Multi-site evaluation to reduce parameter uncertainty in a conceptual hydrological modeling within the GLUE framework

Kairong Lin, Pan Liu, Yanhu He and Shenglian Guo

ABSTRACT

Reducing uncertainty of hydrological modeling and forecasting has both theoretical and practical importance in hydrological sciences and water resources management. This study focuses on reducing parameter uncertainty by multi-sites validating for the conceptual Xinanjiang model. The generalized likelihood uncertainty estimation (GLUE) method was used to conduct the uncertainty analysis with Shuffled Complex Evolution Metropolis (SCEM-UA) sampling. The discharge criterion of interior gauge station was added to select the behavioral parameters, and then two comparable schemes were established to illustrate how well the uncertainty can be reduced by considering the observations of the interior sites' flow information. The Dongwan watershed, a sub-basin of the Yellow River basin in China, was selected as the case study. The results showed that the number and standard deviation of behavioral parameter sets decreased, and the simulated runoff series by the Xinanjiang model with the behavioral parameter sets can fit better with the observed runoff series when setting the threshold value at the interior sites. In addition, considering the interior sites' flow information allows one to derive more reasonable prediction bounds and reduce the uncertainty in hydrological modeling and forecasting to some degree.

Key words | GLUE, multi-site evaluation, parameter uncertainty, SCEM-UA, Xinanjiang model

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INTRODUCTION

Hydrological models have been accepted as effective tools in the description of dynamic relations between hydrological processes, meteorological behaviors, land use and land cover, and also the changes of vegetation coverage within a watershed, providing theoretical and practical support for river basin management (Wagener & Gupta 2005; Hejazi *et al*. 2008). The hydrological system is complicated by climate changes such as atmospheric circulation, precipitation, air temperature, and the underlying surface properties such as the geological conditions, vegetation and soil conditions (Lin *et al*. 2009). As a result, the complexity of the hydrological system poses great challenges for the hydrological modeling practices, and uncertainty analysis is still an important issue for hydrological modeling and forecast.

The treatment of uncertainty engaged with the explosion of methods devoted to deriving meaningful uncertainty bounds for hydrological model predictions (e.g., Beven & Freer 2001; Thiemann *et al.* 2001; Vrugt *et al*. 2003; Moradkhani *et al*. 2005; Ajami *et al.* 2007; Benke *et al*. 2007; Vrugt & Robinson 2007; Li *et al*. 2010; Mousavi *et al*. 2012). Prediction in ungauged basins (PUB) is an initiative that emerged out of discussions among International Association of Hydrological Sciences (IAHS) members on the worldwide web and during a series of IAHS sponsored meetings in Maastricht (July 18–27, 2001), Kofu (March 28–29, 2002), and Brasilia (November 20–22, 2002) about the need to reduce the predictive uncertainty in hydrological science and practice (Sivapalan *et al*. 2003). Indeed, the final aim of studying uncertainty is to find the ways and

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measures to reduce the uncertainty in hydrological modeling and forecasting, so as to increase the accuracy and reliability of hydrological forecasting.

One of the efficient ways of reducing uncertainty is to use new and all available information (Beven & Binley 1992). For example, Goodman (2002) pointed out that the statistical methods that lend themselves to correct quantification of the uncertainty were also effective for combining different sources of information, and concluded that one way to reduce uncertainty was to use all the available data. Freer *et al.*'s (2004) research showed that further constraining of the model responses using the fuzzy water table elevations at both locations considerably reduced the number of behavioral parameter sets. Uhlenbrook & Sieber (2005) also pointed out that the potential restriction of the uncertainty clearly depended on the goodness of the simulation of the additional data set. Gallart *et al.* (2007) used conditioning on water table records and the distribution of parameters obtained from point observations to reduce the uncertainty of predictions for both streamflow and groundwater contribution. Maschio *et al.* (2009) dealt with uncertainty mitigation by using observed data, integrating the uncertainty analysis and the history-matching processes. The main characteristic of their study was the use of observed data as constraints to reduce the uncertainty of the reservoir parameters. Lumbroso & Gaume (2012) used the analysis of various types of data that can be collected during post-event surveys and consistency checks to reduce the uncertainty in indirect discharge estimates.

In fact, interior hydrological information has been used to improve the performance of hydrological models in many literatures. The study by Gupta *et al.* (1998) proposed the use of the multiple and non-commensurable measures of information to improve calibration of hydrologic models. Thereafter, many studies have proved that it is helpful to use interior hydrological information to improve the hydrological modeling to some degree for both conceptual model and distributed model (e.g., Krysanova *et al.* 1999; Andersen *et al.* 2001; Moussa *et al.* 2007; Das *et al.* 2008; Feyen *et al.* 2008). There could be more uncertainty if only the error at the outlet is considered, and this uncertainty can be considerably reduced by using more available information, such as the interior sites' flow information. Therefore, based on the idea of inputting more available useful information for evaluation to gain less uncertainty, the objective of this study is to reduce parameter uncertainty by using multi-site evaluation in the performance of the Xinanjiang model, based on the generalized likelihood uncertainty estimation (GLUE) method with the Shuffled Complex Evolution Metropolis (SCEM-UA) sampling algorithm. Undoubtedly, utilization of the multi-site evaluation may be of theoretical and practical merit in obtaining some insight into the causes behind the hydrological modeling uncertainty, one of the crucial but tough problems in the hydrological modeling practices. The rest of this paper is organized as follows: the section below briefly describes the uncertainty estimation schemes and the Xinanjiang model; then, in the next section, we introduce the study area and associated hydrological data; results are discussed and analyzed in the section after that; finally, the last section contains the major conclusions.

METHODOLOGY

Uncertainty estimation technique

The GLUE method proposed by Beven & Binley (1992) to estimate parameter uncertainty has been widely used in many complex and nonlinear models. The GLUE method is devoted to the investigation of hydrological modeling uncertainty by producing the prediction limits for the modeled streamflow series and a set of behavioral parameters (e.g., Freer *et al.* 1996; Beven & Freer 2001; Blazkova & Beven 2002; Montanari 2005; McMichael *et al.* 2006; Jin *et al.* 2010; Ng *et al.* 2010). The popularity of the GLUE method is probably best explained by its conceptual simplicity, relative ease of implementation, the ability to handle different error structures and models without major modifications to the method itself.

The SCEM-UA algorithm (Vrugt *et al.* 2003) can be used to improve the efficiency of the GLUE, which has a heavy computational burden. The SCEM-UA algorithm is an adaptive Markov Chain Monte Carlo (MCMC) sampler, which has good ability to infer the posterior probability distribution of hydrologic model parameters (e.g., Gong 2006; Blasone & Vrugt 2008; McMillan & Clark 2009; Dotto *et al.* 2012; Xu *et al.* 2013). Due to the merits of the SCEM sampling and the GLUE method, these two methods can be combined together. For example, the initial range of parameter samples can be wide without necessarily increasing computational requirements (Dotto *et al*. 2012). Blasone & Vrugt (2008) compared performance of the informal likelihoods in the SCEM-UA algorithm with the GLUE method and demonstrated that the targeted sampling resulted in better predictions of the model output (and that the uncertainty limits were less sensitive to the number of retained solutions).

Therefore, the GLUE method with SCEM algorithm was adopted for uncertainty analysis in our study. In this study, two schemes were established by using the GLUE method with the SCEM-UA sampling algorithm, to study how well parameter uncertainty can be reduced by considering the observations of the interior sites' flow information in an alternative strategy. It is notable that the proposed idea of the utility of the interior sites' information is not limited to the GLUE or MCMC methods. The flowcharts of these two schemes are shown in Figure 1. Scheme I sets the threshold of likelihood measure only at the outlet, and scheme II sets the threshold of likelihood measure at both the outlet and interior sites. First, in this study, the Nash–Sutcliffe efficiency index (NE) (Nash & Sutcliffe 1970) is selected as the likelihood measure, which is defined as:

$$\mathrm{NE} = 1.0 - \frac{\sum_{i=1}^{n}\left[Q_{\mathrm{obs}}(i) - Q_{\mathrm{sim}}(i)\right]^2}{\sum_{i=1}^{n}\left[Q_{\mathrm{obs}}(i) - \overline{Q}_{\mathrm{obs}}\right]^2} \tag{1}$$

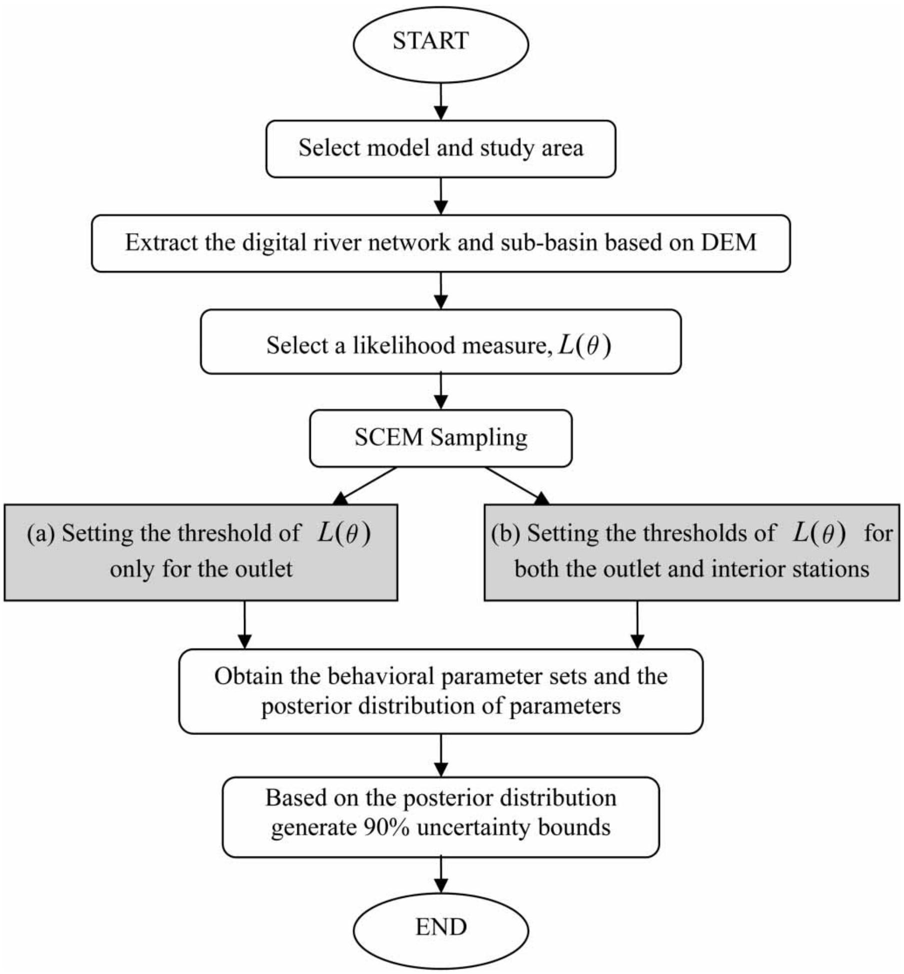

Figure 1 | Flowchart of GLUE method with SCEM-UA sampling algorithm.

where $Q_{\mathrm{obs}}(i)$, $Q_{\mathrm{sim}}(i)$, and $\overline{Q}_{\mathrm{obs}}$ denote the observed runoff, simulated runoff and the mean value of the observed runoff series, respectively, n is the length of the observed data series.

Second, instead of the Monte Carlo method, the SCEM-UA algorithm was used to generate a sample of parameter sets. In this study, the SCEM-UA algorithm produces NE-dependent samples before setting a threshold, so the simulation associated with each of the parameter sets has equal weight. After that, a threshold value of likelihood measure is decided and the behavioral parameter sets whose likelihood values are greater than the thresholds are chosen. Then the discharge predictions from the behavioral parameter sets were ranked in order of magnitude and, using the likelihood weights associated with each behavioral parameter set, which is defined as:

$$W(i) = \frac{L(\theta_i)}{\sum_{i=1}^{n} L(\theta_i)} \tag{2}$$

where $W(i)$ and $L(\theta_i)$ are likelihood weight and likelihood measure value associated with behavioral parameter set θ_i, respectively, n is the number of behavioral parameter sets.

Finally, a cumulative probability distribution for the ranked discharge predictions is obtained by Equation (3):

$$P(Q \le Q_i) = \frac{\sum_{j=1}^{i} W(j)}{\sum_{j=1}^{n} W(j)} \tag{3}$$

where Q represents discharge, and Q_i is the ranked discharge prediction which is ranked at the ith place, n has the same meaning as Equation (2).

According to the cumulative probability distribution, an uncertainty bound can be obtained for a given certainty level.

In this study, three indices were adopted to evaluate the uncertainty interval. One is the containing ratio (CR), which is defined as the ratio of the number of the observations falling within their respective uncertainty intervals to the total number of observations (Beven & Binley 1992; Montanari 2005; Xiong & O'Connor 2008; Lin et al. 2010). The calculated formula is:

$$\mathrm{CR} = \frac{\sum_{i=1}^{n} J[Q_{\mathrm{obs}}(i)]}{n} \tag{4}$$

where,

$$J[Q_{\mathrm{obs}}(i)] = \begin{cases} 1, & Q_{\mathrm{low}}(i) < Q_{\mathrm{obs}}(i) < Q_{\mathrm{up}}(i) \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The confidence interval of discharge at each time step is the major result by the GLUE method in terms of evaluations of hydrological modeling uncertainty. Interval width (IW) is usually adopted as one of the major indices to evaluate the uncertainty interval, but it depends on the magnitudes of discharge which makes it impossible to compare across basins. In this study, a relative interval width (RIW) is used, which is defined by the following equation:

$$\mathrm{RIW} = \frac{\sum_{i=1}^{n} [Q_{\mathrm{up}}(i) - Q_{\mathrm{low}}(i)]}{n\overline{Q}_{\mathrm{obs}}} \tag{6}$$

where $Q_{\mathrm{low}}(i)$ and $Q_{\mathrm{up}}(i)$ denote the lower and the upper uncertainty bounds at time i, respectively, the meaning of $\overline{Q}_{\mathrm{obs}}$ is the same as in Equation (1).

The Nash–Sutcliffe efficiency index of the median values $MQ_{0.5}$ (NE($MQ_{0.5}$)) is also used as an evaluation index to judge whether or not the median values $MQ_{0.5}$ and the uncertainty intervals are effective crisp simulations of the observation of total flow.

Xinanjiang conceptual model

The Xinanjiang model, developed in 1973 and published in 1980 (Zhao et al. 1980), is one conceptual hydrological model and has been widely used in China. Its main feature is the concept of runoff formation on repletion of storage, which denotes that runoff is not produced until the soil moisture content of the aeration zone reaches field capacity, and thereafter runoff equals the rainfall excess without further loss (Zhao & Liu 1995). Based on the concept of runoff formation on repletion of storage, the total runoff, *R*, of the basin is calculated by using a soil moisture storage capacity distribution curve in the Xinanjiang model. After that, the total runoff, *R*, is separated into only two components, i.e., the surface runoff and the groundwater runoff in the early version of the Xinanjiang model (e.g., Zhao *et al.* 1980). In the subsequent application of the Xinanjiang model, the runoff, *R*, is separated into three components, i.e., surface runoff (RS), ground water runoff (RG), and interflow (RI) with the aim of simulating the real runoff processes in the correct way (Zhao & Liu 1995), and this version of the Xinanjiang model is used in this study. The model consists of four major parts (Figure 2): evapotranspiration, runoff production, runoff separation, and flow routing. There are 15 parameters when using the Muskingum method for flow routing, which may be grouped as follows: evapotranspiration parameters KE, X, Y, C; runoff production parameters WM, B, IMP; runoff separation parameters SM, EX, KI, KG; and runoff concentration parameters CI, CG, N, NK, XE, K. The meanings of the model parameters are listed in Table 1.

STUDY REGIONS AND DATA

River basins

The Dongwan watershed was selected as the case study, and is a sub-watershed of the Yellow River basin and located in Henan Province in China, at longitude 111°23′ to 112°51′ and latitude of 33°51′ to 34°37′ (Figure 3). It drains an area of 2,623 km^2, rising in the mountain Funiu situated in the Qinling Mountain. Vegetation cover of the watershed is good and soil erosion is not serious. The Dongwan watershed belongs to a monsoon climate area and its rainfall varies greatly with different seasons. The inter-annual variation of precipitation is very large and climatic tendencies produce the highest flooding in the period July to August. The mean annual precipitation and runoff are 791 and 276 mm, respectively. Figure 3 shows eight rainfall gauge stations and three hydrological gauge stations (Luanchan, Tantou, and Dongwan) located in the Dongwan watershed. The data selected for modeling are hourly rainfall and discharges over the same period of 1 June to 30 October in seven consecutive years from 1993 to 1998. In this study,

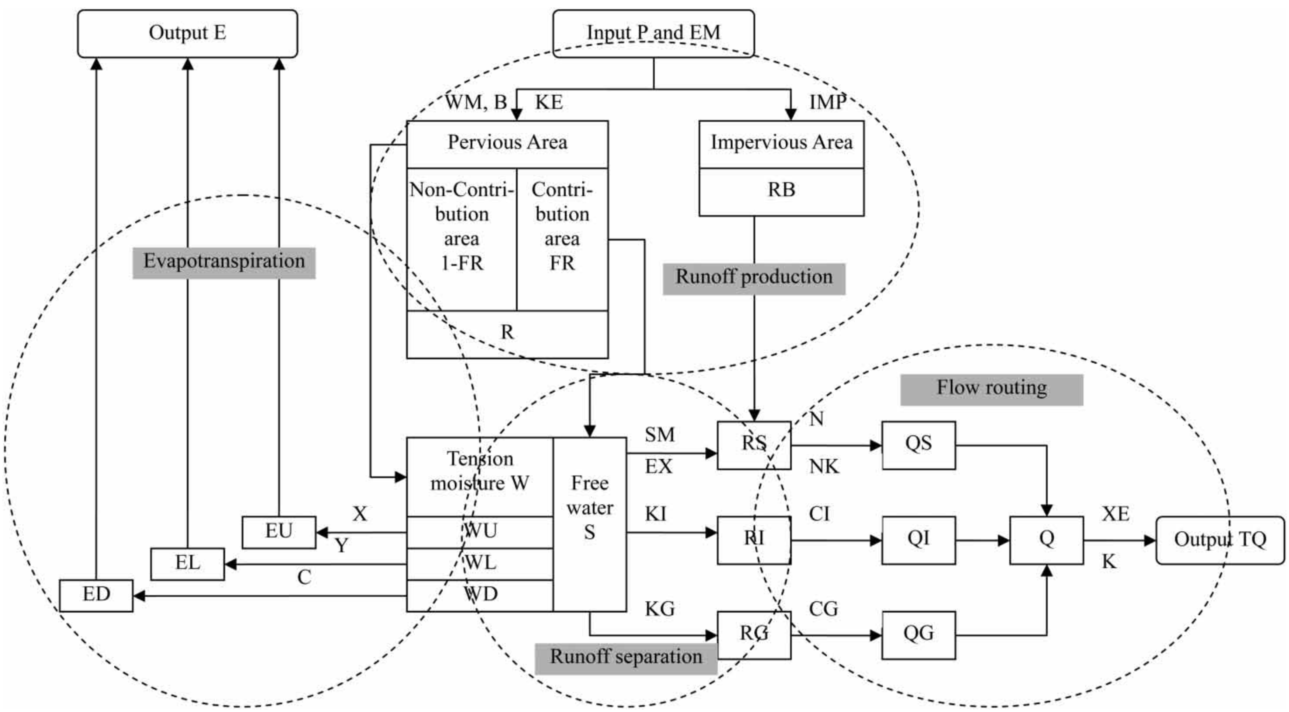

Figure 2 | Flowchart of the Xinanjiang model.

Table 1 | Parameters of the Xinanjiang model and their prior ranges

Parameter	Range	Description
WM/(mm)	100–200	Areal soil moisture storage capacity
X	0.05–0.2	Proportion of soil moisture storage capacity of the upper layer (WUM) to WM
Y	0.4–0.7	Proportion of soil moisture storage capacity of the lower layer (WLM) to (1 – X)*WM
KE	0.8–1.5	Ratio of potential evapotranspiration to pan evaporation
B	0.1–0.4	The exponent of the soil moisture storage capacity curve
SM/(mm)	10–50	Areal mean free water capacity of the surface soil layer
EX	1–1.5	The exponent of the free water capacity curve
KI	0.1–0.3	The outflow coefficients of the free water storage to interflow
KG	0.1–0.4	The outflow coefficients of the free water storage to groundwater
IMP	0.01	The ratio of the impervious to the total area of the basin
C	0.08–0.18	The coefficient of deep evapotranspiration
CI	0.9–0.93	The recession constant of the lower interflow storage
CG	0.997	The recession constant of groundwater storage
N	1–5	Number of reservoirs in the instantaneous unit hydrograph
NK	4–10	Common storage coefficient in the instantaneous unit hydrograph
XE	0.45	The weighting factor of the Muskingum method
K/(h)	5	The storage time constant of the Muskingum method

the data from 1993 to 1996 are selected as the calibration period, and the data from 1997 to 1998 are selected as the validation period.

As shown in Figure 3, eight land cover types were identified in the Dongwan watershed in which there were three main kinds of land cover: woodland, cropland and wooded grassland, with slightly different subdivisions. The Dongwan watershed consists of three main kinds of soil types: Calcaric Cambisols (CMc), Eutric Cambisols (CMe), and Calcic Luvisols (LVk), all of which are almost evenly distributed in the watershed. Therefore, the parameters are considered as homogeneous over the whole basin in this study.

Extraction of the digital river network and sub-basin based on digital elevation model (DEM)

Based on DEM data with a map scale of 1:250,000, the digital river network, sub-watersheds, and topological relations of the study area are extracted automatically by using Arc Hydro Tools, including the related hydrological topography features, such as the area, river length, and gradient, etc. In this study, the Dongwan watershed was divided into four sub-watersheds by three hydrological gauge stations (Luanchan, Tantou, and Dongwan), with areas of 340, 729, 626, and 928 km^2 respectively (Figure 3).

Model parameter ranges

Based on previous studies of the Xinanjiang model (Zhao *et al.* 1980; Zhao 1992; Zhao & Liu 1995) and the characteristics of the Dongwan watershed, such as climate, land use, land cover, and vegetation and soil conditions, the prior ranges of the Xinanjiang model in this study were determined and listed in Table 1. In detail, the value of the ratio of the impervious to the total area of the basin (IMP) is taken as 0.01 because the study area is a natural basin. The parameters of the Muskingum method XE and K are estimated by the trial and error method using the observed discharge, which are equal to 0.45 and 5 h respectively. Thus, 14 parameters were selected for the uncertainty analysis.

RESULTS

Comparison of the behavioral parameter sets

To assess the impact of using the interior sites' flow information on the uncertainty of hydrological modeling, this study accepted 12 scenarios (as shown in Table 2) by taking the threshold values of the Nash–Sutcliffe efficiency index (NE-outlet) at the outlet (Dongwan station) as 50,

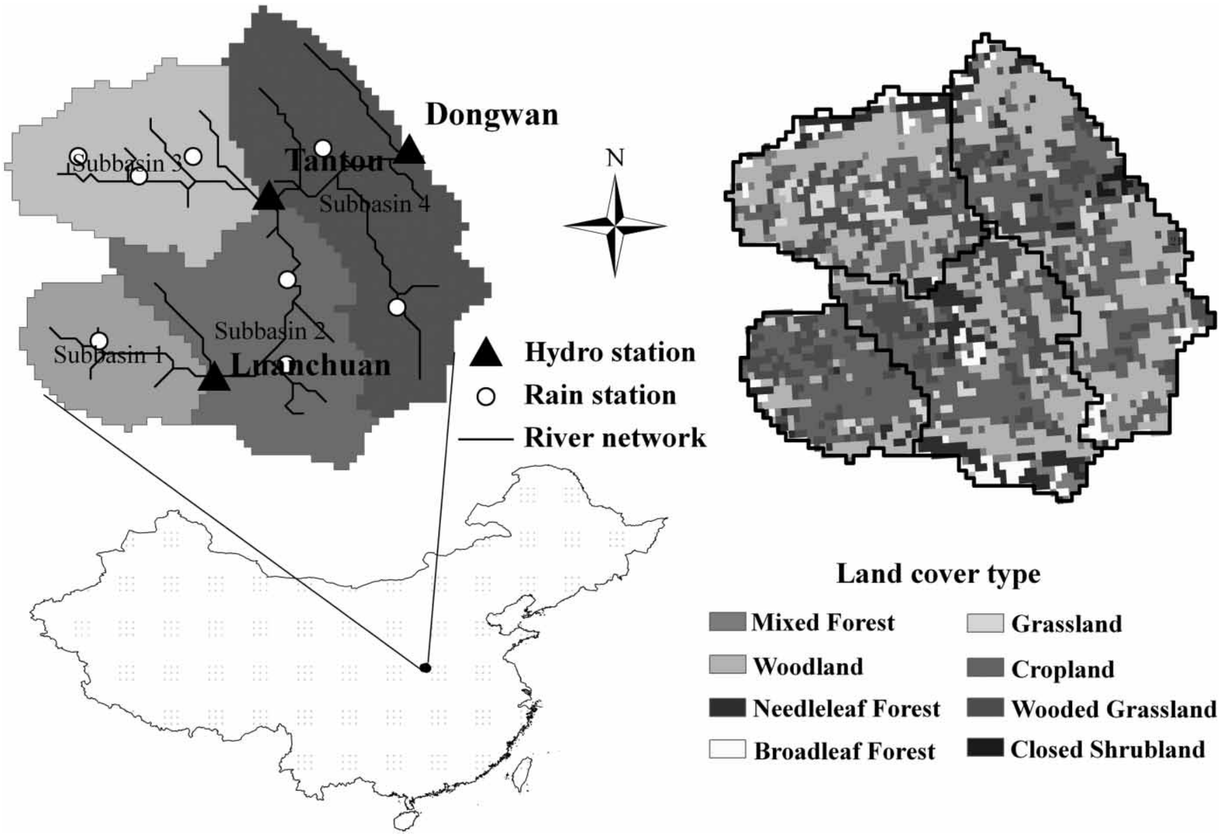

Figure 3 | Location, digital river network, and land cover of the Dongwan basin.

Table 2 | Comparison of number of behavior parameters of different scenarios

Threshold of NE-Interior site / Threshold of NE-Outlet	Scheme I	70% Luanchan	70% Tantou	70% Luanchuan and Tantou
50%	4,927	3,513	4,273	3,225
60%	4,872	3,507	4,270	3,218
70%	4,645	3,448	4,200	3,184

Scheme I represents the scenario without setting the threshold value at the interior site; NE-Outlet and NE-Interior sites are the Nash–Sutcliffe efficiency indices at the outlet and interior sites, respectively.

60, and 70% without setting the threshold value at the interior sites and setting the threshold values of different interior sites (NE-interior site) as 70%. The Xinanjiang model was used to perform the hydrological modeling, and the GLUE method with the SCEM-UA sampling algorithm was adopted for the uncertainty analysis. The total number of behavioral parameter sets of the above 12 scenarios are listed in Table 2, which showed that the number of behavioral parameter sets decreased when setting the threshold value at the interior site under all the threshold values at the outlet, especially for setting the threshold value at all interior sites, i.e., Luanchuan and Tantou. Figure 4 shows the scatter map between the Nash efficiency indices at the outlet and interior sites under the threshold of the Nash efficiency index at the outlet as 50%. From Figure 4, although it does not show direct relationship, it can be seen that the Nash efficiency index at the outlet is sensitive with that at the interior sites, and with the greater value of the Nash–Sutcliffe efficiency index at the interior sites, it is easier to get the greater value of that at the outlet.

For further analysis of the difference in behavioral parameter sets among different threshold values at the interior sites, two schemes were selected from the above 12 scenarios. Scheme I sets the threshold of likelihood measure only at the outlet as 70% (NE = 70%), and

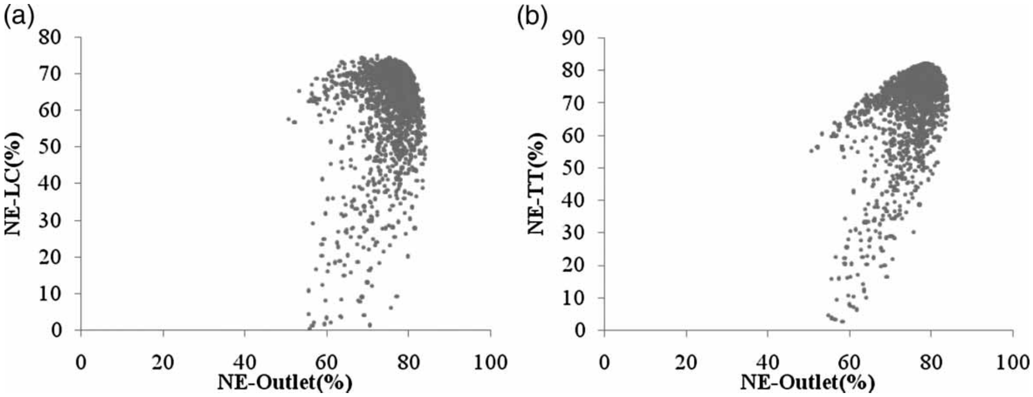

Figure 4 | The scatter map between the Nash–Sutcliffe efficiency indices at the outlet and interior stations under threshold of the Nash–Sutcliffe efficiency index at the outlet as 50%.

scheme II sets the threshold of likelihood measure at both the outlet and interior sites (Dongwan station, Luanchuan and Tantou stations) as 70% ($NE_1 = NE_2 = NE_3 + 70\%$). Table 3 lists part of the behavioral parameter sets and associated likelihood measure values in scheme I. As shown in Table 3, the parameter sets based only on the runoff at the outlet do not always produce high likelihood measure values at the interior sites. Typically, some values were even smaller than 50% (the shaded numbers in Table 3). That is, many unreasonable behavioral parameter sets were obtained by using scheme I. It is indicated that some unreasonable parameter sets can be removed by setting

Table 3 | Part of the behavioral parameter sets obtained by scheme I

WM	X	Y	KE	B	SM	EX	KI	KG	C	CI	N	NK	NE-LC/%	NE-TT/%	NE-Outlet/%
114.03	0.06	0.63	1.09	0.14	17.34	1.47	0.24	0.32	0.15	0.93	1.07	7.35	43.90	45.80	71.40
161.78	0.12	0.67	1.30	0.25	28.63	1.00	0.23	0.28	0.13	0.92	1.64	5.26	60.40	70.50	79.70
124.65	0.06	0.57	1.22	0.25	21.04	1.36	0.11	0.13	0.18	0.91	1.88	8.95	64.90	70.30	75.10
129.60	0.13	0.60	1.38	0.23	48.05	1.32	0.26	0.38	0.16	0.91	1.52	8.64	67.10	73.80	81.50
111.35	0.17	0.53	1.31	0.14	30.41	1.26	0.10	0.19	0.17	0.91	3.91	6.20	66.90	73.20	77.10
152.56	0.17	0.65	0.96	0.36	10.78	1.48	0.40	0.19	0.10	0.92	2.51	8.89	50.20	54.90	74.00
142.76	0.15	0.42	1.43	0.20	29.11	1.13	0.30	0.24	0.13	0.91	1.51	7.88	64.40	73.70	82.20
111.73	0.06	0.65	1.26	0.28	29.33	1.09	0.28	0.31	0.09	0.90	2.97	4.97	73.30	66.80	71.70
136.84	0.13	0.56	1.50	0.16	27.88	1.38	0.29	0.16	0.09	0.91	3.29	9.49	53.00	70.60	83.60
154.24	0.10	0.62	1.36	0.36	17.12	1.33	0.28	0.33	0.10	0.92	3.02	9.20	71.70	69.00	71.50
116.07	0.08	0.52	1.03	0.27	11.69	1.41	0.17	0.34	0.13	0.92	2.47	5.69	63.60	57.80	71.90
134.56	0.18	0.58	1.16	0.14	41.46	1.26	0.13	0.23	0.10	0.93	4.50	6.98	47.10	59.50	77.80
120.91	0.15	0.51	1.45	0.24	42.02	1.41	0.40	0.26	0.12	0.92	3.80	4.32	57.80	69.80	82.70
138.11	0.09	0.49	1.04	0.23	16.37	1.22	0.18	0.30	0.14	0.92	2.94	4.04	35.50	37.00	72.30
159.70	0.19	0.47	1.17	0.14	18.99	1.37	0.17	0.20	0.16	0.93	2.66	4.10	52.30	66.40	82.80
138.70	0.16	0.66	1.43	0.14	49.51	1.08	0.24	0.37	0.15	0.92	1.28	4.25	71.20	77.20	78.90
155.49	0.07	0.57	0.96	0.37	33.05	1.47	0.13	0.28	0.17	0.91	3.30	7.33	47.90	46.60	70.70
104.84	0.11	0.61	1.30	0.22	29.13	1.31	0.18	0.32	0.12	0.90	1.52	7.28	74.00	69.70	70.30
115.28	0.13	0.69	1.19	0.13	18.13	1.18	0.15	0.26	0.16	0.90	4.50	4.36	71.30	71.50	71.60
146.48	0.13	0.54	1.49	0.12	35.55	1.15	0.15	0.29	0.16	0.90	2.98	7.56	72.80	77.10	75.20

NE-LC, NE-TT, and NE-Outlet are the Nash–Sutcliffe efficiency indices at Luanchuan, Tantou, and outlet respectively.

the threshold of the likelihood measure at the interior sites. The mean and standard deviation of behavioral parameter sets and efficiency coefficients of scheme I and scheme II were gained and are shown in Figure 5. Referring to Figure 5, it can be seen that the standard deviation of most behavioral parameter sets decreased greatly when setting the threshold value at the interior sites, and the same with the Nash–Sutcliffe efficiency indices at the outlet and interior sites. All of the above results and analysis indicated that taking the interior sites' information into consideration can reduce parameter uncertainty to some degree.

Comparison of parameters' posterior distributions

Figure 6 illustrates comparisons between the parameters' posterior distributions of the Xinanjiang model obtained by scheme I and scheme II, respectively. As shown in Figure 6, the posterior distributions all show distinct non-uniform distribution, and have peak value mostly in the two schemes. Blasone & Vrugt (2008) have indicated that the SCEM-UA-derived initial sample contains numerous solutions in the high probability density (HPD) region of the parameter space, so that the average distance of the various parameter combinations to the optimal model is small. Furthermore, most of the parameters' posterior distributions obtained by scheme II showed more peak than those obtained by scheme I. This finding implied that the posterior distributions obtained by scheme II can evolve into the HPD region of the parameter space with higher frequency, so as to obtain more reasonable posterior distributions of the hydrological parameters, since scheme II further filters the alternative simulation results using the interior flow information.

Comparison of uncertainty intervals

To investigate how the interior sites' information affects the efficiency of uncertainty interval in the Xinanjiang modeling, three indices including the CR, RIW, and the Nash–Sutcliffe efficiency index of the median $MQ_{0.5}$ presented above, were selected to evaluate the efficiency of

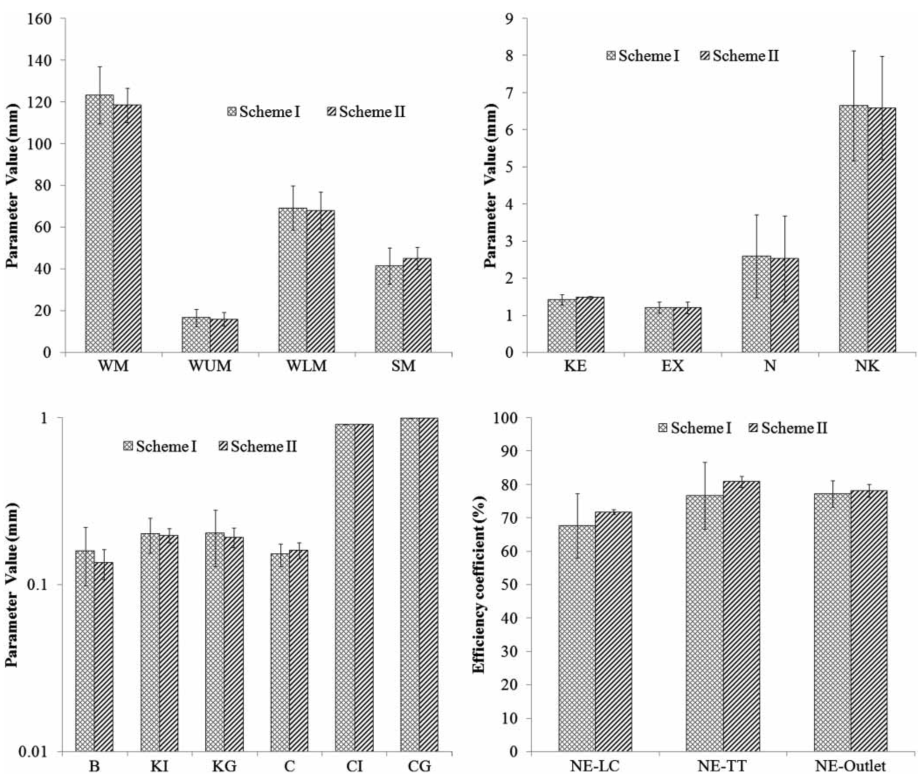

Figure 5 | Comparisons of the mean and standard deviation of behavior parameters and Nash–Sutcliffe efficiency index of different schemes under threshold of the Nash–Sutcliffe efficiency index at the outlet as 70%.

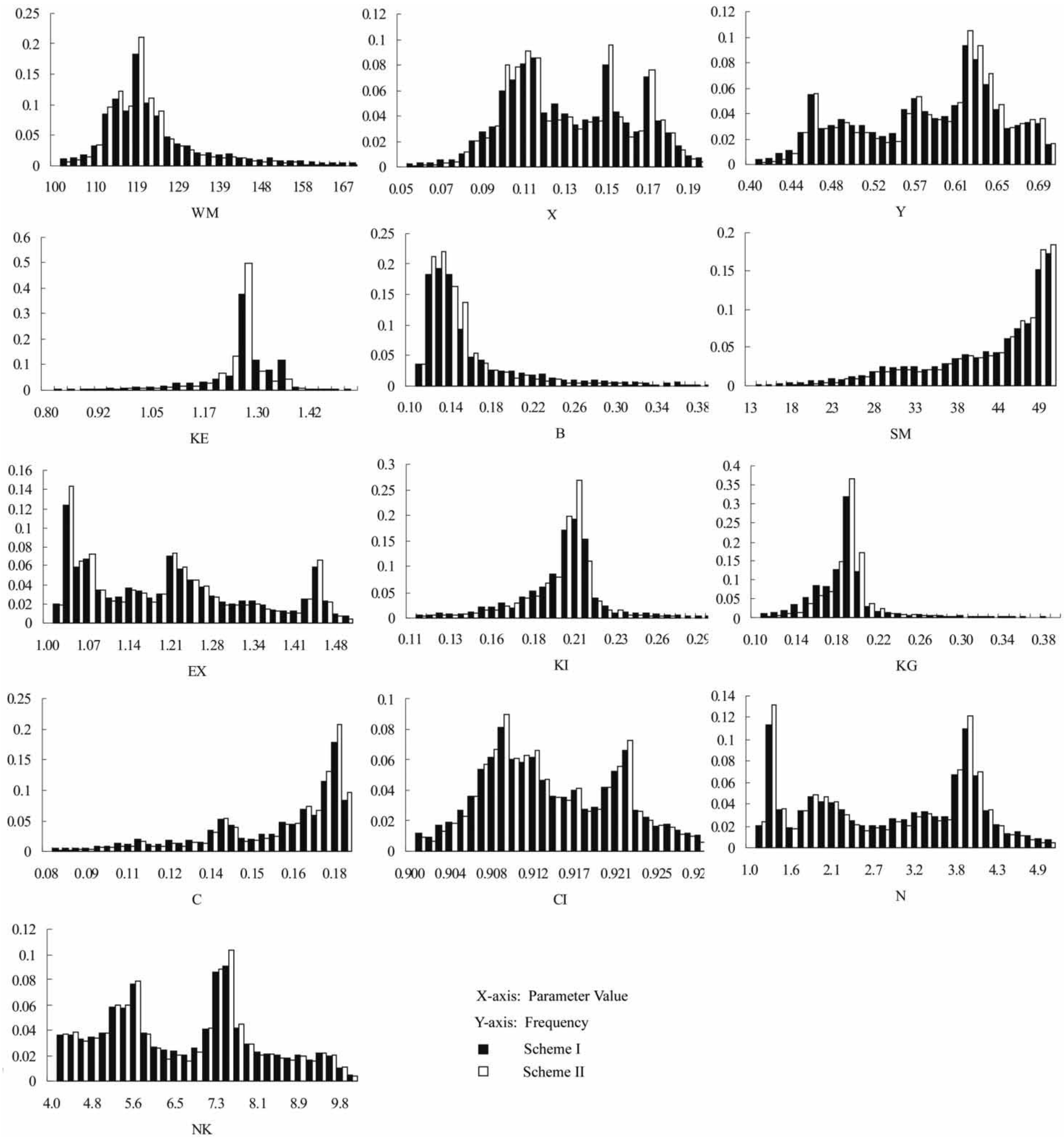

Figure 6 | The posterior distribution of parameters obtained by scheme I and scheme II.

uncertainty. The uncertainty intervals for a given confidence level of 90% are obtained by using the GLUE method with setting a given threshold value of NE as 70%. Table 4 displays the results of the uncertainty evaluation indices of the Xinanjiang model obtained by scheme I and scheme II. NE($MQ_{0.5}$) in Table 4 represents the Nash–Sutcliffe efficiency index of the median $MQ_{0.5}$ produced from the uncertainty analysis by fitting the observed runoff series.

Table 4 | Assessing indices of uncertainty for different schemes

Evaluation index		Dongwan (Outlet) Scheme I	Dongwan (Outlet) Scheme II	Dongwan (Outlet) RI%	Tantou Scheme I	Tantou Scheme II	Tantou RI%	Luanchuan Scheme I	Luanchuan Scheme II	Luanchuan RI%
RIW	Calibration	0.606	0.524	– 13.58	0.589	0.524	– 11.05	0.575	0.524	– 8.89
	Verification	0.617	0.538	– 12.91	0.607	0.538	– 11.37	0.665	0.538	– 19.13
CR	Calibration	0.683	0.660	– 3.35	0.677	0.661	– 2.42	0.666	0.652	– 2.15
	Verification	0.693	0.674	– 2.74	0.628	0.612	– 2.60	0.631	0.607	– 3.84
$NE(MQ_{0.5})$	Calibration	0.803	0.807	0.59	0.848	0.850	0.24	0.779	0.783	0.54
	Verification	0.859	0.861	0.23	0.808	0.811	0.38	0.747	0.754	0.83

RI is the percentage of IW decrease from scheme II to scheme I; RIW is relative interval width; CR is containing ratio; $NE(MQ_{0.5})$ is the Nash–Sutcliffe efficiency index of the median value $MQ_{0.5}$.

Figures 7 and 8 illustrate the uncertainty intervals and observed flow during the time period of 24 July–12 October 1996 (calibration period) and 19 July–13 October 1998 (validation period) at Dongwan obtained by scheme I and scheme II, respectively.

It can be found from Table 4 and Figures 7 and 8 that the CR did not decrease by much but a more significant decrease can be found in the RIW, implying that considering the interior sites' flow information can reduce parameter uncertainty to some degree. It can be also observed from Table 4 and Figures 7 and 8 that the Nash–Sutcliffe efficiency index of the median $MQ_{0.5}$, NE ($MQ_{0.5}$) increased with setting the thresholds at the interior sites, which indicated that, when considering the interior sites' flow information, the simulated runoff series by

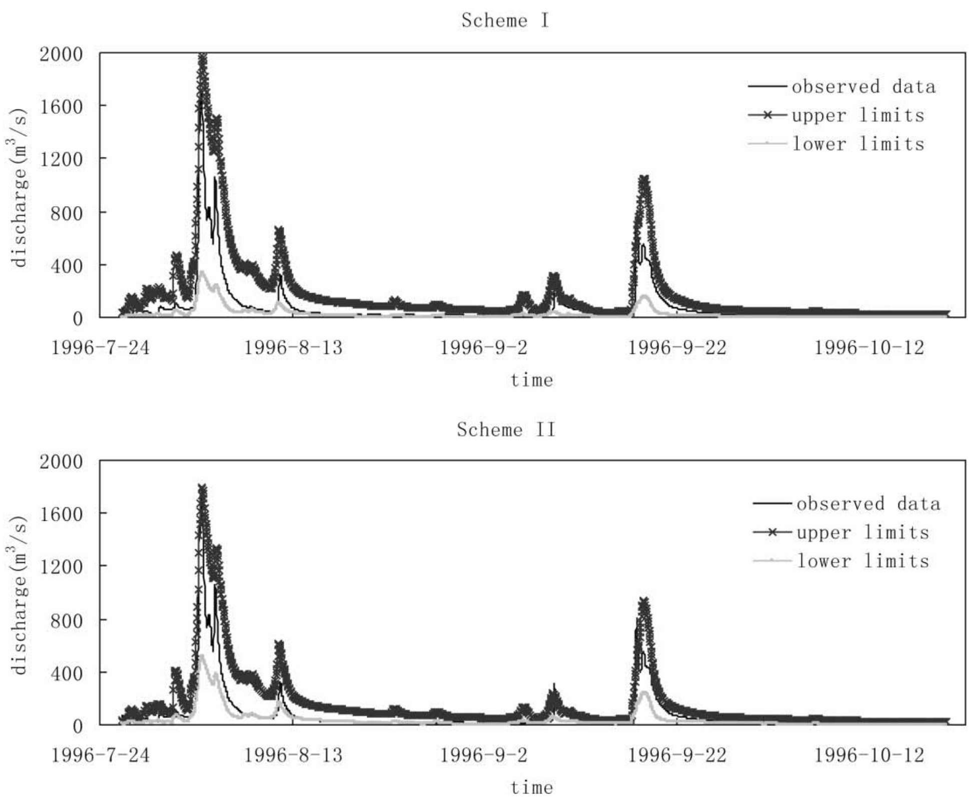

Figure 7 | The runoff uncertainty intervals and observed flow during the time period 24 July–12 October at the outlet obtained by scheme I and scheme II.

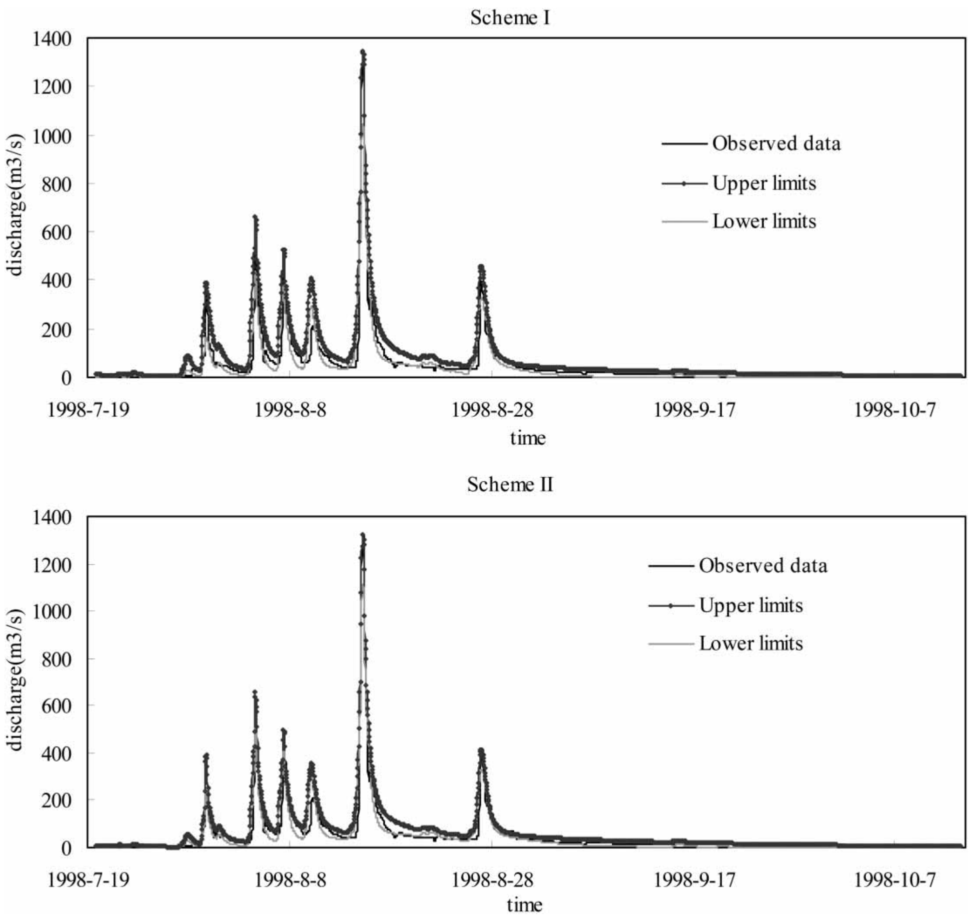

Figure 8 | The runoff uncertainty intervals and observed flow during the time period 19 July–13 October at the outlet obtained by scheme I and scheme II.

the Xinanjiang model with the behavioral parameter sets will fit better with the observed runoff series. Referring to Table 4, the results also showed that the total coverage ratios in both calibration and validation are not very high. It was found that the coverage ratios are high at the high flow, but they are low at the low flow, and the period of low flow is longer than that of high flow. As we know, there can be uncertainty due to many reasons, e.g., input uncertainty, model structure uncertainty, parameter uncertainty; however, in this case, the reason for this result is that the model used in this study cannot perform very well at the low flow in the study area. As pointed out by Beven *et al.* (2011), we should not expect such periods to be well predicted by the set of behavioral models identified in calibration. We should also not expect that such periods would be covered by any statistical representation of the calibration errors, since the epistemic uncertainties of inconsistent periods in prediction might be quite different to those in calibration. The only response to this would appear to be to moderate our expectations of what a model, or set of models, can do in prediction. Other relative issues need to be carried out in the future.

CONCLUSION

The aim in researching uncertainty is to find the ways and measures to reduce parameter uncertainty in hydrological modeling and forecasting, so as to increase the accuracy and reliability of hydrological forecasting. Using all the available and new data for multi-site evaluation is one of the valid ways to reduce parameter uncertainty in hydrological modeling and forecasting. Based on the GLUE method with the SCEM-UA sampling algorithm, this study focuses on reducing hydrological modeling uncertainty by using the interior hydrological information in the performance of the Xinanjiang model.

Comparison of the results between 12 scenarios showed that, under the same threshold of the Nash–Sutcliffe efficiency index at the outlet, the number and standard deviation of behavioral parameter sets decreased greatly when setting the threshold value at the interior sites. The uncertainty analysis confirmed that the GLUE method with the SCEM-UA sampling algorithm, which periodically updates the size and direction of the proposal distribution, was able to locate the HPD region of the parameter space efficiently. In addition, the CR decreased by not much but a more significant decrease can be found in the RIW, implying that considering the interior sites' flow information, which makes the selection of behavior parameters stricter, can reduce parameter uncertainty to some degree. As well, the Nash–Sutcliffe efficiency of the median value, $MQ_{0.5}$, increased when the interior sites' flow information was taken into consideration, which indicated that when considering the interior sites' flow information, the simulated runoff series by the Xinanjiang model with the behavioral parameter sets can fit better with the observed runoff series, and correspondingly, the abstracted median value, $MQ_{0.5}$, can be improved for better prediction of the runoff.

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