Changes of extreme climate events and related risk exposures in Huang-Huai-Hai river basin under 1.5–2°C global warming targets based on high resolution combined dynamical and statistical downscaling dataset

Jia Wu  |  Zhenyu Han  |  Rouke Li  |  Ying Xu  |  Ying Shi

National Climate Center, China
Meteorological Administration, Beijing, China

Correspondence
Zhenyu Han, National Climate Center, China Meteorological Administration, Beijing 100081, China.
Email: hanzy@cma.gov.cn

Funding information
National Key Research and Development Program of China, Grant/Award Number: 2018YFB1502803, 2018YFA0606301, 2017YFA0605004; National Natural Science Foundation of China, Grant/Award Number: 41805074; GEIGC Science and Technology Project, Grant/Award Number: 101662227

Abstract
Extreme climate events and related risk exposures in Huang-Huai-Hai (HHH) river basin were projected under global warming of 1.5–2°C using the high-resolution combined dynamical and statistical downscaling dataset. Firstly, evaluation indicated that the dataset can well reproduce the spatial distribution of all temperature extremes and most of the precipitation extremes, providing a reliable ability for future projections. Then, projections showed that the hot events were projected to increase, while the cold events were projected to decrease substantially in the whole HHH river basin for 1.5°C and 2°C global warming. The additional 0.5°C of warming roughly accelerated the increase of extreme temperatures by 0.6°C, and increased the number of heat days by 2.7 days. In addition, the rainfall events and the precipitation intensity were projected to increase while the drought events were projected to decrease, with the slight changes due to the additional 0.5°C warming. The gross domestic product (GDP) exposures to heat events and heavy rainfall increased more than nine fold for 1.5°C and 2°C global warming, while the growing population (POP) exposures to that increased by more than 100% and 20%, respectively. For the increased exposures to heat events, the changes in GDP (POP) were as important as changes in interaction effect between climate and GDP (POP), while the exposures to heavy rainfall events was mainly dominated by GDP (POP). In addition, the enhanced interaction effect was the most important factor to the increase of exposures due to additional 0.5°C warming. Notably, the largest increases of heat events and heavy rainfall events were projected in Huaihe river basin due to the additional 0.5°C warming, accompanied by greatest increase of exposures, implying larger risk in the future.

Keywords
1.5–2°C warming, exposure, extreme events, Huang-Huai-Hai
INTRODUCTION

The global mean surface temperature has increased 0.85°C (0.65°C to 1.06°C) over the period 1880–2012 (compared to the pre-industrial period). Furthermore, it will likely increase by 0.3–0.7°C in the near future (IPCC, 2013). As the planet gets warmer, the significantly increased trend of climate extreme events has been observed around the world (WMO, 2010; IPCC, 2013; Piras et al., 2016; Aslam et al., 2017), characterized by a decrease in the numbers of cold days and nights, an increase in the numbers of warm days and nights, while an increase in the frequency of heat waves and extreme precipitation events (Alexander et al., 2006; Min et al., 2011; Coumou and Rahmstorf, 2012; IPCC, 2013). In addition, the change of extreme events will likely result in related risks to natural and human ecosystems (IPCC, 2014). To avoid the severe risks, the Paris Climate Agreement aims to maintain global mean surface warming below 2.0°C above preindustrial and proposes to pursue efforts to limit the temperature increase to 1.5°C (UNFCCC, 2015).

With regard to China, similar changes in extreme climate events have been observed, for example, the hot events and the heavy rainfall events have increased (Zhai and Pan, 2003; Zhai et al., 2005; Wang, Zhang, et al., 2012; Wang, Sun, et al., 2012; Sun et al., 2014; Chen and Zhai, 2017; Wu et al., 2017), which have already severely affected on the society, the economy and the natural ecosystems of China, bringing associated disastrous droughts and floods (Zhai et al., 2005; Chen et al., 2012; Wang, Zhang, et al., 2012; Wang, Sun, et al., 2012; Lang and Sui, 2013; Sun and Ao, 2013; Wu et al., 2013; Cheng et al., 2014; Chen and Sun, 2015; Liu et al., 2015; Liu et al., 2017; Ye et al., 2018). In particularly, as the one of most vulnerable area of China, the Huang-Huai-Hai (HHH) river basin (including the Yellow River basin, Huaihe River basin and Haihe River basin) is deeply sensitive to climate change (Zhang and Wang, 2007), and the flood caused by extreme precipitation events occurred intensively in recent years (Pei et al., 2004; She et al., 2011; He and He, 2014; Jin et al., 2018), which poses serious challenges to local decision makers.

As we known, the changing nature of physical hazards and the exposure and vulnerability of society to hazards are two factors which influence on risk associated with climate change (IPCC, 2012). At present, most risk researches on the HHH river basin mentioned above focused on the changes in spatial distribution, intensity and frequency of the physical hazards, however with less attention to the potential economy and population change. Nevertheless, the increase of the population and economic assets exposed to extreme events is one of main factors for the growing economic losses (Schumacher and Strobl, 2011; Zhan et al., 2019). As the economic and social development in the future, the growing population (POP) and gross domestic product (GDP) will face greater climate risks. So understanding how continuing increases in global mean temperature will exacerbate GDP and POP exposures to extreme climate events is an importance question, which is helpful to provide research results and risk management strategies for local policy makers. However, the attempts to quantify potential changes in exposure and vulnerability to extreme events are still less, as the IPCC fifth Assessment Report indicated (Smith et al., 2014). Furthermore, limited attention focused on the relative contributions to the change of exposures, especially in the small river basin scale (Chen et al., 2019). For the HHH river basin of China, the hazards were projected to increase due to the global warming (Xu et al., 2011; Gu et al., 2014; Yin et al., 2016; Wu et al., 2020). However, to date, the assessment on the GDP and POP exposure change in response to the additional 0.5°C warming in HHH river basin has receive less attention.

Additionally, at present, there are many studies regarding the climate change over major rivers in China (Li et al., 2008; Zhang et al., 2009; Bao et al., 2012; Liu et al., 2012; Wang, Zhang, et al., 2012; Wang, Sun, et al., 2012; Liu et al., 2013; Chen and Sun, 2015; Liu et al., 2015; Liu et al., 2017; Ye et al., 2018). In particularly, as the one of most vulnerable area of China, the Huang-Huai-Hai (HHH) river basin of China, the hazard over most of HHH river basin will increase considerably in the future, which will result in larger flood risk. However, GCMs still show major deficiencies when it comes to small scale. Therefore, in order to generate more reliable climate change signals at a local or regional scale, it is necessary to apply downscaling techniques (Giorgi et al., 2009), especially for quantitative impact assessment and risk analysis, such as water resources and associated risk and disasters (IPCC, 2015).

The dynamical downscaling by using a regional climate model (RCM) and the statistical downscaling (SD) are two common approaches to acquire high resolution datasets. Many previous studies have reported that the RCMs provide more reliable information due to their finer resolution (Gao et al., 2008, 2012; Giorgi et al., 2009; Yu et al., 2010, 2015; Zou and Zhou, 2013; Ji and Kang, 2015; Niu et al., 2015; Shi et al., 2018), especially in small river basin, which shows a better description over areas with complex terrains (Wu et al., 2020). Recently, the available resolutions of 25–50 km in China are still coarser for impact assessments over river basin scale. However, high resolutions (greater than 10 km) and multi-GCMs driven dynamical downscaling are very costly. In order to reduce the computational costs, as did...
by Han et al. (2019), the RCM and SD methods are combined in order to obtain a 6.25 km resolution and multi-member downscaling dataset for future climate over HHH river basin. Several previous studies have been conducted based on the similar approach (Wang et al., 2015; Kim et al., 2016; Zhou et al., 2018; Han et al., 2019), but has not been applied and evaluated in the HHH river basin. So in this paper, based on ensemble of high resolution combined dynamical and statistical downscaling datasets, we aim to address the question as follows: How the extreme events change in HHH river basin? With the increasing hazards in the future, how their potential impacts on the exposures over HHH river basin? And how will the GDP and POP exposure to extreme events differ in 1.5°C warming target compared with a 2°C target? Which factor is the most important driver for the changes in exposure? The remainder of the paper is organized as follows. Section 2 introduces the data and methods used. Then, the result is presented in Section 3, including the evaluation of the downscaled dataset (Section 3.1), future changes in extreme climate events (Section 3.2) and related risk exposures (Section 3.3). Finally, discussion and the key conclusions are summarized in Section 4.

2 | DATA AND METHODS

2.1 | Study area

HHH river basin (32°10′–43°N and 95°53′–122°60′) is presented in Figure 1, which consists of three first-class water resources regionalization (the Yellow river basin, Huaihe river basin and Haihe river basin) and covers the entire or parts of Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, Hebei, Shandong, Anhui, Jiangsu, Beijing and Tianjin, accounting for 15.0% of total area of China (Shen et al., 2002) and 20.4% farmland (Liu et al., 2010). As providing 23.6% of the nation’s grain yield, it plays a crucial role in Chinese agriculture production (Liu et al., 2010; She et al., 2011). In addition, the elevation drops dramatically from west to the east, varying from above 3,000 m to below 100 m, so the diverse climate conditions exist.

2.2 | Downscaling methods

Five sets of RCM dynamical downscaling simulation with a horizontal of 25 km were obtained by using the RegCM4.4 (http://gforge.ictp.it/gf/project/regcm). The model was driven by five GCMs from CMIP5, including CSIRO-Mk3.6.0, EC-EARTH, HadGEM2-ES, MPI-ESM-MR, and NorESM1-M. The simulating period is from 1979 to 2099, in which the period 1979–2005 represents historical simulation, while the period 2006–2099 is for RCP4.5 (the medium–low radiative forcing scenario with radiative forcing peaking at 4.5 Wm⁻² by 2,100, Taylor et al., 2012) simulation. Following the international Coordinated Regional Climate Downscaling Experiment (CORDEX)-East Asia phase II (Giorgi et al., 2009), the domain for the downscaling simulations encompassed the whole continental China and the adjacent areas. The detailed information of parameterization schemes, evaluation and applied studies, have been reported (Han et al., 2017; Zhang et al., 2017; Gao et al., 2018; Shi et al., 2018; Wu et al., 2020; Wu and Gao, 2020).

To validate the high-resolution combined dynamical and statistical downscaling dataset, 770 national stations over HHH river basin from 2,400 station of China were chosen, with the time period from 1986 to 2005. The downscaled variables were interpolated using the nearest grid to the locations of the 770 stations to facilitate the comparison. Note that, the global warming of 1.5 and 2°C are defined as the global mean surface temperature.
of 1.5°C and 2°C higher than pre-industrial levels, respectively, while future projections under 1.5–2°C global warming targets are relative to the present period (1986–2005) (IPCC, 2013, 2018). The statistical significance was conducted by using Student’s t test.

### 2.3 Warming targets and extreme indices

Following the previous studies (Huang et al., 2017; Li et al., 2018; Wu et al., 2020), the 1.5°C and 2°C of warming used in the models was defined as the 11 year smoothed global mean surface air temperature derived from the above five driven GCMs, which increased by 1.5°C and 2°C relative to the pre-industrial period (1861–1900), respectively. The timings of the GCMs would increase by 1.5°C and 2°C are presented in Table 1. For future projection analysis, the ensemble mean of the above timings was calculated using the equal-weighted average method (Han et al., 2019; Wu et al., 2020).

Four extreme temperature and four precipitation indices were employed in this study, which based on the definitions of the Expert Team on Climate Change Detection and Indices (ETCCDI; Sillmann et al., 2013). The temperature-related indices used included the annual maximum value of maximum temperature (TXx), the annual minimum value of minimum temperature (TXn), the number of heat days (maximum temperature ≥ 35°C, HD) and frost days (minimum temperature <0°C, FD), while the precipitation-related indices included the number of precipitation days (R1mm), the number days of heavy precipitation (precipitation ≥20 mm, R20mm), annual maximum number of consecutive days (precipitation <1 mm, CDD) and simple precipitation intensity index (SDII). Notably, the HD is not included in ETCCDI, but has been widely used in China, as well as the other indices (Gao et al., 2017; Hui et al., 2018; Li et al., 2018; Shi et al., 2018; Li et al., 2020; Wu et al., 2020), which provide a direct analysis of climate extreme.

#### Table 1 The timing difference of GCMs to reach 1.5 and 2°C

| Model name   | 1.5°C | 2°C   |
|--------------|-------|-------|
| CSIRO-Mk3.6.0 | 2030–2040 | 2045–2055 |
| EC-EARTH     | 2015–2025 | 2035–2045 |
| HadGEM2-ES   | 2025–2035 | 2038–2048 |
| MPI-ESM-MR   | 2019–2029 | 2040–2050 |
| NorESM1-M    | 2034–2044 | 2066–2076 |
| ENS          | 2026–2036 | 2044–2054 |

### 2.4 GDP and POP exposure

According to the corresponding relationship between the Representative Concentration Pathways (RCPs) and the Shared Socioeconomic Pathways (SSPs; O’Neill et al., 2014; van Vuuren et al., 2014), the projected population density and GDP under the moderate development scenario (SSP2) was selected to analyse the characteristics of POP and GDP exposure to extreme events over HHH river basin. The future projected POP data comes from the Inter-Sectoral Impact Model Inter-comparison Project (ISIMIP, https://www.isimip.org/gettingstarted/details/62/), with spatial resolution of 1/24° × 1/24° and temporal resolution of 1 year (Jones and O’Neill, 2016). The future projected GDP data originates from the Institute of climate impact in Potsdam (PIK, http://dataservices.gfz-potsdam.de/pik/showshort.php?id=escidoc:2740907), with the spatial resolution of 1/12° × 1/12° and temporal resolution of 10 years (Geiger et al., 2017). These data can better consider the impact of urban expansion/contraction and the interaction between cities on the spatial distribution of future GDP and POP, which are downscaled from the national socioeconomic projection outputs provided by IPCC (Jones and O’Neill, 2016; Murakami and Yamagata, 2019). In order to facilitate the calculation, the linear interpolation method was used to interpolate the GDP and POP data onto the spatial resolution of 6.25 km × 6.25 km and the time resolution of 1 year.

For heat and flood hazard, the normalization was conducted for the HD and R20mm, respectively. Hence, the GDP (POP) exposure to HD and R20mm is defined as the corresponding GDP (POP) on the grid point multiplied by the normalized hazards (Jones et al., 2015). To be specific, for each grid point, GDP and POP exposure are respectively calculated by multiplying the GDP and POP in each grid box by the normalized annual number of HD and R20mm for the corresponding grid box. As did in the previous study (Sun et al., 2017; Chen et al., 2019; Zhan et al., 2019), the units of ‘Billion yuan’ and ‘Thousand person’ are used to measure the exposure of hazards on GDP and POP, respectively. Exposure refers to the range or quantity of the disaster bearing body that is adversely affected by the hazard factors. The larger value indicates the greater exposure, which might exacerbate risk (IPCC, 2012).

To access the contribution of the factors to the change of exposures and evaluate the uncertainty of five simulations, we use the approach similar to the ‘factor separation method’, which is widely used in the analysis of numerical model simulations, allowing the isolation of the contribution of a factor from the others (Stein and Alpert, 1993; Jiang, 2008; Torma and Giogi, 2014, Jones et al., 2015; Wu et al., 2017; Li et al., 2020). As an example
of the method, in order to obtain the contribution of HD to GDP exposure changes, firstly, we isolated the impact of HD on GDP exposure by holding GDP constant at present level but allowing HD to change according to different simulation projection. Then we recalculated the exposure. Note that, in this paper we considered the contribution of GDP (POP), the extreme climate, and their interaction effect (the change in exposure caused by concurrent changes in GDP (POP) and extreme climate; Jones et al., 2015; Li et al., 2020).

3 | RESULTS

3.1 | Evaluation of the downscaled dataset

Taylor diagrams (Figure 2) were used to conduct a concise statistical analysis of the ability of the downscaled dataset to represent the observed spatial distribution of the extreme indices in terms of the spatial correlation coefficient (COR), the root-mean-square error (RMSE), and ratio of variances over HHH river basin (Taylor, 2001). As can be seen from the Figure 2a, all of the ensemble means of downscaled data showed a good performance in reproducing TXx, TNn, HD and FD. All of the CORs were greater than 0.95 and the ratios of the variances of the simulations to the observations mainly around 1, which indicated the reasonable performance of the downscaled dataset in reproducing temperature extremes. In addition, the precipitation-related indices (Figure 2b) also showed high CORs (greater than 0.95) except for that of CDD (0.58), while the ratios compared to the observations were also mainly around 1, except for CDD (1.5). The relatively lower COR and larger RMSE in CDD was partly caused by the uncertainty of observation, which showed a big difference between station data and CLDAS (Han et al., 2019).

To further evaluate the downscaled dataset, the biases were presented in Figures 3 and 4. As can be seen from the Figure 3a,b, the spatial distribution of biases for the TXx and TNn were well represented by downscaled dataset, with biases of ±1°C in most stations over HHH river basin. The biases for HD (Figure 3c) were ranging from −5 d to 5 d, thus indicating that HD was also well reproduced by downscaled dataset. The FD (Figure 3d) presented bigger biases of ±10 d, and with more stations showing significant bias (cross markers). For precipitation extremes (Figure 4), the bias of ±10% can be seen in most stations in R1mm, while the underestimation of −50% to −10% are dominated in R20mm and SDII, and the overestimation greater than 50% can be found in CDD, especially around Yellow river basin. Compared to the temperature-related indices, more stations with significant biases can be seen in the precipitation-related indices due to the uncertainty of the observation (e.g., lack of observation stations over mountainous areas and river valleys and the discrepancy between station data and CLDAS), and the biases inherited from RCM dynamical downscaling data as well (Wu and Gao, 2013; Han et al., 2019; Wu et al., 2020). Overall, compared with the biases in RCM

FIGURE 2 | Multivariable Taylor diagrams of the (a) temperature extremes and (b) precipitation extremes in China during 1986–2005. Each shape represents an individual index.
(Wu et al., 2020), the biases in combined dynamical and statistical downscaled dataset were largely reduced (figures not shown).

### 3.2 Changes in extreme climate events

Figure 5 shows the spatial distribution of changes in the temperature extremes over HHH river basin due to 1.5°C and 2°C of warming based on the RCP4.5 scenario. Substantial warming can be seen in TXx (Figure 5a,b) throughout HHH river basin in the 1.5°C and 2°C warmer climates, with the larger increase occurring for 2°C of warming. An regional average increase of 1.10°C and 1.78°C existed in the whole HHH river basin due to 1.5°C and 2°C of warming, respectively. These changes were significant at the 90% confidence level. Difference between 2°C and 1.5°C (Figure 5c) showed a significant warmer over most of HHH region, except for small areas over northern Huang and Haihe river basin.

In addition, Table 2 presents the changes in the four extreme temperature indices averaged over Yellow, Huaihe, Haihe and HHH river basin due to 1.5–2°C of global warming in order to compare the differences among different river basins and understand the changes more intuitively. As can be seen from Table 2, TXx was projected to increase over the three river basins, and the greater warming occurred for 2°C global target. Notably, compared to the other river basins, the increase (0.98°C) was lowest in Huai river basin for 1.5°C global warming.
however it accelerated greatly to 2.0°C for 2°C global warming, which tended to the areas with largest increase among the three river basins. The difference was 1.02°C between 2°C and 1.5°C in Huaihe river basin, while the lower values were 0.57°C and 0.47°C in Yellow and Haihe river basin, respectively, indicating the higher

**TABLE 2** The changes in the extreme temperature indices averaged over yellow, Huaihe, Haihe and HHH river basin due to 1.5°C/2°C/the difference between 2°C and 1.5°C of global warming

|        | TXx (°C)       | TNN (°C)      | HD (d)        | FD (d)         |
|--------|----------------|---------------|---------------|----------------|
| Yellow | 1.14/1.71/0.57 | 1.45/2.03/0.58| 1.9/3.0/1.1   | -6.7/-11.8/-5.1|
| Huaihe | 0.98/2.00/1.02 | 1.27/2.00/0.73| 6.8/11.7/4.9  | -7.4/-11.8/-4.4|
| Haihe  | 1.16/1.63/0.47 | 1.43/2.03/0.61| 4.2/6.4/2.2   | -5.5/-9.5/-4.0 |
| HHH    | 1.10/1.78/0.69 | 1.39/2.02/0.63| 4.3/7.0/2.7   | -6.5/-11.0/-4.5|

**FIGURE 5** Projected changes (relative to 1986–2005) for 1.5°C and 2°C of global warming and the difference between 2°C and 1.5°C in (a–c) TXx (°C), (d–f) TNN (°C), (g–i) SU (d), and (j–l) FD (d) across HHH river basin. The results are based on the RCP4.5 scenario. The oblique areas represent changes that are significant at the 90% confidence level based on the Student's t test.
sensitivity of temperature extremes response to the increased warming in Huai river basin.

For 1.5°C and 2°C of global warming, TNn was projected to increase significantly (significant at the 90% confidence level, Figure 5d,e), with the greater magnitude of the increase (the regional average increases of 1.39°C and 2.02°C over HHH river basin, respectively) than that of TXx (Figure 5a,b). For 1.5°C of global warming, the lower increase in TNn occurred in the Huaihe river basin, which is consistent with the results of TXx. In addition, the relatively larger difference between 2°C and 1.5°C also can be found in Huaihe river basin, with the value of 0.73°C, while the lower values were 0.58°C and 0.61°C in Yellow and Haihe river basin, respectively.

HD was also projected to increase significantly (significant at the 90% confidence level) under 1.5°C and 2°C of global warming (Figures 5g and h), with the exception of a slight change in some areas of western Yellow river basin, which is consistent with the previous study conducted by RCMs (Wu et al., 2020). Thus, as can be seen from the results presented in Table 2, the regional average increase for 1.5°C global warming in HD was the lowest in the Yellow river basin, with the increase of 1.9 d, while the largest change occurred in the Huaihe river basin.

**FIGURE 6** Same as in Figure 5 but for percentage changes (units: %) in (a–c) R1mm, (d–f) RX5day, (g–i) SDII, and (j–l) CDD. The oblique areas represent changes that are significant at the 90% confidence level based on the Student’s t test.
basin, with increase of 6.8 d. As the warming increased to 2°C, the largest increase in HD also existed in Huaihe river basin, with the greatest difference of 4.9 d between 2°C and 1.5°C, which similar to the TXx and TNn.

For 1.5–2°C of global warming, FD was projected to decrease significantly (significant at the 90% confidence level) in most parts of HHH river, except for a slight change over northern Yellow river basin (Figure 5j,k). For 1.5°C global warming, the maximum decrease in FD occurred over western Yellow river basin, while the largest regional average decrease occurred in the Huaihe river basin, with decrease value of 7.4 d. The decreases over the three river basins increased for 2°C of global warming, with the values of −11.8 d, −11.8 d, and −9.5 d, respectively. It should be noted that, in the Yellow river basin, a larger difference occurred (Figure 5l), which is not consistent with the larger differences in other temperature indices over Huaihe river basin.

The spatial distribution of the changes in precipitation extremes for 1.5°C and 2°C global warming over HHH river basin are presented in Figure 6. An increase in R1mm occurred in most part of HHH river basin for 1.5°C of global warming (Figure 6a,b), with values less than 6%, which exhibited the slight amount of change. A decrease of less than 6% also can be found in some portions, especially in Huang and Haihe river basin at 1.5°C global warming target. The increases were projected to increase slightly as the global warming was increased to 2°C. And a small area with significant increase (significant at the 90% confidence level) only occurred in northwestern Yellow river basin for 2°C of global warming, which also showed greatest difference between 2°C and 1.5°C (Figure 6c).

Similar to the temperature extremes, the Table 3 shows the changes in the four extreme precipitation indices averaged over Yellow, Huaihe, Haihe and HHH river basin for 1.5°C and 2°C of global warming. As can be seen from Table 3, R1mm was projected to increase over all of the three river basins, with the greatest increase occurring in the Yellow river basin (increases by 1.1% and 3.0% for 1.5°C and 2°C of global warming, respectively), which also showed a greater difference (1.9%) between 2°C and 1.5°C.

Figures 6d,e shows that although R20mm was generally projected to increase over the whole HHH river basin under 1.5°C and 2°C of global warming targets, few places experienced statistically significant increases at the 90% confidence level. Additionally, the maximum increase occurred in different place for different warming target. Notably, the increases (2.2% and 4.5%) in R20mm was lowest in Huaihe river basin for both 1.5°C and 2°C, but with the greatest difference and an increase (2.3%) between 2°C and 1.5°C, while a decrease can be found in Yellow and Haihe river basin, as well as the whole HHH river basin due to the additional 0.5°C (Table 3).

Similar to R20mm, the changes in SDII (Figure 8g,h) were projected to increase in most parts of HHH river basin under 1.5°C and 2°C of global warming, meanwhile with the lowest increase in Huaihe river basin and more areas significant at the 90% confidence level. The greater increase occurred in Yellow and Haihe river basin for 1.5°C global warming, however the increase was projected to decrease as the warming target increase. As can be seen from Table 3, although all of the three river basins were projected to experience an increase for both warming targets, the slight decrease occurred in Yellow and Haihe river basin, with regional average differences of −0.6% and −0.2% between 2°C and 1.5°C, respectively.

CDD (Figure 6j,k) was projected to decrease in most part of HHH river basin for 1.5–2°C of global warming. However, few changes were significant at the 90% confidence level. The increase increased in Yellow and Haihe river basin as the degree of global warming was increased, while decreased in Huaihe river basin. As can be seen from Table 3, the maximum decrease (−2.3%) in CDD was found in Huaihe river basin for 1.5°C of global warming, however it shifted to Haihe river basin (−3.1%) for 2°C of global warming due to the increase occurred in southern Huaihe river basin (Figure 6k). The biggest difference between 2°C and 1.5°C existed in Huaihe river basin, with the increase value of 2.6% in CDD.

The above analysis indicated that the increases in SDII were mainly affected by the increases in R20mm, while the changes in CDD were related to the changes in R1mm, which is consistent with previous studies (Chen et al., 2015; Li et al., 2017; Wu et al., 2020). Note that, the changes in precipitation extremes are not significant at 90% confidence level over most areas of HHH river basin, due to the large inter-annual changes of precipitation extremes in this region. In addition, the largest increase

| Table 3 | Same as in Table 2 but for extreme precipitation indices |
|---------|----------------------------------------------------------|
|         | R1mm (%)     | R20mm (%)     | SDII (%)     | CDD (%)     |
| Yellow  | 1.1/3.0/1.9  | 17.5/15.7/−1.8| 4.6/4.0/−0.6| −1.7/−2.6/−0.9|
| Huaihe  | 1.0/1.6/0.6  | 2.2/4.5/2.3   | 1.7/3.6/1.9 | −2.8/−0.3/2.6|
| Haihe   | 0.2/1.4/1.2  | 12.6/10.6/−2.0| 4.7/4.5/−0.2| −2.3/−3.1/−0.8|
| HHH     | 0.8/2.0/1.2  | 10.8/10.3/−0.5| 3.7/4.0/0.3 | −2.3/−2.0/−0.3|
in heat events and heavy rainfall were projected in Huaihe river basin due to the additional 0.5°C of warming.

3.3 | Change in GDP and POP exposure

Figure 7 includes the spatial distribution of changes for GDP and POP over HHH river basin due to 1.5°C and 2°C of warming based on the SSP2 scenario. Compared to present period (Figure 7a), substantial growth of GDP (Figure 7c,e) can be seen throughout HHH river basin under the 1.5°C and 2°C warmer targets, with the greater growth occurring for 2°C of warming (Figure 7g). An regional average increase of 0.5, 3.3 and 5.1 billion yuan existed in the whole HHH river basin due to present period, 1.5°C and 2°C of warming, respectively. In addition, Figure 7g indicated that the increase (1.9 billion yuan) between 2 and 1.5°C occurred in most part of HHH region, especially for Yellow and Haihe river basin. Compared to present period (Figure 7b), the total population for SSP2 was projected to grow in the 1.5°C and 2°C warmer targets (Figure 7d,f), with the regional average growth of 1.0 thousand person and 0.6 thousand person, respectively. The greater POP density was evident in Huaihe and Haihe river basin. Notably, the growth showed a decrease of −0.4 thousand person between 2°C and 1.5°C of warming (Figure 7h) due to the decrease of population after the peak period around 2030s under the SSP2 (Figure 8d).

To better understand the changes of the hazards (HD and R20mm) and corresponding GDP and POP over three river basin, the temporal evolution of above variables are presented in Figure 8. As shown in the figure, the projected growth of HD (Figure 8a) over three river basins among different simulations were almost linear before 2070s and then tended to stabilize following RCP4.5 pathway. Similar to HD, the increases in R20mm (Figure 8b) were also evident before the mid-21st century over three river basins, and then tended to stabilize with larger inter-annual variability compared to HD. The GDP

FIGURE 7 Present period (1986–2005) and projected changes (relative to 1986–2005) for 1.5°C and 2°C of global warming and the difference between 2°C and 1.5°C in (a,c,e,g) GDP (unit: billion yuan), (b, d,f,h) POP (unit: thousand person) across HHHH river basin
(Figure 8c) also showed similar trends as HD, with the linear increase occurred before 2070s and then stabilized in the end of this century. For POP (Figure 8d), the growth can be found before 2030s and then a decline occurred. Due to the declining birth rates, both the world and China’s population were projected to reach a peak and then start to decline under the SSP2 scenario of assuming to maintain the current level of fertility (KC and Lutz, 2017; Huang et al., 2019). It is noted that the greater growth of HD, GDP (Figure 8c) and POP (Figure 8d) in Huaihe river compared to the other river basins can be observed throughout 21st century, while the lowest growth of these variables can be found over Yellow river basin.

Figure 9 shows the spatial patterns of annual GDP and POP exposures to HD during present period (1986–2005) and projected changes for 1.5°C and 2°C of global warming. As can be seen from the Figure 9a and Figure 9b, the GDP and POP exposures for present period in most areas of HHH river basin were roughly less than 0.2 billion yuan and 2.0 thousand person, respectively, with the maximum exposures in excess of 0.2 billion yuan and 2.0 thousand person existing in eastern Huaihe river basin, respectively. The regional average GDP and POP exposures to HD (Figure 5g,h). Moreover, the additional 0.5°C of warming from 1.5°C to 2°C led to enhanced GDP and POP exposures, with the regional average increases of 0.6 billion yuan and 0.3 thousand person, respectively (Figure 9g,h). Notably, although the whole HHH river basin exhibited population decline for the additional 0.5°C warming (Figure 7h), a dominant increase in POP exposure still can be found (Figure 9h).

The spatial patterns of annual GDP and POP exposures to R20mm during present period and projected changes for 1.5°C and 2°C of global warming are presented in Figure 10. Similar to exposures to HD, the largest exposures to R20mm occurred over Huaihe river basin, with the maximum values in excess of 0.2 billion yuan and 3.0 thousand person, respectively. For 1.5–2°C of global warming, the GDP and POP exposures to R20mm were projected to increase remarkably, both with the greater magnitude occurred in Huaihe river basin. In addition, the increases of GDP exposure to R20mm were projected to increase due to the additional 0.5°C warming from 1.5°C to 2°C, with the increase of 0.5 billion yuan (Figure 10g). In contrast, the additional 0.5°C resulted in a slight change in POP exposure mainly due to the slight change of R20mm (Figures 6f and 8b) and POP (Figures 7h and 8d).

To understand the changes and the simulation uncertainties in exposures more intuitively, Figure 11 presents the changes in the exposures averaged over HHH and its three main river basins, as well as the uncertainty range of the five simulation, due to 1.5°C and 2°C of global warming. Compared to present period, the exposures to HD and R20mm were projected to increase over all of three river basins. For GDP and POP exposures to HD (Figure 11a,b), the greater increase occurred for 2°C of global warming. In addition, the
increase was highest in Huaihe river basin with the regional averaged GDP (POP) exposures of 1.5 billion yuan (2.5 thousand person) and 2.6 billion yuan (3.0 thousand person) for 1.5°C and 2°C global warming, respectively, however a smaller increase occurred in Yellow river basin, which is corresponding with a larger uncertainty in the changes in Huaihe river basin and less uncertainty in Yellow river basin. The GDP exposure to heat events increased more than nine fold compared to present period, while the POP exposure to heat events tended to double.

The GDP and POP exposures to R20mm (Figure 11c, d) were also projected to increase for 1.5°C and 2°C global warming. Similar to exposures to HD, the largest increase also existed in Huaihe river basin, with the regional averaged GDP (POP) exposures reaching 2.0 billion yuan (3.5 thousand person) and 3.0 billion yuan (3.5 thousand person) for 1.5°C and 2°C global warming, respectively. The lowest increases also occurred in Yellow river basin, corresponding with a larger uncertainty in the changes in Huaihe river basin and less uncertainty in Yellow river basin. Compared to present period, the GDP exposure to heavy rainfall increased more than 10 fold for 1.5°C and 2°C global warming, while the POP exposure to heavy rainfall increased roughly by 20%.

Regional mean of the relative contributions (ratios) to the change of exposures to HD from the different variables are presented in Table 4. As can be seen from the table, for 1.5°C global warming, the contribution of climate change to the increased GDP or POP exposure to HD was minor in all of three river basins, while the change in GDP and POP contributed by approximately 60% to the increase of that, however the contribution of interaction effect was roughly 30%. The contributions of GDP and POP were projected to decrease over all river basins over HHH due to the additional 0.5°C of warming
FIGURE 10  Same as in Figure 9 but for GDP and POP exposures to R20mm

FIGURE 11  Present period (1986–2005) and projected changes (relative to 1986–2005) in GDP and POP exposures to (a,b) HD and (c,d) R20mm over HHH and its three river basins under 1.5°C and 2°C warming targets. The black bars indicate the uncertainty ranges of the five simulations.
The regional mean relative contributions (ratios, %) to the change of exposures to HD over yellow, Huaihe, Haihe and HHH river basin from GDP/POP, extreme climate and their interact effect, due to 1.5°C and 2°C of global warming.

| GDP exposure | POP exposure |
|--------------|--------------|
|              | GDP Climate Interaction | POP Climate Interaction |
| Yellow (1.5°C) | 71 (58 to 86) 4 (2 to 5) 25 (12 to 32) | 80 (62 to 94) −7 (−3 to −15) 27 (10 to 43) |
| Yellow (2°C) | 61 (51 to 75) 3 (2 to 4) 37 (23 to 46) | 68 (47 to 85) −6 (−19 to 9) 38 (24 to 44) |
| Huaihe (1.5°C) | 59 (48 to 71) 5 (3 to 7) 36 (25 to 46) | 55 (36 to 63) 15 (−9 to 31) 30 (26 to 34) |
| Huaihe (2°C) | 44 (36 to 57) 4 (3 to 5) 50 (40 to 60) | 33 (17 to 45) 34 (22 to 53) 33 (32 to 36) |
| Haihe (1.5°C) | 54 (45 to 75) 5 (4 to 7) 41 (20 to 48) | 48 (35 to 78) 16 (2 to 22) 36 (20 to 43) |
| Haihe (2°C) | 46 (34 to 65) 4 (3 to 5) 50 (33 to 61) | 34 (23 to 59) 23 (10 to 32) 42 (30 to 46) |
| HHH (1.5°C) | 61 (51 to 77) 5 (3 to 7) 34 (11 to 42) | 61 (45 to 78) 8 (−3 to 12) 31 (19 to 40) |
| HHH (2°C) | 50 (40 to 66) 4 (3 to 5) 45 (32 to 56) | 45 (29 to 63) 18 (5 to 31) 37 (29 to 42) |

Note: The range of uncertainty in contributions was presented in parentheses.

| GDP exposure | POP exposure |
|--------------|--------------|
|              | GDP Climate Interaction | POP Climate Interaction |
| Yellow (1.5°C) | 96 (92 to 99) 1 (0 to 1) 3 (12 to 32) | 97 (95 to 100) 0 (−2 to 7) 3 (−2 to 7) |
| Yellow (2°C) | 89 (82 to 95) 1 (0 to 1) 10 (23 to 46) | 94 (90 to 98) −6 (−12 to 1) 11 (4 to 18) |
| Huaihe (1.5°C) | 96 (93 to 100) 0 (−2 to 1) 3 (25 to 46) | 95 (91 to 101) 2 (−4 to 7) 3 (−9 to 10) |
| Huaihe (2°C) | 94 (91 to 98) 1 (−4 to 5) 5 (40 to 60) | 95 (88 to 100) 1 (−4 to 5) 5 (−5 to 10) |
| Haihe (1.5°C) | 94 (68 to 128) 1 (0 to 1) 5 (−24 to 20) | 85 (74 to 94) 5 (0 to 12) 8 (−21 to 22) |
| Haihe (2°C) | 90 (84 to 94) 1 (−4 to 5) 9 (−4 to 15) | 90 (83 to 105) 1 (0 to 3) 9 (−7 to 17) |
| HHH (1.5°C) | 95 (84 to 109) 1 (−1 to 1) 4 (4 to 33) | 92 (87 to 98) 2 (−2 to 9) 4 (−11 to 13) |
| HHH (2°C) | 91 (84 to 96) 1 (−2 to 4) 8 (20 to 40) | 93 (87 to 101) −1 (−5 to 3) 7 (−3 to 15) |

from 1.5°C to 2°C, while the significant increase can be found in the contribution of interaction effect. In addition, the contribution of increased HD showed a slight decrease to GDP exposure and a remarkable increase to POP exposure. Notably, the negative contribution (less than 10%) of climate to POP exposure can be found in Yellow river basin where experienced a slight increased HD (Figure 8c), however, positive contribution existed in other river basins.

Similar to HD, Table 5 shows the regional mean of the relative contributions to the change of exposures to R20mm from the different variables. For both 1.5°C and 2°C global warming, the contributions of GDP and POP change to exposures were largest in all of three river basins, with the contribution in excess of 90% existed in most of river basins, while the contributions of R20mm change and interaction effect were minor, with values less than 10% or even negative over some river basin. For GDP exposure to R20mm, the contributions of GDP was projected to decrease slightly over all river basins over HHH, while the increased contribution of interaction effect existed in all river basins as the additional 0.5°C of warming occurred. For POP exposure to R20mm, the contributions of POP and climate were projected to change slightly over HHH river, while the contribution of interaction effect increased due to the additional 0.5°C of warming. Note that, the changes in contributions to the changes of exposures to R20mm were relatively small compared to that to HD.

It is indicated that the increase of GDP exposure to heat events mostly resulted from the increases of GDP and interaction effect over HHH river basin, and the interaction effect aggravated the increase due to the additional 0.5°C of warming. The increase of POP exposure to heat events was also mainly related to the increase of POP and interaction effect, and both the increased heat events and interaction effect accelerated the increase of exposure due to the additional 0.5°C of warming. However, the increase of exposures to heavy rainfall events was mainly dominated by the increase of GDP and POP.
Therefore, for the additional 0.5°C of warming, the increase change of increased GDP exposure and the slight change of increased POP exposure to heavy rainfall events were largely related to the increase change of GDP and slight change of POP, respectively. Besides, above results showed broad agreement across five simulations (at least three out of the five simulations are consistent, figures not shown).

4 | CONCLUSION AND DISCUSSION

Based on high resolution combined dynamical and statistical downscaling dataset driven by five GCM simulations under the RCP4.5 scenario, the ability of the dataset to reproduce extreme climate events in HHH river basin was investigated. Then, future changes in extreme events, as well as the related risk exposures to heat events and heavy rainfall events, were projected under 1.5°C and 2°C of global warming.

The evaluation indicated that the dataset can well reproduce the spatial distribution of all extreme temperature indices and most of the extreme precipitation indices. Although the biases in combined dynamical and statistical downscaled dataset were largely reduced compared to that in RCM, they were still larger in some precipitation-related indices, indicating the important effects of the observation dataset and the biases inherited from RCM (Wu and Gao, 2013; Han et al., 2019; Wu et al., 2020).

For 1.5°C and 2°C of global warming, TXx, TNn, and HD were projected to increase substantially over the whole HHH river basin in the future. There are strong increases in those indices due to additional 0.5°C, with larger increase magnitudes at the Huaiane river basin. In generally, FD substantially decreased under 1.5°C and 2°C of global warming. The projected R1mm, R20mm and SDII increased under 1.5°C and 2°C of global warming, while a slightly decreased was projected in CDD. In addition, unlike temperature extremes, the slightly changes in the magnitudes of extreme precipitation events existed due to the additional 0.5°C warming. Note that, although added value was evident in the projections based on the high resolution combined dynamical and statistical downscaling dataset, the above results were generally consistent with previous studies which conducted by coarse GCMs or RCMs (Xu et al., 2011; Gu et al., 2014; Yin et al., 2016; Wu et al., 2020).

The exposures to heat event and heavy rainfall event were projected to increase over all of three river basins, with the highest increase occurred in Huaiane river basin. For heat event, the increases of GDP (POP) and interaction effect played important roles to the increase of GDP (POP) exposure, furthermore, the interaction effect was the most significant contributor to the increase of GDP (POP) exposure due to the additional 0.5°C of warming. However, the increase of GDP (POP) exposure to heavy rainfall event was mainly dominated by the increase of GDP (POP). So caution was required when the impact assessments and risk projection were analysed over HHH river basin with global warming.

Limitation to this study includes several aspects. Firstly, the indices used as the hazards are rather simple. For example, considering the maximum and minimum temperature or humidity to the definition of heat events (Jones et al., 2015) might helpful to better understand the projected changes in exposures to heat events. Secondly, in this work we address the ensemble by using only five simulations conducted by RCMs due to the costly dynamical downscaling. Finally, the uncertainty was analysed based on a single emission pathway (RCP4.5) of global climate forcing and as well as a single scenario of Shared Socioeconomic Pathways (SSP2). So further data collection, multiple emissions and scenarios of future GDP and POP development are required to reduce the uncertainty of projected extreme events and related exposures.

ACKNOWLEDGEMENTS

This work was jointly supported by the National Key Research and Development Program of China (2017YFA0605004, 2018YFA0606301, and 2018YFB1502803), the National Natural Science Foundation of China (41805074), and the GEIGC Science and Technology Project (101662227).

ORCID

Jia Wu https://orcid.org/0000-0003-2270-7464
Zhenyu Han https://orcid.org/0000-0002-2452-527X
Ying Shi https://orcid.org/0000-0002-4929-8739

REFERENCES

Alexander, L.V., Zhang, X., Peterson, T.C., Caesar, J., Gleason, B., Klein Tank, A.M.G., Haylock, M., Collins, D. and Trewin, B. (2006) Global observed changes in daily climate extremes of temperature and precipitation. Journal of Geophysical Research, 111, D05109. https://doi.org/10.1029/2005JD006290.

Aslam, A.Q., Ahmad, S.R., Ahmad, I., Hussain, Y. and Hussain, M. S. (2017) Vulnerability and impact assessment of extreme climatic event: a case study of southern Punjab, Pakistan. Science of the Total Environment, 580, 468–481. https://doi.org/10.1016/j.scitotenv.2016.11.1155.

Bao, Z., Fu, G. and Wang, G. (2012) Hydrological projection for the Miyun Reservoir basin with the impact of climate change and human activity. Quaternary International, 282, 96–103.
Cannon, A.J., Sobie, S.R. and Murdock, T.Q. (2015) Bias correction of GCM precipitation by quantile mapping: how well do methods preserve changes in quantiles and extremes? *Journal of Climate*, 28, 6938–6959.

Chen, H.P. and Sun, J.Q. (2015) Changes in drought characteristics over China using the standardized precipitation evapotranspiration index. *Journal of Climate*, 28, 5430–5447.

Chen, H.P., Sun, J.Q. and Fan, K. (2012) Decadal features of heavy rainfall events in eastern China. *Acta Meteorologica Sinica*, 26, 289–303 https://doi.org/10.1007/s13351-012-0303-0.

Chen, X.L., Guo, Z., Zhou, T.J., Li, J., Rong, X.Y., Xin, Y.F., Chen, H.M. and Su, J.Z. (2019) Climate sensitivity and feedbacks of a new coupled model CAMS-CSM to idealized CO$_2$ forcing: a comparison with CMIP5 models. *Journal of Meteorological Research*, 33(1), 31–45. https://doi.org/10.1007/s13351-019-8074-5.

Chen, Y. and Zhai, P.M. (2017) Revisiting summertime hot extremes in China during 1961–2015: overlooked compound extremes and significant changes. *Geophysical Research Letters*, 44, 5096–5103.

Chen, X.C., Xu, Y. and Yao, Y. (2015) Changes in climate extremes over China in a 2 °C, 3 °C, and 4 °C warmer world. *Chinese Journal of Atmospheric Sciences*, 39(6), 1123–1135. http://dx.doi.org/10.3878/j.issn.1006-9895.1502.14224 (in Chinese).

Cheng, J., Wu, J.J., Xu, Z.W., Zhu, R., Wang, X., Li, K.S., Li, Y.W., Yang, H.H. and Su, H. (2014) Associations between extreme precipitation and childhood hand, foot and mouth disease in urban and rural areas in Heifei, China. *Science of the Total Environment*, 497–498, 484–490. https://doi.org/10.1016/j.scitotenv.2014.08.006.

Counou, D. and Rahmstorf, S. (2012) A decade of weather extremes. *Nature Climate Change*, 2(7), 491–496.

Gao, X.J., Shi, Y., Han, Z.Y., Wang, M.L., Wu, J., Zhang, D.F., Xu, Y. and Giorgi, F. (2017) Performance of RegCM4 over major river basins in China. *Advances in Atmospheric Sciences*, 34, 441–455. https://doi.org/10.1007/s00376-016-6179-7.

Gao, X.J., Shi, Y., Song, R.Y., Giorgi, F., Wang, Y.G. and Zhang, D.F. (2008) Reduction of future monsoon precipitation over China: comparison between a high resolution RCM simulation and the driving GCM. *Meteorology and Atmospheric Physics*, 100, 73–86.

Gao, X.J., Shi, Y., Zhang, D.F., Wu, J., Giorgi, F., Ji, Z.M. and Wang, Y.G. (2012) Uncertainties of monsoon precipitation projection over China: results from two high resolution RCM simulations. *Climate Research*, 52, 213–226.

Gao, X.J., Wu, J., Shi, Y., Wu, J., Han, Z.Y., Zhang, D.F., Tong, Y., Li, R.K., Xu, Y. and Giorgi, F. (2018) Future changes in thermal comfort conditions over China based on multi-RegCM4 simulations. *Atmospheric and Oceanic Science Letters*, 11(4), 291–299. https://doi.org/10.1007/s12637-018-7675-7.

Geiger, T., Murakami, D., Frieler, K. and Yamagata, Y. (2017). Spatially-explicit gross cell product (GCP) time series: past observations (1850-2000) harmonized with future projections according the shared socioeconomic pathways (2010-2100). GFZ Data Services doi: https://doi.org/10.5880/pik.2017.007.

Giorgi, F., Jones, C. and Asrar, G. (2009) Addressing climate information needs at the regional level: the CORDEX framework. *WMO Bulletin*, 58, 175–183.

Gu, H.H., Yu, Z.B. and Wang, J.G. (2014) Future extreme climates projection over Huang-Huai-Hai region of China. *Advanced Materials Research*, 955–959, 3887–3892. https://doi.org/10.4028/www.scientific.net/AMR.955-959.3887.

Han, Z.Y., Shi, Y., Wu, J., Xu, Y. and Zhou, B.T. (2019) Combined dynamical and statistical downscaling for high-resolution projections of multiple climate variables in the Beijing–Tianjin–Hebei region of China. *Journal of Applied Meteorology and Climatology*, 58, 2387–2403.

Han, Z.Y., Zhou, B.T., Xu, Y., Wu, J. and Shi, Y. (2017) Projected changes in haze pollution potential in China: an ensemble of regional climate model simulations. *Atmospheric Chemistry and Physics*, 17, 10 109–10 123. https://doi.org/10.5194/acp-17-10109-2017.

He, Z. and He, J.P. (2014) Temporal and spatial variation of extreme precipitation in the Yellow River Basin from 1960 to 2012. *Resource Science*, 36(3), 490–501.

Huang, J., Qin, D., Jiang, T., Wang, Y., Feng, Z., Zhai, J., Cao, L., Chao, Q., Xu, X., Wang, G. and Su, B. (2019) Effect of fertility policy changes on the population structure and economy of China: from the perspective of the shared socioeconomic pathways. *Earth's Future*, 7, 250–265.

Huang, J.P., Yu, H.P., Dai, A.G., Wei, Y. and Kang, L.T. (2017) Drylands face potential threat under 2°C global warming target. *Nature Climate Change*, 7, 417–422. https://doi.org/10.1038/nclimate3275.

Hui, P.H., Tang, J.P., Wang, S.Y., Niu, X.R., Zong, P.S. and Dong, X. N. (2018) Climate change projections over China using regional climate models forced by two CMIP5 global models. Part II: projections of future climate. *International Journal of Climatology*, 38(Supplement 1, e78–e94.

Intergovernmental Panel on Climate Change (IPCC). (2012) Managing the Risks Of Extreme Events and Disasters to Advance Climate Change Adaptation. Aspeical Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge, UK and New York, NY: Cambridge University Press, p. 582.

Intergovernmental Panel on Climate Change (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, UK and New York, NY: Cambridge University Press, p. 1535.

Intergovernmental Panel on Climate Change (IPCC). (2014) *Summary for Policymakers: Climate Change 2014: Impact, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York, NY: Cambridge University Press, p. 14.

Intergovernmental Panel on Climate Change (IPCC). (2015) *Workshop on Regional Climate Projections and their Use in Impacts and Risk Analysis Studies. IPCC Working Group I Technical Support Unit*. Bern, Switzerland: University of Bern, p. 171.

Intergovernmental Panel on Climate Change (IPCC). (2018) *Summary for Policymakers: Global Warming of 1.5°C. an IPCC Special Report on the Impacts of Global Warming of 1.5 °C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways*, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty. Geneva, Switzerland: World Meteorological Organization, p. 32.

Ji, Z.M. and Kang, S.C. (2015) Evaluation of extreme climate events using a regional climate model for China. *International Journal of Climatology*, 35, 888–902.
Jiang, D.B. (2008) Projected potential vegetation change in China under the SRES A2 and B2 scenarios. *Advances in Atmospheric Sciences*, 25(1), 126–138.

Jin, J.L., Wang, G.Q., Zhang, J.Y., Yang, Q.L., Liu, C.S., Liu, Y.L., Bao, Z.X. and He, R.M. (2018) Impacts of climate change on hydrology in the Yellow River source region, China. *Journal of Water and Climate Change*, 22, 67–83. https://doi.org/10.1007/s11027-015-9664-x.

Jones, B. and O’Neill, B.C. (2016) Spatially explicit global population scenarios consistent with the shared socioeconomic pathways. *Environmental Research Letters*, 11(8), 084003.

Jones, B., O’Neill, B.C., McDaniel, L., McGinnis, S., Mearns, L.O. and Tebaldi, C. (2015) Future population exposure to US heat extremes. *Nature Climate Change*, 5(7), 652–655. https://doi.org/10.1038/nclimate2631.

KC, S. and Lutz, W. (2017) The human core of the shared socioeconomic pathways: population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change*, 42, 181–192.

Kim, M.K., Kim, S., Kim, J., Heo, J., Park, J.S., Kwon, W.T. and Suh, M.S. (2016) Statistical downscaling for daily precipitation in Korea using combined PRISM, RCM, and quantile mapping: part 1, methodology and evaluation in historical simulation. *Asia-Pacific Journal of Atmospheric Sciences*, 52, 79–89. https://doi.org/10.1007/s13143-016-0010-3.

Lang, X.M. and Sui, Y. (2013) Changes in mean and extreme climates over China with a 2°C global warming. *Chinese Science Bulletin*, 58, 1453–1461.

Li, D.H., Zhou, L.W. and Zhou, T.J. (2017) Changes of extreme indices over China in response to 1.5°C global warming projected by a regional climate model. *Advances in Climate Change Research*, 12(4), 446–457 (in Chinese).

Li, H.X., Chen, H.P., Wang, H.J. and Yu, E.T. (2018) Future precipitation changes over China under 1.5°C and 2.0°C global warming targets by using CORDEX regional climate models. *Science of the Total Environment*, 640–641, 543–554. https://doi.org/10.1016/j.scitotenv.2018.05.324.

Li, L., Hao, Z.C., Wang, J.H., Wang, Z.H. and Yu, Z.B. (2008) Impact of future climate change on runoff in the head region of the Yellow River. *Journal of Hydrological Engineering*, 13(5), 347–354.

Li, R.K., Han, Z.Y., Xu, Y., Shi, Y. and Wu, J. (2020) An ensemble projection of GDP and population exposure to high temperature events over Jing-Jin-Ji district based on high resolution combined dynamical and statistical downscaling datasets. *Climate Change Research*, 16(4), 491–504 (in Chinese).

Liu, L.L., Xu, H.M., Wang, Y. and Jiang, T. (2017) Impacts of 1.5 and 2°C global warming on water availability and extreme hydrological events in Yiluo and Beijiang River catchments in China. *Climatic Change*, 145, 145–158. https://doi.org/10.1007/s10584-017-2072-3.

Liu, M., Wu, J.J., Lv, A.F., Zhao, L. and He, B. (2010) The water stress of winter wheat in Huang-huai-hai plain of China under rain-fed condition. *Progress in Geography*, 29(4), 427–432 (in Chinese).

Liu, R., Chen, L.S., Cicerone, R.J., Chein-Jung, S., Jun, L.I., Wang, J. and Zhang, Y. (2015) Trends of extreme precipitation in eastern China and their possible causes. *Advances in Atmospheric Sciences*, 32, 1027–1037. https://doi.org/10.1007/s00376-015-5002-1.

Liu, Y., Zhang, J., Wang, G., He, R., Wang, H., Liu, C. and Jin, J. (2012) Assessing the effect of climate natural variability in water resources evaluation impacted by climate change. *Hydrological Processes*, 27, 1061–1071.

Min, S.K., Zhang, X., Zwiers, F.W. and Hegerl, G.C. (2011) Human contribution to more-intense precipitation extremes. *Nature*, 470(7334), 378–381.

Murakami, D. and Yamagata, Y. (2019) Estimation of gridded population and GDP scenarios with spatially explicit statistical downscaling. *Sustainability*, 11(7), 2106. https://doi.org/10.3390/su11072106.

Niu, X.R., Wang, S.Y., Tang, J.P., Lee, D.K., Gao, X.J., Wu, J., Hong, S.Y., Gutowski, W.J. and McGregor, J. (2015) Multi-model ensemble projection of precipitation in eastern China under A1B emission scenario. *Journal of Geophysical Research: Atmospheres*, 120(19), 9965–9980. https://doi.org/10.1002/2015JD023853.

O’Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallett, S., Carter, T.R., Mathur, R., van Vuuren, D.P. (2014) A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climate Change*, 122(3), 387–400. http://dx.doi.org/10.1007/s10584-013-0905-2.

Pei, Y.S., Wang, J.H. and Luo, L. (2004) Analysis of effect of south-to-north water transfer project on aquatic ecosystems of Hailie River basin. *Acta Ecologica Sinica*, 24(10), 2115–2123.

Piras, M., Mascaro, G., Deidda, R. and Vivoni, E.R. (2016) Impacts of climate change on precipitation and discharge extremes through the use of statistical downscaling approaches in a Mediterranean basin. *Science of the Total Environment*, 543, 952–964. https://doi.org/10.1016/j.scitotenv.2015.06.088.

Schumacher, I. and Strobl, E. (2011) Economic development and losses due to natural disasters: the role of hazard exposure. *Economic Geographies*, 72, 97–105.

She, D.X., Xia, J., Zhang, Y.Y. and Du, H. (2011) The trend analysis and statistical distribution of extreme rainfall events in the Huaihe River basin in the past 50 years. *Acta Geographica Sinica*, 66(9), 1200–1210 (in Chinese).

Shen, F.X., Geng, L.H., Qin, F.X. and Xu, P.B. (2002) Analysis of water saving in received area in Huanghe-Huaihe-Haihe watersheds and eastern and middle lines of water transferring project from south to north China. *Advances in Water Science*, 13(6), 768–774 (in Chinese).

Shi, C., Jiang, L., Zhang, T., Xu, B., and Han, S. (2014). Status and plans of CMA Land Data Assimilation System (CLDAS) Project. Abstracts, *EGU General Assembly Conference*, Vienna, Austria: European Geosciences Union, 16, EGU2014-5671, Available at: http://meetingorganizer.copernicus.org/EGU2014/EGU2014-5671.pdf.

Shi, C., Xie, Z., Qian, H., Liang, M. and Yang, Y. (2011) China land soil moisture EnKF data assimilation based on satellite remote sensing data. *Science China Earth Sciences*, 54, 1430–1440. https://doi.org/10.1007/s11430-010-4160-3.

Shi, Y., Wang, G.L. and Gao, X.J. (2018) Role of resolution in regional climate change projections over China. *Climate Dynamics*, 51(5–6), 2375–2396. https://doi.org/10.1007/s00382-017-4018-x.

Sillmann, J., Kharin, V.V., Zhang, X., Zwiers, F.W. and Bronaugh, D. (2013) Climate extreme indices in the CMIP5 multimodel ensemble: part 1. Model evaluation in the present
climate. *Journal of Geophysical Research: Atmospheres*, 118, 1716–1733.

Smith, K.R., Woodward, A., Campbell-Lendrum, D., Chadee, D.D., Honda, Y., Liu, Q., Olwoch, J.M., Revich, B. and Sauerborn, R. (2014) *Human Health: Impacts, Adaptation, and Co-benefits*. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the IPCC*. Cambridge, UK and New York, NY: Cambridge University Press, pp. 709–754.

Stein, U. and Alpert, P. (1993) Factor separation in numerical simulations. *Journal of the Atmospheric Sciences*, 50, 2107–2115.

Sun, H., Wang, Y., Chen, J., Zhai, J., Jing, C., Zeng, X., Ju, H., Zhao, N., Zhan, M., Luo, L., Su, B. (2017) Exposure of population to droughts in the Haihe River Basin under global warming of 1.5 and 2.0 °C scenarios. *Quarterly International*, 453, 74–84. http://dx.doi.org/10.1006/qiinta.2017.05.005.

Sun, J.Q. and Ao, J. (2013) Changes in precipitation and extreme precipitation in warming environment in China. *Science Bulletin*, 58, 1395–1401. https://doi.org/10.1007/s11434-012-5542-z.

Sun, Q.H., Miao, C.Y., Duan, Q.Y., Kong, D.X., Ye, A.Z., Di, Z.H. and Gong, W. (2014) Would the “real” observed dataset stand up? A critical examination of eight observed gridded climate datasets for China. *Environmental Research Letters*, 9, 015001.

Taylor, K.E. (2001) Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research*, 106, 7183–7192. https://doi.org/10.1029/2000JD900719.

Taylor, K.E., Stouffer, R.J. and Meehl, G.A. (2012) An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, 93, 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1.

Tong, Y., Gao, X.J., Han, Z.Y., Xu, Y.Q., Xu, Y. and Giorgi, F. (2020) Bias correction of temperature and precipitation over China for RCM simulations using the QM and QDM methods. *Climate Dynamics*. In press, https://doi.org/10.1007/s00382-020-05447-4.

Torma, C. and Giorgi, F. (2014) Assessing the contribution of different factors in regional climate model projections using the factor separation method. *Atmospheric Science Letters*, 15, 239–244. https://doi.org/10.1002/asl2.491.

United Nations Framework Convention on Climate Change (UNFCCC). (2015) *FCCC/CP/2015/L.9/rev.1: Adoption of the Paris Agreement*. Paris: UNFCCC, p. 32.

van Vuurens, D., Kriegler, E., O’Neill, B.C., Ebi, K.L., Riahi, K., Carter, T.R., Edmonds, J., Hallegraeve, S., Kram, T., Mathur, R. and Winkler, H. (2014) A new scenario framework for climate change in China: facts, simulation and projection. *Meteorologische Zeitschrift*, 21, 279–304. https://doi.org/10.1127/0941-2948/2012/0330.

Wang, X., Huang, G., Lin, Q., Nie, X. and Liu, J. (2015) High-resolution temperature and precipitation projections over Ontario, Canada: a coupled dynamical-statistical approach. *Quarterly Journal of the Royal Meteorological Society*, 141, 1137–1146. https://doi.org/10.1002/qj.2421.

World Meteorological Organization Current Extreme Weather Events (WMO) (2010). Available at: www.wmo.int/pages/mediacentre/news/extremeweathersequence_en.html.

Wu, J. and Gao, X.J. (2013) A gridded daily observation dataset over China region and comparison with the other datasets. *Chinese Journal of Geophysics*, 56(4), 1102–1111. https://doi.org/10.6038/cjg20130406 in Chinese.

Wu, J. and Gao, X.J. (2020) Present day bias and future change signal of temperature over China in a series of multi-GCM driven RCM simulations. *Climate Dynamics*, 54, 1113–1130. https://doi.org/10.1007/s00382-019-05047-x.

Wu, J., Gao, X.J., Giorgi, F. and Chen, D.L. (2017) Changes of effective temperature and cold/hot days in late decades over China based on a high resolution gridded observation dataset. *International Journal of Climatology*, 37(s1), 788–800. https://doi.org/10.1002/joc.5038.

Wu, J., Han, Z.Y., Xu, Y., Zhou, B.T. and Gao, X.J. (2020) Changes in extreme climate events in China under 1.5°C–4°C global warming targets: projections using an Ensemble of Regional Climate Model Simulations. *Journal of Geophysical Research: Atmospheres*, 125, e2019JD031057. https://doi.org/10.1029/2019JD031057.

Wu, Z.Y., Lu, G.H., Liu, Z.Y., Wang, J.X. and Xiao, H. (2013) Trends of extreme flood events in the Pearl River basin during 1951-2010. *Advances in Climate Change Research*, 4(2), 110–116.

Xu, C.H., Luo, Y. and Xu, Y. (2011) Projected changes of precipitation extremes in river basins over China. *Quaternary International*, 244(2011), 149–158.

Ye, J.S., Pei, J.Y. and Fang, C. (2018) Under which climate and soil conditions the plant productivity—precipitation relationship is linear or nonlinear? *Science of The Total Environment*, 616–617, 1174–1180. https://doi.org/10.1016/j.scitotenv.2017.10.203.

Yin, J., Yan, D.H., Yang, Z.Y., Yuan, Z., Yuan, Y. and Zhang, C. (2016) Projection of extreme precipitation in the context of climate change in Huang-Huai-Hai region. China. *Journal of Earth System Science*, 125(2), 417–429.

Yu, E.T., Sun, J.Q., Chen, H.P. and Xiang, W.L. (2015) Evaluation of a high-resolution historical simulation over China: climatology and extremes. *Climate Dynamics*, 45, 2013–2031. https://doi.org/10.1007/s00382-014-2452-6.

Yu, E.T., Wang, H.J. and Sun, J.Q. (2010) A quick report on a dynamical downscaling simulation over China using the nested model. *Atmospheric and Oceanic Science Letters*, 3, 325–329.

Zhai, P. and Pan, X. (2003) Trends in temperature extremes during 1951-1999 in China. *Geophysical Research Letters*, 30(17), 1913.

Zhai, P., Zhang, X., Wan, H. and Pan, X.H. (2005) Trends in total precipitation and frequency of daily precipitation extremes over China. *Journal of Climate*, 18(7), 1096–1108.

Zhan, M., Zhai, J., Sun, H., Li, X., Xia, L. (2019) Observed exposure of population and gross domestic product to extreme precipitation events in the Poyang Lake basin, China. *Atmosphere*, 10(12), 817. http://dx.doi.org/10.3390/atmos10120817.

Zhang, D.F., Han, Z.Y. and Shi, Y. (2017) Comparison of climate projections between driving CSIRO-Mk3.6.0 and downsampling simulation of RegCM4.4 over China. *Advances in Climate
Zhang, J.Y. and Wang, G.Q. (2007) Impacts of climate change on hydrology and water resources, Vol. 2007. Beijing, China: Science Press (in Chinese).

Zhang, J.Y., Wang, G.Q., He, R.M. and Liu, C.S. (2009) Variation trends of runoffs in the middle Yellow River basin and its response to climate change. *Advance in Water Science*, 20(2), 153–158 (in Chinese).

Zhou, X., Huang, G., Wang, X., Fan, Y. and Cheng, G. (2018) A coupled dynamical-copula downscaling approach for temperature projections over the Canadian prairies. *Climate Dynamics*, 51, 2413–2431. https://doi.org/10.1007/s00382-017-4020-3.

Zou, L.W. and Zhou, T.J. (2013) Near future (2016–40) summer precipitation changes over China as projected by a regional climate model (RCM) under the RCP8.5 emissions scenario: comparison between RCM downscaling and the driving GCM. *Advances in Atmospheric Sciences*, 30, 806–818. https://doi.org/10.1007/s00376-013-2209-x.

**How to cite this article:** Wu J, Han Z, Li R, Xu Y, Shi Y. Changes of extreme climate events and related risk exposures in Huang-Huai-Hai river basin under 1.5–2°C global warming targets based on high resolution combined dynamical and statistical downscaling dataset. *Int J Climatol*. 2021; 41:1383–1401. [https://doi.org/10.1002/joc.6820](https://doi.org/10.1002/joc.6820)