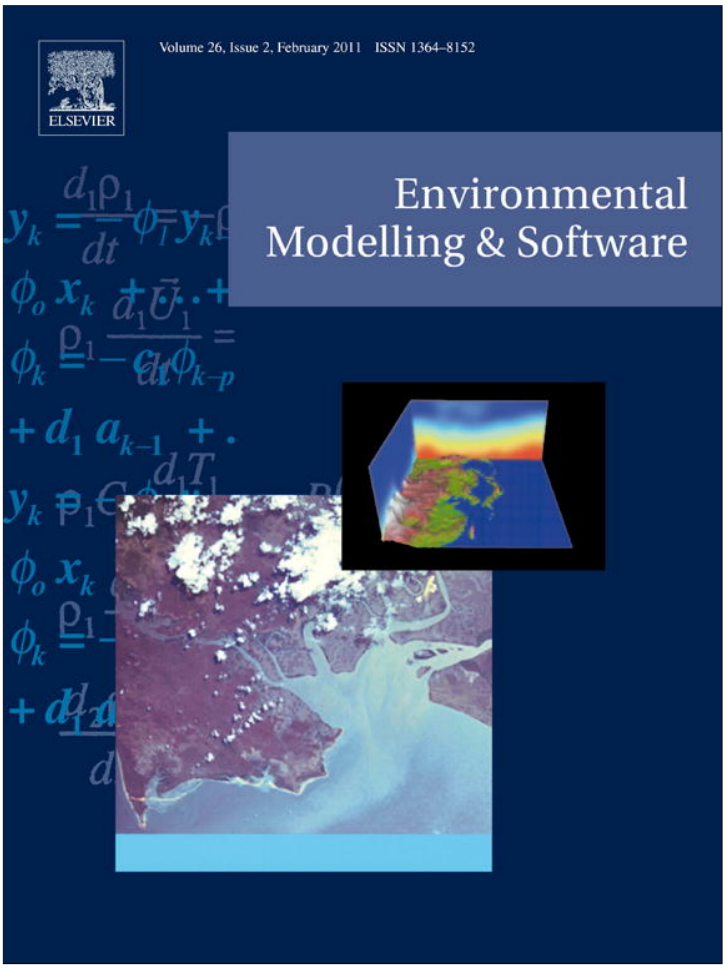

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Application of a pseudo simulator to evaluate the sensitivity of parameters in complex watershed models

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ABSTRACT

In this paper, the issue of nonlinear sensitivity analysis for dimensionality reduction in hydrologic model calibration is discussed, and a novel method to quantify the sensitivity of each parameter that considers the nonlinear relationship in the model is presented. The method is based on computing the absolute variation of the nonlinear function represented by the model in its parameter space. The paper discusses the theoretical background of the method and presents the algorithm. The algorithm employs neural network as a pseudo simulator to reduce the computational burden of the analysis. The proposed approach of sensitivity analysis is illustrated through a case study on a physically based distributed hydrologic model. The results indicate that the method is able to rank the parameters effectively, and the ranking can be interpreted in the context of the physical processes being considered by the model.

1. Introduction

All physics based distributed complex hydrologic models are generally characterized by a multitude of parameters. Due to spatial variability in the processes, the value of many of these parameters will not be known exactly. Further, many of them may not be directly measurable too. Therefore in most cases model calibration is necessary. During a model calibration, selected parameters are allowed to vary within predefined bounds, until an optimal correspondence between the model outputs and actual measurements are obtained. However, when the number of parameters in a model is large, the calibration process becomes complex and computationally extensive (Cibin et al., 2010; Sorooshian and Gupta, 1995; Rosso, 1994). In such cases, sensitivity analysis (SA) is helpful to identify and rank parameters that have significant impact on specific model outputs of interest (Saltelli et al., 2008). Generally, SA is employed prior to the calibration process in order to identify a candidate set of important factors for calibration so that complexity of calibration process can be reduced. This may allow dimensionality reduction of the parameter space where the calibration is made.

1.1. Background on sensitivity and uncertainty analysis

Sensitivity and uncertainty analysis of model parameters is usually considered to be one of the primary steps in the development and evaluation of models used for natural resources management (Jakeman et al., 2006). Consequently, parameter sensitivity and uncertainty in catchment modeling has received considerable attention over a long period of time (Beck, 1987; Jakeman and Hornberger, 1993; Gallagher and Dohert, 2007). The sensitivity analysis has become an important tool to explore the high dimensional spaces, assess parameter identifiability and understand the sources of uncertainty (Hornberger and Spear, 1981; Freer et al., 1996; Saltelli et al., 1999; Wagener et al., 2001, 2003; Hall et al., 2005; Muleta and Nicklow, 2005; Pappenberger et al., 2006, 2008; Demaria et al., 2007; Tang et al., 2007a,b). Norton (2008) proposed algebraic sensitivity analysis of models, equation by equation, and discussed its advantages and limitations. They demonstrated that their method can save much computational experiment. The sensitivity and uncertainty analysis help in understanding the models' parameters and also help in understanding the way the uncertainties of different orders are propagated to the output variables.

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A lot of approaches for quantifying uncertainty have been proposed, which include the Generalized Likelihood Uncertainty Estimator (GLUE) (Beven and Binley, 1992), frequentist approaches (Montanari and Brath, 2004), standard Bayesian approaches (Feyen et al., 2007; Kuczera and Parent, 1998; Kavetski et al., 2006a,b), Bayesian hierarchical models (Kuczera et al., 2006), Bayesian model averaging (Duan et al., 2007; Marshall et al., 2007), and bootstrap approach (Selle and Hannah, 2010). Beven et al. (2008) suggest that since the real information content of the data used in modeling is not clearly known *a priori*, it is difficult to make a reasonable choice between methods of uncertainty estimation for real applications. It may be noted that unless carefully performed, the model calibration and modeling efficiency analysis may induce the modeller excessively confident in the model results when data are scarce (Freni et al., 2009a,b).

1.2. Current methods of SA: a critique

A number of different techniques exist for sensitivity analysis, which can be broadly grouped into two: local approaches and global approaches (Salteli et al., 2008; Muleta and Nicklow, 2005). Local techniques aim at identifying the output responses by sequentially varying each of the input factors and by fixing all other factors to constant nominal (near optimal) values (Turanayi and Rabitz, 2000; Spruill et al., 2000; Holvoet et al., 2005; Hill and Tiedeman, 2007). The farther the perturbation moves away from the nominal value, the less reliable the analysis results become (Helton, 1993). Also, when the relationship between the input and output are nonlinear (which is typically the case in most hydrologic models), it is difficult and unreliable to employ local techniques. In addition, individual perturbation of the parameters can provide only the independent impact of parameter to the model output the interactive effects of parameters cannot be derived. However, if the parameters are correlated (which is also the case in most hydrological models) this assumption is not appropriate as far as the system represented by the model is concerned, as a change in one input feature may be accompanied by a change in another covariant feature.

Global SA (GSA) methods, in contrast, explore the entire range of parameters and all the parameters are simultaneously perturbed, allowing investigation of output variation as a result of all parameters and their possible nonlinear interaction. While there are a variety of GSA techniques available, variance decomposition based methods are the widely employed techniques, in which the output variance between simulations is decomposed into variance contribution from individual parameter component. Fourier amplitude sensitivity test (FAST) (Cukier et al., 1973) and Sobol's methods (Sobol', 1993) are the most popular and widely investigated (Homma and Saltelli, 1996; Francos et al., 2003; Cariboni et al., 2007; Ratto et al., 2001) variance based methods. The main features of both these techniques are: model independence, capacity to capture full range of variation of each variable, identification of interaction between parameters, and SA can be performed on subgroups of input variables (Lilburne et al. 2006). It has been reported that the classical FAST method is not efficient in addressing higher order interaction terms (Saltelli and Bolado, 1998). On the other hand, Sobol's method can estimate the interactions between the parameters and total sensitivity index of individual parameters (Sobol' 1993; 2001). Nonetheless, their application is difficult in cases where the model contains a large number of parameters or/and it is computationally too expensive (Cariboni et al., 2007), such as distributed hydrological models (especially physically based).

1.3. Scope for research

Generally in any SA method a 'sufficient' number of parameter combinations are sampled using any preferred sampling technique, and the model is executed on these parameter samples. It is followed by further analyses to provide a qualitative or quantitative measure of output uncertainty induced by each parameter. The major limitation of the existing methods is that local methods consider the strength of linear relationship between the parameters and the measure of sensitivity (Fogila et al., 2007, 2009), and GSA methods require large computational time (Cibin et al., 2010). While local methods are useful when models are computationally demanding (Fogila et al., 2007, 2009), they do not work well for parameters characterized by discrete instead of continuous values. Hence a method for computing the strength of nonlinear relationship between the parameters and the model output with less computational time is needed to identify parameters that have most influence on predictive uncertainly over the entire range of parameter space, and not just the small range considered in the linear sensitivity analysis.

This paper presents the concepts and the procedures of a novel multi-parameter nonlinear sensitivity analysis that can be used for parameter dimensionality reduction during calibration of complex hydrologic models. The method employs the concept of pseudo simulator to reduce the computational burden in the analysis. The method is illustrated through case study on a physically based distributed hydrologic model. The proposed method results in ranking of the parameter, and brings out the interactions between them with reference to the hydrologic processes considered.

2. Theoretical background

Any hydrologic model can be described by the functional relationship:

$$y = f(x, \lambda) \tag{1}$$

in which the y is the response variable of the model, x represent the input variable(s) and λ is the parameter vector. Consider this relationship to be evaluated at a set of points S (Monte Carlo simulations of parameter set, λ) lying inside a domain D (parameter range). If the magnitudes of the partial derivatives of the function with respect to the parameters are a measure of significance, it is implicitly assumed that the variables can change freely and independently from one another. This assumption is valid only if the influencing factors can be varied individually but if they are correlated, this assumption is not appropriate.

The inter relationships between the various parameters of the model and the output could be taken into account by focusing on the variations of f that actually occur inside the domain D (Schmitz et al., 1999). This is done by measuring the variation of f when moving between the points in S. This variation $v(f)$ of the function $f(x,\lambda)$ between the points i and j is defined as the absolute value of the directional derivative of $f(x,\lambda)$ integrated along a straight line between the two points λ_i and λ_j. Thus

$$v_{ij}(f) = \int_{\lambda_i}^{\lambda_j} |\Delta f(\mathrm{x}, \lambda) \cdot u| d\lambda \tag{2}$$

where u is unit vector in direction λ_i and λ_j. This variation can be computed between all pairs of points in S. When an attribute is insignificant to the function for the domain D, the variation in the function will be unrelated to the variation in the attribute. Thus a measure of the significance of an attribute (parameter) for

a function f over a data set S would be the correlation between the absolute variation of the function and the absolute variation of that attribute taken between all possible pairs of points in S. Hence, by computing the absolute variation for all the parameters of the model, the parameters can be ranked in terms of their sensitivity. Further, it is expected that the forcing data (x) do not vary from one simulation to the other during the analysis, suggesting that the parameter vector (λ) is the only variable, which is responsible for the variation in the performance of the model.

However, a practical application of this analysis is very complex because the function has to be evaluated (simulation of the models) at each and every discrete point, and hence involves a number of model runs resulting in long computational time and effort. It is proposed to address this issue by replacing the original model with a suitable pseudo simulator, which can understand the behaviour of the actual model and perform simulations as done by the model, to evaluate the objective of the SA. The pseudo simulator, being a simple mathematical equation, can considerably reduce the time required for evaluating the objective function of the optimizer. The characteristics of the pseudo model should be that it takes lesser time to compute the sensitivity index of the SA without increasing uncertainty in the model outputs.

Artificial neural network (ANN) can be a viable choice for such a pseudo simulator (Rao et al., 2004). An ANN attempts to mimic, in a very simplified way, the human mental and neural structure and functions (Hsieh, 1993). It can be characterized as massively parallel interconnections of simple neurons that function as a collective system (ASCE, 2000). The network topology consists of a set of nodes (neurons) connected by links and usually organized in a number of layers. Each node in a layer receives and processes weighted input from the previous layer and transmits its output to nodes in the following layer through links. Each link is assigned a weight, which is a numerical estimate of the connection strength. The weighted summation of inputs to a node is converted to an output according to a transfer function. Most ANNs have three layers or more: an input layer, which is used to present data to the network; an output layer, which is used to produce an appropriate response to the given input; and one or more intermediate layers, which are used to act as a collection of feature detectors. The goal of the ANN here is to establish a relation of the form:

$$(Y^m) = f(X^n) \tag{3}$$

where, X^n is an n dimensional input vector consisting of $x_1, x_2, \ldots x_n$; and Y^m is an m dimensional output or target vector consisting of resulting variables of interest $y_1, y_2, ..y_n$; and $f(.)$ is the transfer function.

The network is trained generally, using a back propagation algorithm that will adjust the weights and biases so as to minimize the error function given by:

$$E = \sum_P \sum_p (y_i - t_i)^2 \tag{4}$$

where, y_i is the ANN output, and t_i is the desired output, p is the number of output nodes, and P is the number of training patterns or data sets. ANNs are reported to be capable of modeling the hydrological processes (or any other nonlinear processes) due to their ability to generalize patterns in noisy and ambiguous input data and to synthesize a complex model without prior knowledge or probability distributions (Maier et al., 2010).

The use of pseudo simulator is based on the assumption that once an ANN model is trained and tested for generalization properties, the trained model represents the functional relationship of the system. When the neural network constitutes a generalized representation of a given set of data, a new artificial data set with approximately the same distribution as the original data can subsequently be generated. Randomly sampling the parameter space, and computing the target values for these sampled points by means of the trained neural network accomplish this. In order to ensure that the newly generated data is representative of the original training data set, it is essential that sampling be only allowed in the neighborhood of points or clusters present in the training data set. This can be achieved by using a nearest neighbor method; discrete samples of parameters are made along the Euclidean distance between two nearest points in the training data set.

3. Methodology

The algorithm for the proposed method of sensitivity analysis is as follows:

1. Select the model and identify the parameters to be tested
2. Set the range of each parameter to include expected variations that may occur for the watershed under consideration
3. Generate a series of parameter combinations within the design range.
4. Execute the model using the selected parameter sets and calculate a measure of sensitivity
5. Develop the pseudo simulator using the sampled parameter sets as input and the corresponding measure of sensitivity as target
6. Evaluate the absolute variation of the function using Eq. (2) between any given two points in the parameter space (λ_i and λ_j).
7. Compute the correlation between the absolute variation of the function and the absolute variation of each parameter.
8. Rank the parameters according to the magnitude of correlation computed at step 7.

At step 6, it is required to evaluate the function for a selected number of discrete points between the two points (λ_i and λ_j); performing numerical integration along the path of λ_i to λ_j accomplish this. Since the function evaluations are required at every discrete points between λ_i and λ_j, model runs are required at these points. However, a pseudo simulator eliminates the actual model runs since it directly produces the measure of sensitivity at these discrete points. One of the model performance measures, the root mean square error (RMSE), is a function of model output and the measured values; any variation of output due to parameter change would cause a change in RMSE. Consequently, RMSE is proposed to be used as an index of sensitivity in cases where measured values of the output are available. The purpose of the sensitivity analysis herein is to identify and rank the parameters according to their sensitivity; therefore the direction of sensitiveness (positive or negative correlation) is not considered in this approach. However, one can easily modify this algorithm for taking the direction of sensitivity in to account by evaluating a non-absolute measure of the variation.

4. Illustrative case example

4.1. The model description

The soil and water assessment tool (SWAT) is used to demonstrate the nonlinear sensitivity analysis proposed herein. SWAT is a watershed scale operational or conceptual model that operates on a daily time step. The SWAT model divides a watershed into smaller sub-watersheds, based on topographic information. The sub basins are further divided into smaller spatial modeling units known as

Table 1
The parameters of the SWAT model that influence stream flow simulation in the model and their recommended range of perturbation.

Parameter	Description	Unit	Min	Max	Influencing hydrologic process
CN_f[a]	Curve Number	%	−25	15	Surface runoff
SOL_AWC[a]	Soil Available Water Capacity	%	−0.3	2	Soil moisture
REVAPMN	Threshold depth of water in the shallow aquifer for 'revap' to occur	mm	0	30	Soil evaporation, ground water loss
ALPHA_BF	Baseflow Recession coefficient	%	0	1	Baseflow
ESCO	Soil Evaporation Compensation Coefficient	–	0.01	1.00	Evapotranspiration
SMFMX	Maximum melt rate for snow	^{0}C	0	10	Snow melt during the year
GW_REVAP	Ground water revap Coefficient	–	0.02	0.20	Groundwater loss
SMFMN	Minimum melt rate for snow	^{0}C	0	10	Snow melt during the year

[a] These parameters were changed as a percentage of their default values to maintain heterogeneity.

Hydrologic Response Units (HRU), depending on the heterogeneity of land uses and soil types within the watershed. An HRU is a fundamental spatial unit upon which SWAT simulates the water balance. Briefly, the hydrological processes modeled in SWAT are precipitation, surface runoff, soil and root zone infiltration, evapotranspiration, soil and snow evaporation and baseflow (Arnold et al., 1998). SWAT models the complete nutrient cycle for nitrogen and phosphorus as well as the fate and transport of any pesticides applied in an HRU. Being a physically based distributed parameter model, SWAT considers both upland and stream processes that occur in a watershed. The upland processes include hydrology, erosion, climate, soil temperature, plant growth, nutrients, pesticides, and land management. Stream processes considered by the model include water balance, routing, and sediment, nutrient and pesticide dynamics. Among others, Gassman et al. (2007), Arnold and Fohrer (2005), Jayakrishnan et al. (2005), and White and Chaubey (2005) have provided detailed overview of model application in making watershed response predictions.

The SWAT model is one of the most popular hydrologic models (Arnold et al., 1998; Arnold and Fohrer, 2005; Confesor and Whittaker, 2007; Zhang et al., 2008). The model has gained international recognition as is evidenced by a large number of applications of this model (Gassman et al., 2007; Anand et al., 2007). The SWAT model is also characterized by a large number of parameters, and despite a plethora of applications using SWAT, a comprehensive evaluation of its parameter sensitivity is still lacking (Cibin et al., 2010). Some limited studies about parameter sensitivity of SWAT have been reported (Arnold et al., 2000; Spruill et al., 2000; Lenhart et al., 2002; Francos et al., 2003; Osidele and Beck, 2001; White and Chaubey, 2005; Holvoet et al., 2005; van Griensven et al., 2006; Arabi et al., 2007; Muleta et al., 2007; Stow et al., 2007); most of them used local sensitivity methods.

The computations in the SWAT model is based on the premise that the simulation of the hydrology of a watershed can be separated into two major divisions. The first division is the land phase of the hydrologic cycle. The land phase of the hydrologic cycle controls the amount of water, sediment, nutrient and pesticide loadings to the main channel in each sub basin. The second division is the water or routing phase of the hydrologic cycle, which can be defined as the movement of water, sediments, etc. through the channel network of the watershed to the outlet. The land phase of the hydrologic cycle is modeled in the SWAT based on the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day,i} - Q_{surf,i} - E_{a,i} - w_{seep,i} - Q_{gw,i}\right) \qquad (5)$$

where SW_t is the final soil water content (mm), SW_0 is the initial soil water content (mm), t is the time (days), $R_{day,i}$ is the amount of precipitation on day i (mm), $Q_{surf,i}$ is the amount of surface runoff on day i (mm), $E_{a,i}$ is the amount of evapotranspiration on day i (mm), $w_{seep,i}$ is the amount of percolation and bypass flow exiting the soil profile bottom on day i (mm), and $Q_{gw,i}$ is the amount of return flow on day i (mm). Each component of the water balance equation (Eq. (5)) is modeled using very well established relationships in hydrology thus making the SWAT a very complex, distributed hydrological model. In this study, the stream flow modeling of SWAT is taken into consideration for sensitivity analysis.

The parameters of the SWAT model that affect the stream flow computations are identified through a detailed literature review and are presented in Table 1, along with their recommended range of perturbations (Neitsch et al., 2002; Arabi et al., 2007). The parameter ranges used in the SA are generally advised for SWAT applications and were not derived for specific conditions of the watershed (Neitsch et al., 2002). The parameter ESCO, soil evaporation compensation factor, is related to evaporation process. ESCO controls the soil evaporative demand that is to be met from different depths of the soil. It works in such a way that the smaller the value of ESCO, the more the extraction of the evaporative demand from lower levels that the model allows. The parameter CN_f represents the Curve Number in calculating the surface runoff from the basin using SCS–Curve Number method. The parameters such as ALPHA_BF and GW_REVAP are ground water simulation parameters of SWAT. ALPHA_BF, the base flow recession coefficient, is a direct index of ground water flow response to changes in recharge. GW_REVAP, ground water revap coefficient, controls the reverse water movement from shallow aquifer to the unsaturated soil layers. The soil moisture characteristics are represented in the model by soil available water capacity, SOL_AWC, which is estimated as the difference between the field capacity and the wilting point moisture contents. The parameters SMFMX and SMFMN are related to the snow melt processes represented in the model and are the melting factors. It may be noted that there are a large number of parameters in SWAT model, the current study considered only those presented in Table 1.

Initial values for these parameters were assigned using the soil characteristics, land use pattern and the topography of the watershed. Following Muleta and Nicklow (2005), during the Monte Carlo simulation of SWAT, some of these parameters (see Table 1) have been forced to assume uniform values within the watershed, and other parameters were allowed to vary uniformly by a percent change from their initial values in order to maintain their variability in different HRUs. Note that the sampling of the parameters was performed in their complete recommended range.

5. Description of study area and data

The SWAT model has been applied to Illinois River basin in Arkansas, USA, which is one of the major watersheds of the Northwest Arkansas. Illinois River, flowing west across the Arkansas–Oklahoma border into Oklahoma, crosses the state line just south of Siloam Springs at the Arkansas Highway 59 Bridge. This watershed is used in this study for the demonstration of the proposed method for SA. The outlet of the watershed is the USGS gauging site 07195430 on Illinois River, South of Siloam Springs, Arkansas. The geo-reference for the

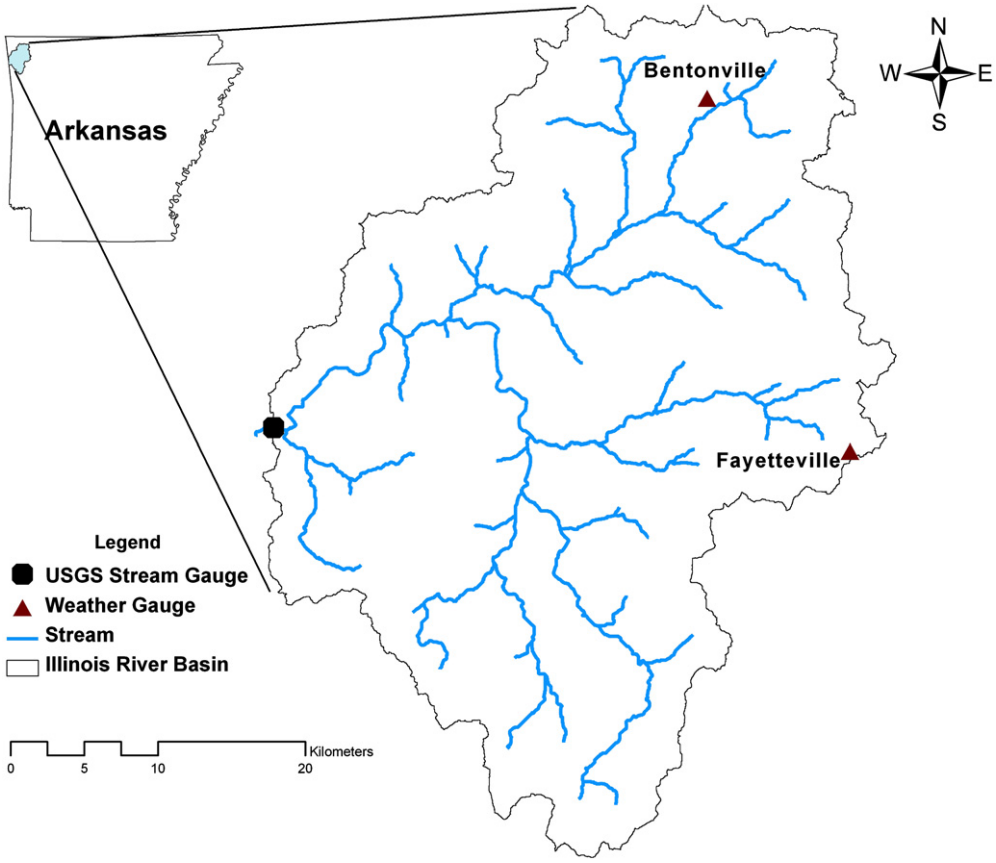

Fig. 1. Location of the Illinois River Watershed–Arkansas, USA and the USGS gauging stations within the watershed.

gauging site is 36°06′33.32" Latitude and 94°32′04.3" Longitude (NAD83). The drainage area of the watershed up to this gauging site is 1490 km^2. The watershed boundary, delineated using SWAT model (with ArcView interface), is shown in Fig. 1 for reference.

The elevation of the IRDA watershed varies from 279.6 m to 600.0 m with a mean elevation of about 380.5 m. The digital elevation map obtained from United States Geological Survey (USGS) at 30-m resolution is used to provide the GIS file of elevation in the SWAT model. The land use information of the Illinois watershed has been obtained from the 'Arkansas Land-use/Land-cover, 1999' data prepared by Center for Advanced Spatial Technologies (CAST), University of Arkansas. Major land use categories of the watershed are pasture under tall fescue and Bermuda followed by forests and residential areas. United States Department of Agriculture (USDA), Natural Resources Conservation Service (NRCS) database, Soil Survey Geographic (SSURGO), for Benton County and Washington County, Arkansas are used for extracting soil information in the watershed. Major soil types in the watershed are Nixa, Captina, Clarksville, and Enders covering an area of more than 5%. There are several minor soil types having a share of less than 5% in the watershed. Weather data from stations within the region, Fayetteville Experiment Station, and Bentonville, are incorporated to provide the most representative precipitation and temperature data available. Other meteorological data required by SWAT (solar radiation, wind speed, and relative humidity) are estimated using the SWAT weather generator.

The SWAT model is setup for the Illinois River watershed for 7 years, 1996–2002, out of which first three years were considered as warm up period. Thus, effectively 4 years' data were considered for the analysis. The measured daily stream flow values from USGS gauging station 07195430 of Illinois River south of Siloam Springs (Fig. 1) were used for the analysis. Illinois basin experiences an average annual rainfall of 90.5 cm. The daily flow ranged from a minimum of 2.4 m^3/s to a maximum of 538 m^3/s during the period of analysis. The mean flow during the period was 16.5 m^3/s with a standard deviation of 33.7 m^3/s. The Illinois River basin lies in the southern region of the USA and experiences high temperature, and evaporation is a dominant hydrological process in this basin, with average annual potential evaporation of 105 cm. The SWAT setup for Illinois River watershed had 26 sub basins and 286 HRUs.

6. Results and discussions

6.1. Development of pseudo simulator

As discussed earlier, eight parameters of SWAT were identified that influence the computation of stream flow by the model, after

Table 2
The performance of ANN as a pseudo simulator for estimating the RMSE statistic of SWAT simulations in Illinois River Basin from parameters.

Sample Length	Training Efficiency	Correlation	Validation Efficiency	Correlation
100	0.892	0.951	0.798	0.932
200	0.895	0.951	0.882	0.931
300	0.905	0.958	0.886	0.934
400	0.918	0.961	0.898	0.948
500	0.923	0.963	0.901	0.950
100[a]	0.886	0.948	0.882	0.929
200[a]	0.901	0.953	0.885	0.931
300[a]	0.892	0.949	0.883	0.929
400[a]	0.912	0.958	0.896	0.939
200[a]	0.897	0.949	0.883	0.935
300[a]	0.902	0.951	0.885	0.931

[a] These are bootstrapped (randomly picked up) samples.

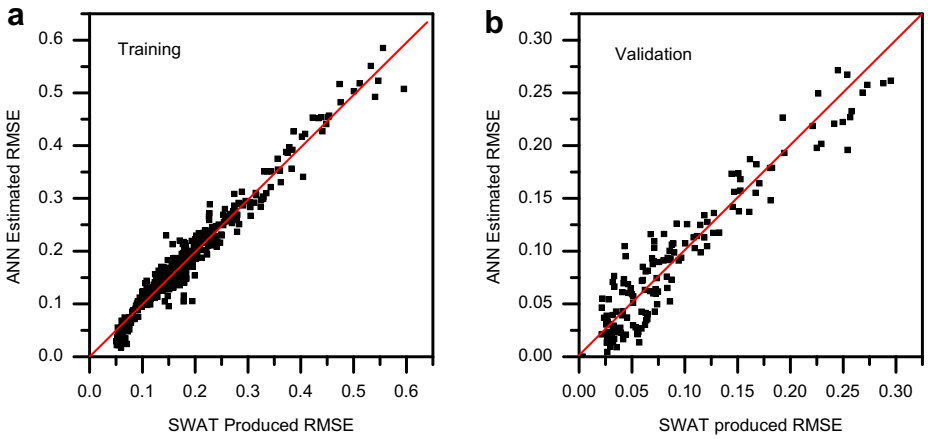

Fig. 2. Comparison between the ANN estimated error response of SWAT (RMSE) and the actual RMSE produced by SWAT for Illinois River Basin (a) during training of ANN (b) during validation of ANN.

screening and parameterization (Muleta and Nicklow, 2005). The sampling of parameters in the entire range of variation was done using Latin Hypercube Sampling (LHS) technique (Mckay et al., 1979). Since the parameter probability density function was not available, a uniform distribution is assumed (Freer et al., 1996; Manache and Melching, 2008). LHS method generates samples from the assigned probability distribution of parameters using a stratified approach. To generate a sample size of N for the variables $\theta = [\theta_1,\theta_2,\ldots,\theta_k]$ from their corresponding probability distributions, the range of each θ_1 is stratified into N disjoint intervals of equal probability and one value from each of these strata is randomly selected without replacement and randomly combined with second parameter from an interval, this two parameter combination is combined with value of third parameter and so on till all the k parameters are sampled. The SWAT model was executed for each parameter combination, and the error from the model is computed. The root mean square error (RMSE) of the daily flow computations was used as index for the sensitivity analysis. During this exercise 800 sets of parameters and their corresponding error (RMSE) were computed.

The generated configurations of the parameter vector (800 patterns), and corresponding error responses (RMSE) of the SWAT model, are fed as inputs and outputs to train the artificial neural network (ANN). As mentioned earlier, 500 patterns were used for training and the rest for cross validation and testing. The data was normalized in the range of 0–1, since it is a general recommended practice in ANN model development. The trained ANN is then used instead of the SWAT model as a pseudo simulator. The ANN used here is the three layer feed forward network, trained using the standard back propagation algorithm. The transformation function used in the hidden layer is hyperbolic tangent function and that in the output layer is sigmoid function, which were fixed after various trials.

The number of hidden neurons in the network, which is responsible for capturing the dynamic and complex relationship between various input and output variables was identified by various trials (Eberhart and Dobbins, 1990; Maier and Dandy, 2000). The trial and error procedure started with two hidden neurons initially, and the number of hidden neurons was increased up to 10 during the trails with a step size of 1 in each trial. For each set of hidden neurons, the network was trained in batch mode to minimize the mean square error at the output layer. In order to check any over-fitting during training, a cross validation (Bishop, 1995) was performed by keeping track of the efficiency (Nash and Sutcliffe, 1970) of the fitted ANN model. The training was stopped when there was no significant improvement in the efficiency, and the model was then tested for its generalization properties. The parsimonious structure that resulted in minimum error and maximum efficiency during training as well as testing was selected for validation. Alternatively one can use the cascade correlation algorithm for fixing the hidden neurons (Karunanithi et al., 1994). A total of 500 input–output pairs were used for training the network. The remaining data sets were used for cross validation (150 patterns) and final testing (150 patterns).

The study investigated the impact of length of samples required for developing the pseudo simulator, since a good performance of the ANN has to be ensured before it can be used for simulating the SWAT model. The details of the analysis in this direction are also provided in Table 2. The first 5 sets of samples in the Table 2 are selected in sequence, and the rest are bootstrapped (randomly sampled) combinations. It is noted that when the training is performed with only 100 data sets from the Monte Carlo simulations, the ANN model show efficiency (Nash and Sutcliffe, 1970) of 0.798 during validation (see Table 2). It can be seen from Table 2 that even when the training data length has been increased, the performance of the ANN does not vary significantly, although a slight improvement is observed. The maximum performance was observed when all the 500 sets of parameters were used for training (92% efficiency during calibration and 90% efficiency during validation). Consequently the ANN model that has been trained using 500 patterns has been employed for further analysis in this study. Although it cannot be generalized that 500 patterns are sufficient enough to mimic the SWAT model performance, in this example the performance of the ANN model is found to be satisfactory. Nonetheless, the more the examples for training, the better will be the performance of ANN.

Fig. 2 depicts a scatter plot between the ANN simulated RMSE values and the corresponding SWAT generated RMSE (targeted values for ANN model) of the pseudo simulator during training (Fig. 2a) and validation (Fig. 2b) respectively. Note that the RMSE values presented in this figure corresponds to the normalized values used in ANN model development. It is to be noted that the data points do not deviate much from the 1:1 line (solid line in the plot), which is evident from the high r^2 value of 0.96 during training of ANN and 0.90 during validation. The plot shows a very close scatter, which indicates that the developed pseudo simulator is able to mimic the performance of SWAT model fairly well. Nonetheless, it is worth mentioning that determination of an appropriate network architecture, and its training, is one of the most important, but also one of the most difficult, tasks in the ANN model-building

Table 3
Cross correlation matrix of absolute variance of parameters and RMSE.

	CN2	ESCO	ALPHA_BF	GW_REVAP	REVAPMN	SMFMX	SMFMN	SOL_AWC	RMSE
CN2	1.0000	−0.1055	0.1290	0.0169	0.1177	0.0482	0.0013	−0.0575	**0.4418**
ESCO		1.0000	−0.0475	−0.0809	−0.0287	0.0354	0.0656	0.0673	−0.1948
ALPHA_BF			1.0000	0.2020	0.5610	−0.0199	−0.1621	−0.0163	0.1290
GW_REVAP				1.0000	0.2593	−0.0071	−0.0694	−0.0404	0.1771
REVAPMN					1.0000	0.1134	−0.0388	−0.0571	0.2053
SMFMX						1.0000	0.1674	−0.0353	0.0590
SMFMN							1.0000	−0.0804	0.0442
SOL_AWC								1.0000	−0.3721

process. Unless carefully designed and trained an ANN model can lead to over parameterization, resulting in an unnecessarily large network.

6.2. Sensitivity analysis

The sensitivity analysis is performed by the method of absolute variance discussed earlier. During this exercise, numerical integration of the function represented by the developed ANN model between a pair of parameter combination, by moving along the line between the pair, is performed for all the 800 sampled parameter configurations. The identified eight parameters, which are considered having influence on the stream flow prediction in the SWAT model, are tested for their sensitivity. Table 3 presents the correlation matrix between the absolute variation of the model output (RMSE in this case) and the variation in each parameter obtained during sensitivity analysis. According to the proposed method, the parameter whose absolute variance has the highest correlation with the RMSE is considered the most sensitive parameter. It can be noted that the absolute variance of curve number (CN_f) has high correlation (0.4418) with the output, and is considered to be the most sensitive parameter for the model in the Illinois River watershed. Similarly, the snow melt rates have the least correlation (0.0442). Thus they can be considered as the least sensitive parameter of SWAT model in Illinois River watershed, among the parameters that are considered in this study.

It can be noted from Table 3 that the proposed method of sensitivity analysis clearly brings out the interaction between the parameters. For instance, the base flow index, ALPHA_BF, is highly correlated to the parameters that influence the ground water loss (to REVAPMN with a correlation of 0.5610 and to GW_REVAP with a correlation of 0.2020). The parameter ALPHA_BF is also correlated to the minimum snow melt rate (SMFMN) with a correlation of −0.1621 indicating that as the snow melt rate increases, the base flow decreases, which is obvious in any watershed. It is also noted from Table 3 that the sign of the correlation between parameters clearly indicate their actual interaction in the watershed. For example, the soil evaporation compensation factor (ESCO) is negatively correlated with all the factors that influence the ground water flow process (ALPHA_BF, GW_REVAP, REVAPMN), and is positively correlated with all those affect the surface flow (SMFMN, SMFMX, SOL_AWC). The results illustrate that the proposed method is effective in identifying the interacting parameters in the SWAT model.

Table 4
Ranking of the parameters of the SWAT model for Illinois watershed identified by the proposed method.

Parameter of SWAT	Rank according to the proposed SA
CN2	1
SOL_AWC	2
REVAPMN	3
ESCO	4
GW_REVAP	5
ALPHA_BF	6
SMFMX	7
SMFMN	8

The ranking of the parameters in the order of their sensitivity are presented in Table 4. In the Illinois River watershed, the parameter CN_f (curve number factor) is ranked at first according to the proposed method, followed by SOL_AWC, which accounts for the available soil water in the HRU (Table 4). As discussed earlier, the CN_f is the major driving parameter in runoff estimation and therefore is expected to be highly sensitive in most of the watersheds. It may be noted that in the Illinois River watershed the evaporation losses are higher as it is in the southern parts of United States where relatively greater values of temperature and radiation are observed. Consequently, the parameters REVAPMN, ESCO and GW_REVAP, which directly influence the evapotranspiration losses from the watershed, are found to be sensitive in Illinois. This is in agreement with the results reported by Migliaccio and Chaubey (2008) and Chaubey and Garg (2006), wherein they reported that ESCO is a sensitive parameter in Illinois River watershed. The snow melt rates are the least sensitive parameters for the study watershed, which is in accordance with the fact that snowfall is small in the Illinois watershed representing only 3.89% of the total precipitation (44.25 mm of snow fall (water equivalent) compared to 1137.1 mm of precipitation during 1995–2004).

It is worth mentioning that the results from this study is consistent with the results from Cibin et al. (2010), which used Sobols' method for SA in Illinois River watershed. According to Cibin et al. (2010), the first four of the sensitive parameters of SWAT model in Illinois basin identified by Sobols' method include those found in this study, except that their sensitivity ranking are different. This variation in ranking can be attributed to the difference in the methodology employed in both the methods; Sobols' method is based on the decomposition of variance of output produced by the model, while the proposed method considers the absolute variation between the parameters and model output. Therefore, the method of sensitivity analysis proposed in this study can be considered as an effective precursor for calibration, where only the most sensitive parameters of the model need to be estimated. One of the advantages of the proposed method is that it eliminates a large number of Monte Carlo simulations of the SWAT model, as compared to Sobols' method (Cibin et al., 2010) thereby reducing a lot of computational time. Note that Cibin et al. (2010) used 28,000 simulations of SWAT, while the current method used only 800 SWAT simulations.

The foregoing discussions illustrate that the proposed method of sensitivity analysis is effective in identifying the most sensitive parameters that influence the stream flow computations in SWAT model in less time. Nonetheless, it is worth mentioning that the effectiveness of the method lies on the performance of the pseudo simulator.

7. Summary and conclusions

Any hydrologic model is characterized by a large number of parameters that cannot be measured directly. These parameters will severely limit the accuracy of simulation by the model and hence they have to be carefully estimated. However, estimating a large number of parameters through calibration is a complex and computationally expensive task. Calibration of such models is generally preceded by a parameter sensitivity analysis in order to reduce the dimensionality of calibration parameters. The currently available techniques for sensitivity analysis generally consider the linear relationship between the parameter and the measure of sensitivity or they are computationally intensive. In this study, a novel nonlinear sensitivity analysis method is proposed that can be applied to any complex hydrologic model. The method is based on computing the correlation between the absolute variation of the function that the model represents and the absolute variation of each of the parameters within the parameter space. The theoretical considerations behind the concept and the methodology are presented in the paper. In order to reduce the computational burden of the proposed method, ANN is employed as a pseudo simulator to reproduce the models simulations. The method is demonstrated by a case study on SWAT model parameters that influence the stream flow computations in the model. It is noted that the proposed method is able to rank the parameters of the SWAT model effectively in accordance with the hydrological processes considered. The ranking of the parameters will help developing an efficient calibration procedure that uses only the sensitive parameters. It is worth mentioning that the effectiveness of the method would depend on the performance of pseudo simulator in reproducing the error statistic of the actual model.

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