Hindawi
Advances in Meteorology
Volume 2019, Article ID 4795853, 16 pages
https://doi.org/10.1155/2019/4795853

Research Article

Flood Prediction in Ungauged Basins by Physical-Based TOPKAPI Model

Xiangyi Kong,[1] **Zhijia Li**,[1] **and Zhiyu Liu**[2]

[1]*College of Hydrology and Water Resources, Hohai University, 1 Xikang Road, Nanjing 210098, China*
[2]*Ministry of Water Resources Information Center, 2 Lane, Baiguang Road, Beijing 100053, China*

Correspondence should be addressed to Xiangyi Kong; kysadeur@yeah.net

Received 6 March 2019; Revised 23 May 2019; Accepted 12 June 2019; Published 5 September 2019

Academic Editor: Francesco Viola

Scarce historical flood data in ungauged basins make it difficult to establish empirical and conceptual model forecast in these areas. The physical-based distributed model TOPKAPI is introduced for flood prediction in an ungauged basin by parameter transplant. Five main parameters are selected, and the sensitivity is analyzed by the GLUE method. The Xixian basin and Huangchuan basin in the upper Huaihe basin in China are chosen as study areas. The Xixian basin is regarded as a gauged basin for parameter calibration, and the Huangchuan basin is regarded as an ungauged basin by ignoring the historical discharge data. The model is calibrated in gauged Xixian basin, and then parameters are directly transplanted to adjacent "ungauged" Huangchuan basin to simulate flood forecast in an ungauged basin. The sensitivity analysis shows that soil thickness and soil saturated water content are the most sensitive parameters, and the Manning coefficient of main channel with high Strahler also significantly affects forecast results. According to the simulation results, the TOPKAPI model exhibits good performance in building and the prediction of the ungauged basin, in which the qualified rate of volume and peaks reaches 69.23%, and the average NSE criterion is over 0.67, which is acceptable forecast accuracy and has positive implication for the hydrological forecasting research.

1. Introduction

The hydrological model is a vital tool for the current flood forecasting work by simulating the hydrological process. To estimate the outflow process at the exit section, it generates a certain flood runoff process in the basin under the circumstance of a certain structure and parameters [1]. The hydrological model basing on physical theory, according to the description method and generalization degree of the hydrological process, can be split into conceptual hydrological model and physical-based model [2]. The Xin'anjiang model proposed by Zhao of Hohai University is one of the conceptual hydrological models [3]. It is characterized by less model parameters and high forecasting accuracy, and it has been widely used in flood forecasting in various river basins in China [4]. However, as hydrogeological conditions of basins are highly generalized [5], the parameters should be calibrated using historical flood data [6], making it difficult to build a forecast model in the ungauged basins or basins using partial missing observation data [7]. Though the world's construction of hydrological stations continues to develop, there are still many small basins without monitoring stations; these small basins are often the focus areas of flood disaster research. For this reason, the flood forecasting of ungauged basins has become the focus and hot topic of existing research, as well as a challenge for all hydrologists [8].

The study on ungauged basin flood forecasting aroused the attention from hydrologists in the end of last century. Vandewiele et al. [9] used the method of regionalization of model parameters to forecast monthly discharge in ungauged region in 1991. Despite using the conventional regression equations to get model parameters, Burn and Boorman [10] employed the basin classification method to find similar basins. Since usually there are insufficient historical discharge data in ungauged basins, the commonest approach to build the hydrological model in ungauged is parameter transferring [11–13], suggesting that the

parameters required for models were calibrated in nearby basins with sufficient discharge data and then transplanted to ungauged basins. This approach, however, is based on the similarity of these two basins [14]. Günter [15] summarized several methods for ungauged basin prediction using both event models and explicit soil moisture accounting (ESMA) models. To solve the description of characteristics of ungauged basins, Murugesu [16] proposed the approach of physical controls (basin form and function) of the instantaneous unit hydrograph (IUH), which has been latterly achieved by Ellouze-Gargouri [17], using geomorphological instantaneous unit hydrograph (GIUH) and Copulas. In 2012, Moore et al. [18] made a prediction in ungauged basins in British Columbia (BC) by transposing model parameter from adjacent basin; they also achieved good results. Patil and Stieglitz [19], using a model developed themselves, analyzed selectively transferring sensitive versus insensitive parameters on flood forecasting in ungauged basins. Athira et al. [20] used SWAT model to explore the appropriate functional relationship between the parameters and basin characteristics. Waseem et al. [21] compared different interpolation schemes on parameter spatial distribution in ungauged basins. Hyun and Choi [22] analyzed the relationship between flooding index and rainfall pattern to forecast flood severity in ungauged basins. Sahoo et al. [23] adopted a novel routing method VPMD at ungauged rivers to plot rating curves. Cánovas et al. [24], using the 2D hydraulic model in Spain, conducted the research on flood discharge in ungauged basins.

With the advancement of geographic information technology, remote sensing technology, and computer science, even in the absence of hydrological observatories, the geography of the watershed can be obtained from remote sensing images, including digital elevation model (DEM) [5] and land use and soil classification maps [25]. To fully exploit the advantage of such development, the physical-based distributed hydrological models were created [2, 26]. They describe the underlying surface conditions of basins using physical parameters from remote senses, making it possible to simulate ungauged basin and become a new topic in the field of hydrological forecasting [27]. Among them, the TOPKAPI rainfall-runoff model refers to a distributed hydrological model with grid-based computational unit based on physical basis [28].

Professor Ezio Todini from the University of Bologna in Italy proposed the TOPKAPI (Topographic Kinematic Approximation and Integration) hydrological model in 1995 [29]. This model refers to a physics-based distributed hydrological model based on the study of rainfall-runoff relationship to explore the potential of hydrological model prediction based on physical theory in mountain flood forecast [29]. The model consists of several modules (e.g., evapotranspiration, snowmelt, soil flow, surface runoff, river runoff, and groundwater) [30]. In this model, the whole basin is split into cell grids, and each grid is considered a single calculation unit. Each calculation unit reflects the whole physical hydrological process [31]. This model, compared with conventional conceptual hydrological models (e.g., Xin'anjiang Model [3] and Sacramento Model [32]), fully considers the spatial heterogeneity of the underlying surface conditions, exhibiting the advantage of relatively simple structure, clear parameter meaning, large spatial scale elasticity, as well as wide application fields [33]. Flood simulation and forecasting by this model have been widely performed in many river basins in Italy, Germany, Spain, and other countries; good results have been achieved as well [30].

In this study, the capability to simulate flood in ungauged basin of TOPKAPI model is tested to give suggestions on flood forecast in ungauged basins. The sensitivity of the main parameters of the TOPKAPI model was analyzed, laying the theoretical basis for the parameter transplantation to build forecast model in ungauged basins. The Xixian basin located in the upstream of Huaihe River in China and the adjacent Huangchuan basin were taken as the research basins. The Huangchuan basin was considered the ungauged basin by ignoring the historical flood data. Parameters were calibrated in the Xixian basin and transplanted to the adjacent Huangchuan basin for flood simulation to test the application of TOPKAPI model in ungauged basins without parameter calibration.

2. The TOPKAPI Model

2.1. Model Introduction. The TOPKAPI model refers to a distributed hydrological model based on physical characteristics. It splits the study basin into detailed grids, and thus the difference of physical characteristic in spatial distribution can be fully considered under the calculation unit subdividing [34]. It can also give the specific condition of soil saturation, runoff yield, and confluence depth at each calculation unit point in the basin, which is of high reference implication in real-time flood forecasting, land use and environmental impact assessment, and hydrological process simulation in ungauged basins [35].

According to this model, the hydrological process in each calculation unit is generalized into three nonlinear reservoir equations, which are similar in structure, representing drainage in soil, surface runoff, and channel runoff on saturated soil and impermeable surface, respectively. The finite difference method is used in the calculation, so the correlated four surrounding grids are considered during the calculation of each grid unit [36]. The parameters used to describe the underlying surface conditions (e.g., soil thickness, vertical and horizontal saturated hydraulic conductivity, coefficient of nonlinear reservoir equation, and Manning coefficient of surface and evaporation coefficient of vegetation) could be extracted directly from the soil type classification map and land surface utilization map. Besides, the elevation and gradient distribution of the basin could be reflected by DEM (digital elevation model).

In terms of specific mechanism, TOPKAPI model employs Thornthwaite evaporation formula to calculate the potential evaporation of different vegetation covers in different growth stages; it also calculates the actual evaporation according to the actual wettability of upper soil [28]. According to the change of soil water content in the upper unsaturated region, the runoff in the soil and the surface

runoff are first calculated and then aggregated to the total runoff. In the confluence part, the nonlinear reservoir equation is adopted to merge surface runoff and underground runoff for confluence calculation [28, 37]. The main parts and approaches of TOPKAPI model are listed in Figure 1.

To describe the movement of water in surface, soil, and river channel, TOPKAPI model adopts three nonlinear reservoir equations with a similar structure. In the earliest version, the variable step five-stage Runge–Kutta numerical method is employed to solve the differential equations. Later, it was found that under appropriate approximation conditions, these equations could be solved using analytical methods [28].

2.2. Comparison with Conceptual Model. From the aspect of data required for the model building, the conceptual hydrological model should be based on the previous historical hydrological data. Taking Xin'anjiang model as an example, the parameters, including water storage capacity (WM), evapotranspiration coefficient (K), outflow and regression coefficient of the basin (KI and KG), should be calibrated through historical floods [3]. In other words, conceptual model is based on high-degree generalization of those physical parameters to reflect the characteristics of basins. This model has the advantage of relatively flexible adjustable parameters that can be fully adjusted to give optimized forecast results and avoid some relatively complex mechanisms in the hydrological process [38]. However, the disadvantage lies in the reliance on historical flood data, which is particularly evident in some areas in the absence of historical rainfall and runoff data where it is almost likely to calibrate parameters [39]. The existing feasible method is to search for data basins with similar geological and hydrological conditions for parameter transplantation, which will inevitably face systematic error of the model. In contrast, most of the data required for describing hydrological conditions and underlying surface conditions of watershed based on physical basis can be obtained through actual measurement (e.g., DEM, soil classification and soil thickness, hydraulic conductivity, and evaporation coefficient of land classification) [34]. These parameters are relatively easy to obtain online, including the Shuttle Radar Topography Mission (SRTM) launched by the Consultative Organization for International Agricultural Research (CGIAR), which can obtain the global 90 m resolution digital elevation model free of charge from its official website; the accessible website of the University of Maryland (UMD) in the United States. On this point, the hydrological model based on physical basis has obvious advantages over the conventional conceptual hydrological model when it is relatively easy to obtain the parameters required for model building in ungauged areas [28, 40].

3. Study Area and Dataset

3.1. Study Area. The neighboring Xixian and Huangchuan river basins (Figure 2) above the Wangjiaba basin in the upper reaches of the Huaihe River were taken as research area. The Wangjiaba basin is located in the southern part of Henan Province of China. It is a monsoon climate with an average annual rainfall of 1060 mm [30]. About 50% of the rainfall concentrates in the flood season, and the Xixian and Huangchuan river basins are the origins of the upstream river. The control area of Xixian Hydrological Station is 10 190 km^2. There are two large reservoirs in Nanwan (water catchment area 1058 km^2) and Shishankou (water catchment area 306 km^2) [41]. After deducting two large reservoirs, the catchment area is 8400 km^2 [42]. The elevation range of the Xixian County is 37–963 m [43]. The terrain in the northeast is relatively flat, being mountainous in the west, southwest, and south. The soil type is mostly clay soil. It has soil types (e.g., loam, sandy loam, and clay). Most of the land is farmland, with a small portion of forest land and mixed forest land. The Huangchuan basin outlet station has a controlled area of 1989 km^2 with Pohe reservoir built inside [44]. The elevation range of the area is 36–984 m. The watershed is mostly mountainous, the north is relatively flat, most of the soil types are clay and sandy loam, and the surface vegetation is primarily farmland [45, 46].

The digital elevation data of the basins could be obtained from the SRTM global 90 m digital elevation model provided by the Consultative Group on International Agricultural Research (Figure 3). GIS software was employed to extract the simulated stream nets and basin boundaries in the Xixian and Huangchuan basins. The rainfall data of 13 rainfall stations and the discharge data of Xixian hydrological station and that of the two reservoirs were collected from 1980 to 2003 according to the distribution of stations in the basin. The discharge data, as well as the rainfall data of 5 rainfall stations in the Huangchuan basin and the discharge data of the Huangchuan hydrological station from 2003 to 2005, were processed into 1 h interval. The meteorological data of Xinyang, Zhumadian, and Guangshan meteorological stations (including daily maximum and minimum temperatures, wind speed, humidity, and sunshine hours) were collected from 1980 to 2005.

3.2. Underlying Surface Analysis. The underlying surface parameters of the TOPKAPI model were transplanted on the premise that the soil types and land cover of underlying surface of the two basins should be of the same type or have similar physical properties, so the distribution of soil (Figure 4 and Table 1) and surface in the two basins (Figure 5 and Table 2) significantly affected the ungauged area prediction [47]. According to the collected data, the Xixian and Huangchuan basins were located close to each other. Their soil types were similar to clay, and most of the land surface was the same type of farmland. The soil parameters and land use parameters calibrated by the Xixian basin in the TOPKAPI model were applicable to the adjacent Huangchuan basin. The soil data are derived from the FAO soil map of the world, Global soil profile databases, which is available online at http://www.ngdc.noaa.gov/seg/eco/cdroms/reynolds.htm. The land cover map is derived from National Administration of Surveying Mapping and

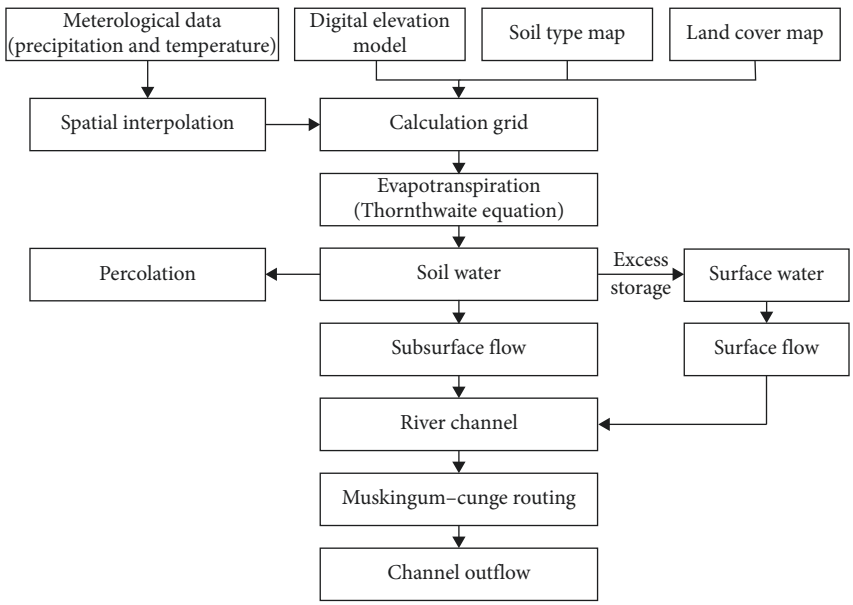
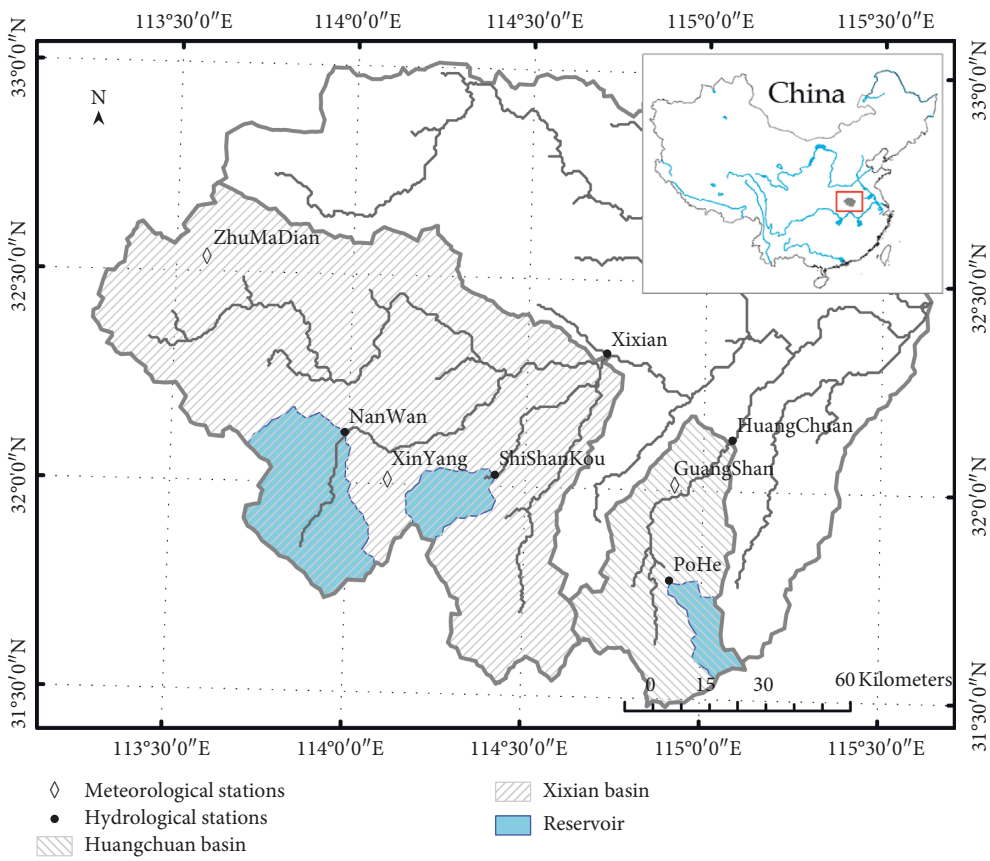
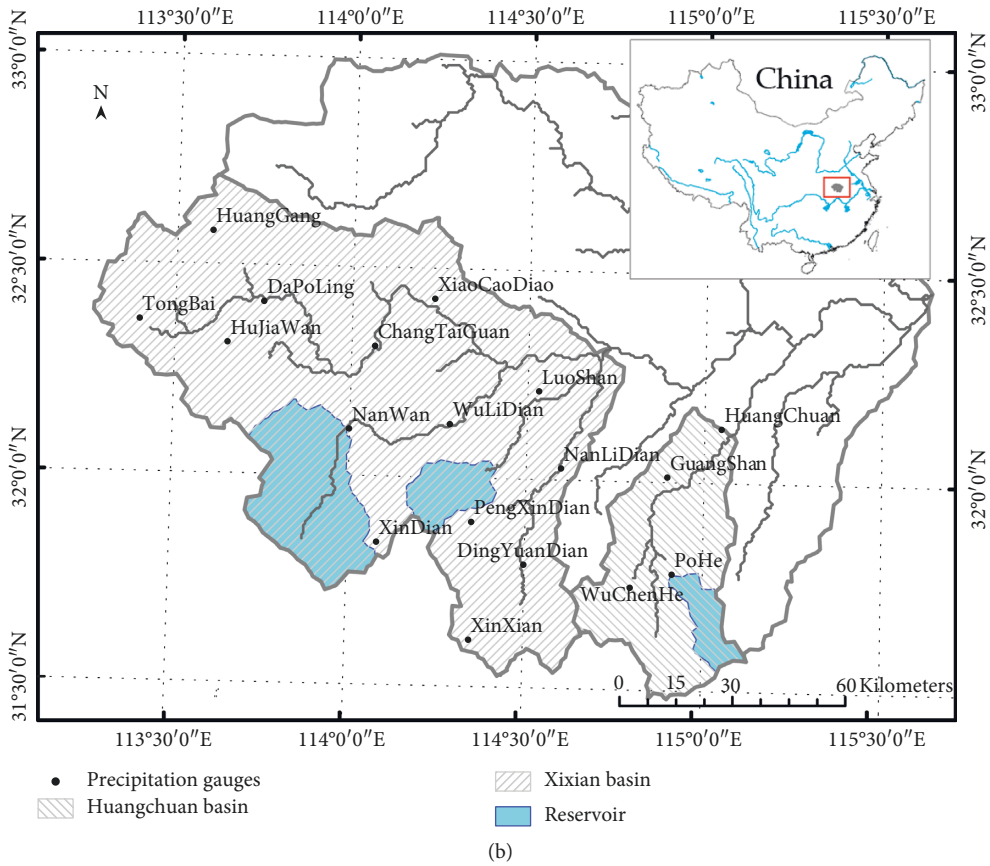


Figure 1: Main components and mechanism of TOPKAPI model.



(a)

Figure 2: Continued.



(b)

Figure 2: Location of the study area Xixian and Huangchuan basins and the distribution of reservoirs and (a) meteorological and hydrological stations and (b) precipitation gauges.

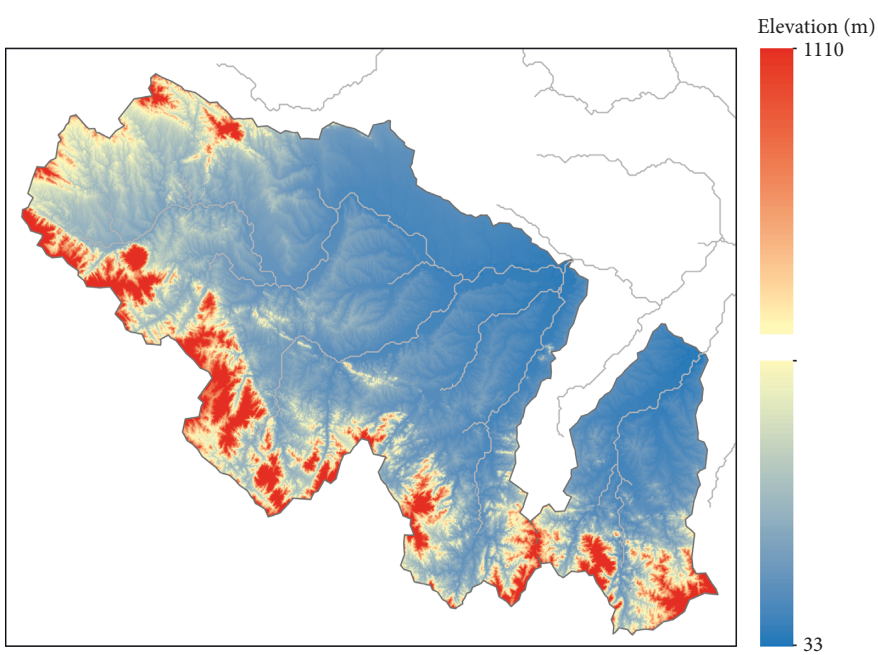


Figure 3: The digital elevation model of study area.

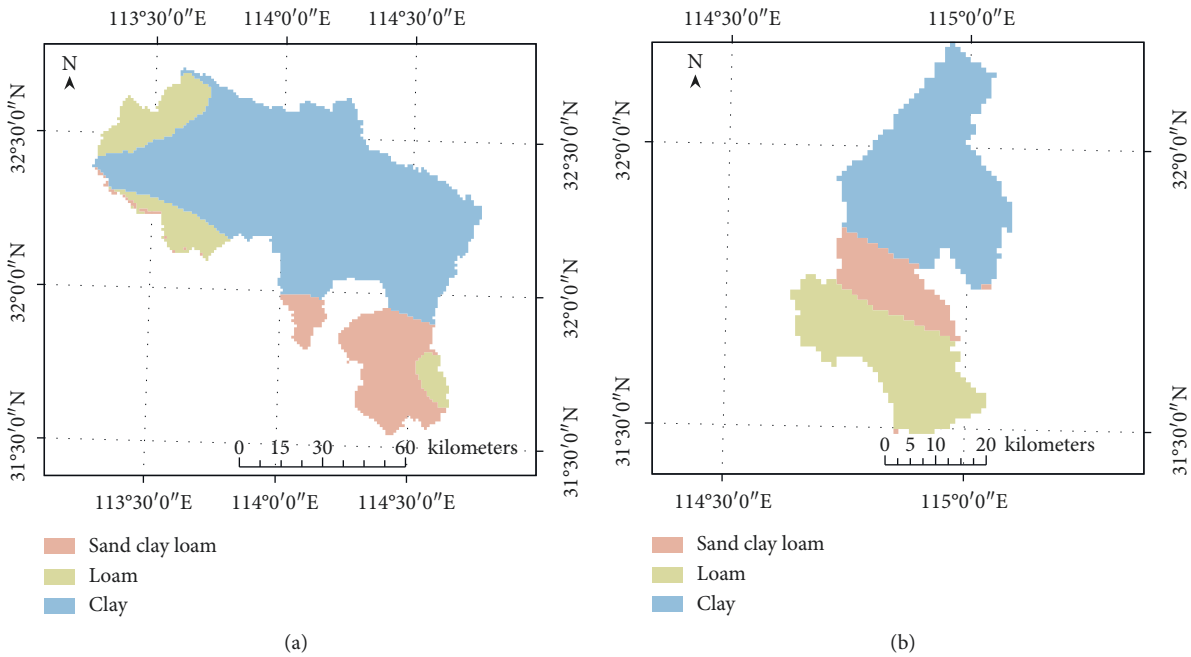


Figure 4: Soil types map of (a) Xixian basin and (b) Huangchuan basin.

Table 1: Component of soil types in Xixian and Huangchuan basin.

	Soil type	Code	Percentage (%)
Xixian basin	Loam	3085	15.65
	Sandy loam	3963	12.87
	Clay	4326	71.48
Huangchuan basin	Loam	3085	14.14
	Sandy loam	3963	32.12
	Clay	4326	53.74

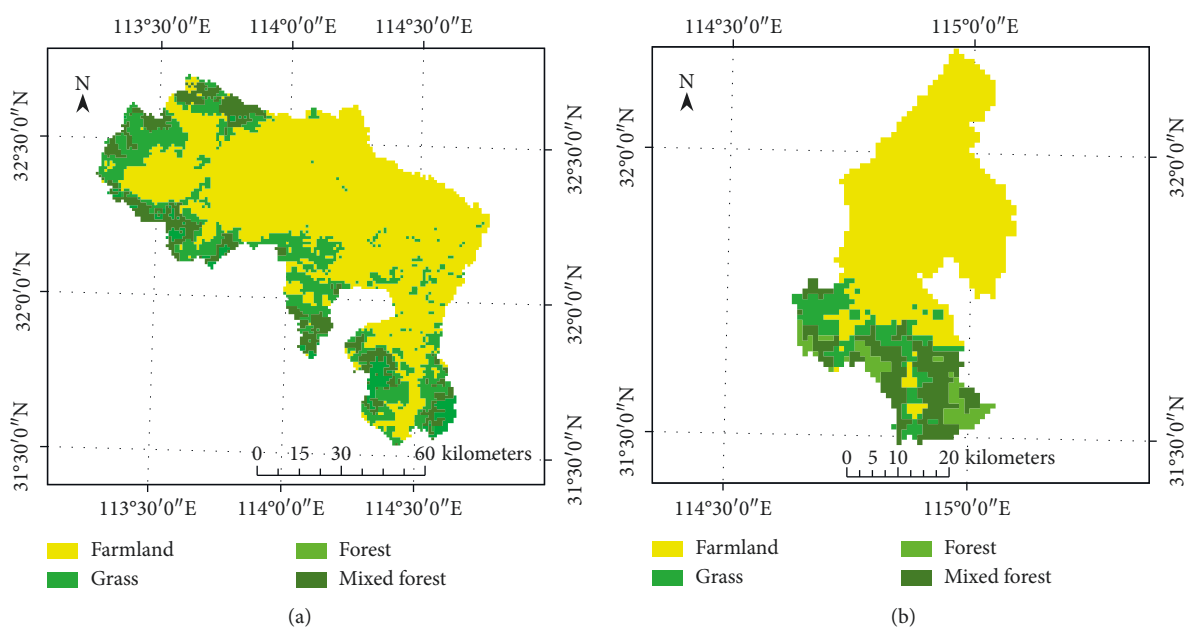


Figure 5: Land use map of (a) Xixian basin and (b) Huangchuan basin.

Table 2: Component of land use in Xixian and Huangchuan basins.

	Land use type	Code	Percentage (%)
Xixian basin	Farmland	6	67.70
	Forest	8	18.41
	Mixed forest	10	2.81
	Grass	11	11.09
Huangchuan basin	Farmland	6	69.92
	Forest	8	10.55
	Mixed forest	10	5.03
	Grass	11	14.50

Geoinformation of China (NASG), which is free downloadable for all Internet at http://www.globallandcover.com/GLC30Download/index.aspx and the characteristic data for each type of land cover are derived from Corinne Land Cover 2006 raster data by European Environment Agency, which is accessible at https://www.eea.europa.eu/data-and-maps/data/clc-2006-raster.

4. Parameter Sensitivity Analysis

4.1. Parameter Selection. In TOPKAPI model, the nonlinear reservoir equation can be written as

$$\frac{dy}{dt} = a - by^c, \tag{1}$$

where the variable y denotes average soil water content, river storage, surface water depth, etc. Variables a, b, and c keep constant in a single time step.

In the calculation of groundwater, the variables a, b, and c are expressed as follows:

$$\begin{aligned} a &= \frac{pX^2 + Q_0^{\mathrm{u}} + Q_s^{\mathrm{u}}}{X^2}, \\ b &= \frac{C_s}{X}, \\ c &= a_s, \end{aligned} \tag{2}$$

where p denotes the precipitation, X is the size of grid unit, Q_0^{u} and Q_s^{u} refer to surface and subsurface inflow of a grid unit, respectively, and C_s is the local hydraulic conductivity.

In the calculation of surface water, the variables a, b, and c are expressed as follows:

$$\begin{aligned} a &= \frac{1}{XW_o}\frac{V_{\mathrm{exf}}}{dt}, \\ b &= \frac{\tan(\beta)^{1/2}}{n_0 X}, \\ c &= a_0, \end{aligned} \tag{3}$$

where W_{o} denotes the width of grid without river channel, V_{exf} represents the net precipitation, and a_0 is index in Manning equation with a constant value of 5/3.

In the calculation of channel water propagation, the variables a, b, and c are expressed as follows:

$$\begin{aligned} a &= r_{\mathrm{c}} + Q_{\mathrm{c}}^{\mathrm{u}}, \\ b &= \frac{\sqrt{s_0}(\sin\gamma)^{2/3}}{2^{2/3} n_{\mathrm{c}} (\tan\gamma)^{1/3} X^{4/3}}, \\ c &= \frac{4}{3}, \end{aligned} \tag{4}$$

where r_{c} denotes the lateral inflow, including soil outflow to surface and channel.

The calculation formulas show that the main influence in the calculation of soil water originates from the upstream inflow, grid size, and hydraulic conductivity, in which hydraulic conductivity as the unknown coefficient of the nonlinear equation will directly affect the solution of the unknown term. Thus, hydraulic conductivity is considered the key parameter to be investigated. The calculation of surface water on slope is affected by slope, precipitation and surface Manning coefficient, and surface runoff after deducting infiltration is associated with soil conditions on underlying surface. Accordingly, in the part of surface flow calculation, the Manning coefficient of surface, the saturated water content associated with soil characteristics, and the soil thickness describing soil volume were taken as the key research parameters. In the calculation of channel flow using nonlinear reservoir method, the Manning coefficient of river roughness was taken as the main calibration parameter. All the selected parameters are listed in Table 3.

4.2. Sensitivity Analysis. The GLUE method was first proposed by Beven and Binley in 1992 based on the RSA (regionalized sensitivity analysis) method proposed by Hornberger and Spear in 1981 [48]. Beven and Binley proposed that this method is not the numerical value of a single parameter, but the value of a group of parameters that significantly affect the prediction results of the model. In this method, Monte Carlo method is adopted to sample a series of parameter combinations in prior parameter range and substitute them into the model calculation. Likelihood function is selected as the evaluation and instruction of the parameter sets. The parameter set whose likelihood function value is higher than a certain threshold is considered to be able to represent the characteristic of study basin (which is called "behavioral"), whereas the parameter set with likelihood function value lower than the threshold is considered fail at reflecting it and be abandoned [49].

Table 3: Main parameters of the TOPKAPI model.

Modules	Parameter	Description
Groundwater	Horizontal hydraulic conductivity	Reflecting water conduction rate in soil
Surface runoff	Surface Manning coefficient	Calculating factors of water conduction rate on the surface
	Saturated water content	When the soil water content reaches the saturated state, the volume percentage of water content
	Soil thickness	The soil depth between soil and bedrock reflects the total volume of soil on the underlying surface in the calculation unit
Channel runoff	Riverbed Manning coefficient	Calculation factors of water conduction rate in rivers

Several criterions could be used to describe the prediction performance of a model, among which the Nash–Sutcliffe model efficiency coefficient (NSE) [50] has been most widely used in model prediction performance judgment. In this study, the NSE is chosen as the likelihood function. The Nash–Sutcliffe model efficiency coefficient is expressed as

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{T}\left(Q_{\mathrm{m}}^{t} - Q_{\mathrm{o}}^{t}\right)^{2}}{\sum_{t=1}^{T}\left(Q_{\mathrm{o}}^{t} - \overline{Q_{\mathrm{o}}}\right)^{2}}, \quad (5)$$

where Q_{m}^{t} and Q_{o}^{t} denote the modeled and observed discharge at time t, respectively, and $\overline{Q_{\mathrm{o}}}$ is the average value of observed discharge over the whole time series.

In this study, 3000 sets of parameters including those selected in the previous part were generated by random Monte Carlo sampling methodology within the prior range in Table 4. A threshold of 0.7 NSE is chosen to check whether these parameter sets are behavioral. Parameter uncertainty was analyzed by 8 floods in Xixian basin from 1980 to 2002 in TOPKAPI model. A total of 283 sets of parameters were found to be behavioral achieving 0.7 NSE likelihood.

Posterior parameter distribution was derived from 283 behavioral parameter sets. To get visual impression of these parameter sets, the histograms of all 18 parameters distribution are plotted in Figure 6. Histograms with sharp peaks or steep slopes means parameter are well identified, whereas parameters with relative flat histograms are associated with more uncertainty [51]. Because all the behavioral sets have performance over threshold in common, narrow and sharp peaks reflect relative strong relationship with model results and show that this parameter has more sensitivity, which means variation in this parameter may significantly affect model results. A statistic of parameter frequency was conducted in Table 5 by calculating standard deviation of frequencies of each parameter to get a numerical comparison.

In Table 5, the standard deviations of parameters frequency distribution are listed. It can be clearly seen that horizontal hydraulic conductivity has the least values and the histograms are all relatively flat, meaning that this parameter has low sensitivity and high uncertainty. This sort of parameters are difficult to be calibrated due to their weak relationship with model outputs, but they can only slightly affect the model performance. However, emphasis in calibration should be put on those parameters with high standard deviation and sensitivity such as soil thickness, saturated water content, and riverbed Manning coefficient. Soil type with high coverage percentage such as clay (with 71.48% coverage) has significantly high standard deviation value for both thickness and saturated water content. This is the same for the land use Manning coefficient of farmland (with 67.70% coverage) and the riverbed Manning coefficient of V level river channel.

5. Application in Ungauged Basins

To verify the effectiveness of the model in ungauged basins, experiments were performed. The Xixian basin and adjacent Huangchuan basin in Wangjiaba were taken as study areas. The parameters of the model were calibrated in Xixian basin and subsequently transferred to Huangchuan basin, and flood simulations were carried out to verify the application effect of the model in ungauged basins.

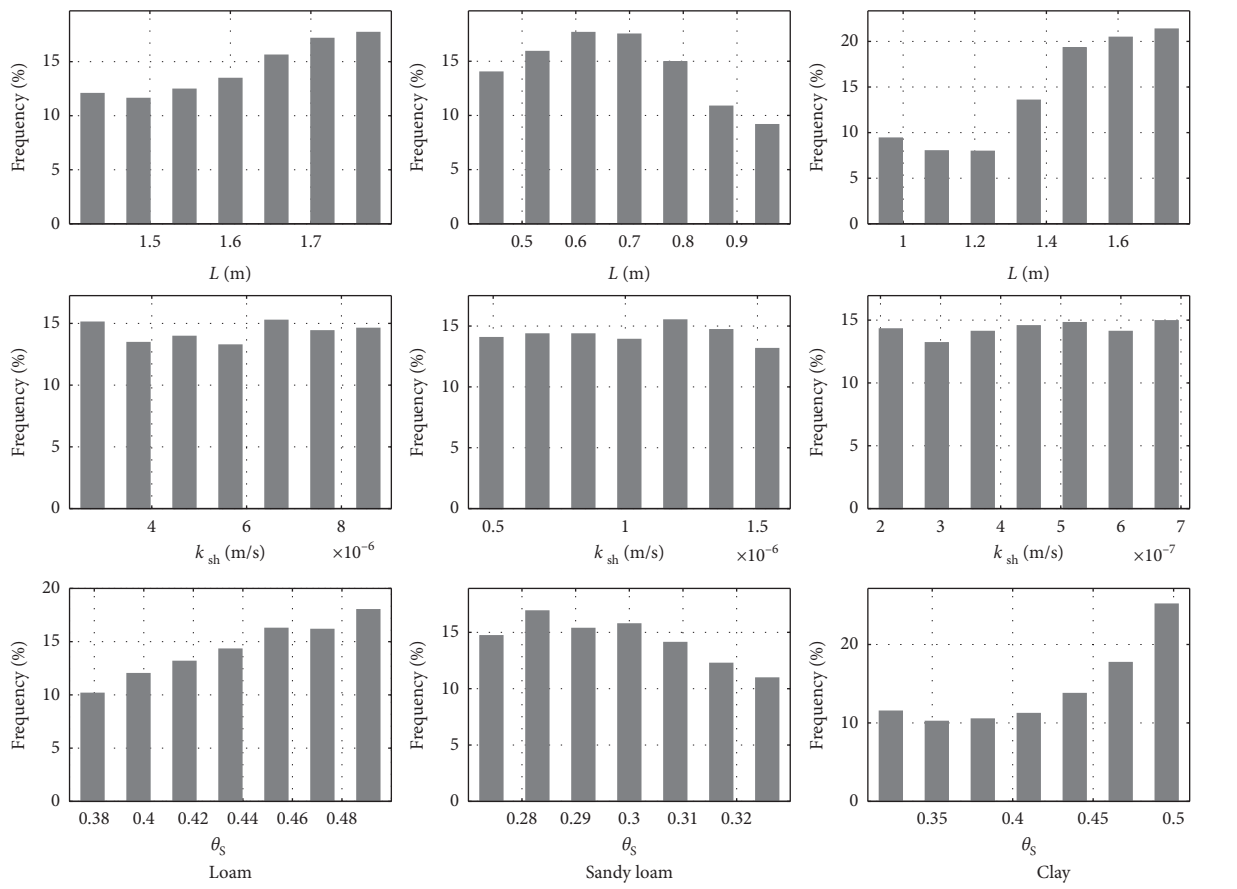
The calibration and validation results are evaluated by "qualified rates" [52]. A flood forecast with flood volume and flood peak error less than 20% is considered to be "qualified," and the "qualified rate" means the percentage of qualified flood simulations over the total number. The whole forecast scenario accuracy will be evaluated to a certain level according to Table 6.

5.1. Parameter Calibration. Most parameters in physical-based hydrological model could be obtained by actual measurement; however, the measured values acquired on the point measurement might not be sufficiently representative at the calculation unit scale and might not reflect the temporal and spatial scale change within the unit. Thus, the parameters obtained by measurement or reference to the literature should be fine-tuned by trial before the simulation to compensate for the error caused by the spatial generalization of the parameters and the time generalization of the input parameters, making the results of the simulation closer to the actual situation.

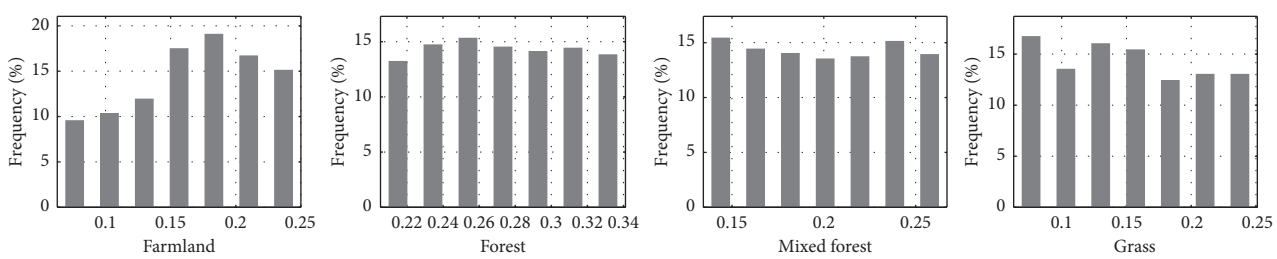
The calibration parameters included soil horizontal water conductivity, saturated water content, land surface, and riverbed Manning coefficient for Muskingum algorithm. In the previous GLUE assessment, 3000 sets of parameters have been generated. Several "best" performed sets of parameters with reasonable values and high NSE are chosen for manually adjustment. These parameters were calibrated by the rainfall and discharge data of 16 floods from 1991 to 2003

Table 4: Prior range of parameters.

	Loam	Sandy loam	Clay		
Soil thickness (m)	1.3–1.8	0.4–1.1	0.8–1.6		
Horizontal hydraulic conductivity (10^{-6} m/s)	2.26–9.05	0.40–1.62	0.17–0.71		
Saturated water content	0.35–0.50	0.27–0.33	0.30–0.55		
	Farmland	Forest	Mixed forest	Grass	
Surface Manning coefficient	0.06–0.25	0.20–0.35	0.12–0.27	0.06–0.25	
	I	II	III	IV	V
Riverbed Manning coefficient	0.05–0.30	0.02–0.15	0.02–0.15	0.02–0.15	0.02–0.15

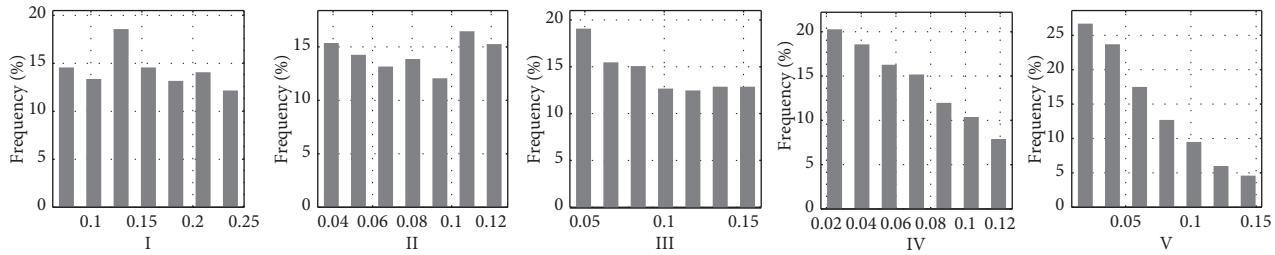


(a)



(b)

Figure 6: Continued.



(c)

Figure 6: Frequency histograms of (a) soil thickness L, horizontal hydraulic conductivity (k_{sh}), and saturated water content of three types of soil, (b) surface Manning coefficient of fore types of land use, and (c) riverbed Manning coefficient of five river classifications.

Table 5: Standard deviation of parameter frequency distribution.

	Loam	Sandy loam	Clay		
Soil thickness (m)	2.5123	3.2393	6.0154		
Horizontal hydraulic conductivity (10^{-6} m/s)	0.7734	0.7244	0.5807		
Saturated water content	2.7310	2.0651	5.4510		
	Farmland	Forest	Mixed forest	Grass	
Surface Manning coefficient	3.7226	0.6719	0.7198	1.7073	
	I	II	III	IV	V
Riverbed Manning coefficient	2.0449	1.4837	2.4079	4.5080	8.5721

Table 6: Forecast scenario classification level.

Forecast level	*A*	*B*	*C*
Qualified rate (%)	QR > 85.0	85 > QR > 70.0	70.0 > QR > 60.0
NSE	NSE > 0.90	0.90 > NSE > 0.70	0.70 > NSE > 0.60

in Xixian basin. Run the TOPKAPI model with the meteorological data (including precipitation and temperature) of 13 floods in Huangchuan watershed from 2003 to 2005 together with the calibrated parameters and adjusted these parameter according to the outcome flood results. Furthermore, to verify the accuracy of the simulation and to demonstrate the application of the model in ungauged basins, the flood simulation results were compared with the measured results.

The flood peak and NSE were taken as objective functions to calibrate the parameters. The percentage of initial soil water content in the basin would significantly affect the simulation results of the early floods in the basin. In this calibration, to determine the initial soil moisture, the "warm-up" method [53] was adopted to simulate the initial state through natural situation, which was initiated 30 days before the first flood in advance.

Figure 7 shows that, in the calibration, most of the stream flow series are well reproduced. Floods with large water volume are simulated better than those with low volume. From the results of model calibration in Table 7, the simulation results of the model in Xixian basin were good, and the average NSE were above 0.8. Among the 16 floods used in the calibration, 14 floods had NSE over 0.8, taking up 87.5% and 6 floods over 0.9. In terms of Nash–Sutcliffe model efficiency coefficient, the model exhibited certain applicability in this basin. According to the simulated flood volume, the qualified rate of TOPKAPI model flood volume was 81.3% in the 16 floods used for calibration and 93.8% in the flood peak simulation. From the results, it is revealed that under the underlying elevation data, soil and land use distribution parameters and basin hydrometeorological data meet the demand, the model achieved relatively good simulation in the study area. The average NSE were all above 0.7, achieving the accuracy of Class B forecasting [52], and the average error between flood volume and flood peak was controlled within 20%. This is associated with the wet area where the research basin is located. The full storage and runoff yield models used in the model were applicable to the wet area of Huaihe River, and the better the hydrogeological conditions of the basin, the smaller the error of the model confluence calculation will be. Thus, TOPKAPI model exhibits good applicability in this basin. All the calibrated parameters are listed in Tables 8–10.

From the process of model building, TOPKAPI model did not adjust too much parameters in the calibration process, and the prediction results were good. Accordingly, TOPKAPI model based on physical basis exhibited better applicability when building model in adjacent areas without historical flood data. However, the prediction accuracy of TOPKAPI model depended on the high-precision partition of computational grids, whereas high-resolution grids would increase the requirement of computational ability. Thus, to obtain higher prediction accuracy, the model requires better operation equipment and long calculation time.

5.2. Parameter Validation. The parameters obtained by the calibration in adjacent basin were directly applied in Huangchuan basin. Besides, the flood discharge process of

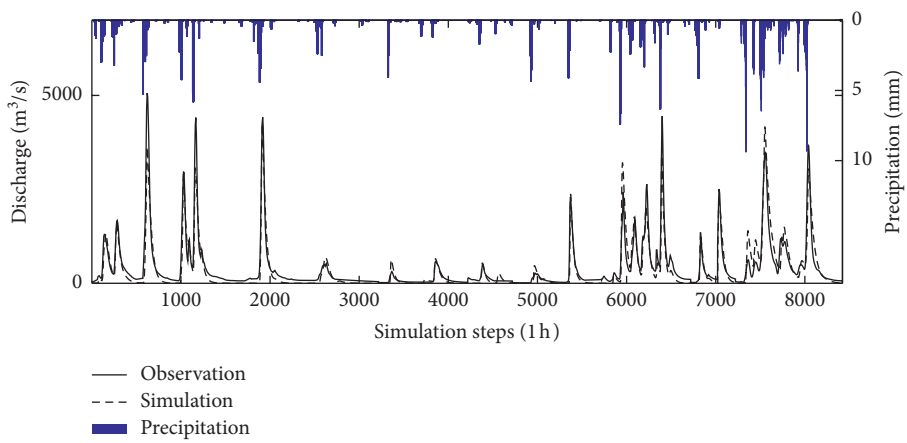


Figure 7: Calibration hydrograph from 1991 to 2003.

Table 7: Calibration results in Xixian basin.

Flood no.	Flood volume		Flood peak		NSE
	Observation (10^4 m^3)	Simulation error percentage (%)	Observation (m^3/s)	Simulation error percentage (%)	
19910523	39933.54	8.87	1300	1.77	0.76
19910530	46156.68	3.72	1670	−2.86	0.89
19910612	110651.16	−24.55	5060	−28.19	0.83
19910629	73803.71	15.33	2960	−1.97	0.91
19910805	92912.93	−10.04	4420	−3.97	0.83
19921002	19089.25	−7.37	579	12.61	0.84
19930518	14123.72	3.36	516	3.86	0.7
19950707	42848.26	−1.2	2300	2.68	0.78
19960717	81739.98	−22.99	4450	−19.46	0.89
19960802	25732.97	−5.79	875	1.87	0.71
19970629	24946.02	2.81	1220	12.41	0.91
19980630	54968.35	16.86	2510	−12.89	0.94
20020622	97511.4	14.1	5080	−0.62	0.9
20020627	61223.48	1.34	2820	−8.32	0.85
20020723	55287.15	13.27	2790	−6.49	0.84
20030629	107940.6	6.67	3900	−13.52	0.77
Abs. average		8.64		8.34	
Average		2.15		−3.94	0.84
Qualified rate		93.75%		93.75%	100.00%

Table 8: Calibrated soil parameters.

	Loam	Sandy loam	Clay
L (m)	1.7675	0.78856	1.4715
k_{sh} (m/s)	$4.55e-6$	$8.4e-7$	$4.13e-7$
θ_s	0.48511	0.307	0.49886

*L: soil thickness; k_{sh}: horizontal hydraulic conductivity; θ_s: saturated water content.

Table 9: Calibrated surface Manning coefficient.

	Farmland	Forest	Mixed forest	Grass
N_{Surf}	0.182871	0.274005	0.239738	0.11128

*N_{Surf}: surface Manning coefficient.

the outlet section was calculated using the rainfall data of 13 floods in 2003–2005 as input to simulate the application of the model in the ungauged basin. From the statistical

Table 10: Calibrated channel Manning coefficient.

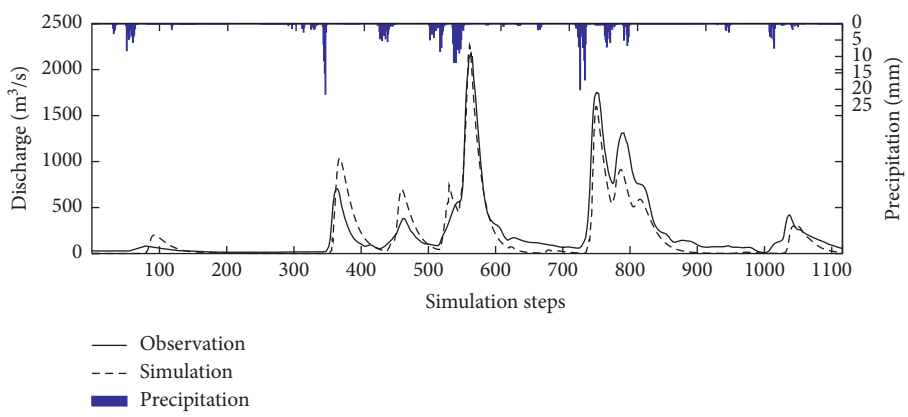
	Order I	Order II	Order III	Order IV	Order V
$N_{Channel}$	0.15918	0.085962	0.058017	0.046145	0.03347

*$N_{Channel}$: channel Manning coefficient.

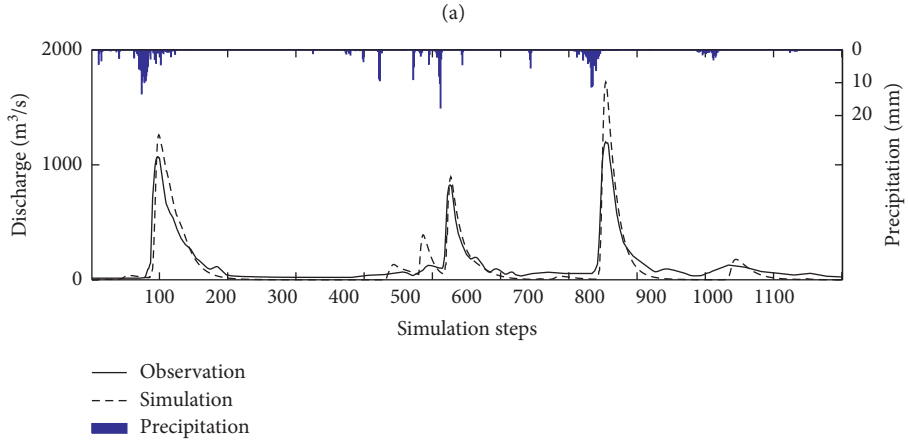
Table 11, Figure 8, and the box plot Figure 9 of calculation and results, it is revealed that the overall NSE was relatively lower because of parameter transplantation. The average NSE was 0.67, and the qualified rate of flood volume and peak simulation was 69.23%. This was probably because Xixian is in the warm temperate zone and belongs to the semihumid basin, and the overall basin is dominated by excess of storage mode, which is consistent with the basic assumption of TOPKAPI model runoff generation. The accuracy forecast in ungauged basins, compared with the calibration results, decreased in varying degrees. This was because the parameter transplantation inevitably brings

Table 11: Application results in ungauged basin.

Flood no.	Flood volume		Flood peak		NSE
	Observation (10^4 m^3)	Simulation error percentage (%)	Observation (10^4 m^3)	Simulation error percentage (%)	
20030622	6872.8	41.84	705	30.78	0.65
20030626	4765.9	38.09	380	54.42	0.8
20030629	28032.16	−7.07	2180	2.48	0.83
20030707	39802.79	−25.56	1750	−5.62	0.79
20030719	6711.57	−34.86	419	−18.61	0.48
20030815	4060.62	−13.1	173	39.97	0.63
20040716	15826.68	2.48	1070	11.64	0.72
20040801	11528.6	5.97	825	5.6	0.67
20040813	14726.48	−0.84	1200	28.18	0.85
20050726	9259.52	−16.38	600	−5.13	0.62
20050820	8599	−14.45	402	19.06	0.5
20050828	9145.8	−7.8	733	−6.9	0.59
20050902	11192.11	−17.65	666	2.81	0.57
Abs. average		17.39		17.78	
Average		−3.79		12.21	0.67
Qualified rate		69.23%		69.23%	38.46%

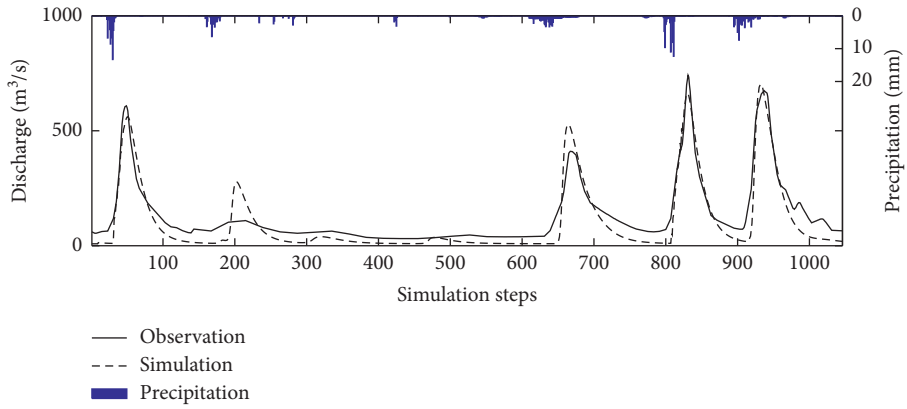


(a)



(b)

Figure 8: Continued.



(c)

Figure 8: Hydrograph of simulation in ungauged basins in 2003, 2004, and 2005.

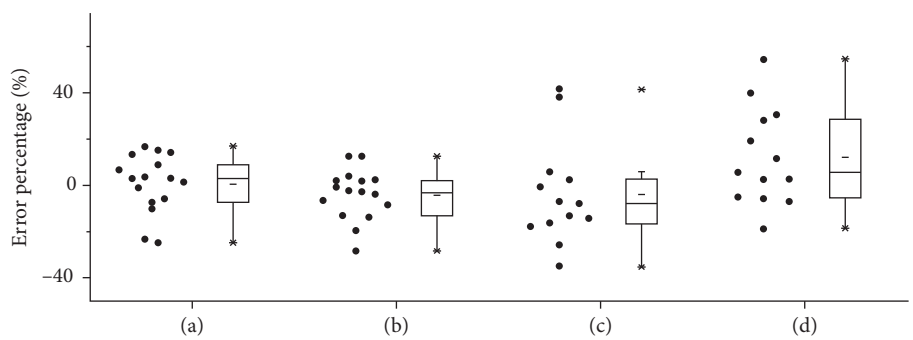


Figure 9: Box plot error percentage of (a) calibration flood volume, (b) calibration flood peak, (c) ungauged flood volume, and (d) ungauged flood peak.

about inconsistencies with the actual conditions, which is also the most important problem facing the prediction of ungauged basins.

It was found that the flood process of TOPKAPI model had steep rise and fall just, as shown in the hydrographs. Accordingly, following the flood peak priority calibration strategy, the systematic error of overall smaller flood volume appeared. The water confluence process was faster than the actual situation, which is also one of the parts of the model to be further optimized. Nevertheless, TOPKAPI model still reflects good transplantability in flood peak prediction in ungauged basins. Since remote sensing data could reflect actual topography, vegetation, and soil types as much as possible, the eligibility rate of flood peak prediction reached about 70%. This is the advantage brought by detailed hydrological process based on the physical basis of the distributed model, fully displaying the physical conditions of underlying surface.

6. Discussion and Conclusion

In this study, a physically based distributed hydrological model TOPKAPI was applied in upper Huaihe, Xixian, and adjacent Huangchuan basin. The model uncertainty caused by spatial and temporal generalization of model parameters was evaluated using GLUE method. Through uncertainty analysis and comparison of calibration simulation results with measured data and prediction results of the model in adjacent similar ungauged basins, parameter transplantation was tested. Based on the results, the following conclusions were drawn:

(1) The description of basin characteristics in TOPKAPI model can be characterized by underlying surface data from land use and soil type obtained using remote sensing technology, which is easy to obtain and use. In this study, it was assumed that Huangchuan basin is an ungauged basin without any hydrological stations, whereas underlying surface data can still be acquired from satellite or remote sensing equipment, making it likely to describe the basin in hydrological model.

(2) According to the results of the sensitivity analysis of the model parameters, the soil thickness and surface Manning coefficient, with a large proportion of coverage, significantly affected the prediction results of the model. The horizontal hydraulic conductivity has the least sensitivity. Since the classification of river depends on the area of the whole river basin and other factors, some differences would exist among different river basins for the same order. In this study, this is also a reason for the reduction of

prediction accuracy of ungauged river basins. The rules of parameter transplantation in prediction research should be elucidated further.

(3) The model exhibits good applicability in the upper Huaihe basin. The base assumptions of TOPKAPI model made it feasible in humid semihumid area, and thus the flood volume flood peak as long as NSE all achieved high accuracy in calibration.

(4) In the prediction of ungauged basins, it was found that under premise of sufficient remote sensing data of underlying surface, the transplantation of parameters among similar basins could achieve good forecasting results.

Besides, the high prediction accuracy of TOPKAPI model should be based on detailed meshing of computing units. For instance, the grid resolution adopted in this study was 200 m, and the prediction results were relatively good. However, the calculation period took a long time. If the model is applied in a larger watershed, the problem will be more prominent. Thus, how to make an optimal trade-off between the calculation time of the model and the prediction accuracy needs further studies.

Data Availability

The digital elevation model data can be acquired from CGIAR (http://srtm.csi.cgiar.org/). The soil data are derived from the FAO soil map of the world, Global soil profile databases, which is available online at http://www.ngdc.noaa.gov/seg/eco/cdroms/reynolds.htm. The land cover map is derived from National Administration of Surveying Mapping and Geoinformation of China (NASG), which is freely downloadable for all Internet at http://www.globallandcover.com/GLC30Download/index.aspx and the characteristic data for each type of land cover are derived from Corine Land Cover 2006 raster data by European Environment Agency, which is accessible at https://www.eea.europa.eu/data-and-maps/data/clc-2006-raster.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the National Key Research and Development Program of China (grant no. 2018YFC1508103) and the Fundamental Research Funds for the Central Universities (grant no. 2016B04714).

Supplementary Materials

The following data are available in supplementary materials: the precipitation data, temperature, and discharge data used for parameter calibration in Xixian basin and the coordinate of meteorological stations and precipitation gauges used in this research. (*Supplementary Materials*)

References

[1] R. Johnston and V. Smakhtin, "Hydrological modeling of large river basins: how much is enough?," *Water Resources Management*, vol. 28, no. 10, pp. 2695–2730, 2014.

[2] M. Cai, S. Yang, H. Zeng, C. Zhao, and S. Wang, "A distributed hydrological model driven by multi-source spatial data and its application in the Ili river basin of Central Asia," *Water Resources Management*, vol. 28, no. 10, pp. 2851–2866, 2014.

[3] R. J. Zhao and X. R. Liu, "The Xinanjiang model," *Computer Models of Watershed Hydrology*, vol. 135, pp. 371–381, 1995.

[4] Z. Ren-Jun, "The Xinanjiang model applied in China," *Journal of Hydrology*, vol. 135, no. 1–4, pp. 371–381, 1992.

[5] A. H. A. Suliman, M. Jajarmizadeh, S. Harun, and I. Z. Mat Darus, "Comparison of semi-distributed, GIS-based hydrological models for the prediction of streamflow in a large catchment," *Water Resources Management*, vol. 29, no. 9, pp. 3095–3110, 2015.

[6] A. Kushwaha and M. K. Jain, "Hydrological simulation in a forest dominated watershed in Himalayan Region using SWAT model," *Water Resources Management*, vol. 27, no. 8, pp. 3005–3023, 2013.

[7] A. C. Guzha and T. B. Hardy, "Application of the distributed hydrological model, TOPNET, to the big darby creek watershed, Ohio, USA," *Water Resources Management*, vol. 24, no. 5, pp. 979–1003, 2010.

[8] W. Thorsten and M. Alberto, "Convergence of approaches toward reducing uncertainty in predictions in ungauged basins," *Water Resources Research*, vol. 47, no. 6, pp. 453–460, 2011.

[9] G. L. Vandewiele, C.-Y. Xu, and W. Huybrechts, "Regionalisation of physically-based water balance models in Belgium. Application to ungauged catchments," *Water Resources Management*, vol. 5, no. 3-4, pp. 199–208, 1991.

[10] D. H. Burn and D. B. Boorman, "Estimation of hydrological parameters at ungauged catchments," *Journal of Hydrology*, vol. 143, no. 3-4, pp. 429–454, 1993.

[11] L. Oudin, V. Andréassian, C. Perrin, C. Michel, and N. L. Moine, "Spatial proximity, physical similarity, regression and ungaged catchments: a comparison of regionalization approaches based on 913 French catchments," *Water Resources Research*, vol. 44, no. 3, pp. 893–897, 2008.

[12] L. Oudin, A. Kay, V. Andréassian, and C. Perrin, "Are seemingly physically similar catchments truly hydrologically similar?," *Water Resources Research*, vol. 46, no. 11, 2010.

[13] R. Singh, S. A. Archfield, and T. Wagener, "Identifying dominant controls on hydrologic parameter transfer from gauged to ungauged catchments—a comparative hydrology approach," *Journal of Hydrology*, vol. 517, pp. 985–996, 2014.

[14] S. A. Archfield and R. M. Vogel, "Map correlation method: selection of a reference streamgage to estimate daily streamflow at ungaged catchments," *Water Resources Research*, vol. 46, no. 10, pp. 5613–5618, 2010.

[15] B. Günter, "Rainfall-runoff modeling of ungauged catchments," in *Encyclopedia of Hydrological Sciences*, M. G. Anderson and J. J. McDonnell, Eds., John Wiley & Sons, Ltd., Hoboken, NJ, USA, 2006.

[16] S. Murugesu, "Prediction in ungauged basins: a grand challenge for theoretical hydrology," *Hydrological Processes*, vol. 17, no. 15, pp. 3163–3170, 2010.

[17] E. Ellouze-Gargouri and Z. Bargaoui, "Runoff estimation for an ungauged catchment using geomorphological instantaneous

unit hydrograph (GIUH) and copulas," *Water Resources Management*, vol. 26, no. 6, pp. 1615–1638, 2012.

[18] R. D. D. Moore, J. W. Trubilowicz, and J. M. Trubilowicz, "Prediction of streamflow regime and annual runoff for ungauged basins using a distributed monthly water balance model," *Jawra Journal of the American Water Resources Association*, vol. 48, no. 1, pp. 32–42, 2012.

[19] S. Patil and M. Stieglitz, "Modelling daily streamflow at ungauged catchments: what information is necessary?," *Hydrological Processes*, vol. 28, no. 3, pp. 1159–1169, 2014.

[20] P. Athira, K. P. Sudheer, R. Cibin, and I. Chaubey, "Predictions in ungauged basins: an approach for regionalization of hydrological models considering the probability distribution of model parameters," *Stochastic Environmental Research and Risk Assessment*, vol. 30, no. 4, pp. 1131–1149, 2016.

[21] M. Waseem, J.-y. Shin, and T.-W. Kim, "Comparing spatial interpolation schemes for constructing a flow duration curve in an ungauged basin," *Water Resources Management*, vol. 29, no. 7, pp. 2249–2265, 2015.

[22] A. J. Hyun and H. I. Choi, "A new flood index for use in evaluation of local flood severity: a case study of small ungauged catchments in Korea," *Jawra Journal of the American Water Resources Association*, vol. 49, no. 1, pp. 1–14, 2013.

[23] B. Sahoo, M. Perumal, T. Moramarco, and S. Barbetta, "Rating curve development at ungauged river sites using variable parameter muskingum discharge routing method," *Water Resources Management*, vol. 28, no. 11, pp. 3783–3800, 2014.

[24] J. A. B. Cánovas, M. Eguibar, J. M. Bodoque, A. Díez-Herrero, M. Stoffel, and I. Gutiérrez-Pérez, "Estimating flash flood discharge in an ungauged mountain catchment with 2d hydraulic models and dendrogeomorphic paleostage indicators," *Hydrological Processes*, vol. 25, no. 6, pp. 970–979, 2011.

[25] R. Xu and X. Huang, L. Li and S. Cai, A new grid-associated algorithm in the distributed hydrological model simulations," *Science in China Series E: Technological Sciences*, vol. 53, no. 1, pp. 235–241, 2010.

[26] E. Sisay, A. Halefom, D. Khare, L. Singh, and T. Worku, "Hydrological modelling of ungauged urban watershed using swat model," *Modeling Earth Systems and Environment*, vol. 3, no. 2, pp. 693–702, 2017.

[27] M. Saber, T. Hamaguchi, T. Kojiri, K. Tanaka, and T. Sumi, "A physically based distributed hydrological model of wadi system to simulate flash floods in arid regions," *Arabian Journal of Geosciences*, vol. 8, no. 1, pp. 143–160, 2015.

[28] E. Todini and L. Ciarapica, "The TOPKAPI model," in *Mathematical Models of Large Watershed Hydrology*, V. P. Singh, D. K. Frevert, and S. P. Meyer, Eds., pp. 471–550, Water Resources Publications, Littleton, CO, USA, 2002.

[29] L. Ciarapica and E. Todini, "TOPKAPI: a model for the representation of the rainfall-runoff process at different scales," *Hydrological Processes*, vol. 16, no. 2, pp. 207–229, 2002.

[30] Z. Liu, M. L. V. Martina, and E. Todini, "Flood forecasting using a fully distributed model: application of the TOPKAPI model to the upper Xixian catchment," *Hydrology and Earth System Sciences*, vol. 9, no. 4, pp. 347–364, 2005.

[31] Z. Liu and T. Ezio, "Assessing the TOPKAPI non-linear reservoir cascade approximation by means of a characteristic lines solution," *Hydrological Processes*, vol. 19, no. 10, pp. 1983–2006, 2005.

[32] R. J. C. Burnash, R. L. Ferral, and R. McGuire, *A Generalized Streamflow Simulation System; Conceptual Modeling for Digital Computers*, U.S. Department of Commerce, National Weather Service, and State of California, Department of Water Resources, Sacramento, CA, USA, 1973.

[33] P. Deng, Z. Li, and Z. Liu, "Numerical algorithm of distributed TOPKAPI model and its application," *Water Science & Engineering*, vol. 1, no. 4, pp. 14–21, 2008.

[34] Z. Liu, "Application of GIS-based distributed hydrological model to flood forecasting," *Journal of Hydraulic Engineering*, vol. 35, pp. 70–75, 2004.

[35] G. Coccia and E. Todini, "Recent developments in predictive uncertainty assessment based on the model conditional processor approach," *Hydrology and Earth System Sciences*, vol. 15, no. 10, pp. 3253–3274, 2011.

[36] S. Sinclair and G. G. S. Pegram, "A comparison of ASCAT and modelled soil moisture over South Africa, using TOPKAPI in land surface mode," *Hydrology and Earth System Sciences*, vol. 14, no. 4, pp. 613–626, 2010.

[37] L. I. Zhijia, X. Wang, L. Yanxiang, L. Chen, and L. I. Lanru, "Application of TOPKAPI model and comparison with Xin'anjiang model," *Water Power*, vol. 11, 2013.

[38] S. Yang, G. Dong, D. Zheng, H. Xiao, Y. Gao, and Y. Lang, "Coupling Xinanjiang model and SWAT to simulate agricultural non-point source pollution in Songtao watershed of Hainan, China," *Ecological Modelling*, vol. 222, no. 20–22, pp. 3701–3717, 2011.

[39] H. Lü, T. Hou, R. Horton et al., "The streamflow estimation using the Xinanjiang rainfall runoff model and dual state-parameter estimation method," *Journal of Hydrology*, vol. 480, pp. 102–114, 2013.

[40] S. Sinclair and G. G. S. Pegram, "A sensitivity assessment of the TOPKAPI model with an added infiltration module," *Journal of Hydrology*, vol. 479, pp. 100–112, 2013.

[41] P. Zhang, S. Jiang, H. Chen, M. Zhao, and M. Li, "Hydrological simulation capability of TRMM satellite precipitation data in Xixian catchment, Huai River basin," *Journal of Water Resources Research*, vol. 6, no. 2, pp. 148–155, 2017.

[42] L. Liang, L. Zhao, D. Qi, C. Wang, H. Bao, and Y. Zhang, "The experiment of hydrologic probabilistic forecast based on the precipitation forecast calibrated by bayesian model averaging," *Journal of Applied Meteorological Science*, vol. 4, 2013.

[43] P. Deng and L. I. Zhijia, "Comparison of three hydrological models in flood simulation for Xixian basin of Huaihe River," *Journal of Hohai University*, vol. 41, pp. 377–382, 2013.

[44] Y. Y. Han and T. Cai, "The impacts of different land use patterns on water volume in the Xixian watershed, China," *Applied Mechanics and Materials*, vol. 737, pp. 728–731, 2015.

[45] P. Shi, C. Chen, R. Srinivasan et al., "Evaluating the SWAT model for hydrological modeling in the Xixian watershed and a comparison with the XAJ model," *Water Resources Management*, vol. 25, no. 10, pp. 2595–2612, 2011.

[46] P. Shi, Y. Hou, Y. Xie et al., "Application of a SWAT model for hydrological modeling in the xixian watershed, China," *Journal of Hydrologic Engineering*, vol. 18, no. 11, pp. 1522–1529, 2013.

[47] Y. Y. Han and T. Cai, "The impacts of land-use change patterns on soil erosion in the Xixian basin, China," *Applied Mechanics and Materials*, vol. 737, pp. 762–765, 2015.

[48] G. M. Hornberger and R. C. Spear, "An approach to the preliminary analysis of environmental systems," *Journal of Environmental Management*, vol. 12, no. 1, pp. 7–18, 1981.

[49] R.-S. Blasone, J. A. Vrugt, H. Madsen, D. Rosbjerg, B. A. Robinson, and G. A. Zyvoloski, "Generalized likelihood uncertainty estimation (GLUE) using adaptive Markov chain

Monte Carlo sampling," *Advances in Water Resources*, vol. 31, no. 4, pp. 630–648, 2008.

[50] J. E. Nash and J. V. Sutcliffe, "River flow forecasting through conceptual models part I—A discussion of principles," *Journal of Hydrology*, vol. 10, no. 3, pp. 282–290, 1970.

[51] X. Jin, C.-Y. Xu, Q. Zhang, and V. P. Singh, "Parameter and modeling uncertainty simulated by glue and a formal bayesian method for a conceptual hydrological model," *Journal of Hydrology*, vol. 383, no. 3-4, pp. 147–155, 2010.

[52] Standards Press of China, "Standard for hydrological information and hydrological forecasting (Gb/T 22482-2008)," in *Ministry of Water Resources of the People's Republic of China*, Standards Press of China, Beijing, China, 2008.

[53] C. Gabriele, M. Cinzia, E. Ortiz, and T. Ezio, "Application of the TOPKAPI model within the DMIP 2 Project," in *Proceedings of the 23rd Conference on Hydrology*, Phoenix, AZ, USA, January 2009.