Impact of Parameter Uncertainty on Critical SWAT Output Simulations

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Abstract. *Watershed models are increasingly being utilized to evaluate alternate management scenarios for improving water quality. The concern for using these tools in extensive programs such as the national Total Maximum Daily Load (TMDL) program is that the certainty of model results and efficacy of management scenarios are not often measured and therefore are not well known. In this study, we used the mean value first-order reliability method (MFORM), a computationally efficient uncertainty analysis method, to determine the contribution of parameter uncertainty to total model uncertainty in streamflow, sediment, and nutrient outputs in a small Maryland watershed. Examination of sensitive and uncertain parameters revealed that parameters not considered highly sensitive contributed to model output uncertainty to a large extent. Therefore, highly sensitive parameters should not be the only parameters considered in uncertainty or calibration analyses. Measures of output uncertainty showed that sediment had the largest amount of variance from its mean value (CV = 28%), while nitrate, phosphate, and streamflow had considerably less variance, with annual average CVs of 19%, 17%, and 15%, respectively. The largest amounts of model uncertainty occurred during wet periods. This study concluded that with improved knowledge of the true value and associated uncertainty of input parameters, and improved algorithms to capture the variability of rainfall and associated flow, watershed water quality models will be of much greater use to TMDL studies and studies alike.*

Keywords. *MFORM, Parameter uncertainty, SWAT, TMDL.*

Water is one of the most essential, life-sustaining substances on earth. Unfortunately, the quantity and quality of water is constantly being threatened by both natural and anthropogenic sources. Hydrologic and water quality models are tools used to identify and strategize mitigation of such threats by estimating the past, present, and future status of our water resources under different scenarios (e.g., changing climate, land uses, and land management practices). Information gathered from model estimates is normally used to decide the course of action to improve water conditions. Model-simulated data are often used to supplement monitored data; however, in the absence of monitored data, e.g., in un-gauged or partially gauged basins, model-simulated data are the only viable data available.

Given the utility of models to help manage water resources, the U.S. EPA's Total Maximum Daily Load (TMDL) program (U.S. Congress, 1972) leans heavily on models to assist in setting limitations on the amount of impairing pollutants that can be released into waterbodies. This program has the potential to bring impaired U.S. waters to a level of wellness that has not been achieved for the last several decades. However, the program has been met with several challenges, including the need to improve watershed and water quality modeling efforts and uncertainty analysis techniques (USEPA, 2002).

The Soil and Water Assessment Tool (SWAT; Arnold et al. 1998) is a well-known watershed-scale water quality model included in the slate of TMDL modeling tools. It has been widely used and tested in different regions of the world (Arnold et al., 1999; Boorman, 2003; Sohrabi et al., 2003; Srinivasan, et al., 1998; Vandenberghe et al., 2001). Calibration and validation studies on SWAT have revealed a great deal of information about its performance and appropriate uses (Chu and Shirmohammadi, 2004; Benaman et al., 2005; Behera and Panda, 2006; Reungsang et al., 2007; Sexton et al., 2010; Tolson and Shoemaker, 2007). However, further exploration of SWAT's applicability is needed, especially because the performance of TMDL modeling tools, including SWAT, seems to be inconsistent and in need of advancement (Benham et al., 2006; Borah et al., 2006; Muñoz-Carpena et al., 2006; Shirmohammadi et al., 2006; Wagner et al., 2007).

Output uncertainty of models used for TMDL analysis is a major concern, especially because of the legal, financial, and environmental ramifications of making decisions based on model results. In an article published recently as a result of the collective effort of a multi-disciplinary panel of experts to evaluate the current status of TMDL modeling technology (Shirmohammadi et al., 2006), it was suggested that the explicit quantification of model uncertainty be an integral part of the TMDL process. In watershed-scale water quality mod-

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eling, this is largely accomplished by examining uncertainty in model parameters (Tung, 1996).

Several methods are available to tabulate model uncertainty based on parameter uncertainty, including Monte Carlo based approaches (Sohrabi et al., 2002; Dubus et al., 2003; Sohrabi et al., 2003), first-order error analysis (Melching and Yoon, 1996; Zhang and Yu, 2004; Shen et al. 2008), and Bayesian methods (Gallagher and Doherty, 2007; Li et al., 2009; Yang et al., 2008). Model uncertainty has been shown to be watershed condition specific (Eckhardt et al., 2003; Wagner et al., 2007). In other words, parameters have different levels of importance in model uncertainty depending on, e.g., land cover/land use, management scenarios, and other characteristic watershed properties. In watershed assessments in which numerous management scenarios are tested (e.g., TMDLs), computationally efficient uncertainty methods would be quite beneficial. Thus, first-order error analysis has this advantage over probabilistic methods (Monte Carlo and Bayesian), which require hundreds or thousands of model runs before a solution will converge.

The mean value first-order reliability method (MFORM; Melching and Bauwens, 2001) is an uncertainty analysis approach that allows the user to determine the uncertainty of the dependent variable as well as the uncertainty contributed by each model input parameter. Determination of parameter uncertainty is useful to identify parameters that require special attention during field measurement and model calibration, which would reduce their contribution to model output uncertainty. MFORM has the advantage of being very efficient because it only requires calculation of the first two statistical moments (mean and variance) of the model parameters. It does not require parameter probability density functions (PDFs), which are quite difficult to determine and often require making a number of assumptions. Parameter covariance can be considered in MFORM. However, the relationship between parameters is often unknown; thus, the parameters are often assumed to have no correlation. Therefore, the covariance component of MFORM (see eq. 3 in the Uncertainty Analysis Method section) is often not accounted for.

The main shortcoming of MFORM is its linear approximation of the model. The method assumes that a single linearization of the model output function at the mean parameter values represents the statistical properties of model output over the complete range of parameter values (Melching and Yoon, 1996). The more nonlinear the model, the less accurate the method become, as parameters depart from their mean values. Approximating to higher-order derivatives may increase the accuracy of this method (Bobba et al., 1996); however the level of complexity also increases, especially for complex, black-box models such as SWAT. Several studies of nonlinear water quality models (Bobba et al., 1996; Zhang and Haan, 1996; Brown, 2001; Melching and Bauwens, 2001) have compared uncertainty methods that assume linearity (such as MFORM) to those that do not (such as Monte Carlo) and have obtained the same or similar results. These studies give credence to the accuracy of MFORM in light of its simplistic assumption.

MFORM and other first-order error analysis methods have been effectively used in numerous hydrologic/water quality modeling studies, but not extensively in SWAT. Melching and Bauwens (2001) evaluated uncertainty in coupled nonpoint-source and stream water quality models applied to a suburban watershed. They used the Latin hypercube sampling (LHS) and mean value first-order reliability method (MFORM) to determine prediction uncertainty of dissolved oxygen (DO) concentrations. The two uncertainty methods, LHS and MFORM, agreed well in determining key sources of uncertainty. 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). Both the first-order analysis (FOA) and Monte Carlo simulation (MCS) methods were used to quantify model parameter uncertainties. The two different approaches produced reasonably close results in indicating which parameters contributed the most uncertainty to the 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, respectively. Zhang and Yu (2004) applied first-order error analysis (FOEA) to a complex model (HSPF) to determine margin of safety (MOS) values for TMDL analysis. Precipitation was found to be the major source of uncertainty.

The majority of studies that have evaluated uncertainty in SWAT have used methods that require a considerable amount of computational time (Sohrabi, et al., 2003; Bubb and Meixner, 2005; Arabi et al., 2007; Shen et al., 2008; Yang et al., 2008; Karamouz et al., 2009; Li et al., 2009). Yang et al. (2008) evaluated several uncertainty analysis techniques using SWAT. In that study, the sequential uncertainty fitting algorithm (SUFI-2), parameter solution (Parasol), generalized likelihood uncertainty estimation (GLUE), and a Bayesian inference framework required 3000, 7000, 10,000, and 45,000+ model runs, respectively, in order to obtain results. Those numbers of runs are not very efficient, especially if output uncertainty must be determined for multiple watershed management scenarios, as suggested by Wagner et al. (2007), due to watershed-dependent uncertainty. Li et al. (2009) employed the Bayesian approach to estimate parameter uncertainty and its contribution to SWAT model simulation uncertainty. They found parameter uncertainties as well as their contribution to model simulation uncertainty to be relatively small. Arabi et al. (2007) used a three-step procedure including one-factor-at-a-time (OAT) sensitivity analysis and GLUE to analyze the uncertainty in SWAT model estimates of water quality benefits of best management practices (BMPs). BMP effectiveness varied by less than 10%, making the model suitable for use in watershed management plans such as TMDLs. However, uncertainties associated with sediment and nutrient outputs of the model were too large, potentially limiting its application for point estimates of design quantities.

Of the SWAT uncertainty studies listed above, only one (Shen et al., 2008) explicitly identified the uncertainty contributed by each parameter and discussed the effect on model uncertainty and outputs. Shen et al. (2008) used first-order error and Monte Carlo analyses to analyze the effect of parameter uncertainty on model outputs. They found that the curve number parameter contributed the largest amount of uncertainty to runoff, sediment, organic N, nitrate, and TP uncertainty. Since the runoff parameters were the main source of uncertainty, the runoff process was mainly responsible for the uncertainty of nonpoint-source pollution load. Based on our literature review, this was the only SWAT uncertainty study

that used first-order error analysis to characterize parameter and model output uncertainty; however, it was conducted on a watershed located in a mountainous region of China. Hence, there is a need to apply first-order methods such as MFORM to SWAT in U.S. watersheds of various physiographic and characteristic regions to determine watershed-specific parameters needing more careful evaluation or measurement to reduce uncertainty and to quantify model output uncertainty. Such methods can potentially be used to quantify uncertainty in the TMDL framework.

The objective of this study was to (1) identify both sensitive and uncertain parameters in SWAT using MFORM, (2) quantify uncertainties in streamflow, sediment, and nutrient outputs of the SWAT model, and (3) compare the sensitivity and uncertainty results obtained by MFORM in this study with other similar studies of SWAT cited in the literature. This will substantiate the potential use of MFORM in TMDL uncertainty assessments.

Materials and Methods

Site Description

Warner Creek watershed is located in Frederick County, Maryland, within the piedmont physiographic region. The watershed area is approximately 340 ha (840 acres) and drains into Little Pipe Creek, a tributary of the Monocacy River (fig. 1). The Monocacy river basin is known to contribute high levels of nutrients to the larger Chesapeake Bay watershed (Blankenship, 2007; USDA-SCS, 1990). Several of its water bodies are listed in Maryland's 303(d) list of impaired waters (MDE, 2008). Nutrient loads in the study watershed can mostly be attributed to nonpoint-sources, including grazing cattle and excess nutrients from croplands.

There are two dominant soil types in Warner Creek watershed, Manor-Edgemont-Brandywine soils (~1/3 of the watershed) and Penn-Reading-Croton soils (~2/3 of the watershed). All are well drained soils except for Croton, which is poorly drained. Most of the upland agricultural soils belong to the Penn silt loam series, with slopes ranging from 3% to 8%. The land uses consist of mixed agriculture (~76%), urban (~13%), forest (~11%), and water (<1%).

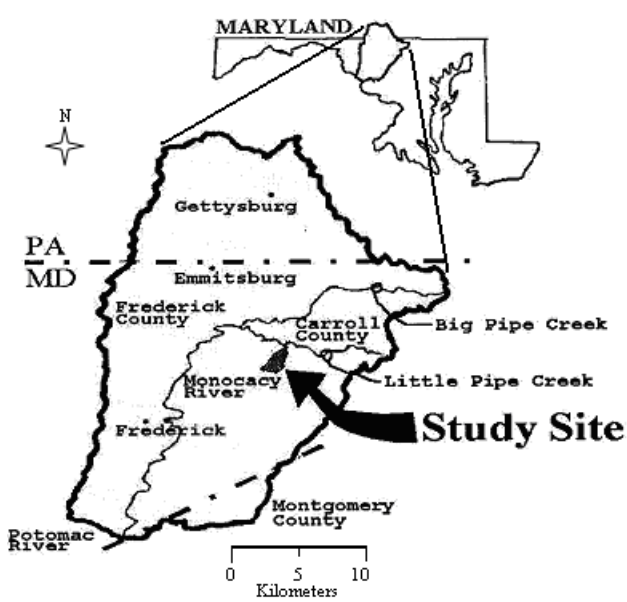

Figure 1. Location of Warner Creek watershed in Maryland.

Model Description and Data Acquisition

SWAT (Arnold et al., 1998) is a process-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. The version of SWAT used in this study was AVSWATX-2003, which operates in the ArcView GIS interface (DiLuzio et al., 2004).

Daily climatic data measured in subbasin 2 (fig. 2) were used during the simulation period. Missing rainfall and temperature data were filled in using daily measurements from a nearby monitoring station approximately 19 km (12 mi.) distant in Emmitsburg, Maryland (fig. 1). Daily solar radiation, wind speed, and relative humidity data were generated using SWAT's weather generator. Observed flow and chemical loading data were obtained from field measurements; however, supplementary data were obtained from Chu and Shirmohammadi (2004) and Chu et al. (2004). Streamflow was separated into surface flow and baseflow using the streamflow partitioning method of Linsley et al. (1982).

The three basic GIS maps required to run SWAT include digital elevation model (DEM), land cover/land use, and soils data. A U.S. Geological Survey (USGS) National Elevation Dataset (NED) with 30 m resolution was obtained from GIShydro2000 software (Moglen, 2004). Land uses for each field were identified by aerial photos obtained from the USDA Agricultural Stabilization and Conservation Service (USDA-ASCS). The land use map was created in the ERDAS IMAGINE GIS system (Searing and Shirmohammadi, 1994). A SSURGO soil map of Frederick County, Maryland, was downloaded from the USDA-NRCS Soil Data Mart server.

Based on the configuration of stream segments, the watershed was delineated into eight subbasins (fig. 2). Within each subbasin, the superimposing of similar landuses and soil types created 53 hydrologic response units (HRUs). A threshold value of 15% was chosen for both soil and land use types. Therefore, similar soils and land uses that made up less than 15% of a subbasin area were not assigned to an HRU. The watershed is fairly small (340 ha), and the variation in land use

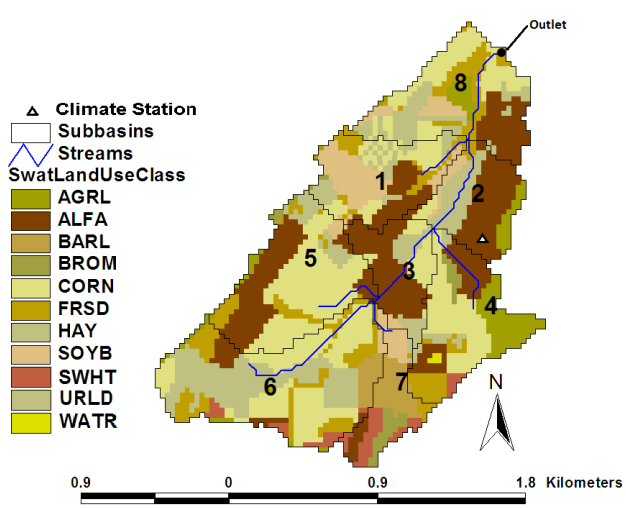

Figure 2. Location of subbasins and land use configuration.

Table 1. Description of SWAT input parameters evaluated in uncertainty analysis.

Parameter	Description
Streamflow	
CNOPwgs	SCS runoff curve number during winter growing season
CNOPskp	SCS runoff curve number during spring kill/planting season
CNOPsgs	SCS runoff curve number during spring growing season
ESCO	Soil evaporation compensation factor
GW_REVAP	Groundwater "revap" coefficient
HRUSLP	Average slope steepness (m m^{-1})
RCHRG_DP	Deep aquifer percolation factor
SMFMN	Melt factor for snow on December 21 (mm H_2O °C^{-1} d^{-1})
SOL_AWC1	Available water capacity of soil layer 1 (mm H_2O mm^{-1} soil)
SOL_AWC2	Available water capacity of soil layer 2 (mm H_2O mm^{-1} soil)
SOL_K1	Saturated hydraulic conductivity of soil layer 1 (mm h^{-1})
SOL_K2	Saturated hydraulic conductivity of soil layer 2 (mm h^{-1})
Sediment	
ADJ_PKR	Peak rate adjustment factor for sediment routing in the subbasin
BIOMIX	Biological mixing efficiency
CH_COV	Channel cover factor
CH_EROD	Channel erodibility factor
SLSUBBSN	Average slope length (m)
SPCON	Linear parameter to calculate maximum sediment re-entrained
SPEXP	Exponent parameter to calculate maximum sediment re-entrained
USLE_P	USLE equation support practice factor
Nitrate	
ANION_EXCL	Fraction of porosity from which anions are excluded
CMN	Rate factor for humus mineralization of active organic nutrients (N and P)
FRT_SURF	Fraction of fertilizer applied to the top 10 mm of soil
SOL_NO3_1	Initial NO_3 concentration in soil layer 1 (mg kg^{-1})
SOL_NO3_2	Initial NO_3 concentration in soil layer 2 (mg kg^{-1})
NPERCO	Nitrate percolation coefficient
Phosphate	
PPERCO	Phosphorus percolation coefficient (10 m^3 Mg^{-1})
SOL_LABP1	Initial soluble P concentration in soil layer 1 (mg kg^{-1})

and soil types is not very extensive. Therefore, this level of detail was considered to be suitable for the project. The SWAT user's manual suggests that thresholds between 10% and 20% are adequate in most cases (Winchell et al., 2007).

Uncertainty Analysis Method

The mean value first-order reliability method (MFORM) was chosen to quantify uncertainties in the model prediction of streamflow, sediment, nitrate, and phosphate loads. 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. 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 variables, and the level of parameter importance during preliminary model calibration (Sexton, 2007). Depth into the soil layer and seasonal variation of curve number were also considered in the examined parameters. A description of each basic variable considered in this study is listed in table 1.

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

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

where Y is the dependent variable or model output of interest, $g(X_e)$ is the function representing the simulation process 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 variable. Therefore, the mean and variance of the dependent variable can be approximated as:

$$E(Y) \approx g(X_m) \quad (2)$$

$$Var(Y) = \sigma_Y^2 \approx \sum_{i=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)_{X_m}^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)_{X_m} \left(\frac{\partial g}{\partial x_j} \right)_{X_m} \cdot C_v(x_i, x_j) \quad (3)$$

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. If basic variables are not correlated, then $C_v(x_i, x_j)$ is equal to zero. In this case, the variance of the output can be written as:

$$Var(Y) = \sigma_Y^2 \approx \sum_{i=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)_{X_m}^2 \sigma_i^2 \quad (4)$$

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:

$$\frac{\partial g}{\partial x} = \frac{g(x_0 + \Delta x) - g(x_0)}{\Delta x} \quad (5)$$

where x_0 is the initial value of the basic variable, Δx is the change in the basic variable, and all other symbols are de-

fined 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. 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. Numerous studies using the forward difference scheme have changed parameters between 1% and 10% (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. We know that models such as SWAT are not linear, but for small perturbations they can be assumed linear. In modeling, there is always a balancing act between efficiency and accuracy. In this study, the forward difference numerical method with 5% parameter increase was chosen to tabulate the sensitivity coefficient because it is a suitable method that gives valid results and it requires fewer model runs than, for example, a central difference scheme. This efficiency is very beneficial, especially for studies requiring a large number of repeated simulations to test and compare different scenarios (e.g., in TMDL analysis).

The sensitivity coefficient is often normalized to get a dimensionless index that 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:

$$S = \left| \frac{g(x_0 + \Delta x) - g(x_0)}{\Delta x} \times \frac{x_0}{g(x_0)} \right| \tag{6}$$

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 is an attractive method to use over other uncertainty techniques because of its simplicity. It only requires the mean and variance of basic variables. These descriptive statistics can be determined in a number of different ways, the simplest and most efficient method being to survey the literature and use engineering judgment (Zhang and Yu, 2004). When there is not enough information in the literature about parameter statistics, a more detailed numerical method can be used.

In this study, descriptive statistics were determined for each basic variable (table 2) by assigning a range and probability distribution to each parameter and using the appropriate equations for mean and standard deviation. The assigned range of each variable was determined based on the suggested range in the SWAT user's manual (Neitsch et al., 2001), the range of realistic perturbation values observed during preliminary calibration, and the ranges specified in the literature (Sohrabi et al., 2003). It should be noted that the model was run with HRU-specific (spatially variable) parameter values as needed (e.g., different mean curve numbers for different land uses). However, table 2 shows watershed-scale parameter statistics.

Probability distributions were chosen for each parameter based on information synthesized from the literature. In all cases, a bounded distribution was necessary because each parameter has an upper and lower limit. 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. A gamma distribution requires 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 the scale and shape factors (Brighton Webs, 2007). That information was not readily available for this study. 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, 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. Variables in this study assigned to the beta distribution were considered to have a shape similar to that of the log-normal distribution. 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. The equations used to tabulate the means and standard deviations of the beta, uniform, and log-uniform distributions are listed in table 3.

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. Descriptive statistic results using LHS verified those obtained using the equations for the distributions (beta, uniform, and log-uniform) listed in table 3. Mean values of all variables were then used as input to SWAT to perform model runs (1 run using all mean values and 28 runs for 5% change of each input parameter). Means and standard deviations for all parameters were used as input for MFORM tabulation of model output uncertainty.

In this study, we conducted a thorough examination of SWAT input parameters to determine their descriptive statistics for use in MFORM. This was necessary, since previous literature did not provide this information. However, the values derived in this section can now be referenced in future studies that require this information. In addition, the methods used here for tabulating parameter descriptive statistics can be utilized in other modeling studies including SWAT where watershed-specific parameter statistics must be obtained.

Table 2. Watershed averaged minimum, maximum, range, mean, median, standard deviation (SD), and coefficient of variation (CV) of basic variables.

No.	Parameter	Units	File Location	Distribution	Assigned Range	Min.	Max.	Range	Mean	Median	SD	CV
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	67-85	68	83	15	76	76	3.01087	0.03962
8	CNOPskp	--	mgt2	Beta	56-71	58	70	12	63	64	2.49791	0.03934
9	CNOPsgs	--	mgt2	Beta	61-71	62	70	8	66	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^{-1}	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 H_2O °C^{-1} d^{-1}	bsn	Uniform	1.4-8.5	1.43	8.49	7.06	4.94924	4.945	2.0541	0.4150
19	SOL_AWC1	mm H_2O mm^{-1} 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 H_2O mm^{-1} 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 h^{-1}	sol	Beta	22.18-80.64	23	77.9	54.9	41.6868	40.55	10.51184	0.25216
22	SOL_K2	mm h^{-1}	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^{-1}	chm	Uniform	100-250	111	241	130	175	175	25.1376	0.1436
24	SOL_NO3_1	mg kg^{-1}	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^{-1}	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

Table 3. Equations used to tabulate means and standard deviations of parameter distribution types.[a]

Distribution Type	Mean	Standard Deviation
Beta	$\mu_X = A + \frac{p}{(p+q)}(B-A)$	$\sigma_X = \sqrt{\frac{pq}{(p+q)^2(p+q+1)}(B-A)^2}$
Uniform	$\mu_X = \frac{1}{2}(A+B)$	$\sigma_X = \sqrt{\frac{1}{12}(B-A)^2}$
Log-uniform	$\mu_X = \frac{B-A}{\ln B - \ln A}$	$\sigma_X = \sqrt{(B-A)\frac{(\ln B - \ln A)(B+A) - 2(B-A)}{2(\ln B - \ln A)^2}}$

[a] A and B are lower and upper limits of the parameter range; p and q are shape factors assigned to 2 and 4, respectively, based on Wyss and Jorgensen (1998); and μ_X and σ_X are the mean and standard deviation, respectively, of the random variable.

Results and Discussion

Sensitivity Analysis

Input parameters were ranked by comparing the magnitude of sensitivity displayed in output parameters using the normalized sensitivity coefficient (S in eq. 6). Based on average annual S values, table 4 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 #9), 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 effect on changes in streamflow output. Several studies have found the SCS curve number to be one of the most sensitive input parameters for streamflow prediction (Chu and Shirmohammadi, 2004; White and Chaubey, 2005). Compared to CNOPwgs, recharge to the deep aquifer (RCHRG_DP), available water capacity of soil layers 1 and 2 (SOL_AWC1

Table 4. Rank of important input parameters for sensitivity of average annual streamflow, sediment, nitrate, and phosphate output variables.[a]

	Streamflow			Sediment			Nitrate			Phosphate		
Rank	Input Parameter	*S*	% *S*	Input Parameter	*S*	% *S*	Input Parameter	*S*	% *S*	Input Parameter	*S*	% *S*
1	CNOPwgs	1.40	68	SPEXP	0.58	38	ANION_EXCL	0.32	75	SOL_LABP1	0.93	84
2	RCHG_DP	0.20	10	CH_COV	0.29	19	BIOMIX	0.09	21	BIOMIX	0.18	16
3	SOL_AWC2	0.15	7	CH_EROD	0.29	19	SOL_NO3_2	0.01	2	PPERCO	0.00	0
4	SOL_AWC1	0.08	4	HRUSLP	0.14	9	FRT_SURF	0.01	1			
5	HRU_SLP	0.07	3	USLE_P	0.08	6	SOL_NO3_1	0.00	0			
6	SOL_K1	0.06	3	ADJ_PKR	0.04	3	CMN	0.00	0			
7	CNOPskp	0.05	2	SLSUBBSN	0.04	3	NPERCO	0.00	0			
8	ESCO	0.02	1	BIOMIX	0.04	3						
9	CNOPsgs	0.02	1	SPCON	0.00	0						
10	GW_REVAP	0.01	1									
11	SOL_K2	0.01	0									
12	SMFMN	0.00	0									

[a] *S* = normalized sensitivity coefficient (eq. 6), and %*S* = percentage of total *S*.

and SOL_AWC2), average slope steepness (HRU_SLP), and saturated hydraulic conductivity of soil layer 1 (SOL_K1) were moderately sensitive. Snow melt factor (SMFMN) had the least effect on changes in streamflow. In a watershed or region where significant snowfall and accumulation are prevalent, this parameter would likely be more sensitive.

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 4). Channel cover (CH_COV) and erodibility (CH_EROD) had the same moderate to high level of sensitivity, while average slope steepness (HRU_SLP) and support practice factor (USLE_P) were next in importance to sensitivity of sediment prediction. Sediment output was least sensitive to ADJ_PKR, SLSUBBSN, and BIOMIX. Shen et al. (2008) found HRU_SLP, USLE_P, and BIOMIX to be sensitive parameters in sediment simulation as well. In comparing our sensitive and uncertain parameters to those of other studies, it is important to note that most major input parameters in this study were adjusted for only one output variable (e.g., curve number was only adjusted for streamflow calibration, and not for sediment and nutrient calibrations) to avoid model overfitting and diminishing of previously calibrated components (e.g., hydrology). Therefore, previously adjusted parameters that were highly sensitive or uncertain in one component were not considered in the remaining output calibrations.

Nitrate prediction was most sensitive to the fraction of porosity from which anions are excluded (ANION_EXCL) (table 4). This parameter determines the portion of anions, such as nitrate, that is transported away from the surface of soil particles. The percolation coefficient for nitrate (NPERCO) had no effect on nitrate sensitivity. Biological mixing efficiency (BIOMIX) was a moderately sensitive parameter for both nitrate and phosphate prediction. As BIOMIX increases, nitrate and phosphate loads decrease 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 4). In a study examining total phosphorus sensitivity using one-at-a-time (OAT) sensitivity analysis, SOL_LABP was ranked #2 out of the phosphorus-related parameters (Arabi et al., 2007). Percolation coefficients for phosphate (PPERCO) had no effect on phosphate sensitivity.

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 5 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, contributing to only 10% of streamflow sensitivity (table 4). The variance in this parameter makes a difference in its ranking.

CH_COV and CH_EROD were the leading contributors to uncertainty in sediment output, with annual percentage totals of 40% (table 5). Their contribution to sediment sensitivity, however, was significantly less, 19% (table 4). SPEXP did not contribute as much to sediment FOV (15%, ranked #3) as it did to sediment sensitivity (38%, ranked #1). Shen et al. (2008) found SPEXP to contribute 8.36% (ranked #4) of the variance in sediment output; however, it was not ranked within their top ten parameters contributing to sediment sensitivity. This, again, illustrates the significant difference in the contribution of one parameter to sensitivity compared to uncertainty. Input parameters that had significance in the uncertainty of nitrate and phosphate simulation had the same rank in sensitivity results (tables 4 and 5). ANION_EXCL and BIOMIX where ranked #1 and #2, respectively, for nitrate sensitivity and uncertainty contribution, and SOL_LABP1 and BIOMIX where ranked #1 and #2, respectively, for phosphorus.

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 parameters not deemed as highly sensitive (e.g., RCHRG_DP, CH_COV, and CH_EROD) 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 than if the true value is known.

Table 5. Ranking of important input parameters to streamflow, sediment, and nutrient prediction uncertainty based on average annual fraction of variance (FOV) contribution (eq. 4).[a]

	Streamflow			Sediment			Nitrate			Phosphate		
Rank	Input Parameter	FOV $(mm)^2$	% TV	Input Parameter	FOV $(kg\ ha^{-1})^2$	% TV	Input Parameter	FOV $(kg\ ha^{-1})^2$	% TV	Input Parameter	FOV $(kg\ ha^{-1})^2$	% TV
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									

[a] FOV = average annual FOV, and %TV = percentage of total variance.

Table 6. Predicted annual loads simulated using mean values (MV) of input parameters, standard deviations (SD), 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
SD (mm)	37.0	40.0	92.0	33.0	84.0	53.0	31.0	14.0	48.0
Variance (mm^2)	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 $(kg\ ha^{-1})$	2158.0	1815.0	5997.0	1204.0	2187.0	1931.0	1485.0	558.0	2167.0
SD $(kg\ ha^{-1})$	743.0	526.0	1688.0	392.0	493.0	452.0	312.0	197.0	600.0
Variance $(kg\ ha^{-1})^2$	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 $(kg\ ha^{-1})$	4.9	5.1	11.4	3.3	11.2	5.3	3.4	1.3	5.7
SD $(kg\ ha^{-1})$	0.8	1.3	2.3	0.3	0.9	1.6	0.6	0.4	1.0
Variance $(kg\ ha^{-1})^2$	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 $(kg\ ha^{-1})$	3.2	2.4	6.3	1.3	1.8	2.2	1.7	0.6	2.4
SD $(kg\ ha^{-1})$	0.5	0.4	1.1	0.2	0.3	0.5	0.3	0.1	0.4
Variance $(kg\ ha^{-1})^2$	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

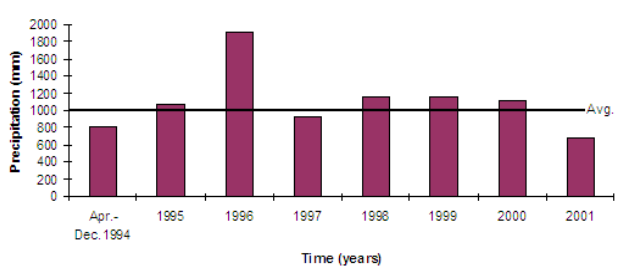

Figure 3. Annual precipitation and line of annual average precipitation in Warner Creek watershed.

Output Variance

Table 6 shows predicted annual loads simulated using mean values (MV) of input parameters, standard deviations (SD) 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 occurred in 1996. Variances were 8510 mm^2, 2847800, 5.1, and 1.2 $(kg\ ha^{-1})^2$ for streamflow, sediment, nitrate, and phosphate, respectively, in 1996 (table 6). For sediment and phosphate, variance was an order of magnitude larger in 1996 than in all other years. Record amounts of rainfall fell in 1996, as shown in figure 3. 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 (fig. 3). These results show that larger amounts of model uncertainty occur during extremely wet years.

Sexton (2007) highlighted the use of the SCS curve number method to calculate surface runoff as one of the main reasons for poor model performance during wet periods. 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. This issue points to the need to reduce uncertainties associated with rainfall input as well as runoff parameters. In addition, the algorithms used to equate runoff may require further development or replacement by

another method. For example, an infiltration-based method, such as the Green and Ampt modified by Mein and Larson (Mein and Larson, 1973) excess rainfall method, may prove to be a better approach to account for surface runoff. As a result of high parameter uncertainty values, Shen et al. (2008) also discussed the need to properly identify SWAT parameters relevant to the runoff process. Identifying the parameters contributing to the largest amount of uncertainty helps to pinpoint the model processes that need further development.

Comparison of average coefficients of variation in table 6 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%). Other studies have also found more uncertainty in SWAT sediment and nutrient outputs than in streamflow outputs (Arabi et al., 2007; Shen et al., 2008). One likely reason for this effect is the fact that the simulation of sediments and nutrients is dependent upon flow processes. Therefore, uncertainties in those output variables will be associated with parameters and algorithms dependent and independent of flow processes. Hence, uncertainty is compounded for constituent pollutant outputs.

Summary and Conclusions

This article addresses the need to improve watershed water quality modeling efforts including the quantification of parameter and model uncertainties. The uncertainty method MFORM was used to tabulate the uncertainty contribution of individual input parameters as well as the uncertainty of model outputs including streamflow, sediments, and nutrients. This method is attractive because of its computational efficiency. In this study, only 29 model runs (1 + the number of parameters) were needed to tabulate model uncertainty. Other methods would require hundreds or even thousands of model runs. Results of this study using MFORM were comparable to results of other studies cited in the literature that used other methods of uncertainty with SWAT. This qualifies its potential use as a reliable and computationally efficient method to account for uncertainties in TMDL studies.

The sensitivity coefficient and fraction of variance, two component equations of MFORM, were used to evaluate sensitive and uncertain parameters, respectively. Results revealed that sensitive parameters should not be the only parameters considered for model calibration and contribution to model uncertainty. Parameters that were not highly sensitive contributed to model uncertainty to a larger extent. These parameters should therefore be determined more precisely and also considered during model calibration to improve model performance and reduce model uncertainty. In assessing the variance in the output variables, the largest amount of output variance occurred during wet periods. This is likely due to the limitation of the model to properly account for extreme flow events by the use of the empirically based SCS curve number method (Chu and Shirmohammadi, 2004; Sexton, 2007). The infiltration-based Green and Ampt modified by Mein and Larson excess rainfall method may prove to be a better approach to account for surface runoff in SWAT; however, that method requires more detailed precipitation and soils data. Further evaluation of model algorithms and parameters representing runoff processes is needed.

These findings point to the need for more studies to determine the true value of input parameters for models used in TMDL studies, whether by field measurements or other means of derivation. Although these models tend to be physically based, many parameters are difficult to determine due to natural variability or incomplete knowledge about the physical meaning. This further establishes the need to quantify the uncertainty associated with those parameters as it relates to output uncertainty. Lastly, the existence of watershed-dependent uncertainty calls for the application of uncertainty methods to SWAT simulations in other characteristic regions, e.g., karst areas, or the various physiographic regions where different parameters will likely be more uncertain and require further attention.

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