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across China: spatiotemporal patterns and implications for flood
and drought hazards**

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Future joint probability behaviors of precipitation extremes across China: spatiotemporal patterns and implications for flood and drought hazards

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Abstract: Observed daily precipitation from 527 meteorology stations in China

during 1960-2005, and simulated daily precipitation from five Earth System Models (ESMs) under historical, RCP2.6 and RCP8.5 scenarios from Coupled Model Intercomparison Project Phase 5 (CMIP5) datasets are analyzed to investigate joint probability behaviors of precipitation extremes in China during 2021-2050 and 2071-2100. Five joint return periods based on six extreme precipitation indices are defined. These joint return periods consider co-occurrence of extreme heavy and weak precipitation, as well as joint extreme heavy precipitation events in terms of different combinations of extreme precipitation amount, intensity, fractional contribution to annual precipitation days, and consecutive wet periods. Weather Generator Model (WGEN) is used to downscale the outputs of ESMs, and Copula is applied to construct joint probability distributions. The variations of joint return periods with 5-year marginal values (marginal values larger than their 5-year return period values respectively) and 20-year marginal values are discussed to represent changes in joint probability behaviors. Results show that: (1) during 1960-2005, spatial distributions of joint return periods with 5-year marginal values are similar to those with 20-year marginal values; (2) changes in marginal distributions and bivariate relationships between extreme indices may be the causes of joint probability distributions shift; (3) in general, during 2021-2050 and 2071-2100, there are less co-occurrence of consecutive wet and dry days, and more joint

extreme heavy precipitation events with various aspects, implying less risk of co-occurrence of floods and droughts in the same year but higher risk of floods in China. But north China may face higher risk of co-occurrence of severe floods and droughts in the same year; and (4) changes in joint return periods under RCP8.5 are more remarkable than under RCP2.6. Even under RCP2.6, a scenario 2°C global average warming target is met, the changes in joint return periods are still considerable.

Key words: Joint return period; Copula; extreme precipitation; CMIP5; China

1. Introduction

Change in climatic extremes is one important aspect of global climate change (Easterling et al., 2000; IPCC, 2007; Min et al., 2011). Climatic extremes are one of the crucial drivers of meteorological and hydrological hazards, such as floods and droughts (Zhang et al., 2008). Hence, the change in climatic extremes, especially precipitation extreme, may alter the occurrence, duration, and intensity of floods and droughts (Ely et al., 1993; Mirza, 2002). The increasing catastrophic losses as a result of natural hazards arouse the public awareness of extreme events in recent years (e.g. Beniston and Stephenson, 2004; Zolina et al., 2004). By 2100, the mean annual global surface temperature increases by 1.4 - 5.8 °C, and future climatic

extremes tend to increase and intensify correspondingly (Houghton et al., 2001; Beniston et al., 2007; IPCC, 2007). Therefore, it is of great merits to investigate future variations of precipitation extremes to provide scientific insight into probable changes in floods and droughts, and similar studies could be practically helpful for water resources management.

The regional responses of precipitation extremes to climate changes are diverse. Sillmann et al., (2013) used the Coupled Model Intercomparison Project Phase 5 (CMIP5) multimodel ensembles to analyze changes in extreme precipitation indices over the 21st century relative to the period of 1981-2000, and found out that extreme precipitation generally increases in most regions, except for Australia, Central America, South Africa and the Mediterranean region. Kothavala (1997) found out that more wet and dry spells would occur and the frequency of extreme precipitation would increase in the Midwest USA under enhanced greenhouse conditions based on an atmospheric Global Circulation Model (GCM). Frei et al. (2006) used six European Regional Climate Models to analyze the precipitation extremes under A2 scenario, indicating that winter precipitation extremes increase in north to about 45°N, and those to the south decrease or change insignificantly.

Recently, with the release of the CMIP5 datasets, some GCMs are coupled to biogeochemical components, i.e. vegetation and atmospheric chemistry, and the

ocean and land carbon cycle (Moss et al., 2010; Taylor et al., 2012). These GCMs are called Earth System Models (ESMs) (Collins et al., 2011). ESMs consider more components of the real physical world, but they are with simplified equations and coarser spatial resolutions compared to GCMs (Moss et al., 2010). Meanwhile, a new type of scenario called “Representative Concentration Pathway” (RCP) is also proposed by CMIP5. One of advantages of RCP is that it takes into account the policy interventions to achieve certain emission targets (Moss et al., 2010). Such improvements in CMIP5 provide a more robust and detailed picture about the future climate conditions.

Many previous literatures investigate probabilistic behaviors of precipitation (e.g. Groisman et al., 1999; Frei and Schär, 2001; Palmer et al., 2002). Recently, increasing concerns have been drawn to the joint behaviors of precipitation extremes. Hashino (1985) studied the joint distributions of precipitation intensity and maximum storm surge in Osaka Bay, Japan, via the Freund bivariate exponential distribution. Yue (2001) used the bivariate extreme value distribution with Gumbel marginal to investigate the joint probability distribution of the annual maximum rainfall intensity and amount. However, these studies are basically based on one of these assumptions: precipitation variables each have the same type of marginal distribution; or variables are assumed to follow or can be transformed to the normal

distribution (Zhang and Singh, 2007). Copula is considered as a flexible and important tool in bivariate analysis of precipitation extreme, and no assumption is needed (Salvadori and De Michele, 2004; Zhang and Singh, 2007; Leonard et al., 2008). Zhang and Singh (2007) employed the Archimedean Copulas to estimate joint return periods of precipitation and this application was tested using the precipitation data from the Amite River basin in Louisiana, United States. Zhang et al. (2013a) investigated spatiotemporal patterns of historical precipitation extremes in China during 1960-2005 based on Copula. Wang et al. (2010) applied weighted likelihood Copula to construct joint return periods of extreme precipitation in the state of Connecticut.

China is a developing country with high exposure to the threats of floods and droughts, and it's heavily relying on the agriculture, which makes China more vulnerable to these threats (Zhang et al., 2012). Changing properties of historical precipitation extremes and corresponding joint probability behaviors, and future possible changes in univariate precipitation extremes in China are analyzed in previous studies (Li et al., 2013a and 2013b; Zhang et al., 2013a). A study about future joint probability behaviors of precipitation extremes in China is important for better understanding of the regional responses of precipitation extremes to climate change and for reference to the water resources management and also for floods and

droughts control. In this case, this paper aims to investigate the possible spatiotemporal patterns of changes in joint probability behaviors of precipitation extremes in China during 2021-2050 and 2071-2100 based on Copula and ESMs from CMIP5. In this study, firstly, a case study is discussed to present how to estimate the observed and future joint distributions and joint return periods by using Copula and downscaling technique. Then spatial patterns of joint return periods of precipitation extremes in China during 1960-2005 are investigated to give the historical picture of joint return periods of precipitation extremes in China. Finally, possible changes in joint return periods of precipitation extremes during 2021-2050 and 2071-2100 are presented.

2. Data

The gridded daily precipitation data from five ESMs under historical, RCP2.6 and RCP8.5 scenarios provided by the World Climate Research Program's (WCRP's) CMIP5 multi-model dataset are applied (Table 1) (Taylor et al., 2012). The RCP2.6 and RCP8.5 scenarios are future RCP scenarios. The RCP2.6, a scenario where the 2°C global average warming target is met, assumes that the radiative forcing increases to a peak at approximately 3 W/m² before 2100 and then decline to 2.6 W/m² by the end of the 21st century (van Vuuren et al., 2011). In RCP8.5, the

radiative forcing is assumed to increase in a high rate and reach 8.5 W/m^2 by the end of the 21st century (Riahi et al., 2011). ESMs are adopted based on the availabilities of their outputs under considered scenarios and their institutions. Multimodel ensemble is used in this study. One of the most important assumptions of establishing the multimodel ensemble is that the error of each model may be cancelled if models are independent (Tebaldi and Knutti, 2007), so the multimodel ensemble is usually expected to be more robust and less uncertain than individual model (Sillmann et al., 2013). Some institutions release more than one ESMs. These ESMs usually have lots of similarities, which offend the above assumption to some extent. Therefore only one ESM is chosen from an institution. Furthermore, it should be noted that most ESMs use 365-day calendar, in which the leap days are excluded, so no leap day in ESM outputs is considered in this study (Griffies et al., 2004).

Observed daily precipitation during 1960-2005 from 527 meteorology stations in China provided by the National Climate Center of China Meteorological Administration is used (Fig. 1). A station with total observed precipitation amount ranking 75th percentile among 527 considered stations during 1960-2005 is chosen to carry out case study. This station is called the 75th station. Observed daily precipitation and the outputs of ESMs under historical scenario during 1960-2005 are used to develop the downscaling relationship, and then based on this relationship,

the outputs of ESMs under RCP2.6 and RCP8.5 during 2021-2050 and 2071-2100 are downscaled to the site scale.

Six extreme precipitation indices, including Consecutive Wet Days (CWD), Consecutive Dry Days (CDD), Number of Extreme Heavy Precipitation Days (D90), The Total Amount of Extreme Heavy Precipitation (P90), The Intensity of Extreme Heavy Precipitation (I90), and Annual Precipitation Fraction Due to Extreme Heavy Precipitation (RT90) are defined to represent precipitation extremes in different aspects (Tab. 2). Some of these indices were proposed by Frich et al. (2002) and are widely used by IPCC and international academic communities (IPCC, 2007; Sillmann and Roeckner, 2008). The other indices were used in previous studies (e.g. Zhang et al., 2013a).

In this study, the joint probability behaviors of five combinations of above indices are studied, including {CWD, CDD}, {CWD, D90}, {P90, RT90}, {D90, P90}, and {P90, I90}. The {CWD, CDD} denotes the co-occurrence of extreme heavy and weak precipitation within the same year in terms of consecutive wet and dry days, implying the co-occurrence of floods and droughts in the same year; the {CWD, D90} represents a joint extreme heavy precipitation event in terms of consecutive wet days and number of extreme heavy precipitation; the {P90, RT90} denotes a joint extreme heavy precipitation event in terms of precipitation amount

and contribution to annual precipitation of the extreme heavy precipitation; the {D90, P90} represents a joint extreme heavy precipitation event that considers the number of extreme heavy precipitation days and the amount of extreme heavy precipitation, and; the {P90, I90} represents a joint extreme heavy precipitation event in terms of the amount and intensity of extreme heavy precipitation.

3. Methodologies

3.1. Weather Generator Model

The outputs of ESMs are in gridded scale, while the observation and the definitions of the precipitation extreme indices are in site scale. Therefore, in order to estimate the joint probabilities of extreme precipitation, the outputs of ESMs should firstly be downscaled to the site scale from the gridded scale. Weather Generator Model (WGEN) is the downscaling technique used in this study.

WGEN is a stochastic weather model originally designed to simulate the daily weather variables, such as daily temperature, precipitation and etc. (Richardson, 1981; Richardson and Wright, 1984; Wilks and Wilby, 1999). The application of WGEN then is extended to downscale daily precipitation by Wilks (1999a and 1999b). The procedure of using WGEN to downscale daily precipitation is briefly introduced here.

In WGEN, the occurrence and amount of daily precipitation are simulated separately. A two-state first-order Markov chain is used to denote the probability of the occurrence of daily precipitation (Gabriel and Neumann, 1962). It is assumed that the probability of the occurrence of precipitation on any day relies only on whether the previous day was wet or dry. Gamma distribution is used to model the daily precipitation amount (Richardson and Wright, 1984). In different months, the features of the occurrence and amount of daily precipitation are quite different, so occurrence and amount models of precipitation in each month are estimated.

To estimate the future changes in site scale, downscaling relationship between site scale observation and gridded scale ESMs outputs under historical scenario during 1960-2005 is developed. The gridded projections of ESMs during 2051-2050 and 2071-2100 are downscaled to the site scale based on the downscaling relationship. Then occurrence and amount models of precipitation of the future in site scale are obtained. The details of downscaling can be found in Wilks and Wilby (1999).

The future daily precipitation is simulated based on the downscaled models. A uniform $[0, 1]$ variable u is generated randomly for each day to simulate whether the considered day is a rainy day based on the occurrence model. Once a day is simulated as a wet day, the precipitation amount would be generated randomly

according to the amount model. Instead of applying the nonzero precipitation to define rainy day as Wilks (1999b) did, this paper defines the rainy day as the day with daily precipitation larger than or equal to 1 mm. This is agree with the definitions of many extreme precipitation indices. If a day is simulated as rainy day, and its simulated precipitation amount is less than 1 mm, then its precipitation amount would be set to 1 mm arbitrarily.

Finally, based on the simulated daily precipitation series, extreme precipitation indices are calculated according to their definitions. In this paper, parameters of the multimodel ensemble are the averages of the downscaled models of 5 considered ESMs. Then daily precipitation series is generated based on the multimodel ensemble model. Li et al. (2013b) assessed the performance of WGEN in downscaling precipitation indices, which include some of the indices used in this study, and indicated that WGEN works well in downscaling heavy extreme precipitation and consecutive dry days.

3.2. Marginal distribution

Among precipitation extreme indices, CWD, CDD, and D90 are discrete variables, while D90, I90, and RT90 are continuous variables. In previous studies, usually, the marginal distribution of a random variable is constructed by a pre-assigned theoretical distribution or by choosing the best-fitting theoretical

distribution among a set of distributions based on one or several pre-assigned selection criteria (Zhang et al., 2013a). Typically, it's hard to reach an agreement that which theoretical distribution is the best one to construct the distribution of a particular index. On the other hand, in this study, the marginal distribution is used to calculate the value of a specific return period or to estimate the return period of a specific value. Such calculations of continuous variables are commonly seen in many previous studies, but seldom calculations of discrete variables can be found. Based on these concerns, empirical distribution rather than theoretical distribution is used to represent marginal distribution of extreme indices as below:

Let T denote the considered return period, then p_T is the corresponding exceeding probability. A time series is firstly sorted in descending order. The sorted series is denoted by X . Then for the i^{th} value $x(i)$ in X , its empirical exceeding probability p_i is:

$$p_i = R(X) = \frac{i}{m+1} \quad (1)$$

where i is the rank of that value in the sorted series, and m is the sample size.

Then the value of T return period x_T , or called T -year value, for a discrete variable is calculated as below:

$$x_T = \begin{cases} x(1) & \text{if } p_1 \geq p_T \\ x(\lceil (m+1)p_T \rceil) + \left[\left(\lceil (m+1)p_T \rceil - (m+1)p_T \right) [x(\lceil (m+1)p_T \rceil) - x(\lceil (m+1)p_T \rceil - 1)] \right] & \text{if } p_m \geq p_T > p_1 \\ x(m) & \text{if } p_T > p_m \end{cases} \quad (2)$$

where $\lceil \cdot \rceil$ denotes the ceiling function, while $\lfloor \cdot \rfloor$ denotes the floor function.

For continuous variables, x_T is calculated just a linear interpolation:

$$x_T = \begin{cases} x(1) & \text{if } p_1 \geq p_T \\ x(i) + (p_i - p_T) \frac{x(i-1) - x(i)}{p_i - p_{i-1}} & \text{if } p_m \geq p_T > p_1 \\ x(m) & \text{if } p_T > p_m \end{cases} \quad (3)$$

Where i is an integer satisfies that $p_i \geq p_T$ and $p_{i-1} < p_T$. The return period T of a known value x_T can be calculated by the inverse of the above procedure.

One of the biggest limitations of this method is that it only can estimate values in the range of the minimum and maximum of X , and return periods in the range of $\frac{1}{p_1}$ and $\frac{1}{p_m}$ of X .

3.3 Copula

Copula is a flexible representation of multivariate joint distribution (Nelsen, 2006; Zhang et al., 2013a). In this study, only the bivariate Copula is discussed. X and Y are two random variables, with the marginal distributions $F(x) = P[X \leq x]$ and $G(y) = P[Y \leq y]$. The joint distribution of X and Y , $H(x, y) = P[X \leq x, Y \leq y]$, can be denoted by the Copula function C as below:

$$H(x, y) = C(F(x), G(y)) \quad (4)$$

Let $\{(x_k, y_k)\}_{k=1}^n$ denote the observed X and Y series and n denote the size of series. Then the empirical Copula C_e can be formulated as:

$$C_e\left(\frac{i}{n}, \frac{j}{n}\right) = \frac{n_{i,j}}{n} \quad (5)$$

where $1 \leq i, j \leq n$. Let $x(i)$ denote the rank i of the x series arranged in ascending

order; $y(j)$ denotes the rank j of the y series arranged in the ascending order, then $n_{i,j}$ denotes the number of observed values that $x_k \leq x_{(i)}, y_k \leq y_{(j)}$.

The Gumbel Copula, Clayton Copula, Frank Copula, Gauss Copula, and t Copula are employed in this study. The Gauss Copula and t Copula are members of the elliptical Copula family, and the coefficient of linear correlation ρ is their parameter. The other three Copulas belong to the Archimedean Copula family. Each Archimedean Copula is constructed using a different generating unit ϕ with parameter θ .

The identification of a Copula follows the procedure proposed by Genest and Rivest (1993):

(1) The Kendall correlation coefficient τ is given by:

$$\tau = \frac{\sum_{i < j} \text{sign}[(x_i - x_j)(y_i - y_j)]}{\frac{n(n-1)}{2}} \quad (6)$$

where n denotes size of the sample, $i, j = 1, 2, \dots, n$; if $x_i \leq x_j$ and $y_i \leq y_j$, then $\text{sign}() = 1$, else $\text{sign}() = -1$.

(2) The generating unit parameter θ of Gumbel, Clayton, and Frank Copulas, as well as the parameter ρ of the Gauss and t Copulas was computed by τ .

(3) Construct the Copula function with θ or ρ .

(4) Use a statistical method, such as the Akaike Information Criterion (Akaike,

1974), to select the most appropriate Copula family.

3.4. Akaike Information Criterion

The Akaike Information Criterion (AIC) (Akaike, 1974) was used to evaluate the goodness-of-fit of the Copulas. Two segments were considered in AIC: bias of fit and the unreliability from the number of the model parameters. AIC is expressed as:

$$AIC = n \log(RSS / n) + 2m \quad (7)$$

where n is the sample size, m is the number of parameters, and RSS is the residual sum of squares. The smaller the AIC value, the better the model is.

3.5. Bivariate joint return period

Let $F(x, y)$ be the joint distribution function of X and Y . Then the bivariate joint return period is (Salvadori and de Michele, 2004):

$$T_{\{X>x, Y>y\}} = \frac{1}{P(X > x, Y > y)} = \frac{1}{1 - F_x(x) - F_y(y) + F(x, y)} \quad (8)$$

where $T_{\{X>x, Y>y\}}$ denotes the joint return period with both X and Y exceeding their specific thresholds. Let $x_{T'}$ denotes the T' -year x estimated from the observation during 1960-2005, and $y_{T'}$ denotes the T' -year y estimated from the observation during 1960-2005, the $T_{\{X>x_{T'}, Y>y_{T'}\}}$ is denoted by $T_{T'\{X, Y\}}$ in this study. For example, $T_{5\{CWD, CDD\}}$ denotes the joint return period of the event that CWD and CDD exceed their 5-year values which are estimated from their observations during 1960-2005. It should be noted that when mentioning the $T_{5\{CWD, CDD\}}$ during 2021-2050 or

2071-2100 under RCP2.6 or RCP8.5, the 5-year CWD and CDD are still estimated from the observations during 1960-2005.

Then the change in joint return period during 2021-2050 or 2071-2100 under RCP2.6 or RCP8.5 relative to historical during 1960-2005 is denoted by the changing rate (%) calculated as below:

$$\text{Changing rate} = \frac{T_{T\{X,Y\}f} - T_{T\{X,Y\}h}}{T_{T\{X,Y\}h}} \times 100\% \quad (9)$$

Where $T_{T\{X,Y\}f}$ denotes $T_{T\{X,Y\}}$ during 2021-2050 or 2071-2100 under RCP2.6 or RCP8.5, and $T_{T\{X,Y\}h}$ denotes $T_{T\{X,Y\}}$ during 1960-2005 under historical.

With the consideration of the lengths of the study period 2021-2050 and 2071-2100, which are 30 years, the limitation of the method used to estimate T -year value, and return periods used in previous studies, 5-year and 20-year values are discussed in this study.

3.6 Metrics for comparing observed and simulated joint return periods

The coefficient of variation of the root mean square error (CVRMSE) and normalized mean bias error (NMBE) are used to compare observed and simulated joint return periods (Reddy, 2011; Ben Alaya et al., 2014). CVRMSE is the root mean square error (RMSE) normalized by the mean of observation, and NMBE is the mean bias error (MBE) normalized by the mean of observation. A CVRMSE value of 20% indicates the root mean value of the unexplained variation in

observation is 20% of the mean value of observation. A low CVRMSE and a NMBE near 0% implies better performance.

4. Results

4.1. Case Study

The 75th station is chosen to carry out case study to illustrate how Copulas of precipitation extremes in a station are estimated and how to estimate the joint return periods. The joint return periods of observation and downscaled historical simulation during 1960-2005, and those of RCP2.6 and RCP8.5 during 2071-2100 are estimated. To estimate joint return periods from ESMs simulations, 100 realizations of daily precipitation series are generated by multimodel ensemble. Extreme indices are calculated from the daily precipitation series. Then joint distributions and joint return periods are estimated.

The bivariate relationships and coefficient τ between considered combinations in 75th station under observation and historical simulation during 1960-2005, as well as RCP2.6 and RCP8.5 during 2071-2100 are investigated (Tab. 3). CWD and CDD, and CWD and D90 have insignificant relationships under all cases. P90 is positively correlated with RT90, and their Kendall coefficients are significant and larger than 0.65 in all cases. The coefficients during 2071-2100 are

smaller than those during 1960-2005, and coefficient under RCP8.5 is less than under RCP2.6. This implies change in bivariate relationships between P90 and RT90. D90 and P90 have similar change in relationships. Coefficients of downscaled historical simulation are close to those of observation, however, their differences are relatively large compared with differences of coefficients between 1960-2005 and 2071-2100. This indicates considerable uncertainties exist in changes in bivariate relationships, and further studies should be carried out.

On the other hand, marginal distribution of univariate precipitation index also changes. In this study, variation in marginal distribution is reflected by changes in 5-year and 20-year values (Tab. 4). Comparison of 5-year and 20-year extreme indices between observation and historical simulation indicates WGEN can downscale probability distributions of these indices well. For discrete variables, the 5-year and 20-year values of CWD and D90 increase slightly during 2071-2100, and those of CDD decrease. As for the continuous variables, 5-year and 20-year values of P90, RT90 and I90 during 2071-2100 are larger than those during 1960-2005. This result indicates extreme heavy precipitation in the 75th station becomes stronger in the future, while there is less extreme weak precipitation in terms of CDD in the future.

Since Kendall coefficients and marginal distributions of considered

combinations change in the future, their joint distributions may also change correspondingly. In order to investigate the changes in joint distributions, Copulas should be estimated first. The best Copula for a combination is chosen among Clayton, Frank, Gumbel, Gauss, and t Copulas by the AIC criterion. Then joint distribution of a combination can be constructed based on marginal distributions, the Kendall coefficient τ , and the best Copula type. The joint distributions of CWD and CDD, as well as P90 and RT90 during 1960-2005 and 2071-2100 are shown in Fig. 2. For Copula under historical, RCP2.6 and RCP8.5, the realization, the 5-year joint return period of which is the closet to the mean of 100 realizations, is plotted in Fig. 2. Joint distributions of CWD and CDD of observation and historical are similar, but discrepancy is relatively large when CWD or CDD is large (Fig. 2a). Joint return periods of P90 and RT90 of observation and historical simulation are quite similar, showing good performance of downscaling techniques (Fig. 2c). Figs. 2b and 2d indicate joint distributions during 2071-2100 are different from those during 1950-2005.

To investigate joint probability behaviors across China, it is hard to depict joint distributions in all stations. Therefore, changes in joint return periods are used to denote changes in joint distributions. Through Eq. (8), joint return periods can be estimated (Tab. 5). Joint return periods in Tab. 5 are the mean of 100 realizations.

Downscaled historical simulation overestimates joint return periods of CWD and CDD, but underestimates those of P90 and RT90. Joint return periods with 5-year values are better estimated than those with 20-year values. During 2071-2100, the $T_{5\{CWD, CDD\}}$ decreases to 16.1 years and 14.1 years under RCP2.6 and RCP8.5 respectively, indicating it is more frequent to have 5-year CWD and CDD in the same year in the future. During 1960-2005, the $T_{20\{CWD, CDD\}}$ is 347.3 years, indicating that the occurrence of this event is very rare. The $T_{5\{P90, RT90\}}$ in the future decreases to 3.4 years and 1.9 years under RCP2.6 and RCP8.5, respectively, and the $T_{20\{P90, RT90\}}$ also decreases. The remarkable decrease in $T_{5\{P90, RT90\}}$ implies the occurrence of heavy extreme precipitation event with large extreme precipitation amount and high contribution to the annual precipitation increases prominently.

This case study in the 75th station shows the computation procedure of constructing joint distribution and estimating joint return period. This procedure is applied to each station under observation, historical, RCP2.6, and RCP8.5 scenarios. The best-fitting Copula is selected for each combination in each station during each period. This case study shows marginal distribution, bivariate relationship, and the joint return period in a station may change in the future.

4.2. Comparison between observed and downscaled joint return periods

A comparison between downscaled and observed joint return periods in all considered stations is made to assess performance of downscaling techniques in estimating joint return periods. Li et al. (2013b) assessed the performance of WGEN in downscaling univariate extreme precipitation index which are mostly considered in this study, and found that WGEN can downscale extreme heavy precipitation and CDD well. So comparison in this study focuses on joint return periods directly.

In this section, the observed and modeled daily precipitation data under historical scenario during 1960-1989 are used to develop the downscaling relationships across China. Then gridded daily precipitation under historical scenario during 1976-2005 is downscaled to site scale based on downscaling relationships. 100 realizations of joint return periods are generated. CVRMSE and NMBE of each realization and observation are calculated. The mean of CVRMSE and NMBE of 100 realizations of 527 stations are shown in Tab. 6. It should be noted that there is an overlap between periods for developing downscaling relationships (1960-1989) and for comparison (1976-2005). The overlap may influence the validation result, but such division in periods is a compromise to ensure the first period is long enough to develop downscaling relationships and at the same time the second period is long enough to estimate joint return periods for validation.

Tab. 6 indicates joint return periods of P90 and RT90, D90 and P90, and P90 and

I90 can be estimated in an acceptable level by downscaling simulation, especially for 5-year joint return periods. Downscaled simulation basically can represent 5-year joint return periods of CWD and D90, and CWD and CDD with high CVRMSE and low NMBE. But 20-year joint return periods of CWD and D90, and CWD and CDD are simulated poorly.

Therefore, it is more confident to interpret variations in P90 and RT90, D90 and P90, and P90 and I90, but less confident in CWD and CDD, and CWD and D90; more confident in 5-year joint return periods but less confident in 20-year joint return periods. Further study about improving accuracy of downscaling joint distribution and joint return period is necessary.

4.3. The observed joint return periods during 1960-2005

Spatial distributions of observed joint return periods in China during 1960-2005 are investigated at first to have an understanding about the observed condition of joint return periods (Fig. 3). Joint return periods of each station are calculated. Then inverse distance weighted technique (IDW) is applied to interpolate joint return periods across China (De By, 2001; Zhang et al., 2013b).

In most parts of China, the $T_{5\{CWD, CDD\}}$ mainly ranges from 15 to 35 years, indicating that the extreme event that CWD and CDD both exceed their 5-year

values in one year may occur every 15 - 35 years in average in most parts of China (Fig. 3a). This joint return period implies the risk of co-occurrence of floods and droughts in the same year. In the most west China, and some parts of the upper and lower Yellow River basin and the middle Yangtze River, the $T_{5\{CWD, CDD\}}$ are relatively higher, implying that the co-occurrences of floods and droughts are in lower probability in these areas. The $T_{20\{CWD, CDD\}}$ in the southeast rivers basin, the upper Pearl River basin, the upper Yangtze River, the Haihe River, and the northeast China are mainly 200 - 400 years (Fig. 3b). The $T_{20\{CWD, CDD\}}$ in other parts, especially in the west China, are much higher, all are larger than 1000 years, implying that it's almost impossible that the CWD and CDD exceed the 20-year values in the same year. Interestingly, the area with very high $T_{20\{CWD, CDD\}}$, except the west China, mainly locate on the windward slopes of huge mountains.

Fig. 3c shows that $T_{5\{CWD, D90\}}$ mainly range from 10 to 18 years, indicating that in average, every 10 - 18 years, the consecutive wet days and the number of extreme heavy precipitation days may exceed their 5-year values in the same year, which may bring considerable risks of floods. Nevertheless, the $T_{5\{CWD, D90\}}$ in the Yangtze River basin are relatively larger (>20 years). The $T_{20\{CWD, D90\}}$ has similar spatial pattern with $T_{5\{CWD, D90\}}$ (Fig. 3d). The $T_{20\{CWD, D90\}}$ in the majority of China range from 150 to 250 years. Those in the Yangtze River are larger than 550 years,

indicating that the co-occurrences of the CWD and D90 both exceeding their 20-year values within a year is rare in the Yangtze River.

The $T_{5\{P90, RT90\}}$ in the whole China are quite low, and ranging from 6 - 7 years in most parts of China (Fig. 3e). The $T_{20\{P90, RT90\}}$ in the majority of middle and east China are mainly 20 - 40 years, indicating that once P90 exceeds its 20-year value, the RT90 probably may also exceed its 20-year value, and vice versa (Fig. 3f). The $T_{20\{P90, RT90\}}$ in the west China are relatively larger, ranging from 40 to 70 years.

When D90 exceeds its 5-year value, P90 may probably exceed its 5-year value too, and vice versa, because the $T_{5\{D90, P90\}}$ in China are mainly 5 - 7 years (Fig. 3g). In general, the $T_{5\{D90, P90\}}$ in west China is smaller than in east China. Fig. 3h shows that compared to the east China, the $T_{20\{D90, P90\}}$ in west China are also relatively smaller, mainly ranging from 30 to 45 years. In the middle Yangtze River, the $T_{20\{D90, P90\}}$ are the largest, ranging from 45 to 70 years, indicating that the joint extreme heavy precipitation event may occur relatively less in the middle Yangtze River.

The $T_{5\{P90, I90\}}$ in the most north part of west China, the southwest rivers basin, the upper Yangtze River, the middle Yellow River, the southeast rivers basin, and the northeast China are relatively larger, ranging from 15 to 25 years (Fig. 3i). As for the other regions, the $T_{5\{P90, I90\}}$ in the west regions are smaller than that in the east regions. The $T_{20\{P90, I90\}}$ in the majority of China ranges from 50 to 150 years, and

the largest $T_{5\{P90, I90\}}$ are found in the southwest China (Fig. 3j).

In general, the spatial patterns of joint return periods of different combinations are quite different, but the spatial patterns of joint return periods with 5-year and 20-year marginal values of the same combination are quite similar. Comparison between the joint return periods of different combination shows that the higher the Kendall coefficient, the smaller their joint return periods of that combination are. This is because a combination with higher Kendall coefficient means that if the value of one variable is larger, it would be higher possibility that the value of the other variable is larger.

4.4. The changes in joint return periods during 2021-2050 and 2071-2100

The spatiotemporal changes in joint return periods can represent spatiotemporal changes in joint behaviors of precipitation extremes during the future from historical during 1960-2005. The changing rate is estimated from the means of considered joint return periods from 100 realizations during future period (2021-2050 or 2071-2100) and historical period (1960-2005).

During 2021-2050 under RCP2.6, $T_{5\{CWD, CDD\}}$ in a majority of China increases, indicating the co-occurrences of CWD and CDD exceed their 5-year values in the same year decreases (Fig. 4a). $T_{5\{CWD, CDD\}}$ in east China mainly increases by 10% -

20%, that in southwest China mainly increases by more than 60%, while that in the northwest China decreases slightly by 10% - 20%. The changes in $T_{5\{CWD, CDD\}}$ during 2071-2100 under RCP2.6 are almost the same as during 2021-2050, except that in the middle Yellow River increases by more than 100% (Fig. 4c). As for RCP8.5, during 2021-2050 under RCP8.5, the spatial distribution of changes in $T_{5\{CWD, CDD\}}$ is similar with under RCP2.6, but the increasing rates are larger (Fig. 4e). The $T_{5\{CWD, CDD\}}$ in the Pearl River and the Yellow River increases by 50% - 80%. During 2071-2100 under RCP8.5, $T_{5\{CWD, CDD\}}$ from southwest to northeast China increases dramatically by more than 80%, while that in the Pearl River increases less compared to during 2021-2050 under RCP8.5 (Fig. 4g). Nevertheless, the $T_{20\{CWD, CDD\}}$ decreases in a majority of China during 2021-2050 under RCP2.6, except in the most west China (Fig. 4b). The decrease rates are mostly from -20% to -40%. This indicates that the co-occurrences of CWD and CDD exceed their 20-year values in the same year increases. During 2071-2100, more areas in south China are detected with increasing $T_{20\{CWD, CDD\}}$ (Fig. 4d). Similar patterns are found during 2021-2050 and 2071-2100 during RCP8.5 (Figs. 4f and 4h). This implies co-occurrences of 20-year CWD and CDD decreases in south China while increases in north China. Generally, co-occurrences of 5-year and 20-year CWD and CDD decrease in south China. But for north China, co-occurrences of 5-year values

decrease while those of 20-year values increases. Such changes imply joint distributions of CWD and CDD in south China shift in south China, and the shapes of those in north China may also change. The spatial patterns under RCP2.6 and RCP8.5 are similar, but changes under RCP8.5 are more remarkable.

During 2021-2050 under RCP2.6 and RCP8.5, $T_{5\{CWD, D90\}}$ in most parts of China decreases by 30% - 60%, while that in the Yangtze River increases slightly by 0% - 20% (Figs. 5a and 5e). During 2071-2100 under RCP2.6, $T_{5\{CWD, D90\}}$ in the whole China decreases by 20% - 70% (Fig. 5c). During 2071-2100 under RCP8.5, tremendous decrease in $T_{5\{CWD, D90\}}$ is detected (Fig. 5g). Decreasing rates in south China are mainly from 50% to 70%, and those in north China are around 80%. During 2021-2050 under RCP2.6, $T_{20\{CWD, D90\}}$ in China decreases by 30% - 70%, and that in the Yangtze River decreases relatively less (Fig. 5b). The same pattern is found during 2021-2050 under RCP8.5, but $T_{20\{CWD, D90\}}$ decreases relatively more (Fig. 5f). During 2071-2100 under RCP8.5, $T_{20\{CWD, D90\}}$ across China decreases remarkably by 90% (Fig. 5h). Considering that $T_{20\{CWD, D90\}}$ in the majority of China range from 150 to 250 years in observation, those during 2071-2100 under RCP8.5 would be around 15 - 25 years (Fig. 3d), showing that the frequency of co-occurrence of 20-year maximum consecutive wet days and numbers of extreme heavy precipitation days would be much higher, which may induce higher risks of

floods due to consecutive wet days and high occurrences of extreme heavy precipitation.

During 2021-2050 under RCP2.6, $T_{5\{P90, RT90\}}$ in the majority of China decreases by 10% - 40%, while that in northeast China, Haihe River, parts of northwest China and the middle of Yangtze River increases slightly by 10% - 20% (Fig. 6a). The $T_{5\{P90, RT90\}}$ in southeast rivers, southwest China and the most northwest China decrease more, ranging from -30% to -50%. During 2071-2100 under RCP2.6 and during 2021-2050 under RCP8.5, spatial patterns are similar to that during 2021-2050 under RCP2.6, but $T_{5\{P90, RT90\}}$ in south China decreases more, ranging from -40% to -60%. (Figs. 6c and 6e). During 2071-2100 under RCP8.5, $T_{5\{P90, RT90\}}$ in the whole China decreases (Fig. 6g). In south China, $T_{5\{P90, RT90\}}$ decreases relatively more, ranging from -70% to -80%, while that in north China decreases relatively less, ranging from -40% to -50%. For $T_{20\{P90, RT90\}}$, the spatial pattern is similar with that of $T_{5\{P90, RT90\}}$ during 2021-2050 under RCP2.6, but it decreases in most parts of China and the decreasing magnitudes are larger than those of $T_{5\{P90, RT90\}}$ during 2021-2050 under RCP2.6 (Fig. 6b). The spatial patterns of changes in during 2021-2050 under RCP8.5 and during 2071-2100 under RCP2.6 and RCP8.5 are similar (Figs. 6d, 6f and 6h). During 2071-2100 under RCP8.5, $T_{20\{P90, RT90\}}$ in south China and northwest China decreases by -40% - -70%, and that in other areas

decreases relatively less by -5% - -20% (Fig. 6h). The changes in $T_{5\{P90, RT90\}}$ and $T_{20\{P90, RT90\}}$ indicate that once extreme heavy precipitation amount exceeds its 5-year or 20-year value, it is more probable that its contribution to the annual precipitation also reaches 5-year or 20-year value in the future. In observation, $T_{20\{P90, RT90\}}$ usually ranges from 20 - 40 years (Fig. 3f). Therefore, $T_{20\{P90, RT90\}}$ during 2071-2100 under RCP8.5 would be only 6 - 16 years.

The changes in $T_{5\{D90, P90\}}$ and $T_{20\{D90, P90\}}$ are very close to those of $T_{5\{P90, RT90\}}$ and $T_{20\{P90, RT90\}}$ (Figs. 6 and 7). During 2021-2050 under RCP2.6 and RCP8.5, the $T_{5\{D90, P90\}}$ in the Yangtze River and the Liaohe River basin increases slightly by 0% - 20%, and $T_{5\{D90, P90\}}$ in the west China decreases by 40% - 50% (Figs. 7a and 7e). During 2071-2100 under RCP2.6 and RCP8.5, the entire China has decreasing $T_{5\{D90, P90\}}$ (Fig. 7c and 7g). Under RCP2.6, the decreasing rates are -30% - -50% in most parts of China, and those in southwest China and northwest China are around -60% - -70% (Fig. 7c). Under RCP8.5, $T_{5\{D90, P90\}}$ across China decreases significantly by -50% - -80% (Fig. 7g). Since $T_{5\{D90, P90\}}$ in observation are 5 - 7 years, those at the end of 21st under RCP8.5 would be 1 - 3.5 years, indicating that the co-occurrence of more extreme heavy precipitation days and large extreme heavy precipitation amount would be more frequent. The $T_{20\{D90, P90\}}$ during 2021-2050 under RCP2.6 across China decreases (Fig. 7b). Those in the upper Pearl

River, the Yangtze River and Haihe River decrease relatively less by 0% - 20%, while those in other parts decrease relatively more by 50% - 70%. During 2071-2100 under RCP2.6, the decreasing rates of $T_{20\{D90, P90\}}$ in the upper Pearl River, the Yangtze River and Haihe River reach -30% - -50% (Fig. 7d). The changing pattern in $T_{20\{D90, P90\}}$ during 2021-2050 under RCP8.5 is similar with that under RCP2.6, but the $T_{20\{D90, P90\}}$ decreases more with decreasing rates from -50% - -70% (Fig. 7f). During 2071-2100 under RCP8.5, $T_{20\{D90, P90\}}$ across China decreases dramatically by -70% - -90%, indicating the $T_{20\{D90, P90\}}$ in the future would be around 5 - 15 years (Figs. 3h and 7h). Therefore, in the future, China would suffer more occurrences of the joint extreme heavy precipitation event which has large number of extreme heavy precipitation days and large precipitation amount.

During 2021-2050 under RCP2.6, $T_{5\{P90, I90\}}$ in Songhuajiang River, Haihe River, the middle Yellow River, the middle Yangtze River, and the upper Pearl River increase by 0% - 20%, indicating that once extreme heavy precipitation amount exceeds 5-year value, it is less possible that the intensity of extreme heavy precipitation also exceeds its 5-year value in the same year (Fig. 8a). In other words, the co-occurrence of 5-year extreme heavy precipitation amount and intensity in the same year would be less frequent. In southeast rivers, the lower Pearl River and the west China, $T_{5\{P90, I90\}}$ decreases by -40% - -50%, meaning that once extreme heavy

precipitation amount exceeds 5-year value, it is more possible that the intensity also exceeds its 5-year value. During 2071-2100 under RCP2.6, $T_{5\{P90, I90\}}$ in the majority of south China decreases also with rates of -40% - -50% (Fig. 8c). During 2021-2050 under RCP8.5, the changing pattern and decreasing rates of $T_{5\{P90, I90\}}$ are similar to those during 2071-2100 under RCP2.6 (Fig. 8e). When it comes to 2071-2100 under RCP8.5, $T_{5\{P90, I90\}}$ across China turns to decrease dramatically (Fig. 8f). In southwest rivers and the north of Pearl River, $T_{5\{P90, I90\}}$ decrease most dramatically by -80% - -90%, those in other parts mainly decrease by -60% - -70%. The $T_{20\{P90, I90\}}$ in all circumstances decreases across most parts of China (Figs. 8b, 8d, 8f and 8h). Relatively, $T_{20\{P90, I90\}}$ in middle Yellow River and Haihe River decrease less dramatically. During 2021-2050 under RCP2.6, the decreasing rates in most parts of China are ranging from -40% to -60%, and those during other circumstances are mainly from -50% to -70%. During RCP8.5, the decreasing rates during 2071-2100 are almost the same as those during 2021-2050. Generally, China may face more frequent joint extreme heavy precipitation event that has large amount and high intensity.

5. Discussion

According to observation, spatial distributions of the $T_{5\{X, Y\}}$ and $T_{20\{X, Y\}}$ are

basically the same (Fig. 3). In other words, if the $T_{5\{X, Y\}}$ in a place is larger relative to other places, the $T_{20\{X, Y\}}$ in that place is probably also larger. For instance, the windward slopes of huge mountains have relatively larger $T_{5\{CWD, CDD\}}$ and $T_{20\{CWD, CDD\}}$ (Figs. 3a and 3b).

The future possible changes in the joint return periods of different combinations under different scenarios in different regions are diverse. In general, climate change raises $T_{\{CWD, CDD\}}$ in south China, making less co-occurrence of floods and droughts within in a year in the future (Fig. 4). Li et al., (2013b) used ESMs from CMIP5 to analyze the univariate changes in statistical behaviors of precipitation extremes, and their results indicate the CDD and CWD in south China mainly decrease. Then correspondingly, the joint return periods of the co-occurrence of extreme heavy and weak precipitation in terms of rainy days in the south China increase. As for north China, $T_{5\{CWD, CDD\}}$ increases but $T_{20\{CWD, CDD\}}$ decreases. This implies co-occurrence of relatively shorter duration of consecutive wet days and consecutive dry days is less frequent, while co-occurrence of longer duration is more frequent in the future. It should be noted that the uncertainties and biases in $T_{20\{CWD, CDD\}}$ are large, so it is less confident in interpreting changes in $T_{20\{CWD, CDD\}}$.

Climate change reduces the joint return periods of $\{CWD, D90\}$, $\{P90, RT90\}$, $\{D90, P90\}$, and $\{P90, I90\}$, meaning more joint extreme heavy precipitation in

terms of various combinations in the future (Figs. 5-8). According to Li et al., (2013b), probability distributions of D90, P90, and RT90 in China shift and change by the end of 21st century. At the same time, bivariate correlation relationships between precipitation extremes may also change. Given these two aspects, future joint return periods may change. The increase of extreme heavy precipitation indices and the change in bivariate relationships between indices contribute to considerable decreases in the joint return periods of extreme heavy precipitation events in the future.

Under RCP8.5, a scenario where the radiative forcing reaches 8.5 W/m² by the end of 21st century, the changes in joint return periods are more remarkable than under RCP2.6. For example, during 2071-2100, the $T_{5\{P90, RT90\}}$ and $T_{20\{P90, RT90\}}$ under RCP2.6 decreases not as dramatically as under RCP8.5 (Figs. 6c, 6d, 6g and 6h).

Basically, in the future, floods may be much easier to happen because of increasing joint extreme heavy precipitation events, and floods and droughts occurring within the same year may be less possible, except in north China, it is more frequent to have severe floods and droughts in the same year. Even under RCP2.6, in which the 2°C global average warming target is met, the changes in joint return periods are still considerable.

6. Conclusion

The possible changes in the joint return periods of precipitation extremes in China during 2021-2050 and 2071-2100 are investigated based on the outputs of ESMs under historical, RCP2.6 and RCP8.5 from CMIP5 dataset and the observed 1960-2005 daily precipitation from 527 stations across China. Six extreme precipitation indices representing extreme weak and heavy precipitation events from different aspects are defined. Then five joint return periods considering the co-occurrence of extreme weak and heavy precipitation as well as the joint extreme heavy precipitation with different combinations of aspects are applied. WGEN is used to downscale the outputs of ESMs from gridded scale to site scale, and Copula is applied to construct the joint distribution of extreme indices. The spatial distribution of the observed joint return periods during 1960-2005 is first discussed, then the possible changes in the joint return periods during 2021-2050 and 2071-2100 under RCP2.6 and RCP8.5 are analyzed. Based on the results, following conclusions can be drawn:

- 1) During 1960-2005, the spatial patterns of the joint return periods with 5-year marginal values are quite similar to the spatial patterns of the joint return periods with 20-year marginal values;

- 2) The changes in joint return periods may be caused by the changes in marginal distributions and the bivariate relationships between extreme indices;
- 3) During 2021-2050 and 2071-2100, in China, the co-occurrence of extreme heavy and weak precipitation in terms of the consecutive wet and dry days would occur less frequently, implying it's less possible to have floods and droughts within the same year. In north China, co-occurrence of relatively shorter duration of consecutive wet days and consecutive dry days is less frequent, however, co-occurrence of longer duration is more frequent;
- 4) The occurrences of the joint extreme heavy precipitation events in terms of consecutive wet days and the number of extreme heavy precipitation days, the amount and contribution of extreme heavy precipitation, the number of extreme heavy precipitation and its amount, as well as the amount and intensity, would increase considerably in the future, indicating the joint probability distributions of extreme heavy precipitation shift and implying higher risk of floods during the 21st century;
- 5) The changes in joint return periods under RCP8.5 are more dramatic than under RCP2.6. But even under RCP2.6, where the 2°C global average warming target can be met, the changes are still quite considerable. Water resource management should pay attention to such changes and draw up plan to face the potential

challenges.

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Figure 1 The meteorological stations considered in this study. The number denotes river basin: 1, Songhuajiang River; 2, Liaohe River; 3, Haihe River; 4, Yellow River; 5, Huaihe River; 6, Yangtze River; 7, southeast rivers; 8, Pearl River; 9, southwest rivers; and 10, northwest rivers. The red dot denotes the 75th station.

Figure 2. The joint distributions of CWD and CDD during (a) 1960-2005 and (b) 2071-2100, as well as of P90 and RT90 during (c) 1960-2005 and (d) 2071-2100 in the 75th station. For the period of 1960-2005 in (a) and (c), the red curves denote

observation, the blue denote downscaled historical simulation. For the period of 2071-2100 in (b) and (d), the red curves denote RCP2.6, the blue denote RCP8.5.

Figure 3. The spatial distribution of observed (a) $T_{5\{CWD, CDD\}}$, (b) $T_{20\{CWD, CDD\}}$, (c) $T_{5\{CWD, D90\}}$, (d) $T_{20\{CWD, D90\}}$, (e) $T_{5\{P90, RT90\}}$, (f) $T_{20\{P90, RT90\}}$, (g) $T_{5\{D90, P90\}}$, (h) $T_{20\{D90, P90\}}$, (i) $T_{5\{P90, I90\}}$, and (j) $T_{20\{P90, I90\}}$ during 1960-2005 (unit: year)

Figure 4. The spatial distribution of changing rates (%) of $T_{5\{CWD, CDD\}}$ during (a) 2021-2050 and (c) 2071-2100 under RCP2.6, and during (e) 2021-2050 and (g) 2071-2100 under RCP8.5, as well as $T_{20\{CWD, CDD\}}$ under (b) 2021-2050 and (d) 2071-2100 under RCP2.6, and (f) 2021-2050 and (h) 2071-2100 under RCP8.5.

Figure 5. The same as Figure 4, but for $T_{5\{CWD, D90\}}$ and $T_{20\{CWD, D90\}}$.

Figure 6. The same as Figure 4, but for $T_{5\{P90, RT90\}}$ and $T_{20\{P90, RT90\}}$.

Figure 7. The same as Figure 4, but for $T_{5\{D90, P90\}}$ and $T_{20\{D90, P90\}}$.

Figure 8. The same as Figure 4, but for $T_{5\{P90, I90\}}$ and $T_{20\{P90, I90\}}$.

Table 1. Details of ESMs from CMIP5

ESM	Modeling	Resolution (Lon×Lat)	Historical	Data duration	
	Center			RCP2.6	RCP8.5
CanESM2	CCCma	128×64	1850-2005	2006-2300	2006-2100
GFDL-ESM2G	GFDL	144×90	1861-2005	2006-2100	2006-2100
MIROC-ESM-C	MIROC	128×64	1850-2005	2006-2100	2006-2100
HEM					
MPI-ESM-MR	MPI-M	192×96	1850-2005	2006-2100	2006-2100
NorESM1-M	NCC	144×96	1850-2005	2006-2100	2006-2100

Table 2. Definitions of extreme precipitation indices

Index	Name	Definition	Unit
CWD	Consecutive wet days	Maximum number of consecutive wet days (days with daily precipitation ≥ 1 mm)	day
CDD	Consecutive dry days	Maximum number of consecutive dry days (days with daily precipitation < 1 mm)	day
D90	Number of extreme heavy precipitation days	Number of days with daily precipitation exceeding the 90 th percentile of wet day (daily precipitation > 1 mm) during 1961-1990	day
P90	The total amount of extreme heavy precipitation	Annual total precipitation amount of days with daily precipitation exceeding the 90 th percentile of wet day during 1961-1990	mm
I90	The intensity of extreme heavy precipitation	The average daily precipitation intensity of extreme heavy precipitation	mm/d
RT90	Annual precipitation fraction due to extreme heavy precipitation	Fraction of annual total precipitation due to events exceeding the 90 th percentile of wet day (daily precipitation > 1 mm) during 1961-1990	%

Table 3. The Kendall coefficients τ of considered combinations in the 75th station of observation and downscaled historical simulation during 1960-2005, as well as RCP2.6 and RCP8.5 during 2071-2100. The underline denotes the coefficient is significantly different from 0. For historical, RCP2.6 and RCP8.5, the mean of τ from 100 realizations are shown, and the underline denotes coefficients of more than 50% of the realizations are significantly different from 0.

Combination	Observation	Historical	RCP2.6	RCP8.5
{CWD, CDD}	0.0358	-0.0019	-0.0041	-0.0193
{CWD, D90}	0.1753	0.1196	0.1542	0.1519
{P90, RT90}	<u>0.7643</u>	<u>0.7019</u>	<u>0.6862</u>	<u>0.6652</u>
{D90, P90}	<u>0.7772</u>	<u>0.7589</u>	<u>0.7421</u>	<u>0.7069</u>
{P90, I90}	<u>0.4667</u>	<u>0.3008</u>	<u>0.3267</u>	<u>0.3491</u>

Table 4. The 5-year and 20-year values of extreme indices in the 75th station under observation, historical, RCP2.6 and RCP8.5. For historical, RCP2.6 and RCP8.5, the mean of 100 realizations are shown.

Return period	Scenario	CWD (d)	CDD (d)	D90 (d)	P90 (mm)	RT90 (%)	I90 (mm)
5-year	Observation	9	56	11	712.8	53.0	73.1
	Historical	8.9	50.5	12.2	757.3	54.6	68.5
	RCP2.6	9.1	46.5	13.4	898.1	59.5	72.6
	RCP8.5	9.1	48.6	14.6	1064.8	65.6	79.6
20-year	Observation	11	82	15	1129.8	63.7	76.6
	Historical	11.8	71.1	15.2	987.1	62.2	81.4
	RCP2.6	12.6	66.4	16.8	1174.0	66.4	86.3
	RCP8.5	12.5	70.4	18.3	1394.1	72.0	95.7

Table 5. The $T_{5\{CWD, CDD\}}$, $T_{20\{CWD, CDD\}}$, $T_{5\{P90, RT90\}}$, and $T_{20\{P90, RT90\}}$ under observation and downscaled historical simulation during 1960-2005, and RCP2.6 and RCP8.5 during 2071-2100 (year)

Scenario	$T_{5\{CWD, CDD\}}$	$T_{20\{CWD, CDD\}}$	$T_{5\{P90, RT90\}}$	$T_{20\{P90, RT90\}}$
Observation	22.6	347.3	7.5	70.5
Historical	27.8	590.7	7.1	47.3
RCP2.6	16.1	639.7	3.4	15.8
RCP8.5	14.1	424.9	1.9	4.8

Table 6. CVRMSE and NMBE of observed and simulated joint return periods (%)

Joint return period	CVRMSE	NMBE
$T_{5\{CWD, CDD\}}$	53.4	-1
$T_{20\{CWD, CDD\}}$	221.5	20.1
$T_{5\{CWD, D90\}}$	40.1	15.0
$T_{20\{CWD, D90\}}$	93.5	39.2
$T_{5\{P90, RT90\}}$	13.4	3.3
$T_{20\{P90, RT90\}}$	50.7	9.2
$T_{5\{D90, P90\}}$	8.3	1.6
$T_{20\{D90, P90\}}$	30.0	4.4
$T_{5\{P90, I90\}}$	28.8	6.1
$T_{20\{P90, I90\}}$	61.4	10.2