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RESEARCH ARTICLE

Predicting the spatiotemporal characteristics of flash droughts with downscaled CMIP5 models in the Jinghe River basin of China

Hui Ran[1] · Jing Li[1] · Zixiang Zhou[2] · Cheng Zhang[1] · Chengyan Tang[1] · Yuyang Yu[1]

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Abstract

Climate warming greatly affects the frequency and intensity of flash droughts, which can cause huge damage to agriculture. It is important to understand the changing rules of future flash droughts and take precautionary measures in advance. Thus, we focused on the flash drought characteristic of the Jinghe River basin using variable infiltration capacity (VIC) model and four-model ensemble in the two representative concentration pathway scenarios. Four-model ensemble mean can well capture hydrological changes in the reference period. The heat wave flash drought (HWFD) and the precipitation deficit flash drought (PDFD) mainly occur in the northern during reference period. The HWFD and PDFD have shown a linear growth trend in the future and both shown higher growth rates in the RCP8.5 scenario. The frequency of occurrence (FOC) increments of flash droughts were relatively high in the southern Jinghe River basin. And the HWFD and the PDFD mainly occurred in May–September. Further results indicate that the contribution of the maximum temperature to HWFD was the biggest (greater than 0.7), followed by evapotranspiration (ET) and soil moisture (SM). The contribution of maximum temperature to PDFD was the biggest (greater than 0.5), followed by precipitation and ET. Global warming in the twenty-first century is likely to lead to intensification of flash droughts. Therefore, measures and suggestions were proposed to effectively respond to flash droughts in our study.

Keywords The heat wave flash drought · The precipitation deficit flash drought · CMIP5 · VIC model · Recommendations · The Jinghe River basin

Introduction

There is no denying the fact that climate changes and human activities are main reason of global warming (IPCC 2013). The global warming has resulted to diversification in spatial-temporal distribution and pattern of water resources at different scales around the world, which has exacerbated the occurrence of extreme droughts. Research by Gul et al. (2019) has shown that climate change has a beneficial effect on agricultural products in Chitral, and the opposite effect in some other places. This highlights the importance of capturing droughts in the future. The well-known conventional drought can last more than several months (Mishra and Singh 2010). However, if low SM content and high intensity ET occur simultaneously with drought and heat wave events, drought also occurred. And due to its sudden, abnormal intensity and devastating impacts, it was called "flash droughts" (Ford et al. 2015; Mark et al. 2002). The frequency of flash droughts has been increasing in the past few years and could cause tremendous crop yield losses and threaten the ecological sectors (Jin et al. 2019; Otkin et al. 2016). Studying the possible regularities of flash drought characteristics is very important for coping with climate change and enhancing crop yield.

To quantify the risk of a flash drought, some methods need to be used for identification. Drought index has been a major choice for drought monitoring over the past years. The Palmer Drought Severity Index (PDSI) and the standardized precipitation evapotranspiration index (SPEI) were widely accepted (Palmer 1965; Vicente-Serrano et al. 2010), but both of them

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✉ Jing Li
lijing@snnu.edu.cn

1 School of Geography and Tourism, Shaanxi Normal University, Xi'an 710119, China

2 College of Geomatics, Xi'an University of Science and Technology, Xi'an 710054, China

were used to analyze the trends and characteristics of long-term drought through the monthly temperature and precipitation of observed data, and unable to effectively monitor the flash droughts. In recent years, scholars began to try various methods to define flash droughts. Basara et al. (2019) applied the standardized evaporative stress ratio (SESR) to summarize the spatiotemporal characteristics and evolution of flash droughts in the USA. Mozny et al. (2011) calculated the Soil Moisture Index (SMI) of the Czech Republic to study variations in flash droughts based on observed values of soil humidity in different soil layers. Liu et al. (2020) defined flash droughts by concentrate on decay rate of soil moisture percentile per week. These studies only capture flash droughts from the perspective of soil moisture or evapotranspiration. Flash droughts require a comprehensive assessment by definition. Therefore, we use temperature, precipitation, evapotranspiration (ET), and soil moisture (SM) indicators to evaluate flash droughts. However, SM and ET observations with daily time steps are difficult to obtain. Although the land surface model has error and uncertainty, it is still an effective tool for simulating SM and ET which are necessary to capture flash droughts. The VIC model can simulate the hydrological cycle and energy flux at the watershed scale to obtain accurate daily weather data (Liang and Lettenmaier 1994). For example, Zhang (2009) found that the VIC hydrological model can simulate the spatial distribution of soil moisture in China. In addition, Zhang et al. (2017) obtained SM and ET by running the VIC in the study of flash droughts in Ganjiang River Basin, and thought that the soil moisture simulated and output by VIC model could be better used in the analysis of flash drought characteristics. So the VIC hydrological model was considered to be one of the good tools for obtaining daily data.

Global warming was likely to make the climate drier, making extreme events more common (Liu et al. 2019). As an effective tool for exploring future climate change, the Coupled Model Intercomparison Project Phase 5 (CMIP5) contains many climate models, which have greater advantages than CMIP3 (Taylor et al. 2012). So many scholars began to use CMIP5 models to study past and future droughts in different regions. Ullah et al. (2019) used the CMIP5 models and crop model to quantify and predict climate change and its impact on agricultural products in arid and semi-arid climate conditions. Sun et al. (2019) have predicted four conventional droughts in the Yangtze River basin based on ten climate models and SWAT model. But they are used to calculate long-term droughts, and few studies have used CMIP5 to predict future flash droughts, especially semi-humid and semi-arid regions. Exploring the driving factors behind droughts has important reference value for proposing measures. For example, Liu et al. (2016) used the method of partial correlation analysis to analyze the driving factors of drought characteristics in Jiangsu Province, but there is still a lack of research on the main control factors of spatial differentiation and the contribution rate. Geodetector can detect spatial stratified heterogeneity through statistical methods, reveal the driving factors behind a phenomenon, and analyze the explanatory degree of dependent variables to independent variables (Wang and Xu 2017). Geodetector can detect numerical data and qualitative data, and was widely used in ecological landscape, natural disasters, economics, and other fields (Chen et al. 2020; Gao et al. 2020; Wang et al. 2016a, b).

The Jinghe River basin is not only a well-known grain-producing area in Northwest China but also a region with frequent drought events in the semi-humid and semi-arid regions (Zhang et al. 2016; Tang et al. 2019). The Jinghe River basin has suffered from 110 drought disasters in the Ming Dynasty (277 years), with an average of 2.52 years (Lv and zhao 2009). Dryness without warning may restrict crop growth, which may lead to reduced crop yields or crop failure (Liu et al. 2015a). Long et al. (2012) found that the risk of agricultural drought in the Jinghe River basin is higher. Liu et al. (2015b) used the CMIP5 to analyze the temporal-spatial trends and characteristics of future climate change factors in the Jinghe River basin. However, few people are currently studying the flash droughts in the Jinghe River basin. Therefore, four CMIP5 models under two representative concentration pathways (RCP4.5 scenario and RCP8.5 scenario) were used to input into the hydrologic model of Variable Permeability Capacity to forecast the flash droughts characteristics in the Jinghe River basin and explore the driving factors of flash droughts.

In our research, downscaled CMIP5 models and VIC model were used to forecast the characteristics of flash drought that was defined using ET, SM, and temperature in the Jinghe River basin in the next 30 years. Our main objectives are to (1) assess the applicability of the VIC model and the simulation capability of the four-model ensemble mean; (2) summarize the temporal-spatial characteristics of HWFD and PDFD under RCP4.5 and RCP8.5 scenarios; and (3) use geodetector to explore the driving factors of flash droughts and propose preventive and remedial measures to reduce economic losses.

Data sources and research methods

Study basin

The Jinghe River basin (106 ° 14′~108 ° 42′, 34 ° 46′~37 ° 19′) spans Ningxia, Gansu, and Shaanxi provinces, with developed agricultural production. It is the main production base of agricultural products, livestock products, and fruit in the two provinces of Shaanxi and Gansu. The total length is 455 km, and the basin area is 45,421 km^2. The Jinghe River basin has a continental monsoon climate, and the rainfall and temperature gradually decrease from southeast to northwest. The annual average precipitation of the river system is 506.8 mm, and the annual average temperature is about 10 °C. In addition, due to the impact of topography, in the south side of the mountain, rainfall is higher than that in the north. Since 2000–2015, flash droughts occurred more than ten times in the entire basin, which has caused serious damage to crops (Fig. 1).

Hydrological modeling and input data

As a typical land surface hydrological model, VIC can comprehensively consider topographic, soil, vegetation, climate, and land cover and other factors in the basin. The VIC-3L model used in Jinghe River basin considered three layers of soil in the vertical direction, and the top layer of soil is a thin layer of soil that describes the dynamic changes in rainfall and increases the interlayer circulation (Liang and Lettenmaier 1994). Compared to other similar models, the VIC model has the advantage of being based on physical interpretation and has wide applicability to different climate zones (Wen 2017; Ma et al. 2019; Shayeghi et al. 2019).

The data needed by the VIC models include land cover, topography, vegetation information, and climatic factors. The land cover data at 30-m resolution was derived from the data center for Resources and Environment Data Cloud Platform (http://www.resdc.cn/). Topography data with a resolution of 30 m, that is, the digital elevation model, comes from the geospatial data cloud (http://www.gscloud.cn/). The vegetation information with a resolution of 1 km used in this research was derived from the University of Maryland. Soil data with a resolution of 1 km were derived from the world soil database (HWSD). The precipitation and temperature data were derived from the China Meteorological Data Service Center (http://data.cma.cn/), covering the period from 1976 to 2015. The soil moisture data and evapotranspiration data come from GLDAS v2.1/Noah, whose spatial resolution is 0.25 degrees. GLDAS v2.1/Noah (https://earthdata.nasa.gov/search?q=GLDAS+v2.1%2FNoah) data is mainly used to compare and verify the reliability of the soil moisture data and evapotranspiration data simulated in the Jinghe River basin in the VIC model.

CMIP5 models

The NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset has been treated by statistically downscaled and bias corrected for 21 original CMIP5

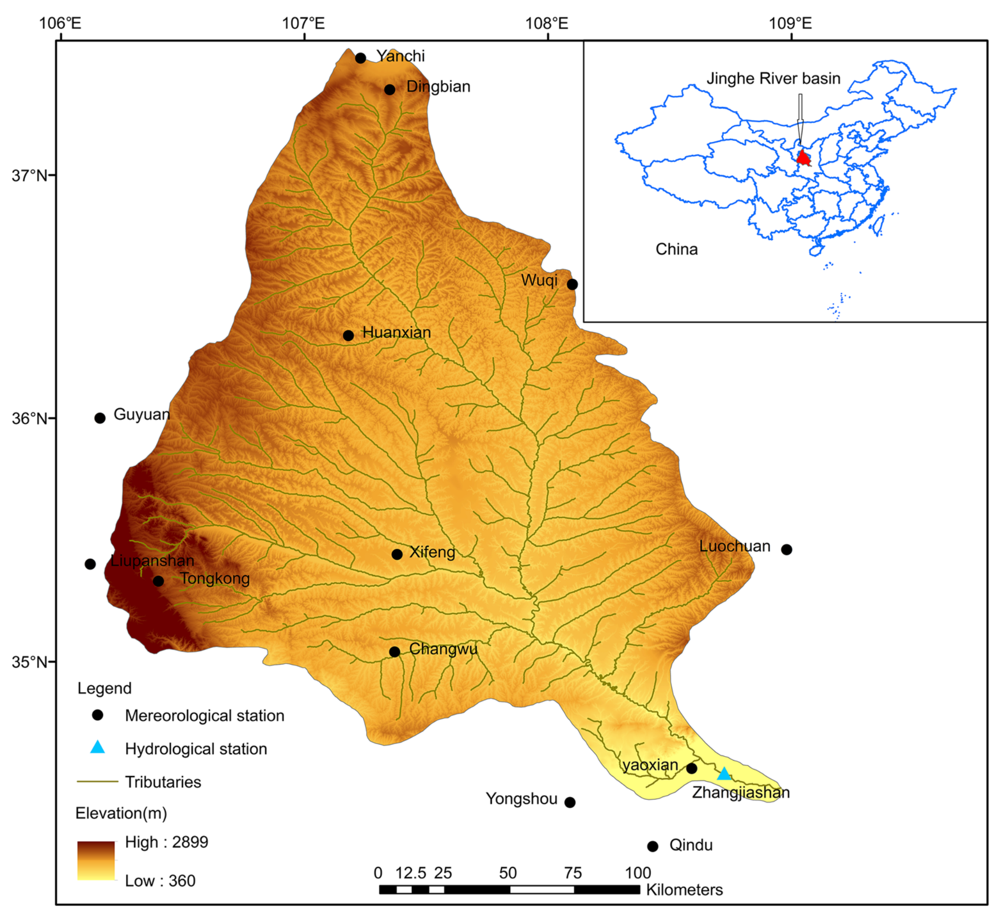

Fig. 1 Jinghe River basin with hydrological and meteorological stations

models. The spatial resolution of each climate model is 0.25 × 0.25 and can be downloaded from Internet (https://www.nccs.nasa.gov/services/climate-data-services).

In order to calculate flash droughts in Jinghe River basin, we inputted NEX-GDDP data into the VIC that has been calibrated. And we have selected four CMIP5 models from reference period (1976–2005) and future period (2031–2060) respectively. In particular, the future period contains two scenarios (RCP4.5 and RCP8.5), and each scenario contains four CMIP5 models. It was as shown in Table 1.

Drought and heat wave indices

In this paper, maximum temperature (Tmax), minimum temperature (Tmin), precipitation, SM and ET were used to explore flash droughts characteristics. SM and ET were derived from the VIC hydrological model. In the soil moisture research, the standard soil moisture depth is 5 cm, 10 cm, 20 cm, 50 cm, 100 cm, and 200 cm (Bell et al. 2013). First, research by Mo et al. showed that the use of 1-m-deep soil moisture can effectively capture flash droughts. Secondly, the Jinghe River basin was dominated by cultivated land. The soil moisture of 1 m deep can meet the needs of most crop roots for moisture and nutrient absorption (Natural Resources Conservation Service 2005). Therefore, we used 1-m-deep soil moisture to capture flash droughts. Because those meteorological data have a huge impact on the growth and development of plants, such flash droughts will affect the flowering and pollination of crops, resulting in a large reduction in crop yields. Therefore, this study focused on the characteristics of flash droughts from March to October (crop growth period). We adopted pentad time scale (5-day average) to study the flash droughts. There are 49 pentads each year, 1470 pentads in the reference period (1976–2015), and 1470 pentads in the future period (2031–2060). Flash droughts can be divided into HWFD and PDFD. HWFD is mainly driven by temperature. The Tmax anomaly is greater than one STD, which represents a high-temperature situation. When a HWFD appears, the temperature has risen markedly and rapidly. High temperatures cause the increase of ET, which in turn makes SM below 40%. The threshold of 40% of soil moisture represents the start of local dryness compared with normal conditions, which can effectively capture flash droughts in China (Liu et al. 2020; Zhang et al. 2017; Wang et al. 2016a, b; Mo and Lettenmaier 2015). PDFD is mainly driven by precipitation. When a PDFD occurs, insufficient precipitation begins to appear about two pentads before the onset and its intensity increased during onset. Precipitation anomalies below 40% are at the beginning of drought (Zhang et al. 2017; Mo and Lettenmaier 2016; Chen et al. 2016; Fu and Jin 2012). Insufficient precipitation kept SM and ET at low levels, leading to higher temperature. According to Mo and Lettenmaier (2015, 2016) and Zhang et al. (2017), the criteria for HWFD and PDFD are as follows in in sequence:

$$\text{Tmax anomaly} > 1\ \text{STD}, \text{ET anomaly} > 0, \text{and SM} < 40\text{th percentile} \quad (1)$$

$$\text{Tmax anomaly} > 1\ \text{STD}, \text{ET anomaly} < 0, \text{and } P < 40\text{th percentile} \quad (2)$$

In the formulas, Tmax anomaly is the anomaly of the maximum temperature; STD is the standard deviation; SM% is the percentile of soil moisture during study period; and P is the percentile of precipitation during study period.

In this study, the FOC of flash droughts was calculated based on the pentad time scale and grid space scale. Equation:

$$\text{FOC} = \frac{F}{F_{\text{total}}} \times 100\% \quad (3)$$

where F_{total} represents the amount of total pentads (1470 pentads) in the reference period and in the future period

Table 1 CMIP5 models used in this study

Model	Institute	NEX-GDDP resolution(lon × lat)	scenarios
CNRM-CM5	Centre National de Recherches Météorologiques/Centre Européen de Recherche et Formation Avancée en Calcul Scientifique, France	0.25° × 0.25°	Reference RCP4.5 RCP8.5
INMCM4	Institute for Numerical Mathematics, Russia	0.25° × 0.25°	Reference RCP4.5 RCP8.5
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, Japan	0.25° × 0.25°	Reference RCP4.5 RCP8.5
MRI-CGCM3	Meteorological Research Institute, Japan	0.25° × 0.25°	Reference RCP4.5 RCP8.5

respectively and F represents the amount of pentads that flash droughts occurrences during the entire period.

Results

Evaluation of the performance of VIC model and CMIP5 models

Model evaluation is a necessary means to quantify its output reliability. These outputs are considered to be reliable if the evaluation statistics fall within the allowable limits (Moriasi et al. 2007). Relative error (RE) and Nash-Sutcliffe efficiency (NSE) are widely accepted tools for validating the simulation effects of hydrological models (Nash and Sutcliffe 1970). When NSE is closing to 1 and RE is closing to 0, the model is suitable for this study area.

In this study, 2000–2005 was used as the model warm-up period, 2006–2010 as the model calibration period, and 2011–2015 as the model verification period to check the operation results. VIC model runs daily data, and the results were summarized as the month stream flow of Zhangjiashan Hydrological station, which is the main stream of this research area. From Table 2, we can see the simulation performance results of the VIC model in this study area. The REs between the observed and simulated stream flow were less than 0.05 and the NSE coefficients were all above 0.75. The observed and simulated stream flow from 2006 to 2015 at the Zhangjiashan Hydrological Station is shown in Fig. 2. The simulated monthly values can basically capture the characteristics of actual stream flow. In order to verify the reliability of other data in this study, we made a correlation analysis between the VIC model data results (soil moisture and evapotranspiration) and GLDAS v2.1/Noah data. When the significance level P is less than 0.05, correlation coefficient is above 0.78 between VIC model outputs and GLDAS v2.1/Noash data for ET and SM (Fig. 3). In general, the simulation results of the VIC model can well reflect the hydrological characteristics in Jinghe River basin.

In order to perform future simulations, we compare the CMIP5 data with the observed values during the reference period (1976–2005) firstly, as shown in Fig. 4. The four-model ensemble mean undervalued some precipitation peaks, but it was basically consistent with the observed values and r was 0.78 (Fig. 4a). For Tmax and Tmin, The r between four-model ensemble mean values and observed values was above 0.95 (0.98 and 0.99 for Tmax and Tmin, respectively). Both of the Tmax and Tmin derived from CMIP5 were matched well with observed values (Fig. 4b, c). At the same times, the distribution range of the four-model ensemble mean were also relatively consistent with the observed values. In conclusion, the downscaled four-model ensemble mean can be used to predict flash droughts in this research area.

Table 2 Performance of VIC model for stream flow simulation for Zhangjiashan Hydrological station

Hydrological station	Calibration period		Validation period	
	RE	NSE	RE	NSE
Zhangjiashan	0.006	0.79	0.05	0.82

Variations in time series of flash droughts

The inter-annual process of flash droughts in this research area can be seen in Fig. 5. Based on the VIC model, the FOC of flash droughts from 1976 to 2005 was used as a reference period. HWFD generally grown significantly in both representative concentration pathways. Under the RCP8.5 scenario, mean of HWFD FOCs has grown at a rate of 9.848 from 2031 to 2060. However, the mean values increased only at a rate of 0.967 in the RCP4.5 scenario from 2031 to 2060. The standard deviation ratios of future climate scenarios and reference period for HWFD occurrences were above 1. This showed that the FOCs of HWFD will fluctuate greatly in the future with global warming. The standard deviation ratio in the RCP8.5 scenario was 2.19, whereas in the RCP4.5 scenario it is 1.08. This means that under the RCP8.5 scenario, the climate conditions are more volatile and it is more difficult for HWFD to accurately warn in advance.

At the same time, we also calculated future changes in PDFD in the Jinghe River basin (Fig. 6). It can be known from the calculation results that the drought in the Jinghe River basin was increasing rapidly. Under RCP8.5 scenario, mean values for flash droughts increased faster than those under the RCP4.5 scenario, which increased at a rate of 5.991 and 2.977 respectively. The standard deviation ratios of both two climate scenarios and reference period for PDFD occurrences were also above 1. This showed that the FOCs of PDFD will also fluctuate greatly in the future. In addition, the standard deviation ratios of PDFD FOCs were smaller than those of HWFD FOCs under RCP8.5 scenario, but the opposite was true in the RCP4.5 scenario. This suggested that PDFD FOCs were greater stable than HWFD FOCs under RCP8.5 scenario and poorer stable than HWFD FOCs under RCP4.5 scenario.

The differences in monthly mean FOCs between future scenarios (RCP4.5 and RCP8.5) and reference period (1976–2005) are shown in Fig. 7. The FOCs of HWFD would generally increase from May to September (Fig. 7a). July and August were most vulnerable to HWFD. The FOCs of HWFD in the RCP8.5 scenario were generally higher than those in other scenarios. It is worth mentioning that the FOCs of HWFD in July were the highest in the reference period. The FOCs of PDFD would generally increase from May to September (Fig. 7b). The basin was vulnerable to PDFD from

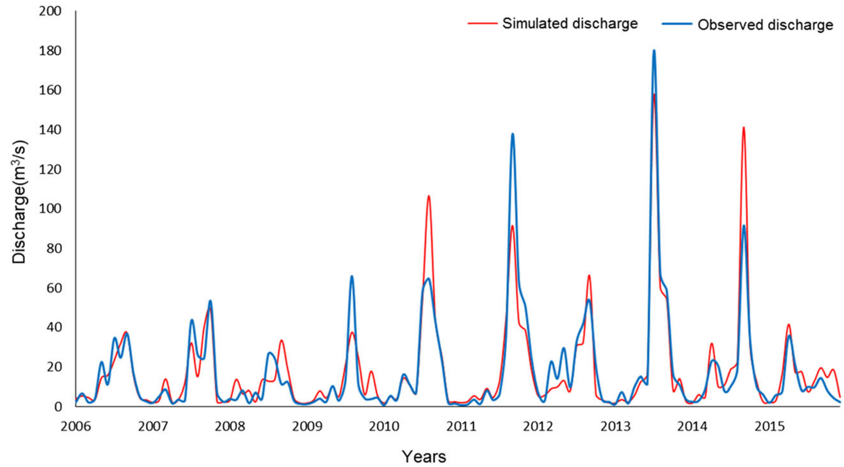

Fig. 2 Calibration of VIC model of Jinghe River basin from 2006 to 2015

June to August and PDFD occurs most frequently under the RCP8.5 scenario, followed by RCP4.5 scenario and reference period.

Spatial variation features in flash droughts

This section used the above identification approaches to study the spatial characteristics of flash droughts. Spatial pattern of flash droughts from March to October in the historical period can be seen in Fig. 8. According to our research, the variation range of FOC of HWFD in the Jinghe River basin during the historical period was generally between 7 and 12%. The FOC of HWFD in the south of the basin was less than 9%. However, in the northern of the basin, the FOC of HWFD reached 9–12%. Thus, the probability of HWFD was higher in the north of basin. The FOC of PDFD experienced more and varied between 9 and 15%. The FOC of PDFD decreased in order from north to south. It indicates that PDFD was also more likely to occur in the north of basin. We also found that the overall FOC of PDFD was higher than that of HWFD.

The spatial FOC changes of flash droughts under three scenarios (RCP4.5, RCP8.5, and RCP8.5–RCP4.5) are shown in Fig. 9. The FOC increments for HWFD showed a stepwise distribution, with the highest frequency occurring in the south of the Jinghe River basin. The FOC increments were projected to decrease by 0–8% in north and increase by 0–10% (even up to 20%) in some places in southern of the Jinghe River basin under RCP4.5 (Fig. 9a). Compared with the RCP4.5, the range of the FOC increments in the RCP8.5 was not changed much, but the area that the FOC increments (increase by 0–10%) has increased (Fig. 9b). If the future climate scenarios rise from the RCP4.5 to the RCP8.5, the FOC increments of HWFD are forecasted to increase throughout the Jinghe River basin, with the larger increase by 2–3.6% in the mid-southern of the basin (Fig. 9c). For PDFD, the FOC increments of PDFD were forecasted to increases by 0–4% in most of the basin in the RCP4.5, and the largest increase in some areas was 6.3% (Fig. 9d). Compared with the RCP4.5, the range of the FOC increments in the RCP8.5 does not changed much, but the area that the FOC increments (increase by 4–8.3%) has increased (Fig. 9e). If the future climate scenarios rises from

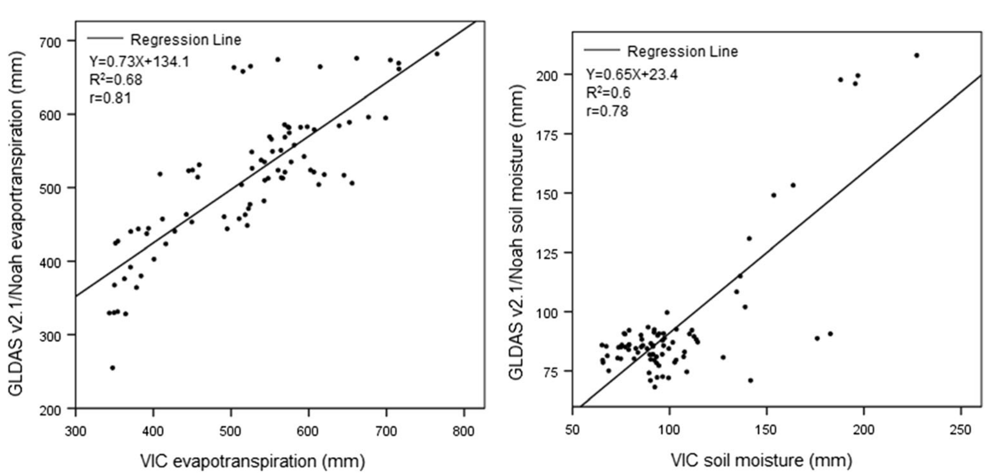

Fig. 3 Comparison of output results of VIC model and GLDAS in 2015 ($P < 0.05$)

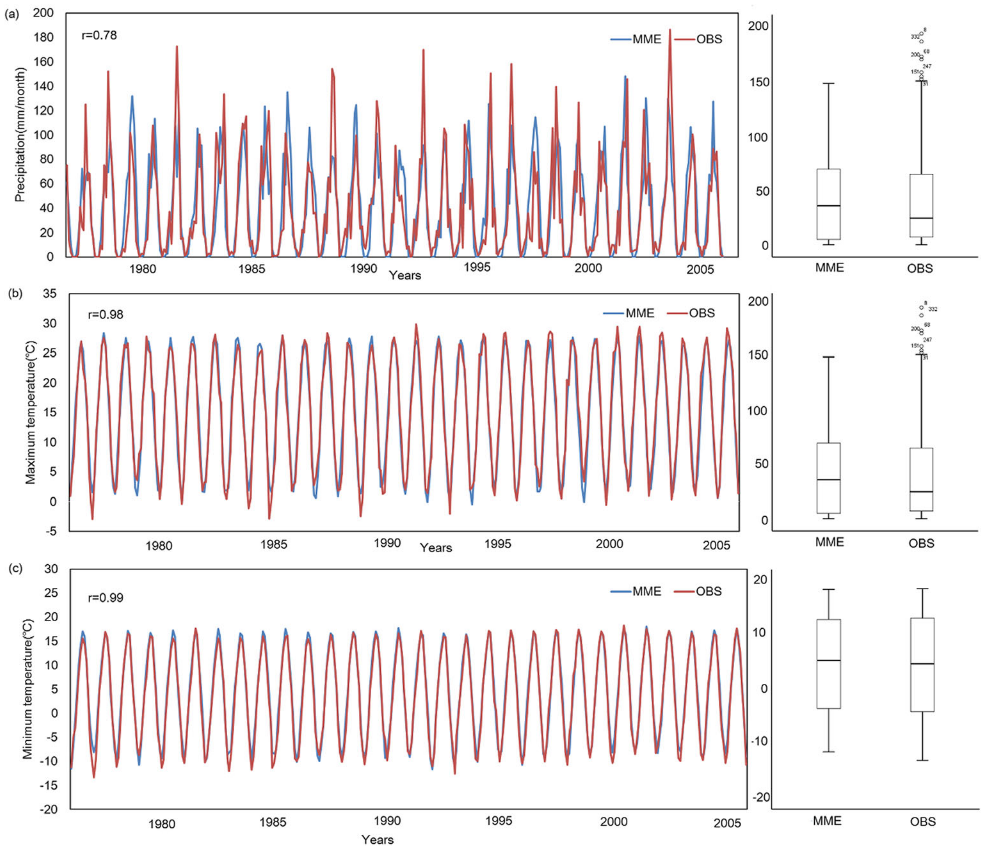

Fig. 4 CMIP5 model downscaling data simulates monthly changes in precipitation, maximum temperature, and minimum temperature from 1976 to 2005

the RCP4.5 to the RCP8.5, the FOC increments of PDFD are forecasted to increase throughout all of the basin, and largest increase are 2–3% in the southern of the basin (Fig. 9f).

In summary, the FOC increments of HWFD decreased in the northern region, but increased in the southern region in the RCP4.5 and RCP8.5. The FOC increments of PDFD were forecasted to increase in most areas, while decrease in some areas in the RCP4.5 and RCP8.5 scenarios. If the future climate scenarios rise from the RCP4.5 to the RCP8.5, HWFD and PDFD are forecasted to increase by 3% in most of the basin.

There was a significant negative correlation between referential FOC and future increments for flash droughts in the matter of spatial distribution. As is shown in Fig. 10, the r was less than -0.7 for HWFD, while the r of PDFD was less than -0.5. This shown that the correlation of FOCs between reference periods and future increments was more significant for HWFD than for PDFD. There was an obvious phenomenon that massive increases in low-value areas (< 10% FOCs in HWFD and < 14% FOCs in PDFD during reference period) corresponding to both types of flash droughts under RCP4.5 and RCP8.5 scenarios, especially for HWFD. If the climate

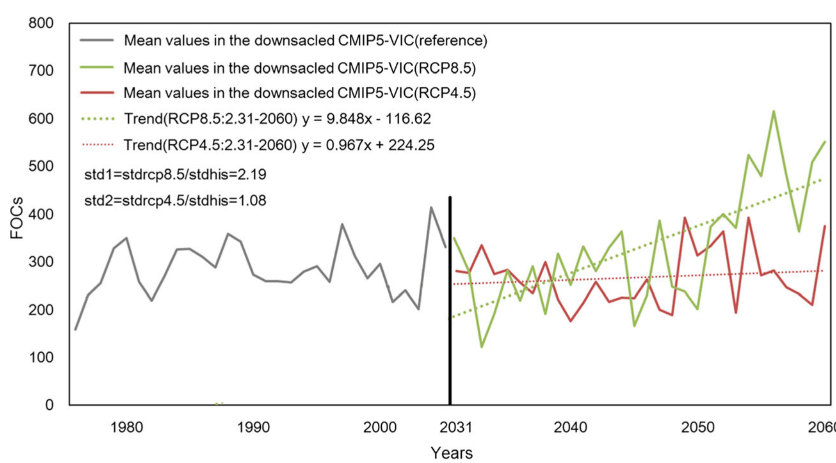

Fig. 5 Number of FOCs under HWFD per year sum in the Jinghe River basin based on multi-model ensemble simulation ($P < 0.05$). std1 represents the standard deviation. stdhis stands for reference period

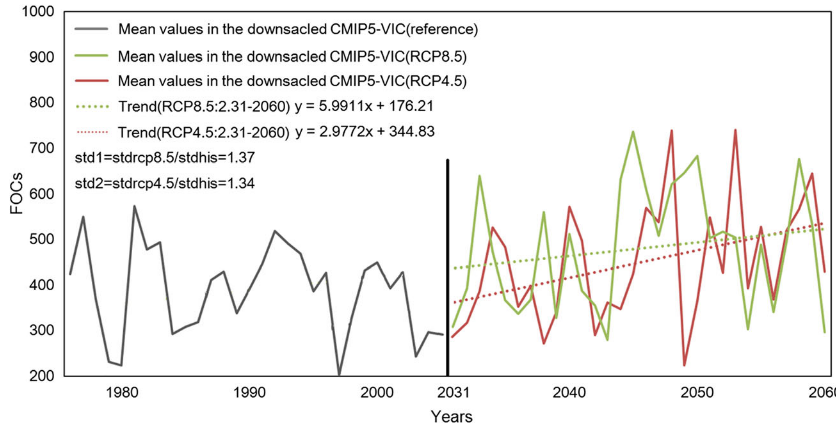

Fig. 6 Similar to Fig. 4, but for PDFD

scenarios increase from RCP4.5 to RCP8.5, there is no significant correlation between the reference period and future increments for HWFD and PDFD. However, the HWFD FOC increments increased by about 20% when the FOC of HWFD varies between 8 and 11% in the reference period. The PDFD FOCs increments increased by 5–10% when the FOC of HWFD varies between 11 and 14% in the reference period.

Discussion

Discussion on the causes of flash droughts

Flash drought is an agricultural drought characterized by rapid occurrence and short duration. As the main food supply area, Jinghe River basin is of great significance to study the temporal and spatial distribution of its sudden drought. The research results show that the northern of the basin was prone to both HWFD and PDFD, and the flash droughts mainly occurred from May to September. It is worth noting that the FOC of PDFD was higher than that of HWFD, contrary to the Zhang et al. (2018). We infer that the Jinghe River basin is located in northwestern China and belongs to semi-humid and semi-arid area. Precipitation deficit makes it more vulnerable to PDFD.

Both of the HWFD and PDFD showed a nonlinear increase in the future, and the growth was faster in RCP8.5 scenario. Because of the influence of radiation forcing, different scenarios predicted different heating rates (Meinshausen et al. 2011), which will lead to a certain degree of fluctuation rise in precipitation and temperature. Geodetector is a new statistical method to reveal the driving factors behind the event (Wang and Xu 2017). Thus, this article further explored the contribution of variables to flash droughts using Geodetector. The results are shown in Table 3. For HWFD, the contribution of Tmax to the flash droughts was the biggest. As different scenarios show different warming trends, the contribution of Tmax to HWFD was slightly different. For PDFD as shown in Table 4, the contribution of ET and P was the biggest in the reference period, while the contribution of Tmax was the biggest in the RCP4.5 and RCP8.5 scenarios. We thought the possible reason is that PDFD is driven by precipitation, but its frequency increase trend is related to high temperature (Mo and Lettenmaier 2016). At the same time, we found that in reference low-value areas, the FOC increments of flash droughts in the future increased significantly. Nonlinearity increase of extreme events may hap pen globally or regionally under different global warming thresholds (Good et al. 2016; Schleussner et al. 2016).

The difference between flash droughts and conventional droughts

Flash drought was known for its rapid occurrence, which has a devastating effect on the critical period of crop growth. Under

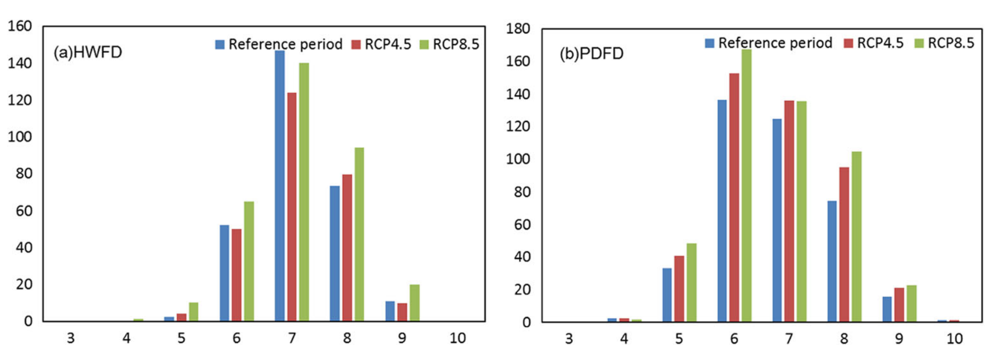

Fig. 7 Monthly statistics in FOCs for HWFD and PDFD in the entire Jinghe River basin. Multi-model ensemble mean is calculated with 30-year average against different scenarios (reference period, RCP4.5, and RCP8.5). $P < 0.05$

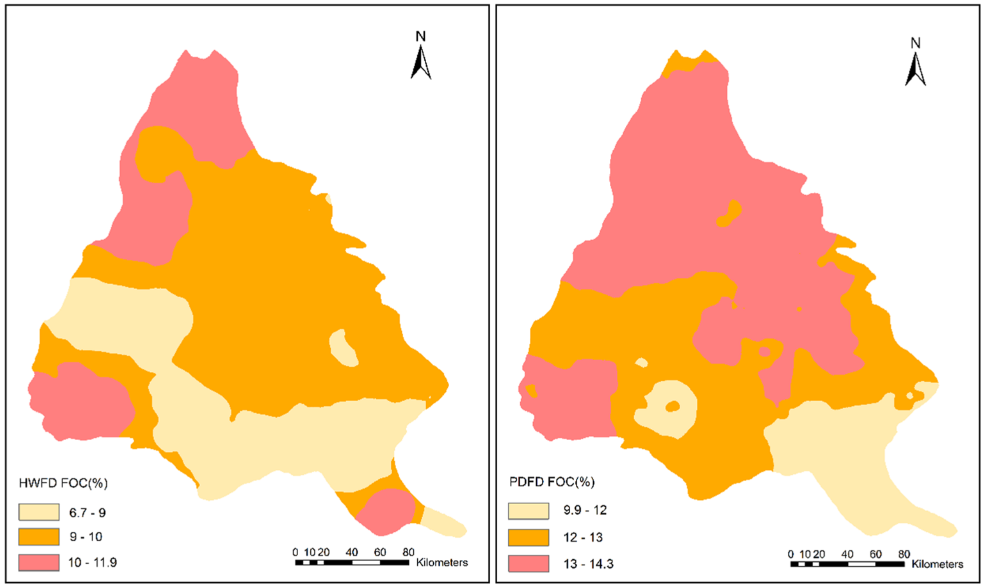

Fig. 8 Downscaled CMIP5–VIC simulation FOCs of flash drought during March–October from 1976 to 2005. Unit: percentage

normal circumstances, flash droughts last for 1 to 2 weeks without any warning. There are four types of conventional droughts that people call meteorological drought, agricultural drought, hydrological drought, and economic drought. Although the definitions of the above four drought types are different, they all revolve around the key point that they are all phenomena of regional hydrological imbalance caused by the lack of precipitation and the abnormally dry weather lasting for a long time (American Meteorological Society 1997; Yuan and Zhou 2014). Therefore, there are two main differences between flash droughts and conventional droughts. First, they are inconsistent in time. Flash droughts occur in a relatively short time, usually 1 or 2 weeks. The conventional drought time scale is generally 1 month, 3 months, 12 months, or even 12 months. Second, from the definition of flash droughts, it generally requires a positive temperature anomaly (that is high temperature). However, conventional droughts only require a lack of precipitation for a period of time. More importantly, there is no inevitable connection between it and high temperature. In summary, flash drought is a new type of drought.

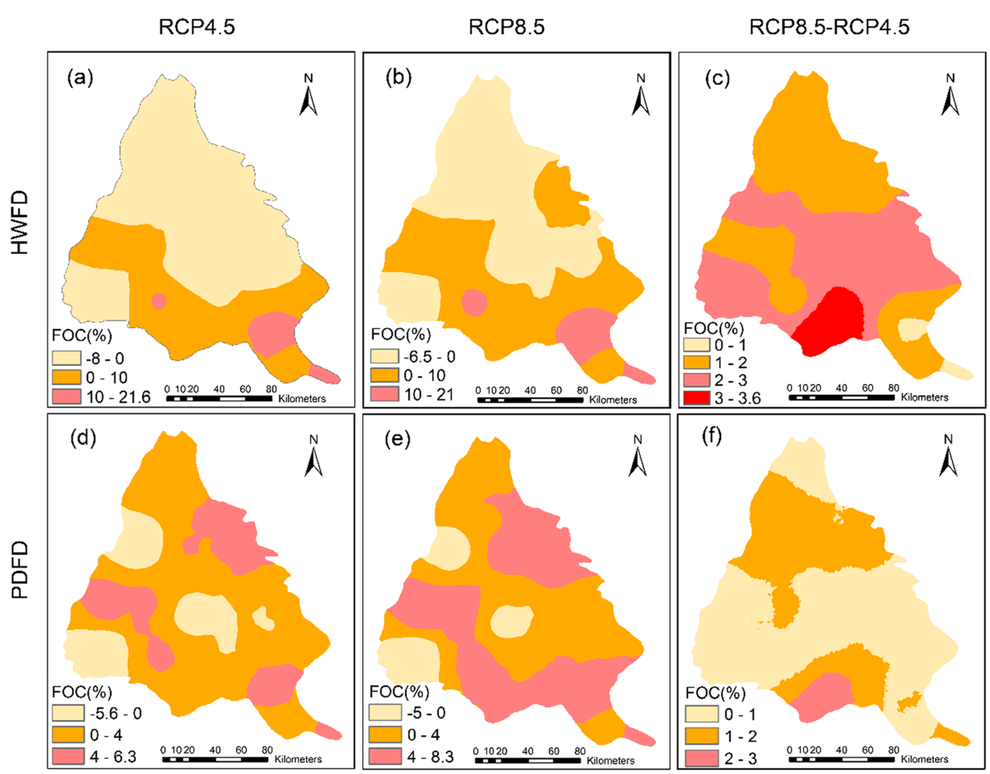

Fig. 9 Future changes relative to the reference period in FOCs for HWFD and PDFD under RCP4.5 and RCP8.5 scenarios and another situation (change of RCP8.5 relative to RCP4.5 scenario)

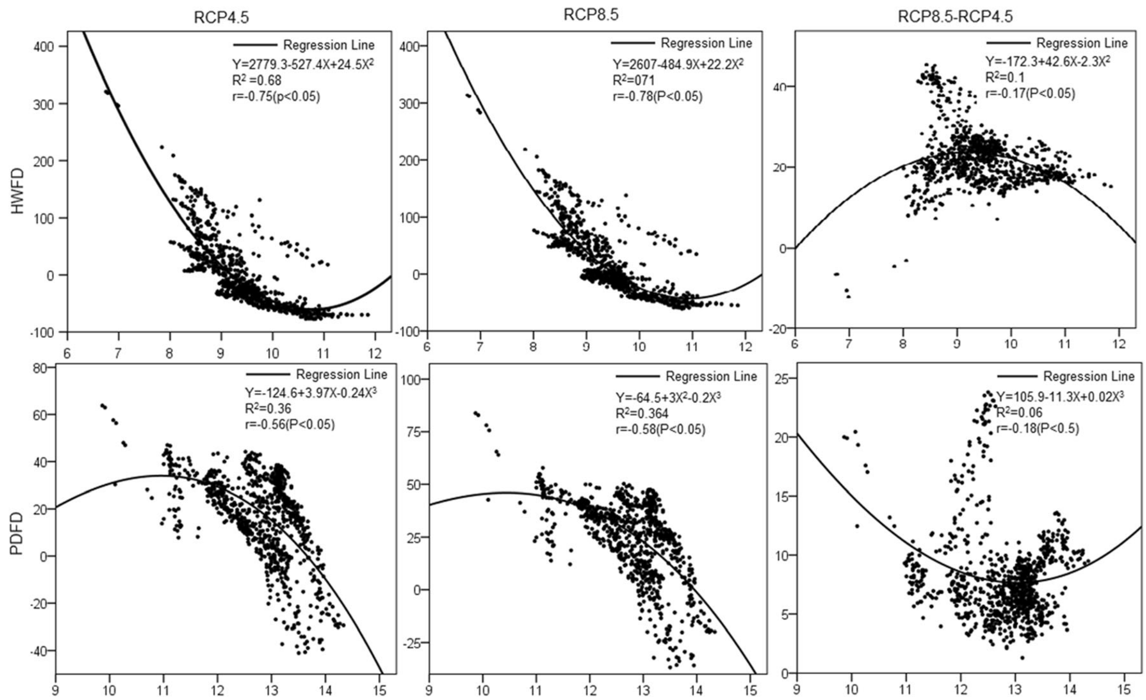

Fig. 10 Curve fitting graph of Jinghe River basin FOCs for HWFD and PDFD against different future scenarios (RCP4.5, RCP8.5, and RCP8.5–RCP4.5) relative to the reference period. *x*-axis is reference FOCs and *y*-axis is changes in future FOCs

Recommendations of flash droughts

The Jinghe River basin has developed agriculture and fragile ecological environment (Ran and Wu 2003). Once a flash drought occurs without warning, it will cause immeasurable losses to the Jinghe River basin. Some preventive and remedial measures are urgently needed to reduce economic losses in the basin.

First of all, the HWFD will be further strengthened in south of basin. Continuous high temperature and low rainfall will easily cause drought to affect the growth and development of plants, resulting in a decline in the agricultural yield and quality. The high temperature and hot summer weather accompanied by atmospheric drought and soil deficit occurred, which caused the occurrence of severe drought or aggravated the severity of drought and severely damaged the crops. Therefore, this study proposes the following suggestions for the HWFD: (1) The prediction of high-temperature heat waves and the release of early warning should be strengthened; (2) Establishing a system for monitoring, assessment, and reporting high-temperature heat waves and soil moisture; (3) Establishing a unified command system and a coordinated emergency plan for relevant departments. Secondly, the predicted PDFD have rapidly increased in almost the entire basin. The sensitivity of crops to water varies at different stages of growth (Liu et al. 2015a). Some studies have shown that the physiological process of crops is complicated during the period of pistil formation and flowering grouting and is most susceptible to drought (Ding and Jia 2001). PDFD seriously affects the growth and development of crops, which may lead to serious crop loss or failure. There are some suggestions for PDFD: (1) Cultivate crops that are compatible with local climate conditions and beneficial to people. The occurrence of drought mainly depends on the anomaly of precipitation, not the amount of local average precipitation (Gong 1998). Although climate change can also cause yield fluctuations, it can meet the needs of crop growth in most cases. (2) We can collect precipitation using reservoirs, etc. Irrigation during the critical period of water demand for crops to resolve the contradiction

Table 3 Contribution of various hydrological variables to HWFD

Factors	Reference period	RCP4.5	RCP8.5
Tmax[a]	0.71	0.92	0.93
ET[b]	0.43	0.85	0.87
SM[c]	0.38	0.67	0.67

[a] Tmax, [b] ET, and [c] SM are abbreviations for maximum temperature, evapotranspiration, and soil moisture, respectively

Table 4 Contribution of various hydrological variables to PDFD

Factors	Reference period	RCP4.5	RCP8.5
Tmax	0.78	0.57	0.56
ET	0.86	0.25	0.23
P[d]	0.86	0.27	0.28

[d] P is abbreviations for precipitation

between water demand and precipitation time misalignment. (3) By adding organic fertilizers to improve the soil structure and the soil is covered with straw to prevent ineffective losses such as evaporation to accumulate water. (4) Improve the irrigation systems. Improve ground irrigation and promote water-saving micro-irrigation technology to improve irrigation efficiency.

Uncertainty analysis

There are some uncertainties in the prediction of flash droughts in this study area, including CMIP5 models and the NEX-GDDP dataset. The CMIP5 models we used have large uncertainties in different models when predicting future flash droughts, even if multi-model ensemble mean we used can effectively simulate reference meteorological variables. The range of uncertainty is generally affected by the original CMIP5 models and various downscaling methods (Taylor et al. 2012; Mezghani et al. 2019; Yue et al. 2019). Multi-model ensemble mean can effectively decrease those uncertainties of the CMIP5 model and improve the ability to simulate and predict hydrological conditions in the basin (Ahmed et al. 2019; Noor et al. 2019; Terada et al. 2020). The NEX-GDDP dataset (downscaled by the bias correction method) used in this paper has been well accepted (Abiodun et al. 2019; Singh et al. 2019; Thrasher et al. 2012). However, because flash drought was defined by a combination of multiple hydrological variables, even small errors in hydrological variables during the downscaling of the NEX-GDDP dataset will magnify errors in flash drought simulations (Zhang et al. 2018). And we need to further strengthen the research on the mechanism of flash droughts and establish a sound monitoring and early warning system for informing drought policy-making to reduce drought impacts in the Jinghe River basin.

Conclusions

Flash drought is a newly discovered agricultural natural disaster in recent years, which can cause serious damage to human society and economy. Therefore, we need to focus on flash droughts, especially on the basin scale. In this paper, the downscale CMIP5 and VIC model were used to predict the FOCs of flash droughts in the next 30 years. The paper focused on the temporal-spatial characteristics of HWFD and PDFD in Jinghe River basin.

1. VIC model and four-model ensemble mean can well simulate the hydrological condition of Jinghe River basin.
2. The FOCs of HWFD and PDFD showed a nonlinear increase in the next 30 years. Both of the HWFD and PDFD shown higher growth rates in the RCP8.5 scenario. And flash droughts mainly occurred in May–September. HWFD FOCs are projected to occur most in July and August, and PDFD FOCs are projected to occur most in June–August.
3. In the past, HWFD and PDFD mainly occurred in the north of the basin and the overall FOC of PDFD was higher than that of HWFD. In the future, there are massive increases in reference low-value areas corresponding to both types of flash droughts under three scenarios (RCP4.5, RCP8.5, and RCP8.5–RCP4.5), especially for HWFD.
4. Tmax contributes the most to HWFD and was the main driving factor. For PDFD, the contribution of ET and P was the biggest in the reference period, while the contribution of Tmax was the biggest in the RCP4.5 and RCP8.5 scenarios. This study suggests that early warning and countermeasures should be taken from both high temperature and precipitation.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Abiodun BJ, Mogebisa TO, Petja B, Abatan AA, Roland TR (2019) Potential impacts of specific global warming levels on extreme rainfall events over southern Africa in CORDEX and NEX-GDDP ensembles. Int J Climatol 40:3118–3141. https://doi.org/10.1002/joc.6386

Ahmed K, Sachindra DA, Shahid S, Demirel MC, Chung E-S (2019) Selection of multi-model ensemble of general circulation models for the simulation of precipitation and maximum and minimum temperature based on spatial assessment metrics. Hydrol Earth Syst Sci 23:4803–4824. https://doi.org/10.5194/hess-23-4803-2019

American Meteorological Society (1997) Meteorological Droughtpolicy statement. B Am Meteorol Soc 78:847–849

Basara JB, Christian JI, Wakefield RA, Otkin JA, Hunt EH, Brown DP (2019) The evolution, propagation, and spread of flash drought in the Central United States during 2012. Environ Res Lett 14:084025. https://doi.org/10.1088/1748-9326/ab2cc0

Bell JE, Palecki MA, Baker CB, Collins WG, Lawrimore JH, Leeper RD, Hall ME, Kochendorfer J, Meyers TP, Wilson T, Diamond HJ (2013) U.S. Climate Reference Network soil moisture and temperature observations. J Hydrometeorol 14(3):977–988. https://doi.org/10.1175/JHM-D-12-0146.1

Chen Y, Xiong G, Liu W (2016) Drought temporal and spatial distribution of Hanjiang River basin based on standardized precipitation index. China Rural Water Conservancy Hydropower 4:82–88 (Chinese)

Chen T, Feng Z, Zhao H, Wu K (2020) Identification of ecosystem service bundles and driving factors in Beijing and its surrounding areas. Sci Total Environ 711:134687. https://doi.org/10.1016/j.scitotenv.2019.134687

Ding S, Jia H (2001) Study on agricultural drought and its countermeasures. J Henan Univ (Social Science) 41:20–23. https://doi.org/10.15991/j.cnki.411028.2001.03.007 (Chinese)

Ford TW, McRoberts DB, Quiring SM, Hall RE (2015) On the utility of in situ soil moisture observations for flash drought early warning in Oklahoma, USA. Geophys Res Lett 42:9790–9798. https://doi.org/10.1002/2015GL066600

Fu P, Jin C (2012) A comparative study on the application of three drought indexes in the extreme drought in Yunnan from 2009 to 2010. People's Pearl River 033(002):4–6

Gao P, Liu S, Qi W, Qi H (2020) The nexus between poverty and the environment: a case study of Lijiang, China. Sustainability 12(3). https://doi.org/10.3390/su12031066

Gong D (1998) The reason of agriculture drought and its mitigation strategy in Inner Mongolia. Clim Environ Res 3:282–288 (Chinese)

Good P, Booth BB, Chadwick R, Hawkins E, Jonko A, Lowe JA (2016) Large differences in regional precipitation change between a first and second 2 K of global warming. Nat Commun 7:13667. https://doi.org/10.1038/ncomms13667

Gul F, Jan D, Ashfaq M (2019) Assessing the socio-economic impact of climate change on wheat production in Khyber Pakhtunkhwa, Pakistan. Environ Sci Pollut Res 26:6576–6585. https://doi.org/10.1007/s11356-018-04109-7

IPCC (2013) Climate change 2013: the physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge

Jin C, Luo X, Xiao X, Dong J, Li X, Yang J, Zhao D (2019) The 2012 flash drought threatened US Midwest agroecosystems. Chin Geogr Sci 29:768–783. https://doi.org/10.1007/s11769-019-1066-7

Liang X, Lettenmaier DP (1994) A simple hydrologically based model of land surface water and energy fluxes for general circulation models. J Geophys Res 99:14415–14428. https://doi.org/10.1029/94JD00483

Liu X, Zhu X, Pan Y, Li S, Liu Y (2015a) Agricultural drought monitor: progress, challenges and prospect. Acta Geograph Sin 70:1835–1848. https://doi.org/10.11821/dlxb201511012 (Chinese)

Liu S, Huang Q, Wang Y, Xie Y, Ren Y, Li J (2015b) Simulation and prediction of climatic elements in Jinghe River basin using downscaling method and CMIP5. Trans Chin Soc Agric Eng 31:138–144. https://doi.org/10.11975/j.issn.1002-6819.2015.23.018 (Chinese)

Liu S, Su S, Liang L, Tong X (2016) Analysis of drought characteristics and its driving factors based on vegetation condition index:a case study in Jiangsu Province. Resour Environ Yangtze Basin 25(12): 1927–1933. https://doi.org/10.11870/cjlyzyyhj201612017 (Chinese)

Liu Y, Zhu Y, Ren L, Yong B, Singh VP, Yuan F, Jiang S, Yang X (2019) On the mechanisms of two composite methods for construction of multivariate drought indices. Sci Total Environ 647:981–991. https://doi.org/10.1016/j.scitotenv.2018.07.273

Liu Y, Zhu Y, Zhang L, Ren L, Yuan F, Yang X, Jiang S (2020) Flash droughts characterization over China: from a perspective of the rapid intensification rate. Sci Total Environ 704:135373. https://doi.org/10.1016/j.scitotenv.2019.135373

Long X, Zhen L, Di S (2012) Quantitative risk assessment of agricultural drought in the Jinghe watershed of Western China. Resour Sci 34(11):2197–2205 (Chinese)

Lv X, Zhao J (2009) Study on the drought and causes in Ming Dynasty in Jinghe River Basin. J Arid Land Resour Environ 23:87–93. https://doi.org/10.13448/j.cnki.jalre.2009.12.006 (Chinese)

Ma M, Cui H, Wang W, Huang X, Tu X (2019) Projection of spatiotemporal patterns and possible changes of drought in the Yellow River basin, China. Theor Appl Climatol 138:1971–1989. https://doi.org/10.1007/s00704-019-02914-9

Mark S, Doug L, Mike H, Richard H, Karin G, Jim A, Brad R, Rich T, Mike P, David S (2002) The drought monitor. B Am Meteorol Soc 83:1181–1190. https://doi.org/10.1175/1520-0477-83.8.1181

Meinshausen M, Smith SJ, Calvin K, Daniel JS, Kainuma MLT, Lamarque JF, Matsumoto K, Montzka SA, Raper SCB, Riahi K, Thomson A, Velders GJM, van Vuuren DPP (2011) The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. Clim Chang 109:213–241. https://doi.org/10.1007/s10584-011-0156-z

Mezghani A, Dobler A, Benestad R, Haugen JE, Parding KM, Piniewski M, Kundzewicz ZW (2019) Subsampling impact on the climate change signal over Poland based on simulations from statistical and dynamical downscaling. J Appl Meteorol Climatol 58:1061–1078. https://doi.org/10.1175/jamc-d-18-0179.1

Mishra AK, Singh VP (2010) A review of drought concepts. J Hydrol 391:202–216. https://doi.org/10.1016/j.jhydrol.2010.07.012

Mo KC, Lettenmaier DP (2015) Heat wave flash droughts in decline. Geophys Res Lett 42:2823–2829. https://doi.org/10.1002/2015gl064018

Mo KC, Lettenmaier DP (2016) Precipitation deficit flash droughts over the United States. J Hydrometeorol 17:1169–1184. https://doi.org/10.1175/jhm-d-15-0158.1

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. T Asabe 50:885–900. https://doi.org/10.13031/2013.23153

Mozny M, Trnka M, Zalud Z, Hlavinka P, Nekovar J, Potop V, Virag M (2011) Use of a soil moisture network for drought monitoring in the Czech Republic. Theor Appl Climatol 107:99–111. https://doi.org/10.1007/s00704-011-0460-6

Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models, part 1: a discussion of principles. J Hydrol 10:282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Natural Resources Conservation Service (2005) National irrigation guide//National Engineering Handbook. Somerset

Noor M, Ismail T, Shahid S, Nashwan MS, Ullah S (2019) Development of multi-model ensemble for projection of extreme rainfall events in Peninsular Malaysia. Hydrol Res 50:1772–1788. https://doi.org/10.2166/nh.2019.097

Otkin JA, Anderson MC, Hain C, Svoboda M, Johnson D, Mueller R, Tadesse T, Wardlow B, Brown J (2016) Assessing the evolution of soil moisture and vegetation conditions during the 2012 United States flash drought. Agric For Meteorol 218-219:230–242. https://doi.org/10.1016/j.agrformet.2015.12.065

Palmer WC (1965) Meteorological droughts. U.S. Department of Commerce weather bureau research paper 45, 58 pp.

Ran D, Wu Y (2003) Discussion on controlling guideline and eco-environmental construction of soil and water conservation in Jinghe River Basin. Res Soil Water Conserv 10:58–59+100 (Chinese)

Schleussner C-F, Lissner TK, Fischer EM, Wohland J, Perrette M, Golly A, Rogelj J, Childers K, Schewe J, Frieler K, Mengel M, Hare W, Schaeffer M (2016) Differential climate impacts for policy-relevant limits to global warming: the case of 1.5 °C and 2 °C. Earth Sys Dyn 7:327–351. https://doi.org/10.5194/esd-7-327-2016

Shayeghi A, Azizian A, Brocca L (2019) Reliability of reanalysis and remotely sensed precipitation products for hydrological simulation over the Sefidrood River Basin, Iran. J Sci Hydrol 65:296–310. https://doi.org/10.1080/02626667.2019.1691217

Singh V, Jain SK, Singh PK (2019) Inter-comparisons and applicability of CMIP5 GCMs, RCMs and statistically downscaled NEX-GDDP based precipitation in India. Sci Total Environ 697:134–163. https://doi.org/10.1016/j.scitotenv.2019.134163

Sun F, Mejia A, Zeng P, Che Y (2019) Projecting meteorological, hydrological and agricultural droughts for the Yangtze River basin. Sci Total Environ 696:134076. https://doi.org/10.1016/j.scitotenv.2019.134076

Tang C, Li J, Zhou Z, Zeng L, Zhang C, Ran H (2019) How to optimize ecosystem services based on a Bayesian model: a case study of Jinghe River Basin. Sustainability-Basel 11:4149. https://doi.org/10.3390/su11154149

Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design. B Am Meteorol Soc 93:485–498. https://doi.org/10.1175/bams-d-11-00094.1

Terada M, Minobe S, Deutsch C (2020) Mechanisms of future changes in equatorial upwelling: CMIP5 intermodel analysis. J Clim 33:497–510. https://doi.org/10.1175/jcli-d-19-0128.1

Thrasher B, Maurer EP, McKellar C, Duffy PB (2012) Technical note: Bias correcting climate model simulated daily temperature extremes with quantile mapping. Hydrol Earth Syst Sci 16:3309–3314. https://doi.org/10.5194/hess-16-3309-2012

Ullah A, Ahmad I, Ahmad A, Khaliq T, Saeed U, Habib-ur-Rahman M, Hussain J, Ullah S, Hoogenboom G (2019) Assessing climate change impacts on pearl millet under arid and semi-arid environments using CSM-CERES-Millet model. Environ Sci Pollut Res Int 26:6745–6757. https://doi.org/10.1007/s11356-018-3925-7

Vicente-Serrano SM, Beguería S, López-Moreno JI, Angulo M, El Kenawy A (2010) A new global 0.5° gridded dataset (1901–2006) of a multiscalar drought index: comparison with current drought index datasets based on the Palmer Drought Severity Index. J Hydrometeorol 11:1033–1043. https://doi.org/10.1175/2010jhm1224.1

Wang J, Xu C (2017) Geodetector: principle and prospective. Acta Geograph Sin 72:116–134. https://doi.org/10.11821/dlxb201701010 (Chinese)

Wang L, Yuan X, Xie Z, Wu P, Li Y (2016a) Increasing flash droughts over China during the recent global warming hiatus. Sci Rep 6:30571. https://doi.org/10.1038/srep30571

Wang S, Wang Y, Lin X, Zhang H (2016b) Spatial differentiation patterns and influencing mechanism of housing prices in China: based on data of 2872 counties. Acta Geograph Sin 71(8):1329–1342. https://doi.org/10.11821/dlxb201608004 (Chinese)

Wen S (2017) Research of the impact of land use change on runoff in the Jing River Basin based on VIC-3L model. Dissertation, North China University of Water Resources and Electric Power. (Chinese)

Yuan W, Zhou G (2014) Theoratical study and research prospect on drought indices. Adv Earth Sci 06:107–116 (Chinese)

Yue TX, Zhao N, Fan ZM, Li J, Chen CF, Lu YM, Wang CL, Gao J, Xu B, Jiao YM, Wilson JP (2019) Methods for simulating climate scenarios with improved spatiotemporal specificity and less uncertainty. Glob Planet Chang 181:102973. https://doi.org/10.1016/j.gloplacha.2019.05.013

Zhang X (2009) Analysis and evaluation of soil moisture characteristics in China. Dissertation, China University Of Geosciences. (Chinese)

Zhang HB, Gu L, Xin C, Yu Q (2016) Investigation on the spatial-temporal variation of drought characteristics in Jinghe River Basin. Journal of North China University of Water Resources and Electric Power (Natural Science Edition) 37(03):1–10 (Chinese)

Zhang Y, You Q, Chen C, Li X (2017) Flash droughts in a typical humid and subtropical basin: a case study in the Gan River Basin, China. J Hydrol 551:162–176. https://doi.org/10.1016/j.jhydrol.2017.05.044

Zhang Y, You Q, Mao G, Chen C, Ye Z (2018) Short-term concurrent drought and heatwave frequency with 1.5 and 2.0 °C global warming in humid subtropical basins: a case study in the Gan River Basin, China. Clim Dyn 52:4621–4641. https://doi.org/10.1007/s00382-018-4398-6