Responses of Precipitation and Runoff to Climate Warming and Implications for Future Drought Changes in China

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Abstract The Clausius-Clapeyron relationship holds that the atmospheric water vapor content enhances with warming temperatures, suggesting intensifications of precipitable water and also altering runoff generation. Drought conditions are determined by variations in water fluxes such as precipitation and runoff, which tightly connect with temperature scaling characteristics. However, whether and how water fluxes’ scaling with temperatures may affect the evolution of droughts under climate change has not yet been systematically investigated. This study develops a cascade modeling chain consisting of the climate model ensemble, bias correction technique, and hydrological models to investigate the precipitation and runoff scaling relationships with warming temperatures under the current (1961–2005) and future periods (2011–2055 and 2056–2100), as well as their implications on future drought changes across 151 catchments in China. The results show that (1) precipitation (runoff) scaling relationships with temperatures are stable during different time periods; (2) return level analysis indicates drought risks are projected to become (1–10 times) more severe across central and southern catchments, where the precipitation (runoff) strengthens with rising temperatures up to a peak point and then decline in a hotter environment. The northeastern and western catchments, where a monotonic increasing scaling type dominated, are accompanied by drought mitigations for two future periods; (3) future changes in hydrological droughts relative to the baseline are (1–5 times) larger than those in meteorological droughts. These results imply that changes in future drought risks are highly dependent on the present precipitation (runoff)-temperature relationships, suggesting a meaningful implication of scaling types for future drought prediction.

Plain Language Summary Drought hazards are determined by variations in water fluxes such as precipitation and runoff. Global climate warming has altered these terrestrial hydrological processes and subsequently changed drought conditions. Characterizing the responses of precipitation and runoff to warming climates and investigating their implications on future drought changes are important for drought early warning and prediction. Here we show that monthly precipitation and runoff either exhibit a monotonic increasing or the peak-like structure (in which precipitation and runoff increase with warming temperatures up to a peak point and decline thereafter) with temperatures. The increasing relationship typically suggests future drought mitigation, while the hook structure type, which prevails in central and southern catchments in China, implies increasing drought risks. Our findings facilitate a better understanding of drought changes under climate change and provide a scientific basis for drought adaptation to climate change.

1. Introduction

Global warming has been manifested in alteration of the water cycle and resulted in more severe weather-related hazards such as droughts (Naumann et al., 2018). As key elements of the water cycle, precipitation and runoff respond divergently to climate warming. As precipitation intensities are governed by atmospheric moisture supply, it is sensitive to warming temperatures due to their close relationship with moisture holding capacity in the atmosphere. The Clausius-Clapeyron (C-C) relationship suggests that the atmospheric moisture holding capacity should exponentially enhance with rising temperatures at a rate of
Drought episodes mainly induced by abnormally dry climatic conditions are among the most destructive and need to be adequately understood (Zhai et al., 2020). Some departures, such as negative scaling rates, have also been detected at high temperatures probably due to limited atmospheric moisture availability and observation artifacts (Hardwick Jones et al., 2010; Nie et al., 2018). Despite such variations in scaling rates, there is a consensus that global precipitation is increasing within both observational and modeling worlds (Ali & Mishra, 2018; Lochbihler et al., 2017; Wang et al., 2017; Westra et al., 2014). Intensification of precipitation has received great attention, because it would play a major role in altering elements in hydrological cycle such as runoff. The responses of river runoff to the warming climates are more complicated because the runoff generation process is governed not only by atmospheric factors but also by the underlying surface conditions (Farinosi et al., 2019). For example, at the daily scale, the nonlinear increase in runoff coefficient contributes to higher scaling rates of runoff to warming temperatures than that of precipitation (Huang et al., 2014; Yin et al., 2018). At a longer temporal scale (e.g., monthly), the responses of river runoff to global warming may be attributed to different physical mechanisms. Runoff generation at longer temporal scales is determined by the partitioning of evapotranspiration to precipitation. Studies generally show positive C-C relationships regarding evapotranspiration sensitivity to temperatures (Zhang et al., 2019). The synchronously positive responses of monthly precipitation and evapotranspiration to warming climates will affect the partitioning of precipitation between evapotranspiration and runoff, with consequences to altering runoff production. Zhang et al. (2014) investigated monthly runoff sensitivity to global warming directly based on the CMIP5 outputs. It is projected that global mean runoff would increase at a rate of about 2.9%/°C, with positive down to negative relationships with rising temperatures. Despite the variations between precipitation and runoff, their scaling relationships with temperature can be summarized into three types: (1) monotonically increasing, (2) monotonically decreasing, and (3) a hook structure in which precipitation and runoff strengthen with temperatures up to a maximum and decline after that (Lepore et al., 2015; Utsumi et al., 2011; Yin et al., 2018). In a hot environment, the local ascent rate and atmospheric moisture availability can be constrained, resulting in negative scaling rates between precipitation and temperatures (Hardwick Jones et al., 2010). Simultaneously, both the vapor pressure deficit in the atmosphere and total vegetation water use can increase with warming, triggering intensified negative responses of runoff to climate change (Cook et al., 2020; Montaldo & Oren, 2018). Given that drought conditions are highly dependent on the atmospheric and terrestrial water budgets, the responses of monthly precipitation and runoff to climate warming play a key role in understanding such hazards and need to be adequately understood (Zhai et al., 2020).

Drought episodes mainly induced by abnormally dry climatic conditions are among the most destructive weather-related hazards and bring about mass socio-economic and environmental losses in China. For example, during the early 21st century, droughts damaged more than 40 million hectares of crops in North China (Wang et al., 2011). Due to their complex nature, they are typically classified into four categories: meteorological droughts, hydrological droughts, agricultural droughts, and socio-economic droughts (Chen, Li, et al., 2019; Dehghani & Zargar, 2019; Mishra & Singh, 2010; Yeh, 2019). Precipitation and runoff are determining drivers for meteorological and hydrological droughts, respectively (Haslinger et al., 2014). A few studies have investigated changes in meteorological and/or hydrological drought risks under climate change (Haile et al., 2020; Leng et al., 2015; Sun et al., 2019). Su et al. (2018) project meteorological drought losses in China under different warming targets and identify soaring losses even in a sustainable development pathway. Zhai et al. (2020) investigated hydrological drought responses to different warming levels and reported shifts towards increasing droughts risks in southeastern China under 2.0°C to 1.5°C. Moreover, some studies diagnosed the potential mechanisms behind the changing drought conditions under global warming. For example, oscillation modes of large-scale circulation and climate variability, that is, the El Nino-Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), may be changed in response to a warming climate and subsequently modulate regional droughts through the teleconnection (Haston & Michaelsen, 1994; Yang et al., 2012). Besides, anomalous atmospheric circulations like the blocking (quasi-) stationary wave may cause local persistent anticyclonic circulation anomalies, typically leading to more intensive and prolonged droughts (Petoukhov et al., 2013). At the local scale, changes in antecedent soil moisture with global warming might extend drought persistence by decreasing evapotranspiration and
recycled precipitation via land-atmosphere coupling (Dominguez et al., 2009). These studies all confirmed that there has been a wide range of factors on the causes of the changing drought conditions, through altering water fluxes, for example, precipitation and runoff, variations in the context of global warming. However, there is still much to understand about the direct relationships between precipitation and runoff responses to warming temperatures and future drought variations under climate change. Whether and how the temperature scaling relationships of precipitation and runoff would affect future droughts need further investigation.

Here we build upon existing studies to understand responses of monthly precipitation and runoff to rising temperatures and investigate their implications on future drought changes as climate warms. Focusing on 151 typical catchments over China, future climate scenarios are projected by correcting outputs of 31 GCMs under the Representative Concentration Pathway 8.5 (RCP 8.5). Four lumped conceptual hydrological models are selected as candidates for hydrological simulations and projections. We then examine the precipitation and runoff sensitivity to temperatures and extract the meteorological and hydrological drought episodes. After obtaining a realistic picture of changes in drought risks from a bivariate perspective (i.e., duration and severity) by a copula-based approach, the potential implications of precipitation and runoff scaling with temperatures on future drought changes are explored.

2. Data

2.1. Climate Model Simulation

A set of large climate model ensemble involving 31 GCMs (Table S1 in the supporting information) under the historical reference (1961–2005) and the highest RCP 8.5 scenario (the near future period, 2011–2055; the far future period, 2056–2100) from the CMIP5 archive is used (Taylor et al., 2012). This ensemble comprises daily precipitation and temperature over China. For a sake of robustly capturing climate change signals and representing modeling uncertainty, the selected models involve both sophisticated Earth System models and fully coupled Atmospheric-Oceanic models (Knutti et al., 2010). All the 31 GCM outputs are bilinearly interpolated to a resolution of 0.5° × 0.5° to be in line with the observation dataset to facilitate bias correction.

2.2. Observation

A daily high-resolution (0.5° × 0.5°) gridded dataset consisting of precipitation and maximum, minimum, and average temperatures over China is used as a reference to bias correct GCM outputs and calibrate hydrological models. This gridded dataset derives from 2472 gauges and was spatially interpolated by the Thin Plate Spline (TPS) method. It is consecutive and covers a period of 1961–2016 and has been strictly checked and examined before releasing. Details can be found in Zhang et al. (2009) and Zhao et al. (2014). A daily runoff dataset across 151 catchments over mainland China spanning the period of 1961–2010 is collected from the water resources commission, affiliated with the Chinese Ministry of Water Resources.

3. Methodology

3.1. Generation of Climate Scenarios

As GCM outputs are usually too bias to represent catchment-scale climate features, an empirical quantile mapping (QM) method, namely, the daily bias correction (DBC) method (Chen et al., 2013) is used to reduce their biases. The DBC method conquers the deficiency of unrealistic wet-day frequency in traditional QM methods (Lafon et al., 2013; Maraun, 2013) by incorporating a local intensity scaling (LOCI) technique (Schmidli et al., 2006) into a QM (i.e., daily translation, DT) method to correct the wet-day frequency. For a specific month (i.e., January–December), the precipitation occurrence of a climate model simulation is firstly corrected to the same as that of the observed data by a determined threshold in the reference period (1961–2005). The determined threshold is then applied to future periods (2011–2055 and 2056–2100) to correct wet-day frequency of future climate projections. In the DT technique, a distribution mapping technique is applied to establish a relationship between observed percentiles of precipitation $P_{obs,perc}$ or temperature $T_{obs,perc}$ and GCM simulations $(P_{GCM,ref,perc}, T_{GCM,ref,perc})$ during the reference period for a particular month. The ratios of precipitation (or differences of temperature) between observations and GCM outputs
The river stream is simulated by four lumped conceptual hydrological rainfall-runoff models, and the best performing model (with the highest Kling-Gupta efficiency, KGE) (Gupta et al., 2009) is used to simulate streamflow series for each time period.

### 3.2. Hydrological Simulation

The river streamflow is simulated by four lumped conceptual hydrological rainfall-runoff models, and the best performing model (with the highest Kling-Gupta efficiency, KGE) (Gupta et al., 2009) is used to simulate streamflow series for each time period.

#### 3.2.1. Hydrological Models

The GR4J model (Arsenault et al., 2015) is a coupled model of the GR4J (modèle du Génie Rural à 4 paramètres Journalier) and CemaNeige module considering the snow accumulation and melting processes. The GR4J model (Edijatno et al., 1999), consisting of a production reservoir, two-unit hydrographs, and a routing reservoir, involves four parameters. The CemaNeige module was proposed by Valéry et al. (2014). This model has two free settings and uses a degree-day method to calculate snowmelt (Troin et al., 2016); precipitation is first divided into rainfall and snowfall according to daily air temperature. It accounts for the daily evolution of snowpack, and snowmelt occurs in relation to the thermic state of snowpack.

The Xinanjiang (XAJ) model is proposed by Zhao et al. (1980) and has been used across all major river basins in China (Shi et al., 2011). It comprises 15 free parameters. Runoff in this model consists of the surface, subsurface, and groundwater flows. The Muskingum routing scheme simulates the channel routings. The potential evapotranspiration is estimated by using a temperature-based method (Oudin et al., 2005). Similar to the GR4J model, snow accumulation and snowmelt module, CemaNeige, is added to the original XAJ model for consideration of snow-related catchments.

The HMETS developed by École de technologie supérieure (Martel et al., 2017) has been widely used in climate change impact studies (Arsenault et al., 2015; Chen, Brissette, et al., 2019). Twenty-one free parameters are used to describe the model. The model structure can be divided into four parts: vertical water balance, horizontal transfer components, snow melting and refreezing processes, and evapotranspiration. The vertical water balance involves exchanges between the surface, infiltration, and groundwater flows. There are four horizontal transfer components: surface runoff, delayed runoff, and two-unit hydrographs. Snow accumulation, snow melting, and refreezing processes are decently controlled by 10 parameters. Evapotranspiration is calculated by the product of a free parameter and the potential evapotranspiration based on the temperature.

The HBV (Hydrologiska Byrans Vattenbalansavdelning) model was proposed by the Swedish Meteorological and Hydrological Institute (SMHI) (Bergström, 1995; Lindström et al., 1997). It involves 15 free parameters in total and contains five routines: snow accumulation and snowmelt, soil water accounting, hillslope scale routing, channel routing, and evaporation routine. Snow routine is calculated by a degree-day concept. The soil moisture accounting process is represented by the sum of rainfall and snowmelt as input. Three reservoirs are considered by the hillslope scale routing. The channel routine is formulated by a lumped routing model. The evapotranspiration routine calculated by the potential evapotranspiration is estimated by a temperature-based method proposed in DVWK (1996).

#### 3.2.2. Model Calibration and Efficiency Criterion

Daily precipitation and temperature are the inputs of the above four hydrological models. Twenty-one daily runoff records with the lowest missing data ratios across the whole period (1961–2010) are identified for model calibration and validation, which are implemented by a cross validation method (e.g., Arsenault et al., 2017; Gu, Yin, et al., 2020). Daily runoff records in the odd years of the 20-year period are used to calibrate the hydrological model parameters, while the even years are used for validation. The shuffled complex...
The SCE-UA optimization algorithm is used to optimize the parameters of the four hydrological models (Duan et al., 1992). The optimized parameters are determined by maximizing the $KGE$ values in the calibration period:

$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2},$$

where $r$ indicates the Pearson’s linear correlation coefficient between the daily observed and simulated runoff series for a catchment, $\alpha$ is the ratio of standard deviations of daily observations dividing by simulated runoff, while $\beta$ is the ratio of means of daily observations dividing by simulations.

### 3.3. Binning Scaling of Water Fluxes with Temperature

To explicitly quantify the responses of precipitation and runoff to rising temperatures, the equal-number bins scaling method is employed in this study (Drobinski et al., 2018; Hardwick Jones et al., 2010; Lenderink et al., 2011). Initially, monthly precipitation (runoff) exceeding 1 mm (above 0) is stratified into 12 bins according to the near-surface temperature. The median values of monthly precipitation (runoff) in each bin are extracted and paired with the median values of temperature in that bin. Secondly, the scaling types (i.e., the hook structure type, the monotonic increasing type, or the monotonic decreasing scaling type) are identified using the locally weighted regression smoothing (LOWESS) method (Cleveland, 1979). Specifically, the scaling types are determined by the location of the peak point temperature ($T_{pp}$) following precious studies (Yin et al., 2018), which refers to the bin temperature with maximum precipitation (runoff) among the total 12 bins. If the $T_{pp}$ lies in the last (the first) bin, that is, $T_{pp}$ denotes the median values of temperature in the last (the first) bin, the monotonic increasing (decreasing) type is determined; while if the $T_{pp}$ locates within the range of the 12 temperature bins, a hook structure is identified (Figure 1). For the monotonic increasing and the hook structure scaling types, we estimate the scaling rate by only focusing on the ascending branch following previous studies (e.g., Wang et al., 2017; Yin et al., 2019). In other words, the scaling rate is determined by stratified bins before the peak point temperature ($T_{pp}$). For the monotonic decreasing scaling type, the scaling factor is estimated by all 12 temperature bins:

$$P_2 = P_1 (1 + 0.01 \times \alpha_p)^{\Delta T},$$

$$R_2 = R_1 (1 + 0.01 \times \alpha_r)^{\Delta T},$$

where $\alpha_p$ ($\alpha_r$) is the scaling rate of precipitation (runoff) estimated by the least squared linear method (the significance is evaluated at $p < 0.05$) (Chatterjee & Hadi, 1986). $P_1$ and $P_2$ ($R_1$ and $R_2$) refer to precipitation (runoff) variations with temperature changes ($\Delta T$) between the adjacent two bins. The $T_{pp}$, scaling type, and scaling rate are derived for each catchment at the three time periods, respectively.

![Figure 1](image-url). Precipitation and runoff Scaling types. X-axis denotes temperatures; the y-axis denotes precipitation or runoff variations. The scatters indicate monthly precipitation or runoff amounts pairing with temperatures, and a solid curve indicates the fitting results using the LOWESS method. The gray dashed (solid) lines indicate C-C (doubled C-C) scaling rate.
3.4. Meteorological and Hydrological Drought Indices

The commonly used Standardized Precipitation Index (SPI) and Standardized Runoff Index (SRI) are employed to represent the meteorological and hydrological dry/wet conditions and inputted to identify drought events (Jiao & Yuan, 2019; Lee & Kim, 2013; McKee et al., 1993; Shukla & Wood, 2008; Xia et al., 2019). For a specific calendar month $m (m = 1, 2, ..., 12)$, a gamma distribution is used to fit the monthly precipitation series $p (p > 0)$ during the historical period:

$$G_m(p) = \frac{1}{b^\alpha \Gamma(\alpha)} \int_0^p t^{\alpha - 1} e^{-t/b} dt,$$

where $G_m(p)$ denotes the cumulative distribution function (CDF) of the gamma distribution for the $m$ month. $\alpha$ and $b$ are parameters estimated by using the maximum likelihood method.

The nonprecipitation condition ($p = 0$) is considered as follows:

$$H_m(p) = q_m + (1 - q_m)G_m(p),$$

where $q_m$ denotes the probability of zero precipitation. $H_m(p)$ is the modified CDF.

Then, the historical SPI value can be obtained by a standard normal transforming process ($\Phi^{-1}$):

$$SPI = \Phi^{-1}(H_m).$$

The determined parameters ($\alpha$ and $b$) for the $m$ month in the historical period are then used in future period(s) to obtain future SPI values (Dubrovsky et al., 2009; Leng et al., 2015).

The calculation process of SRI is similar to that of SPI, but with a different distribution (i.e., the Person type-III distribution) for fitting the monthly runoff series in China following previous work (Hong et al., 2015):

$$F_m(r) = \frac{\beta^\alpha}{\Gamma(\alpha)} \int_0^r (r - \omega)^{\alpha - 1} e^{-\beta(r - \omega)} d\omega,$$

where $r$ means the monthly runoff series for a specific calendar month $m$ (i.e., $m = 1-12$). $F_m(r)$ denotes the CDF of the Person-III distribution. $\alpha$, $\beta$, and $\omega$ represent the three parameters of the distribution and are calculated by using the L-moment method (Hosking, 1990).

A meteorological (or hydrological) drought episode is identified using the run theory (Yevjevich, 1967). A meteorological (or hydrological) drought episode commences when the SPI (or SRI) value falls below a threshold, while the drought episode terminates when the SPI (or SRI) value rises above the threshold.

Then, the drought episode can be characterized by the drought duration and the cumulative SPI (or SRI) values (drought severity) during a meteorological (or hydrological) drought episode. Since a high threshold (e.g., 0) may not be enough for distinguishing droughts from the “dry” condition, and a low threshold (e.g., −1) which excludes substantial minor drought episodes may result in an insufficient sample size for bivariate frequency, the threshold is defined as −0.5 (Chen et al., 2018).

3.5. Bivariate Return Period and Most Likely Selection Method

Due to the multifaceted nature of droughts, the bivariate copula functions were employed to consider the interdependence between drought duration and severity. The marginal distributions of drought duration and severity are fitted by a gamma distribution (Shiau et al., 2007). Three commonly used Archimedean Copulas (i.e., Clayton, Frank, and Gumbel copula) are selected as candidates to link the marginal distributions of drought duration and severity (Sakamoto et al., 1986; Zhang et al., 2015; Zscheischler & Seneviratne, 2017). Since adverse consequences can result from either long drought duration or high drought severity, the OR scenario ($P_{or} = P(D > d \cup S > s) = 1 - C(d,s)$) is employed in drought occurrence assessment (e.g., Gu, Chen, et al., 2020):

$$T_{or} = \frac{\mu}{1 - F(d, s)} = \frac{\mu}{1 - C(F_d(d), F_S(s))}$$

where $\mu$ is the mean interarrival time between two consecutive drought events (i.e., $\mu = 1$ year), $F(d, s) = P(D \leq d, S \leq s)$ is depicted by a copula function $C(F_d(d), F_S(s))$, and $F_d(d)$ and $F_S(s)$ denote the marginal distribution functions of $D$ and $S$, respectively.
Among feasible combinations with equal return periods \(T_{ru}\), one hazard scenario, the most likely scenario event, is selected to project drought risk under climate warming (Figure S1). The most likely scenario, coinciding with the combination of risks on a given joint return period \(T_{ru}\), refers to the highest joint density level is expressed as follows (Salvadori et al., 2011):

\[
\begin{align*}
\{ (d^*, s^*) = \arg \max_{(d, s)} f(\{F_D(d), F_S(s)\}) f_D(d) f_S(s) \}
\end{align*}
\]

where \(f(d, s)\) denotes the joint probability density function of drought duration and severity, \(c(F_D(d), F_S(s)) = C(F_D(d), F_S(s)) = 1 - \mu/T_{or}\) (11) indicates the density function of the selected copula, and \(f_D(d)\) and \(f_S(s)\) are probability density functions of duration \(D\) and severity \(S\), respectively.

4. Results and Discussion

4.1. Performance of Bias Correction and Hydrological Models

To examine the performance of the bias-correction method, Figure 2 presents the biases of daily temperatures (absolute biases, °C) and precipitation (relative biases, %) in July for the raw and corrected climate model outputs during 1961–2005 over China. Significant biases are observed for all 31 climate model simulations before bias correction. The maximum temperatures are underestimated with a range from −5.0°C to −0.5°C, while biases of the minimum temperature range between −5°C and 4°C. Biases of temperatures are in similar magnitudes for other months (Figures S2–S5). On the other hand, the raw climate models generally overestimate July precipitation, with relative biases ranging between 10% and 100%. This overestimation is even more remarkable in the dry season (e.g., January and February), partly due to lower absolute values (of precipitation) in this dry period (Figures S4 and S5). After bias correction, the systematic biases are effectively reduced for both temperature and precipitation. Though biases of the maximum temperatures are slightly higher than that of the minimum temperatures, both of them are reduced to nearly 0°C, whereas biases of the July precipitation are reduced to below 5% across grids in China. The bias-corrected temperature and precipitation in the remaining months also show similar good performances. In short, those results exhibit a reasonable performance of the DBC method with respect to reproducing the climate statistics of observed data.

As different mechanisms govern the precipitation-runoff processes across the 151 studied catchments in China, four lumped conceptual hydrological models (i.e., GR4J, HBV, HMETS, and XAJ) are employed for runoff simulations. The 0.5° × 0.5°gridded daily meteorological data spanning 1961–2016 are used to calibrate hydrological models. The basin-averaged precipitation and temperature series are derived by using the Thiessen polygon algorithm and then inputted in hydrological model calibrations. The best-performing hydrological models with the largest KGE values are selected and presented in Figure 3a. We observe that XAJ and HMETS models perform better over the majority of the 151 catchments. The obtained sets of parameters from the best-performing models yield KGE values greater than 0.6 for both the calibration and validation periods for all catchments (Figures 3b and 3c), with 80% of catchments showing KGE values larger than 0.75. This implies a satisfactory performance in their representation of runoff simulations.

We are conscious of the fact that human activities can alter the hydrological regime for a watershed, especially for the outlet streamflow. For instance, the construction and operation of hydraulic engineering (e.g., cascade reservoirs operation) can remarkably alter interannual and intra-annual runoff variations (He et al., 2019). Land use and land cover change leads to changes in soil water retention capacity, and associated base flow, evapotranspiration and precipitation processes, further alters runoff yield (Krishnaswamy et al., 2013; Lean & Warrilow, 1989). To avoid this terrestrial disturbance, we only select small-sized catchments (below 30,000 km²) with weak human activities. Furthermore, we use odd years of measured runoff data for calibration and even years for validation to minimize the influence of human activities following previous studies (Arsenault et al., 2017; Gu, Yin, et al., 2020). We assume the underlying surface conditions are constant during the 20-year calibration and validation periods. In this way, the streamflow is simulated and projected during the historical (1961–2005) and future periods (2011–2055; 2056–2100) for each catchment, respectively. Finally, we quantify the differences between future projected runoff and historical...
simulated runoff (rather than observed runoff) to represent climatic impacts. Since the changing variables across different time periods are only climatic inputs, we deem the changes in runoff are mainly induced by precipitation and temperature variations rather than land-surface changes.

4.2. Changing Pattern of Hydro-Meteorological Variables Under Climate Warming

Projected changes in annual mean temperature, precipitation, and runoff for the near and far future periods relative to historical reference are examined (Figure 4). As presented by the multimodel ensemble mean results, future climate will be evidently featured by warming temperatures for these catchments (Figures 4d and 4g). For annual precipitation, it will slightly increase for near future (around 5%–10%) and

![Figure 2. Biases of maximum temperature, minimum temperature (Absolute biases, °C), and precipitation (relative biases, %) in July. The results derived from the raw (a,c,e) and corrected (b,d,f) multimodel ensemble outputs in the reference period (1961–2005) across 0.5° × 0.5° grids in China, respectively. The x-axis denotes 31 GCMs and the y-axis indicates biases. Each box consists of biases for all the 0.5° × 0.5° land grids (3,825 grid cells) over China.](image)

![Figure 3. Hydrological model calibration and validation efficiency. (a) presents the best-performing hydrological model for the 151 catchments in China; (b,c) demonstrate daily KGE values in the calibration and validation periods, respectively.](image)
will further increase for far future (around 10%–40%) over China. Spatially, catchments located in the northeastern and western China are projected to show higher increasing magnitudes comparing to the central and southern China, in line with previous work (Xu et al., 2019; Zhang et al., 2017). In terms of the river runoff, a divergent spatial pattern regarding the sign of changes on the annual time scale is observed. For the majority of the central and southern catchments, they are subject to a decreasing runoff tendency for the near future period, while they will slightly increase for the far future. For northeastern and western alpine regions, consistent increases in annual runoff can be found for both near and far future climates. Overall, this seems to indicate a “dry, getting wetter–wet, getting drier” response pattern under future climate warming.

To further gain insight into the sensitivity of precipitation and runoff to warming climates, we identify the scaling rates and types for precipitation- and runoff-temperature relationships during historical, near, and far future periods. Positive scaling rates can be found in precipitation-temperature relationships during historical period for all catchments (Figure 5), significant at $p < 0.05$ (Figure S6). Furthermore, the scaling rates typically show super C-C behaviors and are higher in western catchments, at roughly a double C-C rate. This indicates a strong response of precipitation to the warming temperatures, which may be associated with the reinforcing moisture convergence by monsoons (Zhang et al., 2019). As for scaling types, the hook structure and monotonic increasing scaling types dominate China (Figure 6). The results show that northeastern and western catchments, where the annual precipitation amounts are relatively low but demonstrate large increasing magnitudes during future warming climates, present the monotonic increasing scaling type. In other words, precipitation can monotonically increase with warming temperatures, under the measured scaling rates. In contrast, the hook structure type prevails over the central and southern catchments. This suggests a potential limitation of the positive responses of precipitation to the warming temperatures (featured by the parabola, Figure 6h), regardless of strong C-C scaling rates. In the context of climate warming, nuanced changes in the scaling rates (Figure 5) and scaling types (Figure 6) are observed. Most
catchments maintain the monotonic increasing type (or the hook structure type) spanning from the historical baseline to future periods. It should be noted that the historical hook structure scaling types in central and southern China are accompanied by some increases in future annual mean precipitation. This is explainable because in the hook structure, $T_{pp}$ is not fixed but shifts towards the warming side during future periods. Compared to the historical baseline, $T_{pp}$ is projected to increase around 1°C and 2°C for the near future and will be up to 3°C–5°C for the far future (Figure 6). Correspondingly, the maximum precipitation amount pairing with the $T_{pp}$ will increase, to some extent releasing the constraint denoted by the hook structure (Figure 6h). In all, the responses of precipitation to temperatures in the hook structure (varying from positive to negative rates) somewhat weaken the wetting patterns in precipitation over central and southern catchments in China.

For river runoff, positive scaling rates also dominate catchments in China (Figure 5), (see Figure S6 for significance test result). Generally, they differ from those of precipitation scaling rates. This may be explained by nonlinear relationships between rainfall-runoff generation processes (Lan et al., 2016). Comparing to precipitation, the more scattered spatial patterns in runoff scaling rates can be attributed to varying terrestrial conditions across different catchments. For example, differences in catchment characteristics such as areas, elevation, slope, and vegetation index lead to divergent runoff regimes (Huang et al., 2020) and further varied sensitivity to rising temperatures. If a catchment owes high vegetation index, the associated large surface roughness and low albedo can weaken runoff sensitivity to future warming climates (Lean & Warrilow, 1989). In addition, these scaling rates are typically lower than those for precipitation. This reflects the role of evapotranspiration at the monthly time scale, especially in future warming climates. Changes in monthly runoff depend not only on the precipitation scaling with temperatures but also on the

Figure 5. Precipitation and runoff scaling rates during the 1961–2005 (historical), 2011–2055 (Future1), and 2056–2100 (Future2) periods across 151 catchments in China.
Figure 6. The precipitation-temperature (a,c,e,h,k) and runoff-temperature (b,d,f,i,l) scaling types and $T_{pp}$ during 1961–2005, 2011–2055 (Future1), and 2056–2100 (Future2) periods. For (a–f), dark and red colors indicate the monotonic decreasing (D) and increasing (I) scaling types, respectively. (h–i) present the shifting pattern of the hook structure for precipitation- and runoff-temperature relationships over an example catchment (located in (g) filled with blue color); (k–l) present the pattern of the monotonic increasing scaling type for precipitation and runoff-temperature relationships over an example catchment (located in (j) filled with blue color). The shading is derived by 31 GCMs; the solid curve indicates the multimodel ensemble mean result. The dashed lines mean the C-C scaling rate (7%/°C).
evapotranspiration relative to precipitation under climate warming. Climate change has increased atmospheric evaporative demand and thus contributes to runoff drying (Cook et al., 2020). In the case of scaling types, almost identical spatial patterns in the runoff scaling with temperatures to those in the precipitation can be observed (Figure 6). We infer that though the runoff scaling rates are synergistically modulated by climates and terrestrial conditions, the scaling types are dominated by climatic conditions. The monotonic increasing type is detected over the northeastern and western catchments, while the hook structure type is prevalent in the central and southern catchments during the three time periods. For catchments with an increasing scaling type, increasing runoff can occur attributed to future warming climates (Figure 6l). For catchments indicating a scaling type of the hook structure, the positive responses of runoff to warming climates may be constrained at hot conditions (i.e., after the local temperature exceeding the $T_{pp}$) (Figure 6i). As with the case in precipitation, the $T_{pp}$ in runoff scaling will increase during future warming climates. This partly buffers the constraint by the negative side in the parabola of the hook structure and reflects in slight increases in annual mean runoff over catchments in central and southern China for the far future period. Overall, the local runoff is highly sensitive to warming temperatures and how it implicates future drought changes needs further investigation.

4.3. Projected Meteorological and Hydrological Drought Conditions

Do the increases in annual precipitation (or in annual runoff) under future climate warming imply mitigated drought conditions? To answer this question, the drought frequency, drought duration, and severity across
drought events in each time period from 31 climate model simulations are evaluated (Figures 7–9). For the historical period, a high meteorological drought frequency (around 100–110 times) is found over all catchments in China (Figure 7). These drought events with short durations (around 1–1.5 months) and moderate severity (around 1.5–2) exhibit frequent but mild magnitudes. The changes of meteorological drought characteristics (i.e., frequency, duration, and severity) under global warming are shown in Figures 8 and 9a–9c, which are characterized by an explicit spatial pattern. Decreased drought frequency, shortened mean duration, and mitigated mean severity can be observed in northeast China and western alpine regions, while some increases in these drought characteristics are projected in central and southern China for the near future. For the far future period, drought conditions in northeastern and western China (and in central and southern China) will be further mitigated (deteriorated).

We empirically find that the frequency of hydrological drought episodes is only about half (i.e., around 55–60) that of meteorological episodes (approximately 100–110) during the historical period (Figure 7). However, compared to meteorological droughts, the hydrological droughts are greatly enhanced, as evidenced by the average drought length increasing to 3 and 4 months and severity soaring to 3–5. This might be attributed to that several contiguous meteorological drought episodes can jointly trigger one large hydrological episode (Liu et al., 2019). Abnormally dry climates (e.g., abnormal decreases in precipitation) lead to meteorological drought episodes. Further, they precede and drive low flows to trigger hydrological droughts. The differences in the characteristics between meteorological and hydrological drought episodes suggest that abnormally dry conditions on their own do not last long. However, when they are transferred

Figure 8. Projected meteorological (SPI) and hydrological (SRI) drought changes in frequency (a,d), duration (b,e), and severity (c,f) during the 2011–2055 (Fut1) period relative to the 1961–2005 period. The pure color indicates a high model agreement (>60%, 19 out of 31 models agree on the sign of change); colored hatching denotes low model agreement (<60%).
to the surface water budget, droughts with enlarged magnitudes and lengthened temporal scales can be induced (Zhou et al., 2019). The spatial patterns of future changes in hydrological drought characteristics (relative to the baseline period) follow those of meteorological drought episodes (Figures 8 and 9d–9f). Hydrological drought, in terms of both duration and severity, are projected to increase in central and southern China, whereas northeast China and western alpine regions are dominated by drought mitigations. Specifically, prolonged durations over central and southern catchments reached between 4% and 20% for the near future period and between 12% and 30% for the far future period; whereas the changing magnitudes are greater in severity, with relative changes ranging between 12% and 35% for the near future and becoming more than 28% for the far future.

Apparently, future drought characteristics under climate warming can largely differ from those demonstrated in the past. At the same time, it should be noted that a wetting atmosphere does not imply mitigation in meteorological drought conditions. Variations in annual runoff are not much connected with future hydrological drought changes. On the other hand, for a specific catchment, changing magnitudes in drought duration and severity of a meteorological (or hydrological) drought event are somewhat different. The signs of changes are even reverse between duration and severity (e.g., shortened duration and increased severity). This makes it hard to accurately characterize changes of drought episodes and predict their consequent impacts under warming climates. Therefore, in the next section, we examine changes of return periods from a bivariate perspective to give further insight into drought variations with climate warming.

Figure 9. Projected meteorological (SPI) and hydrological (SRI) drought changes in frequency (a,d), duration (b,e), and severity (c,f) during the 2056–2100 (Fut2) period relative to the 1961–2005 period. The pure color indicates a high model agreement (>60%, 19 out of 31 models agree on the sign of change); colored hatching denotes low model agreement (<60%).
4.4. Projected Changes in Bivariate Drought Risks

After modeling the bivariate distribution of drought duration and severity, we focus on projected changes for different return periods (i.e., 20-, 50-, and 100-year) (Figures S7 and S8). Taking the 50-year event as an example, compared to the historical period, the frequency of 50-year meteorological droughts is projected to soar in southern China for both future periods, while they are projected to decrease in the northeastern and western China (Figure 10). In addition, the changes in return periods of meteorological drought episodes will intensify with warming levels increasing (i.e., compare changes for the near future to the far future). For instance, for the near future period, the 50-year meteorological drought episodes in central and southern China will increase by 1 to 2 times (relative to the historical baseline), while for the far future period, they project to increase by 5 to 10 times more frequently. Also, the decreased drought risks featured by less frequent drought episodes over the northeastern and western alpine regions of China for the near future climate will further decrease for the far future climate. This result highlights the high sensitivity of meteorological drought episodes to climate warming.

For hydrological drought episodes, the spatial patterns of changes in joint return periods bear a high resemblance to those of the meteorological episodes. In detail, compared to the baseline period, the 50-year hydrological droughts are projected to occur more frequently over catchments in central and southern China, while their frequencies are expected to decrease over northeastern and part of western watersheds. This is consistent with previous work (Yuan et al., 2019). On the other hand, amplified changes in return periods from meteorological to hydrological drought episodes are observed over catchments in China for both future periods. For instance, in southern China, 50-year hydrological droughts are projected to occur 5 to 10 times more frequently for the near future period (1 and 2 times for meteorological droughts) and more than 10 times (5–10 times for meteorological droughts) for the far future (Figure 10). The stronger responses of hydrological droughts than those of meteorological droughts to future warming climates should be paid attention in mitigation and adaptation strategies.

On the other hand, there is an important issue that needs special attention when interpreting the results, that is, the uncertainty related to the choice of a climate model. Among various uncertainty sources (i.e., global climate models, greenhouse gas concentration pathways, bias-correction techniques, and hydrological models), climate model uncertainty typically accounts for the major one (Ahmadalipour et al., 2018;
Chen et al., 2011; Najafi et al., 2011; Rana et al., 2017) and is specifically considered in this study. Thirty-one climate model simulations are employed to make the multimodel ensemble. Figure 11 presents the 50-year joint return periods and associated most likely scenarios of meteorological (SPI drought) and hydrological drought (SRI drought) for the two representative catchments (Figures 6g and 6j) in China during the historical, near future and far future periods, respectively. As shown in the figure, the uncertainty envelopes are remarkable, especially

Figure 11. The 50-year joint return periods (isolines) and most likely scenarios (dots) of meteorological (SPI drought) and hydrological drought (SRI drought) for two typical catchments in China. Thirty-one colored isolines in each panel derive from 31 global climate models, whereas the dark thick isoline denotes the multimodel ensemble mean results. (a–f) present the results for the catchment in Figure 6g; while (g–l) present the results for the catchments in Figure 6j.
during future climates. Additionally, for a certain catchment, the climate model uncertainty tends to be larger in the hydrological droughts than in the meteorological droughts. This emphasizes the necessity to employ adequate number of climate models to cover the range of uncertainty when performing impact studies. Besides, future studies can involve more uncertainty components and further investigate their relative contributions.

Finally, we identify strong relationships between the precipitation- and runoff-temperature scaling types and the changes in drought risks under climate change. In northeastern and western alpine catchments where both the precipitation and runoff follow a monotonic increasing scaling type, future drought risks are projected to be mitigated. In contrast, in central and southern catchments where precipitation and runoff present a hook-like structure scaling type, the drought risks are projected to become more severe. Why do these two scaling types show such different implications for drought changes? The hook structure is shaped by constraints from atmospheric dynamics such as moisture and energy limitation under warm temperatures (Wang et al., 2017). The temperature changes can be viewed as an index of climate warming (Zhang et al., 2014). The intensification of precipitation and associated runoff driven by thermodynamics are projected to be constrained by moisture and energy availability under climate warming (Yin et al., 2018), leading to drought deterioration. For a monotonic increasing scaling type, there is a stronger impact of thermodynamics on local moisture availability than dynamic constraints. It contributes to the intensification of future column-integrated water vapor content and mitigates the drought risks under future warming climates (Yin et al., 2019).

5. Conclusions

This study quantifies the temperature scalings of precipitation and runoff at the monthly scale and attempts to reveal their implications for future drought changes. We consider both meteorological and hydrological drought changes using 31 climate model simulations under RCP 8.5 over 151 catchments in China. The main conclusions are as follows:

1. Monthly precipitation and runoff are highly sensitive to rising temperatures over all the catchments in China, with stable scaling types and scaling rates. The scaling types demonstrate an explicit spatial pattern, in which the monotonic increasing type dominating the northeastern and western regions, whereas the hook structure exhibits in the central and southern catchments. Near and super C-C scaling rates for monthly precipitation and runoff prevail over those catchments, with higher rates in precipitation than in river runoff.

2. Future changes in hydrological droughts relative to the historical baseline are larger than in meteorological droughts. This reflects the enlarging effects of warming climate impacts on drought transferability from meteorological to hydrological propagation.

3. Future drought changes are closely associated with scaling types. A hook structure scaling type usually relates to drought deterioration, whereas a monotonic increasing type can imply drought mitigation in the context of climate warming. It is a challenge for this study to explicitly quantify the relationships between scaling behaviors and drought evolutions, but our study may provide an essential potential reference for projecting and predicting future droughts. Future research may develop an integrated model to quantificationally characterize the mechanical interplay between future drought variations and water fluxes responses to warming climates.

Data Availability Statement

The hydrological simulation data are being uploaded to an open-access repository (https://osf.io/phqe3/%3Fview%5Fonly%3Dd8f66bbe81d348918e936d56df89598).

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