200.94	329.56
Dec-97	0.08	100.21

Appendix B-3

Measured and Simulated Nitrate and Phosphate Loads at the Outlet of the Watershed from 1994 to 2001

Table B3 Measured and simulated monthly NO3-N and PO4-P Loadings at the outlet of the watershed from 1994 to 2001.

Month	NO3-N Loadings (kg/ha)		PO4-P Loadings (kg/ha)	
	Adjusted Measured	SWAT Simulated	Adjusted Measured	SWAT Simulated
Apr-94	1.749	0.73	0.318	0.04
May-94	0.453	1.46	0.053	0.24
Jun-94	0.079	0.00	0.028	0.00
Jul-94	0.109	0.11	0.076	0.04
Aug-94	0.607	0.24	0.371	0.14
Sep-94	0.16	0.09	0.125	0.04
Oct-94	0.261	0.07	0.096	0.02
Nov-94	2.521	1.61	0.451	0.42
Dec-94	3.492	1.98	0.278	0.21
Jan-95	4.527	4.20	1.315	0.87
Feb-95	1.105	1.10	0.08	0.65
Mar-95	1.39	1.05	0.024	0.01
Apr-95	0.266	0.19	0.022	0.02
May-95	0.279	0.97	0.272	0.12
Jun-95	0.367	0.27	0.62	0.07
Jul-95	0.913	0.47	0.536	0.41
Aug-95	0.2	0.10	0.037	0.03
Sep-95	0.06	0.03	0.028	0.01
Oct-95	0.541	1.04	0.428	0.21
Nov-95	3.408	1.48	0.438	0.25
Dec-95	3.779	1.10	0.211	0.66
Jan-96	8.874	2.64	1.079	3.74
Feb-96	1.133	1.52	0.121	0.76
Mar-96	4.21	1.90	0.361	0.35
Apr-96	2.67	1.81	0.173	0.12
May-96	2.181	3.30	0.371	0.35
Jun-96	2.937	1.65	0.519	0.47
Jul-96	2.624	1.63	0.521	1.25
Aug-96	0.892	0.74	0.155	0.38
Sep-96	0.602	0.55	0.452	0.50
Oct-96	1.07	2.07	0.54	0.48
Nov-96	3.577	2.75	1.288	0.40
Dec-96	1.4	4.56	0.084	0.46
Jan-97	2.269	2.14	0.161	0.63
Feb-97	4.207	1.62	0.082	0.32
Mar-97	1.357	2.81	0.178	0.18
Apr-97	0.77	0.23	0.059	0.01
May-97	0.123	0.12	0.011	0.01
Jun-97	0.072	0.26	0.017	0.05
Jul-97	0.006	0.00	0.007	0.00

Table B3 Continued.

Month	NO3-N Loadings (kg/ha)		PO4-P Loadings (kg/ha)	
	Adjusted Measured	SWAT Simulated	Adjusted Measured	SWAT Simulated
Aug-97	0.018	0.04	0.052	0.01
Sep-97	0.055	0.04	0.124	0.01
Oct-97	0.325	0.04	0.252	0.00
Nov-97	2.921	1.57	3.016	0.50
Dec-97	0.707	0.63	0.051	0.03
Jan-98	5.7775	6.06	0.80	1.07
Feb-98	3.2251	4.42	0.36	0.29
Mar-98	3.7378	2.77	0.50	0.56
Apr-98	3.6261	1.60	0.28	0.22
May-98	1.3533	4.14	0.31	0.37
Jun-98	0.4849	0.12	0.08	0.01
Jul-98	0.1854	0.15	0.05	0.05
Aug-98	0.1934	0.05	0.11	0.01
Sep-98	0.0697	0.00	0.06	0.00
Oct-98	0.0948	0.07	0.09	0.02
Nov-98	0.0873	0.00	0.06	0.00
Dec-98	0.1457	0.10	0.05	0.00
Jan-99	2.5694	2.02	1.62	2.02
Feb-99	0.7428	0.96	0.25	0.07
Mar-99	1.8514	2.31	0.22	0.26
Apr-99	2.0533	1.71	0.17	0.09
May-99	0.3026	0.07	0.05	0.01
Jun-99	0.0623	0.01	0.04	0.00
Jul-99	0.1026	0.00	0.07	0.00
Aug-99	0.2834	0.34	0.15	0.12
Sep-99	1.4334	1.36	0.91	1.30
Oct-99	6.4294	1.00	0.74	0.24
Nov-99	0.2114	0.15	0.02	0.01
Dec-99	2.8686	1.90	0.42	0.28
Jan-00	1.7573	0.00	0.09	0.00
Feb-00	3.3594	4.19	0.27	1.27
Mar-00	3.0421	2.24	0.41	0.49
Apr-00	0.9793	3.53	0.27	0.36
May-00	1.5363	1.02	0.25	0.11
Jun-00	0.5379	0.29	0.10	0.19
Jul-00	0.5473	0.25	0.16	0.13
Aug-00	0.3123	0.09	0.06	0.01
Sep-00	1.8566	0.85	1.57	0.69
Oct-00	0.3369	0.03	0.13	0.00
Nov-00	0.1330	0.25	0.03	0.04
Dec-00	0.0728	1.22	0.01	0.86

Table B3 Continued.

Month	NO3-N Loadings (kg/ha)		PO4-P Loadings (kg/ha)	
	Adjusted Measured	SWAT Simulated	Adjusted Measured	SWAT Simulated
Jan-01	1.0515	0.45	0.15	0.54
Feb-01	0.7858	0.37	0.03	0.05
Mar-01	1.9798	1.38	0.13	0.24
Apr-01	1.5805	1.01	0.11	0.09
May-01	0.0434	0.50	0.01	0.04
Jun-01	0.0000	0.21	0.00	0.03
Jul-01	0.0000	0.02	0.00	0.00
Aug-01	0.0000	0.10	0.00	0.01
Sep-01	0.0000	0.10	0.00	0.04
Oct-01	0.0216	0.00	0.01	0.00
Nov-01	0.0393	0.07	0.04	0.00
Dec-01	0.0112	0.20	0.01	0.00

Appendix C

MATLAB Program Scripts for MFORM Tabulation

Appendix C-1

Matlab Scripts to Tabulate MFORM Results for *Monthly* and *Annual* Streamflow, Sediment, Nitrate, and Phosphate *Loads*

MFORMSolverA4.m
calc29Ann4.m

```
%M-File Name: MFORMSolverA4.m
%M-File Description: This program will load output files from SWAT to calculate Mean
%                    Value First Order Reliability Method (MFORM) or uncertainty for
%                    annual and monthly streamflow, sediment, nitrate and phosphate
%                    output variables.
%

clear
rootdir = ['C:\Documents and Settings\Aisha\Desktop\Input29Eg']; % directory where the
                                                    % files are stored
cd (rootdir);            % move to the directory where the files are stored
sourcefiles = dir;       % Names of the elements in the start_folder directory - struct array
numfiles = length(dir); % Number of elements in the start_folder directory
first=3;                 % first position where starting counting
for i = first:numfiles
    name = sourcefiles(i).name; %name of the file
    fname = sprintf('%s\\%s',rootdir,name);           % directory path of the file
    trick=['my_file',int2str(i),'=load(fname);'];     %load file and call it my_file
    eval(trick); %execute trick for each i
end
cd 'C:\Documents and Settings\Aisha\Desktop\mfiles' % back to the initial directory
                                           %  where the script is stored
Mout=zeros(96,6,29); % Creates a matrix of zeros for monthly data (2-D Matrix
                     % 96rows=#months 6columns=Date&OutputVars
                     % 29depth=29input files)
Aout=zeros(8,4,29); % This is same as Aoutmv in calc29Ann4 (2-D Matrix
                    %8rows=#years94-01 4columns=OutputVars 29depth=29input files)
for ii=3:31
    eval(['a=sortrows(my_file',int2str(ii),',[1]);']) % For each file named 'my_file#(3-31)'
                     % sortrows in descending order *using the 1st row, hence [1]
    if(ii==3)

[Mout(:,:,ii),Aout(:,:,ii),AnMzistr,AnMzised,AnMziNO3,AnMziMinP,Mmzistr,Mmzised,
MmziNO3,MmziMinP]=calc29Ann4(a); % Take info in brackets from specified file
                                        % using the function calc29Ann4(a)
    else
       [Mout(:,:,ii),Aout(:,:,ii)]=calc29Ann4(a);
    end
end
%
%Annual new output arrays
%
FlowCNwgs=Aout(:,1,4);
FlowCNskp=Aout(:,1,5);
FlowCNsgs=Aout(:,1,6);
FlowES=Aout(:,1,7);
```

```
FlowHR=Aout(:,1,9);
FlowRC=Aout(:,1,10);
FlowSM=Aout(:,1,11);
FlowSA1=Aout(:,1,12);
FlowSA2=Aout(:,1,13);
FlowSK1=Aout(:,1,14);
FlowSK2=Aout(:,1,15);
AnNzistr= [ FlowCNwgs FlowCNskp FlowCNsgs FlowES FlowGW FlowHR FlowRC
FlowSM FlowSA1 FlowSA2 FlowSK1 FlowSK2]'; %Creates array of annual changes in
                                         %"FLOW" output
                                         %Apostrophe to transpose the array

SedAP=Aout(:,2,16);
SedBM=Aout(:,2,17);
SedCC=Aout(:,2,18);
SedCE=Aout(:,2,19);
SedHR=Aout(:,2,9);
SedSL=Aout(:,2,20);
SedSPC=Aout(:,2,21);
SedSPE=Aout(:,2,22);
SedUP=Aout(:,2,23);
AnNzised= [SedAP SedBM SedCC SedCE SedHR SedSL SedSPC SedSPE SedUP]';
% Creates array of annual changes in "Sed" output
%
NO3AE=Aout(:,3,24);
NO3BM=Aout(:,3,17);
NO3CMN=Aout(:,3,25);
NO3FS=Aout(:,3,26);
NO3S_NO3_1=Aout(:,3,27);
NO3S_NO3_2=Aout(:,3,28);
NO3NP=Aout(:,3,29);
AnNziNO3= [NO3AE NO3BM NO3CMN NO3FS NO3S_NO3_1 NO3S_NO3_2
NO3NP]';
%
MinBM=Aout(:,4,17);
MinPPP=Aout(:,4,30);
MinPS_LP=Aout(:,4,31);
AnNziMinP= [MinBM MinPPP MinPS_LP]';
%
%Monthly new output arrays
%
MFlowCNwgs=Mout(:,3,4);
MFlowCNskp=Mout(:,3,5);
MFlowCNsgs=Mout(:,3,6);
MFlowES=Mout(:,3,7);
MFlowGW=Mout(:,3,8);
MFlowHR=Mout(:,3,9);
```

```
MFlowRC=Mout(:,3,10);
MFlowSM=Mout(:,3,11);
MFlowSA1=Mout(:,3,12);
MFlowSA2=Mout(:,3,13);
MFlowSK1=Mout(:,3,14);
MFlowSK2=Mout(:,3,15);
Mnzistr= [ MFlowCNwgs MFlowCNskp MFlowCNsgs MFlowES MFlowGW
MFlowHR MFlowRC  MFlowSM MFlowSA1 MFlowSA2 MFlowSK1 MFlowSK2]';
                        % Creates array of monthly changes in "FLOW" output
                        % Apostrophe to transpose the array
MSedAP=Mout(:,4,16);
MSedBM=Mout(:,4,17);
MSedCC=Mout(:,4,18);
MSedCE=Mout(:,4,19);
MSedHR=Mout(:,4,9);
MSedSL=Mout(:,4,20);
MSedSPC=Mout(:,4,21);
MSedSPE=Mout(:,4,22);
MSedUP=Mout(:,4,23);
Mnzised= [MSedAP MSedBM MSedCC MSedCE MSedHR MSedSL MSedSPC
MSedSPE MSedUP]'; % Creates array of annual changes in "Sed" output
%
MNO3AE=Mout(:,5,24);
MNO3BM=Mout(:,5,17);
MNO3CMN=Mout(:,5,25);
MNO3FS=Mout(:,5,26);
MNO3S_NO3_1=Mout(:,5,27);
MNO3S_NO3_2=Mout(:,5,28);
MNO3NP=Mout(:,5,29);
MnziNO3= [MNO3AE MNO3BM MNO3CMN MNO3FS MNO3S_NO3_1
MNO3S_NO3_2 MNO3NP]';
%
MMinBM=Mout(:,6,17);
MMinPPP=Mout(:,6,30);
MMinPS_LP=Mout(:,6,31);
MnziMinP= [MMinBM MMinPPP MMinPS_LP]';
%
load meanxistr3.txt; load meanxised3.txt; load meanxiphos3.txt; load meanxinitr3.txt;
load stdevxistr3.txt; load stdevxised3.txt; load stdevxinitr3.txt; load stdevxiphos3.txt;
%****************************************************************
%**************MFORM Output Tabulations*************************
%****************************************************************
% Annual Streamflow uncertainty
newxistr = meanxistr3*1.05;
dxistr = newxistr-meanxistr3;
dzistr = AnNzistr-AnMzistr;
```

```
b = [size(dzistr)];        % size of array # of rows and columns in dzistr
h = b(2);                  % number of columns in dzistr
FOVstr = (dzistr./dxistr(:,ones(h,1))).^2.*(stdevxistr3(:,ones(h,1))).^2;
                %the term (:,ones(h,1)) duplicates the first and only column h times
                %creating 8Xh matrix/array
FOSTDEVstr = sqrt (FOVstr);
VARZstr = sum (FOVstr);
STDZstr = sqrt (VARZstr);
%
% Annual Sediment uncertainty
newxised = meanxised3*1.05;
dxised = newxised-meanxised3;
dzised = AnNzised-AnMzised;
c = [size(dzised)];        % size of array # of rows and columns in dzised
d = c(2);                  % number of columns in dzised
FOVsed = (dzised./dxised(:,ones(d,1))).^2.*(stdevxised3(:,ones(d,1))).^2;
                %the term (:,ones(d,1)) duplicates the first and only column d times
                %creating 8Xd matrix/array
FOSTDEVsed = sqrt (FOVsed);
VARZsed = sum (FOVsed);
STDZsed = sqrt (VARZsed);
%
% Annual Nitrogen uncertainty
newxinitr = meanxinitr3*1.05;
dxinitr = newxinitr-meanxinitr3;
dzinitr = AnNziNO3-AnMziNO3;
n = [size(dzinitr)];            %  size of array # of rows and columns in dzinitr
p = n(2);                       %  number of columns in dzinitr
FOVnitr = (dzinitr./dxinitr(:,ones(p,1))).^2.*(stdevxinitr3(:,ones(p,1))).^2;
                %the term (:,ones(p,1)) duplicates the first and only column p times
                %creating 8Xp matrix/array
FOSTDEVnitr = sqrt (FOVnitr);
VARZnitr = sum (FOVnitr);
STDZnitr = sqrt (VARZnitr);
%
% Annual Phosphate uncertainty
newxiphos = meanxiphos3*1.05;
dxiphos = newxiphos-meanxiphos3;
dziphos = AnNziMinP-AnMziMinP;
k = [size(dziphos)];            % size of array # of rows and columns in dziphos
m = k(2);                       % number of columns in dziphos
FOVphos = (dziphos./dxiphos(:,ones(m,1))).^2.*(stdevxiphos3(:,ones(m,1))).^2;
                % the term (:,ones(m,1)) duplicates the first and only column m times
                % creating 8Xm matrix/array
FOSTDEVphos = sqrt (FOVphos);
VARZphos = sum (FOVphos);
```

```
STDZphos = sqrt (VARZphos);
%
VarStDev=[VARZstr;STDZstr;VARZsed;STDZsed;VARZnitr;STDZnitr;VARZphos;ST
DZphos];
%**********************************************************************
%**********************************************************************
%**********************************************************************
% Monthly Streamflow uncertainty
mdzistr = Mnzistr-Mmzistr;
mb = [size(mdzistr)];          % size of array # of rows and columns in mdzistr
mh = mb(2);                    % number of columns in mdzistr
mSensCoefstr=
abs((mdzistr./dxistr(:,ones(mh,1))).*(meanxistr3(:,ones(mh,1))./Mmzistr));
mFOVstr = (mdzistr./dxistr(:,ones(mh,1))).^2.*(stdevxistr3(:,ones(mh,1))).^2;
               % the term (:,ones(mh,1)) duplicates the first and only column mh times
               % creating 8Xmh matrix/array
mFOSTDEVstr = sqrt (mFOVstr);
mVARZstr = sum (mFOVstr);
mSTDZstr = sqrt (mVARZstr);
%
% Monthly Sediment uncertainty
mdzised = Mnzised-Mmzised;
mc = [size(mdzised)];          % size of array # of rows and columns in mdzised
md = mc(2);                    % number of columns in mdzised
mSensCoefsed=
abs((mdzised./dxised(:,ones(md,1))).*(meanxised3(:,ones(md,1))./Mmzised));
mFOVsed = (mdzised./dxised(:,ones(md,1))).^2.*(stdevxised3(:,ones(md,1))).^2;
               % the term (:,ones(md,1)) duplicates the first and only column md times
               % creating 8Xmd matrix/array
mFOSTDEVsed = sqrt (mFOVsed);
mVARZsed = sum (mFOVsed);
mSTDZsed = sqrt (mVARZsed);
%
% Monthly Nitrogen uncertainty
mdzinitr = MnziNO3-MmziNO3;
mn = [size(mdzinitr)];         % size of array # of rows and columns in mdzinitr
mp = mn(2);                    % number of columns in mdzinitr
mSensCoefnitr=
abs((mdzinitr./dxinitr(:,ones(mp,1))).*(meanxinitr3(:,ones(mp,1))./MmziNO3));
mFOVnitr = (mdzinitr./dxinitr(:,ones(mp,1))).^2.*(stdevxinitr3(:,ones(mp,1))).^2;
               % the term (:,ones(mp,1)) duplicates the first and only column mp times
               % creating 8Xmp matrix/array
mFOSTDEVnitr = sqrt (mFOVnitr);
mVARZnitr = sum (mFOVnitr);
mSTDZnitr = sqrt (mVARZnitr);
%
```

```
%Monthly Phosphate uncertainty
mdziphos = MnziMinP-MmziMinP;
mk = [size(mdziphos)];          % size of array # of rows and columns in mdziphos
mm = mk(2);                     % number of columns in mdziphos
mSensCoefphos=
abs((mdziphos./dxiphos(:,ones(mm,1))).*(meanxiphos3(:,ones(mm,1))./MmziMinP));
mFOVphos = (mdziphos./dxiphos(:,ones(mm,1))).^2.*(stdevxiphos3(:,ones(mm,1))).^2;
                %the term (:,ones(mm,1)) duplicates the first and only column mm times
                %creating 8Xmm matrix/array
mFOSTDEVphos = sqrt (mFOVphos);
mVARZphos = sum (mFOVphos);
mSTDZphos = sqrt (mVARZphos);
%
mVarStDev=[mVARZstr;mSTDZstr;mVARZsed;mSTDZsed;mVARZnitr;mSTDZnitr;m
VARZphos;mSTDZphos];
```

```
%M-File Name: calc29Ann4.m
%M-File Description: This program sorts and converts the data from SWAT output files
%                         and creates the arrays for annual and monthly
%                         streamflow, sediment, nitrate and phosphate output variables.
%                         Output from this script is fed into MFORMSolverA4.m
%
function
[g,Aoutmv,AnMzistr,AnMzised,AnMziNO3,AnMziMinP,Mmzistr,Mmzised,MmziNO3,
MmziMinP]=calc29Ann4(a)
%
SubDat= a(769:864, 1:2);    % extracting first 2 columns (Subbasin# and Date) from txt
file
Flow_Out= a(769:864, 4);      % extracting column 4 (Flow_Out)
disp(size(SubDat))
for t=1:96
if round(SubDat(t,2)/10000)==2         %This for loop divides date column (b) by 10000
                                        % and rounds to nearest integer to selected
      Flow_Out(t)=Flow_Out(t)*86400*28/335.3/10000*1000;        %specific months to
                        % convert Flow_Out (c) from m3/s to mm/month according to
    elseif (round(SubDat(t,2)/10000)==4 | round(SubDat(t,2)/10000)==6 |
round(SubDat(t,2)/10000)==9 | round(SubDat(t,2)/10000)==11)    % # days in month
      Flow_Out(t)=Flow_Out(t)*86400*30/335.3/10000*1000;        % e.g. in this equation
                               % 30 days in months 4(Apr),6(Jun),9(Sept),and 11(Nov)
    else
      Flow_Out(t)=Flow_Out(t)*86400*31/335.3/10000*1000;
    end
end
Sed_Out= a(769:864, 8)*1000/335.3;   %extracting Column 8 (Sed_Out) and converting
                                      % from MT to kg/ha
NO3_Out= a(769:864, 15)/335.3;        %extracting Column 15(NO3_Out) and converting
                                      % from kg to kg/ha
MinP_Out= a(769:864, 21)/335.3;        %extracting Column 15(MinP_Out) and
converting from kg to kg/ha
g= [SubDat Flow_Out Sed_Out NO3_Out MinP_Out];           %Creates Array of
                                                % monthly values of output variables
%
Aoutmv=ones(8,4);   %Creates a matrix of ones with dimensions 8x4
Aoutmv(1,:)=sum(g(1:12,3:6));   %Sum of 12 months of 1st year for each output variable
                                % "Flow_Out" "Sed_Out" "NO3_Out" "MinP_Out"
Aoutmv(2,:)=sum(g(13:24,3:6)); %          "
Aoutmv(3,:)=sum(g(25:36,3:6)); %          "
Aoutmv(4,:)=sum(g(37:48,3:6)); %          "
Aoutmv(5,:)=sum(g(49:60,3:6)); %          "
Aoutmv(6,:)=sum(g(61:72,3:6)); %          "
Aoutmv(7,:)=sum(g(73:84,3:6)); %          "
Aoutmv(8,:)=sum(g(85:96,3:6)); % Sum of 12 months of 8th year
```

```
%
Flowmv=Aoutmv(:,1);  % Column of mean flow values with each row representing a
                     % year
AnMzistr=Flowmv(:,ones(12,1))';   % repeats flow column for # of flow parameters(in
                                  % this case 12 (columns))then transpose columns to rows
%
Sedmv=Aoutmv(:,2);
AnMzised=Sedmv(:,ones(9,1))';
%
NO3mv=Aoutmv(:,3);
AnMziNO3=NO3mv(:,ones(7,1))';
%
MinPmv=Aoutmv(:,4);
AnMziMinP=MinPmv(:,ones(3,1))';
%
Flow=g(:,3);
Mmzistr=Flow(:,ones(12,1))';
Sed=g(:,4);
Mmzised=Sed(:,ones(9,1))';
NO3=g(:,5);
MmziNO3=NO3(:,ones(7,1))';
MinP=g(:,6);
MmziMinP=MinP(:,ones(3,1))';
```

Appendix C-2

**Matlab Scripts to Tabulate MFORM Results for *Daily*
Streamflow, Sediment, Nitrate, and Phosphate *Concentrations***

DailyMFORMSolver.m
calc29Daily.m

```
%M-File Name: DailyMFORMSolver.m
%M-File Description: This program will load output files from SWAT to calculate
%                    Mean Value First Order Reliability Method (MFORM) or
%                    uncertainty for daily streamflow, sediment, nitrate and phosphate
%                    output varaibles.
%
clear
rootdir = ['C:\Documents and Settings\Aisha\Desktop\DailySLOutput']; %directory
                                                % where the files are stored
cd (rootdir);           % move to the directory where the files are stored
sourcefiles = dir;      % Names of the elements in the start_folder directory - struct array
numfiles = length(dir); % Number of elements in the start_folder directory
first=3;                % first position where starting counting
for i = first:numfiles
   name = sourcefiles(i).name; %name of the file
   fname = sprintf('%s\\%s',rootdir,name);           % directory path of the file
   trick=['my_file',int2str(i),'=load(fname);'];     % load file and call it my_file
   eval(trick);                                       % execute trick for each i
end
cd 'C:\Documents and Settings\Aisha\Desktop\mfiles'       % back to the initial directory
where the script is stored
Dout=zeros(2922,6,29);       % This is same as g in calc29Daily (2-D Matrix
                             % #rows=2922 days #columns=6 Date&OutputVars
                             % #depth=29 input files)
for ii=3:31
   eval(['a=sortrows(my_file',int2str(ii),',[1]);'])     % For each file named 'my_file#(3-
                   % 31)' sortrows in descending order *using the 1st row, hence [1]
   if(ii==3)
     [Dout(:,:,ii),DMzistr,DMzised,DMziNO3,DMziMinP]=calc29Daily(a);
       %Take info in brackets from specified file using the function calc29Ann4(a)
   else
     [Dout(:,:,ii)]=calc29Daily(a);
   end
end
%
%Daily new output arrays
%
dFlowCNwgs=Dout(:,3,4);
dFlowCNskp=Dout(:,3,5);
dFlowCNsgs=Dout(:,3,6);
dFlowES=Dout(:,3,7);
dFlowGW=Dout(:,3,8);
dFlowHR=Dout(:,3,9);
dFlowRC=Dout(:,3,10);
dFlowSM=Dout(:,3,11);
dFlowSA1=Dout(:,3,12);
```

```
dFlowSA2=Dout(:,3,13);
dFlowSK1=Dout(:,3,14);
dFlowSK2=Dout(:,3,15);
DNzistr= [ dFlowCNwgs dFlowCNskp dFlowCNsgs dFlowES dFlowGW dFlowHR
dFlowRC dFlowSM dFlowSA1 dFlowSA2 dFlowSK1 dFlowSK2]';
                        % Creates array of annual changes in "FLOW" output
                        % Apostrophe to transpose the array
dSedAP=Dout(:,4,16);
dSedBM=Dout(:,4,17);
dSedCC=Dout(:,4,18);
dSedCE=Dout(:,4,19);
dSedHR=Dout(:,4,9);
dSedSL=Dout(:,4,20);
dSedSPC=Dout(:,4,21);
dSedSPE=Dout(:,4,22);
dSedUP=Dout(:,4,23);
DNzised= [dSedAP dSedBM dSedCC dSedCE dSedHR dSedSL dSedSPC dSedSPE
dSedUP]';               %Creates array of annual changes in "Sed" output
%
dNO3AE=Dout(:,5,24);
dNO3BM=Dout(:,5,17);
dNO3CMN=Dout(:,5,25);
dNO3FS=Dout(:,5,26);
dNO3S_NO3_1=Dout(:,5,27);
dNO3S_NO3_2=Dout(:,5,28);
dNO3NP=Dout(:,5,29);
DNziNO3= [dNO3AE dNO3BM dNO3CMN dNO3FS dNO3S_NO3_1 dNO3S_NO3_2
dNO3NP]';
%
dMinBM=Dout(:,6,17);
dMinPPP=Dout(:,6,30);
dMinPS_LP=Dout(:,6,31);
DNziMinP= [dMinBM dMinPPP dMinPS_LP]';
%
%
load meanxistr3.txt; load meanxised3.txt; load meanxiphos3.txt; load meanxinitr3.txt;
load stdevxistr3.txt; load stdevxised3.txt; load stdevxinitr3.txt; load stdevxiphos3.txt;
%*******************************************************************
****
%**************MFORM Output
Tabulations*******************************
%*******************************************************************
****
% Daily Streamflow uncertainty
newxistr = meanxistr3*1.05;
dxistr = newxistr-meanxistr3;
```

```
ddzistr = DNzistr-DMzistr;
db = [size(ddzistr)];          % size of array # of rows and columns in ddzistr
dh = db(2);                    % number of columns in ddzistr
dFOVstr = (ddzistr./dxistr(:,ones(dh,1))).^2.*(stdevxistr3(:,ones(dh,1))).^2;
        % the term (:,ones(dh,1)) duplicates the first and only column dh times
        % creating 8Xdh matrix/array
dFOSTDEVstr = sqrt (dFOVstr);
dVARZstr = sum (dFOVstr);
dSTDZstr = sqrt (dVARZstr);
%
% Daily Sediment uncertainty
newxised = meanxised3*1.05;
dxised = newxised-meanxised3;
ddzised = DNzised-DMzised;
dc = [size(ddzised)];          % size of array # of rows and columns in ddzised
dd = dc(2);                    % number of columns in ddzised
dFOVsed = (ddzised./dxised(:,ones(dd,1))).^2.*(stdevxised3(:,ones(dd,1))).^2;
        % the term (:,ones(dd,1)) duplicates the first and only column dd times
        % creating 8Xdd matrix/array
dFOSTDEVsed = sqrt (dFOVsed);
dVARZsed = sum (dFOVsed);
dSTDZsed = sqrt (dVARZsed);
%
% Daily Nitrogen uncertainty
newxinitr = meanxinitr3*1.05;
dxinitr = newxinitr-meanxinitr3;
ddzinitr = DNziNO3-DMziNO3;
dn = [size(ddzinitr)];         % size of array # of rows and columns in ddzinitr
dp = dn(2);                    % number of columns in ddzinitr
dFOVnitr = (ddzinitr./dxinitr(:,ones(dp,1))).^2.*(stdevxinitr3(:,ones(dp,1))).^2;
        % the term (:,ones(dp,1)) duplicates the first and only column dp times
        % creating 8Xdp matrix/array
dFOSTDEVnitr = sqrt (dFOVnitr);
dVARZnitr = sum (dFOVnitr);
dSTDZnitr = sqrt (dVARZnitr);
%
% Daily Phosphate uncertainty
newxiphos = meanxiphos3*1.05;
dxiphos = newxiphos-meanxiphos3;
ddziphos = DNziMinP-DMziMinP;
dk = [size(ddziphos)];         % size of array # of rows and columns in ddziphos
dm = dk(2);                    % number of columns in ddziphos
dFOVphos = (ddziphos./dxiphos(:,ones(dm,1))).^2.*(stdevxiphos3(:,ones(dm,1))).^2;
        % the term (:,ones(dm,1)) duplicates the first and only column dm times
        % creating 8Xdm matrix/array
dFOSTDEVphos = sqrt (dFOVphos);
```

```
dVARZphos = sum (dFOVphos);
dSTDZphos = sqrt (dVARZphos);
%
dVarStDev=[dVARZstr;dSTDZstr;dVARZsed;dSTDZsed;dVARZnitr;dSTDZnitr;dVAR
Zphos;dSTDZphos]';
```

%M-File Name: calc29Daily.m

%M-File Description: This program sorts and converts the data from SWAT output files
%   and creates the arrays for daily streamflow, sediment, nitrate
%   and phosphate output variables.
%   Output from this script is fed into DailyMFORMSolver.m
%
function [g,DMzistr,DMzised,DMziNO3,DMziMinP]=calc29Daily(a)
%
SubDat= a(23375:end, 1:2);   % extracting first 2 columns (Subbasin# and Date) from txt file
Flow_Out= a(23375:end, 4)*1000*86400;   % extracting column 4 (Flow_Out) and converting from m3/s to L/d
Sed_Out= a(23375:end, 8)*1000*1000000./Flow_Out;   %extracting Column 8 (Sed_Out) and converting from MT to mg
NO3_Out= a(23375:end, 15)*1000000./Flow_Out;   %extracting Column 15(NO3_Out) and converting from kg to mg
MinP_Out= a(23375:end, 21)*1000000./Flow_Out;   %extracting Column 15(MinP_Out) and converting from kg to mg
g= [SubDat Flow_Out Sed_Out NO3_Out MinP_Out];   %Creates Array of daily values of output variables
%
%
DMzistr=Flow_Out(:,ones(12,1))';   %repeating flow column for # of flow parameters (in this case 12 columns) then transpose column to rows
DMzised=Sed_Out(:,ones(9,1))';   %each column then representing days and rows representing each important parameter
DMziNO3=NO3_Out(:,ones(7,1))';
DMziMinP=MinP_Out(:,ones(3,1))';

Appendix D

**Comparison of daily NO3-N concentration, MFORM STD (standard deviation),
with precipitation for each year of study (1994-2001)**
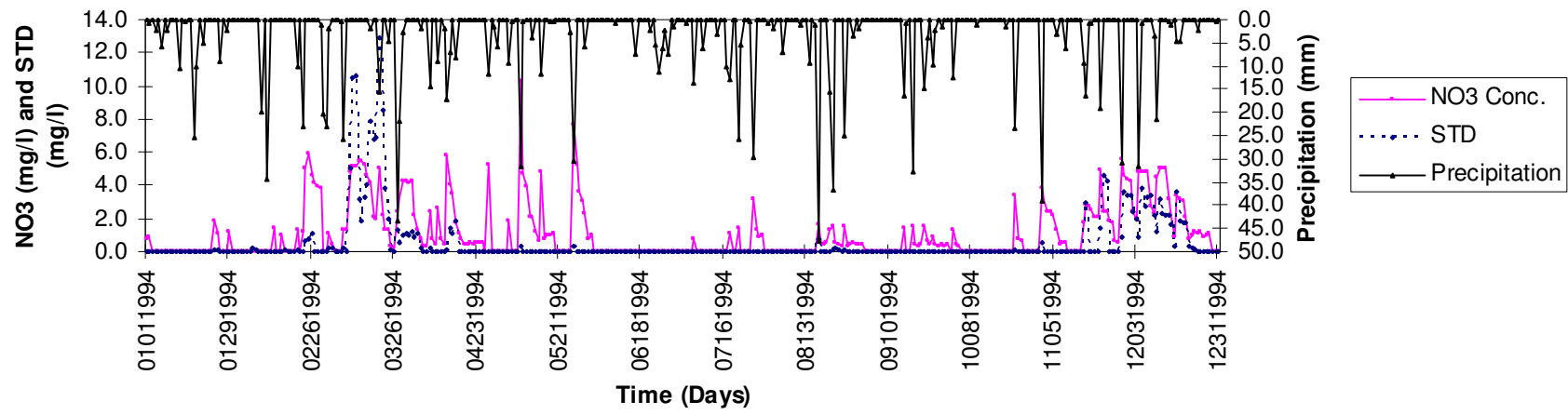
Figure D1 Comparison of daily NO3-N concentration, MFORM STD (standard deviation), with Precipitation during 1994.

217
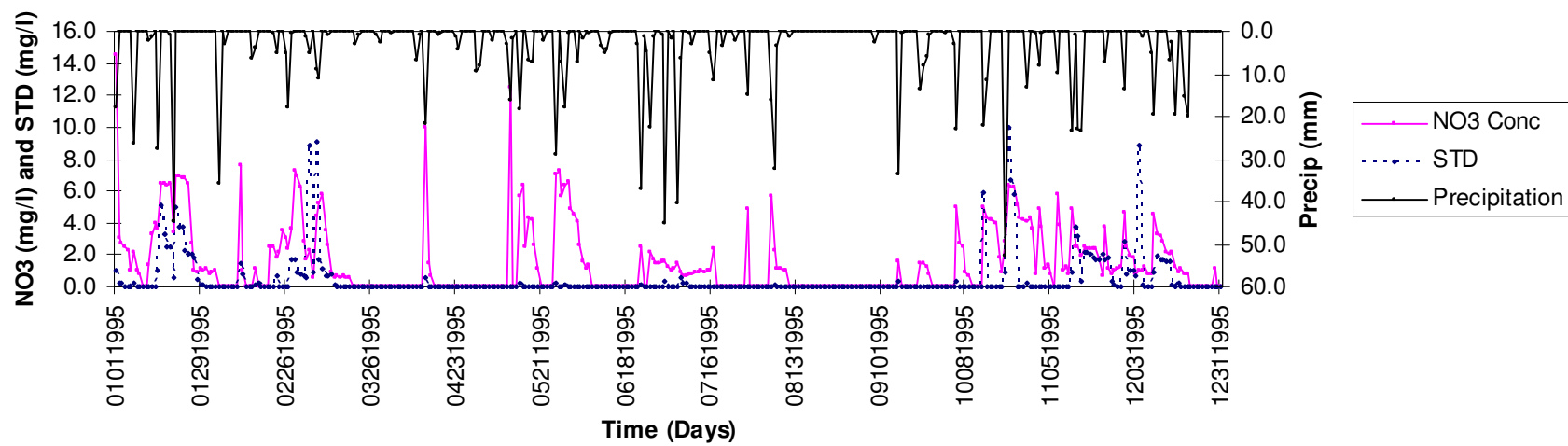
**Figure D2 Comparison of daily NO3-N concentration, MFORM STD (standard deviation), with precipitation during 1995.**
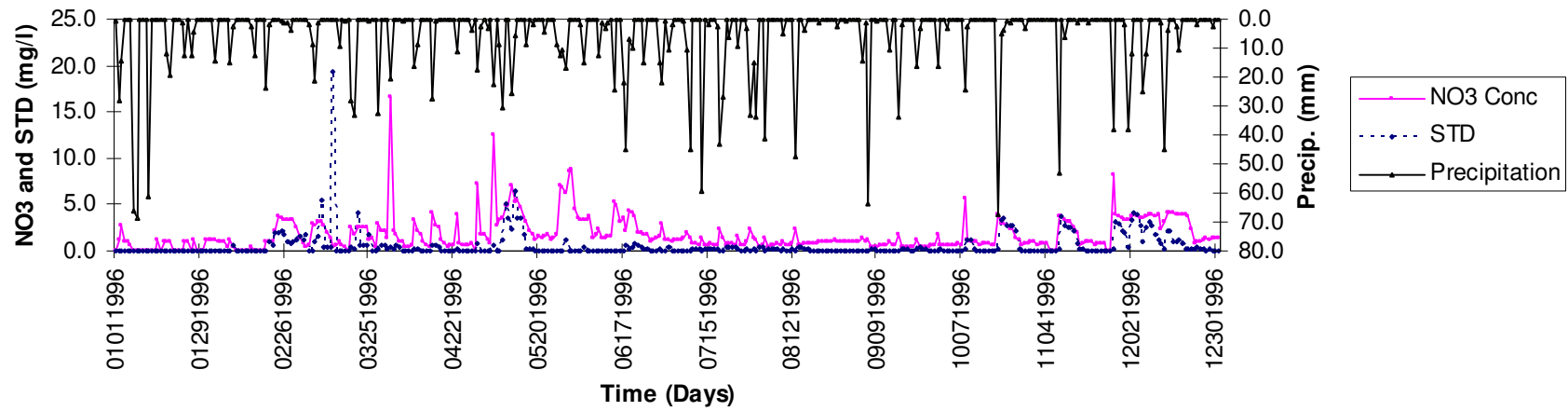
Figure D3 Comparison of daily NO3-N concentration, MFORM STD (standard deviation), with precipitation during 1996.
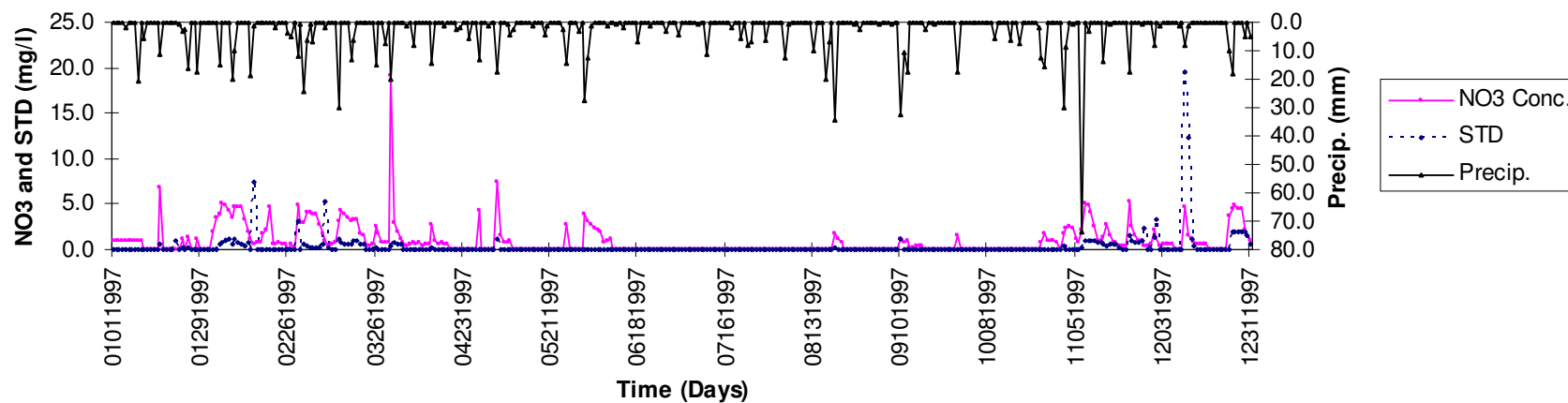
Figure D4 Comparison of daily NO3-N concentration, MFORM STD (standard deviation), with precipitation during 1997.
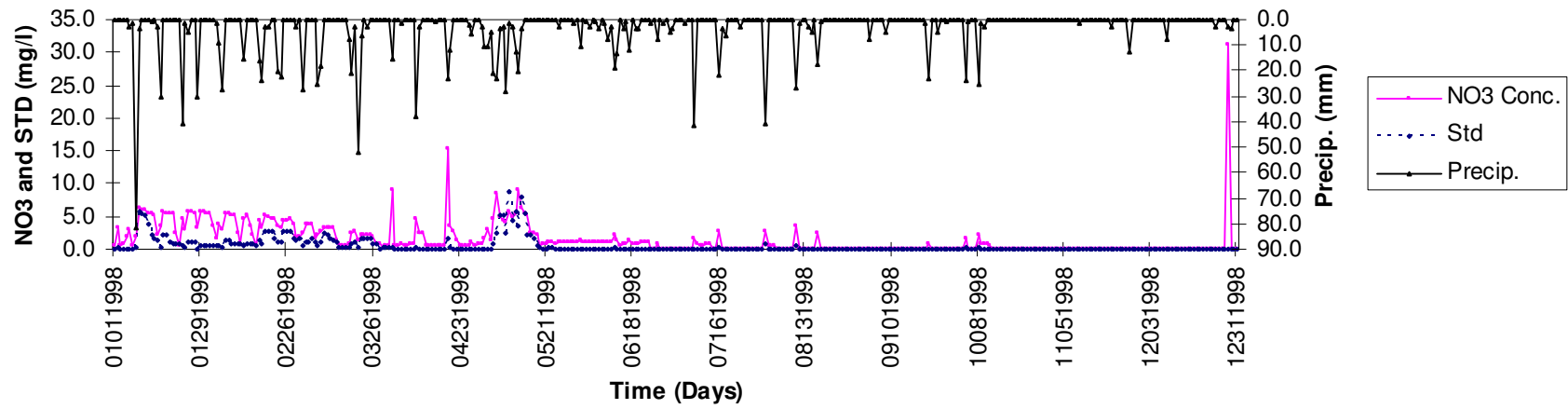
Figure D5 Comparison of daily NO3-N concentration, MFORM STD (standard deviation), with precipitation during 1998.
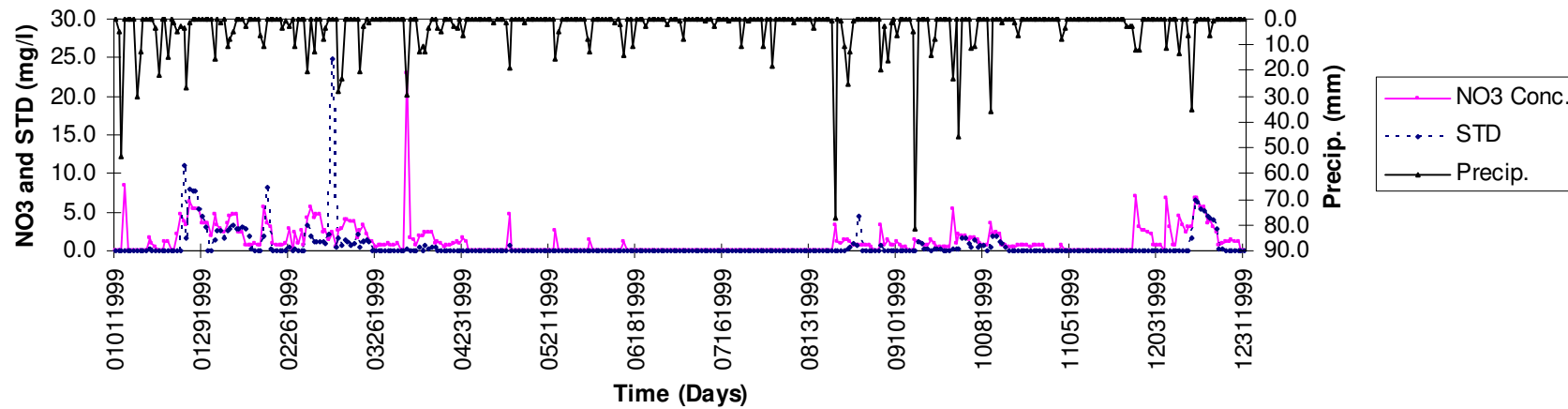
Figure D6 Comparison of daily NO3-N concentration, MFORM STD (standard deviation), with precipitation during 1999.
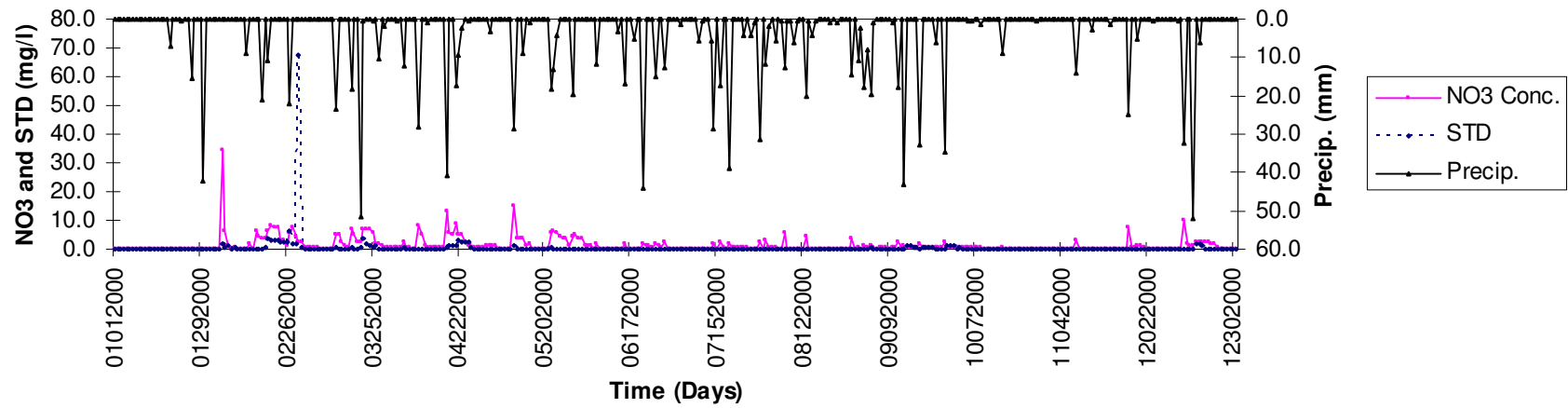
Figure D7 Comparison of daily NO3-N concentration, MFORM STD (standard deviation), with precipitation during 2000.
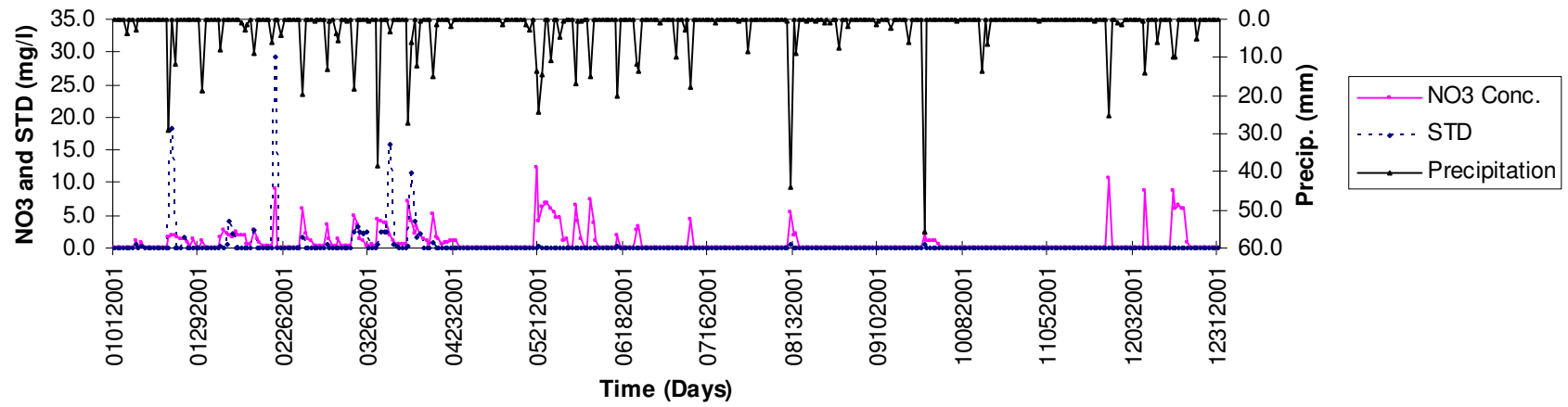
Figure D8 Comparison of daily NO3-N concentration, MFORM STD (standard deviation), with precipitation during 2001.

Appendix E

Monthly normalized sensitivity coefficients for all important input parameters based on years 1994 to 2001

The sensitivity coefficient is often normalized to get a dimensionless index which provides a more unbiased ranking of basic parameters for sensitivity analysis. The normalized sensitivity coefficient S is defined as:

$$S = \left| \frac{g(x_0 + \Delta x) - g(x_0)}{\Delta x} \times \frac{x_0}{g(x_0)} \right|$$
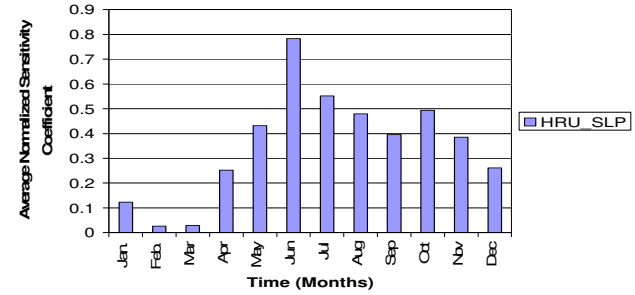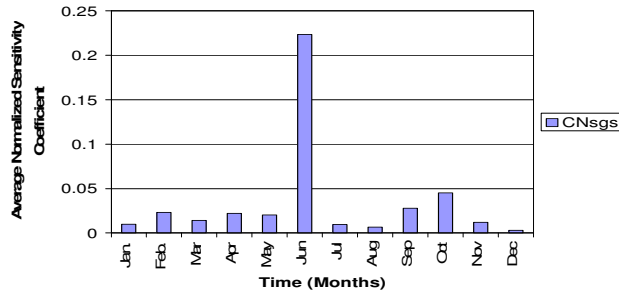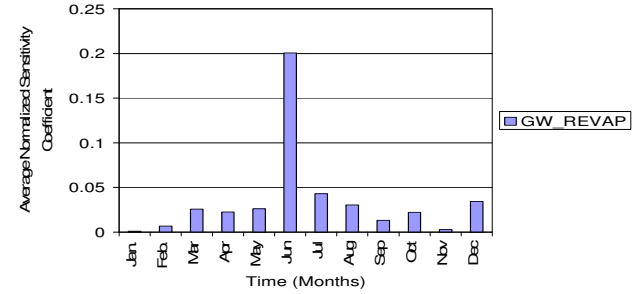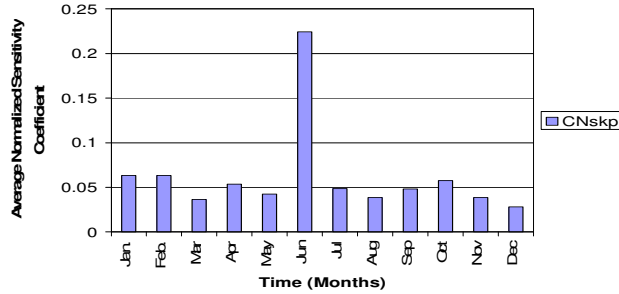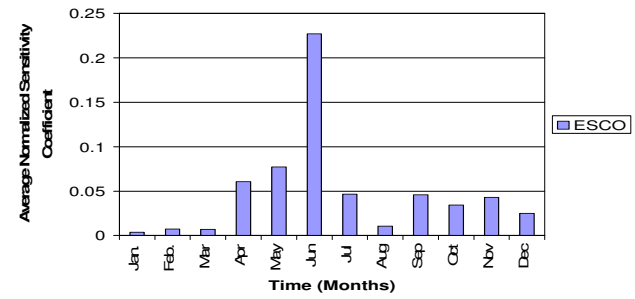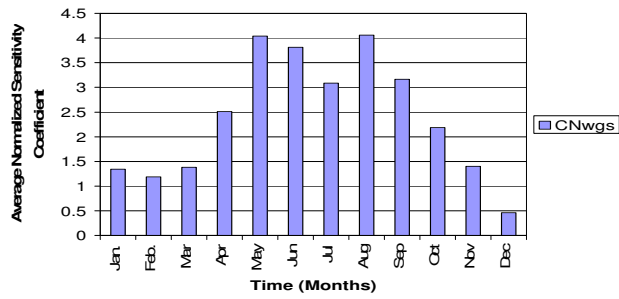
Figure E1 Monthly normalized sensitivity coefficients for important input parameters to streamflow output based on years 1994 to 2001.
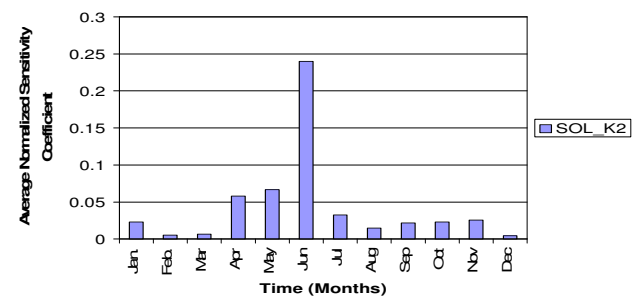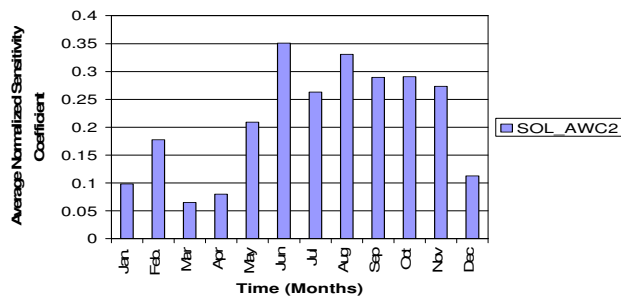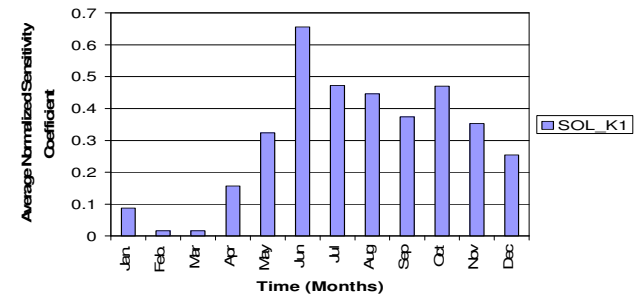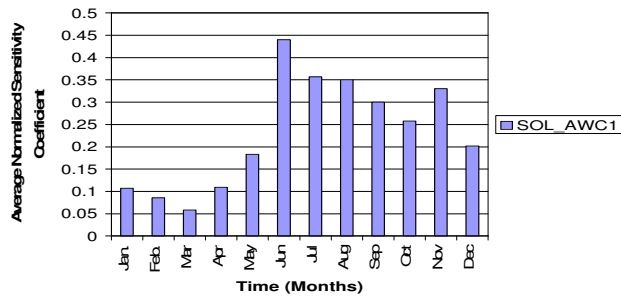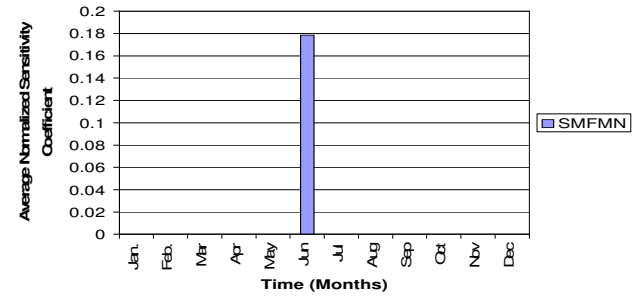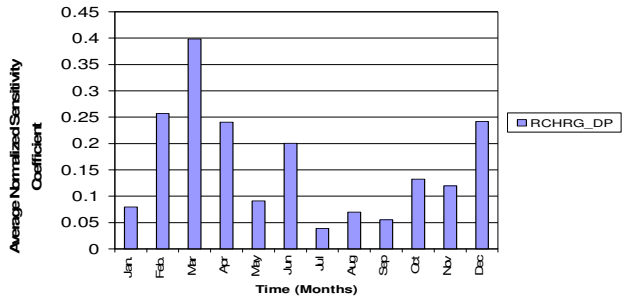
Figure E2 Monthly normalized sensitivity coefficients for important input parameters to streamflow output based on years 1994 to 2001.
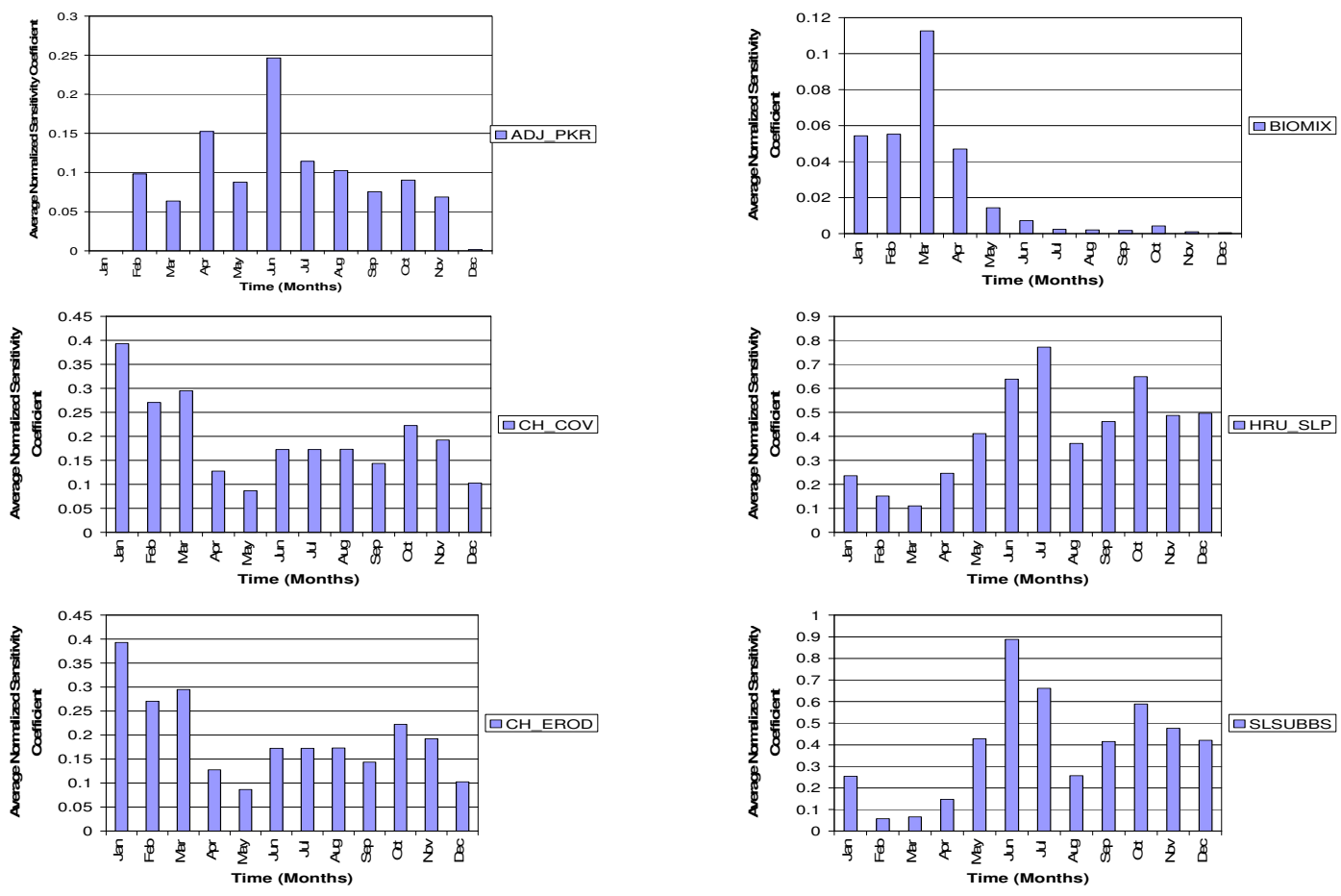
Figure E3 Monthly normalized sensitivity coefficients for important input parameters to sediment output based on years 1994 to 2001.
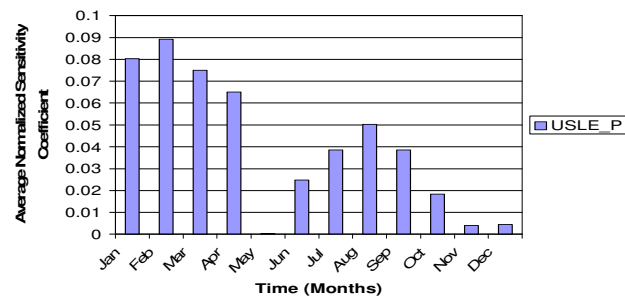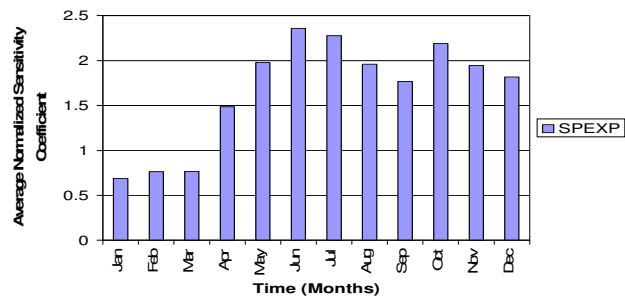
Figure E4 Monthly normalized sensitivity coefficients for important input parameters to sediment output based on years 1994 to 2001.
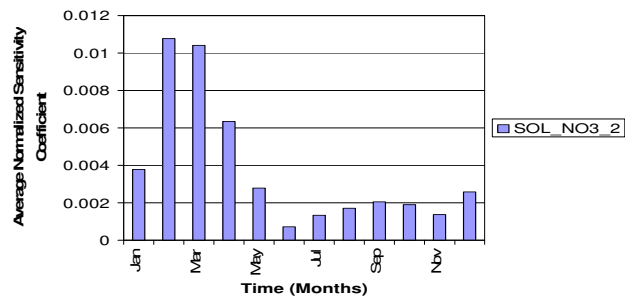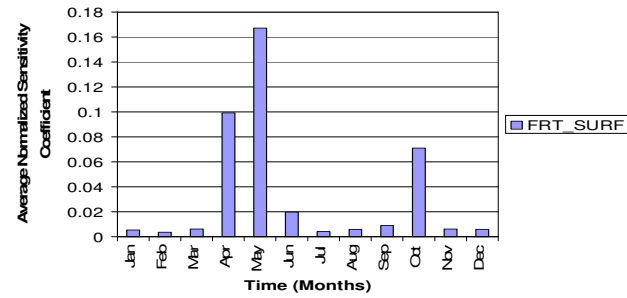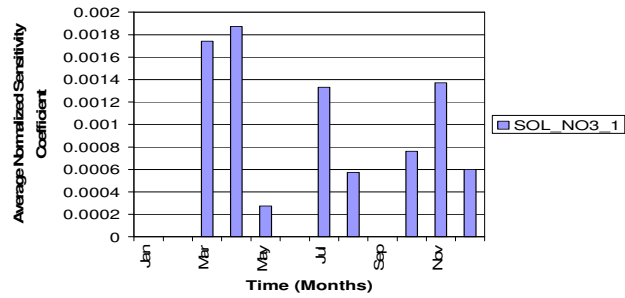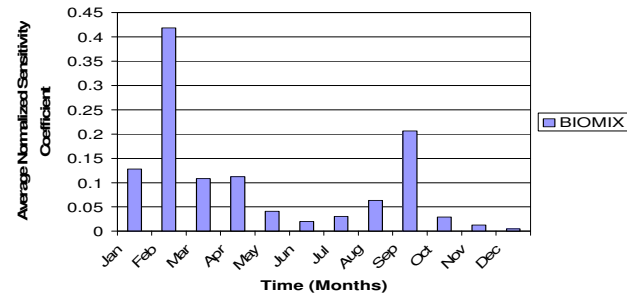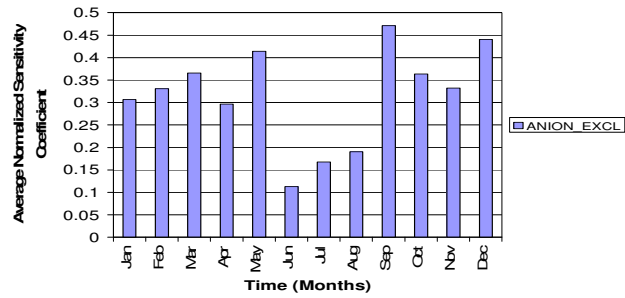
Figure E5 Monthly normalized sensitivity coefficients for important input parameters to nitrate output based on years 1994 to 2001.
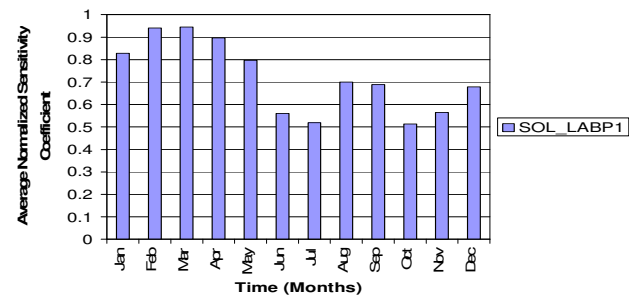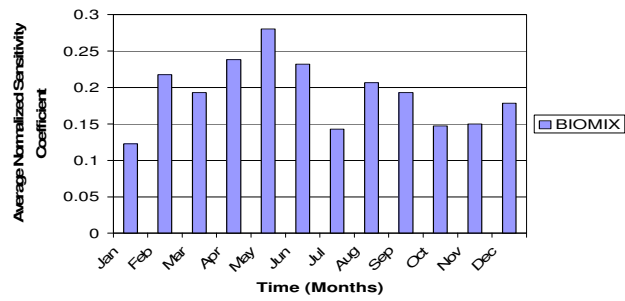
Figure E6 Monthly normalized sensitivity coefficients for important input parameters to phosphate output based on years 1994 to 2001.

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