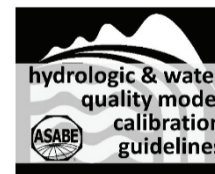# HYDROLOGIC AND WATER QUALITY MODELS: SENSITIVITY

Y. Yuan, Y. Khare, X. Wang, P. B. Parajuli, I. Kisekka, S. Finsterle

ABSTRACT. *This article is part of a collection of articles that provides a comprehensive description of hydrologic and water quality (H/WQ) model calibration and validation concepts and processes. Sensitivity analysis (SA), which is often used to quantify the strength of relationships between model inputs and outputs, is an essential evaluation of any kind of modeling. SA is crucial in H/WQ models due to various aspects involved in H/WQ modeling processes, such as empiricism, spatiotemporal scales, and complexity, that require an assessment of parameters' influence on the model's prediction. This study synthesized SA applications for 25 H/WQ models in the special collection on model use, calibration, and validation published in 2012 and provides guidance on their future applications. Commonly used SA methods are summarized along with tools to implement them. While SA was not employed for all 25 models in the special collection, a wide range of SA methods (from partial derivatives to variance-based global methods) and sensitivity measures (from scatter plots to variance decomposition measures) were used in the literature. Some model parameters were found to be important in most sensitivity applications performed for the models; however, their relative importance varied from study to study, underscoring the necessity of SA for every new model application. Nevertheless, summarizing important model parameters can still serve as a starting point for model users. Since most studies concentrated on model parameters alone; future SA applications in H/WQ modeling should also consider other inputs (climate data, boundary conditions, etc.) and non-parametric aspects, such as features and processes considered in the model.*

Keywords. Hydrologic and water quality modeling, One-at-a-time, Parameters, Sensitivity analysis, Sensitivity measures, Sensitivity methods.

This article is part of a collection of articles that provides a comprehensive description of hydrologic and water quality (H/WQ) model calibration and validation concepts and processes. Other topics in the collection are: terminology (Zeckoski et al., 2015), hydrological processes and model representation (Arnold et al., 2015), spatial and temporal scales (Baffaut et al., 2015), parameterization (Malone et al., 2015), calibration and validation strategies (Daggupati et al., 2015), per-

formance measures and evaluation criteria (Moriasi et al., 2015), uncertainty in model calibration and validation (Guzman et al., 2015), and documentation and reporting (Saraswat et al., 2015).

Sensitivity analysis (SA) is primarily used to quantify and/or explore the strength of relationships between model inputs and outputs (Lane and Ferreira, 1980; Saltelli et al., 2004). Although uncertainty and SA are often carried out in tandem, they serve different purposes; the former focuses on propagation of uncertainty from inputs to outputs (Saltelli et al., 2000a), while the latter focuses on the influence of model inputs on model outputs. In this study, model input refers to anything subjected to analysis. SA is used in a number of applications, including parameter fixation, identification of important model parameters and components, allocation of resources for parameter and data measurement, model or algorithm corroboration, and development of recommendations for decision making (Campolongo et al., 2011). H/WQ models, which can range from simple empirical submodels to complex mechanistic process-based components, may involve a large number of adjustable parameters (Yen et al., 2014, 2015). Thus, SA is necessary to investigate the influence of a subset of model inputs (represented by adjustable parameters that reflect one or multiple unknown or uncertain, potentially transformed input variables to the numerical simulator) on selected model outputs, which represent a performance measure of interest. SA is therefore most useful when it addresses parameters that are difficult to measure or uncertain and that impact the model

The authors are **Yongping Yuan, ASABE Member,** Research Hydrologist, U.S. EPA Office of Research and Development, NERL-ESD-Landscape Ecology Branch, Las Vegas, Nevada; **Yogesh Khare, ASABE Member,** Post-Doctoral Research Associate, Department of Agricultural and Biological Engineering, University of Florida, Gainesville, Florida; **Xiuying Wang,** Research Scientist, Blackland Research and Extension Center, Temple, Texas; **Prem B. Parajuli, ASABE Member,** Associate Professor, Department of Agricultural and Biological Engineering, Mississippi State University, Mississippi State, Mississippi; **Isaya Kisekka, ASABE Member,** Assistant Professor, Kansas State University Southwest Area Extension, Garden City, Kansas; **Stefan Finsterle,** Staff Scientist, Lawrence Berkeley National Laboratory, Earth Sciences Division, Berkeley, California. **Corresponding author:** Yongping Yuan, P.O. Box 93478, 944 East Harmon Ave., Las Vegas, NV 89119; phone: 702-798-2112; e-mail: yuan.yongping@epa.gov.

Transactions of the ASABE

Vol. 58(6): 1721-1744   2015 American Society of Agricultural and Biological Engineers   ISSN 2151-0032   DOI 10.13031/trans.58.10611   1721

prediction of interest (Lane and Ferreira, 1980). SA is also conducted to guide data collection for model calibration and validation (Yuan et al., 2005, 2009). For example, in evaluating the phosphorous component of the AnnAGNPS, Yuan et al. (2005) found that soil phosphorous content in the top soil layer was the most sensitive variable for P loss simulation. Thus, an intensive soil survey was conducted along with other purposes (Yuan et al., 2009). As detailed by Yuan et al. (2009), soil samples were collected from the center of each 2×2 m grid established in the study watershed, and routine soil testing was performed for collected soil samples. The tested results were then used in AnnAGNPS model evaluation.

Comprehensive H/WQ models contain a number of components and their corresponding parameters, each of which can be subjected to calibration. Many combinations of model inputs may give the same or almost the same model performance, a condition known as equifinality, which reflects a high level of interaction between parameters in the model. For SA to serve as a useful calibration guideline, it must be able to reveal these interactions (Ratto et al., 2001).

The objectives of this study were: (1) to provide an overview of SA methods and measures, (2) to provide an overview of independent SA tools for H/WQ models, (3) to review and synthesize the SA (SA methods, measures and tools used, sensitive parameters identified, and output evaluated) performed for H/WQ models described in the 2012 special collection (Moriasi et al., 2012), and (4) to provide guidance on future model applications.

METHODS AND PROCEDURES

With SA of H/WQ models being a core part of model application, it is natural to have a substantial body of SA-related work in the literature. This study synthesizes SA methods, available tools to implement SA, and related applications in the context of H/WQ modeling, especially for the models described in the special collection (Moriasi et al., 2012). A diagram summarizes SA methods (fig. 1a), tools for SA (fig. 1b), and SA conducted for H/WQ models in the special collection (Moriasi et al., 2012) reviewed in this study (fig. 1c).

OVERVIEW OF SENSITIVITY METHODS AND MEASURES

A variety of SA methods and measures have been used in H/WQ modeling, and each has its own advantages and disadvantages, which are discussed subsequently. Figure 2 shows SA method classification. The most widely recognized classification is based on exploration of the parameter space. When SA is performed by varying individual parameters in a small vicinity of a base point, the method is classified as local. The procedure is similar to the calculation of partial numerical derivatives. On the other hand, if SA is performed by varying all parameters within their entire uncertainty ranges simultaneously, the method is classified as global. Local methods are usually more computationally efficient; however, their results are often not reliable because they are applicable only around the base point and cannot account for model nonlinearity, non-monotonicity, and parameter interactions. Global SA methods overcome some or all of the drawbacks of local SA (Saltelli et al., 2000b, 2008). Another way of classifying SA methods is based on the purpose of the application. Some low computational cost methods capable of qualitatively identifying influential parameters are categorized as screening or qualitative methods, which are often used to
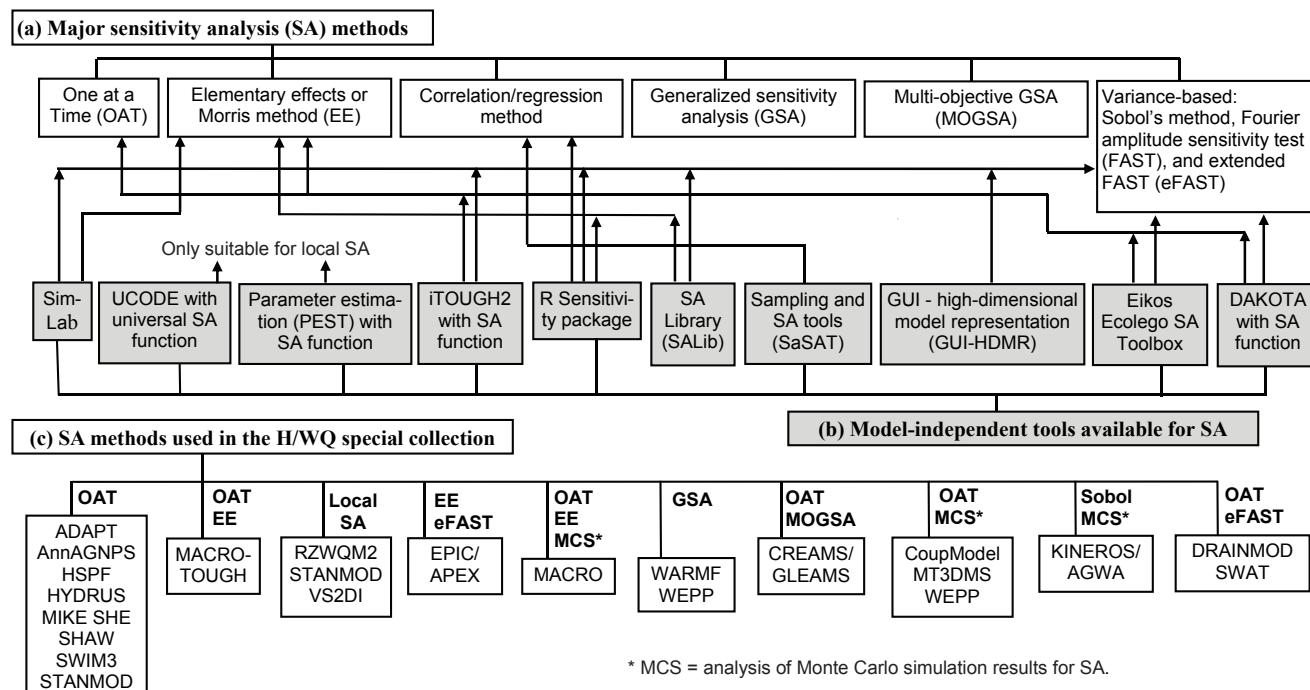

Figure 1. Diagram of (a) SA methods reviewed, (b) model-independent tools available for these SA methods (indicated by arrows), and (c) SA methods used for the models in the 2012 special collection on hydrology and water quality modeling (Moriasi et al., 2012).
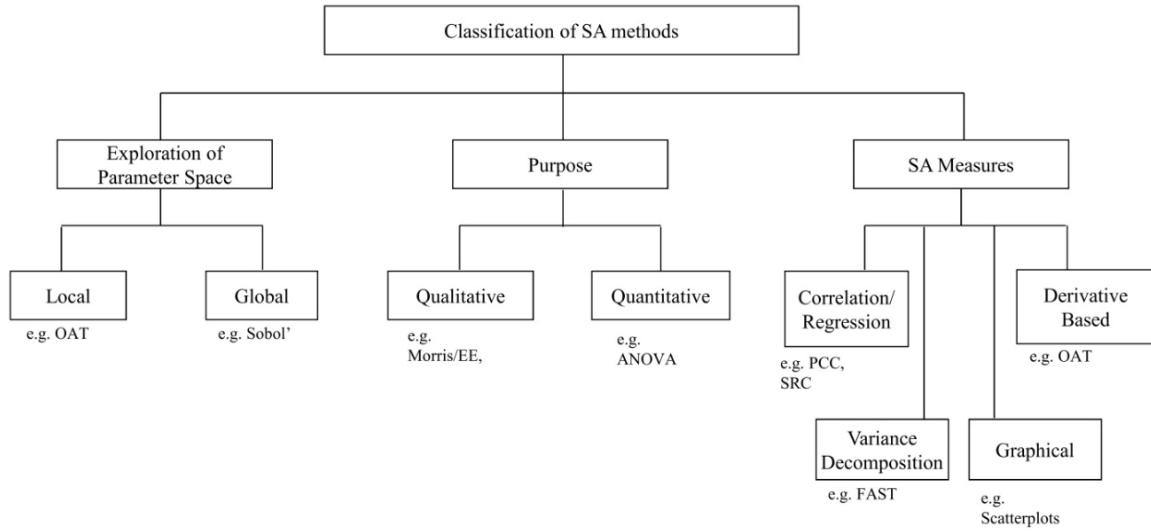
Figure 2. Classification of sensitivity analysis (SA) methods.

reduce the burden on further model analysis (Campolongo et al., 2007; Muñoz-Carpena et al., 2007). On the contrary, methods that quantify the contributions of individual parameters to output variance, often at a very high computational cost, are known as quantitative methods. The third way of classifying the SA methods is based on sensitivity assessment (sensitivity measure), which ranges from simple visual inspection of input vs. output plots to robust and sophisticated variance-based sensitivity indices.

One at a Time

One of the simplest and most commonly used SA methods is changing one parameter at a time (OAT) while keeping all others fixed at their base values (Nearing et al., 1990; Haan and Skaggs, 2003; White and Chaubey, 2005). Sensitivity is commonly measured by the ratio of change in output to change in an individual parameter. OAT appears to be a reasonable approach, as any output change will unambiguously be due to the single parameter changed. However, this approach needs to be used cautiously because, for nonlinear models, this sensitivity measure strongly depends on the point in the parameter space at which it is being evaluated. Being "local" in nature, this approach has other disadvantages, as mentioned above.

A commonly used sensitivity measure is the relative sensitivity (McCuen, 1973):

$$S_r = \frac{x_{bc}}{y_{bc}} \times \frac{\Delta y}{\Delta x} \qquad (1)$$

where x_{bc} is the baseline value of parameter x, y_{bc} is the corresponding output, and Δy is the change in the model output corresponding to change Δx in parameter x. The relative sensitivity (S_r) represents the ratio of a relative normalized change in output to a normalized change in input. A negative value indicates that the input and output are inversely related. The greater the absolute value of S_r, the greater the impact an input parameter has on a particular output. Because S_r is dimensionless, it provides a basis for comparison among input parameters and output variables of different types.

In actual applications of OAT, modelers have used variations of equation 1 and have defined other sensitivity measures of their own. For example, Nearing et al. (1990) used extreme values of x (instead of values that are relatively close to the point where the sensitivity is evaluated) and corresponding model outputs to evaluate the sensitivity.

The sensitivity of the model to changes in input parameters was also assessed by the maximum absolute ratio of variation of model output and variation of the model input (MAROV) (Dubus and Brown, 2002):

$$\text{MAROV} = \max \left| \frac{(\Delta y)}{(\Delta x)} \times \frac{(x_{bc})}{(y_{bc})} \right| \qquad (2)$$

where x_{bc}, y_{bc}, Δx, and Δy are the same as defined previously. Hence, MAROV is essentially similar to S_r but involves multiple OAT experiments based on different perturbation values (e.g., $\Delta x / x_{bc} = 10\%, 20\%, 30\%, \ldots, 100\%$, etc.). The maximum value of the absolute value of S_r for an individual parameter is MAROV.

Elementary Effects (EE) Method

The EE method can be considered an extension of the OAT approach. However, unlike OAT, the EE method is a global method because OAT experiments are repeated over the entire parameter space in order to assess sensitivity. The first step in the EE method is to generate a parameter sample, which is done from the k-dimensional parameter hyperspace divided into a p-level grid. A p-level grid implies that each parameter can take only p distinct values $\{0, 1/(p-1), 2/(p-1), \ldots, 1\}$. Next, r trajectories (or paths), each consisting of $(k+1)$ points, are generated. Within any given trajectory, two parameter samples differ from each other in only one parameter by a fixed amount $\Delta = p/[2(p-1)]$. The EE associated with the ith model parameter is calculated as:

$$\text{EE}_i = \left[Y(x_1, \ldots, x_{i-1}, x_i + \Delta, x_{i+1}, \ldots, x_k) \right. $$
$$\left. - Y(x_1, \ldots, x_{i-1}, x_i, x_{i+1}, \ldots, x_k) \right] \div \Delta \qquad (3)$$

where Y is the model output to the corresponding input set.

Because each trajectory provides one EE value for each of the k parameters, r independent trajectories give r EE values for each parameter. These EEs can then be statistically analyzed. Morris (1991) proposed to use the mean (μ_i) and standard deviation (σ_i) calculated from the EE distribution associated with the ith parameter as sensitivity measures, where μ_i is an indicator of total or overall importance (i.e., primary and interaction effects), and the standard deviation (σ_i) indicates parameter interactions and nonlinearity associated with the ith parameter. The total computational cost associated with this method equals the time needed to perform $r(k + 1)$ simulation runs. Different articles report different numbers for r, ranging from 2 to 80, although some studies (Herman et al., 2013; Wainwright et al., 2014) have indicated that an r of less than 20 trajectories is sufficient for reliable parameter screening.

Campolongo et al. (2007) and Saltelli et al. (2005) proposed an improvement to this method in which the modified Morris measure is the mean (μ^*_i) of the distribution of absolute values of the EE_i. Campolongo et al. (2007) showed that μ^*_i is a better sensitivity measure than μ_i for ranking parameters in order of importance. For some non-additive, non-monotonic models, EEs of a particular input may be positive or negative for different trajectories, which may cancel each other and thus not be reflected in the calculated μ_i, ultimately not being identified as influential in spite of strongly affecting the model output. This modified Morris sensitivity measure has been widely accepted as the standard for screening exercises using the EE method (Pujol, 2009; Campolongo et al., 2011). Campolongo et al. (2007) also proposed a modified sampling strategy to select final r trajectories from a pool of about 500 to 1000 trajectories based on a distance maximization criterion. Pujol (2009), Campolongo et al. (2011) and Ruano et al. (2012) also proposed different types of parameter sampling strategies for the EE method.

Correlation/Regression Methods

A number of SA methods involve multiple model simulations with randomly or quasi-randomly selected parameter sets. Correlation or regression coefficients between inputs and model outputs are calculated and used as sensitivity measures. In the SA literature, these methods are often referred to as correlation/regression methods or as sampling-based techniques. Typical sensitivity measures include the Pearson product moment coefficient (PEAR), standardized regression coefficient (SRC), partial correlation coefficient (PCC), Spearman coefficient (SPEAR), standardized rank regression coefficient (SRRC), and partial rank correlation coefficient (PRCC). The strengths and weaknesses of these methods have been assessed in a number of studies (Saltelli and Marivoet, 1990; Helton and Davis, 2002; Manache and Melching, 2008).

PEAR is the usual linear correlation coefficient calculated on output variables Y_i and input parameter X_{ij}, while SRCs are calculated by fitting a multi-linear regression model. The linear regression coefficients b_j obtained from this model are then multiplied by the ratio of variance of the jth parameter to total model variance. The PCC between output Y and input parameter X_j is obtained from sequential

regression models. Two models are constructed first:

$$\hat{Y} = b_0 + \sum_{i \neq j} b_i x_i \qquad (4)$$

$$\hat{X}_j = c_0 + \sum_{i \neq j} c_i x_i \qquad (5)$$

where $\hat{Y}$ and $\hat{X}_j$ are response variables of the regression models. Next, new variables ($Y - \hat{Y}$ and $X_j - \hat{X}_j$) are calculated. The correlation coefficient between them is the PCC between Y and X_j.

One of the drawbacks of PEAR, SRC, and PCC is that they perform well only if the model is linear. Hence, while applying these methods, it is recommended to calculate the coefficient of determination (R^2) for the regression model to test the degree of linearity of the model. Saltelli et al. (2004) suggested $R^2 > 0.7$ as a limit of applicability for linear regression-based sensitivity techniques. SPEAR, SRRC, and PRCC are the rank-based counterparts of PEAR, SRC, and PCC, respectively, as they are calculated by the same procedure but on ranked inputs and outputs. Hence, these can be used as sensitivity indices if the model is nonlinear but monotonic (continuous and smooth rising or falling response). SRC and PCC produce identical parameter rankings if the inputs are independent but may differ in cases of correlated parameters. Iman and Helton (1988) proposed the use of PCC when parameters are correlated, as it provides a measure of the strength of the linear relationship between output variables and input parameters after a correction has been made for the linear effects of the other input parameters. However, a rank-based restrictive correlation structure, as proposed by Iman and Conover (1982), needs to be specified while sampling parameter sets.

The success of these methods depends on the scheme used to sample the input parameters. Among several sampling techniques available, e.g., random sampling, importance sampling, and fixed samples, Latin hypercube sampling (LHS) has been found to produce stable results (Helton and Davis, 2002). In LHS, marginal distributions of parameters are divided into intervals of equal probability. Samples are then drawn randomly from each interval for every parameter, which ensures full coverage of the range of each variable (McKay et al., 2000).

Generalized SA, Regionalized SA, and Hornberger-Spear-Young Method

The generalized SA (GSA) technique is a global method first presented by Spear and Hornberger (1980) and Hornberger and Spear (1981) for Monte Carlo filtering purposes. Based on model output values, model runs and hence parameter values are partitioned into behavioral (acceptable) and non-behavioral (non-acceptable) categories. Distributions of a given parameter from the two categories are compared to assess the statistical difference by the Kolmogorov-Smirnov (KS) two-sample test (Massey, 1951). If the difference is statistically significant, then the model is considered sensitive to that parameter. One advantage of this approach is that no assumption is made about the covari-

ance of parameters, i.e., it is a non-parametric SA method (Beven, 2011). However, GSA cannot identify the relative importance of a parameter within the behavioral class (Saltelli et al., 2000a), making it somewhat qualitative in nature.

Multi-Objective Generalized SA (MOGSA)

Multi-objective generalized SA (MOGSA) was developed by Bastidas (1998) as an extension of GSA to make it more suitable for models with a large number of parameters, which is typical of geophysical models. In MOGSA, the concept of a singular criterion for behavioral or non-behavioral model runs is replaced by multi-criteria filtering based on a Pareto optimal set. Essentially in MOGSA, n behavioral parameter sets are separated from m non-behavioral parameter sets based on N selection criteria, which are then tested for statistical significance using the KS test to identify the model output's sensitivity to a particular parameter.

Variance-Based Methods

Variance-based methods use analysis of variance (ANOVA)-like techniques to break output variance into components. Two of the most commonly used variance-based global SA techniques are the Sobol method and the Fourier amplitude sensitivity test (FAST).

Sobol Method: Based on the work of Sobol (1993), the main idea is to decompose the function $f(\mathbf{X})$ (i.e., model response Y) into summations of increasing dimensionality:

$$f(x_1, x_2, \ldots, x_k) = f_0 + \sum_{i=1}^{k} f_i(x_i) + \sum_{1 \le i \le j \le k} f_{ij}(x_i, x_j) + \ldots + f_{1,2,\ldots,k}(x_1, x_2, \ldots, x_k) \quad (6)$$

Sobol (1993) further showed that this decomposition is unique and all terms can be evaluated via multidimensional integrals. The contribution of each term in equation 6 to the total variance V can be easily obtained:

$$V = \sum_{i=1}^{k} V_i + \sum_{1 \le i \le j \le k} V_{ij} + \ldots + V_{1,2,\ldots,k} \quad (7)$$

The equation can be standardized by dividing throughout by V to give:

$$1 = \sum_{i=1}^{k} S_i + \sum_{1 \le i \le j \le k} S_{ij} + \ldots + S_{1,2,\ldots,k} \quad (8)$$

where S_i are first-order sensitivity indices, S_{ij} are second-order sensitivity indices (and so on), and k is the number of model parameters. The total effect index of the ith parameter is calculated by adding its first-order index and its contribution to higher-order indices. For example, if $k = 3$, then the total effect index for the first parameter is calculated as $ST_1 = S_1 + S_{12} + S_{13} + S_{123}$; $\Sigma S_i = 1$ indicates that the model is perfectly linear.

In practice, only the first-order and total effect sensitivity indices are calculated as follows:

$$S_i = \frac{V[E(Y|X_i)]}{V(Y)} \quad (9)$$

$$S_{Ti} = \frac{E[V(Y|X_{\sim i})]}{V(Y)} = 1 - \frac{V[E(Y|X_{\sim i})]}{V(Y)} \quad (10)$$

where $V[E(Y|X_i)]$ is the variance of expectation of Y over the ith parameter, $V[E(Y|X_{\sim i})]$ is the variance of expectation of Y over all but the ith parameter, and similarly $E[V(Y|X_{\sim i})]$ is the expectation of variance of Y over all but the ith parameter.

The computational cost for traditionally used algorithms to implement the Sobol method is $N(2k + 2)$, where N is the number of model runs per index. Saltelli (2002) extended the original approach of Sobol (1993). This modification has enabled calculation of the first-order and total effect sensitivity indices along with $(k - 2)$th-order effects with $N(k + 2)$ model runs. There are various variance decomposition schemes and two parameter sampling schemes: LP_τ sequences and winding stairs. Saltelli and Annoni (2010) showed that Jansen's variance decomposition formula (Jansen, 1999) coupled with LP_τ sequences produces stable total sensitivity indices at lower Ns.

FAST and Extended FAST (eFAST): The Fourier amplitude sensitivity test (FAST) was first proposed by Cukier et al. (1973, 1978) and subsequently modified by a number of scientists. Originally, FAST could only identify EE or first-order indices. The main idea is to convert multidimensional integrals (as seen in Sobol) to one-dimensional integrals in s by multi-dimensional Fourier transforms. A search curve is defined that explores the k dimensional unit hypercube parameter space by a set of parametric equations:

$$x_i(s) = G_i(\sin \omega_i s) \quad (11)$$

where x_i is the ith parameter as a function of s, G_i is the transformation function, $s = [-\pi, \pi]$ is a scalar variable, and ω_i is a set of integer angular frequencies.

Saltelli et al. (1999) extended this idea by defining a different transformation function that is more efficient and allowed resampling by the introduction of a random phase lag. This enabled the calculation of total effects, and the method is known as extended FAST or eFAST. Details of sensitivity indices (first order and total order) for eFAST can be found in Saltelli et al. (1999). The cost of computation or the number of model evaluations required per parameter is given by:

$$N_s = N_r(2M\omega_{\max} + 1) \quad (12)$$

where N_r is the number of resamples (or phase lags), M is the interference factor, and $\omega_{\max}$ is the maximum of parameter frequencies. Saltelli et al. (1999) also provided a procedure to calculate frequencies assuming $N_r = 2$ and $M = 4$. They recommended using $N_s \sim 500$ to 1000 to achieve robust results.

CORRELATED PARAMETERS, OTHER SA METHODS, AND RECENT DEVELOPMENTS

SA Methods for Models with Correlated Parameters

Large H/WQ models, or their specific applications, often involve parameters correlated among themselves. In such cases, it is not possible to directly apply the SA methods discussed previously. For example, the variance-based methods (Sobol as well as FAST) assume that the parameters are orthogonal, i.e., non-correlated. To perform SA for models with correlated parameters, PCCs and PRCCs can be used based on samples with restricted rank correlation structure (Iman and Conover, 1982) and decomposition of variance into correlated and independent components (Xu and Gertner, 2008). Kucherenko et al. (2012) briefly summarized developments in variance-based techniques for the correlated parameter case. However, no implementations of those techniques in H/WQ SA studies were found. Another way to tackle the correlation issue is to account for the correlation, either by defining the relationship between correlated parameters and using it as a part of the model or by combining correlated parameters into another independent parameter and then performing variance-based SA (Khare et al., 2013).

Other SA Methods and Recent Developments

Apart from calculating sensitivity measures, useful information about the influence of parameters can be extracted by merely plotting inputs against outputs in various ways, such as scatter plots, radar graphs, cobweb plots, etc. Although the EE method is the most widely used method for parameter screening, other methods can be used, such as sequential bifurcation design (Bettonvil, 1990; Bettonvil and Kleijnen, 1997). The first-order reliability method (FORM) and the second-order reliability method (SORM) are used for SA in the context of reliability engineering. Another popular method is Bayesian SA, which is often used in decision modeling. A good review of these methods can be found in Saltelli et al. (2000a, 2000b) and Cacuci and Ionescu-Bujor (2004).

Some of the recent efforts in SA methods have focused on: (1) improving the EE method, especially the sampling strategies (Campolongo et al., 2011; Pujol, 2009; Ruano et al., 2012), (2) variance decomposition for the Sobol method (Saltelli et al., 2010), (3) approximations for efficient calculation of the Sobol index (Wainwright et al., 2014; Wu et al., 2012), and (4) derivative-based global sensitivity measures (Kucherenko et al., 2009).

MODEL-INDEPENDENT TOOLS FOR IMPLEMENTING SA

With the exception of a few models (SWAT, MIKE, HYDRUS 2D/3D, RZWQM2), most H/WQ models do not have a built-in capability to perform SA. Model-independent SA tools, i.e., tools external to the model, such as SimLab (Saltelli et al., 2004), UCODE (Poeter and Hill, 1998), and PEST (Doherty, 2008), can offer modelers the opportunity to implement SA in a time-saving and scientifically reproducible way. In this section, examples of commonly used model-independent tools for SA are summarized.

SimLab

SimLab is a model-independent software program for performing Monte Carlo-based uncertainty and SA developed by the European Commission Joint Research Centre (JRC) (Saltelli et al., 2004). SA is based on performing multiple model simulations using probabilistically selected sets of inputs. Using the related model outputs, uncertainty in model predictions and sensitivity measures of input parameters are quantified (Saltelli et al., 2004). SimLab can be used for performing screening (EE method) and global SA. The sampling methods in SimLab include Morris trajectories, fixed samples, Latin hypercube, sampling for FAST, quasi-random LP$_\tau$, and random samples. The stepwise SA procedure in SimLab includes (1) parameter generation, (2) model execution in SimLab or an external environment and storing outputs of interest, and (3) statistical analysis to calculate sensitivity indices. Examples of SimLab applications in H/WQ models in the special collection (Moriasi et al., 2012) include KINEROS2 (Yatheendradas et al., 2008), EPIC (Wang et al., 2005a), DRAINMOD-N II (Wang et al., 2005b), and APEX (Wang et al., 2006b; Yin et al., 2009). SimLab is public domain software and is available for download at http://ipsc.jrc.ec.europa.eu/?id=756.

The main advantage of SimLab is that it can perform global SA using screening or variance-based methods. One limitation of version 2.2 of SimLab, the version currently distributed by JRC (SimLab, 2008), is that some recent advancements in SA methods, such as the trajectory sampling scheme for the extended Morris method, have not yet been incorporated. However, JRC has developed and maintains a set of routines, written in Matlab or FORTRAN, to link SimLab version 2.2 with Matlab to implement new SA methodologies (extended Morris, Jansen's variance decomposition). New routines are made available regularly. These routines can be downloaded from the same website as that of SimLab.

UCODE

UCODE was developed for inverse modeling posed as a parameter estimation problem using arbitrary external models (Poeter and Hill, 1998). Although UCODE was developed for groundwater flow models (specifically MODFLOW), it can be used with any type of application. UCODE can be used to perform SA, data needs assessment, and model calibration and prediction uncertainty analysis (Poeter and Hill, 1998). The only requirements for using UCODE are that process models must have text-only input and output files, the numbers in the text files must have sufficient significant digits, and all the required models must be run from a single batch file (Poeter and Hill, 1998). UCODE uses forward or central difference perturbation to calculate local sensitivity related to each parameter. Details can be found in Poeter and Hill (1998). One limitation of UCODE is that it cannot perform global SA. The ability of UCODE to handle a set of related application models makes it a powerful tool, especially for large models made up of different modules. Examples of UCODE applications for SA in H/WQ models in the special collection (Moriasi et al., 2012) include WARMF (Geza et al.,

2009) and VS2DI (Niswonger and Prudic, 2003). The software is in the public domain and can be obtained at http://igwmc.mines.edu/freeware/ucode/?CMSPAGE=igwmc/freeware/ucode/.

PEST

PEST (parameter estimation) is a model-independent nonlinear parameter estimation and predictive uncertainty analysis tool that produces sensitivity measures as by-products of parameter estimation. During optimization of the objective function, PEST linearizes the relationship between the model output and model parameters. PEST then uses forward or central difference perturbation to calculate the perturbation sensitivity for each parameter (Doherty et al., 2008). Sensitivities calculated using the perturbation method are usually not very accurate (Poeter and Hill, 1998). Composite sensitivities (indicating the importance of observations as a whole to a single parameter, compared with the accuracy of the observations) are provided as by-products of parameter estimation in PEST. The requirements to link PEST to any model are that the model can be run from the command line and should have text-only input and output files. The modeler needs to specify parameter ranges, initial parameter values, and parameter increments. The modeler can also specify prior information for individual parameters or relationships between parameters. PEST only performs a local SA. Examples of PEST applications in H/WQ models in the special collection (Moriasi et al., 2012) include SWAT (Vandenberghe et al., 2001), AnnAGNPS (Baginska et al., 2003), and RZWQM2 (Ma et al., 2000). PEST is public domain software and can be downloaded at www.pesthomepage.org.

iTOUGH2

Similar to UCODE and PEST, iTOUGH2 provides inverse modeling, sensitivity, and uncertainty propagation analysis capabilities. While it is tightly linked to the TOUGH2 non-isothermal multiphase flow and transport simulator, it can also be linked to any external code. It uses the same file protocol as PEST and UCODE but employs its own algorithms (Finsterle and Zhang, 2011). iTOUGH2 evaluates local sensitivity coefficients and related composite sensitivity measures. It can also perform global SA using the Morris and Sobol methods. iTOUGH2 is described by Finsterle et al. (2012); its SA capabilities are discussed by Wainwright et al. (2013, 2014). iTOUGH2 can be licensed at http://esd.lbl.gov/tough.

R Sensitivity Package

The R programming language and statistical computing environment includes a package called Sensitivity, which is a collection of functions for performing various SA methods, such as factor screening, global SA, and reliability SA on model output (R Development Core Team, 2008). The R methods with "tell" and "ask" syntax are used to decouple simulations and sensitivity measures, which allows R to run external process computational models. Examples of SA methods implemented in R include eFAST (Saltelli et al., 1999), Morris (Morris, 1991), PCCs (Iman et al., 1985), Monte Carlo estimation of the Sobol sensitivity indices, and other variations of the Sobol method. The Sensitivity package of R can be obtained from the CRAN repository; R version 2.7.0 or greater is required. The main document describing how to use the R Sensitivity package is Pujol et al. (2015). R is a public domain programming language and statistical computing environment and can be downloaded at: http://cran.r-project.org/bin/windows/base/.

Other Tools

Other SA tools that could be linked to H/WQ models include SALib (SA Library; Herman and Reed, 2013), SaSAT (Sampling and SA Tools, Hoare et al., 2008), GUI-HDMR (GUI - High-Dimensional Model Representation; Ziehn and Tomlin, 2009), DAKOTA (Adams et al., 2013), and Eikos (Ekström, 2005). SALib is a set of routines in Python to implement SA. SALib can be used to implement the Sobol, Morris, and FAST SA methods with an arbitrary model using an approach similar to the Sensitivity package in R. SaSAT is another tool for implementing SA with any arbitrary model. SaSAT consists of a SA tool built in Matlab. However, Matlab is not required to use SaSAT because it is compiled as a standalone executable. GUI-HDMR comprises a set of Matlab functions for performing variance-based SA. DAKOTA is written in C++ and implements OAT, Morris, and variance decomposition (Sobol) techniques for SA. Eikos is another Matlab toolbox for implementing local and global SA. For all these tools, the process of implementing SA is similar to that described in the three steps under SimLab.

SYNTHESIS OF SA STUDIES ON H/WQ MODELS

SA studies performed on H/WQ models, especially those in the special collection (Moriasi et al., 2012), were reviewed. To gain insight and provide guidance for future H/WQ model applications, information on the SA methods used, input parameters analyzed, outputs evaluated, ranking of influential parameters, number of simulations needed to perform SA, sensitivity measures, and indices used to evaluate the sensitivity of input parameters are summarized in the following section and in the Appendix.

RESULTS OF SA STUDIES ON H/WQ MODELS

ADAPT

Chung et al. (1992) analyzed the sensitivity of the ADAPT model, which showed that surface runoff is sensitive to changes in the curve number, and subsurface drainage estimates are sensitive to deep seepage predictions. Other sensitive parameters include hydraulic conductivity, depth of the impeding layer, partitioning factor for surface runoff and subsurface drainage, leaf area index, and effective rooting depth (Chung et al., 1992). Soil erosion prediction is sensitive to field size (DAOVR), average slope (AVGSLP), slope length of the overland flow profile (SLNGTH), soil erodibility factor (KSOIL), and soil loss ratio (CFACT) parameters (Gowda et al., 1999). For nutrient prediction such as total nitrogen and phosphorus, nitrate-N and labile-N concentrations, and potentially mineralizable nitrogen in each soil horizon are sensitive parame-

ters (Gowda et al., 2012). Pesticide properties such as soil half-life (SOLLIF) and partitioning coefficient (KOC) are sensitive parameters for pesticide prediction (Gowda et al., 2012).

ANNAGNPS

Das et al. (2008) performed SA of AnnAGNPS runoff and sediment yield output for variations of 16 parameters for a Canadian watershed (Canagagigue Creek, a minor tributary of the Grand River) located in the northwest part of the Grand River basin. The Grand River is one of the largest rivers in southern Ontario and a tributary to Lake Erie. About 80% of the land within the 150 km^2 watershed is under agricultural activities, and 10% is woodlot (Das et al., 2008). In this study, each selected parameter was changed by an increment or decrement of 5% while keeping the other parameters as baseline values (OAT). The gradient of the output variation with respect to the selected parameter was graphically plotted to quantify the sensitivity of selected parameters. It was concluded that both runoff and sediment yield were mostly sensitive to SCS curve number and depth to subsurface drainage, followed by soil bulk density and soil hydraulic conductivity. Secondly, the peak flow was also sensitive to Manning's "n" for both cell and reach. Thirdly, sediment was also sensitive to soil erodibility factor, support practice, and cover management factors (see Appendix).

Yuan et al. (2003, 2005) performed SA (OAT) to identify the input parameters with the greatest impact on nitrogen (N) and phosphorus (P) yields in a small agricultural watershed located in the Mississippi Delta area. A single value to represent the sensitivity of the output parameter to the range of the input parameter (S_r) was used to measure the sensitivity of tested parameters. SA results indicated that the most sensitive variables of those selected were initial soil N and P contents, N and P application rates, and plant N and P uptakes (see Appendix).

APEX

Wang et al. (2006b) conducted an extensive sensitivity test for 159 sites representative of agricultural conditions across the U.S. to identify influential parameters for APEX outputs of crop grain yields, runoff and water yield, water and wind erosion, nutrient loss, and soil carbon change for a national assessment project: the cropland component of the Conservation Effects Assessment Project (CEAP). A test case from the representative sets of APEX model data was analyzed using both eFAST and the enhanced Morris method, which confirmed the reliability of the enhanced Morris measure in screening subsets of influential and non-influential parameters. Because the national analysis effort could only focus on the influential parameters for calibration purposes, the enhanced Morris method was used for SA at the remaining selected sites. Statistical analyses identified the key influential parameters (see Appendix) in APEX. However, because it was a national-scale study, parameter screening was limited to 15 parameters.

Yin et al. (2009) performed SA for 13 key parameters affecting surface runoff and sediment loss using eFAST prior to APEX calibration for three plots located in the

middle Huaihe River watershed in China. Both the first-order and total-order sensitivity indices were considered for ranking the importance of tested parameters. The curve number (CN2) and curve number index coefficient were both found to strongly influence surface runoff and affected water-induced sediment yield. Sediment yield was also found to be sensitive to the erosion control practice factor (PEC) and peak runoff rate and rainfall energy adjustment factor (APM).

COUPMODEL

CoupModel is a conglomerate of models, such as water, heat, tracer, chloride, nitrogen, and carbon, which can be linked together per modeling requirements to simulate terrestrial ecosystems at any user-specified spatial and temporal scale (Jansson, 2012). Conrad and Fohrer (2009) (see Appendix) performed SA of CoupModel to screen important parameters for GLUE-based uncertainty analysis. They assessed nitrogen leaching from grasslands under two fertilization scenarios by including water, heat, carbon, and nitrogen models. OAT SA was performed considering 350 parameters and 29 outputs. Parameters were changed by ±25% of their base values. Thirty parameters were shortlisted and then considered for uncertainty analysis. Among these 30 parameters, the decomposition process parameter, efficiency of decay litter and nitrification process parameter, and compensatory nitrogen uptake from soil were the most important.

Lundmark and Jansson (2008) used CoupModel to study the environmental effects of de-icing salt in roadside environments. A Monte-Carlo SA for water balance and salt content dynamics in soil considering 29 parameters indicated that plowed snow and airborne salt deposition amounts were the most important model parameters. In all, 1000 simulations were performed, and SRRCs were calculated as the sensitivity measures.

CREAMS/GLEAMS

CREAMS and its subsequent improvement GLEAMS are field-scale models that simulate hydrology, erosion, plant nutrients, and pesticide components of various agricultural management practices (Knisel and Douglas-Mankin, 2012). Both models have a rich application and literature history that includes uncertainty and SA. In the Appendix, only a few studies have been reported.

Lane and Ferreira (1980), as a part of CREAMS documentation, performed OAT-based SA of submodels of CREAMS. For the runoff submodel, curve number, plant-available water, evaporation parameters, mean monthly temperature and radiation, and percolation parameters were found to impart sensitivity to model outputs, while Manning's "n" for overland flow, channel, and friction slope were important for erosion. A number of P and N related parameters were influential for the nutrient submodel. On the other hand, for the pesticide submodel, depth and efficiency of incorporation, decay constant, and application rate were some of the important parameters. In another study on only the erosion component of CREAMS, Silburn and Loch (1989) found that the submodel was highly sensitive to specific gravity of sediment and slope steepness

while moderately sensitive to a number of parameters including peak runoff rate, slope length, kinematic viscosity, erodibility parameter, etc. (see Appendix).

SA of the pesticide and chemical loss components of GLEAMS (Persicani 1996; Cryer and Havens, 1999; Chinkuyu et al., 2003) indicated that, in general, curve number, field capacity, degradation, and partition coefficients were important, apart from some application-specific sensitive parameters. In another application to model nitrogen removal for municipal wastewater treatment, based on local derivatives, GLEAMS was found to be sensitive to soil evaporation, grass rooting depth, wilting point, rainfall nitrogen, and dry matter ratio.

DRAINMOD

Haan and Skaggs (2003) performed SA of the DRAINMOD model using the OAT method based on data from an experimental agricultural field at the Tidewater Research Station (TRS) in the North Carolina Coastal Plain. The predominant Portsmouth sandy loam soil type and continuous corn were used in the simulations. Maximum surface storage (STMAX), saturated soil water content (THETAS), lateral saturated hydraulic conductivity (K_{satH}), residual soil water content (THETAR), and drainage coefficient (DC) had the most potential to affect subsurface drainage volume and cumulative water stress during the growing season. Both THETAR and the minimum air volume required to able to work the land (MAV) were influential on relative crop grain yield.

Wang et al. (2006a) conducted SA for DRAINMOD subsurface drain flow predictions using the eFAST method. The simulations used data from the Southeast Purdue Agricultural Center (SEPAC) drainage field with Clermont silt loam soil and continuous corn. Eight parameters were considered, and input sets were generated using SimLab. A FAST sampling designed for all total-order and first-order effects was used. No correlation was assigned between parameters. An SAS macro programming interface was developed to couple the SimLab tool with DRAINMOD for automatic input file updating and multiple model runs. A total of 1,992 input sets were generated. Lateral saturated hydraulic conductivity (K_{satH}), vertical saturated hydraulic conductivity of the restrictive layer (K_{satV}), surface micro storage (S1), and soil moisture at 0 cm tension (W) were identified as important for DRAINMOD subsurface drain flow predictions.

EPIC

SA was performed for crop grain yield and soil organic carbon dynamics simulated with the EPIC model using data from the Arlington Agricultural Research Station in Wisconsin (Wang et al., 2005a). Nine parameters were considered for both uncertainty and SA. The eFAST first-order and total-order sensitivity indices based on both model output and likelihood measure were calculated. The study identified that the available soil water capacity, potential heat units (PHU), biomass-energy ratio (WA), and harvest index (HI) were influential for the crop grain yield, and that microbial decay rate coefficient (parm20) and fraction of humus in the passive pool (FHP) were influential for the

soil organic carbon dynamics. However, when the SA was based on likelihood weights, it revealed that good results were not driven by a particular parameter but by a set of interactive parameters. Causarano et al. (2007) conducted similar SA for the two components of EPIC for an experiment field in the Coastal Plain of central Alabama. They included 15 parameters, and their results for influential parameter selection for the crop growth and SOC modules agreed with Wang et al. (2005a), except for microbial activity in the top layer (parm51), which was not considered for SA by Wang et al. (2005a).

HSPF

Sensitivity studies of HSPF-predicted discharge showed that the predicted discharge was most sensitive to the lower zone nominal storage, soil infiltration capacity index, groundwater recession coefficient, and upper zone nominal storage (Laroche et al., 1996; Fontaine and Jacomino, 1997). Engelmann et al. (2002) evaluated additional hydrologic parameters and found that the model was also sensitive to the fraction of groundwater inflow lost to deep groundwater; moderately sensitive to the fraction of potential evapotranspiration that can be satisfied from baseflow, the fraction of potential evapotranspiration that can be satisfied from groundwater, and the interception storage capacity; and somewhat sensitive to Manning's "n" for overland flow, overland flow plane length, and overland flow plane slope. Engelmann et al. (2002) also showed that sediment concentration was sensitive to the coefficient in the soil detachment equation, the coefficient in the detached sediment washoff equation, the exponent in the detached sediment washoff equation, the coefficient in the matrix soil scour equation, and the exponent in the matrix soil scour equation (see Appendix).

Fontaine and Jacomino (1997) performed sensitivity analysis for the flux of suspended sediment and the flux of Cs^{137} to input parameters. Under normal flow conditions, sediment flux was most sensitive to the exponent in the matrix soil scour equation and moderately sensitive to the coefficient in the matrix soil scour equation, the lower zone soil moisture, the soil infiltration capacity index, the lower zone nominal storage, and the upper zone nominal storage at the hillslope location. The suspended sediment was also sensitive to groundwater recession and silt deposition at the watershed outlet. However, under flood conditions, the sensitivity of sediment at the hillslope site was different from that at the catchment site. The sediment flux was sensitive to the exponent and coefficient in the matrix soil scour equation and the amount of overland runoff generated at the hillslope location. The sediment flux was also sensitive to the scour of cohesive bed sediment and the magnitude of streamflow generated at the catchment location. Parameters affecting sediment results also affected the simulation of Cs^{137} flux, which was also sensitive to the concentration of Cs^{137} in sediment eroded from hillslopes.

Laroche et al. (1996) simulated atrazine transport in a 78 ha agricultural watershed at the Agriculture Canada experimental farm in Lennoxville, Quebec. Their study found that atrazine concentration was sensitive to the concentration of atrazine permanently fixed on the soil, the coeffi-

cient and exponent of the Freundlich equation, and the degradation rate.

Paul et al. (2004) evaluated the sensitivity of peak instream fecal coliform concentration to changes in 13 water quality parameters for Salado Creek in Bexar County, Texas. In this study, each selected water parameter was changed by an increment or decrement of 10% from its base value to evaluate its effect on peak in-stream fecal coliform concentration. Relative sensitivity index (S_r) was used to measure the sensitivity of evaluated parameters. Results showed that the peak in-stream fecal coliform concentration was most sensitive to the maximum storage of fecal coliforms on the land surface and the rate of surface runoff that would remove 90% of fecal coliforms from the pervious land surface, second-most sensitive to the temperature correction coefficient for first-order decay rate of fecal coliforms, third-most sensitive to the in-stream water temperature and first-order decay rate for fecal coliforms (see Appendix), and not sensitive to the initial storage of fecal coliforms on the pervious land surface, the rate of accumulation of bacteria on the pervious land surface, the bacterial concentration of the constituent in interflow outflow, the bacterial concentration of active groundwater outflow, storage of fecal coliforms on the impervious land surface, the rate of accumulation of bacteria on the impervious land surface, maximum storage of bacteria on the impervious land surface, and the rate of surface runoff that would remove 90% of stored bacteria from the impervious land surface.

HYDRUS

HYDRUS (HYDRUS-1D, HYDRUS 2D/3D, etc.) are numerical codes that are used to simulate transient or steady-state water flow, solute transport, and/or heat transfer in the subsurface (including vadose zone) (Šimůnek et al., 2012). Rocha et al. (2006) and Šimůnek et al. (1998) performed SA of HYDRUS 2D and HYDRUS-1D, respectively, to study the effects of soil hydraulic properties on simulating water movement in the vadose zone, considering pressure heads and water content as model outputs. While the first study was intended for simulation of water movement below furrows during two successive irrigation events, the latter study was mainly focused on parameter estimation. In both studies, the shape factor of the soil water retention curve (n) was found to be the most important parameter, followed by the saturation soil moisture content, based on the spatiotemporal output sensitivity coefficient (Šimůnek and van Genunchten, 1996).

Cheviron and Coquet (2009) modeled the fate of a nonvolatile pesticide for three soil scenarios using the transient mobile-immobile (MIM) version of HYDRUS-1D. In an OAT SA considering instantaneous and mean annual pesticide concentrations at 1 m depth as the model outputs, MIM-HYDRUS was most sensitive to the Freundlich exponent associated with nonlinear sorption. In addition, pesticide degradation rate, its energy of activation, and the pesticide sorption coefficient had substantial effects on model output. Among soil hydraulic properties, the shape parameter (n) had significant influence on model outputs, while MIM parameters, including saturated mobile and immobile water contents (top layer), were found to be important. The ratio of variation between output and input was considered the sensitivity measure.

In another study that modeled atrazine (pesticide loss) using HYDRUS-1D, Persicani (1996) found the model to be most sensitive to the sorption parameter, followed by the degradation parameter and soil bulk density. Persicani (1996) drew conclusions about model sensitivity by looking at input-output curves obtained using an OAT approach. The difference between the observations of Persicani (1996) and other studies (water and/or pesticide transport) are likely due to the different model settings (e.g., use of different model options for moisture retention), which were not clearly documented.

KINEROS2/AGWA

KINEROS2/AGWA is a spatially distributed, event-based watershed model that routes water and sediment over a cascade of overland elements that flow into trapezoidal channel model elements (Goodrich et al., 2012). It has been widely used in a variety of applications ranging from urbanization to manure runoff.

Yatheendradas et al. (2008) used KINEROS2/AGWA to model rainfall-runoff events within the USDA's Walnut Gulch Experimental Watershed in the semi-arid region of southeastern Arizona to investigate the reliability of the model predictions for scenarios of uncertain input parameter boundary conditions. The particular study area consisted of a subbasin of the Walnut Gulch watershed, called the WG11 basin, a ~7.5 km^2 watershed located in the upper reaches of Walnut Gulch with land use ranging from desert bush to range grassland and with a wide sand bed channel. This predictive uncertainty-sensitivity study was conducted considering two scenarios: (1) radar rain input (RainM) to be uncertain (24 factors total) and (2) radar rain input to be perfect (23 factors total). Global SA was performed using the Sobol method for both scenarios with 102,400 and 98,304 runs for scenarios 1 and 2, respectively. A number of likelihood functions were defined based on observed and simulated streamflows. Overall SA results indicated that hillslope factors (saturated soil hydraulic conductivity, volumetric rock fraction, and surface roughness) were highly influential parameters. On the other hand, only one channel parameter (bed soil roughness) was important. The model was found to be extremely sensitive to hillslope initial moisture when a likelihood function related to flash-flooding was the model output of interest. In scenario 1 (i.e., when RainM was uncertain), RainM had the most significant impact on likelihood measures.

An MCS-based SA of KINEROS2 was done by Hantush and Kalin (2005) for runoff and sediment yield simulation in a small USDA-operated watershed near Treynor, Iowa. Parameter sensitivity was calculated using the condition number, which is the ratio of the coefficient of variation of output to the coefficient of variation of input. Two storm events were considered, and 1000 MCS were performed for each event. The antecedent soil saturation was the most influential parameter, followed by overland surface roughness, for four output variables: peak flow, total flow, sediment discharge, and total sediment yield. The remaining

two outputs (time to peak flow and time to peak sediment discharge) were not sensitive to those parameters. However, for these two outputs, channel roughness was the most important parameter.

Al-Qurashi et al. (2008) applied KINEROS2 in an arid-region watershed in Oman to model streamflows. As part of this study, they performed MCS-based SA of KINEROS, considering 11 parameters to be uncertain for 27 recorded storm events (20,000 runs for each event). A number of goodness-of-fit measures were defined for flow outputs to divide the simulations for each storm event into good (behavioral) and bad (non-behavioral) categories. The Kolmogorov-Smirnov test statistic was used as a sensitivity measure. Overall, the model was most sensitive to saturated hydraulic conductivity, followed by capillary drive, overland and channel roughness, and rainfall parameters.

MACRO

As described by Jarvis and Larsbo (2012), MACRO has been used as a research tool to investigate the effects of preferential flow on hydrology and contaminant transport and transformation. Parameters regulating the degree of preferential flow in the dual-permeability water flow and solute transport model are difficult or impossible to derive from direct measurements. Thus, sensitivity is a prerequisite for successful parameter identification, and parameters that are identified as insensitive can be held constant during calibration to reduce the computational demand. However, SA is not sufficient, since parameter correlation may hamper parameter identification.

As listed in the Appendix, several SA studies were performed to identify influential parameters for model calibration (Larsbo and Jarvis, 2006; Dubus and Brown, 2002; Dubus et al., 2003). Larsbo and Jarvis (2006) conducted SA to identify parameters that had the greatest effect on MACRO model outputs. In their study, the Morris method (Morris, 1991) was used to perform SA. Sensitivity measures were calculated for high time-resolution data of percolation rate and effluent and resident concentrations. For percolation rate, saturated macropore water content was the most sensitive parameter, followed by saturated micropore hydraulic conductivity (K_b), saturated macropore hydraulic conductivity ($K_{mac,sat}$), the kinematic exponent reflecting macropore size distribution and tortuosity, and van Genuchten alpha. For effluent concentration, the diffusion path length, macroporosity, and K_b were the most sensitive parameters because the diffusion path length and K_b are important parameters for regulating the distribution of solutes between pore domains. The high sensitivity of macroporosity was probably due to its large impact on macropore water flow, which influences the timing of solute breakthrough. For the resident concentration, the diffusion path length, K_b, and dispersivity (D_v) were the most sensitive parameters. In contrast, van Genuchten N, micropore tortuosity, and inaccessible water due to anion exclusion were the least sensitive parameters (smallest EE values).

Dubus and Brown (2002) and Dubus et al. (2003) performed SA on accumulated water percolation and pesticide loss in different soils (coarse-textured soil and finer-textured soil). They found that the identified sensitive parameters varied with soil properties (see Appendix). The accumulated water percolation in the finer-textured soil was more dependent on crop properties, such as maximum root depth and correlation factor for wet canopy evaporation, than the coarse-textured soil. Furthermore, pesticide loss in the finer-textured soil was more sensitive to parameters related to soil properties, such as soil water content at saturation, pore size distribution factor for macropores, and hydraulic conductivity, while pesticide loss in the coarse-textured soil was more sensitive to parameters related to pesticide properties, such as pesticide sorption coefficient and degradation (see Appendix).

MIKE SHE

MIKE SHE is a physically based, fully distributed watershed-scale model that simulates surface and subsurface processes simultaneously. However, the model is mainly a water flow model with limited water quality modules (Jaber and Shukla, 2012). An important feature of MIKE SHE is the built-in SA-calibration tool called AUTOCAL. The SA studies on MIKE SHE reported in the Appendix range widely in terms of watershed characteristics, including size, land use, topography, and climatic conditions. All of them used some goodness-of-fit measures (R^2, RMSE, or NSE) based on simulated streamflow variables, water table, and/or total water balance. These studies used the OAT method for SA except Wijesekara et al. (2010), who did not mention the methodology used. None of these studies explicitly stated if the AUTOCAL tool was used.

Four studies (Xevi et al., 1997; Dai et al., 2010; Wang et al., 2012a; Wijesekara et al., 2010; see Appendix), found that saturated soil hydraulic conductivity was the most influential parameter, followed by surface roughness, which was found to be important in three (the first two and the last) of the studies. The model was found to be sensitive to surface detention storage by Dai et al. (2010) and Wijesekara et al. (2010), while plant rooting depth substantially influenced model results in Dai et al. (2010) and Wang et al. (2012a). For the studies involving large watersheds, (Wang et al., 2012a; Wijesekara et al., 2010), baseflow time delay coefficients were also important. Wang et al. (2012a) found specific yield, vadose zone boundary parameter, and an evapotranspiration parameter to be influential.

Xevi et al. (1997) assessed effect of grid size on cumulative outflow and concluded that it was very influential. Other studies (Vázquez et al., 2002) on MIKE SHE also evaluated the effects of grid size. Finally, a number of studies have assessed uncertainty in MIKE SHE applications (Vázquez et al., 2009) and could be good references for model users.

MT3DMS

Zheng and Wang (1999) and Zheng et al. (2012) applied the MT3DMS to evaluate the sensitivity of the model for flow, sediment, and nutrients. The hydraulic conductivity, cell width along rows and columns, specific discharge, and porosity factors were found to be the sensitive parameters for flow prediction. The bulk density for sediment, sorption constants for chemicals, and chemical reaction rate con-

stants were sensitive parameters for phosphorus and nitrogen prediction. However, the authors did not discuss the SA methods used in their study.

RZWQM2

Ma et al. (2000) evaluated the sensitivity of RZWQM for plant nitrogen uptake, silage yield, and nitrate leaching using LHS to obtain input sets for model realizations and using linear regression analysis to analyze model input sets. The sensitivity of pesticide fate and surface runoff was analyzed by Ma et al. (2004) using local SA (LSA). In general, the saturated hydraulic conductivity of the surface layer, the presence of macropore flow, and surface crusting were influential parameters for runoff prediction (Ma et al., 2012). The N supply from soil, photorespiration rate, death rate constant for heterotrophs (kdhet), and saturated hydraulic conductivity were influential for N uptake and leaching. The adsorption constant, kinetic adsorption, macrospore flow, and volatilization were found to be influential for pesticide loss.

SHAW

As introduced by Flerchinger et al. (2012), SA on the SHAW model was conducted in several studies (Flerchinger and Hardegree, 2004; Flerchinger and Pierson, 1997; Flerchinger, 1991). Flerchinger (1991) performed a thorough SA on soil freezing. As shown in the Appendix, sensitivity of the maximum frost depth and time of complete thaw was performed in relation to a wide range of parameters, including initial and boundary conditions, surface heat transfer parameters, thermal conduction parameters, and soil hydraulic properties. Among these, weather conditions such as air temperature and snow depth in particular drive the dynamics of the system; thus, they are the most crucial input for accurate soil frost simulation. Simulated frost depth was very sensitive to small changes in air temperature and initial snow depth and moderately sensitive to initial water content. Changes in solar radiation had little effect on frost depth because of the offsetting influence of simulated cloud cover and incoming longwave radiation.

Simulated frost depth may be very sensitive to soil temperature at the lower boundary depending on proximity to the freezing front. However, reliable boundary conditions are usually not available. Simulated frost depth is often obtained by simulating a profile sufficiently deep that temperature and water changes at the boundary can be negligible (Pierson et al., 1991). Simulated frost depth is sensitive to surface, residue, and soil parameters such as slope, surface roughness, residue layer thickness, bulk density, and thermal conductivity of soil minerals. Thus, reasonable estimates of these parameters are required. Because estimating the slope and residue layer thickness as well as the range for bulk density is relatively simple, these parameters do not normally create a problem for simulating soil freezing. However, measurement of the thermal conductivity of soil minerals is more difficult, although it has a fairly limited probable range, as does the soil bulk density. The range of thermal conductivity of soil minerals depends on soil organic matter and quartz content. Although surface roughness parameters are more difficult to estimate accurately

and may vary considerably, they have a much smaller effect on simulated frost depth. Soil hydraulic parameters are not crucial to simulating frost depth. Since the OAT method was used in the SA, interactions between parameters were not considered. Model sensitivity may be different under different site and weather conditions.

Flerchinger and Pierson (1997) applied the SHAW model on a semi-arid sagebrush rangeland to simulate vegetation effects on the spatial and temporal variations of soil temperature and water. To better estimate the critical leaf water potential (ψ_c) and the stomatal resistance exponent (n) for model application, they performed SA on those two parameters. It was found that transpiration was sensitive to both parameters, and their relationship with transpiration was not linear. For critical leaf water potentials of -100, -200, and -300 m, the simulated evapotranspiration was 278, 293, and 299 mm, respectively. Changing ψ_c from -100 to -200 m had a much larger effect on transpiration than the change from -200 to -300 m; thus, as the critical leaf water potential approached -300 m, it approached the typical range of values when the sagebrush was actively transpiring. Total simulated evapotranspiration for a stomatal resistance exponent (n) of 5, 3, and 1 with ψ_c fixed at -100 m was 278, 287, and 314 mm, respectively. As n decreased, the effect of the exponent decreased, and transpiration tended to increase rapidly as n approached 1. A decrease in n from 5 to 3 caused a 9 mm increase in simulated evapotranspiration, while a decrease in n from 3 to 1 caused an increase of 27 mm.

Because the measured evapotranspiration was not available for quantifying the improvements made by parameter adjustment, measured soil water potentials were used. Adjusting ψ_c from -100 to -300 m or n from 5 to 1 caused the soil profile to dry out at approximately the time measured. Adjustment of ψ_c gave a better overall comparison with measured water potential. Varying values of n from 5 with ψ_c equal to -300 m did not improve simulated water potential when compared with measured values. Changes in either of these parameters had almost no effect on simulated soil temperatures. Thus, ψ_c of -300 m and n of 5 best represented the response of the sagebrush based on the SA results.

Flerchinger and Hardegree (2004) used the SHAW model for simulating historical and potential seedbed conditions following the fire season. Soil temperature and water were simulated from early October through the spring germination period, and simulated soil temperature and water content were compared with measured values for the seeding germination period from March through May. To improve model performance and minimize the root mean square difference (RMSD), SA was performed for soil water because the soil temperature was simulated reasonably well. First, each soil hydraulic parameter was varied independently to determine which parameter minimized the average RMSD for the soil water content. During each subsequent iteration, all remaining parameters were varied while holding constant the parameter that minimized the average RMSD in the previous iteration. The simulation results were most sensitive to saturated water content and

pore size distribution index for the study sites (fig. 3 in Flerchinger and Hardegree, 2004).

STANMOD

STANMOD is a Windows-based software program that integrates seven separate codes for evaluating solute transport in soils and groundwater using analytical solutions of the advection-dispersion equation (van Genuchten et al., 2012). The software includes a range of one-dimensional (CFITM, CFITIM, CXTFIT, CHAIN, and SCREEN) and multi-dimensional (3DADE and N3DADE) solute transport models. All of these solute transport models have been widely used over the years (van Genuchten et al., 2012). Jury et al. (1984) performed SA on the one-dimensional solute transport model SCREEN and found that the pesticide volatilization flux rate was sensitive to evaporation rate, water content, organic carbon fraction, and diffusion boundary layer thickness (see Appendix).

The Marquardt-Levenberg-type weighted nonlinear least squares optimization approach (Marquardt, 1963) has been implemented in STANMOD for parameter estimation and SA (van Genuchten et al., 2012). Solute concentrations for all models in STANMOD can be predicted for a prescribed set of transport parameters, such as pore volume, pore water velocity, dispersion coefficient, zero-order production, and first-order degradation coefficients using this optimization approach. Thus, model users are recommended to use this approach to gain an understanding of how transport parameters influent solute transport.

SWAT

The SWAT model has been used worldwide. Arnold et al. (2012) showed sensitivity curves of surface runoff, baseflow, recharge, and soil ET in response to variations in the curve number, available soil water capacity, and soil evaporation coefficient for three USGS 8-digit HUC watersheds in the upper Mississippi River basin. Spruill et al. (2000) performed SA of 15 SWAT parameters for a 5.5 km^2 watershed in Kentucky. Francos et al. (2003) used the Morris screening procedure and FAST for the Ouse watershed (3,500 km^2) in the U.K. Holvoet et al. (2005) and van Griensven and Meixner (2006) used the (LH) OAT method. Santhi et al. (2001, 2006), Kannan et al. (2007), and White and Chaubey (2005) also performed SA in their studies. Collectively, the condition II curve number, available water capacity of the soil layer, soil evaporation compensation factor, and plant uptake compensation factor were important for surface runoff. The groundwater "revap" time (GW_REVAP), threshold depth of water in the shallow aquifer for movement to the root zone, threshold depth of water in the shallow aquifer for revap to occur, fraction of percolation from the root zone that recharges the deep aquifer, and groundwater delay time were influential for baseflow. For the sediment component, the influential parameters included Universal Soil Loss Equation (USLE) support practice factor, maximum value of USLE equation cover factor, channel erodibility factor, channel cover factor, linear coefficient for sediment routing, exponent coefficient for sediment routing, and peak rate adjustment factor for sediment routing. The organic P settling rate in the reach at 20°C, rate constant for mineralization of P to dissolved P, fraction of algal biomass that is phosphorus, phosphorus percolation coefficient, and phosphorus soil partitioning coefficient were identified as influential for phosphorus loss. For nitrogen loss, the influential parameters included the rate constant for hydrolysis of organic N to NH_4 in the reach at 20°C, nitrate percolation coefficient, and denitrification threshold water content. In general, the soil adsorption coefficient normalized for soil organic carbon content, degradation half-life of the chemical in the soil, and solubility of the chemical in water were influential to pesticide loss.

SWIM3

Huth et al. (2012) provided two case studies (the Liverpool Plains region of New South Wales, Australia, and Rutherglen in northeast Victoria, Australia) to investigate water balance and productivity using the Soil Water Infiltration and Movement (SWIM3) model. These studies compared the influence of different cropping systems and treatments, including perennial grasses, on hydrology. The authors indicated that the curve number, saturated hydraulic conductivity, baseflow factor, alpha factor, and potential evapotranspiration (PET) methods for flow; the depth of soil layers for sediment; and the C:N ratio of surface residues, soils and their type, and nitrate and ammonia adsorption for phosphorus and nitrogen simulation were sensitive parameters.

TOUGH

The sensitivity of TOUGH2 output variables with respect to the input parameters is supported by the iTOUGH2 simulation-optimization code (Finsterle et al., 2012). In addition to SA, iTOUGH2 supports parameter estimation and uncertainty propagation analysis. The resulting Jacobian matrix is rescaled to make the sensitivity coefficients comparable with each other. Summary sensitivity measures are calculated to identify the most sensitive parameters as well as the model output most affected by the selected parameters. From an inverse perspective, these values show the information content of individual data points, data sets, and observation types. Furthermore, correlation coefficients between the parameters are calculated, which can be used to detect parameter combinations that lead to a similar or very different system behavior. The iTOUGH2 model also includes the global sensitivity methods of Morris and Sobol (Wainwright et al., 2013, 2014).

VS2DI

VS2DI is a software program simulating water, solute, and heat transport through soils or other porous media (Healy and Essaid, 2012). Simulation of water exchange between streams and surrounding sediments requires inputs such as hydraulic and thermal parameters. Hydraulic conductivity, which quantifies the resistance of a porous material to water flow, can vary by orders of magnitude from one streambed to another. In contrast, thermal conductivity, which quantifies the resistance of the material to heat flow, varies little between streambeds. Niswonger and Prudic (2003) performed SA on the VS2DI model (see Appendix).

For water transport, they concluded that streambed seepage was strongly dependent on hydraulic conductivity of sediments, which depended on sediment texture (represented by grain size) and horizontal and vertical hydraulic conductivity. Streambed seepage was also dependent on porosity and dispersivity. For heat transport, the heat capacity of dry sediments, thermal conductivity of saturated sediments, and heat capacity of water were sensitive variables in simulating heat transfer.

WARMF

Zheng and Keller (2006) conducted an SA of the Watershed Analysis Risk Management Framework (WARMF) for the Santa Clara River watershed in southern California. They investigated model sensitivity for hydrology, sediment, and pesticide transport using several model parameters and 10,000 runs. The precipitation weighting factor (PWF), soil layer thickness, and saturation moisture were the most sensitive parameters for predicting flow. Cropping, soil erosivity, and detachment velocity factors were sensitive parameters for sediment prediction. Fertilization rate, reaction rate (k), adsorption coefficient (α), and soil mineral content were sensitive parameters for phosphorus and nitrogen prediction; and initial concentration, decay rate, and adsorption isotherm were sensitive parameters for pesticide prediction (Zheng and Keller, 2006). The SA should reflect management concerns early in the process to identify parameters that can influence management decisions (Zheng and Keller, 2006).

WEPP

Nearing et al. (1990) found that rill erodibility, rill residue cover, and rill hydraulic friction factors were the most sensitive parameters for soil loss prediction by WEPP. Saturated hydraulic conductivity and interrill erodibility were moderately sensitive parameters, and canopy height, interrill cover, soil bulk density, antecedent moisture, rill width and spacing, and sediment characteristics had relatively less influence on output. Alberts et al. (1995) and Bhuyan et al. (2002) also found that rill and interrill erodibility, effective hydraulic conductivity, and critical shear stress were sensitive parameters in WEPP. Effective hydraulic conductivity was also identified as influential by Brazier et al. (2000). Tiscareno-Lopez et al. (1995) identified interrill erodibility, rill erodibility, and critical hydraulic shear stress as critical parameters for soil loss.

DISCUSSION OF SA STUDIES ON H/WQ MODELS

SA was performed for most of the models featured in the special collection (Moriasi et al., 2012). Sensitivity studies were not found for the WAM model, and SA was performed for the DAISY model but was documented in Danish. The Appendix contains a compilation of the SA methods and sensitivity measures used for the H/WQ models. While these SA methods and measures are not necessarily as extensive as possible for each model, they provide insights into the choices of methods applied. Many sensi-

tivity studies were conducted under various conditions for some models, such as SWAT and CREAMS/GLEAM. For other models, such as CoupModel and MT3DMS, just a couple of sensitivity studies were conducted. Furthermore, SA studies were conducted in great detail in some cases, while only short discussions were provide in other cases (see Appendix).

Depending on the purpose of the model application, various SA methods were used. OAT was the most commonly used method (see Appendix), mainly due to its simplicity and low computational cost. OAT was used for 20 of the 25 models listed in the Appendix, and for five models (ADAPT, AnnAGNPS, HYDRUS, SHAW and SWIM3), only the OAT method was reported. MCS and eFAST were the second most frequently used methods among the H/WQ models. These two methods were used for five of the 25 models, as shown in the Appendix, followed by local SA (LSA) (perturbation) and Morris. The number of simulations conducted for SA ranged from seven for OAT to 200,000 for GSA.

The sensitivity of model output to changes in input can be assessed quantitatively and qualitatively, and it can be expressed using a range of techniques that vary in their complexity and sophistication. Sensitivity measures used in the H/WQ models included visual inspection while using OAT (percent change in output to percent change in input, output vs. input scatter plot), S_r while using OAT, first-order and total-order indices (S_i and S_{Ti}) while using eFAST or Sobol, sensitivity coefficients, SRRCs while using MCS, average EE while using the Morris method, and normalized sensitivity coefficients while using LHS. Monitoring the changes in statistical measures (mean, standard deviation, R^2, RMSE, index of agreement, NSE, or percent change in output) versus the change in input was also performed while using OAT for SA.

Furthermore, the SA results for environmental models are known to be site and condition specific (Ferreira et al., 1995). For example, SA performed on MACRO showed how results of sensitivity studies differ at different sites (Larsbo and Jarvis, 2006; Dubus and Brown, 2002; Dubus et al., 2003). Because SA results depend on the site and scenario considered, a limited SA is often useful when conditions are different from those for which prior sensitivity information is available (Ferreira et al., 1995). Nevertheless, the summary of results from previous SA studies on important model parameters can serve as a good starting point for future model users to perform SA. Finally, performing SA for H/WQ model applications makes communicating the recommendations derived from a particular modeling study more credible, particularly in decision making and management, where various scenarios need to be reported and understood.

SUMMARY AND RECOMMENDATIONS

This article contributes to a special collection of articles that comprehensively describes calibration and validation concepts and processes for H/WQ model application. Sensitivity analysis (SA), which helps to identify the impact of

model inputs on outputs, is essential to any modeling exercises, as it helps improve overall model accuracy, calibration, validation, and verification by identifying key model parameters. The main objectives of this article were to provide overviews of SA methods, SA measures, and independent SA tools for H/WQ models as well as review and synthesize SA studies performed on H/WQ models in the previous 2012 special collection so insights can be gained to guide future model applications. First, an overview of the SA methods and measures was provided. The methods can be broadly categorized as local or global. Although local SA is simple and computationally efficient, it can lead to misinterpretation for nonlinear models. Global SA, although computationally intensive, provides more robust insights since it explores the entire feasible parametric space. The decision to use an efficient, derivative-based local SA method or employ a much more costly, sampling-based global SA method depends on the modeler's assumptions about certainty and linearity of the parameters. Descriptions of the differences between various SA methods can help modelers select appropriate methods based on the intended model application. Parameter sensitivity can be assessed in various ways, ranging from simple visual inspection of input vs. output plots to robust and sophisticated variance-based sensitivity indices. In addition, an overview of model-independent tools (SimLab, UCODE, and PEST) for performing SA was provided, although some of the models in the special collection (Moriasi et al., 2012) have built-in SA tools (SWAT, MIKE, ADAPT, and APEX). The overview provides model users more options of tools for performing SA. Finally, SA studies performed on H/WQ models were reviewed and synthesized to gain insights and provide guidance for future model SA studies and applications.

A review of SA studies performed on H/WQ models found that OAT is the most commonly used method regardless of its limitations, and the relative or normalized sensitivity index (S_r) is the most common index used to evaluate SA results. Modelers should always consider performing SA, as it aids the model calibration and validation processes. Depending on the available resources and the intended model application, modelers may perform a detailed, robust SA, such as GSA, or a simple SA, such as OAT. For a new model user, a local SA is recommended before performing a global SA due to its simplicity. Although parameter sensitivity can be expressed in various ways based on the SA method used, visual inspection of input vs. output plots and the relative sensitivity index (ratio of the change in output to the change in input) are recommended for a new model user because they are straightforward in showing how input changes affect output changes. Furthermore, results of SA have been found to be site and condition specific, which emphasizes the importance of performing SA before model application regardless of previous SA studies on the model. Finally, the summary of sensitive parameters identified from past SA studies of each H/WQ model will be useful for future model applications. This article, together with the others in this special collection, will help model users evaluate parameter sensitivity and perform model calibration and validation more consistently, which will result in more efficient and accurate model simulations for intended uses.

Future SA studies should consider: (1) climate variability (long-term, short-term, mid-century, late-century), (2) different contaminants (sediment, nutrients, pesticides, chemicals, pathogens), (3) different watershed models (field scale, watershed scale, storm event based, continuous simulation, built-in SA vs. external methods), and (4) surface water and groundwater interaction vs. surface water or groundwater only.

REFERENCES

Adams, B. M., Ebeida, M. S., Eldred, M. S., Jakeman, J. D., Swiler, L. P., Bohnhoff, W. J., Dalbey, K. R., Eddy, J. P., Hu, K. T., & Vigil, D. M. (2013). DAKOTA version 5.3.1+ user's manual. Albuquerque, N.M.: Sandia National Laboratory.

Alberts, E. E., Nearing, M. A., Weltz, M. A., Risse, L. M., Pierson, F. B., Zhang, X. C., Laflen, J. M., & Simanton, J. R. (1995). Chapter 7. Soil component. In D. C. Flanagan, & M. A. Nearing (Eds.), USDA-Water Erosion Prediction project: Hillslope profile and watershed model documentation. NSERL Report No. 10. West Lafayette, Ind.: USDA-ARS National Soil Erosion Research Laboratory.

Al-Qurashi, A., McIntyre, N., Wheater, H., & Unkrich, C. (2008). Application of the Kineros2 rainfall-runoff model to an arid catchment in Oman. J. Hydrol., 355(1), 91-105. http://dx.doi.org/10.1016/j.jhydrol.2008.03.022.

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., & Jha, M. K. (2012). SWAT: Model use, calibration, and validation. Trans. ASABE, 55(4), 1491-1508. http://dx.doi.org/10.13031/2013.42256.

Arnold, J. G., Youssef, M. A., Yen, H., White, M. J., Sheshukov, A. Y., Sadeghi, A. M., Moriasi, D. N., Steiner, J. L., Amatya, D. M., Skaggs, R. W., Haney, E. B., Jeong, J., Arabi, M., & Gowda, P. H. (2015). Hydrological processes and model representation: Impact of soft data on calibration. Trans. ASABE, 58(6), 1637-1660. http://dx.doi.org/10.13031/trans.58.10726.

Baffaut, C., Dabney, S. M., Smolen, M. D., Youssef, M. A., Bonta, J. V., Chu, M. L., Guzman, J. A., Shedekar, V., Jha, M. K., & Arnold, J. G. (2015). Hydrologic and water quality modeling: Spatial and temporal considerations. Trans. ASABE, 58(6), 1661-1680. http://dx.doi.org/10.13031/trans.58.10714.

Baginska, B., Milne-Home, W., & Cornish, P. S. (2003). Modelling nutrient transport in Currency Creek, NSW, with AnnAGNPS and PEST. Environ. Model. Software, 18(8), 801-808. http://dx.doi.org/10.1016/S1364-8152(03)00079-3.

Bastidas, L. A. (1998). Parameter estimation for hydrometeorological models using multicriteria methods. PhD diss. Tucson, Ariz.: University of Arizona, Department of Hydrolology and Water Resources.

Bettonvil, B. (1990). Detection of Important Factors by Sequential Bifurcation. Tilburg, Holland: Tilburg University Press.

Bettonvil, B., & Kleijnen, J. P. (1997). Searching for important factors in simulation models with many factors: Sequential bifurcation. European J. Oper. Res., 96(1), 180-194. http://dx.doi.org/10.1016/S0377-2217(96)00156-7.

Beven, K. J. (2011). *Rainfall-Runoff Modelling: The Primer.* Chichester, U.K.: John Wiley and Sons.

Bhuyan, S. J., Kalita, P. K., Janssen, K. A., & Barnes, P. L. (2002). Soil loss predictions with three erosion simulation models. *Environ. Model. Software, 17*(2), 137-146. http://dx.doi.org/10.1016/S1364-8152(01)00046-9.

Brazier, R. E., Beven, K. J., Freer, J., & Rowan, J. S. (2000). Equifinality and uncertainty in physically based soil erosion models: Application of the GLUE methodology to WEPP, the Water Erosion Prediction Project, for sites in the U.K. and U.S. *Earth Surface Proc. Landforms, 25*(8), 825-845. http://dx.doi.org/10.1002/1096-9837(200008)25:8<825::AID-ESP101>3.0.CO;2-3.

Cacuci, D. G., & Ionescu-Bujor, M. (2004). A comparative review of sensitivity and uncertainty analysis of large-scale systems: II. Statistical methods. *Nuclear Sci. Eng., 147*(3), 204-217. http://dx.doi.org/10.13182/04-54CR.

Campolongo, F., Cariboni, J., & Saltelli, A. (2007). An effective screening design for sensitivity analysis of large models. *Environ. Model. Software, 22*(10), 1509-1518. http://dx.doi.org/10.1016/j.envsoft.2006.10.004.

Campolongo, F., Saltelli, A., & Cariboni, J. (2011). From screening to quantitative sensitivity analysis: A unified approach. *Comput. Physics Comm., 182*(4), 978-988. http://dx.doi.org/10.1016/j.cpc.2010.12.039.

Causarano, H. J., Shaw, J. N., Franzluebbers, A. J., Reeves, D. W., Raper, R. L., Balkcom, K. S., & Izaurralde, R. C. (2007). Simulating field-scale soil organic carbon dynamics using EPIC. *SSSA J., 71*(4), 1174-1185. http://dx.doi.org/10.2136/sssaj2006.0356.

Chen, C. W., Herr, J. W., Goldstein, R. A., Ice, G., & Cundy, T. (2005). Retrospective comparison of watershed analysis risk management framework and Hydrologic Simulation Program Fortran applications to Mica Creek watershed. *J. Environ. Eng., 131*(9), 1277-1284. http://dx.doi.org/10.1061/(ASCE)0733-9372(2005)131:9(1277).

Cheviron, B., & Coquet, Y. (2009). Sensitivity analysis of transient-MIM HYDRUS-1D: Case study related to pesticide fate in soils. *Vadose Zone J., 8*(4), 1064-1079. http://dx.doi.org/10.2136/vzj2009.0023.

Chin, D. A., Sakura-Lemessy, D., Bosch, D. D., & Gay, P. A. (2009). Watershed-scale fate and transport of bacteria. *Trans. ASABE, 52*(1), 145-154. http://dx.doi.org/10.13031/2013.25955.

Chinkuyu, A. J., Meixner, T., Gish, T. J., & Daughtry, C. S. (2003). Sensitivity analysis of GLEAMS using multi-objective sensitivity analysis procedure. ASABE Paper No. 1401234. St. Joseph, Mich.: ASABE.

Chung, S. O., Ward, A. D., & Schalk, C. W. (1992). Evaluation of the hydrologic component of the ADAPT water table management model. *Trans. ASAE, 35*(2), 571-579. http://dx.doi.org/10.13031/2013.28635.

Conrad, Y., & Fohrer, N. (2009). A test of CoupModel for assessing the nitrogen leaching in grassland systems with two different fertilization levels. *J. Plant Nutrition Soil Sci., 172*(6), 745-756. http://dx.doi.org/10.1002/jpln.200800264.

Cryer, S. A., & Havens, P. L. (1999). Regional sensitivity analysis using a fractional factorial method for the USDA model GLEAMS. *Environ. Model. Software, 14*(6), 613-624. http://dx.doi.org/10.1016/S1364-8152(99)00003-1.

Cukier, R. I., Fortuin, C. M., Shuler, K. E., Petschek, A. G., & Schaibly, J. H. (1973). Study of the sensitivity of coupled reaction systems to uncertainties in rate coefficients: I. Theory. *J. Chem. Physics, 59*(8), 3873-3878. http://dx.doi.org/10.1063/1.1680571.

Cukier, R. I., Levine, H. B., & Shuler, K. E. (1978). Nonlinear sensitivity analysis of multiparameter model systems. *J.*

Comput. Physics, 26(1), 1-42. http://dx.doi.org/10.1016/0021-9991(78)90097-9.

Daggupati, P., Pai, N., Ale, S., Douglas-Mankin, K. R., Zeckoski, R. W., Jeong, J., Parajuli, P. B., Saraswat, D., & Youssef, M. A. (2015). A recommended calibration and validation strategy for hydrologic and water quality models. *Trans. ASABE, 58*(6), 1705-1719. http://dx.doi.org/10.13031/trans.58.10712.

Dai, Z., Li, C., Trettin, C., Sun, G., Amatya, D., & Li, H. (2010). Bi-criteria evaluation of MIKE SHE model for a forested watershed on South Carolina coastal plain. *Hydrol. Earth Syst. Sci., 14*(6), 1033-1046. http://dx.doi.org/10.5194/hess-14-1033-2010.

Das, S., Rudra, R. P., Gharabaghi, B., Gebremeskel, S., Goel, P. K., & Dickinson, W. T. (2008). Applicability of AnnAGNPS for Ontario conditions. *Canadian Biosyst. Eng., 50*(1), 1-11.

Doherty, J. (2008). PEST: Model-independent parameter estimation. Brisbane, Australia: Watermark Numerical Computing.

Dubus, I. G., & Brown, C. D. (2002). Sensitivity and first-step uncertainty analyses for the preferential flow model MACRO. *J. Environ. Qual., 31*(1), 227-240. http://dx.doi.org/10.2134/jeq2002.2270.

Dubus, I. G., Brown, C. D., & Beulke, S. (2003). Sensitivity analyses for four pesticide leaching models. *Pest Mgmt. Sci., 59*(9), 962-982. http://dx.doi.org/10.1002/ps.723.

Dukes, M. D., & Ritter, W. F. (2000). Validation of GLEAMS nutrient component for wastewater application in the Mid-Atlantic region. *Bioresource Tech., 74*(2), 89-102. http://dx.doi.org/10.1016/S0960-8524(00)00010-9.

Ekström, P. A. (2005). A simulation toolbox for sensitivity analysis. MS project. Uppsala, Sweden: Uppsala University, Faculty of Science and Technology.

Engelmann, C. J. K., Ward, A. D., Christy, A. D., & Bair, E. S. (2002). Application of the BASINS database and NPSM model on a small Ohio watershed. *JAWRA, 38*(1), 289-300. http://dx.doi.org/10.1111/j.1752-1688.2002.tb01552.x.

Ferreira, V. A., Weesies, G. A., Yoder, D. C., Foster, G. R., & Renard, K. G. (1995). The site and condition specific nature of sensitivity analysis. *J. Soil Water Cons., 50*(5), 493-497.

Finsterle, S. (2004). Multiphase inverse modeling. *Vadose Zone J., 3*(3), 747-762.

Finsterle, S., & Zhang, Y. (2011). Solving iTOUGH2 simulation and optimization problems using the PEST protocol. *Environ. Model. Software, 26*(7), 959-968. http://dx.doi.org/10.1016/j.envsoft.2011.02.008.

Finsterle, S., Kowalsky, M. B., & Pruess, K. (2012). TOUGH: Model use, calibration and validation. *Trans. ASABE, 55*(4), 1275-1290. http://dx.doi.org/10.13031/2013.42240.

Finsterle, S., Sonnenthal, E. L., & Spycher, N. (2013). Advances in subsurface modeling using the TOUGH suite of simulators. *Comput. Geosci., 65*, 2-12. http://dx.doi.org/10.1016/j.cageo.2013.06.009.

Flerchinger, G. N. (1991). Sensitivity of soil freezing simulated by the SHAW model. *Trans. ASAE, 34*(6), 2381-2389. http://dx.doi.org/10.13031/2013.31883.

Flerchinger, G. N., & Hardegree, S. P. (2004). Modelling near-surface temperature and moisture of post-wildfire seedbed for germination response predictions. *J. Arid Environ., 59*(2), 369-385. http://dx.doi.org/10.1016/j.jaridenv.2004.01.016.

Flerchinger, G. N., & Pierson, F. B. (1997). Modelling plant canopy effects on variability of soil temperature and water: Model calibration and validation. *J. Arid Environ., 35*(4), 641-653. http://dx.doi.org/10.1006/jare.1995.0167.

Flerchinger, G. N., Caldwell, T. G., Cho, J., & Hardegree, S. P. (2012). Simultaneous Heat and Water (SHAW) model: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1395-

1411. http://dx.doi.org/10.13031/2013.42250.

Fontaine, T. A., & Jacomino, V. M. F. (1997). Sensitivity analysis of simulated contaminated sediment transport. *JAWRA, 33*(2), 313-326. http://dx.doi.org/10.1111/j.1752-1688.1997.tb03512.x.

Francos, A., Elorza, F. J., Bouraoui, F., Bidoglio, G., & Galbiati, L. (2003). Sensitivity analysis of distributed environmental simulation models: Understanding the model behaviour in hydrological studies at the catchment scale. *Reliability Eng. Syst. Safety, 79*(2), 205-218. http://dx.doi.org/10.1016/S0951-8320(02)00231-4.

Geza, M., Poeter, E. P., & McCray, J. E. (2009). Quantifying predictive uncertainty for a mountain-watershed model. *J. Hydrol., 376*(1), 170-181. http://dx.doi.org/10.1016/j.jhydrol.2009.07.025.

Goodrich, D. C., Bums, I. S., Unkrich, C. L., Semmens, D. J., Guertin, D. P., Hernandez, M., & Levick, L. R. (2012). KINEROS 2/AGWA: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1561-1574. http://dx.doi.org/10.13031/2013.42264.

Gowda, P., Ward, A., White, D., Lyon, J., & Desmond, E. (1999). The sensitivity of ADAPT model predictions of streamflows to parameters used to define hydrologic response units. *Trans. ASAE, 42*(2), 381-389. http://dx.doi.org/10.13031/2013.13369.

Gowda, P. H., Mulla, D. J., Desmond, E. D., Ward, A. D., & Moriasi, D. N. (2012). ADAPT: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1345-1352. http://dx.doi.org/10.13031/2013.42246.

Guzman, J. A., Shirmohammadi, A., Sadeghi, A. M., Wang, X., Chu, M. L., Jha, M. K., Parajuli, P. B., Harmel, R. D., Khare, Y., & Hernandez, J. (2015). Uncertainty considerations in calibration and validation of hydrologic and water quality models. *Trans. ASABE, 58*(6), 1745-1762. http://dx.doi.org/10.13031/trans.58.10710.

Haan, P. K., & Skaggs, R. W. (2003). Effect of parameter uncertainty on DRAINMOD predictions: I. Hydrology and yield. *Trans. ASAE, 46*(4), 1061-1067. http://dx.doi.org/10.13031/2013.13968.

Hantush, M. M., & Kalin, L. (2005). Uncertainty and sensitivity analysis of runoff and sediment yield in a small agricultural watershed with KINEROS2. *Hydrol. Sci. J., 50*(6), 1151-1171. http://dx.doi.org/10.1623/hysj.2005.50.6.1151.

Healy, R. W., & Essaid, H. I. (2012). VS2DI: Model use, calibration and validation. *Trans. ASABE, 55*(4), 1249-1260. http://dx.doi.org/10.13031/2013.42238.

Helton, J. C., & Davis, F. J. (2002). Illustration of sampling-based methods for uncertainty and sensitivity analysis. *Risk Anal., 22*(3), 591-622. http://dx.doi.org/10.1111/0272-4332.00041.

Herman, J., & Reed, P. (2013). Sensitivity Analysis Library (SALib). Retrieved from http://jdherman.github.io/SALib/.

Herman, J. D., Kollat, J. B., Reed, P. M., & Wagener, T. (2013). From maps to movies: High-resolution time-varying sensitivity analysis for spatially distributed watershed models. *Hydrol. Earth Syst. Sci., 17*(12), 5109-5126. http://dx.doi.org/10.5194/hess-17-5109-2013.

Herr, J. W., & Chen, C. W. (2012). WARMF: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1387-1396. http://dx.doi.org/10.13031/2013.42249.

Hoare, A., Regan, D. G., & Wilson, D. P. (2008). Sampling and sensitivity analyses tools (SaSAT) for computational modeling. *Theor. Biol. Med. Model., 5*(4). http://dx.doi.org/10.1186/1742-4682-5-4.

Holvoet, K., van Griensven, A., Seuntjens, P., & Vanrolleghem, P. A. (2005). Sensitivity analysis for hydrology and pesticide supply toward the river in SWAT. *Physics Chem. Earth A/B/C, 30*(8), 518-526. http://dx.doi.org/10.1016/j.pce.2005.07.006.

Hornberger, G. M., & Spear, R. C. (1981). An approach to the preliminary analysis of environmental systems. *J. Environ. Mgmt., 12*(1), 7-18.

Huth, N. I., Bristow, K. L., & Verburg, K. (2012). SWIM 3: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1303-1313. http://dx.doi.org/10.13031/2013.42243.

Iman, R. L., & Conover, W. J. (1982). A distribution-free approach to inducing rank correlation among input variables. *Comm. Stats. Simul. Comput., 11*(3), 311-334. http://dx.doi.org/10.1080/03610918208812265.

Iman, R. L., & Helton, J. C. (1988). An investigation of uncertainty and sensitivity analysis techniques for computer models. *Risk Anal., 8*(1), 71-90. http://dx.doi.org/10.1111/j.1539-6924.1988.tb01155.x.

Iman, R. L., Shortencarier, M. J., & Jonson, J. D. (1985). A FORTRAN 77 and user's guide for calculation of partial correlation function and standardized coefficient. Albuquerque, N.M.: Sandia National Laboratory.

Jaber, F. H., & Shukla, S. (2012). MIKE SHE: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1479-1489. http://dx.doi.org/10.13031/2013.42255.

Jacomino, V. M. F., & Fields, D. E. (1997). A critical approach to the calibration of a watershed model. *JAWRA, 33*(1), 143-154. http://dx.doi.org/10.1111/j.1752-1688.1997.tb04091.x.

Jansen, M. J. (1999). Analysis of variance designs for model output. *Comput. Physics Comm., 117*(1), 35-43. http://dx.doi.org/10.1016/S0010-4655(98)00154-4.

Jansson, P. E. (2012). CoupModel: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1337-1346. http://dx.doi.org/10.13031/2013.42245.

Jarvis, N., & Larsbo, M. (2012). Macro (v5. 2): Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1413-1423. http://dx.doi.org/10.13031/2013.42251.

Jury, W. A., Farmer, W. J., & Spencer, W. F. (1984). Behavior assessment model for trace organics in soil: II. Chemical classification and parameter sensitivity. *J. Environ. Qual., 13*(4), 567-572. http://dx.doi.org/10.2134/jeq1984.00472425001300040012x.

Kannan, N., White, S. M., Worrall, F., & Whelan, M. J. (2007). Sensitivity analysis and identification of the best evapotranspiration and runoff options for hydrological modelling in SWAT-2000. *J. Hydrol., 332*(3), 456-466. http://dx.doi.org/10.1016/j.jhydrol.2006.08.001.

Khare, Y. P., Martinez, C. J., & Muñoz-Carpena, R. (2013). Parameter variability and drought models: A study using the Agricultural Reference Index for Drought (ARID). *Agron. J., 105*(5), 1417-1432. http://dx.doi.org/10.2134/agronj2013.0167.

Knisel, W. G., & Douglas-Mankin, K. R. (2012). CREAMS/GLEAMS: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1291-1302. http://dx.doi.org/10.13031/2013.42241.

Kucherenko, S., Rodriguez-Fernandez, M., Pantelides, C., & Shah, N. (2009). Monte Carlo evaluation of derivative-based global sensitivity measures. *Reliability Eng. Syst. Safety, 94*(7), 1135-1148. http://dx.doi.org/10.1016/j.ress.2008.05.006.

Kucherenko, S., Tarantola, S., & Annoni, P. (2012). Estimation of global sensitivity indices for models with dependent variables. *Comput. Physics Comm., 183*(4), 937-946. http://dx.doi.org/10.1016/j.cpc.2011.12.020.

Lane, L. J., & Ferreira, V. A. (1980). Chapter 6: Sensitivity analysis. In W. G. Knisel (Ed.), *CREAMS: A Field-Scale Model for Chemicals, Runoff, and Erosion from Agricultural Management Systems* (pp. 113-158). Conservation Report No. 26. Washington, D.C.: USDA-SEA.

Laroche, A., Gallichand, J., Lagace, R., & Pesant, A. (1996). Simulating atrazine transport with HSPF in an agricultural watershed. *J. Environ. Eng., 122*(7), 622-630.

http://dx.doi.org/10.1061/(ASCE)0733-9372(1996)122:7(622).

Larsbo, M., & Jarvis, N. (2006). Information content of measurements from tracer microlysimeter experiments designed for parameter identification in dual-permeability models. *J. Hydrol., 325*(1), 273-287. http://dx.doi.org/10.1016/j.jhydrol.2005.10.020.

Lundmark, A., & Jansson, P. E. (2008). Estimating the fate of de-icing salt in a roadside environment by combining modelling and field observations. *Water Air Soil Poll., 195*(1-4), 215-232. http://dx.doi.org/10.1007/s11270-008-9741-9.

Ma, L., Ascough, J. C., Ahuja, L. R., Shaffer, M. J., Hanson, J. D., & Rojas, K. W. (2000). Root zone water quality model sensitivity analysis using Monte Carlo simulation. *Trans. ASAE, 43*(4), 883-896. http://dx.doi.org/10.13031/2013.2984.

Ma, L., Ahuja, L. R., Nolan, B. T., Malone, R. W., Trout, T. J., & Qi, Z. (2012). Root zone water quality model (RZWQM2): Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1425-1446. http://dx.doi.org/10.13031/2013.42252.

Ma, Q., Wauchope, R. D., Rojas, K. W., Ahuja, L. R., Ma, L., & Malone, R. W. (2004). The pesticide module of the Root Zone Water Quality Model (RZWQM): Testing and sensitivity analysis of selected algorithms for pesticide fate and surface runoff. *Pest Mgmt. Sci., 60*(3), 240-252. http://dx.doi.org/10.1002/ps.790.

Malone, R. W., Yagow, G., Baffaut, C., Gitau, M. W., Qi, Z., Amatya, D. M., Parajuli, P. B., Bonta, J. V., & Green, T. R. (2015). Parameterization guidelines and considerations for hydrologic models. *Trans. ASABE, 58*(6), 1681-1703. http://dx.doi.org/10.13031/trans.58.10709.

Manache, G., & Melching, C. S. (2008). Identification of reliable regression-and correlation-based sensitivity measures for importance ranking of water-quality model parameters. *Environ. Model. Software, 23*(5), 549-562. http://dx.doi.org/10.1016/j.envsoft.2007.08.001.

Marquardt, D. W. (1963). An algorithm for least-squares estimation of nonlinear parameters. *J. Soc. Ind. Appl. Math., 11*(2), 431-441. http://dx.doi.org/10.1137/0111030.

Massey, F. J. (1951). The Kolmogorov-Smirnov test for goodness of fit. *J. American Stat. Assoc., 11*(2), 68-78. http://dx.doi.org/10.1080/01621459.1951.10500769.

McCuen, R. H. (1973). The role of sensitivity analysis in hydrologic modeling. *J. Hydrol., 18*(1), 37-53. http://dx.doi.org/10.1016/0022-1694(73)90024-3.

McKay, M. D., Beckman, R. J., & Conover, W. J. (2000). A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics, 42*(1), 55-61. http://dx.doi.org/10.1080/00401706.2000.10485979.

Mohamed, M., & Latif, K. (2005). Uncertainty and sensitivity analysis of runoff and sediment yield in a small agricultural watershed with KINEROS2. *Hydrol. Sci. J., 50*(6), 1151-1171.

Moriasi, D. N., Wilson, B. N., Douglas-Mankin, K. R., Arnold, J. G., & Gowda, P. H. (2012). Hydrologic and water quality models: Use, calibration, and validation. *Trans. ASABE, 55*(4), 1241-1247. http://dx.doi.org/10.13031/2013.42265.

Moriasi, D. N., Gitau, M. W., Pai, N., & Daggupati, P. (2015). Hydrologic and water quality models: Performance measures and evaluation criteria. *Trans. ASABE, 58*(6), 1763-1785. http://dx.doi.org/10.13031/trans.58.10715.

Morris, M. D. (1991). Factorial sampling plans for preliminary computational experiments. *Technometrics, 33*(2), 161-174. http://dx.doi.org/10.1080/00401706.1991.10484804.

Muñoz-Carpena, R., Zajac, Z., & Kuo, Y. M. (2007). Global sensitivity and uncertainty analyses of the water quality model VFSMOD-W. *Trans. ASABE, 50*(5), 1719-1732. http://dx.doi.org/10.13031/2013.23967.

Nearing, M. A., Deer-Ascough, L., & Laflen, J. M. (1990). Sensitivity analysis of the WEPP hillslope profile erosion model. *Trans. ASAE, 33*(3), 839-849. http://dx.doi.org/10.13031/2013.31409.

Niswonger, R. G., & Prudic, D. E. (2003). Modeling heat as a tracer to estimate streambed seepage and hydraulic conductivity. In D. A. Stonestrom, & J. Constantz (Eds.), *Heat as a Tool for Studying the Movement of Groundwater Near Streams* (pp. 81-90). USGS Circular 1260. Reston, Va: U.S. Geological Survey.

Paul, S., Haan, P. K., Matlock, M. D., Mukhtar, S., & Pillai, S. D. (2004). Analysis of the HSPF water quality parameter uncertainty in predicting peak in-stream fecal coliform concentration. *Trans. ASAE, 47*(1), 69-78. http://dx.doi.org/10.13031/2013.15872.

Persicani, D. (1996). Pesticide leaching into field soils: Sensitivity analysis of four mathematical models. *Ecol. Model., 84*(1), 265-280. http://dx.doi.org/10.1016/0304-3800(94)00136-7.

Pierson, F. B., & Wight, J. R. (1991). Variability of near-surface soil temperature on sagebrush rangeland. *J. Range Mgmt., 44*(5), 491-497. http://dx.doi.org/10.2307/4002751.

Poeter, E. P., & Hill, M. C. (1998). Documentation of UCODE, a computer code for universal inverse modeling. USGS Water-Resources Investigations Report 98-4080. Reston, Va: U.S. Geological Survey.

Probert, M. E., Dimes, J. P., Keating, B. A., Dalal, R. C., & Strong, W. M. (1998). APSIM's water and nitrogen modules and simulation of the dynamics of water and nitrogen in fallow systems. *Agric. Syst., 56*(1), 1-28. http://dx.doi.org/10.1016/S0308-521X(97)00028-0.

Pujol, G. (2009). Simplex-based screening designs for estimating metamodels. *Reliability Eng. Syst. Safety, 94*(7), 1156-1160. http://dx.doi.org/10.1016/j.ress.2008.08.002.

Pujol, G., Iooss, B., & Janon, A. (2015). Package 'sensitivity.' Vienna, Austria: The Comprehensive R Archive Network. Retrieved from https://cran.r-project.org/web/packages/sensitivity/sensitivity.pdf.

R Development Core Team. (2008). *R: A Language and Environment forStatistical Computing.* Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org.

Ratto, M., Tarantola, S., & Saltelli, A. (2001). Sensitivity analysis in model calibration: GSA-GLUE approach. *Comput. Physics Comm., 136*(3), 212-224. http://dx.doi.org/10.1016/S0010-4655(01)00159-X.

Rocha, D., Abbasi, F., & Feyen, J. (2006). Sensitivity analysis of soil hydraulic properties on subsurface water flow in furrows. *J. Irrig. Drainage Eng., 132*(4), 418-424. http://dx.doi.org/10.1061/(ASCE)0733-9437(2006)132:4(418).

Ruano, M. V., Ribes, J., Seco, A., & Ferrer, J. (2012). An improved sampling strategy based on trajectory design for application of the Morris method to systems with many input factors. *Environ. Model. Software, 37*(1), 103-109. http://dx.doi.org/10.1016/j.envsoft.2012.03.008.

Saltelli, A. (2002). Making best use of model valuations to compute sensitivity indices. *Comput. Physics Comm., 145*(2), 280-297. http://dx.doi.org/10.1016/S0010-4655(02)00280-1.

Saltelli, A., & Annoni, P. (2010). How to avoid a perfunctory sensitivity analysis. *Environ. Model. Software, 25*(12), 1508-1517. http://dx.doi.org/10.1016/j.envsoft.2010.04.012.

Saltelli, A., & Marivoet, J. (1990). Non-parametric statistics in sensitivity analysis for model output: A comparison of selected techniques. *Reliability Eng. Syst. Safety, 28*(2), 229-253. http://dx.doi.org/10.1016/0951-8320(90)90065-U.

Saltelli, A., Tarantola, S., & Chan, K. S. (1999). A quantitative model-independent method for global sensitivity analysis of model output. *Technometrics, 41*(1), 39-56.

http://dx.doi.org/10.1080/00401706.1999.10485594.

Saltelli, A., Chan, K. S., & Scott, E. M. (2000a). *Sensitivity Analysis.* Chichester, U.K.: John Wiley and Sons.

Saltelli, A., Tarantola, S., & Campolongo, F. (2000b). Sensitivity analysis as an ingredient of modeling. *Stat. Sci., 15*(4), 377-395. http://dx.doi.org/10.1214/ss/1009213004.

Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models.* Hoboken, N.J.: John Wiley and Sons.

Saltelli, A., Ratto, M., Tarantola, S., & Campolongo, F. (2005). Sensitivity analysis for chemical models. *Chem. Rev., 105*(7), 2811-2828. http://dx.doi.org/10.1021/cr040659d.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., & Tarantola, S. (2008). *Global Sensitivity Analysis: The Primer.* Hoboken, N.J.: John Wiley and Sons.

Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., & Tarantola, S. (2010). Variance-based sensitivity analysis of model output. Design and estimator for the total sensitivity index. *Comput. Physics Comm., 181*(2), 259-270. http://dx.doi.org/10.1016/j.cpc.2009.09.018.

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. *JAWRA, 37*(5), 1169-1188. http://dx.doi.org/10.1111/j.1752-1688.2001.tb03630.x.

Santhi, C., Srinivasan, R., Arnold, J. G., & Williams, J. R. (2006). A modeling approach to evaluate the impacts of water quality management plans implemented in a watershed in Texas. *Environ. Model. Software, 21*(8), 1141-1157. http://dx.doi.org/10.1016/j.envsoft.2005.05.013.

Saraswat, D., Frankenberg, J. R., Pai, N., Ale, S., Daggupati, P., Douglas-Mankin, K. R., & Youssef, M. A. (2015). Hydrologic and water quality models: Documentation and reporting procedures for calibration, validation, and use. *Trans. ASABE, 58*(6), 1787-1797. http://dx.doi.org/10.13031/trans.58.10707.

Silburn, D. M., & Loch, R. J. (1989). Evaluation of the CREAMS model. I. Sensitivity analysis of the soil erosion sedimentation component for aggregated clay soils. *Soil Res., 27*(3), 545-561. http://dx.doi.org/10.1071/SR9890545.

SimLab. (2008). User manual for simulation environment for uncertainty and sensitivity analysis, version 2.2. Brussels, Belgium: Joint Research Centre of the European Commission. Retrieved from http://ipsc.jrc.ec.europa.eu/?id=756.

Šimůnek, J., & Genuchten, M. V. (1996). Estimating unsaturated soil hydraulic properties from tension disc infiltrometer data by numerical inversion. *Water Resources Res., 32*(9), 2683-2696. http://dx.doi.org/10.1029/96WR01525.

Šimůnek, J., van Genuchten, M. T., & Wendroth, O. (1998). Parameter estimation analysis of the evaporation method for determining soil hydraulic properties. *SSSA J., 62*(4), 894-905. http://dx.doi.org/10.2136/sssaj1998.03615995006200040007x.

Šimůnek, J., van Genuchten, M. T., & Šejna, M. (2012). Hydrus: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1263-1276. http://dx.doi.org/ 10.13031/2013.42239.

Sobol, I. M. (1993). Sensitivity estimates for nonlinear mathematical models. *Math. Model. Comput. Exp., 1*(4), 407-414.

Spear, R. C., & Hornberger, G. M. (1980). Eutrophication in Peel Inlet: II. Identification of critical uncertainties via generalized sensitivity analysis. *Water Res., 14*(1), 43-49. http://dx.doi.org/10.1016/0043-1354(80)90040-8.

Spruill, C. A., Workman, S. R., & Taraba, J. L. (2000). Simulation of daily and monthly stream discharge from small watersheds using the SWAT model. *Trans. ASAE, 43*(6), 1431-1439. http://dx.doi.org/10.13031/2013.3041.

Tiscareno-Lopez, M., Weltz, M. A., & Lopes, V. L. (1995).

Assessing uncertainties in WEPP's soil erosion predictions on rangelands. *J. Soil Water Cons., 50*(5), 512-516.

van Genuchten, M. T., Šimůnek, J., Leij, F. J., Toride, N., & Sejna, M. (2012). STANMOD: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1355-1368. http://dx.doi.org/10.13031/2013.42247.

van Griensven, A., & Meixner, T. (2006). Methods to quantify and identify the sources of uncertainty for river basin water quality models. *Water Sci. Tech., 53*(1), 51-59. http://dx.doi.org/10.2166/wst.2006.007.

van Griensven, A., Meixner, T., Grunwald, S., Bishop, T., Diluzio, M., & Srinivasan, R. (2006). A global sensitivity analysis tool for the parameters of multi-variable catchment models. *J. Hydrol., 324*(1), 10-23. http://dx.doi.org/10.1016/j.jhydrol.2005.09.008.

Vandenberghe, V., van Griensven, A., & Bauwens, W. (2001). Sensitivity analysis and calibration of the parameters of ESWAT: Application to the River Dender. *Water Sci. Tech., 43*(7), 295-301.

Vázquez, R. F., Feyen, L., Feyen, J., & Refsgaard, J. C. (2002). Effect of grid size on effective parameters and model performance of the MIKE SHE code. *Hydrol. Proc., 16*(2), 355-372. http://dx.doi.org/10.1002/hyp.334.

Vázquez, R. F., Beven, K., & Feyen, J. (2009). GLUE-based assessment on the overall predictions of a MIKE SHE application. *Water Resources Mgmt., 23*(7), 1325-1349. http://dx.doi.org/10.1007/s11269-008-9329-6.

Wainwright, H. M., Finsterle, S., Zhou, Q., & Birkholzer, J. T. (2013). Modeling the performance of large-scale CO_2 storage systems: A comparison of different sensitivity analysis methods. *Intl. J. Greenhouse Gas Control, 17*, 189-205. http://dx.doi.org/10.1016/j.ijggc.2013.05.007.

Wainwright, H. M., Finsterle, S., Jung, Y., Zhou, Q., & Birkholzer, J. T. (2014). Making sense of global sensitivity analyses. *Comput. Geosci., 65*, 84-94. http://dx.doi.org/10.1016/j.cageo.2013.06.006.

Wang, S., Zhang, Z., Sun, G., Strauss, P., Guo, J., Tang, Y., & Yao, A. (2012a). Multi-site calibration, validation, and sensitivity analysis of the MIKE SHE model for a large watershed in northern China. *Hydrol. Earth Syst. Sci., 16*(12), 4621-4632. http://dx.doi.org/10.5194/hess-16-4621-2012.

Wang, X., He, X., Williams, J. R., Izaurralde, R. C., & Atwood, J. D. (2005a). Sensitivity and uncertainty analyses of crop yields and soil organic carbon simulated with EPIC. *Trans. ASAE, 48*(3), 1041-1054. http://dx.doi.org/10.13031/2013.18515.

Wang, X., Youssef, M. A., Skaggs, R. W., Atwood, J. D., & Frankenberger, J. R. (2005b). Sensitivity analyses of the nitrogen simulation model DRAINMOD-N II. *Trans. ASAE, 48*(6), 2205-2212. http://dx.doi.org/10.13031/2013.20106.

Wang, X., Frankenberger, J. R., & Kladivko, E. J. (2006a). Uncertainties in DRAINMOD predictions of subsurface drain flow for an Indiana silt loam using the GLUE methodology. *Hydrol. Proc., 20*(14), 3069-3084. http://dx.doi.org/10.1002/hyp.6080.

Wang, X., Potter, S. R., Williams, J. R., Atwood, J. D., & Pitts, T. (2006b). Sensitivity analysis of APEX for national assessment. *Trans. ASAE, 49*(3), 679-688. http://dx.doi.org/10.13031/2013.20487.

Wang, X., Williams, J. R., Gassman, P. W., Baffaut, C., Izaurralde, R. C., Jeong, J., & Kiniry, J. R. (2012b). EPIC and APEX: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1447-1462. http://dx.doi.org/10.13031/2013.42253.

White, K. L., & Chaubey, I. (2005). Sensitivity analysis, calibration, and validations for a multisite and multivariable SWAT Model 1. *JAWRA, 41*(5), 1077-1089. http://dx.doi.org/10.1111/j.1752-1688.2005.tb03786.x.

Wijesekara, G. N., Gupta, A. C., Valeo, C., Hasbani, J. G., & Marceau, D. J. (2010). Impact of land-use changes on the hydrological processes in the Elbow River watershed in southern Alberta. In *Proc. iEMSs 2010*. Manno, Switzerland: International Congress on Environmental Modelling and Software. Retrieved from www.iemss.org/iemss2010/index.php?n=Main.Proceedings.

Wu, Q.-L., Cournéde, P.-H., & Mathieu, A. (2012). An efficient computational method for global sensitivity analysis and its application to tree growth modeling. *Reliability Eng. Syst. Safety, 107*(1), 35-43. http://dx.doi.org/10.1016/j.ress.2011.07.001.

Xevi, E., Christiaens, K., Espino, A., Sewnandan, W., Mallants, D., Sørensen, H., & Feyen, J. (1997). Calibration, validation, and sensitivity analysis of the MIKE SHE model using the Neuenkirchen catchment as case study. *Water Resources Mgmt., 11*(3), 219-242. http://dx.doi.org/10.1023/A:1007977521604.

Xu, C., & Gertner, G. Z. (2008). Uncertainty and sensitivity analysis for models with correlated parameters. *Reliability Eng. Syst. Safety, 93*(10), 1563-1573. http://dx.doi.org/10.1016/j.ress.2007.06.003.

Yatheendradas, S., Wagener, T., Gupta, H., Unkrich, C., Goodrich, D., Schaffner, M., & Stewart, A. (2008). Understanding uncertainty in distributed flash flood forecasting for semiarid regions. *Water Resources Res., 44*(5). http://dx.doi.org/10.1029/2007WR005940.

Yen, H., Wang, X., Fontane, D. G., Arabi, M., & Harmel, R. D. (2014). A framework for propagation of uncertainty contributed by input data, parameterization, model structure, and calibration/validation data in watershed modeling. *Environ. Model. Software, 54*, 211-221. http://dx.doi.org/10.1016/j.envsoft.2014.01.004.

Yen, H., Jeong, J., Tseng, W.-H., Kim, M.-K., Records, R. M., & Arabi, M. (2015). Computational procedure for evaluating sampling techniques on watershed model calibration. *J. Hydrol. Eng.* 20(7), 04014080. http://dx.doi.org/10.1061/(ASCE)HE.1943-5584.0001095.

Yin, L., Wang, X., Pan, J., & Gassman, P. W. (2009). Evaluation of APEX for daily runoff and sediment yield from three plots in the middle Huaihe River watershed, China. *Trans. ASABE, 52*(6), 1833-1845. http://dx.doi.org/10.13031/2013.29212.

Yuan, Y., Bingner, R. L., & Rebich, R. A. (2001). Evaluation of AnnAGNPS on Mississippi Delta MSEA watersheds. *Trans. ASAE, 44*(5), 1183-1190. http://dx.doi.org/10.13031/2013.6448.

Yuan, Y., Bingner, R. L., & Rebich, R. A. (2003). Evaluation of AnnAGNPS nitrogen loading in an agricultural watershed. *JAWRA, 39*(2), 457-466. http://dx.doi.org/10.1111/j.1752-1688.2003.tb04398.x.

Yuan, Y., Bingner, R. L., Theurer, F. D., Rebich, R. A., & Moore, P. A. (2005). Phosphorus component in AnnAGNPS. *Trans. ASAE, 48*(6), 2145-2154. http://dx.doi.org/10.13031/2013.20100.

Yuan, Y., Locke, M. A., & Gaston, L. A. (2009). Tillage effects on soil properties and spatial variability in two Mississippi Delta watersheds. *Soil Sci., 174*(7), 385-394.

Zeckoski, R. W., Smolen, M. D., Moriasi, D. N., Frankenberger, J. R., & Feyereisen, G. W. (2015). Hydrologic and water quality terminology as applied to modeling. *Trans. ASABE, 58*(6), 1619-1635. http://dx.doi.org/10.13031/trans.58.10713.

Zheng, C., & Wang, P. P. (1999). MT3DMS: A modular three-dimensional multi-species transport model for simulation of advection, dispersion, and chemical reactions of contaminants in groundwater systems: Documentation and user's guide, Contract Report SERDP-99-1. Vicksburg, Miss.: U.S. Army Corps of Engineers Research and Development Center.

Zheng, C., Hill, M. C., Cao, G., & Ma, R. (2012). MT3DMS: Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1549-1559. http://dx.doi.org/10.13031/2013.42263.

Zheng, Y., & Keller, A. A. (2006). Understanding parameter sensitivity and its management implications in watershed-scale water quality modeling. *Water Resources Res., 42*(5). http://dx.doi.org/10.1029/2005WR004539.

Ziehn, T., & Tomlin, A. S. (2009). GUI-HDMR: A software tool for global sensitivity analysis of complex models. *Environ. Model. Software, 24*(7), 775-785. http://dx.doi.org/10.1016/j.envsoft.2008.12.002.

See next page for Appendix

APPENDIX

Summary of sensitivity approaches and analyses performed by developers and model users of the H/WQ models in the 2012 special collection.

Model and Sensitivity Method[a]	Output Evaluated	Influential Parameters Analyzed and Identified[b]	Runs	Sensitivity Measure	Reference
ADAPT					
OAT	Flow, sediment, nutrients, pesticides	Flow: soil hydraulic conductivity, rooting depth, leaf area index, drainage coefficient, and soil moisture retention curves. Sediment: field size (DAOVR), average slope (AVGSLP), slope length of the overland flow profile (SLNGTH), soil erodibility factor (KSOIL), and soil loss ratio (CFACT). Phosphorus: labile-P concentration and potentially mineralizable phosphorus in each soil horizon are important parameters in predicting phosphorus losses. Nitrogen: nitrate-N and labile-N concentrations, and potentially mineralizable nitrogen in each soil horizon are important parameters in predicting nitrate-N. Pesticides: pesticide properties, such as soil half-life (SOLLIF) and partitioning coefficient (KOC).	16 scenarios of soil type, tillage, and drainage practices	Observed and predicted means, standard deviation, R^2, RMSE, index of agreement	Gowda et al. (1999), Gowda et al. (2012), Chung et al. (1992)
AnnAGNPS					
OAT	Runoff	Curve number***, depth to subsurface drainage (tile depth)***, hydraulic conductivity**, soil bulk density**.	NA	Graphical: Percent change in output to percent change in input parameters	Das et al. (2008)
OAT	Peak flow	Curve number***, depth to subsurface drainage (tile depth)***, hydraulic conductivity**, soil bulk density**, Manning's "n" for both cell and reach*.			
OAT	Sediment yield	Curve number***, depth to subsurface drainage (tile depth)***, hydraulic conductivity**, soil bulk density**, erodibility factor*, support practice factor*, cover management factor*.			
OAT	N and P	Initial soil N content***, initial soil P content***, fertilizer (N/P) application rate**, crop N/P uptake**, fertilizer mixing code*.	NA	NSE, R^2, t-test	Yuan et al. (2001, 2003, 2005), Nearing et al. (1990)
APEX					
eMorris, eFAST	Runoff	Initial condition 2 curve number (CN2)***, NRCS curve number index coefficient (parm42)**, Hargreaves PET equation exponent (parm34) if using Hargreaves*.	2895 (eFAST), 2509 (eFAST), 160 (eMorris)	FAST first-order and total-order indices (based on model output)	Wang et al. (2006b), Yin et al. (2009), Wang et al. (2012b)
	Crop grain yield	Moisture fraction required for seed germination (parm11)***, potential heat unit (PHU)**, root growth soil strength (parm5)*.			
	Sediment	Erosion control practice factor (PEC)***, RUSLE C factor residual coefficient (parm46)**, RUSLE C factor exponential crop height coefficient (parm47)**, sediment routing exponent (parm18)**, channel cover factor (RCHC)*.			
	Soil organic C	Fraction of humus in passive pool (FHP)***, exponential coefficient of tillage effect on residue decay rate (parm52)**, microbial decay rate coefficient (parm70)*.			
	N and P	Biological mixing efficiency (parm29)**, soluble P runoff coefficient (parm8)***, P upward movement by evaporation coefficient (parm59)**, nitrate leaching ratio (parm14)***, denitrification soil water threshold (parm35)*, volatilization and nitrification partitioning coefficient (parm72)**, nitrogen fixation coefficient (parm7)*.			
CoupModel					
OAT	Multiple	Efficiency of decay of litter***, compensatory nitrogen uptake from soil***, a number of parameters**.	-	S_r	Conrad and Fohrer (2009)
MCS	Multiple outputs related to water balance and soil salt content	Plowed snow proportion***, airborne salt deposition***, maximum canopy conductance**, root depth**, leaf area index**, interception capacity**, pore size distribution**, saturation water content**.	1000	SRRCs	Lundmark and Jansson (2008)
CREAMS/GLEAMS					
Local derivatives and relative sensitivity index	Soil nitrate concentration and plant nitrate uptake	Soil evaporation parameter (CONA), grass rooting depth, wilting point of soil in horizon A, nitrogen in rainfall, dry matter ratio.	-	S_r	Dukes and Ritter (2000)
OAT	Percent atrazine (pesticide) loss	Sorption constant***, degradation constant***, field capacity***, curve number***, hydraulic conductivity**, potential evapotranspiration**, leaf area index**.	-	Visual inspection of output vs. parameter curves	Persicani (1996)
Fractional factorial analysis	Chemical loss (pesticide) in combined runoff	Curve number, soil porosity, soil evaporation parameter, equilibrium partition coefficient, degradation constant.	-	Variance-based sensitivity indices	Cryer and Havens (1999)
MOGSA	Multiple	Runoff: curve number, porosity, field capacity. Soil moisture: field capacity and rooting depth. Nutrient and pesticide outputs: initial nutrient concentrations, partitioning coefficient, degradation parameter, fraction of pesticide applied to soil, washoff fraction.	20,000	Sum of squared errors	Chinkuyu et al. (2003)
-	Total sediment yield	Specific gravity***, slope steepness***, erodibility parameter in USLE**, cover and support practices**, shear parameter**, peak runoff rate**, storm erosivity**, slope length** size distribution** kinematic viscosity**.	-	Percent change in sediment yield	Silburn and Loch (1989)
OAT	Multiple	Runoff submodel: curve number, plant-available water at field capacity, soil evaporation parameter, mean monthly temperature, mean monthly radiation, percolation parameters. Erosion submodel (sediment yield): Manning's "n" for overland flow, channel slope and friction slope. Nutrient submodel: soil porosity, soluble P, soil P, P extraction coefficient, P enrichment parameters, soil N, N extraction coefficient, N enrichment parameters, water use. Pesticide submodel: depth of incorporation, efficiency of incorporation, fraction applied to soil, decay constants, application rate.	-	Percent change in outputs	Lane and Ferreira (1980)
DRAINMOD					
OAT	Subsurface drainage flow	Maximum surface storage (STMAX)***, saturated soil water content (THETAS)**, horizontal saturated hydraulic conductivity (K_{satH})**, residual soil water content (THETAR)*.	-	Relative sensitivity (based on average annual model output)	Haan and Skaggs (2003)
	Relative yield	Saturated soil water content (THETAS)**, minimum air volume required to be able to work the land (MAV)*.			

Summary of sensitivity approaches and analyses performed by developers and model users of the H/WQ models in the 2012 special collection.

Model and Sensitivity Method[a]	Output Evaluated	Influential Parameters Analyzed and Identified[b]	Runs	Sensitivity Measure	Reference
eFAST	Subsurface drainage flow	Horizontal saturated hydraulic conductivity (K_{satH})***, vertical saturated hydraulic conductivity of restrictive layer (K_{satV})***, surface micro storage (S1)**, soil moisture at 0 cm tension (W)*.	1992	FAST first-order and total-order indices (based on output)	Wang et al. (2006a)
EPIC					
eFAST	Crop grain yield	Soil water capacity (FC-WF)***, potential heat unit (PHU)**, biomass:energy ratio (WA)**, harvest index (HI)*.	1500	FAST first-order and total-order indices (based on output, likelihood measure)	Wang et al. (2005a), Causarano et al. (2007)
	Soil organic C	Microbial decay rate coefficient (parm20)**, fraction of humus in passive pool (FHP)***, microbial activity in the top layer (parm51)*.			
HSPF					
OAT	Monthly discharge	Lower zone soil moisture***, upper zone soil moisture***, soil infiltration capacity index***, groundwater recession coefficient***, fraction of groundwater inflow lost to deep groundwater***, fraction of potential evapotranspiration that can be satisfied from baseflow**, fraction of potential evapotranspiration that can be satisfied from groundwater**, interception storage capacity**, Manning's "n" for overland flow*, overland flow plane length*, overland flow plane slope*.	NA	Change in NSE and R^2	Engelmann et al. (2002)
	Sediment concentrations	Coefficient in soil detachment equation, coefficient in detached sediment washoff equation, exponent in detached sediment washoff equation, coefficient in matrix soil scour equation, exponent in matrix soil scour equation.			
OAT	Daily average streamflow	Lower zone soil moisture, upper zone soil moisture, soil infiltration capacity index, groundwater recession coefficient.	NA	Percent change in outputs	Laroche et al. (1996), Fontaine and Jacomino (1997)
	Flux of suspended sediment	Exponent in soil matrix scour equation, coefficient in soil matrix scour equation, lower zone soil moisture, soil infiltration capacity index, upper zone soil moisture, groundwater recession coefficient, silt deposition, amount of runoff, scour of cohesive bed sediment.	NA	Percent change in outputs	Fontaine and Jacomino (1997)
	Flux of Cs^{137} on sediment	Exponent in soil matrix scour equation, coefficient in soil matrix scour equation, lower zone soil moisture, soil infiltration capacity index, upper zone soil moisture, groundwater recession coefficient, silt deposition, amount of runoff, scour of cohesive bed sediment, concentration of Cs^{137} on sediment.	NA	Percent change in outputs	Fontaine and Jacomino (1997)
	Atrazine	Concentration of chemical permanently fixed in the soil, coefficient of Freundlich equation, exponent of Freundlich equation, surface degradation rate.	-	-	Laroche et al. (1996)
OAT	Fecal coliform concentrations	Maximum storage of fecal coliforms on pervious land surface***, rate of surface runoff that will remove 90% of stored bacteria from pervious land surface***, temperature correction coefficient for first-order decay rate of bacteria**, constant in-stream water temperature**, first-order decay rate for bacteria**.	NA	S_r	Paul et al. (2004)
HYDRUS					
OAT	Percent atrazine (pesticide) loss	Sorption constant***, bulk density of soil**, degradation constant**.	-	Visual inspection of output vs. parameter curves	Persicani (1996)
-	Pressure head, water content, and cumulative flux	Shape factor (n) in soil moisture retention curve, saturated soil moisture content.	-	Sensitivity coefficients defined by Šimůnek and van Genuchten (1996)	Rocha et al. (2006)
-	Pressure head and water content	Shape factor (n) in soil moisture retention curve, saturated soil moisture content.	-	Sensitivity coefficients defined by Šimůnek and van Genuchten (1996)	Šimůnek et al. (1998)
OAT-type approach	Pesticide concentration time series	Freundlich exponent, pesticide degradation rate and its energy of activation, pesticide sorption constant, shape factor (n) in soil moisture retention curve, MIM parameters: saturated immobile and mobile water content.	-	Ratio of variation between output and input (time dependent)	Cheviron and Coquet (2009)
KINEROS/AGWA					
Sobol	Streamflow	Saturated soil hydraulic conductivity for hillslope***, soil volume rock fraction for hillslope***, channel soil surface roughness, rainfall (input)***, initial soil moisture, hillslope soil surface roughness**, hillslope soil net capillary drive**.	Two separate analyses, each with ~100,000 runs	First-order and total-order sensitivity indices based on multiple likelihood measures	Yatheendradas et al. (2008
MCS	Multiple outputs related to discharge and sediment yield	Initial soil moisture, hillslope and channel soil roughness.	Two storm events × 1000 runs	Condition number (ratio of CV for output to CV for input)	Hantush and Kalin (2005), Mohamed and Latif (2005)
MCS	Multiple discharge outputs	Saturated hydraulic conductivity, capillary drive, and soil surface roughness for hillslope.	27 storm events × 20,000 runs	Kolmogorov - Smirnov statistic for multiple goodness-of-fit measures on outputs	Al Qurashi et al. (2008)
MACRO					
OAT	Accumulated water percolation in coarse-textured (Wick) soil	Boundary soil water content***, root distribution**, maximum root depth**, initial soil moisture*, wilting point*, correlation factor for wet canopy evaporation*.	1436 for OAT	MAROV	Dubus and Brown (2002)
	Accumulated water percolation in finer-textured (Hodnet) soil	Boundary soil water content***, root distribution**, initial soil moisture**, wilting point**, maximum root depth**, water content at saturation**, correlation factor for wet canopy evaporation*.			
	Pesticide loss in percolation in coarse-textured	Pesticide sorption (Freundlich distribution coefficient*** and Freundlich exponent***) and degradation (degradation rates and exponent in temperature response curve for degradation).			

Summary of sensitivity approaches and analyses performed by developers and model users of the H/WQ models in the 2012 special collection.

Model and Sensitivity Method[a]	Output Evaluated	Influential Parameters Analyzed and Identified[b]	Runs	Sensitivity Measure	Reference
	(Wick) soil				
	Pesticide loss in percolation in finer-textured (Hodnet) soil	Soil hydrology (soil water content at saturation, pore size distribution factor for macropores, hydraulic conductivity, water content at micropore-macropore boundary) and Freundlich exponent.			
MCS	Pesticide loss in percolation in coarse-textured (Wick) soil	Degradation rate***, sorption coefficient***, Freundlich exponent***, exponent temperature response**, average temperature, pore size distribution index, boundary hydraulic conductivity.	1000 for MCS. (table 8 in Dubus and Brown, 2002)	SRRCs	
	Pesticide loss in percolation in finer-textured (Hodnet) soil	Degradation rate***, sorption coefficient***, Freundlich exponent***, exponent temperature response**, average temperature, water content at saturation***, pore size distribution index**, maximum root depth**.			
OAT	Percolation	Boundary soil water content***, wilting point**, water content at saturation** initial soil moisture content*.	NA	MAROV, XMPOR, RPIN, ROOTMAX, THETAINI, WILT (page 967 in Dubus et al., 2003)	Dubus et al. (2003)
	Pesticides losses in coarse-textured (Wick) soil	Degradation rate***, Freundlich exponent***, sorption coefficient***, rainfall intensity***, exponent temperature response**, boundary soil water content**, water content at saturation**.	NA		
	Pesticides losses in finer-textured (Hodnet) soil	Water content at saturation***, pore size distribution index**, maximum root depth**.	NA		
Morris	Percolation rate	Macroporosity***, saturated micropore hydraulic conductivity**, kinematic exponent*, van Genuchten alpha*.	NA	Average EE	Larsbo and Jarvis (2006)
	Effluent concentration	Macroporosity***, saturated micropore hydraulic conductivity**, diffusion path length (d)**			
	Resident concentration	Diffusion path length (d)***, saturated micropore hydraulic conductivity**, dispersivity**, van Genuchten N*, micropore tortuosity*, inaccessible water due to anion exclusion*.			
MIKE SHE					
OAT	Hydrograph peak, cumulative outflow	Grid size, vertical and horizontal hydraulic conductivity, roughness.	-	Change in RMSE and R^2	Xevi et al. (1997)
OAT	Streamflow, water table depth	Surface detention storage, drainage depth, soil hydraulic properties, plant rooting depth, surface roughness.	-	Change in RMSE and NSE	Dai et al. (2010)
OAT	Streamflow	Specific yield and time constant for baseflow, saturated soil hydraulic conductivity, lower unsaturated zone boundary parameter, ET parameter C2, rooting depth.	-	Change in NSE, correlation coefficient, and mean residual error of log transformed data	Wang et al. (2012a)
-	Streamflow, total water balance error	Roughness***, detention storage**, saturated hydraulic conductivity**, time constants for inter and baseflow**.	-	Change in NSE	Wijesekara et al. (2010)
MT3DMS					
OAT, MCS	Flow, nutrient	Flow: hydraulic conductivity, cell width along rows and columns, specific discharge, porosity factors. Sediment: bulk density. Phosphorus: sorption constants for chemicals, chemical reaction rate constant. Nitrogen: sorption constants for chemicals, chemical reaction rate constant.	NA	Mean, R^2, variance-covariance for both sensitivity analysis methods	Zheng and Wang (1999), Zheng et al. (2012)
RZWQM2					
LHS, LSA	Runoff	K_{sat} at surface layer, presence of macropore flow, surface crusting.	500	Normalized sensitivity coefficients	Ma et al. (2000, 2004, 2012)
	Tile flow	K_{sat} and lateral K_{sat}, tile spacing, tile depth, lateral flow below tile controlled by lateral hydraulic gradient, drainable porosity and water table leakage rate.			
	N uptake, NO3-N leaching	N supply from soil, e.g., manure application rate (M)***, photorespiration rate (R1)**, specific leaf weight (SLW)**, death rate constant for heterotrophs (kdhet)*, saturated hydraulic conductivity (K_{sat})*.			
	Pesticide	Adsorption constant, kinetic adsorption, macrospore flow, volatilization.			
SHAW					
OAT	Evapotranspiration	Critical leaf water potential (ψ_c)*, stomatal resistance exponent (n)* (fig. 4 in Flerchinger and Pierson, 1997).	Seven runs	Compared with measured value	Flerchinger and Pierson (1997)
OAT	Maximum frost depth and time of complete thaw	Initial and boundary conditions: snow depth***, air temperature***, soil temperature, solar radiation*, humidity, wind speed, soil temperature at lower boundary, initial water content**. Surface heat transfer parameters: slope**, residue albedo, dry-soil albedo, fraction of surface area covered by residue, thermal roughness parameter**, momentum roughness parameter. Thermal conduction parameters: residue layer thickness**, amount of surface residue, thermal conductivity of soil particles**, soil bulk density**. Soil hydraulic properties*: saturated conductivity of soil, air entry potential, pore-size distribution parameter.	NA	Graphical: time series compared with measured values. Relative changes of output to input (figs. 4, 5, and 6 in Flerchinger, 1991)	Flerchinger (1991)
OAT	Soil water content	Initial soil hydraulic parameters: saturated water-content***, saturated hydraulic conductivity of the soil*, air entry potential*, pore-size distribution index***.	-	Average RMSD between simulated and measured soil water content	Flerchinger and Hardegree (2004)
STANMOD					
LSA	Solute concentration	Pore water velocity, dispersion coefficient, zero-order production, first-order degradation coefficients.	NA	Statistical: minimum value of nonlinear weighted objective function.	van Genuchten et al. (2012)
OAT	Volatilization flux rate	Evaporation rate**, water content*, organic carbon fraction*, diffusion boundary layer thickness*.	NA	Graphical: time series (Marquardt-Levenberg-type weighted nonlinear	Jury et al. (1984)

Summary of sensitivity approaches and analyses performed by developers and model users of the H/WQ models in the 2012 special collection.

Model and Sensitivity Method[a]	Output Evaluated	Influential Parameters Analyzed and Identified[b]	Runs	Sensitivity Measure	Reference
SWAT				least-squares optimization approach)	
OAT, eFAST	Surface runoff	Initial condition 2 curve number (CN2)***, available water capacity of soil layer (AWC)***, soil evaporation compensation factor (ESCO)**, plant uptake compensation factor (EPCO)*.	-	S_r. FAST first-order and total-order indices (based on output)	Santhi et al. (2001), Santhi et al. (2006), Kannan et al. (2007), White and Chaubey (2005), Arnold et al. (2012), Francos et al. (2003), Holvoet et al. (2005), van Griensven et al. (2006), Spruill et al. (2000)
	Base-flow	Groundwater "revap" time (GW_REVAP)***, threshold depth of water in shallow aquifer for movement to root zone (REVAPMN)**, threshold depth of water in shallow aquifer for revap to occur (GW_QWN)**, fraction of percolation from root zone that recharges deep aquifer (RCHRG_DP)**, groundwater delay time (GW_DELAY)*.			
	Sediment	USLE support practice factor (USLE_P)***, maximum value of USLE cover factor (USLE_C)**, channel erodibility factor (CH_EROD)**, channel cover factor (CH_COV)**, linear coefficient for sediment routing (SPCON)**, exponent coefficient for sediment routing (SPEXP)**, peak rate adjustment factor for sediment routing (PRF)*.			
	Crop yield	Potential heat unit (PHU)***, maximum potential leaf area index (BLAI)**, maximum stomatal conductance at high solar radiation and low vapor pressure deficit (GSI)*.			
	Phosphorus	Organic P settling rate in the reach at 20°C (RS5)***, rate constant for mineralization of P to dissolved P (BC4)**, fraction of algal biomass that is P (AI2)**, P percolation coefficient (PPERCO)**, P soil partitioning coefficient (PHOSKD)*.			
	Nitrogen	Rate coefficient for organic N settling in the reach at 20°C (RS4)***, rate constant for hydrolysis of organic N to NH_4 in the reach at 20°C (BC3)**, nitrate percolation coefficient (NPERCO)**, denitrification threshold water content (SDNCO)*.			
	Pesticide	Soil adsorption coefficient normalized for soil organic carbon content (KOC)***, degradation half-life of chemical in the soil (HL_SOIL)**, solubility of chemical in water (WSOL)*.			
Response surface iterative scheme	Bacteria	Bacteria loading rate (CFRT_KG)***, bacteria soil partitioning coefficient (BACTRDQ)**, dieoff factor for bacteria in streams (WDPRCH)**, dieoff factor for bacteria in soils (WDPQ)**, direct nonpoint-source flux (BCNST)**, bacteria percolation partitioning coefficient (BACTMIX)*.	-	-	Chin et al. (2009)
SWIM3					
OAT	Flow, sediment, nutrient	Flow: curve number, saturated hydraulic conductivity, baseflow factor, alpha factor, PET methods. Sediment: depth of soil layers. Nitrogen: C:N ratio of surface residues, soil, and their type, nitrate and ammonia adsorption.	NA	Mean, R^2	Huth et al. (2012), Probert et al. (1998)
TOUGH					
OAT, Morris	Any output variable of the non-isothermal multi-phase, multi-component subsurface flow and transport simulator; link to any simulation model possible.	Any input parameter to the non-isothermal multi-phase, multi-component subsurface flow and transport simulator; link to any simulation model possible.	NA	Scaled local sensitivity coefficients and summary measures; Morris EE, |EE|, and V; Saltelli sensitivity and total sensitivity indices.	Finsterle (2004), Finsterle et al. (2013), Wainwright et al. (2013, 2014)
VS2DI					
LSA	Streambed seepage	Saturated hydraulic conductivity (m s^{-1})***, horizontal and vertical hydraulic conductivity ratio***, porosity (m^3 m^{-3})**, dispersivity (m)**.	NA	Minimizing the sum of squared deviation between simulated and measured observations; Graphical: time series.	Healy and Essaid (2012), Niswonger and Prudic (2003)
	Heat (temperature)	Heat capacity of dry sediments**, thermal conductivity of saturated sediments (W m^{-1} °C^{-1})^3***, heat capacity of water at 20°C^4 (J m^{-3} °C^{-1})*			
WARMF					
GSA	Flow, sediment, pesticide	121 parameters tested. Flow: precipitation weighting factor (PWF), soil layer thickness, saturation moisture. Sediment: cropping factor, soil erosivity factor, detachment velocity factor. Phosphorus: fertilization rates, reaction rates (k), adsorption coefficients (α), soil mineral content. Nitrogen: fertilization rates, reaction rates (k), adsorption coefficients (α). Pesticide: initial concentration, decay rate, adsorption isotherm.	10,000	Univariate analysis, covariance	Zheng and Keller (2006), Herr and Chen (2012), Chen et al. (2005)
WEPP					
OAT, GSA, MCS	Soil loss	Interrill erodibility (K_i)**, rill erodibility (K_r)***, effective hydraulic conductivity**, critical hydraulic shear stress*.	-	S_r	Nearing et al. (1990), Alberts et al. (1995), Tiscareno-Lopez et al. (1995), Brazier et al. (2000), Bhuyan et al. (2002)

[a] EE = elementary effects, eMorris = enhanced Morris method, eFAST = extended Fourier amplitude sensitivity test, FAST = Fourier amplitude sensitivity test, GSA = generalized SA (Spear and Hornberger, 1980), LHS = Latin hypercube sampling, LSA = local SA, MAROV = maximum absolute ratio of variation, MCS = Monte Carlo simulation, OAT = one-at-a-time, SRRCs = standardized rank regression coefficients, and S_r = relative or normalized sensitivity index.

[b] Asterisks indicate sensitivity: *** = most sensitive, ** = secondary sensitivity, * = least sensitive.