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Review Paper

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

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SUMMARY

Sensitivity analysis (SA) aims to identify the key parameters that affect model performance and it plays important roles in model parameterization, calibration, optimization, and uncertainty quantification. However, the increasing complexity of hydrological models means that a large number of parameters need to be estimated. To better understand how these complex models work, efficient SA methods should be applied before the application of hydrological modeling. This study provides a comprehensive review of global SA methods in the field of hydrological modeling. The common definitions of SA and the 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 categorize research into global SA methods and their applications, with an emphasis on the research accomplished in the hydrological modeling field. The advantages and disadvantages are also discussed and summarized. An application framework and the typical practical steps involved in SA for hydrological modeling are outlined. Further discussions cover several important and often overlooked topics, including the relationship between parameter identification, uncertainty analysis, and optimization in hydrological modeling, how to deal with correlated parameters, and time-varying SA. Finally, some conclusions and guidance recommendations on SA in hydrological modeling are provided, as well as a list of important future research directions that may facilitate more robust analyses when assessing hydrological modeling performance.

Contents

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1. Introduction

Hydrological models have developed significantly over the past three decades (Beven, 2009) in terms of their greater complexity (from rational methods to distribution models) and their diverse uses 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). To obtain better model predictions, we need to assess and improve models using different approaches such as parameter optimization, operational management, design space exploration, sensitivity analysis (SA), 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 include substantial uncertainties with respect to the input data, forcing data, initial and boundary conditions, model structure, and parameters due to a lack of data and poor knowledge of hydrological response mechanisms (Ye et al., 2008; Doherty and Welter, 2010; Shi and Zhou, 2010; Zhang et al., 2011; Gupta et al., 2012; Foglia et al., 2013). These uncertainties have negative effects on the model accuracy, thereby inducing uncertainties in the simulated results, thus the model uncertainty is an important issue when constructing a modeling system (Beck, 1987). Good modeling practice requires an evaluation of the confidence in the model as well as the model per se, which includes a quantification of the uncertainty in model results (i.e., uncertainty analysis, UA) and an evaluation of how much each input/parameter contributes to the output uncertainty (i.e., SA) (Loosvelt et al., 2013). In general, UA refers to the determination of the uncertainty in the model outputs that result from uncertainty in the model inputs/parameters, and SA refers to the determination of the contributions of individual uncertain inputs/parameters to the uncertainty in the model outputs. Ideally, SA and UA should be performed in tandem because both are essential parts of model development and quality assurance, as shown in Fig. 1.

In practice, the large number of parameters (from tens to hundreds) in most hydrological models leads to the curse of dimensionality where parameter estimation becomes a high-dimensional and mostly nonlinear problem. Numerous optimiza-

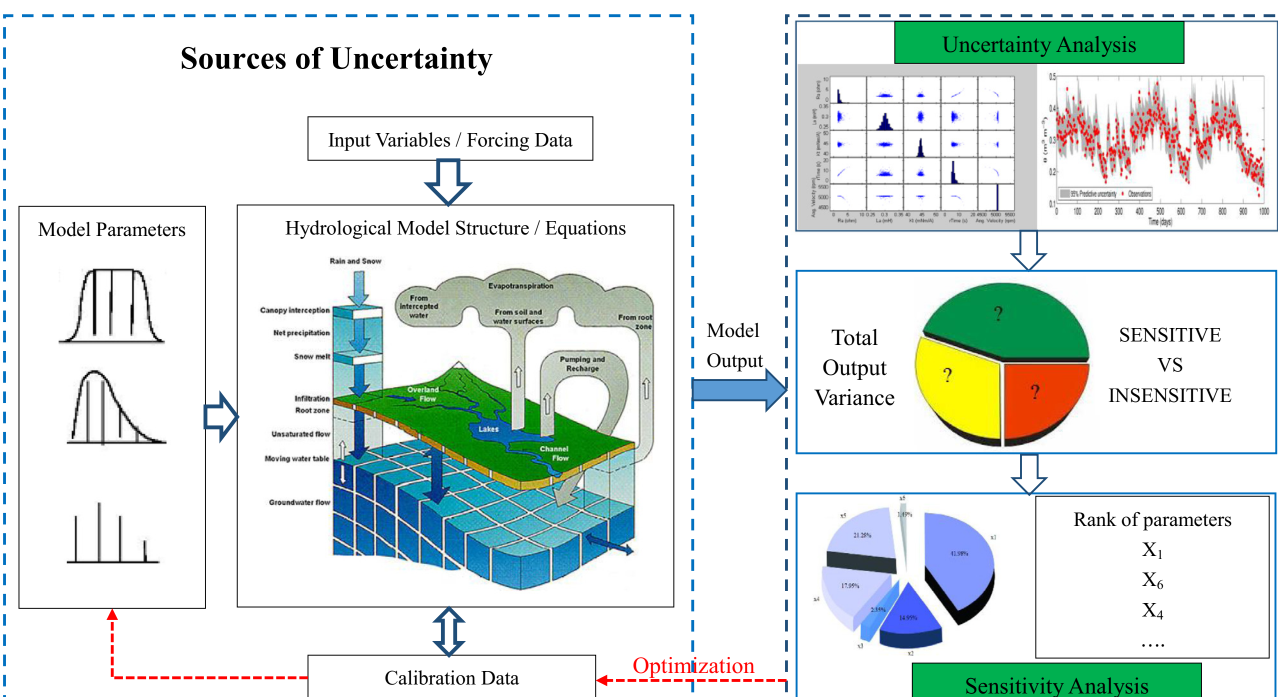

Fig. 1. Sketch for the relationship between uncertainty and sensitivity analysis in hydrological modeling. Global uncertainty analysis propagates all the uncertainties, using a model, to the model's outputs while sensitivity analysis determines the contribution of each input factor to the uncertainty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

tion algorithms have been developed to address this problem (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), but it is often not feasible or necessary to include all of the model parameters in the calibration process to achieve efficient optimization. For example, over-parameterization is another well-known problem in rainfall–runoff modeling (van Griensven et al., 2006). Therefore, when we estimate the model parameters, unimportant or insensitive parameters should be locked at a fixed value to facilitate more efficient calibration (SA). At present, various SA methods (e.g., local or global methods, qualitative or quantitative methods, and screening or refined methods) are used widely in different fields, such as complex engineering systems, economics, physics, and the social sciences (Frey and Patil, 2002; Iman and Helton, 1988). However, there are large differences among these methods in terms of their sampling schemes, applicability, algorithm structures, and the importance measures used for the parameters. Given the wide range of SA methods available, it is very important that a practitioner has a clear understanding of the methods that are appropriate for a specific application in terms of selecting a particular SA method, fitting the method to existing models, and presenting and interpreting the results.

This study aims to review, analyze, and classify the SA research with an emphasis on global SA efforts in the area of hydrological modeling. Many reviews of SA methods have been conducted in different fields. In particular, Hamby (1994) reviewed the literature on parameter SA for environmental models; Frey and Patil (2002) and Mokhtari and Frey (2005) reviewed the SA methods used for food safety; Coyle et al. (2003) discussed the SA measures employed in the field of economics; Saltelli et al. (2005, 2012) focused on SA in chemical models; Borgonovo (2007) investigated sensitivity and uncertainty measures; Mishra et al. (2009) reviewed the global SA methods used in groundwater models; Peter and Dwight (2010) discussed numerical SA approaches for aerodynamic optimization; Perz et al. (2013) reviewed the global SA and UA methods applied to ecological resilience; Tian (2013) summarized the application of SA methods to building energy analysis; and Wu et al. (2013) review recent advances in SA for infectious disease models. Some of these reviews explicitly highlighted the advantages and disadvantages of various methods and they provided very good summaries of these topics. To the best of our knowledge, few comprehensive and up-to-date reviews have tracked the advances in SA for hydrological modeling. The present study represents a unique contribution to the literature because our objective was to summarize the advances in the application of various global SA methods in hydrological modeling. The depth of the review of the topics covered in this study generally varies with the popularity of the topic in hydrological modeling, thus the discussion revolves largely around uncertainty quantification and optimization applications. This paper is organized as follows. Section 2 briefly describes the typical definitions and categories of SA. Section 3 explains the objectives and roles of SA in hydrological modeling. Section 4 reviews the key SA techniques and approaches that are applied in hydrological models, as well as describing their corresponding advantages and disadvantages. Section 5 proposes the steps and an evaluation framework for SA in hydrological modeling. Section 6 focuses on several topics related to the implementation of SA in hydrological modeling. These topics include: how to deal with correlated parameters, the applications of SA in model evaluation; and time-varying SA in hydrological modeling. Section 7 provides a summary and some concluding remarks.

2. Definitions and categories of SA methods

In general, when referring to the extent that a parameter affects the model output, we can use the terms "sensitive", "important", "most influential", "major contributor", "effective", or "correlated" interchangeably (Hamby, 1994). There are different definitions among fields, which are listed in Table 1. Regardless of how SA is defined in different areas, 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, thereby resulting in a large contribution to the overall output uncertainty; and (2) model outputs can be highly correlated with a parameter such that small changes in the input value result in significant changes in the output. In hydrological modeling, we define SA as the investigation of the response function that links the variation in the model outputs to changes in the input variables or/and parameters, which allows the determination of the relative contributions of different uncertainty sources to the variation in outputs using qualitative or quantitative approaches under a given set of assumptions and objectives.

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

Literature	Context/discipline	Definition
Viel et al. (1995)	Medicine	A series of analyses of a data set to assess whether altering any of the assumptions made leads to different final interpretations or conclusions
Pannell (1997)	Economic models	To determine how different values of an independent variable will impact a particular dependent variable under a given set of assumptions
Nestorov (1999)	Pharmacokinetic and pharmacodynamic systems	The systematic investigation of the model responses to either perturbations of the model quantitative factors or variations in the model qualitative factors
U.S. EPA (2001)	Environmental models	Sensitivity refers to the variation in output of a model with respect to changes in the values of the model's inputs, and SA attempts to provide a ranking of the model inputs based on their relative contributions to model output variability and uncertainty
Frey and Patil (2002)	Food-safety risk assessment models	The assessment of the impact of changes in input values on model outputs
Saltelli et al. (2004)	Chemical/environmental models	The study of how the variation (uncertainty) in the output of a statistical model can be apportioned, qualitatively or quantitatively, to different variations in the inputs of the model
Schneeweiss (2006)	Medicine	To determine the robustness of an assessment by examining the extent to which results are affected by changes in methods, models, values of unmeasured variables, or assumptions with the aim of identifying "results that are most dependent on questionable or unsupported assumptions"
European Commission (EC) (2009)	Impact assessment	To explore how the impacts of the options you are analyzing would change in response to variations in key parameters and how they interact
Matott et al. (2009)	Environmental models	To study the degree to which model output is influenced by changes in model inputs or the model itself
Thabane et al. (2013)	Clinical trials	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	Application cases
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, relatively low computational cost, no self-verification, local effect of individual parameters	Local sensitivity measures, main effect
	Global	Evaluate the effect in the entire ranges of uncertain parameters	Estimating the effect of all the inputs or their combined effect on the variation of output based on many model runs	Main and joint effect of multiple inputs
2	Mathematical	Estimate the local or linear sensitivity of output to individual parameter	Providing the uncertainty effect of parameters on the output, not address the variance of output	Deterministic analysis, inputs for linear models, verification and validation
	Statistical	Analyze the influence of various inputs on model output with running simulations based on sampling design methods	Qualitatively or quantitatively estimate sensitivity indices with huge computational demand based on many model runs	Probabilistic analysis, main effect, joint effect of multiple inputs, verification
	Graphical	Complement the mathematical or statistical methods for better representation with graphical plot	Graphical representation with more direct-viewing and clear	Graphical representation, it can be used as a screening method before further analysis, and to complement the results of other methods
3	Screening	Be used to make a preliminary identification of sensitive inputs	Relatively simple, easy of operation, not be robust for some key model characteristics, such as nonlinearity, interactions, and different types of inputs	Many input factors or parameters, non-quantitative analysis
	Refined	Adequately consider complex model characteristics and need greater expertise and resources to implement	Providing quantitative results with more accuracy, relatively difficult to implement	Quantitative analysis, main and joint effect of multiple inputs, more data requirement
4	Qualitative	Providing a heuristic score to intuitively represent the relative sensitivity of parameters	Be aimed at screening a few active parameters within a system with many non-influential ones, relatively fewer model runs	Ranking results of input parameters, used as screening important or sensitive parameter
	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 of variance explained by each parameter, a large number of model runs	Quantify the effect of individual or multiple parameter, deterministic or probabilistic analysis, few inputs or parameters

SA methods can be classified based on their scope, applicability, and characteristics. The simplest and most common classifications are local SA and global SA (e.g., Saltelli et al., 2004; van Griensven et al., 2006; Hill and Østerby, 2003). Local SA is focused on the effects of uncertain inputs around a point (or base case), whereas global SA is focused more on the influences of uncertain inputs over the whole input space (Tian, 2013). Recently, local–global hybrid method is proposed, such as Kucherenko et al. (2009) and Rakovec et al. (2014). In their work, derivative-based methods were used to obtain the distribution of parameter sensitivity across the parameter space, which merged the conceptual of local and global sensitivity analysis. Additionally, Campolongo et al. (2000) suggested another common classification, which is based largely on the extent of the input variable range that the technique assesses. In the present study, the techniques are divided into three levels: screening, local methods, and global methods. This classification is also used widely in SA studies, but this arrangement is ambiguous because the classification of a technique as local or global depends on whether the range is sufficiently large 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, Saltelli et al. (2004) proposed four settings, i.e., factors prioritization setting, factors fixing setting, variance cutting setting, and factors mapping setting. These settings can also be linked to Type I and Type II errors. In general, a Type I error is the incorrect rejection of a true null hypothesis, while a Type II error is the failure to reject a false null hypothesis. In SA, Type I errors occur when erroneously defining a non-influential factor as important, whereas Type II error occurs when we classify an important factor as non-influential (Zhan et al., 2013). If we are particularly interested in avoiding Type I errors, then main effects and factors prioritization setting will be target analysis. Alternatively, if Type II errors are to be avoided, total effects and factor fixing need to be considered. In the present study, we emphasize four 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 summarized briefly in Table 2.

3. Implications and roles of SA in hydrological modeling

SA is generally recognized as a worthwhile step to diagnose and remedy difficulties in identifying model parameters. That is, SA is one of the simplest aids in the diagnosis and remediation of poor identifiability in models because it allows parameters to be estimated more reliably (Shin et al., 2013). SA also aims to establish the relative importance of the parameters involved in the model by answering questions such as the following (Cariboni et al., 2007; Neumann, 2012; Song et al., 2012a).

- Which of the uncertain parameters has the greatest influence in determining how variability affects the inference?
- If the uncertainty of some parameters could be eliminated, which should be selected to reduce the minimum variance of the output of interest?
- Are there parameters with such low effects on the output that they could be confidently fixed anywhere in their ranges of variation without affecting the results?

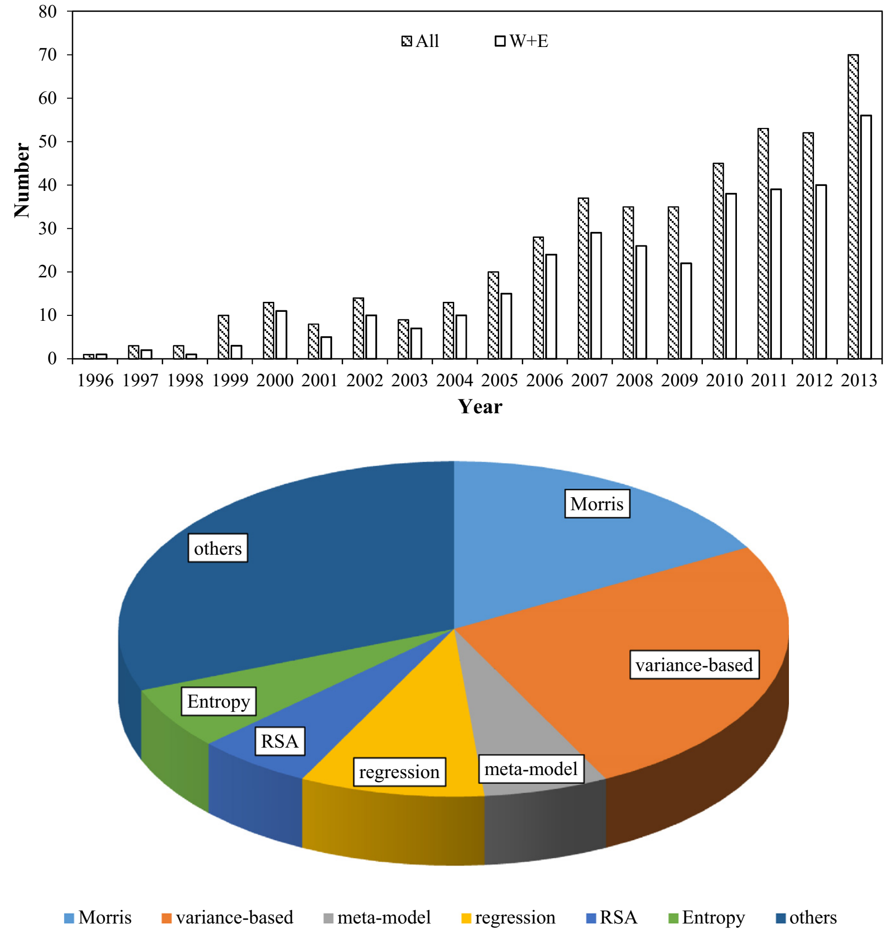

Fig. 2. Yearly publications on sensitivity analysis in the field of water sciences and the contribution rate of these common methods in hydrological modeling from the Web of Science Core Collection. "All" is based on the search terms "sensitivity analysis" + "hydrological model" + "parameter sensitivity analysis" in the Web of Science. "W + E" represent the selected publications based on the categories "water resources" and "environmental sciences" in the Web of Science.

- If these parameters deviate from expectations, what will their effect be on the model output and which are those that cause 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 have shown that the SA can reduce the output variance to a lower threshold by simultaneously fixing the smallest number of input parameters (Saltelli et al., 2000, 2004, 2008). This is important for the implementation of SA for complex hydrological models, especially for those with large numbers of uncertain parameters. However, we also 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 required for model calibration by focusing estimation efforts on parameters that are important for calibration metrics and predictions (e.g., Anderman et al., 1996; Hamm et al., 2006; Zambrano-Bigiarini and Rojas, 2013); (c) determine the 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 the 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 the 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.

Table 3
Recent global SA studies in hydrological modeling.

Models	Number of parameters	SA methods	Objective or output functions	The number of runs for hydrological models	Source
BSM1	32	Regression	EQI, OCI	5 × 1000	Flores-Alsina et al. (2009)
DHSVM	4	GLUE	NSE	10,000	Surfleet et al. (2010)
DTVGM	14	Morris, Meta-modeling	WB, NSE, RC	600, 4000	Zhan et al. (2013)
ESTEL-2D	9	MMGSA(Sobol', K-L entropy, Morris)	NSE	1280	Cloke et al. (2007)
HBV	11	RSA	BIAS, RSME, NSE	60,000	Abebe et al. (2010)
HBV	12	Sobol'	RMSE, ROCE	10,000	Herman et al. (2013a)
HBV	15	Sobol', RSA	WB, NSE	8192, 10,000	Zelelew and Alfredsen (2013)
HEC-RAS	6	Sobol, K-L entropy, Morris, RSA, regression	NSE, MAE	Not reported	Pappenberger et al. (2008)
HEC-RAS	7	SARS-RT, Correlation, RSA	Normalized performance measure	4000	Pappenberger et al. (2006)
HL-RDHM	31 × 13	Sobol'	RMSE	40,000	Tang et al. (2007a)
HL-RDHM	18	RSA, ANOVA, Sobol'	RMSE, $RMSE_{Box\text{-}cox}$	8192	Tang et al. (2007b)
HL-RDHM	78 × 14	Morris, Sobol'	RMSE	Over 6 million (Sobol'), about 20,000 (Morris)	Herman et al. (2013b)
HL-RDHM	78 × 14	Morris	RMSE, ROCE	21,860	Herman et al. (2013c)
HYDRUS-2D	11	Sobol', mutual entropy, RSA	Output discharge	260,000 × 11 (Sobol'), 260,000 (mutual entropy, RSA)	Massmann and Holzmann (2012)
HYMOD	5	Sobol', Morris, SRC, RSA, SDP	NSE	18,000, 3000, 3000, 3000, 500	Yang (2011)
HYMOD	5	Sobol'	RMSE, ROCE	10,000	Herman et al. (2013a)
LU4-R-N	41	RSA, GLUE	Relative RMSE, NSE	100,000	Medici et al. (2012)
MARTHE	20	Sobol' with Gaussian process	NSE	300	Marrel et al. (2009)
MARTHE	5	SDP	NSE	1024	Garambois et al. (2013)
MIKE 11	5	ANOVA	Water temperature error	Not reported	Wang et al. (2013b)
MIKE/NAM	9	Morris with Pareto ranking	$RMSE_{peak}$, $RMSE_{low}$	Not reported	Liu and Sun (2010)
MUSIC	13	Bayesian	NSE	10,000	Dotto et al. (2009)
REALM	14	Morris	Yield	3 × 6000	King and Perera (2013)
SAC-SMA	17	Sobol' method	RMSE, ROCE	10,000	Herman et al. (2013a)
SAC-SMA	14	Sobol' method	RMSE, $RMSE_{Box\text{-}cox}$, SFDCE, ROCE	7.5×10^6	Van Werkhoven et al. (2009)
SAC-SMA	14	Sobol' method	RMSE, $RMSE_{Box\text{-}cox}$, SFDCE, ROCE	130,000	Van Werkhoven et al. (2008a)
SAC-SMA	14	Sobol' method	RMSE, $RMSE_{Box\text{-}cox}$, SFDCE, ROCE	Not reported	Wagener et al. (2009)
SAC-SMA	14	Regression-based method, screening-based method, variance-based method, meta-modeling method	MAE	280 (Morris), 400–600 (other screening methods), 2777 (FAST), 360 and more than 1000 (McKay method), 1050 (Sobol)	Gan et al. (2014)
SLUPR	10 × 6	Meta-modeling and ANOVA	NSE	Not reported	Wu et al. (2012)
SNOW17	10	RSA	NSE	10,000	He et al. (2011)
SVAT	30	Meta-modeling	Rn, LE, HF, Tair, Mo	400	Petropoulos et al. (2009)
SWAP	7	Sobol' method	RMSE	7168	Baroni and Tarantola (2014)

Table 3 (*continued*)

Models	Number of parameters	SA methods	Objective or output functions	The number of runs for hydrological models	Source
SWAT	28	Sobol' method	RMSE, NSE, ROCE, SFDCE	60,000	Zhang et al. (2013)
SWAT	26	Sobol' method	NSE	336,000, 72,000	Nossent et al. (2011)
SWAT	13	Sobol' method	RMSE	28,000	Cibin et al. (2010)
SWAT	8	FAST	NSE, MRE, RMSE, SMSE, PDIFF, LCS	243	Guse et al. (2014)
TNT2	16, 19, 6	Morris, ANOVA	20 output objective	1700 (16 inputs), 2000 (19 inputs), 9375 (6 inputs)	Moreau et al. (2013)
TOPMODEL	9	FAST, EFAST, Sobol'	MAD	1289(SimLab, FAST), 487 (R package, FAST), 5632 (Sobol, SimLab), 5000 (EFAST)	Reusser et al. (2011)
VIC	10	MCAT-RSA	RMSE, ARE, $RMSE_{Box\text{-}cox}$	59,049	Demaria et al. (2007)
WASH	13	Entropy analysis, stepwise regression	TP loading	250	Mishra (2009)
WaSiM-ETH	11	FAST	RMSE	487	Reusser et al. (2011)
WDS	21	Sobol'	Resilience index, combined measure	2000	Fu et al. (2012)
XAJ	15	Morris, meta-modeling	NSE, WB, GE, DE	640, 4000	Song et al. (2013)
XAJ	6	GLUE	NSE	60,000	Zhang et al. (2012)

Models: BSM1: benchmark simulation model No1; DHSVM: distributed hydrology soil vegetation model; DTVGM: distributed time variant gain model; ESTEL-2D: a finite element subsurface flow model; HBV: Hydrologiska Byråns Vattenbalansavdelning; HEC-RAS: Hydrologic Engineering Centers River Analysis System; HL-RDHM: Hydrology Laboratory- Research Distributed Hydrologic Model; HYDRUS-2D: a two-dimension finite element model; HYMOD: hydrologic model based on the probability distributed model; LU4-R-N: four-response lumped model coupling riparian tank and nitrogen; MARINE: Modélisation et Anticipation du Ruissellement et des Inondations pour des évèNements Extrêmes; MIKE11: hydrological and hydraulic model; MIKE/NAM: a rainfall-runoff model developed by DHI; MUSIC: the model for urban stormwater improvement conceptualization; RELAM: Resource Allocation Model; SAC-SMA: Sacramento soil moisture accounting; SLURP: semi-distributed land use-based runoff process; SNOW17: a lumped process-based model that simulates snow accumulation and ablation; SVAT: soil–vegetation-atmosphere modeling; SWAP: soil–water-atmosphere-plant model; SWAT: the soil and water assessment tool; TNT2: Topography-based Nitrogen Transfer and Transformations model; TOPMODEL: topography based hydrological model; VIC: variable infiltration capacity macroscale hydrologic model; WASH: Watershed water quality model; WaSiM-ETH: water flow 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 high-flow; HF: daily average sensible heat flux; LCS: longest common sequence; LE: daily average latent heat flux; MAD: mean absolute difference; MAE: Mean Absolute Errors; Mo: daily average surface moisture; NSE: Nash–Sutcliffe efficiency coefficient; OCI: operating cost index; PDIFF: Peak difference; RC: correlation coefficient; RMSE: root-mean-square error; $RMSE_{Box\text{-}cox}$: root-mean-square error of Box-Cox transformation; Rn: daily average net radiation; ROCE: Runoff coefficient error; SFDCE: Slope of the flow duration curve error; SMSE: 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 (adapted from Yang (2011)).

	Morris screening method	Regression-based method	Variance-based method	Meta-modeling based method	RSA	Entropy 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	Monte Carlo	Monte Carlo
Computational requirements①	$r(n+1)$ Cheap	m Cheap	$m(n+2) \sim m(2n+2)$ High	m Cheap	Depends on the filtering criterion	m Cheap
Characteristics of sensitivity measure	Qualitative/screening	Quantitative	Quantitative	Quantitative	Qualitative	Quantitative
Applicability	Model-independence	Linear model or monotonic model	Model-independence	Model-independence	Model-independence	Model-independence
Reliability	High	Depends on R^2	High	High (with dependence on R^2)	Weak	High
Parameter interaction	Yes/qualitative	Depends on the regression form	Yes/quantitative	Yes/quantitative	No	Yes
Coping with nonlinearity	Yes	Depends on the regression form	Yes	Yes	Yes	Yes

①: r represents the number of the trajectories, m is the sample size, and n is the number of factors.

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 $X = (x_1, x_2, \ldots, x_k)$, the elementary effect of the i-th parameter is defined as:

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

where Δ is a value in $\{1/(p-1), \ldots, 1\text{-}1/(p-1)\}$, 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):

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

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

where $d_i(j)$ is the elementary effect for input i using the j-th base sample point, $j = 1, 2, \ldots, r$ (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^*:

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

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:

$$y_i = b_0 + \sum_j b_j x_{ij} + \varepsilon_i \quad (5)$$

where x_j ($j = 1, 2, \ldots, k$) are the jth parameters; $i = 1, 2, \ldots, N$ 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:

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

where

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

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 ($V_i = V[E(Y|x_i)]$) and V_{ij} ($V_{ij} = V[E(Y|x_i, x_j)] - V_i - V_j$) to $V_{1\ldots k}$ the interactions among k factors. The variance of the conditional expectation, $V[E(Y|x_i)]$, 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. 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 method captures interaction effects; and (iii) 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 adaptive 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,b, 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., 2007; 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, Wagener et al. (2001) 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. Salient issues of sensitivity analysis

The typical SA evaluation framework for hydrological models is shown in Fig. 3. Though the field is currently rapidly developing, there are no established standards in the choice of particular techniques for specific application. Below we briefly outline the most popular GSA approaches currently in use, and we also consider some practical issues, such as the determination of parameter ranges, the choice of sampling design method, objective functions, and adequate SA methods. In general, all global SA techniques are designed to allow exploration of the model behavior in the space of the model inputs. Therefore, they employ various sampling algorithms for extraction of parameter sets from predefined areas of parameter space. Then for each parameter set the model outputs are calculated, and various objective functions and SA methods are applied to deduce particular metrics to quantitatively describe model input–output relationships. Thus, one way of classifying the existing GSA implementations would be to characterize them with regard to their choice of above techniques.

5.1. Selection of the ranges for parameters and sampling design

The first crucial step is to determine the ranges for the inputs and select the appropriate sampling design methods when implementing SA in hydrological modeling (Zhan et al., 2013). The ranges and distributions of parameters depend mainly on the prior information. Some studies have highlighted the effects of the ranges and distributions of inputs on the SA results. For example, Tong and Graziani (2008) noted that the appropriate specification of the ranges and shapes of the distributions can dramatically affect the outcome of the analysis. Shin et al. (2013) stated that reducing or expanding the ranges will affect the sensitivity indices, thereby causing insensitive parameters to become sensitive or vice versa. Wang et al. (2013a) also showed that different parameter ranges for the WOFOST crop growth model resulted in differences in the sensitive parameter. The sensitivity of parameters can be affected strongly by the ranges of inputs, thus it is important that the ranges used yield parameter sets that are considered plausible (Shin et al., 2013). In addition, Ben Touhami et al. (2013) investigated the effects of different distributions (e.g., Gaussian distribution, normal distribution, and uniform distribution) of parameters on the SA results. They found there were notable differences among the different distribution conditions in terms of their sensitivity. Normal and uniform distributions are often used in practice (Esmaeili et al., 2014), but it is necessary to consider different types of distributions (Kucherenko et al., 2012). In general, probability distributions can be constructed based on expert elicitation if there is not sufficient information. Even with expert elicitation, however, it is still challenging to build distributions with high confidence. Therefore, more work needs to be conducted to determine the ranges of the inputs as well as investigating their distributions and response surface shapes. For most global SAs, after defining the probability distributions of model parameters, it is necessary to implement sampling strategies to generate samples. 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). Screening and variance-based methods usually require special sampling methods (Saltelli et al., 2008; Tian, 2013), e.g., the Morris one-at-a-time sampling design should be used in Morris screening and the FAST sampling design should be used with the FAST method.

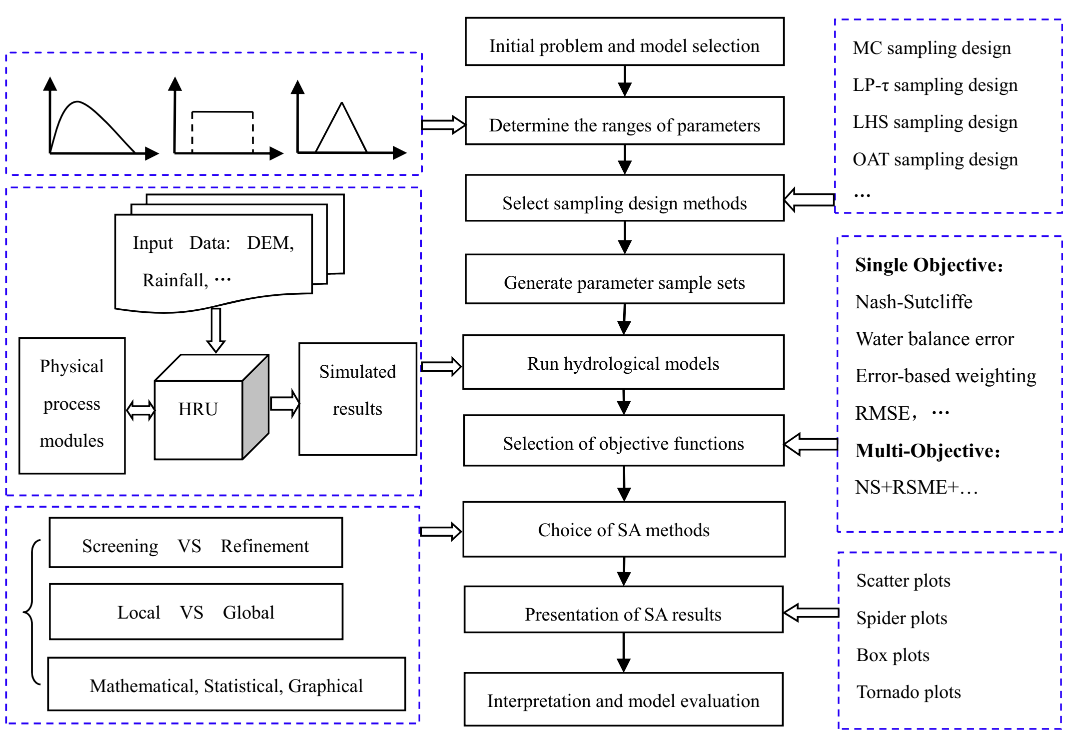

Fig. 3. Flow chart for SA in hydrological models.

5.2. Selection of objective functions for SA

It is also essential to select appropriate objective functions, which have immediate effects on the SA results (Shin et al., 2013; Song et al., 2013). For example, Zhan et al. (2013) showed that the most sensitive or important parameters for three different objective functions differed according to the distributed time-variant gain model. Song et al. (2013) highlighted the differences in the sensitivity indices among four objectives for the Xinanjiang model. The same conclusions were obtained for the Sacramento model and MIKE/NAM model by van Werkhoven et al. (2008a, 2009) and Liu and Sun (2010), respectively. However, Foglia et al. (2009) suggested that a well-designed single objective function that includes many data types can also be useful. In general, the contributions to the objective function are weighted, where the weighting considers the various units and precision of the 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 by combining the contributions of different functions into a single objective function (Song et al., 2012c). Therefore, SA should be implemented based on multi-objective functions or by combining single functions for different objectives, which can provide valuable and comprehensive insights into the parameters of hydrological models (Hill and Tiedeman, 2007; Foglia et al., 2009; Shin et al., 2013).

5.3. Selection of SA methods for hydrological models

Given the wide range of SA methods, practitioners require adequate resource to better understand the methods that 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 complexity of the model, (d) the computing time for a single model simulation, and (e) the analyst's time available to perform a SA (Cacuci et al., 2013; Saltelli et al., 2005, 2012; Wallach et al., 2006; Zajac, 2010).

In practice, the objective of the analysis is the crucial step when selecting appropriate SA methods. For example, if the focus is ranking characteristic parameter sensitivity measures, qualitative analysis or screening-based methods can be selected. However, if the goal is obtaining insights into the characteristics of sensitivity indices, quantitative methods may be the best choice. 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 possibly to fix their values, then the total-order sensitivity index may be a reasonable measure.

It is also well known that the dimensions of parameters have significant effects on the selection and application of SA methods in hydrological models, i.e., the performance efficiency of SA depends largely on the parameter dimensions. In general, the global screening method is preferred if the number of parameters is much greater than tens. Screening methods are designed to handle hundreds of model input factors but they can only provide qualitative sensitivity measures (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 quantitative SA more tractable.

Generally, increasing model complexity has important effects on model uncertainty, thus increasing the degree of the difficulty for sensitivity analysis in hydrological modeling. For example, Shin et al. (2013) also investigate the issue "which rainfall–runoff models tend to be more difficult to identify" for the four routinely-used lumped conceptual hydrological models: IHACRES, GR4J, Sacramento and SIMHYD models. There are of varying complexity, from four to thirteen parameters. To some extent, the complexity of model structure is consistent with the number of model parameters. They found that SA supported prior observations that model structures are problematic if they have many insensitive parameters with any objective functions, and simpler conceptual model structures may be preferable. As a result, for a hydrological model with high complexity, we suggest the hydrologists can refer to the choice of SA methods when the hydrological models exist a large number of parameters. That is, the combination of the screening method and other methods is preferred.

The computational cost of a single model run is another constraint that determined the choice of SA method in hydrological modeling. For example, SA is usually 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, the computational cost is a problem for many practical SA implementations. Some methods for reducing the computational costs include the use of meta-modeling methods (for large models) and screening methods (for reducing the dimensionality of the problem).

Therefore, synthetic SA approaches that consider the advantages and disadvantages of various analysis methods, as well as combining these methods in 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 scientific fields and a flowchart showing this integration method is provided in Fig. 4. For example, Francos et al. (2003) integrate the Morris method with FAST for qualitative and quantitative analyses (the two-step analysis method) to estimate parameter sensitivity for the SWAT model. Sun et al. (2012) also showed that when the number of input factors in the model is too high to allow 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 allow the clear and efficient identification of the effects of parameters on the model outputs from the DTVGM and Xinanjiang models. According to these results, the integrated technique facilitated qualitative and quantitative SA, and greatly reduced the computational costs with fewer model runs.

6. Other relative issues to SA in hydrological models

6.1. Analysis of correlated parameters in hydrological models

It is not unusual for the input parameters to be correlated in hydrological models. The correlations among hydrological or hydraulic parameters have important effects on the estimation of hydrological parameters, as well as significant effects on the predictions and associated uncertainties of hydrological modeling (Ahn, 1996; 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 to predictive uncertainties is also critical for uncertainty reduction (Rojas et al., 2009; Fox et al., 2010). The correlations among parameters may be strong in some cases (Xu and Gertner, 2007), but existing SA methods for hydrological models typically assume that parameters are independent (e.g., Li and Yeh, 1998; Boateng, 2007; Zhu et al., 2010; Zhan et al., 2013). However, for example, for models featuring dependent parameters, the use of Sobol' indices may lead to a wrong interpretation because the sen-

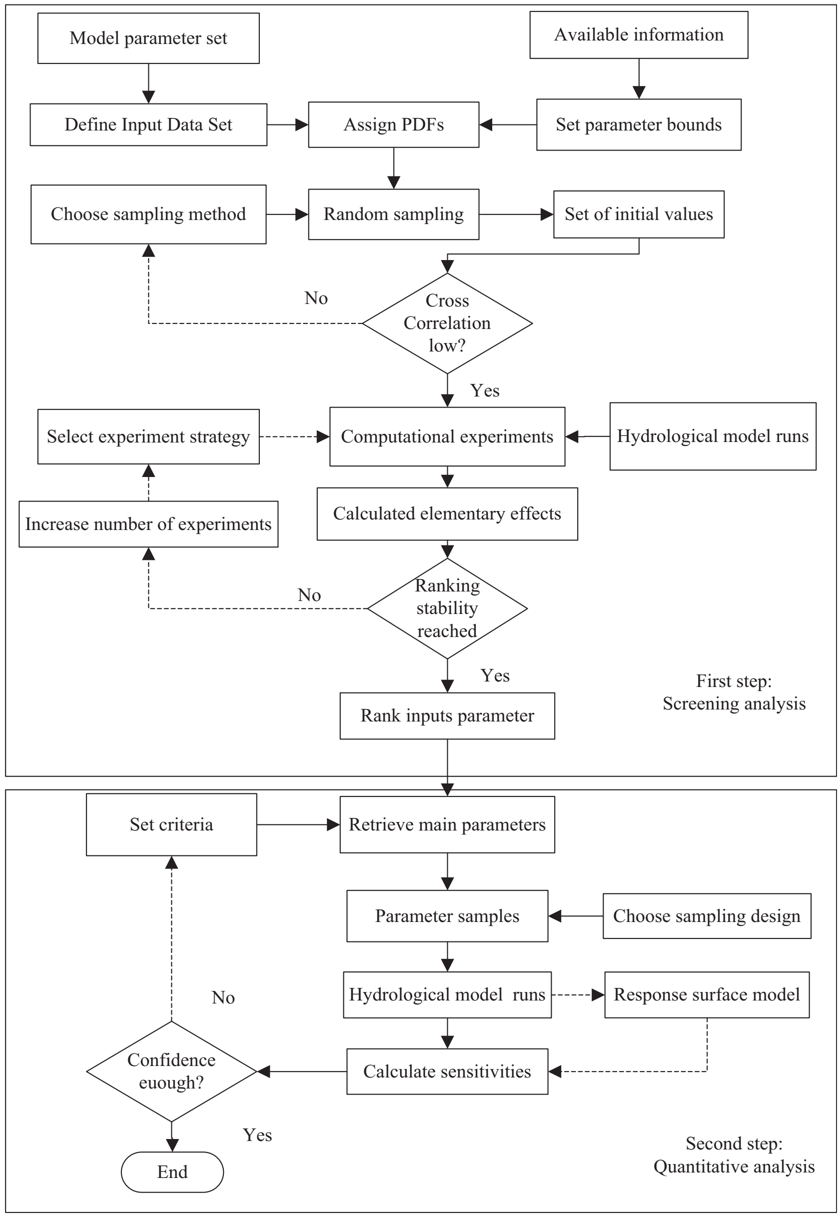

Fig. 4. Framework of two-step integration sensitivity analysis in hydrological models based on qualitative screening and quantitative analysis methods.

sitivity induced by the dependence between two factors is implicitly included in their Sobol' indices. Thus a straightforward solution consists in computing Sobol' sensitivity indices for independent groups of dependent variables. First introduced by Sobol' (1993), this idea is exploited in practice by Jacques et al. (2006), Borgonovo (2007), Borgonovo and Tarantola (2008) and Borgonovo et al. (2011). In addition, other studies have also applied SA with correlated parameters (e.g., Elston, 1992; Helton et al., 1995; Fang et al., 2004; Jacques et al., 2006; Pan et al., 2011). For example, Iman et al. (2002) proposed partial correlation as a measure of parameter sensitivity for models with correlated inputs based on the LHS method. Xu and Gertner (2008a) proposed a regression-based method for deriving the correlated contribution (based on variations in parameter that were correlated with other parameters) and the uncorrelated contribution (based on variations in parameters that were uncorrelated with other parameters). Unfortunately, their methods assumed that the effects of parameters are approximately linear. In general, for complex hydrological models, it can be expected that the effects of parameter are too nonlinear to allow these methods to yield reliable results. Fang et al. (2004) proposed the use of sequential sampling to approximate a differential sensitivity index. Saltelli et al. (2004) proposed a correlation ratio method based on McKay's one-way ANOVA method, which is based on replicated Latin hypercube sampling and it is suitable for nonlinear and nonmonotonic models. However, Bedford (1998) found that Sobol' evaluations depend on the order of the parameters. According to Xu and Gertner (2008b), the method of Fang et al. (2004) and the correlation ratio method require a large sample size, which would be impractical for complex models. Many techniques have been proposed to generalize variance-based SA methods to correlated or dependent variables (Kucherenko et al., 2012; Xu, 2013), but have been very few successful applications in hydrological modeling. Thus, further research should consider using these methods to investigate the influence of correlated parameters in hydrological models on the model outputs.

6.2. Applications of SA in model evaluations

As mentioned earlier, the distributed modeling of catchment hydrology is a valuable approach for understanding, reproducing, and predicting the behavior of hydrological systems. However, distributed hydrological models are still simplified and imperfect representations of physical processes, which use uncertain observation data to estimate model inputs (e.g., parameters and initial conditions). Thus, parameter estimation is critical for developing useful models of complex hydrological systems, where the important characteristics cannot be measured accurately or in sufficient detail to define the model input values (Matott et al., 2009; Song et al., 2012d). In practice, SA is generally a required step and a necessary prerequisite before other steps, as discussed below.

6.2.1. SA and parameter identification

For hydrological models, parameter identification has become an increasing problem as the model complexity increases with the high dimensions of model parameters. Model identification involves choosing a suitable model structure and degree of complexity, thus it is important to ensure that the model description and parameterization remain as simple as possible to allow adequate calibration, but it must also be distributed to capture the spatial variability in the key model parameters. Thus, the dimensionality of the parameter space must be limited to avoid model over-parameterization. For efficient parameter identification, SA is useful in providing the qualitative and quantitative indices needed to identify important and non-important parameters (Yang, 2011; Pappenberger et al., 2008; Confalonieri et al., 2010). It might be difficult to estimate these parameters efficiently when there are many parameters with no clearly identifiable influence on output variables, or when many parameters have similar effects (or interactions) on the output variables. In these cases, SA will be crucial for parameter identification. Thus, SA and parameter identification are usually performed together during model calibration. For example, Castaings et al. (2009) and Cibin et al. (2010) showed that the 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 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

In generally, the contribution of parameter uncertainty depends on the model structure, which is also related to the parametric sensitivity in modeling systems. Saltelli and Annoni (2010) stated that the objective of UA is to answer the question: "How uncertain is this inference?" whereas that of SA is to answer: "Where does this uncertainty come from?" In general, SA can be used to characterize a pure UA (Kennedy, 2007). Irrespective of the terminology used, SA is intended to complement UA rather than being an alternative. The two tasks have different objectives but they are often coupled in most cases (Saltelli and Annoni, 2010). For example, Mishra (2009) discussed the use of various UA methods (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 the results of UA were consistent with those obtained 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 can support our understanding of the uncertainty effects of model parameters on output variables and the structural characteristics of hydrological modeling systems from different points of view. Currently, the two approaches are usually employed together. Beven and Binley (1992) developed the generalized likelihood uncertainty estimation (GLUE) method, which is as an extension of the regionalized SA (RSA) method proposed by Spear and Hornberger (1980), for estimating parameter uncertainty and demonstrating the equifinality of 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 that coupled the GLUE and variance-based SA methods, and found that this integrated application enhanced the efficiency of performing calibration procedures.

6.2.3. SA and parameter optimization

Model calibration or parameter optimization is challenging for complex models due to the uncertainty of a large number of parameters (Fienen et al., 2009; Foglia et al., 2009; Keating et al., 2010; Ye et al., 2014). In practice, it is also difficult to ensure the accuracy of model applications and the reliability of predictions by empirical estimation or automatic optimization (Ciriello et al., 2013). Thus, while we seek more efficient and reliable optimization algorithms, we also require SA and UA to estimate the effects of parameters on model predictions. As mentioned by Rakovec et al. (2014) and Ye et al. (2014), parameter SA can reduce the time of model calibration by focusing the estimation efforts on the important parameters for model predictions. Therefore, SA may be a better choice before model calibration for complex hydrological models with many parameters. 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 used the SAC-SMA model as an example and suggested that it can reduce the complexity of calibration, while still obtaining high quality model predictions. Liu and Sun (2010), suggested that no single objective function is adequate for measuring how a model fails to predict the important characteristics of the observed data, thus multiple criteria should be considered. They coupled 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. Their results showed that the integrated method could identify the optimal Pareto front and it maintained reasonable diversity in the front obtained 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, thereby enabling representation of the spatial variability of watershed processes at the cost of increasing model complexity, which poses several challenges in terms of model identification and diagnosis (Herman et al., 2013c). Given the widespread applications of distributed models, there is still a need for diagnostic methods to study these models in terms of their full spatial and temporal complexity. Some of the model parameters often represent processes that only matter during specific time periods, i.e., specific modes of the system, such as recession constants or parameters that control the extent of saturated areas in a catchment during a flood event. These parameters are only likely to be identifiable if these periods can be isolated, or if they have sufficient impacts on a global objective function. It has often been observed that the important parameters during low flow periods, when errors are generally small, or parameters that 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, thereby determining the dynamics of model controls in 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). In general, the SA methods used for time-varying analysis include local and global approaches. Regardless of the method applied, they are generally used to estimate the sensitivity at each time step or for a running window (Massmann et al., 2014). In addition, several studies that focused on event-scale spatial sensitivities (Tang et al., 2007a; van Werkhoven et al., 2008b; Wagener et al., 2009) proposed the use of observations to identify representative events for a watershed. However, if the dynamics of a watershed cannot be restricted accurately to one of several event classifications, the selection of representative events may fail to account for the full range of the process's variability. Therefore, Herman et al. (2013c) extended the event-scale approach mainly to investigate the full dynamics of spatially distributed model controls based on the Morris screening method. To some extent, time-varying and spatial-scale SA provides a valuable opportunity to overcome the complexity of distributed parameter identification by restricting the search only to those parameters that are active at a specific time and location, thereby helping to improve the models representation of hydrological processes and to enhance the understanding of the hydrological cycle system.

7. Summary and outlook

In general, the aim of SA is to determine the model parameters with the greatest influence on model results. This information then allows unimportant parameters to be fixed or not incorporated into the model, as well as providing direction for future research to reduce parameter uncertainties and increase the model accuracy. It is widely accepted that identifying the most relevant parameters in a model is essential for hydrological modeling because of its roles in supporting effective parameterizations as well as the development of the model itself. Various SA methods are employed in hydrological modeling but practical experience suggests that no single analysis method is better than any other. Regression-based methods (e.g., SRC and SRRC) are simple to implement and easy to interpret, thus they may be still the first choice because they only incur moderate computational costs with hydrological models. However, for a complex hydrological model with many parameters and high computational costs, the Morris screening methods may be the preferred choice for qualitative analysis, although better choices may be meta-model approaches, while the integration of both methods is the best choice (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 while quantitative method (e.g., variance-based methods) can quantify the influence of each input in the output variance. The RSA method, which is a graphical SA, can provide information about the relationships between the output response and the input parameters, thereby improving our understanding of the model results. However, the results obtained using RSA depend mainly on the choice of filtering criterion, thus it should be used with care. Entropy-based methods are more competitive for delineating nonlinear and nonmonotonic multivariate relationships than regression-based methods.

Most previous studies have employed only one methodology to compute sensitivities, although various SA methods may rank the importance of the model factors differently. Instead, we suggest that several different sensitivity measures should be used in tandem. In addition, it is necessary to build more realistic, integrated hydrological models to represent real-world thresholds, nonlinearities, and feedbacks, which are capable of representing the implications of environmental change. The construction of these necessarily more complex models must also be accompanied by the development of significantly more powerful identification and evaluation algorithms. These algorithms, which should combine optimization and SA methods while considering uncertainty, need to be capable of examining how models represent hydrological cycle systems and determining whether this presentation is consistent with the perception of the actual system. Finally, we present our viewpoints on development trends, research issues, and hotspots related to 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. Performing hundreds or thousands of model evaluations for global SA (e.g., variance-based methods) is very inconvenient and it incurs high computational costs (e.g., greater than days or months), especially when the number of parameters exceeds hundreds. Meta-modeling approaches have been applied often for SA of hydrological models, but there some technical issues still need to be resolved concerning the reliability and goodness-of-fit of meta-models. For physical-based, distributed hydrological models, practitioners who use meta-models to represent the response relationship between parameters and model outputs should consider the following questions: (1) do the meta-models reflect the usual characteristic relationships between the parameters and outputs of the 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) The convergence and reliability of SA is another problem for scientists. Given 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 nonlinearity, nonmonotonicity, highly correlated parameters, and intensive computational requirements (Yang, 2011). Many previous studies 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 showed that no SA method is ideal and they explicitly stated that it is important to avoid erroneous interpretations of the model outputs' sensitivity to the parameters. Therefore, appropriate and correctly integrated methods must be selected based on their advantages and disadvantages to meet the actual requirements. In addition, multi-objective SA and parameter optimization are more important for complex hydrological models when evaluating the simulation results obtained based on different criteria.

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

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