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Response of long-term water availability to more extreme climate in the Pearl River Basin, China

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Abstract

Under global warming, increasing temporal variability of climatic factors at various time scales (e.g. from inter-daily to inter-annual) has been reported in many places of the world over the past decades. The changes of temporal variability can be characterized by more extreme climate, such as more frequent and intensive heavy precipitation, less light rain days, and longer dry spells. These changes can subsequently bring about more frequent and intensive hydrologic extremes, including floods and droughts. This study shows that increase in inter-daily variability of precipitation and temperature not only triggers more intensive hydrologic extremes, but also causes considerable impacts on long-term water availability. Sixteen climate scenarios are designed to separate overall changes of precipitation and temperature into two aspects: (1) change in monthly mean, and (2) change in inter-daily variability. Runoff of the Pearl River Basin (PRB) is simulated by the Variable Infiltration Capacity (VIC) model under these scenarios. The results indicate that increase in inter-daily variability of the climate alone can lead to considerable increase in long-term water availability with reduced actual evapotranspiration (AET). The simulations also show that the inter-daily interaction between precipitation and temperature (i.e. lower temperature on a rain day) is important for long-term hydrologic simulations. The changing directions of simulated AET under scenarios
with this interaction are opposite to those under scenarios without the interaction.

Keywords: Climate change; Temporal variability; Variable Infiltration Capacity

model; Water availability; Pearl River Basin

1. Introduction

Human-induced global warming not only causes changes in the long-term mean of climatic factors, e.g. long-term averages of precipitation and temperature, but also intensifies their extremes, e.g. heavy precipitation and heat waves (IPCC, 2013). The more extreme climate can be generalized as increases in temporal variability at various time scales, e.g. from inter-daily to inter-annual. These changes in climatic factors accelerate regional hydrologic cycle with consequences of changes in water availability and hydrologic extremes including floods and droughts (e.g. Alan et al., 2003; Held and Soden, 2006; Reichstein et al., 2013; Chen et al., 2015). Impacts of changes in climate on long-term streamflow have been extensively analyzed in previous studies. For instance, Jones et al. (2006) indicated that the sensitivities of annual streamflow in 22 Australian catchments were around 2.1%-2.5% for 1% change in mean annual rainfall. Chiew et al. (2009) used a conceptual rainfall-runoff model SIMHYD to evaluate the climate change impacts on runoff across southeastern Australia. A decrease of mean annual runoff across southeastern Australia was
identifying under a scenario of 0.9°C global warming in the future in their study. Dan et al. (2012) found that compared to increase in mean temperature, increase in mean precipitation was more influential to streamflow in Huang-Huai-Hai Plain region of China under the future climate.

More extreme climate, or higher temporal variability, has been examined by changing statistical behaviors of precipitation and temperature, such as longer consecutive wet days, longer Consecutive Dry Days (CDD), more heavy precipitation, and less light rain days. Zolina et al. (2010) analyzed the duration of consecutive rain days in Europe in the period of 1950-2008 and found that wet spells became longer and led to more abundant precipitation. According to the study of Zhang et al. (2011), the number and total precipitation amount of the maximum consecutive wet days increased in northwestern China, but those in the Yellow, Liaohe, and Haihe river basins decreased during the period of 1960-2005, showing an uneven spatial pattern of changes in temporal variability of precipitation. Zhang et al. (2012) detected fewer rain days as well as shorter but more intensive wet spells in the Pearl River Basin (PRB) during 1960-2005. More extreme climate in the future has been projected in many previous studies. For example, Sushama et al. (2010) concluded that the mean number of CDD and return levels of maximum dry days would increase over Canada in the 21st century. According to Chen (2015), medium,
large and heavy rainfall events were projected to be more frequent and intensive,
while light rainfall events were expected to decrease in China during the end of the
21st century based on the Couple Model Intercomparison Project 5 (CMIP5) simulations.

Intensifying climate extremes are a major driver for more intensive and frequent
floods and droughts (Milly et al., 2002). Groisman et al. (2001) found a significant
relationship between the frequency of heavy precipitation and high streamflow events
in the contiguous United States. They pointed out that the increase of high streamflow
over the eastern United States was related to the increase of heavy precipitation.
Andreadis et al. (2005) indicated that the shorter wet spells were the main reason of
the aggravation of drought during the 1930s and 1950s in the United States.
Increasing and more frequent droughts in terms of different hydrologic variables,
including soil moisture, precipitation, streamflow, etc., were also detected in China
over the past half century (e.g. Wang et al. 2011; Chen and Sun, 2015; Zhang and
Zhou, 2015).

However, little attention has been paid to impacts of changes in temporal
variability of climatic factors at a short time scale (e.g. inter-daily scale) on
hydrologic conditions at a long scale (e.g. mean annual). Understanding of these
impacts has scientific and practical merits. For example, in hydrologic projections,
hydrologic models are usually forced by direct or statistically downscaled outputs of Global Climate Models (GCMs), which are known as being capable of simulating the long-term climatology, but requiring considerable improvements in simulating short-term extremes (Dai, 2006). By answering how short-term temporal variability impacts long-term hydrologic simulations, we can understand more about uncertainties in hydrologic projections. Furthermore, downscaling techniques are an important tool to downscale GCM outputs from coarse spatial resolutions to a finer resolution so to meet the input requirements of hydrologic models. Some statistical downscaling methods, such as Change Factor (CF) (Minville et al., 2008; Prudhomme et al., 2010) and transfer function (Fowler et al., 2007), only consider the long-term statistics and ignore short-term temporal variability of climatic factors. Different climatic factors may be downscaled separately without consideration of the interactions among them (e.g. lower temperature on a rainy day). Therefore, an investigation of impacts of changes in temporal variability on hydrologic simulations helps improve the knowledge of the responses of hydrologic cycle to climate change and understand uncertainties in hydrologic simulations. Therefore, the present paper aims to: 1) estimate the responses of long-term water availability to changes in temporal variability of precipitation and temperature at inter-daily scale across the PRB; 2) quantify the contributions of changes in inter-daily variability to long-term water
availability under future climate change; and 3) discuss implications of changes in
temporal variability on hydrologic simulations.

2. Data and Methodology

2.1. Study Area

The PRB is a rain-fed basin in South China and is the second largest river in
China in terms of annual discharge (Fig. 1). The drainage area of the PRB is around
4.42×10^5 km^2 and extends from 102 °E to the eastern coastline of 117 °E, and 21 °N to
28 °N from the south to the north. The PRB consists of three major tributary basins: Dongjiang, Beijiang, and Xijiang basins. Xijiang is the largest tributary basin
covering 77.8% of the area of the PRB. The PRB is dominated by tropical and sub-
tropical climate zones and largely influenced by the summer monsoon climate with
annual precipitation ranging from 1000 mm to 2000 mm, while summer precipitation
accounts for 72%-88%, and with annual mean temperature varying from 14 °C to 22
°C. The PRB is an important water source for the Pearl River Delta which is an
important economic and social region in China. In the recent decades, the increase of
water demand caused by the rapid economic development and population growth has
induced greater and greater pressure in the water system of the PRB. The Dongjiang
basin provides approximately 80% of Hong Kong’s water demands. The uneven
spatial and temporal distribution of precipitation and streamflow affects the efficiency of water usage. The changes of mean state and temporal variability of precipitation and temperature caused by global warming introduce further uncertainties to the water supply across the PRB.

2.2. Data

In this study, we collect observed daily precipitation and maximum and minimum temperature data for the period of 1961-2010 covering the PRB at a spatial resolution of 0.5°×0.5° from the National Meteorological Information Center (NMIC) of China Meteorological Administration (CMA). These gridded datasets were generated by the NMIC based on observations of 2,472 meteorological stations across China (Shen et al., 2010; Xu 2012; Zhao 2012b). The station-scale observations were interpolated into the 0.5°×0.5° spatial resolution by using the Thin Plate Spline method with consideration of the spatial heterogeneity in elevation (Hutchinson 1998a,b). These datasets have been applied in previous studies (e.g. Sun et al., 2015; Gao et al., 2016). Wind speed is set as a constant of 3 m/s that is close to the average across the PRB (Guo et al., 2011) to minimize impacts of wind speed under scenarios of precipitation and temperature changes (see Section 2.4). Observed daily streamflow of the Boluo, Shijiao, and Wuzhou stations of 1961-2005 are obtained from the Hydrologic Yearbook. Boluo, Shijiao, and Wuzhou are the primary stations of Dongjiang,
Beijiang, and Xijiang basins, respectively. We also acquire bias-corrected outputs of HadGEM2-ES from the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) (Jones et al., 2011; Warszawski et al., 2014). The HadGEM2-ES is a Global Climate Model (GCM) with a spatial resolution of $1.875^\circ \times 1.25^\circ$ (longitude $\times$ latitude) developed by the Met Office Hadley Center (Martin et al., 2011). Among the GCMs in the ISI-MIP, the original spatial resolution of HadGEM2-ES is the highest and hydrologic simulations driven by it have been assessed to be close to observations at the Boluo and Wuzhou stations (Li et al., 2016). The raw outputs of HadGEM2-ES were interpolated to the resolution of $0.5^\circ \times 0.5^\circ$ in the ISI-MIP (Hempel et al., 2013). Outputs of precipitation and temperature of 1971-2000 under the historical scenario and those of 2070-2099 under the Representative Concentration Pathways 8.5 (RCP8.5) scenario are collected. The RCP8.5 is a high emission scenario compared to other future scenarios in the CMIP5 (Taylor et al., 2012). RCP8.5 is also a scenario that does not include any climate mitigation target (Riahi et al., 2011). The radiative forcing in this scenario increases consistently over the 21st century and reaches 8.5 W/m$^2$ by 2100. Under this high emission scenario, a majority of GCMs project more extreme climate at the end of the 21st century with more frequent and intensive precipitation and higher temperature (Li et al., 2016). Therefore, outputs of HadGEM2-ES are used as a representative of these GCMs to study responses of water
availability to changes in temporal variability under future extreme climate. Water availability has been implicitly or explicitly defined as runoff mean in previous studies (e.g. Doll et al., 2003; Manabe et al., 2004; Milly et al., 2005). Therefore, we also use runoff mean during a particular period, e.g. 1961-1985, 1986-2010, etc., to define water availability.

2.3. Variable Infiltration Capacity Model

We use the Variable Infiltration Capacity (VIC) model to simulate daily runoff at a 0.5°×0.5° spatial resolution over the PRB (Liang et al., 1994). The VIC model has been widely used across the world with good performance, e.g. in Minnesota River (Cherkauer and Lettenmaier, 2003), the western United States (Shi et al., 2008), China (Wu et al., 2007), Australia (Sivapalan et al., 1997), etc. The VIC is a semi-distributed macroscale hydrologic model which can resolve water and energy balances within a grid cell (Gao et al., 2010). Variable infiltration curve is used in the VIC to consider the spatial heterogeneity of runoff generation (Zhao, 1992). Saturation, excess runoff, infiltration, snow melting and soil freeze-thaw processes are considered in the VIC (Liang et al., 1996; Nijssen et al., 2001b; Dan et al., 2012). The VIC can be run in water balance mode or water-and-energy balance mode. In water balance mode, soil surface temperature is equal to air temperature and surface energy balance is unsolved. The energy balance mode solves surface energy balance by iterative
processes, which are more demanding for computational time. In evapotranspiration modeling, three types of evaporation are considered in the VIC model, including canopy evaporation, vegetation transpiration, and evaporation from bare soil (Liang et al. 1994). The potential evapotranspiration (PET) is calculated from the Penman-Monteith equation based on temperatures (Shuttleworth, 1993). The actual evapotranspiration (AET) from the three types are estimated based on different formulations (e.g. formulation from Ducoudre et al. (1993) for vegetation transpiration and Arno formulation for soil evaporation) with consideration of parameters for different vegetation types, soil properties, soil moisture, etc. More details of the VIC can be found in Gao et al. (2010).

In this study, the global parameters at the $0.5^\circ \times 0.5^\circ$ spatial resolution generated by Nijssen et al. (2001a,b) are used. The soil textural parameters and soil bulk densities were derived from the Food and Agriculture Organization (FAO, 1998) combined with the World Inventory of Soil Emission Potentials pedon database (Batjes, 1995). Vegetation types were obtained from 1 km AVHRR (Advanced Very High Resolution Radiometer)-based land classification from Hansen et al. (2000). Despite these physically-derived parameters, there are seven soil parameters subject to calibration, including infiltration parameter $b_i$, fraction of maximum base flow $D_s$, maximum velocity of base flow $D_m$, fraction of maximum soil moisture content of the third layer...
$W_s$, and thicknesses of the three soil layers $d_1$, $d_2$ and $d_3$ (Xie et al. 2007). The VIC is implemented for Dongjiang, Beijiang and Xijiang basins with 3 soil layers at a daily time step with the water balance mode. After solving the water balance in a grid cell, base flow and runoff are determined at the end of the time step. A routing model is employed to rout surface runoff and base flow to the outlet of grid cells then into the river channel of that basin (Lohmann et al., 1998). The routing model calculates the concentration time for runoff to the outlet of a grid cell and the channel flow in the river network (Gao et al., 2010). The within-cell routing is solved by a linear transfer function based on the internal impulse response function. Then the linearized Saint-Venant equation is used for channel routing.

The Shuffled Complex Evolution (SCE-UA) method, a global optimization procedure developed by Duan (1992, 1993), is used to calibrate VIC by optimizing the seven aforementioned parameters. Two measures are incorporated into the objective function: the Nash-Sutcliffe efficiency measure $E$ (Nash and Sutcliffe, 1970) and the bias $B$ (total model error divided by total observed streamflow). The objective function $F$ is a weighted combination of $E$ and a logarithmic function of $B$ as indicated by Viney (2009)

$$F = E - 5|\ln(1+B)|^{2.5}$$

The coefficients of this function control the severity and shape of the bias constraint
penalty (Zhao et al., 2012a). The best ten sets of parameters are selected automatically by SCE-UA. Afterward, among these sets of parameters, we choose the one that can best fit the seasonal pattern and extremes of streamflow. The ranges of these parameters for calibration are shown in Tab. 1. The period of 1961-1970 is used as the calibration period for the VIC model, while the period of 1971-1980 is used as the validation period. The PRB has been experiencing rapid economic development and widespread land use changes since the 1980s and these changes significantly affected the hydrologic conditions (Seto et al., 2002). The selection of these two periods is to minimize the effects of human activities on calibration and validation of the VIC model.

2.4. Scenarios design: changes in monthly mean and inter-daily variability

The overall changes in precipitation/temperature can be divided into two aspects: (1) monthly mean and (2) inter-daily variability. Fig. 2 illustrates changes in these two aspects of daily precipitation between 1975 and 2000 at a grid cell in the PRB. Fig. 2a shows time series of daily precipitation in 1975 and 2000. The differences in monthly precipitation between 1975 and 2000 are clearly shown in Fig. 2b with significant reduction in 2000. However, it is difficult to infer inter-daily variability from Fig. 2b. For example, the precipitation amount of a month with a couple of extreme heavy rainfall days may be the same as that of another month with many light rain days.
However, their impacts on inter-daily hydrologic conditions, such as daily soil moisture, runoff generation and evaporation can be very different. These differences can accumulate for a long time and hence affect inter-monthly or even inter-annual hydrologic conditions. Fig. 2c shows the differences of inter-daily variability of May in 1975 and 2000. We scale the precipitation mean amount of May in 2000 to that in 1975 so as to control the influences of the precipitation mean amounts. Therefore, in Fig. 2c, there is no difference for precipitation of May in 1975 and 2000 in monthly scale. However, in daily scale, heavy precipitation is more intense and rain days are less frequent in May of 2000; while precipitation in May of 1975 is mainly contributed by a number of light rain days. This study aims to evaluate how such changes in inter-daily variability of precipitation and temperature affect long-term water availability.

According to Zhang et al. (2009), precipitation across the PRB changed abruptly in the 1980s, so the observation period of 1961-2010 is divided into two parts: the first period (1961-1985), or called the reference period, and the second period (1986-2010), or called the changed period. Relative to the reference period, the climate changes to be more extreme during the changed period. Only changes in precipitation and temperature are considered when we design the climate scenarios. Other hydroclimatic variables and physical parameters of the basin are controlled or derived...
from precipitation and temperature. Wind speed is set as a constant rate of 3 m/s.

Constant wind speed forcing has been used for hydrologic models in many previous studies (e.g. Bao et al. 2012; Wang et al. 2012; Zhao et al. 2012a). We also compare discharge simulations forced by a constant wind speed and daily average wind speed from the NCEP-NCAR reanalysis (Kalnay et al. 1996), and find very similar results with difference in $E < 0.01$ (details not shown). Similar to previous studies using VIC (e.g. Maurer et al. 2002; Shi et al. 2008; Zhang et al. 2014), other climatic factors, such as humidity, incoming shortwave radiation, incoming longwave radiation, etc., are referred to precipitation and temperature based on a variety of algorithms in the VIC model, such as the MTCLIM algorithms (Kimball et al., 1997) and the Tennessee Valley Authority algorithms (Bras, 1990). As shown in Fig. 2, characteristics of precipitation series can be divided into monthly mean and inter-daily variability.

Precipitation series is denoted by $P_{ij}$, where $i = 0$ indicates monthly mean amount of each month is equal to that of the corresponding month during the reference period, while $i = 1$ means monthly mean amount is equal to that during the changed period; $j = 0$ indicates inter-daily variability of each month is the same that of the correspondingly month during the reference period, while $j = 1$ means inter-daily variability is the same as that during the changed period. Therefore, daily precipitation series of the $k^{th}$ month (denoted by $P_{ijk}$) can be calculated by
\[ P_{ij,k} = \begin{cases} P_{r,k} & (i=0, j=0) \\ P_{r,k} & (i=1, j=1) \\ \bar{P}_{r,k} & (i=0, j=1) \\ \bar{P}_{r,k} & (i=1, j=0) \\ P_{c,k} & (i=1, j=1) \end{cases} \]  

(2)

where \( P_{r,k} \) denotes the daily precipitation series of the \( k^{th} \) month during the reference period; \( P_{c,k} \) denotes the daily precipitation series of the \( k^{th} \) month during the changed period; \( \bar{P}_{r,k} \) denotes the monthly precipitation mean of the \( k^{th} \) month during the reference period; and \( \bar{P}_{c,k} \) denotes the monthly precipitation mean of the \( k^{th} \) month during the reference period. Similarly, we have temperature series \( T_{ij} \), and the daily temperature series of the \( k^{th} \) month (denoted by \( T_{ij,k} \)) can be calculated by

\[ T_{ij,k} = \begin{cases} T_{r,k} & (i=0, j=0) \\ \bar{T}_{r,k} & (i=0, j=1) \\ \bar{T}_{c,k} & (i=1, j=0) \\ T_{c,k} & (i=1, j=1) \end{cases} \]  

(3)

where \( T_{r,k} \) denotes the daily temperature series of the \( k^{th} \) month during the reference period, \( T_{c,k} \) denotes the daily temperature series of the \( k^{th} \) month during the changed period, \( \bar{T}_{r,k} \) denotes the monthly temperature mean of the \( k^{th} \) month during the reference period, and \( \bar{T}_{c,k} \) denotes the monthly temperature mean of the \( k^{th} \) month during the changed period. The four precipitation series \( P_{ij} \) and the four temperature series \( T_{ij} \) combine together to form sixteen climate scenarios as shown in Tab. 2. The monthly mean and inter-daily variability of precipitation and temperature under \( S_{P_{00}T_{00}} \) are the same as those under the reference period, and those under \( S_{P_{11}T_{11}} \) are the same as those under the changed period. These 16 scenarios represent different
combinations of monthly mean and inter-daily variability of precipitation and
temperature. For example, compared $S_{P_{01}T_{00}}$ to $S_{P_{00}T_{00}}$, the difference is that the
inter-daily variability of precipitation under $S_{P_{01}T_{00}}$ is the same as the changed
period. The difference between $S_{P_{10}T_{00}}$ and $S_{P_{00}T_{00}}$ is that the monthly precipitation
mean under $S_{P_{10}T_{00}}$ is the same as the changed period.

2.5. Inter-daily interaction between precipitation and temperature

Precipitation and temperature are interrelated at various scales (Isaac and Stuart
1992; Huang et al., 2009; Cong and Brady, 2012; Li et al., 2015). For example, at
inter-daily scale, temperature is more likely to be lower on a rain day compared to the
neighboring days, and high temperature is more associated with dry spells. Among
some climate scenarios in Tab. 2, this inter-daily interaction between precipitation and
temperature are maintained by keeping the inter-daily variability of precipitation and
temperature in the same period. For example, the inter-daily variability of
precipitation and temperature under the scenarios of $S_{P_{00}T_{00}}$, $S_{P_{00}T_{10}}$, $S_{P_{10}T_{00}}$, and
$S_{P_{10}T_{10}}$ are under the reference period. And for $S_{P_{01}T_{01}}$, $S_{P_{01}T_{11}}$, $S_{P_{11}T_{01}}$, and $S_{P_{11}T_{11}}$,
the inter-daily variability of precipitation and temperature are the same as those of the
changed period. For these scenarios, the day-to-day correlation between precipitation
and temperature are maintained, although their monthly mean may be scaled. For the
other scenarios that the inter-daily variability of precipitation and temperature are not
in the same period, such as \( S_{P_0 T_0}, S_{P_0 T_{11}}, S_{P_{01} T_0}, S_{P_{01} T_{11}}, S_{P_{10} T_0}, S_{P_{10} T_{11}}, \) \( S_{P_{11} T_0} \), and \( S_{P_{11} T_{11}} \), this inter-daily interaction is damaged. In other words, under these scenarios, the day-to-day variability of temperature is irrelevant to the inter-daily variability of precipitation.

3. Results

We calibrate the VIC model to obtain the optimum parameters as the first step of this study. Secondly, changes in means and inter-daily variability of precipitation and temperature are analyzed. Thirdly, the VIC model is used to quantify the impacts of changes in monthly mean and inter-daily variability on long-term water availability. Finally, the VIC model is forced by the projected precipitation and temperature from HadGEM2-ES under RCP8.5 to estimate how changes in monthly mean and inter-daily variability affect future water availability.

3.1. Calibration and validation of the VIC

The aforementioned seven parameters \( bi, D_s, D_m, W_s, d_1, d_2 \) and \( d_3 \) are adjusted to optimize the objective function by comparing the simulated and observed streamflow at Boluo, Shijiao, and Wuzhou during 1961-1970. The optimum parameters for the three basins after calibration are listed in Tab. 1. The VIC model is validated based on the streamflow of 1971-1980. Tab. 3 lists the daily and monthly \( E \) and \( B \) in the
calibration and validation. The monthly $E$ values for three basins are all above 0.9 in the calibration and above 0.8 in the validation. $B$ values are generally within -0.10 and 0, except those of Shijiao and Wuzhou during validation. The comparison of the VIC simulations against observations during the periods of calibration and validation (Fig. 3) is in good agreement with the results in Tab. 3. The VIC captures the timing of wet and dry months well (e.g. high $E$ values) but tends to underestimate the extremely high streamflow (e.g. slightly negative $B$ values). As introduced above, wind speed is controlled as a constant rate of 3 m/s and other hydroclimatic factors are estimated from precipitation and temperature from the algorithms in the VIC model. As shown in Tab. 3 and Fig. 3, this setting does not significantly affect the performance of the VIC model. Overall, the VIC is capable of simulating streamflow in the PRB at both daily and monthly scales.

3.2. Changes in monthly mean and inter-daily variability of precipitation and temperature

The monthly mean and inter-daily variability of $P_{00}$ are the same as those of the reference period. Compared to $P_{00}$, only the monthly mean changes to the changed period in $P_{10}$, and the inter-daily variability of precipitation remains the same as during the reference period. The mean precipitation of $P_{10}$ decreases by 2%-4% across the PRB compared to $P_{00}$ (Fig. 4a). In the western part, the mean decreases more with
a decreasing rate of 8%. Because the inter-daily variability of $P_{10}$ is the same as that of $P_{00}$, the Cumulative Distribution Functions (CDFs) of CDD and heavy precipitation extremes (>99th percentile) of $P_{00}$ and $P_{10}$ are almost the same (Fig. 4d-i). In fact, the inter-daily variability is related with more extremes, but we only use CDD and heavy extremes as examples here.

In $T_{10}$, the monthly mean changes and inter-daily variability are the same compared to $T_{00}$. Maximum temperature is found to increase in the southeastern PRB with a rate of 2%-4% (Fig. 4b). In other places, the changes in maximum temperature are between -2% to 2%, which is unremarkable. Minimum temperature increases more remarkably, with a rate of 2%-4% for most of the area (Fig. 4c). In the western parts, the minimum temperature mean increases by more than 6%.

Under $P_{01}$, a scenario where only inter-daily variability of precipitation changes compared to $P_{00}$, the large CDD (CDFs larger than 0.9) are larger than those of $P_{00}$, indicating that extreme CDD becomes more persistent. Furthermore, the change in inter-daily variability of precipitation causes heavy precipitation more intensive (Fig. 4e-i). Overall, compared to $P_{00}$, although the mean precipitation of $P_{01}$ is the same, the CDD is longer and precipitation extremes are more intensive, indicating a more extreme climate.

3.3. Impacts of inter-daily interaction between precipitation and temperature on
To understand the impacts of the inter-daily interaction on hydrologic simulations, we compare AET simulated from the VIC under the scenarios with/without this interaction. In $S_{P_0T_0}$, where the inter-daily interaction of precipitation and temperature remains as that in the reference period and only mean temperature increases, the AET change unremarkably, indicating the increase in mean temperature does not affect AET considerably (Fig. 5). In another scenario $S_{P_0T_0}$, where the inter-daily relation of precipitation and temperature is damaged and the monthly mean of precipitation and temperature are the same as those of the reference period, the AET increases measurably, demonstrating remarkable impacts of the lack of this interaction on AET. In Fig. 5, under the scenarios where such interaction is damaged (i.e. $S_{P_0T_0}$, $S_{P_0T_1}$, $S_{P_0T_0}$, $S_{P_0T_1}$, $S_{P_1T_0}$, $S_{P_0T_1}$, $S_{P_0T_0}$, and $S_{P_1T_0}$), the AET generally increases. In general, in daily scale, temperature is lower on a rain day. As a rainy event may provide sufficient surface water, temperature may become the controlling factor for AET. Therefore lower temperature implies lower AET. If the inter-daily interaction of precipitation and temperature is damaged, this relation would disappear and hence AET on rain days may increase due to the increase in temperature. In reality, the mechanism behind the increase of AET under a damaged interaction between precipitation and temperature may be more complex,
and the above is only one explanation.

Under other scenarios where such interaction remains and the inter-daily variability are the same as those in the reference period (i.e. $S_{P_{00}}T_{10}$, $S_{P_{10}}T_{00}$ and $S_{P_{10}}T_{10}$), the increase in temperature mean does not lead to considerable changes in AET (i.e. $S_{P_{00}}T_{10}$), but the decrease in precipitation mean causes reductions of AET by 2%-4% in the western parts (i.e. $S_{P_{10}}T_{00}$). For scenarios where the interaction remains and the inter-daily variability changes to those in 1986-2010, including $S_{P_{01}}T_{01}$, $S_{P_{01}}T_{11}$, $S_{P_{11}}T_{01}$ and $S_{P_{11}}T_{11}$, AET decreases considerably relative to those under scenarios with inter-daily variability of the reference period, implying that the changes in inter-daily variability in precipitation and temperature (i.e. $S_{P_{01}}T_{01}$) cause more considerable impacts on AET than changes in monthly mean (i.e. $S_{P_{10}}T_{10}$). As for climate conditions of 1986-2010 (i.e. $S_{P_{11}}T_{11}$), the decrease in AET is the combined result of the changes in $S_{P_{01}}T_{01}$ and $S_{P_{10}}T_{10}$. According to the above results, the inter-daily interaction of precipitation and temperature play an indispensable role in hydrologic simulations. Therefore, in the following analysis, we only discuss the scenarios where this interaction remains.

### 3.4. Impacts of changes in monthly mean and inter-daily variability of precipitation/temperature on long-term water availability

In this section, we present the impacts of the changes in monthly mean and inter-
daily variability of precipitation/temperature on long-term water availability. Fig. 6 shows the change in water availability under different climate scenarios relative to the reference period. The increase of temperature mean introduces negligible changes in water availability (i.e. \( S_{P_{00},T_{10}} \)). When the inter-daily variability of precipitation and temperature change, water availability increases by 2%-8%, especially in the western and northern PRB (i.e. \( S_{P_{01},T_{01}} \)). When only the decrease in precipitation mean and the increase in temperature mean are considered, the water availability decreases considerably in the southern and the most western parts of the PRB, with a decreasing rate of < -6% (i.e. \( S_{P_{10},T_{10}} \)). Comparisons \( S_{P_{01},T_{11}} \) between \( S_{P_{01},T_{01}} \) and, as well as \( S_{P_{11},T_{01}} \) and \( S_{P_{11},T_{11}} \) indicate that increase in temperature does not significantly affect water availability. In \( S_{P_{11},T_{11}} \), the changes in water availability are the combined result of changes in inter-daily variability and monthly mean. In this climate scenario, water availability decreases by < 4% in the southern and the most western PRB, but not as dramatically as that under \( S_{P_{10},T_{10}} \). The northern and eastern PRB is detected with a slight increase of water availability, which is one of the characteristics of \( S_{P_{01},T_{01}} \). This comparison indicates the changes in inter-daily variability of precipitation and temperature raises water availability, while the decrease in precipitation mean reduces water availability. The increase in temperature mean causes negligible impacts on changes in water availability.
According to the CDFs of precipitation under different scenarios in Fig. 7, annual mean precipitation in Dongjiang basin under different scenarios changes negligibly (Fig. 7a). As a result, the discharge (routed from grid cells across Dongjiang basin) at the Boluo station also change negligibly under different scenarios (Fig. 7d). In Beijiang, the CDFs of precipitation mean of \( P_{00} \) are similar with those of \( P_{10} \), while CDFs of \( P_{11} \) are similar with \( P_{01} \), implying that the CDFs are mainly determined by inter-daily variability (Fig. 7b). For the upper-right tail of CDFs (precipitation > 5.5 mm/day) and the lower-left trail of CDFs (precipitation < 4 mm/day), wet years are more frequent under \( P_{00} \) and \( P_{10} \) while dry years are more frequent under \( P_{01} \) and \( P_{11} \). Correspondingly, annual mean discharge at Shijiao station under \( P_{00} \) and \( P_{10} \) is larger in the upper-right tail (Fig. 7e). For Xijiang, annual mean precipitation of \( P_{11} \) is considerably lower than precipitation of \( P_{00} \) (Fig. 7c). However, for \( P_{01} \), where only the change in inter-daily variability is taken into account, the large annual precipitation (precipitation > 4 mm/day) occurs the most frequently. Similar results also can be found in the CDFs of annual mean discharge at Wuzhou station (Fig. 7f).

3.5. Contribution of changes in monthly mean and inter-daily variability to the change in water availability under RCP8.5

The above results show the discernible impacts of change in inter-daily
variability on long-term water availability across the PRB during 1961-2010. During this period, in fact, monthly mean of precipitation does not change dramatically (only decrease by 2%-4% after 1985). Therefore, one may argue that impacts of changes in inter-daily variability are discernible only when the mean changes insignificantly. One may also argue that in the future scenario, precipitation mean may change more dramatically, and hence the impacts of the change in inter-daily variability could be negligible and ignored. In order to understand the role of the changes in inter-daily variability in the future extreme climate, we use simulations of HadGEM2-ES under the historical (1971-2000) and RCP8.5 (2070-2099) scenarios to generate 16 climate scenarios with the same procedure described in Section 2.4.

During 2070-2099, the mean precipitation across the PRB increases by more than 18% compared to 1971-2000 (Fig. 8a). In the southern part, the change rates are less than 9%. The maximum precipitation increases more considerably than the mean (Fig. 8a-d). In the scenario where only the change in inter-daily variability of precipitation is considered (i.e. $P_{01}$), the maximum precipitation increases by 15%-30% (Fig. 8b). The increase in the south is higher than that in the north. When only the change in precipitation mean is considered (i.e. $P_{10}$), maximum precipitation also increases by 15%-40%, but the spatial pattern is different from those under $P_{01}$ (Fig. 8b, c). The increase rate is higher in the northern part. When changes of monthly
mean and inter-daily variability are considered (i.e. $P_{11}$), maximum precipitation increases by more than 55% in the most western and eastern PRB (Fig. 7d). In the middle part, maximum precipitation also increases by 25%-40%.

Under $S_{P_{01}T_{01}}$, a scenario where only the changes in inter-daily variability of precipitation and temperature are considered, an increase of 10%-20% is detected across the PRB except in the Beijiang basin and the southern part of the PRB (Fig. 8e). Under $S_{P_{11}T_{11}}$, the 18%-24% increase in the mean precipitation (Fig. 8c) brings about 30%-40% increase in water availability (Fig. 8f). When both the changes in monthly mean and inter-daily variability are considered (i.e. $S_{P_{11}T_{11}}$), the long-term water availability increases by 40%-60% (Fig. 8g).

Discharge under different scenarios in the future indicates that only changes in inter-daily variability can cause considerable changes in CDFs of mean discharge (Fig. 9). At the same time, when only increases in mean precipitation and temperature are considered, annual mean discharge also increases remarkably (i.e. $S_{P_{10}T_{10}}$), although AET may increase due to increase in precipitation and temperature.

Generally, at Shijiao and Wuzhou, compared to change in inter-daily variability, the increase in precipitation mean contributes more to the increase in discharge. However, at Boluo station, the outlet of the smallest sub-basin of the PRB, the contribution of the changes in inter-daily variability of precipitation to water availability is as high as
that of the changes in precipitation mean. Therefore, under RCP8.5, the changes in
inter-daily variability contribute considerably to the increase in water availability in
the PRB.

4. Discussion

Previous studies have shown that the change in temporal variability can bring
about significant impacts on floods (Milly et al., 2002; Groisman et al., 2001). Our
results indicate that changes in inter-daily variability also introduce considerable
impacts on long-term water availability. In the PRB, the change in inter-daily
variability of precipitation is characterized by fewer rain days, more intense heavy
precipitation and longer CDD. In the VIC model, the Arno formulation is used to
calculate soil AET when the top soil layer is not saturated (Todini 1996; Gao et al.,
2010). In the Arno formulation, AET is positively associated with the average soil
moisture content. Lower soil moisture content implies lower AET. In a more extreme
climate with higher inter-daily variability, there are fewer rain days and longer CDD,
which affect AET from two aspects. First, there would be more days with low soil
moisture, and these dry spells become longer and more consistent. Second, as dry
spells become longer, the soil moisture would become lower and lower as time goes
by during dry spells, hence daily soil AET would be lower and lower as well. These
two effects at daily scale accumulate for a certain time so as to lower long-term AET and hence raise long-term water availability under a more extreme climate. Therefore, fewer rain days but more intense heavy precipitation indicate higher water availability at a long-term scale, which seems to be beneficial to water supply. However, because of the increase in temporal variability of precipitation and temperature, such increase in water availability is characterized by significant increases in floods in wet seasons but decreases in soil moisture in dry seasons, implying challenges for the future water management and agriculture.

So far, studies that consider the influence of the change in inter-daily variability on long-term hydrologic cycle are limited, which may lead to underestimation of the impacts of climate change on long-term water availability in hydrologic projections. For instance, the CF method is a commonly used method to downscale the coarse GCM outputs to a finer resolution to drive hydrologic models (Minville et al., 2008; Prudhomme et al., 2010). One of the caveats of CF is that CF only considers changes in mean, maxima and minima of climatic factors and ignores the change in inter-daily variability (Diaz-Nieto and Wilby, 2005). So the downscaled outputs from CF may underestimate the impacts of the changing climate on the extremes (e.g. floods) as well as the long-term mean (e.g. water availability) of the hydrologic cycle.

As shown in Section 4.3, the inter-daily interaction between precipitation and
temperature is important for hydrologic simulations. For example, temperature may be lower on a rain day, and hence reduces daily AET. When such interdependent relation is damaged, AET may increase as shown in Fig. 5. Therefore, for hydrologic simulations, this inter-daily interaction should be considered in hydrologic studies to increase the accuracy of hydrologic simulations. However, in some of the hydrologic projections, multiple climatic factors were usually downscaled for hydrologic simulations without consideration of their interactions, which might introduce more uncertainties in the hydrologic simulations (Fowler et al., 2007).

Last but not least, we apply the outputs of HadGEM2-ES to represent the future climate. In this GCM, mean precipitation is projected to increase under RCP8.5. In general, precipitation mean projected from various GCMs may be very different, but most projections agree that precipitation extremes become more intense in the future (Li et al., 2013, 2016). Therefore, the impacts of changes in inter-daily variability on hydrologic conditions at long-term scales should be well considered in hydrologic projections driven by GCMs.

5. Conclusions

In this study, we evaluate impacts of change in inter-daily variability and monthly mean of precipitation/temperature on long-term water availability by using
the VIC model. Sixteen climate scenarios with consideration of changes in monthly
mean and/or inter-daily variability of precipitation/temperature are designed.
Simulations from the VIC model under these scenarios are compared. The following
conclusions can be drawn from the results:
(1) More extreme climate raises long-term water availability with decreasing AET
across the PRB. After 1985, the increase of inter-daily variability of precipitation can
be characterized by fewer rain days, more intensive extremes and longer CDD. Such
increase in inter-daily variability raises long-term water availability by 2%-8%.
(2) The climate is expected to be more extreme in the future under RCP8.5, and the
potential increase in inter-daily variability considerably contributes to the increase in
long-term water availability at the end of the 21st century. The increase in inter-daily
variability of precipitation and temperature from HadGEM2-ES under RCP8.5 raises
the long-term water availability by 10%-20%.
(3) The inter-daily interaction of precipitation and temperature is important for
hydrologic simulations. Compared to the scenarios where this interaction relation is
maintained, scenarios without this interaction bring about increases in AET.
Therefore, the changes in inter-daily variability and the inter-daily interaction between
precipitation and temperature should be well considered in hydrologic simulations and
projections. These characteristics may be damaged by data preprocessing, statistical
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Figure 1. The Pearl River Basin and hydrologic stations. Stations Wuzhou, Shijiao, and Boluo are the primary stations of Xijiang, Beijiang and Dongjiang basins, respectively. The grids with grey outline show the spatial resolution (0.5°×0.5°) of the configuration of the VIC.
Figure 2. Daily precipitation of the years of 1975 and 2000 (a), monthly means of precipitation in 1975 and 2000 (b) and daily precipitation of May in 1975 and 2000 (c) of the grid cell centered at (111.25°E, 23.25°N). In (a), the period between the dash lines indicates May. In (c), the monthly mean amount of May in 2000 is scaled to that in 1975.
Figure 3. Calibration and validation of the VIC simulations at the (a) Boluo, (b) Shijiao, and (c) Wuzhou stations.
Figure 4. Change rate (%) of mean precipitation (a) of P$_{10}$ with reference to P$_{00}$, and mean maximum temperature (b) and mean minimum temperature (c) of T$_{10}$ with reference to T$_{00}$. CDFs of CDD in Dongjiang (d), Beijiang (e) and Xijiang (f) basins, and precipitation extremes (>99$^{th}$ percentile) in Dongjiang (g), Beijiang (h) and Xijiang (i) basins of P$_{00}$ (red), P$_{01}$ (blue), P$_{10}$ (green), and P$_{11}$ (black).
Figure 5. Change rate (%) of mean actual evapotranspiration across the PRB under different scenarios with reference to $S_{p_{00}T_{00}}$. 
Figure 6. Change rate (%) of water availability across the PRB under different scenarios with reference to $S_{p00T00}$. 
Figure 7. CDFs of areal average of annual mean precipitation (mm/d) across Dongjiang (a), Beijiang (b), and Xijiang (c) basins and annual mean discharge (m$^3$/s) at Boluo (d), Shijiao (e), and Wuzhou (f) stations.
Figure 8. Change rate (%) of annual mean precipitation of $P_{10}$ (a), and of annual maximum precipitation of $P_{01}$ (b), $P_{10}$ (c) and $P_{11}$ (d) with reference to $P_{00}$, as well as water availability of $S_{P_{01}T_{01}}$ (e), $S_{P_{10}T_{10}}$ (f), and $S_{P_{11}T_{11}}$ (g) with reference to $S_{P_{00}T_{00}}$ under RCP8.5.
Figure 9. CDFs of areal annual mean discharge (m$^3$/s) at Boluo (a), Shijiao (b), and Wuzhou (c) under RCP8.5.
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<td>Maximum velocity of base flow (mm/day)</td>
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<td>Thickness of the third soil layer (m)</td>
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Table 2. Definitions of the sixteen climate scenarios. 0 denotes the monthly mean or inter-daily variability is the same as the reference period (1961-1985), and 1 denotes the monthly mean or inter-daily variability is the same as the changed period (1986-2010).

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Table 3. Daily and monthly $E$ and $B$ of calibration and validation at Boluo, Shijiao, and Wuzhou

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<th>Shijiao</th>
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