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Using genetic algorithm and TOPSIS for Xinanjing model calibration with a single procedure

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Abstract

Genetic Algorithm (GA) is globally oriented in searching and thus useful in optimizing multiobjective problems, especially where the objective functions are ill-defined. Conceptual rainfall-runoff models that aim at predicting streamflow from the knowledge of precipitation over a catchment have become a basic tool for flood forecasting. The parameter calibration of a conceptual model usually involves the multiple criteria for judging the performances of observed data. However, it is often difficult to derive all objective functions for the parameter calibration problem of a conceptual model. Thus, a new framework to the multiple criteria parameter calibration problem, which combines GA with TOPSIS (technique for order performance by similarity to ideal solution) for Xinanjiang model, is presented. The current method integrates the two parts of Xinanjiang rainfall-runoff model calibration together, simplifying the procedures of model calibration and validation and easily demonstrating the intrinsic phenomenon of observed data in integrity. Comparing results with two-step procedure show that the current methodology is also feasible and robust, but simpler and easier to be applied in practice.

Keywords: Genetic algorithm; Rainfall-runoff model; Calibration; Multiple objectives; TOPSIS

Introduction

Every system, even the most complicated one, can be modeled if its behavior is fully known and understood. However the current knowledge of the flood is still not sufficient to create a full model of its behavior. The rainfall-runoff process is very complex considering the space-time variability of rainfall, soil moisture, and evapotranspiration. Other relevant factors involved include land use, vegetation cover, land and channel slopes, and soil

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drainage properties. The lack of adequate data and model imperfections has been found to limit the application of models for flood forecast. Conceptual rainfall-runoff models (CRRMS) aiming at predicting streamflow from the knowledge of precipitation over a catchment have become basic tools for flood forecasting. These models permit calculation of the runoff generated by precipitation events by simulating the physical processes that affect the movement of water over and through the soil. The accuracy of these calculations depends both on the structure of the model and on how the relevant parameters are defined. CRRMS generally have a large number of parameters, which cannot be directly obtained from measurable quantities of catchment characteristics, and hence model calibration is entailed. The ultimate purpose of the calibration is to determine the values of the parameters of the CRRM so that the model simulates the hydrological behavior of the catchment as closely as possible.

The process of model calibration is normally performed either manually or by using computer-based automatic procedures. The process of manual calibration is a very tedious and time consuming task. In this method, because of the involved subjectivity, it is difficult to explicitly assess the confidence of the model simulations. Due to this, a great deal of research has been directed to development of automatic calibration procedures (e.g., Gupta and Sorooshian, 1985). Research into optimization methods had led to the use of population-evolution based optimization algorithms such as genetic algorithms (Wang, 1991, 1997), shuffled complex evolution algorithm (Duan et al., 1992, 1994) and simulated annealing (Sumner et al., 1997).

On the other hand, calibration based on a single objective function is often inadequate to simulate all the important characteristics of the observed data. Recently, automatic routines that use a multi-objective formulation of the calibration problem have been introduced in rainfall-runoff modeling (Lindström, 1997; Liong et al., 1996, 1998; Gupta et al., 1998; Yapo et al., 1998; Madsen, 2000; Boyle et al., 2000; Cheng et al., 2002).

Genetic algorithm is a global search technique, modeled after the process of natural selection, which can be used to find near optimal solutions to highly nonlinear optimization problems. It has become one of the most widely used techniques for solving a number of hydrology and water resources problems (Wang, 1997; Ritzel and Wayland Eheart, 1994; Franchini, 1996; Franchini and Galeati, 1997; Savic et al., 1999; Vasques et al., 2000; Sharif and Wardlaw, 2000; Khu et al., 2001; Cheng et al., 2002). Recently, Cheng et al. (2002) presented a new methodology that calibrates the Xinanjiang model parameters with multiple objectives through dealing with water balance and runoff routing respectively. The method adopts a two-step procedure to calibrate parameters, especially requiring preprocessing and adjustment of the pure precipitation values in each time interval in order to eliminate the errors between the observed and simulated water balance for each flood event before the runoff routing calibration procedure. Its obvious disadvantages are to split the whole procedure into two parts and difficult to grasp the best behaviors of model during calibration procedure in integrity.

In this paper we propose a new framework for automatic calibration of a conceptual rainfall-runoff model. In comparison with the previous method presented in the paper (Cheng et al., 2002), the parameter calibration and validation in the current methodology is an integral procedure without splitting into two parts: the water balance and runoff routing. TOPSIS (technique evaluation adopts for order performance by similarity to ideal solution), which was first developed by Hwang and Yoon (1981) for solving a multiple criteria decision making problem, was adopted to evaluate and select the most-fit chromosomes to mate and reproduce according to the ranking order of all chromosomes. Except of initial set of parameter values, integral calibration and validation procedures are automatically performed. This paper is organized as follows. The steps in the estimation process, including model parameterisation and choice of calibration parameters, the calibration criteria and the optimization algorithm are first presented. A test example is presented and comparison is made with the two-step procedure.

The model parameterisation and choice of calibration parameters

Conceptual rainfall-runoff models are used for river flow simulation and flood forecast. The model used in this study is the Xinanjiang rainfall-runoff model, which is developed by Zhao et al. (Zhao et al. 1980; Zhao, 1992). The original Xinanjiang model consists of a runoff generating component and a runoff routing component. The basin is divided into a set of sub-areas and runoff is first transformed into discharge by a linear system calculated from the water balance component. The outflow hydrograph from each sub-area is finally routed down the channels to the main basin outlet by the Muskingum method. In this study, the runoff generating and runoff routing components are combined together. It includes seven runoff generating component parameters: U_m, L_m, D_m, B, I_m, K, C; and 10 runoff routing component parameters: S_m, E_x, K_g, K_i, C_g, C_i, C_s, K_e, X_e, L. The model parameters are listed in Table 1. During the calibration, the parameter must satisfy the constraints of the Muskingum method for each channel of sub-basin.

$$2KeXe \le \Delta t \le 2Ke - 2KeXe$$

INSERT Table 1 NEAR HERE

In the initial model parameterisation process sensitivity analysis can be conducted to investigate the sensitivity of the model responses to its parameters, and hence to identify those which should be further refined via calibration.

The sensitivities depend on the parameter values, and the parameters that seem to be insensitive may have important correlations with other parameters that are essential for the model behavior. The last runoff routing parameter L, the lag time of routing for each sub-area, is an empirical value which is mainly dependent on the length and slope of a stream. It is insensitive to the model response. So it can be determined before the calibration.

The parameter space is usually defined by specifying lower and upper limits on each parameter. These limits are chosen according to physical and mathematical constraints, information about physical characteristics of the system, and from modeling experiences.

The model parameterisation and model calibration is an iterative process. If the calibration results in poorly defined parameter values, we should reconsider the model parameterisation and define a simpler conceptual model that includes fewer calibration parameters. On the other hand, if the model is not able to sufficiently describe the response of the system, we should reconsider key model parameters or include other process descriptions in the calibration.

Calibration criteria and Choice of optimisation algorithm

According to the national criteria for flood forecasting in China, the percentage error of peak discharge, peak time and total runoff volume are important performance measures to evaluate real-time flood forecasting and flood simulation. The result of forecasting is qualificatory relative to peak value, peak time and total runoff volume for this flood if the absolute percentage error of peak discharge between the simulated and observed floods is less than 20%, if the difference in peak time is within a routing period and if the total runoff volume error is less than 3 mm or absolute percentage error less than 20%, respectively. The evaluation of parameter calibration is counting the three ratios of qualificatory criteria relative to the peak discharge, peak time and total runoff volume, respectively. So, the parameter calibration of the model is a multiple objective optimization problem with constraints.

The flood forecasting is a highly non-linear problem. For calibration of the conceptual hydrological models, the global population-evolution-based algorithms are more effective than local search procedures. So in this paper, the genetic algorithm (GA) is adopted. Unlike the standard search techniques, genetic algorithms search among a population of points, work with a coding of the parameter set and use probabilistic transition rules. There are four GA parameters: crossover probability parameter P_c, mutation probability parameter P_m, population size parameter P_{size} and the maximum number of generation T_{max}.

In this study, arithmetic crossover operation is selected which is simple and effective to real code. The crossover operation is not always applied to selected chromosomes. The application of crossover is governed by a crossover probability, denoted by P_c. This parameter controls the frequency of the crossover operation. If P_c is too large, then the structure of a high quality solution could be prematurely destroyed; if P_c is too small, then the searching efficiency can be very low. Generally, P_c is chosen between 0.5 and 0.8.

A non-uniform mutation is selected and designed to the mutation operation in this paper. The mutation operator is used as a means to escape from local minima in that the mutated chromosome, which may have a worse quality, can possibly lead to new search direction in the solution space. This parameter is a critical factor in extending the diversity of the population. If P_m is too small, then new gene segment could not be induced; if P_m is too big, then the genetic evolution degenerates into a random local search. Generally, P_m is often chosen between 0.001 and 0.1.

The parameter P_{size} critically affects the efficiency and solution quality of the genetic algorithm. If P_{size} is too small, and thus, insufficient samples are provided, then the genetic evolution will be degenerated or no useful result can be obtained; if P_{size} is too large, then the amount of computation time needed may exceed a tolerable limit, and, more importantly, time of convergence could be prolonged. Generally, P_{size} is set to be a value between 150 and 300.

In order to select the most-fit chromosomes to mate and reproduce, a $(\mu+\lambda)$ selection method is used to produce offspring for the next generation in this study. The method first generates λ children chromosomes from μ parent chromosomes by crossover and mutation operations, then selects strong chromosomes as a new population but keeps a mating pool as large as the selected original population. The procedure mentioned above is in fact a multiple criteria decision making (MCDM) problem with limited alternatives (Cheng et al., 2002). The problem herein is to find the ranking order of all chromosomes and select the better ones as next generation whose total number is $P_{size.}$

Fitness calculation is a problem-oriented process. Here, TOPSIS, which is a well-known MCDM method and can give the ranking order of all alternatives, is employed. Alternatives here are chromosomes and the attributes of multiple criteria are the flood characteristics such as peak value, peak time and total runoff volume.

It is supposed that the total number of attributes for a chromosome evaluation is m, and the total number of chromosomes through crossover and mutation operation is n. In determining the ranking order of all n chromosomes, a MCDM problem for the parameter calibration of a conceptual model can be concisely expressed in matrix as

$$D = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_m \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots & A_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array}$$

$$W = \begin{bmatrix} w_1 & w_2 & \cdots & W_m \end{bmatrix}$$

where A_1, A_2, … , A_n are the chromosomes with the performance measure criteria: $C_1, C_2, \ldots, C_m$. x_{ij} is the ith rating of chromosome A_j ($i = 1,2,\ldots,m; j = 1,2,\cdots n$). w_i is the weight of criterion C_i.

The decision matrix D should be normalized. In general, attributes can be classified into two types: benefit and cost. In this paper, we choose the following normalization formula. For benefit criteria, the equation becomes

$$r_{ij} = x_{ij} / x_{i\max} \quad (1)$$

Otherwise, the following equation should be used

$$r_{ij} = (1 - x_{ij}) / x_{i\max} \quad (2)$$

where $x_{i\max} = \vee_{j=1}^{n} x_{ij}$. After the transformation, the normalized decision making matrix is represented as

$$R = (r_{ij})_{m \times n} \quad (3)$$

Considering the different importance of each criterion, we can construct the weighted normalized fuzzy decision matrix as:

$$V = (v_{ij})_{m \times n} \quad (4)$$

The positive-ideal solution and negative-ideal solution (Hwang and Yoon, 1981) are defined as

$$A^* = (\underbrace{1,1,\cdots,1}_{m}) = (a_i^*)_{m\times 1}$$

$$A^- = (\underbrace{0,0,\cdots,0}_{m}) = (a_i^-)_{m\times 1}$$

The distance of each alternative (chromosome) from A^* and A^- can be calculated as

$$d_j^* = \sum_{i=1}^{m} d(v_{ij}, a_i^*)$$

$$d_j^- = \sum_{i=1}^{m} d(v_{ij}, a_i^-)$$

The closeness coefficient of each alternative is calculated as

$$CC_j = d_j^- / (d_j^* + d_j^-),\ j = 1,2,\cdots,n \quad (5)$$

By sorting the values of CC_j, the ranking order of all alternatives can be obtained. When compared with the procedure reproducing offspring in GA for the next generation, CC_j can be defined as the fitness of *j*th chromosome.

Generally, the weights of attributes are determined from experience depending on the individual problem. In this study, the weights of three attributes are 0.3, 0.4, and 0.3 for peak value, peak time and total runoff volume, respectively.

The stopping criterion for the optimization algorithm is the maximum number of model evaluations. For a model calibration that includes all 16 parameters, a maximum number of model evaluations in the range 2000~4000 normally ensures an efficient calibration.

The steps of the methodology used in this study which combining GA and TOPSIS can be summarized as Figs. 1 and 2. When the calibration procedure for model parameters has been performed, the software system will proceed with the validation procedure as shown in Figure 2. The dash boxes in Fig.1 and Fig.2 are the perquisite basic data, which are based on the databases.

INSERT FIGURE 1 NEAR HERE
INSERT FIGURE 2 NEAR HERE

Application example

Shuangpai Reservoir in Hunan province is used in this study. The reservoir, with a drainage area of 10,594 km^2 and a water holding capacity of up to 373.8 million cubic meters, is used for power generation, flood control, as well as for irrigation purposes. The details of model calibration data and the reservoir are referred to the paper (Cheng et al., 2002).

A total of 34 historical floods of 12 years data were used for calibration whilst 11 floods between 1999 and 2000 are used for parameter validation. The initial parameter values and the GA parameters are preseted as follows: p_c=0.8, p_m=0.1, P_{size}=150, and

T_{max}=1500. Table 2 shows the results of parameter calibration. Table 3 lists performances of the calibrated parameters. Table 4 lists performances of the validated parameters. Table 5 depicts the comparisons about calibration and validation between the current method and previous one (Cheng et al., 2002).

INSERT Table 2 NEAR HERE

INSERT Table 3 NEAR HERE

INSERT Table 4 NEAR HERE

INSERT Table 5 NEAR HERE

It can be seen from Table 5 that when using the current method, the ratios of qualifying peak discharge, peak time and total runoff volume for the calibrated results are 82.35 %, 91.18% and 97.06% respectively and those for the validated results are 90.91%, 100% and 90.91%. When the previous method is used, the calibrated results are 88.24%, 88.24% and 100% and the validated results are 90.91%, 100% and 100%. The results of two methods are basically similar, which demonstrates the single procedure is also feasible and robust, but simpler and more objective through the removal of error adjustment in the two-step procedure.

Conclusions

A general framework for automatic calibration of the Xinanjiang model has been presented. The framework includes model parameterisation and choice of calibration parameters, the calibration criteria and the optimization algorithm. The automatic optimisation procedure based on the current methodology is an integral procedure without splitting into two parts: the water balance and runoff routing, simplifying calibration steps and easily describing the intrinsic phenomenon of model in integrity.

An application example has been presented that illustrates the use of the proposed calibration framework. Compared with previous work, the results of the calibration are basically similar. This illustrates that this procedure is also feasible and robust. Since the calibration in this paper is an integral procedure without splitting into two parts, it is better employed in practice and without the rich experiences and specific training.

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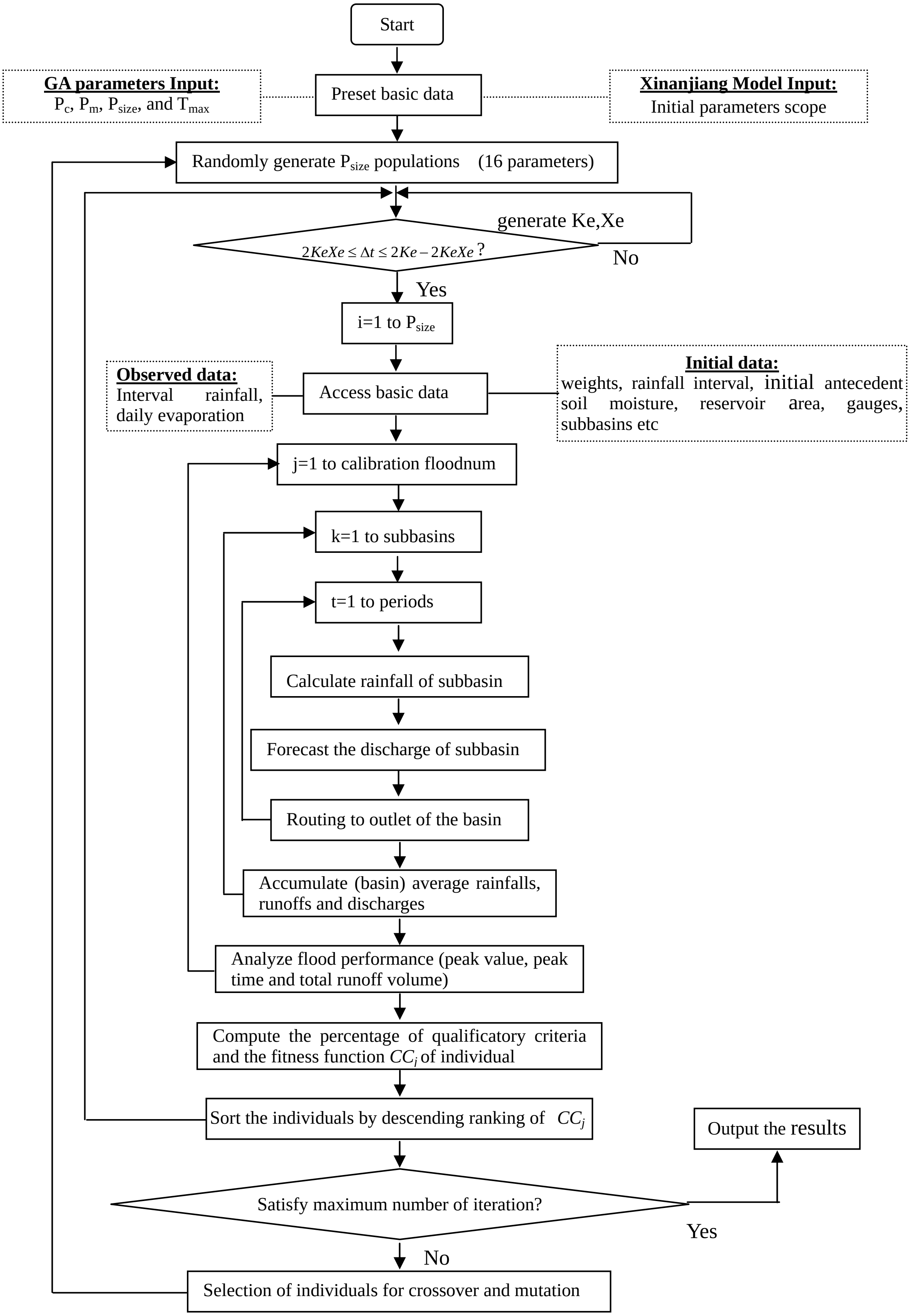

Figure 1 Flowchart of the calibration procedure for the Xianjinag model parameters

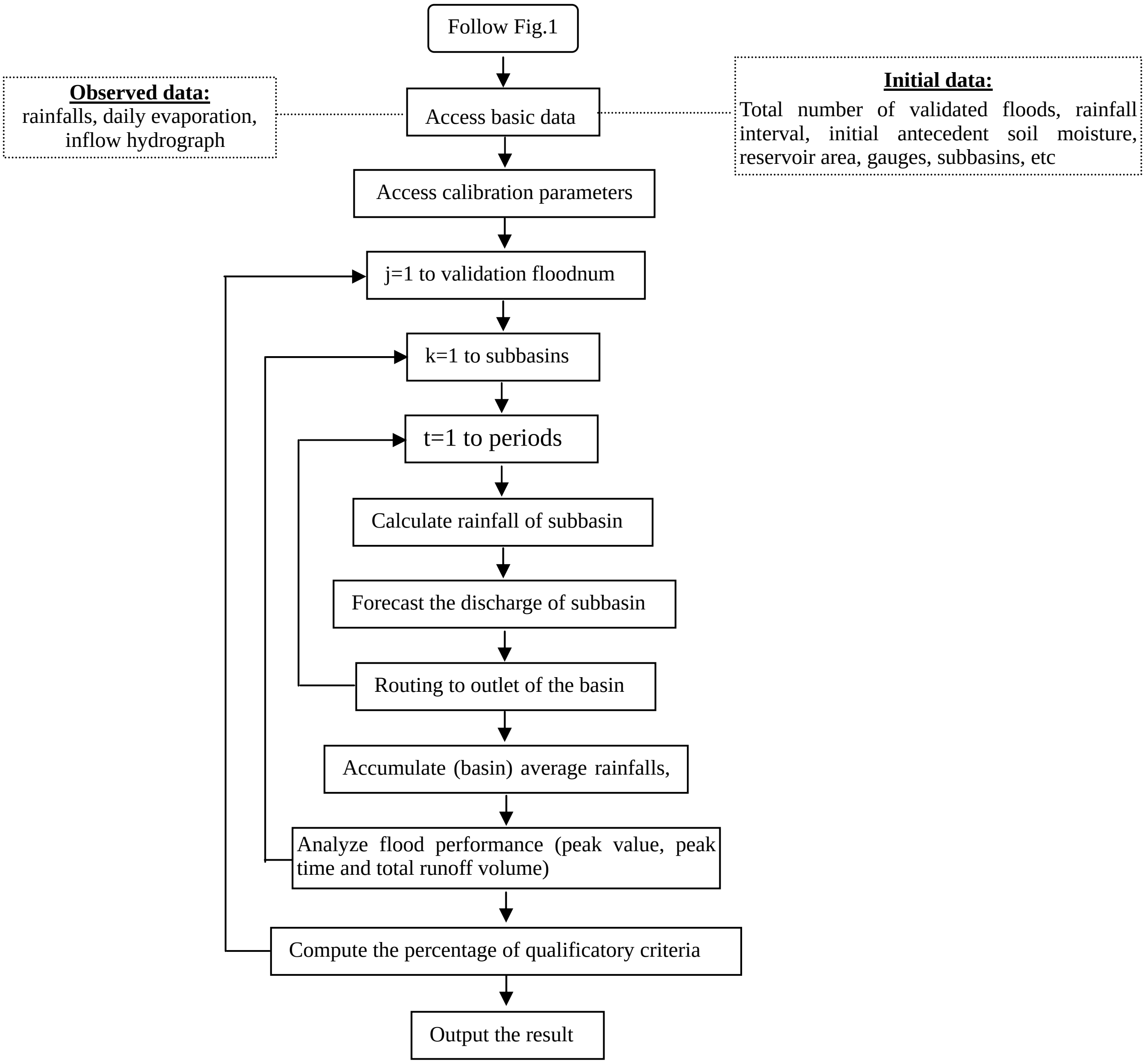

Figure 2. Flowchart of the validation procedure for the Xianjiang model parameters

Table 1. Parameters of Xinanjiang model

Notation	Definition
U_m (mm)	Averaged soil moisture storage capacity of the upper layer
L_m (mm)	Averaged soil moisture storage capacity of the lower layer
D_m (mm)	Averaged soil moisture storage capacity of the deep layer
B	Exponential parameter with a single parabolic curve, which represents the non-uniformity of the spatial distribution of the soil moisture storage capacity over the catchment
I_m (%)	Percentage of impervious and saturated areas in the catchment
K	Ratio of potential evapotranspiration to pan evaporation
C	Coefficient of the deep layer, that depends on the proportion of the basin area covered by vegetation with deep roots
S_m (mm)	Areal mean free water capacity of the surface soil layer, which represents the maximum possible deficit of free water storage
E_x	Exponent of the free water capacity curve influencing the development of the saturated area
K_g	Outflow coefficients of the free water storage to groundwater relationships
K_i	Outflow coefficients of the free water storage to interflow relationships
C_g	Recession constants of the groundwater storage
C_i	Recession constants of the lower interflow storage
C_s	Recession constants in the lag and route method for routing through the channel system within each sub-basin
K_e	Parameter of the Muskingum method
X_e	Parameter of the Muskingum method
L	Lag in time

Table 2. Results of calibrated model parameters

Parameter	B	I_m	K	C	U_m	L_m	D_m	S_m
Value	0.58	0.03	0.66	0.11	29.84	89.31	49.96	12.34

Parameter	E_x	K_g	K_i	C_i	C_g	C_s	K_e	X_e
Value	1.09	0.29	0.45	0.14	0.87	0.27	1.75	0.11

Table 3. Performance of calibrated parameters.

Floods	Flood discharge			Peak time			Total runoff volume
	Observed (m^3/s)	Simulated (m^3/s)	Percentage error (%)	Observed (yyyy-mm-dd hh:mm)	Simulated (yyyy-mm-dd hh:mm)	Error (number)	Percentage error (%)
19840416	1130	1519	**−34.45**	1984-04-17 14:00:00	1984-04-17 11:00:00	−1	2.60
19840530	4310	4411	−2.34	1984-06-01 17:00:00	1984-06-01 14:00:00	−1	4.00
19850411	1200	1729	**−44.13**	1985-04-12 23:00:00	1985-04-12 23:00:00	0	−9.43
19850527	5770	4827	16.34	1985-05-27 23:00:00	1985-05-27 23:00:00	0	9.82
19850610	1370	1104	19.42	1985-06-11 23:00:00	1985-06-11 17:00:00	**−2**	10.13
19860706	2560	2206	13.82	1986-07-06 20:00:00	1986-07-06 20:00:00	0	−3.56
19870404	1790	2046	−14.29	1987-04-05 20:00:00	1987-04-05 23:00:00	1	−14.74
19870515	1720	1412	17.89	1987-05-16 05:00:00	1987-05-16 05:00:00	0	0.86
19870521	1840	1702	7.50	1987-05-22 02:00:00	1987-05-22 02:00:00	0	6.08
19870606	1080	986	8.69	1987-06-07 11:00:00	1987-06-07 14:00:00	1	5.78
19870614	1350	1367	−1.23	1987-06-14 23:00:00	1987-06-14 20:00:00	−1	−4.13
19870722	1740	1098	**36.90**	1987-07-23 11:00:00	1987-07-23 14:00:00	1	9.32
19870729	2170	1073	**50.55**	1987-07-29 20:00:00	1987-07-29 20:00:00	0	**43.32**
19880903	1960	2305	−17.58	1988-09-05 08:00:00	1988-09-04 20:00:00	**−4**	0.97
19890511	2870	2612	8.99	1989-05-13 14:00:00	1989-05-13 11:00:00	−1	−4.17
19890522	1890	1769	6.40	1989-05-22 23:00:00	1985-05-22 23:00:00	0	1.40
19890529	1880	1669	11.22	1989-05-31 05:00:00	1989-05-31 02:00:00	−1	17.12
19900530	2770	2484	10.31	1990-06-01 02:00:00	1990-06-01 02:00:00	0	−5.64
19900607	2110	2254	−6.82	1990-06-08 11:00:00	1990-06-08 11:00:00	0	3.20
19910616	1010	887	12.18	1991-06-16 23:00:00	1991-06-16 20:00:00	−1	12.87
19920423	2320	2530	−9.07	1992-04-24 11:00:00	1992-04-24 14:00:00	1	−12.89
19920516	3020	2870	4.98	1992-05-17 17:00:00	1992-05-17 14:00:00	−1	12.45
19920705	3760	5262	**−39.95**	1992-07-06 20:00:00	1992-07-06 17:00:00	−1	−17.76
19930513	2560	2674	−4.44	1993-05-14 14:00:00	1993-05-14 14:00:00	0	−9.80
19930607	2010	1856	7.69	1993-06-09 11:00:00	1993-06-09 14:00:00	1	−2.99
19930615	1940	2206	−13.71	1993-06-16 02:00:00	1993-06-15 23:00:00	−1	−12.11
19940421	5070	4321	14.77	1994-04-23 20:00:00	1994-04-23 17:00:00	−1	7.11
19940525	2700	2614	3.19	1994-05-26 14:00:00	1994-05-26 17:00:00	1	3.26
19940614	3330	2722	18.26	1994-06-18 08:00:00	1994-06-17 17:00:00	**−5**	3.07
19940723	5810	5239	9.83	1994-07-24 05:00:00	1994-07-24 05:00:00	0	2.88
19940805	2660	2967	−11.54	1994-08-06 11:00:00	1994-08-06 14:00:00	1	−4.14
19950425	2040	2132	−4.51	1995-04-26 11:00:00	1995-04-26 08:00:00	−1	−19.50
19950526	1400	1871	**−33.64**	1995-05-26 17:00:00	1995-05-26 20:00:00	1	−16.55
19950614	3880	3948	−1.75	1995-06-17 02:00:00	1995-06-17 02:00:00	0	9.36

Notes. (1) The total number of floods, which are qualificatory relative to the error of peak discharge, is 28 and the ratio of qualifying simulation is 82.35 %. (2) The total number of floods, which are qualificatory relative to the error of peak time, is 31 and the ratio of qualifying simulation is 91.18%. (3) The total number of floods, which are qualificatory relative to the error of total runoff volume, is 33 and the ratio of qualifying simulation is 97.06%.

Table 4. Performance of validated parameter

Floods	Peak discharge			Peak time			total runoff volume
	Observed (m^3/s)	Simulated (m^3/s)	Percentage error(%)	Observed (yyyy-mm-dd hh:mm)	Simulated (yyyy-mm-dd hh:mm)	Error (number)	Percentage error (%)
19990426	2550	1847	**27.56**	1999-04-25 20:00:00	1999-04-25 23:00:00	1	**31.22**
19990526	4893.	3934	19.60	1999-05-26 17:00:00	1999-05-26 17:00:00	0	13.67
19990618	1690	1636	3.23	1999-06-18 20:00:00	1999-06-18 23:00:00	1	6.32
19990627	1111	1107	0.40	1999-06-25 17:00:00	1999-06-25 17:00:00	0	4.32
19990831	1965	1617	17.69	1999-08-31 23:00:00	1999-08-31 23:00:00	0	13.40
20000403	1628	1894	－16.40	2000-04-02 23:00:00	2000-04-02 23:00:00	0	－9.95
20000410	1798	1965	－9.28	2000-04-09 20:00:00	2000-04-09 17:00:00	－1	－10.85
20000426	909	848	6.71	2000-04-26 20:00:00	2000-04-26 20:00:00	0	－9.76
20000510	1039	1071	－3.12	2000-05-10 02:00:00	2000-05-10 02:00:00	0	1.93
20000528	3163	3113	1.56	2000-05-28 14:00:00	2000-05-28 17:00:00	1	－7.96
20000611	1096	1265	－15.43	2000-06-12 05:00:00	2000-06-12 02:00:00	－1	8.52

Notes. (1) The total number of floods, which are qualificatory relative to the error of peak discharge, is 10 and the ratio of qualifying simulation is 90.91%.

(2) The total number of floods, which are qualificatory relative to the error of peak time, is 11 and the ratio of qualifying simulation is 100%.

(3) The total number of floods, which are qualificatory relative to the error of total runoff volume, is 9 and the ratio of qualifying simulation is 90.91 %.

Table 5. Result comparisons of the current method and previous one [Cheng et al., 2002]

Calibration method	Ratio of qualifying peak discharge (%)		Ratio of qualifying peak time (%)		Ratio of qualifying total runoff volume (%)	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
Previous method	88.24%	90.91%	88.24%	100%	100%	100%
Current method	82.35 %	90.91%	91.18%	100%	97.06%	90.91%