Environmental Earth Sciences (2018) 77:470
https://doi.org/10.1007/s12665-018-7619-8

ORIGINAL ARTICLE

Parameter estimation of SWAT and quantification of consequent confidence bands of model simulations

Nithya Krishnan[1] · Cibin Raj[2] · I. Chaubey[3,4] · K. P. Sudheer[1,3]

Received: 12 June 2017 / Accepted: 18 June 2018 / Published online: 26 June 2018
© Springer-Verlag GmbH Germany, part of Springer Nature 2018

Abstract
Soil and Water Assessment Tool (SWAT) is a river basin scale model widely used to study the impact of land management practices in large, complex watersheds. Even though model output uncertainties are generally recognized to affect watershed management decisions, those uncertainties are largely ignored in model applications. The uncertainties of SWAT simulations are quantified using various methods, but simultaneous attempt to calibrate a model so as to reduce the uncertainty are seldom done. This study aims to use an uncertainty reduction procedure that helps calibrate the SWAT model. The shuffled complex evolutionary metropolis algorithm for uncertainty analysis is employed for this purpose, and is demonstrated using the data from the St. Joseph River basin, USA. The values of the performance indices, the r^2 and the Nash–Sutcliffe efficiency (NSE) for the simulations during calibration period was found to be 0.81 (same for r^2 and NSE) and 0.79 for validation period indicating a good simulation by the model. The results also indicate that the algorithm helps reduce the uncertainty (percentage of coverage = 62% and average width = 19.2 m^3/s), and also identifies the plausible range of parameters that simulate the processes with less uncertainty. The confidence bands of simulations are obtained that can be employed in making uncertainty-based decisions on watershed management practices.

Keywords SWAT · Uncertainty analysis · SCEM-UA · Prediction band

Introduction

Hydrological models are employed as simulation models to evaluate water availability, various management scenarios of cropping, and to assess its impact on water quality. Several models, varying from simple conceptual models to complex distributed models, have been used widely for land use planning decisions, flood forecasting, and water resources planning and management (Singh 1995; Abbaspour et al. 2015; Hasan and Pradhanang 2017). Such models provide an approximate, lumped description of the dominant sub-watershed scale processes that contribute to the overall watershed scale hydrologic response of the system (Boyle et al. 2000; Sudheer et al. 2007; Devia et al. 2015; Fukunaga et al. 2015). These hydrological models are mathematical models, and are characterized by various empirical/non-empirical parameters, which are to be estimated or defined. Many of them may not be directly measurable, and hence need to be estimated through calibration using an observed set of information. During a model calibration, the parameters are allowed to vary within predefined bounds, until a sufficient correspondence between the model outputs and actual measurements are obtained.

The abstract representation of the real-world process induces certain level of uncertainty in the model simulations. These uncertainties mainly come from input, model parameters, and model structure. The input uncertainty is mainly due to measurement and sampling error. The parametric uncertainty lies in the inability to identify unique set of best parameters of the model, plausibly due to equifinality of parameters (Beven et al. 2000; Beven 2006). The simplification, inadequacy and ambiguity in description of real-world process through mathematical equation leads

✉ K. P. Sudheer
sudheer@iitm.ac.in

1 Department of Civil Engineering, Indian Institute of Technology, Madras, Chennai 600036, India

2 Department of Agricultural and Biological Engineering, Penn State University, University Park, PA 16802, USA

3 Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, USA

4 Department of Earth, Atmospheric and Planetary Sciences, Purdue University, West Lafayette, USA

to model structural uncertainty. Consequently, the model outputs cannot be a single reliable value due to various uncertainties that persist during modelling, and therefore, should be represented with a confidence range (Beven and Binley 1992; Gupta et al. 1998; Green and Van Griensven 2008). This uncertainty in simulation may get propagated to the consequent decisions arrived at using the simulations, and unless carefully done, the decisions can become less reliable. Therefore, an appropriate assessment of the uncertainty in the model output is apparent for developing reliable decisions.

Soil and Water Assessment Tool (SWAT) is one of the most widely employed simulation model for planning and management of agricultural watersheds (Heathman et al. 2008; Zhang et al. 2008; Gassman et al. 2010; Song and Liu 2010; Arnold et al. 2012; Worku et al. 2017). The SWAT is capable of comprehensively simulating the hydrological processes, as well as the nutrient cycle and transport (Vazquez-Amabile et al. 2006; Cibin and Chaubey 2015), and has become a popular choice to make management decisions in agricultural watersheds. Many researchers have linked the SWAT model with an optimizer to arrive at an optimal crop placement so as to have minimum impact on the environment (Maringanti et al. 2011; Sudheer et al. 2011; Cibin and Chaubey 2015). The SWAT is characterized by a large number of parameters, and hence the simulation uncertainty needs to be assessed before it is applied to any decision-making.

While a lot of studies dealt with uncertainty evaluation of SWAT model simulations, most of them considered quantifying the simulation uncertainty after the calibration is performed (Abbaspour et al. 2007; Yang et al. 2008; Zhang et al. 2009a, b; Gassman et al. 2010; Shen et al. 2012; Srivastava et al, 2013; Roth et al. 2016). Pluntke et al. (2014) suggested that an appropriate calibration strategy can help improve the simulations, as well as reduce the uncertainty. A plausible approach could be to evaluate the uncertainty along with calibration process itself so that the range of parameters that produce less uncertain simulations can be identified. In addition, an evaluation of the uncertainty of SWAT parameters generally assume uniform probability distribution of the parameters (Yesuf et al. 2016), which may not always be true. This is plausibly because of lack of knowledge about the probability distribution of parameters (Athira and Sudheer 2015). Knowledge about the probability distribution of parameters help generate ensemble of simulations so that the uncertainty bounds of the simulation can be estimated. Therefore, this study is planned to simultaneously calibrate the model, and also to assess and quantify the uncertainty in SWAT model simulations. The posterior probability distribution of SWAT parameters is proposed to be estimated. Accordingly, this study is planned with three specific objectives: (1) to evaluate the effectiveness of shuffled complex evolutionary metropolis algorithm for uncertainty analysis (SCEM-UA) on SWAT model calibration and uncertainty assessment, (2) to identify SWAT parameters and simulations in a confidence band that can be employed for developing reliable watershed management decisions, and (3) to develop the posterior probability distribution of SWAT parameters. This study is focused on the uncertainty arising from the model parameters, though the other sources of uncertainty (input uncertainty and structural uncertainty) are also equally important. The objectives are demonstrated on a case study of SWAT application to the St. Joseph River Basin, IN, USA.

Shuffled complex evolutionary metropolis algorithm (SCEM-UA)

Many methods have been developed to address parameter uncertainty and include multi-normal approximation to parameter uncertainty (Kuczera and Mroczkowski 1998), evaluation of likelihood ratios (Beven and Binley 1992), parametric bootstrapping and Markov Chain Monte Carlo (MCMC) methods (Kuczera and Parent 1998; Tarantola 2005). shuffled complex evolutionary metropolis algorithm for uncertainty analysis (SCEM-UA), developed by Vrugt et al. (2003), is an effective and efficient evolutionary MCMC-based uncertainty analysis method, which considers tuning the prior probability distribution of parameters towards achieving an appropriate posterior probability distribution, during each evolution. The SCEM-UA is a modification of the shuffled complex evolutionary algorithm for uncertainty analysis (SCE-UA) developed by Duan et al. (1992). Many studies have reported the efficiency of SCEM-UA in finding global optimum results for parameter sets, with simultaneous quantification of uncertainty (Vrugt et al. 2003; Feyen et al. 2007). The advantage of the SCEM-UA is that the method identifies the optimal parameter sets for the model during calibration, and also quantifies the uncertainty simultaneously. Specifically, the SCEM-UA can calculate parameter uncertainty and give the posterior distribution of the parameters. Hence, SCEM-UA is employed in this study.

The meaningful quantification of uncertainty in hydrological model outputs is a challenging task since complete knowledge about the hydrologic system is still lacking (Kasiviswanathan and Sudheer 2014). In the case of any model, including complex hydrologic models, the aim is to develop a relationship between the input and output variables in the system. A general representation of the model can be of the following form (Eq. 1):

$$\mathbf{y} = f(\mathbf{x}, \boldsymbol{\lambda}) + \boldsymbol{\varepsilon}, \tag{1}$$

where $\mathbf{y}$ is the vector of outputs, x is a vector of inputs that are expected to influence the outputs, and $\boldsymbol{\lambda}$ is the vector of random parameters that describe the relationship between the input–output variables. The term **ε** indicates the presence of residuals in the model, which are assumed to be statistically independent error values following normal distribution with an expected value of zero and constant variance. In the classical approach to model calibration, the aim is to identify appropriate values of **λ** such that the values of **ε** is forced to be as close to zero as possible (Gupta et al. 1998). Further, when an optimization algorithm is employed to search for the best parameter set for a model, it is generally impossible to find a single point in the parameter space associated with good simulations. There could be many points in the parameter space in the vicinity of the global optimum solution that are more or less equal in performance. This poor identifiability (Cibin et al. 2010) may induce considerable uncertainty in the model output, and make it unreliable to relate the parameter values to measurable watershed characteristics (Schaap and Feike 1998; Vrugt et al. 2002). Hence, for an application of the model, it is necessary that these parameters have very little variance. The shuffled complex evolutionary metropolis algorithm (SCEM-UA) is an effective method used for identifying such parameters for simulation models (Vrugt et al. 2003).

The SCEM-UA algorithm works on the principle of Bayesian statistics (Vrugt et al. 2003). According to the Bayesian statistics, the model parameters are considered as probabilistic variables having a joint posterior probability density function (PDF), instead of fixed values (Box and Tiao 1973). With the available observed data for the model, it is possible to capture the probabilistic beliefs of the model parameters. The prior PDF of the parameters gives the prior information on the parameters. The probability distribution of parameters **λ** is generally unknown a priori, and hence modelers assume uniform probability distribution during analysis (Brazier et al. 2000). The uniform prior PDF of parameters essentially gives equal probability to the entire parameter range. The traditional method of estimating the posterior PDF of the parameters is using first-order Taylor series expansions of the nonlinear model parameters, evaluated at the globally optimal parameter estimates. This method of calculating the posterior PDF for parameters works well for the linear hydrologic models (linear in its parameters) and gives a good approximation of the actual parameter uncertainty (Vrugt et al. 2003). However, estimation of parameter uncertainty by this method, for nonlinear hydrological models gave unsatisfactory results (Kuczera and Parent 1998; Vrugt et al. 2002). In the case of nonlinear hydrological models, along with the strong and nonlinear parameter interdependence, the surface of parameter posterior PDF can significantly deviate from multi-normal distribution. There are high chances of having local optima and discontinuous derivatives (Duan et al. 1992). In view of these considerations, it is evident that an explicit expression of the joint and marginal probability density functions is often not possible. The MCMC samplers are very well suited to dealing with the peculiarities encountered in the posterior PDF of hydrologic model parameters (Vrugt et al. 2003).

The aim of original SCE-UA algorithm is to find a single unique best parameter set from the feasible parameter space. The parameter values are sampled randomly from the feasible search space, using the downhill simplex searching technique to evolve continuously to a better performing region. Even though this search technique targets its search towards higher probability region, many studies have shown that the algorithm gets trapped in the local minima (Vrugt et al. 2003).Thus, the replacement of downhill simplex technique with Metropolis Hastings strategy, which is more efficient and effective in finding global optimum points, reduced the risk of falling into local minima (Metropolis et al. 1953; Vrugt et al. 2003). Hence, the evolution of SCEM-UA occurred by merging the strength of SCE-UA and Metropolis Hastings algorithm.

The flow chart of the step by step procedure of SCEM-UA is shown in the Fig. 1 (Vrugt et al. 2003). As mentioned earlier, a uniform probability distribution is assumed as the prior probability distribution of the parameters, since there is no knowledge about the prior distribution. The algorithm begins with creating the initial population, by random sampling using the prior probability distribution of the parameter feasible space. For each sampled value,

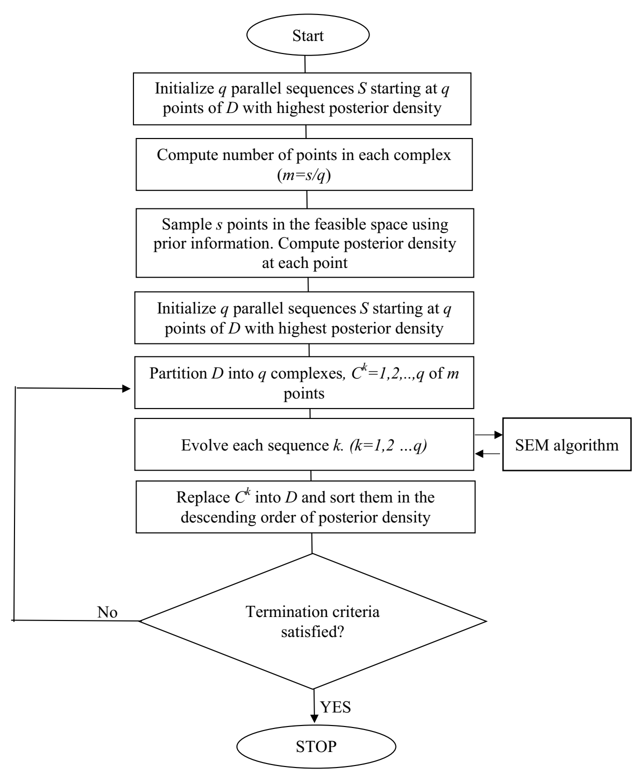


Fig. 1 Flowchart of SCEM-UA algorithm

the posterior density is calculated and ranked according to the descending order of probability density, such that the sample with the highest probability density comes first. The posterior probability is calculated using Bayesian inference scheme (Misirli et al. 2003). The entire population is divided into a number of complexes, and in each complex, a parallel sequence is created with the points of higher posterior density. A multi-normal distribution creates a new candidate point in the sequence, which is centered on the mean of the points in the complex augmented with covariance structure induced between the points in the complex (Vrugt et al. 2003). The Metropolis Annealing technique decides whether a new candidate should be added or rejected to the sequence. Replacement of the lower probability density candidate occurs, when a new candidate appears to have a higher probability than the old one. Information among the complexes are exchanged during the shuffling process of complexes, which will favor the sample search to higher probability density region. The SCEM-UA uses Gelman Rubin convergence criteria as the termination criteria and is given for scaling the value of the parameter (Gelman et al. 1996).

Details of the study area and data

St. Joseph watershed (USGS 8 digit HUC-05120107) covers an area of 280,000 ha in Northeast Indiana, Northwest Ohio, and South central Michigan (Fig. 2). The watershed includes seven counties namely Allen, DeKalb, Steuben and Noble in Indiana; Hillsdale in Michigan; and Williams and Defiance in Ohio State. Seventy-one percent of the watershed is farm land/agriculture dominated by corn (17%) and soybean (22%), followed by pasture (25%). Rest of the watershed area is composed of forest (12%), urban area (10%), wetlands (7%), and other small agricultural fields (6%) (USDA-NASS, 2013). Sixty-six percent area of the watershed has a slope ranging from 0 to 3% and the remaining area has a slope over 3%.

For the model calibration, observed daily stream flow data for the watershed outlet was available from the United States Geological Survey (USGS) website for the period of analysis (1990–2009). Data on sediment concentration in the streams was obtained from Indiana Department of Environmental Management (IDEM) water quality gauging site. Besides, measured data for nitrate and total phosphorus

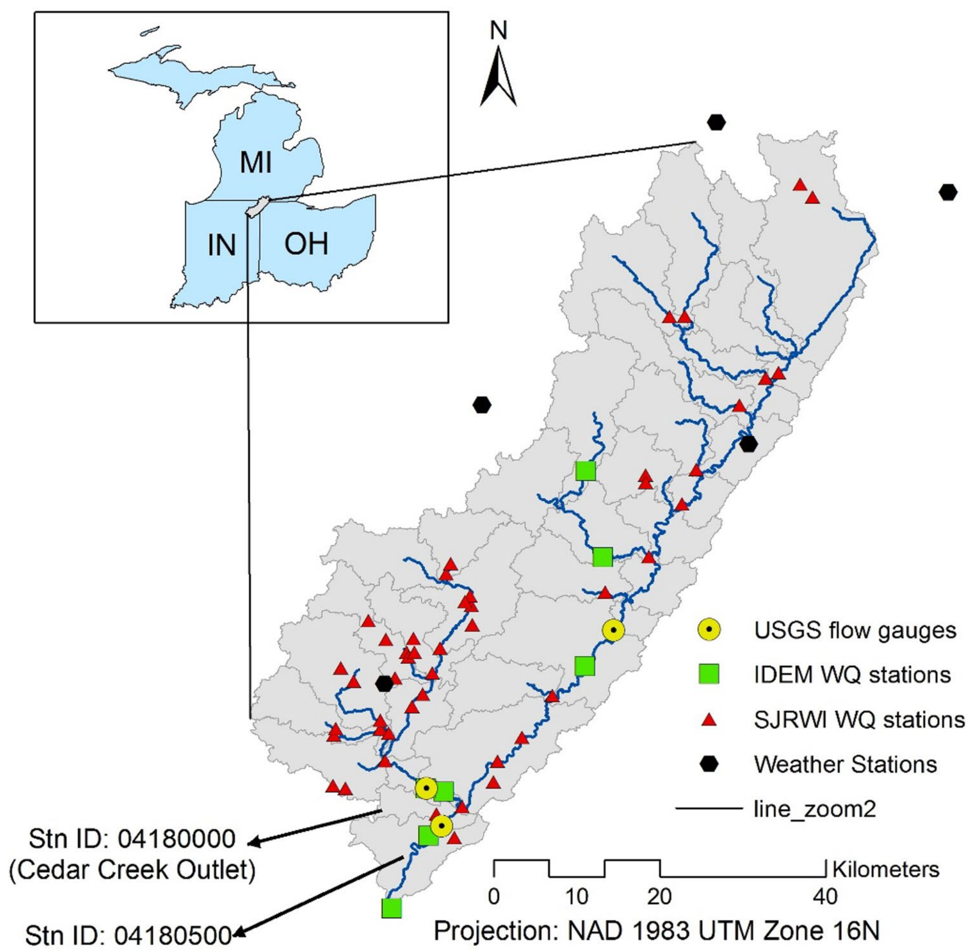


Fig. 2 Location map of St. Joseph River Watershed in USA along with weather, stream and water quality gauge locations

(TP) in streams was also available from the St. Joseph River Watershed Initiative (SJRWI) program. Figure 2 shows the location of the St. Joseph River watershed, and the locations of the gauging stations of water quality, and flow. The sediment data were available for the IDEM station (2001–2009) that coincides with the USGS station near the watershed outlet and were included in the analysis. Nutrient data (nitrate and TP) were available for 25 stations. All the water quality data were in the form of discrete daily data, with no measurements being made in the winter season (November–March). The observed stream flow was measured for a period of 1990–2009 from USGS station with Station ID 04180500. The minimum flow observed was 0.99 m^3/s and the maximum flow to be 436.08 m^3/s, with a mean and standard deviation of 30.25 and 40.20 m^3/s, respectively.

Methodology

SWAT model setup

The SWAT model to be set up for a watershed, the GIS input files corresponding to digital elevation model (DEM), land use/cover and soil data are essential. The DEM, i.e., the elevation data, with 30 m resolution was obtained from National Elevation Dataset (NED NAD 83, http://seamless.usgs.gov). The land use data for the watershed was collected from the Cropland Data Layer (CDL, 2009) (http://www.nass.usda.gov/research/Crop-land/SARS1a.htm). The USDA Natural Resources Conservation Service (NRCS) maintains the Soil Survey Geographic Database (SSURGO) for Indiana, Michigan and Ohio. There were a total of 40 different soil types for all the seven counties combined. The separate data for these three states were merged to get a single soil layer, and was used in this study. ArcSWAT (version 2012.10_1.13) was used to parameterize the watershed, and all the data layers were projected to NAD 83 (North American Datum) UTM 16N coordinate system.

Weather data (precipitation, minimum and maximum temperature) for SWAT model simulation was obtained from the National Climate Data Centre (NCDC). There were five weather stations (see Fig. 2) with long-term availability of weather data, and were considered in the present study. The selected stations were Hillsdale and Hudson 3E in Michigan, Angola and Garrett 1S in Indiana and Montpelier in Ohio. The Hudson 3E was not included as a station for temperature data due to lack of sufficient data. The SWAT model includes a weather generator and was used to fill a few missing data points (3.5% of temperature data and 2.6% precipitation data). The relative humidity, solar radiation and wind data corresponding to the study area were obtained from the official SWAT website, where the climatic data for many watersheds are uploaded.

The DEM, the weather data, and the land use/soil/slope were given as input to the ArcSWAT (SWAT version 615). There were 54 sub-basins after the watershed delineation. Land use/soil/slope data were used for HRU definition. Three slope classes were considered for HRU classification; 0–2, 2–5 and above 5%. A threshold of 50 ha was considered for the soil type, and 10 ha threshold on slope. No threshold limit was given for land use (0%) to consider all the land use categories present in the watershed since the model was later used for land use change analysis. A total of 3062 HRU's were obtained after the HRU delineation. The SWAT model was run for 20 years (1990–2009), with first 3 years as warm up period (1990–1992) for the model. Warm up period is given to the model for stabilizing the soil moisture and the soil chemical composition.

In agricultural watersheds, crop management practices play an important role in controlling water and nutrient dynamics. The present cropping pattern in the watershed is majorly corn–soybean rotation, and was considered for the analysis. The "drain" option was turned on to include tile drainage present in agricultural fields in the watershed. The management practices used in the model were same as reported in Cibin et al. (2016). In the case of cropping options to plant *Miscanthus* and Switch grass in different scenario simulation, 122 and 152.5 kg/ha of urea fertilizer was considered to be applied 15 days after the planting date for each crop, respectively (Cibin 2013).

Sensitivity analysis of SWAT model parameters

A total of 28 model parameters are reported (Arabi et al. 2007) to influence the stream flow simulation in SWAT (Table 1). Since the calibration of all 28 parameters is a difficult task, a sensitivity analysis was performed on the SWAT parameters for St. Joseph River basin. The present study used the one-at-a-time (OAT) sensitivity analysis method to prune the number of parameters to be calibrated. In this method, one parameter value was changed at a time, and the output results were analyzed to check the influence of that parameter in the output results. Nash Sutcliffe Efficiency (NSE, Nash and Sutcliffe 1970) was used as the sensitivity index to evaluate the changes in simulated results corresponding to the changes in parameter value. This procedure was repeated for all the 28 SWAT parameters. Sub-basin level and HRU level parameters are used for sensitivity analysis. The sensitivity analysis indicated 15 stream flow parameters to be sensitive (Table 1). All of the 15 parameters were considered for the model calibration.

Calibration and validation of SWAT model

The SWAT model was calibrated for stream flow using the SCEM-UA algorithm. However, the requirement of large

Table 1 List of parameters considered for sensitivity analysis

Sl. no.	Parameter	File	Description	Hydrological process affected	Parameter value range	Calibrated value
1	SFTMP	.bsn	Snow melt base temperature (°C)	Snow	−5 to 5	−1.69
2	SURLAG	.bsn	Surface runoff lag co-efficient (days)	Surface runoff	0 to 12	1.83
3	SMFMX	.bsn	Maximum snowmelt factor for June 21(mm H_2O/°C/day)	Snow	0 to 10	1.87
4	TIMP	.bsn	Snow pack temperature lag factor	Snow	0.01 to 1	0.83
5	ESCO	.hru	Soil evaporation compensation factor	Evapotranspiration	0 to 1	0.88
6	SLOPE	.hru	Average HRU slope steepness (%)	Surface runoff	−0.50 to 1	0.58
7	SLSBBSN	.hru	Average slope length of HRU (%)	Surface runoff	−0.5 to 0.5	−0.48
8	DEP_IMP	.hru	Depth to impervious layer (mm)	Ground water	0 to 6000	0.02
9	EPCO	.hru	Plant uptake compensation factor	Evapotranspiration	0 to 1	0.52
10	ALPHA_BF	.gw	Base flow recession co-efficient (days)	Groundwater	0 to 1	0.15
11	GWQMN	.gw	Threshold depth of water in the shallow aquifer for return flow to occur (mm H_2O) (mm)	Groundwater	0 to 5000	1027.44
12	CN_2	.mgt	Curve number (%)	Surface runoff	−0.25 to 0.15	−0.07
13	SOL_AWC	.sol	Available soil water capacity	Infiltration	0.3 to 1	0.48
14	SOL_k	.sol	Saturated hydraulic conductivity (%)	Infiltration	−0.25 to 0.25	0.17
15	SOL_z	.sol	Depth from soil surface to the bottom layer (%)	Infiltration	−0.50 to 1	0.05
16	OV_N	.hru	Manning's *N* for overland flow	Overland flow	0.1 to 0.3	NA
17	RSDIN	.hru	Initial residue cover (kg/ha)	Infiltration	0 to 2000	NA
18	GW_DELAY	.gw	Ground water delay time (days)	Groundwater	0 to 500	NA
19	GW_REVAP	.gw	Revap co-efficient	Groundwater	0.02 to 0.2	NA
20	BIOMIX	.mgt	Biological mixing efficiency	Infiltration	0.01 to 1	NA
21	DDRAIN	.mgt	Depth to subsurface drain (%)	Tile drain	0.001 to 0.6	NA
22	TDRAIN	.mgt	Time to drain soil to field capacity (%)	Tile drain	0.1 to 150	NA
23	GDRAIN	.mgt	Drain tile lag time (%)	Tile drain	0.01 to 0.3	NA
24	CH_COV1	.rte	Channel erodibility factor	Channel flow	−1.5	NA
25	CH_KII	.rte	Effective hydraulic conductivity in main channel (mm/h)	Channel flow	−0.5	NA
26	CH_NII	.rte	Manning's *N* for main channel	Channel flow	−1.3	NA
27	CH_SII	.rte	Average slope of main channel (%)	Channel flow	−0.5	NA
28	CHCOV2	.rte	Channel cover factor (%)	Channel flow	−0.1	NA

number of simulations for the SCEM-UA was a major concern. The SWAT model for this study took about 4 min for each run and was anticipated to take approximately 400–500 h with 16 complexes having a population size of 96 for the SCEM-UA. Therefore, methods to reduce this computational requirement were explored. One of the available options was to perform the SCEM-UA under a parallel computing framework, instead of the existing sequential computing environment (Her et al. 2015). Accordingly, the algorithm was implemented in a parallel computing framework. The parallel computing framework essentially perform the model simulations in parallel in different processors, and the simulations are done at the Purdue supercomputer facility (https://www.rcac.purdue.edu) to further reduce the time requirement. A total '*s*' number of parameter sets are sampled using the Latin hypercube sampling (LHS) procedure (described in Sect. 4.4). These *s* points (parameter sets) are divided among *Y* parallel processors. These parallel processors would compute the posterior density of each sample individually. Subsequently, the results from each processor are combined together to arrange the sample according to the decreasing order posterior density. The remaining steps are same as that of the sequential SCEM-UA. The study used 16 complexes, with a population size of 96 and 10,000 function evaluations as termination criteria.

The model was initially calibrated for stream flow on a daily time scale with the available observed data from the watershed outlet (corresponding to USGS station IDs 04180000—Fig. 2). The SWAT model for St. Joseph River watershed was calibrated for a period of 7 years (01/01/1993–31/12/1999) and validated for 10 years (01/01/2000–31/12/2009). The objective function considered for the calibration was to minimize the root mean square error (RMSE), which is evaluated using the Eq. (2):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_i^n (O_i - P_i)^2}{n}}, \quad (2)$$

where O_i is observed (measured) data for day i, and P_i is the predicted (simulated) data for day, and n is the number of observations.

The stream flow calibration of the model was followed by the sediment calibration. Data on sediment concentration was limited. Many researchers have employed Load Estimator (LOADEST) (Runkel et al. 2004) for verification of the sediment simulation by SWAT model in the absence of sufficient observed data (Jha et al. 2007; Femeena 2013; Cibin 2013; Duru 2015). Accordingly, the LOADEST model was employed in this study too. The daily sediment interpolation by LOADEST induces high uncertainty in the results, and hence monthly calibration was performed for sediments.

The parameters influencing sediment erosion and sediment transport in SWAT includes (1) SLSUBBSN (average slope length of HRU), (2) HRU_SLP (average HRU slope steepness) (3) PRF (peak rate adjustment factor for sediment routing in main channel), (4) SPCON (linear parameter for calculating the maximum amount of sediment that can be re-entrained) and (5) SPEXP (exponential factor for calculating sediment re-entrained) at the sub-basin level, and (6) USLE_P (USLE equation support practice factor) at the HRU level. Out of the six parameters, the SLSUBBSN and the HRU_SLP were only found to be sensitive during the sensitivity analysis and were included in the model calibration. Some of the other four parameters (PRF and SPEXP) are the parameters that affect the routing of sediment. Since this study considered only the sediment generation at the source level itself (i.e., no routing), these parameters were assumed to have the default values. The other parameters too, since were not very sensitive, were provided with the default values. Nonetheless, an exercise was conducted to check the influence of these parameters on the sediment output by the model, by perturbing the value from their default value. It was found that altering the values for these parameters did not produce significant difference in the final sediment loading. This analysis was performed through a visual inspection of the plots of sediments. Hence, the parameter values obtained after the calibration of stream flow was taken as the best parameter values for sediment load simulation also.

The major parameters that can influence the nutrients (nitrate and total phosphorus) in the SWAT model are BIOMIX (biological mixing efficiency), NPERCO (nitrate percolation co-efficient), PPERCO (phosphorus percolation co-efficient), and parameters related to tile drains (TDRAIN, GDRAIN, DDRAIN). During sensitivity analysis, BIOMIX and tile drain parameters were found to be non-sensitive. An exercise with the perturbed values of NPERCO, PPERCO and certain other parameters did not show significant difference in the nutrient loading. Consequently, the parameter values obtained after the calibration of stream flow was taken as the best parameter values for nutrient simulation also.

Creation of ensembles of parameters and simulations

As mentioned earlier, the major focus of this study is to assess the impact of parameter uncertainty in the model simulations on the consequent decisions. Therefore, the quantified parametric uncertainty needs to be transformed into the model simulation uncertainty. To achieve this, an ensemble simulation approach is considered in this study. A total of 1500 parameter sets were sampled using the LHS technique for this purpose. The LHS is a stratified sampling technique, in which the samples of a parameter are generated considering the probability distribution followed by the parameter. This technique can be used to generate input values for the estimation of expected function values of the output variables (McKay et al. 1979). The LHS technique can reduce the sampling sizes when compared to Monte Carlo random sampling method (Wu and Chen 2015). In this technique, the parameter range is divided into number of equal probability regions. Hence, the regions with higher probability will have less width, and the regions with lower probability will have larger widths. Then, equal number of samples is drawn from each region. Thus, in the overall sampling, more samples are taken from high probability region and less number of samples are taken from the low probability region, thus preserving the probability distribution of the variable in the total samples. This exercise can be done by considering the cumulative distribution function of the variable. The cumulative density function, cdf, on the y-axis range 0–1 is divided into number of equal subintervals. The corresponding intervals in the x-axis gives a smaller x range when the slope is steep and a wider x range when the slope is flatter. This again produces the regions with high probability with smaller width and larger width for lower probability region. Then, equal number of y-values is sampled from each subinterval. The corresponding x-values are then determined.

In the ensemble approach, the parametric uncertainty is transferred into simulation uncertainty by constructing the prediction interval for the model output (Kasiviswanathan and Sudheer 2013). The coverage probability (also known as percentage of coverage) and width of the prediction interval are the two major indices reported in the literature for evaluating prediction interval (Zhang et al. 2009a, b; Alvisi and Franchini 2011; Kasiviswanathan and Sudheer 2013). The coverage probability measures the percentage of observed values that fall within the prediction band. In theory, if the width of prediction band is wider, it covers most of the observed values. However, To include more observed values in the prediction band, compromising on the width of the prediction band is not desirable. Since these measures are conflicting, a desired solution is to have maximum coverage with a narrow prediction band. The two uncertainty indices, i.e., percentage of coverage (POC) and average width (AW) are defined as follows:

$$\mathrm{POC} = \left(\frac{1}{n} \sum_{i=1}^{n} c_i \right) \times 100, \tag{3}$$

$$\mathrm{AW} = \frac{1}{n} \sum_{i=1}^{n} \left[\hat{y}_i^U - \hat{y}_i^L \right], \tag{4}$$

where n is the total number of patterns used for constructing the prediction interval; $\hat{y}_i^U$ and $\hat{y}_i^L$ are the upper and lower bound estimation of the ith pattern; $c_i = 1$ if the observed values of target fall in the prediction band $\left[\hat{y}_i^U, \hat{y}_i^L \right]$, otherwise $c_i = 0$.

Results and discussions

Efficacy of calibration of SWAT by SCEM-UA

The calibrated values of the 15 parameters, along with their uncertainty calibration bounds, are presented in Table 1. The calibrated values were comparable with the reported values of the parameters for the same basin (Femeena 2013). The simulated flow hydrograph along with observed, during the calibration period as well as the validation period, are presented in Fig. 3. The simulated stream flow was found to match reasonably good with the observed flows both in the calibration and validation periods, except for a few high flow events. The summary statistics along with statistical model performance measures are presented in Table 2. It can be noted from Table 2, that the values of the r^2 and the NSE for the simulations during calibration period are the same (0.81), indicating a good simulation by the model (Engel et al. 2007; Moriasi et al. 2007). The values of the indices are similar during the validation period (0.79 and 0.78 for r^2 and NSE, respectively). The RMSE value of the simulation is found to be much less than the observed mean flow value of the flow series (18.52 and 18.86 m^3/s as compared to 29.72 and 30.77 m^3/s, during the calibration and validation period, respectively). The summary statistics of the simulated stream flow series were comparable with that of the observed stream flow series.

The flow duration curve and the mass curve of the stream flow are indicators for the volume reliability of the stream

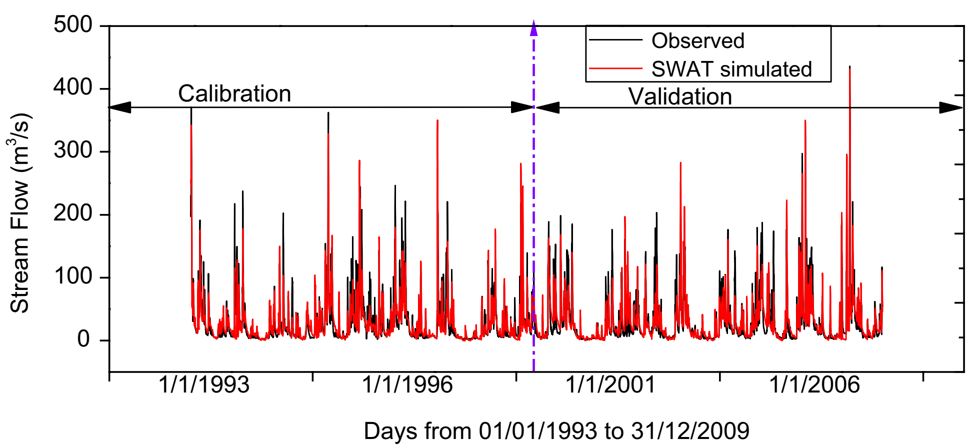


Fig. 3 Daily time series plot for the calibration (left section) and validation (right section) period

Table 2 Calibration and validation statistics

	Daily flow			Monthly flow		Observed daily mean (m^3/s)	Simulated daily mean (m^3/s)
	r^2	NSE	RMSE (m^3/s)	r^2	NSE		
Calibration	0.81	0.81	18.52	0.89	0.88	29.72	29.78
Validation	0.79	0.78	18.86	0.88	0.88	30.77	31.07

flow, and accordingly a comparison of the flow duration curve and mass curve of the observed and simulated stream flow series is performed. Figure 4a, b depict the flow duration and mass curve, respectively. An average deviation of 9% is observed between the two flow duration curves, derived from the observed and the simulated flow series. A similar behavior is found in the case of mass curve also. Nonetheless, in general, the model simulations can be considered good.

Figure 5 shows the plot of SWAT-simulated sediment yield and the LOADEST estimated annual sediment loading at the watershed outlet. It can be seen that most of the SWAT simulations are contained within the 95% confidence range created by the LOADEST model, except for a few time periods. As mentioned earlier, it was observed that altering the values for parameters, for sediment simulation, did not produce considerable difference in the final sediment loading.

Though the number of discrete measurements of nitrate and total phosphorous (TP) were limited, the available measured data was visually compared with the SWAT-simulated nutrient concentration for evaluating the effectiveness of the model simulation. Figure. 6 presents the visual comparison for nitrate and TP, respectively, and it can be observed that the simulated nutrients (nitrate and TP) were following the trend of variation of these nutrients in the observed data. Consequently, the values of parameters for nutrient simulation were not altered any further.

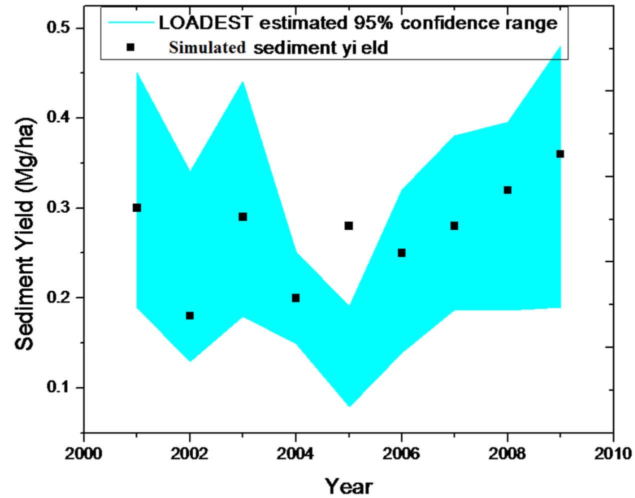


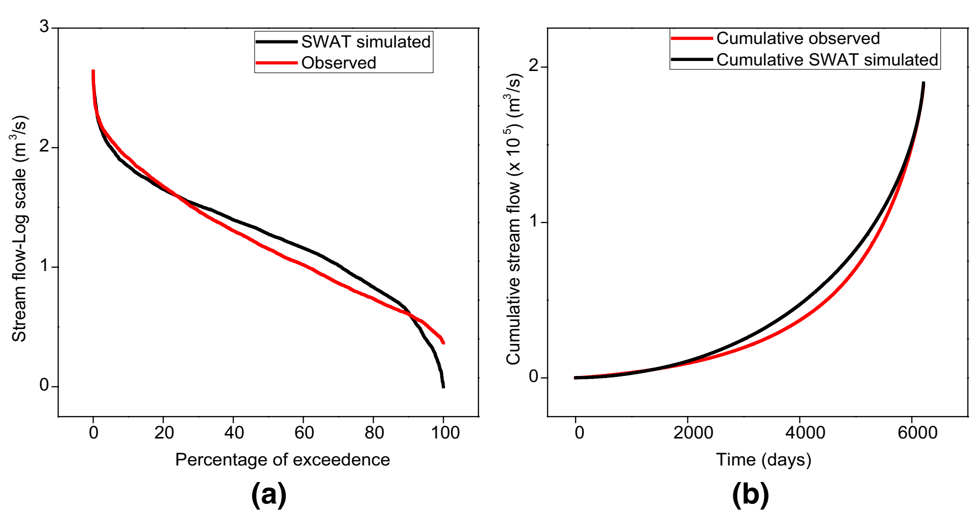
Fig. 5 Time series plot of SWAT simulated, LOADEST estimated 95% confidence range for annual sediment yield (2001–2009)

Evaluation of uncertainty of SWAT model simulations

It is to be noted that the SCEM-UA converged to an acceptable level of error (RMSE in this case) with less number of generations. The study considered 16 complexes consisting of 6 points each, thereby making 96 function evaluations in one iteration (generation). The Fig. 7 provides the box plot of the RMSE variations in each generation. From Fig. 7, the variation of error after 25 generations was not very significant. The change in RMSE after 25 generations were to the tune of 0.30 m^3/s. Therefore, the algorithm was assumed to have converged at 25th generation, and the parameters were selected for further analysis. The RMSE value of the model at convergence was observed to be 18.52 m^3/s (NSE of 0.81). Twenty-five generations in SCEM-UA corresponds to 2400 model evaluations. Therefore, the SCEM-UA can be considered to be a relatively better algorithm in the case of model calibration.

The probability distribution (posterior) of the SWAT parameters inferred by the SCEM-UA algorithm for the St. Joseph River watershed are presented in Fig. 8. The converged probability distribution functions were derived using a Best fit program, @Risk (Palisade Corp. CA, USA). This

Fig. 4 **a** Flow duration curve for the entire simulation period (1993–2009). **b** Mass curve for the entire simulation period (1993–2009)



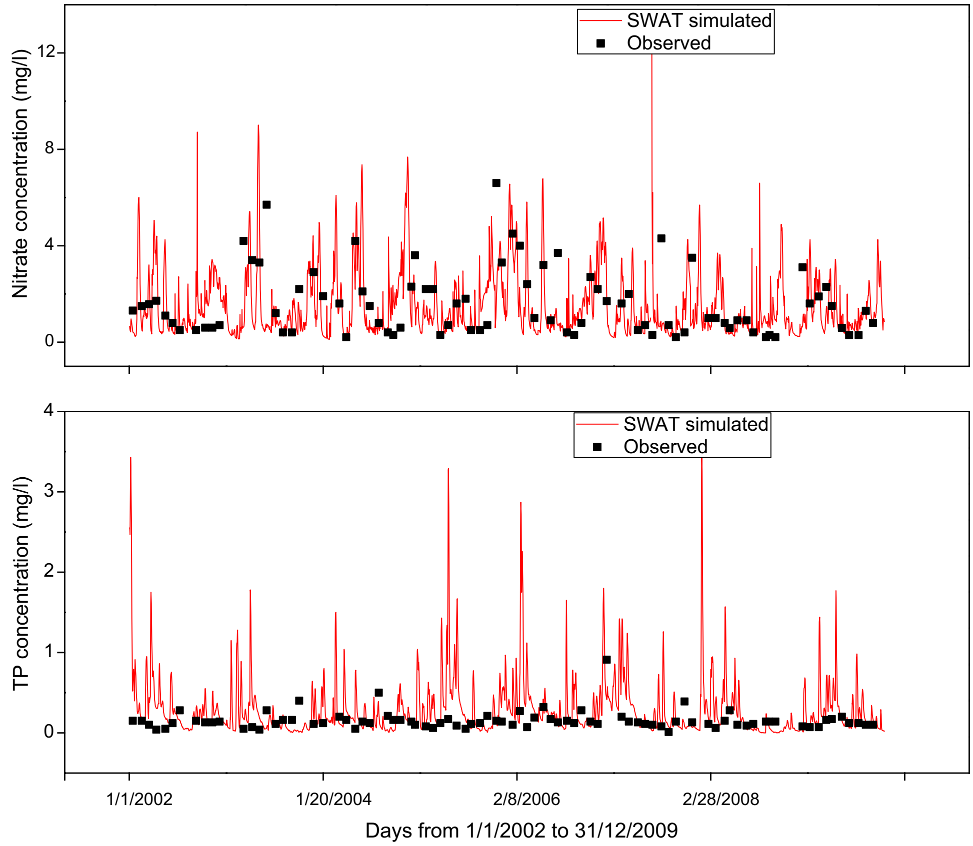


Fig. 6 Time series plot of SWAT-simulated- and -measured nitrate and total phosphorous during the simulation period

program considers 28 different distributions to the data, and ranked them according to the specified goodness of fit criterion. The Chi-square goodness of fit criterion was used to evaluate and rank the distributions and the parameters of the distributions were estimated using the maximum likelihood estimator, and are presented in Table 3. The analysis suggested that the parameters followed varying distribution with different shape and location parameters. Table 4 provides the range of each parameter considering 95% confidence interval. The data presented in the table indicate that the SCEM-UA sampling helps reduce the effective range of parameters after the calibration. For instance, the effective range for SURLAG has reduced as 1.22–1.88 from 1.0–12.0. The parameter ESCO range shrunk as 0.77–0.99 from its original range of 0.0–1.0. The lower and upper bound of the 95% confidence level range of the 15 SWAT parameters for St. Joseph River watershed is presented in Table 4. A reduction in range, similar to that for SURLAG and ESCO, can be seen in the case of other parameters also (see Table 4).

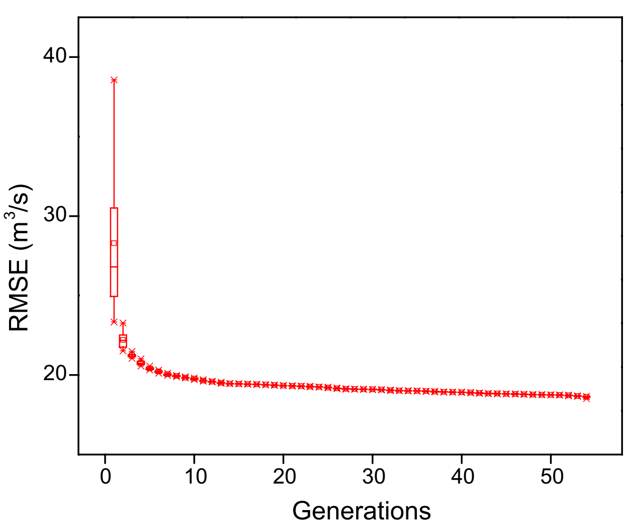


Fig. 7 Progressive variation of RMSE along the number of generations in SCEM-UA

Performance of the ensemble simulations

As mentioned earlier, a total of 1500 parameter sets were sampled using the LHS technique for creating the ensemble simulations. The variability of these parameter values in the 95% confidence range is shown in Fig. 9. The performance of the members of ensemble simulations was evaluated, and all of them were simulating the stream flow at acceptable levels; the NSE and r^2 value for all of them were above 0.50.

The ensemble prediction interval of the stream flow hydrograph, along with the observed values, is presented in Fig. 10 for the calibration and validation period, respectively.

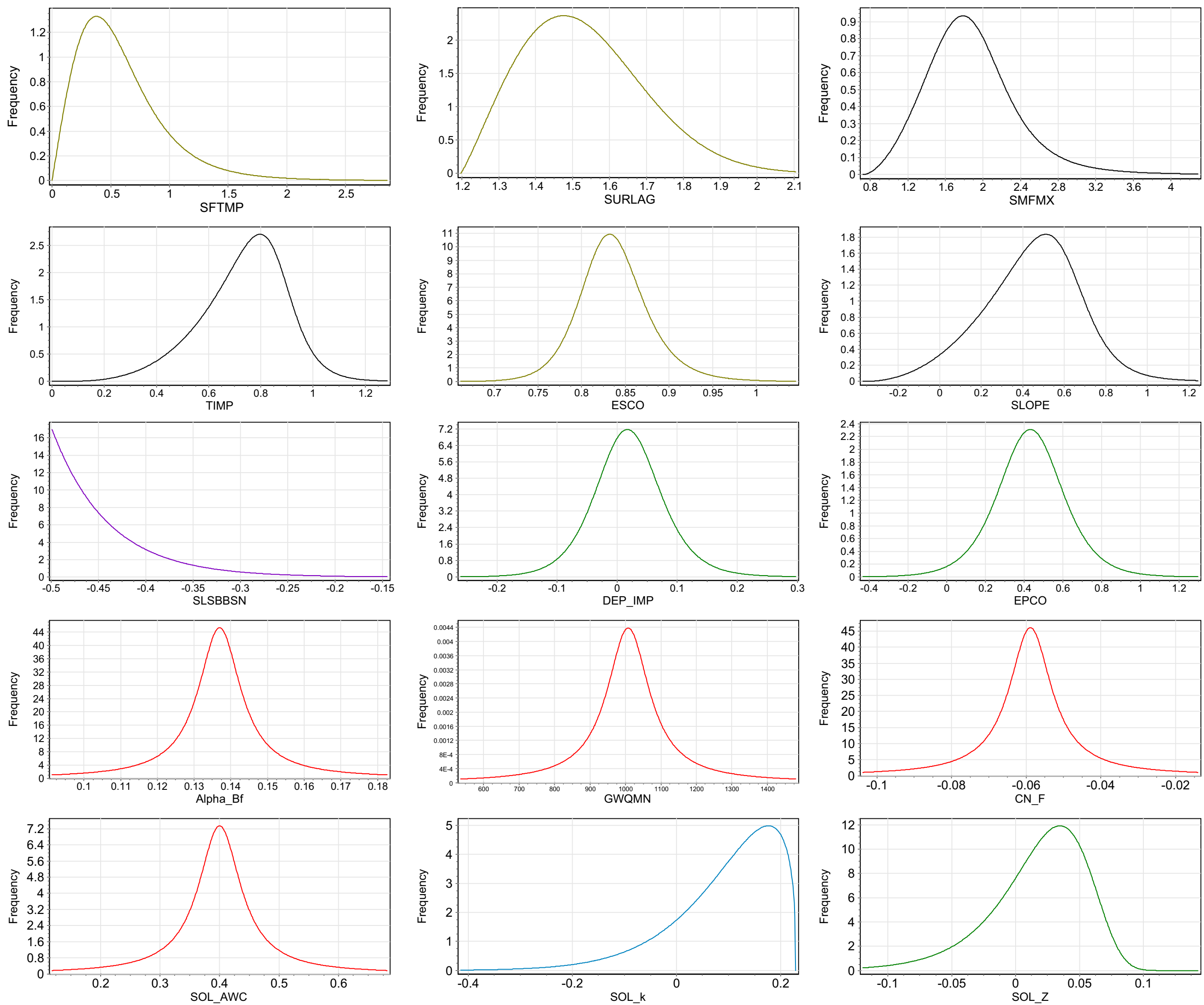


Fig. 8 Derived posterior probability function for stream flow parameters

Note that, the hydrograph in Fig. 10 is plotted for a representative runoff event during the periods of evaluation, for clarity of information. It may be noted that most of the observed points fall within the prediction interval of the ensembles (Fig. 10). The generated ensemble showed a POC of 62% with an average width of 19.2 m^3/s for the entire period of analysis. It is noted that during certain stages of flow (plausibly in the falling limb) the average width of the prediction interval is narrow, and it can be attributed to the deficiency of the model in appropriately representing the flow dynamics at peak and after the peak. It can also be due to the fact that the interaction between the parameters of the SWAT was not explicitly considered during calibration as well as the ensemble generation. The prediction interval derived from the ensemble indicates an acceptable level of plausible error due to an uncertainty in the model parameters. The ensemble consists of independent model simulations with different parameter sets that have neutralizing error on the mean of ensembles, and the mean of ensemble can be considered as a good forecast for applications.

Variability of performance statistics across the ensembles were assessed by analysing the output corresponding to a few (5 in this study) selected parameter sets from the 1500 ensembles. This selection is done in such a way that they range over the entire uncertainty space. The rationale behind the selection of these five sets were, (1) one set representing the upper bound of the prediction band, (2) one set representing the lower bound of the prediction band, (3) one set representing the average of the prediction band, and (4) two parameter sets from the intermediate range [between the average and boundaries (upper and lower) of the simulation]. The flow simulation

Table 3 Probability distribution functions of parameters

Sl. no.	Parameter	Probability distribution function (PDF)	PDF parameters	PDF equation
1	SFTMP	Burr	$k=3; \alpha=2; \beta=1; \gamma=0$	$f(x)=\frac{\propto k\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}}{\beta\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{k+1}}$
2	SURLAG	Burr (4P)	$k=84.50; \alpha=2.13; \beta=3.041; \gamma=1.19$	$f(x)=\frac{\propto k\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}}{\beta\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{k+1}}$
3	SMFMX	Dagum	$k=0.50; \alpha=5.47; \beta=1.35; \gamma=0.722$	$f(x)=\frac{\propto k\left(\frac{x-\gamma}{\beta}\right)^{\alpha k-1}}{\beta\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{k+1}}$
4	TIMP	Dagum	$k=0.24; \alpha=16.87; \beta=0.89; \gamma=0$	$f(x)=\frac{\propto k\left(\frac{x-\gamma}{\beta}\right)^{\alpha k-1}}{\beta\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{k+1}}$
5	ESCO	Burr	$k=0.78; \alpha=48.40; \beta=1.01; \gamma=-0.18$	$f(x)=\frac{\propto k\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}}{\beta\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{k+1}}$
6	SLOPE	Dagum	$k=0.22; \alpha=14.19; \beta=1.03; \gamma=-0.37$	$f(x)=\frac{\propto k\left(\frac{x-\gamma}{\beta}\right)^{\alpha k-1}}{\beta\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{k+1}}$
7	SLSBBSN	Erlang	$m=1; \beta=0.05; \gamma=-0.49$	$f(x)=\frac{(x-\gamma)}{\beta^{m}\Gamma(m)}\exp\left(-\frac{x-\gamma}{\beta}\right)$
8	DEP_IMP	Log-logistic	$\alpha=8.83\text{E}+07; \beta=8.39\text{E}+05; \gamma=-8.39\text{E}+05$	$f(x)=\frac{\propto}{\beta}\left(\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}\right)\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{-2}$
9	EPCO	Log-logistic	$\alpha=4.39; \beta=0.33; \gamma=0.08$	$f(x)=\frac{\propto}{\beta}\left(\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}\right)\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{-2}$
10	ALPHA_BF	Cauchy	$\sigma=0.006; \mu=0.136$	$f(x)=\left(\pi\sigma\left(1+\left(\frac{x-\mu}{\sigma}\right)^{2}\right)\right)^{-1}$
11	GWQMN	Cauchy	$\sigma=68.41; \mu=1008.0$	$f(x)=\left(\pi\sigma\left(1+\left(\frac{x-\mu}{\sigma}\right)^{2}\right)\right)^{-1}$
12	CN_F	Pert	$m=-0.05; a=-0.08; b=-0.02$	$f(x)=\frac{1}{B(\alpha_1,\alpha_2)}\frac{(x-a)^{\alpha_1-1}(b-x)^{\alpha_2-1}}{(b-a)^{\alpha_1+\alpha_2-1}}$
13	SOL_AWC	Cauchy	$\sigma=0.04; \mu=0.40$	$f(x)=\left(\pi\sigma\left(1+\left(\frac{x-\mu}{\sigma}\right)^{2}\right)\right)^{-1}$
14	SOL_K	Generalized extreme value	$k=-0.62; \sigma=0.09; \mu=0.08$	$f(x)=\left\{\begin{array}{ll}\frac{1}{\sigma}\exp\left(-(1+\text{kz})^{-\frac{1}{k}}\right)(1+\text{kz})^{-1-\frac{1}{k}} & k\neq 0\\ \frac{1}{\sigma}\exp(-z-\exp(-z)) & k=0\end{array}\right\}$
15	SOL_Z	Weibull	$\alpha=1.79\text{E}+06; \beta=14{,}124; \gamma=-14{,}124$	$f(x)=\frac{\propto}{\beta}\left(\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}\right)\left(\exp-\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)$

Table 4 Upper and lower bound of stream flow parameters corresponding to 95% confidence interval

Parameter	Upper bound corresponding to 95% confidence interval	Lower bound corresponding to 95% confidence interval
SFTMP	−4.81	−1.35
SURLAG	1.22	1.88
SMFMX	0.89	3.90
TIMP	0.34	0.99
ESCO	0.79	0.90
SLOPE	−0.14	0.85
SLSBBSN	−0.50	−0.12
DEP_IMP	−0.02	0.06
EPCO	0.23	0.87
ALPHA_BF	0.09	0.15
GWQMN	205.59	1226.44
CN_f	−0.08	−0.03
SOL_AWC	0.30	0.64
SOL_k	−0.15	0.23
SOL_z	0.02	0.05

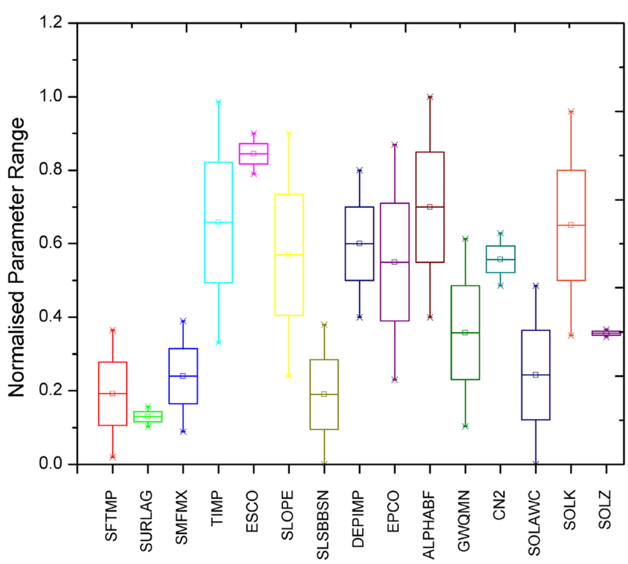


Fig. 9 Variability of LHS sampled parameter values in the 95% CI range

performance of these parameter sets, and the simulated nutrient (at the watershed outlet) using these parameter sets are reported in Table 5. It is to be noted that the flow simulation by these parameter sets does not vary significantly (29.83–33.13 m^3/s). All of them obtained similar values of r^2 and NSE (Table 5), which indicates that the simulations are good, and were comparable across the ensembles. No significant variation was observed within the ensembles for nutrient simulation also. These results suggest that the 1500 ensembles generated from the identified parameter range by SCEM-UA were effective, and help understand the uncertainty in the model simulations. This uncertainty is helpful in suggesting management plans using the simulated results.

Summary and conclusions

The SCEM-UA, which is an automatic Bayesian parameter inference algorithm based on Markov Chain Monte Carlo (MCMC) methods, was found to be efficient in calibrating the SWAT model parameters with less number of generations. Since the pseudo-simulators could not be employed during the calibration of the model, the computational requirement of the SCEM-UA was addressed by performing the calibration in a parallel processing framework. The major advantage of the SCEM-UA algorithm is that it helps quantify the uncertainty of the model parameters, along with the calibration process. The results also indicated that the SCEM-UA can achieve the calibration process in less number of function evaluations of the model as compared to other optimization algorithms. It was seen that the algorithm helps reduce the uncertainty (POC = 62% and AW = 19.2 m^3/s), and also identifies the plausible range of parameters that simulate the processes with less uncertainty. The prediction band of the stream flow, developed using the generated ensembles, was found to be acceptable for further applications of the SWAT model for St. Joseph River watershed. It is noted that only 62% of the observed stream flows were well within the developed prediction band, and warrants investigation of other sources of uncertainty. The suggested uncertainty bounds by SCEM-UA could be used to evaluate the reliability of decisions that uses the model simulations as input.

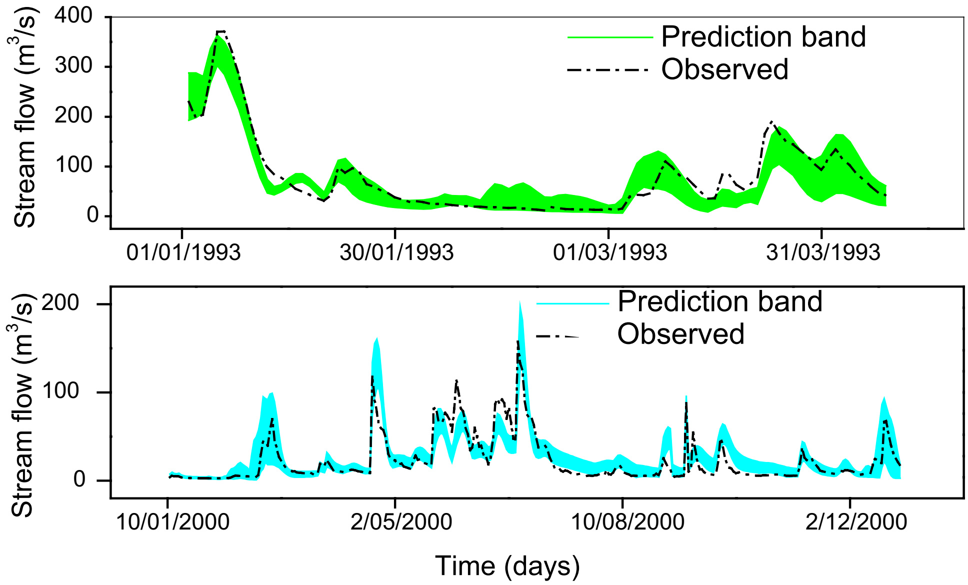


Fig. 10 Prediction band for calibration (upper) and validation (lower) period

Table 5 Performance statistics and nutrient simulations using representative parameter sets

	Parameter set number				
	#1	#2	#3	#4	#5
Mean flow (m^3/s)	26.91	33.13	30.6	29.83	32.2
RMSE	19.48	20.9	19.23	19.9	19.65
r^2	0.78	0.76	0.79	0.77	0.79
NSE	0.78	0.75	0.79	0.77	0.78
Nitrate (kg/ha/year)	11.00	9.60	7.90	9.90	10.00
TP (kg/ha/year)	0.90	0.80	0.81	0.88	1.00

References

Abbaspour KC, Vejdani M, Haghighat S, Yang J (2007) SWAT-CUP calibration and uncertainty programs for SWAT. In: Oxley L, Kulasiri D (eds) MODSIM 2007 international congress on modelling and simulation. Modelling and Simulation Society of Australia and New Zealand, Melbourne, pp 1596–1602

Abbaspour KC, Rouholahnejada E, Vaghefia S, Srinivasan R, Yang H, Kløve B (2015) A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high-resolution large-scale SWAT model. J Hydrol 524:733–752

Alvisi S, Franchini M (2011) Fuzzy neural networks for water level and discharge forecasting with uncertainty. Environ Model Softw 26(4):523–537

Arabi M, Govindaraju RS, Engel B, Hantush M (2007) Multiobjective sensitivity analysis of sediment and nutrient processes with a watershed model. Water Resour Res 43:W06409

Arnold JG, Moriasi DN, Gassman PW, Abbaspour KC, White MJ, Srinivasan R, Santhi C, Harmel RD, Van Griensven A, Van Liew MW, Kannan N, Jha MK (2012) SWAT: model use, calibration, and validation. Trans ASABE 55(4):1491–1508

Athira P, Sudheer KP (2015) A method to reduce the computational requirement while assessing uncertainty of complex hydrological models. Stoch Environ Res Risk Assess 29(3):847–859

Beven K (2006) A manifesto for the equifinality thesis. J Hydrol 320(1–2):18–36

Beven K, Binley A (1992) The future of distributed models: model calibration and uncertainty prediction. Hydrol Process 6:279–298

Beven KJ, Freer J, Hankin B, Schulz K (2000) The use of generalized likelihood measures for uncertainty estimation in higher-order models of environmental systems. In: Fitzgerald Smith RC, Walden AT, Young PC (eds) Nonlinear and nonstationary signal processing. Cambridge University Press, Cambridge

Box GEP, Tiao GC (1973) Bayesian inference in statistical analysis. Addison-Wesley Publishing Company, Boston, pp 10–20

Boyle DP, Gupta HV, Sorooshian S (2000) Toward improved calibration of hydrologic models: combining the strengths of manual and automatic methods. Water Resour Res 36(12):3663–3674

Brazier RE, Beven K, Freer J, Rowan JS (2000) Equifinality and uncertainty in physically based soil erosion models: application of the GLUE methodology to WEPP—the Water Erosion Prediction Project—for sites in the UK and USA. Earth Surf Proc Landf 25(8):825–845

Cibin R (2013) Optimal Land Use Planning on Selection and Placement of Energy Crops for Sustainable Biofuel Production (Ph.D. dissertation). In: Department of Agricultural and Biological Engineering, Purdue University, ProQuest, UMI Dissertations Publishing

Cibin R, Chaubey I (2015) A computationally efficient approach for watershed scale spatial optimization. Environ Model Softw 66:1–11

Cibin R, Sudheer KP, Chaubey I (2010) Sensitivity and identifiability of stream flow generation parameters of the SWAT model. Hydrol Process 24(9):1133–1148

Cibin R, Trybula E, Chaubey I, Brouder SM, Volenec JJ (2016) Watershed-scale impacts of bioenergy crops on hydrology and water quality using improved SWAT model. GCB Bioenergy 8:837–848

Devia GK, Ganasri BP, Dwarakish GS (2015) A review on hydrological models. Aquat Proc 4:1001–1007

Duan Q, Sorooshian S, Gupta V (1992) Effective and efficient global optimization for conceptual rainfall-runoff models. Water Resour Res 28(4):1015–1031

Duru U (2015) Modeling sediment yield and deposition using the swat model: a case study of Cubuk I and Cubuk II reservoirs, Turkey (Doctoral dissertation, Colorado State University. Libraries)

Engel B, Storm D, White M, Arnold J, Arabi M (2007) A hydrologic/water quality model application. J Am Water Resour Assoc 43(5):1223–1236

Femeena PV (2013) Spatial optimization of cropping pattern in an agricultural watershed for food and biofuel production with minimum downstream pollution (Master thesis). Department of Civil Engineering, Indian Institute of Technology Madras, Chennai

Feyen L, Vrugt JA, Nualláin B, Van Der Knijff J, De Roo A (2007) Parameter optimization and uncertainty assessment for large-scale stream flow simulation with the LISFLOOD model. J Hydrol 332(3):276–289

Fukunaga DC, Cecílio RA, Zanetti SS, Oliveira LT, Caiado MAC (2015) Application of the SWAT hydrologic model to a tropical watershed at Brazil. Catena 125:206–213

Gassman PW, Williams JR, Wang X, Saleh A, Osei E, Hauck LM, Izaurralde RC, Flowers JD (2010) The agricultural policy environmental extender (APEX) model: an emerging tool for landscape and watershed environmental analyses. Trans ASABE 53(3):711–740

Gelman A, Roberts G, Gilks W (1996) Efficient metropolis jumping rules. Bayesian Stat 42:599–608

Green CH, Van Griensven A (2008) Auto calibration in hydrologic modeling: using SWAT2005 in small-scale watersheds. Environ Model Softw 23(4):422–434

Gupta HV, Sorooshian S, Yapo PO (1998) Towards improved calibration of hydrologic models: multiple and no commensurable measures of information. Water Resour Res 34(4):751–763

Hasan MA, Pradhanang SM (2017) Estimation of flow regime for a spatially varied Himalayan watershed using improved multisite calibration of the Soil and Water Assessment Tool (SWAT) model. Environ Earth Sci 76:787. https://doi.org/10.1007/s12665-017-7134-3

Heathman GC, Flanagan DC, Larose M, Zuercher BW (2008) Application of the Soil and Water Assessment Tool and annualized agricultural non-point source models in the St. Joseph River watershed. J Soil Water Conserv 63(6):552–568

Her Y, Cibin R, Chaubey I (2015) Application of parallel computing methods for improving efficiency of optimization in hydrologic and water quality modeling. Appl Eng Agric 31(3):455–468

Jha MK, Gassman PW, Arnold JG (2007) Water quality modeling for the Raccoon River watershed using SWAT. Trans ASABE 50(2):479–493

Kasiviswanathan KS, Sudheer KP (2013) Quantification of the predictive uncertainty of artificial neural network based river flow forecast models. Stoch Environ Res Risk Assess 27(1):137–146

Kasiviswanathan KS, Sudheer KP (2014) Discussion of comparison of three global optimization algorithms for calibration of the Xinanjiang model parameters by Dong-mei Xu, Wen-chuan Wang, Kwokwing Chau, Chun-tian Cheng and Shou-yu, 2013. J Hydroinform 15(1):174–193. https://doi.org/10.2166/hydro.2012.053 (**Journal of Hydroinformatics 16(6):1461–1463**)

Kuczera G, Mroczkowski M (1998) Assessment of hydrologic parameter uncertainty and the worth of multiresponse data. Water Resour Res. https://doi.org/10.1029/98WR00496 (**ISSN: 0043–1397**)

Kuczera G, Parent E (1998) Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm. J Hydrol 211(1):69–85

Maringanti C, Chaubey I, Arabi M, Engel B (2011) Application of a multiobjective optimization method to provide least cost alternatives for NPS pollution control. Environ Manag. https://doi.org/10.1007/s00267-011-9696-2:448-461

McKay MD, Beckman RJ, Conover WJ (1979) Comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics 21(2):239–245

Metropolis N, Rosenbluth AW, Rosenbluth MN, Teller AH, Teller E (1953) Equation of state calculations by fast computing machines. J Chem Phys 21(6):1087–1092

Misirli F, Gupta HV, Sorooshian S, Thiemann M (2003) Bayesian recursive estimation of parameter and output uncertainty for watershed models. In: Duan Q et al (eds) Calibration of watershed models, Water science and application, vol 6. AGU, Washington, D. C., pp 113–124

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE 50(3):885–900

Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models part I—a discussion of principles. J Hydrol 10(3):282–290

Pluntke T, Pavlik D, Bernhofer C (2014) Reducing uncertainty in hydrological modelling in a data sparse region. Environ Earth Sci 72:4801. https://doi.org/10.1007/s12665-014-3252-3

Roth V, Nigussie TK, Lemann T (2016) Model parameter transfer for streamflow and sediment loss prediction with SWAT in a tropical watershed. Environ Earth Sci 75:1321. https://doi.org/10.1007/s12665-016-6129-9

Runkel RL, Crawford CG, Cohn TA (2004) Load estimator (LOADEST)—A FORTRAN program for estimating constituent loads in streams and rivers, Techniques and methods, Chapter A5. US Geological Survey, Reston, Virginia

Schaap MG, Feike JL (1998) Using neural networks to predict soil water retention and soil hydraulic conductivity. Soil Tillage Res 47(1):37–42

Shen ZY, Chen L, Chen T (2012) Analysis of parameter uncertainty in hydrological and sediment modeling using GLUE method: a case study of SWAT model applied to three gorges reservoir region, China. Hydrol Earth Syst Sci 16:121–132. https://doi.org/10.5194/hess-16-121-2012

Singh VP (1995) Watershed modeling. In: Singh VP (ed) Computer models of watershed hydrology. Water Resources Publications, Littleton, pp 1–22

Song L, Liu P (2010) Study of agricultural non-point source pollution based on SWAT. Adv Mater Res 113–114:390–394

Srivastava PK, Han D, Rico-Ramirez MA, Islam T (2013) Sensitivity and uncertainty analysis of mesoscale model downscaled hydrometeorological variables for discharge prediction. Hydrol Process. https://doi.org/10.1002/hyp.9946

Sudheer KP, Chaubey I, Garg V, Migliaccio KW (2007) Impact of time-scale of the calibration objective function on the performance of watershed models. Hydrol Process 21(25):3409–3419

Sudheer KP, Lakshmi G, Chaubey I (2011) Application of a pseudo simulator to evaluate the sensitivity of parameters in complex watershed models. Environ Model Softw 26(2):135–143

Tarantola A (2005) Inverse problem theory and methods for model parameter estimation. Society for Industrial and Applied Mathematics, Philadelphia, pp 41–51

Vazquez-Amabile G, Engel BA, Flanagan DC (2006) Modeling and risk analysis of nonpoint source pollution caused by atrazine using SWAT. Trans ASABE 49(3):667–678

Vrugt JA, Bouten W, Gupta HV, Sorooshian S (2002) Toward improved identifiability of hydrologic model parameters: the information content of experimental data. Water Resour Res 38(12):48–51

Vrugt JA, Gupta HV, Bastidas LA, Bouten W, Sorooshian S (2003) Effective and efficient algorithm for multiobjective optimization of hydrologic models. Water Resour Res. https://doi.org/10.1029/2002WR001746 (**ISSN: 0043–1397**)

Worku T, Khare D, Tripathi SK (2017) Modeling runoff-sediment response to land use/land cover changes using integrated GIS and

SWAT model in the Beressa watershed. Environ Earth Sci 76:550. https://doi.org/10.1007/s12665-017-6883-3

Wu H, Chen B (2015) Evaluating uncertainty estimates in distributed hydrological modeling for the Wenjing River watershed in China by GLUE, SUFI-2, and ParaSol methods. Ecol Eng 76:110–121

Yang J, Reichert P, Abbaspour K, Xia J, Yang H (2008) Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. J Hydrol 358:1–23

Yesuf HM, Melesse AM, Zeleke G, Alamirew T (2016) Streamflow prediction uncertainty analysis and verification of SWAT model in a tropical watershed. Environ Earth Sci 75:806. https://doi.org/10.1007/s12665-016-5636-z

Zhang X, Srinivasan R, Liew M Van (2008) Multi-Site calibration of the SWAT model for hydrologic modeling. Trans ASABE 51(6):2039–2049

Zhang X, Srinivasan R, Bosch D (2009a) Calibration and uncertainty analysis of the SWAT model using genetic algorithms and bayesian model averaging. J Hydrol 374(3–4):307–317. https://doi.org/10.1016/j.jhydrol.2009.06.023

Zhang X, Srinivasan R, Kaiguang Z, Liew M Van (2009b) Evaluation of global optimization algorithms for parameter calibration of a computationally intensive hydrologic model. Hydrol Process 23(3):430–441