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Sensitivity and identifiability of stream flow generation parameters of the SWAT model

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Abstract:

Implementation of sensitivity analysis (SA) procedures is helpful in calibration of models and also for their transposition to different watersheds. The reported studies on SA of Soil and Water Assessment Tool (SWAT) model were mostly focused on identifying parameters for pruning or modifying during the calibration process. This paper presents a sensitivity and identifiability analysis of model parameters that influence stream flow generation in SWAT. The analysis was focused on evaluating the sensitivity of the parameters in different climatic settings, temporal scales and flow regimes. The global sensitivity analysis (GSA) technique based on classical decomposition of variance, Sobol', was employed in this study. The results of the study indicate that modeled stream flow show varying sensitivity to parameters in different climatic settings. The results also suggest that the identifiability of a parameter for a given watershed is a major concern in calibrating the model for the specific watershed, as it might lead to equifinality of parameters. The SWAT model parameters show varying sensitivity in different years of simulation suggesting the requirement for dynamic updation of parameters during the simulation. The sensitivity of parameters during various flow regimes (low, medium and high flow) is also found to be uneven, which suggests the significance of a multi-criteria approach for the calibration of models.

KEY WORDS global sensitivity analysis; identifiability analysis; Sobol' method; SWAT

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INTRODUCTION

The use of distributed hydrological models has become increasingly popular in both research and operational settings. Many of these models are highly complex and are generally characterized by a multitude of parameters. Due to spatial variability in the processes simulated by these models, the value of many of these parameters may not be exactly known. Further, many of them may not be directly measurable. Therefore, in most model applications, a calibration is necessary to estimate model parameter values. Model calibration helps reduce the parameter uncertainty, which in turn reduces the uncertainty in the simulated results. During a model calibration, selected parameters are allowed to vary within predefined bounds until a sufficient correspondence between the model outputs and actual measurements are obtained. However, when the number of parameters in a model is large (either due to large number of sub-processes being considered or due to the model structure itself) the calibration process becomes complex and computationally extensive (Rosso, 1994; Sorooshian and Gupta, 1995). 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.*, 2000). Generally, SA is employed prior to the calibration process in order to identify a candidate set of important parameters that are critical for efficient model calibration.

Techniques employed to perform SA can be grouped into two broad categories: local SA and global sensitivity analysis(GSA) (Saltelli *et al.*, 2000; Muleta and Nicklow, 2005; van Griensven *et al.*, 2006). Local SA, also known as the one-at a –time (OAT) method, identifies the output responses by sequentially varying each model parameter by a certain fraction while other parameters are kept at their nominal values (Spruill *et al.*, 2000; Turanyi and Rabitz, 2000; Holvoet *et al.*, 2005). Even though the OAT method is widely applied to various models due to its ease of operation, the assumption of the linear relationship between the parameter and the corresponding output is a major limitation. As the parameter perturbation moves farther away from the nominal parameter value, the OAT analysis results become less reliable (Helton, 1993).

Global SA (GSA) methods, in contrast, explore the entire range of parameters. In this method, all parameters under consideration are simultaneously perturbed allowing investigation of parameter interactions and their impacts on model outputs. The variance decomposition based GSA method is a widely employed technique in which the output variance between simulations is decomposed into the contribution from individual parameters. The main features of variance decomposition based GSA techniques are: model independence, potential to

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capture the full range of model parameter values, and the ability to identify interactions among parameters (Liburne *et al.*, 2006). The 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; Ratto *et al.*, 2001; Francos *et al.*, 2003; Cariboni *et al.*, 2007) variance decomposition based methods. It has been reported that the 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 the total sensitivity index of individual parameters (Sobol' 1993, 2001). It should be noted that though Sobol's method has found numerous applications in many fields of science and engineering, its application in hydrology is very limited (Pappenberger *et al.*, 2006, 2008; Tang *et al.*, 2007a,b; Cloke *et al.*, 2008).

The Soil and Water Assessment Tool (SWAT) is a hydrologic model widely used to evaluate the impact of climate, land use, and land management decisions on stream flow and water quality (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 (Anand *et al.*, 2007; Gassman *et al.*, 2007). SWAT is a process-based distributed simulation model operating on a daily time step. The SWAT is also characterized by a large number of parameters. Despite a plethora of applications using SWAT, a comprehensive evaluation of its parameter sensitivity is still lacking. While a few studies about parameter sensitivity in SWAT have been reported (Arnold *et al.*, 2000; Spruill *et al.*, 2000; Osidele and Beck, 2001; Lenhart *et al.*, 2002; Francos *et al.*, 2003; Holvoet *et al.*, 2005; White and Chaubey, 2005; van Griensven *et al.*, 2006; Arabi *et al.*, 2007; Muleta *et al.*, 2007; Stow *et al.*, 2007), these were primarily focused on identifying the parameters that should be considered for model calibration. The sensitivity of model parameters may vary considerably among watersheds, time periods of simulation, and the simulation time step (Wagner *et al.*, 2001; Demaria *et al.*, 2007; Tang *et al.*. 2007a,b). With the exception of a few recent studies, most of the SA studies pertaining to watershed models have not comprehensively evaluated these variations in sensitivity (Tang *et al.*, 2007b; van Werkhoven *et al.*, 2008).

Another concern in hydrologic modeling is the equifinality of model parameters where multiple combinations of parameter values may yield the same model output (Johnston and Pilgrim, 1976; Beven and Binley, 1992; Wagener and Kollat, 2007). Consequently, the identifiability of optimal combinations of parameters that result in a truly calibrated model is a major challenge. Therefore, the identifiability of parameters should also be evaluated, in addition to SA, prior to a model calibration so that confidence in the calibrated parameter values is enhanced. While identifiability evaluation has been reported for a few hydrologic models (Wagener *et al.*, 2003; Wagener and Kollat, 2007), we are not aware of any study that has evaluated the identifiability of SWAT parameters.

The focus of this study was to critically evaluate the sensitivity and identifiability of thirteen SWAT parameters that influenced stream flow generation at various temporal scales and flow regimes. We investigated the parameter sensitivity using Sobol's method in two watersheds located in the USA: (i) the St. Joseph River watershed located in Indiana, Michigan, and Ohio; and (ii) the Illinois River watershed located in Arkansas. The remainder of the paper is organized as follows: Following this introduction, a brief description about the methodology is presented, in which discussions about SWAT and its parameters are provided. This is followed by details about the study watersheds and data availability. Subsequently, the details about Sobol's SA method and its implementation are discussed. The results of the sensitivity and identifiability analysis are examined and discussed in the subsequent sections.

METHODOLOGY

The GSA employed Monte Carlo simulation of the SWAT using an ensemble of parameter sets generated by a suitable sampling technique. The predicted stream flow was used to compute the sensitivity of the SWAT parameters. The identifiability of parameters was investigated through visual evaluation. In this study, 13 parameters of the SWAT (Table I) that impacted the simulated stream flow were analysed for their sensitivity and identifiability.

The latin hypercube sampling (LHS) technique (Mckay *et al.*, 1979) was used to effectively sample the high-dimensional parameter sampling space. The LHS method generates samples from the assigned probability distribution of parameters using a stratified sampling approach. Since the parameter probability density function (PDF) of most of the model parameters was not known, a uniform distribution was assumed (Freer *et al.*, 1996; Manache and Melching, 2008). To generate a sample size of N for the variables $\theta_i = (\theta_1, \theta_2, \ldots, \theta_k)$, the range of each θ_i was stratified into N disjointed intervals of equal probability and one value from each of these strata was randomly selected without replacement. This process was repeated until all 13 parameters under consideration were sampled. Once the Monte Carlo simulations were completed for all combinations of parameter values, Sobol's method was employed for the SA. The details about Sobol's method are discussed in later sections. A performance index of the model (Root Mean Square Error (RMSE) or Nash-Sutcliffe efficiency) for all the simulations was plotted against the corresponding parameter value. A unique clear trough (RMSE) or a unique clear peak (efficiency) in the plot was used as an indicator of identifiability of parameter values for model calibration.

Soil and water assessment tool (SWAT) model

SWAT model developed by the United States Department of Agriculture is a conceptual, distributed hydrologic model that operates on a daily time step (Arnold

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

Symbol	Description	Unit	Min.	Max.	Process
ALPHA_BF	Base flow recession coefficient	Days	0	1	Groundwater
CN_f[a]	Curve number	%	−25	15	Surface runoff
ESCO	Soil evaporation coefficient	—	0·001	1	Evapotranspiration
GW_DELAY	Groundwater delay time	Day	1	500	Groundwater
GW_REVAP	Revap coefficient	—	0·02	0·2	Groundwater
GWQMN	Depth of water in shallow aquifer	mm	0	5000	Groundwater
OV_N	Manning's N	—	0·1	0·3	Overland flow
SFTMP	Snowfall temperature	°C	−5	5	Snow
SLOPE[a]	Slope	%	−0·5	1	Surface runoff
SLSUBBSN[a]	Slope sub-basin	%	−0·5	1	Surface runoff
SOL_AWC[a]	Available water capacity	%	−0·3	2	Groundwater, evaporation
SOL_K[a]	Saturated hydraulic conductivity	%	−0·5	1	Groundwater
SURLAG	Surface lag	Day	1	12	Surface runoff

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

et al., 1993). The model was developed to assist water resource managers in assessing the impact of different management practices on long-term water supplies and non-point source pollution in large river basins. Spatially, the model divides a watershed into sub watersheds or sub-basins based on topographic information. The sub-basins are further divided into smaller spatial modeling units known as hydrologic response units (HRU), depending on the heterogeneity of land use and soil types. An HRU is the fundamental spatial unit upon which SWAT simulates the water balance. The hydrological processes modeled in SWAT are surface runoff, soil and root zone infiltration, evapotranspiration, soil and snow evaporation, and baseflow (Arnold *et al*., 1998). SWAT also simulates the fate and transport of nutrients, sediment, pesticides, and bacteria in both land and water phases.

SWAT divides the hydrology of a watershed into two major phases. The first division is the land phase of the hydrologic cycle, which 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 considers the movement of water, sediments, etc. through the channel network to the watershed outlet. The land phase of the hydrologic cycle is modeled in SWAT based on the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{\text{day}} - Q_{\text{surf}} - E_{\text{a}} - w_{\text{seep}} - Q_{\text{gw}}) \tag{1}$$

where SW_t is the final soil water content (in mm H_2O), SW_0 is the initial soil water content (mm), t is the time (days), R_{day} is the amount of precipitation on day i (mm), Q_{surf} is the amount of surface runoff on day i (mm), E_{a} is the amount of evapotranspiration on day i (mm), w_{seep} is the amount of percolation and bypass flow exiting the soil profile bottom on day i (mm), and Q_{gw} is the amount of return flow on day i (mm). Each component of the water balance equation (Equation 1) is modeled using well established relationships in hydrology (Neitsch *et al*., 2002).

The SWAT parameters that affect stream flow generation

The parameters of the SWAT affecting the stream flow were identified through a detailed literature review (Table I) (Neitsch *et al*., 2002; Arabi *et al*., 2007) which resulted in the identification of 13 parameters used in this study of the SA. The range of parameter values were taken directly from the SWAT user's manual (Neitsch *et al*., 2002). SFTMP and SURLAG are sub-basin level parameters. SFTMP is the snowfall temperature or the mean air temperature at which precipitation is equally likely to be rain or snow. SURLAG controls the fraction of the total water that is allowed to enter the stream on any specific day. In large basins with a time of concentration greater than 1 day, only a portion of surface runoff will reach the main channel in 1 day. The parameters ALPHA_BF, GW_DELAY, GW REVAP and GWQMN affect groundwater flow. ALPHA_BF or the base flow recession coefficient is a direct index of ground water flow response to changes in recharge. GW_DELAY is the lag between the times that water exits the soil profile and enters the shallow aquifer. GW_REVAP or the ground water 'revap' coefficient controls the water movement from shallow aquifer to the unsaturated soil layers. GWQMN is the threshold depth of water in the shallow aquifer required for return flow to occur. The soil evaporation compensation factor or ESCO controls the soil evaporative demand that is to be met from different depths of the soil. OV_N (overland Manning's n), SLOPE, SLSUBBSN and CN_f (curve number), contribute directly to surface runoff generation. Soil moisture characteristics are represented by SOL_AWC and SOL_K in the model. SOL_AWC or plant available water is estimated as the difference between the field capacity and the wilting point. SOL_K or saturated hydraulic conductivity relates soil water flow rate to the hydraulic conductivity.

Study area and data availability

St. Joseph Watershed. The St. Joseph River watershed (USGS Hydrologic Unit Code or HUC No. 04 100 003; Figure 1), with a drainage area of 2800 km^2, is located in

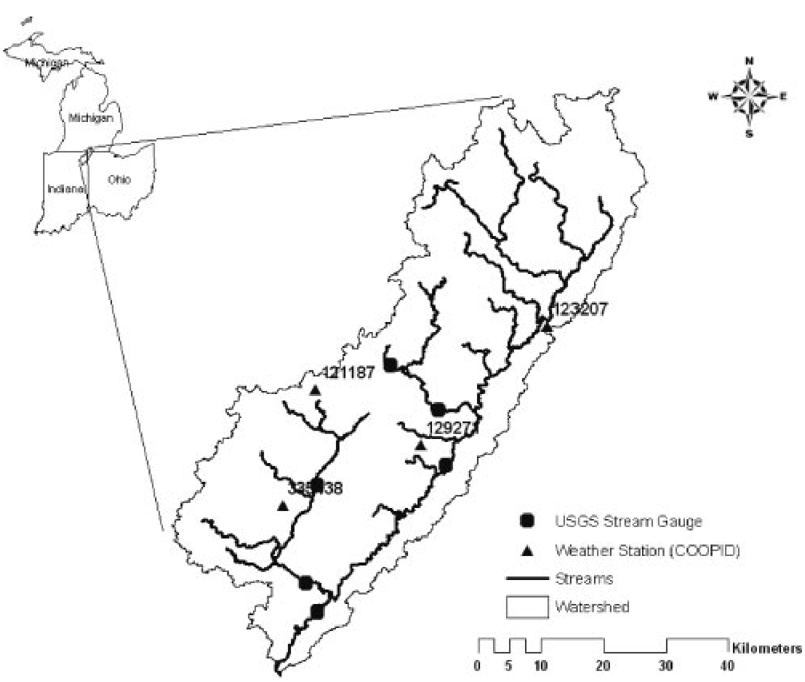

Figure 1. Location map of St. Joseph River basin, USA

Indiana, Michigan, and Ohio, USA. The St. Joseph River is approximately 100 km long and is the main outlet for the watershed. Input files for SWAT (topographic, land use, soil, and stream network data) were organized based on GIS data supplied by the St. Joseph River Watershed Initiative. A 30 m resolution digital elevation model (DEM) from National Elevation Dataset (NED NAD-83), developed by USGS was used to delineate the watershed. The United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) State Soil Geographic Database (STATSGO) for Indiana, Ohio, and Michigan was to characterize soils in the watershed.

Land used in the St. Joseph River watershed is primarily agricultural with corn and soybean identified as major crops. The major land use classes are agriculture (59·2%), pasture (20·7%), forest (13·1%), wetland (3·9%), and urban (3·1%). Major soils in the watershed are Glynwood, Pewamo, and Brookston, which cover about 87% of the total watershed area. These soils are somewhat poorly drained and the parent material is compacted glacial till. The predominant soil textures are silt loam, silt clay loam and clay loam. The predominant soil hydrologic group of the watershed is C, covering 74·5% of the total area, followed by groups B and A covering 23 and 2·5% of the total area, respectively. The elevation of the watershed varies from 230 to 335·3 m with an average terrain elevation of 281 m. The slope of the area varies from 0 to 2%.

Weather data from four weather stations and daily stream discharge data from five stream gauge stations were obtained from the National Climatic Data Center (NCDC) and the United States Geological Survey (USGS) websites, respectively. Data from the four weather stations were spatially interpolated to the centroid of $0{\cdot}1^\circ \times 0{\cdot}1^\circ$ grid cells covering the entire watershed using a Kriging technique. The interpolated precipitation data was used to drive SWAT for the watershed. The model was set up for 13 years from 1987–1999, out of which the first 3 years were considered the model warm up period. Thus, 10 years of data (1990–1999) were available for analysis. Measured daily stream flow data from USGS gauging station 4 180 000 was used for the analysis. SWAT used 50 sub-basins and 431 HRUs to represent the St. Joseph River watershed.

Illinois River watershed. The Illinois River watershed (USGS 8 digit HUC 11 110 103), located in Northwest Arkansas, has an area of about 1490 km^2 (Figure 2). The data used to set up the SWAT (GIS database of elevation, soil and land use details, and tabular weather data) were obtained from the Watershed Modeling group of the University of Arkansas, Fayetteville, Arkansas, USA.

The digital elevation map of the area with a 30 m resolution was obtained from the USGS (http://seamless.usgs.gov/website/seamless/viewer.htm) and used to provide elevation details for the SWAT and to delineate watershed boundaries. Watershed elevation varies from 280 to 600 m with a mean elevation of 381 m. The major land use category (55% of the total land area) in the watershed was pasture under tall Fescue and Bermuda. The major soil types of the basin were Captina, Nixa, Clarksville, and Enders which covered about 75% of the total area. The soil information for the watershed was obtained from the USDA-NRCS Soil Survey Geographic (SSURGO) database. The predominant soil hydrologic group of the watershed was C, which covers 66·3% of the total area, followed by groups B and D which cover 30·6 and 3·1% of the total area, respectively.

For the Illinois River watershed, the SWAT was applied for 9 years (1995–2003), for which the first 3 years

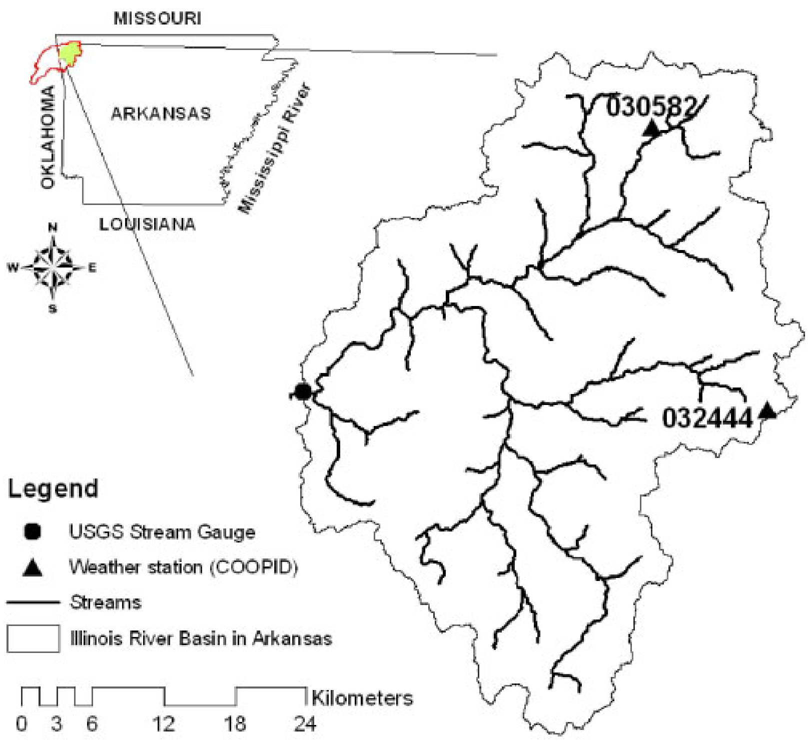

Figure 2. Location map of Illinois River basin, USA

were considered as warm up period. Thus, data for 6 years (1998–2003) was considered for the analysis. The measured daily stream flow values from the USGS gauging station 07 195 430 (Illinois River south of Siloam Springs) were used for model calibration and evaluation. The SWAT setup used 26 sub-basins and 286 HRUs to represent the Illinois River watershed.

The St. Joseph River watershed experienced an average annual precipitation of 82·5 cm over the study period. The watershed lies in the mid-west region of the USA and experiences snowfall during winter. The 10 years (1990–1999) for which the SWAT was set up for this basin, were characterized with a minimum daily flow of 0·6 m^3/s and maximum daily flow of 147·7 m^3/s. The mean daily flow during this period was 8·3 m^3/s with a standard deviation of 13·1 m^3/s. The Illinois River basin experienced an average annual rainfall of 90·5 cm over the study period. The daily flow ranged from a minimum of 2·4 m^3/s to a maximum of 538 m^3/s between 1998 and 2003. The mean flow during this 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 an average annual potential evaporation of 105 cm (Safari and De Smedt, 2008).

Sobol's sensitivity analysis

Sobol's method (Sobol', 1993) is a variance based GSA method in which the total output variance within an ensemble is decomposed into the variance caused by each parameter. The model output variance is expressed as the variance in model performance measures such as RMSE or Nash-Sutcliffe efficiency. RMSE was used in this study. The method described below is adopted from Tang *et al.*, (2007b).

Consider a generic model described by:

$$y = f(x|\theta) \tag{2}$$

where, $f(.)$ is the function described by the model, $\mathbf{y}$ is the output from the model (stream flow in this study) corresponding to the inputs $\mathbf{x}$ (rainfall, temperature, evaporation, etc.) and θ is the vector of parameters of the model. If the model output varies with time, there could be a time subscript added to each of these variables. Sobol's variance decomposition is:

$$D(y) = \sum_i D_i + \sum_{i<j} D_{ij} + \sum_{i<j<k} D_{ijk} + D_{12\ldots m} \tag{3}$$

where $D(y)$ is the total variance of the model, D_i is the measure of individual variance due to the i^{th} parameter, and D_{ij} is the variance induced due to the interaction between i^{th} parameter and j^{th} parameter, m is the total number of parameters. For this study, the primary interest was to get each parameters' individual contribution (first order indices) and the total contribution (total order) to the output. The first order and total order Sobol's sensitivity indices are defined as:

$$\text{First order index}: \ S_i = D_i/D(y) \tag{4}$$

$$\text{Total order index}: \ S_{\text{Ti}} = 1 - (D_{\sim i}/D(y)) \tag{5}$$

where S_i refers to the sensitivity of i^{th} parameter to the model output, S_{Ti} refers the total order sensitivity that is the sum of independent and interactive effects of i^{th}

$$A = \begin{bmatrix} \theta_1^1 & \cdots & \theta_l^1 & \cdots & \theta_k^1 \\ \theta_1^2 & \cdots & \theta_l^2 & \cdots & \theta_k^2 \\ \vdots & & \vdots & \ddots & \vdots \\ \theta_1^{N/2} & \cdots & \theta_l^{N/2} & \cdots & \theta_k^{N/2} \end{bmatrix} \qquad B = \begin{bmatrix} \theta_1^{\frac{N}{2}+1} & \cdots & \theta_l^{\frac{N}{2}+1} & \cdots & \theta_k^{\frac{N}{2}+1} \\ \theta_1^{\frac{N}{2}+2} & \cdots & \theta_l^{\frac{N}{2}+2} & \cdots & \theta_k^{\frac{N}{2}+2} \\ \vdots & & \vdots & \ddots & \vdots \\ \theta_1^N & \cdots & \theta_l^N & \cdots & \theta_k^N \end{bmatrix}$$

$$D_l = \begin{bmatrix} \theta_1^1 & \cdots & \theta_l^{\frac{N}{2}+1} & \cdots & \theta_k^1 \\ \theta_1^2 & \cdots & \theta_l^{\frac{N}{2}+2} & \cdots & \theta_k^2 \\ \vdots & & \vdots & \ddots & \vdots \\ \theta_1^{N/2} & \cdots & \theta_l^N & \cdots & \theta_k^{N/2} \end{bmatrix} \qquad C_l = \begin{bmatrix} \theta_1^{\frac{N}{2}+1} & \cdots & \theta_l^1 & \cdots & \theta_k^{\frac{N}{2}+1} \\ \theta_1^{\frac{N}{2}+2} & \cdots & \theta_l^2 & \cdots & \theta_k^{\frac{N}{2}+2} \\ \vdots & & \vdots & \ddots & \vdots \\ \theta_1^N & \cdots & \theta_l^{N/2} & \cdots & \theta_k^N \end{bmatrix}$$

Figure 3. Illustration of parameter matrix formulation in Sobol's method. The matrices A and B are the base matrices of sampled parameters. C and D are derived from A and B by swapping the column of l^{th} parameter. Model simulations using all the sampled parameters in A, B, C, and D help to perform Sobol's method for sensitivity analysis

parameter to the output, $D_{\sim i}$ is the average variance resulting from all the parameters, except i^{th} parameter.

The variance terms of Equations (3)–(5) $-D$, D_i and $D_{\sim i}$, are calculated by numerical integration within a Monte Carlo approximation framework (Sobol', 1993, 2001; Tang *et al.*, 2007b). The total variance D is the statistical variance of the RMSE across the simulations. The Monte Carlo approximation for the variance terms are:

$$\hat{f}_0 = \frac{1}{n}\sum_{s=1}^{n} f(\theta_s) \tag{6}$$

$$\hat{D} = \frac{1}{n}\sum_{s=1}^{n} f^2(\theta_s) - f_0^2 \tag{7}$$

$$\hat{D}_i = \frac{1}{n}\sum_{s=1}^{n} f(\theta_s^{\mathrm{a}}) f(\theta_{(-i)s}^{\mathrm{b}}, \theta_{\mathrm{is}}^{\mathrm{a}}) - \hat{f}_0^2 \tag{8}$$

$$\hat{D}_{-i} = \frac{1}{n}\sum_{s=1}^{n} f(\theta_s^{\mathrm{a}}) f(\theta_{(-i)s}^{\mathrm{a}}, \theta_{\mathrm{is}}^{\mathrm{b}}) - \hat{f}_0^2 \tag{9}$$

where n defines the Monte Carlo sample size, θ_{s} represent the sampled individual in the unit hypercube, and (a) and (b) are two different sets of samples. Parameters from the sample set (a) denoted as $\theta^{\mathrm{a}}{}_{\mathrm{s}}$ and $\theta^{\mathrm{b}}{}_{\mathrm{is}}$ show the i^{th} parameter taken from sample (b). $\theta^{\mathrm{a}}{}_{(-\mathrm{i})\mathrm{s}}$ denote that all the parameters from sample set (a) are taken except i^{th} parameter. Equations (6)–(9) provide a way to compute the first order and total order sensitivity of each parameter of the model.

Implementation of sensitivity and identifiability analysis

Equations (6)–(9) depict the Monte Carlo approximation formulae for estimating the terms in the decomposition of total variance. However, a robust computation strategy proposed in Liburne *et al.*, (2006) for the Sobol's method was applied in this study for computing the variance terms D, D_i and $D_{\sim i}$ as below.

- For each parameter, 2000 different parameter values were generated using the LHS technique.
- The parameter values were split into two equal matrices (A and B) (Figure 3).
- Two matrices C_i and D_i were derived by swapping i^{th} columns of A and B (Figure 3).
- Monte Carlo simulation of the model was performed using all the samples in all four matrices (A, B, C and D), and the model performance index for each simulation was computed.
- Sensitivity using Equations (10)–(12) were calculated.

According to Liburne *et al.*, (2006), the first order and total order equations are:

$$S_i = \frac{\hat{D}_i}{\hat{D}} = \frac{Y_{(A)}Y_{(\mathrm{Ci})} - f_0^2}{Y_{(A)}Y_{(A)} - f_0^2} \tag{10}$$

$$S_{\mathrm{Ti}} = \frac{\hat{D}_{-i}}{\hat{D}} = 1 - \frac{Y_{(A)}Y_{(\mathrm{Di})} - f_0^2}{Y_{(A)}Y_{(A)} - f_0^2} \tag{11}$$

where, the mean

$$f_0 = \frac{1}{n}\sum_{s=1}^{n} Y_A^{\mathrm{S}} \tag{12}$$

Note that the $\mathrm{S_i}$ and $\mathrm{S_{Ti}}$ can be computed in eight different ways (Liburne *et al.*, 2006) using Equations (10) and (11) by interchanging the simulation matrices A, B, C, and D in (10) and (11). The average value of these eight ensembles of sensitivity indices is considered to be the representative value of sensitivity for the parameter.

The total number of simulations required for this computation is $((k+1) \times n)$, where k is the number of parameters and n is the sample size. Consequently, in the current study, 28 000 model simulations were performed for the SA (13 parameters and 2000 samples each).

The identifiability of parameters was analysed by visual examination of scatter plots of model parameter values and their corresponding Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970). A parameter was considered identifiable through calibration only if the scatter plot had a definite maximum.

Parameter sensitivity and identifiability analysis for two watersheds of contrasting climates, different years of simulation, and different flow regimes. The above procedure was implemented to evaluate if the parameter sensitivity and identifiability were different for the two watersheds. As discussed above, the two watersheds are located in contrasting climates. Similarly, the sensitivity and identifiability of model parameters in simulating stream flow in different years was also evaluated in this study.

It is well understood that the dynamics of stream flow generation mechanism varies in different ranges of flow as the interaction between the basin characteristics and the climatic inputs are different at various ranges of flow (Zhang and Govindaraju, 2000). Consequently, the model parameters may also exhibit different sensitivity in different ranges of flow. In order to assess this, the total flow was grouped into three distinct clusters. The sensitivity of model parameters in each of these clusters was estimated. The clustering algorithms classify the data into different groups according to the underlying structure of the data. In many real situations, fuzzy clustering is more natural than distinct clustering with sharp boundaries, as objects on the boundaries between several classes are not forced to fully belong to one of the classes, but rather are assigned membership degrees between 0 and 1 indicating their relative associations among different groups. Fuzzy C-means (FCM) clustering is one of the most commonly used methods (Bezdek, 1981), which is based on the minimization of an objective function called *C-means functional* (Bezdek, 1981). The input vector for FCM clustering was obtained by a procedure proposed by Sudheer *et al*., (2002). Once the classification of data points into three different clusters (corresponding to low, medium and high flow conditions) was performed, the sensitivity and identifiability analysis was conducted in each of these clusters.

RESULTS AND DISCUSSIONS

Parameter sensitivity and identifiability analysis for two watersheds of contrasting climate

The Sobol's sensitivity indices for the two watersheds are presented in Table II. For the St. Joseph River watershed, SURLAG and CN_f were the two most sensitive parameters with the sensitivity index values of 0·51 and 0·346, respectively. The fraction of runoff that reaches the watershed outlet on any given day is controlled by SURLAG. The sensitivity of daily runoff simulations to SURLAG in the St. Joseph watershed was expected since this basin has a relatively longer time of concentration. The parameter CN_f is the primary influence on the amount of runoff generated from a hydrologic response unit, and hence a relatively greater sensitivity index can be expected for most of the watersheds.

Table II. Sobol's sensitivity indices for SWAT parameters for St. Joseph River watershed and Illinois River watershed

Parameter	St. Joseph River		Illinois River	
	Sobol' first order indices	Rank	Sobol' first order indices	Rank
SFTMP	0·032	3	0·002	7
SURLAG	0·510	1	0·001	8
ALPHA_BF	0·000	9	0·015	5
GW_DELAY	0·000	9	0·000	9
GW_REVAP	0·000	9	0·000	9
GWQMN	0·000	9	0·000	9
ESCO	0·015	4	0·421	1
OV_N	0·005	7	0·000	9
SLOPE	0·002	8	0·018	4
SLSUBBSN	0·007	6	0·000	9
CN_f	0·346	2	0·385	2
SOL_AWC	0·010	5	0·162	3
SOL_K	0·000	9	−0·003	6

Other model parameters having relatively minor impact on hydrologic response predictions in the watershed were SFTMP, ESCO, SOL_AWC, and SLOPE with sensitivity indices of 0·032, 0·015, 0·01, and 0·002, respectively. It should be noted that the sum of the first order sensitivity indices was close to one (= 0·93) for the St. Joseph River watershed suggesting that there was some interaction among the thirteen parameters considered in this analysis.

For the Illinois River watershed, stream flow was most sensitive to ESCO and CN_f with corresponding sensitivity indices of 0·421 and 0·385, respectively (Table II). The evaporation losses were higher in the Illinois River watershed compared to the St. Joseph River watershed, primarily due to greater mean air temperature and solar radiation in the watershed. Consequently, stream flow is sensitive to ESCO, which directly influences the evapotranspiration losses from the watershed, in the Illinois River watershed. Other researchers have also reported ESCO to be a parameter SWAT is sensitive to in the Illinois River watershed (Migliaccio and Chaubey, 2008). Gassman *et al*., (2007) summarized the results of the SWAT calibration and reported that CN_f was an important parameter affecting hydrologic simulations in all of the model applications. Other parameters affecting stream flow in the Illinois River watershed were SOL_AWC, SLOPE, ALPHA_BF, SOL_K, SFTMP, and SURLAG. It should be noted that SFTMP was ranked third for the St. Joseph River watershed, but eighth for the Illinois River watershed. This was reasonable since the St. Joseph River lies in Mid-west USA and experiences considerably more snowfall compared to the Illinois River basin. The parameter SURLAG did not play a major role in the Illinois River watershed as the time of concentration was considerably less compared to the St. Joseph River watershed. It should be noted that the parameters related to groundwater flow such as GW_DELAY, GWQMN, and GW_REVAP were not significant in either

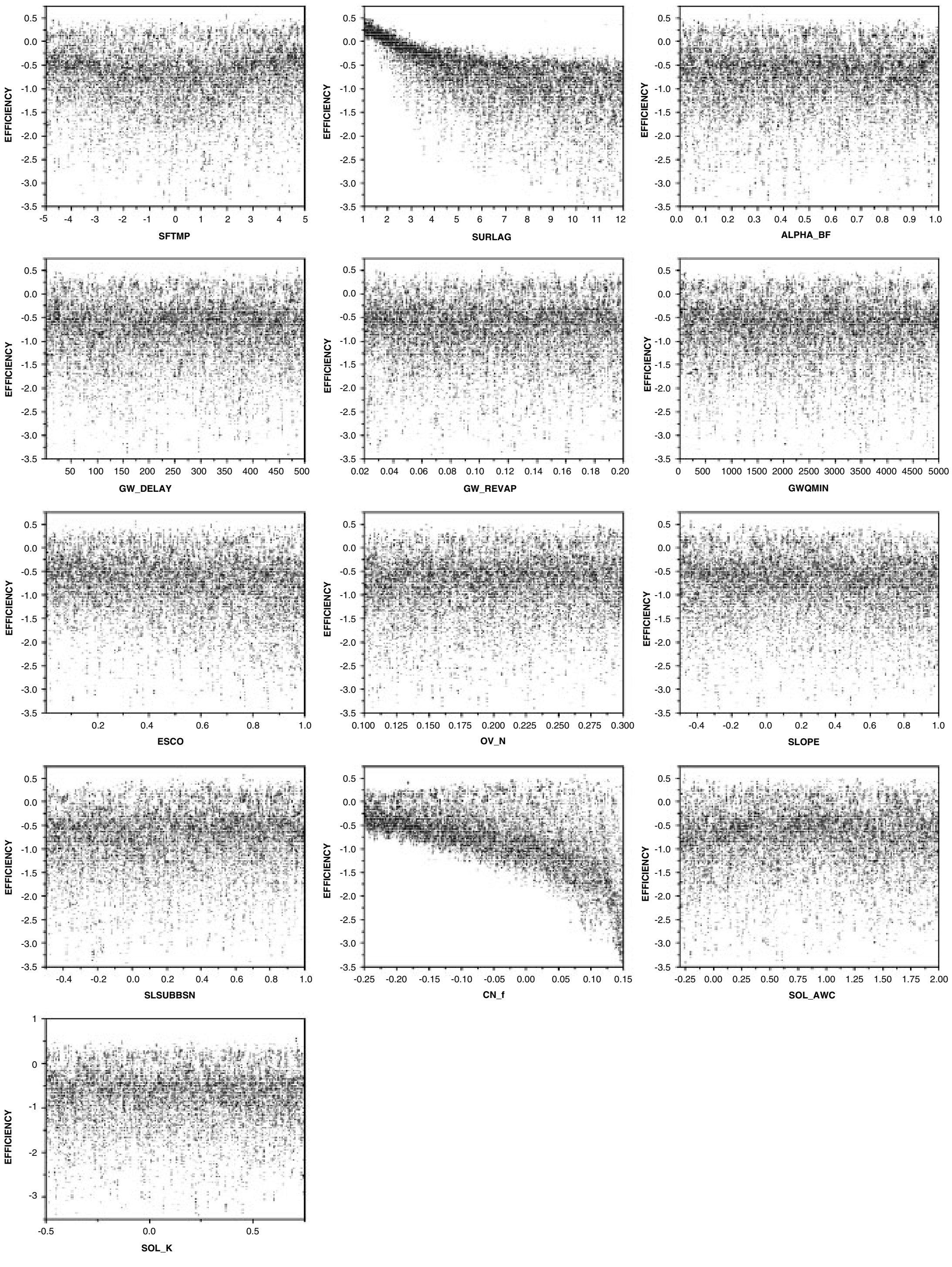

Figure 4. Scatter plot of likelihood values of simulations along the variation of parameters for identifiability analysis (St. Joseph River basin)

watershed implying that these parameters may not play a critical role in calibrating the SWAT.

Figure 4 presents the variation of Nash-Sutcliffe efficiency for the St. Joseph River watershed as a function of variation in each of the 13 parameters considered in this study. It is evident from Figure 4 that SURLAG and CN_f were the only two parameters identifiable for the St. Joseph River watershed. However, it should be noted that non-identifiability of a parameter does not indicate that the model was not sensitive to these parameters. The variation of Nash-Sutcliffe efficiency as a function of variability in model parameters is shown in Figure 5 for the Illinois River watershed. The identifiable parameters for this watershed were ESCO, CN_f and SOL_AWC (Figure 5). However, presence of multiple peaks in the Nash-Sutcliffe model efficiency for SOL_AWC indicated that estimation of this parameter may not be trivial.

The identifiable parameters were not consistent between watersheds, except for CN_f. The CN_f parameter is the primary control on the abstraction of runoff from precipitation and has been reported to be a significant driver of model output by many researchers (Arnold

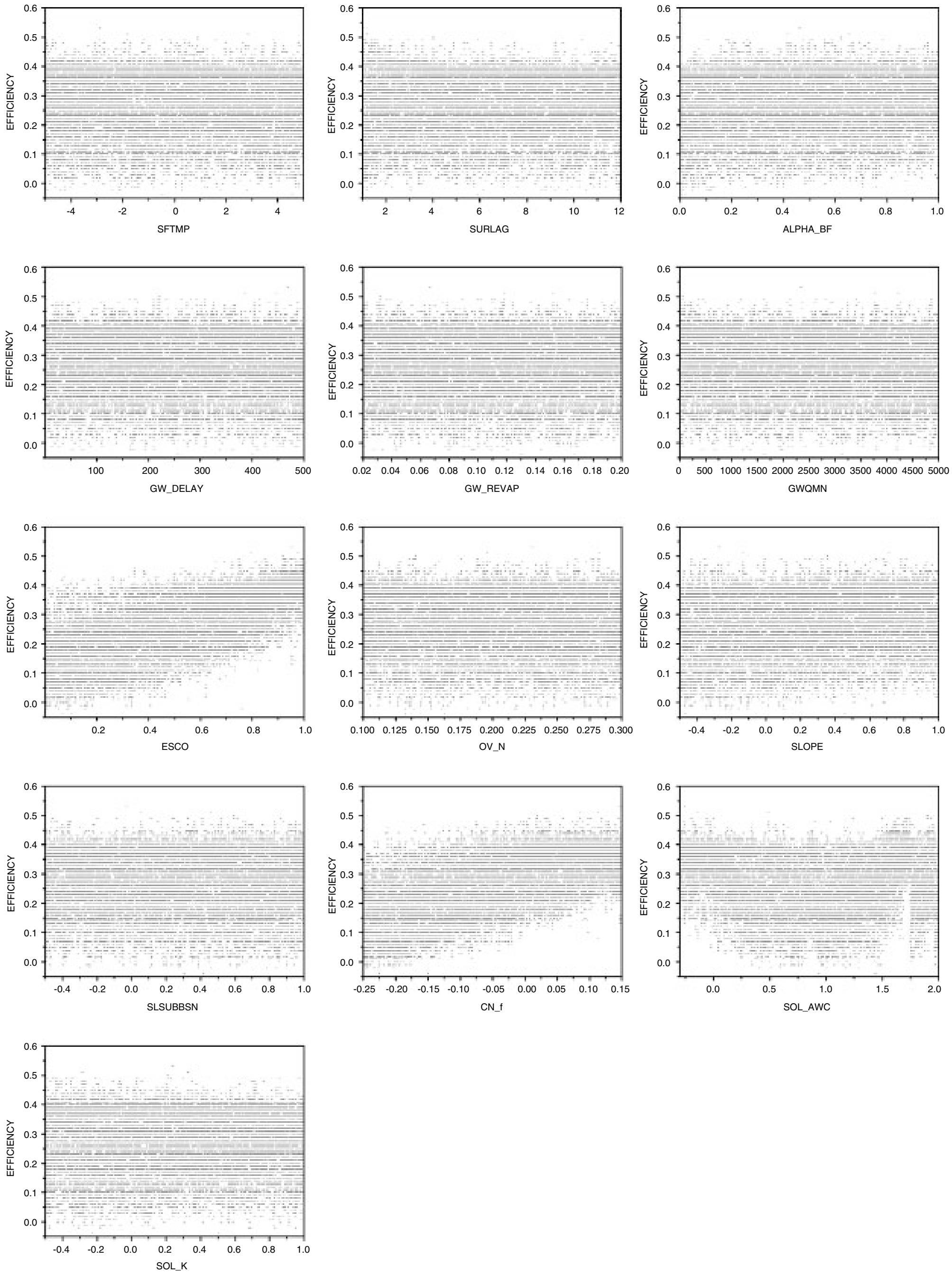

Figure 5. Scatter plot of likelihood values of simulations along the variation of parameters for identifiability analysis (Illinois River basin)

et al., 2000; Francos *et al.*, 2003; White and Chaubey, 2005; Holvoet *et al.*, 2005; van Griensven *et al.*, 2006; Arabi *et al.*, 2007; Muleta *et al.*, 2007). The results from this study indicate that the value of CN_f can be estimated without much difficulty during calibration. However, estimation of non-identifiable parameters, such as SFTMP and ESCO for the St. Joseph River watershed, would be difficult as there may be many combinations of these parameters that would result in similar model performance.

The results indicate that the sensitivity of SWAT parameters varied between the two watersheds suggesting the importance of SA for any watershed under SWAT modeling consideration. Even though many of the parameters were sensitive and affected the stream flow simulation, only a small number of the sensitive parameters were identifiable. Similar results were reported by Demaria *et al.*, (2007). Care must be taken when calibrating the SWAT with non-identifiable parameters as these may lead to equifinality of the parameter values. Under such cases, a user should check if the final parameter values correspond to the watershed characteristics and its underlying hydrologic processes.

Parameter sensitivity and identifiability analysis for different years of simulation

Temporal variation in the sensitivity of the SWAT to parameters during different years was evaluated for the

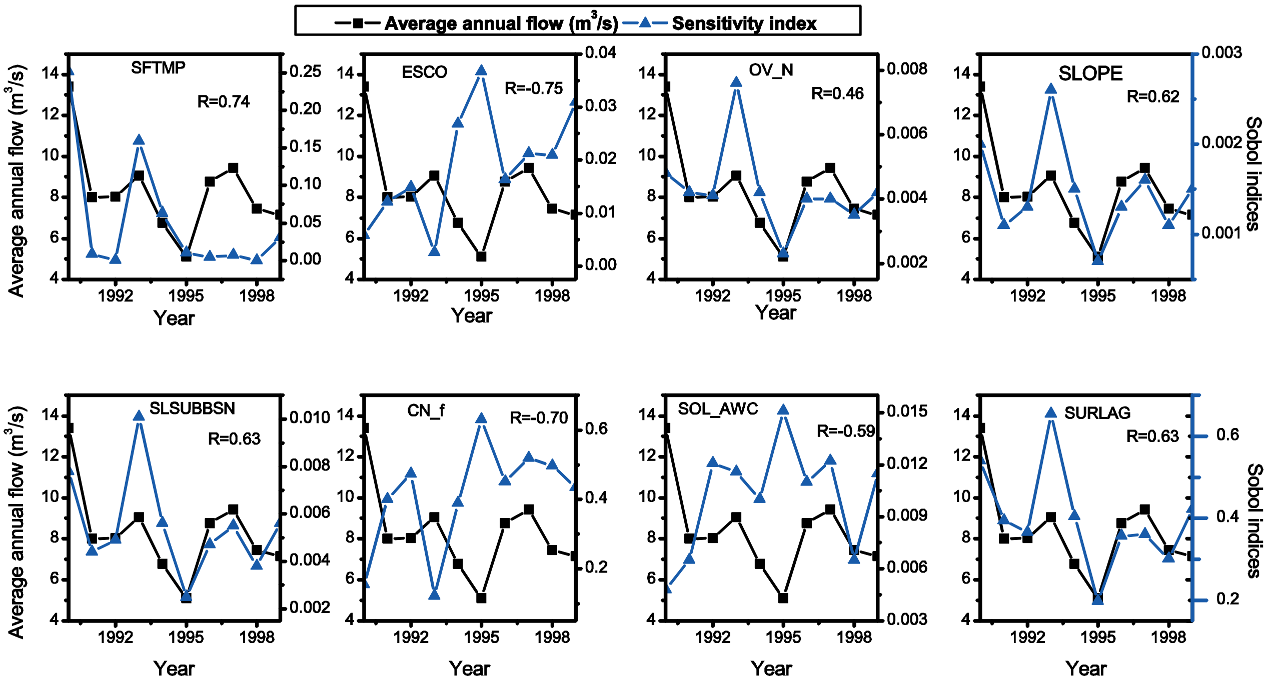

Figure 6. The variation of Sobol's sensitivity of SWAT parameters along the wetness of the years

St. Joseph River watershed. This analysis helped identify the impact of weather variations as well as the initial condition of the watershed at the beginning of each simulation year on the model parameter. The temporal variation of sensitivity indices in terms of their relative importance (% of the total) are presented in Table III. While the sensitivity values were not consistent from 1 year to the other, SURLAG and CN_f were the most sensitive parameters for all simulation years. A clear relationship between the wetness of the watershed as indicated by the stream flow and the parameter sensitivity in different years is evident. This relationship is also supported by Figure 6, in which the variation in sensitivity of the parameters is plotted against the annual stream flow. It can be observed from Figure 6 that SFTMP, SURLAG, SLOPE, and SLSUBBSN were positively correlated with the stream flow. Since all these parameters generally affected highflow simulations, the observed correlation of sensitivity with the stream flow is reasonable. On the other hand, ESCO, CN_f, SOL_AWC, and SOL_K were negatively correlated with the stream flow implying that the sensitivity of the parameter is greater in the dry years compared to the wet years. For example, in 1990 (a relatively wet year), the SURLAG and SFTMP were found to be highly sensitive with sensitivity index values of 0·54 and 0·25, respectively. The sensitivity index for CN_f was 0·15 in this wet year and was much smaller compared to the sensitivity index for the entire simulation period (= 0·35, Table II). Further, in 1995, a relatively dry year, the sensitivity index for CN_f was 0·63 as corresponding to the SURLAG and SFTMP values of 0·2 and 0·01, respectively.

Figure 7 shows the variation of identifiability of SURLAG and CN_f for the St. Joseph River watershed with RMSE as the identifiability indicator. SURLAG was identifiable during each of the 10 years of simulation even though the general relationship between the parameter values and the RMSE varied among years. On the other hand, the CN_f shows a contrasting behavior, compared to SURLAG, as the trough of the RMSE was located corresponding to different values of CN_f in different years. Further, the minimum value of RMSE was not clearly distinguishable in every year (for example, 1993 and 1997) suggesting that the estimation of optimal value of this parameter may be a challenging task, especially when the data corresponding to these years was employed for the model calibration.

Table III. Variation of relative importance of SWAT parameters along the wetness (mean annual flow) of the year

Year	1995	1998	1997	1990
Mean annual flow (m^3/s)	5·1	7·4	9·4	13·4
Relative importance of parameters (%)				
SFTMP	1·2	0·0	0·8	25·9
SURLAG	22·1	35·9	38·7	55·7
ESCO	4·1	2·5	2·3	0·6
OV_N	0·3	0·4	0·4	0·5
SLOPE	0·1	0·1	0·2	0·2
SLSUBBSN	0·3	0·5	0·6	0·8
CN_f	70·3	59·3	55·7	15·8
SOL_AWC	1·7	0·8	1·3	0·5
SOL_K	0·1	0·2	0·1	0·0

Parameter sensitivity and identifiability analysis for different flow regimes

In order to analyse the sensitivity of SWAT parameters in various flow regimes, Sobol's sensitivity index for each parameter was computed for different clusters of flow data. As discussed earlier, a FCM clustering scheme

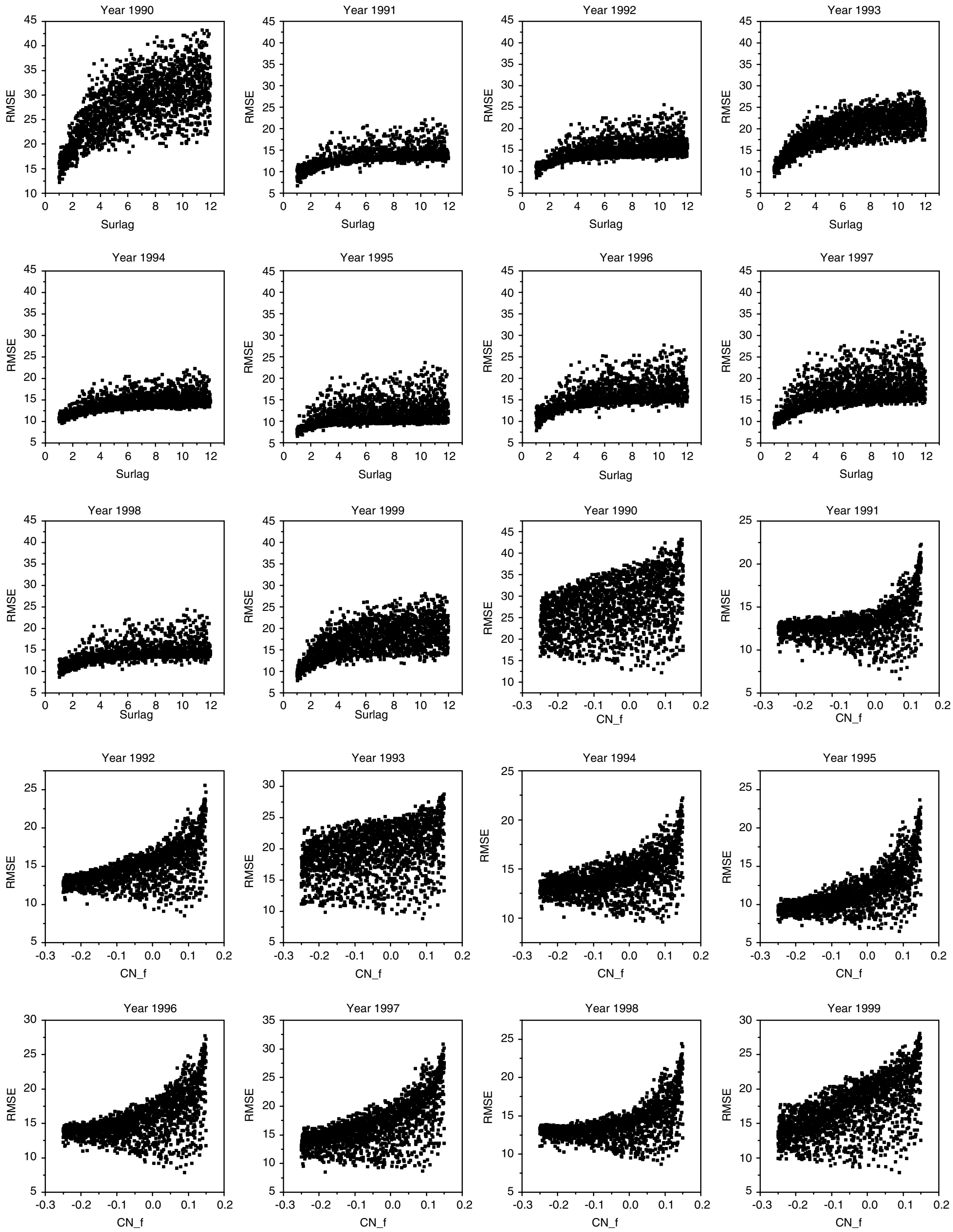

Figure 7. Plot depicting the variability of identifiability of two SWAT parameters (SURLAG and CN_f) along the years of simulation: St. Joseph River watershed

was used to group the flow series into three different clusters. The characteristics of three clusters and the sensitivity of each parameter in each cluster are given in Table IV for the St. Joseph River watershed. Clusters 1, 2, and 3 represent the high flow, medium flow, and low flow conditions, respectively. Sensitivity of SURLAG was greatest in cluster 1 (high flow). However, CN_f had the greatest sensitivity index in cluster 3 (low flow). Note that these parameters exhibited a similar sensitivity for different simulations years, i.e. SURLAG was highly sensitive in wet years and curve number was more sensitive in dry years.

In the high flow regime (cluster 1), 86% of the total variation of RMSE among the 28 000 model simulations was caused by SURLAG (Table IV). It was also evident that SWAT was sensitive to parameters such as SFTMP, OV_N, and SLSUBBSN in the high flow regime. In the medium flow regime (cluster 2), the greatest sensitivity was found towards the parameters SURLAG, CN_f, and SFTMP with sensitivity index values of 0·49, 0·29,

Table IV. Sobol's sensitivity indices (first order) for parameters at different ranges of flow and the cluster characteristics

Cluster characteristics	Cluster1	Cluster2	Cluster3
Minimum flow (m^3/s)	9·1	2·9	0·6
Maximum flow (m^3/s)	147·7	86·6	23·7
Parameters	*Sobol Indices*	*Sobol Indices*	*Sobol Indices*
SFTMP	0·03	0·12	0·01
SURLAG	0·86	0·49	0·10
ALPHA_BF	0·00	0·00	0·00
GW_DELAY	0·00	0·00	0·00
GW_REVAP	0·00	0·00	0·00
GWQMN	0·00	0·00	0·00
ESCO	0·00	0·01	0·04
OV_N	0·01	0·00	0·00
SLOPE	0·00	0·00	0·00
SLSUBBSN	0·01	0·01	0·00
CN_f	0·00	0·29	0·77
SOL_AWC	0·00	0·01	0·02
SOL_K	0·00	0·00	0·00

and 0·12, respectively. In the low flow regime (cluster 3), CN_f contributed to 77% of the total variation in RMSE. The SWAT was found to be relatively less sensitive to SURLAG in this flow regime. In the low flow regime, SWAT was also found to be sensitive to ESCO and SOL_AWC. It should be noted that both of these parameters affect simulation of evapotranspiration processes in the SWAT.

Many researchers have reported difficulty in achieving good SWAT simulations for low flow conditions (van Liew and Garbrecht, 2003; Sudheer *et al*., 2007; Migliaccio and Chaubey, 2008). This could be attributed to the inability of the runoff curve number (CN_f) to adequately account for hydrologic abstractions for various antecedent soil moisture conditions. The curve number represents an overall response of each HRU and does not account for near-stream saturation excess runoff or contributions from variable source areas (van Liew and Garbrecht, 2003). An improved SWAT performance is reported when such processes are included in the SWAT (Easton *et al*., 2008).

Figure 8 shows that the identifiability of SURLAG in the St. Joseph River watershed varied for different ranges of flow. A distinct minima in the RMSE was obtained for medium and high flow conditions. However, a similar pattern was not obtained for the low flow conditions, indicating that estimation of SURLAG for low flow simulations may be difficult. The identifiability of CN_f was observed to be different for different ranges of flow. The minimum value of RMSE corresponds to different values of the parameter in the low, medium, and high flow ranges. This result indicates that the optimal value of the parameter will be different based on flow ranges, suggesting the adoption of a multi-criteria method for calibration. For the Illinois River watershed (Figure 9) no clear minimum RMSE was observed for low flow range for any of the parameters. In medium and high flow ranges, though some of the parameters were identifiable, the parameter values corresponding to minimum RMSE were different in both flow regimes for CN_f and SOL_AWC. These results further indicate a need to perform calibration using a multi-criteria approach based on the model performance in different flow ranges.

SUMMARY AND CONCLUSIONS

The implementation of SA procedures is helpful in calibration of hydrologic models and also for their transposition to different watersheds. This paper presents results of a detailed sensitivity and identifiability analysis performed for the SWAT on two watersheds located in contrasting climate conditions in the USA: (i) the St. Joseph River watershed located in Indiana, Michigan, and Ohio and (ii) the Illinois River watershed located in Arkansas. The Sobol's variance decomposition technique was used in this study. Thirteen parameters that affected stream flow simulation by the SWAT were evaluated using 28 000 different model simulations.

The results from this study indicated that the identifiability of certain SWAT parameters could be limited and lead to equifinality problems in calibration. The results also indicated that the sensitivity of model parameters was closely connected to the climatic and hydrologic characteristics of the watershed. The parameter SURLAG was found to have a significant impact on the simulation of hydrologic response in the St. Joseph River watershed due to a longer time of concentration in this watershed. On the other hand, SWAT was not sensitive to this parameter in the Illinois River watershed due to a smaller time of concentration in the Illinois River watershed. Further, the sensitivity index of ESCO was greater for the Illinois watershed as the evapotranspiration process was a more dominant control of the soil moisture in this basin.

The results from this study indicated that the sensitivity of the SWAT parameters varied during different years of simulation. There was a direct relationship between the stream flow and the parameter sensitivity. For example, SWAT was more sensitive to CN_f and ESCO under low stream flow conditions than under high or medium flows. This result suggests that a single value for a parameter may not appropriately represent hydrologic processes during various flow regimes. A multi-criteria calibration approach may be viable in such situations, however, further studies are needed to evaluate if such approaches could improve the SWAT performance. The parameter identifiability analysis indicated the parameter identifiability varied in different flow regimes. Greater parameter sensitivity does not mean that the parameter is also identifiable. Model calibration with non-identifiable parameters may lead to equifinality problems during the model calibration.

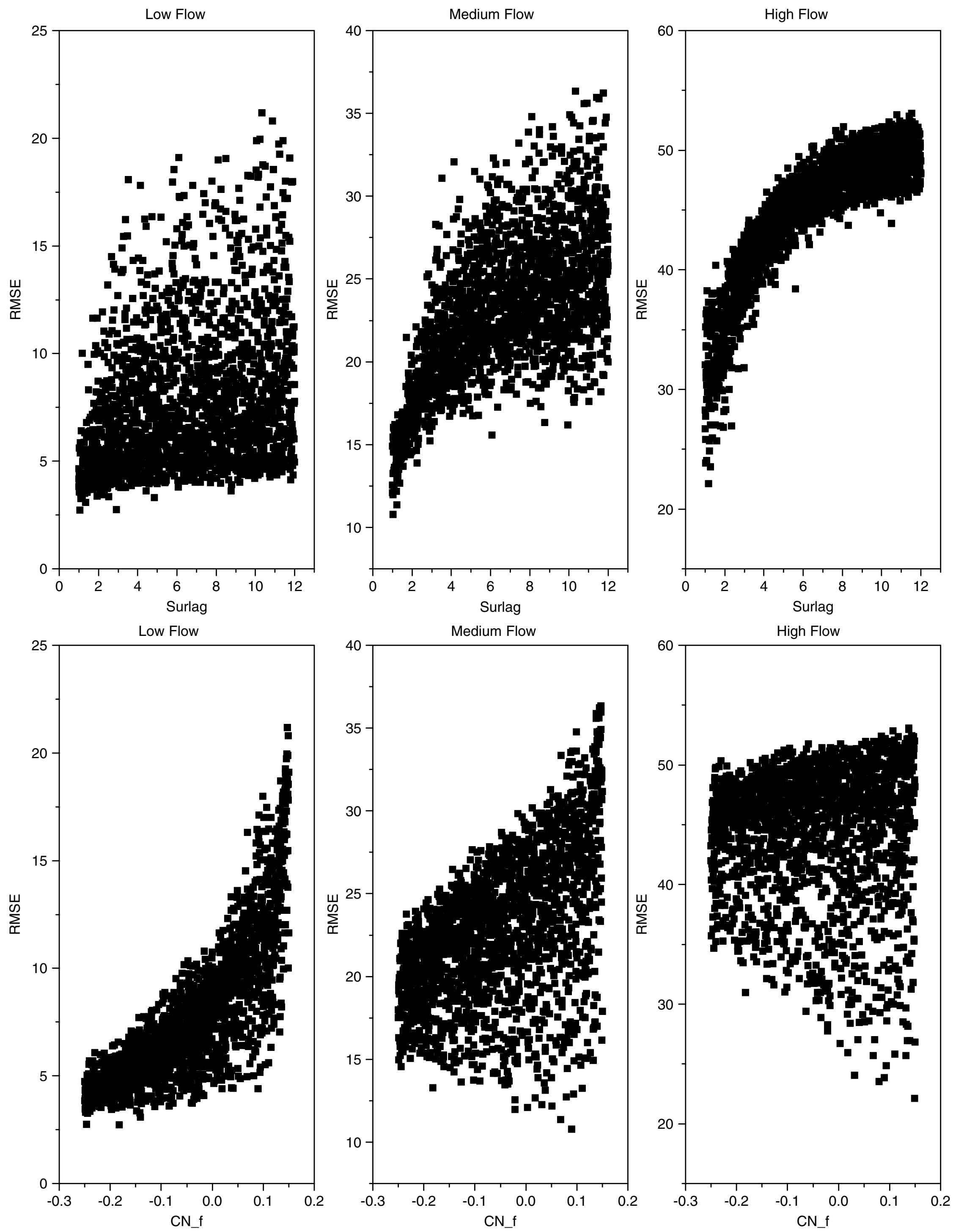

Figure 8. Plot depicting the variability of identifiability of two SWAT parameters (SURLAG and CN_f) along different ranges of flow: St. Joseph River watershed

The variation in inter-annual sensitivity of SWAT parameters brings in a research question about the current calibration procedures. Under currently accepted calibration procedures constant values for parameters during the simulation period are generally assumed despite varying performance by the model during different simulation periods. Therefore, the question that arises is whether there should be dynamically changing parameter values during the period of simulation so as to improve model simulations? It is worth mentioning that some parameters of the SWAT (e.g. CN_f) are updated based on the antecedent moisture condition, tillage or crop management practices in the watershed, and the growth stages of the crop. This is reflected in the sensitivity of CN_f for the low and medium stream flow regimes (Table IV). It will be interesting to see if the SWAT results can be improved if a dynamic parameter variation along the simulation period is implemented.

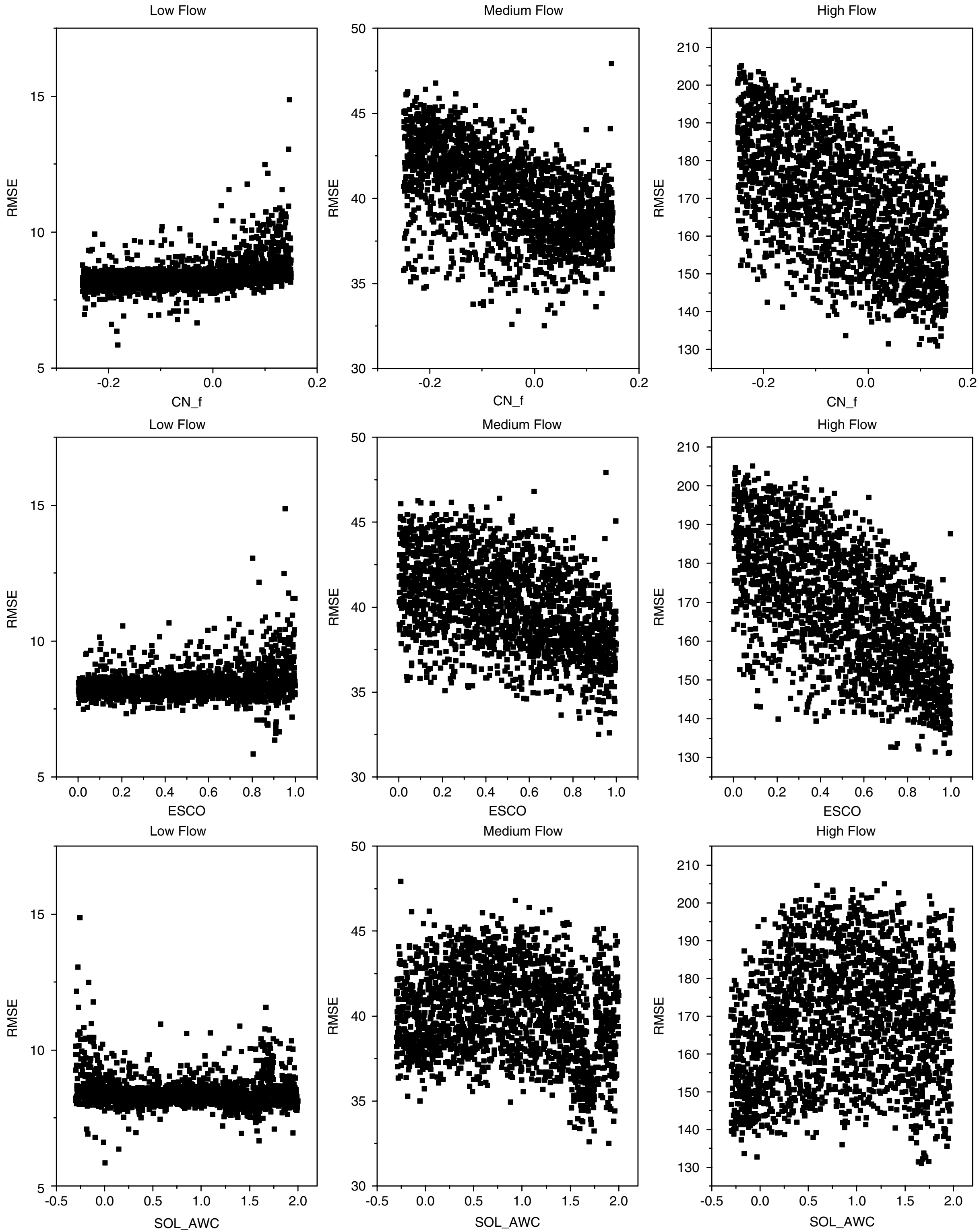

Figure 9. Plot depicting the variability of identifiability of three SWAT parameters (CN_f, ESCO and SOL_AWC) along different ranges of flow: Illinois River watershed

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