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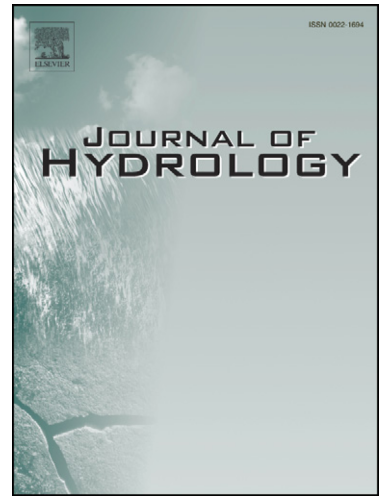


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# Sobol′'s sensitivity analysis for a distributed hydrological model of Yichun River Basin, China

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**Abstract**

This paper aims to provide an enhanced understanding of the parameter sensitivities of the Soil and Water Assessment Tool (SWAT) using a variance-based global sensitivity analysis, i.e., Sobol′'s method. The Yichun River Basin, China, is used as a case study, and the sensitivity of the SWAT parameters is analyzed under typical dry, normal and wet years, respectively. To reduce the number of model parameters, some spatial model parameters are grouped in terms of data availability and multipliers are then applied to parameter groups, reflecting spatial variation in the distributed SWAT model. The SWAT model performance is represented using two statistical metrics - Root Mean Square Error (RMSE) and Nash-Sutcliffe Efficiency (NSE) and two hydrological metrics – RunOff Coefficient Error (ROCE) and Slope of the Flow Duration Curve Error (SFDCE). The analysis reveals the individual effects of each parameter and its interactions with other parameters. Parameter interactions contribute to a significant portion of the variation in all metrics considered under moderate and wet years. In particular, the variation in the two hydrological metrics is dominated by the interactions, illustrating the necessity of choosing a global sensitivity analysis method that is able to consider interactions in the SWAT model identification process. In the dry year, however, the individual effects control the variation in the other three metrics except SFDCE. Further, the two statistical metrics fail to identify the SWAT parameters that control the flashiness (i.e., variability of mid-flows) and overall water balance. Overall, the results obtained from the global sensitivity analysis provide an in-depth understanding of the underlying hydrological processes under different metrics and climatic conditions in the case study catchment.

**Keywords** Climate conditions; Sensitivity analysis; Hydrological modeling; Sobol′'s method; Hydrological metrics; SWAT

## 1. Introduction

Distributed hydrological models have gained increasing attention in recent years due to the increasing availability of spatially distributed data and advances in computing power (Beven and Kirkby, 1979; Abbott et al., 1986; Boyle et al., 2001; Panday and Huyakorn, 2004; Duffy, 2004). These models have been applied to advance scientific understanding of underlying hydrological processes, analyse the potential impacts of land use and climate change, and develop water quantity and quality management options for informed decision making (e.g., Beven and Binley, 1992; Tang et al., 2007a).

The Soil and Water Assessment Tool (SWAT) is a particular example of complex, spatially distributed hydrological models (Arnold et al., 1993). To determine the most influential parameters of a SWAT model, the Latin Hypercube-One factor At a Time (LH-OAT) algorithm is often applied, as this method is incorporated in SWAT (van Griensven et al., 2006). The LH-OAT method provides an estimation of the parameters' ranking according to their influence on the model output. However, it does not provide an estimation of the proportion of the total influence that one parameter has on the output, nor its interactions with other parameters. Therefore, this method might not be able to identify some influential parameters, whose effects are mainly from interactions with other parameters.

Sobol′'s method is a global sensitivity analysis method and is able to provide the impacts of each parameter and its interactions with other parameters on the model output (Sobol′, 1993). Recently Sobol′'s method has become increasingly popular in hydrological modeling due to its ability to incorporate parameter interactions and the relatively straightforward interpretation of its indices (e.g., Pappenberger et al., 2008; van Werkhoven et al., 2008; Yang, 2011; Fu et al., 2012). Tang et al. (2007b) comprehensively compared Sobol′'s method with three other sensitivity analysis tools including the Parameter Estimation Software (PEST) (Doherty, 2004), Regional Sensitivity Analysis (RSA) (Young, 1978; Hornberger and Spear, 1981), and Analysis of Variance (ANOVA) (Neter et al., 1996; Mokhtari and Frey, 2005). They found that Sobol′'s method is the most effective approach to globally characterize single- and multi-parameter interactive sensitivities for lumped watershed models. Build on this prior study, Tang et al. (2007a) used Sobol′'s method to a distributed hydrological watershed model termed as the Hydrology Laboratory Research Distributed Hydrologic Model (HL-RDHM), and the sensitivity analysis results obtained demonstrated that the method provides robust sensitivity rankings and that these rankings could be used to significantly reduce the number of parameters when calibrating the HL-RDHM. Further, Wagener et al. (2009) highlighted the importance of using multiple performance metrics to analyse the sensitivities of a distributed hydrological model using the Sobol′'s method.

More recently the Sobol′'s sensitivity analysis method has been applied to SWAT (e.g., Cibin et al., 2009; Nossent et al., 2011). Cibin et al. (2009) used Sobol′'s method to analyse the sensitivities of SWAT models for two watersheds with different climatic settings and flow regimes, by considering each parameter's individual contribution (first order index) and the total contribution (total order index) to the model output in terms of two commonly used statistical metrics, i.e., Root Mean Square Error (RMSE) and Nash-Sutcliffe Efficiency (NSE). The results indicated that modeled stream flows show varying sensitivity to parameters in different climatic settings and flow regimes. Nossent et al. (2011) presented a Sobol′'s sensitivity analysis for a SWAT model of the Kleine Nete River watershed, Belgium, by analyzing the first order, second order and total sensitivity effects of model parameters on one single model performance metric -

NSE. The results indicated that the curve number factor is the most important parameter of the model and that no more than 9 parameters (out of 26) are needed to have an adequate representation of the model variability. It is also shown that there are significant interactions between three pairs of variables, which otherwise cannot be revealed by other methods only analyzing the impacts of individual parameters. The prior researches have demonstrated the benefits of Sobol′'s method in identification of SWAT models, but are limited in analyzing multiple model performance metrics (such as hydrological metrics) and discussing the detailed interactions between model parameters.

In this paper, Sobol′'s method is used to perform a detailed sensitivity analysis for a SWAT model of Yichun River Basin, China, by analyzing the individual effects of each parameter and its interactions with other parameters on the model output regarding four different metrics: RMSE, NSE, runoff coefficient error (ROCE) and slope of the flow duration curve error (SFDCE). Further, the model parameter sensitivities are evaluated for wet, moderate, and dry years with the intent of identifying the key parameters and parameter interactions under different climate conditions. The results from this study provide an in-depth understanding of the sensitivity of the SWAT parameters and highlight the significance of the interactions between model parameters. In addition, this paper also shows the effectiveness of the variance-based Sobol′'s method in sensitivity analysis of SWAT models.

## 2. Methodology

### 2.1 Overview of SWAT Model

The SWAT model is a catchment-scale distributed hydrological model developed by the Agricultural Research Service of the United States Department of Agriculture

(Arnold et al., 1998). The model is based on physical processes and is capable of continuous simulation over long time periods. SWAT was developed with an aim to predict the impact of land management practices on water, sediment and agriculture chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time. The model is a catchment-scale dynamic simulation model and thus can use the spatial information provided by Geographic Information System and Remote Sensing to simulate a number of hydrological response units. SWAT was designed as a long-term yield model. Although the model can be run at a daily time step when the Soil Conservation Service (SCS) curve number method is used to calculate surface runoff, the simulation results can be reported on a daily, monthly or yearly basis. It is not designed to accurately simulate detailed, single-event flood routing (Neitsch et al., 2001).

The SWAT model has been widely used to evaluate the impact of climate, land use, and land management decisions on stream flow and water quality, and gained international recognition as is evidenced by a large number of applications of this model (Arnold et al., 1998; Arnold and Fohrer, 2005; Confesor and Whittaker, 2007; Zhang et al., 2008; Anand et al., 2007; Gassman et al., 2007). Take China as a particular example, the SWAT applications include the Heihe Basin (Huang and Zhang, 2004; Wang et al., 2003), the Luohe Watershed (Zhang et al., 2003a and b), the Yuzhou Reservoir Basin (Zhang et al., 2004), the Luxi Watershed (Hu et al., 2003), the Huai River Basin (Wang and Xia, 2010), the Biliu River Basin (Chu et al., 2012; Zhang et al., 2012), and the Huifa River Basin (Zhang et al., 2012). However, none of the above applications includes a global sensitivity analysis to advance the understanding of the effects of model parameters on the model performance in terms of traditional model evaluation metrics (statistical error) and additional hydrological metrics.

## 2.2 Sobol′'s Method

Sobol′'s method (Sobol′, 1993) is a global sensitivity analysis approach based on variance decomposition. Non-linear and non-monotonic models could be represented in the following functional form:

$$Y = f(X) = f(X_1, \ldots, X_p) \tag{1}$$

where $Y$ is the goodness-of-fit metric of model output, and $X = (X_1, \ldots, X_p)$ is the parameter set. In Sobol′'s method, the total variance of function $f$, $D(y)$, is decomposed into component variances from individual parameters and their interactions:

$$D(y) = \sum_i D_i + \sum_{i<j} D_{ij} + \sum_{i<j<k} D_{ijk} + \ldots + D_{12\cdots p} \tag{2}$$

where $D_i$ is the amount of variance due to the $i$th parameter $X_i$, and $D_{ij}$ is the amount of variance due to the interaction between parameter $X_i$ and $X_j$. The sensitivity of single parameter or parameter interaction, i.e. Sobol′'s sensitivity indices of different orders, is then assessed based on their percentage contribution to the total variance $D$:

$$\text{First-order index} \quad S_i = \frac{D_i}{D} \tag{3}$$

$$\text{Second-order index} \quad S_{ij} = \frac{D_{ij}}{D} \tag{4}$$

$$\text{Total-order index} \quad S_{Ti} = 1 - \frac{D_{\sim i}}{D} \tag{5}$$

where $D_{\sim i}$ is the amount of variance due to all of the parameters except for $X_i$, $S_i$ measures the sensitivity from the main effect of $X_i$, $S_{ij}$ measures the sensitivity from the interactions between $X_i$ and $X_j$, and $S_{Ti}$ measures the main effect of $X_i$ and its interactions with all the other parameters.

The variances in Eq. (2) can be evaluated using approximate Monte Carlo numerical integrations, particularly when the model is highly nonlinear and complex. The Monte Carlo approximations for $D$, $D_i$, $D_{ij}$, and $D_{\sim i}$ are defined as presented in the following prior studies (Sobol′, 1993, 2001; Hall et al., 2005):

$$\hat{f}_0 = \frac{1}{n}\sum_{s=1}^{n} f\left(X_s\right) \tag{6}$$

$$\hat{D} = \frac{1}{n}\sum_{s=1}^{n} f^2\left(X_s\right) - \hat{f}_0^{\,2} \tag{7}$$

$$\hat{D}_i = \frac{1}{n}\sum_{s=1}^{n} f\left(X_s^{(a)}\right) f\left(X_{(\sim i)s}^{(b)}, X_{is}^{(a)}\right) - \hat{f}_0^{\,2} \tag{8}$$

$$\hat{D}_{ij}^{c} = \frac{1}{n}\sum_{s=1}^{n} f\left(X_s^{(a)}\right) f\left(X_{(\sim i,\sim j)s}^{(b)}, X_{(i,j)s}^{(a)}\right) - \hat{f}_0^{\,2} \tag{9}$$

$$\hat{D}_{ij} = \hat{D}_{ij}^{c} - \hat{D}_i - \hat{D}_j \tag{10}$$

$$\hat{D}_{\sim i} = \frac{1}{n}\sum_{s=1}^{n} f\left(X_s^{(a)}\right) f\left(X_{(\sim i)s}^{(a)}, X_{is}^{(b)}\right) - \hat{f}_0^{\,2} \tag{11}$$

where $n$ is the sample size, $X_s$ is the sampled individual in the scaled unit hypercube, and superscripts $(a)$ and $(b)$ represent two different samples. All of the parameters take their values from sample $(a)$ are represented by $X_s^{(a)}$. The variables $X_{is}^{(a)}$ and $X_{is}^{(b)}$ denote that parameter $X_{is}$ uses the sampled values in sample $(a)$ and $(b)$, respectively. The symbols $X_{(\sim i)s}^{(a)}$ and $X_{(\sim i)s}^{(b)}$ represent cases when all of the parameters except for $X_{is}$ use the sampled values in sample $(a)$ and $(b)$, respectively. The symbol $X_{(i,j)s}^{(a)}$ represents parameters $X_{is}$ and $X_{js}$ with sampled values in sample $(a)$. Finally, $X^{(b)}_{(\sim i,\sim j)s}$ represents the case when all of the parameters except for $X_{is}$ and $X_{js}$ utilize sampled values from sample $(b)$.

Although Sobol′'s method has intensive computational requirements, its sensitivity indices have been shown to be more effective than other approaches in capturing the interactions between a large number of variables for highly nonlinear models (Tang et al., 2007a and b). Building on the recommendations of Tang et al. (2007a), the Latin Hypercube sampling method (McKay et al., 1979) was used for implementing Sobol''s method. Overall computing the first-order, second-order and total-order sensitivity indices requires $n \times (m+2)$ model evaluations where $n$ is the number of Latin Hypercube samples and $m$ is the number of parameters being analyzed.

## 2.3 Latin Hypercube Sampling

Monte Carlo sampling is in general robust, but may require a high number of samples and consequently a large amount of computational resources (time and disk memory). The concept of the Latin Hypercube Sampling (LHS) (McKay et al., 1979; McKay, 1988) is based on the Monte Carlo Simulation but uses a stratified sampling approach that allows efficient estimation of the output statistics. LHS divides the distribution of each parameter into $N$ ranges, each with a probability of occurrence equal to $1/N$. Random values of the parameters are generated such that each range is sampled only once, that is, $N$ samples are generated for each parameter. The process can be repeated $p$ times for all the variables so that a sample of total size $N \times p$ is created with random sample combinations of different variables. The LHS method was chosen in this paper due to its popularity and effectiveness in hydrological and water quality modeling (Tang et al., 2007a and b; Fu et al., 2009; Fu et al., 2011).

### 2.4 Bootstrap method

The bootstrap method (Efron and Tibshirani, 1993) was used to provide confidence intervals for the parameter sensitivity rankings for the Sobol′'s method. Essentially, the samples generated by LHS were resampled *n* times when calculating the sensitivity indices for each parameter, resulting in a distribution of the indices. The percentile method and the moment method were used for attaining the bootstrap confidence intervals. The moment method is based on large sample theory and requires a sufficiently large resampling dimension to yield symmetric 95% confidence intervals. The percentile method is very simple, but a higher number of resamples are necessary for the moment method to achieve a reliable estimate of the percentiles. The moment method can result in a poorly estimated confidence interval if the bootstrap distribution is skewed (Archer et al., 1997).

## 3. Case Study

### 3.1 Yichun River Basin Description

The SWAT model is used to simulate the case study catchment, Yichun River Basin, China, with a daily time step. The basin boundary and the associated SWAT model sub-watershed boundaries are presented in **Error! Reference source not found.**. Yichun River Basin has a drainage area of 2405.7km$^2$, and is a major tributary to the Tang-Wang River. Yichun River Basin is dominated by dark brown soils (>71%) and forest land use (>74%). There are 10 sub-watersheds defined in Yichun River Basin, where 7 rain gauges and 1 streamflow gauge are located. The Tang-Wang River is the first level tributary of the left bank of the Song-Hua River. The total length of the Tang-Wang River is approximately 509km. Its basin drains an area of 20383km$^2$. The climate of the Tang-Wang River basin, located in the middle and high latitudes, is continental monsoon of cold temperate zone. The seasonal change of the Tang-Wang River basin is obvious, and the mean annual precipitation and evaporation is about 617.4mm and 541mm respectively.

### 3.2 Data Set

The data requirement for SWAT modeling primarily includes: the Digital Elevation Model (DEM), the digital river network, the land use and soil data, the hydrometeorological data (precipitation, temperature, solar radiation, weed speed, relative humidity and stream flow).

(1) DEM data (raster resolution: 90m×90m) were obtained from the International Scientific Data Service Platform of the Computer Network Information Center, Chinese Academy of Sciences (http://srtm.csi.cgiar.org).

(2) Soil data (scale = 1:$10^6$) and land use data (scale = 1:$10^5$) for the 1980s were collected from Data Center for Resources and Environmental Sciences Chinese Academy of Sciences (RESDC, http://www.resdc.cn/).

(3) Digital river network data (scale = 1:2.5×$10^5$) were obtained from 1:4M-scale Topographic Database of the National Fundamental Geographic Information System of China.

(4) Daily Meteorological data (temperature, solar radiation, weed speed, relative humidity) were obtained from China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/) and presented in Table 1.

(5) Daily precipitation data and stream flow data were obtained from Hydrological Administration of Heilongjiang Province and presented in Table 1.

### 3.3 Model Setup and Parameterization

To evaluate SWAT model parameter sensitivities for wet, moderate, and dry years with the intent of identifying the key parameters impacting different years (wet, moderate, and dry years), three scenarios are constructed: (1) daily sensitivity analysis using a wet year of observations, (2) daily sensitivity analysis using a moderate year of observations, and (3) daily sensitivity analysis using a dry year of observations. Fig. 2a shows the annual precipitation time series of Yichun River Basin between 1979 and 2001. Fig. 2b shows the exceedance probabilities of annual precipitation for Yichun River Basin. It can be seen that years 1982-1985 are a typical representation of the catchment climate from wet to dry, that is, year 1982 is dry, years 1983 and 1984 are moderate, and year 1985 is wet. The time series of the four years' precipitation and observed streamflow are presented in Fig. 3.

The flow-related parameters of the SWAT and their ranges are listed in Table 2. These 28 model parameters impact snowmelt, surface runoff, groundwater, lateral flow and evapotranspiration predictions. The parameter ranges were based mainly on the default ranges in the SWAT2000 model documentation.

Note that some SWAT model parameters in this case study are not regarded as a spatial variable but instead a constant value across all model spatial units, for example, those parameters related to snowmelt. Many other parameters such as SCS curve numbers and soil properties are spatially varied and therefore can be assigned different values for different spatial units. If all parameters of different spatial units are considered for model calibration, the total number of parameters increases to more than 100. This could significantly increase the complexity and computational requirement of a sensitivity analysis. Since the analysis in this paper is based on one monitoring location only due to data availability, thus spatially varying model parameters were not analyzed for each spatial unit. Instead, a single factor was used to represent spatial variation, by increasing or decreasing spatially varying parameter values from their base or default values. For each parameter, this approach maintains the relative differences in the base or default parameter values assigned to different spatial units.

For each scenario, the first two months (January and February) are used as a warm up period for model simulation. And the rest of time periods in each scenario are used to assess the model's performance in the sensitivity analysis process.

### 3.4 Goodness-of-fit metrics

The sensitivity analyses for SWAT model with Sobol′'s method consider four goodness-of-fit metrics: two statistical metrics and two hydrological metrics. This allows for a more accurate capture of model performance from different aspects. Statistical metrics focus on the hydrograph (i.e., errors and trends), while hydrological metrics focus on different functional behaviors of the basin (e.g., peakedness and flow duration curve).

The two statistical metrics - root mean squared error (RMSE) and Nash-Sutcliffe Efficiency (NSE) - are used to address flow prediction errors and trends, respectively. The RMSE and NSE metrics are computed using equations (12) and (13), respectively,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_{pi} - Q_{ti}\right)^2} \tag{12}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Q_{pi} - Q_{ti}\right)^2}{\sum_{i=1}^{n}\left(Q_{ti} - \overline{Q_t}\right)^2} \tag{13}$$

where $Q_{pi}$ and $Q_{ti}$ are the simulated and measured flows on day $i$, $n$ is the total number of days and $\overline{Q_t}$ is the mean daily measured flows in the analyzed period.

The runoff coefficient error (ROCE) and slope of the flow duration curve error (SFDCE) metrics are used to evaluate the model's accuracy in simulating a basin's water balance and flashiness (i.e., variability of mid-flows), respectively. The ROCE metric is computed as the absolute difference between the simulated and observed average annual runoff coefficient:

$$ROCE = abs\left(\frac{\overline{Q_p}}{\overline{P}} - \frac{\overline{Q_t}}{\overline{P}}\right) \tag{14}$$

where $\overline{Q_p}$ represents the simulated average annual flow and $\overline{Q_t}$ is the observed average annual flow. Both flows are normalized by the observed average annual precipitation $\overline{P}$.

The SFDCE metric is computed as the absolute error in the slope of the flow duration curve between the 30th and 70th percentiles of predicted and observed flows to measure the error of the model generated distribution of mid-range flows:

$$SFDCE = abs\left(\frac{Q_{p,70} - Q_{p,30}}{40} - \frac{Q_{t,70} - Q_{t,30}}{40}\right) \tag{15}$$

where $Q_{p,30}$ and $Q_{p,70}$ are the simulated 30th and 70th percentile flows within the simulated flow duration curve and $Q_{t,30}$ and $Q_{t,70}$ are the observed 30th and 70th percentile flows within the simulated flow duration curve.

## 3.5 Sensitivity Analysis Implementation

Statistical sample size is a key parameter for Sobol′'s method. Tang et al. (2007b) used a sample size of 8192 for Sobol′ analysis when considering 18 model parameters, and suggested that this number is extremely conservative. Fu et al. (2012) used a set of 2000 LHS samples for 21 parameters in a hydraulic analysis of water distribution network. Tang et al. (2007a) used a sample size of 2000 for 403 variables in a distributed hydrologic model and this number was proved sufficient to maintain the accuracy and repeatability of Sobol′ analysis. On the basis of these prior studies, a

LHS sample size of 2000 was used in this study for all three scenarios resulting in 2000×(28 + 2) = 60,000 model runs for each scenario. A comparison of results with smaller sample sizes show this sample size is sufficient and the sensitivity indices are reliable.

## 4. Results and Discussion

The first- and total-order sensitivity indices of 28 parameters are shown in Fig.4. In Fig.4, each column of panels represents one of the three scenarios: dry year (1982), moderate year (1983-1984) and wet year (1985), and each row represents one of the four metrics. In each panel, the *x*-axis represents parameter numbers, and *y*-axis represents first- and total- order sensitivity indices. The first order indices are represented by black bars, which measure individual parameter contributions to the variance of the four goodness-of-fit metrics. The total-order indices are presented by the total height of bars measuring individual and interactive parameter contributions to the variance of the four goodness-of-fit metrics. It should be noted that the grey bars measure the total interactive contribution of one parameter with all the other parameters. Fig.5 provides a detailed description of the second-order indices, i.e., the contributions of the interactions between two parameters to the variance of the four goodness-of-fit metrics in the three scenarios. Sensitive parameters are defined with a 10% threshold of total order index in Fig.4, and similarly significant second-order interactions are defined with a 1% threshold in Fig.5. These thresholds are subjective and their ease-of-satisfaction decreases with increasing numbers of parameters or parameter interactions (Tang et al., 2007a and b). The main findings are analysed for each metric below.

## 4.1 Statistical metrics: RMSE and NSE

For the RMSE metric, there are three sensitive parameters (total order index>10%) for the 1982 dry year scenario, i.e., the lateral flow travel time (LAT_TTIME), base flow alpha factor (ALPHA_BF), and maximum canopy storage (CANMX). However, in the 1983-1984 year scenario, the metric variance is attributed to more parameters, that is, there are a total of seven parameters with a total-order index greater than 10%, including deep aquifer percolation fraction (RCHRG_DP), runoff curve number multiplicative factor (CN2), groundwater delay time (GW_DELAY), and threshold groundwater depth for return flow (GWQMN) in addition to the three parameters LAT_TTIME, ALPHA_BF, and CANMX in the dry year scenario. Similarly, in the wet year scenario, five parameters are highly sensitive with a total-order index bigger than 10%. Amongst these sensitive parameters, LAT_TTIME is the most sensitive parameter, accounting for 59%, 27%, and 36% of the total variance in the dry, moderate, and wet scenarios, respectively. The above results confirm the finding by Nossent et al. (2011) that only a small number of parameters are highly sensitive in SWAT.

The amount of lateral flow discharged to the main channel on any given day is controlled by LAT_TTIME. The sensitivity of daily runoff simulations to LAT_TTIME in Yichun River Basin was expected due to lesser mean annual precipitation in the basin. The moderate and wet scenarios have smaller total-order sensitivity indices of LAT_TTIME than the dry scenario due to more precipitation. Furthermore, it should be noted that the parameters related to groundwater flow, i.e., GW_DELAY, ALPHA_BF, GWQMN, and RCHRG_DP have a more significant interactions with other parameters from a dry year 1982 through transition years 1983-1984 to a wet year 1985. This is because the interactions between regional surface water and groundwater become more and more frequent with the increase of precipitation and water in soil profile and shallow aquifer in a wetter year. These interactions could not be revealed by using other methods such as LH-OAT.

Additionally, it should be noted that first-order indices of parameters account for most proportion of their total-order indices for the 1982 dry year scenario in Yichun River Basin due to few interactions between parameters, especially the few interactions between regional surface water and groundwater, in the situations where little precipitation occurs and stream flow is generated. From dry year through moderate year to wet year, the proportions of the effects of parameter interactions on the model output to their total-order indices increase gradually, especially the parameters related to groundwater flow and having substantial interactions with surface water, e.g., ALPHA_BF and GWQMN. However, some parameters related to groundwater flow, such as GW_DELAY and RCHRG_DP, having a highly interactive effect on the model output for the 1983-1984 year scenario, have less interactive effects on the model output for the 1985 wet year scenario. The reason is that the soil and shallow aquifer have been saturated in a wetter year, and the changes of these parameter values tend to have less influence on other parameters.

It is interesting to note the similarity of the sensitivity results for the two statistical metrics (RMSE and NSE) for every scenario analyzed due to their focus on addressing flow prediction errors and trends with the simulated and measured flows.

## 4.2 Hydrological metrics: ROCE and SFDCE

For the ROCE metric, there are three sensitive parameters (total order index>10%) for the 1982 dry year scenario, i.e., LAT_TTIME, CANMX, and GWQMN. In the 1983-1984 year scenario, three parameters, i.e., GWQMN, RCHRG_DP, and CANMX, are highly sensitive. In the wet year scenario, three parameters, i.e., GWQMN, RCHRG_DP, and GW_DELAY, are highly sensitive. Amongst these sensitive parameters, LAT_TTIME is the most sensitive parameter in the dry scenario, accounting for 34% of the total variance, and GWQMN is the most sensitive parameter in the moderate and wet scenarios, accounting for 53% and 59% of the total variance, respectively.

The overall parameter sensitivity for the long-term water balance metric (ROCE) is distinctly different from those statistical metrics. Rather than addressing flow prediction errors and trends with the simulated and measured flows, the model performance in terms of ROCE is controlled by parameters that affect the volume of ET losses across all watersheds, i.e., LAT_TTIME, CANMX, GWQMN, RCHRG_DP, and GW_DELAY. This result reflects the fact that these parameters largely control the volume (rather than the shape in the case of statistical metrics) of the hydrograph, which impacts the long-term water balance. In the SWAT model, ET losses occur primarily from stream flow, water intercepted by the plant canopy, water in soil profile and shallow aquifer. The amount of losses from each of the above processes depends on the demand (potential ET for that time of year) and the supply (water content of the storage). The parameters that are sensitive to the long-term water balance are those affecting not only the size of these storages (i.e., the potential volume of losses) but also the amount of water that goes into these storages. The amount of lateral flow discharged to the main channel on any given day is controlled by LAT_TTIME. The values of LAT_TTIME and CANMX are more influential on the model output as compared to the other parameters for the 1982 dry year scenario in the Yinchun River Basin because the stream flow and water intercepted by the plant canopy are effectively available for ET losses for the dry year scenario. In the moderate and wet years, the water that goes into soil profile and shallow aquifer are more effectively available for ET losses. Therefore, it is reasonable that GWQMN is more sensitive than other parameters, and the parameters related to groundwater flow have significant interactions with other parameters affecting stream flow for the 1983-1984 year and the wet year scenarios in Yichun River Basin. Some parameters related to lateral flow and groundwater flow, such as LAT_TTIME and RCHRG_DP, have many interactive effects on the model output for the 1983-1984 year scenario similarly, however, have less interactive effects on the model output for the 1985 wet year scenario because the soil and shallow aquifer have been saturated in a wetter year, and the changes of these parameter values tend to have less influence on ET losses.

For the SFDCE metric, there are six sensitive parameters (total order index>10%) for the 1982 dry year scenario, i.e., CANMX, GWQMN, GW_DELAY, LAT_TTIME, ALPHA_BF, and RCHRG_DP. In the 1983-1984 year scenario, five parameters, i.e., GWQMN, CANMX, LAT_TTIME, RCHRG_DP, and GW_DELAY, are highly sensitive. In the wet year scenario, three parameters, i.e., GWQMN, RCHRG_DP, and GW_DELAY are highly sensitive. Amongst these sensitive parameters, CANMX is the most sensitive parameter in the dry scenario, accounting for 49% of the total variance, and GWQMN is the most sensitive parameter in the moderate and wet scenarios, accounting for 37% and 76% of the total variance, respectively.

It is interesting to note the similarity and difference of the sensitivity results for the two hydrological metrics (ROCE and SFDCE) for every scenario analyzed. The similarity of the sensitivity results for the two hydrological metrics is due to their common characteristics of hydrological metrics. The difference of the sensitivity results for the two hydrological metrics is due to their focuses on different functional behaviors of the basin. The metric, SFDCE, evaluates the error in the slope of the flow duration curve between the 30 and 70 percentile flow magnitudes. It thus captures the parameter impacts on the variability in flow magnitudes (rather than their impact on long-term runoff volume as for ROCE). Comparing sensitivities across the basin for this metric, it is seen that the ET controlling parameters (CANMX and GWQMN) again become sensitive for SFDCE as they do for ROCE. However, the number of sensitive parameters for SFDCE is larger than that for ROCE and more interactions between parameters in the 1982 dry year scenario, e.g., the interactive effects of GWQMN with great influences on the interactions between groundwater flow and stream flow, and the number of sensitive parameters for SFDCE is less with the increase of precipitation for the 1983-1984 year and the 1985 wet year scenarios because the SFDCE metric is computed to capture the parameter sensitivities for the 30-70 percentile range of flows, i.e., the sensitivities of the parameters more frequently 'activated' over the 30-70 percentile range of flows. Wagener et al. (2009) found that the sensitivities of hydrological metrics are more evenly distributed to model parameters compared to the two statistical metrics under a single rainfall event. However in this case study the same finding is revealed for the dry year only and is not shown for the moderate and wet years. This highlights the importance of considering different climate conditions in analyzing the sensitivities of model parameters.

The Sobol"s sensitivity indices can have a high degree of uncertainty due to the difficulty in numerical approximation (Tang et al., 2007a & b). In this study, we used statistical bootstrapping to provide 95% confidence intervals for Sobol"s method. Figure 4 provides the confidence intervals for the total-order indices computed for different metrics in the three climate scenarios. It can be seen from Figure 4 that similar to the findings from Tang et al. (2007a & b) the intervals are rather large, which cannot be reduced even when a larger number of samples are used. However, with the presence of the confidence intervals, the uncertainty of the sensitivity indices could be revealed, informing the selection of sensitive model parameters.

### 4.3 Interactive effects

The pairwise interactions that are revealed by the Sobol′'s method elucidate some important model processes and in particular how one process influences another.

Recall from Fig.4 that RCHRG_DP has a lot of interactive effects on all the four metrics in the case of 1983-1984 year scenario. In Fig.5, it can be seen that this parameter interacts with LAT_TTIME and CANMX only, particularly LAT_TTIME, for the two statistical metrics. The above interactions could be expected, as these parameters have a large influence on the interactions between groundwater flow and stream flow, particularly the interactions between lateral flow and water flow in shallow aquifer, and the definition on the stream flow response of the system. The more water is diverted to stream flow from plant canopy and lateral flow, the less water is diverted from groundwater. This also leads to a trade-off between the parameter values. GWQMN also has a lot of interactive effects on all the four metrics for 1983-1984 year scenario in Fig.4, but Fig.5 shows that GWQMN has few interactions with other parameters for the two statistical metrics. That means that the interactive effect of GWQMN do not come from second-order interactions, so it might come from higher order interactions (3-order, 4-order ….). For the two hydrological metrics in the case of 1983-1984 year scenario, the RCHRG_DP vs. GWQMN interaction has a significant influence on the model output variability and system ET losses. The relation between RCHRG_DP and GWQMN gives more insight on how the groundwater flow is regulated in the SWAT model and how both parameters contribute to the simulated outflow and storage in shallow aquifer. RCHRG_DP defines the fraction of the recharge that goes to the deep aquifer, and the remaining goes to the shallow aquifer and partly determines the amount of water in this storage. If this amount of water is higher than the GWQMN value, return value occurs and contributes to the total outflow. In this way, RCHRG_DP and GWQMN have an interactive influence on the simulated flow, as RCHRG_DP has an impact on the storage in the shallow aquifer and thus on GWQMN.

Similarly, Fig.4 shows that GWQMN and ALPHA_BF have a lot of interactive effects on two statistical metrics in the case of the 1985 wet year scenario. In Fig.5, these interactions can be further revealed and mainly come from five pairwise interactions: GWQMN vs. GW_DELAY, GWQMN vs. RCHRG_DP, GWQMN vs. LAT_TTIME, ALPHA_BF vs. LAT_TTIME, and ALPHA_BF vs. CN2. These parameters have a large influence on the interactions between groundwater flow and stream flow, and the definition on the stream flow response of the system. This also leads to a trade-off between the parameter values. Additionally, Fig.4 shows that GW_DELAY, GWQMN and RCHRG_DP have a lot of interactive effects on two hydrological metrics in the case of the 1985 wet year scenario. In Fig.5, these interactions can be further revealed and mainly come from three pairwise interactions: GW_DELAY vs. GWQMN, GW_DELAY vs. RCHRG_DP, and GWQMN vs. RCHRG_DP. These interactions have a significant influence on the groundwater flow and storage in the shallow aquifer, and determine the amount of water in the shallow aquifer and system ET losses.

The results from this study indicate that the sensitivity of the SWAT parameters varies significantly in the dry, normal and wet years simulated, and suggest that a single set of parameter values may not appropriately represent hydrologic processes during various flow regimes. Dynamic updating of parameters during the simulation may be viable in such situations, however, further studies are needed to evaluate if such approaches could improve the SWAT performance.

The results from this study also indicate that the use of the two commonly used statistical metrics RMSE and TRMSE fails to identify the SWAT model's parameters that control the flashiness (measured by SFDCE) and water balance (measured by ROCE) of Yichun River Basin. This confirms the finding by Wagener et al. (2009) that the choice of performance metrics has a significant impact on the parameter sensitivities of a distributed hydrological model. Further study is currently in progress to investigate how the results obtained from this study can be used to improve the optimization efficiency in the model calibration process.

## 5. Conclusions

This paper provides a variance-based sensitivity analysis for a SWAT model of Yichun River Basin, China. The analysis reveals the individual effects of each parameter and its interactions with other parameters on the model performance regarding two statistical metrics - RMSE and NSE and two hydrological metrics - ROCE and SFDCE. Model parameter sensitivities are analysed under three difference climate conditions: wet, moderate, and dry years. The main findings from the results obtained are summarized below.

(1) The results obtained in this paper confirm that only a small number of model parameters are highly sensitive for all the four metrics considered in SWAT. This is also true when different climatic conditions are considered.

(2) The sensitivity of the SWAT parameters varies significantly in the dry, normal and wet years simulated. For example, the lateral flow travel time is very sensitive in most cases, but has little impact on SFDCE in the dry year. Further, the curve number factor, identified as the most important parameter in prior study, is not

sensitive in most cases considered in this study when parameter interactions are considered.

(3) Parameter interactions contribute to a significant portion of the variation in all metrics considered under moderate and wet years. In particular, the variation in the two hydrological metrics is mainly dominated by the interactions. Sensitive parameters could not be identified if the interactions are discounted. However, in the dry year, the individual effects control the variation in the other three metrics except SFDCE.

(4) The two statistical metrics (RMSE and NSE) have a very similar performance in terms of sensitive parameters identified. This is because both of them measure flow prediction errors and trends with the simulated and measured flows. However, the two statistical metrics fail to identify the SWAT parameters that control the flashiness and water balance, illustrating the importance of considering the two hydrologic metrics, i.e., SFDCE and ROCE, in the model identification process.

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## List of Figure Captions

**Fig. 1** Yichun river catchment.

**Fig. 2** Distinction of annual rainfall for Yichun River Basin between different years. Fig. 2a shows annual rainfall for Yichun River Basin from year 1979 to 2001, Fig. 2b shows the exceedance probability plot of annual rainfall for Yichun River Basin.

**Fig. 3** Hydrographs for Yichun River Basin from year 1982 to 1985.

**Fig. 4** First-order indices, total-order indices and their confidence intervals computed using different measures for the 28 parameters in the three scenarios. The parameter numbers in the *x*-axis are shown in Table 2.

**Fig. 5** Second-order indices computed using the four goodness-of-fit metrics in the three scenarios. The parameter numbers in the *x*-axis are shown in Table 2.

Table 1 Hydrometeorological data for Yichun river basin

| Time Scale | Hydrological/meteorological element | Station | Period |
|---|---|---|---|
| Daily | Precipitation | 7 gauges, such as Kaiyuan | 1979~2001 |
| | Streamflow | Yichun | 1979~2001 |
| | Temperature, relative humidity, weed speed and solar radiation | Yichun | 1979~2001 |

Table 2 Parameter list

| No. | Name | Brief Description (units) | Minimum | Maximum |
|---|---|---|---|---|
| 1 | SFTMP | snow fall temperature ($^{o}$C) | -5 | 5 |
| 2 | SMTMP | snowmelt temperature threshold ($^{o}$C) | -5 | 5 |
| 3 | SMFMX | melt factor for snow on June 21 (mm/$^{o}$C) | 1.5 | 8 |
| 4 | SMFMN | melt factor for snow on December 21 (mm/$^{o}$C) | 0 | 10 |
| 5 | TIMP | snowpack temperature lag factor | 0.01 | 1 |
| 6 | ESCO | soil evaporation compensation factor | 0.001 | 1 |
| 7 | EPCO | plant uptake compensation factor | 0 | 1 |
| 8 | SURLAG | surface runoff lag coefficient | 1 | 24 |
| 9 | GW_DELAY | groundwater delay time (days) | 0.001 | 500 |
| 10 | ALPHA_BF | base flow alpha factor | 0.001 | 1 |
| 11 | GWQMN | threshold groundwater depth for return flow (mm) | 0.001 | 500 |
| 12 | GW_REVAP | groundwater “revap” coefficient | 0.02 | 0.2 |
| 13 | REVAPMN | threshold depth of water in the shollow aquifer for “revap” or percolation to the deep aquifer to occur (mm) | 0 | 500 |
| 14 | RCHRG_DP | deep aquifer percolation fraction | 0 | 1 |
| 15 | SLSUBBSN[a] | average slope length multiplicative factor | 0.75 | 1.25 |
| 16 | SLOPE[a] | average slope steepness multiplicative factor | 0.75 | 1.25 |
| 17 | LAT_TTIME | lateral flow traveltime (days) | 0.001 | 180 |
| 18 | CANMX | maximum canopy storage (mm) | 0 | 100 |
| 19 | BIOMIX | biological mixing efficiency | 0 | 1 |
| 20 | CN2[a] | runoff curve number multiplicative factor | 0.75 | 1.25 |
| 21 | BLAI[a] | maximum potential leaf area index | 0.75 | 1.25 |
| 22 | CH_N2 | manning’s “n” value for the main channel | -0.01 | 0.3 |
| 23 | CH_K2 | effective hydraulic conductivity in main channel alluvium (mm/hr) | -0.01 | 500 |
| 24 | SOL_Z[a] | soil profile total depth multiplicative factor | 0.75 | 1.25 |
| 25 | SOL_AWC[a] | available water capacity multiplicative factor | 0.75 | 1.25 |
| 26 | SOL_K[a] | saturated hydraulic conductivity multiplicative factor | 0.75 | 1.25 |
| 27 | SOL_Alb[a] | moist soil albedo multiplicative factor | 0.75 | 1.25 |

| | | | | |
|---|---|---|---|---|
| 28 | TLAPS | temperature lapse rate ($^{o}$C/km) | 0 | 50 |

[a]Parameters are multiplicative factors used to adjust the spatial variation across all model units.

Fig. 1



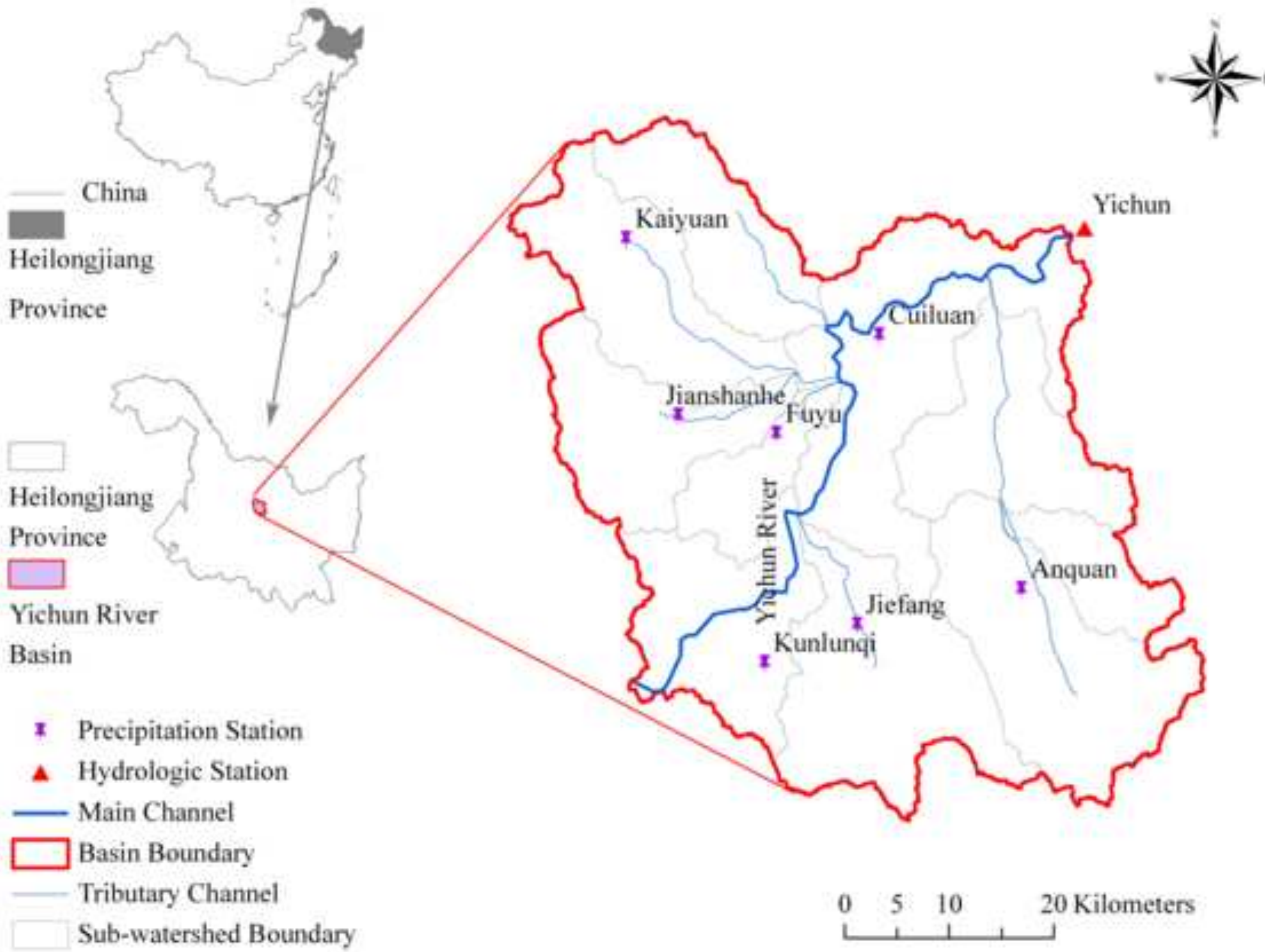
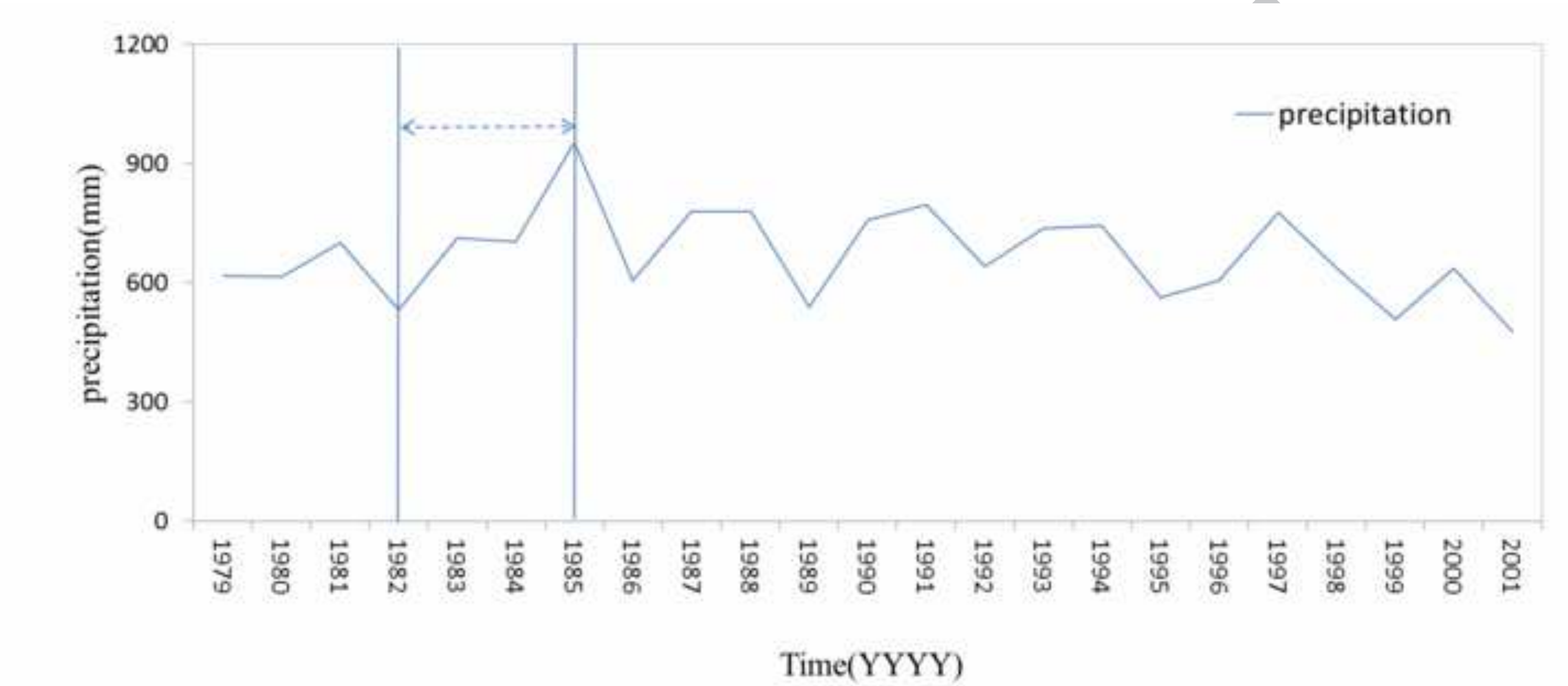

China
Heilongjiang Province
Heilongjiang Province
Yichun River Basin
Precipitation Station
Hydrologic Station
Main Channel
Basin Boundary
Tributary Channel
Sub-watershed Boundary
Kaiyuan
Yichun
Cuiluan
Jianshanhe
Fuyu
Yichun River
Anquan
Jiefang
Kunlunqi
0 5 10 20 Kilometers

Fig. 2a

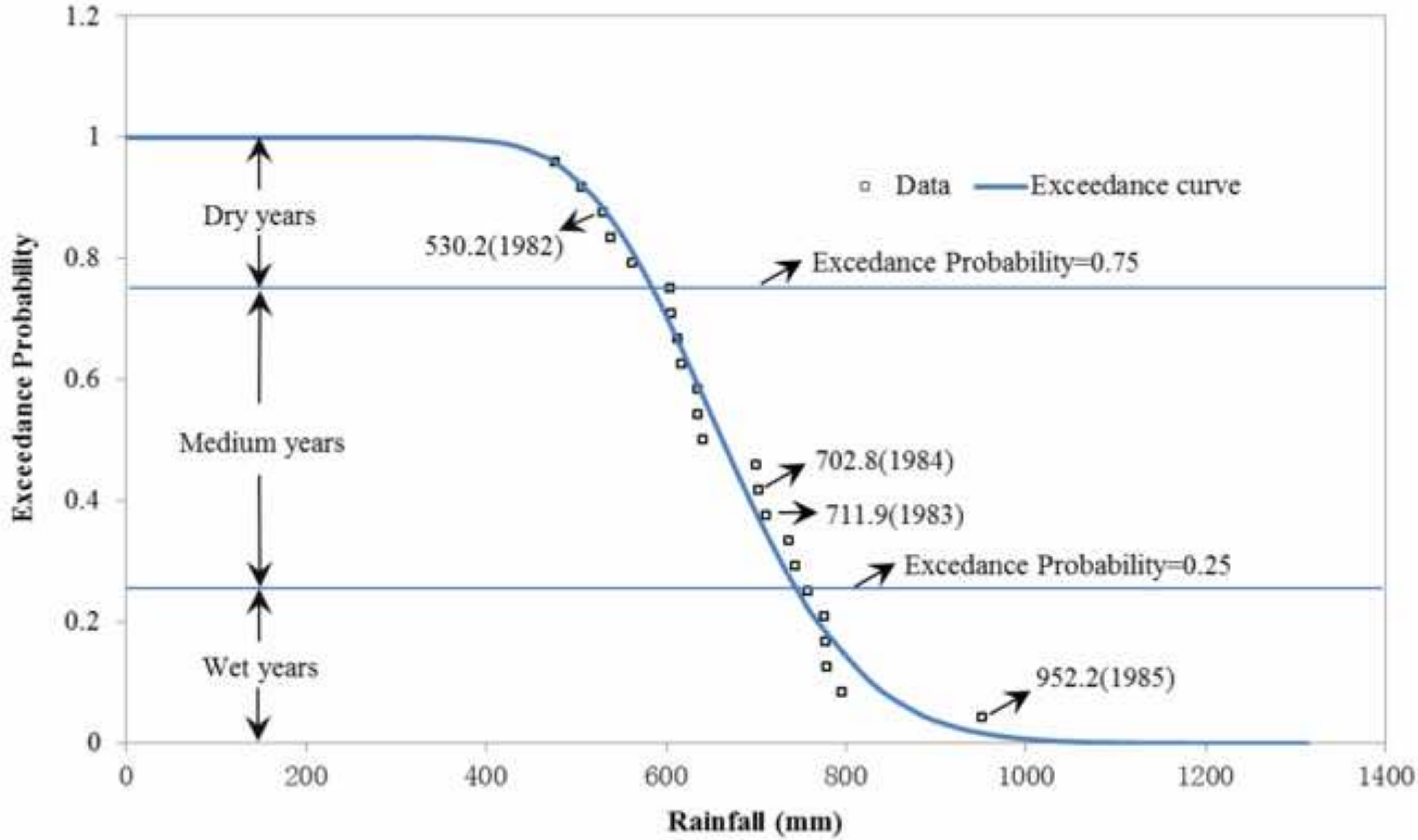




1200
900
600
300
0
precipitation(mm)
precipitation
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
Time(YYYY)

Fig. 2b

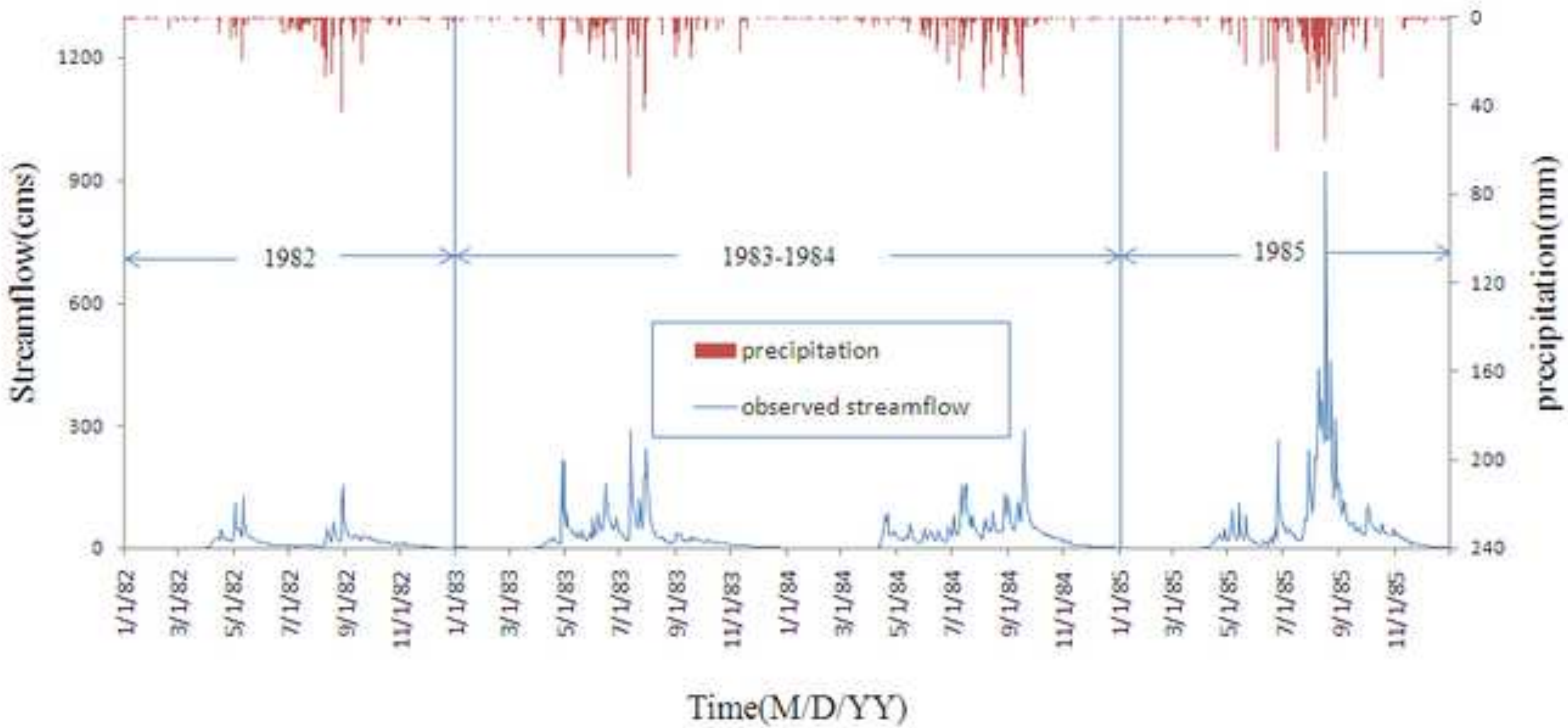




1.2
1
0.8
0.6
0.4
0.2
0
0
200
400
600
800
1000
1200
1400
Exceedance Probability
Rainfall (mm)
Dry years
Medium years
Wet years
Data
Exceedance curve
530.2(1982)
Excedance Probability=0.75
702.8(1984)
711.9(1983)
Excedance Probability=0.25
952.2(1985)

Fig. 3

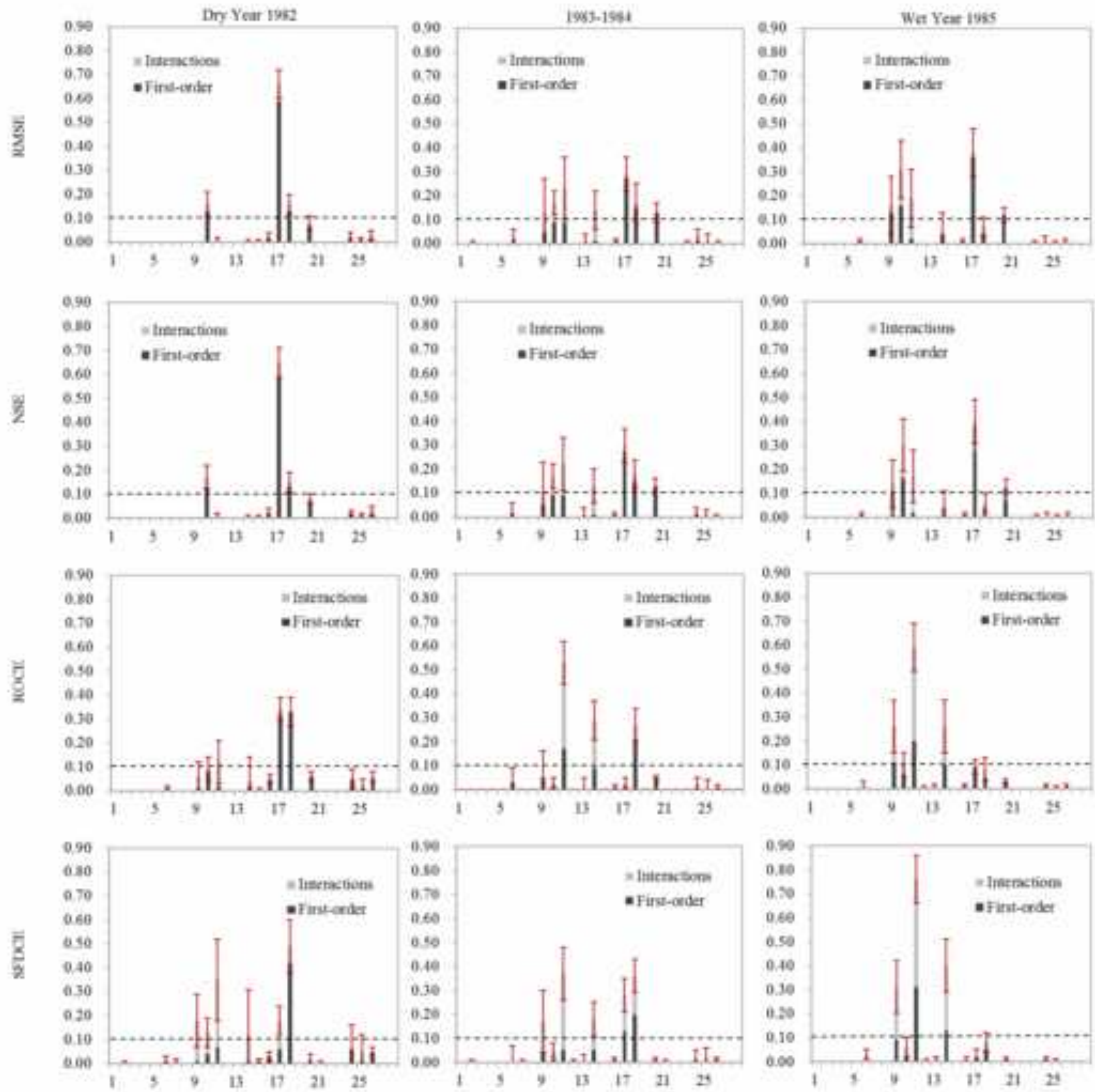




Streamflow(cms)
precipitation(mm)
1200
900
600
300
0
0
40
80
120
160
200
240
1982
1983-1984
1985
precipitation
observed streamflow
1/1/82
3/1/82
5/1/82
7/1/82
9/1/82
11/1/82
1/1/83
3/1/83
5/1/83
7/1/83
9/1/83
11/1/83
1/1/84
3/1/84
5/1/84
7/1/84
9/1/84
11/1/84
1/1/85
3/1/85
5/1/85
7/1/85
9/1/85
11/1/85
Time(M/D/YY)

Fig. 4

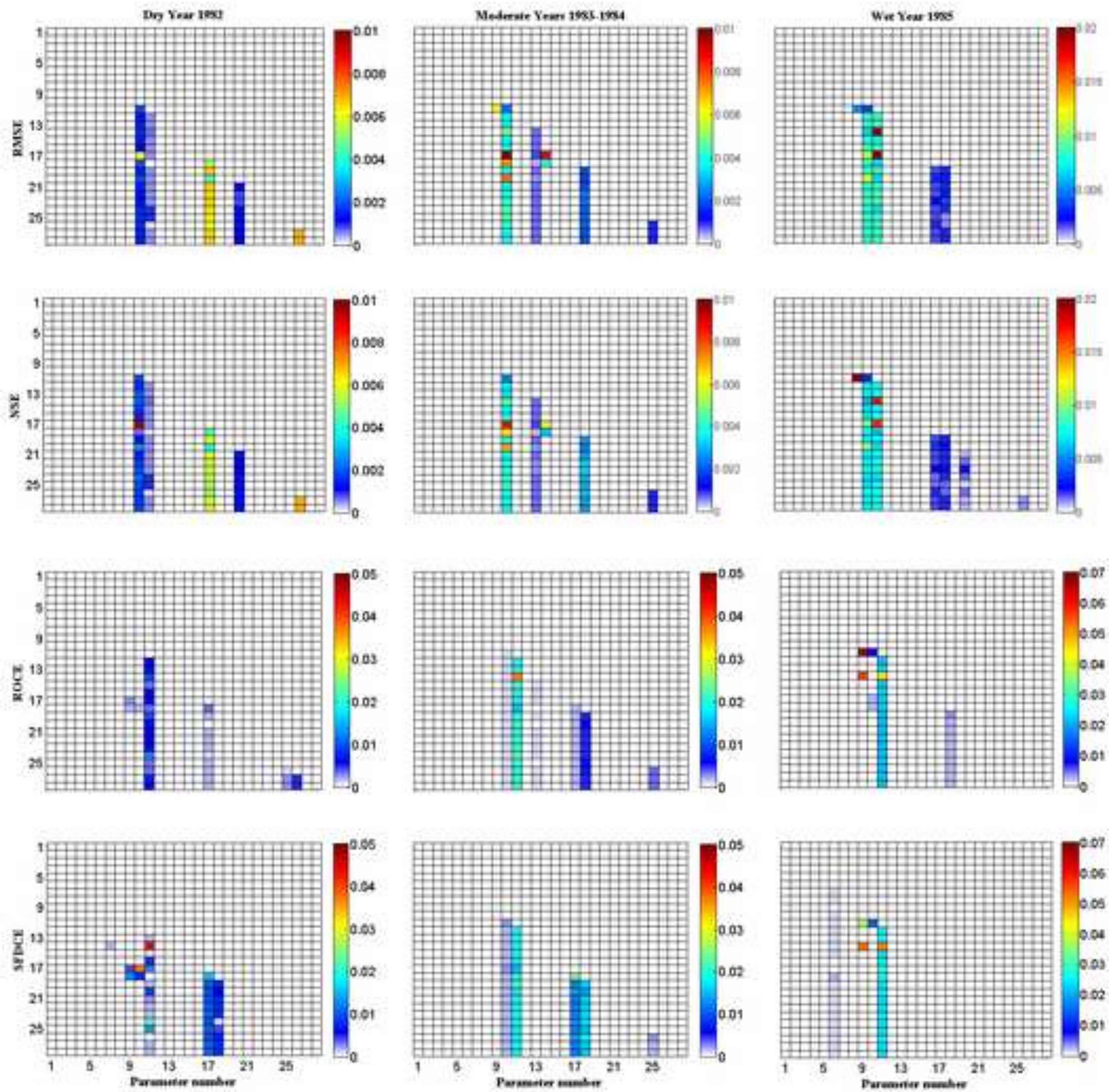




Dry Year 1982
1983-1984
Wet Year 1985
RMSE
NSE
ROCE
SFDCE
Interactions
First-order

Fig. 5




Dry Year 1992
Moderate Years 1993-1994
Wet Year 1995
RMSE
NSE
ROCE
SFDCE
Parameter number

We analysed the effects of key parameters and their interactions on four metrics.
The parameter sensitivities vary significantly in different climate conditions.
Increasing precipitation can lead to more interactive effects between parameters.
Statistical metrics fail to identify the parameters related to hydrological metrics.
Sobol′'s method advances our understanding of the underlying hydrological processes.