SENSITIVITY AND FIRST-ORDER/MONTE CARLO UNCERTAINTY ANALYSIS OF THE WEPP HILLSLOPE EROSION MODEL

J. C. Ascough II, D. C. Flanagan, M. A. Nearing, B. A. Engel

ABSTRACT. *Performing a comprehensive sensitivity/uncertainty analysis is a valuable step in understanding and using a predictive hydrologic/water quality (H/WQ) model. This article applies one-factor-at-a-time (OAT) sensitivity analysis (SA) and first-order error analysis (FOEA)/Monte Carlo simulation with Latin hypercube sampling (LHS) uncertainty analysis techniques for evaluation of a complex, process-based water erosion prediction tool, the USDA Water Erosion Prediction Project (WEPP) model (version 2010.1). Assessment of the WEPP hillslope profile model on a Midwestern U.S. Miami silt loam soil for three cropping/management scenarios and three erosion process cases (as defined by topography) is described. WEPP model runoff, soil loss, and corn (*Zea mays *L.) yield output responses in the form of expected values and error variances were determined to illustrate model prediction uncertainty. The OAT SA showed that WEPP runoff and soil loss output responses were most sensitive to changes in the baseline effective hydraulic conductivity (K_b) and sand content. WEPP model corn yield output response was most sensitive to crop input parameters affecting the simulation of biomass development. The FOEA showed that the largest contributions to runoff, soil loss, and corn yield total error variance came from K_b and sand/clay content, K_b and baseline soil erodibility factors, and the biomass energy ratio of a crop and harvest index, respectively. The FOEA total variances presented in this study for runoff and soil loss were considerably larger than the corresponding Monte Carlo LHS simulation total variances. The Monte Carlo LHS total variance results were reasonable, making Monte Carlo LHS appear to be a better alternative for quantifying WEPP output response error variance. The Monte Carlo LHS soil loss output responses were also compared to Universal Soil Loss Equation (USLE) soil loss predictions. The USLE soil loss estimates were within the Monte Carlo LHS 90% prediction intervals for six of the nine cropping/management and erosion process cases. Results of this study illustrate the usefulness of combining SA and Monte Carlo LHS for providing detailed uncertainty analysis information for complex, physically based models such as WEPP.*

Keywords. *Erosion modeling, First-order error analysis (FOEA), Monte Carlo simulation, Sensitivity analysis, Soil erosion, Uncertainty analysis, WEPP model.*

Hydrologic/water quality (H/WQ) models are simplified realizations of physical processes governing the hydrology and water quality of a natural system (e.g., a field or watershed). Bobba et al. (1995) presented two fundamental reasons for constructing mathematical representations of natural systems: (1) they increase the current level of understanding regarding cause-effect relationships operative in natural environments, and (2) models provide a synthesis of understanding that is increasingly important in a regulatory context. If a model is going to be used in the policy arena (e.g., to target water quality initiatives) or for consulting or management purposes (e.g., to meet production level and/or environmental constraints), the model must represent reality in terms of the impact of these practices on environmental factors. Thus, realistic assessment of model performance requires an assessment of model output response validity. Moreover, the user should consider errors or aspects of uncertainty that may be present in the model before application to a situation (Reckhow, 1994).

Model evaluation can include sensitivity analysis (SA), uncertainty analysis, calibration, and validation. SA is of primary importance in evaluating any model and is potentially useful in all phases of model development, including model formulation, model calibration, and model verification (McCuen and Snyder, 1986). Saltelli et al. (2004) defined SA as "the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input." The goal of SA is to determine how sensitive the output of a model is with respect to the elements of the model that are subject to uncertainty or variability. As

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The authors are **James C. Ascough II,** Research Hydraulic Engineer, USDA-ARS Agricultural Systems Research Unit, Fort Collins, Colorado; **Dennis C. Flanagan, ASABE Fellow,** Research Agricultural Engineer, USDA-ARS National Soil Erosion Research Laboratory, West Lafayette, Indiana; **Mark A. Nearing,** Research Agricultural Engineer, USDA-ARS Southwest Watershed Research Center, Tucson, Arizona; and **Bernard A. Engel, ASABE Member,** Professor and Head, Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, Indiana. **Corresponding author:** James C. Ascough II, USDA-ARS Northern Plains Area, Agricultural Systems Research Unit, 2150 Centre Ave., Bldg. D, Suite 200, Fort Collins, CO, 80526; phone: 970-492-7371; e-mail: jim.ascough@ars.usda.gov.

such, SA can aid in identifying parameters that greatly influence processes of the physical system and can also be used to ascertain the impact of parameter variability on the modeled variance (Nearing et al., 1990). SA methods are typically classified as local (i.e., derivative-based) or global (Saltelli et al., 2008). Local one-factor-at-a-time (OAT) sensitivity analyses typically assume that: (1) input parameters are independent of one another (i.e., parameter covariances are ignored); (2) expected model response is equal to the model response using the mean value of each parameter; and (3) model error predictions can be approximated by testing small linear perturbations in the input parameters (Gardner et al., 1981). Although the OAT perturbation method, in which the parameters are varied individually, makes complex interactions difficult to determine, it provides a quick way to establish a ranked list of parameters to which particular attention should be paid for further uncertainty analysis.

Uncertainties are inherent in parameterization and model estimation; therefore, error must be expected but the level of uncertainty should be quantified. Classical uncertainty analysis (UA) involves the determination of the variation or imprecision in the model response that results from the collective variation in the model variables (Iman and Helton, 1988). The importance of incorporating uncertainty analysis into H/WQ modeling has been illustrated by numerous authors (e.g., Bobba et al., 1995; Haan et al., 1995, 1998; Hession et al., 1996; Beck, 1987, 1999; Melching and Bauwens, 2001; Wu et al., 2006; Shen et al., 2008, 2010; Harmel et al., 2010). Due to the complexity of most contemporary H/WQ models, evaluation of model credibility using calibration, verification, and post-audit procedures is required. Furthermore, there is a need for clearly displaying model reliability in the decision-making arena, and it should be addressed as quantitatively as possible (Thomann, 1982).

The Water Erosion Prediction Project (WEPP) was initiated in 1985 by several federal agencies to develop new-generation soil erosion prediction technology to replace the mature technology of the Universal Soil Loss Equation (USLE) (Foster and Lane, 1987). Advantages of the WEPP model over USLE erosion prediction technology include its ability to estimate spatial and temporal distributions of soil loss, as well as predict sediment deposition and delivery (Flanagan et al., 2007). WEPP is a continuous simulation model with daily time steps and contains the fundamentals of stochastic weather generation, infiltration theory, hydrology, soil physics, plant science, hydraulics, erosion mechanics, and many other components that make it more applicable than the USLE for erosion prediction (Flanagan et al., 2001, 2007). Several sensitivity and uncertainty analyses have been conducted for parameterization and improvement of WEPP algorithms. Nearing et al. (1990) conducted an SA for the WEPP hillslope profile model for cropland conditions using the single-event storm option. They used a relative normalized sensitivity index for the extremes of the input parameter ranges and determined that rill erodibility, rill cover, critical hydraulic shear, and rill friction factors were the most important factors for accurately estimating soil loss with WEPP. Flanagan and Nearing (1991) conducted an updated SA for the WEPP hillslope profile model on cropland that reflected model changes since 1990. The relative normalized sensitivity index of Nearing et al. (1990) was used, and the results showed that the model was most sensitive to input parameters affecting average rainfall intensity along with erodibility, slope, and infiltration (i.e., effective hydraulic conductivity). Tiscareno-Lopez et al. (1993, 1994) assessed uncertainty in WEPP hydrologic and soil erosion predictions for rangeland applications using Monte Carlo simulation and experimental data from the Walnut Gulch Experimental Watershed near Tombstone, Arizona. WEPP sensitivity results for hillslope input parameters showed that hydrologic and erosion predictions were very sensitive to attributes that define a storm event (amount, duration, and time to peak and intensity) and to the effective hydraulic conductivity parameter (Tiscareno-Lopez et al., 1993). Estimates of sediment detachment occurring in the channel bed and total sediment yield at the watershed outlet were highly sensitive to total Manning's n, but only slightly sensitive to erodibility and critical shear stress channel parameters (Tiscareno-Lopez et al., 1994).

Baffaut et al. (1997) used the WEPP watershed model to evaluate the effects of watershed discretization for selected events within one-year continuous simulations by comparing results for two watersheds under various discretization schemes. Impacts of channel input parameters were assessed by comparing the value of a linear sensitivity coefficient for user-specified parameters. Hillslope length, Manning's coefficients, and channel slope were found to be key parameters in the prediction of watershed sediment yields. Erodibility and critical shear stress were found to be important for events where channel scour was active, and the results were sensitive to the hydraulic conductivity for events with small runoff and small sediment contributions from hillslopes. Brunner et al. (2004) used WEPP to determine the impact of spatial distribution of soil types on soil loss for a hillslope in Uganda. Model performance was evaluated by an SA, which showed that WEPP was sensitive to vertical changes in soil properties to a depth of 40 cm. High sensitivity to soil texture indicated that the catenary sequence at the study site may have had a strong influence on model simulations. Pandey et al. (2008) performed an SA on WEPP model input parameters for a small hilly watershed (Karso) in India. The analysis showed that sediment yield was highly sensitive to interrill erodibility and effective hydraulic conductivity, whereas runoff was sensitive to effective hydraulic conductivity only. Mullan et al. (2012) used WEPP to simulate soil erosion rates under climate change scenarios for a case study hillslope in Northern Ireland. A simple SA approach was employed to investigate the previously unstudied impacts of sub-daily rainfall intensity changes. Results indicated a mix of soil erosion increases and decreases depending on which scenarios were considered. For example, downscaled climate change projections in isolation generally resulted in erosion decreases, whereas large increases were projected when land use was changed from grass to a tilled row crop and/or where large changes in sub-daily rainfall intensity were applied.

Chaves and Nearing (1991) used the modified point estimate method (Harr, 1989) to evaluate error propagation in WEPP model output responses for single storm events. Maximum coefficients of variation for peak runoff rate, average soil loss, sediment yield, and sediment enrichment ratio were 196%, 267%, 323%, and 47%, respectively. The coefficient of variation was less for larger runoff and erosion events, which account for a large percentage of the total soil loss at a location over extended time periods. Additionally, Chaves and Nearing (1991) found that the inclusion of correlation between input parameters significantly reduced the coefficient of variation for the model output responses. Tiscareno-Lopez (1995) used a Monte Carlo simulation scheme (with correlated variable generation) to assess uncertainties in WEPP model predictions. The contribution of parameter variance and model bias on the mean square error of model output response variables was quantified, with significant findings including: (1) WEPP prediction errors were found to be uniformly distributed for runoff volume, (2) there was a moderate tendency for errors to increase for peak runoff, and (3) errors increased significantly for sediment yield predictions. All three error types tended to increase for large rainfall events, and model bias contributed the most to total error. Brazier et al. (2000, 2001) utilized the Generalized Likelihood Uncertainty Estimation (GLUE; Beven and Freer, 2001) approach for assessing the degree of uncertainty surrounding WEPP model output for two sets of runoff/soil loss plot replicates. Results indicated that the generated uncertainty bounds were often wide, with attention brought to the problem of underprediction of large events and overprediction of small events as an area where WEPP model improvements could be made (particularly in the case of relatively dry years).

While these studies demonstrate distinctive sensitivity and statistical uncertainty analysis techniques for assessing WEPP, an integrated sensitivity/uncertainly analysis methodology for straightforward and comparable WEPP model evaluation has not yet been presented. In addition, a multitude of corrections and enhancements to the WEPP model code (v2010.1) used in this article have been made since the last published articles on WEPP SA/UA. In this study, application of SA and first-order error analysis (FOEA)/Monte Carlo simulation to the continuous WEPP hillslope profile model (version 2010.1) is discussed, focusing on crop management effects on model output responses. Specific study objectives are to: (1) evaluate WEPP runoff, soil loss, and corn (*Zea mays* L.) yield model output responses using one-factor-at-a-time (OAT) SA, FOEA, and Monte Carlo simulation with Latin hypercube sampling (LHS); (2) determine WEPP output response overall error variances; and (3) compare and contrast the SA, FOEA, and Monte Carlo LHS methodologies and recommend those best suited for evaluating WEPP and other H/WQ models.

Methods and Materials

This section briefly describes the WEPP model and defines the scenarios and respective input parameters used to analyze model uncertainty. Analysis techniques include OAT SA, FOEA, and Monte Carlo LHS simulation, for which methodology is also briefly presented.

WEPP Scenarios and Input Parameters

The WEPP model was developed to simulate the major processes of overland flow, sheet and rill erosion, and erosion from small channels such as ephemeral gullies. The spatial scale for hillslope profile simulations is typically from 1 to ~100 m in length, although in some situations longer hillslopes of several hundred meters may be adequately simulated (Flanagan et al., 2012). Hillslope profiles may also be subdivided into multiple overland flow elements (OFEs), which are unique spatial regions having homogeneous soils and cropping/management. The simplest type of WEPP model simulation is for a single storm event and a single hillslope profile with basic input files including slope, soil, management, and climate. Detailed description of WEPP model hillslope and channel processes can be found in Foster et al. (1995) and Flanagan and Nearing (2000). Additionally, Flanagan et al. (2012) discuss WEPP use, calibration, and validation and also present model single storm hillslope profile and continuous simulation watershed case study applications selected from the literature.

Soil type and management conditions representing the Midwestern U.S. were selected for this study. A Miami silt loam soil under management conditions for conventional tillage corn (CT, spring plow), no-till corn (NT), and tilled fallow (tilled throughout summer for weed control) was used. Table 1 lists statistics, assigned probability distributions, and additional information for Miami silt loam gathered from SSURGO soils data from the USDA Natural Resources Conservation Service (NRCS) and from field data (Elliot et al., 1989). Table 2 lists statistics for WEPP model cropping and management parameter values (all parameters in this table were assigned a normal probability distribution). The cropping and management parameter values in table 2 and all input parameter probability distributions were determined by literature review and expert opinion of university and USDA-NRCS agronomists.

All WEPP OAT SA, FOEA, and Monte Carlo LHS simulation runs were made for 100 years and used CLIGEN 5.3 (Nicks et al., 1995) generated weather data (i.e., precipitation, temperature, solar radiation, and wind speed) for West Lafayette, Indiana. In addition, 100-year WEPP baseline simulation runs for the SA and FOEA were made using baseline values (table 1) for all input parameters to establish expected values for model output responses. Baseline effective hydraulic conductivity (K_b), soil erodibility factors (interrill erodibility factor K_i, and rill erodibility factor K_r), and critical hydraulic shear stress (τ_c) were calculated from recommended equations in the WEPP User Summary (Flanagan and Livingston, 1995) using baseline soil parameter values.

For ease of tabular presentation, some WEPP variable names are used instead of a lengthy text description. To assist the reader with the interpretation of the tables, the definitions of some of the less common variable names are

Table 1. Statistics and probability distributions for WEPP model Miami soil input parameters.

Parameter[a]	Units	Distribution Type	Baseline Value	Coefficient of Variation (%)	Variance	Range of Test (min. to max.)
Sand	%	Normal	18	25	20.25	12 to 30
Clay	%	Normal	16	17.2	7.57	11 to 22
Organic matter	%	Normal	1.5	25	0.141	1.0 to 2.5
CEC	meq/100 g	Normal	15	11.7	3.08	10 to 17
Soil albedo	unitless	Normal	0.23	20.0	0.0021	0.2 to 0.4
K_b	mm h^{-1}	Lognormal	2.85[b]	54[c]	1.4[c]	2.5 to 4.4
K_i	kg·s·m^{-4}	Normal	5,171,920[b]	28	2.079×10^{12}	2×10^6 to 8.5×10^6
K_r	s m^{-1}	Normal	0.0124[b]	73	8.25×10^{-5}	0.002 to 0.0225
τ_c	Pa	Normal	3.5[b]	60	4.43	3.0 to 4.0

[a] All values are for the A horizon. CEC = cation exchange capacity, K_b = effective hydraulic conductivity, K_i = interrill erodibility factor, K_r = rill erodibility factor, and τ_c = critical shear stress.
[b] Baseline values calculated from WEPP User Summary (Flanagan and Livingston, 1995) recommended equations.
[c] Coefficient of variation (CV) and variance calculated from WEPP soils in like textural classes.

Table 2. Statistics for WEPP model cropping and management input parameters.

Parameter[a]	Units	Baseline Value	Coefficient of Variation (%)	Variance	Range of Test (min. to max.)
Management					
Planting date	days	125	6	56.25	110 to 140
Harvest date	days	288	2.6	56.25	275 to 301
BB	unitless	3.6	20.83	0.5625	3 to 5
BBB	unitless	3.0	25	0.5625	2 to 5
BEINP	kg MJ^{-1}	28	26.8	56.25	15 to 40
ORATEA and ORATER	unitless	0.0065	38.5	6.25×10^{-6}	0.005 to 0.01
GDDMAX	°C-days	1700	23.5	1.6×10^5	500 to 2000
HI	unitless	0.5	10	0.0025	0.4 to 0.6
Ridge random roughness[b]					
Fertilizer applicator	m	0.01524	33.3	2.6×10^{-5}	0.008 to 0.025
Tandem disk	m	0.02032	25.0	2.6×10^{-5}	0.010 to 0.030
Field cultivator	m	0.01778	28.6	2.6×10^{-5}	0.009 to 0.028
Row planter with sweeps coulter	m	0.01016	50.0	2.6×10^{-5}	0.005 to 0.020
Row cultivator	m	0.01778	28.6	2.6×10^{-5}	0.009 to 0.028
Moldboard plow	m	0.04826	10.5	2.6×10^{-5}	0.038 to 0.058
Row planter with smooth coulter	m	0.01016	50.0	2.6×10^{-5}	0.005 to 0.020
Ridge height[b]					
Fertilizer applicator	m	0.0254	50.0	1.61×10^{-4}	0.013 to 0.051
Tandem disk	m	0.0508	25.0	1.61×10^{-4}	0.025 to 0.076
Field cultivator	m	0.0254	50.0	1.61×10^{-4}	0.013 to 0.051
Row planter with sweeps coulter	m	0.0508	25.0	1.61×10^{-4}	0.025 to 0.076
Row cultivator	m	0.0762	16.7	1.61×10^{-4}	0.051 to 0.102
Moldboard plow	m	0.0762	16.7	1.61×10^{-4}	0.051 to 0.102
Row planter with smooth coulter	m	0.0508	25.0	1.61×10^{-4}	0.025 to 0.076

[a] BB and BBB = parameters describing the relationship between crop canopy cover and vegetative aboveground live biomass, respectively; BEINP = parameter describing the biomass energy ratio of a crop; ORATEA = maximum rate of surface residue decay under optimum conditions; ORATER = maximum rate of decay for dead root biomass; GDDMAX = potential accumulation of growing degree days from planting to crop maturity; and HI = harvest index. All parameters were assigned a normal probability distribution.
[b] Minimum value reflects smoother surface effect; maximum value reflects rougher surface effect.

given. The following variable names are used for the remainder of this article: CEC = cation exchange capacity, BB and BBB = parameters describing the relationship between crop canopy cover and vegetative aboveground live biomass and between crop canopy height and aboveground live biomass, respectively, BEINP = a parameter describing the biomass energy ratio of a crop (i.e., it reflects the potential growth rate of a crop per unit of intercepted photosynthetically active radiation), ORATEA = maximum rate of surface residue decay under optimum conditions, ORATER = maximum rate of decay for dead root biomass, GDDMAX = potential accumulation of growing degree days from planting to crop maturity, and HI = harvest index.

SENSITIVITY ANALYSIS

An OAT SA, based on Nearing et al. (1990), was performed for the three cropping/management scenarios to identify the relative importance of model parameters and error propagation of the WEPP hillslope profile model when applied to Midwest cropland conditions. All WEPP SA runs were made with a uniform slope of 5% for 100 m length as the baseline profile. Relative sensitivity coefficients (S) were calculated at 1% increments from the minimum to maximum values using:

$$S = \left| \frac{\dfrac{(O_b - O_{1\%})}{O_b}}{\dfrac{(I_b - I_{1\%})}{I_b}} \right| \tag{1}$$

Table 3. WEPP slope input parameters and values for sensitivity analysis (OFE = overland flow element).

Input Parameter	Units	Baseline Value	Range of Test (min. to max.)
Aspect	degrees from north	200	0 to 359
OFE length	m	100	20 to 200
Profile width	m	50	20 to 100
Average slope	%	5	3 to 12

Table 4. Covariance values for WEPP model Miami soil parameters.

Miami Soil Parameter[a]	Covariance Values		
	Sand	CEC	Clay
K_b	10.83	-1.9	-
K_i	-	-	-43736.3
K_r	-	-	-0.029

[a] K_b = baseline effective hydraulic conductivity, K_i = interrill erodibility factor, K_r = rill erodibility factor, and CEC = cation exchange capacity.

where

I_b = baseline value for the input parameter

$I_{1\%}$ = input parameter perturbed by 1%

O_b = WEPP model output response when all input parameters are set to baseline values

$O_{1\%}$ = model output response when one input parameter is varied.

In addition to all input parameters listed in tables 1 and 2, the WEPP topography parameters (representing slope length, width, and average slope) listed in table 3 were also perturbed. An average relative sensitivity coefficient was calculated from the perturbed (incremental) sensitivity responses for the three cropping/management scenarios. Finally, the input parameters were ranked according to their sensitivities for the WEPP output responses of interest: average annual runoff (mm), average annual soil loss (kg·m^{-2}), and average annual corn yield (kg·m^{-2}).

First-Order Error Analysis

First-order error analysis (FOEA) is a straightforward technique for approximation of the mean model response and variance from Taylor series expansions of the model response around baseline parameter estimates. The expected value of model output is obtained by performing model calculations using the mean or baseline value of each input parameter. The output variance is obtained by evaluating the partial derivative of the model with respect to a particular variable at its mean value. The overall method as implemented in this study can be defined as (Benjamin and Cornell, 1970; Melching and Yoon, 1996):

$$E(y) \approx g(\bar{X}) \tag{2}$$

$$\mathrm{Var}(y) \approx \sum_{i=1}^{m}\left(\frac{\partial g}{\partial x_i}\right)^2 \mathrm{Var}(x_i) + 2\sum_{i=1}^{m}\sum_{j=i+1}^{m}\frac{\partial g}{\partial x_i}\frac{\partial g}{\partial x_j}\mathrm{Cov}(x_i, x_j) \tag{3}$$

where

$E(y)$ = expected value

y = function of a set of random variables, $y = g(x_1, x_2, \ldots, x_m)$

m = number of basic variables

$\partial g/\partial x$ = partial derivative evaluated at $\bar{X}$

$\mathrm{Cov}(x_i, x_j)$ = covariance of basic variables i and j.

The first term in equation 3 represents contributions to overall output variance from the variance of each input variable. The second term in equation 3 denotes contributions to uncertainties in the predicted value from correlation among the different pairs of input variables. Higher-order terms are not considered in FOEA.

FOEA for the WEPP hillslope profile model was performed using equation 3, and the output responses of interest were the same as those described for the SA. The FOEA provides two types of information concerning WEPP model output response: (1) a ranked listing of input variables and their individual contribution to the total error variance, and (2) statistics describing the overall model output response. Model runs were conducted using the baseline value (table 1) for each input variable. One input variable was perturbed by 1%; this perturbed value was used while the remaining input variables were held at their baseline values. An expected model output response was computed from all FOEA runs, and each individual contribution to the total response variance was used to rank the input variables. The FOEA simulation runs were made for three erosion process cases. The first case is referred to as the "interrill" case because it is a short, flat profile of 20 m in length with a 2% slope; therefore, interrill processes should govern. The second case was selected to simulate both interrill and rill erosion processes. It is termed the "mixed" case and is a 40 m profile with 5% slope. The third case is referred to as the "rill" case because it is a long, steep profile of 40 m in length with a 10% slope; therefore, rill erosion processes should dominate. The three erosion process cases each had uniform slopes to simplify model output response analysis and demonstrate soil detachment but not deposition.

The assumption of parameter independence may not be true for most complex, physically based natural resource models, that is, interactions among model input parameters should be considered for output response error analysis. Field data were collected for the WEPP soil input parameters, so rudimentary estimation of correlations and relationships was possible. Data from the WEPP relationships for erodibility factors (Elliot et al., 1989) were used to calculate soil input parameter covariances. Table 4 lists covariance values calculated for the following Miami soil parameters: sand content, CEC, clay content, K_b, K_i, and K_r. Relationships between soil characteristics and baseline effective hydraulic conductivity were derived from WEPP cropland soil field erodibility experiments. Risse et al. (1994) determined calibrated values for effective hydraulic conductivity from these data. For the purpose of this study, all other WEPP model input parameters (e.g., cropping and management) were assumed to be independent due to the lack of available experimental data for the remaining parameters.

Monte Carlo Simulation with Latin Hypercube Sampling (LHS)

Typical Monte Carlo simulations use random sampling of input variables, which may cause spurious correlations of input parameter values; however, only correlations existing between soil parameters (table 4) were considered for this study. Trial runs were made to determine the number of Monte Carlo simulations needed; the number of runs needed to stabilize the mean was found to be between 450 and 550, depending on the scenario. Therefore, five-hundred 100-year simulation runs (i.e., 50,000 simulation years) were made with WEPP for each of the three cropping/management scenarios. All scenarios were also run for each of the three erosion process cases. The WEPP model output responses of interest for the Monte Carlo simulation were the same as those described for SA and FOEA.

Use of Latin hypercube sampling (LHS) methodology (Iman and Conover, 1982) ensured that sampling occurred from the complete distribution of each input parameter and significantly reduced the number of simulation runs. Each input parameter distribution (tables 1 and 2) was divided into 100 sections of equal probability, and random sampling from each equal probability section was performed to produce a probability distribution function (pdf) representing plausible realizations of WEPP model output responses. The Monte Carlo LHS simulations produce model predictions in which the variance is a function of multiple parameter variability as translated by the WEPP model equations. This variance can be used to quantify the dependence of model predictions on multiple parameter uncertainty (Gardner et al., 1981). Correlations between soil input parameters were taken into consideration, and the LHS method was used to ensure proper sampling with Spearman correlation coefficients. Table 5 lists the Spearman or rank correlation coefficients for the Miami soil input parameters tested in this study.

WEPP model soil loss pdf output responses generated using Monte Carlo LHS simulation were compared to a well-accepted method for soil loss prediction, the Universal Soil Loss Equation (USLE; Wischmeier and Smith, 1978). The USLE is often described in the literature as:

$$A = R * K * LS * C * P \tag{4}$$

where

A = average (mean) annual soil loss (mass/area) over the long term (e.g., 10 to 20 years)

R = rainfall-runoff erosivity factor

K = soil erodibility factor

L and S = topographic factors that depend on slope length and gradient

C = cover management factor

P = soil conservation practice factor.

Equation 4 is commonly shown in the literature; however, Kinnell (2008) notes the USLE works mathematically in two steps since it is based on the unit plot concept (where the unit plot is defined as a bare fallow area 22.1 m long on a 9% slope with cultivation up and down the plot). In equation 4, only R and K have units, whereas LS, C, and P are “reduced” variables that are mathematically forced to take on values of 1.0 for the unit plot. Consequently, the USLE first predicts erosion for the unit plot condition $UP = R * K$, and then multiplies the result by the appropriate values of LS, C, and P to account for the difference between the area of interest and the unit plot, i.e., $A = UP * LS * C * P$. A detailed description of the USLE inputs and subsequent calculations performed for comparison to the WEPP Monte Carlo LHS simulations is beyond the scope of this study; however, the general procedure was based on Wischmeier and Smith (1978) as follows:

1. Determine the rainfall-runoff erosivity factor (R) for West Lafayette, Indiana.
2. Determine the K soil erodibility factor based on Miami silt loam soil texture information (table 2).
3. Determine the LS value based on the uniform slope gradient and length conditions for the interrill (20 m profile with 2% slope), mixed (40 m profile with 5% slope), and rill (40 m profile with 10% slope) erosion process cases.
4. Determine stages of growth for the crop (corn), dates for the stages, and the percentage of soil exposed for x amount of time. Multiply the soil loss ratios for each growth period by the percentage of annual erosion expected during each period. Read the soil loss ratios for each growth period from table 5 in Wischmeier and Smith (1978) and determine the percentage of annual erosion expected in each growth period. Sum the products and express the total as a decimal value for the C factor value.
5. Select the P factor based on the support practice used (P set to 1 for up and down slope farming).
6. Multiply the five factors together to obtain the USLE soil loss estimates.

Table 5. Spearman or rank correlation coefficients for WEPP model Miami soil input parameters.

Miami Soil Parameter[a]	Spearman Correlation Coefficients						
	Sand	CEC	Clay	K_b	K_i	K_r	τ_c
Sand	1	-	-	-	-	-	-
CEC	0	1	-	-	-	-	-
Clay	0	0	1	-	-	-	-
K_b	0.90	-0.17	0	1	-	-	-
K_i	0	0	0.017	0	1	-	-
K_r	0	0	-0.77	0	0	1	-
τ_c	0	0	0	0	0	0	1

[a] CEC = cation exchange capacity, K_b = baseline effective hydraulic conductivity, K_i = interrill erodibility factor, K_r = rill erodibility factor, and τ_c = baseline critical shear stress.

RESULTS

SENSITIVITY ANALYSIS

Table 6 lists WEPP model 100-year mean output responses for the baseline slope case and the three erosion process cases. Average annual runoff (mm), soil loss (kg·m^{-2}), and corn yield (kg·m^{-2}) sensitivity values for the cropping/management scenarios are reported in table 7. A natural break normally appeared in the results at an average sensitivity coefficient of 0.2. This delineation point indicates input parameters for which the model output response is sensitive (>0.2), and those parameters for which the model output response is not very sensitive (<0.2).

WEPP runoff output responses were most sensitive to the

Table 6. Mean output responses for 100-year WEPP simulation runs. No measured data were available for runoff, soil loss, or corn yield.

Cropping/Management Scenario[a]	Runoff (mm)[b]	Soil Loss ($kg \cdot m^{-2}$)	Corn Yield ($kg \cdot m^{-2}$)
Baseline slope case (100 m profile at 5% slope)			
CT corn	92.4	7.1	0.80
NT corn	70.3	0.06	0.74
Tilled fallow	132.3	13.4	N/A
Interrill erosion process case (20 m profile at 2% slope)			
CT corn	87.5	0.86	0.78
NT corn	67.0	0.05	0.75
Tilled fallow	128.6	1.9	N/A
Mixed erosion process case (40 m profile at 5% slope)			
CT corn	92.3	3.6	0.76
NT corn	70.8	0.06	0.70
Tilled fallow	134.2	7.2	N/A
Rill erosion process case (40 m profile at 10% slope)			
CT corn	94.3	8.3	0.70
NT corn	73.2	0.08	0.66
Tilled fallow	138.4	18.9	N/A

[a] CT = conventional tillage, NT = no-till.
[b] Annual average runoff from rainfall.

baseline effective conductivity (K_b) for all cropping/ management scenarios (table 7). For soils such as Miami with less than 40% clay content, the WEPP K_b parameter is a function of sand content and CEC (which are also parameters with high runoff sensitivity coefficients). Runoff output responses for the cropping/management scenarios were also sensitive to clay content (for high clay soils, K_b is a function of only clay content). The WEPP variable relating the speed in which a crust forms (CKE, based on the analysis of natural runoff plot data by Risse et al., 1994) is a function of sand/clay content and CEC; therefore, runoff prediction is highly sensitive to changes in these input parameters. In the NT scenario, the lack of tillage would make crust formation more important when considering runoff output response sensitivity.

The soil loss output response was highly sensitive to changes in average slope steepness and profile length for the CT and tilled fallow scenarios (table 7). These parameters affect shear stress, transport capacity, and the interrill slope adjustment factor. The sensitivity of soil loss to τ_c in the CT scenario is primarily due to rill erosion (under tilled conditions). This explains why the soil loss output response is also sensitive to changes in K_r for the tilled scenarios. In these scenarios, rill detachment dominates, whereas the NT scenario is largely dominated by interrill detachment and transport (although soil loss for this scenario was not particularly sensitive to K_i). The soil loss output response for the NT scenario was the most sensitive to BEINP, K_b, and planting date, as crop input parameters that control the amount of biomass, and ultimately residue, available on the field were strongly influential. BEINP impacts the amount of biomass production simulated by WEPP; thus, it is an important parameter in erosion prediction for NT conditions. The soil loss output response for the NT scenario was also sensitive to changes in sand content, perhaps due to the crusting factor (CKE).

The corn yield output response was most sensitive to the BEINP and the HI parameters for the CT and NT cropping/management scenarios (table 7). These crop input parameters impact biomass production and yield levels in the WEPP crop growth component and therefore would be expected to be highly sensitive parameters for crop yield. GDDMAX was also important in crop yield estimation, as it controls the length of the simulated growing season in WEPP. Planting and harvest dates slightly impacted corn yield output response sensitivity in that they control the length and timing of the growing season. Changes in these parameters control the amount of biomass production and therefore the predicted yield.

First-Order Error Analysis (FOEA)

Tables 8 through 10 list the FOEA rankings of error variance percent contributions for the WEPP model output responses (runoff, soil loss, and corn yield) across the three erosion process cases. Only those variables contributing at least 1% to the total error variance of the output responses are presented. The FOEA rankings are similar to the SA rankings in that they provide WEPP model users with information on which input parameters contribute the largest

Table 7. Average sensitivity values for WEPP model output responses.[a]

Cropping and Management Scenario	Runoff (mm)		Soil Loss ($kg \cdot m^{-2}$)		Corn Yield ($kg \cdot m^{-2}$)	
	Input Variable	Sensitivity	Input Variable	Sensitivity	Input Variable	Sensitivity
CT corn	K_b	1.02	Average slope	1.67	BEINP	1.28
	% Sand	0.68	OFE length	1.01	HI	0.92
	CEC	0.31	K_r	0.93	GDDMAX	0.53
	% Clay	0.22	% Clay	0.88	Planting date	0.27
			τ_c	0.77	Harvest date	0.21
			K_b	0.61		
NT corn	K_b	0.81	BEINP	1.54	BEINP	1.21
	% Sand	0.56	K_b	0.89	HI	0.96
	% Clay	0.30	Planting date	0.78	GDDMAX	0.50
	CEC	0.22	GDDMAX	0.72	Planting date	0.23
	GDDMAX	0.20	% Sand	0.61	Harvest date	0.21
Tilled fallow	K_b	1.03	Average slope	1.74	N/A	N/A
	% Sand	0.64	K_r	1.21		
	CEC	0.46	OFE length	0.82		
	% Clay	0.35	% Clay	0.77		
			K_b	0.59		
			τ_c	0.54		

[a] CT = conventional tillage, NT = no-till, K_b = baseline effective hydraulic conductivity, CEC = cation exchange capacity, τ_c = baseline critical shear stress, BEINP = a parameter describing the biomass energy ratio of a crop, GDDMAX = potential accumulation of growing degree days from planting to crop maturity, and HI = harvest index.

percentage to the total error variance for a particular model output response.

FOEA runoff results (table 8) indicate that K_b and sand content contributed the most error variance for all cropping/management scenarios and erosion process cases. GDDMAX, BEINP, and ORATEA contributed slightly to the runoff total error variance for the CT and NT scenarios, indicating that the presence of ground cover and biomass is important for interception of rainfall and maintaining of soil macropores. Sand content and K_b error variance for the cropping/management scenarios were very similar across the three erosion process cases. Clay content and CEC were the remaining input parameters with greater than 1% contribution towards runoff total error variance.

FOEA soil loss results for the CT scenario (table 9) in the mixed and rill erosion process cases showed that K_r was the major contributor to soil loss total error variance. Rill erosion processes dominated in the CT scenario; therefore, the influence of K_r was not surprising. K_r is also a function of clay content; clay and τ_c also contributed significant soil loss total error variance for the mixed and rill erosion process cases because small changes in τ_c influence the critical shear stress threshold for rill detachment. The interrill erosion process case had little rill erosion by design. In this case, K_b, which influences runoff, and K_i were the dominant contributors to the soil loss total error variance for the CT

Table 8. FOEA ranking of error variance percent contribution for runoff (mm).[a]

Cropping and Management Scenario	Interrill Erosion Process Case: Input Variable	Interrill: Error Variance Contribution (%)	Mixed Erosion Process Case: Input Variable	Mixed: Error Variance Contribution (%)	Rill Erosion Process Case: Input Variable	Rill: Error Variance Contribution (%)
CT corn	K_b	74.2	K_b	72.3	K_b	72.6
	% Sand	17.2	% Sand	18.0	% Sand	18.4
	% Clay	4.2	% Clay	3.6	% Clay	4.2
	GDDMAX	1.6	CEC	2.8	GDDMAX	1.7
	BEINP	1.4	GDDMAX	1.3	BEINP	1.3
	CEC	1.2	BEINP	1.1	CEC	1.1
NT corn	% Sand	45.4	% Sand	45.0	% Sand	47.4
	K_b	41.3	K_b	43.7	K_b	42.3
	CEC	7.9	CEC	7.5	CEC	5.1
	BEINP	2.9	BEINP	1.9	BEINP	1.8
	% Clay	1.1	% Clay	1.6	% Clay	1.3
	ORATEA	1.0			ORATEA	1.2
Tilled fallow	K_b	42.8	K_b	45.7	K_b	45.3
	% Sand	38.4	% Sand	39.7	% Sand	39.2
	% Clay	9.9	% Clay	8.9	% Clay	9.2
	CEC	7.3	CEC	5.0	CEC	5.4

[a] CT = conventional tillage, NT = no-till, K_b = baseline effective hydraulic conductivity, CEC = cation exchange capacity, GDDMAX = potential accumulation of growing degree days from planting to crop maturity, BEINP = a parameter describing the biomass energy ratio of a crop, and ORATEA = maximum rate of surface residue decay under optimum conditions.

Table 9. FOEA ranking of error variance percent contribution for soil loss ($kg \cdot m^{-2}$).[a]

Cropping and Management Scenario	Interrill Erosion Process Case: Input Variable	Interrill: Error Variance Contribution (%)	Mixed Erosion Process Case: Input Variable	Mixed: Error Variance Contribution (%)	Rill Erosion Process Case: Input Variable	Rill: Error Variance Contribution (%)
CT corn	K_b	42.1	K_r	30.3	K_r	40.1
	K_i	34.6	τ_c	26.5	% Clay	26.8
	BEINP	9.0	% Clay	20.2	K_b	11.3
	% Sand	6.5	K_b	8.8	τ_c	8.5
	RRO3	3.3	BEINP	5.4	GDDMAX	5.1
	Planting date	1.7	GDDMAX	3.6	BEINP	4.2
	RRO5	1.4	ORATEA	3.3	ORATEA	3.2
	ORATER	1.0	% Sand	1.3		
NT corn	BEINP	25.5	% Sand	26.2	ORATEA	36.4
	ORATEA	21.3	BEINP	22.6	BEINP	30.6
	GDDMAX	18.5	ORATEA	18.0	GDDMAX	23.6
	% Sand	14.9	GDDMAX	16.8	% Sand	4.6
	K_b	12.7	K_b	14.2	K_b	1.9
	CEC	5.1	CEC	1.6	% Clay	1.2
	% Clay	1.2			K_r	1.2
Tilled fallow	K_i	41.4	K_r	35.3	K_r	39.8
	K_b	34.2	% Clay	25.6	% Clay	32.5
	% Sand	15.5	τ_c	20.8	K_b	10.5
	CEC	5.5	% Sand	8.6	% Sand	8.3
	RHO3	2.0	K_b	7.2	τ_c	6.4
	RHO4	1.1	CEC	1.8	CEC	2.0

[a] CT = conventional tillage, NT = no-till, K_r = baseline rill erodibility factor, τ_c = baseline critical shear stress, K_b = baseline effective hydraulic conductivity, BEINP = a parameter describing the biomass energy ratio of a crop, GDDMAX = potential accumulation of growing degree days from planting to crop maturity, ORATEA = maximum rate of surface residue decay under optimum conditions, CEC = cation exchange capacity, HI = harvest index, RRO3 = random roughness after tillage for field cultivator, RRO5 = random roughness after tillage for row cultivator, RHO3 = ridge height after tillage for row cultivator, and RHO4 = ridge height after tillage for moldboard plow.

scenario. Input parameters influencing the soil surface, such as the plant cover and the roughness due to field and row cultivators, were moderately important for soil loss total error variance in the interrill erosion process case. Figure 1 shows the breakdown of the type of interrill detachment occurring for each erosion process case across the three cropping/management scenarios.

The soil loss output response for the NT scenario was largely driven by soil and crop growth processes that influence runoff and near-surface soil moisture. BEINP and ORATEA contributed significant error variance for all three erosion process cases. Change in decomposition rates for the NT scenario erosion process cases strongly affects the amount of residue present on the soil surface. Canopy and ground cover parameters influence the amount of rainfall reaching the soil surface, and changes in these parameters (i.e., ORATEA and GDDMAX) affect the soil loss total error variance. Sand content and K_b also contributed moderate soil loss error variance for the NT scenario.

Soil loss FOEA results for the tilled fallow scenario showed that K_r was the largest error variance contributor for the mixed and rill erosion process cases. Clay content also contributed large error variance for these cases, which was anticipated since K_r is a function of clay content. As expected, K_i was the largest error variance contributor for the tilled fallow interrill erosion case. Parameters influencing runoff (i.e., sand content, τ_c, K_b, and CEC, which impact the shear stress and crust formation calculations) and soil surface effects (i.e., ridge height after tillage for row cultivator) also contributed to the soil loss total error variance at a minimal level.

FOEA corn yield results (table 10) showed that the largest error variances were contributed by BEINP and HI for all cropping/management scenarios and erosion process cases. Again, these crop input parameters impact biomass production and yield levels in the WEPP crop growth component. Soil albedo and GDDMAX also contributed minor error variance for all cropping/management scenarios and erosion process cases. GDDMAX controls the length of the growing season that WEPP calculates for biomass development. The soil albedo parameter is used to estimate the net radiation reaching the soil surface, which is then used in the evapotranspiration calculations within the WEPP water balance routines.

Statistics for the WEPP model output responses were analyzed for the combination of all FOEA simulation runs. Tables 11 through 13 display runoff (mm), soil loss (kg·m^{-2}), and corn yield (kg·m^{-2}) FOEA statistics for the cropping/management scenarios and erosion process cases. Table 11 shows that the FOEA mean response for average annual runoff went from lower to higher for the interrill to the mixed to the rill erosion process cases across the cropping/management scenarios. WEPP model runoff error variances also followed these trends. The tilled fallow scenario produced the most runoff, followed by the CT and NT scenarios, respectively. WEPP model runoff error variances were similar for the CT and NT scenarios across all erosion process cases; however, these variances were much larger than for the tilled fallow scenario. The FOEA mean runoff response trends between the cropping/management scenarios and erosion process cases were reasonable and followed expected WEPP model

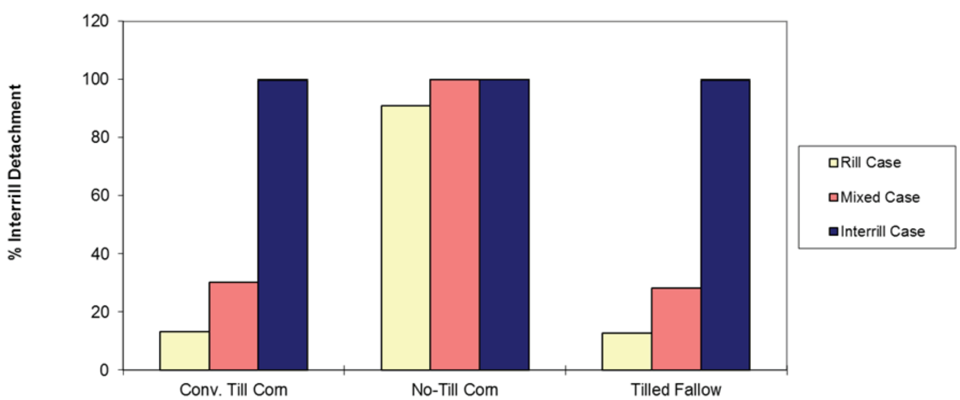

Figure 1. Percent interrill detachment on a Miami soil for the FOEA erosion process case simulations.

Table 10. FOEA ranking of error variance percent contribution for corn yield (kg·m^{-2}).[a]

Cropping and Management Scenario	Interrill Erosion Process Case: Input Variable	Interrill: Error Variance Contribution (%)	Mixed Erosion Process Case: Input Variable	Mixed: Error Variance Contribution (%)	Rill Erosion Process Case: Input Variable	Rill: Error Variance Contribution (%)
CT corn	BEINP	80.3	BEINP	77.7	BEINP	81.5
	HI	14.6	HI	15.3	HI	12.2
	Soil albedo	4.6	Soil albedo	4.9	Soil albedo	4.3
	GDDMAX	1.3	GDDMAX	1.3	GDDMAX	1.2
NT corn	BEINP	76.6	BEINP	73.5	BEINP	76.3
	HI	15.4	HI	19.2	HI	15.1
	GDDMAX	4.3	GDDMAX	3.8	GDDMAX	4.6
	Soil albedo	3.2	Soil albedo	3.3	Soil albedo	3.3

[a] CT = conventional tillage, NT = no-till, BEINP = a parameter describing the biomass energy ratio of a crop, HI = harvest index, and GDDMAX = potential accumulation of growing degree days from planting to crop maturity.

behavior as reported in the literature.

Table 12 shows that the FOEA mean response for soil loss went from lower to higher from the interrill to the mixed to the rill erosion process cases across the cropping/ management scenarios. WEPP model soil loss error variances also followed these trends. Across all scenarios and erosion process cases, the greatest soil loss and error variance were predicted for the tilled fallow scenario. The NT scenario had the smallest error variances, followed by the CT and tilled fallow scenarios (this trend also follows expected model behavior). In general, one would expect the tilled fallow scenarios to experience the highest soil loss, with the NT scenarios experiencing the lowest.

The FOEA mean response for annual average corn yield (table 13) went from higher to lower from the interrill to the mixed to the rill erosion process case scenarios. The decrease in corn yields, albeit by minor amounts, when the slope steepness increases may indicate that WEPP is simulating plant water stress conditions due to lower amounts of rainfall infiltration on steeper slopes. Error variances between the erosion process cases were very similar, with the CT scenarios having slightly higher variances than the NT scenarios.

Monte Carlo LHS Simulation

Monte Carlo LHS Variance Analysis

Tables 11 through 13 display runoff (mm), soil loss ($kg \cdot m^{-2}$), and corn yield ($kg \cdot m^{-2}$) Monte Carlo LHS simulation statistics for the cropping/management scenarios and erosion process cases. The statistics calculated for the Monte Carlo LHS runs represent uncertainty in model output responses as affected by an assumed combined input parameter error. In general, the overall results for Monte Carlo LHS simulation are quite similar to FOEA results.

Monte Carlo LHS runoff simulation results showed that runoff increased as the slope increased, i.e., runoff was lowest for the interrill case and greatest for the rill erosion process case for all cropping/management scenarios (table 11). Monte Carlo LHS runoff error variances also followed these trends. All erosion process cases showed identical trends for runoff and variance rankings within the scenarios. The tilled fallow scenario had the greatest amount of runoff, followed by the CT and NT scenarios. This order is reasonable in that the tilled fallow scenarios would be expected to have the largest runoff totals, while the NT scenarios should have the least. Monte Carlo LHS soil loss simulation results exhibited the same trend as the runoff results, that is, soil loss increased as the slope increased

Table 11. WEPP first-order error analysis (FOEA) and Monte Carlo Latin hypercube sampling (LHS) output results for runoff (mm).

Erosion Process Case	Cropping and Management Scenario[a]	FOEA Arithmetic Mean	FOEA Median	FOEA Error Variance	Monte Carlo LHS Arithmetic Mean	Monte Carlo LHS Median	Monte Carlo LHS Variance
Interrill	CT corn	87.8	87.8	159.2	93.7	93.5	27.1
	NT corn	67.1	67.2	160.8	73.1	72.6	52.9
	Tilled fallow	129.0	128.9	87.1	133.5	134.1	63.9
Mixed	CT corn	90.4	90.4	209.1	96.2	95.4	30.2
	NT corn	68.2	68.2	221.9	75.6	74.3	56.0
	Tilled fallow	132.3	132.3	102.1	136.9	137.6	68.2
Rill	CT corn	94.8	94.8	237.2	101.0	100.4	31.3
	NT corn	71.9	71.9	251.0	78.8	78.5	61.6
	Tilled fallow	138.3	138.3	147.4	143.1	143.4	75.6

[a] CT = conventional tillage, NT = no-till.

Table 12. WEPP first-order error analysis (FOEA) and Monte Carlo Latin hypercube sampling (LHS) output results for soil loss ($kg \cdot m^{-2}$).

Erosion Process Case	Cropping and Management Scenario[a]	FOEA Arithmetic Mean	FOEA Median	FOEA Error Variance	Monte Carlo LHS Arithmetic Mean	Monte Carlo LHS Median	Monte Carlo LHS Variance
Interrill	CT corn	0.84	0.85	0.12	0.91	0.90	0.03
	NT corn	0.05	0.05	0.0007	0.07	0.06	0.002
	Tilled fallow	1.6	1.6	0.16	2.0	2.0	0.07
Mixed	CT corn	3.2	3.3	6.9	4.0	4.0	0.78
	NT corn	0.06	0.06	0.001	0.09	0.08	0.004
	Tilled fallow	7.0	7.0	19.3	7.6	7.5	1.3
Rill	CT corn	9.1	9.2	62.5	10.1	10.1	7.9
	NT corn	0.08	0.09	0.003	0.11	0.12	0.03
	Tilled fallow	19.8	19.9	161.6	20.7	20.7	14.4

[a] CT = conventional tillage, NT = no-till.

Table 13. WEPP first-order error analysis (FOEA) and Monte Carlo Latin hypercube sampling (LHS) output results for corn yield ($kg \cdot m^{-2}$).

Erosion Process Case	Cropping and Management Scenario[a]	FOEA Arithmetic Mean	FOEA Median	FOEA Error Variance	Monte Carlo LHS Arithmetic Mean	Monte Carlo LHS Median	Monte Carlo LHS Variance
Interrill	CT corn	0.77	0.78	0.05	0.83	0.83	0.05
	NT corn	0.77	0.76	0.05	0.81	0.81	0.04
Mixed	CT corn	0.77	0.77	0.05	0.82	0.82	0.04
	NT corn	0.76	0.76	0.05	0.81	0.82	0.04
Rill	CT corn	0.76	0.76	0.05	0.81	0.81	0.05
	NT corn	0.75	0.76	0.05	0.80	0.80	0.04

[a] CT = conventional tillage, NT = no-till.

(table 12). Error variances also followed these trends. When analyzing soil loss predictions between scenarios, the tilled fallow scenario had the largest soil loss, followed by the CT and NT scenarios. Monte Carlo LHS corn yield simulation results were greatest for the interrill erosion process case and lowest for the rill erosion process case, although the results were very similar (table 13). The NT scenarios had identical corn yield predictions for the interrill and mixed erosion process cases. The results indicate that WEPP is correctly simulating biomass production trends that are linked to management and topography. Since runoff increases with increased slope steepness, less of the rainfall is available in the soil for plant uptake.

Monte Carlo LHS Assessment of WEPP Predictive Ability

It is difficult to use a physically based model for a particular situation and rapidly assess the effect of input parameter changes (i.e., soil, topographic, or management conditions) on the model output response. It should be expected that the uncertainty bounds associated with a model will be useful in determining whether changes in predicted model output response due to input parameter changes are statistically significant and within the limits of predictive uncertainty. The results of a study by Binley et al. (1991) suggest that the uncertainty bounds for physically based models will be quite wide even when the input parameters have been calibrated.

While the use of historical data is best for comparison to model results, average annual runoff and soil loss data were not available for this study. This is not unusual, since in many cases models are applied to situations with little or no observed data. In this section, Monte Carlo LHS simulation results are graphically presented (in the form of pdfs) to assess the degree of effort necessary for parameterizing setups similar to the ones analyzed in this study and to determine a probable range (i.e., predictive interval) for WEPP model soil loss predictions. In addition, the WEPP model soil loss pdf output responses were compared to a well-accepted method for soil loss prediction, the USLE (Wischmeier and Smith, 1978). USLE estimates for the cropping/management scenarios and erosion process cases were calculated as previously described and are shown in table 14. They were then compared with WEPP model output response distributions from the Monte Carlo LHS simulation results to evaluate statistical differences between the USLE and WEPP soil loss predictions.

Intervals specifying the range of model output responses for a designated probability distribution are helpful in indicating that future model predictions will lie within that range. Confidence intervals are often constructed to provide this type of information. The central limit theorem states that when the number of samples, or in this case, simulations, approaches infinity, the distribution of the sum of *n* random variables approaches the normal distribution. When random variables follow the normal distribution, the area within ±2 standard deviations of the mean contains approximately 95% of the observations. While this is true for a normal distribution, the same representation for a non-normal distribution is not likely to hold, and the calculation becomes more complicated. Figures 2 through 4 demonstrate that the majority of the WEPP model output responses (distributions) are not normally distributed, so that traditional assignment of confidence intervals is inadequate. Therefore, the method of prediction intervals as employed by Scavia et al. (1981) and Binley et al. (1991) for continuous simulation process-based models was used. Prediction intervals reflect the range of a random variable corresponding to a response function such that there is a specified probability that a future observation of the random variable will be found within that range (Graybill, 2000). For this study, prediction limits were computed by rejecting the lower and upper 5% of the simulation responses. Using the Unifit II software package, 90% prediction intervals were determined for each Monte Carlo LHS WEPP simulation soil loss output response (figs. 2 through 4).

The USLE estimates were plotted with WEPP soil loss output response distributions from the Monte Carlo LHS simulations to illustrate statistical differences between WEPP and USLE predictions. The goal was to investigate how a well-accepted standard for annual average soil loss prediction and WEPP soil loss predictions statistically (and directly) compare. While no measured data were available for average annual soil loss, the USLE is an empirically based model based on 10,000 plot-years of natural runoff data. For the CT scenario, the USLE estimates were at the lower end of the WEPP soil loss output response pdfs, but still fell within the 90% prediction interval for all three erosion process cases (figs. 2a to 2c). The USLE estimate was well above the 90% prediction interval for the NT scenario in the mixed and rill erosion process cases (figs. 3b to 3c), and was also high for the tilled fallow scenario in the interrill erosion process case (fig. 4a). Overall, the USLE estimates and the WEPP soil loss output responses agreed the most often for the CT scenario and agreed the least often for the NT scenario. It is interesting to note that the USLE estimate was always high (i.e., in the upper 5% tail) for the three cropping/management scenarios and erosion process cases, where it did not fall within the 90% prediction interval. Additional explanation for this is given in the Discussion section.

Table 14. USLE average annual soil loss (kg m^{-2}) calculations for WEPP soil loss output response evaluation.

Cropping and Management Scenario[a]	Erosion Process Case		
	Interrill	Mixed	Rill
CT corn	0.85	2.9	7.5
NT corn	0.09	0.33	0.83
Tilled fallow	2.4	8.1	20.8

[a] CT = conventional tillage, NT = no-till.

DISCUSSION

COMPARISON OF SENSITIVITY AND FOEA UNCERTAINTY ANALYSIS TECHNIQUES

The SA for this study was conducted using a baseline slope case profile of 100 m length with 5% slope, whereas the FOEA was conducted for three separate erosion process cases. Although the SA and FOEA results are from different baseline slope conditions, the results from the SA can be

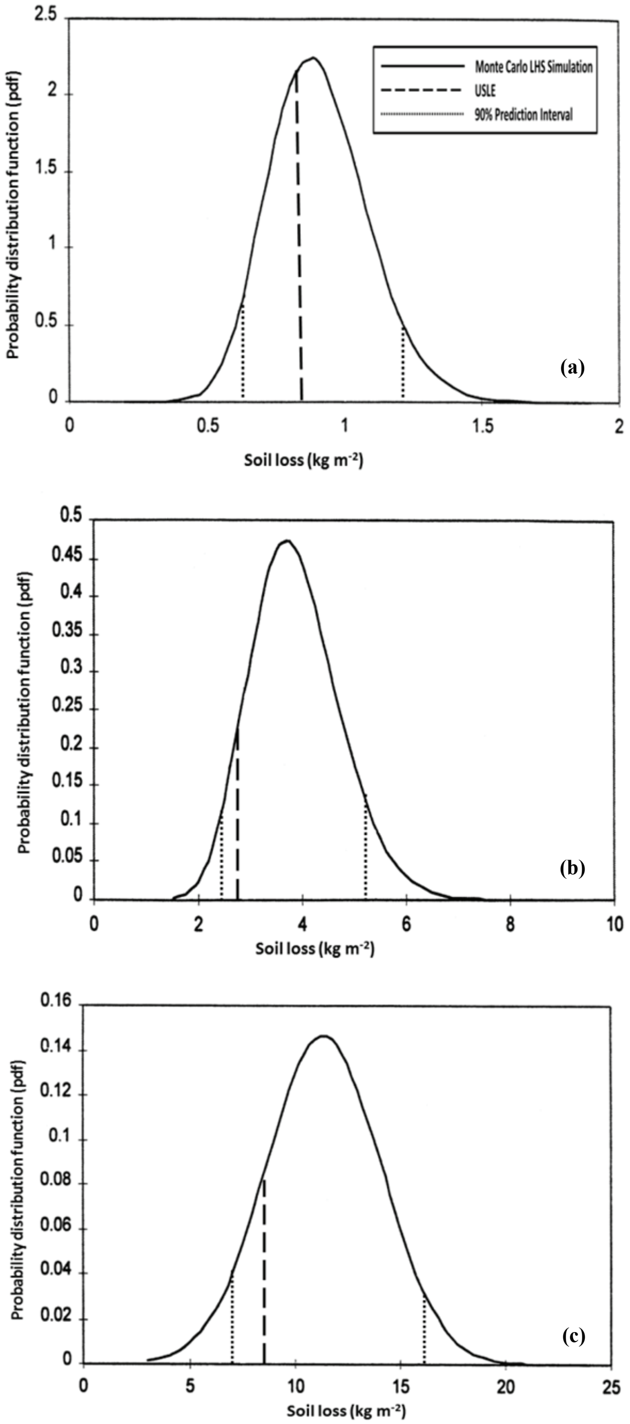

Figure 2. Monte Carlo LHS WEPP soil loss output prediction intervals for the CT scenario and the (a) interrill, (b) mixed, and (c) rill erosion process cases.

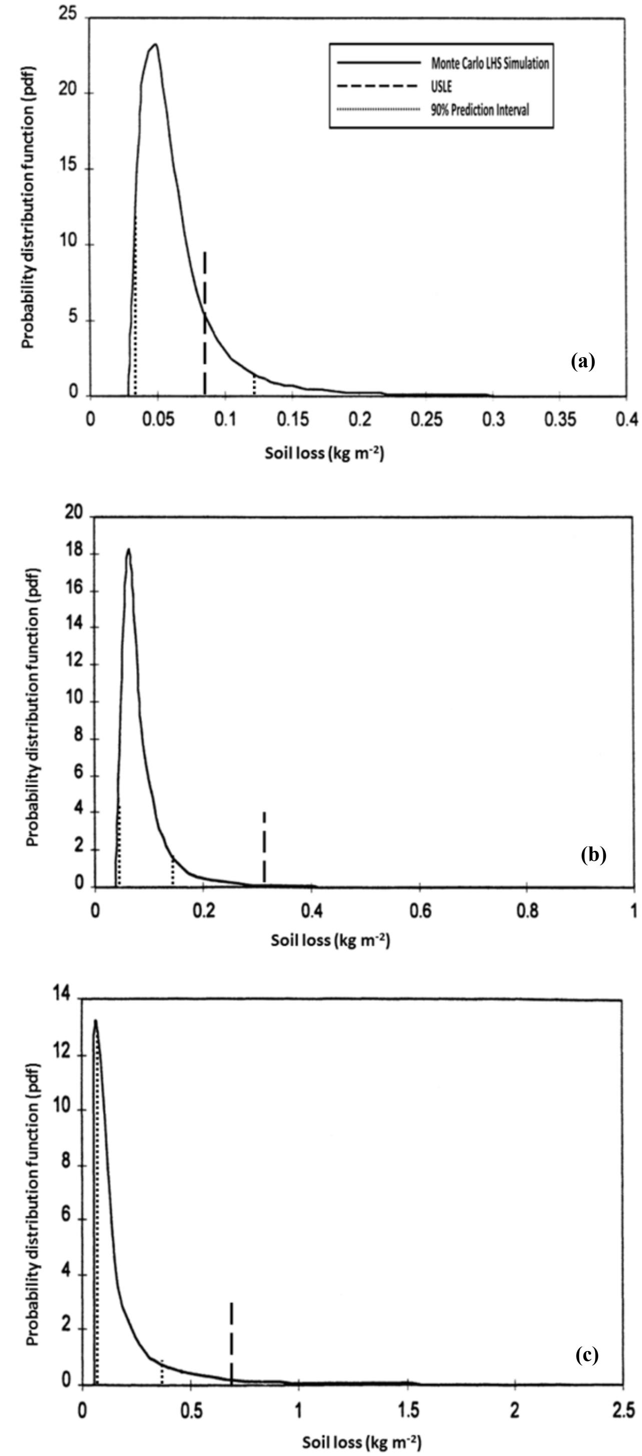

Figure 3. Monte Carlo LHS WEPP soil loss output prediction intervals for the NT scenario and the (a) interrill, (b) mixed, and (c) rill erosion process cases.

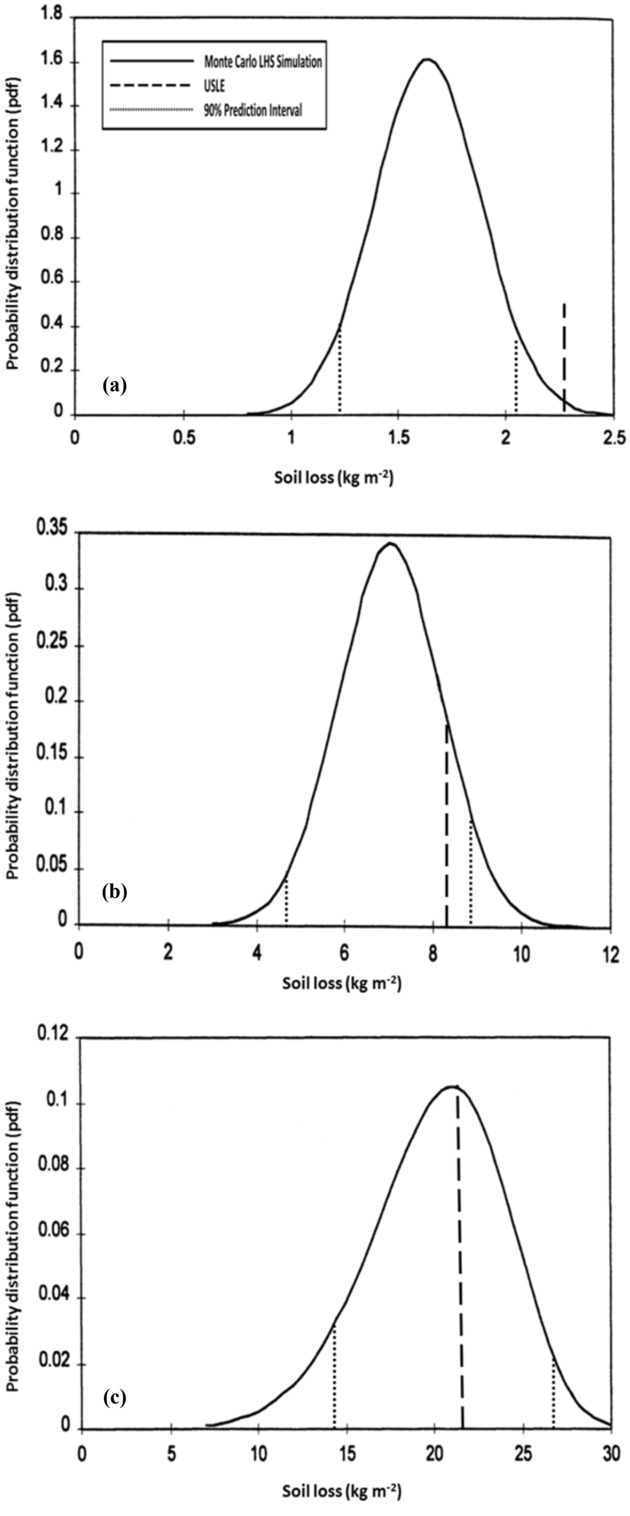

Figure 4. Monte Carlo LHS WEPP soil loss output prediction intervals for the tilled fallow scenario and the (a) interrill, (b) mixed, and (c) rill erosion process cases.

compared to the FOEA mixed erosion case results. The WEPP-predicted runoff output response for the CT scenario was similar for both analyses in that K_b was the dominant parameter, followed by sand content. CEC and clay content also were consistently important in both analyses, reaffirming the importance of the crust adjustment factor in predicting runoff. Key input parameters for the NT scenario runoff output response were also similar for both analyses in that sand content, K_b, CEC, and clay content were important. The SA showed GDDMAX to be important, while the FOEA included BEINP. The trend of K_b and sand content importance continued for the tilled fallow scenario runoff output response, with CEC and clay content also of moderate importance for both analyses.

The SA and FOEA differed for the CT scenario soil loss output response in that average slope and OFE length were the most sensitive input parameters, while K_r and clay content contributed the largest error variance. However, both analyses showed that K_b and τ_c were important input parameters for soil loss output response, although these parameters were ranked much higher for the FOEA. Both analyses for the NT scenario soil loss output response were similar, except that CEC and ORATEA contributed to soil loss total error variance but were not shown to be particularly sensitive. Important input parameters (e.g., K_b, K_r, clay content, and τ_c) were similar for the fallow scenario soil loss output response; however, the SA showed that average slope and OFE length were highly sensitive, while K_r and clay content contributed the largest error variance in the FOEA (K_r was also the second most sensitive parameter). Both analyses for CT and NT scenario corn yield output response were similar, except that the FOEA showed soil albedo contributing minor error variance, although it was not a parameter with significant sensitivity. Additionally, planting and harvest date were sensitive parameters for corn yield output response but contributed little or no error variance. Although the rankings may not directly correspond, it is important to note that the input parameters appearing in both analyses as important to runoff, soil loss, and corn yield model output responses were quite similar. Ranking order may shift due to the variance of the parameter, so consideration of the overall parameter listing is more important.

Comparison of FOEA and Monte Carlo LHS Uncertainty Analysis Techniques

Both analyses show that runoff and soil loss increased as slope length and steepness increased, i.e., the relative ranking order for runoff and soil loss showed both output responses increasing from the interrill to the mixed to the rill erosion process cases. Both analyses also describe identical trends for corn yield output response within the erosion process cases. Corn yield output response decreased for both analyses as slope length and steepness increased, with the exception of the NT scenario in the Monte Carlo LHS output response, where the yield remained the same.

The Monte Carlo LHS arithmetic mean simulation results for the runoff, soil loss, and corn yield output responses were greater than the baseline simulation and FOEA results. For the FOEA, one input parameter at a time was perturbed per simulation run to produce the error variance associated with a particular input parameter and associated model output response. Because only a single parameter is evaluated for a run, the output response should be similar to the baseline response except in the case where a small perturbation in an input parameter causes a large change in the model output response. The statistics for the WEPP model output responses show that small perturbations of the input parameters did not significantly alter the arithmetic mean response from the baseline response; therefore, the FOEA and baseline results were similar. In addition to differences in the arithmetic mean for the FOEA and Monte Carlo LHS model output responses, the total error variances were also dissimilar. In comparing the total error variance calculated by the FOEA and Monte Carlo LHS simulation methods, the values from the FOEA were less realistic for runoff and soil loss (i.e., much higher than the Monte Carlo LHS variances, except for soil loss in the NT case), indicating that the FOEA technique may not be applicable for a nonlinear model such as WEPP. The Monte Carlo LHS simulation results appeared to be realistic for all model output responses. However, the variances were fairly consistent (the Monte Carlo LHS simulation variances were slightly lower than the FOEA variances) among the cropping/management scenarios for the corn yield output response in all three erosion process cases.

In theory, the Monte Carlo LHS output responses should approach the baseline model output values, given a sufficient number of simulations. For this study, Monte Carlo simulation runs were made in increments to determine the number needed to stabilize the variation in the mean response. While 1000 simulation runs were made for each output response variable, all cases had reached a mean stabilization between 700 and 850 runs (data not shown). Further examination is necessary to determine whether modification of input parameter pdfs would provide Monte Carlo LHS simulation response values closer to the baseline values. Examination and performance of Monte Carlo LHS simulation for each input parameter individually may also provide insight on which parameter (if any) may be described incorrectly. Because of limited observed data for many of the WEPP input parameters (particularly the cropping and management parameters) and uncertainty in parameterization, there is some degree of error in the pdfs for these parameters. Additionally, with the exception of the WEPP soil input parameters listed in table 4, the input parameters were assumed to be independent of one another due to the lack of observed data. Further study should be undertaken to determine the impacts of this assumption.

Comparison of USLE and Monte Carlo LHS WEPP Soil Loss Predictions

In general, the USLE has been found to overestimate soil loss at sites with relatively low erosion potential and underestimate at sites with high erosion potential (Risse et al., 1993; Rapp et al., 2001). The USLE C factors are generally recognized to be too high for no-till conditions; therefore, soil loss is overpredicted. In theory, WEPP erosion prediction technology should respond better than the USLE to conditions such as no-till with more accurate estimates of soil loss. The USLE has inherent shortcomings, most conspicuously that it does not explicitly represent the fundamental erosion processes of detachment, transport, and deposition by the separate major erosive agents of raindrop impact and surface runoff. Furthermore, USLE erosion prediction technology calculates erosion as a spatial average over a particular landscape profile within a field. However, erosion varies greatly along these profiles and between profiles within a field. Estimates of total productivity loss for a field based on these spatially averaged erosion predictions can contain substantial uncertainty (Perrens et al., 1985). These limitations must be considered when directly comparing predictions from the two models. It should also be noted that the USLE has been found to have a relative prediction error of up to ±100% (e.g., Risse et al., 1993) at the lower soil loss rates (i.e., ≤ 5 kg m^{-2}), as predicted for many of the cropping/management scenarios and erosion process cases in this study. If these error limits were included in the figures, the prediction intervals would overlap and show that the USLE and WEPP prediction responses were similar. In addition to weaknesses in the USLE noted above, the potentially large relative error in the USLE should be considered when comparing WEPP model soil loss output responses and USLE estimates. Finally, the soil loss comparison was performed to determine the cropping/management scenarios and erosion process cases for which the USLE and WEPP soil loss predictions are statistically similar (or different). The comparison does not provide information that the WEPP hillslope profile model does not accurately predict soil loss for certain cropping/management scenarios and erosion process cases. However, it does offer a straightforward and objective method for gauging uncertainty in the erosion prediction performances of WEPP and the USLE.

Conclusions and Future Research

Results of this study illustrate the usefulness of combining SA and Monte Carlo LHS for providing detailed uncertainty analysis information for complex, physically based models such as WEPP. SA is valuable in determining input parameters that are dominant for each model response; therefore, the selection of input parameters for use in an uncertainty analysis should be made only after a thorough SA has been conducted. The OAT SA performed in this study showed that WEPP runoff and soil loss output responses were most sensitive to changes in baseline effective hydraulic conductivity (K_b) and sand content. The WEPP model corn yield output response was most sensitive to crop input parameters affecting the simulation of biomass development. The variances resulting from the FOEA and Monte Carlo LHS analyses should be indicative of the variance that would be found for adequate data measured in the field. The FOEA runoff and soil loss variances calculated in this study were considerably larger than the corresponding Monte Carlo LHS simulation variances. This indicates that the WEPP model is likely nonlinear (at least for the processes affecting runoff and soil loss); therefore, FOEA may not be the best uncertainly analysis technique for WEPP. It is important to note that local OAT SA and FOEA approaches are derivative-based. Therefore, the input-output relationship for the analyses is only true at the point where taken. When the input is uncertain or the input-output relationship is unknown, the results of the OAT SA and FOEA become unwarranted. In addition, the input-output relationship can change depending on model assumptions (scenarios). Interactions among model inputs may also contribute significantly to the sensitivity of parameters, especially for nonlinear models.

Monte Carlo LHS simulation works well with nonlinear models and is an expedient technique to estimate model output response error variances for WEPP and other H/WQ models when FOEA is not appropriate. However, care should be exercised in selecting the input parameters for a Monte Carlo LHS simulation (i.e., through a comprehensive SA), as this reduces the overall computational effort required. For this study, results were as expected between the Monte Carlo LHS erosion process cases and among the Monte Carlo LHS scenarios for runoff, soil loss, and corn yield as slope length and steepness were increased. However, the Monte Carlo LHS mean model responses did not approach the baseline simulation run values as expected. If the model response standard deviation is considerably larger than the mean value, this indicates that a skewed, non-normal distribution best represents the model output response. The WEPP output response pdfs in figures 2 through 4 were often non-normally distributed, which further implies that Monte Carlo LHS is a more suitable uncertainty analysis technique than FOEA for complex, nonlinear natural resource models such as WEPP.

Future research should include development of a model evaluation framework incorporating more advanced sensitivity and uncertainty analysis techniques as integrated components of further WEPP evaluation to determine which model input parameters require the most certainty. Global SA methods, such as the Fourier Amplitude Sensitivity Test (FAST; Saltelli et al., 1999), and the Sobol' (1993) technique, can determine not only sensitivity to individual factors but also sensitivity to interactions between factors. These variance-based methods are well accepted, can be used to derive cumulative distribution functions (CDFs) for uncertainty analysis (Saltelli et al., 2000), and can easily be incorporated within a model evaluation framework. Because of its flexibility, ease of implementation, and suitability for parallel implementation on distributed computer systems, the GLUE method has been used in a wide variety of applications and can also be easily incorporated within a model evaluation framework. However, the Monte Carlo based sampling strategy of the prior parameter space typically utilized in GLUE is not particularly efficient. This becomes especially problematic for high-dimensional parameter estimation problems and also for complex simulation models that require significant computational time to run and produce the desired output. Therefore, combining different types of Markov chain Monte Carlo schemes (e.g., Makowski et al., 2002; Blasone et al., 2008) with GLUE to improve computational efficiency represents a worthwhile area for future research. Perhaps most importantly, since they can be difficult to determine precisely due to the intrinsic variability in natural processes, costly monitoring, or data measurement error, input data and model parameters are rarely if ever known with certainty for agroecosystem models like WEPP (Wang et al., 2005). Therefore, performing an SA/UA within a model evaluation framework is desirable in order to correctly estimate model parameters and generate accurate model predictions (Makowski et al., 2002).

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