Projection of future streamflow changes of the Pearl River basin in China using two delta-change methods
Fei Yuan, Yeou-Koung Tung and Liliang Ren

ABSTRACT
Considerable biases in precipitation simulations in climate models have required the adoption of delta-change approaches to construct future precipitation scenarios for hydrological climate change impact studies. However, different delta-change methods yield different future precipitation scenarios that might significantly affect the projected future streamflow. To assess these effects, two delta-change methods were compared: the simple delta-change (SDC) method with a constant scaling factor and the quantile-quantile delta-change (QQDC) method with a quantile mapping-based non-uniform delta factor. The Xinanjiang (XAJ) hydrological model was applied using historical climatic data and two future precipitation scenarios for streamflow simulations in the Pearl River basin, China. The results show that the two delta-change methods have significant influences on future precipitation and streamflow projections, and these impacts become more distinct at finer and extreme event time scales. For instance, the QQDC method projects the 20-year daily maximum precipitation to be 8.1–98.6% higher than the SDC method. Consequently, the XAJ model with the QQDC future precipitation produces the 20-year daily maximum streamflow to be approximately 7.0–65.0% higher than that using the SDC precipitation. It implies that future precipitation transformation methods are a source of uncertainty, affecting future discharge projections. Such uncertainty should be considered in water resources management and flood control strategies for future climate change adaptations.

Key words | bias-correction, climate change, precipitation–runoff modeling, regional climate model, streamflow

INTRODUCTION
Projections of future climate change impacts on terrestrial hydrology are typically based on large-scale hydrological modeling driven by climate scenario simulations from either general circulation models (GCMs) or regional climate models (RCMs). These studies are associated with large uncertainties resulting from emission scenarios, climate models with statistical or dynamical downscaling schemes, post-processing methods for bias-correcting climate model outputs, and hydrological models, etc. Recently, these multiple uncertainty sources and their contributions to the total uncertainty of the projected future river flow have been investigated. Prudhomme & Davies (2009) revealed that GCMs are the dominant uncertainty source in four mesoscale British watersheds and uncertainty arising from hydrological models is negligible in two out of four basins. Meanwhile, they concluded that uncertainty due to emission scenarios and bias-correction methods are of comparable magnitude. Bosshard et al. (2013) found that, in general, climate models are the dominant source in summer and autumn in a Swiss catchment. However, uncertainties due to hydrological models and bias-correction methods gain importance in winter and spring. Dobler et al. (2012) demonstrated that the high uncertainty in hydrological projections is mainly due to the choice of GCM and RCM, and uncertainty due to bias-correction has greatest influence on extreme flow projections in an Alpine catchment in Austria. Therefore,
Bias-correction methods are an important uncertainty source in hydrological climate impact projections and should be studied thoroughly.

Bias-correction methods are widely used in regional hydrological climate change impact studies because biases in simulated precipitation intensity, proportion of heavy rains, and occurrence of no-rain days are generally significant in RCMs (Teutschbein & Seibert 2010) and these biases potentially lead to irrational hydrological simulations of historical river flows and unrealistic projections of future discharges. Therefore, bias-correction of RCM forcing data is recommended if a realistic description of the hydrology is sought (Rojas et al. 2011). Two types of bias-correction approaches have been widely applied: the direct bias-correction method and the delta-change method. The direct bias-correction method is based on the principle that biases between simulated historical climate time series and observations are identified and then used to correct both control and scenario runs of climate models; nevertheless, this is based on the stationary assumption that the applied correction procedure and parameters are defined to be constant over time, e.g., when moving from current conditions to scenario simulations (Teutschbein & Seibert 2010). The delta-change approach follows the principle that the observed historical climatic data set is directly adopted to be the baseline climatology and the climate change signals projected by climate models are imposed on observed precipitation and temperature to construct future climate data sets (Lettenmaier et al. 1999; Hay et al. 2000; Olsson et al. 2009; Teutschbein & Seibert 2010).

The commonly used simple delta-change (SDC) approach constructs future precipitation scenarios by multiplying observed precipitation by a constant delta-change factor. However, the main limitation of this approach is that estimates of future precipitation follow a temporal pattern similar to those of the historically observed. For instance, changes in the number of precipitation days and the coefficient of variation (CV) of precipitation are not considered (Lenderink et al. 2007; Xu & Yang 2012). Also, the signals of extreme precipitation change projected by climate models may be partly lost in the delta-transfer process. Thus, the future extreme precipitations are obtained from the historical extremes through amplification or attenuation in accordance with the delta-change factor (Xu & Yang 2012).

To overcome the drawback of the SDC method, several modified delta-change methods have been developed by researchers. An example is the delta-change method with the quantile-quantile mapping technique (Shabalova et al. 2003; Olsson et al. 2009; Xu & Yang 2012). Instead of using a constant delta factor to scale precipitation events at all levels in a specific season or month, the quantile-quantile delta-change (QQDC) method uses different factors for light and heavy precipitation with the scaling factor defined as the ratio of the quantile of the RCM-simulated future precipitation to the quantile of the RCM-simulated historical precipitation at the same cumulative frequency. With this method, the signals originally projected by climate models, e.g., changes in precipitation extremes, are generally well preserved in future precipitation projections.

Different delta-change methods might lead to considerable uncertainties in projecting future precipitation and further impact the projected streamflow. Shabalova et al. (2003) showed that in comparison with the SDC method, the QQDC method projected a significant increase in CV in future precipitation in all seasons except autumn in the Rhine River basin in western Europe. Olsson et al. (2009) indicated that the QQDC method projected a much higher increase (20–60%) in heavy rainfall than the SDC method, whereas light rain events would remain stable or decrease in the Kalmar City area, Sweden. In addition, Mpelasoka & Chiew (2009) found that the QQDC method generally gave higher extreme and annual runoffs than the SDC method in Australia. Shabalova et al. (2003) showed that the extreme high flow obtained using the two different delta approaches differed significantly; for instance, a 15% difference was observed in projected extremes in a 20-year return period in the River Rhine. Therefore, although emission scenarios, climate models, and hydrological models co-influence hydrological climate change impact analyses, the projected future changes in river flows are, to some extent, sensitive to the methods for constructing future precipitation scenarios. Meanwhile, it should be noted that sensitivities of the projected future streamflow to the two delta-change methods might be closely related to temporal scales, and the projected streamflow change might differ in magnitude at various time scales. However, the impact of the two delta-change methods in relationship with time scales have not yet been sufficiently discussed. Thus, it is...
necessary to comprehensively analyze the impact at multiple time scales, with focus on the extreme storm and flood events.

The Pearl River is the largest and most economically important river in South China, where floods and droughts have recently become more frequent and severe due to global warming. Several studies have been carried out to assess future climate change impacts in the Pearl River basin. Liu et al. (2009) projected upward trends in seasonal temperature and annual precipitation from 2011 to 2060 using GCM ECHAM5/MPI-OM. Zhai et al. (2010) used the monthly precipitation data of GCM ECHAM5/MPI-OM to calculate the Standardized Precipitation Index and projected that the Pearl River basin would have an obvious trend toward wetter conditions in the first 50 years of the 21st century under Inter-governmental Panel on Climate Change (IPCC) and Special Report on Emission Scenarios (SRES) A1 scenario. Liu et al. (2012) used the precipitation and temperature data from three GCMs under SRES A2, A1B and B1 scenarios to drive the hydrological model HBV-D, and projected upward trends in seasonal precipitation and runoff from May to October for the period from 2011 to 2099, while downward trends were projected from December to February; meanwhile, more severe flooding situations would appear after 2050 relative to the reference period of 1961–1990. In general, most studies in the Pearl River basin mainly employed a modeling chain framework to analyze the projected changes in climatology and hydrological variables, but the uncertainty from the modeling chain was not explicitly considered. Liu et al. (2013) carried out the first study in the Pearl River basin to quantify the contribution of different sources (emission scenarios, GCMs, and downscaling techniques) to the total uncertainty in the projected flood events and found that all these sources have considerable uncertainty contributions with their dominances being closely related to flood lead-time and return periods. However, the effects of different delta-change methods on the projected future precipitation and runoff regimes were not clearly addressed, which is the focus of this study.

Therefore, the objectives of this paper are: (1) to investigate how the SDC and QQDC methods affect the projections of future precipitation at various temporal scales and future extreme storm events in the Pearl River basin, China; and (2) to analyze further the manner by which the differences in future precipitation scenarios arising from the two delta-change methods affect the estimates of future river flows at different temporal scales and future flood risk assessment. To achieve these aims, the Xinanjiang (XAJ) hydrological model was used for streamflow simulations, driven by the observed historical precipitation and two future precipitation data sets obtained from the SDC and QQDC methods. This study provides a first study in the Pearl River basin to comprehensively explore the impacts of the two delta-change methods on future precipitation and streamflow projections at multiple time scales.

**STUDY AREA**

In terms of drainage area, the Pearl River is the third largest river in China, next to the Yangtze and Yellow Rivers, with a total drainage area of 4.54 × 10^5 km^2, of which 4.42 × 10^5 km^2 are located in China and 0.12 × 10^5 km^2 are in Vietnam. The river system is mainly composed of the West, North and East Rivers that flow through the provinces of Yunnan, Guizhou, Guangdong, Guangxi, Jiangxi, and Hunan, and converge at Guangzhou, along with the Pearl River delta region that links Guangzhou to Hong Kong and the South China Sea (Figure 1). The basin is dominated by a tropical and subtropical climate characterized by abundant precipitation and generally high temperature. The mean temperature ranges between 14 and 22 °C. The mean annual precipitation is 1,200–2,200 mm with a distinct increase from west to east. Precipitation mainly occurs from April to October, which accounts for 72–88% of annual precipitation (Zhang et al. 2009; Chen et al. 2010). Snow generally occurs in the mountainous regions of the western and northern parts of the basin. The spatiotemporal distribution of runoff depth is similar to precipitation. The West River has an annual runoff of 636 mm, the North River 1,090 mm, and the East River 950 mm.

**DATA AND METHODOLOGY**

Figure 2 shows the designed modeling framework to project the possible future climate change impacts on the streamflow of the Pearl River basin. First, two methods for
constructing future climate forcing were used to analyze the climate change signals of the RCM-simulated future and historical climatic variables. These signals were then added to the observed historical forcing data to construct the future forcing. The historical and future climatic forcing data sets were then used to drive a hydrological model to simulate climate change impacts on streamflow.
the historical and future river flows. Finally, future climate change impacts on streamflow were analyzed by comparing the simulated historical and future streamflow time series. The following sections provide a detailed description of the data, models, and methodology used in this study.

Data

Observed climatic data

Observed climatic data from 47 weather stations within the Pearl River basin were collected (Figure 1). These data were provided by the China Meteorological Administration and include daily records of maximum and minimum air temperature and precipitation during the period between 1961 and 1990. All the station-based daily precipitation and air temperature data were interpolated to each 0.25° grid cell using the nearest neighbor method. Topographical effects were not considered in precipitation interpolation. However, near-surface air temperature was assumed to decrease by 0.65°C per altitude rise of 100 m.

Observed streamflow data

Observed daily streamflow data from 24 streamflow stations (Figure 1) at the main rivers of the basin were provided by the Ministry of Water Resources, China for hydrological model calibration. The time period of these data falls between 1961 and 1989.

RCM forcing data

Outputs of the RCM Providing Regional Climates for Impacts Studies (PRECIS) (Metoffice 2002) were used to derive the future climate forcing data for the hydrological model. PRECIS runs on 50-km grid cells, with the lateral boundary given by the output of GCM HadAM3H. The model consists of climate simulations of a baseline (1961–1990) and a future scenario A1B (2011–2040). A1B is one of the future emission storylines in IPCC-SRES (IPCC 2001). PRECIS outputs contain daily precipitation as well as daily maximum and minimum air temperatures covering the whole Pearl River basin. Linear interpolation was performed to transform the PRECIS-simulated forcing data from a 50-km resolution to a 0.25° resolution.

Future forcing transformation methods

Two delta-change approaches were adopted to construct the future climatic forcing data sets for future streamflow simulations, in which the RCM-simulated climate changes between the baseline and future climate runs are superimposed upon the observed historical precipitation and temperature time series. The baseline climatology for driving the hydrological model corresponds to the observed climate data set.

SDC method

The SDC method superimposes the mean monthly anomalies between the RCM-simulated baseline and future climate on the observed historical meteorology to represent future forcing data. The baseline and future daily precipitation and air temperature time series for each 0.25° grid cell in the Pearl River basin are given by:

$$P_{bs}(m, d) = P_{obs}(m, d)$$  \hspace{1cm} (1)

$$P_{fut}(m, d) = P_{obs}(m, d) \times \frac{P_{precis,A1B}(m)}{P_{precis,bs}(m)}$$  \hspace{1cm} (2)

$$T_{bs}(m, d) = T_{obs}(m, d)$$  \hspace{1cm} (3)

$$T_{fut}(m, d) = T_{obs}(m, d) + \left[ T_{precis,A1B}(m) - T_{precis,bs}(m) \right]$$  \hspace{1cm} (4)

where $m$ denotes the month; $d$ is the $d$th day of month $m$; $P_{bs}$ and $P_{fut}$ represent the constructed baseline and future daily precipitation time series used as the inputs of the hydrological model, respectively; $P_{obs}$ denotes the observed historical daily precipitation; $P_{precis,bs}$ and $P_{precis,A1B}$ are the PRECIS-simulated mean monthly precipitation under the baseline and future A1B scenarios, respectively; $T_{bs}$ and $T_{fut}$ represent the transformed baseline and future daily air temperature time series, respectively; $T_{obs}$ stands for the observed historical daily air temperature; and $T_{precis,bs}$ and
are the PRECIS-simulated mean monthly air temperature under the baseline and future A1B scenarios, respectively.

The SDC future forcing data are generated by scaling the historical climate linearly with a monthly constant delta-change factor. This process results in a situation in which the temporal pattern of future climate is quite similar to that of historical climate. The future extreme precipitation also follows a pattern similar to that of historical climate, being linearly enhanced or dampened based on the delta factor.

**QQDC method**

The QQDC method was employed to overcome the drawback of the SDC method and to generate the future precipitation time series for hydrological simulations. The QQDC method is based on the quantile-quantile mapping technique (Wood et al. 2004; Deque 2007; Xu & Yang 2012). For each 0.25° grid cell in the Pearl River basin, three empirical cumulative distribution functions (CDFs) were, respectively, established for the observed historical precipitation, PRECIS-simulated historical precipitation, and PRECIS-simulated future precipitation for all days within a certain month group. As shown in Figure 3, the value of the observed historical precipitation on day \( d \) of month \( m \) was located on its CDF curve along with its corresponding cumulative probability. Subsequently, the precipitation quantiles at the same cumulative probability were located on the CDF curves of the PRECIS-simulated historical and future precipitation. Finally, these precipitation values were used to construct the future precipitation for future streamflow simulations. For each 0.25° grid cell, the baseline and future daily precipitation time series are given by:

\[
P_{\text{bs}}(m, d) = P_{\text{obs}}(m, d) \tag{5}
\]

\[
P_{\text{fut}}(m, d) = P_{\text{obs}}(m, d) \frac{P_{\text{precis,A1B}}(m, \text{CDF}_{\text{obs}})}{P_{\text{precis,bs}}(m, \text{CDF}_{\text{obs}})} \tag{6}
\]

where \( \text{CDF}_{\text{obs}} \) represents the cumulative probability of the observed historical precipitation on the \( d \)th day of month \( m \) (\( P_{\text{obs}}(m, d) \)); \( P_{\text{precis,bs}}(m, \text{CDF}_{\text{obs}}) \) and \( P_{\text{precis,A1B}}(m, \text{CDF}_{\text{obs}}) \) are the PRECIS-simulated baseline and future daily precipitation at the cumulative probability \( \text{CDF}_{\text{obs}} \), respectively; \( \frac{P_{\text{precis,A1B}}(m, \text{CDF}_{\text{obs}})}{P_{\text{precis,bs}}(m, \text{CDF}_{\text{obs}})} \) is the delta-change factor that is inconstant and dependent on the ratio of the PRECIS-simulated future precipitation quantile and the baseline precipitation quantile at the same CDF level; and the other terms are the same as those in Equations (1)–(4).

RCMs, to some extent, tend to exhibit some disagreement in rainless day simulations. Therefore, prior to quantile-quantile mapping, corrections of the rainless days in PRECIS precipitation data sets should be applied. For each grid cell, the observed and PRECIS-simulated historical precipitation

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**Figure 3** | Schematic diagram of the QQDC method.
data were compared in terms of the number of rainless days within a given month group. If PRECIS underestimated the rainless events for \( N \) days within a certain month group in the historical climate, \( N \) light rain days (precipitation rate less than 10 mm/d) in the PRECIS historical precipitation data were randomly selected and assigned to be rainless. Meanwhile, \( N \) light rain days in the PRECIS-simulated future precipitation time series were randomly selected and processed to be rainless days in the same way. In a case wherein PRECIS-simulated \( N \) more rainless days in the historical climate, \( N \) rainless days in the PRECIS historical precipitation time series were randomly selected and replaced with light rain days with a randomly assigned precipitation rate of 0.1–10 mm/d. Correspondingly, \( N \) rainless days in PRECIS future precipitation data were randomly substituted by light rain days via the same method. In this study, the precipitation threshold was defined as 10 mm/d according to the statistics on occurrence frequencies of various precipitation events. This threshold indicates that PRECIS has relatively large errors in simulating light rain (<10 mm/d) and rainless events (not presented in this study). This method, when used to correct rainless days, is likely to induce biases in light rain projections and low flow simulations. However, in this way, the signal of future changes in rainless events, as indicated by the PRECIS RCM, is preserved in the QQDC future precipitation data set. On the other hand, the commonly used SDC method generally does not correct rainless events. It constructs future precipitation data directly by scaling the historical precipitation time series with a constant factor. In this way, the SDC future precipitation retains the same rainless days as the historical climate, which is also the drawback of the SDC method.

Given that this paper focuses on addressing how the different delta-change methods affect the projections of future precipitation, the future air temperature for driving the XAJ model was constructed merely by the SDC method. It projects that with reference to the baseline period (1961–1990), air temperature under the A1B scenario (2011–2040) undergoes a moderate increase of 0.82–1.48 °C throughout the year.

**XAJ hydrological model**

The XAJ model (Zhao 1992), is a lumped, conceptual rainfall–runoff model and is widely and successfully applied in humid and semi-humid regions in China for flood forecasting, water resources evaluation, flood and water quality accounting design. The XAJ model was adopted by Yuan & Ren (2009) for streamflow simulations in the Pearl River basin with good results. In this study, the XAJ model modified by Yuan & Ren (2009) was employed for streamflow simulations and projections. This model is a grid-based spatially distributed hydrological model. The model employs the saturation excess runoff mechanism for runoff calculation in each grid cell within the studied watershed. In the permeable regions of a grid cell, runoff production occurs when soil tension water storage is filled to its capacity value. At the impervious part of a grid cell, direct runoff is generated when precipitation is higher than open-water evaporation. The evapotranspiration (ET) component of XAJ is presented as a model of three soil layers. In the upper layer, ET occurs at the potential rate (PE). Upon the exhaustion of soil tension water in the upper layer, ET proceeds to the lower layer at a decreased rate that is proportional to the tension water content in that layer. When the total ET in the upper and lower layers is less than a pre-set threshold, represented as a fraction of PE, ET further proceeds to the deep layer to maintain this pre-set minimum value. The daily PE in XAJ is calculated through the air temperature-based Hargreaves method (Hargreaves & Samni 1982). The streamflow routing component is composed of three processes: (1) total runoff is separated into three components, namely surface runoff, interflow runoff, and groundwater runoff by a gravitational water reservoir; (2) runoff concentration on the outflow of each sub-watershed or grid cell is represented by a linear reservoir; and (3) the routing effect of the channel system connecting each sub-catchment or grid cell is parameterized by the Muskingum routing algorithm. Among the 14 XAJ model parameters, two are insensitive parameters with predefined values, and the other 12 have clear physical meanings and need to be calibrated. For the description of the XAJ model parameters and their suggested physical values, please refer to Zhao (1992).

In this study, the entire Pearl River basin was partitioned into 747 grid cells on a 0.25° resolution. The XAJ model was applied to calculate daily total runoff depth at each grid cell and to route the produced runoff to the watershed outlet. The XAJ model parameters were calibrated by fitting the calculated historical daily streamflow against the observed data...
with the aid of the Shuffled Complex Evolution (SCE-UA) automatic optimization method (Duan et al. 1992, 1993), and the Nash-Sutcliffe model efficiency coefficient (NASH) (Nash & Sutcliffe 1970) and the relative error between the simulated and the observed total runoff (BIAS) were used as the objective function for SCE-UA. With the calibrated parameters, the XAJ model was driven by the baseline daily climatology and the projected future daily climate data sets from the SDC and QQDC methods for baseline and future daily streamflow simulations, respectively. Finally, the impacts of future precipitation construction methods on the projected streamflow were analyzed by comparing the simulated historical streamflow with the projected SDC and QQDC future streamflow time series.

RESULTS

Historical streamflow simulations

Historical daily streamflows at 24 hydrologic stations (Figure 1) were simulated using the XAJ model fed with the observed precipitation and air temperature data. This paper focused on the simulated streamflow at three streamflow stations to represent the hydrologic situations of the three main rivers in the Pearl River basin, namely, Wuxuan (control area: 196,255 km², West River), Shijiao (control area: 38,363 km², North River), and Boluo (control area: 25,325 km², East River) hydrologic stations. According to the suggestion by Moriasi et al. (2007), streamflow simulations with BIAS < ±0.10 and NASH > 0.75 are ‘very good’ simulations. Table 1 shows that the XAJ model can provide ‘very good’ streamflow simulations in calibration and validation periods, except for the Boluo station in validation periods with NASH being slightly lower than 0.75. In terms of BIAS and NASH, the modeling accuracy is similar to previous studies on streamflow simulations in the Pearl River basin (Jiang et al. 2007; Liu et al. 2012; Niu et al. 2013). The observed streamflow at all three rivers represents various typical high-flow events and low flow periods, and the XAJ model is proven capable of capturing most of the flood peaks and low flow processes (Figure 4).

Future precipitation changes

Daily precipitation

Figure 5(a) shows the distribution of the PRECIS-simulated raw baseline (1961–1990) and A1B (2011–2040) daily precipitation, along with the observed historical precipitation quantiles (1961–1990) in Boluo watershed. The CDF curve of the raw PRECIS baseline precipitation is not in close agreement with the observations, with large biases in heavy precipitation quantiles. Therefore, the raw PRECIS baseline precipitation should not be directly adopted to represent the historical precipitation for climate change impact analysis. However, the difference in the CDF curves of the raw PRECIS baseline and A1B precipitation may reflect the signals of future precipitation change. Figure 5(b) illustrates that PRECIS mainly projects an evident increase in A1B precipitation in the heavy precipitation quantiles (see right side of Figure 5(b)) and predicts a minor drop in A1B precipitation in the light rain quantiles (see left side of Figure 5(b)). The other two watersheds also demonstrate a similar situation (not shown in this paper). This condition indicates that the Pearl River basin will be subject to more severe heavy rainstorms and relatively less light rain events in the future.

Table 1 | Performance of daily streamflow simulations at three chosen stations in the Pearl River basin

<table>
<thead>
<tr>
<th>Regions in the Pearl River basin</th>
<th>Streamflow stations</th>
<th>Calibration</th>
<th>Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Time period</td>
<td>NASH</td>
</tr>
<tr>
<td>West River</td>
<td>Wuxuan</td>
<td>1969–1979</td>
<td>0.922</td>
</tr>
<tr>
<td>North River</td>
<td>Shijiao</td>
<td>1961–1979</td>
<td>0.908</td>
</tr>
<tr>
<td>East River</td>
<td>Boluo</td>
<td>1961–1979</td>
<td>0.843</td>
</tr>
</tbody>
</table>

NASH is the Nash-Sutcliffe model efficiency coefficient and BIAS is the relative error (BIAS) between the simulated and the observed total streamflow.
The SDC and QQDC methods were applied to generate the future daily precipitation time series in the IPCC-SRES A1B scenario. The terms SDC-A1B and QQDC-A1B are used to represent the future precipitation data sets produced by the SDC and QQDC methods, respectively. Figure 5(c) and 5(d) compare the quantiles of the SDC-A1B and QQDC-A1B future daily precipitation with the baseline precipitation that corresponds to the observed historical data. In Boluo watershed, future daily precipitation at a higher cumulative probability (≥90%) tends to increase. Nevertheless, the QQDC method calculates a much higher increase in future heavy precipitation than the SDC method. Meanwhile, these two delta-change methods both compute a drop in light rain quantiles and the QQDC
Figure 5 | Daily precipitation quantiles in Boluo watershed.
method has a slightly larger magnitude of light precipitation decrease. Figure 5(b) and 5(d) also indicate that the signals of future precipitation change as detected in the raw PRECIS data sets are generally well preserved in the QQDC-A1B data, whereas the signals found in SDC-A1B are considerably weaker.

According to the China Meteorology Administration’s guidelines for rainfall event classification, the occurrence frequencies of non-rainy weather and the six categories of rainfall events were calculated (Table 2) for the baseline, QQDC-A1B and SDC-A1B daily precipitation data sets. Table 2 shows that the changes in frequencies of various rainfall events are very small. The occurrence frequency of rainless events would increase by 0.50–1.07% in QQDC-A1B and by 0.15–0.38% in SDC-A1B. The number of rainless days in SDC-A1B should be equal to that of the baseline, but in this work, the dry day statistics also include the light rain days with precipitation of less than 1 mm/d. The likelihood of light rain events exhibits a slight decrease of 1.13–1.50% in QQDC-A1B and 0.46–1.04% in SDC-A1B. Furthermore, considering the magnitude of relative change, the frequencies of extreme events were projected to change significantly. Future severe events such as rainstorm (50–100 mm/d) and heavy rainstorm (100–250 mm/d) might occur more often than the baseline (Table 2). The QQDC method always predicts higher frequencies of these severe storms than the SDC method. For instance, in Shijiao watershed, the heavy rainstorm events in SDC-A1B would occur twice as frequently as those in the baseline, but in QQDC-A1B, the rainstorm events are four times more often than those in the baseline period. In addition, no extreme heavy rainstorm (≥250 mm/d) appears in the baseline and SDC-A1B in Boluo watershed, whereas these extreme events would occur under QQDC-A1B at a frequency of 0.03%. These results imply that, in the future, non-rainy weather is likely to occur slightly more frequently, less light rain events would occur, and the probability of severe rainstorm events would increase considerably. The QQDC-A1B scenario would encounter more severe extreme weather situations with increased rainless days and more frequent storm events.

### Seasonal cycle of precipitation

Figure 6(a) shows the future changes in mean monthly precipitation relative to the baseline level in Boluo watershed. The QQDC-A1B and SDC-A1B monthly precipitation agree basically with the study of Liu et al. (2012), who projected an increase in precipitation from May to October and a drop from December to February in the Pearl River basin. Meanwhile, during the wet season, the variation range of the 2 monthly precipitation data sets would be

Table 2 | Occurrence frequencies of non-rainy event and six rainfall events for the baseline and future A1B daily precipitation data sets

<table>
<thead>
<tr>
<th>Regions</th>
<th>Data types</th>
<th>No rain (0–1 mm)</th>
<th>Light rain (1–10 mm)</th>
<th>Moderate rain (10–25 mm)</th>
<th>Heavy rain (25–50 mm)</th>
<th>Rainstorm (50–100 mm)</th>
<th>Heavy rainfallstorm (100–250 mm)</th>
<th>Extreme heavy rainfallstorm (≥250 mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wuxuan (West)</td>
<td>Baseline (1961–1990)</td>
<td>49.77</td>
<td>38.53</td>
<td>9.83</td>
<td>1.82</td>
<td>0.05</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>River</td>
<td>SDC-A1B (2011–2040)</td>
<td>50.10 ↑</td>
<td>37.50 ↓</td>
<td>10.08 ↑</td>
<td>2.23 ↑</td>
<td>0.08 ↑</td>
<td>0.00 ↑</td>
<td>0.00 ↑</td>
</tr>
<tr>
<td></td>
<td>QQDC-A1B (2011–2040)</td>
<td>50.27 ↑↑</td>
<td>37.09 ↓↓</td>
<td>10.15 ↑↑</td>
<td>2.36 ↑↑</td>
<td>0.14 ↑↑</td>
<td>0.00 ↑↑</td>
<td>0.00 ↑↑</td>
</tr>
<tr>
<td>Shijiao (North)</td>
<td>Baseline (1961–1990)</td>
<td>57.15</td>
<td>28.05</td>
<td>10.55</td>
<td>3.49</td>
<td>0.75</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>River</td>
<td>SDC-A1B (2011–2040)</td>
<td>57.53 ↑</td>
<td>27.01 ↓</td>
<td>10.70 ↑</td>
<td>3.71 ↑</td>
<td>1.02 ↑</td>
<td>0.04 ↑</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>QQDC-A1B (2011–2040)</td>
<td>58.01 ↑↑</td>
<td>26.55 ↓↓</td>
<td>10.23 ↓↓</td>
<td>3.93 ↑↑</td>
<td>1.19 ↑↑</td>
<td>0.10 ↑↑</td>
<td>0.00 ↑↑</td>
</tr>
<tr>
<td>Boluo (East)</td>
<td>Baseline (1961–1990)</td>
<td>59.58</td>
<td>25.02</td>
<td>10.02</td>
<td>4.20</td>
<td>1.05</td>
<td>0.13</td>
<td>0.00</td>
</tr>
<tr>
<td>River</td>
<td>SDC-A1B (2011–2040)</td>
<td>59.73 ↑</td>
<td>24.56 ↓</td>
<td>9.98 ↓</td>
<td>4.18 ↓</td>
<td>1.38 ↓</td>
<td>0.17 ↓</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>QQDC-A1B (2011–2040)</td>
<td>60.65 ↑↑</td>
<td>23.99 ↓↓</td>
<td>9.56 ↓↓</td>
<td>4.06 ↓↓</td>
<td>1.50 ↓↓</td>
<td>0.22 ↓↓</td>
<td>0.03 ↓↓</td>
</tr>
</tbody>
</table>

Symbols ‘↑’ and ‘↓’ denote whether the occurrence frequency of a type of rainfall event in the A1B scenarios shows an increasing or decreasing trend relative to the baseline; the double-arrow symbols denote a considerably higher increase or decrease magnitude of the given events in the QQDC-A1B and SDC-A1B scenarios.
amplified (Figure 6(b)), indicating a possible higher variability in future monthly precipitation.

To test the differences in QQDC-A1B and SDC-A1B monthly precipitation data sets of Boluo watershed, the paired-sample Wilcoxon signed-rank test was conducted, which compares two dependent and non-normal samples and assesses whether their population mean ranks differ significantly. Table 3 shows that in summer and early autumn (June–September), the QQDC-A1B precipitation is significantly higher than SDC-A1B at a 5% significance level, whereas the spring (March–April) precipitation of QQDC-A1B is significantly lower than that of SDC-A1B at the same significance level. The other two watersheds also have a similar trend (not shown in this paper).

**Annual precipitation**

Table 4 shows that the SDC-A1B mean annual precipitation undergoes an increase of 4.4% in Wuxuan, 6.1% in Shijiao, and 4.6% in Boluo; the QQDC-A1B mean annual precipitation has a slightly larger increase rate (6.8%, 9.6%, and 7.5% in Wuxuan, Shijiao, and Boluo, respectively). These upward trends in annual precipitation basically agree with the study of Liu et al. (2009), who projected an obvious increase in annual precipitation from 2011 to 2060 using GCM ECHAM5/MPI-OM. The paired-sample Wilcoxon signed-rank test (Table 4) confirms that future annual precipitation time series are greater than the baseline at a 5% significance level, and the QQDC method yields a significantly higher annual precipitation than the SDC algorithm at the same significance level. With respect to the variability of annual precipitation, the standard deviations of SDC-A1B and QQDC-A1B are, respectively, 2.7–10.7% and 8.8–17.9% higher than the baseline, indicating a mild increase in fluctuation magnitudes of future annual precipitation. Considering the increased annual mean precipitation, the CVs of the two future data sets do not change evidently, compared with the baseline CV. Moreover, the first quartile (Q1), median, the third quartile (Q3), and maxima of the annual precipitation time series in both A1B scenarios of all three watersheds are consistently larger than the baseline, in particular with significantly higher values in QQDC-A1B (Table 4). This finding implies that more wet years would likely occur in the future, especially in the QQDC-A1B scenario.

**Extreme precipitation**

To quantify the future changes in extreme precipitation, the annual maximum daily precipitation series in the baseline and two future scenarios were fitted by the Pearson type III distribution:

\[
 f(x) = P(p_{\text{max}} \geq x) = \frac{1}{\beta \Gamma(\alpha)} \left( \frac{x-c}{\beta} \right)^{\alpha-1} \frac{x-c}{\beta} e^{-\left( \frac{x-c}{\beta} \right)}/\beta \quad (7)
\]

where \(c\) is the location parameter; \(\alpha\) is a scale parameter; and \(\beta\) is a shape parameter. Figure 7 shows the Pearson type III plots of basin-averaged annual maximum daily precipitation \(p_{\text{max}}\) in the three watersheds. All the curves are L-moment fits to the annual maximum daily precipitation, with the
goodness-of-fit coefficient higher than 0.95. Using two delta-change methods, a considerable increase in future extreme precipitation is obtained in all watersheds and the QQDC method projects much more extreme storm events in the future than the SDC method. Under the SDC-A1B scenario, extrapolation of the fitted Pearson type III distribution to a 100-year return period reveals an increase of 20.4%, 29.9%, and 5.1% over the baseline precipitation in Wuxuan, Shijiao, and Boluo watersheds, respectively. However, the QQDC-A1B scenario would have significantly higher extreme precipitation, with an increase of 32.3% and 69.7% in the 100-year event over the baseline in Wuxuan and Shijiao watersheds, respectively. In Boluo watershed in particular, the 100-year extreme in QQDC-A1B would rise by 144.2% relative to the baseline level (from 201.8 mm/d in the baseline to 492.7 mm/d under the QQDC-A1B scenario).

### Future streamflow changes

#### Daily streamflow

The daily streamflow quantiles of the baseline, QQDC-A1B and SDC-A1B are compared in Figure 8. In all three watersheds, daily high-flow quantiles (cumulative frequency of

### Table 3 | Statistical properties of QQDC-A1B and SDC-A1B monthly precipitation in Boluo watershed

<table>
<thead>
<tr>
<th>Month</th>
<th>Data</th>
<th>Precipitation quartiles (mm)</th>
<th>Paired-sample Wilcoxon signed-rank test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Min</td>
<td>Q1</td>
</tr>
<tr>
<td>January</td>
<td>QQDC-A1B</td>
<td>0.3</td>
<td>9.3</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>0.4</td>
<td>8.7</td>
</tr>
<tr>
<td>February</td>
<td>QQDC-A1B</td>
<td>5.4</td>
<td>23.2</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>7.5</td>
<td>25.4</td>
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<td>QQDC-A1B</td>
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<td>78.4</td>
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<td></td>
<td>SDC-A1B</td>
<td>11.0</td>
<td>86.7</td>
</tr>
<tr>
<td>April</td>
<td>QQDC-A1B</td>
<td>33.6</td>
<td>128.3</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>36.1</td>
<td>135.6</td>
</tr>
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<td>QQDC-A1B</td>
<td>49.7</td>
<td>280.4</td>
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<td>275.9</td>
</tr>
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<td>QQDC-A1B</td>
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<td>239.3</td>
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<td>SDC-A1B</td>
<td>93.0</td>
<td>238.7</td>
</tr>
<tr>
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<td>88.3</td>
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<td>SDC-A1B</td>
<td>89.1</td>
<td>157.1</td>
</tr>
<tr>
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<td>QQDC-A1B</td>
<td>97.9</td>
<td>150.9</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>101.5</td>
<td>148.1</td>
</tr>
<tr>
<td>September</td>
<td>QQDC-A1B</td>
<td>60.4</td>
<td>97.2</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>55.4</td>
<td>93.1</td>
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<tr>
<td>October</td>
<td>QQDC-A1B</td>
<td>0.0</td>
<td>20.9</td>
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<td>SDC-A1B</td>
<td>0.2</td>
<td>38.6</td>
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<td>November</td>
<td>QQDC-A1B</td>
<td>0.1</td>
<td>5.6</td>
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<td></td>
<td>SDC-A1B</td>
<td>0.1</td>
<td>3.0</td>
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<tr>
<td>December</td>
<td>QQDC-A1B</td>
<td>0.1</td>
<td>2.1</td>
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<tr>
<td></td>
<td>SDC-A1B</td>
<td>0.5</td>
<td>6.8</td>
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</tbody>
</table>

$Z_{cal}$, Z-score of the calculated Wilcoxon statistics; $Z_{crit}$, Z-score of the critical Wilcoxon statistics at a 5% significance level.

*Two-tailed Z score of the critical Wilcoxon statistics at a 5% significance level.

One-tailed Z score of the critical Wilcoxon statistics at a 5% significance level; $>$ QQDC-A1B monthly precipitation is significantly greater than the SDC-A1B data; $=$ QQDC-A1B and SDC-A1B monthly precipitation data sets are not significantly different; $<$ QQDC-A1B monthly precipitation is significantly less than the SDC-A1B data.
Table 4 | Statistical properties of annual precipitation under the baseline, QQDC-A1B, and SDC-A1B scenarios

<table>
<thead>
<tr>
<th>Watersheds</th>
<th>Data</th>
<th>Mean (mm)</th>
<th>SD (mm)</th>
<th>CV</th>
<th>Min</th>
<th>Q1</th>
<th>Median</th>
<th>Q3</th>
<th>Max</th>
<th>Paired-sample Wilcoxon signed-rank test</th>
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<tbody>
<tr>
<td>Wuxuan</td>
<td>Baseline</td>
<td>1,344.5</td>
<td>138.2</td>
<td>0.103</td>
<td>1,019.1</td>
<td>1,257.9</td>
<td>1,366.2</td>
<td>1,438.8</td>
<td>1,602.1</td>
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</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>1,404.8</td>
<td>142.5</td>
<td>0.101</td>
<td>1,088.0</td>
<td>1,312.4</td>
<td>1,427.0</td>
<td>1,499.2</td>
<td>1,659.5</td>
<td>(a4.772 &gt; 1.64^c) 0.0000</td>
</tr>
<tr>
<td></td>
<td>QQDC-A1B</td>
<td>1,435.4</td>
<td>150.3</td>
<td>0.105</td>
<td>1,128.2</td>
<td>1,320.8</td>
<td>1,464.2</td>
<td>1,534.4</td>
<td>1,717.9</td>
<td>(b4.669 &gt; 1.64^c) 0.0000</td>
</tr>
<tr>
<td>Shijiao</td>
<td>Baseline</td>
<td>1,666.4</td>
<td>272.1</td>
<td>0.163</td>
<td>1,088.5</td>
<td>1,508.0</td>
<td>1,628.5</td>
<td>1,754.1</td>
<td>2,310.9</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>1,768.3</td>
<td>301.3</td>
<td>0.170</td>
<td>1,048.3</td>
<td>1,588.5</td>
<td>1,718.7</td>
<td>1,914.3</td>
<td>2,501.2</td>
<td>(a4.566 &gt; 1.64^c) 0.0000</td>
</tr>
<tr>
<td></td>
<td>QQDC-A1B</td>
<td>1,826.7</td>
<td>320.8</td>
<td>0.176</td>
<td>1,076.9</td>
<td>1,619.5</td>
<td>1,772.4</td>
<td>1,924.3</td>
<td>2,622.1</td>
<td>(b4.566 &gt; 1.64^c) 0.0000</td>
</tr>
<tr>
<td>Boluo</td>
<td>Baseline</td>
<td>1,792.8</td>
<td>307.8</td>
<td>0.172</td>
<td>924.8</td>
<td>1,608.9</td>
<td>1,761.5</td>
<td>1,901.2</td>
<td>2,433.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>1,876.3</td>
<td>319.8</td>
<td>0.170</td>
<td>932.1</td>
<td>1,699.6</td>
<td>1,842.8</td>
<td>2,000.2</td>
<td>2,541.4</td>
<td>(a4.648 &gt; 1.64^c) 0.0000</td>
</tr>
<tr>
<td></td>
<td>QQDC-A1B</td>
<td>1,927.3</td>
<td>339.4</td>
<td>0.176</td>
<td>910.1</td>
<td>1,704.3</td>
<td>1,934.5</td>
<td>2,129.6</td>
<td>2,591.0</td>
<td>(b3.743 &gt; 1.64^c) 0.0000</td>
</tr>
</tbody>
</table>

\(Z_{cal}\), Z-score of the calculated Wilcoxon statistics; \(Z_{cri}\), Z-score of the critical Wilcoxon statistics at a 5% significance level.

*Paired-sample Wilcoxon signed-rank test for comparing the baseline and SDC-A1B annual precipitation time series.

*bPaired-sample Wilcoxon signed-rank test for comparing the SDC-A1B and QQDC-A1B annual precipitation time series.

*cOne-tailed Z-score of the critical Wilcoxon statistics at a 5% significance level; \(>\) SDC-A1B annual precipitation is significantly greater than the baseline data or that the QQDC-A1B annual precipitation is significantly greater than SDC-A1B.

---

Figure 7 | Pearson type III plots of annual maximum daily precipitation in different watersheds under the baseline, SDC-A1B, and QQDC-A1B scenarios.
under the SDC-A1B and QQDC-A1B scenarios would rise consistently relative to the baseline level, with a larger magnitude of high-flow increase in QQDC-A1B. In Boluo watershed, for instance, the 99% streamflow quantile in QQDC-A1B is 4,840 m³/s, an increase of 37.9% over the baseline streamflow, whereas the corresponding daily streamflow quantile in SDC-A1B is merely 3,890 m³/s, a 10.8% increase. Despite the relatively fewer light rain events, slightly more rainless days and warmer climate in the future, low flow under the two A1B scenarios is not expected to decrease in all three watersheds (Figure 8). The 0–40% daily streamflow quantiles in Shijiao and the 0–1% quantiles in Boluo would drop slightly. However, Wuxuan watershed would have a minor increase in low flow at a non-exceedance frequency of 0–10%. In addition to precipitation and ET, antecedent soil moisture and groundwater storage are key factors that jointly influence low flow regimes. Wuxuan watershed is extensively covered by dense forests, thus with higher soil water storage capacity. Considering the more frequent storm events in the future, more runoff would be produced in Wuxuan watershed, much of which would be stored underground. This groundwater storage would release water to river channels during the dry season, potentially contributing to the rise of base flow. Furthermore, low flow in QQDC-A1B is slightly lower than that in SDC-A1B, because the former method projects slightly more rainless events than the latter.

**Seasonal cycle**

The mean monthly runoffs in QQDC-A1B and SDC-A1B were compared with the baseline runoff in Boluo watershed (Figure 9(a)). Similar signals of monthly runoff change were detected under both future scenarios. An overall increase in mean monthly runoff during the wet season (May–October)
was found, which can primarily be attributed to the rise in wet season precipitation (Figure 6(a)). In winter, runoff would generally drop because of the decrease in precipitation, except for a substantial increase in December runoff induced by a minor rise in precipitation (Figure 6(a)). The projected changes in seasonal runoff are similar to the study of Liu et al. (2015), who projected upward trends in runoff from May to October and downward trends from December to February in the years 2011–2099. In terms of runoff variation, the temporal pattern of minimum monthly runoff in QQDC-A1B and SDC-A1B is very similar to that of the baseline (Figure 9(b)). However, considerably higher maximum monthly runoff during the wet season is projected under both future scenarios (Figure 9(b)). This finding reflects the increased runoff variability in the wet season.

Although the simulated monthly runoff depth under the QQDC-A1B and SDC-A1B scenarios follows a similar temporal pattern, considerable differences remain between these two monthly runoff time series. The paired-sample Wilcoxon signed-rank test indicates that, in Boluo watershed, the June–August runoff in QQDC-A1B is significantly greater than that in SDC-A1B at a 5% significance level (Table 5). By contrast, the late spring (April–May) runoff in QQDC-A1B is significantly less than that in SDC-A1B at the same significance level. These runoff differences basically agree with the precipitation differences as shown in Table 3. The other two watersheds also have a similar situation (not shown in this paper).

Annual streamflow

Table 6 shows that future annual runoff depth of all three watersheds is inclined to rise slightly relative to the baseline level, with a higher level of runoff increase under the QQDC-A1B scenario. The paired-sample Wilcoxon signed-rank test (Table 6) confirms that both the SDC-A1B and QQDC-A1B annual runoff depths are significantly greater than the baseline runoff at a 5% significance level and that the QQDC-A1B annual runoff has a slightly higher increase in runoff. This phenomenon can very likely be attributed to the fact that the QQDC method tends to project mildly higher annual precipitation in the Pearl River basin compared with the SDC method. With respect to the variability of annual runoff, both the simulated SDC-A1B and QQDC-A1B annual runoff display a minor increase in standard deviation than the baseline, but the CVs of these three annual runoff time series do not change significantly. In addition, the first, second, and third quartiles (Q1, median, and Q3) as well as the maximum annual runoff in SDC-A1B and QQDC-A1B show an overall increase over the baseline level, indicating more high-flow years in the future.

Extremes

The simulated annual maximum daily streamflow series under the baseline, QQDC-A1B, and SDC-A1B scenarios were fitted by the Pearson type III distribution with the L-moment method. Figure 10 demonstrates evident changes in the magnitude and occurrence of extreme flooding events. Under QQDC-A1B and SDC-A1B, the annual maximum daily streamflow at longer return periods (e.g., 20 years and 50 years) at all three stations would consistently
increase. Similarly, Liu et al. (2013) projected more severe extreme flooding situations in the West River (the largest tributary of the Pearl River) using the modeling chain with three emission scenarios, three GCMs, and three downscaling methods. Meanwhile, QQDC projected much higher extreme streamflow than SDC at all three stations. The Boluo station has the most extreme situation. The magnitude of the 20-year maximum daily discharge at Boluo station, for example, increases by 6.1% in SDC-A1B and by 75.1% in QQDC-A1B; the return period of the baseline 20-year event would be reduced to approximately 10 years under SDC-A1B and drop to less than 5 years under QQDC-A1B (Figure 10).

To project the climate change impacts on extreme river flow, four discharge levels were defined: extreme high flow, moderate high flow, extreme low flow, and moderate low flow. Extreme high flow may cause severe flood events and is defined as daily streamflow larger than the 99% baseline streamflow quantile. Moderate high flow can result in modest flooding and is defined as the daily streamflow in the range of the 95% and 99% baseline streamflow quantiles. Extreme low flow is defined as daily discharge less than 20% of the baseline streamflow.

### Table 5: Statistical properties of the simulated monthly runoff depth under the QQDC-A1B and SDC-A1B scenarios in Boluo watershed

<table>
<thead>
<tr>
<th>Month</th>
<th>Scenarios</th>
<th>Runoff quartiles (mm)</th>
<th>Paired-sample Wilcoxon signed-rank test</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Min</td>
<td>Q1</td>
<td>Median</td>
</tr>
<tr>
<td>January</td>
<td>QQDC-A1B</td>
<td>23.1</td>
<td>33.1</td>
<td>38.7</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>22.9</td>
<td>33.0</td>
<td>38.0</td>
</tr>
<tr>
<td>February</td>
<td>QQDC-A1B</td>
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<td>26.8</td>
<td>32.7</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>16.4</td>
<td>27.0</td>
<td>31.9</td>
</tr>
<tr>
<td>March</td>
<td>QQDC-A1B</td>
<td>18.0</td>
<td>32.8</td>
<td>46.2</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
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<td>47.8</td>
<td>74.8</td>
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<tr>
<td></td>
<td>SDC-A1B</td>
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<td>49.2</td>
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<td>QQDC-A1B</td>
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<td>SDC-A1B</td>
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<td>July</td>
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<td>86.7</td>
<td>109.2</td>
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<td>SDC-A1B</td>
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<td>110.7</td>
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<tr>
<td>August</td>
<td>QQDC-A1B</td>
<td>34.1</td>
<td>95.5</td>
<td>128.6</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
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<td>92.8</td>
<td>121.1</td>
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<tr>
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<td>QQDC-A1B</td>
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<td>SDC-A1B</td>
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<td>72.5</td>
<td>86.6</td>
</tr>
<tr>
<td>October</td>
<td>QQDC-A1B</td>
<td>21.6</td>
<td>54.9</td>
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<td>SDC-A1B</td>
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<td>56.8</td>
<td>68.9</td>
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<td>SDC-A1B</td>
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<td>37.9</td>
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<td>SDC-A1B</td>
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<td>38.6</td>
<td>43.7</td>
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</tbody>
</table>

$Z_{cal}$, Z-score of the calculated Wilcoxon statistics; $Z_{crit}$, Z-score of the critical Wilcoxon statistics at a 5% significance level.

*Two-tailed Z score of the critical Wilcoxon statistics at a 5% significance level.

One-tailed Z score of the critical Wilcoxon statistics at a 5% significance level; > QQDC-A1B monthly runoff is significantly greater than the SDC-A1B data; < QQDC-A1B monthly runoff is significantly less than the SDC-A1B data.

*QQDC-A1B and SDC-A1B monthly runoff is not significantly different; = QQDC-A1B monthly runoff is significantly equal to the SDC-A1B data.

Z. Yuan et al. (2013) projected more severe extreme flooding situations in the West River (the largest tributary of the Pearl River) using the modeling chain with three emission scenarios, three GCMs, and three downscaling methods. Meanwhile, QQDC projected much higher extreme streamflow than SDC at all three stations. The Boluo station has the most extreme situation. The magnitude of the 20-year maximum daily discharge at Boluo station, for example, increases by 6.1% in SDC-A1B and by 75.1% in QQDC-A1B; the return period of the baseline 20-year event would be reduced to approximately 10 years under SDC-A1B and drop to less than 5 years under QQDC-A1B (Figure 10). To project the climate change impacts on extreme river flow, four discharge levels were defined: extreme high flow, moderate high flow, extreme low flow, and moderate low flow. Extreme high flow may cause severe flood events and is defined as daily streamflow larger than the 99% baseline streamflow quantile. Moderate high flow can result in modest flooding and is defined as the daily streamflow in the range of the 95% and 99% baseline streamflow quantiles. Extreme low flow is defined as daily discharge less than 20% of the baseline streamflow.
Table 6 | Statistical properties of simulated annual runoff depth in the baseline, QQDC-A1B, and SDC-A1B scenarios

<table>
<thead>
<tr>
<th>Watersheds</th>
<th>Data</th>
<th>Mean (mm)</th>
<th>SD (mm)</th>
<th>CV</th>
<th>Min</th>
<th>Q1</th>
<th>Median</th>
<th>Q3</th>
<th>Max</th>
<th>Paired-sample Wilcoxon signed-rank test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wuxuan</td>
<td>Baseline</td>
<td>633.4</td>
<td>117.3</td>
<td>0.185</td>
<td>367.6</td>
<td>559.4</td>
<td>645.4</td>
<td>711.5</td>
<td>902.8</td>
<td>(z_{\text{cal}}) (z_{\text{cri}}) (p)-value</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>688.7</td>
<td>122.7</td>
<td>0.178</td>
<td>417.9</td>
<td>616.2</td>
<td>694.1</td>
<td>785.3</td>
<td>945.0</td>
<td>(a4.772 &gt; 1.64c) 0.0000</td>
</tr>
<tr>
<td></td>
<td>QQDC-A1B</td>
<td>696.4</td>
<td>128.8</td>
<td>0.185</td>
<td>427.4</td>
<td>606.9</td>
<td>695.0</td>
<td>778.8</td>
<td>956.7</td>
<td>(b2.057 &gt; 1.64c) 0.0192</td>
</tr>
<tr>
<td>Shijiao</td>
<td>Baseline</td>
<td>1,015.7</td>
<td>263.5</td>
<td>0.259</td>
<td>385.8</td>
<td>845.1</td>
<td>959.5</td>
<td>1,113.9</td>
<td>1,620.5</td>
<td>(a4.463 &gt; 1.64c) 0.0000</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>1,093.6</td>
<td>286.8</td>
<td>0.262</td>
<td>360.3</td>
<td>910.3</td>
<td>1,071.4</td>
<td>1,239.4</td>
<td>1,776.4</td>
<td>(b4.648 &gt; 1.64c) 0.0000</td>
</tr>
<tr>
<td></td>
<td>QQDC-A1B</td>
<td>1,149.2</td>
<td>306.1</td>
<td>0.266</td>
<td>383.7</td>
<td>944.8</td>
<td>1,101.6</td>
<td>1,252.2</td>
<td>1,887.4</td>
<td>(b4.093 &gt; 1.64c) 0.0000</td>
</tr>
<tr>
<td>Boluo</td>
<td>Baseline</td>
<td>967.4</td>
<td>241.5</td>
<td>0.250</td>
<td>357.6</td>
<td>836.8</td>
<td>945.2</td>
<td>1,082.7</td>
<td>1,573.7</td>
<td>(a4.422 &gt; 1.64c) 0.0000</td>
</tr>
<tr>
<td></td>
<td>SDC-A1B</td>
<td>1,029.4</td>
<td>241.4</td>
<td>0.235</td>
<td>375.9</td>
<td>891.5</td>
<td>1,021.9</td>
<td>1,165.6</td>
<td>1,517.2</td>
<td>(b4.093 &gt; 1.64c) 0.0000</td>
</tr>
<tr>
<td></td>
<td>QQDC-A1B</td>
<td>1,086.6</td>
<td>260.2</td>
<td>0.240</td>
<td>368.1</td>
<td>929.5</td>
<td>1,072.6</td>
<td>1,226.2</td>
<td>1,594.3</td>
<td>(a4.422 &gt; 1.64c) 0.0000</td>
</tr>
</tbody>
</table>

\(z_{\text{cal}}\), Z-score of the calculated Wilcoxon statistics; \(z_{\text{cri}}\), Z-score of the critical Wilcoxon statistics at a 5% significance level.

\(a\)Paired-sample Wilcoxon signed-rank test for comparing the baseline and SDC-A1B annual runoff time series.

\(b\)Paired-sample Wilcoxon signed-rank test for comparing the SDC-A1B and QQDC-A1B annual runoff time series.

\(c\)One-tailed Z score of the critical Wilcoxon statistics at a 5% significance level; > SDC-A1B annual runoff is significantly greater than the baseline or the QQDC-A1B annual runoff is significantly greater than the SDC-A1B runoff.

Figure 10 | Pearson type III plots of annual maximum daily discharge under the baseline, SDC-A1B, and QQDC-A1B scenarios.
than the 1% baseline streamflow quantile, which might result in severe drought events. Moderate low flow is used to represent modest droughts and is assigned to be the discharge within the range of the 1% and 5% baseline streamflow quantiles. The probability of each category of extreme events was calculated as the ratio of the number of days at a given discharge level to the total number of days over 30 years. Figure 11 shows that all three watersheds would be subject to more frequent extreme high-flow events, with a significantly higher probability under the QQDC-A1B scenario. Similarly, moderate high-low events in Wuxuan and Shijiao watersheds would occur more frequently in both A1B scenarios. However, at Boluo streamflow station, the likelihood tends to decline. In the warmer future with increased rainless days, the probability of the extreme low flow events would rise slightly in Shijiao and Boluo watersheds, but Wuxuan watershed might experience less extreme low flows, probably because of the enhanced groundwater discharge during the dry season. As for the moderate low flow, the likelihood would rise in Shijiao watershed but will tend to decrease at Wuxuan and Boluo stations.

**DISCUSSION AND CONCLUSIONS**

A modeling system for projecting future changes in the Pearl River flows was established. The core of the system is the conceptual large-scale distributed XAJ hydrological model, driven by the observed historical and future forcing data to simulate historical runoff variations and project future streamflows. Two different delta-change methods were applied for constructing future precipitation scenarios: one with a constant scaling factor and the other with a non-uniform delta-change factor determined by the ratio between RCM-simulated future and baseline precipitation quantiles. Compared with the baseline situation, the two future precipitation data sets obtained from the two delta-change methods

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**Figure 11** Frequencies of extreme streamflow events in the baseline, SDC-A1B, and QQDC-A1B scenarios (the frequency is equal to the ratio of the number of days at a given discharge level to the total number of days over 30 years).
have a similar trend of change, such as more rainless days, increased occurrence frequency of heavy rainstorm events, a considerable rise in heavy precipitation quantiles and a minor decrease in light rain quantiles. In addition, the future annual precipitation amount would rise mildly, with an obvious increase in wet season precipitation and a slight decrease during the dry season. This finding also implies that in the future the watersheds would be subject to significantly more severe extreme rainstorm events. The signals of precipitation change largely determine the trend of future streamflow. Specifically, these signals include the rising risks of extreme flood events and the slightly increasing annual runoff with increased wet season discharge and decreased dry season streamflow.

The predicted changes in future precipitation are, to some extent, sensitive to the methods of future precipitation constructions. Although the two delta-change methods generate an overall consistent trend of future precipitation change, the magnitude of precipitation change differs. The QQDC method generally estimates a significantly larger increase in heavy precipitation quantiles than the SDC method in the Pearl River, because with the quantile-quantile mapping in QQDC, the delta-change factor of heavy rainfall quantiles is relatively larger than the uniform scaling factor adopted in SDC. Olsson et al. (2009) also obtained a similar finding when using the two delta-change methods to construct the future precipitation in a Swedish city. In this study, the QQDC method tends to estimate much higher extreme precipitation values in all three watersheds of the Pearl River than SDC. For instance, the QQDC method projects the 20-year extreme daily precipitation to be 8.1–98.6% higher than that predicted by the SDC method. Owing to the non-uniform scaling factor, the QQDC method also estimates a slightly higher increase in annual and wet season precipitation than the SDC method. These differences in the projected future precipitation data sets from methods are due to the finding that the signals of future precipitation change detected by the PRECIS RCM are generally well preserved by QQDC, whereas the signals in the SDC future precipitation are considerably weaker (Figure 5(b) and 5(d)). Therefore, it is preferable to adopt the QQDC method for future hydrological climate change impact analyses in the Pearl River basin.

The aforementioned differences in transformed future precipitation are likely to influence future streamflow estimates further. This paper finds that the sensitivities of the projected future streamflow to the two delta-change methods are closely related to temporal scales. As regards the mean annual runoff, the QQDC-A1B estimate is merely 1.1–5.6% higher than that of SDC-A1B. When runoff regimes are evaluated at finer time scales (e.g., monthly and daily scales) and in extreme situations, the differences in the baseline and future discharge become more pronounced, with the most significant differences in extreme high flow. In all three watersheds, the XAJ model with the QQDC-A1B precipitation always projects more severe flooding situations than the case of the SDC-A1B precipitation, with the former being 7.0–65.0% higher than the latter in terms of 20-year extreme daily streamflow estimation (Figure 10). The results obtained in this study are similar to those of Shabalova et al. (2003), who estimated a 15% difference in the 20-year extreme daily flow of the River Rhine using two different delta-change methods.

The given impacts of precipitation transformation methods may depend on the geographic location of catchments and the choices of the regions. Our results reveal that in a watershed with stronger precipitation change signals, more distinct estimates of future precipitation and streamflow by different delta-change methods will be obtained. It was found that among the three watersheds in the Pearl River basin, Boluo is the most sensitive to the precipitation transformation methods, given that the PRECIS model projects more apparent non-linear changes in daily precipitation in this area, especially in the heavy precipitation quantiles (Figure 5).

Interestingly, although distinct daily precipitation distributions were derived from two different delta approaches, the CVs of the two corresponding future annual precipitation time series remain almost the same as the CV of the baseline annual precipitation (Table 4). Despite the application of various delta factors, when the QQDC daily precipitation is accumulated into an annual term, the effect of precipitation transformation methods will be neutralized or offset. Therefore, similar to the SDC method, the QQDC method will not obviously change the variability of the projected future annual precipitation in terms of the CV. As a result, the corresponding future annual runoff would retain the similar variability to the baseline situation (Table 6).
Uncertainties in projecting future streamflow also depends on factors other than the chosen methods of meteorological forcing projection. Adopted climate models and greenhouse emission scenarios are the key factors, and missing or mis-parameterized physical processes in the hydrological models might further affect the simulated discharges. Several studies (Jasper et al. 2004; Wilby & Harris 2006; Kay et al. 2009; Jung et al. 2011) showed that the uncertainty of the climate inputs to the hydrological model is much higher than that of the hydrological model itself. Therefore, the hydrological effects of precipitation transformation methods largely depend on the choices of climate models and greenhouse emission scenarios. In this work, only PRECIS-simulated climatology under the economy-oriented IPCC-SRES A1B greenhouse emission scenario was adopted for numerical simulation and analysis. Sensitivity analysis should be conducted to quantify the hydrological impacts of the precipitation transformation methods with multiple emission scenarios and climate models in the future.

Although the aforementioned various uncertainties and biases might influence the modeling results, the methodology introduced in this paper reveals that precipitation transformation methods are a source of uncertainty affecting future discharge projections. Therefore, this uncertainty should be considered in water resources management and flood control strategies aimed at addressing future climate change adaptation. In the Pearl River, for example, the frequency and magnitude of extreme high flows are projected to increase, but in various amplitudes with the two delta-change methods. This finding implies that the return period of designed floods for current hydraulic structural works would be shortened in the future, and it is necessary to re-evaluate the flood control levels of existing structural works under future scenarios. This uncertainty in future flood flow projections arising from precipitation transformation should be carefully considered in the design standards of structural flood-protection projects in the Pearl River basin.

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REFERENCES


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