Research Article

Effect of Baseflow Separation on Uncertainty of Hydrological Modeling in the Xinanjiang Model

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Based on the idea of inputting more available useful information for evaluation to gain less uncertainty, this study focuses on how well the uncertainty can be reduced by considering the baseflow estimation information obtained from the smoothed minima method (SMM). The Xinanjiang model and the generalized likelihood uncertainty estimation (GLUE) method with the shuffled complex evolution Metropolis (SCEM-UA) sampling algorithm were used for hydrological modeling and uncertainty analysis, respectively. The Jiangkou basin, located in the upper of the Hanjiang River, was selected as case study. It was found that the number and standard deviation of behavioral parameter sets both decreased when the threshold value for the baseflow efficiency index increased, and the high Nash-Sutcliffe efficiency coefficients correspond well with the high baseflow efficiency coefficients. The results also showed that uncertainty interval width decreased significantly, while containing ratio did not decrease by much and the simulated runoff with the behavioral parameter sets can fit better to the observed runoff, when threshold for the baseflow efficiency index was taken into consideration. These implied that using the baseflow estimation information can reduce the uncertainty in hydrological modeling to some degree and gain more reasonable prediction bounds.

1. Introduction

Since Crawford and Linsley developed the Stanford Watershed Model [1]; conceptual rainfall-runoff models have been widely used to tackle many practical and pressing issues in the planning, design, operation, and management of water resources. The successful application of hydrological models depends largely on whether or not the model is reasonably built and the selection of suitable models to represent the hydrological properties of study basins. Due to the complexity of hydrologic processes in watershed hydrology, hydrological models are often developed for specific problems and limited to the knowledge and experiences of model developers. Model uncertainty lies mainly in the inadequate knowledge and techniques and definite mathematic descriptions of the hydrological phenomena.

Model structure error associated with the mathematical representation or equation is an important cause for prediction uncertainty [2], but it is very difficult to quantify. Traditionally model calibration and validation are based on observed flow rates, while internally a number of additional states and fluxes are calculated. Many studies sought ways and measures to reduce prediction uncertainty in hydrological modeling by using other available information [3, 4]. For example, Gallart et al. used water table records to reduce the uncertainties of discharge and baseflow predictions [5]. Choi and Beven proposed a method by using multiperiod and multicriteria model conditioning to reduce the prediction uncertainty in TOPMODEL [6]. Maschio et al. dealt with uncertainty mitigation by using observed data integrated with uncertainty analysis and history-matching [7]. Schmittner et al. used isotope tracer observations to reduce the

uncertainty of ocean diapycnal mixing and climate-carbon cycle projections [8]. Karasaki et al. tried to reduce the uncertainty of hydrologic models by using data from a surface-based investigation in Hokkaido, Japan [9]. Lumbroso and Gaume used the analysis of various types of data that can be collected during postevent surveys and the consistency check to reduce the uncertainty in indirect discharge estimates [10]. Lin et al. used multisite evaluation to reduce parameter uncertainty in the Xinanjiang model within the GLUE framework [11].

Recently, Rouhani et al. adopted a graphical baseflow estimation method to calibrate and validate the SWAT (soil water assessment tool) model [12]. Ferket used a baseflow estimation method based on a physically-based digital baseflow filter to validate the internal model dynamics of two widely used rainfall-runoff models [13]. However, most of the baseflow separation methods including the physically-based digital baseflow separation algorithm are parametric methods [14], which often result in more uncertainty. While the smoothed minima method (SMM) [15] is a relatively objective method and is widely used in the world [14–16], which can obtain the continue baseflow processes and is easy to perform. Therefore, the aim of this paper is to study how well the uncertainty can be reduced by considering baseflow estimation information obtained from the SMM method in the Xinanjiang model, which is a conceptual model, and has been widely used in many regions of China and in some other regions of the world for flood forecasting and water resources planning and assessment [17]. The generalized likelihood uncertainty estimation (GLUE) method with shuffled complex evolution Metropolis (SCEM-UA) sampling was used to analyze the uncertainties in hydrological modeling.

2. Methodology

2.1. The Xinanjiang Model. The core concept of the Xinanjiang model is to model the depletion of storage; in another word, the runoff is not produced until the soil moisture content reaches its field capacity, and thereafter the runoff equals the excessive rainfall without further loss [18]. The flow chart of the Xinanjiang model is shown in Figure 1. It can be seen from Figure 1 that the Xinanjiang model involves four major parts, that is, evapotranspiration, runoff production, runoff separation, and flow routing procedure. It is notable that two runoff components, surface runoff and groundwater flow, are used in the part of runoff separation. As listed in Table 1, there are 13 parameters in the Xinanjiang model, including four parameters (KE, X, Y, and C) for evapotranspiration, three parameters (WM, B, and IMP) for runoff production, four parameters (SM, EX, and KG) for runoff separation, and four parameters (CG, N, and NK) for runoff concentration.

2.2. Model Calibration Method. One crucial step in hydrological modeling is model calibration, in which the closed values of model parameters are identified [19]. In this study, the SCE-UA (shuffled complex evolution) method proposed by Duan et al. was selected to calibrate the model [20].

The Nash-Sutcliffe efficiency coefficient was used to assess the effectiveness of model calibration. The Nash-Sutcliffe efficiency index NE [21] is expressed as follows:

$$NE = \left(1 - \frac{\sum (Q_i - \widehat{Q}_i)^2}{\sum (Q_i - \overline{Q}_c)^2} \right) \times 100\%, \quad (1)$$

where Q_i is the observed discharge (m^3/s), $\widehat{Q}_i$ is the simulated discharge (m^3/s), and $\overline{Q}_c$ is the mean observed discharge in calibration period (m^3/s).

2.3. The Smoothed Minima Method. In practice, it is very difficult to separate a hydrograph into three components due to the lack of the observed data for a given basin. All available hydrograph separation methods including the SMM method used in this study attempt to separate a hydrograph into surface runoff and baseflow [14, 22, 23]. The baseflow separation procedure in the SMM method is described as follows [16].

- Daily flows, $q_t, t = 1, \dots, n$ are divided into m nonoverlapping 5-day blocks starting at the beginning of the daily flow time series. If n is not a multiple of 5, then the final $q_{5m+1}, \dots, q_n$ are ignored.
- For each block, the minimum daily flow is identified, and these form the $\bar{q}_1, \bar{q}_2, \dots, \bar{q}_m$ series of minima.
- Turning points among $\bar{q}_i$ are identified such that when the flow value is multiplied by 0.9, which is smaller than both neighbors; that is, $\bar{q}_i$ is a turning point if $0.9 \cdot \bar{q}_i < \bar{q}_{i-1}$ and $0.9 \cdot \bar{q}_i < \bar{q}_{i+1}$.
- The turning points become baseflow ordinates, and baseflow values between turning points are linearly interpolated in time under the condition that the baseflow cannot exceed the total daily flow, since baseflow is part of the daily flow.

In order to compare the discharge components, an efficient index for the baseflow efficiency (NE_b) is defined as

$$NE_b = \left(1.0 - \frac{\sum_{i=1}^n [Q_{b,\text{SMM}}(i) - Q_{b,\text{sim}}(i)]^2}{\sum_{i=1}^n [Q_{b,\text{SMM}}(i) - \overline{Q}_{b,\text{SMM}}]^2} \right) \times 100\%, \quad (2)$$

where $Q_{b,\text{SMM}}(i)$, $Q_{b,\text{sim}}(i)$, and $\overline{Q}_{b,\text{SMM}}$ denote the baseflow obtained by the smoothed minima method (SMM), the simulated baseflow from the Xinanjiang model, and the mean baseflow from the SMM method, respectively. n is the size of the baseflow data.

2.4. The Uncertainty Estimated Method. GLUE is a parameter uncertainty estimation method proposed by Beven and Binley [24]. It has been widely used in many complex and nonlinear models [25, 26]. However, the Monte Carlo (MC) based sampling strategy of the prior parameter space typically utilized in GLUE is not particularly efficient in finding behavioral simulations. This becomes especially problematic for high-dimensional parameter estimation problems and in

FIGURE 1: Flowchart of the Xinanjiang model.

TABLE 1: Parameters of the Xinanjiang model and related prior ranges.

Parameter	Range	Description
WM/(mm)	100–250	Areal soil moisture storage capacity
X	0.1–0.2	Proportion of mean tension water capacity of the upper layer to WM
Y	0.3–0.7	Proportion of mean tension water capacity of the lower layer to $(1 - X) * WM$
KE	0.8–1.5	Ratio of potential evapotranspiration to pan evaporation
B	0.1–1.0	Exponent of soil moisture storage capacity curve
SM/(mm)	10–50	Areal mean free water capacity of the surface soil layer
EX	1–1.5	Exponent of free water capacity curve
KG	0.1–0.5	Outflow coefficients of free water storage to groundwater
IMP	0.001–0.1	Ratio of the impervious to the total area of the basin
C	0.1–0.3	Coefficient of deep evapotranspiration
CG	0.6–0.99	Recession constant of groundwater storage
N	1–5	Number of reservoirs in instantaneous unit hydrograph
NK	1–4	Common storage coefficient in instantaneous unit hydrograph

the case of complex simulation models that require significant computational time to produce the desired outputs [27]. In a separate line of research, Markov Chain Monte Carlo (MCMC) method has been developed to locate the high probability density (HPD) region of the parameter space efficiently. Therefore, Blasone et al. proposed a revised GLUE method by constructing the initial sample using the SCEM-UA sampling algorithm and deriving the associated estimates of model outputs (as the median of the distribution) and uncertainty bounds (as percentiles of the output prediction) using the GLUE method [27]. The SCEM-UA algorithm is a modified version of the original SCE-UA global optimization algorithm [20]. This algorithm is Bayesian in nature and operates by merging the strengths of the Metropolis algorithm, controlled random search, competitive evolution,

and complex shuffling to continuously update the proposal distribution and evolve the sampler to the posterior target distribution [28]. Blasone et al. found that the GLUE method with the SCEM-UA sampling algorithm can find the behavioral simulations more efficiently [27]. A revised GLUE method with SCEM-UA sampling algorithm was used to estimate the uncertainty by Lin et al. [11], which is also adopted to estimate the uncertainty in this study. The flow chart of this method is shown in Figure 2. In the SCEM-UA sampling, a predefined number of different Markov Chains are initialized from the highest likelihood values of the initial population. Each chain evolves independently according to the Sequence Evolution Metropolis (SEM) algorithm, and this evolution is performed until the Gelman and Rubin convergence criteria [29] are satisfied. A detail description

FIGURE 2: Flowchart of the GLUE method with SCEM-UA sampling algorithm.

and explanation of this method can be found in Vrugt et al. [28]. The standard values of the parameters presented in Vrugt et al. [28] were adopted in this study.

Besides the Nash-Sutcliffe efficiency coefficient for total flow (NE) and baseflow (NE_b), two other indices, that is, containing ratio (CR) and relative interval width (RIW), were adopted to evaluate uncertainty interval in this study. The definitions of these two indices are well introduced in the literatures [14, 24, 30–32] and can be calculated as follows:

$$CR = \frac{\sum_{i=1}^n J[Q_{obs}(i)]}{n}. \quad (3)$$

In which,

$$J[Q_{obs}(i)] = \begin{cases} 1, & Q_{low}(i) < Q_{obs}(i) < Q_{up}(i), \\ 0, & \text{otherwise,} \end{cases} \quad (4)$$

$$RIW = \frac{\sum_{i=1}^n [Q_{up}(i) - Q_{low}(i)]}{n\bar{Q}_{obs}},$$

where $Q_{low}(i)$ and $Q_{up}(i)$ denote the lower and upper uncertainty bounds at time i , respectively. $Q_{obs}(i)$ and $\bar{Q}_{obs}$ denote

the observed flow and its mean value, respectively. n is the length of the series.

The Nash-Sutcliffe efficiency index (NE) and the baseflow efficiency index (NE_b) are used to evaluate the median values, $MQ_{0.5}$, against the observations of the total flow and baseflow.

3. Case Study: River Basin and Model Parameter Range

The Jiangkou basin was selected as case study, which is located in the upper Hanjiang River (Figure 3), which is one of the largest tributaries to the Yangtze River. The Hanjiang River is the headwater or sources water of the middle route for the South-to-North water transfer in China (SNWTP). The Jiangkou basin drains 2803 km² and the mean annual precipitation and runoff are 825 mm and 337 mm per unit area, respectively.

Daily rainfall and runoff data from 1980 to 1987 were used in this study. Based on the previous studies of the Xinanjiang model [18, 33, 34], the prior ranges of parameters for the Xinanjiang model were listed in Table 1.

TABLE 2: Optimized parameter values of the Xinanjiang model.

WM	WUM	WLM	KE	B	SM	EX	KG	IMP	C	CG	N	NK	NE (%)
130.2	16.0	40.4	1.33	0.99	32.9	1.50	0.10	0.10	0.10	0.95	1.01	1.14	90

TABLE 3: Comparison of the BFI values obtained by different methods.

Method	SMM	QG	Arnold's digital filter	Spongberg's digital filter	Graphical approach
BFI	0.45	0.46	0.41	0.47	0.49

FIGURE 3: Location map of the Jiangkou River Basin.

FIGURE 4: The total flow and baseflow estimated by the SMM method and the groundwater flow (QG) simulated by the Xinanjiang model.

4. Results and Discussions

4.1. Estimation of Baseflow. The Xinanjiang model for the study basin was first calibrated using the SCE-UA method. The optimization parameters of the Xinanjiang model are listed in Table 2. Shown in Figure 4 are the simulated total

TABLE 4: Comparison of the number of behavior parameter sets in different scenarios.

Threshold of NE (%)	Threshold of NE_b (%)					
	*	0	40	50	60	70
50	5913	4276	2691	2410	1722	362
60	5627	4238	2676	2401	1718	362
70	5318	4182	2654	2388	1713	362

* represents the scenario without threshold for the baseflow efficiency index.

flows, the baseflow estimated by the SMM method, and groundwater flow (QG) simulated by the Xinanjiang model. It showed that the SMM baseflow correlated well with QG.

The baseflow index (BFI), a volume ratio of baseflow to the total flow, is often used to evaluate the characteristic of baseflow. To validate the results of the SMM method, the digital filter and graphic approach were used for comparison in this study. In which, Arnold's digital filter that used three passes of the filter and filter parameters of 0.925 [22], Spongberg's digital filter that used two passes: forward and backward [23], and Graphical approach that adopted the oblique line separation method [35] were used to separate the baseflow in the study area. Table 3 listed the BFI values obtained by different methods. Referring to Table 3, the BFI indices for the baseflow obtained from SMM, QG calculated by the Xinanjiang model, Arnold's digital filter, Spongberg's digital filter, and Graphical approach were equal to 0.45, 0.46, 0.41, 0.47, and 0.49, respectively. Both Figure 4 and Table 3 showed that the baseflow obtained by the SMM method and the groundwater flow (QG) from the Xinanjiang model were comparable. Therefore, the groundwater flow (QG) was taken as baseflow obtained by the Xinanjiang model, so as to compare with the baseflow obtained by the SMM method.

4.2. Comparison of the Behavioral Parameter Sets. In order to assess the impact of baseflow simulation on model uncertainty, 18 scenarios were tested in this study, which were created by using the threshold values of 50%, 60%, and 70% for the Nash-Sutcliffe efficiency index (NE) to be combined with no threshold and with different threshold values of 0%, 40%, 50%, 60%, and 70% for baseflow efficiency index (NE_b). The Xinanjiang model and the SCEM-UA based GLUE method were used for uncertainty analysis. The total number of behavioral parameter sets for each scenario was listed in Table 4. It showed that the number of behavioral parameter sets decreased as NE_b increased.

FIGURE 5: Comparisons of the mean and standard deviation of behavior parameter sets and efficiency coefficients under different thresholds for the baseflow efficiency index (* represents the scenario without threshold for the baseflow efficiency index).

The mean and the standard deviation of behavior parameter sets and efficiency indices under different thresholds for the baseflow efficiency index were compared in Figure 5. Referring to Figure 5, the standard deviation of most behavior parameter sets decreased greatly with the increase of the threshold value of baseflow efficiency index and the same for the Nash-Sutcliffe efficiency index and baseflow efficiency index. Results also showed that the mean of the Nash-Sutcliffe efficiency index increased slightly with the increase of the threshold value of the baseflow efficiency index, while the mean of every behavior parameter sets varied differently. Figure 6 showed the scatter map between the Nash-Sutcliffe efficiency index and the baseflow efficiency index when the

threshold value for the Nash-Sutcliffe efficiency index was at 70%. Referring to Figure 6, it can be seen that the high Nash-Sutcliffe efficiency coefficients corresponded well with the high baseflow efficiency coefficients.

4.3. Comparison of Uncertainty Intervals. The results from Section 4.2 showed that baseflow has a great impact on behavioral parameter sets in hydrological modeling. This study also investigated the effect of baseflow on the uncertainty intervals in the Xinanjiang model. Four indices, that is, the containing ratio (CR), relative interval width (RIW), the Nash-Sutcliffe efficiency index, and the baseflow efficiency index of the median value, $MQ_{0.5}$ were selected to evaluate

FIGURE 6: The scatter map between the Nash efficiency index and baseflow efficiency index with the threshold for the Nash efficiency index at 70% ((a) without threshold for the baseflow efficiency index; (b) zero threshold for the baseflow efficiency index).

FIGURE 7: Comparison of observed flow and with 90% confidence intervals of the simulated total flow ((a) without threshold for baseflow efficiency index; (b) with the threshold for the baseflow efficiency index at 50%).

the efficiency of model uncertainty intervals. The uncertainty intervals of the 90% confidence level were obtained by the SCEM-UA-based GLUE analysis. Table 5 compared the uncertainties evaluation of the Xinanjiang model with respect to different thresholds for the baseflow efficiency index. NE ($MQ_{0.5}$) and NE_b ($MQ_{0.5}$) in the table represented the Nash-Sutcliffe efficiency index and the baseflow efficiency index for the median value, $MQ_{0.5}$, which was calculated from the uncertainty analysis by fitting the observed and simulated runoff series. Figures 7 and 8 illustrated the uncertainty intervals of total flow and baseflow for a six-month period in 1981 without the threshold and with the threshold value for the baseflow efficiency index at 50%, respectively.

As shown in Table 5, and in Figures 7 and 8, CR did not decrease by much as the threshold value increases, but there was a significant decrease for RIW, which implied the inclusion of baseflow efficiency in the proposed method can reduce model uncertainties. It can be also observed from Table 5, NE ($MQ_{0.5}$) and NE_b ($MQ_{0.5}$) increased when the thresholds of baseflow efficiency index increased, which

indicated the simulated runoff from the Xinanjiang model with the behavioral parameter sets can fit the observed runoff series better when the baseflow efficiency index was considered.

5. Conclusions

Hydrologic and environmental models often face the problem with uncertainties in model results. Uncertainty reduction has both theoretical and practical importance in hydrological science. In this study, the baseflow estimated by the SMM method was used to validate the Xinanjiang model. The reduction in model uncertainty was evaluated through the GLUE method with the SCEN-UA sampling algorithm.

Uncertainty analysis from 18 scenarios showed that, under the same threshold of the Nash-Sutcliffe efficiency index, the number and standard deviation of behavioral parameter sets decreased greatly with the increase of the threshold value of the baseflow efficiency index. It also showed that the inclusion of baseflow efficiency can reduce

TABLE 5: Assessing indices of uncertainty under different thresholds for the baseflow efficiency index with threshold for the Nash efficiency index at 70%.

Threshold of NE_b (%)	*	0		40		50		60		70	
		Value	RI/%	Value	RI/%	Value	RI/%	Value	RI/%	Value	RI/%
Total flow											
RIW	0.51	0.41	9.93	0.26	24.10	0.23	27.09	0.19	31.37	0.30	20.65
CR	0.697	0.663	4.88	0.601	13.77	0.562	19.37	0.505	27.55	0.582	16.50
NE (MQ0.5)	88.84	89.48	0.72	89.77	1.05	89.80	1.08	89.90	1.19	89.83	1.11
Baseflow											
RIW	0.97	0.79	17.80	0.54	42.80	0.47	49.79	0.35	61.85	0.40	56.70
CR	0.713	0.695	2.52	0.630	11.64	0.595	16.55	0.525	26.37	0.606	15.01
NE_b (MQ0.5)	43.11	56.74	31.62	63.28	46.79	63.98	48.41	65.97	53.03	72.18	67.43

* is for scenario without threshold for the baseflow efficiency index; RI is the change percentage of RIW between the scenarios with and without threshold for the baseflow efficiency index.

(a)

(b)

FIGURE 8: Comparison of baseflow obtained by SMM and with 90% confidence intervals of the simulated baseflow ((a): without threshold for the baseflow efficiency index; with the threshold for the baseflow efficiency index at 50%).

the modeling uncertainty in the Xinanjiang model and the simulated runoff from the Xinanjiang model with the behavioral parameter sets can fit the observed runoff better, which could mean the abstracted median value, $MQ_{0.5}$, can be improved for better runoff forecasts. This indicates that when taking the baseflow estimation information into consideration, the uncertainty in hydrological modeling can be reduced to some degree and more reasonable prediction bounds can be gained.

Furthermore, it is notable that the SMM method included in this study was just an alternative method for comparable baseflow processes to study the impact of baseflow separation on parameter uncertainty in hydrological modeling. In the future, with the development of the isotopes and distributed temperature sensing techniques, it would be possible to obtain a long enough time series of baseflow instead of the SMM result. The use of these methods, however, falls outside the scope of this paper.

Conflict of Interests

The authors declare that there is no conflict of interests regarding to the publication of this paper.

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