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ORIGINAL PAPER

Uncertainty in high and low flows due to model structure and parameter errors

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Abstract This paper aims to investigate the uncertainty in simulated extreme low and high flows originating from hydrological model structure and parameters. To this end, three different rainfall-runoff models, namely GR4J, HBV and Xinanjiang, are applied to two subbasins of Qiantang River basin, eastern China. The Generalised Likelihood Uncertainty Estimation approach is used for estimating the uncertainty of the three models due to parameter values, henceforth referred as parameter uncertainty. Uncertainty in simulated extreme flows is evaluated by means of the annual maximum discharge and mean annual 7-day minimum discharge. The results show that although the models have good performance for the daily flows, the uncertainty in the extreme flows could not be neglected. The uncertainty originating from parameters is larger than uncertainty due to model structure. The parameter uncertainty of the extreme flows increases with the observed discharge. The parameter uncertainty in both the extreme high flows and the extreme low flows is the largest for the HBV model and the smallest for the Xinanjiang model. It is noted that the extreme low flows are mostly underestimated by all models with optimum parameter sets for both subbasins. The largest underestimation is from Xinanjiang model. Therefore it is not reliable enough to use only one set of the parameters to make the prediction and carrying out the uncertainty study in the extreme discharge simulation could give an overall picture for the planners.

Keywords Uncertainty analysis · GLUE · GR4J · HBV · Xinanjiang · Extreme flows

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1 Introduction

Due to the impact of global climate change, the frequency and intensity of extreme natural hazards such as flooding and drought have increased in the past decades causing significant damages to the economy (IPCC 2002). It is expected that the frequency and intensity of extreme events will continue to increase in the future due to climate change in many areas in the world (IPCC 2007). One of the most commonly used tools to assess the impact of climate change on extreme events is a hydrological model.

Hydrological models have been widely used in the past decades for water resources management analysis, water balance evaluation at basin scale, flood prediction and design. The hydrological models can be used to analyze the impact of climate change and human activities on water quantity and quality.

In rainfall-runoff modelling, most hydrologists used to search for an optimum stream flow simulation through calibrating model parameters using observed catchment responses. However, the reality is that it is not possible to assume an optimum model structure or an optimum set of parameters due to the fact that there are many acceptable representations of reality, which cannot be easily rejected and that should be considered in assessing the uncertainty associated with the prediction (Beven 2006). Because of the limited understanding of nature and simplifications in representing the hydrological processes, all model structures must be in error to some extent. Then, there is no reason to expect that any set of parameter values will represent a true parameter set to be found by some calibration procedures (Beven 1988).

Therefore the importance of carrying out uncertainty analyses has been stressed by several authors (Refsgaard et al. 2007; Xu et al. 2007; Warmink et al. 2010). Refsgaard et al. (2007) pointed out that uncertainty assessment is not something to be added after the completion of the modelling work but should be seen as a red thread throughout the modelling study starting from the very beginning. First of all, we need to define the sources of uncertainty. There are many different classifications of the sources of uncertainty. For instance, Walker et al. (2003) indentified different locations of uncertainty that should be taken into account in uncertainty analysis, namely those originating from model context, input, model structure and parameters. Other authors distinguished the uncertainty in the context of a problem, the data, model structure and parameterization, expert judgment and indicators (Van der Sluijs et al. 2003). It is commonly accepted that input data, model parameter values and model structure are three major sources of uncertainty in conceptual hydrological models (Refsgaard et al. 2006).

A number of researchers have developed methods to assess uncertainties stemming from parameters and model structure. Beven and Binley (1992) proposed the Generalized Likelihood Uncertainty Estimation (GLUE) method for uncertainty estimation of hydrological models. Afterwards, the GLUE method has been widely applied and studied not only for rainfall-runoff modelling, but also for flood frequency estimation (Cameron 2007; Montanari 2005), groundwater and capture zone modelling (Christensen 2004; Feyen et al. 2001), soil erosion modelling (Brazier et al. 2001; Vigiak et al. 2006) and water quality modelling (Mannina and Viviani 2010; Mannina 2011). The GLUE method is easy to implement and it has a flexible definition of likelihood function which allows for no strong assumptions on the error model (Jin et al. 2010). Some researchers pointed out that the parameter distribution and uncertainty limits are entirely subjective (Blasone et al. 2008), and the GLUE method is inconsistent with the Bayesian inference process (Mantovan and Todini 2006). But in real cases, due to the multiple sources of uncertainties, it appears to be inapplicable of the definition of coherence to the extent that the choice of a formal likelihood function based on a simple error structure may be an incoherent choice. The empirical results indicated that flexibility of the GLUE method has advantage in providing more coherent and robust choices of model evaluation (Beven et al. 2008). Another important and popular approach in uncertainty estimation for the hydrological modelling is Markov Chain Monte Carlo (MCMC), which is based on Monte-Carlo method and creates a sample from the posterior distribution by constructing a Markov Chain (Bates and Campbell 2001; Kuczera and Parent 1998; Smith and Marshall 2008). MCMC has a solid conceptual basis and a robust performance, but it requires a large number of simulations to get a good approximation. (Yang et al. 2008). Recently, Bayesian Model Average (BMA) which takes weighted averages over different competitive models has been proposed to assess the uncertainty in model prediction. BMA has been applied to different fields like weather forecasting, medicine, and management. It has shown good performance in uncertainty analysis and produced more accurate and reliable predictions than other techniques (Madigan et al. 1996; Raftery et al. 2005).

Previous studies have investigated the uncertainties of discharges in input data, hydrological models and parameters. Many of the studies measured the uncertainties from different sources separately, and some has taken several sources into account and the integrated uncertainties from multiple sources are considered (Wilby and Harris 2006; Renard et al. 2010; Bastola et al. 2011). Uncertainties are estimated for mean flows rather than extreme flows in most cases. However, there is relatively less study looking into the uncertainties of extreme flows. It is worth noting that for the extreme flows it is of fundamental interest to investigate how the uncertainty would be due to model structure or parameters. The evaluation of extreme flows has been done by several researchers in different ways (Cameron 2007; Shrestha et al. 2009; Xu et al. 2010). But to the knowledge of the authors, there is a gap in the study of the impact of hydrological models structures and parameters on extreme flows. Practically, the extreme flows varied with locations strongly for the parameters of hydrological models are affected by local spatial heterogeneities and non-stationarities. In the past 130 years, a significant upward trend of streamflow was detected in the middle reach of Yangtze River, and the occurrence frequency of annual maximum water level increased at the lower reach of Yangtze River to which our study area is close (Zhang et al. 2006). Since the extreme flows has a key important influence on human life and society, and they are surely subject to the uncertainties in modelling process, therefore it is meaningful to carry out this study to give a support for robust decision making and the development of adaption strategies.

In this study extreme high and low flows in the upper Qiantang River basin are investigated, as they are closely related to the safety and possession of the local inhabitants. The Qiantang River basin, as the most important river basin of Zhejiang Province in East China, has a large population but suffers from extreme weather. Extreme discharges are evaluated by means of the annual maximum discharge (MHQ) and the mean annual 7-day minimum discharge (MAM7) for two subbasins in the upper parts of the Qiantang River basin.

We mainly investigate the uncertainties originating from hydrological models and parameter values and their impacts on extreme high and low flows. The GLUE method is employed to study the parameter uncertainty. The aim of GLUE is not to obtain a single optimal parameter set for a given model structure, but many parameter sets that are 'behavioural'. All the behavioural parameter sets are used for performing simulations. Different hydrological models are applied to represent the model structure uncertainty. The objectives of the present study are therefore to: (1) estimate the uncertainty from the parameters in hydrological models by using the GLUE method; (2) estimate the uncertainty due to the model structure by using three hydrological models with different complexity; (3) assess the impact of uncertainties from parameters and model structures on extreme high and low flows of the eastern China river basins.

The paper is organized as follows. Section 2 outlines an introduction to the study area and data used, a brief description of the three hydrological models, the GLUE method and the indices chosen to express extreme flows and. Section 3 presents the results of the analysis to determine the uncertainty in extreme flows due to parameter values and model structures and their impacts on extreme flows. We make comparisons between the results from two different basins and three different models. Finally, conclusions are drawn in Sect. 4.

2 Methods and data

2.1 Study area and data

The Qu River basin and Jinhua River basin are two subbasins of the Qiantang River, which is located in Zhejiang Province in East China (Fig. 1). The Qiantang River basin is the largest and one of the most important river basins in Zhejiang Province. The two subbasins in this study are the southern tributaries of the Qiantang River basin. Qu River basin and Jinhua River basin have a catchment area of 5,290 and 5,996 km^2 respectively. Qu River basin is dominated by mountains and hills, while Jinhua River basin has mainly plain area. Due to the uneven temporal distribution of precipitation, Qu River and Jinhua River are the two tributaries of Qiantang River that are most severely affected by floods and droughts. The climate in both basins is semi-humid with an average annual total precipitation of 1,500 and 1,800 mm for Qu River basin and Jinhua River basin respectively. They are characterized by hot rainy summers and cold dry winters. More than 50 % of the annual total precipitation occurs in the period from May to July. The average temperature is about 15–18 °C, and maximum temperature is around 40 °C.

There are eight meteorological stations and two discharge stations in the study area. The location of the two basins and the distribution of the meteorological and discharge stations are shown in Fig. 1. In this study, daily precipitation, potential evapotranspiration (PET) and discharge data are used. The PET is estimated using the Penman–Monteith equation (Monteith 1965). The observed data are available from 1981 to 1995 for both two basins. We use the first 10 years (1981–1990) for the model calibration, and the remaining 5 years (1991–1995) for the model validation (Table 1).

2.2 Hydrological models

In order to address model structure uncertainty, three models with different complexities are studied and compared: the GR4J model with four parameters (Perrin et al. 2003); the HBV model with eight parameters (Lindström

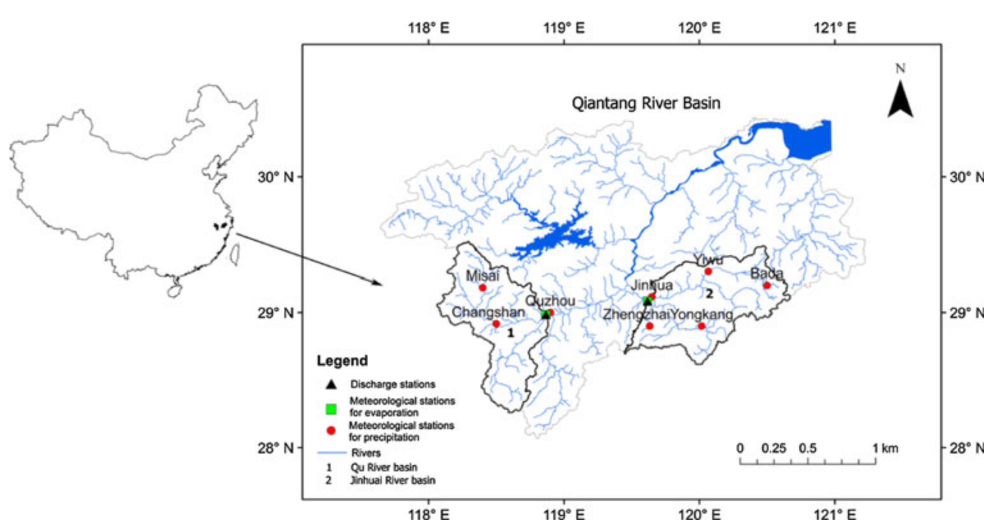

Fig. 1 Locations of Jinhua River basin and Quzhou River basin. The meteorological and discharge stations located in the study areas are also shown

Table 1 The information of the observed stations

	Latitude (N°)	Longitude (N°)
Discharge and meteorological stations		
Quzhou	28.98	118.87
Jinhua	29.08	119.62
Precipitation stations		
Bada	29.20	120.50
Yiwu	29.30	120.07
Yongkang	28.90	120.02
Zhengzhai	28.90	119.63
Misai	29.18	118.40
Changshan	28.92	118.50

et al. 1997) and the Xinanjiang model with 13 parameters (Zhao 1992).

Figure 2 shows the simplified model structures. For each model, we assess the uncertainty from the model parameters using the GLUE method. The reason we choose these three models is that they have different complexities, so we can make a comparison between the impact of uncertainties from different model structures. Besides, these three models are very commonly used by many researchers. A number of references to applications of the GR4J, HBV and the Xinanjiang model can be found. The GR4J model is simple but effective. It has a minimum level of complexity to be included in a model. The Xinanjiang model has been developed in China and is suitable for semi-humid or humid regions, which is also the type of study area in this paper. The HBV model has been widely used to simulate hydrological processes, e.g. in the German Rhine basin (Menzel et al. 2006),, Colombia (Marin and Ramirez 2006), southwestern Norway (Engeland and Hisdal 2009) and the Hindukush-Karakorum-Himalaya region (Akhtar et al. 2009).

2.3 GR4J model

The GR4J conceptual model is a lumped rainfall-runoff model based on the GR3J model proposed by Edijatno et al. (1999). It has been applied worldwide (Aubert et al. 2003; Le Moine et al. 2008; Oudin et al. 2008; Wu et al. 2010). The GR4J model is operated at a daily time step with daily time series of precipitation and PET as input, and the output is the daily runoff. There are four parameters in GR4J: the maximum capacity of the production store, the groundwater exchange coefficient, the one day ahead capacity of the routing store and the time base of the unit hydrograph. The description and explanation of the four free parameters are shown in Table 2. All four parameters are used to estimate the parameter uncertainty.

The stream flows are obtained from daily precipitation and evapotranspiration in three steps: firstly the effective rainfall is calculated by deduction of the evaporation and interception. Secondly, part of the effective rainfall goes into the production store and the left effective rainfall is divided into two components. 90 % of the flow with a unit hydrograph and a nonlinear routing store infiltrates into the ground and forms the slow flow, and 10 % of the flow with a unit hydrograph forms the fast flow. Finally, after water exchange, the final discharge is calculated by adding the two components together.

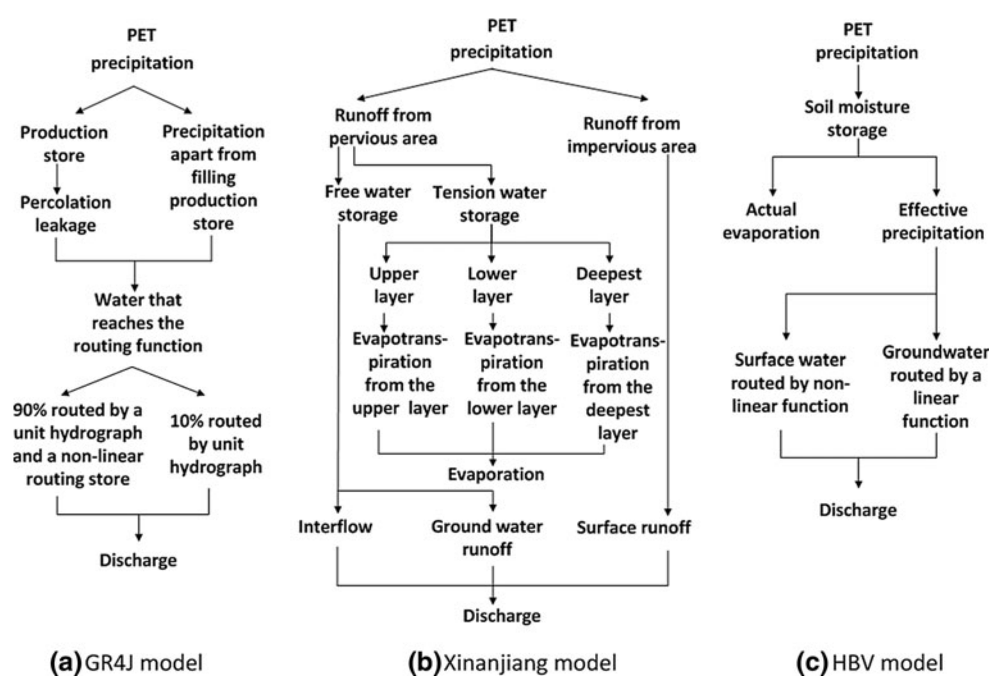

Fig. 2 Model structures of **a** GR4J, **b** Xinanjiang and **c** HBV

Table 2 Parameters of GR4J, HBV and Xinanjiang model and their ranges in calibration and uncertainty analysis

Parameter	Explanation	Minimum	Maximum	Unit
GR4J model				
X1	Capacity of the production store	10	2000	mm
X2	Groundwater exchange coefficient	−8	6	mm
X3	One day ahead capacity of the routing store	10	500	mm
X4	Time base of the unit hydrograph	0	4	d
HBV model				
FC	Maximum soil moisture capacity	100	500	mm
LP	Soil moisture threshold for reduction of evapotranspiration	0.3	1	–
BETA	Shape coefficient	1	5	–
CFLUX	Maximum capillary flow from upper response box to soil moisture zone	1	2	mm/d
ALFA	Measure for non-linearity of low flow in quick runoff reservoir	0	1	–
KF	Recession coefficient for quick flow reservoir	0.01	0.5	d^{-1}
KS	Recession coefficient for base flow reservoir	0.001	0.1	d^{-1}
PERC	Maximum flow from upper to lower response box	0	6	mm/d
Xinanjiang model				–
SM	Areal mean free water capacity of the surface soil layer	5	35	mm
KG	Outflow coefficient	0.01	0.8	–
CS	Recession constant of the surface storage	0.2	0.7	–
CI	Recession constant of the interflow storage	0.1	0.9	–
CG	Recession constant of the groundwater storage	0.8	0.99	–

2.4 Xinanjiang model

The Xinanjiang model is a semi-distributed conceptual rainfall-runoff model developed by Zhao (1992) for use in humid and semi-humid regions. The input data of the Xinanjiang model are time series of daily precipitation and PET, and the output is the daily runoff. The free parameters in this study are listed in Table 2. The key hypothesis of the model is that it presumes that runoff is not produced until the soil moisture content of the aeration zone reaches field capacity.

The model structure consists of four parts: evaporation, runoff production, separation of runoff components and flow routing. The evaporation is also divided into three layers: an upper, lower and deep layer. The evapotranspiration occurs in the lower layers only when the water storage in the upper layer is exhausted. The runoff production is based on the repletion of storage. The runoff is separated into three components: surface, subsurface and groundwater runoff. The flow routing transfers the local runoff to the outlet of each subbasin.

2.5 HBV model

The HBV model is a semi-distributed conceptual rainfall-runoff model for continuous simulation. The HBV model has been originally developed by the Swedish Meteorological and Hydrological Institute (SMHI) in the early 1970s (Bergström 1976). Since then, the model has been widely applied in numerous studies, e.g. to compute design floods (Lindström and Harlin 1992), to forecast flash floods (Kobold and Brilly 2006), to estimate parameter uncertainty (Harlin and Kung 1992) and to carry out climate change impact studies (Akhtar et al. 2008; Andersson et al. 2011). The input data of the HBV model are time series of daily precipitation and PET, and the output is the daily runoff. The eight free parameters are listed in Table 2.

The HBV model consists of five subroutines: a precipitation and snow accumulation and melt routine, a soil moisture accounting routine, two runoff generation routines and a routing procedure. (Harlin and Kung 1992; Lindström et al. 1997; Seibert 1997; Booij 2005). Since there is no snow pack in the study area, the snow routine is not used in this study. In the soil routing, there are three parameters which controls the formation of the effective precipitation and soil moisture storage. Then, the excess water from the soil moisture storage is transformed to runoff with the response functions in the runoff generation routing. One flow routing represents the slow flow and another one represent the fast flow. Finally, two flows get together as the final discharge.

2.6 GLUE method

The GLUE method is a Bayesian analysis based Monte Carlo method for model calibration and uncertainty analysis. The core concept of the GLUE method is the equifinality thesis, which emphasizes that there are many acceptable parameter sets that cannot be easily rejected and should be taken into account in assessing the uncertainty (Beven 2006). Four steps can be distinguished in the GLUE method:

(1) Generation of a large number of parameter sets by Latin hypercube sampling based on prior parameter distributions (Tang 1993). In this study, the uniform distribution with upper and lower limits is used to represent the prior distribution. The uniform distribution is recommended by Beven and Binley (1992), and it is also the choice of many other researchers who applied the GLUE method. The upper and lower limits of each parameter are based on the range of calibrated values from other model applications (Zhao 1992; Seibert 1997; Perrin et al. 2003).

(2) Definition of the likelihood function, setting the threshold value for behavioral parameter sets, and calculating the likelihood value. The choices of the likelihood function and threshold value are subjective matters. The well known Nash–Sutcliffe efficiency (NS) coefficient is chosen as the likelihood function (Nash and Sutcliffe 1970).

$$L(\theta_i|Y) = 1 - \frac{\sum_{t=1}^{T}(Q_{obs,t} - Q_{sim,t})^2}{\sum_{t=1}^{T}(Q_{obs,t} - \bar{Q}_{obs})^2} \tag{1}$$

where $L(\theta_i|Y)$ is the likelyhood value; $Q_{obs,t}$ is the observed discharge at time t; $Q_{sim,t}$ is the simulated discharge at time t; $\bar{Q}_{obs}$ is the mean observed discharge.

We also use the relative volume error (RVE) to show the goodness-of-fit of the total water balance. Jin et al. (2010) used the NS efficiency coefficient and compared the model uncertainty with threshold of 0.8 and 0.6. They found that the lower the threshold value, obviously the wider the confidence interval (CI) of the output uncertainty. Neither a too high nor a too low threshold is appropriate for the threshold value. In order to both preserve the equifinality and have a reasonable computation time, we choose a medium value of 0.7, which means parameter sets resulting in NS values <0.7 are rejected. In total 300,000 parameter sets are generated for each model.

(3) Calculation of the posterior likelihood distribution for behavioral parameter sets.

$$L_p[\theta|Y] = C \times L[\theta|Y] \times L_o[\theta] \tag{2}$$

where $L_p[\theta|Y]$ is the posterior likelihood weight; $L[\theta|Y]$ is the likelihood weight that has been calculated in step (2); $L_o[\theta]$ is the prior likelihood. The behavioral parameter sets are retained and the likelihood values of these behavioral parameter sets are considered as their likelihood weights. All these weights are rescaled, and C is the scaling factor so their sum is equal to 1.

(4) Estimation of the quantiles for the predictions at every time step based on the cumulative likelihood weighted distributions.

$$P_t(Z_t < z) = \sum_{i=1}^{m} L_p[\theta_i|Z_{t,i} < z] \tag{3}$$

where $P_t(Z_t < z)$ is the cumulative probability of the variable Z less than the threshold z; $L_p[\theta_i|Z_{t,i} < z]$ is the posterior likelihood weight of the parameter sets θ_i. In this study, lower 5 % and upper 95 % quantiles are calculated.

2.7 Extreme value statistics

Extreme value statistics are commonly used to describe extreme discharges, including intensity, duration and severity. A number of different indices have been developed for different uses in recent decades. Smakhtin (2001) has given a review on low flow hydrology and described a variety of low flow indices and their applications. Mishra and Singh (2010) also provided a review on the definition and classification of drought and drought indices along with their limitations. In this study, we choose the mean annual 7-day minimum discharge (MAM7) and annual maximum daily discharge (MHQ) to describe extreme low and extreme high flows respectively. MAM7, also known as dry weather flow (Hindley 1973), is the lowest mean flow of seven consecutive days in a year. MAM7 eliminates the day-to-day variation in the artificial component of river flow and is less sensitive to measurement errors (Smakhtin 2001). The MHQ is the flow index used to analyze the annual extreme high flows. It is widely used in flood studies and design of river construction.

We use the GLUE method to estimate the effect of parameter uncertainties on these extreme indices. According to the local policies for design of flood control measures, the design flood for the biggest cities like Quzhou and Jinhua in these two basins is the one referred to a return period of 50 years. MAM7 and MHQ are fitted to the GEV type III and Gumbel distributions respectively to estimate the indices with a return period of 50 years for each basin. The probability distribution function of GEV type III distribution is like:

$$(x) = 1 - exp\left\{-[1 - \frac{k(x-\mu)}{\alpha}]^{1/k}\right\} \tag{4}$$

where μ is the location parameter; k is the shape parameter and α is the scale parameter. When $k > 0$, the GEV distribution is the type III. The probability distribution function of Gumbel distribution is like:

$$F(x) = 1 - exp\left[-exp\left(\frac{x-\alpha}{\beta}\right)\right] \quad (5)$$

where α is location parameter and β is scale parameter.

MAM7 and MHQ are derived from both model simulation and observation. Filliben's probability (Filliben 1975) plot correlation test is applied to assess whether the indices can be described by the GEV and Gumbel distributions or not. The formula is as follows:

$$R = \frac{\sum_{t=1}^{m}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt[2]{\sum_{t=1}^{m}(x_i - \bar{x})^2 \sum_{t=1}^{m}(y_i - \bar{y})^2}} \quad (6)$$

where x_i and y_i is the the ith observed and statistic discharge from the distribution; $\bar{x}$ and $\bar{y}$ is the mean observed and statistic discharge from the distribution.

3 Results and discussion

3.1 Optimum simulation results

The three hydrological models GR4J, HBV and Xinanjiang are applied to both subbasins. The parameters calibration was carried out for the period 1981–1990 and the identified parameter sets were used for validation. The simulation was run for each day of the period. 30,000 parameter sets are randomly generated in the GLUE method for each model. For each parameter sets, the NS are calculated. The optimum simulation results for each model are obtained through the parameter sets with the maximum NS value. The optimum NS and the corresponding RVE of the three models for the calibration period and validation period are shown in Table 3. The calibration period is 1981–1990 and the validation period is 1991–1995.

Results show that the optimum NS values of the three models in the calibration and validation for both subbasins are above 0.80. The NS values vary among different models. The GR4J and HBV model have a higher NS values (more than 0.9) than the Xinanjiang model for both calibration and validation. For the GR4J and HBV model, the optimum NS values are slightly higher for the validation than those in the calibration. In terms of the NS values, the GR4J and HBV model performs better in Qu River basin than in Jinhua River basin, while the Xinanjiang model performs better in Jinhua River basin than Qu River basin. The value of RVE for all models and subbasins is <10 % in most cases except for HBV model in Qu River basin for both calibration and validation and Xinanjiang model for Jinhua River basin for calibration.

It's found that although the NS value is high (all are above 0.9 with the highest 0.94 for Qu River basin in the validation), the corresponding RVE can still be large (more than −10 %) for the HBV model. For Xinanjiang model, the total volume of simulated discharge is seriously underestimated for Jinhua River basin in calibration with RVE of −14.8 %. It's mainly due to the deficiency that the optimum parameter set tend to underestimate both extreme high and low flows, and the objective function is the NS but not RVE. It illustrates that different objective functions may lead to different optimum parameter sets. If we only focus on the optimum simulation results from a single perspective, we may fall into the situation of taking one into consideration but neglecting the others. The objectives are also a kind of uncertainty source, and many studies have been carried out on evaluating the impact of objective functions on the results, e.g. Cheng (2005) and Booij and Krol (2010). Here we mainly focus on the uncertainty from parameters and model structure, so we did not use multiple objective functions.

Table 3 Optimum NS and the corresponding RVE of GR4J, HBV and Xinanjiang for Qu River basin and Jinhua River basin in the calibration and validation

	GR4J		HBV		Xinanjiang	
	NS	RVE (%)	NS	RVE(%)	NS	RVE (%)
Calibration						
Jinhua River	0.91	2.7	0.91	−2.5	0.88	−14.8
Qu River	0.93	-1.1	0.92	−12.4	0.86	−2.6
Validation						
Jinhua River	0.93	2.3	0.91	−2.1	0.89	7.8
Qu River	0.94	2.0	0.94	−11.1	0.83	−4.3

As an example, Fig. 3 illustrates the daily observed discharge, the optimum simulated discharge (with the highest NS) and the 90 % CI for the Jinhua River for one year (1994) for the GR4J, HBV and Xinanjiang simulated situation. The CI is obtained based on the cumulative likelihood weighted distribution of the behavior parameters and the formulas were given in Sect. 2.3. The results are also similar in other years. Since the year 1994 is representative with both extreme high flows and low flows, it is shown here. In general, the observed daily discharge is captured by the 90 % CI for all three models most of the time. The CI is narrow for low flows and wide for high flows. In order to reveal the relationship between the CI and observed discharges, we calculated the relative CI, which is the average difference between upper and lower limit divided by observed discharge. The results are shown in Table 4. The relative CI for Jinhua River basin is larger than that for Qu River basin for the HBV and Xinanjiang model, and the GR4J model has a similar relative CI for both basins. That is, the parameter uncertainty of HBV and Xinanjiang model is larger for Jinhua River basin than for Qu River basin for the daily discharges. For both river

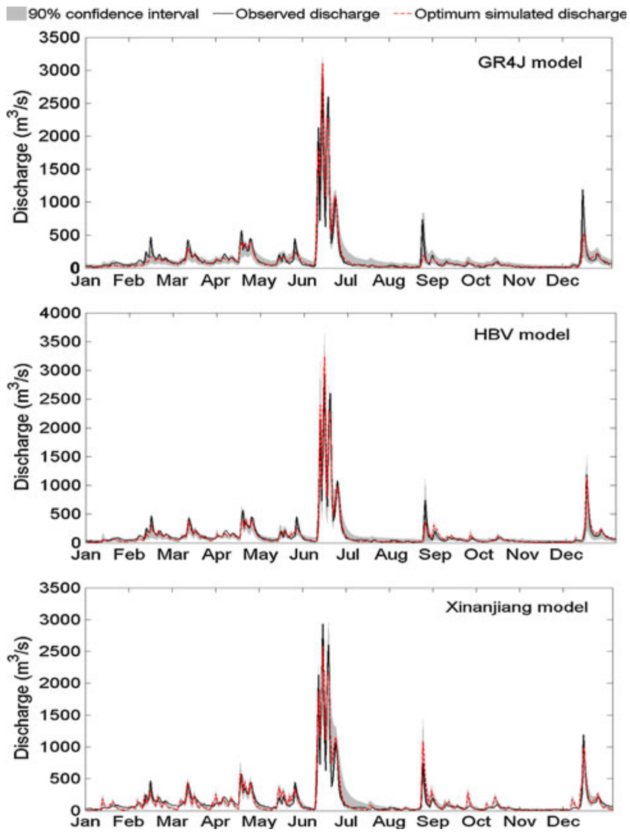

Fig. 3 Comparison of observed daily discharge (*continuous black line*), optimum simulated daily discharge (*red dotted line*), and 90 % CI (*grey shade*) estimated with the GR4J, HBV and Xinanjiang models for the Jinhua River basin for 1994. (Color figure online)

basins, the relative CI simulated with the Xinanjiang model is the smallest (80 and 56 % for two basins respectively) and the GR4J model the largest (112 and 114 %), with the HBV model in between (85 and 68 %). The results suggest that the parameter uncertainty for the mean discharge is the largest from the GR4J model and the smallest from the Xinanjiang model. The results also indicate that the parameter uncertainty cannot be neglected because it is large compared to the observed runoff. The smallest relative CI for the daily discharge due to parameter uncertainty is more than 50 % of the observed discharge, while the largest relative CI is 114 % of the observe discharge.

3.2 Impact of parameter uncertainty on high and low flows

Figure 4 shows the frequency distribution of the observed MHQ (MHQ_O), the optimum simulated MHQ (MHQ_S) and the 90 % CI for the three models for both river basins. The straight line has been drawn by fitting the Gumbel distribution to the observed MHQ. The correlation values from the probability plot correlation test for the three models in both basins are larger than the critical value at a significance level of 0.05. It means the observations could have been drawn from the fitted distribution.

The CI and the MHQ_S estimated with each model for each subbasin are different. We firstly compare the MHQ_S and MHQ_O. Generally, the bias between MHQ_S and MHQ_O tend to become larger as the return period increases for the GR4J and Xinajiang model, while for the HBV model the MHQ_S is close to the MHQ_O for all the return periods. For the GR4J model, the MHQ_S is similar to the MHQ_O for Jinhua River basin, but for Qu River basin it is smaller than the MHQ_O when the return period is <2 years but it becomes larger than the MHQ_O when the return period is larger. For the HBV model, the bias of MHQ_S is small with slight variation around the MHQ_O. The Xinanjiang model always underestimates MHQ_O. The bias between MHQ_O and MHQ_S is the largest for the Xinanjiang model and the smallest for the HBV model. Furthermore, the bias of MHQ_S in the Qu River basin is larger than that in the Jinhua River basin independent of the models. Qu River basin has a larger volume of the MHQ_O than Jinhua River basin. It indicates that the bias is likely related to the volume of the discharge.

The uncertainty range of the MHQ_S is investigated as well. Generally the CI is wider with increasing discharge for the three models. However, the extent of variation of the upper and lower limits of the uncertainty ranges is different for each model. The wider CI means a larger uncertainty. The uncertainty becomes larger as the discharge increases, which is in accordance with the conclusion by other researchers that the uncertainty increases with the stream flow magnitude (Viola et al. 2009). It's mainly due to the reason that when the discharge becomes more

Table 4 Mean relative lower and upper limits of CI and relative CI for daily discharge for the GR4J, HBV and Xinanjiang models for 1981–1995

Basins		Jinhua River basin			Qu River basin		
	Items	GR4J (%)	HBV (%)	Xinanjiang (%)	GR4J (%)	HBV (%)	Xinanjiang (%)
Relative upper limit	$(L95\text{-}Q_O)/Q_O$	62	39	37	62	13	27
Relative lower limit	$(Q_O\text{-}L5)/Q_O$	50	46	43	52	55	29
Relative CI	$(L95\text{-}L5)/Q_O$	112	85	80	114	68	56

L5, L95 and Q_O represent the 5th quantile, 95th quantile of the simulated values and observed daily discharge respectively

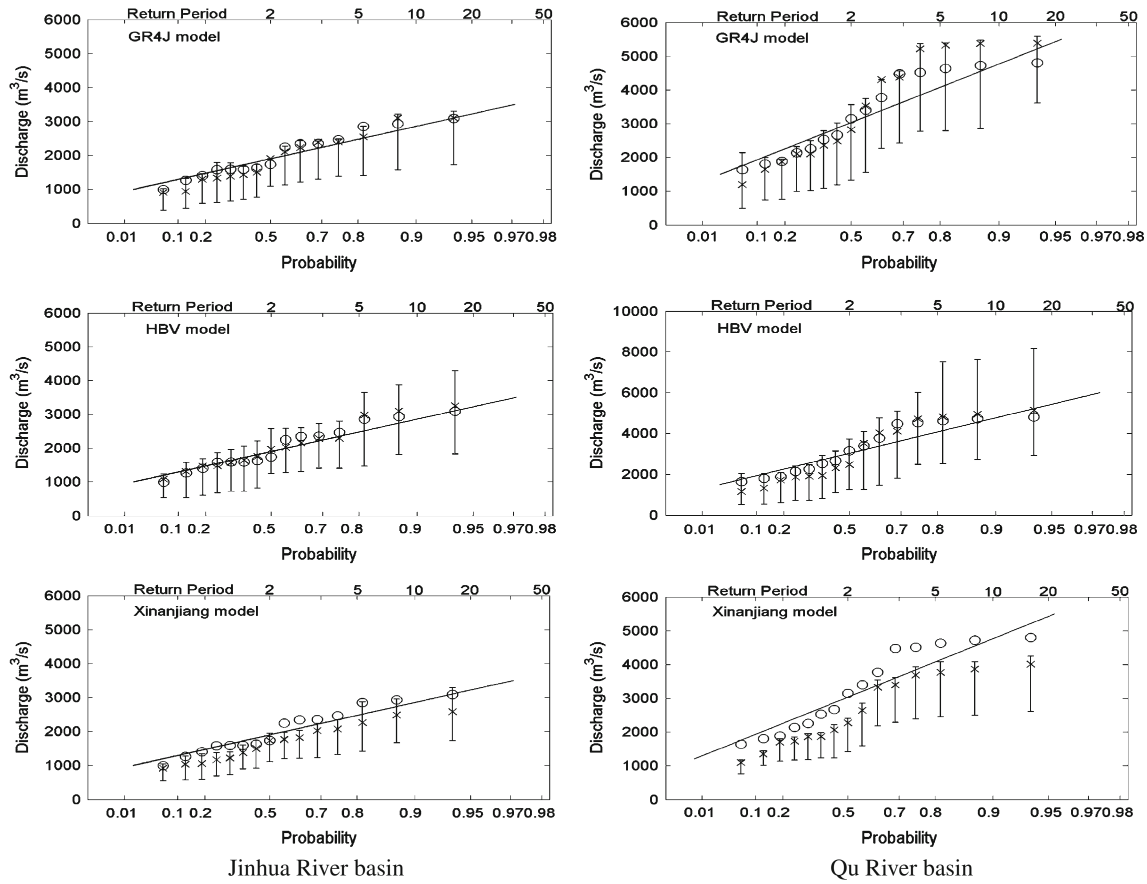

Fig. 4 Comparison of annual maximum discharge (MHQ) as a function of return period for Jinhua River and Qu River simulated with GR4J, HBV and Xinanjiang models for 1981–1995. *Circles* represent the observed MHQ, *crosses* represent the optimum simulated MHQ, *vertical bars* represent 90 % CI, and *straight lines* represent Gumbel distribution fitted to observed data

extreme, there is not as many observed data as the normal discharge. And the lack of the information may cause a larger uncertainty range. Table 5 shows the mean relative lower and upper limits of CI and relative CI for MHQ_S for the three models. It reveals the relationship between the parameter uncertainty and MHQ_O. For MHQ_S, the relative CI estimated from the HBV model is the largest and the Xinanjiang model is the smallest in both river basins. It is different for the daily discharge that the relative CI from GR4J is the largest. The number of parameters used in the GLUE method is four, five and eight for the GR4J, Xinanjiang and HBV model respectively. So there is no direct relationship between the number of calibration parameters and parameter uncertainty. Bastola et al. (2011) also have found that a model with fewer parameters could produce a larger parameter uncertainty interval than a model with more parameters. The number of the parameters is only one of the factors that contribute to the parameter uncertainties. In addition, the range of the parameters is another factor that may affect the relative CI. For the three models the relative lower limit is larger than relative upper limit, which means for three models the probability of underestimating the extreme high flows are larger than overestimating it. For the GR4J model, MHQ_O remains in the top of the CI for all return periods for the two basins. The relative lower limit is 49 and 44 % larger than relative higher limit in Jinhua and Qu River basin. For the HBV model, the position of MHQ_O is in the top of CI and then goes down to the middle as the discharge increases. When the discharge becomes larger, the probability for overestimating the observed high flows becomes larger. The relative lower limit is 21 % larger than the relative lower limit for Jinhua River basin, and the overtake of the relative upper limit to the relative lower limit increases to 42 % for Qu River basin. For the Xinanjiang model, the MHQ_O is almost out of the width of the CI for Jinhua River basin, and it is more apparent for Qu River basin for the MHQ_O is totally beyond the limits. It shows that the Xinanjiang model is likely to underestimate the extreme high flows. It is perhaps because of the Xinanjiang model's structure which was built for the regions with low surface runoff and high interflows with assumption that the surface runoff is produced only when the accumulated rainfall is larger than the capacity of the soil storage, but in

Table 5 Mean relative lower and upper limits of CI and relative CI for MHQ for the GR4J, HBV and Xinanjiang models for 1981–1995

	GR4J (%)	HBV (%)	Xinanjiang (%)
Jinhua River basin			
Relative upper limit	1	25	−2
Relative lower limit	50	46	48
Relative CI	51	71	46
Qu River basin			
Relative upper limit	3	12	−15
Relative lower limit	47	56	48
Relative CI	50	68	33

The formulas of the relative upper/lower limits are shown in Table 4

some cases like in the mountainous area and the cities the flood could happen when the intensity of rainfall is large without filling up the soil storage.

Figure 5 shows the frequency of observed MAM7 ($MAM7_O$), the optimum simulated MAM7 ($MAM7_S$) and the CI for the three models in the Jinhua River basin and Qu River basin. The curve is drawn by fitting the GEV type III distribution to the $MAM7_O$ and shows a good fit as illustrated by the result of the probability plot correlation test.

It is clearly shown in Fig. 5 that the $MAM7_O$ is underestimated by optimum simulated results for all three models in both river basins. For GR4J model, although the RVE is small for the daily discharge, there is obvious underestimation in the extreme low flows. The largest underestimation is found from the Xinanjiang model for Jinhua River basin. For the HBV model, the RVE is negative for both the calibration and validation, and the MHQ_O is also underestimated by the MHQ_S.

The width of the CI shows that the uncertainty of the extreme low flows goes down with the decreasing discharge for the three models. The lower limits of the CI are quite close to zero for the three models, and it is especially apparent for Xinanjiang model, as is shown in Table 6 where the relative lower limits are 100 % for Xinanjiang model. However, the relative upper limits of the CI are different for each model. The impact of parameter uncertainty on low flows from GR4J is the largest, followed by HBV model and the Xinanjiang is the smallest. However, it is noticed that the cost of the smallest uncertainty is that the

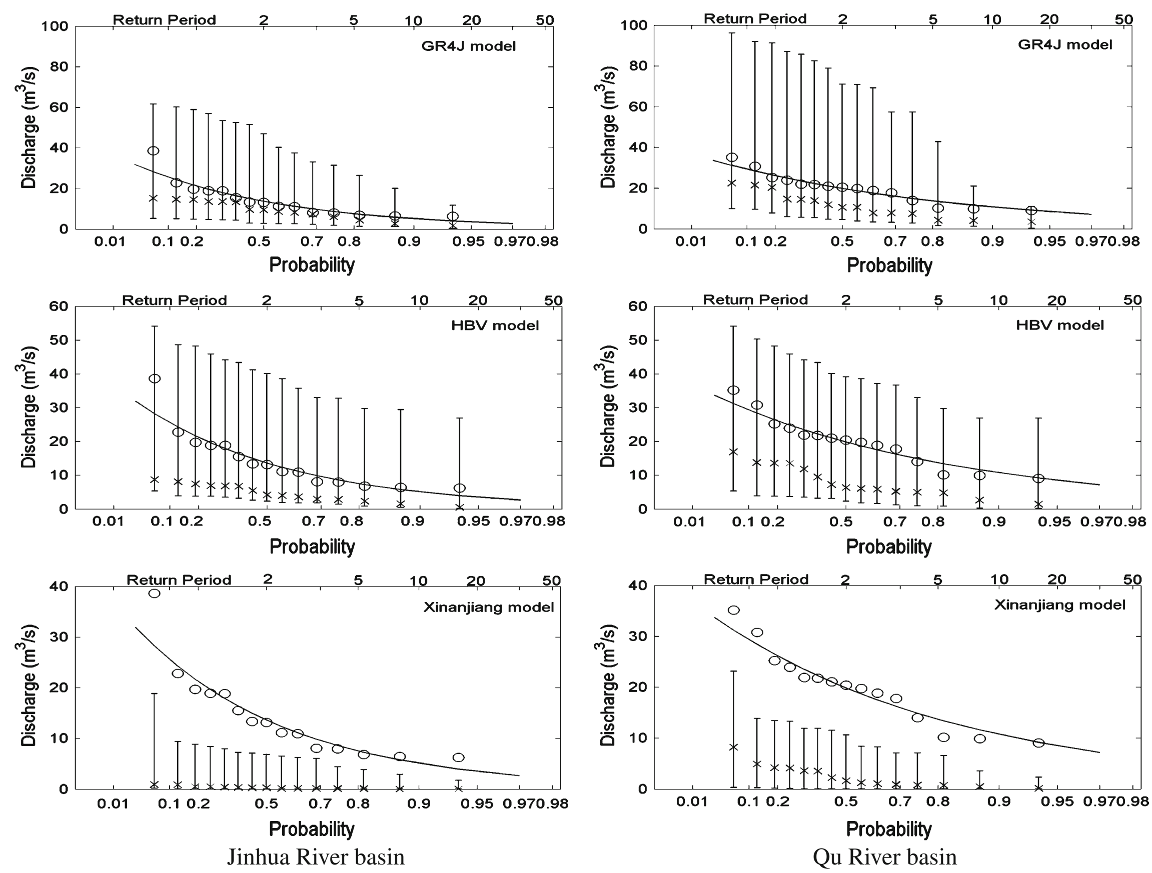

Fig. 5 Comparison of mean annual 7-day minimum discharge (MAM7) as a function of return period for Jinhua River and Qu River simulated with GR4J, HBV and Xinanjiang models for 1981–1995. *Circles* represent the observed MAM7, *crosses* represent the optimum simulated MAM7, *vertical bars* represent 90 % CI, and *curves* represent GEV type III distribution fitted to observed data

Table 6 Mean relative lower and upper limits of CI and relative CI for MAM7 for the GR4J, HBV and Xinanjiang models for 1981–1995

	GR4J (%)	HBV (%)	Xinanjiang (%)
Jinhua River basin			
Relative upper limit	194	171	−51
Relative lower limit	79	83	100
Relative CI	263	254	49
Qu River basin			
Relative upper limit	238	98	−49
Relative lower limit	77	88	100
Relative CI	315	186	51

The formulas of the relative upper/lower limits are shown in Table 4

width of CI from Xinanjiang model did not cover all the observations. It underestimates the extreme low flows with all the behavioral parameter set. There are many factors that contribute to the width of the CI. It depends on models structures, which parameter ranges are sampled, which likelihood measures are evaluated and how they are combined (Montanari 2005). The choice of the parameter ranges is quite subjective (Montanari 2005; Mantovan and Todini 2006).

The relative CI for low flows is surprisingly high as it could be 315 % of the observed discharge for GR4J model for Qu River basin. The relative CI reveals the ratio between uncertainty and the observation. Comparing MAM7 and MHQ, the absolute value of the uncertainty is obviously larger for high flows than for low flows, but the relative uncertainty is much larger for low flows.

3.3 Impact of model uncertainty on high and low flows

Figure 6 shows the uncertainty in high and low flows with a return period of 50 years for the GR4J, HBV and Xinanjiang model, expressed in terms of 90 % CI. By extrapolating the MHQ_O, MHQ_S and upper and lower limits of the 90 % CI, it is possible to estimate the 50 year return periods for MHQ_O, MHQ_S and its 90 % CI, and similarly for the low flows. Figure 6 compares the differences in high and low flow uncertainties stemming from different models and for different basins.

For high flows, the biases of MHQ_S compared to MHQ_O are larger in Qu River basin than those in Jinhua River basin for the three models. In Jinhua River basin, the MHQ_S fluctuates around the MHQ_O within 500 m^3/s. While in Qu River basin, the largest bias is up to about 1,100 m^3/s for HBV. The GR4J and HBV have a good simulation of the MHQ_O with a return period of 50 years in Jinhua River basin, while the Xinanjiang model underestimates MHQ_O. For Qu River basin the GR4J model and HBV model overestimate the MHQ_O, while the Xinanjiang model underestimates it.

The width of CI is larger for Qu River than for Jinhua River basin for all the models. For Jinhua River basin, the MHQ_O with a return period of 50 years is 3,700 m^3/s and the width of CI are 2100–3900, 2260–4760 and 2100–3300 m^3/s for GR4J, HBV and Xinanjiang respectively. For Qu River basin, the MHQ_O with a return period of 50 years is 6,300 m^3/s. The uncertainty intervals are 4240–7550, 3650–9900 and 3350–5520 m^3/s for GR4J, HBV and Xinanjiang respectively. On average, the parameter uncertainty for high flows of HBV is larger, followed by GR4J and Xinanjiang.

For low flows, the value of $MAM7_O$ with a return period of 50 years is around 2 and 6 m^3/s for Jinhua and Qu River basins respectively. The $MAM7_O$ is underestimated by $MAM7_S$ for all models. The widths of CI in two basins are similar for the HBV model and Xinanjiang model. The GR4J model has a larger width of CI in Qu River basin than in Jinhua River basin. For all three models, the lower limits of the CI are all very close to zero and the upper limits vary among the different models. The upper limits for GR4J, HBV and Xinanjiang are 15, 21 and 1 m^3/s for Jinhua River basin and 21, 22 and 2 m^3/s for Qu River basin.

For low flows, the parameter uncertainty is the largest for the HBV model, followed by the GR4J model and the smallest one is from the Xinanjiang model. The order is the same for the high flows. It indicates that the uncertainty interval from one model is consistent in MHQ and MAM7. If the uncertainty interval in MHQ is large, it could also be large for MAM7, and vice versa.

In General, for the daily discharge, the performance is equally good for the GR4J model and the HBV model, and the Xinanjiang model takes the third place. For the extreme high flows, the HBV model has a better performance than the GR4J and the Xinanjiang model, while for the extreme low flows the GR4J model gives a closest simulation to observation. The Xinanjiang model is the most complex model and the GR4J model is the simplest in this study. The uncertainty for the Xinanjiang model is the smallest and the GR4J model is in the middle, the HBV model has the largest uncertainty. It illustrates that the number of the parameters and the complexity of the model structures do not have a direct relationship with the goodness of fit and the uncertainty range.

The smallest uncertainty range for the Xinanjiang model is likely due to the fact that only five most important parameters are chosen to be calibrated and assess the parameter uncertainty, which may lead to a lower uncertainty interval. But additional experiments are taken to verify that the increased number of calibrated parameters does not enlarge the uncertainty interval very much to the extent to cover the observation. So it could be caused by the assumption in the Xinanjiang model that after the filtration process is stable all the rainfall which filtrated to the soil goes directly into the ground water storage, while the truth is that there is aeration zone in the soil which is able to adjust the ground water. Without the adjust function the water is pro to come and go faster, when the next rainfall comes, it needs to saturate the soil first and then form the surface water. However, to verify the assumption more studies are needed.

The intersection of the width of CI represents the common uncertainty from different models. If it is larger than the different part between two models, it means the uncertainty from parameters is larger than that from the model structure, and vice versa. For high flows, the overlapping parts of the different models are larger than the different part in most cases. It indicates parameter uncertainty generally has a larger contribution than the model structure uncertainty for these river basins. For low flows, the overlapping parts are large for the GR4J and HBV models. The overlapping part of Xinanjiang model and other two models are small. Overall, in our study the parameter uncertainty is found to be larger than the models structure uncertainty for both high and low flows.

4 Conclusions

The results of hydrological models are affected by uncertainty mainly due to input data, model parameters and model structures. Uncertainty analysis allows identifying where the uncertainty comes from and providing quantitative information on the uncertainty to be associated with the output of the model. This study addressed the uncertainty assessment for extreme flows in the Jinhua and Qu River basins, East China, as simulated by the GR4J, HBV and Xinanjiang hydrological models, by using the GLUE methodology. The main objective is to study the impact of parameter uncertainty and model structure uncertainty on extreme high and low flows.

The simulation results show that the three models perform well for the daily discharges, but there is an underestimation for the extreme high flows. The observed daily discharge is captured by the 90 % CI for all three models for more than 95 % of the time. For the extreme high flows, the bias between the observed discharges and simulated discharges is the largest for the Xinanjiang model and the smallest for the HBV model, and the bias increases with the increasing observed discharges. Comparing two subbasins, the bias for the annual maximum daily discharge in Qu River basin is larger than that in Jinhua River basin for the same model.

The parameter uncertainty of the high flows becomes larger as the discharge increases. The parameter uncertainty in high flows is the largest for the HBV model and the smallest for the Xinanjiang model. For the HBV model, when the discharge is larger, the probability of overestimating the observed high flows becomes larger. The Xinanjiang model is prone to underestimate high flows and the underestimation is more apparent with increasing discharge in Qu River basin. For extreme low flows, the observed mean annual 7-day minimum discharges are underestimated by the optimum simulation results for all models for both basins. The largest underestimation is from Xinanjiang model. Therefore, if only the optimum set of parameters from calibration is used, it could cause a large bias in the prediction of the discharges particularly for the extreme low flows. The lower limits of the CI are quite close to zero for the three models. For both the low and high flows, the effects of parameter uncertainty are the largest from the HBV model, followed by the GR4J model and they are the smallest for Xinanjiang model.

Extrapolation is then used to estimate the uncertainty in high and low flows for a return period of 50 years, and the 90 % CI of the parameter uncertainty from different models are compared. The variability of the 90 % CI, which mainly depends on the magnitude of the discharge and the models, reveals the impact of uncertainties from

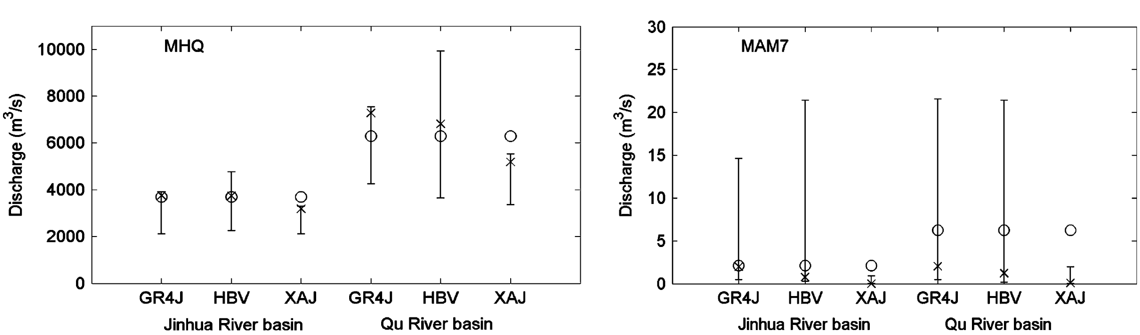

Fig. 6 The 90 % confidence interval of the annual maximum discharge (MHQ) and mean annual 7-day minimum discharge (MAM7) for a return period of 50 years for each model for the Jinhua River and Qu River. *Circles* represent the observed values and *crosses* represent the optimum simulated values, *vertical bars* represent the 90 % CI

the models on the discharge. The uncertainty increases with the discharge, and the uncertainty from the parameters is larger than that from model structures in both high and low flows.

Extreme flow assessment taking uncertainty into account is important for robust decision making. In this study, we did not cover every aspect of uncertainty. Only parameter and model structure uncertainty are considered. Additionally, it needs to be aware that these results for the model and parameter uncertainty are case specific. They may be different in other river basins because of different geographic and climatic conditions. The large uncertainty intervals may be related to the number of parameters, the models, the discharge behavior and also the method to assess the uncertainty itself. For instance, there is also a discussion about the fact that the GLUE method does not strictly follow the Bayesian inference process which could cause an overestimation of the model prediction uncertainty (Mantovan and Todini 2006). But it is still an open question. More researches are needed to assess the method.

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