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A probabilistic approach for analysis of uncertainty in the evaluation of watershed management practices

Mazdak Arabi [a], Rao S. Govindaraju [b,*], Mohamed M. Hantush [c]

[a] *Department of Agricultural and Biological Engineering, Purdue University, 225 South University Street, West Lafayette, IN 47907, United States*
[b] *School of Civil Engineering, Purdue University, 1284 Civil Engineering Building, 550 Stadium Mall Drive, West Lafayette, IN 47907-1284, United States*
[c] *National Risk Management Research Laboratory, US environmental Protection Agency, Cincinnati, OH 45268, United States*

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Summary A computational framework is presented for analyzing the uncertainty in model estimates of water quality benefits of best management practices (BMPs) in two small (<10 km^2) watersheds in Indiana. The analysis specifically recognizes the significance of the difference between the magnitude of uncertainty associated with absolute hydrologic and water quality predictions, and uncertainty in estimated benefits of BMPs. The Soil and Water Assessment Tool (SWAT) is integrated with Monte Carlo-based simulations, aiming at (1) adjusting the suggested range of model parameters to more realistic site-specific ranges based on observed data, and (2) computing a scaled distribution function to assess the effectiveness of BMPs. A three-step procedure based on the One-factor-At-a-Time (OAT) sensitivity analysis and the Generalized Likelihood Uncertainty Estimation (GLUE) was implemented for the two study watersheds. Results indicate that the suggested range of some SWAT parameters, especially the ones that are used to determine the transport capacity of channel network and initial concentration of nutrients in soils, required site-specific adjustment. It was evident that uncertainties associated with sediment and nutrient outputs of the model were too large, perhaps limiting its application for point estimates of design quantities. However, the estimated effectiveness of BMPs sampled at different points in the parameter space varied by less than 10% for all variables of interest. This suggested that BMP effectiveness could be ascertained with good confidence using models, thus making it suitable for use in watershed management plans such as the EPA's Total Maximum Daily Load (TMDL) program. The potential impact of our analysis on utility of models and model uncertainties in decision-making process is discussed.

* Corresponding author. Tel.: +1 765 496 3402; fax: +1 765 496 1988.
E-mail address: govind@ecn.purdue.edu (R.S. Govindaraju).

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Introduction

The analysis of uncertainty associated with the utility of simulation models is an important consideration in the development of watershed management plans. Modeling uncertainty should be rigorously addressed in development and application of models, especially when stakeholders are affected by the decisions contingent upon model-supported analyses (NRC, 2001). Watershed models are commonly utilized to investigate rainfall-runoff generation, and fate and transport of contaminants resulting from nonpoint source activities. Nonpoint source activities are perceived to be the most important source of pollution in the United States (Ice, 2004). The evaluation of the success of best management practices (BMPs) in meeting their original goals has also been facilitated by watershed models (Griffin, 1995; Edwards et al., 1996; Mostaghimi et al., 1997; Saleh et al., 2000; Santhi et al., 2001; Kirsch et al., 2002; Santhi et al., 2003; Arabi et al., 2006). Uncertainty associated with absolute estimates of design quantities tends to be very high because of data sparsity and model limitations (Osidele et al., 2003; Benaman and Shoemaker, 2004). Thus, models are found to be more useful when making relative comparisons rather than making absolute predictions. It may be more meaningful to implement the uncertainty associated with effectiveness of BMPs in the planning process.

The common modeling approach entails the {calibrate → validate → predict} process. The thrust of the calibration procedure is to identify a set of model parameters by optimizing a goodness-of-fit statistic between observed and predicted values such as the Nash–Sutcliff coefficient of efficiency. The calibrated model is then used to examine the impact of various management scenarios on the future behavior of the system. Such an analysis is subject to *identifiability*, and *non-uniqueness* of the optimal (calibrated) parameter set (Beck, 1987), i.e. there may be several sets of model parameters that fit the observed data equally (Beven and Binely, 1992). Calibration of a simulation model for a given watershed will reduce, but not totally remove, modeling uncertainties associated with both structure of the model and parameter estimates. Even with the best model structure, parameter estimation contains *residual uncertainty* (Beck, 1987) that propagates forward into model predictions and evaluation of effectiveness of management practices.

Although the literature is replete with sensitivity analysis and uncertainty analysis methods (Spear and Hornberger, 1980; Beven and Binely, 1992; Spear et al., 1994; Saltelli et al., 2000), implications of uncertainty associated with model predictions have not been widely endorsed in the decision making process mainly as a result of large uncertainty estimates. The magnitude of uncertainty itself is a key factor in its acceptance as the cost of implementation of management actions such as the Total Maximum Daily Load (TMDL) program may significantly increase with larger uncertainty estimates (Dilks and Freedman, 2004). In a case study in the Cannonsville Reservoir system watershed (1178 km^2) located in upstate New York, Benaman and Shoemaker (2004) concluded that even in the presence of observed data it was not possible to reduce the uncertainty of absolute sediment predictions in their study to practical values for the TMDL program. The argument, however, is that if the goal of a modeling study is to examine the impact of management scenarios on water quality of a study area, it may be neither practical nor necessary to incorporate large uncertainty of absolute predictions in the decision making process. It would be perhaps more feasible (and more desirable) to communicate and implement uncertainty of estimated effectiveness of management scenarios rather than uncertainty of absolute predictions (Zhang and Yu, 2004). Moreover, the importance of such a formulation would be particularly appreciated when the reduction of a variable of concern (sediment, nutrients, etc.) due to implementation of an abatement action is less than estimated uncertainty of absolute predictions. In such cases, evaluation of impact of management scenarios would not be inhibited by uncertainty of model outputs.

The impact of modeling uncertainties on evaluation of management practices has not been addressed sufficiently, as studies have generally focused on uncertainty of point predictions. Specifically, a computational procedure that can be used to establish uncertainty bounds for the estimated effectiveness of BMPs has not been developed to the best of our knowledge. In this paper, a Monte Carlo-based probabilistic approach is utilized (i) to develop a computational procedure for analysis of uncertainty; (ii) to examine the effect of modeling uncertainties on evaluation of long-term water quality impacts of BMPs using a distributed watershed model, SWAT; and (iii) to provide a comparison between magnitudes of uncertainties associated with absolute predictions versus effectiveness of BMPs. The analysis is demonstrated for two small watersheds in Indiana where water quality data were collected and several structural BMPs were implemented.

Theoretical considerations

Watershed model

Soil and Water Assessment Tool (SWAT) (Neitsch et al., 2002) is a process-based distributed-parameter simulation model, operating on a daily time step. The model was originally developed to quantify the impact of land management practices in large, complex watersheds with varying soils, land use, and management conditions over a long period of time. SWAT uses readily available inputs and has the capability of routing runoff and chemicals through streams and reservoirs, and allows for addition of flows and inclusion of measured data from point sources. Moreover, SWAT has the capability to evaluate the relative effects of different management scenarios on water quality, sediment, and agricultural chemical yield in large, ungaged basins. Major components of the model include weather, surface runoff, return flow, percolation, evapotranspiration (ET), transmission losses, pond and reservoir storage, crop growth and irrigation, groundwater flow, reach routing, nutrient and pesticide loads, and water transfer. Table 1 provides a listing of important SWAT input parameters corresponding to the above-mentioned components.

For simulation purposes, SWAT partitions the watershed into subunits including subbasins, reach/main channel seg-

Table 1 Listing of the parameters used in uncertainty analysis: LB and UB refer to lower and upper bounds of parameter vector, parameters identified by * were altered as a percentage of the default value, parameters identified by ** were considered in sensitivity analysis but not in uncertainty analysis

Parameter	Description	Units	Range	
			LB	UB
CN2*	SCS runoff curve number	%	30	98
SOL-AWC	Available soil water capacity	mm/mm	0.01	0.4
ESCO	Soil evaporation compensation factor		0	1
OV-N	Manning's ''*n*'' value for overland flow		0.1	0.3
SLOPE*,**	Average slope steepness	m/m	0	0.6
SLSUBBSN	Average slope length	m	0.15	1.2
GWQMN	Minimum threshold depth of water in the shallow aquifer for return flow to occur	mm	0	5000
REVAPMN	Minimum threshold depth of water in the shallow aquifer for ''revap'' to occur	mm	0	500
GW-REVAP	Groundwater ''revap'' coefficient		0.02	2
GW-DELAY	Groundwater delay	days	0	500
ALPHA-BF	Baseflow α factor for recession constant	days	0	1
SURLAG	Surface runoff lag time		1	12
SFTMP	Snowfall temperature	°C	−5	5
*CH—S1**,**	Average slope for tributary channels	m/m	0	10
CH-N1	Manning's ''*n*'' value for tributary channels		0.008	0.065
CH-K1	Effective hydraulic conductivity in tributary channels	mm/h	0	150
*CH—S2**,**	Average slope for the main channels	m/m	0	10
CH-N2	Manning's ''*n*'' value for the main channel		0.01	0.3
CH-K2	Effective hydraulic conductivity in the main channel	mm/h	0	150
CH-EROD	Channel erodibility factor	cm/h/Pa	0	0.6
CH-COV	Channel cover factor		0	0.6
PRF	Peak rate adjustment factor for in-stream channel routing		0	2
SPCON	Linear coefficient for in-stream channel routing		0	0.001
SPEXP	Exponent coefficient for in-stream channel routing		1	1.5
BIOMIX	Biological mixing efficiency		0.01	1
BIOMIN	Minimum plant biomass for grazing	kg/ha	0	1
USLE-P	USLE equation support practice factor		0.1	1
*USLE-C**	Minimum value of USLE equation cover factor	%	0.001	0.5
USLE-K	USLE equation soil erodibility factor		0.01	0.65
ORGP-AG	Initial organic P in soils for agriculture land use	mg/kg	1	1000
ORGP—PAST	Initial organic P in soils for pasture land use	mg/kg	1	500
LABP-AG	Initial soluble P in soils for agriculture land use	mg/kg	1	100
LABP—PAST	Initial soluble P in soils for pasture land use	mg/kg	1	50
ORGN-AG	Initial organic N in soils for agriculture land use	mg/kg	1	10,000
ORGN-PAST	Initial organic N in soils for pasture land use	mg/kg	1	5000
SOLN-AG	Initial NO_3 in soils for agriculture land use	mg/kg	0.1	5
SOLN-PAST	Initial NO_3 in soils for pasture land use	mg/kg	0.1	3

ments, impoundments on main channel network, and point sources to set up a watershed. Subbasins are divided into hydrologic response units (HRUs) that are portions of subbasins with unique land use/management/soil attributes.

SWAT uses a modification of the SCS curve number method (USDA Soil Conservation Service, 1972) or Green and Ampt infiltration method (Green and Ampt, 1911) to compute surface runoff volume for each HRU. Peak runoff rate is estimated using a modification of the Rational Method. Daily or sub-daily rainfall data are used for calculations. Flow is routed through the channel using a variable storage coefficient method developed by Williams (1969) or the Muskingum routing method. In this study, SCS curve number and Muskingum routing methods along with daily climate data were used for surface runoff and streamflow computations.

Erosion and sediment yield are estimated for each HRU with the modified universal soil loss equation (MUSLE) (Williams, 1975). Sediment deposition and degradation are the two dominant channel processes that affect sediment yield at the outlet of the watershed. Whether channel deposition or channel degradation occurs depends on the sediment loads from upland areas and transport capacity of the channel network. If sediment load in a channel segment is larger than its sediment transport capacity, channel deposition will be the dominant process. Otherwise, channel degradation (i.e. channel erosion) occurs over the channel segment. SWAT estimates the transport capacity of a channel segment as a function of the peak channel velocity. The peak velocity in a reach segment at each time step is calculated by the Manning's equation.

Movement and transformation of several forms of nitrogen and phosphorus over the watershed are accounted for within the SWAT model. Nutrients are introduced into the main channel through surface runoff and lateral subsurface flow, and transported downstream with channel flow. Major phosphorous sources in mineral soil include organic phosphorus available in humus and mineral phosphorus that is not soluble. Phosphorus may be added to the soil in the form of fertilizer, manure, and residue application. Surface runoff is deemed as the major mechanism of phosphorus removal from a field. Unlike phosphorus that has low solubility, nitrogen is highly mobile. Major nitrogen sources in mineral soil include organic nitrogen available in humus, mineral nitrogen in soil colloids, and mineral nitrogen in solution. Nitrogen may be added to the soil in the form of fertilizer, manure, or residue application. Plant uptake, denitrification, volatilization, leaching, and soil erosion are the major mechanisms of nitrogen removal from a field.

One-factor-At-a-Time (OAT) sensitivity analysis

The OAT is a sensitivity analysis technique that falls under the category of screening methods (Saltelli et al., 2000). In the OAT, each model run involves perturbation of only one parameter in turn. This way, the variation of model output can be unambiguously attributed to the perturbation of the corresponding factor. For each input parameter, local sensitivities are computed at different points of the parameter space, and then the global (main) effect is obtained by taking their average. The elementary effect of a small perturbation Δ of the ith component of the p-dimensional parameter vector (α_i) at a given point in the parameter space $\alpha = (\alpha_1, \ldots, \alpha_{i-1}, \alpha_i, \alpha_{i+1}, \ldots, \alpha_p)$ is (Morris, 1991):

$$d(\alpha_i|\alpha) = \frac{[y(\alpha_1, \ldots, \alpha_{i-1}, \alpha_i + \Delta, \alpha_{i+1}, \ldots, \alpha_p) - y(\alpha)]}{\Delta} \quad (1)$$

where $y(\alpha)$ corresponds to the model output of interest. The results are quantitative, elementary, and exclusive to the parameter α_i. However, the elementary effect computed from Eq. (1), i.e. $d(\alpha_i|\alpha)$, is only a partial effect and depends on the values chosen for the other elements of the parameter vector (α_j). A finite distribution (F_i) of elementary effects of parameter α_i is obtained by sampling at different points of the space, i.e. different choices of parameter set α. The mean of the distributions is indicative of the overall influence of the parameter on the output, while the variance demonstrates interactions with other parameters and nonlinearity effects.

Generalized likelihood uncertainty estimation (GLUE) method

The GLUE methodology is based on recognition of the importance of the set of parameters to produce the behavior of the system, not individual parameters. The acceptable model realizations (i.e. behavior set) obtained from Monte Carlo simulations are given a likelihood weight according to observed data and a likelihood function. Several choices for an appropriate likelihood function can be obtained from Beven and Freer (2001). A likelihood measure based on Nash–Sutcliff efficiency criterion with shaping factor N is defined as (Freer and Beven, 1996):

$$L(\alpha|y) = \left(1 - \frac{\sigma_\varepsilon^2}{\sigma_0^2}\right)^N; \quad \sigma_\varepsilon^2 < \sigma_0^2 \quad (2)$$

where $L(\alpha|y)$ is the likelihood of parameter set (α), given the observed data (y). The quantities σ_ε^2 and σ_0^2 refer to the error variance between model simulations and observed data, and the variance of the observed data, respectively. For $N = 1$, L in Eq. (2) is the well-known Nash–Sutcliff efficiency coefficient that is often used for calibration of hydrologic and water quality models. A negative L value indicates that the corresponding model output is dissimilar to the behavior of the system under study, and the likelihood of such a simulation in mimicking the system behavior is zero. Therefore, the likelihood measure is rewritten as:

$$L(\alpha|y) = \max\left[\left(1 - \frac{\sigma_\varepsilon^2}{\sigma_0^2}\right), 0\right] \quad (3)$$

For each simulation from a random parameter set, a likelihood weight is obtained from Eq. (3). Then, these weights are rescaled by dividing each of them by their total sum. The rescaled likelihood weights are used to construct a cumulative distribution for the output of interest, which can be used for estimation of uncertainty bounds associated with the output by computing its quantiles. The GLUE method is subjective not only to the choice of likelihood function, but also to the cutoff criterion used for classification of Monte Carlo simulations to behavior and non-behavior sets.

Methodology

The computational framework utilized in this study is comprised of (1) a process-based watershed model (SWAT; Soil and Water Assessment Tool, Arnold et al., 1998) employed for simulating the fate and transport of sediment and nutrients in the study watersheds under two scenarios – before and after implementation of BMPs, (2) a BMP representation method (adapted from Arabi et al., 2004) for incorporation of water quality impacts of BMPs, and (3) an uncertainty analysis methodology based on two sampling based methods: One-factor-At-a-Time (OAT) sensitivity analysis (Saltelli et al., 2000), and Generalized Likelihood Uncertainty Estimation (GLUE; Beven and Binely, 1992). A computational method was developed to reduce the "suggested" range of input parameters to site-specific "adjusted" ranges to be used in the GLUE analysis. The methodology was tested on two different watersheds located in northeast Indiana, one with significantly larger number of installed BMPs. This confirmed the versatility of the computational analysis to quantify modeling uncertainties associated with estimated effectiveness of BMPs in study watersheds under influence of a large number as well as a small number of BMPs.

Case study watersheds

The Black Creek watershed (Fig. 1) located in northeast Indiana is a typical watershed in the upper Maumee River

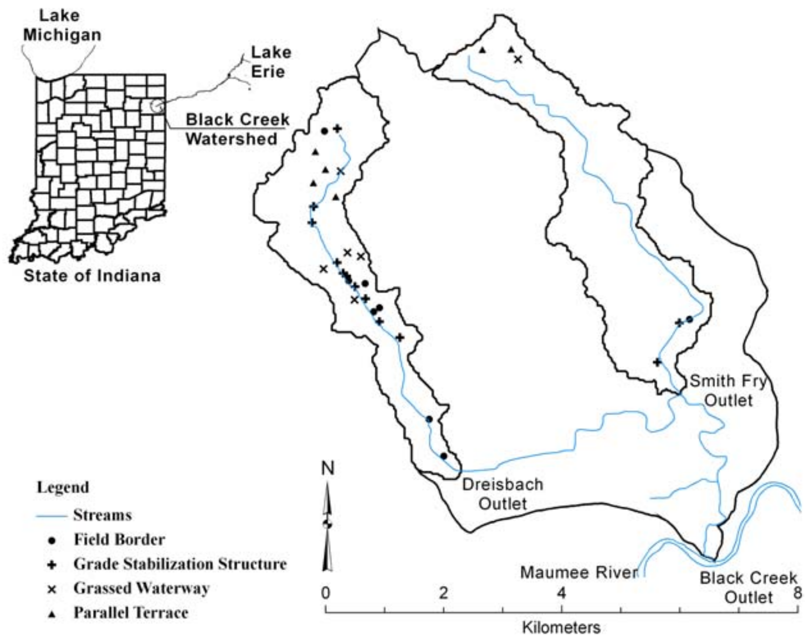

Figure 1 Location map of study watersheds and implemented BMPs.

basin. In mid-1970's and early 1980's several BMPs were implemented in the watershed and detailed water quality monitoring was carried out at various locations within the watershed to examine short-term water quality impacts of soil and water conservation techniques. Daily precipitation, streamflow, sediment, and nutrient data were collected from automated samplers at the outlets of Dreisbach (6.23 km^2) and Smith Fry (7.3 km^2) within the Black Creek watershed during the 1974–1978 time period and were used in this study. Fig. 1 is a depiction of the location of study watersheds.

The dominant hydrological soil group in the study watersheds is type C, representative of medium to poorly drained soils. Land use in Dreisbach is mostly pasture in the upper portion, while row crops are wide spread in the remainder of the watershed. Smith Fry is a predominantly agricultural watershed. Field borders, parallel terraces, grade stabilization structures, and grassed waterways are the structural BMPs installed in the watershed. Table 2 summarizes the number and area under influence of each type of BMP installed in the study watersheds as shown in Fig. 1. Available data, land use distribution, and other information for the watersheds can be obtained from Lake and Morrison (1977), Lake and Morrison (1978), and Morrison and Lake (1983). Black Creek watershed has been listed as an impaired water body in Indiana with nutrients, algal growth, and impaired biotic communities as major concerns (EPA, 2005).

Representation of BMPs

For this study, a method presented by Arabi et al. (2004) was utilized to evaluate the water quality impacts of grassed waterways, grade stabilization structures, field borders and parallel terraces. The method was developed based on published literature pertaining to BMP simulation in hydrological models and considering the hydrologic and water quality processes simulated in SWAT. Based on the function of the BMPs and hydrologic and water quality processes that are directly modified by their implementation, corresponding SWAT parameters were selected and altered. The impacts of the BMPs on other hydrologic/water quality processes were indirectly accounted for through their functional representation within the SWAT model. For example, implementation of grassed waterways prevents gully erosion due to concentrated flow. Thus, channel cover and erodibility factors were set to zero for channel segments with grassed waterways. Also, grassed waterways increase deposition of pollutant loads in the channel network. This impact is captured by increasing the channel Manning's number to

Table 2 BMPs installed in the Dreisbach and Smith Fry watersheds

BMP	Dreisbach		Smith Fry	
	Number	Length/area (unit)	Number	Length/area (unit)
Field border	7	2600 (m)	1	1800 (m)
Parallel terrace	4	2130 (m)	2	480 (m)
Grassed waterway	5	3.50 (ha)	1	0.95 (ha)
Grade stabilization structure	10	–	2	–

0.3 (Fiener and Auerswald, 2006). For parallel terraces, Wischmeier and Smith (1978) recommended a USLE practice factor of 0.1 for terraces on slopes less than 15% with graded channels sod outlets. Table 3 summarizes SWAT parameters and their corresponding values for representation of the BMPs. More information on BMP representation procedure with SWAT model can be obtained from Arabi et al. (2004, 2006).

It is worthwhile to mention that the numerical representation of BMP performances as presented in Table 3 bears some degree of uncertainty. For example, Fiener and Auerswald (2006) assumed *CH_N2* ranges between 0.3 and 0.4 s m$^{-1/3}$ over the year for grassed waterways in case of dense grasses and herbs under non-submerged conditions. Assuming a fixed value for the representative parameters adds additional uncertainty in the BMP evaluation methodology. This uncertainty will perhaps be alleviated once precise numerical representation procedures are developed and validated with experimental data. We have adopted the methodology provided by Arabi et al. (2004) without incorporating the uncertainty of BMP representation procedure.

Analysis of uncertainty

OAT sensitivity analysis

Identifying the most sensitive input parameters is not an essential component of the framework for analysis of uncertainty that is proposed in this paper. The results of such an analysis, however, provide useful information pertaining to model parameters with large uncertainties. The uncertainty associated with parameters that are determined based on topographic, land use, soil, and management attributes could perhaps be reduced by using better spatial resolution for these attributes. Conversely, uncertainty of parameters that are not determined from landscape attributes and are usually estimated through calibration procedure may be reduced only through a systematic site-specific range adjustment process.

In this study, the following procedure was followed for the OAT sensitivity analysis. First, in the absence of any prior information with regard to the distribution of input parameters, a uniform distribution, with minima and maxima specified in Table 1, was considered for all parameters. The same approach was used by Beven and Freer (2001) and Benaman and Shoemaker (2004). Then, OAT sensitivity indices were computed. While a local sensitivity index (d) was computed by applying Eq. (1) for each parameter, global sensitivities were determined by taking the average of these local sensitivities at 50 random points sampled across the entire parameter space. Finally, a rescaled sensitivity index (d_n) was determined by dividing the global OAT sensitivity indices by their total sum. The d_n values range from $[0, 1]$, with values closer to 1 indicating a more sensitive parameter.

Range adjustment

Adjustment of ''suggested'' ranges of sensitive input parameters was found to be an essential step prior to quantifying uncertainty of model outputs. Use of unrealistically large parameter ranges may result in a large number of simulations with negative likelihoods (L in Eq. (2)) that renders the GLUE analysis inefficient and prohibitively expensive. Particularly, ranges of calibration parameters that are not determined from landscape attributes should be investigated. For example, consider the model parameters that are used to determine the transport capacity of the channel network (*SPCON*, *SPEXP*, and *PRF* in Table 1). These parameters are not identified based on topographic and/or soil characteristics of the channel segments, but typically determined based on similar research in the study area or through a calibration procedure.

Table 3 Representation of field borders, parallel terraces, grassed waterways, and grade stabilization structures in SWAT

BMP	Function	Representing SWAT parameter		
		Parameter (input file)	Range	Value when BMP implemented
Field border	Increase sediment trapping	*FILTERW* (.hru)	0–5 (m)	5 (m)
Parallel terrace	Reduce overland flow	*CN2* (.mgt)	0–100	[a]
	Reduce sheet erosion	*USLE_P* (.mgt)	0–1	0.1 (terraced)
	Reduce slope length	*SLSUBBSN* (.hru)	10–150	[b]
Grassed waterway	Increase channel cover	*CH_COV* (.rch)	0–1	0.0 (fully protected)
	Reduce channel erodibility	*CH_EROD* (.rch)	0–1	0.0 (non-erosive)
	Increase channel roughness	*CH_N2* (.rch)	0–0.3	0.3
Grade stabilization structure	Reduce gully erosion	*CH_EROD* (.rch)	0–1	0.0 (non-erosive)
	Reduce slope steepness	*CH_S2* (.rch)	–	[c]

[a] Estimated based on land use and hydrologic soil group of the HRU where it is installed for terraced condition.

[b] Estimated for each parallel terrace based on its features and SWAT assigned overland slope of the HRU where it is installed: $SLSUBBSN = (A \times S + B) \times 100/S$, where S is average slope of the HRU; $A = 0.21$ and $B = 0.9$ (ASAE, 2003).

[c] Estimated for each grade stabilization structure based on its features and SWAT assigned slope, CH_S2_{old}, and length of the channel segment where it is installed: $CH\_S\ (2)_{new} = CH\_S2_{old} - D/CH\_L2$, where D is height of the structure (1.2 m) and CH_L2 is length of the channel segment.

The range adjustment process for important model parameters entailed the following steps:

1. *Establish base-case values for input parameters*: the base-case values for the input parameters in Table 1 could be selected by one the following approaches: (i) insights gained from the OAT sensitivity analysis; (ii) model calibration procedure; and (iii) a suggested value obtained from the literature, previous studies in the study area, or prior experience of the analyst. In this analysis, base-case values were selected from a manual calibration (Arabi et al., 2004).
2. *Perform interval-spaced simulations*: the range of each parameter of concern was divided into 50 equal intervals. A SWAT model simulation was performed for a random realization of the parameter from each interval while other parameters were kept at their base-case values. The simulation timeline covered the 1974–1978 period when hydrologic and water quality data were collected at the outlets of the study watersheds.
3. *Adjust ranges of important parameters*: a method based on a goodness-of-fit measure (Nash–Sutcliff coefficient) was developed to reduce the suggested ranges of important parameters to narrower adjusted ranges for the study watersheds. The acceptable ranges of parameters were determined by plotting the Nash–Sutcliff efficiency coefficients ($E_{\text{N-S}}$; Nash and Sutcliff, 1970) computed for interval-spaced simulations. The $E_{\text{N-S}}$ is defined as:

$$E_{\text{N-S}} = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \overline{O})^2} \tag{4}$$

where O_i and P_i are observed and predicted monthly output variables, respectively, while $\overline{O}$ is the average of monthly observed values. $E_{\text{N-S}}$ ranges from $-\infty$ to 1, with higher values indicating a better 1:1 fit between the observed and simulated values. Model simulations with negative $E_{\text{N-S}}$ were considered ''unacceptable'' (Santhi et al., 2001), and subsequently, the range of the parameter was reduced to those that yielded non-negative $E_{\text{N-S}}$ values.

Uncertainty computations

Adjusted parameter ranges from previous step were used to probabilistically determine the effectiveness of BMP implementation. In the present uncertainty analysis, 5000 model simulations were performed for the 1974–1978 period when water quality data were collected. All model parameters in Table 1 were included in the analysis. For those parameters that required range reduction, adjusted ranges were selected from the range adjustment process. For each realization of the parameter space, the uncertainty analysis entailed the following steps:

1. Select parameter values from their specified ranges in a random fashion.
2. Perform model simulation with the selected values to compute model outputs for the scenario without BMPs.
3. Compute likelihood of the simulation for monthly output variables by applying Eq. (3).
4. Represent BMPs by changing appropriate model parameters from Table 3.
5. Compute model outputs for the scenario with BMPs in place.
6. Using GLUE-likelihood weights computed at step (3), generate a cumulative density function for outputs of interest for both model simulations with and without BMPs.

The main assumption in the numerical procedure described above is that the same cumulative likelihood can be used for the scenarios with BMPs and without BMPs. Water quality data utilized in this study were representative of the state of the watersheds before implementation of BMPs. Thus, the likelihood of a set of model parameters to mimic the behavior of the system was computed for the scenario without BMPs. When adequate hydrologic and water quality data are available for both scenarios with BMPs and without BMPs, the GLUE-likelihood functions should be computed separately.

It should be noted that likelihood functions associated with each set of model parameters in the GLUE analysis are likely to be approximately the same before and after implementation of BMPs, if other watershed characteristics remain the same. Representation of BMPs entails only modification of some model parameters for the fields and/or streams where BMPs are implemented. BMPs are implemented in a relatively small area within the watershed. For example, BMPs in Fig. 1 cover less than 5% of total upland fields and the channel network in the Dreisbach and Smith Fry watersheds. Thus, in the absence of water quality data for computation of GLUE-likelihoods for the scenario with or without BMPs, it is suggested that the same likelihood be used for both scenarios.

Results and discussion

Range adjustment results

The results of the range adjustment analysis indicated that none of hydrology-related parameters of the SWAT model needed range reduction. On the other hand, three sediment-related parameters, one total P-related parameter, and one total N parameter required site specific adjustments. Table 4 provides a listing of top five sensitive SWAT parameters in a descending order for monthly streamflow, sediment, total P, and total N output variables. The term ''min$(E_{\text{N-S}})$'' in the table refers to the minimum of Nash–Sutcliff coefficients computed for 50 interval-spaced model simulations corresponding to each parameter. Values in italics indicate parameters with negative ''min$(E_{\text{N-S}})$'' value for which the range adjustment procedure was applied.

Fig. 2 illustrates one dimensional response surface of model outputs at the outlets of the study watersheds to parameters with reduced ranges. The spider-plots (dashed lines) have been generated by varying one parameter at a time, while other parameters were kept constant at their base-case value. Each panel represents 50 model simulations, where the model output is shown on the left *y*-axis and the right *y*-axis displays the Nash–Sutcliff coefficient in Eq. (4). The *x*-axis is the normalized value of each parameter $\bar{\alpha}_i$, determined from its absolute value α_i, and its

Table 4 Top five sensitive SWAT parameters for streamflow, sediment, total P, and total N computations

Variable	Parameter	d_n	min (E_{N-S})	
			Dreisbach	Smith Fry
Streamflow	*SOL_AWC*	0.30	0.19	0.13
	CN	0.20	0.38	0.13
	GW_REVAP	0.17	0.27	0.36
	ESCO	0.09	0.61	0.56
	CH_KI	0.09	0.40	0.60
Sediment	*SPCON*	0.30	−30.59	−4.9
	PRF	0.12	−0.31	−0.85
	SLOPE	0.09	−2.07	0.11
	CH_N2	0.06	−0.27	−0.2
	CN	0.06	0.60	0.01
Total P	*SLOPE*	0.43	−110.02	−10.66
	ORGP_AG	0.25	−1.69	−0.19
	LABP_AG	0.07	0.03	0.4
	CN	0.06	0.09	0.12
	USLE_K	0.05	0.12	0.05
Total N	*SLOPE*	0.51	−132.94	−11.77
	ORGN_AG	0.11	0.03	−0.5
	USLE_K	0.06	0.12	0.05
	CN	0.07	0.18	0.05
	SOL_AWC	0.06	0.14	0.34

d_n is the OAT sensitivity index, ''min (E_{N-S})'' refers to minimum of Nash–Sutcliff coefficient computed for each 50 simulations in the OAT analysis. Description of parameters can be found from Table 1.

respective upper (U_i) and lower (L_i) bounds summarized in Table 1:

$$\bar{\alpha}_i = \frac{\alpha_i - L_i}{U_i - L_i} \quad (5)$$

Eq. (5) can be used to back calculate the absolute parameter values corresponding to the normalized values shown in Fig. 2. A negative ''min (E_{N-S})'' value indicated the necessity for range reduction. For each panel, a horizontal line was drawn at E_{N-S} (right y-axis) equal to zero. The range of the corresponding parameter vector was reduced to the portion that lies above this line. The top panel to the left in Fig. 2 demonstrates how parameter ranges were adjusted. The new parameter ranges for the study watersheds are presented in Table 5.

Sediment outputs were most sensitive to model parameters that are used to estimate the transport capacity of the channel network, usually determined through calibration procedure and not based on land use/soil/management characteristics. The slope of upland areas represented by parameter *SLOPE* was the most sensitive parameter for total P and total N simulations. However, the range of this parameter was not reduced, because it is directly estimated from digital elevation model (DEM). In the absence of field measurements, the initial concentration of phosphorus and nitrogen in soils were reduced to the values reported in Table 5.

Several issues should be considered in interpretation of the results from range adjustment analysis. First, the threshold value of Nash–Sutcliff coefficient that is used to reduce parameter ranges significantly impacts the method. Obviously, a lower E_{N-S} value would result in acceptance of wider parameter ranges. In this study, this threshold was set at zero because the likelihood of model simulations in GLUE uncertainty analysis with negative E_{N-S} values is assumed to be zero (see Eq. (3)). Second, the number of intervals to be used in the range adjustment process should be selected such that the plot of the goodness-of-fit measure (E_{N-S}) over the entire parameter range (e.g. Fig. 2) forms a relatively smooth curve. Our experience from this study indicated that 20–50 intervals should be adequate. The results of the OAT sensitivity analysis and range adjustment process are site specific, and may be different if the watershed conditions are significantly different than those discussed here. We note that the results of the sensitivity analysis are in general agreement with previous studies such as Lenhart et al. (2002); Heuvelmans et al. (2004); Muleta and Niklow (2005) and White and Chaubey (2005).

Uncertainty analysis results

The computational procedure described previously was performed to quantify the uncertainty associated with both model simulations and estimated effectiveness of BMPs. Figs. 3 and 4 depict the cumulative likelihood distribution of average monthly values for various output constituents at the outlet of the Dreisbach and Smith Fry watersheds, respectively. A likelihood weight from Eq. (3) was assigned to each of 5000 model realizations resulting from Monte Carlo simulations. Each panel in the figures contains two cumulative probability distributions for the two scenarios. The dashed lines correspond to results from the GLUE method

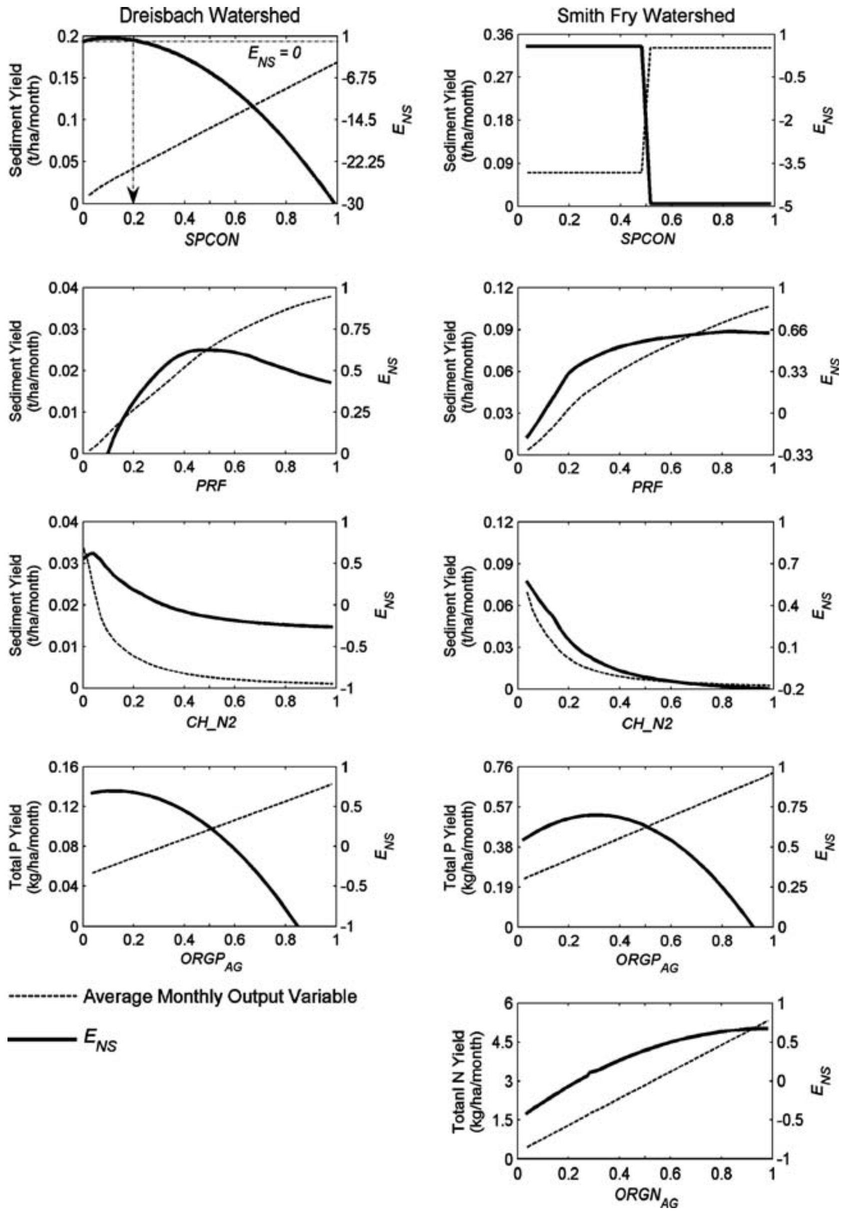

Figure 2 Spider plots for the most sensitive input factors related to water quality computations in SWAT with adjusted ranges in Table 5. Each panel represents 50 model realizations. Subscript ''AG'' refers to agricultural land use.

Table 5 Adjusted parameter ranges for the study watersheds: both suggested ranges and adjusted ranges are based on absolute parameter values

Parameter	Units	Limiting variable	Suggested range	Adjusted range	
				Dreisbach	Smith Fry
SPCON	–	Sediment	0–0.001	0–0.0002	0–0.0005
PRF	–	Sediment	0–2	0.2–2	0.2–2
CH_N2	–	Sediment	0.008–0.3	0.008–0.1	0.008–0.1
ORGP_AG	mg/kg	Total P	0–1000	0–500	0–950
ORGN_AG	mg/kg	Total N	0–10,000	0–10,000	2000–10,000

Description of the parameters can be found in Table 1.

for the scenario without BMPs (scenario A), while the solid lines demonstrate the results for the scenario with BMPs represented in the model (scenario B). Two major trends are evident. First, the difference between GLUE-likelihoods for scenarios A and B was marginal for streamflow, but substantial for sediment, total P, and total N computations.

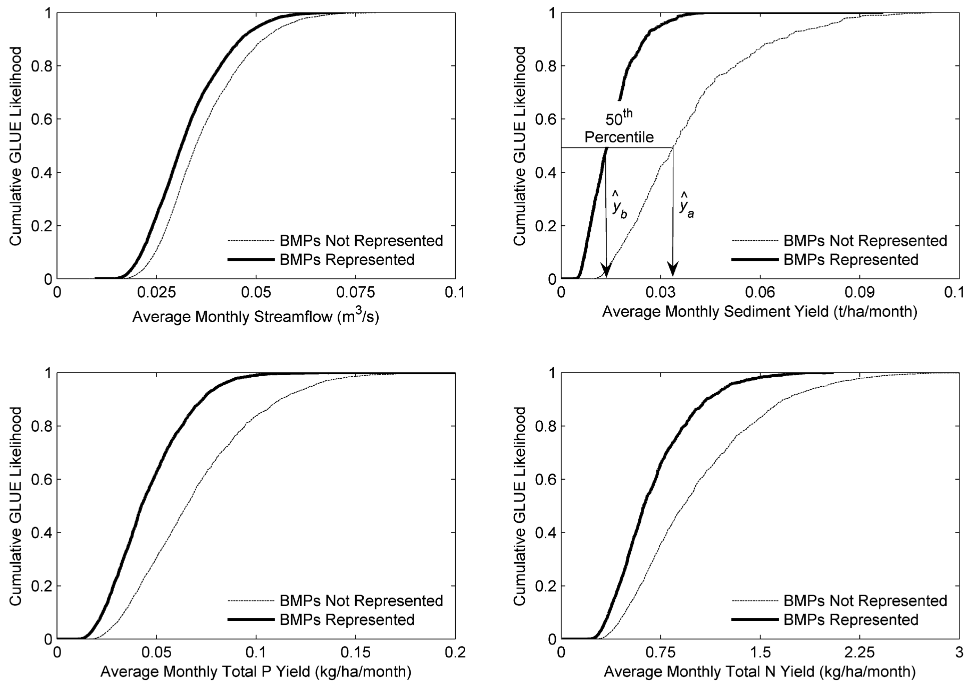

Figure 3 Cumulative GLUE-likelihood for variables simulated at the outlet of the Dreisbach watershed, Indiana. Each panel represents 5000 model realizations. The top panel in the right demonstrates how various percentiles were determined. $\hat{y}_a$ is the median value for scenario A (BMPs not represented), and $\hat{y}_b$ is the median value for scenario B (BMPs represented).

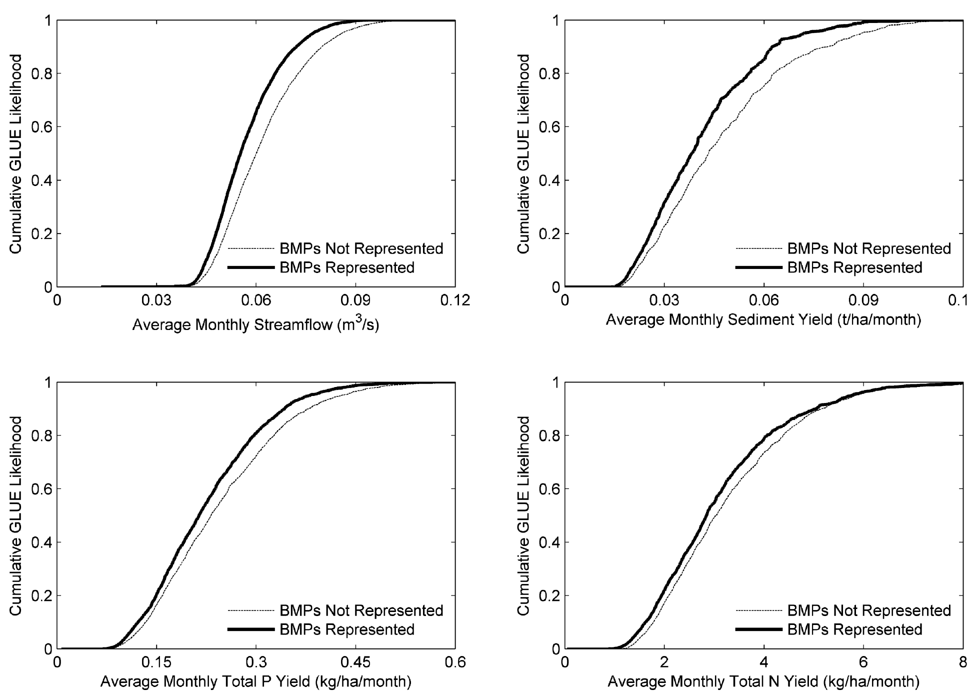

Figure 4 Cumulative GLUE-likelihood for variables simulated at the outlet of the Smith Fry watershed, Indiana. Each panel represents 5000 model realizations.

Second, the trends were quite different in the two study watersheds. Following Figs. 3 and 4, the results are summarized in Table 6 for further discussion.

Lower and upper bounds in Table 6 refer to 5th and 95th percentiles of the cumulative likelihoods, respectively, while the median represents the 50th percentile. The top panel on the right in Fig. 3 demonstrates how various percentiles were determined. For scenario A, comparison of median values to the average of monthly observed data, also presented in Table 6, indicate that averages of monthly

Table 6 Summary of the results from analysis of uncertainty

Watershed	Variable	Units	Average observed value	Scenario A without BMPs		Scenario B with BMPs		Reduction (%)	
				$\hat{y}_a$	Range	$\hat{y}_b$	Range	$\hat{r}_i$	Range
Dreisbach	Streamflow	m^3/s	0.039	0.041	[0.026, 0.062]	0.037	[0.023, 0.056]	9.8	[9.70, 11.5]
	Sediment	t/ha/month	0.031	0.035	[0.015, 0.083]	0.015	[0.007, 0.033]	57.1	[53.3, 60.2]
	Total P	kg/ha/month	0.095	0.069	[0.030, 0.125]	0.046	[0.015, 0.086]	33.3	[31.2, 45.0]
	Total N	kg/ha/month	1.228	1.145	[0.487, 2.385]	0.788	[0.360, 1.502]	31.2	[26.1, 37.0]
Smith Fry	Streamflow	m^3/s	0.054	0.06	[0.045, 0.086]	0.055	[0.042, 0.077]	8.3	[6.70, 10.5]
	Sediment	t/ha/month	0.093	0.043	[0.021, 0.107]	0.037	[0.018, 0.090]	14	[12.8, 15.9]
	Total P	kg/ha/month	0.336	0.267	[0.115, 0.551]	0.243	[0.098, 0.502]	9	[8.90, 14.8]
	Total N	kg/ha/month	6.112	3.026	[1.552, 5.838]	2.847	[1.450, 5.560]	5.9	[4.70, 6.60]

$\hat{y}$ refers to 50th percentile (median) of output variables for 5000 Monte Carlo simulations of the SWAT model, $\hat{r}_i$ is the 50th percentile (median) of estimated reduction of output variables due to implementation of BMPs computed by Eq. (6) for 5000 Monte Carlo simulations of the SWAT model, and ''range'' refers to the 5th and 95th percentile of the Monte Carlo simulations.

observed values for streamflow were within ±15% of the median in both study watersheds, and fell well within the uncertainty ranges from GLUE. Sediment yield measurements at the outlet of the Dreisbach and Smith Fry watersheds were within ±20% of the median values, also well covered by the uncertainty bounds. The median values for total P appeared to adequately match the average of monthly observations as they underpredicted by only 27% and 20% in Dreisbach and Smith Fry, respectively. Moreover, the uncertainty bounds covered the data. The median for total N determined for Dreisbach watershed differed from the average of monthly observed values by only 7%, indicating satisfactory results from GLUE. Total N at the outlet of Smith Fry was the only case where the uncertainty bounds from GLUE did not contain the observed value. The corresponding median underpredicted total N yield by nearly 50%, perhaps because of structural uncertainties involved in simulations. In particular, a lack of proper linkage between fluvial channel processes and in-stream nutrient processes in SWAT could be responsible for these results.

These values may now be compared to corresponding quantities for scenario B listed in Table 6. Comparison of the expected values for scenarios A and B revealed the estimated effectiveness of BMPs, shown as a percent reduction. The percent reduction of each constituent as a result of implementation of BMPs was determined as:

$$r_i = \frac{\hat{y}_{i,a} - \hat{y}_{i,b}}{\hat{y}_{i,a}} \times 100 \qquad (6)$$

where i is the constituent of interest, i.e. streamflow, sediment yield, total P load, or total N load, r_i is percent reduction of constituent i, $\hat{y}_{i,a}$ is the median of constituent i for scenario A, and $\hat{y}_{i,b}$ is the median of constituent i for scenario B. The results indicated that implementation of BMPs as shown in Fig. 1 would not reduce streamflows significantly. This did not come as a surprise because the BMPs implemented in the watersheds were mostly sediment control BMPs. Implementation of the 26 BMPs in the Dreisbach watershed would lower median sediment yield by nearly 57%, from 0.035 t/ha/month to 0.015 t/ha/month. The estimated reduction rates for total P and total N at the Dreisbach outlet were 33% and 31%, respectively. The estimated reduction rates at the outlet of Smith Fry were nearly 14%, 9%, and 6% for sediment yield, and total P and total N loads (Table 6). These rates suggested that implementation of the BMPs in Smith Fry was almost four times less effective than the ones in Dreisbach, which was anticipated because of smaller number of BMPs in the former.

The uncertainty bounds associated with absolute predictions of the SWAT model were much larger than the ones corresponding to the estimated effectiveness of BMPs. For example, the uncertainty bound for monthly sediment yield at the outlet of Dreisbach for the simulation period under scenario A (scenario with no BMP represented) was determined to be [0.015, 0.083] with a median value of 0.035 t/ha/month (Table 6). Incorporation of this large uncertainty in decision making and management may be extremely costly and not feasible. However, as is evident in Table 6, the estimated 5th and 95th uncertainty bounds for estimated effectiveness of BMPs in the Dreisbach watershed in reducing sediment yield at its outlet were [53%,60%] with a median (50th percentile) of 57%. Likewise, the estimated effectiveness of BMPs in Smith Fry was estimated to range between [13%, 16%] with a median of 14%. Similar results were observed for streamflow, total P, and total N computations for the study watersheds.

Discussion

The conceptual simplicity is an attractive feature of the computational analysis developed in this study. The utilized likelihood measure, Nash–Sutcliff coefficient, is widely used by modelers for calibration and validation of watershed models. Also, the OAT-GLUE methodology will, more than likely, produce various sets of model parameters that adequately satisfy calibration criteria that are usually set based on Nash–Sutcliff coefficient. This helps modelers avoid the cumbersome practice of manual calibration. That the uncertainty bounds of various constituents encompassed the corresponding observed values (except for only one case for total N in the Smith Fry watershed) strongly support this suggestion. It appears that for the Dreisbach and Smith Fry watersheds, sediment and nutrient outputs of the SWAT model bear more uncertainty than streamflow simulations.

Consolidation of results in Tables 4 and 6 from the three-step procedure indicate that reducing the uncertainty associated with absolute sediment and nutrient outputs of the SWAT model to practical ranges may not be feasible. Sediment outputs of the model were found to be most sensitive to transport capacity of channel network. Some of the parameters that are used to determine the transport capacity of channel segments (*SPCON*, *SPEXP*, and *PRF* in Table 1) cannot be measured in the field and are usually calibrated from a broad ''suggested'' range. With availability of more data, the three-step procedure used in this study may result in more narrow uncertainty bounds for absolute predictions. Nevertheless, it may still not be adequate for reducing the uncertainty associated with these absolute model predictions to small enough ranges to be useful for practical management decisions. However, *comparison* of sediment and nutrient outputs from model simulations with and without representation of BMPs would not suffer from such limitations as demonstrated here. It is evident that incorporation of modeling uncertainty in informed decision-making is more practical through communicating the uncertainty associated with evaluation of effectiveness of management actions.

The foregoing results indicate that the computational framework developed in this study could be endorsed by watershed management programs such as the TMDL as advocated in Zhang and Yu (2004). Once the level of protection to be provided by the margin of safety (MOS) is specified by decision makers, the probabilistic framework presented in this study could be applied to verify the success of a particular management action in achieving its designated goals. Implementation of the estimated MOS is more feasible in this context, as opposed to the MOS computed from uncertainty analysis of absolute model predictions where the additional cost of implementation may render its consideration impractical. Finally, the methodology can be easily incorporated in watershed models such as SWAT that are commonly used for TMDL development. Land use in the study watershed has changed since data were collected. Thus, application of the results presented herein is limited to demonstration of the methodology.

Conclusions

A computational framework was developed, in which investigation of uncertainty provides complementary quantitative and qualitative information to support management and decision making. The analysis focused specifically on two issues. First, ranges of some model parameters may require site-specific adjustments with available data. This was particularly evident for parameters that are not determined from landscape characteristics. Second, the uncertainty associated with estimated effectiveness of BMPs is substantially smaller than the uncertainty associated with absolute predictions. The computational procedure for analysis of uncertainty was performed for two Indiana watersheds with relatively similar spatial scale, and landscape characteristics, but different number of installed BMPs. It was demonstrated that the computational framework is capable of quantifying uncertainty of effectiveness of implemented BMPs in both watersheds. Future work will focus on investigation of the utility of the developed methodology in the TMDL process. Especially, the means for coping with the margin of safety (MOS) in the TMDL formula should be explored.

References

Arabi, M., Govindaraju, R.S., Hantush, M.M., 2004. ''Source identification of sediments and nutrients in watersheds- Final report.'' EPA/600/R-05/080, National Risk Management Research Laboratory, Office of Research and Development, U.S. Environmental Protection Agency, Cincinnati, OH 45268, 120 pp. Available from: <www.epa.gov/ORD/NRMRL/pubs/600r05080/600r05080.pdf>.

Arabi, M., Govindaraju, R.S., Hantush, M.M., 2006. Role of watershed subdivision on evaluation of long-term impact of best management practices on water quality. Journal of American Water Resources Association 42 (2), 513–528.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment. Part I: model development. Journal of the American Water Resources Association 34 (1), 73–89.

ASAE, 2003. Design, Layout, Construction and Maintenance of Terrace Systems, ASAE Standards S268, 4-Feb-03, St. Joseph, MI.

Beck, M.B., 1987. Water quality modeling: a review of the analysis of uncertainty. Water Resources Research 23 (8), 1393–1442.

Benaman, J., Shoemaker, C.A., 2004. Methodology for analyzing range of uncertain model parameters and their impact on total maximum daily load process. Journal of Environmental Engineering, ASCE 130 (6), 648–656.

Beven, K.J., Binely, A.M., 1992. The future of distributed models: model calibration and uncertainty prediction. Hydrological Processes 6, 279–298.

Beven, K.J., Freer, J., 2001. Equifinality, data assimilation, and uncertainty estimation in mechanistic modeling of complex environmental systems using the GLUE methodology. Journal of Hydrology 249 (2001), 11–29.

Dilks, D.W., Freedman, P.L., 2004. Improved consideration of the Margin of Safety in Total Maximum Daily Load development. Journal of Environmental Engineering, ASCE 130 (6), 690–694.

Edwards, D.R., Daniel, T.C., Scott, H.D., Murdoch, J.F., Habiger, M.J., Burkes, H.M., 1996. Stream quality impacts of Best Management Practices in a Northwestern Arkansas basin. Journal of the American Water Resources Association 32 (3), 499–509.

EPA, 2005. 2002 Section 303(d) List Fact Sheet for INDIANA. Available from: <http://oaspub.epa.gov/waters/state_rept.control?p_state=IN>, accessed on August 2005.

Fiener, P., Auerswald, K., 2006. Seasonal variation of grassed waterway effectiveness in reducing runoff and sediment delivery from agricultural watersheds in temperate Europe. Soil & Tillage Research 87 (2006), 48–58.

Freer, J., Beven, K., 1996. Bayesian estimation of uncertainty in runoff prediction and the value of data: an application of the GLUE approach. Water Resources Research 32 (7), 2161–2173.

Green, W.H., Ampt, G.A., 1911. Studies on soil physics: 1. The flow of air and water through soils. Journal of Agricultural Sciences 4, 11–24.

Griffin, C.B., 1995. Uncertainty analysis of BMP effectiveness for controlling nitrogen from urban nonpoint sources. Journal of the American Water Resources Association 31 (6), 1041–1050.

Heuvelmans, G., Muys, B., Feyen, J., 2004. Evaluation of hydrological model parameter transferability for simulating the impact of land use on catchment hydrology. Physics and Chemistry of the Earth 29 (2002), 739–747.

Ice, G., 2004. History of innovative best management practice development and its role in addressing water quality limited waterbodies. Journal of Environmental Engineering, ASCE 130 (6), 684–689.

Kirsch, K., Kirsch, A., Arnold, J.G., 2002. Predicting sediment and phosphorous loads in the Rock River basin using SWAT. The Transactions of ASAE 45 (6), 1757—1769.

Lake, J., Morrison, J., 1977. Environmental impacts of land use on water quality, Final report on the Black Creek project-project data. EPA-905/9-77-007-C, U.S. Environmental Protection Agency, Chicago, IL.

Lake, J., Morrison, J., 1978. Environmental impact of land use on water quality — Final report on the Black Creek project — Technical report. EPA-905/9-77-007-B, U.S. Environmental Protection Agency, Chicago, IL.

Lenhart, T., Eckhardt, K., Fohrer, N., Frede, H.-G., 2002. Comparison of two approaches of sensitivity analysis. Physics and Chemistry of the Earth 27 (2002), 645—654.

Morris, M.D., 1991. Factorial sampling plans for preliminary computational experiments. Technometrics 33, 161—174.

Morrison, J., Lake, J., 1983. Environmental impacts of land use on water quality, Black Creek Project — Final report. Allen County Soil and Water Conservation District, Fort Wayne, IN.

Mostaghimi, S., Park, S.W., Cook, R.A., Wang, S.Y., 1997. Assessment of management alternatives on a small agricultural watershed. Water Research 31 (8), 1867—1878.

Muleta, M.K., Niklow, J.W., 2005. Sensitivity and uncertainty analysis coupled with automatic calibration for a distributed watershed model. Journal of Hydrology 306 (2005), 127—145.

Nash, J.E., Sutcliff, J.V., 1970. River flow forecasting through conceptual models. Part 1 — a discussion of principles. Journal of Hydrology 10 (1970), 282—290.

Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., King, K.W., 2002. Soil and Water Assessment Tool theoretical documentation, version 2000. Grassland, Soil and Water Research Laboratory, Agricultural Research Service, Temple, TX.

NRC, 2001. Assessing the TMDL approach to water quality management. Committee to Access the Scientific Basis of the Total Maximum Daily Load Approach to Water Pollution Reduction, Water Science and Technology Board, Division on Earth and Life Studies, National Research Council, Washington, DC.

Osidele, O.O., Zeng, W., Beck, M.B., 2003. Coping with uncertainty: a case study in sediment transport and nutrient load analysis. Journal of Water Resources Planning and Management 129 (4), 345—355.

Saleh, A., Arnold, J.G., Gassman, P.W., Hauch, L.M., Rosenthal, W.D., Williams, J.R., McFarland, A.M.S., 2000. Application of SWAT for the Upper North Bosque River watershed. The Transactions of ASAE 43 (5), 1077—1087.

Saltelli, A., Chan, K., Scott, E.M., 2000. Sensitivity Analysis. Wiley, Chichester.

Santhi, C., Arnold, J.G., Williams, J.R., Dugas, W.A., Srinivasan, R., Hauck, L.M., 2001. Validation of the SWAT model on a large river basin with point and nonpoint sources. Journal of the American Water Resources Association 37 (5), 1169—1188.

Santhi, C., Srinivasan, R., Arnold, J.G., Williams, J.R., 2003. A modeling approach to evaluate the impacts of water quality management plans implemented in the Big Cypress Creek Watershed. In: Second conference on Watershed Management to Meet Emerging TMDL Environmental Regulations, Albuquerque, NM, pp. 384—394.

Spear, R.C., Hornberger, G.M., 1980. Eutrophication in Peel Inlet II: identification of critical uncertainties via generalized sensitivity analysis. Water Research 14, 43—49.

Spear, R.C., Grieb, T.M., Shang, N., 1994. Parameter uncertainty and interaction in complex environmental models. Water Resources Research 30 (11), 3159—3169.

USDA Soil Conservation Service, 1972. Section 4 — Hydrology, Chapters 4—10. National Engineering Handbook. UDSA, Washington, DC.

White, K.L., Chaubey, I., 2005. Sensitivity analysis, calibrations, and validation for a multisite and multivariate SWAT model. Journal of the American Water Resources Association 41 (5), 1077—1089.

Williams, J.R., 1969. Flood routing with variable travel time or variable storage coefficients. The Transactions of the ASAE 12 (1), 100—103.

Williams, J.R., 1975. Sediment-yield prediction with universal equation using runoff energy factor, in Present and prospective technology for predicting sediment yield and sources. In: Proceedings of the Sediment Yield Workshop, Oxford, MS, pp. 244—252.

Wischmeier, W.H. Smith, D.D., 1978. Predicting Rainfall Erosion Losses: A Guide to Conservation Planning. Agriculture Handbook No. 537, US Department of Agriculture, Washington, DC.

Zhang, H.X., Yu, S.L., 2004. Applying the first-order error analysis in determining the margin of safety for total maximum daily load computations. Journal of Environmental Engineering 130 (6), 664—673.