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Estimation of baseflow parameters of variable infiltration capacity model with soil and topography properties for predictions in ungauged basins

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Abstract

Equifinality is unavoidable when transferring model parameters from gauged catchments to ungauged catchments for predictions in ungauged basins (PUB). A framework for estimating the three baseflow parameters of variable infiltration capacity (VIC) model, directly with soil and topography properties is presented. When the new parameters setting methodology is used, the number of parameters needing to be calibrated is reduced from six to three, that leads to a decrease of equifinality and uncertainty. This is validated by Monte Carlo simulations in 24 hydro-climatic catchments in China. Using the new parameters estimation approach, model parameters become more sensitive and the extent of parameters space will be smaller when a threshold of goodness-of-fit is given. That means the parameters uncertainty is reduced with the new parameters setting methodology. In addition, the uncertainty of model simulation is estimated by the generalised likelihood uncertainty estimation (GLUE) methodology. The results indicate that the uncertainty of streamflow simulations, i.e., confidence interval, is lower with the new parameters estimation methodology compared to that used by original calibration methodology. The new baseflow parameters estimation framework could be applied in VIC model and other appropriate models for PUB.

1 Introduction

The variable infiltration capacity (VIC) model is a macro-scale hydrological based land surface model (Liang et al., 1994, 1996; Liang and Xie, 2001), which is an effective tool for simulating the processes of the hydrological cycle (Maidment, 1993). Hydrological models can generate predictions of hydrological response to a range of climates for flood forecasting and regional water resources management. On the other hand, they can also provide the feedback of land surface schemes from atmosphere to general circulation models (GCMs) for numerical weather forecasting and future climatic scenarios prediction. Model parameters represent the landscape and climatic properties

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that dominate the basin response to climatic variables. Accordingly, it is critical component for the accuracy of hydrological simulation. Some studies indicate that hydrological models would have satisfying results if the model parameters are appropriately set, vice versa (Gupta et al., 1999; Wood et al., 1998). Traditionally, model parameters are calibrated by optimization algorithms with some objective functions, which are calculated by simulated and observed hydrological variables. However, in many parts of the world, basins are ungauged or poorly gauged, then, there are not sufficient observed data for calibration (Sivapalan et al., 2003). Therefore, Predictions in Ungauged Basins (PUB) becomes a new challenge for hydrologists.

In a general way, PUB is studied by the transfer of model parameters from gauged catchments to ungauged catchments (Blöschl and Sivapalan, 1995; Sivapalan et al., 2003). Three kinds of approaches are widely used: regression, spatial proximity, and physical similarity (Oudin et al., 2008; Zhang and Chiew, 2009). Probably, regression-based approach is most popular, has a long history, and has been studied widely (Abdulla and Lettenmaier, 1997; Hundecha et al., 2007; Jarboe and Haan, 1974; Weeks and Ashkenasy, 1985; Weeks and Boughton, 1987; Young, 2006). The key step of this methodology is to construct nonlinear relationships between optimized model parameters and catchment characteristics (e.g., soil, vegetation, climate, topography, etc.) with regression equations. However, there are complex correlations between model parameters and catchment characteristics (Wagener, 2007). Hence, it is not straightforward to investigate the actual nonlinear relationship between model parameters and catchment characteristics by simple multiple regression equations. Meanwhile, model parameters may change and only represent transient catchment characteristics, as a result of land use/cover change (LUCC) and climatic variation (Brown et al., 2005; Lubès-Niel et al., 2003; Merz et al., 2011). Thereby, it is difficult to calibrate parameters changing with time (Wagener et al., 2010). Due to above limitations, regression-based approach generally results in large errors, when they are verified in other catchments, and have been criticized by some studies (Bardossy, 2007; Huang et al., 2003; Parajka et al., 2007).

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Spatial proximity and physical similarity approaches have been more and more popularly used in recent studies (Bardossy, 2007; Merz and Blöschl, 2004; Parajka et al., 2005; Samuel et al., 2011). In the former, model parameters in ungauged catchments are estimated by interpolation techniques, e.g. inverse distance weighted and kriging, with calibrated parameters from the geographically closest gauged catchments. This approach depends on a hypothesis, that regional catchments are relatively homogeneous and have similar characteristics. The latter approach transfers model parameters from gauged physically similar catchments, which are defined by some similarity indices, e.g. a cosine-pattern similarity and an Euclidean distance. Some studies have been made to compare the three approaches, and attempt to investigate which is the best one, but unfortunately they do not have consistent results (Kay et al., 2006; McIntyre et al., 2005; Oudin et al., 2008; Young, 2006; Zhang and Chiew, 2009).

However, there is an unavoidable limitation about the above three approaches, i.e. calibration-transfer-based methodology: it is difficult to find an authentic parameters set for a gauged catchment. First, it is difficult to investigate the global optimized value under high dimensional parameter space, as a result of multiple local optima and curving multidimensional ridges, etc. (Gan and Biftu, 1996; Vrugt et al., 2003). Second, equifinality is unavoidable due to the cross-correlation among parameters (Beven and Binley, 1992; Beven and Freer, 2001). Probably, there is not a unique "best" parameters set, i.e., hydrological model has similar performance with different parameters set during calibration. But it may lead to considerable uncertainty in model output for verification and forecasting. Third, calibrated model parameters are sensitive to model input, because of the compensation effect of calibration parameters to model structure problems and data problems (Blöschl et al., 2007; Merz et al., 2011). For example, Wagener et al. (2003), Juston et al. (2009), and Merz et al. (2011) all investigated different parameters set for different calibration periods.

Some studies were attempted to evolve approaches for estimating model parameters in ungauged catchments. One approach is to estimate model parameters directly by catchment characteristics based on their physical definition without traditionally

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hydrological calibration. For example, Huang et al. (2003) presented a framework to transfer the b-parameter of VIC model from data-rich areas to data-sparse areas. First, they classified soil data obtained from the State Soil Geographic (STATSGO) database, into clusters by a self-organizing map neural network (Kohonen, 1989) and the K-means clustering method (MacQueen, 1967). Whereafter, highly nonlinear relationships between the b-parameter and soil properties were constructed by a supervised neural network based on a Bayesian regularization method (Foresee and Hagan, 1997; MacKay, 1992). A case study at Illinois River basin near Watts indicated encouraging simulated streamflow compare to the observations, by the presented b-parameter transferability framework using soil data from Arkansas, California, Oklahoma, and Texas. Another approach is to modify model structure to reduce the number of model parameters. Huang and Liang (2006) replaced the original baseflow formulation of VIC model by the concept of kinematic wave and hydrologic similarity to reduce the number of baseflow parameters from three to one needed to be calibrated. That also reduced the impacts of parameters uncertainties on model simulations.

The main objective of this study is to construct a new framework for estimating baseflow parameters of VIC model directly from soil and topography properties, without calibration. In addition, uncertainty of model parameters and output is quantitatively estimated by the generalised likelihood uncertainty estimation (GLUE; Beven and Binley, 1992; Beven and Freer, 2001). The remaining sections of this paper are organized as follows: In Sect. 2, a brief review of the VIC model and GLUE methodology is provided. Section 3 describes a new framework for estimating base flow parameters of VIC model directly from catchments physical properties of soil and topography. In Sect. 4, hydrological simulation, parameters sensitivity and uncertainty analysis, and streamflow simulation uncertainty are compared by the new methodology and original calibration approach in 24 sub-catchments in China. The conclusions are summarized in Sect. 5.

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2 Hydrological model and uncertainty analysis

2.1 A brief review of the VIC model

VIC model is a semi-distributed macro-scale hydrological based land surface model, which can balance both the water and surface energy budgets within the grid cell. The key characters of VIC model are the representation of multiple land cover types, spatial variability of soil moisture capacity, soil water moving between three soil layers, surface flow considering both infiltration excess and saturation excess, and non-linear base flow. With refined describing of hydrologic process on land surface and finer performance of streamflow simulation, VIC has been applied in a number of catchments over the world (Abdulla et al., 1996; Lohmann et al., 1998; Shi et al., 2008; Su et al., 2005; Zhu and Lettenmaier, 2007).

In VIC model, surface runoff generating from the upper two soil layers, is accounted based on the variable soil moisture capacity curve which is described by the Xinanjiang model, in order to represent the sub-grid spatial variability in soil moisture capacity (Zhao et al., 1980; Zhao, 1992). That is expressed as:

$$W = W_{\mathrm{mm}}(1-(1-A)^{1/b}) \tag{1}$$

where W and W_{mm} are the point and maximum point soil moisture capacity, respectively; A is the fraction of area for which the soil moisture capacity is less than W; and b is the soil moisture capacity shape parameter. The surface runoff, Q_{s}, could be calculated as:

$$Q_{\mathrm{s}} = \begin{cases} \mathrm{PE}-(W_{\mathrm{m}}-W_0), \mathrm{PE}+W \geq W_{\mathrm{mm}} \\ \mathrm{PE}-(W_{\mathrm{m}}-W_0)+W_{\mathrm{m}}\left(1-\frac{\mathrm{PE}+W}{W_{\mathrm{mm}}}\right)^{1+b}, \mathrm{PE}+W < W_{\mathrm{mm}} \end{cases} \tag{2}$$

where PE is effective precipitation, and is precipitation minus evapotranspiration; W_{m} is soil moisture capacity of the upper two soil layers; W_0 is initial soil moisture.

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Using the Arno model formulation (Franchini and Pacciani, 1991; Todini, 1996), base flow (sub surface runoff) from the third soil layer is expressed as (Fig. 1):

$$Q_b = \begin{cases} \frac{D_s D_m}{W_s \theta_{3,s}} \theta_3, 0 \le \theta_3 \le W_s \theta_{3,s} \\ \frac{D_s D_m}{W_s \theta_{3,s}} \theta_3 + \left(D_m - \frac{D_s D_m}{W_s} \right) \left(\frac{\theta_3 - W_s \theta_{3,s}}{\theta_{3,s} - W_s \theta_{3,s}} \right)^2, \theta_3 > W_s \theta_{3,s} \end{cases} \tag{3}$$

where D_m is the maximum subsurface flow; D_s and W_s are the fraction of D_m and maximum soil moisture of third layer ($\theta_{3,s}$), respectively; and θ_3 is the current soil moisture of third layer. The base flow recession curve is linear and nonlinear below and above a threshold ($W_s\theta_{3,s}$), respectively.

In VIC model, there are six parameters needing to be calibrated (Table 1). That includes the three baseflow parameters: W_s, D_s, and D_m; variable soil moisture capacity curve parameter: b; and two parameters, d_2 and d_3, that controls the thickness of the second and third soil layer, respectively. The six parameters are calibrated by two objectives: Nash-Sutcliffe coefficient (Nsc) and relative error (Re), which are defined as:

$$\text{Nsc} = 1 - \frac{\sum (Q_{obs} - Q_{sim})^2}{\sum (Q_{obs} - \bar{Q}_{obs})^2} \tag{4}$$

$$\text{Re} = \frac{R_{sim} - R_{obs}}{R_{obs}} \times 100\% \tag{5}$$

where Q_{obs} and Q_{sim} are the observed and simulated streamflow, respectively; $\bar{Q}_{obs}$ is the mean value of Q_{obs}; R_{obs} and R_{sim} are the observed and simulated average annual streamflow, respectively. For more information on the VIC model, the reader is referred to the VIC web-site, http://www.hydro.washington.edu/Lettenmaier/Models/VIC.

2.2 Generalised likelihood uncertainty estimation

GLUE methodology is an innovative uncertainty estimation approach introduced by Beven and Binley (1992), and has been applied in many researches (Hunter et al., 2005; Khu and Werner, 2003; Montanari, 2005; Morse and Pohll, 2003; Rojas et al., 2010; Stedinger et al., 2008; Zheng and Keller, 2007). Based on the concept of equifinality (Beven, 2006; Beven and Freer, 2001) and Bayesian theory, GLUE methodology is an extension of generalized sensitivity analysis (GSA; Hornberger and Spear, 1981; Sepear and Hornberger, 1980), and can estimate parameter uncertainty explicitly, using Monte Carlo (MC) method. In this study, GLUE methodology is applied in the following steps:

1. Based on the MC simulation, VIC model is run with a number of parameters set, the prior probability of which is uniform distribution.

2. The likelihood measure, a measure of goodness-of-fit, is calculated by the observations and simulations in every parameter set. Usually, Nsc is used as the likelihood measure. In order to consider both Nsc and Re, a modified likelihood measure, Mnc indicator, is used in this study:

$$\mathrm{Mnc} = \frac{\mathrm{Nsc} + 1 - \mathrm{Abs(Re)}}{2} \quad (6)$$

3. When the likelihood value is under a given threshold, the parameters set is considered as "nonbehavioral" and is rejected. Then, the likelihoods of the remaining parameters sets are rescaled with a cumulative sum of 1. That is defined as likelihood weight looked like probability, and is regarded as the posterior parameters probability distribution.

4. Estimate the confidence interval of streamflow at each time step for uncertainty analysis, by quantiles ranked in ascending order with likelihood weight.

In addition of confidence interval, a quantitative estimator is used for uncertainty analysis (probabilistic Shannon Entropy measure, H; Klir and Folger, 1988):

$$H = -\sum_{i=1}^{M} l_i \log_2 l_i \quad (7)$$

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where l_i is likelihood weight and M is the number of parameters set.

3 A framework for estimation of baseflow parameters

Equifinality is a critical impediment for model parameters calibration and PUB, especially for non-sensitive parameters. That is because model can perform best with a more extensive range of non-sensitive parameters than sensitive parameters. In VIC model, the three baseflow parameters (W_s, D_s, and D_m) are less sensitive than other three parameters (Demaria et al., 2007). In this study, a framework is presented to estimate the three baseflow parameters directly from physical properties and topography.

1. D_m-parameter. D_m is daily maximum subsurface flow. That occurs when the third soil layer moisture is saturated. By Darcy's Law (Darcy, 1856), D_m-parameter in every sub-grid could be estimated as:

$$D_\mathrm{m} = -K_\mathrm{s}\frac{\partial \Phi(x)}{\partial x} \tag{8}$$

where K_s is saturated hydraulic conductivity, and $\partial \Phi(x)/\partial x$ is horizontal pressure gradient, that could be calculated by the sub-grid average topography slope when the soil moisture is saturated. The K_s values for several soil texture classes are referenced to Rawls et al. (1998).

2. W_s-parameter. Based on unsaturated Darcy's law, the quantity of baseflow depends on unsaturated hydraulic conductivity, K, and pressure gradient. When the soil moisture is over than field capacity, bulk water occurs, and then baseflow increases rapidly as the increase of soil moisture. In VIC model, W_s is the inflexion of soil moisture for baseflow generation, and can be calculated as:

$$W_\mathrm{s} = \frac{W_\mathrm{f}}{W_\mathrm{m}} \tag{9}$$

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where W_f and W_m are sub-grid field capacity and saturated soil moisture, respectively.

3. D_s-parameter. When the sub-grid soil moisture is $W_s W_m$, i.e., W_f, point soil moisture, θ_f, could be calculated by the variable soil moisture capacity curve (Fig. 2). As a fraction, A_0, soil moisture is saturated; but in the remaining fraction, $1-A_0$, soil moisture is θ_f and unsaturated. In the $1-A_0$ fraction, unsaturated hydraulic conductivity, K, can be estimated by the Brooks-Corey equation (Brooks and Corey, 1964; Campbell, 1974):

$$K = K_s \left(\frac{\theta_f}{\theta_s}\right)^{2\lambda+3} \tag{10}$$

where λ is a parameter, that is referenced to Cosby et al. (1984). As a fraction of D_m, D_s-parameter is expressed as:

$$D_s = A_0 + \int_{A_0}^{1} \frac{K}{K_s} dA = A_0 + \int_{A_0}^{1} \left(\frac{\theta_f}{\theta_s}\right)^{2b+3} dA \tag{11}$$

By the above framework, the three baseflow parameters are directly estimated from physical properties and topography. The parameters can be estimated in every sub-grid, and are different in different sub-grid. But using calibration methodology, parameters will be set as same value in the whole catchment. Therefore, using this framework, baseflow parameters will be distributed and more relatively authentic.

4 Results

4.1 Study area and dataset

24 sub-catchments located through China are used in this study (Fig. 3). Table 2 presents an overview of the detailed basic information for the 24 sub-catchments. The

largest catchment is Luoduxi catchment with an area of 38064 km^2, but the smallest one is only 2582 km^2 in Nancha catchment. These catchments covers a large variation of hydro-climatic conditions: from arid to humid areas, and from cold to hot areas, e.g., the annual precipitation, runoff, and mean temperature varies from 387.6 to 1702.4 mm, from 39.9 to 972.2 mm, and from −2.0 to 21.6 °C, respectively.

The daily streamflow data in the 24 hydrological stations is extracted from the "Hydrological Year Book". Most available streamflow data are more than 20 yr. Contemporaneous meteorological data including daily precipitation, mean temperature, maximum temperature and minimum temperature are collected from National Meteorological Administration of China, which applies data quality control before releasing these data.

4.2 Streamflow simulation

VIC model is applied for the streamflow simulation in the 24 catchments at a 0.25° spatial and daily temporal resolution, with two kinds of parameters setting methodologies. One is estimating all six parameters through calibration, called 6 parameters methodology. Another one is estimating three baseflow parameters by physical properties of soil and topography, and the remaining three parameters are calibrated, called 3 parameters methodology. Table 3 summarizes the performance of VIC model for monthly streamflow simulation in the 24 catchments with the two kinds of parameters setting methodologies.

No matter for 6 parameters methodology or 3 parameters methodology, VIC model performs better in humid areas than that in arid areas. For example, by 6 parameters methodology, the average Nsc in Yangtze River is 0.92, and 0.77 in Haihe River, but it is only 0.67 in Yellow River. An example of three sub-catchments, Gaoqitou, Taolinkou, and Minhe catchment, located in Yangtze River, Haihe River, and Yellow River, respectively, is illustrated in Fig. 4. The results indicate that, compared to observation, simulated streamflow has best goodness-of-fit in Gaoqitou catchment, followed by Taolinkou catchment, and the worst one is in Minhe catchment.

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Generally, the 6 parameters methodology has better results than the 3 parameters methodology, but the difference is not significant. The average Mnc values of the 24 catchments are 0.896 and 0.888 by the 6 parameters and 3 parameters methodology, respectively. Meanwhile, there are 15 out of 24 catchments, in which the Mnc value by the 3 parameters methodology is lower than that by the 6 parameters methodology.

4.3 Sensitivity and uncertainty analysis of model parameters

The model parameters sensitivity is estimated by MC simulation, and the results in three kinds of hydro-climatic catchments: Gaoqitou, Taolinkou, and Minhe catchment, are illustrated in Fig. 5. Using 6 parameters methodology, (1) the three baseflow parameters and the d_3-parameter are not sensitive, i.e., the model can perform best within an extensive range of parameters space; (2) b-parameter is not sensitive in humid catchment (Fig. 5a), but is sensitive in arid catchment (Fig. 5c); (3) d_2-parameter is the most sensitive one, with biggest extent in Minhe catchment (Fig. 5c), followed by Taolinkou catchment (Fig. 5b), and then Gaoqitou catchment (Fig. 5a).

Using 3 parameters methodology, some original non-sensitive parameters become sensitive. This is because that the equifinality, i.e., the cross-correlation among parameters, is reduced with the reduction of parameters number. For example, in Gaoqitou catchment, d_3-parameter is not sensitive using 6 parameters methodology, but it becomes sensitive when the 3 parameters methodology is used (Fig. 5a). Meantime, some original sensitive parameters become more sensitive. Therefore, when a threshold of goodness-of-fit is given, the extent of parameters space meeting the conditions in the 3 parameters methodology will be smaller than that in 6 parameters methodology. The general results are summarized in Fig. 6. That may result in the parameters uncertainty being reduced.

Because there are only three parameters needing to be calibrated using 3 parameters methodology, and the d_3-parameter is not sensitive, the uncertainties of b and d_2 parameters are analyzed by their variance when the Mnc value is higher than 0.6 (Fig. 7). For b-parameter, it is more uncertain in humid areas than that in arid areas.

For example, the average variances are 0.070, 0.039, and 0.017 in Yangtze River, Haihe River, and Yellow River, respectively. That are consistent to sensitivity analysis, i.e., if the parameter is more sensitive, the uncertainty will be much lower.

As shown in Fig. 7, the average variances of b (d_2) parameter are 0.052 (0.108) and 0.050 (0.106) in the 6 parameters methodology and 3 parameters methodology, respectively. There are 18 (16) out of 24 catchments, in which the variance of b (d_2) parameters in the 3 parameters methodology is lower than that in the 6 parameters methodology. Overall, the uncertainties of b and d_2 parameters in the 3 parameters methodology are lower than they in the 6 parameters methodology.

4.4 Uncertainty estimation of streamflow simulation

The uncertainty of streamflow simulation are estimated by GLUE methodology, with Mnc higher than 0.6 as a threshold. Using two parameters setting methodology, the 90 % confidence interval and 50 % estimate are illustrated in three catchments: Gaoqitou catchment (Fig. 8), Taolinkou catchment (Fig. 9), and Minhe catchment (Fig. 10). For the three catchments, most of the time, the observations fall within the 90 % confidence interval, except for some peaks in Gaoqitou catchment and some vales in Minhe catchment. The 50 % estimate fits best to observations in Gaoqitou catchment, followed by Taolinkou catchment, and then Minhe catchment. In all the three catchments, the uncertainty, i.e., confidence interval in 3 parameters methodology is lower than that in 6 parameters methodology. For Gaoqitou catchment as an example, the average 90 % confidence interval ($Q_{95} - Q_5$) is 336.39 $m^3 s^{-1}$ in 6 parameters methodology, that is higher than 310.11 $m^3 s^{-1}$ in 3 parameters methodology (Table 4).

In addition, quantitative uncertainty is estimated by probabilistic Shannon Entropy measure, H (Fig. 11). The average H values of the 24 catchments are 8.098 and 8.086 in the 6 parameters and 3 parameters methodology, respectively. There are 14 out of 24 catchments, in which H value in 3 parameters methodology is lower than that in 6 parameters methodology. Overall, the uncertainty of streamflow simulation in the 3 parameters methodology is lower than that in the 6 parameters methodology.

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5 Summary

By comparing Monte Carlo simulations of the six calibrated parameters of VIC model, the results indicate that the three baseflow parameters are less sensitive than other three parameters, that is consistent to the conclusions of Demaria et al. (2007). Therefore, the equifinality of the three baseflow parameters is higher than other three parameters. That leads to large uncertainty on transferring parameters in gauged catchments to ungauged catchments for PUB. Although, Huang and Liang (2006) have reduced the baseflow parameters by replacing the original baseflow formulation of VIC model with the concept of kinematic wave and hydrologic similarity, there is still one parameter needing to be calibrated, and we should modify the original programme of VIC model, when their methodology is used. In order to solve this issue, a framework is presented in this study for estimating the three baseflow parameters directly from physical properties of soil and topography. With their physical meanings, the three parameters are estimated by following stages: (1) Based on Darcy's Law, D_m-parameter is estimated by saturated hydraulic conductivity and sub-grid average topography slope; (2) W_s-parameter is estimated by field capacity and saturated soil moisture; (3) D_s-parameter is estimated by Brooks-Corey equation and the variable soil moisture capacity curve.

In addition, the uncertainty of model parameters and streamflow simulation is estimated by the GLUE methodology, under the two kinds of parameters setting methodologies. Although, the original 6 parameters methodology has better results than the 3 parameters methodology, the difference is not significant. When the 3 parameters methodology is used, some original non-sensitive parameters become sensitive and some original sensitive parameters become more sensitive. This is because that the equifinality is reduced with decrease of parameters number. Therefore, when a threshold of goodness-of-fit is given, the extent of parameters space meeting the conditions in the 3 parameters methodology will be smaller than that in 6 parameters methodology. That will result in the parameters uncertainty being reduced. Consequently, the

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uncertainty of streamflow, i.e., confidence interval and/or Shannon Entropy measure in the 3 parameters methodology will be lower than that in 6 parameters methodology.

Overall, this framework for estimating baseflow parameter could reduce the uncertainty on transferring parameters from gauged catchments to ungauged catchments for PUB, which may be studied as: (1) the three baseflow parameters could be estimated by this framework. (2) b-parameter could be estimated using the methodology introduced by Huang et al. (2003). (3) In this case, there are only two parameters (d_2 and d_3) needing to be calibrated with low equifinality. These two parameters may be estimated by regression, spatial proximity, or physical similarity (Oudin et al., 2008; Zhang and Chiew, 2009). The case study should be investigated in the future researches. Meanwhile, this framework could also be extended to other similar models.

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Table 1. Six parameters of VIC model for calibration and uncertainty analysis.

Parameter	Unit	Description
W_s	N/A	Fraction of the maximum soil moisture of the third soil layer where non-linear baseflow occurs
D_s	N/A	Fraction of D_m where non-linear baseflow begins
D_m	mm day^{-1}	Maximum baseflow that can occur from the third soil layer
b	N/A	Defining the shape of the variable soil moisture capacity curve
d_2	m	Soil depth of the second soil layer
d_3	m	Soil depth of the third soil layer

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Table 2. Basic information of the 24 sub-catchments.

No.	Hydro-station	Major basin	Lon. (E°)	Lat. (N°)	Area (km^2)	P (mm)	R (mm)	T (°C)	R_c
1	Xiaoergou	Songhuajiang River	123.72	49.20	16 761	480.46	195.72	−2.01	0.41
2	Chaersen	Songhuajiang River	121.90	46.32	7827	447.57	88.60	0.19	0.20
3	Wuchang	Songhuajiang River	127.10	44.87	5642	672.45	252.31	3.20	0.38
4	Nancha	Songhuajiang River	129.25	47.13	2582	610.12	314.63	0.13	0.52
5	Xiaolinzi	Liaohe River	122.90	41.35	10 254	808.27	221.99	7.05	0.27
6	Taolinkou	Haihe River	119.05	40.13	5060	650.00	142.00	7.38	0.22
7	Zhangjiafen	Haihe River	116.78	40.62	8506	453.60	64.40	9.12	0.14
8	Weishui	Haihe River	114.13	38.03	5387	610.60	131.90	9.72	0.22
9	Minhe	Yellow River	102.80	36.33	15 342	443.30	123.60	1.80	0.28
10	Wenjiachuan	Yellow River	110.75	38.48	8515	387.56	72.00	7.41	0.19
11	Daning	Yellow River	110.72	36.47	3992	512.96	39.90	8.49	0.08
12	Qinan	Yellow River	105.67	34.90	9805	454.95	41.97	6.82	0.09
13	Longmenzhen	Yellow River	112.47	34.55	5318	736.31	245.92	12.37	0.33
14	Xixian	Huaihe River	114.73	32.33	10 190	1093.60	403.00	14.90	0.37
15	Linyi	Huaihe River	118.40	35.02	10 315	868.60	363.20	12.50	0.42
16	Dengyingyan	Yangtze River	104.73	29.90	14 484	987.43	672.87	15.75	0.68
17	Luoduxi	Yangtze River	106.58	30.33	38 064	1134.20	575.82	15.08	0.51
18	Gaoqitou	Yangtze River	110.35	28.62	17 698	1386.00	791.70	14.71	0.57
19	Laobutou	Yangtze River	111.60	26.27	21 341	1532.83	972.15	17.06	0.63
20	Xiangjiaping	Yangtze River	106.28	32.85	6448	775.48	305.97	10.29	0.39
21	Lijiadu	Yangtze River	116.17	28.22	15 811	1702.43	810.77	17.88	0.48
22	Lanxi	Southeast rivers	119.47	29.22	18 233	1581.70	891.80	17.14	0.56
23	Sancha	Pearl River	108.95	24.47	16 280	1447.60	768.10	19.38	0.53
24	Jinji	Pearl River	110.82	23.23	9103	1629.80	779.40	21.56	0.48

P means average annual precipitation; R means average annual runoff depth; T means average annual mean temperature; R_c means average annual runoff coefficient.

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Table 3. Performance of VIC model in the 24 catchments using two kinds of parameters setting methodologies.

No.	Catchment	6 parameters			3 parameters		
		Nsc	Re(%)	Mnc	Nsc	Re(%)	Mnc
1	Xiaoergou	0.719	−0.141	0.859	0.704	2.943	0.837
2	Chaersen	0.710	0.543	0.852	0.708	0.648	0.851
3	Wuchang	0.735	−2.524	0.855	0.745	4.454	0.850
4	Nancha	0.846	−0.223	0.922	0.840	4.707	0.896
5	Xiaolinzi	0.835	1.001	0.912	0.798	4.530	0.876
6	Taolinkou	0.816	−1.187	0.902	0.801	3.503	0.883
7	Zhangjiafen	0.748	−1.691	0.866	0.746	−2.270	0.862
8	Weishui	0.740	−1.321	0.863	0.748	1.359	0.867
9	Minhe	0.697	−0.857	0.844	0.727	−2.256	0.852
10	Wenjiachuan	0.631	−9.523	0.768	0.577	−8.699	0.745
11	Daning	0.647	−0.815	0.819	0.644	0.082	0.822
12	Qinan	0.683	0.422	0.839	0.683	0.388	0.840
13	Longmenzhen	0.686	−1.087	0.838	0.703	−1.111	0.846
14	Xixian	0.786	−2.867	0.879	0.780	3.319	0.875
15	Linyi	0.885	0.003	0.942	0.826	−0.558	0.910
16	Dengyingyan	0.899	0.011	0.949	0.870	−2.768	0.921
17	Luoduxi	0.927	1.495	0.956	0.921	2.376	0.949
18	Gaoqitou	0.928	0.529	0.961	0.926	0.525	0.960
19	Laobutou	0.917	1.440	0.951	0.918	0.008	0.959
20	Xiangjiaping	0.920	−1.520	0.952	0.910	−0.619	0.951
21	Lijiadu	0.941	−0.018	0.970	0.937	1.317	0.962
22	Lanxi	0.937	0.498	0.966	0.942	−0.255	0.970
23	Sancha	0.871	−0.457	0.933	0.880	0.365	0.936
24	Jinji	0.812	−0.777	0.902	0.822	−1.880	0.902

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Table 4. The average confidence interval (Q_{95}–Q_5) for simulated streamflow in Gaoqitou, Taolinkou, and Minhe catchment by two kinds of parameters setting methodologies.

Interval ($m^3\ s^{-1}$)	Gaoqitou catchment	Taolinkou catchment	Minhe catchment
6 parameters	336.39	35.13	43.94
3 parameters	310.11	29.54	40.43

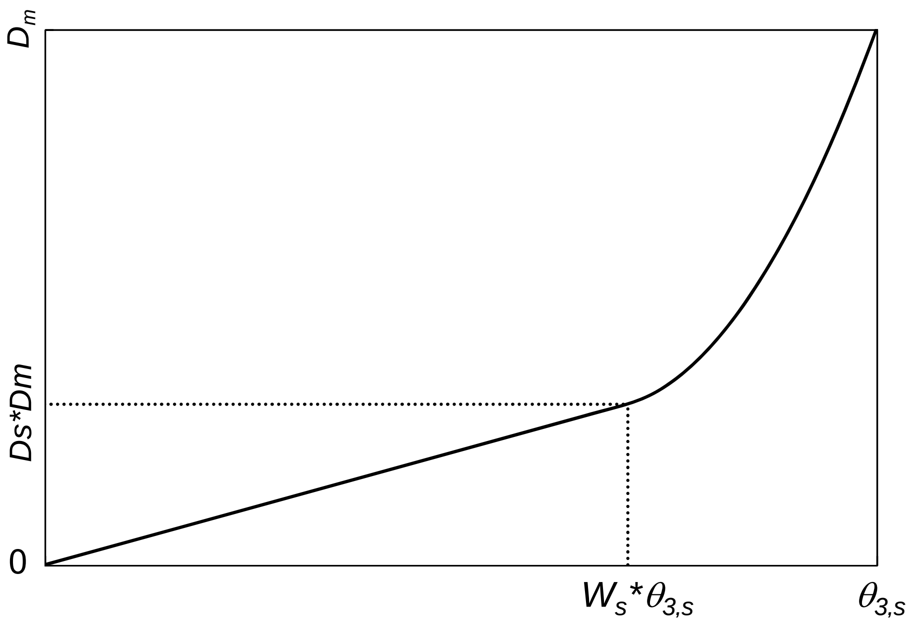

Fig. 1. Schematic representation of Arno baseflow.

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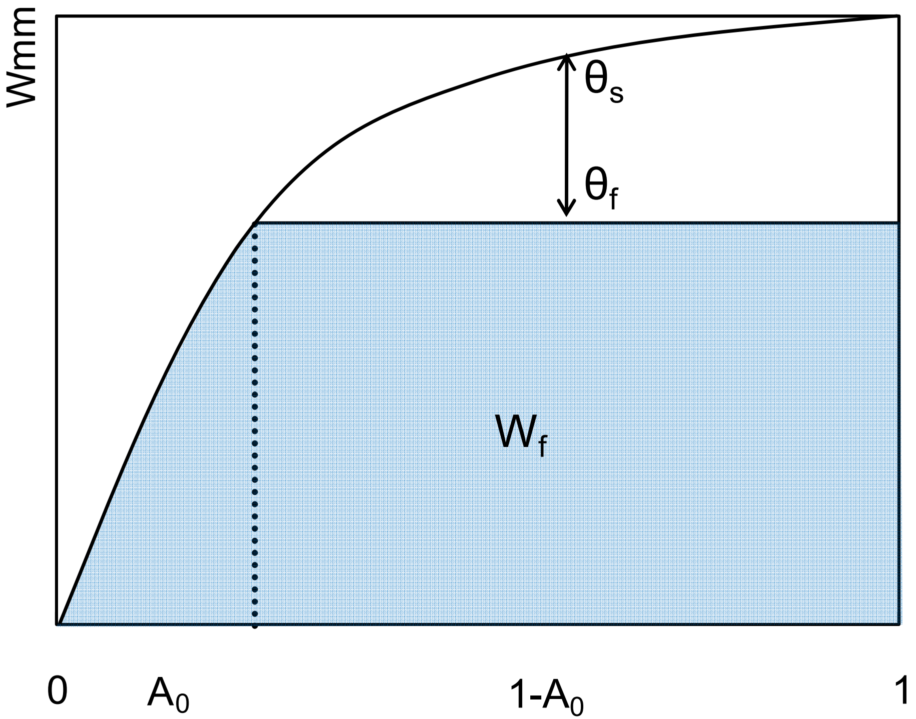

Fig. 2. Schematic representation of soil moisture capacity distribution and estimation of D_s-parameter. The grey area represents the field capacity, W_f, of a sub-grid. Then θ_f could be calculated by the variable soil moisture capacity curve. θ_s means point saturated soil moisture. See details in Sect. 3.

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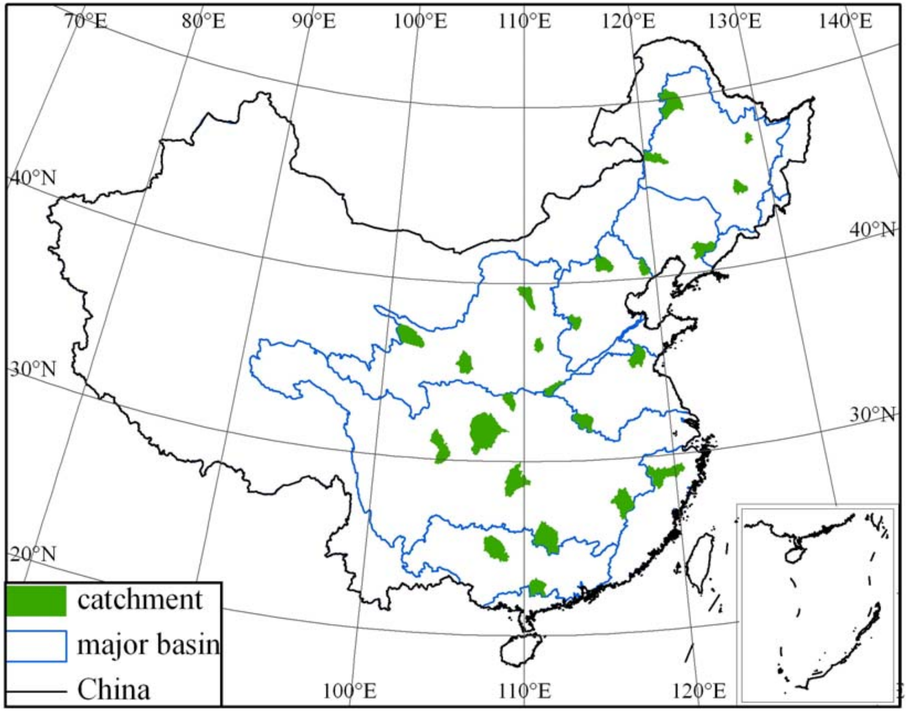

Fig. 3. Locations of the 24 sub-catchments in China.

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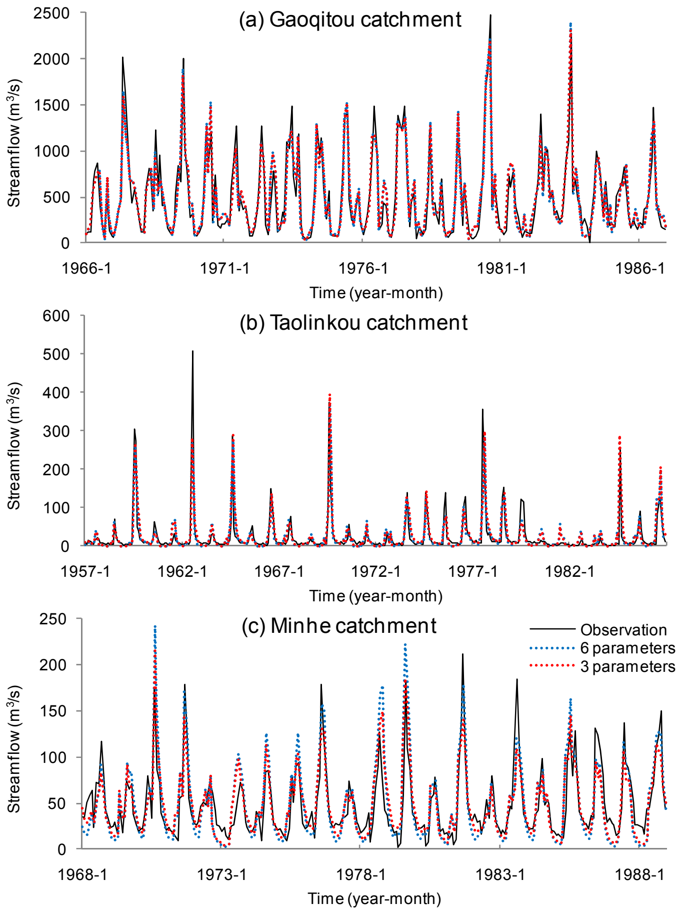

Fig. 4. Observed and simulated monthly streamflow by two kinds of parameters setting methodologies in three catchments. **(a)** Gaoqitou catchment (humid); **(b)** Taolinkou catchment (semi-humid); **(c)** Minhe catchment (arid).

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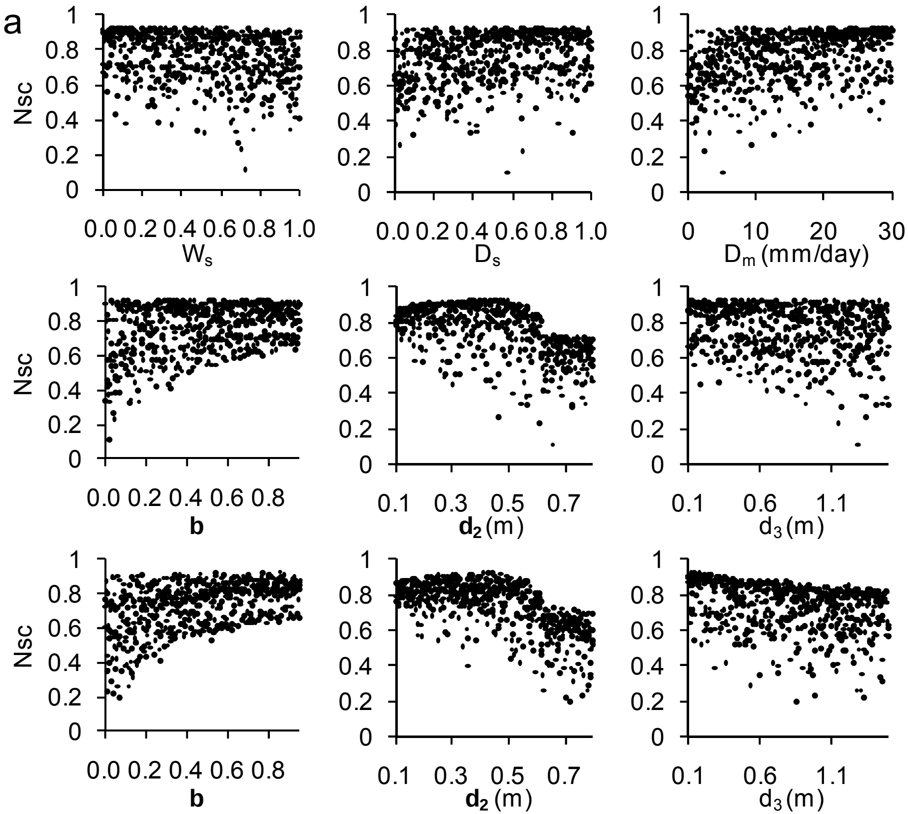

Fig. 5. Scatterplots between model parameters and Nash-Sutcliffe coefficient (Nsc) in three catchments. **(a)** Gaoqitou catchment (humid), **(b)** Taolinkou catchment (semi-humid); **(c)** Minhe catchment (arid). The first 6 figures are under 6 parameters setting methodology, and the last 3 figures are under 3 parameters setting methodology.

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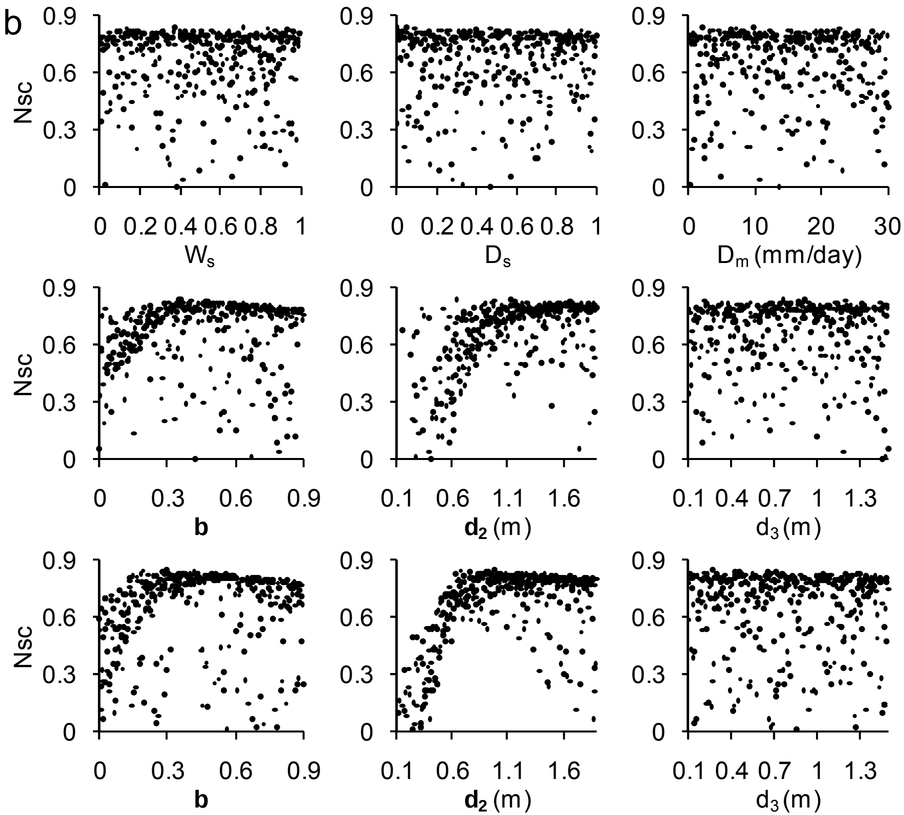

Fig. 5. Continued.

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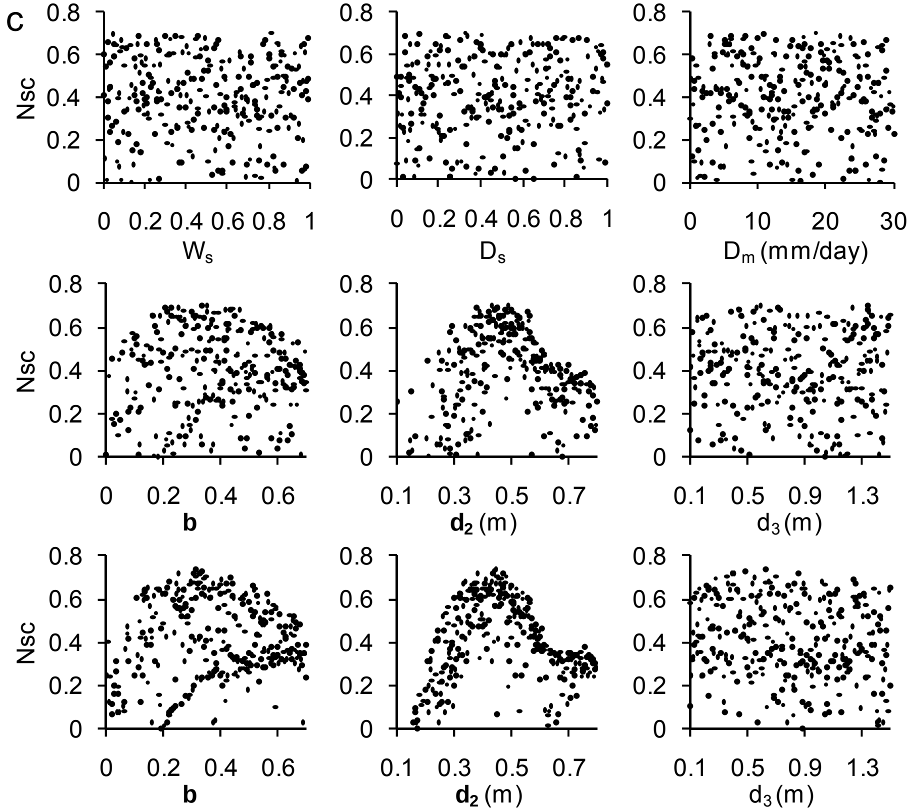

Fig. 5. Continued.

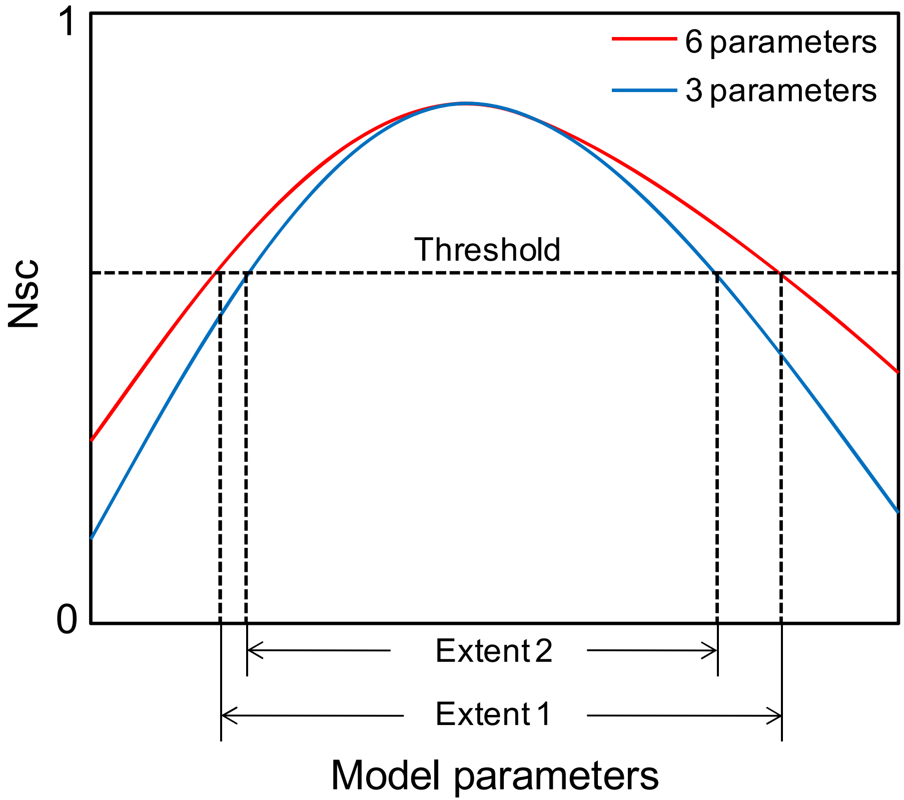

Fig. 6. The extent of model parameters space when Nsc is higher than a threshold.

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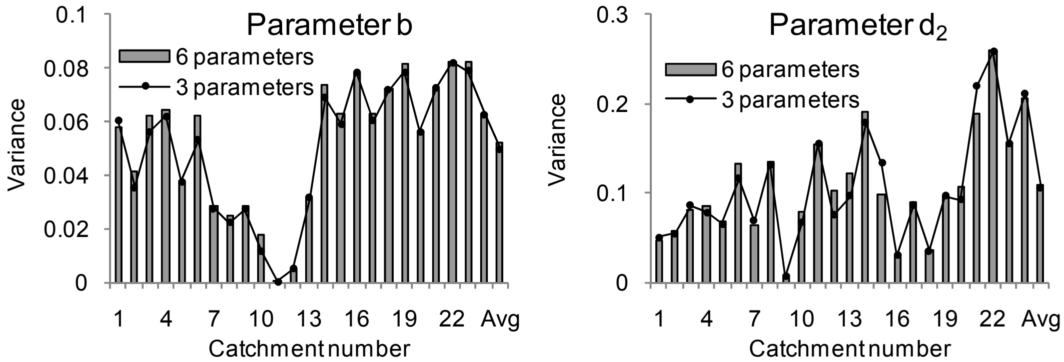

Fig. 7. Comparison of the variance of parameter b and d_2 under two kinds of parameters setting methodologies, when Mnc is higher than the threshold.

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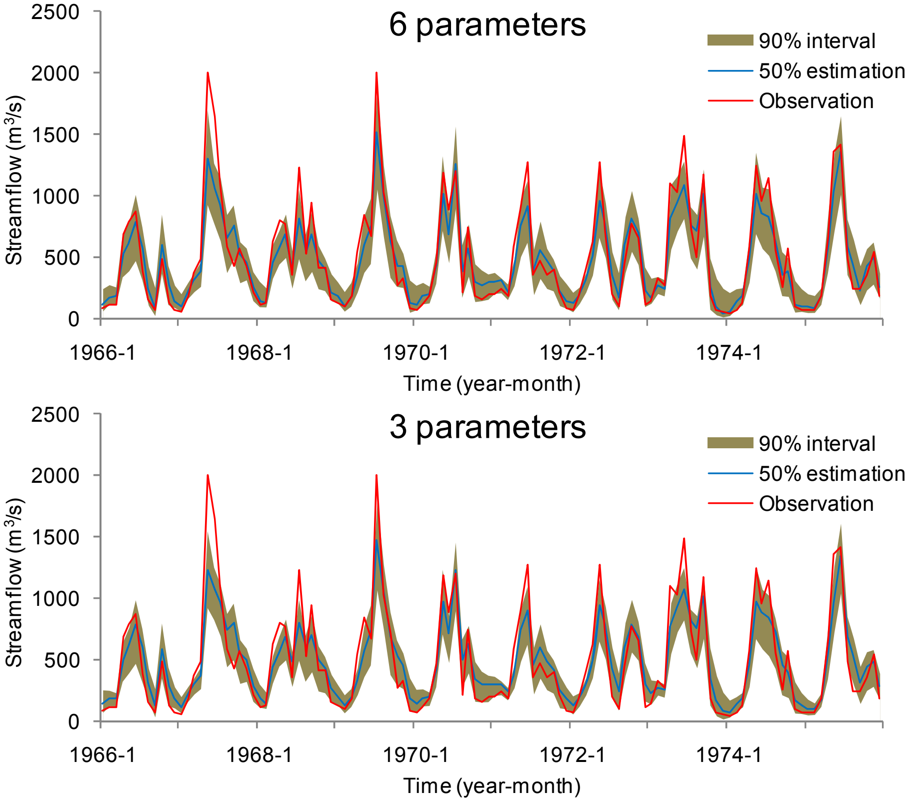

Fig. 8. The 90 % confidence interval and 50 % estimation for simulated streamflow in Gaoqitou catchment by two kinds of parameters setting methodologies.

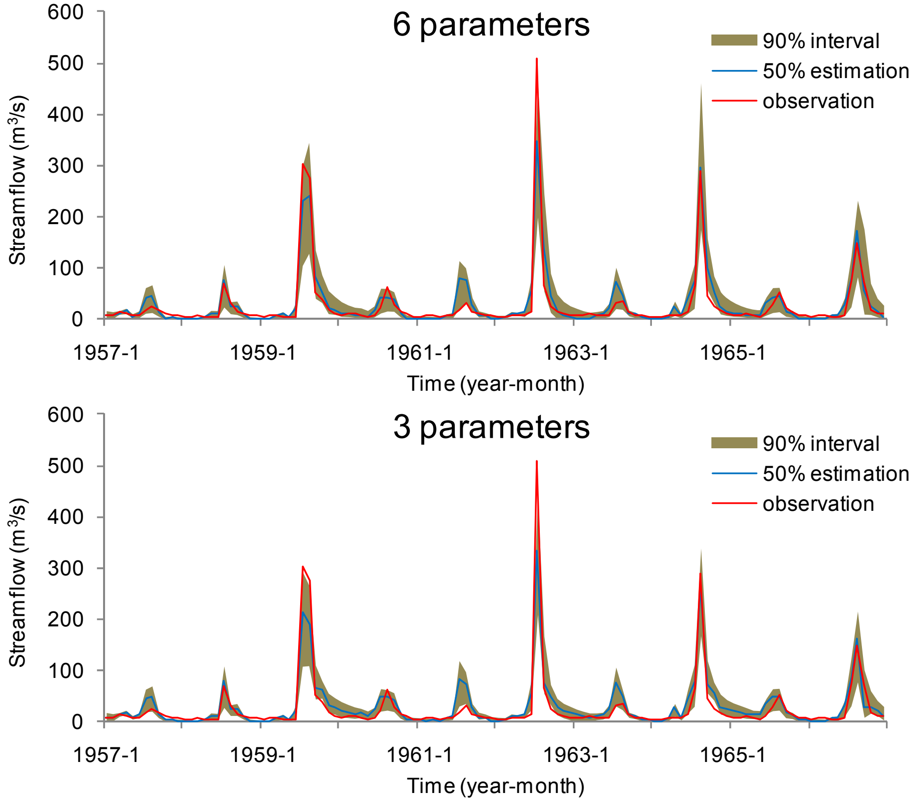

Fig. 9. The 90 % confidence interval and 50 % estimation for simulated streamflow in Taolinkou catchment by two kinds of parameters setting methodologies.

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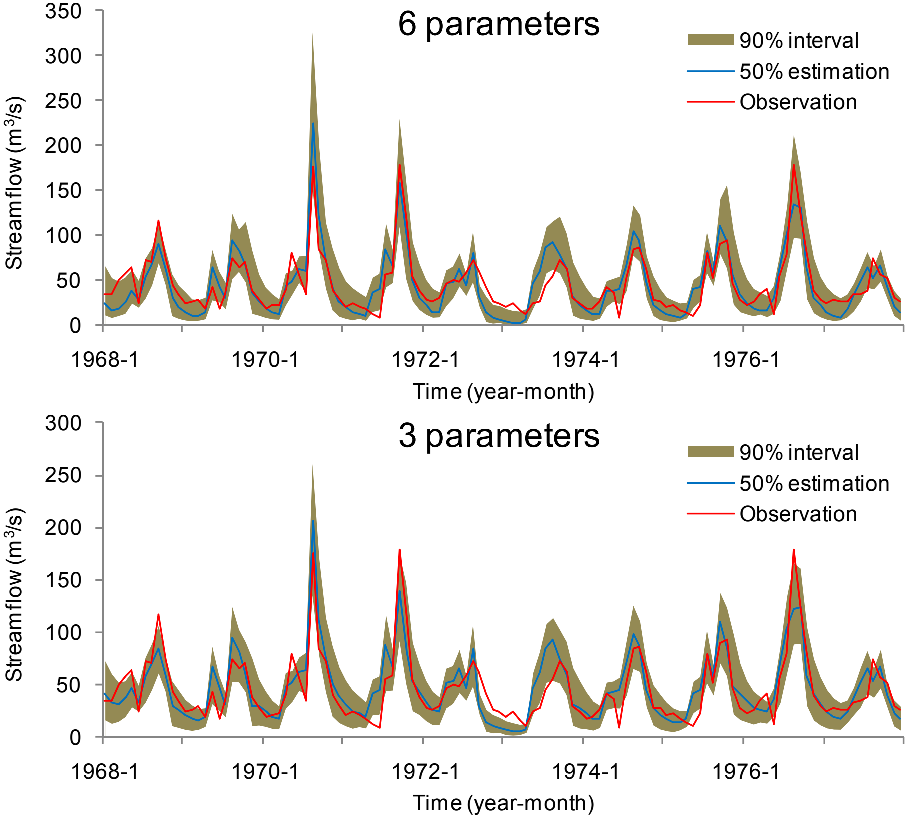

Fig. 10. The 90 % confidence interval and 50 % estimation for simulated streamflow in Minhe catchment by two kinds of parameters setting methodologies.

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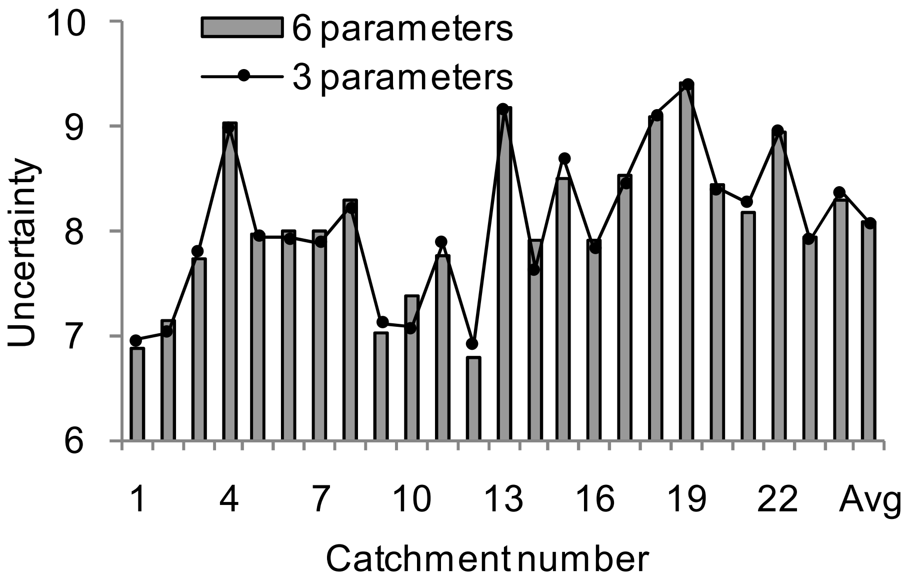

Fig. 11. Uncertainty of streamflow simulation by two kinds of parameters setting methodologies.

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