Paper:

Song, X., Zhang, J., Zhan, C., Xuan, Y., Ye, M. & Xu, C. (2015). Global sensitivity analysis in hydrological modeling: Review of concepts, methods, theoretical framework, and applications. *Journal of Hydrology, 523*, 739-757.

http://dx.doi.org/10.1016/j.jhydrol.2015.02.013

Global sensitivity analysis in hydrological modeling: Review of concepts, methods, theoretical framework and applications

Resubmit to *Journal of Hydrology* (HYDROL15882)

Xiaomeng Song[1, 2*], Jianyun Zhang[1, 2], Chesheng Zhan[3*], Yunqing Xuan[4], Ming Ye[5], Chonggang Xu[6]

1. State Key Laboratory of Hydrology-Water Resources & Hydraulic Engineering, Nanjing Hydraulic Research Institute, Nanjing 210029, China

2. Research Center for Climate Change, Ministry of Water Resources, Nanjing 210029, China

3. Key Laboratory of Water Cycle & Related Land Surface Processes, Institute of Geographical Science & Natural Resource Research, Chinese Academy of Science, Beijing 100101, China

4. College of Engineering, Swansea University, Swansea, SA2 8PP, UK

5. Department of Scientific Computing, Florida State University, Tallahassee, FL 32306, USA

6. Earth and Environmental Sciences Division, Los Alamos National Laboratory, Los Alamos, NM 87545, USA

*Corresponding author (X. Song) at: Hydrology and Water Resources Department, Nanjing Hydraulic Research Institute, No. 225 Guangzhou Road, Gulou District, Nanjing city, Jiangsu Province, 210029, China, Tel.: +86 (25) 85828535; fax: +86 (25) 85828555

*Corresponding author (C. Zhan) at: Room 3231, Institute of Geographical Science & Natural Resource Research, Chinese Academy of Science, No. A1 Datun Road, Chaoyang District, Beijing, 100101, China

Email addresses: xmsong@nhri.cn (X. Song), jyzhang@nhri.cn (J. Zhang), zhancs2006@gmail.com (C. Zhan), Y.Xuan@swansea.ac.uk (Y. Xuan), mye@fsu.edu (M. Ye), xuchongang@gmail.com (C. Xu)

Abstract: Sensitivity analysis (SA) aims to identify the key parameters affecting modeling performance. It plays an important role in model parameterization, calibration, optimization and uncertainty quantification. However, the increasing complexity of hydrological models results in a large number of parameters to be estimated. To better understand how these complex models work, efficient SA methods are required to select and implement before the application of hydrological modeling. This paper focused on the comprehensive review of global SA methods in the field of hydrological modeling. The common definitions of SA and typical categories of SA methods are described. A wide variety of global SA methods have been introduced to provide a more efficient evaluation framework for hydrological modeling. We review, analyze, and categorizes research efforts on global SA methods and applications with an emphasis on the research accomplished in hydrological modeling field. Both advantages and disadvantages are also discussed and summarized. An application framework as well as typical practical steps of SA in hydrological modeling is outlined. Further discussion on the severe important and often overlooked topics is presented, including the relationship between parameter identification, uncertainty analysis and optimization in hydrological modeling, how to deal with correlated parameters, and time-varying sensitivity analysis. Finally, some conclusions and guidance recommendations on sensitivity analysis in hydrological modeling are proposed along with a list of important future research directions to provide more robust analysis in assessing hydrological modeling performance.

Keywords: hydrological model, sensitivity analysis, global method, uncertainty analysis, parameter optimization

1 Introduction

Hydrological models have been benefited from significant developments over the past three decades (Beven, 2009), which have become more complexity (from rational method to distribution model) with more diversified purposes in many applications (Nossent et al., 2011), such as land use

(Park et al., 2013) and climate change scenario analysis (Ntegeka et al., 2014), flood prediction (Cloke and Pappenberger, 2009) and rainfall-runoff modeling (Modarres and Ouarda, 2013). For a better model prediction, we need to assess and improve the model with different approaches such as parameter optimization, operational management, design space exploration, sensitivity and uncertainty analysis (Jakeman et al., 2006; Razavi et al., 2012; Wu and Liu, 2012; Nan et al., 2011; Song et al., 2011). Hydrological models often suffer from substantial uncertainties in input data, forcing data, initial and boundary conditions, model structure, and parameters, due to lack of data and poorly knowledge of hydrological response mechanisms (Ye et al., 2008; Doherty and Welter, 2010; Shi et al., 2010; Zhang et al., 2011; Gupta et al., 2012; Foglia et al., 2013). These uncertainties have negative effects on model accuracy and in turn, inducing uncertainties in the simulated results, in a sense that model uncertainty becomes an important source and foundation for constructing the modeling system (Beck, 1987). Good modeling practice requires an evaluation of the confidence in the model together with the model per se, which includes a quantification of the uncertainty in any model results (i.e. uncertainty analysis, UA) and an evaluation of how much each input/parameter is contributing to the output uncertainty (i.e. sensitivity analysis, SA) (Loosvelt et al., 2013). Generally, UA refers to the determination of the uncertainty in model outputs resulting from uncertainty in model inputs/parameters, and SA refers to the determination of the contributions of individual uncertain inputs/parameters to the uncertainty in model outputs. Ideally, SA and UA should be run in tandem, and both are essential parts of model development and quality assurance, as shown in Fig.1.

Figure 1 is here

For most hydrological models, in practice, the large number of parameters (from tens to hundreds) in these models leads to the curse of dimensionality with the parameter estimation becoming a high-dimensional and mostly non-linear problem. To resolve this problem, a wide range of optimization algorithms have been developed (e.g. Beven and Binley, 1992; Duan et al., 1992; Vrugt et al., 2003, 2005; Hill and Tiedeman, 2007; Abebe et al., 2010; Aster et al. 2013; Moreau et al., 2013; Sen and Stoffa, 2013); however, it is often not feasible, nor is necessary to include all model parameters in the calibration process to obtain an efficient optimization. For example, over-parameterization is also another well-known problem in rainfall-runoff modeling (van Griensven et al., 2006). Therefore, when we estimate model parameters, unimportant or insensitive parameters should be locked in a fixed value to make calibration more efficient (SA). Currently, a variety of SA methods (e.g., local or global methods, qualitative or quantitative methods, screening or refined methods) have been widely used in different fields, such as complex engineering systems, economics, physics, social sciences, and others (Frey and Patil, 2002; Iman and Helton, 1988). However, there is a large difference among these methods in terms of their sampling scheme, applicability, algorithm structure and the importance measure of parameters. Considering the wide range of SA methods, it is therefore very important for a practitioner to have a clearly understanding as to which methods are appropriate for a specific application in terms of selecting particular SA method, fitting the method into existing models, and presenting and interpreting the results.

This paper aims to review, analyze, and classify the research on SA with an emphasis on global SA efforts arising from the hydrological modeling field. Many reviews of SA methods have been conducted in different fields. For example, Hamby (1994) reviews the literature on parameter SA for environmental models; Frey and Patil (2002) and Mokhtari and Frey (2005) review the SA methods for food safety; Coyle et al. (2003) discuss the SA measures in the economics field; Saltelli et al. (2005, 2012) focus on sensitivity analysis in chemical models; Borgonov (2006) investigates the sensitivity and uncertainty measures; Mishra et al. (2009) review the global SA methods in groundwater models; Peter and Dwight (2010) discuss the numerical sensitivity analysis approaches for aerodynamic optimization; Perz et al. (2013) review the global SA and UA methods for ecological resilience; Tian (2013) summarizes the application of SA methods in building energy analysis; Wu et al. (2013) review recent advances in SA of infectious disease models. Some of them explicitly highlight the advantage and disadvantage of various methods and provide very good summaries of this topic. To our knowledge, few comprehensive, up-to-date review tracks the advances in sensitivity analysis for hydrological modeling. This paper represents a unique contribution to the literature, as our objective is to summarize the advances in the application of various global SA methods in hydrological modeling. The depth of the review of the topics covered here generally varies with the popularity of the topic in hydrological modeling and as such, discussion largely revolves around uncertainty quantification and optimization applications. This paper is structured as follows: Section 2 briefly describes the typical definition and categories of SA; Section 3 details the objectives and roles of SA in hydrological modeling; Section 4 reviews key techniques and approaches for SA applied in hydrological models and presents their corresponding advantages and disadvantages; Section 5 proposes the steps and evaluation framework of SA in hydrological modeling; Section 6 focuses on several topics when implementing SA in hydrological modeling. These topics include how to deal with correlated parameters, the applications of SA in model evaluation; and time-varying sensitivity analysis in hydrological modeling; this paper ends with summary and concluding remarks in Section 7.

2 Definition and categories of SA methods

Generally, when referring to the degree to which a parameter affects model output, we can use the terms “sensitive”, “important”, “most influential”, “major contributor”, “effective”, or “correlated” interchangeably (Hamby, 1994). There are some different definitions or understanding for different fields, listed in Table 1. Regardless of how SA is defined within different scopes or points of view, the consensus is that models are sensitive to parameters in two distinct ways: (1) the variability, or uncertainty, associated with a sensitive parameter is propagated throughout the model, resulting in a large contribution to the overall output uncertainty, and (2) model outputs can be highly correlated with a parameter so that small changes in the input value result in significant changes in the output. In view of hydrological modeling, we define SA as the investigation of the response function linking the variation of model outputs to the change of input variables or/and parameters, so as to determine the relative contributions of different uncertainty sources to the variation of output by means of qualitatively or quantitatively apportioning approaches under a given set of assumptions and objectives.

SA methods can be classified in various ways based on their scope, applicability and characteristics. A simple and most common classification is: local SA and global SA (e.g., Satelli et al., 2004; van Griensven et al., 2006). Local SA focused on the effects of uncertain inputs around a point (or base case), whereas global SA focuses more on the influences of uncertain inputs over the whole input space (Tian, 2013). Campolongo et al. (2000) offers another common classification based largely on the extent of the input variable range that the technique assesses. Here, the techniques are divided into three levels: screening, local and global methods. Although this classification is also widely used in SA studies, this arrangement is ambiguous as the classification of a technique as local or global is subject to whether a range is large enough to be perceived as global, or whether the number of simulations used with a local or global method can be considered as a screening experiment (King, 2009). In addition, Satelli et al. (2004) propose four settings, such as factors prioritization (FP) setting, factors fixing (FF) setting, variance cutting (VC) setting and factors mapping (FM) setting. Such settings can also be linked to Type I and Type II errors. Generally, Type I error is the incorrect rejection of a true null hypothesis, and Type II error is the failure to reject a false null hypothesis. In SA, Type I error occurs when erroneously defining as important a non-influential factor, while Type II error occurs when we classify an important factor as non-influential (Satelli et al., 2008; Zhan et al., 2013). If one is particularly interested in avoiding Type I errors, then main effects and factors prioritization setting will be the target analysis. Alternatively, if Type II errors are to be avoided, total effects and factor fixing need to be considered.

In this work, we emphasize three typical categories as follows: (1) local and global SA methods (Saltelli et al., 2004); (2) mathematical, statistical, and graphical methods (Frey and Patil, 2002); (3) screening and refined methods (Song et al., 2014), and (4) qualitative and quantitative SA methods (Li et al., 2013, Zhan et al., 2013), which are briefly summarized in Table 2.

Table 1 and Table 2 are here

----

3 Implication and roles of SA in hydrological modeling

Generally, SA is one of the simplest aids in diagnosing and remedying poor identifiability of models, to allow parameters to be more reliably estimated (Shin et al., 2013). It aims at establishing the relative importance of the parameters involved in the model, answering questions such as (Cariboni et al., 2007; Neumann, 2012; Song et al., 2012a):

- Which of the uncertain parameters are more influential in determining the variability affecting the inference?
- If the uncertainty of some parameters could be eliminated, which one should be chosen in order to reduce to the minimum the variance of the output of interest?
- Are there parameters whose effect on the output is so low that they can be confidently fixed anywhere in their ranges of variation without affecting the results?
- If these parameters deviate from expectations, what will the effect be on model output and which are causing the largest deviations?
- Which parameters are responsible for producing model outputs in a specific region?

Essentially, the primary aim of a SA experiment is to identify the most important factors and then to simplify the model. Many studies highlight that the SA can reduce the output variance to a lower threshold by simultaneously fixing the smallest number of input parameters (Satelli et al., 2000, 2004, 2008). This is important for us to implement SA for complex hydrological models, especially for those with large number of uncertain parameters. But even more than that, we argue that SA is a useful perspective for conceptualizing and understanding hydrological models for several reasons. As indicated by Rakovec et al. (2014), SA can be used to (a) detect when increasing model complexity can no longer be supported by observations and whether it is likely to affect model predictions (e.g., Saltelli et al., 1999; van Werkhoven et al., 2008a; Doherty and Welter, 2010; Rosolem et al., 2012; Gupta et al., 2012; Foglia et al., 2013); (b) reduce the time for model calibration by focusing estimation efforts on parameters important to calibration metrics and predictions (e.g., Anderman et al., 1996; Hamm et al., 2006; Zambrano-Bigiarini and Rojas, 2013); (c) determine priorities for theoretical and site-specific model development (e.g., Hill and Tiedeman, 2007; Saltelli et al., 2008; Kavetski and Clark, 2010); and (d) identify advantageous placement and timing of new measurements (e.g., Tiedeman et al., 2003, 2004).

4 Global SA methods in hydrological models

In practice, global SA methods are usually recommended in hydrological modeling applications because they have certain advantages compared with local SA methods (Makler-Pick et al., 2011; Rosolem et al., 2012; Baroni and Tarantola, 2014; Song et al., 2012a). These include their ability to incorporate the influence of input parameters over their whole range of variation, and be well suited for non-linear and non-monotonic models, thus providing results that are independent of modeler prejudice and not site specific. Currently, various global SA techniques have been widely used in hydrological models, such as the screening method, regression analysis, variance-based method, meta-modeling method, and others (Song et al., 2014). This list is not an exhaustive list of SA techniques. Instead, we mainly include commonly used and often referred global methods in hydrological models. A research database search of SA method and hydrological modeling in Thomson Reuters (ISI) Web of Knowledge is shown in Fig.2. Table 3 summarizes the main studies of global SA in hydrological models published since 2005. Table 4 gives an overview of these global SA techniques including sampling scheme, computational requirements and characteristics of the sensitivity measure.

Figure 2, Table 3 and Table 4 are here

4.1 Screening method

The purpose of screening method is rather to identify which input variables are contributing significantly to the output uncertainty in high-dimensionality models, than to quantify sensitivity exactly (Saltelli et al., 2008). One of the most commonly used screening method is the Morris screening method or the elementary effect method proposed by Morris (1991) and improved by Campolongo et al. (2007). Parameters are taken as a discrete number of values, which are different from other global SA methods in which parameter values are directly from distributions. For a given X=(x_1, x_2, …, x_k), the elementary effect of the i-th parameter is defined as:

$$d_i(X)=\frac{y(x_1,...,x_{i-1},x_i+\Delta,x_{i+1},...,x_k)-y(X)}{\Delta} \tag{1}$$

where Δ is a value in {1/(p-1), …, 1-1/(p-1)}, p is the number of levels, and y(X) is target function value for the parameter values X. Two sensitivity measures, the mean (μ) and standard deviation (σ) of the elementary effects, can be calculated by Eqs. (2) and (3):

$$\mu_i = \frac{1}{r}\sum_{j=1}^{r} d_i(j) \tag{2}$$

$$\sigma_i = \sqrt{\frac{1}{r-1}\sum_{j=1}^{r}[d_i(j) - \frac{1}{r}\sum_{j=1}^{r} d_i(j)]^2} \tag{3}$$

where $d_i(j)$ is the elementary effect for input i using the j-th base sample point, j=1, 2, …, r (r is the number of repeated sampling design or trajectories of sample points in the parameter space). When the model is non-monotonic, some elementary effects with opposite signs may cancel out. Hence, Campolongo et al. (2007) proposed an improved measure μ^*:

$$\mu_i^* = \frac{1}{r}\sum_{j=1}^{r} \left|d_i(j)\right| \tag{4}$$

The μ estimates the overall effect of each parameter on the output, and the σ estimates the higher order effects, such as nonlinearity and interactions between inputs, respectively. If μ_i^* is substantially different from zero, it indicates that parameter i has an important "overall" influence on the output. A large σ_i implies that parameter i has a nonlinear effect on the output, or there are interactions between parameter i and other parameters.

Advantages of the Morris screening method are that it has a lower computational cost compared to other global SA methods, and it is simple to implement and easy to interpret (Shin et al., 2013; Tian, 2013; Zhan et al., 2013). For example, the total number of runs is only 44 if there are 10 parameters with 4 trajectories for each parameter. Hence, the Morris method is more suitable to computationally expensive models, which often have a large number of uncertain parameters. However, the drawback of this method is that it cannot quantify the effects of different factors on outputs (Brockmann and Morgenroth, 2007; Sun et al., 2012), and type II errors (failing to identify some unimportant inputs as important parameters) might occur with the Morris screening method (Zhan et al., 2013). Saltelli et al. (2004) also highlighted that it cannot estimate individual interactions between parameters, thereby giving only the overall interaction of a parameter with the rest of the model. As a result, this method does not allow self-verification, which means the analyst does not know how much of the total variances of outputs have been taken into account in the analysis.

Recently, the Morris screening method has been widely used in hydrological models. For example, Song et al. (2012b, 2013) and Zhan et al. (2013) analyzed the sensitivity of hydrological parameters for a distributed time-variant gain model and Xinanjiang model based on the Morris method and other quantitative methods. Liu and Sun (2010) implemented Morris method based on Pareto ranking strategy to identify the key parameters for MIKE/NAM rainfall-runoff model under the different objective functions. They suggest that no single objective function is adequate to measure the ways in which the model fails to match the important characteristics of the observed data. Moreau et al. (2013) used Morris method to screen for input factors with the greatest influence on hydrological and geochemical output variables for spatially-distributed agro-hydrological model TNT2. Yang et al. (2012) proposed a two-step, multi-objective SA approach, incorporating the Morris method and the SDP (state dependent parameter) method, and estimated WetSpa model parameters with case studies in the Chaohe basin in China and the Margecany basin in Slovakia. Ruano et al. (2011) also used the Morris method to identify these important parameters in a water quality model. It was found to be important to select or optimize a proper repetition number of the elementary effects of the Morris method. Working with a non-proper repetition number could lead to Type I error as well as Type II error, hence emphasizing the importance of finding the optimal repetition number of each study in question. In addition, in view of the limitations of the Morris one-at-a-time (OAT) design, the LH-OAT method, which takes the Latin Hypercube samples as initial points for an OAT design, was proposed to apply to the SWAT model (Holvoet et al., 2005; van Griensven et al., 2006). This method, as a screening tool for the SWAT modeling system, has been widely used in many catchments (e.g. Nossent and Bauwens, 2012; Singh et al., 2012).

4.2 Regression method

The principle of regression methods is to approximate the relationships between an output and the parameters by:

$$y_i = b_0 + \sum_j b_j x_{ij} + \varepsilon_i \tag{5}$$

where x_j (j = 1, 2, …, k) are the jth parameters; i = 1, 2, …, N represents the number of model runs; b_j is the coefficient to be estimated via the least-squares methods for each x_j; and ε_i is random error. Once b_j is determined, the regression model can be rewritten as:

$$\frac{y-\bar{y}}{\hat{s}} = \sum_j \frac{b_j \hat{s}_j}{\hat{s}} \frac{x_j-\bar{x}_j}{\hat{s}_j} \tag{6}$$

where

$$\bar{y} = \sum_{i=1}^{N} \frac{y_i}{N}, \quad \bar{x}_j = \sum_{i=1}^{N} \frac{x_{ij}}{N}, \quad \hat{s} = \left[\sum_{i=1}^{N} \frac{[y_i-\bar{y}]^2}{N-1}\right]^{1/2}, \quad \hat{s}_j = \left[\sum_{i=1}^{N} \frac{[x_{ij}-\bar{x}_j]^2}{N-1}\right]^{1/2} \tag{7}$$

The coefficients $b_j \hat{s}_j / \hat{s}$ in Eq.6 are standardized regression coefficients (SRCs). When the parameters x_j are independent of each other, the SRCs can provide a sensitivity index for the factor x_j. Each SRC gives information about the effect of changing an input from its standard value by a fixed fraction of its standard deviation, while maintaining the other factors at their default values. Regression analysis allows also for the estimation of the model coefficient of determination, R^2, which represents the fraction of the output variance explained by the regression model itself. In the case of linear models, the SRCs exactly quantify the amount of output variance explained by each parameter; when models are moderately non-linear (i.e. R^2>0.7), the SRCs can be still used to qualitatively assess the parameters' importance; finally, when R^2 becomes small, the SRCs cannot be considered as a reliable sensitivity measure (Cariboni et al., 2007).

The advantages of this method are its simplicity and ability to estimate the sensitivity of each parameter, even though all parameters affect model output simultaneously. However, it is not applicable when the relationship between parameters and model output is non-linear or non-monotonic, or when there are interactions among parameters. Although the rank transformation method (standardized rank regression coefficient, SRRC) can be helpful for non-linear models, it fails with non-monotonic models, and the result cannot be transformed back to the original model (Saltelli and Sobol', 1995).

Regression method has also been used to estimate the sensitivity of parameters in hydrological models. For example, Tiscareno-Lopez et al. (1993) address uncertainty in hydrologic and soil erosion predictions from the WEPP watershed model due to errors in model parameter estimation identified using regression, and runoff volume and peak runoff predictions from hillslopes were very sensitive to rainfall characteristics. He et al. (2011) analyzed the parameter sensitivity of the SNOW17 model using the Spearman's rank correlation coefficient method, and the rankings of parameters were determined using the results of significance testing. Zeng et al. (2012) used stepwise regression analysis and mutual entropy analysis method to assess the uncertainty parameters of probability density function of groundwater level series. Regression analysis also has been used in other hydrological models, such as SWAT (Muleta and Nicklow, 2005), SWMM (Wang et al. 2008), HYMOD (Yang, 2011), SAC-SMA (Gan et al., 2014).

4.3 Variance-based method

Variance-based methods use a variance ratio to estimate the importance of parameters with the foundation of variance decomposition (Saltelli et al., 1999; Sobol', 1993). In general, the attribution of total output variance to individual model parameters and their interactions can be written as follow (Saltelli et al., 2004, 2008):

$$V = \sum_{i=1}^{k} V_i + \sum_{i=1}^{k} \sum_{j>i}^{k} V_{ij} + \ldots + V_{1,2,\ldots,k} \tag{8}$$

where V represents the total variance of the model output, V_i represents the first-order variance for each factor x_i (V_i=$V[E(Y \mid x_i)]$) and V_{ij} ($V_{ij} = V[E(Y \mid x_i, x_j)]$-$V_i$-$V_j$) to $V_{1\ldots k}$ the interactions among k factors. The variance of the conditional expectation, $V[E(Y \mid x_i)]$, is sometimes called the main effect and is used to indicate the significance of x_i on the variance of Y. Variance-based methods allow calculation of two indices; i.e., the first-order sensitivity index corresponding to the parameter x_i:

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

and the total-order sensitivity index of a single parameter (index i) and the interaction of more parameters that involve index i and at least one index $j \neq i$ from 1 to k:

$$S_{T_i} = \sum S_i + \sum_{j \neq i} S_{ij} + \cdots + S_{1\ldots k} \tag{10}$$

The difference between the first-order and the total-order sensitivity indices can be regarded as a measure for the interactions of i with others (Massmann and Holzmann, 2012). Because the interactions increase with the number of considered parameters as well as with their variation range, variance decomposition methods are well suited for models with many parameters. There are many techniques to carrying out variance decomposition, such as Sobol' method, the Fourier Amplitude Sensitivity Test (FAST), and the extended FAST methods, etc. Advantages of variance-based methods include: (i) model independence (i.e., it works for non-linear models, non-monotonic models, and models with interaction among parameters); (ii) the ability of capturing the influence of the full range of variation of each parameter; (iii) the method captures interaction effects; and (iv) the method can treat sets of parameters as single parameter. However, it often requires a large number of model evaluations in applications, and it may be very difficult to apply in complex models with a large number of parameters.

Variance-based methods are also widely used for parameter SA in hydrological models (Table 3) as they can provide most accurate and robust sensitivity indices for complex nonlinear models (Tang et al., 2007b; Yang, 2011; Herman et al., 2013b, 2013c; Zhan et al., 2013). For example, Zhang et al. (2013) investigated the parameter sensitivity of SWAT model based on Sobol' method for the four different objective functions; van Werkhoven et al. (2008a) and Wagener et al. (2009) estimated the sensitivity of parameters for the SAC-SMA model, with single-objective and multi-objective functions; Francos et al. (2003) coupled the Morris and variance-based FAST methods to identify and analyze the important or sensitive parameters for the SWAT model. Results showed that the integration framework can be efficiently applied in complex hydrological models with tens or hundreds of parameters.

4.4 Meta-modeling method

The basic idea of meta-modeling method is to simulate the response function between input parameters and model output via various statistical or experimental design methods, to replace the original, complex physical or conceptual models, and then to analyze the parameter sensitivity indices or the influence of parameter variation on model output. The core of the meta-modeling based methods is to select appropriate sampling design and response fitting methods. When we select the response fitting method, the meta-modeling approach can accurately simulate the behavior of real phenomena in the domain of influential parameters; i.e., the meta-model can replace the original model by a mathematical approximation. Currently, there are many fitting methods used in hydrological models, and non-parametric methods have found more application because they do not require much hypothesis generation or prior knowledge of the actual response relationship, such as MARS (multivariate adapative regression splines) (Li et al., 2013; Zhan et al., 2013; Gan et al., 2014), SVM (support vector machine) (Song et al., 2012a), GP (Gaussian processes) (Gan et al., 2014), TGP (treed Gaussian processes) (Gramacy and Taddy, 2010). Similarly, sampling design methods must be selected for response surface analysis, which requires that the sampling design can cover the range of parameters as much as possible. Some sampling design methods have been verified as effective (Razavi et al., 2012), such as central composite design (Montgomery, 2008), full factorial design (Gutmann, 2001), Latin Hypercube sampling (Gan et al., 2014), quasi-random sampling (Elsawwaf et al., 2010; Zhan et al., 2013).

Meta-modeling based sensitivity analysis approach is a two-stage approach. First, a meta-model is created based on the original hydrological models and forcing data, and consequently it can be suitable for these hydrological models. Second, sensitivity measures are calculated based on classical SA methods, where the most common method is variance-based method (Song et al., 2013; Tian, 2013; Zhan et al., 2013; Gan et al., 2014). The immediate advantage is that it can simplify computationally intensive models and thus enables much faster model runs (Storlie et al., 2009), especially for a complex hydrological model with high computational cost of hundreds or thousands of model runs. Therefore, meta-modeling approaches have been particularly used in model evaluation for hydrological models (Razavi et al., 2012; Li et al., 2013; Song et al., 2012c, 2013; Zhan et al., 2013; Gan et al., 2014). However, it requires output values and corresponding values from probability distributions of input parameters calculated in the original hydrological model, and it is calibrated to the data generated from the hydrological model. Thus, it is only valid within the range of values used to generate the calibration dataset. Typically, the effect of all parameters with respect to sensitivity cannot be evaluated in meta-models; most meta-modeling based studies are based on fewer inputs, which are primarily screened out among the list of original parameters. In addition, the uncertainty of analysis results based on meta-model approaches should not be ignored. For example, there is no guarantee that a model parameter deemed insensitive on the basis of meta-model analysis is truly insensitive in the original hydrological model (Razavi et al., 2012). A question that meta-model users need to address in any meta-modeling practice is whether an exact fit to the set of design sites or an approximate fit, possibly with smoothing capabilities, is required. Therefore, it is essential to assess the accuracy of a meta-model for prediction before it can be used for SA studies (Stephens et al., 2011; Borgonovo et al., 2012). Despite advances in meta-modeling based SA in many fields, the uncertainty assessment of meta-modeling based SA should be further explored in the future.

Recently, meta-modeling based SA method has been used in different fields. For example, three meta-modeling techniques (Kriging, Radial-basis function network (RBF), and support vector machines (SVM)) and two popular SA methods (FAST and Sobol') were used to estimate the sensitivity indices of a probabilistic engineering design (Sathyanarayanamurthy and Chinnam, 2009). Ratto et al. (2007) proposed a state-dependent parameter (SDP) method based on the Kalman filter, combined with fixed interval smoothing, and then used the Sobol' method to evaluate sensitivity indices. Song et al. (2012a, 2012b, 2013) combined the Sobol' method and response surface model (RSM) approach (RSMSobol'; e.g., the SVM, multivariate adaptive regression splines (MARS)) to estimate parameter sensitivity for hydrological models, involving the Xinanjiang and distributed time-variant gain models (DTVGM). Borgonovo et al. (2012) pointed out that the meta-model allows an accurate estimation of density-based sensitivity measures when the main structural features of the original model are captured.

4.5 Regionalized sensitivity analysis

Regionalized sensitivity analysis (RSA), also called generalized sensitivity analysis, has been originally developed in the context of environmental models by Spear and Hornberger (1980) and further developed by Beven and Binley (1992) in hydrological models. Generally, it is a graphical approach based on Monte Carlo simulations with parameter combinations taken from their whole distribution range, which is why it is regarded as a global SA method (Massmann and Holzmann, 2012). These parameter sets are classified as behavioral or non-behavioral based on the comparison of the model results with a predefined threshold (Saltelli et al., 2004; Song et al., 2014). Jakeman et al. (1990) summarize the typical steps to implement RSA:

1) Define *a prior* parameter distribution from which the samples will be drawn as well as goodness criterion with a corresponding threshold for separating the results into a behavioral and a non-behavioral group;
2) Run the hydrological model using the parameter sets based on Monte Carlo sampling design
3) Classify the result as behavioral or not
4) Plot the relative cumulative probability distribution against the parameter values
5) Implement statistical analysis (e.g. Kolmogorov-Smirnoff test) to detect significant differences between both groups.

The Kolmogorov-Smirnoff test describes the maximum vertical distance between two cumulative distributions. If the distributions of a parameter x_i in the two groups are dissimilar then the parameter x_i is considered influential, and vice versa. The larger the distance, the more sensitive the parameter is (Yang, 2011). RSA has been widely used in hydrological models (e.g., Lence and Takyi, 1992; Freer et al., 1996; Pappenberger et al., 2006; Sieber and Uhlenbrook, 2005; Ratto et al., 2006; Tang et al., 2007a; Pappenberger et al., 2008; Yang, 2011; Massmann and Holzmann, 2012). From these studies, we can see that its advantage is conceptually simple and easy to implement. Results are easy to understand and the method is model-independent (Yang, 2011). However, the disadvantage is that they need to define a threshold for separating the results into a behavioral and non-behavioral group, which is a highly subjective task that might have important effects on the results (Beven, 2009). To resolve this difficulty, Freer et al. (1996) presented an extension of this method, in which the behavioral parameter sets are sorted from best to worst with respect to their ability to reproduce the observed results. Then they are separated into 10 equally sized groups, with the first group comprising the best 10% parameter sets, the second group the best 10-20% parameter sets and so on. Conclusions about parameter sensitivities are made qualitatively by examining differences in the marginal cumulative distributions of a parameter within each of the ten groups. Ten lines in the RSA plot represent the cumulative distributions of a parameter with respect to ten sampled sub-ranges. If the lines are clustered, the parameter is not sensitive to a specific model performance measure (Demaria et al., 2007; Wagener and Kollat, 2007). In addition, although under certain circumstances the Kolmogorov-Smirnoff test can highlight some interaction effect (Saltelli et al., 2008), the RSA method cannot quantify higher order effects or search for interacting structures (Yang, 2011). This means that the insignificance of the distance does not imply irrelevance of the input factor, due to possible missed interaction effects.

4.6 Entropy-based method

Entropy can be regarded as an indicator of the information content or as a measure of the uncertainty of a random variable (Mogheir et al., 2004; Liu et al., 2006; Auder and Iooss, 2009; Mishra et al., 2009). It also provides comparatively more information since two variables with no mutual information are statistically independent, while two uncorrelated variables are not necessarily independent (Frey and Patil, 2002). Different entropy indicators, which assess the relationship between a dependent and an independent variable, have been described in some studies, such as marginal, joint, conditional and mutual information. The mutual information is being used as an indicator of variable importance in many fields. Mishra and Knowlton (2003) describe a methodology for global SA that combines the mutual information concept with contingency table analysis. More details refer to Mishra and Knowlton (2003), Liu et al. (2006) and Mishra et al. (2009).

The major advantage of the entropy-based method is that it can capture more complete probabilistic sensitivity information by studying the impact of an input variable on the probabilistic distributed rather than on low-order moments such as on performance variance with the variance-based methods. However, it should be noted that the entropy-based method can only give a relative importance ranking of random variables and the absolute values of the measures are hard to interpret, which is the major limitation for the entropy-based method. Some studies also use entropy-based method to analyze the sensitivity of parameters for hydrological models. For example, Pappenberger et al. (2008) applied five different methods (Sobol', Kullback-Leibler entropy, Morris, RSA, and regression) to investigate the sensitivity of parameters of a one-dimensional flood inundation model (HEC-RAS) on the River Alzette. They found that the different methods leaded to completely different ranking of importance of the parameter factors and it was impossible to draw firm conclusions about the relative sensitivity of different factors. Massmann and Holzmann (2012) also discussed the comparison of the three global SA methods (Sobol' method, RSA, mutual entropy) for a rainfall-runoff model. The results revealed that entropy-based method was more robust than the RSA method at a daily scale and the Sobol' method was the least robust method. These results differed from the results obtained by Pappenberger et al. (2008). Neumann (2012) also discussed five SA methods (derivatives, screening, regression, variance decomposition and entropy) for a model predicting micropollutant degradation in drinking water treatment.

5. Evaluation framework of SA in hydrological modeling

The typical evaluation framework of SA in hydrological models is shown in Fig.3. We also discuss some practical issues, such as determination of parameter ranges, the choice of sampling design method, objective functions and adequate SA methods.

Figure 3 is here

5.1 Selection of parameters ranges and sampling design

The first crucial step is to determine the range of the inputs and select the appropriate sampling design methods when we implement SA in hydrological modeling (Zhan et al., 2013). The ranges and distributions of parameters are mainly dependent on the prior information. Some studies highlight the effect of ranges and distributions of inputs on the results of SA. For example, Tong and Graziani (2008) pointed out that the proper prescription of the ranges and shapes of the distributions can dramatically alter the outcome of the analysis. Shine et al. (2013) stated that reducing or expanding the ranges will affect the sensitivity indices, and cause insensitive parameters becoming sensitive or vice versa. Wang et al. (2013a) also showed that different parameter ranges for the WOFOST crop growth model yields differences in sensitive parameter. As the sensitivity of parameters can be strongly influenced by the ranges of inputs, it is important that the ranges used yield parameter sets that are considered plausible (Shine et al., 2013). Besides, Ben Touhami et al. (2013) investigated the different distributions (e.g. Gaussian distribution, normal distribution and uniform distribution) of parameters on the results of SA. They found there were notable differences among the different distribution conditions for their sensitivity. Although normal distribution and uniform distribution are often used in practice (Esmaeili et al., 2014), there is a need to account for different types of distributions (Kucherenko et al., 2012). Generally, probability distributions can be constructed from expert elicitation if there is not enough information. But, even with expert elicitation, it is still challenging to build distributions with great confidence. Therefore, more work needs to be conducted to assist in determining the ranges of inputs and investigate their distributions and response surface shapes. After we define the probability distributions of model parameters, for most global SA, it is necessary to implement sampling strategies for generation of sample. For regression-based and meta-modeling methods, Latin hypercube sampling (LHS) and Sobol' sequence random sampling methods are very popular due to their efficient stratification properties (Zhan et al., 2013; Song et al., 2014). For screening and variance-based methods, they usually require special sampling methods (Saltelli et al., 2008; Tian, 2013), e.g., Morris one-at-a-time sampling design should be used in Morris screening and FAST sampling design should correspond with FAST method.

5.2 Choice of objective functions for SA

It is also utmost important to select the appropriate objective functions, which would immediately affect the results of SA (Shine et al., 2013; Song et al., 2013). For example, Zhan et al. (2013) revealed that the most sensitive or important parameters for three different objective functions are different in distributed time variant gain model. Song et al. (2013) highlighted that there are the differences of sensitivity indices among four objectives for Xinanjiang model. The same conclusions for Sacramento model and MIKE/NAM model obtained by van Werkhoven et al. (2008a, 2009) and Liu and Sun (2010). However, Foglia et al. (2009) suggested that a well-designed single objective function including many data types can also be useful. Generally, contributions to the objective function are weighted, and the weighting accounts for the different units and precision of different contributions to the objective function (Hill and Tiedeman, 2007). The weights allow the statistics to quantify the information provided by different types of observations via combining the contributions of different functions into one objective function (Song et al., 2012c). Therefore, SA should be implemented based on multi-objective functions or combined single function of different objectives, and it can give valuable and comprehensive insight into these parameters for hydrological models (Hill and Tiedeman, 2007; Foglia et al., 2009; Shine et al., 2013).

5.3 Choice of SA methods for hydrological models

Considering the wide range of SA methods, practitioners need adequate resource to better understand which methods are appropriate for a specific application (Ratto et al., 2007; Tang et al., 2007b; Pappenberger et al., 2008; Confalonieri et al., 2010; Yang, 2011; Reusser et al., 2011, Sun et al., 2012; Gan et al., 2014). Different types of SA methods can be selected based on: (a) the objective of the analysis, (b) the number of uncertain input factors, (c) the degree of regularity of the model, (d) the computing time for a single model simulation, and (e) analyst's time for SA (Cacuci et al., 2003; Saltelli et al., 2005; Wallach et al., 2006; Zajac et al., 2010; Saltelli et al., 2012).

In practice, the objective of analysis is the first crucial step to select the appropriate SA methods. For example, if one focuses on ranking characteristics of parameter sensitivity measure, the qualitative analysis or screening-based methods could be selected. Nay rather, if one wants to gain further insight into the characteristics of sensitivity indices, the quantitative methods may be the best choice. As Shin et al. (2013) stated that if the aim of the SA is to select non-influential parameters with respect to the target function and perhaps to fix their values, then the total-order sensitivity index is suggested as a reasonable measure to use. Secondly, it is well known that the dimension of parameters has a significant influence on the selection and application of SA methods in hydrological models; i.e., the performance efficiency for SA largely depends on parameter dimensions. Generally, when the number of parameters is much greater than tens, the global screening method is preferred. Screening methods are designed to handle hundreds of model input factors in a sense that they can only provide qualitative sensitivity measure (Zoras et al., 2007). Using qualitative ranking results, we can fix the non-sensitive parameters and reduce the parameter dimensions or number of parameters to make the quantitative SA more tractable. Thirdly, the computational expense for a single model run is another constraint to dictate the choice of SA methods in hydrological modeling. For example, SA is almost always performed by running the model a number of times, i.e. a sampling-based approach. This can be a significant problem when a single run of the model takes a significant amount of time (minutes, hours or longer), which is not unusual with very complex models, or when the model has a large number of uncertain inputs. Consequently, computational expense is a problem in many practical SA. Some methods of reducing computational expense include the use of meta-modeling methods (for large models) and screening methods (for reducing the dimensionality of the problem). Therefore, synthetic SA approaches, which consider the advantages and disadvantages of various analysis methods and combine these methods as a systematic analysis technique, have been used in complex models. The Morris screening method, coupled with variance-based methods, is a common approach for SA in many science fields, and the flowchart of this integration method is shown in Fig.4. For instance, Francos et al. (2003) integrate the Morris method with FAST for qualitative and quantitative analysis (the two-step analysis method) to estimate parameter sensitivity for the SWAT model. Sun et al. (2012) also highlight that when the number of input factors involved in the model is too high to afford a computationally expensive quantitative analysis, a more efficient two-step procedure based on a screening process (first stage) and a quantitative analysis method (second stage) can be adopted. In addition, Song et al. (2014) integrated the Morris method, RSM, and the Sobol' method to clearly and efficiently identify the influence of parameters on model output from the DTVGM and Xinanjiang models. From these results, the integration technique clearly achieves qualitative and quantitative SA and can largely reduce the computational cost with fewer model runs.

Figure 4 is here

----

6 Other topics related to SA in hydrological models

6.1 Analysis of correlated parameters in hydrological models

It is not uncommon that input parameters may be correlated in hydrological models. The correlations among hydrological or hydraulic parameters have important effects on the estimation of hydrological parameters and further significantly affect the predictions and associated uncertainties of hydrological modeling (Pohlmann et al., 2002; Lemke et al., 2004; Manache and

Melching, 2008; Pan et al., 2011). Understanding the contribution of each parameter and the joint contributions of correlated parameters in predictive uncertainties is also critical to uncertainty reduction (Rojas et al., 2009; Fox et al., 2010). Although the parameter correlations are observed and may be strong in some cases (Xu and Gertner 2007), the existing sensitivity analysis methods of hydrological models typically adopt the assumption of independent parameters (e.g., Li and Yeh, 1998; Boateng, 2007; Zhu et al., 2010; Zhan et al., 2013). Some studies have been devoted to the sensitivity analysis with correlated parameters (e.g., Helton et al., 1995; Fang et al., 2004; Jacques et al., 2006; Pan et al., 2011). For example, Iman et al. (2002) proposed the partial correlation as a measure of parameter sensitivity for models with correlated input based on the Latin Hypercube sampling method. Xu and Gertner (2008a) proposed a regression-based method to derive the correlated contribution (by variations of parameter correlated with other parameters) and the uncorrelated contribution (by variations of parameter uncorrelated with other parameters). Unfortunately, their methods rely on the assumption that the parameter effects are approximately linear. In general, for complex hydrological models, it can be expected that parameter effects are too nonlinear for such methods to yield reliable results. Fang et al. (2004) proposed sequential sampling to approximate a differential sensitivity index. Satelli et al. (2004) proposed a correlation ratio method based on McKay's one-way ANOVA method, which is based on the replicated Latin hypercube sampling and suitable for non-linear and non-monotonic models. But Bedford (1998) found the Sobol' evaluations depend on the order of the parameters. As Xu and Gertner (2008b) said, both Fang et al.'s method and correlation ratio method require a large sample size which would be impractical for complex models. Although many techniques have been proposed to generalize the variance-based SA methods for the case of correlated or dependent variables

(Kucherenko et al., 2012; Xu, 2013), there is hardly any successful application into hydrological modelling up to now. Further work should be considered to use these methods to investigate their influence on model output for the correlated parameters in hydrological models.

6.2 Applications of SA in model evaluations

As previously mentioned, distributed modeling of catchment hydrology is a valuable approach to understand, reproduce and predict the behavior of hydrological systems. However, distributed hydrological models still remain as a simplified and imperfect representation of physical processes, using uncertain observation data to estimate model inputs (e.g., parameters, initial conditions, etc.). Thus, parameter estimation is critical to develop useful models of complex hydrological systems, for which the important characteristics cannot be measured accurately or completely enough to define model input values (Matott et al., 2009; Song et al., 2012d). In practice, SA is generally a required step, and a necessary prerequisite to other steps as discussed below.

6.2.1 SA and parameter identification

Parameter identification of hydrological models has increasingly become a problem as model complexity increases with high-dimensions of model parameters. Model identification involves choosing suitable model structure and degree of complexity; i.e., it is important to keep the model description and parameterization as simple as possible to ensure sufficient calibration, but, at the same time, it must be sufficiently distributed to capture the spatial variability of key model parameters. Thus, the dimensionality of the parameter space must be limited so as to avoid model over-parameterization. With respect to efficient parameter identification, SA is useful to provide the qualitative and quantitative indices needed to identify important and non-important parameters

(Yang et al., 2011; Pappenberger et al., 2008; Confalonieri et al., 2010). It might be difficult to efficiently estimate these parameters when there are a large number of parameters with no clearly identifiable influence on output variables, or many parameters have similar effects (or interactions) on output variables. In these cases, SA will be crucial for parameter identification. Thus, SA and parameter identification usually are performed together in model calibration. For example, Castaings *et al.* (2009) and Cibin et al. (2010) emphasize that global SA of parameters can provide much more information for parameter identification and estimation. Vandenberghe et al. (2001) highlighted the complementarity of the SA for the parameter identification and calibration in practice. To some extent, SA can be regarded as a solution to parameter identification.

6.2.2 SA and UA

Generally, the contribution of parameter uncertainty depends on the model structure, which is also related to the parametric sensitivity in the modeling systems. Saltelli and Annoni (2010) emphasize that the objective of UA is to answer the question, “How uncertain is this inference?”, and that of SA is to answer, “Where is this uncertainty coming from?”. Generally, SA can be used to characterize a pure UA (Kennedy, 2007). Whatever the terminology used, SA is not to be intended as an alternative to UA but rather as a complement to UA. The two tasks, while having different objectives, are often coupled in most cases (Saltelli and Annoni, 2010). For instance, Mishra (2009) discussed various UA (e.g., Monte Carlo simulation, first-order second-moment analysis, the point estimate method, logic tree analysis, and the first-order reliability method) and SA techniques (e.g., stepwise regression, mutual information or entropy analysis, and classification tree analysis) in hydrological models. They found that UA results are consistent with those from SA based on two case studies. The same conclusion was reported by Wang et al. (2010) and

Elsawwaf et al. (2010). These studies demonstrate that the two approaches assist our understanding of the uncertainty effect of model parameters on output variables and the structural characteristics of hydrological modeling systems from different points of view. Currently, the two approaches have more interaction, and they usually do not separate completely from each other. Beven and Binley (1992) developed the generalized likelihood uncertainty estimation (GLUE) method, which is as an extension of the regionalized sensitivity analysis (RSA) method proposed by Spear and Hornberger (1980), to estimate parameter uncertainty and demonstrate the equifinality for different parameters. The GLUE method has often been used for UA and SA in hydrological models. Ratto et al. (2001) proposed a new approach for model calibration, coupling the GLUE and variance-based SA methods, and found that integrated application enhanced the performance efficiency of calibration procedures.

6.2.3 SA and parameter optimization

Model calibration or parameter optimization of complex models is challenging due to the uncertainty of a large number of parameters (Fienen et al., 2009; Foglia et al., 2009; Keating et al., 2010). In practice, it is also difficult to ensure the accuracy of model application and reliability of prediction via empirical estimation or automatic optimization (Ciriello et al., 2013). Hence, while we seek more efficient and steady optimization algorithms, we also need sensitivity and uncertainty analyses to estimate the effect of parameters on model predictions. As mentioned by Rakovec et al. (2014), parameter SA can reduce the time of model calibration by focusing estimation efforts on important parameters to model predictions. Therefore, for complex hydrological models with a large number of parameters, SA may be a better choice to apply before the model calibration. For example, van Werkhoven et al. (2009) investigated the use of global SA as a screening tool to reduce the parametric dimensionality of multi-objective hydrological model calibration problems, while maximizing the information extracted from hydrological response data. They use the SAC-SMA model as an example and suggest that it can reduce the complexity of calibration, while maintaining high quality model predictions. Liu et al. (2010) suggest that no single objective function is adequate to measure how a model fails to predict the important characteristics of the observed data, and multiple criteria should be considered. They couple the Morris screening method with multi-objective differential evolution (MODE) (non-dominated sorting differential evolution, NSDE) to quantify parameters in the MIKE11/NAM rainfall-runoff model. The results showed that the integrated method can identify the optimal Pareto front and maintains reasonable diversity in the obtained front for model calibration.

6.3 Temporal and spatial variations of SA in hydrological models

Distributed hydrological models allow model parameters and forcing data to vary on a spatial scale, aiming to better represent the spatial variability of watershed processes at the cost of increasing model complexity, which poses several challenges for model identification and diagnosing (Herman et al., 2013c). Considering the widespread applications of distributed models, there remains a need for diagnostic methods to study such models at their full spatial and temporal complexity. Often, some of the model parameters will represent processes that only matter during specific time periods, i.e. specific modes of the system, for example recession constants or parameters controlling the extent of saturated areas in a catchment during a flood event. Such parameters are only likely to be identifiable if these periods can be isolated, or if they sufficiently impact a global objective function. It is often observed that parameters which are important during low flow periods, when errors are generally small, or parameters which are only important for a very short time, are not easily identifiable. Therefore, more recent studies have explored time-varying sensitivities at predefined intervals throughout the model simulation, revealing the dynamics of model controls under changing conditions (Wagener et al., 2003; van Werkhoven et al., 2008a; Reusser and Zehe, 2011; Reusser et al., 2011; Garambois et al., 2013; Herman et al., 2013a; Guse et al., 2014). Generally, sensitivity analysis methods used for time-varying analysis include local and global approaches. Regardless of the method applied, they are generally used to estimate sensitivity at each time step or for a running window (Massmann et al., 2014). In addition, several studies that have focused on event-scale spatial sensitivities (Tang et al., 2007a; van Werkhoven et al., 2008b; Wagener et al., 2009) have proposed using observations to identify representative events for a watershed. However, if the dynamics of a watershed cannot be accurately restricted to one of several events classifications, this selection of representative events fail to account for the full range of process variability. Hence, Herman et al. (2013c) extended the event-scale approach to primarily investigate the full dynamics of spatially distributed model controls based on Morris screening method. To some extent, time-varying and spatial-scale sensitivity analysis present a valuable opportunity to overcome the complexity of distributed parameter identification by restricting search to only those parameters which are active at a specific time and location, to improve the modeled representation of hydrological processes and enhance the understanding of the hydrological cycle system.

7 Summary and outlook

Generally, the purpose of SA is to determine which model parameters exert the most influence on model results. This information, in turn, allows unimportant parameters to be fixed or not incorporated into the model and provides direction for future research to reduce parameter uncertainties and increase model accuracy. It is widely accepted that identifying the most relevant parameters in a model is of key importance for the hydrological modeling because of its role in supporting not only effective parameterizations but also the development of the model itself. Although there are various SA methods in hydrological modeling, practical experience shows that no single analysis method is better than others. The regression-based method (e.g., SRC, SRRC) is simple to implement and easy to interpret, and it may be still the first choice because it only requires moderate computational cost in the field of hydrological models. However, for a complex hydrological model with large number of parameters and high computational cost, Morris screening methods should be a preferred choice for qualitative analysis, whereas a better choice may be the meta-model approaches, and the best choice is their integration methods (Francos et al., 2003; Song et al., 2012a, 2013; Zhan et al. 2013). This is because qualitative screening methods can reduce the number of variables for quantitative analysis, and quantitative method (e.g., variance-based method) can quantify their influence of each input for output variance. The RSA method, as a graphical SA, can provide information about the relationship between the output response and the input parameters, which can improve our understanding of the model results. However, the result of RSA primarily depends on the choice of the filtering criterion, that is to say, it should be used with care. Entropy-based method is more competitive for delineating the nonlinear and non-monotonic multivariate relationship than regression-based method.

Most previous work has been embedded into only one methodology to compute sensitivities, despite the fact that different sensitivity analysis methods can lead to a difference in the ranking of the importance of the different model factors. Instead, we suggest that several different sensitivity measures have to be used in tandem. In addition, we need to build more realistic and more integrated hydrological models to represent real-world thresholds, nonlinearities and feedbacks, and which are capable of representing the implications of environmental change. Building these necessarily more complex models must also be accompanied by a development in significantly more powerful identification and evaluation algorithms. Such algorithms, combining optimization and sensitivity analysis methods while considering uncertainty, have to be able to examine how models represent hydrological cycle systems and whether this presentation is consistent with the perception of the actual system and when models are incapable of doing so. Finally, we present our viewpoints on development trends, research issues or hotspots of SA for complex hydrological models.

(1) For complex hydrological models, the computational efficiency of model evaluation and SA may be an unavoidable problem, even with the most effective algorithms or high performance computers. Hundreds and thousands of model evaluations for global SA (e.g., variance-based methods) make it more inconvenient, with expensive computational costs (e.g., greater than days or months), especially when the number of parameters is greater than hundreds. Although meta-modeling approaches have often been used in the hydrological models for SA, there are still some technique issues to be resolved involving the reliability and goodness-of-fit of meta-models. For physical-based, distributed hydrological models, practitioners using meta-models to represent the response relationship between parameters and model outputs should consider the following questions: (1) Do the meta-models reflect the typicality or characteristics between parameters and outputs of original models?; (2) How should the goodness-of-fit of the two models be evaluated based on different criteria?; and (3) How should the adaptive meta-modeling approach be selected

and developed to construct the surrogate models?

(2) Convergence and reliability of SA is another problem for scientists. With the availability of different SA techniques, selecting an appropriate technique, monitoring the convergence and estimating the uncertainty of the SA results are crucial for hydrological models, especially distributed models, due to their non-linearity, non-monotonicity, highly correlated parameters, and intensive computational requirements (Yang, 2011). Currently, there are many studies that have examined the reliability of SA results in complex models, such as Yang (2011), Pappenberger et al. (2008), and Confalonieri et al. (2010). These investigations also show that no SA method is perfect and declare explicitly which conditions are important to avoid erroneous interpretation of model output sensitivity to parameters. Therefore, appropriate and correctly integrated methods must be selected based on their advantages and disadvantages to meet the actual requirement. In addition, multi-objective SA and parameter optimization will become more important for complex hydrological models to evaluate simulation results from different criteria.

(3) Although many SA methods are developed and have been used in these fields, there are too many hypotheses or other limitations in these methods, involving the independence of input variables, monotonicity of response functions, etc. In practice, parameters for hydrological models usually have interactions or correlations, and these parameters may have significant joint effects on output variables of interest. If these parameters are separated to analyze the effect for each parameter, there may be some errors (e.g., Type I or Type II errors) in judgment or decision. As a result, developing an efficient and effective global SA method will be an objective for many scientists in the future.

Acknowledgement

We thank the editor and associate editor, the two anonymous reviewers for highly constructive comments and suggestions, which contributed significantly to improvement of this manuscript. The work was supported by the National Natural Science Foundation of China (Grant Nos. 41330854, 41371063), the Postgraduate Dissertation Foundation of Nanjing Hydraulic Research Institute (LB51302), the National Basic Research Program of China ("973" Program) (Grant Nos. 2010CB951103 and 2010CB428403).

References

Abebe, N.A., Ogden, F.L., Pradhan, N.R., 2010. Sensitivity and uncertainty analysis of the conceptual HBV rainfall-runoff model: Implications for parameter estimation. J. Hydrol. 389, 301-310. http://dx.doi.org/10.1016/j.jhydrol.2010.06.007

Anderman, E. R., Hill, M. C., Poeter, E. P., 1996. Two-dimensional advective transport in ground-water flow parameter estimation. Groundwater, 34(6), 1001-1009. http://dx.doi.org/10.1111/j.1745-6584.1996.tb02165.x

Aster, R. C., Borchers, B., Thurber C. H., 2013. Parameter estimation and inverse problems. Academic Press

Auder, B., Iooss, B., 2009. Global sensitivity analysis based on entropy. In: Martorell, S., Guedes, C., Bernett, J. (Eds.), Safety, Reliability and Risk Analysis: Theory, Methods and Applications. Taylor & Francis Group, London, pp. 2107-2115

Baroni, G., Tarantola, S., 2014. A general probabilistic framework for uncertainty and global sensitivity analysis of deterministic models: A hydrological case study. Environ. Modell. Softw. 51, 26-34. http://dx.doi.org/10.1016/j.envsoft.2013.09.022

Beck, M. B., 1987. Water quality modeling: a review of the analysis of uncertainty. Water Resour. Res. 23(8), 1393-1442. http://dx.doi.org/10.1029/WR023i008p01393

Bedford, T., 1998. Sensitivity indices for (tree-) dependent variables. In: Chan, K., Tarantola, S., Campolongo, F., (Edited), Proceedings of the Second International Symposium on Sensitivity Analysis of Model Output, EUR report, 17-20.

Ben Touhami, H., Lardy, R., Barra, V., Bellocchi, G., 2013. Screening parameters in the Pasture Simulation model using the Morris method. Ecol. Modell. 266, 42-57. http://dx.doi.org/10.1016/j.ecolmodel.2013.07.005

Beven K. J., 2009. Environmental Modelling: An uncertain future? Routledge, London

Beven, K., Binley, A., 1992. The future of distributed models: model calibration and uncertainty predication. Hydrol. Process. 6(3), 279-298. http://dx.doi.org/10.1002/hyp.3360060305

Boateng, S., 2007. Probabilistic unsaturated flow along the textural interface in three capillary barrier models. J. Environ. Eng. 133(11), 1024-1031. http://dx.doi.org/10.1061/(ASCE)0733-9372(2007)133:11(1024)

Borgonovo, E., 2006. Measuring uncertainty importance: investigation and comparison of alternative approaches. Risk Analysis, 26: 1349-1361. http://dx.doi.org/10.1111/j.1539-6924.2006.00806.x

Borgonovo, E., Castings, W., Tarantola, S., 2012. Model emulation and moment-independent sensitivity analysis: An application to environmental modelling. Environ. Modell. Softw. 34, 105-115. http://dx.doi.org/10.1016/j.envsoft.2011.06.006

Brockmann, D., Morgenroth, E., 2007. Comparing global sensitivity analysis for a biofilm model for two-step nitrification using the qualitative screening method of Morris or the quantitative variance-based Fourier amplitude sensitivity test (FAST). Water Sci. Tech. 56, 85-93. http://dx.doi.org/10.2166/wst.2007.600

Cacuci, D.G., Navon, I.M., Ionescu-Bujor, M., 2003. Sensitivity and uncertainty analysis. Chapman & Hall / CRC Press, Boca Raton

Campolongo, F., Cariboni, J., Saltelli, A., 2007. An effective screening design for sensitivity analysis of large models. Environ. Modell. Softw. 22, 1509-1518. http://dx.doi.org/10.1016/j.envsoft.2006.10.004

Campolongo, F., Saltelli, A., Sorensen, T., Tarantola, S., 2000. Hitchhiker's guide to sensitivity analysis. In: Saltelli, A., Chan, K., Scott, E. M., Eds. Sensitivity Analysis. John Wiley & Sons, West Sussex, England, pp.15-47

Cariboni, J., Gatelli, D., Liska, R., Saltelli, A., 2007. The role of sensitivity analysis in ecological modeling. Ecol. Modell. 203(1-2), 167-182. http://dx.doi.org/10.1016/j.ecolmodel.2005.10.045

Castaings,W., Dartus, D., Le Dimet, F. X., Saulnier, G.M., 2009. Sensitivity analysis and parameter estimation for distributed hydrological modeling: potential of variational methods. Hydrol. Earth Syst. Sci. 13, 503-517. http://dx.doi.org/10.5194/hess-13-503-2009

Cibin, R., Sudheer, K. P., Chaubey, I., 2010. Sensitivity and identifiability of stream flow generation parameters of the SWAT model. Hydrol. Process. 24, 1133-1148. http://dx.doi.org/10.1002/hyp.7568

Ciriello, V., Guadagnini, A., Di Federico, V., Edery, Y., Berkowitz, B., 2013. Comparative analysis of formulations for conservative transport in porous media through sensitivity-based parameter calibration. Water Resour. Res. 49, 5206-5220. http://dx.doi.org/10.1002/wrcr.20395

Cloke, H. L., Pappenberger, F., 2009. Ensemble flood forecasting: A review. J. Hydrol. 375(3-4), 613-626. http://dx.doi.org/10.1016/j.jhydrol.2009.06.005

Cloke, H.L., Pappenberger, F., Renaud, J.P., 2007. Multi-method global sensitivity analysis (MMGSA) for modeling floodplain hydrological processes. Hydrol. Process. 22(11), 1660-1674. http://dx.doi.org/10.1002/hyp.6734

Confalonieri, R., Bellocchi, G., Bregaglio, S., Donatelli, M., Acutis, M., 2010. Comparison of sensitivity analysis techniques: A case study with the rice model WARM. Ecol. Modell. 221, 1897-1906. http://dx.doi.org/10.1016/j.ecolmodel.2010.04.021

Coyle, D., Buxton, M.J., O'Brien, B.J., 2003. Measures of importance for economic analysis based on decision modeling. J. Clin. Epidemiol. 56(10), 989-997. http://dx.doi.org/10.1016/S0895-4356(03)00176-8

Crick, M. J., Hill, M. D., Charles, D., 1987. The role of sensitivity analysis in assessing uncertainty. In: Proceedings of an NEA Workshop on Uncertainty Analysis for Performance Assessments of Radioactive Waste Disposal Systems, Paris, OECD, 1-258

Demaria, E.M., Nijssen, B., Wagener, T., 2007. Monte Carlo sensitivity analysis of land surface parameters using the variable infiltration capacity model. J. Geophys. Res. 112, D11113, http://dx.doi.org/10.1029/2006JD007534

Doherty, J., Welter, D., 2010. A short exploration of structural noise. Water Resources Research, 46(5), http://dx.doi.org/10.1029/2009WR008377

Dotto, C.B.S., Deletic, A., Fletcher, T.D., 2009. Analysis of parameter uncertainty of a flow and quality stormwater model. Water Sci. Tech. 60(3), 717-725. http://dx.doi.org/10.2166/wst.2009.434

Duan, Q.Y., Sorooshian, S., Gupta, V., 1992. Effective and efficient global optimization for conceptual rainfall-runoff models. Water Resour. Res. 28(4), 1015-1031. http://dx.doi.org/10.1029/91WR02985

EC, 2009. Impact assessment guidelines, 15 Jan. 2009, Technical Report 92, SEC. http://ec.europa.eu/governance/impact/commission_guidelines/docs/iag_2009_en.pdf (Oct 23, 2013)

Elsawwaf, M., Willems, P., Feyen, J., 2010. Assessment of the sensitivity and prediction uncertainty of evaporation models applied to Nasser Lake, Egypt. J. Hydrol. 395, 10-22. http://dx.doi.org/10.1016/j.jhydrol.2010.10.002

Esmaeili, S., Thomson, N. R., Tolson, B. A., Zebarth, B. J., Kuchta, S. H., Neilsen, D., 2014. Quantitative global sensitivity analysis of the RZWQM to warrant a robust and effective calibration. J. Hdrol. 511, 567-579.

http://dx.doi.org/10.1016/j.jhydrol.2014.01.051

Fang, S., Gertner, G. Z., Anderson, A. A., 2004. Estimation of sensitivity coefficients of nonlinear model input parameters which have a multinormal distribution. Comput. Phys. Comm. 157, 9-16. http://dx.doi.org/10.1016/S0010-4655(03)00488-0

Fienen, M., Hunt, R., Krabbenhoft, D., 2009. Obtaining parsimonious hydraulic conductivity fields using head and transport observations: A Bayesian geostatistical parameter estimation approach. Water Resour. Res. 45(8), W08405. http://dx.doi.org/10.1029/2008WR007431

Flores-Alsina, X., Rodriguez-Roda, I., Sin, G., Gernaey, K.V., 2009. Uncertainty and sensitivity analysis of control strategies using the benchmark simulation model No1 (BSM1). Water Sci. Tech. 59(3), 491-499. http://dx.doi.org/10.2166/wst.2009.871

Foglia, L., Hill, M. C., Mehl, S. W., Burlando, P., 2009. Sensitivity analysis, calibration, and testing of a distributed hydrological model using error-based weighting and one objective function. Water Resour. Res. 45, W06427, http://dx.doi.org/10.1029/2008WR007255

Foglia, L., Mehl, S. W., Hill, M. C., Burlando, P., 2013. Evaluating model structure adequacy: The case of the Maggia Valley groundwater system, southern Switzerland. Water Resour. Res. 49(1), 260-282. http://dx.doi.org/10.1029/2011WR011779

Fox, G.A., Munoz-Carpena, R., Sabbagh, G. J., 2010. Influence of flow concentration on parameter importance and prediction uncertainty of pesticide trapping by vegetative filter strips. J. Hydrol. 384, 164-173. http://dx.doi.org/10.1016/j.jhydrol.2010.01.020

Francos, A., Elorza, F.J., Bouraoui ,F., et al. 2003. Sensitivity analysis of distributed environmental simulation models: understanding the model behavior in hydrological studies at the catchment scale. Reliab. Eng. Syst. Safety 79(2), 205-218. http://dx.doi.org/10.1016/S0951-8320(02)00231-4

Freer, J., Beven, K., Ambroise, B., 1996. Bayesian estimation of uncertainty in runoff, prediction and the value of data: an application of the GLUE approach. Water Resour. Res. 32(7), 2161-2173. http://dx.doi.org/10.1029/95WR03723

Frey, H. C., Patil, R., 2002. Identification and review of sensitivity analysis methods. Risk. Anal. 22(3), 553-377. http://dx.doi.org/10.1111/0272-4332.00039

Fu, G., Kapelan, Z., Reed, P., 2012. Reducing the complexity of multi-objective water distribution system optimization through global sensitivity analysis. J. Water Resour. Plann. Manage. 138(3), 196-207. http://dx.doi.org/10.1061/(ASCE)WR.1943-5452.0000171

Gan, Y., Duan, Q., Gong, W., Tong, C., Sun, Y., Chu, W., Ye, A., Miao, C., Di, Z., 2014. A comprehensive evaluation of various sensitivity analysis methods: A case study with a hydrological model. Environ. Modell. Softw. 51, 269-285. http://dx.doi.org/10.1016/j.envsoft.2013.09.031

Garambois, P.A., Roux, H., Larnier, K., Castaings, W., Dartus, D., 2013. Characterization of process-oriented hydrologic model behavior with temporal sensitivity analysis for flash floods in Mediterranean catchments. Hydrol. Earth Syst. Sci. 17, 2305-2322. http://dx.doi.org/10.5194/hess-17-2305-2013

Gramacy, R. B., Taddy, M., 2010. Categorical inputs, sensitivity analysis, optimization and importance tempering with tgp version 2, an R package for treed Gaussion process models. J. Stat. Softw. 33(6), 1-48. http://www.jstatsoft.org/v33/i06

Gupta, H. V., Clark, M. P., Vrugt, J. A., Abramowitz, G., Ye, M., 2012. Towards a comprehensive assessment of model structural adequacy. Water Resour. Res. 2012, 48(8), http://dx.doi.org/10.1029/2011WR011044

Guse, B., Reusser, D.E., Fohrer, N., 2014. How to improve the representation of hydrological processes in SWAT for a lowland catchment – temporal analysis of parameter sensitivity and model performance. Hydrol. Process. 28(4), 2651-2670. http://dx.doi.org/10.1002/hyp.9777

Gutmann, H. M., 2001. A radial basis function method for global optimization. J. Global Optim. 19(3), 201-227. http://dx.doi.org/10.1023/A:1011255519438

Hamby, D .M., 1994. A review of techniques for parameter sensitivity analysis of environmental models. Environ. Monitor. Assess. 32,135-154. http://dx.doi.org/10.1007/BF00547132

Hamm, N.A.S., Hall, J. W., Anderson, M. G., 2006. Variance-based sensitivity analysis of the probability of hydrologically induced slope instability. Comput. Geosci. 32(6), 803-817. http://dx.doi.org/10.1016/j.cageo.2005.10.007

He, M.X., Hogue,T.S., Franz, K. J., Margulis, S.A., Vrugt, J.A., 2011. Characterizing parameter sensitivity and uncertainty for a snow model across hydroclimatic regimes. Adv. Water Resour. 34, 114-127. http://dx.doi.org/10.1016/j.advwatres.2010.10.002

Helton, J.C., Johnson, J.D., Rollstin, J.A., Shiver, A.W., Sprung, J.L., 1995. Uncertainty and sensitivity analysis of chronic exposure results with MACCS reactor accident consequence model. Reliab. Eng. Syst. Safety 50(2), 137-177. http://dx.doi.org/10.1016/0951-8320(95)00078-G

Herman, J.D., Kollat, J.B., Reed, P.M., Wagener, T., 2013b. Technical note: Method of Morris effectively reduces the computational demands of global sensitivity analysis for distributed watershed models. Hydrol. Earth Syst. Sci. 17(7), 2893-2903. http://dx.doi.org/10.5194/hess-17-2893-2013

Herman, J.D., Kollat, J.B., Reed, P.M., Wagener, T., 2013c. From maps to movies: high-resolution time-varying sensitivity analysis for spatially distributed watershed models. Hydrol. Earth Syst. Sci. 17(12), 5109-5125. http://dx.doi.org/10.5194/hess-17-5109-2013

Herman, J.D., Reed, P.M., Wagener, T., 2013a. Time-varying sensitivity analysis clarifies the effects of watershed model formulation on model behavior. Water Resour. Res. 49, 1400-1414. http://dx.doi.org/10.1002/wrcr.20124

Hill, M.C., and Tiedeman, C.R., 2007, Effective Groundwater Model Calibration: With Analysis of Data, Sensitivities, Predictions, and Uncertainty. Wiley and Sons, Hoboken, N.J.

Holvoet, K., van Griensven, A., Seuntjens, P., Vanrolleghem, P.A., 2005. Sensitivity analysis for hydrology and pesticide supply towards the river in SWAT. Phys. Chem. Earth, Parts A/B/C. 30(8-10), 518-526. http://dx.doi.org/10.1016/j.pce.2005.07.006

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

Iman, R.L., Johnson, M.E., Schroeder, T.A., 2002. Assessing hurricane effects, Part I. Sensitivity analysis. Reliab. Eng. Syst. Safety 78(2), 131-145. http://dx.doi.org/10.1016/S0951-8320(02)00133-3

Jacques, J., Lavergne, C., Devictor, N., 2006. Sensitivity analysis in presence of model uncertainty and correlated inputs. Reliab. Eng. Syst. Safety 91, 1126-1134. http://dx.doi.org/10.1016/j.ress.2005.11.047

Jakeman, A.J., Ghassemi, F., Dietrich, C.R., 1990. Calibration and reliability of an aquifer system model using generalized sensitivity analysis. In: Proceedings ModelCARE90: Calibration and Reliability in Groundwater Modelling. IAHS Publication, p.195

Jakeman, A.J., Letcher, R.A., Norton, J.P., 2006. Ten iterative steps in development and evaluation of environmental models. Environ. Modell. Softw. 21, 602-614. http://dx.doi.org/10.1016/j.envsoft.2006.01.004

Kavetski, D., Clark, M., 2010. Ancient numerical daemons of conceptual hydrological modeling: 2. Impact of time stepping schemes on model analysis and prediction. Water Resour. Res. 43, W03411, http://dx.doi.org/10.1029/2009WR008896

Keating, E. H., Doherty, J., Vrugt, J. A., Kang, Q., 2010. Optimization and uncertainty assessment of strongly nonlinear groundwater models with high parameter dimensionality. Water Resour. Res. 46(10), W10517, http://dx.doi.org/10.1029/2009WR008584

King, D.M., 2009. On the importance of input variables and climate variability to the yield of urban water supply systems. PhD thesis, Victoria University, Melbourne, Australia. http://vuir.vu.edu.au/15534/1/David_King.pdf

King, D.M., Perera, B.J.C., 2013. Morris method of sensitivity analysis applied to assess the importance of input variables on urban water supply yield – a case study. J. Hydrol. 477, 17-32. http://dx.doi.org/10.1016/j.jhydrol.2012.10.017

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

Lemke, L.D., Abriola, L.M., Lang, J.R., 2004. Influence of hydraulic property correlation on predicted dense nonaquesous phase liquid source zone architecture, mass recovery and contaminant flux. Water Resour. Res. 40, W12417, http://dx.doi.org/10.1029/2004WR003061

Lence, B., Takyi, A., 1992. Data requirements for seasonal discharge programs: an application of a regionalize sensitivity analysis. Water Resour. Res. 28, 1781-1789. http://dx.doi.org/10.1029/92WR00763

Li, B., Yeh T.C.J., 1998. Sensitivity and moment analyses of head in variably saturated regimes. Adv. Water Resour. 21(6), 477-485. http://dx.doi.org/10.1016/S0309-1708(97)00011-0

Li, J., Duan, Q., Gong, W., Ye, A., Dai, Y., Miao, C., Di, Z., Tong, C., Sun, Y., 2013. Assessing parameter importance of the Common Land Model based on qualitative and quantitative sensitivity analysis. Hydrol. Earth Syst. Sci. 17(8), 3279-3293. http://dx.doi.org/10.5194/hess-17-3279-2013

Liu, H., Chen, W., Sudjianto, A., 2006. Relative entropy based method for probabilistic sensitivity analysis in engineering design. J. Mech. Des. 128(2), 326-336. http://dx.doi.org/10.1115/1.2159025

Liu, Y., Sun,F., 2010. Sensitivity analysis and automatic calibration of a rainfall-runoff model using multi-objectives. Ecol. Inf. 5, 304-310. http://dx.doi.org/10.1016/j.ecoinf.2010.04.006

Loosvelt, L., Vernieuwe, H., Pauwels, V.R.N., De Baets, B., Verhoest, N.E.C., 2013. Local sensitivity analysis for compositional data with application to soil texture in hydrologic modelling. Hydrol. Earth Syst. Sci. 17(2), 461-478. http://dx.doi.org/10.5194/hess-17-461-2013.

Makler-Pick, V., Gal, G., Gorfine, M., Hipsey, M.R., Carmel, Y., 2011. Sensitivity analysis for complex ecological models – a new approach. Environ. Modell. Softw. 26, 124-134. http://dx.doi.org/10.1016/j.envsoft.2010.06.010

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

Marrel, A., Iooss, B., Laurent, B., Roustant, O., 2009. Calculations of Sobol indices for the Gaussian process metamodel. Reliab. Eng. Syst. Safety 94, 742-751. http://dx.doi.org/10.1016/j.ress.2008.07.008

Massmann, C., Holzmann, H., 2012. Analysis of the behavior of a rainfall-runoff model using three global sensitivity analysis methods evaluated at different temporal scales. J. Hydrol. 475, 97-110. http://dx.doi.org/10.1016/j.jhydrol.2012.09.026

Massmann, C., Wagener, T., Holzmann, H., 2014. A new approach to visualizing time-varying sensitivity indices for environmental model diagnostics across evaluation time-scales. Environ. Modell. Softw. 51, 190-194. http://dx.doi.org/10.1016/j.envsoft.2013.09.033

Matott, L. S., Babendreier, J. E., Purucker ,S. T. ,2009 .Evaluating uncertainty in integrated environmental models: A review of concepts and tools. Water Resour. Res. 45, W06421, http://dx.doi.org/10.1029/2008WR007301

Medici, C., Wade, A.J., Frances, F., 2012. Does increased hydrochemical model complexity decrease robustness? J. Hydrol. 440-441, 1-13. http://dx.doi.org/10.1016/j.jhydrol.2012.02.047

Mishra, S., 2009. Uncertainty and sensitivity analysis techniques for hydrologic modeling. J. HydroInf. 11(3-4), 282-296. http://dx.doi.org/10.2166/hydro.2009.048

Mishra, S., Deeds, N., Ruskauff, G., 2009. Global sensitivity analysis techniques for probabilistic ground water modeling. Ground Water 47, 727-744. http://dx.doi.org/10.1111/j.1745-6584.2009.00604.x

Mishra, S., Knowlton, R.G., 2003. Testing for input-output dependence in performance assessment models. In: Proceedings of the Tenth International High-Level Radioactive Waste Management Conference, Las Vegas, Nevada.

Modarres, R., Ouarda, T.B.M.J., 2013. Modeling rainfall-runoff relationship using multivariate GARCH model. J. Hydrol. 499, 1-18. http://dx.doi.org/10.1016/j.jhydrol.2013.06.044

Mogheir, Y., de Lima, J.L.M.P., Singh, V.P., 2004. Characterizing the spatial variability of groundwater quality using the entropy theory: I. Synthetic data. Hydrol. Process. 18, 2165-2179. http://dx.doi.org/10.1002/hyp.1465

Mokhtari, A., Frey, H. C., 2005. Recommended practice regarding selection of sensitivity analysis methods applied to microbial food safety process risk models. Human and Ecological Risk Assessment: An International Journal 11(3), 591-605. http://dx.doi.org/10.1080/10807030590949672

Montgomery, D. C., 2008. Design and analysis of experiments (7th edition). Wiley, New York

Moreau, P., Viaud, V., Parnaudeau, V., Salmon-Monviola, J., Durand, P., 2013. An approach for global sensitivity analysis of a complex environmental model to spatial inputs and parameters: A case study of an agro-hydrological model. Environ. Modell. Softw. 47, 74-87. http://dx.doi.org/10.1016/j.envsoft.2013.04.006

Morris, M. D., 1991. Factorial sampling plans for preliminary computational experiments. Technometrics. 33(2), 161-174. http://www.jstor.org/stable/1269043

Muleta ,M .K., Nicklow, J .W., 2005. Sensitivity and uncertainty analysis coupled with automatic calibration for a distributed watershed model. J. Hydrol. 306(1-4), 127-145. http://dx.doi.org/10.1016/j.jhydrol.2004.09.005

Nan, Z. T., Shu, L. L., Zhao, Y. B., Li, X., Ding, Y.J., 2011. Integrated modeling environment and a preliminary application on Heihe River Basin, China. Sci. China Tech. Sci. 54, 2145-2156. http://dx.doi.org/10.1007/s11431-011-4410-4

Nestorov, I.A., 1999. Sensitivity analysis of pharmacokinetic and pharmacodynamic systems: I. a structural approach to sensitivity analysis of physiologically based pharmacokinetic models. Journal of Pharmacokinetics and Biopharmaceutics 27(6), 577-596. http://dx.doi.org/10.1023/A:1020926525495

Neumann, M. B., 2012. Comparison of sensitivity analysis methods for pollutant degradation modelling: A case study from drinking water treatment. Sci. Total Environ. 433, 530-537. http://dx.doi.org/10.1016/j.scitotenv.2012.06.026

Nossent, J., Bauwens, W., 2012.Multi-variable sensitivity and identifiability analysis for a complex environmental model in view of integrated water quantity and water quality modeling. Water Sci. Tech. 65(3), 539-549. http://dx.doi.org/10.2166/wst.2012.884

Nossent, J., Elsen, P., Bauwens, W., 2011. Sobol' sensitivity analysis of a complex environmental model. Environ. Modell. Softw. 26, 1515-1525. http://dx.doi.org/10.1016/j.envsoft.2011.08.010

Ntegeka, V., Baguis, P., Roulin, E., Willems, P., 2014. Developing tailored climate change scenarios for hydrological impact assessments. J. Hydrol. 508, 307-321. http://dx.doi.org/10.1016/j.jhydrol.2013.11.001

Pan, F., Zhu, J., Ye, M., Pachepsky, Y.A., Wu, Y.S., 2011. Sensitivity analysis of unsaturated flow and contaminant transport with corrected parameters. J. Hydrol. 397(3-4), 238-249. http://dx.doi.org/10.1016/j.jhydrol.2010.11.045

Pannell, D.J., 1997. Sensitivity analysis of normative economic models: theoretical framework and practical strategies. Agric. Econ. 16(2), 139-152. http://dx.doi.org/10.1016/S0169-5150(96)01217-0

Pappenberger, F., Beven, K. J., Ratto, M., Matgen, P., 2008. Multi-method global sensitivity analysis of flood inundation models. Adv. Water Resour. 31, 1-14. http://dx.doi.org/10.1016/j.advwatres.2007.04.009

Pappenberger, F., Iorgulescu, I., Beven, K.J., 2006. Sensitivity analysis based on regional splits and regression trees (SARS-RT). Environ. Modell. Softw. 21(7), 976-990. http://dx.doi.org/10.1016/j.envsoft.2005.04.010

Park, C., Lee, J., Koo, M. Development of a fully-distributed daily hydrologic feedback model addressing vegetation, land cover, and soil water dynamics (VELAS). J. Hydrol. 493, 43-56. http://dx.doi.org/10.1016/j.jhydrol.2013.04.027

Perz, S. G., Munoz-Carpena, R., Kiker, G., Holt, R. D., 2013. Evaluating ecological resilience with global sensitivity and uncertainty analysis. Ecol. Modell. 263, 174-186. http://dx.doi.org/10.1016/j.ecolmodel.2013.04.024

Peter, J. E. V., Dwight, R. P., 2010. Numerical sensitivity analysis for aerodynamic optimization: A survey of approaches. Computers & Fluids 39, 373-391. http://dx.doi.org/10.1016/j.compfluid.2009.09.013

Petropoulos, G., Wooster, M.J., Carlson, T.N., Kennedy, M.C., Scholze, M., 2009. A global Bayesian sensitivity analysis of the 1d SimSphere soil-vegetation-atmospheric transfer (SVAT) model using Gaussian model emulation. Ecol. Modell. 220, 2427-2440. http://dx.doi.org/10.1016/j.ecolmodel.2009.06.006

Pohlmann, K.F., Hassan, A.E., Chapman, J.B., 2002. Modeling density-driven flow and radionuclide transport at an underground nuclear test: Uncertainty analysis and effect of parameter correlation. Water Resour. Res. 38(5), 1059, http://dx.doi.org/10.1029/2001WR001047

Rakovec, O., Hill, M. C., Clark, M. P., Weerts, A. H., Teuling, A. J., Uijlenhoet, R., 2014. Distributed evaluation of local sensitivity analysis (DELSA), with application to hydrologic models. Water Resour. Res. 50(1), 409-426. http://dx.doi.org/10.1002/2013WR014063

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

Ratto, M., Pagano, A., Young, P., 2007. State dependent parameter metamodelling and sensitivity analysis. Comput. Phys. Comm. 177, 863-876. http://dx.doi.org/10.1016/j.cpc.2007.07.011

Razavi, S., Tolson, B.A., Burn, D.H., 2012. Review of surrogate modeling in water resources. Water Resour. Res. 48, W07401, http://dx.doi.org/10.1029/2011WR011527

Reusser, D.E., Buytaert, W., Zehe, E., 2011. Temporal dynamics of model parameter sensitivity for computationally expensive models with the Fourier amplitude sensitivity test. Water Resour. Res. 47(7), W07551, http://dx.doi.org/10.1029/2010WR009947

Reusser, D.E., Zehe, E., 2011. Inferring model structural deficits by analyzing temporal dynamics of model performance and parameter sensitivity. Water Resour. Res. 47, W07550, http://dx.doi.org/10.1029/2010WR009946

Rojas, R., Feyen, L., Dassargues, A., 2009. Sensitivity analysis of prior model probabilities and the value of prior knowledge in assessment of conceptual model uncertainty in groundwater modeling. Hydrol. Process. 23, 1131-1146. http://dx.doi.org/10.1002/hyp.7231

Rosolem, R., Gupta, H. V., Shuttleworth, W. J., Zeng, X., de Goncalves, L.G.G., 2012. A fully multiple-criteria implementation of the Sobol' method for parameter sensitivity analysis. J. Geophys. Res. 117, D07103, http://dx.doi.org/10.1029/2011JD016355

Ruano, M.V., Ribes, J., Ferrer, J., Sin, G., 2011. Application of the Morris method for screening the influential parameters of fuzzy controllers applied to wastewater treatment plants. Water Sci. Technol. 63(10), 2199-2206. http://dx.doi.org/10.2166/wst.2011.442

Saltelli ,A., Tarantola, S., Campolongo, F., Ratto, M., 2004. Sensitivity analysis in practice – a guide to assessing scientific models. Chichester: John Wiley & Sons, Ltd.

Saltelli, A., Annoni, P., 2010. How to avoid a perfunctory sensitivity analysis. Environ. Modell. Softw. 25, 1508-1517. http://dx.doi.org/10.1016/j.envsoft.2010.04.012

Saltelli, A., Chan, K., Scott, E. M., 2000. Sensitivity analysis. Wiley, New York.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. Global sensitivity analysis, The primer. Chichester: John Wiley & Sons, Ltd.

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., Tarantola, S., Campolongo, F., 2012. Update 1 of: Sensitivity analysis for chemical models. Chem. Rev. 112(5), PR1-21. http://dx.doi.org/10.1021/cr200301u

Saltelli, A., Sobol' I,M., 1995. About the use of rank transformation in sensitivity analysis of model output. Reliab. Eng. Syst. Safety 50(3), 225-239. http://dx.doi.org/10.1016/0951-8320(95)00099-2

Saltelli, A., Tarantola ,S., Chan, K., 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

Sathyanarayanamurthy ,H., Chinnam ,R .B., 2009.Metamodels for variable importance decomposition with applications to probabilistic engineering design. Comput. Indust. Eng. 57, 996-1007. http://dx.doi.org/10.1016/j.cie.2009.04.003

Schneeweiss, S., 2006. Sensitivity analysis and external adjustment for unmeasured confounders in epidemiologic database studies of therapeutics. Pharmacoepidemiol. Drug. Saf. 15(5), 291-303. http://dx.doi.org/10.1002/pds.1200

Sen, M. K., Stoffa, P. L., 2013. Global optimization methods in geophysical inversion. 2nd Edition, Cambridge University Press, http://dx.doi.org/10.1017/CBO9780511997570

Shi, Y.Z., Zhou, H. C., 2010. Research on monthly flow uncertain reasoning model based on cloud theory. Sci. China. Tech. Sci. 53, 2408-2413. http://dx.doi.org/10.1007/s11431-010-4048-7

Shin, M.J., Guillaume, J.H.A., Croke, B.F.W., Jakeman, A.J., 2013. Addressing ten questions about conceptual rainfall-runoff models with global sensitivity analyses in R. J. Hydrol. 503, 135-152. http://dx.doi.org/10.1016/j.jhydrol.2013.08.047

Sieber, A., Uhlenbrook, S., 2005. Sensitivity analyses of a distributed catchment model to verify the model structure. J. Hydrol. 310, 216-235. http://dx.doi.org/10.1016/j.jhydrol.2005.01.004

Singh, A., Imtiyaz, M., Isaac, R. K., Denis, D.M., 2012. Comparison of soil and water assessment tool and multilayer perceptron (MLP) artificial neural network for predicting sediment yield in the Nagwa agricultural watershed in Jharhand, India. Agr. Water Manage. 104, 113-120. http://dx.doi.org/10.1016/j.agwat.2011.12.005

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

Song , X. M., Zhan ,C. S., Xia, J., Kong, F. Z., 2012a. An efficient global sensitivity analysis approach for distributed hydrological model. J. Geogr. Sci. 22(2), 209-222. http://dx.doi.org/10.1007/s11442-012-0922-5

Song ,X. M., Kong ,F. Z., Zhan, C. S., Han, J.W., Zhang, X.H., 2013. Parameter identification and global sensitivity analysis of Xinanjiang model using meta-modeling approach. Water Sci. Eng. 6(1), 1-17. http://dx.doi.org/10.3882/j.issn.1674-2370.2013.01.001

Song ,X. M., Zhan, C. S., Kong, F. Z., Xia, J., 2011. Advances in the study of uncertainty quantification for large-scale hydrological modeling system. J. Geogr. Sci. 21(5), 801-819. http://dx.doi.org/10.1007/s11442-011-0881-2

Song, X. M., Kong, F. Z., Zhan ,C. S., Han, J.W., 2012d. Hybrid optimization rainfall-runoff simulation based on Xinanjiang model and artificial neural network. J. Hydrol. Eng. 17(9), 1033-1041. http://dx.doi.org/10.1061/(ASCE)HE.1943-5584.0000548

Song, X. M., Zhan, C. S., Xia, J., 2012c. Integration of a statistical emulator approach with the SCE-UA method for parameter optimization of a hydrological model. Chin. Sci. Bull. 57(26), 3397-3403. http://dx.doi.org/10.1007/s11434-012-5305-x

Song, X. M., Zhan, C. S., Xia, J., Zhang, Y.Y., 2014. Methodology and application of parameter uncertainty quantification in watershed hydrological models. Beijing: China Water Power Press (in Chinese)

Song, X.M., Kong, F.Z., Zhan, C.S., Han, J.W., 2012b. Sensitivity analysis of hydrological model parameters using a statistical theory approach. Adv. Water Sci. 23(5), 642-649. (in Chinese with English abstract)

Spear, R.C., Hornberger, G. M., 1980. Eutrophication in peel inlet - II. Identification of critical uncertainties via generalized sensitivity analysis. Water Res. 14, 43-49.

Stephens, D. W., Gorissen, D., Crombecq, K., Dhaene, T., 2011. Surrogate based sensitivity analysis of process equipment. Appl. Math. Modell. 35(4), 1676-1687. http://dx.doi.org/10.1016/j.apm.2010.09.044

Storlie, C.B., Swiler, L.P., Helton, J.C., and Sallaberry, C.J., 2009. Implementation and evaluation of nonparametric regression procedures for sensitivity analysis of computationally demanding models. Reliab. Eng. Syst. Safety 94(11), 1735-1763. http://dx.doi.org/10.1016/j.ress.2009.05.007

Sun, X.Y., Newham, L.T.H., Croke, B.F.W., Norton, J.P., 2012. Three complementary methods for sensitivity analysis of a water quality model. Environ. Modell. Softw. 37, 19-29. http://dx.doi.org/10.1016/j.envsoft.2012.04.010

Surfleet, C.G., Skaugset III, A.E., McDonnell, J.J., 2010. Uncertainty assessment of forest road modeling with the distributed hydrology soil vegetation model (DHSVM). Can. J. Forest Res. 40, 1397-1409. http://dx.doi.org/10.1139/X10-057

Tang, Y., Reed, P., van Werkhoven, K., Wagener, T., 2007a. Advancing the identification and evaluation of distributed rainfall-runoff models using global sensitivity analysis. Water Resour. Res. 43, W06415, http://dx.doi.org/10.1029/2006WR005813

Tang, Y., Reed, P., Wagener, T., van Werkhoven, K., 2007b. Comparing sensitivity analysis methods to advance lumped watershed model identification and evaluation. Hydrol. Earth Syst. Sci. 11, 793-817. http://dx.doi.org/10.5194/hess-11-793-2007

Thabane, L., Mbuagbaw, L., Zhang, S., Samaan, Z., Marcucci, M., Ye, C., Thabane, M., Giangregorio, L., Dennis, B., Kosa, D., Debono, V.B., Dillenburg, R., Fruci, V., Bawor, M., Lee, J., Wells, G., Goldsmith, C.H., 2013. A tutorial on sensitivity analysis in clinical trials: the what, why, when and how. BMC Med. Res. Methodol. 13:92, http://dx.doi.org/10.1186/1471-2288-13-92

Tian, W., 2013. A review of sensitivity analysis methods in building energy analysis. Renew. Sustain. Energy Rev. 20, 411-419. http://dx.doi.org/10.1016/j.rser.2012.12.014

Tiedeman, C. R., Hill, M. C., D'Agnese, F. A., Faunt, C. C., 2003. Methods for using groundwater model predictions to guide hydrogeologic data collection, with application to the Death Valley regional groundwater flow system. Water Resour. Res. 39(1), 1010, http://dx.doi.org/10.1029/2001WR001255

Tiedeman, C. R., Hill, M. C., D'Agnese, F. A., Faunt, C. C., 2004. A method for evaluating the importance of system state observations to model predictions, with application to the Death Valley regional groundwater flow system. Water Resour. Res. 40, W12411, http://dx.doi.org/10.1029/2004WR003313

Tiscareno-Lopez, M., Lopes, V. L., Stone, J.J., Lane, L.J., 1993. Sensitivity analysis of the WEPP watershed model for rangeland applications I: Hillslope processes. Trans. ASAE. 36(6), 1659-1672. http://dx.doi.org/10.13031/2013.28509

Tong, C., Graziani, F., 2008. A practical global sensitivity analysis methodology for multi-physics applications. Computational Methods in Transport: Verification and Validation. Lecture Notes in Computational Science and Engineer, 62, 277-299

U.S. EPA, 2001. Risk assessment guidance for superfund: Volume III-Part A, Process for conducting probabilistic risk assessment. EPA 540-R-02-002, Washington, DC, www.epa.gov/superfund/RAGS3A/index.htm

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(1-4), 10-23. http://dx.doi.org/10.1016/j.jhydrol.2005.09.008

van Werkhoven, K., Wagener ,T., Reed ,P., Tang, Y., 2008a. Characterization of watershed model behavior across a hydroclimatic gradient. Water Resour. Res. 44, W01429, http://dx.doi.org/10.1029/2007WR006271

van Werkhoven, K., Wagener, T., Reed, P., Tang, Y., 2008b. Rainfall characteristics define the value of streamflow observations for distributed watershed model identification. Geophys. Res. Lett. 35, L11403, http://dx.doi.org/10.1029/2008GL034162

van Werkhoven, K., Wagener, T., Reed, P., Tang, Y., 2009. Sensitivity-guided reduction of parametric dimensionality for multi-objective calibration of watershed models. Adv. Water Resour. 32(8), 1154-1169. http://dx.doi.org/10.1016/j.advwatres.2009.03.002

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.

Viel, J.F., Pobel, D., Carre, A., 1995. Incidence of leukaemia in young people around the La Hague nuclear waste reprocessing plant: a sensitivity analysis. Stat. Med. 14(21-22), 2459-2472. http://dx.doi.org/10.1002/sim.4780142114

Vrugt, J.A., Diks, C.G.H., Gupta, H.V., Bouten, E., Verstraten, J.M., 2005. Improved treatment of uncertainty in hydrologic modeling: combining the strengths of global optimization and data assimilation. Water Resour. Res. 41(1), http://dx.doi.org/10.1029/2004WR003059

Vrugt, J.A., Gupta, H.V., Bouten, E., Sorooshian, S., 2003. A shuffled complex evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. Water Resou. Res. 39(8), http://dx.doi.org/10.1029/2002WR001642

Wagener, T., Kollat, J., 2007. Numerical and visual evaluation of hydrological and environmental models using the Monte Carlo analysis toolbox. Environ. Modell. Softw. 22(7), 1021-1033. http://dx.doi.org/10.1016/j.envsoft.2006.06.017

Wagener, T., McIntyre, N., Lee, M., Wheater, H., Gupta, H., 2003. Towards reduced uncertainty in conceptual rainfall-runoff modelling: Dynamic identifability analysis. Hydrol. Process. 17, 455-476. http://dx.doi.org/10.1002/hyp.1135

Wagener, T., van Werkhoven ,K., Reed ,P., Tang, Y., 2009. Multiobjective sensitivity analysis to understand the information content in streamflow observations for distributed watershed modeling. Water Resour. Res. 45, W02501, http://dx.doi.org/10.1029/2008WR007347

Wallach, D., Makowski, D., Jones, J.W., 2006. Working with dynamic crop models: evaluation, analysis, parameterization and application. Elsevier, Amsterdam

Wang, G.S., Xia, J., Chen, J.F., 2010. A multi-parameter sensitivity and uncertainty analysis method to evaluate relative importance of parameters and model performance. Geogr. Res, 29(2), 263-270 (in Chinese with English abstract)

Wang, H.C., Du, P.F., Zhao, D.Q., Wang, H.Z., Li, Z.Y., 2008. Global sensitivity analysis for urban rainfall-runoff model. China Environ. Sci. 28(8), 725-729 (in Chinese with English abstract)

Wang, J., Li, X., Lu, L., Fang, F., 2013a. Parameter sensitivity analysis of crop growth models based on the extended Fourier amplitude sensitivity test method. Environ. Modell. Softw. 48, 171-182. http://dx.doi.org/10.1016/j.envsoft.2013.06.007

Wang, Q., Zhao, X., Chen, K., Liang, P., Li, S., 2013b. Sensitivity analysis of thermal equilibrium parameters of MIKE 11 model: A case study of Wuxikou Reservoir in Jiangxi Province of China. Chin. Geogra. Sci. 23(5), 584-593. http://dx.doi.org/10.1007/s11769-013-0628-3

Wu, H., Lye, L.M., Chen, B., 2012. A design of experiment aided sensitivity analysis and parameterization for hydrological model. Can. J. Civ. Eng. 39, 460-472. http://dx.doi.org/10.1139/L2012-017

Wu, Y., Liu, S., 2012. Automating calibration, sensitivity and uncertainty analysis of complex models using the R package Flexible Modeling Environment (FME): SWAT as an example. Environ. Modell. Softw. 31, 99-109. http://dx.doi.org/10.1016/j.envsoft.2011.11.013

Wu, J., Dhingra, R., Gambhir, M., Remais, J.V., 2013. Sensitivity analysis of infectious disease models: methods, advances and their application. J. R. Soc. Interface 10, 20121018, http://dx.doi.org/10.1098/rsif.2012.1018

Xu, C., Gertner, G., 2007. Extending a global sensitivity analysis technique to models with correlated parameters. Comput. Stat. Data Anal. 51, 5579-5590. http://dx.doi.org/10.1016/j.csda.2007.04.003

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

Xu, C., Gertner, G.Z., 2008b. A general first-order global sensitivity analysis method. Reliab. Eng. Syst. Safety 93, 1060-1071. http://dx.doi.org/10.1016/j.ress.2007.04.001

Xu, C., 2013. Decoupling correlated and uncorrelated uncertainty contributions for nonlinear models. Applied Mathematical Modelling, 37(24), 9950–9969. http://dx.doi.org/10.1016/j.apm.2013.05.036

Yang, J., 2011.Convergence and uncertainty analyses in Monte-Carlo based sensitivity analysis. Environ. Modell. Softw. 26(4), 444-457. http://dx.doi.org/10.1016/j.envsoft.2010.10.007

Yang, J., Liu, Y. B., Yang,W. H., Chen, Y., 2012. Multi-objective sensitivity analysis of a fully distributed hydrologic model WetSpa. Water Resour. Manage. 26, 109-128. http://dx.doi.org/10.1007/s11269-011-9908-9

Ye, M., Meyer, P. D., Neuman, S. P., 2008. On model selection criteria in multimodel analysis. Water Resour. Res. 44(3), http://dx.doi.org/10.1029/2008WR006803

Zajac, Z.B., 2010. Global sensitivity and uncertainty analysis of spatially distributed watershed models. Dissertation for PhD degree, University of Florida, USA

Zambrano-Bigiarini, M., Rojas, R., 2013. A model-independent particle swarm optimization software for model calibration. Environ. Modell. Softw. 43, 5-25. http://dx.doi.org/10.1016/j.envsoft.2013.01.004

Zelelew, M.B., Alfredsen, K., 2013. Sensitivity-guided evaluation of the HBV hydrological model parameterization. J. Hydroinf. 15(3), 967-990. http://dx.doi.org/10.2166/hydro.2012.011

Zeng, X., Wang, D., Wu, J., 2012. Sensitivity analysis of the probability distribution of groundwater level series based on information entropy. Stoch. Environ. Res. Risk Assess. 26, 345-356. http://dx.doi.org/10.1007/s00477-012-0556-2

Zhan, C. S., Song ,X. M., Xia ,J., Tong, C., 2013. An efficient integrated approach for global sensitivity analysis of hydrological model parameters. Environ. Modell. Softw. 41, 39-52. http://dx.doi.org/10.1016/j.envsoft.2012.10.009

Zhang ,Y. P., Wang, G. L., Peng ,Y., Zhou, H., 2011. Risk analysis of dynamic control of reservoir limited water level by considering flood forecast error. Sci. China Tech. Sci. 54, 1888-1893. http://dx.doi.org/10.1007/s11431-011-4392-2

Zhang, C., Chu, J., Fu, G., 2013. Sobol's sensitivity analysis for a distributed hydrological model of Yichun river basin, China. J. Hydrol. 480, 58-68. http://dx.doi.org/10.2166/nh.2011.131

Zhang, D., Zhang, L., Guan, Y., Chen, X., Chen X.F., 2012. Sensitivity analysis of Xinanjiang rainfall-runoff model parameters: a case study in Lianghui, Zhejiang province, China. Hydrol. Res. 43(1-2), 123-134. http://dx.doi.org/10.2166/nh.2011.131

Zhu, J., Pohlmann, K.F., Chapman, J.B., Russell, C.E., Carroll, R.W.H., Shafer, D.S., 2010. Sensitivity of solute advective travel time to porosities of hydrogeologic units. Ground Water 48(3), 442-447.

http://dx.doi.org/10.1111/j.1745-6584.2009.00664.x

Zoras, S., Triantafyllou, A.G., Hurley, P.J., 2007. Grid sensitivity analysis for the calibration of a prognostic meteorological model in complex terrain by a screening experiment. Environ. Modell. Softw. 22(1), 33-39. http://dx.doi.org/10.1016/j.envsoft.2005.09.010

Tables and Figures

Table 1 Summary of the definition of SA in the different fields

Literature	Definition
Nesterov (1994)	the systematic investigation of the model responses to either perturbations of the model quantitative factors
Viel et al., 1995	a series of analyses of a data set to assess whether altering any of the assumptions made leads to differe
Pannell, 1997	To determine how different values of an independent variable will impact a particular dependent variab
US. EPA, 2001	sensitivity refers to the variation in output of a model with respect to changes in the values of the m ranking of the model inputs based on their relative contributions to model output variability and uncert
Frey and Patil, 2002	The assessment of the impact of changes in input values on model outputs.
Saltelli et al., 2004	The study of how the variation (uncertainty) in the output of a statistical model can be apportione variations in the inputs of the model
Schneeweiss, 2006	To determine the robustness of an assessment by examining the extent to which results are affecte unmeasured variables, or assumptions with the aim of identifying "results that are most dependent on q
European Commission (EC), 2009	To explore how the impacts of the options you are analyzing would change in response to variations in
Matott et al., 2009	To study the degree to which model output is influenced by changes in model inputs or the model itsel
Thabane et al., 2013	To address the question on "what will the effect be on results, if the key inputs or assumptions changed

Table 2 Summary of three typical categories for SA methods

Type	Methods	Description of the methods	Characteristics
1	Local	Compute local response of model output based on the gradients (derivatives) of the model output with respect to parameter values evaluated at a single location in the parameter space	Easy of operation and interpret, self-verification, local effect of indivi
	Global	Evaluate the effect in the entire ranges of uncertain parameters	Estimating the effect of all the inputs output based on many model runs
2	Mathematical	Estimate the local or linear sensitivity of output to individual parameter	Providing the uncertainty effect of variance of output
	Statistical	Analyze the influence of various inputs on model output with running simulations based on sampling design methods	Qualitatively or quantitatively e computational demand based on many
	Graphical	Complement the mathematical or statistical methods for better representation with graphical plot	Graphical representation with more di
3	Screening	Be used to make a preliminary identification of sensitive inputs	Relatively simple, easy of operati characteristics, such as nonlinearity, i
	Refined	Adequately consider complex model characteristics and need greater expertise and resources to implement	Providing quantitative results wit implement
4	Qualitative	Providing a heuristic score to intuitively represent the relative sensitivity of parameters	Be aimed at screening a few activ non-influential ones, relatively fewer
	Quantitative	Estimating how sensitive the parameter is by computing the impact of the parameter on the variance of model output	To give information on the amount large number of model runs

1247 Table 3 Recent global SA studies in hydrological modeling

Models	Number of parameters	SA Methods	Objective or output functions	The number of runs for hyd
BSM1	32	Regression	EQI, OCI	5×1000
DHSVM	4	GLUE	NSE	10000
DTVGM	14	Morris, Meta-modeling	WB, NSE, RC	600, 4000
ESTEL-2D	9	MMGSA(Sobol’, K-L entropy, Morris)	NSE	1280
HBV	11	RSA	BIAS, RSME, NSE	60000
HBV	12	Sobol’	RMSE, ROCE	10000
HBV	15	Sobol’, RSA	WB, NSE	8192, 10000
HEC-RAS	6	Sobol, K-L entropy, Morris, RSA, regression	NSE, MAE	Not reported
HEC-RAS	7	SARS-RT, Correlation, RSA	Normalized performance measure	4000
HL-RDHM	31×13	Sobol’	RMSE	40000
HL-RDHM	18	RSA, ANOVA, Sobol’	RMSE, $RMSE_{Box\text{-}cox}$	8192
HL-RDHM	78×14 = 1092	Morris, Sobol’	RMSE	Over 6 million (Sobol’), app
HL-RDHM	78×14 = 1092	Morris	RMSE, ROCE	21860
HYDRUS-2D	11	Sobol’, mutual entropy, RSA	Output discharge	260000×11 (Sobol’), 26000
HYMOD	5	Sobol’, Morris, SRC, RSA, SDP	NSE	18000, 3000, 3000, 3000, 5
HYMOD	5	Sobol’	RMSE, ROCE	10000
LU4-R-N	41	RSA, GLUE	Relative RMSE， NSE	100000
MARTHE	20	Sobol’ with Gaussian process	NSE	300
MARTHE	5	SDP	NSE	1024
MIKE 11	5	ANOVA	Water temperature error	Not reported
MIKE/NAM	9	Morris with Pareto ranking	$RMSE_{peak}$, $RMSE_{low}$	Not reported
MUSIC	13	Bayesian	NSE	10000
REALM	14	Morris	Yield	3×6000
SAC-SMA	17	Sobol’ method	RMSE, ROCE	10000

Table 3 *continued*

Models	Number of parameters	SA Methods	Objective or output functions	The number of runs for hyd
SAC-SMA	14	Sobol' method	RMSE, $RMSE_{Box\text{-}cox}$, SFDCE, ROCE	7.5×10^{6}
SAC-SMA	14	Sobol' method	RMSE, $RMSE_{Box\text{-}cox}$, SFDCE, ROCE	130000
SAC-SMA	14	Sobol' method	RMSE, $RMSE_{Box\text{-}cox}$, SFDCE, ROCE	Not reported
SAC-SMA	14	Regression-based method, screening-based method, variance-based method, meta-modeling method	MAE	280 (Morris), 400-600 (oth 2777 (FAST), 360 and m method), 1050 (Sobol)
SLUPR	10×6	Meta-modeling and ANOVA	NSE	Not reported
SNOW17	10	RSA	NSE	10000
SVAT	30	Meta-modeling	Rn, LE, HF, Tair, Mo	400
SWAP	7	Sobol' method	RMSE	7168
SWAT	28	Sobol' method	RMSE, NSE, ROCE, SFDCE	60000
SWAT	26	Sobol' method	NSE	336000, 72000
SWAT	13	Sobol' method	RMSE	28000
SWAT	8	FAST	NSE, MRE, RMSE, SMSE, PDIFF, LCS	243
TNT2	16, 19, 6	Morris, ANOVA	20 output objective	1700 (16 inputs), 2000 (19 i
TOPMODEL	9	FAST, EFAST, Sobol'	MAD	1289(SimLab, FAST), 48 5632 (Sobol, SimLab), 500
VIC	10	MCAT-RSA	RMSE, ARE, $RMSE_{Box\text{-}cox}$	59049
WASH	13	Entropy analysis, stepwise regression	TP loading	250
WaSiM-ETH	11	FAST	RMSE	487
WDS	21	Sobol'	Resilience index, combined measure	2000
XAJ	15	Morris, meta-modeling	NSE, WB, GE, DE	640, 4000
XAJ	6	GLUE	NSE	60000

--Models: BSM1: benchmark simulation model No1; DHSVM: distributed hydrology soil vegetation model; DTVGM: distrib finite element subsurface flow model; HBV: Hydrologiska Byråns Vattenbalansavdelning; HEC-RAS: Hydrologic Engineering

Hydrology Laboratory- Research Distributed Hydrologic Model; HYDRUS-2D: a two-dimension finite element model; HYMO distributed model; LU4-R-N: four-response lumped model coupling riparian tank and nitrogen; MARINE: Modélisation et Ant pour des évèNements Extrêmes; MIKE11: hydrological and hydraulic model; MIKE/NAM: a rainfall-runoff model develo stormwater improvement conceptualization; RELAM: Resource Allocation Model; SAC-SMA: Sacramento soil moisture use-based runoff process; SNOW17: a lumped process-based model that simulates snow accumulation and ablation; SVAT: s soil-water-atmosphere-plant model; SWAT: the soil and water assessment tool; TNT2: Topography-based Nitrogen Transfer topography based hydrological model; VIC: variable infiltration capacity macroscale hydrologic model; WASH: Watershed w and balance simulation model; WDS: Water distribution systems; XAJ: Xinanjiang model

--Objectives: ARE: Absolute relative bias; DE: relative error for low-flow; EQI: effluent quality index; GE: relative error for hig LCS: longest common sequence; LE: daily average latent heat flux; MAD: mean absolute difference; MAE: Mean Absolute Erro Nash-Sutcliffe efficiency coefficient; OCI: operating cost index; PDIFF: Peak difference; RC: correlation coefficient; RMSE: roo root-mean-square error of Box-Cox transformation; Rn: daily average net radiation; ROCE: Runoff coefficient error; SFDCE: Sl Scaled mean square error; Tair: daily average air temperature; TP: total phosphorus; WB: water balance error

Table 4 General overview and comparison of various global SA techniques in hydrological modeling (ada

	Morris screening method	Regression-based method	Variance-based method	Meta-modeling based method
Sampling strategy	Morris one-at-a-time sampling design	Monte Carlo	quasi-random sampling, LHS, FAST sampling	Monte Carlo, LHS, Sobol' quasi-random sampling
Computational requirements[a]	r(n+1) Cheap	m Cheap	m(n+2)~m(2n+2) High	m Cheap
Characteristics of sensitivity measure	Qualitative/screening	Quantitative	Quantitative	Quantitative
Applicability	Model-independence	Linear model or monotonic model	Model-independence	Model-independence
Reliability	High	Depends on R^2	High	High (with dependence on R^2)
Parameter interaction	Yes/qualitative	Depends on the regression form	Yes/quantitative	Yes/ quantitative
Coping with nonlinearity	Yes	Depends on the regression form	Yes	Yes

a: *r* represents the number of the trajectories, *m* is the sample size, and *n* is the number of factors

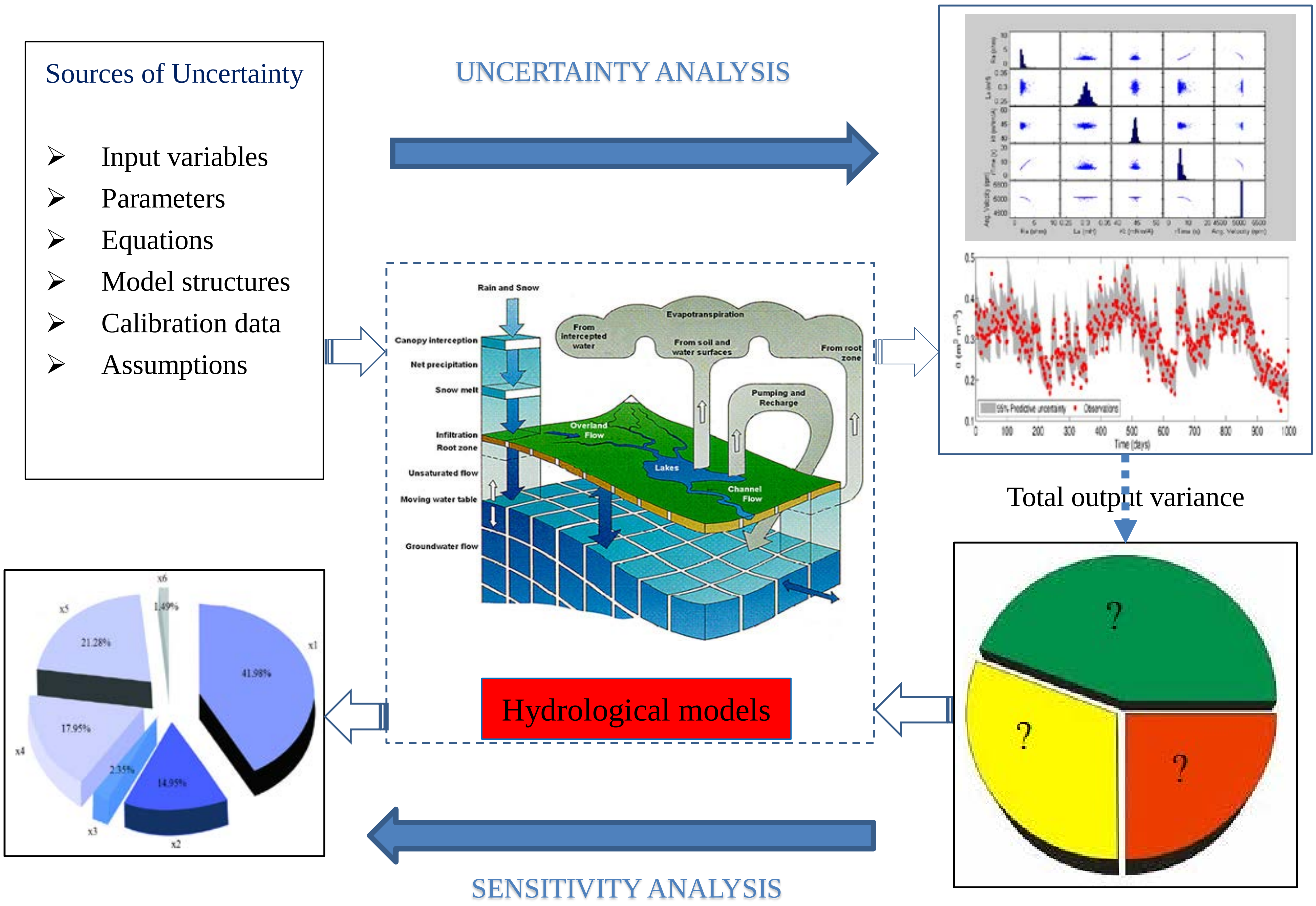
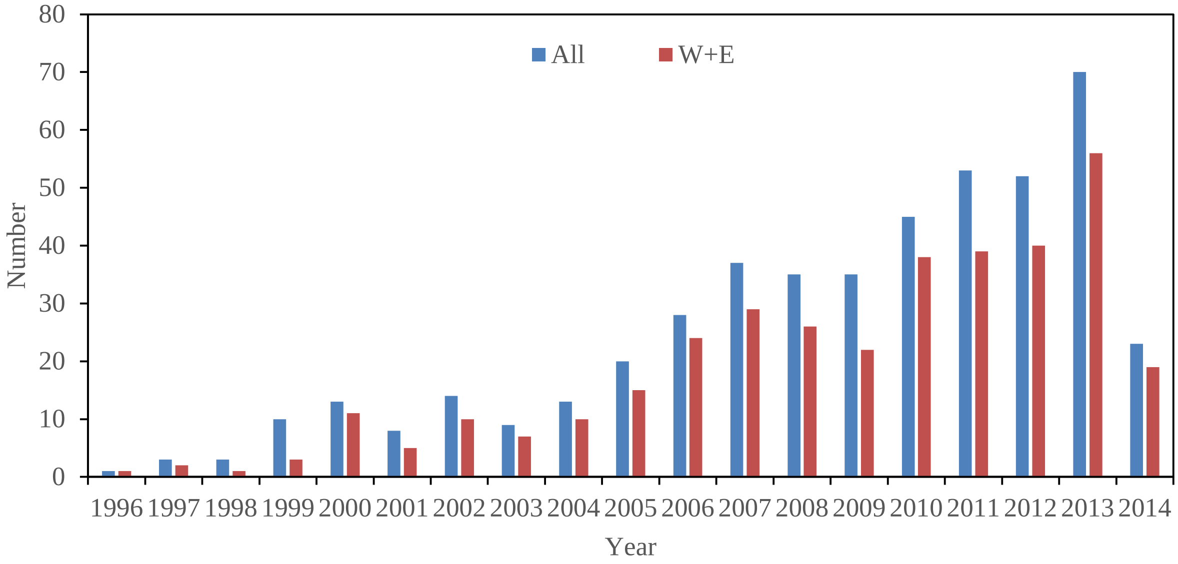


Figure 1 Sketch for the relationship between uncertainty and sensitivity analysis in hydrological modeling. Global uncertainty analysis propagates all the uncertainties, using a model, to the model's outputs while sensitivity analysis determines the contribution of each input factor to the uncertainty of the outputs.



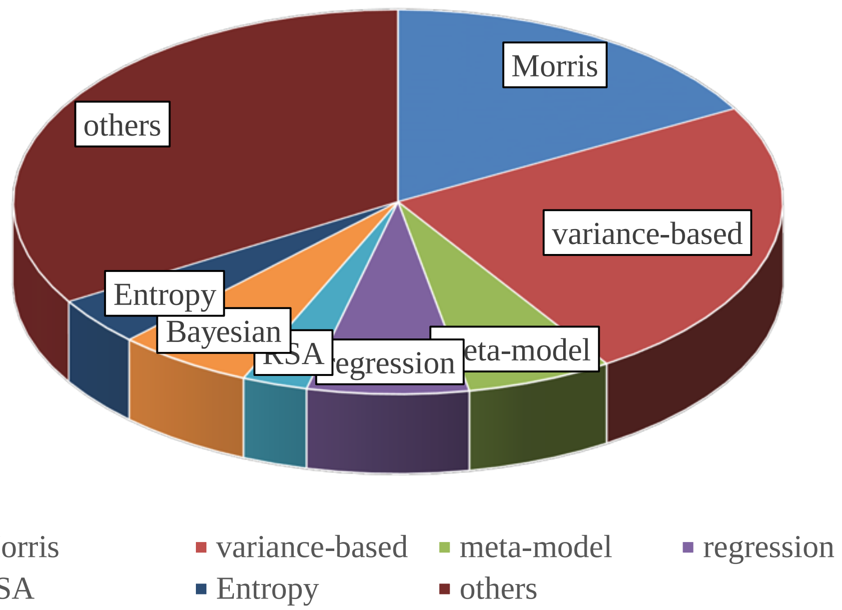


Figure 2 Yearly publications on sensitivity analysis in the field of water sciences and the contribution rate of these common methods in hydrological modeling from the Web of Science Core Collection. “All” is based on the search terms “sensitivity analysis” + “hydrological model”+ “parameter sensitivity analysis” in the Web of Science (Deadline to May 15, 2014). “W+E” represent the selected publications based on the categories “water resources” and “environmental sciences” in the Web of Science. For more details refer to the supplement table.

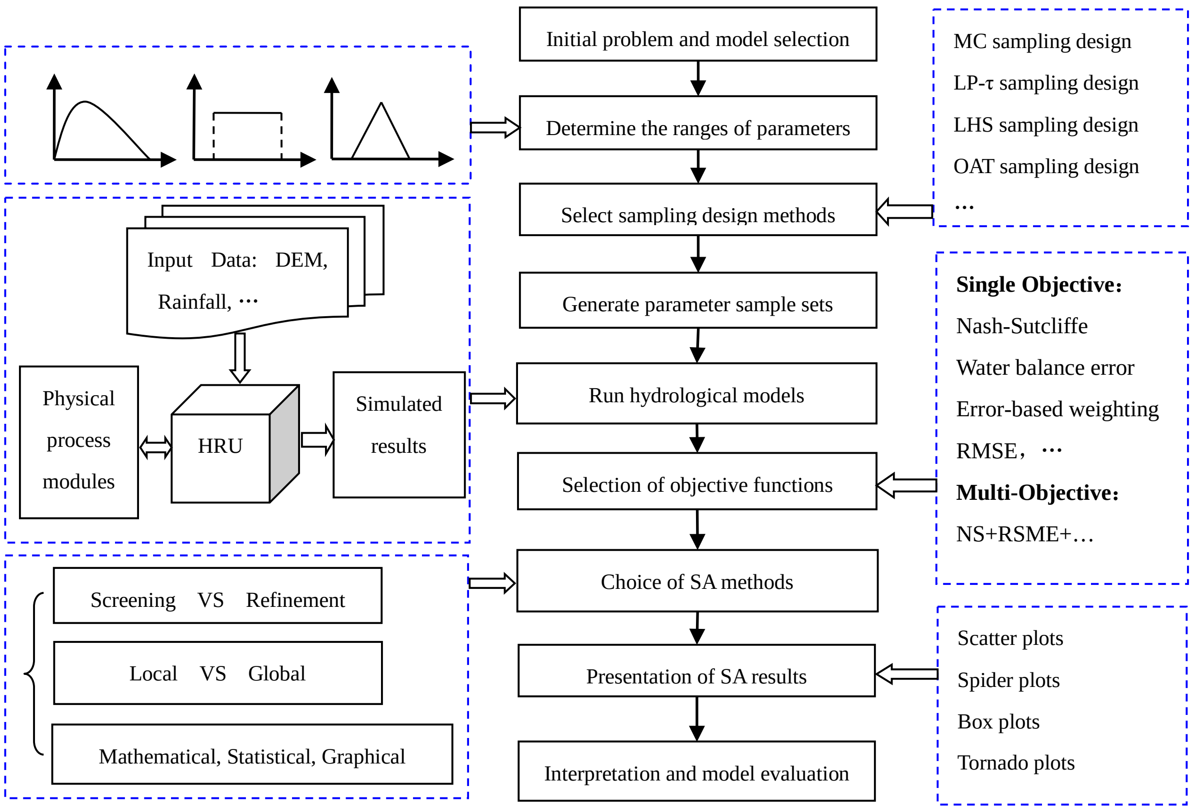


Figure 3 Flow chart for SA in hydrological models

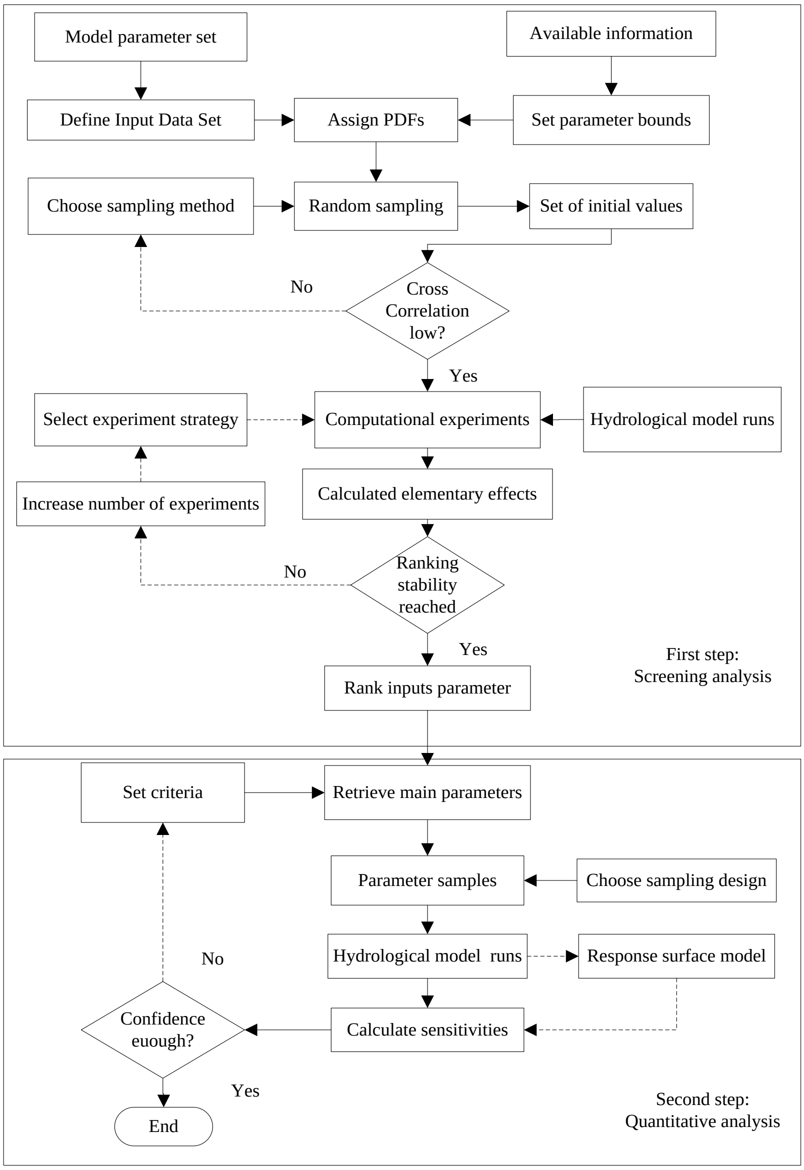


Figure 4 Framework of two-step integration sensitivity analysis in hydrological models based on qualitative screening and quantitative analysis methods