Interactive Impacts of Uncertainties in Bias-Corrected Hydrologic Simulations: Southern China

Chen Li[1], Guohe Huang[1*], Guanhui Cheng[1*]

[1] Institute for Energy, Environment and Sustainable Communities, University of Regina, Regina, Saskatchewan S4S 0A2, Canada

Corresponding author: Guohe Huang (huang@iseis.org); Guanhui Cheng (guanhuicheng@gmail.com).

Key Points:

- An approach was developed to comprehensively examine diverse uncertainties in bias-corrected hydrologic simulations over southern China.
- Uncertainty impacts: bias-correction schemes > temporal scales > streamflow magnitudes > hydrologic models or predictor combinations > watersheds.
- Every uncertainty poses significant impacts on simulations, which further varies with all or part of the other uncertainties.

Abstract:

This study aims to comprehensively examine diverse uncertainties/multiplicities (e.g., performance indicators, bias-correction methods, hydrologic models, bias-correction schemes, predictor combinations, watersheds, streamflow magnitudes, and temporal scales) in bias-corrected hydrologic simulations (BCHS). The focus is placed on the variations of BCHS accuracies (representing climatic impacts on runoffs) with every uncertainty, as well as their interactions with the other uncertainties. To achieve this, an integrated bias-corrected hydro-modeling uncertainty analysis approach (IBCHMUA) is developed based on one advanced hydro-modeling method, i.e., discrete principal-monotonicity inference (DiPMI), and two hydrologic models, i.e., Xin'anjiang and HyMOD. IBCHMUA is applied to two representative watersheds (Xiangxi and Zhongzhou) in southern China. Many findings are revealed. For instance, it is necessary to apply multiple performance indicators and DiPMI is effective in correcting hydro-model biases. Every uncertainty poses significant impacts on BCHS, and the significance of the impacts further varies with all or part of the other uncertainties. BCHS accuracies (or the estimated climatic impacts on runoffs in southern China) increase from daily to monthly scales, from Xiangxi to Zhongzhou Watersheds, from the highest through the lowest to the overall runoff magnitudes, from Xin'anjiang to HyMOD models, and from original to bias-corrected hydrologic simulations. Meanwhile, the impacts of the uncertainties in BCHS decrease from bias-correction schemes, temporal scales, streamflow magnitudes, hydrologic models or predictor combinations, to watersheds. These findings are helpful for reducing the complexity and enhancing the reliability of

BCHS under diverse uncertainties, and point out the importance of taking into account the interactions of the uncertainties in BCHS studies.

Keywords: hydrologic modeling, bias correction, DiPMI, uncertainty analysis, China.

1.Introduction

Hydrologic simulation is crucial for understanding hydrologic systems and mitigating hydrologic risks (e.g., droughts and floods) under climatic and anthropogenic impacts. Nevertheless, biases (i.e., systematic errors) exist because it is challenging for hydrologic models to perfectly reproduce complex hydrologic processes (Piani et al., 2010; Roberto Buizza, 2005). The biases would reduce the robustness of hydrologic simulation, the reliability of the corresponding water resources management schemes, and the reasonableness of socio-economic and eco-environmental development (Piani et al., 2010; Saber et al., 2018). Correcting biases of hydrologic simulation through effective methods is required for eliminating these consequences and enhancing the sustainability and resilience of water resources systems.

Correspondingly, bias correction was proposed. Representative methods consist of linear scaling, power transformation, and quantile mapping (Shrestha et al., 2017). These methods presented encouraging performances in correcting averages, variances, distributions, or other features of biases in hydrologic simulation, while their effectiveness was limited in some cases. Meanwhile, a series of sophisticated statistical methods emerged for hydrosystem analyses and might overperform existing ones in bias correction. As a representative, discrete principal-monotonicity inference (DiPMI) (G. Cheng et al., 2016b, 2016a; G. H. Cheng et al., 2017) can be used to enhance the reliability of hydro-model bias correction, and to reveal the joint, dominant, interactive, and non-monotonic impacts of climatic conditions on streamflow. Correcting biases of hydrologic simulation through both conventional and emerging methods deserves exploration.

In addition, many multiplicities (i.e., uncertainties in most hydrologic, geophysical or other relevant studies) exist and propagate in bias-corrected hydrologic simulation (BCHS) (Cheng et al., 2017; Ehret et al., 2012). Typical ones include the multiplicities/uncertainties of hydrologic models, bias-correction methods, predictor selections, watersheds, temporal scales, streamflow magnitudes, etc. Neglecting them (e.g., choosing one hydrologic model corrected by one method to represent a hydrologic system of uncertain structures) would lead to arbitrary BCHS results, unilateral research findings, and unreliable decision support. Examining these uncertainties is conducive to enhancing the reliability of hydrologic simulation and the related water resources management and engineering practices (Vetter et al., 2017).

In this regard, many studies have been conducted. For instance, Beven et al. (1992) analyzed the uncertainties of hydrologic models by the GLUE method (Beven and Binley, 1992). The selection of bias-correction methods had a more significant impact on runoff extremes than runoff averages (Lenderink et al., 2007). Different simulation structures or conceptualizations might result in significant uncertainties in hydrologic predictions (Arkesteijn and Pande, 2013). Addor et al. (2014) identified the dominant impacts of uncertainties in climate models, emission scenarios, post-processing methods, and catchments. However, few studies took all aforementioned uncertainties into account and revealed their interactive impacts on hydro-simulation reliabilities. This gap may decrease the robustness of hydrologic simulations, increase the unreliability of simulation-based decision support, and hinder the mitigation of hydrologic hazards (e.g., floods and droughts).

Therefore, the objective of this study is to develop an integrated bias-corrected hydro-modeling uncertainty analysis approach (IBCHMUA) for comprehensively examining interactive impacts of diverse uncertainties (especially their interactive impacts) in BCHS. Specifically, Section 2 introduces two representative catchments in southern China, and the necessity of this study for local water resources management. Section 3 presents the principle of DiPMI and the framework of IBCHMUA. Section 4 focuses on the variations of BCHS performances with method-related uncertainties (i.e., performance indicators, bias-correction methods, hydrologic models, bias-correction schemes, and predictor combinations). Section 5 elaborates the variations with non-method uncertainties (i.e., watersheds, streamflow magnitudes, and temporal scales), as well as the interactions of all uncertainties. Section 6 summarizes the innovation, findings, and potential extensions of this study.

2. Study Areas: Southern China

(1) Representative Watersheds

Southern China is one of the most economically active areas across the world. Two large rivers (i.e., Yangtze River and Pearl River) are supporting extensive socio-economic activities (e.g., agriculture, fishery, shipping and industries) over this region. As rapidly developing areas in economics, both river basins are the frontier of scientific and technological innovation in China (Liu et al., 2018; Zhang et al., 2016). In this study, two watersheds (Figure 1) are selected due to their representative characteristics (as specified below) of watersheds in the river basins.

Xiangxi Watershed is an upstream tributary of Yangtze River that is closest to the Three Gorges Dam. It is located between 30.99° N and 31.67° N and between 110.47° E and 111.06° E. Its mainstream, Xiangxi River, reaches a length of 97.3 kilometers and a drainage area of 1189 km^2. This river has two sources, i.e., Shendu River of 64.5 kilometers in the east, and Baisha River of 54 kilometers in the west. Both rivers intersect at Gaoyang Town, Xingshan County. The elevation of the Watershed ranges from 67 to 3088 meters, and the average slope is 1.42%. In contrast, Zhongzhou Watershed (Figure 1) has a length of 136.5 kilometers and a drainage area of 2,328 km^2. Its mainstream, Xiaohuanjiang River, is the secondary tributary of Beijiang River in Pearl River Basin. It is located between 23.96° N and 24.44° N and between 112.02° E and 112.26° E. Its elevation fluctuates from 61 to 1411 meters, and the average slope is 0.76%.

In addition, both mountainous watersheds have narrow and twisted river channels, and fast river flows. High coverages of forests and red soils lead to low sediment concentrations in both watersheds. The forest-coverage rates of Xiangxi and Zhongzhou Watersheds are 80.02% and 72.63%, respectively. Xiangxi Watershed is full of shoals without waterway transportation, the river valley (i.e., ≤ 800 m) is composed of purple sand shales and argillaceous rocks, and the high-altitude area is dolomites, siliceous rocks and limestones. In comparison, Zhongzhou Watershed is characterized by magmatic rocks and granites, few dangerous shoals, efficient shipping conditions, and developed waterway transportation.

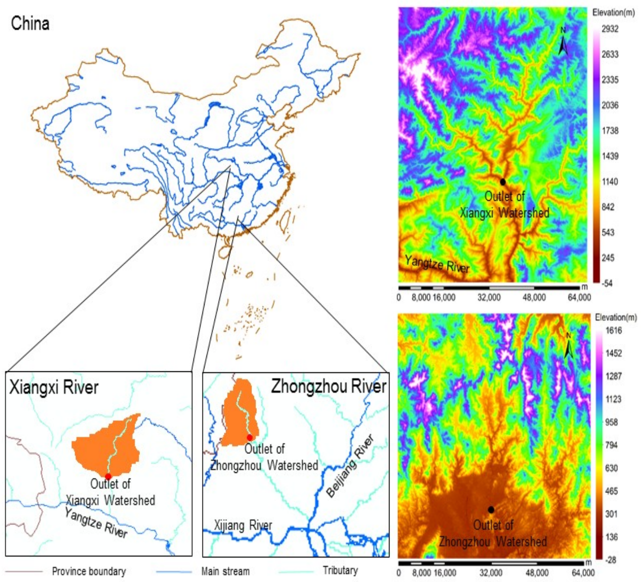


Figure 1. Locations and topographic characteristics of selected watersheds in Southern China.

(2) Climatic and Hydrologic Features

The climatic conditions that significantly drive changes of streamflow are identified through correlation analysis. A group of data for hydrological simulation are obtained by Kriging interpolation. Based on the finalized datasets for both watersheds, hydroclimatic characteristics are primarily analyzed to facilitate subsequent bias-corrected hydrologic simulation. Critical results of the analysis are presented as follows.

Multi-year averages of daily discharges at outlets are 30.2 m^3/s in Xiangxi Watershed and 30.5 m^3/s in Zhongzhou Watershed. Annual average numbers of flood peaks (≥ 100 m^3/s) are 75 and 83 for Xiangxi and Zhongzhou Watersheds, respectively. Both rivers are prone to floods in flooding seasons. Precipitation and evaporation have the highest correlation with runoffs, which are 0.89 and 0.76 respectively. The driving force of the two climate conditions for runoffs is stronger than the others.

Both watersheds belong to subtropical monsoon climates, with flood seasons from April to September, dry seasons from October to March of the next year, and no frozen seasons. Zhongzhou Watershed is more susceptible to heavy precipitation in summer than Xiangxi Watershed, which may be associated with high vulnerability of southeastern coastal areas of China to typhoons. The annual average number of precipitation days in Xiangxi Watershed is 128.8, while that in Zhongzhou Watershed is 159.6. The numbers of days precipitation exceeding 50 and 100 mm in Xiangxi Watershed are 9 (0.49% of total days) and 1 (0.05%), respectively; they are 36 (1.97%) and 8 (0.04%) for Zhongzhou Watershed, respectively. The highest temperature in Xiangxi Watershed is 41.5 ℃ and the lowest is -4.5 ℃; in Zhongzhou Watershed, they are 38.7 and -0.9 ℃, respectively. The numbers of days with above 35 °C in Xiangxi and Zhongzhou Watersheds are 40.6 and 39.8, respectively. Heavy precipitation dominates streamflow changes. This indicates the existence of extreme climatic events in both watersheds.

(3) Research Necessity

Both watersheds as well as many others in southern China are prone to hydrologic hazards, i.e., floods, droughts and the related events (e.g., landslides, mudslides, or mountain torrents). Changing climates, dense populations, and prosperous economies in the watersheds aggravate socio-economic and eco-environmental effects of the hazards. Particularly, both watersheds suffer from varying degrees of economic losses each year. For instance, heavy precipitation triggered a 50-year flood in Xiangxi Watershed on August 23, 2011. As a result, streamflow overtopped river banks, flooded riverine communities, destroyed national road sections, affected over 22,000 people, and caused severe economic losses. In October 2004, the drought area of Zhongzhou Watershed was 7,093 hectare, including 3,000 hectare of serious drought areas. Meanwhile, extreme weather shows higher risks and severer impacts under climate change (McBean et al., 2019).

Reliable hydrologic forecasting is highly required for guiding strategic flood control, drought mitigation, policy making, engineering practices, and public engagement in addressing potential hydrologic hazards over the two watersheds under climate change. This depends on the reliability of hydrologic modeling in reproducing climatic impacts on historical hydrologic regimes. One challenge for this is the existence of biases in hydrologic modeling, and another is diverse uncertainties (e.g., hydrologic models, bias-correction methods, and temporal scales) in correcting them. Hydrologic modeling and forecasting without integrated analyses of the uncertainties in bias correction is hardly reliable for providing scientific decision support, and may aggravate socio-economic and eco-environmental consequences of hydrologic hazards under climate change. Thus, this study focuses on the analyses of diverse uncertainties (especially their interactive impacts on hydroclimatic responsive relationships) in bias-corrected hydrologic simulation of Xiangxi and Zhongzhou Watersheds in southern China.

3. Methodology

(1) Research Framework

An integrated approach is proposed to systematically analyze diverse uncertainties in bias-corrected hydrologic simulations (especially interactive impacts of uncertainties). It is named as integrated bias-corrected hydrologic modeling uncertainty analysis (IBCHMUA) in this study. Its flowchart is shown in Figure 2. Specifically, (i) the historical observations of runoffs and the related climatic conditions are extracted through fundamental data processing; (ii) two hydrologic models are employed to simulate climatic impacts on runoffs; (iii) according to five predictor selection schemes, a set of datasets involving hydrologic simulations and hydroclimatic observations are constructed for bias corrections; (iv) for every dataset, biases in hydrologic simulation are corrected by DiPMI and other methods through four different approaches (e.g., day-to-day or distributional corrections); and (v) twelve indicators such as the Nash-Sutcliffe efficiency coefficient (Krause et al., 2005) and the root mean square error (Ye et al., 2014) are introduced to represent the multi-dimensional accuracies of all simulations.

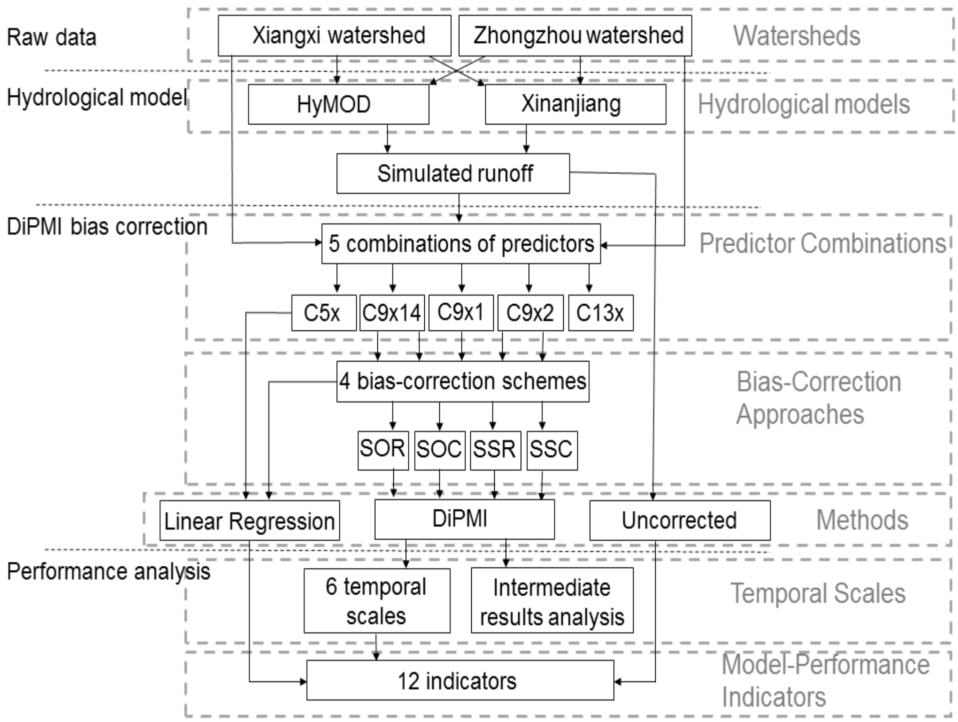


Figure 2. Flowchart of IBCHMUA (all abbreviations are specified in Tables 1 and 2.

(2) DiPMI

DiPMI (i.e., discrete principal-monotonicity inference) is an advanced statistical classifier for quantifying concurrent variations of dependent variables (Y) with independent variables (X) through recursive classifications of X-Y samples and statistical inferences of classified results. The fundamental algorithm of DiPMI is mainly based on the theories of multivariate variance and discrimination analyses (Cheng et al., 2016a). The algorithm is illustrated in Figure 3, and is briefly introduced as follows.

Step 1: A normality test is conducted to analyze whether the predictand (y) (e.g., observed runoffs in this study) is normally distributed. If the test does not pass, y is converted by a discrete method (Cheng et al., 2016a) to a normal distribution based on the inversible transformation between the [0, 1] uniform distribution and the cumulative distribution of y. The distribution of y is restored by the discrete method after construction of a DiPMI-based bias-correction model.

Step 2: Two sub-modules, i.e., classification and clustering, are employed to group the variations of y with multiple predictors (X) (e.g., simulated runoffs and observed climates in this study). Multi-year paired data series (X, y) are classified as a series of different nodes in the former sub-module, while the latter clusters any two similar nodes of (X, y). Both are recursively conducted to discretize the responsive relationship between X and y as nodes (constituting a DiPMI model) (Cheng et al., 2017; Cheng et al., 2017).

Steps 3&4: The Nash coefficient (Ye et al., 2014) is introduced to quantify model accuracies. Two model parameters N_{min} (i.e., the minimum sample size in nodes) and α (i.e., the statistical significance level) are calibrated through greedy search (Steven et al., n.d.) and a two-stage calibration strategy (Cheng et al., 2016a). The performance of the calibrated DiPMI model is verified through another (X, y) series.

DiPMI was initially developed for modeling complicated hydrologic systems under irregular nonlinearities, multivariate dependencies, and data uncertainties (Cheng et al., 2016a). One unique advantage of this method is that it could reveal the joint, dominant, interactive, and non-monotonic impacts of multiple influencing factors (e.g., climatic conditions) on hydrologic variables based on rigorous statistical inferences. As an emerging advanced statistical method, DiPMI may outperform conventional bias-correction methods (e.g., linear regression). Thus, both methods are incorporated into the framework of IBCHMUA to address the uncertainty of bias-correction methods.

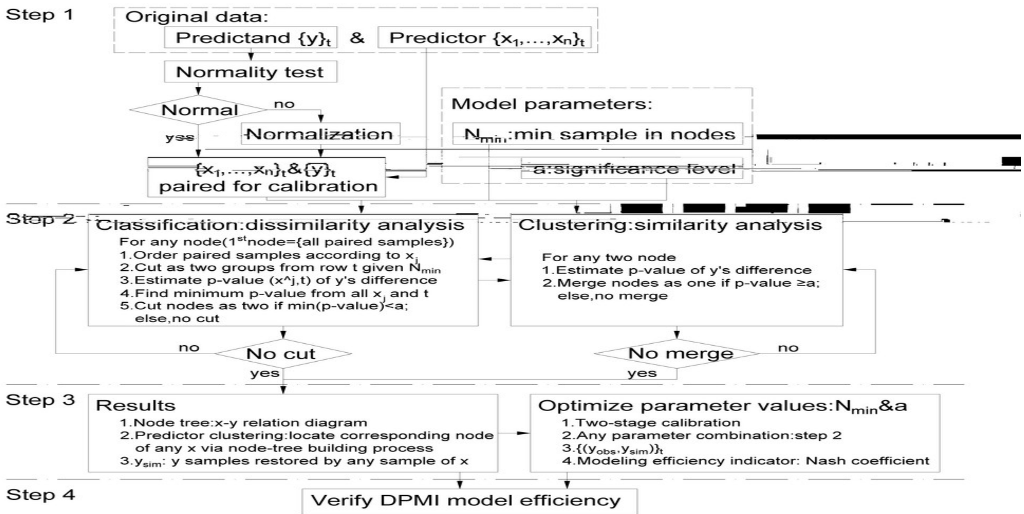


Figure 3. Procedures of discrete principal-monotonicity inference.

(3) Uncertainty of Hydrologic Models

BCHS (i.e., bias-corrected hydrologic simulation) consists of multiple modules, e.g., hydrologic modeling, bias correction, and predictor selection. For each module, multiple models, methods, approaches or options are available, and the uncertainty may pose significant impacts on BCHS results and findings. These uncertainties are named as method uncertainties to structuralize various uncertainties that are taken into account in this study. To reflect each of them, multiple options are employed in the IBCHMUA approach. These options are briefly explained as follows.

It has been reported that the uncertainty of hydrologic models has an essential contribution to hydro-simulation uncertainties. To reflect such an uncertainty, two hydrologic models (i.e., HyMOD and Xinanjiang) are calibrated through the SCEUA algorithm (Tu & Smith, 2018) to simulate runoffs at outlets of the two watersheds (i.e., Xiangxi and Zhongzhou). The HyMOD model (Yin et al., n.d.) conceptualizes runoff generation by a water storage capacity curve, and flow routing by two linear tanks. In comparison, the Xinanjiang model (Yuan et al., 2008) characterizes hydrologic processes as three modules, i.e., three-layer evapotranspiration, runoff generation, and runoff routing. Both models are suitable for southern China of humid climates and their suitability has been verified in previous studies (Liu et al., 2018; Wi et al., 2015; Zhang et al., 2016).

(4) Uncertainty of Bias-Correction Methods & Schemes

In consideration of the uncertainty of bias-correction methods, two methods (i.e., DiPMI and linear regression) are used to correct biases of the two hydrologic models. Meanwhile, multiple schemes exist for any bias-correction method, and such an uncertainty may also significantly influence hydrologic simulations (Chen et al., 2013; Haerter et al., 2011). For instance, correction can focus on either both magnitudes and timing of biases, or overall distributions; the former scheme is suitable for the cases (e.g., flood control) where timing of streamflow is critical, while the latter for those (e.g., engineering design) concentrating on multi-year distributions of streamflow. Besides, the selection of samples for calibration and verification can be either random or chronological at a given ratio (e.g., 4:1); these selections are suitable for stationary and nonstationary cases, respectively, and their differences can help reveal the nonstationarity of hydroclimatic responsive relationships. Accordingly, five bias-correction schemes are proposed as listed in Table 1. In every scheme, 80% and 20% of data series are exacted for calibration and verification, respectively.

Table 1. Five bias-correction schemes.

Abbreviation	Sample pre-processing	Sample selection
SOR	Original samples (X, y): Day-to-day climatic conditions and runoff simulation (X), and runoff observation (y)	Random sampling: randomly extract 4/5 of (X, y) data series for calibration, and the remaining 1/5 for verification
SOC	Original samples	Chronological sampling: extract the first 4/5 of (X, y) data series for calibration, and the remaining 1/5 for verification
SSR	Sorted samples: Sort X by simulated runoff magnitudes (from low to high), and also for y by observed magnitudes	Random sampling
SSC	Sorted samples	Chronological sampling
SUC	Not correct biases	

(5) Uncertainty of Predictor Combinations

Various combinations of predictors (X) (especially climatic conditions) are available for any hydrologic-model bias-correction practice. The variation is related to bias-correction accuracies although the relation may be weaker than that from other uncertainties (e.g., hydrologic models and bias-correction schemes) (Muleta & Nicklow, 2005). In this study, the variation mainly represents the associations of runoff-simulation biases with antecedent climatic conditions of different lag times. Specifically, five lag times between streamflow and climatic conditions are selected as listed in Table 2. In addition to simulated runoffs, four climatic variables, i.e., daily accumulative precipitation (P), daily highest temperature (HT), daily lowest temperature (LT), and daily mean moisture (M), at any lag time are used as predictors in bias-correction modeling based on data availabilities. Cross-comparisons of modeling results under these predictor combinations can differentiate the contributions of incorporating antecedent climatic conditions at different lag times to correcting biases of hydrologic models. This would be helpful for facilitating the other related BCHS practices.

Table 2. Five combinations of predictors in hydro-modeling bias correction.

Abbreviation	Lag time	Selected predictors
C5x	No	R; P, HT, LT, M
C9x14	14 days	R; P, HT, LT, M; P_{14}, HT_{14}, LT_{14}, M_{14}
C9x1	1 day	R; P, HT, LT, M; P_1, HT_1, LT_1, M_1
C9x2	2 days	R; P, HT, LT, M; P_2, HT_2, LT_2, M_2
C13x	Consecutive 2 days	R; P, HT, LT, M; P_1, HT_1, LT_1, M_1; P_2, HT_2, LT_2, M_2

Note: daily accumulative precipitation (P), daily highest temperature (HT), daily lowest temperature (LT), daily mean relative humidity (M), and simulated runoff (R). Subscripts represent the numbers of lag days between streamflow and antecedent climatic conditions.

(6) Uncertainty of Hydro-Modeling Performance Indicators

For any hydrologic or bias-correction model, its accuracy can be represented as various indicators. For instance, correlation coefficients reflect the matchiness of simulation and observation in overall linear/nonlinear trends, error indices for the deviations of simulation with observation, while others for the similarity between them. Any indicator can hardly be suitable for assessing model accuracies from the perspective of all application practices of diverse emphases (Tian & Xu, 2015). To address such an uncertainty, eleven commonly-used indicators are employed to quantify the multi-aspect accuracies of hydrologic modeling and the associated bias correction. The abbreviations, full names, formulas, optimal values, and value ranges of these indicators are specified in Table 3.

Table 3. Indicators of modeling accuracies.

Abbreviation	**Name**	**Formula**	**Perfect/ Interval**
PR	Pearson correlation coefficient	$\frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2}\sqrt{n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y}}$	1/-1~1
KR	Kendall correlation coefficient	$\frac{2\sum_{i<j} \mathrm{sgn}(x_i - x_j)\mathrm{sgn}(y_i - y_j)}{n(n-1)}$	1/-1~1
SR	Spearman correlation coefficient	$1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$	1/-1~1

MAE	Mean absolute error	$\frac{\sum_{i=1}^{n}\lvert y_i - x_i\rvert}{n}$	0/0~+∞
RMSE	Root mean squared error	$\sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$	0/0~+∞
NRE1	Type-1 normalized root mean squared error	$\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n} y_i^2}$	0/0~+∞
NRE2	Type-2 normalized root mean squared error	$\frac{RMSE}{\overline{y}}$	0/0~+∞
RAE	Relative absolute error	$\frac{\sum_{i=1}^{n}\lvert x_i - y_i\rvert}{\sum_{i=1}^{n}\lvert y_i - \overline{y}\rvert}$	0/0~+∞
RRSE	Root relative squared error	$\sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2}}$	0/0~+∞
NSE	Nash-Sutcliffe coefficient	$1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2}$	1/-∞~1
IOA	Similarity coefficient	$1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(\lvert x_i - \overline{x}\rvert + \lvert y_i - \overline{y}\rvert)^2}$	1/-∞~1

Note (taking daily modeling as an example): day i = 1, 2, 3, …, n (n is the total number of samples); x_i: simulated discharge at the i^{th} day; y_i: observed discharge at the i^{th} day; $\overline{x}$: the average of x_i; $\overline{y}$ = the average of y_i; $d_i = rg(x_i) - rg(y_i)$ where rg() is the rank of x_i or y_i for all i.

(7) Non-Method Uncertainties

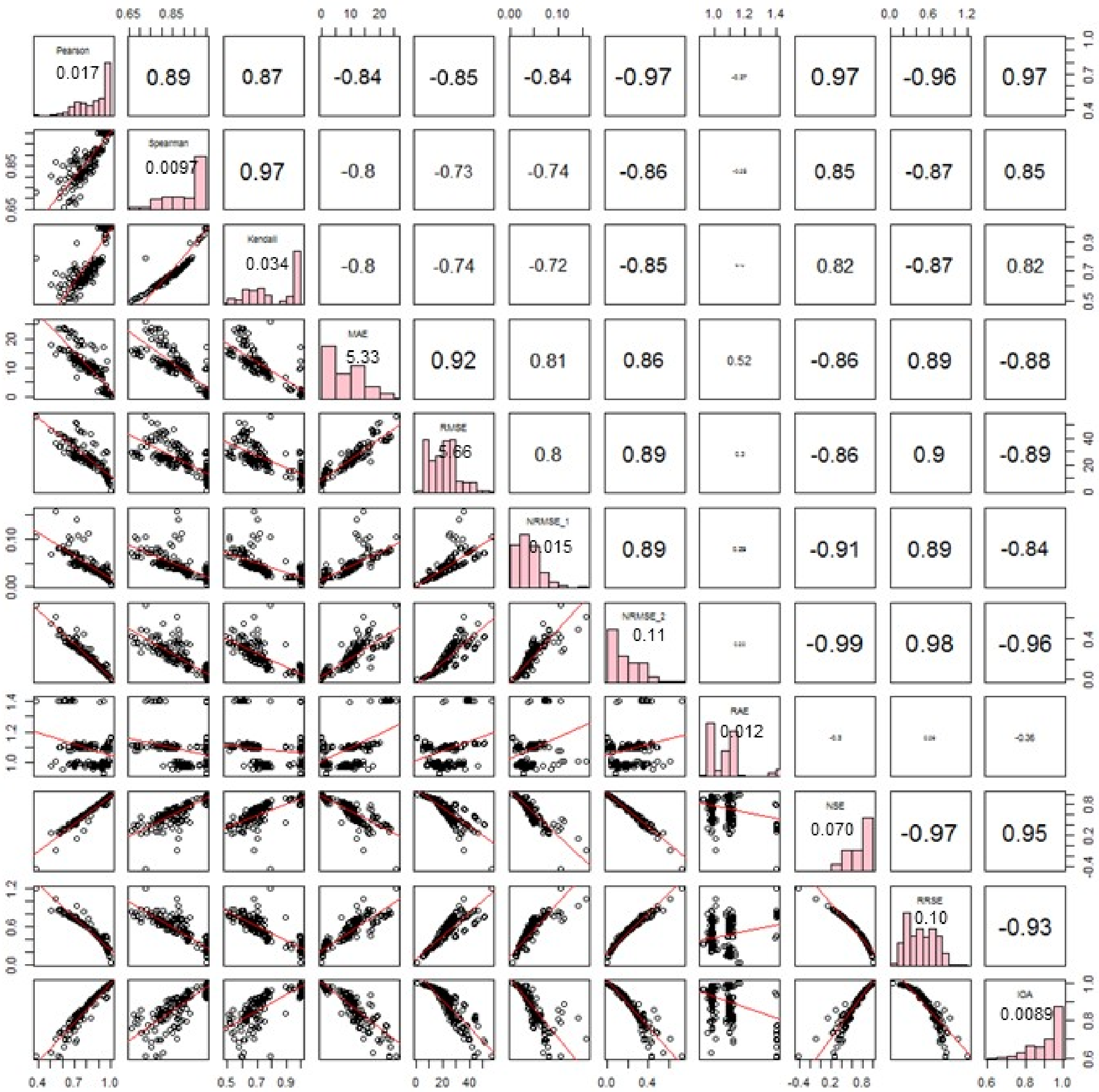
There are also some other uncertainties (or multiplicities) in bias-corrected hydrologic simulation from the perspective of model applications (Ajami et al., 2007; Liu & Gupta, 2007b). For example, the findings of hydroclimatic relationships or modeling practices for one watershed may not be transferable for another. Model users may be interested in low, medium, high, or other magnitudes of streamflow, depending on the discrepant, dynamic or allied importance of these magnitudes for them. Daily, monthly, seasonal or yearly modeling results are required for various water resources management or engineering practices (Brunner et al., 2012). To address these non-method uncertainties, multiple watersheds, streamflow magnitudes, and temporal scales are taken into account in this study. Specifically, (1) two representative watersheds (i.e., Xiangxi and Zhongzhou) of different hydrologic, climatic, geophysical, socio-economic, eco-environmental, and other characteristics in southern China are selected as study areas. The selection is helpful for examining the transferability of key findings of the IBCHMUA approach among different watersheds. (2) Magnitudes of streamflow discharges are refined as six quantile intervals (i.e., 0 to 10%, 10 to 25%, 25 to 50%, 50 to 75%, 75 to 90%, and 90 to 100%) of related simulations or observations. The refining can help reveal the variations of bias-corrected hydrologic simulations and their accuracies with streamflow magnitudes. (3) Modeling results at three temporal scales (i.e., monthly, seasonal, and yearly) are composited to facilitate cross-scale analysis of hydroclimatic relationships and model performances. The relevant modeling results are summarized in Section 5.

4. Impacts of Method Uncertainties

(1) Model-Performance Indicators

A total of 11 indicators are employed to quantify the bias-corrected hydro-modeling accuracy during verification for every combination of hydrologic models, bias-correction methods and schemes, predictor combinations, watersheds, streamflow magnitudes and temporal scales under the diverse uncertainties. The correlation of every pair of the indicators, and the distribution and statistics of every indicator for all combinations are shown in Figure 4. One representative statistic is the coefficient of variation (CV) (Brian et al., 1998) that can characterize the standardized dispersion of the distribution of an indicator under the uncertainties in BCHS. It can be used to reflect the impact of the uncertainties on BCHS accuracies (i.e., the indicators). Meanwhile, the indicators can quantify the impacts of climatic conditions on the trends, absolute magnitudes, relative magnitudes, or other features of runoffs, in addition to indicating BCHS accuracies. Thus, a comparison of the CVs for all indicators implies that the impacts of the uncertainties in BCHS on hydro-modeling accuracies (i.e., on the estimations of climatic impacts on runoffs) vary with performance indicators significantly and generally decrease from the relative magnitudes, through the absolute magnitudes, to the trends of runoffs.

In addition, significant differences exist for the similarities of the indicators. For instance, RAE (i.e., the relative absolute error of a bias-corrected hydrologic model) is significantly different with the other indicators. This implies that the RAE of a hydrologic model calibrated according to the other indicators can hardly be guaranteed and vice versa. This also reflects the significant impacts of the uncertainty of performance indicators on BCHS (e.g., accuracies and results). In contrast, NSE is highly positively/negatively correlated with the other indicators (except RAE); the median of its absolute correlations with the others is equal to 0.91, higher than that for any others. Although NSE cannot perfectly represent all diverse performance indicators (especially RAE), it could be the most representative indicator in BCHS studies. Compared with PR, NRE2, RRSE and IOA (of which the absolute correlations with NSE are higher than 0.90), SR, KR, MAE and RMSE show relatively lower absolute correlations with NSE although the correlations are higher than 0.82 as well as that between RAE and NSE. In the following results analyses, NSE and couple of other indicators are selected to reflect the uncertainty of performance indicators.



	PR	SR	KR	MAE	RMSE	NRE1	NRE2	RAE	NSE	RRSE	IOA
Median	0.920	0.930	0.790	8.90	21.11	0.030	0.140	1.080	0.800	0.440	0.940
CV	0.133	0.101	0.212	0.731	0.515	0.789	0.985	0.106	0.282	0.503	0.096

Figure 4. Distributions, correlations and statistics of bias-corrected hydro-modeling performance indicators under all uncertainties. Upper right: correlation coefficient for every pair of indicators; lower left: scatter plot for every pair of indicators; diagonal

line: distribution and relative variance (i.e., variance / mean) of every indicator; table at the bottom: median, and coefficient of variation (CV = standard deviation / mean) of the distribution of every indicator; performance indicators are defined in Table 3.

(2) Bias-Correction Methods

Table 4 lists the bias-corrected hydro-modeling accuracies for Xiangxi Watershed during the verification period based on two bias-correction methods and three bias-correction schemes. The accuracies under the other combinations of hydrologic models, predictor combinations, and watersheds present similar patterns. Results show that DiPMI is more effective than LM in correcting biases of hydrologic models. The advantages of DiPMI over LM are apparent for all performance indicators. In the bias-correction scheme of SOR, both DiPMI and LM have encouraging performances, e.g., NSE raised by 95.3% and 55.2%, respectively in comparison with original biased hydrologic simulations. In the SOC scheme, the improvement of modeling accuracies is less significant than SOR due to the different foci of the two schemes (i.e., SOR on multi-year streamflow distributions, while SOC on monthly streamflow timing and magnitudes). Besides, modeling accuracies are decreased after bias corrections in some combinations (bold numbers in Table 4) of performance indicators, bias-correction methods, and bias-correction schemes. For example, bias corrections enhance the overall modeling accuracies of hydrologic models (in consideration of the representativeness of NSEs), but lead to higher RAEs (i.e., the relative absolute errors) for the verification period. The cause for this might be the nonstationarity of hydro-model biases or rainfall-runoff relationships between calibration and verification periods. A bias-corrected hydrologic model built for the calibration period may over-correct model biases that differ for the calibration and verification periods, and performs worse than the original hydrologic model in the verification period. This points out the potential limitation of bias corrections for nonstationary rainfall-runoff relationships, and the necessity of applying multiple performance indicators in evaluating bias-corrected hydrologic simulations.

Table 4. Verification accuracies of hydrologic simulations through two bias-correction methods (DiPMI and LM) for Xiangxi Watershed in southern China. Performance indicators are defined in Table 3; bias-correction schemes (SUC, SOC and SOR) are defined in Table 1.

Indicators	**SUC**	**DiPMI-SOC**	**DiPMI-SOR**	**LM-SOC**	**LM-SOR**
KR	**0.61**	0.63	0.99	**0.54**	0.82
RMSE	26.19	25.14	6.99	25.88	11.76
RAE	**1.07**	**1.10**	**1.13**	**1.10**	**1.09**
NSE	0.52	0.57	0.96	0.55	0.90

The impacts of bias-correction methods (i.e., DiPMI and LM) on hydrologic simulations under combinations of watersheds, hydrologic models, temporal scales (e.g., monthly or yearly), bias-correction schemes, and performance indicators are illustrated in Figure 5. Results verify the advantages of DiPMI over LM in correcting biases of hydrologic models, although LM performs better than DiPMI in few cases. Since performance indicators can reflect the impacts of climate change on runoffs, Figure 5 shows the estimated climatic impacts on the streamflow of southern China significantly vary with bias-correction methods for single months, but not for the entire verification period. Namely, the impacts of the uncertainty of bias-correction methods on hydrologic modeling accuracies (or the estimations of climatic impacts on runoffs) increase from yearly to monthly scales. Additionally, the differences of modeling accuracies between bias-correction methods are higher in the SOR scheme than those in the SSR scheme. This implies the impacts of the uncertainty of bias-correction methods significantly vary with bias-correction schemes (e.g., decreasing from SOR to SSR). Besides, it is also shown that the impacts of the uncertainty of bias-correction methods do not significantly vary with hydrologic models and present significant spatial heterogeneity for different watersheds in southern China.

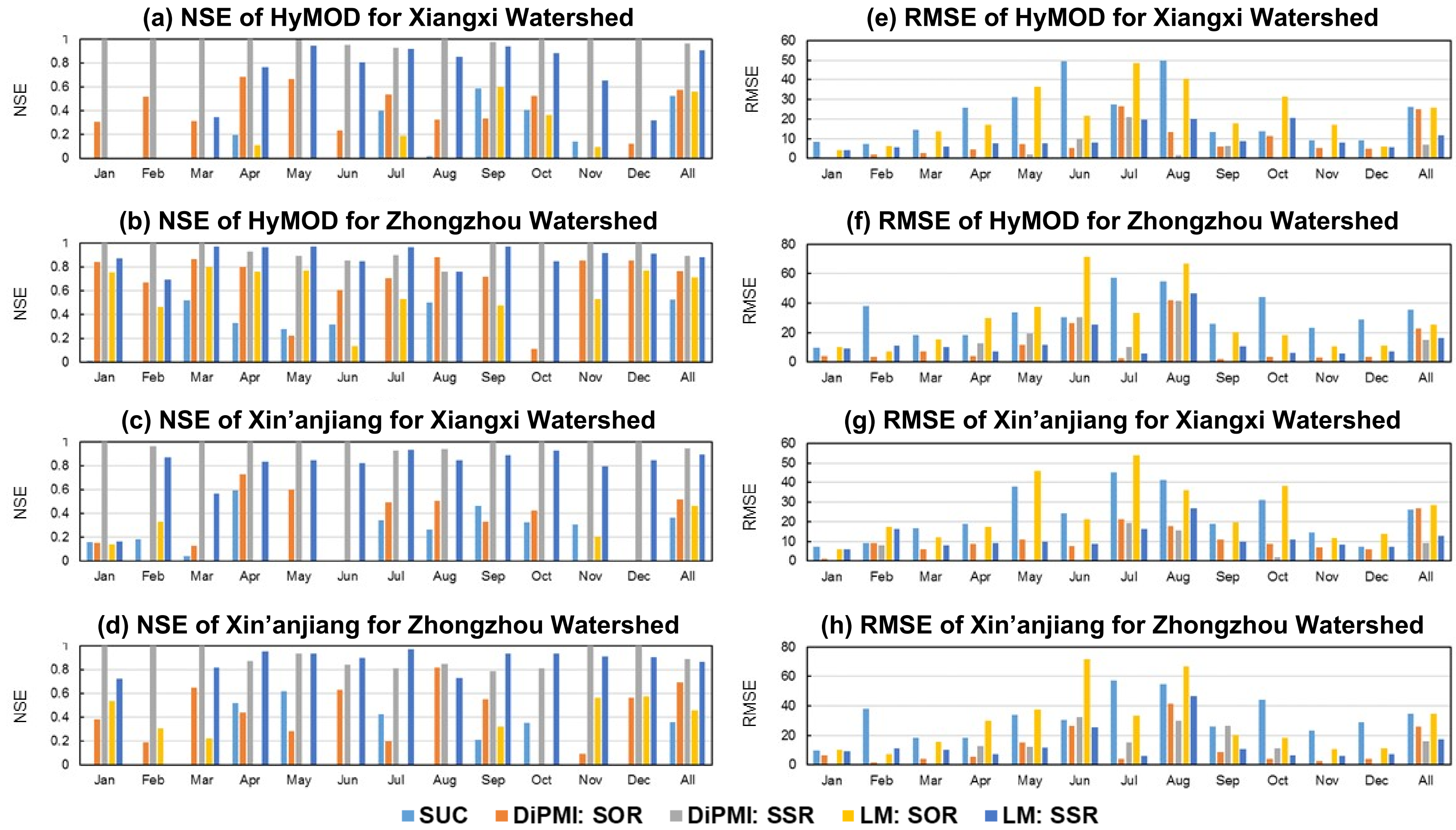


Figure 5. Verification accuracies of hydrologic models (HyMOD and Xin'anjiang) corrected by DiPMI and LM for watersheds (Xiangxi and Zhongzhou) in southern China. Performance indicators (NSE and RMSE) are defined in Table 3; bias-correction schemes (SUC, SOR and SSR) are defined in Table 1.

(3) Hydrologic Models

To examine the impact of the uncertainty of hydrologic models on BCHS, we analyzed the verification accuracies of two hydrologic models (i.e., HyMOD and Xin’anjiang) for the watersheds in southern China under representative scenarios of bias-correction schemes and performance-indicator selections. The relevant results are presented in Table 5. Generally, HyMOD is more capable of capturing the hydrologic processes in southern China under the impact of climate change than Xin’anjiang, which does not significantly differ for various performance indicators; its advantages over Xin’anjiang are shrunk after the biases of original hydrologic simulations being corrected. Meanwhile, HyMOD cannot outperform Xin’anjiang in all cases. For instance, both NRE2 and RRSE of the original HyMOD-based simulation of Zhongzhou Watershed are higher than those of Xin’anjiang, implying that Xin’anjiang performs better than HyMOD in simulating the relative magnitudes of runoffs in southern China under climate change. Furthremore, we may conclude that the uncertainty of hydrologic models poses significant impacts on BCHS accuracies and on the estimations of climatic impacts on runoffs in southern China, and that the significance varies with bias-correction schemes (e.g., decreasing after bias correction).

Table 5. Verification accuracies of two hydrologic models (HM and XAJ) for the watersheds (Xiangxi and Zhongzhou) in southern China under various scenarios of bias-correction schemes (SUC, SOR and SSR in Table 1) and performance-indicator selections (NSE, NRE2 and RRSE in Table 3). HM: the HyMOD hydrologic model; XAJ: the Xin’anjiang hydrologic model.

Watershed	SUC: HM			SUC: XAJ		
	NSE	NRE2	RRSE	NSE	NRE2	RRSE
Xiangxi	0.52	0.29	0.69	0.36	0.40	0.79
Zhongzhou	0.54	**0.55**	**1.16**	0.36	**0.36**	**0.80**
	SOR: HM			SOR: XAJ		
	NSE	NRE2	RRSE	NSE	NRE2	RRSE
Xiangxi	0.58	0.26	0.65	0.52	0.30	0.69
Zhongzhou	0.77	0.16	0.48	0.70	0.21	0.55
	SSR: HM			SSR: XAJ		
	NSE	NRE2	RRSE	NSE	NRE2	RRSE
Xiangxi	0.97	0.020	0.18	0.95	0.034	0.23
Zhongzhou	**0.89**	0.074	0.32	**0.89**	0.080	0.34

(4) Bias-Correction Schemes

In this study, five bias-correction schemes (or literally four, i.e., SOR, SOC, SSR and SSC, and the scheme of no bias correction as the baseline, i.e., SUC) are applied. Their foci differ from each other. SOR and SOC emphasize the timing of runoffs (crucial for water resources management) under the impacts of climate change, while SSR and SSC for the multi-year distribution of runoffs (especially important for relevant engineering designs). On the other hand, SOR and SSR focus on climatic impacts on runoffs in the entire historical period, while SOC and SSC on their nonstationarity (or temporal change) within the period. Comparing them with SUC can reveal the biases of original hydrologic simulations in these different aspects, and comparing all schemes can examine the impacts of the uncertainty of bias-correction schemes on hydrologic simulations.

Some representative results (i.e., verification accuracies of the hydrologic models corrected by the DiPMI method for the watersheds in southern China) are shown in Figure 6. They verify a few of existing findings, e.g., the significant improvement of modeling accuracies by bias correction, and the higher accuracies of hydrologic models in reproducing runoff distributions than timing. In addition, they also reveal a series of new findings. For instance, the overall impacts of climate change on multi-year distributions of runoffs are higher than those on runoff timing. The nonstationarity of rainfall-runoff relationships exists for the watersheds in southern China and poses relatively insignificant impacts on hydrologic simulations; meanwhile, it decreases from Zhongzhou to Xiangxi Watersheds, implying higher impacts of human activities on runoffs in the former watershed than the latter, and does not significantly vary with hydrologic models and performance indicators. Besides, the impacts of the uncertainty of bias-correction schemes on the accuracies of hydrologic simulations (reflecting the estimated climatic impacts on runoffs) are significant for all combinations of watersheds, hydrologic models and performance indicators, especially for Zhongzhou Watershed.

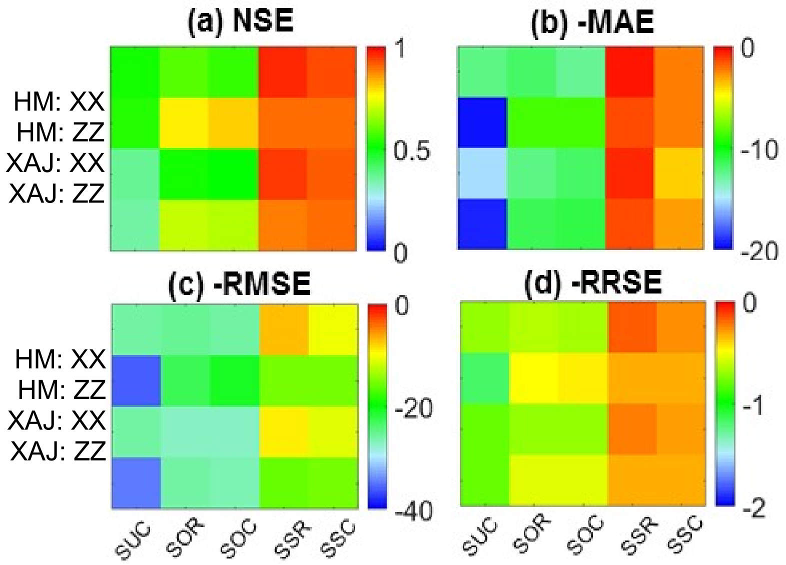


Figure 6. Verification accuracies of hydrologic models for the watersheds in southern

China under various bias-correction schemes (SUC, SOR, SOC, SSR and SSC in Table 1). XX: Xiangxi Watershed; ZZ: Zhongzhou Watershed; HM: the HyMOD hydrologic model; XAJ: the Xin'anjiang hydrologic model; NSE, MAE, RMSE and RRSE: four performance indicators in Table 3.

Furthermore, the intra-annual variations of the impacts of bias-correction schemes on hydrologic simulations are presented in Figure 7. It is shown that, at the monthly scale, the impacts of bias-correction schemes on hydrologic simulations vary with performance indicators significantly. Compared with NSEs (denoting the accuracies of bias-corrected hydrologic models in reproducing the impacts of climatic conditions on both trends and magnitudes of runoffs), RMSEs (denoting those for runoff magnitudes) present V-shape patterns in the Figure. One cause for this is that the accuracies of bias-corrected hydrologic models in simulating runoff magnitudes, or the impacts of climate change on runoff magnitudes show more significant intra-annual variations than those on runoff trends. Another cause is that, in comparison with runoff magnitudes, the impacts of bias-correction schemes on the hydro-modeling accuracies for and the estimated climatic impacts on runoff trends are more significant. In addition, the intra-annual variations of the impacts of bias-correction schemes do not significantly vary with watersheds and hydrologic models; although the impacts for Xiangxi Watershed are intensified from HyMOD to Xin'anjiang, their intra-annual variations seem similar.

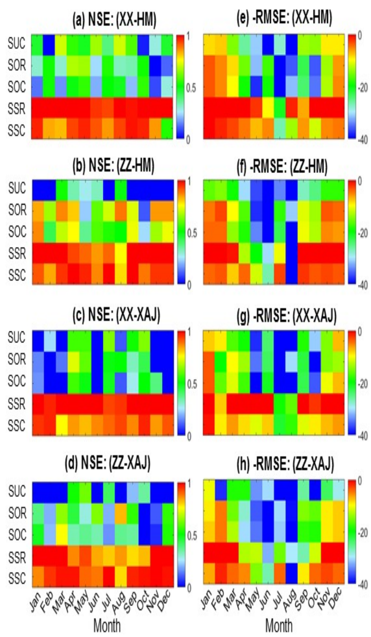


Figure 7. Verification accuracies of hydrologic models for the watersheds in southern China in every month under various bias-correction schemes (SUC, SOR, SOC, SSR

and SSC in Table 1). XX: Xiangxi Watershed; ZZ: Zhongzhou Watershed; HM: the HyMOD hydrologic model; XAJ: the Xin'anjiang hydrologic model; NSE and RMSE: two performance indicators in Table 3.

(5) Predictor Combinations

For any hydrologic simulation, multiple combinations of predictors (e.g., different climatic variables in different lag months) are optional. Such an uncertainty/ multiplicity may diversify hydrologic simulations (e.g., their accuracies representing the impacts of climate change on runoffs) and can differentiate the impacts of various predictors by comparing the simulations. Accordingly, we compared the verification accuracies of bias-corrected hydrologic models for the watersheds in southern China under five predictor combinations (Figure 8). The comparison is helpful for investigating the impacts of the uncertainty/multiplicity of predictor combinations, as well as their variations with the other uncertainties/multiplicities (e.g., hydrologic models, bias-correction schemes, watersheds, performance indicators, and seasons).

Specifically, compared with the other uncertainties, bias-correction schemes pose the most significant impacts on hydrologic simulations under various predictor combinations. According to the foci of the schemes, the impacts of climate change on the multi-year distributions of runoffs are significantly higher than those on runoff timing regardless of the other uncertainties. Besides, the impacts of performance indicators on hydrologic simulations in the bias-correction schemes of SOR and SOC are more significant than those in the other two schemes. This implies that, due to the nonstationarity of climatic impacts on runoffs, the impacts estimation would be more sensitive with the multiplicity of performance indicators. Additionally, the impacts of predictor combinations on hydrologic simulations are less significant than those of the other uncertainties; according to NSEs (i.e., the most representative performance indicator), they significantly vary with watersheds (decreasing from Zhongzhou to Xiangxi Watersheds) and seasons (decreasing from JJA, Son, MAM to DJF) and do not with hydrologic models. Meanwhile, insignificant improvements of hydrologic modeling accuracies from predictor combination C5x to the others reveal that the runoffs in southern China are dominated by the current-day climate under all uncertainties. Generally, the impacts of predictor combinations on hydrologic simulations decrease from bias-correction schemes, performance indicators, seasons, watersheds to hydrologic models.

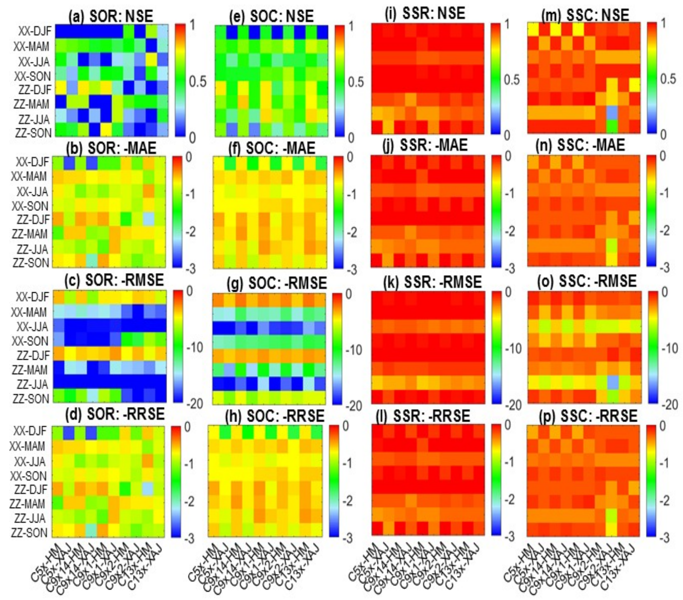


Figure 8. Verification accuracies of bias-corrected hydrologic models for the watersheds in southern China under various predictor combinations. Horizontal axes: predictor combinations (C5x, C9x14, C9x1, C9x2 and C13x in Table 2) and hydrologic models (HM = HyMOD and XAJ = Xin'anjiang); vertical axes: watersheds (XX = Xiangxi and ZZ = Zhongzhou) and seasons (DJF, MAM, JJA and SON); bias-correction schemes (SOR, SOC, SSR and SSC in Table 1); performance indicators (NSE, MAE, RMSE and RRSE in Table 3).

5. Impacts of Non-Method Uncertainties

(1) Watersheds

Two watersheds were selected to represent southern China. Whether and how the accuracies of hydrologic simulations vary with watersheds under all uncertainties can reflect the spatial heterogeneities of climatic impacts on runoffs in southern China, and their interactions with the other diverse uncertainties. To achieve this, analyzed all relevant modeling results. For instance, the enhancements of hydrologic modeling accuracies by bias corrections are more significant for Zhongzhou Watershed than Xiangxi Watershed (Figure 5), especially under the scenarios of HyMOD and dry seasons. Generally, the impacts of climate change on runoffs in Zhongzhou Watershed are higher than those in Xiangxi Watershed (Figure 5), implying the relatively lower impacts of non-climatic factors (e.g., water resources management or other human activities) in Zhongzhou Watershed. As shown in Table 5, the original hydrologic models underestimate the differences of climatic impacts on runoffs between the watersheds in southern China due to the existence of biases and, after bias corrections, the estimated impacts significantly vary with watersheds. Furthermore, the variation with watersheds is shrunk from the HyMOD to Xin'anjiang models (Figure 6) and is higher in the SOR and SOC schemes compared with the other bias-correction schemes (Figure 6 or 7). Besides, the differences of hydrologic simulations between watersheds do not significantly vary with predictor selections (Figure 8).

(2) Streamflow Magnitudes

Climatic impacts on runoffs in southern China may vary with runoff magnitudes (represented as quantile intervals of runoffs as defined in Section 3(7)). To reveal the variational effects and their interactions with the other uncertainties, we analyzed the verification accuracies of bias-corrected hydrologic models under all combinations of watersheds, hydrologic models, predictor selections, runoff magnitudes, bias-correction schemes, and performance indicators (Figure 9).

According to the bias-corrected hydrologic simulations, the overall impacts of climatic conditions on runoff magnitudes and trends in southern China show increasing and decreasing trends with runoff magnitudes, respectively. Namely, drought trends and flood magnitudes are more sensitive with climate change compared with flood trends and drought magnitudes. The impacts of climate change on runoffs increase from runoff timing to distributions, their variations with streamflow magnitudes show opposite trends, and the nonstationarity of rainfall-runoff relationships due to human interferences would intensify these effects. The variations of climatic impacts on runoffs with runoff magnitudes vary significantly with predictor selections in the bias-correction scheme of SOR, while not in the other schemes (i.e., SOC, SSR and SSC). This may be because the latter schemes cannot eliminate anthropogenic impacts on runoffs or specify temporal variability of rainfall-runoff relationships.

The difference of predictor combinations mainly originates the lag time (e.g., 0, 1, 2 or 14 lag days) between climatic conditions and runoffs. In the SOR scheme, the impacts of such a difference on the variations of climatic impacts on runoffs with runoff magnitudes differ for the combinations of watersheds and hydrologic models. Take the impacts of climatic conditions on the runoffs of Xiangxi Watershed estimated by bias-corrected HyMOD models as an example, the impacts on the lowest runoffs (i.e., Q10) are the highest for the climatic conditions in the current, lag-1 and lag-2 days and are the lowest for those in the current days, while the impacts on the highest runoffs (Q100) are the highest for the climatic conditions in the current, lag-1 and lag-2 days and the lowest for those in the current and lag-1 days. Although both watersheds and hydrologic models pose significant impacts on the variations of rainfall-runoff relationships with runoff magnitudes, no significant patterns are found for the impacts. Generally, climatic impacts on runoffs in southern China significantly vary with runoff magnitudes, which further varies with bias-correction schemes, performance indicators, predictor combinations, hydrologic models, and watersheds.

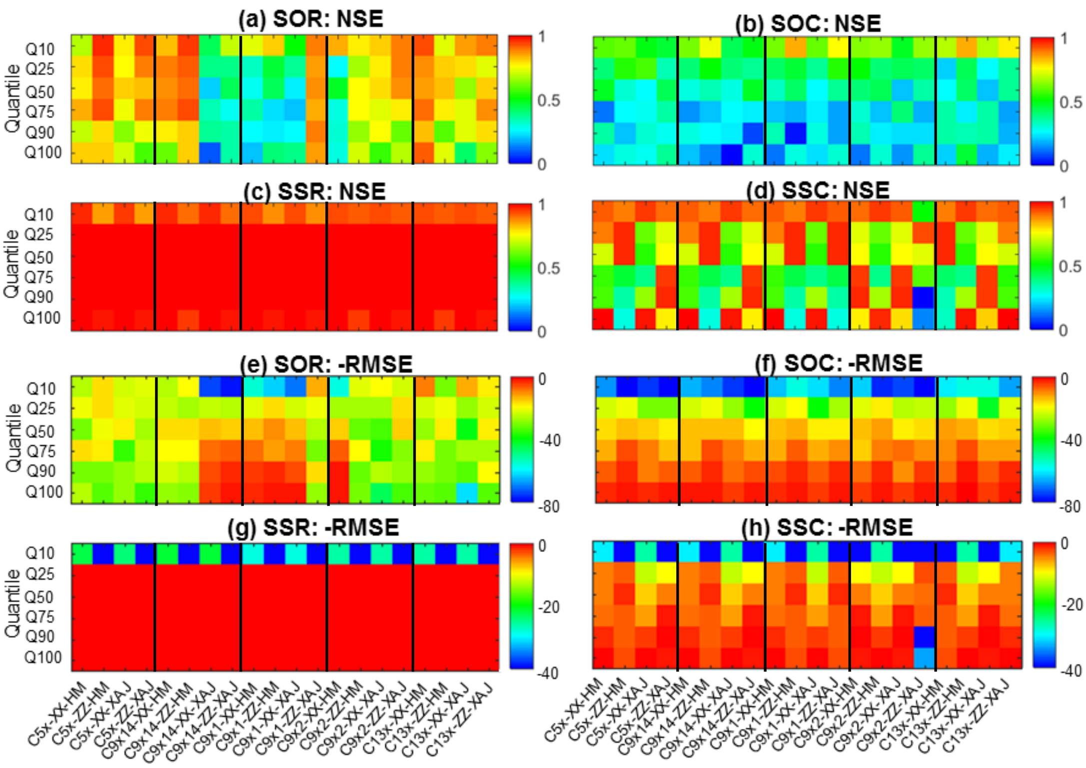


Figure 9. Verification accuracies of bias-corrected hydrologic models in modeling various runoff magnitudes for the watersheds in southern China. Horizontal axes: predictor combinations (C5x, C9x14, C9x1, C9x2 and C13x in Table 2), watersheds (XX = Xiangxi and ZZ = Zhongzhou), and hydrologic models (HM = HyMOD and XAJ = Xin'anjiang); vertical axes: runoff magnitudes represented as quantile intervals (i.e., Q10 = 0 to 10%, Q25 = 10 to 25%, Q50 = 25 to 50%, Q75 = 50 to 75%, Q90 = 75 to 90%, and Q100 = 90 to 100%) of runoffs; bias-correction schemes (SOR, SOC, SSR and SSC in Table 1); performance indicators (NSE and RMSE in Table 3).

(3) Temporal Scales

All analyses above focus on the daily-scale hydrologic simulations for southern China. To reveal the impacts of temporal scales on the simulations, as well as their interactions with every other uncertainty, we estimate the medians of the NSEs at daily and monthly scales, and their differences between both scales. Take the multiplicity/uncertainty of watersheds in southern China as an example, the median of the NSEs during the verification period for all combinations of streamflow magnitudes, predictor combinations, hydrologic models, and bias-correction schemes is calculated for every watershed (i.e., Xiangxi and Zhongzhou). The related results are presented in Figure 10. Due to the significantly low accuracies of the LM bias-correction method and the SUC bias-correction scheme as discussed above, they are excluded in the results. Only two representative predictor combinations (i.e., C13x and C5x in Table 2), and the most representative performance indicator (i.e., the NSE in Table 3) are selected.

Modeling accuracies increase from the daily to monthly scales in most cases, which has been verified in many existing studies and implies the higher impacts of climatic conditions on runoffs in southern China at the monthly scale than those at the daily scale. The increments of climatic impacts on runoffs (except floods corresponding to the highest quantile interval Q100) from the daily to monthly scales show a significantly increasing trend with runoff magnitudes. This is attributable to the significant decreases in climatic impacts at the daily scale, and the insignificant difference of them at the monthly scale as runoff magnitudes increase. The difference of modeling accuracies (or the estimated climatic impacts on runoffs) between temporal scales varies with predictor combinations, watersheds, and hydrologic models, although the variation is not highly significant. In contrast, bias-correction schemes pose significant impacts on the difference that is the highest for the SOC scheme and insignificant for the others. In consideration of the differences of these schemes in characterizing runoff characteristics (e.g., timing versus distributions, and stationarity versus nonstationarity), we may conclude that the estimated nonstationary climatic impacts on runoff timing in southern China significantly vary with temporal scales. Generally, it is shown that the significance of the impacts of temporal scales on hydrologic simulations increases from hydrologic models, watersheds, predictor combinations, bias-correction schemes, to runoff magnitudes.

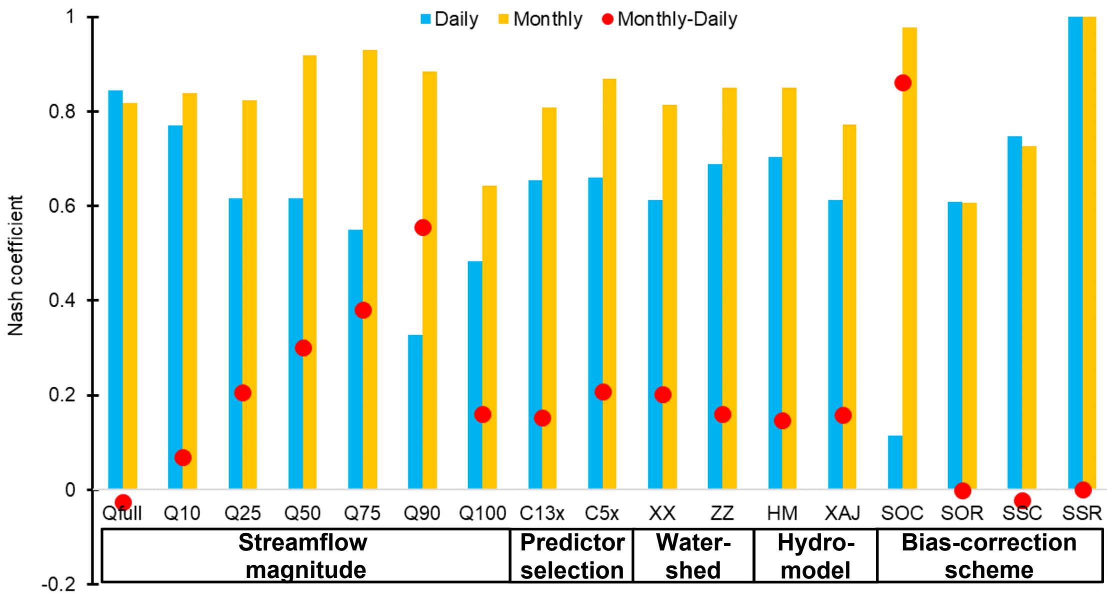


Figure 10. Medians of the Nash coefficients of bias-corrected hydrologic simulations for the watersheds in southern China at daily and monthly scales (and their differences = Monthly-Daily). Streamflow magnitudes: Qfull (full data series), and quantile intervals (i.e., Q10 = 0 to 10%, Q25 = 10 to 25%, Q50 = 25 to 50%, Q75 = 50 to 75%, Q90 = 75 to 90%, and Q100 = 90 to 100%) of multi-year runoff observations; predictor combinations: C13x and C5x (Table 2); watersheds: XX = Xiangxi, and ZZ = Zhongzhou; hydrologic models: HM = HyMOD, and XAJ = Xin'anjiang; bias-correction schemes: SOC, SOR, SSC and SSR (Table 1).

(4) All Uncertainties

To reveal the interactions of the impacts of all uncertainties, we calculate the medians of the NSEs (as the most representative performance indicator) for every predictor combination, every hydrologic model, and every bias-correction scheme under all combinations of temporal scales, watersheds, and streamflow magnitudes. Due to the significantly low accuracies of the LM bias-correction method and the SUC bias-correction scheme as discussed above, they are also excluded in this group of results (Table 6).

It is shown that the modeling accuracies (or the estimated climatic impacts on runoffs) increase from daily to monthly scales, and from Xiangxi to Zhongzhou Watersheds. The accuracies or impacts for various runoff magnitudes are lower than those for the overall runoffs for all predictor combinations, hydrologic models, and most bias-correction schemes at the monthly scale, and for the SSR scheme at the daily scale. As streamflow magnitudes increase, the NSEs decrease for most combinations of temporal scale, watersheds, predictor combinations, hydrologic models, and bias-correction schemes, although they also show nonlinear or insignificant variations for the other combinations. The lag time between precipitation and runoffs tends to be two days for Xiangxi Watershed and zero to one day for Zhongzhou Watershed, and it varies with runoff magnitudes significantly (generally decreasing with them) and temporal scales insignificantly. The HyMOD model is more effective than Xin'anjiang at capturing the impacts of climate change on runoffs in southern China (especially at the monthly scale, for Xiangxi Watershed, and on non-flood or overall runoff magnitudes), although Xin'anjiang also shows higher accuracies in a few of cases. The estimated climatic impacts on runoffs in southern China are the highest for the bias-correction scheme of SSR, do not significantly vary with temporal scales and watersheds for the SOR and SSR schemes, their variations with the SOC and SSC schemes show opposite patterns between the daily and monthly scales. Namely, the variations of the estimated climatic impacts on runoffs with temporal scales, watersheds, and runoff magnitudes are significantly influenced by bias-correction schemes.

Generally, the uncertainties in bias-corrected hydrologic simulations are interactive with each other. As shown in the extension table at the bottom of Table 6, the bias-corrected hydrologic modeling accuracies (or the estimated climatic impacts on runoffs in southern China) increase from daily to monthly scales, from Xiangxi to Zhongzhou Watersheds, from the highest through the lowest to the overall runoff magnitudes, from C9x2, C9x14, C13x, C5x to C9x1 predictor combinations, from Xin'anjiang to HyMOD models, and from SUC, SOC, SOR, SSC to SSR bias-correction schemes. Meanwhile, the impacts of the uncertainties in bias-correction hydrologic simulations decrease from bias-correction schemes, temporal scales, streamflow magnitudes, hydrologic models or predictor combinations, to watersheds.

Table 6. Medians of the verification-period Nash coefficients (NSEs) for every predictor combination (i.e., C5x, C9x14, C9x1, C9x2 and C13x in Table 2), every hydrologic model (i.e., HM = HyMOD and XAJ = Xin'anjiang), and every bias-correction scheme (i.e., SOC, SOR, SSC and SSR in Table 1) for all combinations of temporal scales, southern-China watersheds, and streamflow magnitudes (i.e., all and quantile intervals (Q10 = 0 to 10%, Q25 = 10 to 25%, Q50 = 25 to 50%, Q75 = 50 to 75%, Q90 = 75 to 90%, and Q100 = 90 to 100%) of multi-year runoff observations). The maximum of the Nash coefficients for all predictor combinations, hydrologic models, or bias-correction schemes under every combination of temporal scales, watersheds, and streamflow magnitudes is bolded. The extension table at the bottom lists the medians of the NSEs for every alternative, and their standard deviation (SDV) for all alternatives of every uncertainty/multiplicity.

Temporal scale	Watershed	Streamflow magnitude	Predictor combination					Hydro-model		Bias-correction scheme			
			C5x	C9x1	C9x2	C13x	C9x14	HM	XAJ	SOC	SSC	SOR	SSR
Daily	Xiangxi	All	0.75	0.81	**0.82**	0.81	0.80	**0.83**	0.72	0.55	0.92	0.57	**0.95**
		Q10	0.72	0.68	0.73	**0.77**	0.75	**0.77**	0.73	0.37	0.83	0.57	**0.88**
		Q25	0.59	0.21	0.20	**0.68**	0.50	**0.73**	0.27	0.14	0.27	0.53	**1.00**
		Q50	0.53	0.16	0.47	**0.59**	0.35	**0.47**	0.32	0.07	0.46	0.50	**1.00**
		Q75	0.39	0.12	**0.69**	0.65	0.19	0.26	**0.33**	0.07	0.26	0.52	**1.00**
		Q90	0.27	0.17	**0.70**	0.60	0.27	**0.28**	0.26	0.07	0.28	0.31	**1.00**
		Q100	**0.77**	0.54	0.37	0.32	0.59	**0.52**	0.46	0.03	0.94	0.20	**0.99**
	Zhongzhou	All	**0.85**	0.84	0.59	0.78	0.84	**0.85**	0.71	0.62	0.90	0.67	**0.93**
		Q10	0.74	0.75	0.67	**0.78**	0.77	**0.76**	0.74	0.48	0.77	0.74	**0.80**
		Q25	**0.82**	0.80	0.56	0.56	0.54	0.71	**0.72**	0.18	0.78	0.66	**1.00**
		Q50	0.73	**0.84**	0.52	0.55	0.58	**0.69**	0.56	0.15	0.48	0.67	**1.00**
		Q75	**0.82**	0.04	0.43	0.42	0.47	0.12	**0.65**	0.03	0.12	0.65	**1.00**
		Q90	**0.46**	0.04	0.18	0.28	0.38	0.16	**0.41**	0.04	0.13	0.37	**1.00**
		Q100	0.36	0.12	0.46	**0.71**	0.23	0.37	**0.37**	0.09	0.22	0.37	**0.95**
Monthly	Xiangxi	All	0.70	0.75	0.78	**0.81**	0.74	**0.78**	0.76	0.39	0.92	0.43	**1.00**
		Q10	0.91	0.88	**0.92**	0.85	0.85	**0.90**	0.80	0.99	0.66	-0.75	**1.00**

	Q25	0.80	0.87	**0.94**	0.78	0.86	**0.90**	0.76	0.99	0.66	0.22	**1.00**
	Q50	0.93	**0.94**	0.89	0.91	0.93	**0.92**	0.90	0.99	0.68	0.63	**1.00**
	Q75	0.85	0.88	**0.88**	0.86	0.85	**0.88**	0.87	0.99	0.61	0.69	**1.00**
	Q90	0.89	0.90	**0.90**	0.89	0.83	**0.89**	0.89	0.91	0.65	0.76	**1.00**
	Q100	0.65	0.68	0.65	**0.75**	0.63	0.67	**0.73**	0.36	0.61	0.77	**1.00**
Zhongzhou	All	0.82	**0.83**	0.66	0.82	0.82	**0.84**	0.76	0.58	0.92	0.49	**1.00**
	Q10	0.93	**0.94**	0.81	0.91	0.93	**0.93**	0.91	0.99	0.71	0.07	**1.00**
	Q25	0.90	0.90	0.84	0.86	**0.92**	**0.90**	0.89	0.99	0.75	0.32	**1.00**
	Q50	**0.96**	0.93	0.87	0.89	0.90	**0.92**	0.88	0.99	0.78	0.63	**1.00**
	Q75	**0.95**	0.89	0.87	0.87	0.87	**0.90**	0.87	0.99	0.75	0.65	**1.00**
	Q90	**0.95**	0.90	0.83	0.89	0.89	**0.89**	0.89	0.95	0.72	0.70	**1.00**
	Q100	0.68	0.79	**0.80**	0.64	0.74	0.72	**0.73**	0.21	0.73	0.66	**1.00**

Medians of NSEs for every alternative, and their standard deviation (SDV)

Temporal scale	Daily	Monthly	**SDV**				
	0.56	0.87	**0.22**				
Watershed	Xiangxi	Zhongzhou	**SDV**				
	0.74	0.77	**0.02**				
Streamflow magnitude	All	Q10	Q25	Q50	Q75	Q90	Q100	**SDV**
	0.81	0.78	0.77	0.76	0.72	0.71	0.64	**0.05**
Predictor combination	C5x	C9x1	C9x2	C13x	C9x14	**SDV**		
	0.79	0.81	0.72	0.78	0.76	**0.03**		
Hydrologic model	HyMOD	Xin'anjiang	**SDV**					
	0.78	0.73	**0.03**					
Bias-correction scheme	SOC	SSC	SOR	SSR	**SDV**			
	0.44	0.69	0.57	1.00	**0.24**			

6. Conclusions

In this study, an integrated bias-corrected hydro-modeling uncertainty analysis (i.e., IBCHMUA) approach based on DiPMI (i.e., discrete principal-monotonicity inference) was developed to investigate the impacts of various uncertainties on BCHS (i.e., bias-corrected hydrologic simulations). These uncertainties were classified as two groups, i.e., method uncertainties (e.g., performance indicators, bias-correction methods, hydrologic models, bias-correction schemes, and predictor combinations) and non-method uncertainties (e.g., watersheds, streamflow magnitudes, and temporal scales). The approach was applied to two representative watersheds (Xiangxi and Zhongzhou) in southern China. As summarized below, a series of findings regarding the impacts of these uncertainties were revealed through IBCHMUA.

(1) The impacts of the uncertainties in BCHS on hydro-modeling accuracies (i.e., on the estimations of climatic impacts on runoffs) vary with performance indicators significantly and generally decrease from the relative magnitudes, through the absolute magnitudes, to the trends of runoffs. This points out the necessity of applying multiple performance indicators in evaluating BCHS. Although the Nash coefficient cannot perfectly represent all diverse performance indicators, it could be the most representative indicator in BCHS studies.

(2) DiPMI is more effective than one commonly-used method (i.e., multiple linear regression) in correcting biases of hydrologic models. The impacts of the uncertainty of bias-correction methods on hydro-modeling accuracies (or the estimations of climatic impacts on runoffs) increase from yearly to monthly scales. The impacts of the uncertainty of bias-correction methods significantly vary with bias-correction schemes, do not with hydrologic models, and present significant spatial heterogeneity for watersheds in southern China.

(3) HyMOD is more capable of capturing the hydrologic processes in southern China under the impact of climate change than Xin'anjiang, and Xin'anjiang performs better in simulating the relative magnitudes of runoffs. The uncertainty of hydrologic models poses significant impacts on BCHS accuracies (or the estimations of climatic impacts on runoffs), and the significance varies with bias-correction schemes (e.g., decreasing after bias correction). The nonstationarity of rainfall-runoff relationships decreases from Zhongzhou to Xiangxi Watersheds, implying higher impacts of human activities on runoffs in the former watershed than the latter, and does not significantly vary with hydrologic models and performance indicators.

(4) The impacts of the uncertainty of bias-correction schemes on the accuracies of hydrologic simulations (or the estimated climatic impacts on runoffs) are significant for all combinations of watersheds, hydrologic models and performance indicators, especially for Zhongzhou Watershed. At the monthly scale, the impacts of bias-correction schemes on BCHS vary with performance indicators significantly. The intra-annual variations of the impacts of bias-correction schemes do not significantly vary with watersheds and hydrologic models. Compared with the other uncertainties, bias-correction schemes pose the most significant impacts on BCHS under various predictor combinations. Due to the nonstationarity of climatic impacts on runoffs, the impact estimation is sensitive with the multiplicity of performance indicators.

(5) The impacts of predictor combinations on BCHS are less significant than those of the other uncertainties, significantly vary with watersheds (decreasing from Zhongzhou to Xiangxi Watersheds) and seasons (decreasing from JJA, Son, MAM to DJF) and do not with hydrologic models. The runoffs in southern China are dominated by the current-day climate under all uncertainties. The impacts of predictor combinations on hydrologic simulations decrease from bias-correction schemes, performance indicators, seasons, watersheds to hydrologic models.

(6) The enhancements of hydrologic modeling accuracies by bias corrections are more significant for Zhongzhou Watershed than Xiangxi Watershed. The impacts of climate change on runoffs in Zhongzhou Watershed are higher than those in Xiangxi Watershed, implying the relatively lower impacts of non-climatic factors (e.g., water resources management or other human activities) in Zhongzhou Watershed. The original hydrologic models underestimate the differences of climatic impacts on runoffs between the watersheds in southern China due to the existence of biases and, after bias corrections, the estimated impacts significantly vary with watersheds. The variation with watersheds is shrunk from the HyMOD to Xin'anjiang models and is higher in the SOR and SOC schemes compared with the other bias-correction schemes. The differences of hydrologic simulations between watersheds do not significantly vary with predictor selections.

(7) The overall impacts of climatic conditions on runoff magnitudes and trends in southern China show increasing and decreasing trends with runoff magnitudes, respectively. The impacts of climate change on runoffs increase from runoff timing to distributions, their variations with streamflow magnitudes show opposite trends, and the nonstationarity of rainfall-runoff relationships due to human interferences would intensify these effects. The variations of climatic impacts on runoffs with runoff magnitudes vary significantly with predictor selections in the bias-correction scheme of SOR, while not in the other schemes. Climatic impacts on runoffs in southern China significantly vary with runoff magnitudes, which further varies with bias-correction schemes, performance indicators, predictor combinations, hydrologic models, and watersheds.

(8) The impacts of climatic conditions on runoffs in southern China at the monthly scale are higher than those at the daily scale. The increments of climatic impacts on runoffs (except floods) from the daily to monthly scales show a significantly increasing trend with runoff magnitudes. The estimated nonstationary climatic impacts on runoff timing in southern China significantly vary with temporal scales. The significance of the impacts of temporal scales on BCHS increases from hydrologic models, watersheds, predictor combinations, bias-correction schemes, to runoff magnitudes.

(9) Generally, the uncertainties in BCHS are interactive with each other. The bias-corrected hydrologic modeling accuracies (or the estimated climatic impacts on runoffs in southern China) increase from daily to monthly scales, from Xiangxi to Zhongzhou Watersheds, from the highest through the lowest to the overall runoff magnitudes, from C9x2, C9x14, C13x, C5x to C9x1 predictor combinations, from Xin'anjiang to HyMOD models, and from SUC, SOC, SOR, SSC to SSR bias-

correction schemes. Meanwhile, the impacts of the uncertainties in BCHS decrease from bias-correction schemes, temporal scales, streamflow magnitudes, hydrologic models or predictor combinations, to watersheds.

These findings are of great significance for hydrologic simulations under uncertainties, as well as for water resources management practices over southern China and the other similar watersheds. As one of few attempts to comprehensively examine diverse uncertainties in BCHS, this study can be improved in various aspects. For example, data uncertainty, spatial-scale uncertainty, and uncertainty of climate models may contribute significantly to the uncertainty of hydrologic simulations. An analysis of predictor interactions may help improve simulation efficiencies. A systematic multifactorial analysis would help quantify both individual and interactive impacts of all uncertainties in BCHS. Many subsequent studies will be conducted to achieve these and some other potential improvements of this study.

Acknowledgments

This research was supported by the National Key Research and Development Plan (2016YFC0502800), the Natural Sciences Foundation (51520105013, 51679087), the 111 Program (B14008) and the Natural Science and Engineering Research Council of Canada. Data were collected and are available from Hydrological Yearbook of the People's Republic of China at the National Library of China, and China National Meteorological Information Center (http://data.cma.cn/site/index.html).

References

Addor, N., Rössler, O., Köplin, N., Huss, M., Weingartner, R., & Seibert, J. (2014). Robust changes and sources of uncertainty in the projected hydrological regimes of Swiss catchments. Water Resources Research, 50(10), 7541-7562.

Arkesteijn, L., & Pande, S. (2013). On hydrological model complexity, its geometrical interpretations and prediction uncertainty. Water Resources Research, 49(10), 7048-7063.

Beven, K., & Binley, A. (1992). The future of distributed models: model calibration and uncertainty prediction. Hydrological processes, 6(3), 279-298.

Beven, K., & Binley, A. (1992). The future of distributed models: model calibration and uncertainty prediction. Hydrological processes, 6(3), 279-298.

Buizza, R., Houtekamer, P. L., Pellerin, G., Toth, Z., Zhu, Y., & Wei, M. (2005). A comparison of the ECMWF, MSC, and NCEP global ensemble prediction systems. Monthly Weather Review, 133(5), 1076-1097.

Chen, J., Brissette, F. P., Chaumont, D., & Braun, M. (2013). Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America. Water Resources Research, 49(7), 4187-4205.

Cheng, G. H., Huang, G. H., Dong, C., Baetz, B. W., & Li, Y. P. (2017). Interval Recourse Linear Programming for Resources and Environmental Systems Management under Uncertainty. Journal of Environmental Informatics, 30(2).

Cheng, G., Dong, C., Huang, G., Baetz, B. W., & Han, J. (2016a). Discrete principal−monotonicity inference for hydro−system analysis under irregular nonlinearities, data uncertainties, and multivariate dependencies. Part I: methodology development. Hydrological Processes, 30(23), 4255-4272.

Cheng, G., Dong, C., Huang, G., Baetz, B. W., & Han, J. (2016b). Discrete principal−monotonicity inference for hydro−system analysis under irregular nonlinearities, data uncertainties, and multivariate dependencies. Part II: Applied to streamflow simulation in the Xingshan Watershed. Hydrological Processes, 30(23), 4273-4291.

Cheng, G., Huang, G., Dong, C., Zhou, X., Zhu, J., & Xu, Y. (2017). Climate classification through recursive multivariate statistical inferences: a case study of the Athabasca River Basin, Canada. International Journal of Climatology, 37, 1001–1012.

Cheng, G., Huang, G., Dong, C., Zhu, J., Zhou, X., & Yao, Y. (2017). High-resolution projections of 21st century climate over the Athabasca River Basin through an integrated evaluation-classification-downscaling-based climate projection framework. Journal of Geophysical Research, 122(5), 2595–2615.

Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi, K., & Liebert, J. (2012). HESS Opinions" Should we apply bias correction to global and regional climate model data?". Hydrology and Earth System Sciences, 16(9), 3391-3404.

Evaristo, J., Jasechko, S., & McDonnell, J. J. (2015). Global separation of plant transpiration from groundwater and streamflow. Nature, 525(7567), 91-94.

Everitt, Brian (1998). The Cambridge Dictionary of Statistics. Cambridge, UK New York: Cambridge University Press. ISBN 978-0521593465.

Gupta, H. V, Kling, H., Yilmaz, K. K., & Martinez, G. F. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. Journal of Hydrology, 377(1–2), 80–91.

Haerter, J. O., Hagemann, S., Moseley, C., & Piani, C. (2010). Climate model bias correction and the role of timescales. Hydrology and Earth System Sciences Discussions, 7(5), 7863-7898.

Holliday, C. R., & Thompson, A. H. (1979). Climatological characteristics of rapidly intensifying typhoons. Monthly Weather Review, 107(8), 1022-1034.

Krause, P., Boyle, D. P., & Bäse, F. (2005). Comparison of different efficiency criteria for hydrological model assessment. Advances in geosciences, 5, 89-97.

LaValle, S. M., Branicky, M. S., & Lindemann, S. R. (2004). On the relationship between classical grid search and probabilistic roadmaps. The International Journal of Robotics Research, 23(7-8), 673-692.

Lenderink, G., Buishand, A., & Deursen, W. V. (2007). Estimates of future discharges of the river Rhine using two scenario methodologies: direct versus delta approach. Hydrology and Earth System Sciences, 11(3), 1145-1159.

Liu, W., Zhan, J., Wang, C., Li, S., & Zhang, F. (2018). Environmentally sensitive productivity growth of industrial sectors in the Pearl River Delta. Resources, Conservation and Recycling, 139, 50-63.

McBean, E., Huang, G., Yang, A., Cheng, H., Wu, Y., Liu, Z., ... & Bhatti, M. (2019). The effectiveness of exfiltration technology to support sponge city objectives. Water, 11(4), 723.

Muleta, M. K., & Nicklow, J. W. (2005). Sensitivity and uncertainty analysis coupled

with automatic calibration for a distributed watershed model. Journal of hydrology, 306(1-4), 127-145.
Piani, C., Weedon, G. P., Best, M., Gomes, S. M., Viterbo, P., Hagemann, S., & Haerter, J. O. (2010). Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. Journal of hydrology, 395(3-4), 199-215.
Saber, M., & Yilmaz, K. K. (2018). Evaluation and bias correction of satellite-based rainfall estimates for modelling flash floods over the Mediterranean region: application to Karpuz River Basin, Turkey. Water, 10(5), 657.
Shrestha, M., Acharya, S. C., & Shrestha, P. K. (2017). Bias correction of climate models for hydrological modelling–are simple methods still useful?. Meteorological Applications, 24(3), 531-539.
Tian, Y., Xu, Y. P., Booij, M. J., & Wang, G. (2015). Uncertainty in future high flows in Qiantang River Basin, China. Journal of hydrometeorology, 16(1), 363-380.
Tu, M. C., & Smith, P. (2018). Modeling pollutant buildup and washoff parameters for SWMM based on land use in a semiarid urban watershed. Water, Air, & Soil Pollution, 229(4), 1-15.
Vetter, T., Reinhardt, J., Flörke, M., van Griensven, A., Hattermann, F., Huang, S., ... & Krysanova, V. (2017). Evaluation of sources of uncertainty in projected hydrological changes under climate change in 12 large-scale river basins. Climatic Change, 141(3), 419-433.
Wi, S., Yang, Y. C. E., Steinschneider, S., Khalil, A., & Brown, C. M. (2015). Calibration approaches for distributed hydrologic models in poorly gaged basins: implication for streamflow projections under climate change. Hydrology and Earth System Sciences, 19(2), 857-876.
Wilby, R. L., & Harris, I. (2006). A framework for assessing uncertainties in climate change impacts: Low−flow scenarios for the River Thames, UK. Water resources research, 42(2).
Ye, A., Duan, Q., Yuan, X., Wood, E. F., & Schaake, J. (2014). Hydrologic post-processing of MOPEX streamflow simulations. Journal of hydrology, 508, 147-156.
Yin, Z., Liao, W., Lei, X., Wang, H., & Wang, R. (2018). Comparing the Hydrological Responses of Conceptual and Process-Based Models with Varying Rain Gauge Density and Distribution. Sustainability, 10(9), 3209.
Yuan, F., Ren, L. L., Yu, Z. B., & Xu, J. (2008). Computation of potential evapotranspiration using a two-source method for the Xin'anjiang hydrological model. Journal of Hydrologic Engineering, 13(5), 305-316.
Zhang, X., Dong, Z., Gupta, H., Wu, G., & Li, D. (2016). Impact of the Three Gorges Dam on the hydrology and ecology of the Yangtze River. Water, 8(12), 590.