Environmental Research Communications

PAPER

Future changes in precipitation over the upper Yangtze River basin based on bias correction spatial downscaling of models from CMIP6

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Supplementary material for this article is available online

Abstract

Global climate change will change the temporal and spatial distribution of precipitation, as well as the intensity and frequency of extreme precipitation. The Yangtze River basin is one of the world’s largest basins, and understanding the future precipitation changes should be vital to flood control, water resources supply, and hydropower electricity generation in this basin. In this study, projected future characteristics of precipitation are analyzed in the upper Yangtze river basin (UYRB). To this end, based on the observed data from national meteorological stations, the bias correction spatial downscaling (BCSD) of five models from the Coupled Model Intercomparison Project Phase 6 (CMIP6) is carried out. Then, based on the results of multi model ensemble (MME), we find that, relative to the historical period (1988–2014), the mean annual precipitation in the whole UYRB during 2015–2064 increases by 4.23%, 1.11%, 1.24% under SSP1-2.6, SSP2-4.5, SSP5-8.5, respectively, and it increases more in the long term (2040–2064) than that in the near term (2015–2039). Under SSP1-2.6, the precipitation will increase more significantly, which means lower emission of aerosols and greenhouse gases may increase the risk of flood disaster in the future over the UYRB. Interdecadal precipitation variability is more intense than interannual precipitation variability. Future precipitation changes in four seasons are spatially heterogeneous under three scenarios. Three extreme precipitation indices, including R95p, Rx1day and R10 mm, generally increase in the UYRB. R95p and Rx1day increase more in the WR and YBYCR basins with relatively high mean annual precipitation than that in other three sub-basins. R10 mm changes slightly in all sub-basins. The results reveal that the lower region of the UYRB may face greater risk of extreme precipitation. This study provides a timely updated finding about future changes in precipitation in the UYRB based on more accurate climate projections and ground-based observation.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) has documented that global warming will reach at least 1.5 °C, and warmer climate significantly changes the intensity, frequency and duration of climate extremes (IPCC 2021). Climate extremes then change regional mean runoff (Xiong et al 2013, Yang et al 2015, Birkinshaw et al 2017, Wang et al 2019a) and cause extreme events such as flood (Berghuijs et al 2017) and drought (Dai 2010, 2011). The upper Yangtze river basin (UYRB) suffers considerably from precipitation extremes, which often cause natural flood, resulting in huge economic losses (Zhou et al 2021, Guan et al 2015). For example, the flood induced by extremely high precipitation between June and August (670 mm) in 1998 in the Yangtze river basin (YRB) killed over 4000 people and caused economic losses in excess of $36 billion (Yin and Li 2001, Birkinshaw et al 2017). In 2011, the spring drought and sudden flood in June over the YRB were induced...
by the abnormal location of the western Pacific subtropical high (WPSH) and insufficient water vapor (Deng et al 2013). In 2020, the extremely anomalous Meiyu over the Yangtze–Huai river basin (YHRB) was due to the extremely warm SST in the tropical Indian Ocean (Niu et al 2021). Since 1970, the extreme precipitation events in the YRB showed an increasing trend in both frequency and spatial coverage, which were caused by the ElNiño–Southern Oscillation and Pacific Decadal Oscillation in summer and winter (Li et al 2021). During 1960–2019, mean and extreme precipitation intensities, and the frequency of extremely heavy precipitation in the YRB have significantly increased, which were induced by global warming, La Niña phase of ENSO (Li et al 2020a, 2020b). Considering the severity of precipitation extremes in the UYRB, it is important to figure out the temporal and spatial characteristics of precipitation in the UYRB in the future.

Coupled Model Intercomparison Project (CMIP) has been widely used in projecting the future precipitation changes (Zeng et al 2008, Eyring et al 2016, Zou et al 2019). Several studies analyzed the future precipitation changes in the Yangtze river basin (YRB) based on CMIP5 data (Cao et al 2011, Gu et al 2014, Xu et al 2019, Huang et al 2020). However, most CMIP5 models suffer from overestimation of precipitation in the YRB, and these models cannot capture precipitation characteristics in complex terrain and temporal variation of precipitation with different intensities (Pan et al 2016, Tan et al 2016). CMIP has been in the sixth phase (CMIP6) and Scenario model intercomparison plan (MIP) is one of the 23 sub-experiments of CMIP6. ScenarioMIP combines Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) to generate different future scenario estimation (O’Neill et al 2016, van Vuuren et al 2017, Zhang et al 2019). CMIP6 data has been revealed to be more accurate than CMIP5 in China (Dong and Dong 2021, Zhu et al 2021, You et al 2021). Thus some studies analyzed future precipitation changes in the YRB based on CMIP6 data instead of CMIP5 data (Li et al 2020a, 2020b, Zhu et al 2021). However, these studies generally downscaled CMIP6 data to the finer grid by simple interpolation methods, which cannot eliminate the systematic error (Maurer and Hidalgo 2008, Yue et al 2021), or cannot enhance the temporal variability (Hempel et al 2013). To overcome this problem, Bias correction spatial downscaling is broadly used to generate accurate and high-resolution data set (Xu et al 2019), which can adjust the raw CMIP6 climate model data to more detailed altitude-stratified information associated with observed data (Hempel et al 2013). Hence, the bias correction spatial downscaling method should be used in this study.

When analyzing future precipitation changes based on CMIP6 data, more than 100 models in CMIP6 can be used. Existed studies generally used outputs from few CMIP6 models for analysis (Li et al 2020a, 2020b, Zhu et al 2021, Tian et al 2021, Yue et al 2021). However, some studies have pointed out that the conclusion varied greatly when simply using a single GCM model to project climate change (Li et al 2021, Dong and Dong 2021). Therefore, multi model ensemble methods have been proposed to reduce the uncertainty of the individual GCM model (Yue et al 2021, Zhu et al 2021). The commonly used multi model ensemble methods are equal weighting (EW) (Zhu et al 2021), performance-based ensemble averaging (PEA) (Niu et al 2018), weighted mean (WM) (Feng et al 2010), and reliability ensemble averaging (REA) (Giorgi and Mearns, 2002).

This study selects five models from CMIP6 with relatively good accuracy of precipitation simulation in the YRB and China according to Huang et al (2020), Li et al (2020a, 2020b), Jiang et al (2020a, 2020b) and Tian et al (2021). Then we use bias correction spatial downscaling method to downscale the raw GCMs output based on observed precipitation data. Then, a multi model ensemble method considering both mean annual magnitude and trend of precipitation is introduced to get the ensemble results of the five models. Finally, we analyze the temporal and spatial change characteristics of precipitation in the whole YURB and five sub-basins based on ensemble results of the five models.

2. Study area, data and methods

2.1. Study area

The upper Yangtze river basin (UYRB) is above Yichang hydrological station, located in the region between 97.37°E ~ 110.18°E and between 21.13°N ~ 34.33°N, in the transition zone from high mountain terrain in the source region to low plain in the east, with the elevation ranging from 5000 meters above sea level to less than 500 meters, covering an area of about 1.0 × 10⁶ km² (Zhang et al 2018, Wang et al 2019b). The annual precipitation of the basin is 723 ~ 1134 mm, and the annual average temperature is 8.6 ~ 16.8°C, and the annual runoff is about 400 billion m³, accounting for about 46% of the average annual runoff of the Yangtze river basin (Qin et al 2019, Huang et al 2020). The upper Yangtze River basin is divided into five important sub-basins (in figure 1): Jinsha river basin, Mintuo river basin, Jialing river basin, Wu river basin, Yibin Yichang river basin (Qin et al 2019).
2.2. Data and post-processing

In this study, 366 meteorological stations (in figure 1) within and around the UYRB are selected. The observed daily precipitation data during 1988–2014 are used and they are from the National Meteorological Information Center (NMIC) of the China Meteorological Administration (CMA) (http://data.cma.cn). The gridded precipitation data with 0.08° resolution are interpolated from observed daily precipitation data using the angular distance weight (ADW) method (Willmott and Matsuura1995, Yang et al 2004). The ADW method used in this study is modified by considering the influence of precipitation elevation gradient (Wang et al 2016).

According to Huang et al (2020), Li et al (2020a, 2020b), Jiang et al (2020a, 2020b) and Tian et al (2021), five CMIP6 models (https://esgf-node.llnl.gov/search/CIMIP6/) from scenario model intercomparison plan (MIP) (O’Neill et al 2016) with relatively good simulation accuracy are selected. The detailed information of each CMIP6 model is shown in table 1. The future scenarios are SSP1-2.6, SSP2-4.5, SSP5-8.5. SSP1-2.6 represents the sustainable development pathway, low forcing scenario, and the radiation forcing is stable at 2.6 W·m⁻² in 2100. SSP2-4.5 represents the moderate development pathway, moderate forcing scenario, and the radiation forcing is stable at 4.5 W·m⁻² in 2100. SSP5-8.5 represents the conventional development pathway, high forcing scenario, and the radiation forcing is stable at 8.5 W·m⁻² in 2100. The differences of three future scenarios are that SSP1-2.6, SSP2-4.5, SSP5-8.5 represent sustainability, middle of the road and fossil-fueled development’s shared socio-economic pathways respectively. In terms of forcing level, three future scenarios represent low, middle and high forcing level respectively (O’Neill et al 2016, Zhang et al 2019). The used precipitation data from CMIP6 models include historical experiment data during 1988–2014 and projected data during 2015–2064 (van Vuuren et al 2017).

2.3. Methods

2.3.1. Bias correction spatial downscaling method

Bias correction spatial downscaling of CMIP6 model outputs are essential steps to statistically downscaling the projected precipitation data (Tian et al 2021). The general process of bias correction spatial downscaling is showed in figure 2. The quantile mapping method, a bias correction method is adopted in this study (Boé et al 2007). It can reflect the change of variance of climate elements under the climate change condition and hence is widely used to correct bias in simulated precipitation data (Tiwari et al 2016, Ngai et al 2020, Tong et al 2020). This method is to correct the model simulation outputs based on the observed cumulative frequency curve of daily precipitation, ensuring that the corrected simulated cumulative frequency curve of daily precipitation is
Table 1. Details of the 5 climate models from CMIP6.

| Model name       | Institute                                      | Horizontal resolution (Lat × Lon) | Temporal resolution | convective parameterization scheme                      |
|------------------|------------------------------------------------|----------------------------------|---------------------|---------------------------------------------------------|
| BCC-CSM2-MR      | Beijing Climate Center, Beijing, China         | 1.125° × 1.125°                  | Daily               | BCC-AGCM3 (Wu et al 2019)                               |
| CanESM5          | Canadian Centre for Climate Modelling and Analysis, Canada | 2.8125° × 2.8125°               | Daily               | CanAM5 (Swart et al 2019)                               |
| IPSL-CM6A-LR     | Institute Pierre Simon Laplace, France         | 1.258° 74° × 2.5°               | Daily               | LMDZ6A (Hourdin et al 2020)                             |
| MPI-ESM1-2-LR    | Max Planck Institute for Meteorology, Germany  | 1.875° × 1.875°                  | Daily               | ECHAM6.3 (Müller et al 2018)                            |
| MRI-ESM2-0       | Meteorological Research Institute, Japan       | 1.125° × 1.125°                  | Daily               | MASINGAR mk-2r4c (YUKIMOTO et al 2019)                  |
consistent with the observed cumulative frequency curve. The detailed introduction of this method can be found in Lu et al (2018). Because the precipitation in the UYRB has obvious seasonal variation (Yue et al 2021), our study corrects daily precipitation bias in 12 months, respectively. The bias correction procedure is divided into three steps:

1. Interpolating CMIP6 raw data and 0.08° observation-based interpolated data (mentioned in 2.1) to 1.6° by bilinear interpolation algorithm (BIA) (Yan et al 2021);
2. Calculating the daily correction factor $F$ at each 1.6° grid in each month. The $F$ is defined as the ratio of the corrected CMIP6 daily precipitation to the multi-year mean daily interpolated precipitation;
3. Correcting the 1.6° CMIP6 daily data in each month by quantile mapping method.

The spatial disaggregation method is used in this study for spatial downscaling (Wood 2002, Wood et al 2004). Consistent with bias correction procedure, CMIP6 daily precipitation are spatially downscaled in 12 months, respectively. It is divided into two steps:

1. The daily correction factor $F$ of the 1.6° grid (see 2.3.1) is interpolated to the spatial resolution of 0.08° by bilinear interpolation algorithm in each month.
2. The downscaled 0.08° daily precipitation data is obtained by multiplying the daily correction factor at the spatial resolution of 0.08° by the multi-year mean daily precipitation of 0.08° observation.

2.3.2. Multi model ensemble method
The multi model ensemble method used in this study is derived from Huang et al (2021). It considers the differences of the mean annual precipitation, trend of annual precipitation between the model simulation and the observation during the historical period. The multi model ensemble of CMIP6 is to calculate the model weight. The weight of each model is calculated by:

$$W_i = \frac{M_i}{\sum_i M_i} \quad (1)$$

where, $W_i$ denotes the weight of model $i$; $M_i$ is an intermediate variable; $M_i$ is calculated by:

$$M_i = W_{b,i} \cdot W_{T,i} \quad (2)$$

where, $W_{b,i}$ is a factor to measure the difference of mean annual precipitation between the model $i$ simulation and the observation during the historical period; $W_{T,i}$ is a factor to measure the difference of trend of annual precipitation between the model $i$ simulation and the observation during the historical period.
\( W_{k,i} \) is calculated by:

\[
W_{k,i} = \frac{\text{std}(P)}{\sum_{i} \Delta t |P_{ik} - P_{ok}|}
\]

where, \( P \) is the model \( i \) simulated 27-year series of area average annual precipitation in the historical period (1988–2014); \( \text{std}(P) \) is the standard deviation of \( P \); \( P_{ik}, P_{ok} \) are model \( i \) simulated and observed area average annual precipitation in a certain year \( k \) respectively; \( \Delta t \) is the length of historical year (i.e., 27 in this study).

\[
W_{T,i} = \frac{\text{std}(P)}{|T_{i} - T_{o}| \cdot \Delta t}
\]

where \( T_{o}, T_{i} \) are observed and model \( i \) simulated trend of area average annual precipitation during historical period respectively.

Finally, the multi model ensemble precipitation (\( P_{\text{mmme}} \)) is calculated by:

\[
P_{\text{mmme}} = \frac{\sum_{i}^{N} W_{i} \cdot P_{i}}{\sum_{i}^{N} W_{i}}
\]

where, \( N \) is the total number of CMIP6 models, and \( P_{i} \) is model \( i \) simulated precipitation.

### 2.3.3. Evaluation metrics

For evaluating the spatial accuracy and temporal variability’s performance of bias correction spatial downscaling method in CMIP6 models, the skill score (TSS) (Taylor 2001, Zhu et al. 2020) and interannual variability skill score (IVS) are used (Chen et al. 2011, Zhu et al. 2020). The TSS is calculated as:

\[
\text{TSS} = \frac{4(1 + R)^2}{\left( \frac{\sigma_{so}}{\sigma_{sm}} + \frac{\sigma_{so}}{\sigma_{io}} \right)^2 (1 + R_{o})^2}
\]

where \( R \) is the spatial correlation coefficient between the simulated and observed annual precipitation based on all grids; and \( R_{o} \) is the maximum spatial correlation coefficient, usually 0.999 used (Zhu et al. 2020); \( \sigma_{sm} \) and \( \sigma_{io} \) are the simulated and observed spatial standard deviation of annual precipitation, respectively, \( \sigma_{sm} \) is the standard deviation of simulated annual precipitation of all grids, and \( \sigma_{io} \) is the standard deviation of observed annual precipitation of all grids.

The calculation formula of IVS is shown in (7):

\[
\text{IVS} = \left( \frac{\sigma_{so}}{\sigma_{sm}} - \frac{\sigma_{sm}}{\sigma_{io}} \right)^2
\]

where \( \sigma_{sm} \) and \( \sigma_{io} \) are the temporal standard deviation of the simulation and the observation respectively (Zhu et al. 2020). \( \sigma_{sm} \) is obtained by calculating standard deviation of 27-year simulated annual precipitation in each grid, and \( \sigma_{io} \) is obtained by calculating standard deviation of 27-year observed annual precipitation in each grid.

The TSS is firstly calculated for each year, and then the mean TSS is obtained for the whole historical period. TSS equaling to 1 indicates that the model simulation is spatially perfect, and equaling to 0 indicates it is opposite performance. The IVS is firstly calculated in each grid, and then the mean IVS is obtained for all grids. IVS equaling to 0 indicates that the model simulation is temporally perfect, and larger IVS means worse performance of the simulation.

In addition, we also use mean annual precipitation (MAP) and trend of annual precipitation (TAP) to evaluate the performance of bias correction spatial downscaling method, and we use the relative error (Re), absolute error (Ae), to measure the difference between the model simulation and the observation. The TAP is calculated as the slope of linear regression between annual precipitation series and year numbers in the historical period.

### 2.3.4. Extreme precipitation indices

Three extreme precipitation indices from the Expert Team on Climate Change Detection and Indices (ETCCDI, http://etccdi.pacificclimate.org/list_27_indices.shtml) are selected to evaluate the characteristics of extreme precipitation, including \( R95p \), \( Rx1day \), and \( R10mm \). More details are shown in table 2.

### 2.3.5. Comparison between the BCSD and bilinear interpolation algorithm method

It can improve the raw CMIP6 data’s resolution to 0.08° by the bilinear interpolation algorithm, however, the raw CMIP6 data have systematic error, thus using the bilinear interpolation algorithm directly will not eliminate the systematic error (Maurer and Hidalgo 2008, Yue et al. 2021). Therefore, in order to show the effectiveness of
bias correction spatial downscaling method, a comparison scheme is designed. We use bias correction spatial downscaling and bilinear interpolation algorithm to process the CMIP6 data respectively, for improving its resolution to 0.08°, then we compare the two methods’ performance on spatial accuracy and interannual variability. The bilinear interpolation algorithm is called BIA in the following content.

3. Results

3.1. Evaluation of the results of bias correction spatial downscaling

Table 3 shows the comparison results of TSS, IVS for the five CMIP6 models based on BIA and BCSD. Table 5. The mean annual precipitation under SSP1-2.6 during 2015-2064 increases most, up to 4.23%, followed by that under SSP5-8.5 and SSP2-4.5 respectively.

Table 3. TSS and IVS for the five CMIP6 models based on BIA and BCSD.

| Model           | TSS       | IVS       |
|-----------------|-----------|-----------|
|                 | BIA       | BCSD      | BIA       | BCSD      |
| BCC-CSM2-MR     | 0.34      | 0.86      | 0.57      | 0.33      |
| CanESM5         | 0.31      | 0.86      | 2.46      | 0.14      |
| IPSL-CM6A-LR    | 0.43      | 0.86      | 0.57      | 0.18      |
| MPI-ESM1-2-LR   | 0.31      | 0.86      | 1.41      | 0.20      |
| MRI-ESM2-0      | 0.35      | 0.88      | 0.45      | 0.20      |

*Note: TSS denotes Taylor skill score, IVS denotes interannual variability skill score, BIA denotes bilinear interpolation algorithm, BCSD denotes bias correction spatial downscaling.

3.2. Future change in annual precipitation

This study uses projected precipitation from multi model ensemble as the future precipitation and modeled downscaled precipitation as the historical precipitation in analyzing temporal and spatial changes in future precipitation. For the sake of illustration, the temporal evolution trend of annual precipitation over the historical period (1988–2014) and future period (2015–2064) in the UYRB is shown figure 3. The annual precipitation shows increasing trend under three scenarios in the future period. The mean annual precipitation changes in the UYRB is given in table 5. The mean annual precipitation under SSP1-2.6 during 2015-2064 increases most, up to 4.23%, followed by that under SSP5-8.5 and SSP2-4.5 respectively.
To analyze the mean annual precipitation change in different periods, the future period (2015–2064) is divided into the near term (2015–2039) and the long term (2040–2064). In the near term (2015–2039), the mean annual precipitation increases slightly under SSP2-4.5 while it decreases under SSP1-2.6 and SSP5-8.5. In the long term (2040–2064), the mean annual precipitation increases under three scenarios and it is larger than that in the near term (2015–2039) under three scenarios. The mean annual precipitation in the long term (2040–2064) under SSP1-2.6 is the largest, up to 877.0 mm, increasing by 8.85%, followed by that under SSP5-8.5 and SSP2-4.5 respectively.
The historical downscaled precipitation is shown in figure S1 in the Supplementary File. In the historical period, the mean annual precipitation increases gradually from the source region to southeast in this basin. The mean annual precipitation is larger in part of lower region of Mintuo river (MTR) and Jinsha river (JSR), the southeast of JiaLing river (JLR), the most regions of Wu river (WR) and Yibin Yichang river (YBYCR) basins, more than 1000 mm. Figures 4(a)–(c) shows the spatial distribution of mean annual precipitation under three scenarios in the future period (2015–2064). The heavy precipitation (mean annual precipitation is more than 1000 mm) occurs in part of lower region of MTR and JSR basins, the southeast of JLR basin, the most regions of WR and YBYCR basins. The mean annual precipitation is less than 400 mm in the local region of JSR basin, which is significantly lower than that in other regions.

Figures 4(d)–(f) shows the mean annual precipitation changes in the future period (2015–2064) relative to that in the historical period (1988–2014) under three scenarios. Under SSP1-2.6, the mean annual precipitation increases in most regions of the UYRB, except in part of the JSR basin (orange in figure 4(d)). However, under SSP2-4.5 and SSP5-8.5, the mean annual precipitation decreases in the middle and lower part of JSR basin, most regions of MTR basin, northwest of JLR basin, part of WR and YBYCR basins. Mean annual precipitation can significantly decrease by 6% at most (red in figures 4(e)–(f)). It indicates severer water shortage or drought problems may occur in some regions of the UYRB under higher radiation forcing scenario.

Figure 5 shows temporal evolution trend of the annual precipitation in the historical period (1988–2014) and future period (2015–2064) under three scenarios in five sub-basins. The annual precipitation generally has an increasing trend in five sub-basins under three scenarios. In contrast, the annual precipitation in JLR basin has an insignificantly decreasing trend under SSP2-4.5 during 2015–2064. Trend of annual precipitation under SSP1-2.6 scenario in five sub-basins is the largest compared with that under the other two scenarios, indicating trend of annual precipitation is more obvious under the lower radiation forcing scenario in the future.

Figures 6(a)–(c) shows mean annual precipitation change in the future period (2015–2064), in the near term (2015–2039) and in the long term (2040–2064) relative to that in historical period (1988–2014). The mean annual precipitation increases during 2015–2064 in five sub-basins under three scenarios except in JSR, MTR basins under SSP2-4.5 and SSP5-8.5. The mean annual precipitation decreases in WR, YBYCR basins compared with that in other basins. In the near term, the mean annual precipitation increases in WR, YBYCR basins under three scenarios, but it decreases in JSR, MTR basins under three scenarios. In JLR basin, the mean annual precipitation increases under SSP2-4.5 and SSP5-8.5, but it decreases under SSP1-2.6. In the long term, the mean annual precipitation generally increases in five sub-basins under three scenarios, except in MTR basin under SSP2-4.5 and SSP5-8.5, and especially in WR and YBYCR basins it increases more. Overall, the mean annual precipitation increases more in the long term in five sub-basins under three scenarios, than that in the near term.

Figure 7 shows interannual (1a ~ 1a) and interdecadal (10 ~ 50a) variability of annual precipitation under SSP1-2.6, SSP2-4.5 and SSP5-8.5. (a)–(c) represent the standard deviation of interannual precipitation, which show that interannual precipitation variability is gradually more intense from the source region to the southeast. (d)–(f) represent the standard deviation of interdecadal precipitation, which also show that interdecadal precipitation variability is gradually more intense from the source region to the southeast. Standard deviation of
interdecadal precipitation variability is generally larger than that of interannual precipitation variability over the whole UYRB under SSP1-2.6, SSP2-4.5 and SSP5-8.5, which shows interdecadal precipitation variability is more intense than interannual precipitation variability.

Figure 8 shows the historical mean precipitation, and future changes in the future period (2015–2064) relative to that during 1988–2014 in four seasons in the whole UYRB and five sub-basins in terms of area average. In historical period, the mean precipitation increases from spring to summer, and it decreases gradually from summer to winter, and the mean precipitation in summer is the largest in the whole UYRB and five sub-regions. Future precipitation changes in four seasons are spatially heterogeneous under three scenarios.

In JSR basin, the mean precipitation changes not significantly in four seasons under three scenarios, except in spring under SSP1-2.6, increasing by about 9%. In MTR basin, the mean precipitation increases most in winter under three scenarios, especially under SSP1-2.6, increasing by about 17%, but the mean precipitation decreases in summer under three scenarios. And the mean precipitation increases in spring under three scenarios, in autumn under SSP1-2.6, but it decreases in autumn under SSP2-4.5, SSP5-8.5. In JLR basin, the mean precipitation increases most in autumn and winter under three scenarios, especially under SSP1-2.6, both increasing by about 18%, and it increases in spring under three scenarios, but the mean precipitation decreases in summer under three scenarios. In WR basin, the mean precipitation generally increases in four seasons under three scenarios, especially in autumn under SSP1-2.6, increasing by about 17%, but the mean precipitation decreases slightly in winter under SSP2-4.5. In YBYCR basin, the mean precipitation increases in four seasons.
under three scenarios, especially in autumn under SSP1-2.6, increasing by about 17%. For the whole UYRB, the mean precipitation increases in spring, autumn and winter under three scenarios, especially in autumn under SSP1-2.6, increasing by about 11%, but the mean precipitation decreases slightly in summer under three scenarios.

3.3. Future change in extreme precipitation
The spatial distribution of extreme precipitation indices in the historical period (1988–2014) is shown in figure S2 in the Supplementary File. Distribution of three extreme precipitation indices is spatially heterogeneous. The values of three extreme precipitation indices generally increase from the source area to the southeast.

Figure 9 shows the extreme precipitation changes in the UYRB in the future period (2015–2064) relative to that in the historical period (1988–2014). R95p increases more significantly (up to 9% ~ 13%) in the local region of JSR, WR and YBYCR basins under SSP1-2.6 and SSP5-8.5. Rx1day increases in most regions of the UYRB under three scenarios. However, R10mm changes slightly in most regions of the UYRB, except that in the local region of JSR basin, increasing by more than 4%.

Figures 10(a)–(c) shows the relative change of extreme precipitation in terms of area average, including R95p, Rx1day and R10 mm in the future period (2015–2064) relative to that in the historical period (1988–2014). R95p increases in five sub-basins and in the whole UYRB except in the MTR basin under SSP2-4.5, SSP5-8.5. R95p increases more in the WR, YBYCR basins. Rx1day increases in five sub-basins and in the whole
Figure 8. Relative change of mean precipitation in four seasons in the whole UYRB and five sub-basins in the future period (2015–2064) relative to that during 1988–2014.

Figure 9. Spatial distribution of relative change of extreme precipitation indices in the future period (2015–2064) relative to that during 1988–2014 in the UYRB: (a)–(c) R95p, (d)–(f) R×1day, (g)–(i) R10 mm.
Our study reveals that the precipitation has increasing trend in the future over the UYRB. In the future, global temperature will have significant increasing trend (IPCC 2021), and the climate is also warmer over the YRB (Yue et al 2021). The rising temperature will warm the Indian Ocean, which is conducive to the west of the subtropical high and the south of the subtropical westerly jet, resulting in precipitation increasing in the YRB (Zhou et al 2018). On the other hand, the impact of increasing global surface temperature on the extreme precipitation has field significance, therefore leading to that the extreme precipitation will also increase in the future over the YRB (Lü et al 2018). Furthermore, with the increasing of temperature, the content of water vapor in the atmosphere increases, which will lead to the increase of precipitation in the YRB (Zhou et al 2018).

Our study reveals that the increasing trend of precipitation is more obvious under SSP1-2.6 over the UYRB. SSP1-2.6 represents the sustainable development pathway, low forcing level, and the radiation forcing is stable at 2.6 W m$^{-2}$ in 2100 (Zhang et al 2019). Under SSP1-2.6, lower radiative forcing means lower emission of aerosols and greenhouse gases (Jiang et al 2020a, 2020b), which are conducive to enhancing the East Asian monsoon activity (Wu et al 2015, Zhou et al 2020). According to previous studies, with the increase of the frequency and intensity of East Asian monsoon activity, the precipitation in the YRB will increase more significantly (Wu et al 2015, Zhou et al 2020). Therefore, the precipitation in the YRB will increase more obviously under SSP1-2.6 in the future. However, our study is different from Yue et al (2021), which indicated the precipitation in the YRB would increase most under SSP5-8.5 in the future, followed by that under SSP2-4.5 and SSP1-2.6 respectively. The reasons for different results between the two studies may be selecting different CMIP6 models, as well as different future periods. The future period in our study is from 2015 to 2064, but it is during 2025–2100 in Yue et al (2021). Our study selects 5 CMIP6 models, and there are 23 CMIP6 models in Yue et al (2021). Each CMIP6 model has different dynamic frames, physical processes, parameterization scheme and initial value setting when designed, and each CMIP6 model has different sensitivity to greenhouse gas forcing, which will bring differences when simulating future precipitation projection (Lin et al 2016, 2018). Furthermore, we use BCSD method to process the CMIP6 data for improving the resolution to 0.08°, but the resolution in Yue et al (2021) is 0.5°. Our study region is the YRB, but the study region is the whole YRB in Yue et al (2021). Over the whole YRB, the multi-terraced terrain and interactions between different circulation systems will result in complex climate status in the region, thus the precipitation distribution is spatially heterogeneous and change characteristics are complicated (Chen et al 2014).

Our study finds that the mean precipitation in spring (March to May) increases in JSR, WR and YBYCR basins under SSP1-2.6 and SSP5-8.5, while the mean precipitation in summer (June to August) decreases in JSR basin under three scenarios. It is in contrast with the results in Deng et al (2013), which used CMIP5 models. In terms of extreme precipitation indices, our study finds R10 mm changes slightly in most regions of the whole UYRB under three scenarios, differing from the result in Li et al (2013), which indicated R10 mm would increase
significantly under RCP4.5 and RCP8.5 in the upper JSR basin and MTR basin, by up to about 10%. The different study results may be originated from the discrepancy between CMIP6 and CMIP5 models. The representative concentration pathways (RCPs) scenario in CMIP5 only consider the goal of achieving stable CO2 concentration and corresponding radiation forcing in the next century, but it does not target specific socio-economic development pathways. The scenario in CMIP6 is a combination scenario of different shared socio-economic pathways (SSPs) and RCPs, including the future’s socio-economic development (Zhang et al 2019, Jiang et al 2020a, 2020b), and the combination of SSPs and RCPs makes future scenarios more reasonable (O’Neill et al 2016). Moreover, models from CMIP6 have improved in physical mechanism, dynamical representation and parameterization schemes compared with that from CMIP5 (Eyring et al 2019). Moreover, Li et al (2013) used meteorological observations from 529 stations covering the historical period of 1960–2005, from the NMIC of the CMA.

The uncertainty of BCSD method is from the interpolating process from the 1.6° grid to the spatial resolution of 0.08°. The effectiveness of BSCD method is based on the assumption that large-scale weather exhibits strong influence on small-scale weather (Maraun et al 2010). In our study, we assumed that the large-scale (1.6°) does not interpret any small-scale (0.08°) variability, which is consistent with (Wood et al 2004, Wang and Chen 2014, Lorenz et al 2021). For example, Maurer and Hidalgo (2008) used BCSD to downscale GCMs from 1.4° to 0.125°. The uncertainty of downscaling method has been analyzed by Wood (2002), Maraun (2012, 2013), and the uncertainty of BCSD method on the trend results in our study should be further analyzed.

The above discussions suggest that there are differences when projecting future changes in precipitation in this basin. Reasons for differences may be from selecting different climate models, ground-based observation, resolution and time range. Nevertheless, our study provides a timely updated result based on more accurate climate projections and ground-based observation, and more studies are still needed in the future.

5. Conclusions

Based on CMIP6 data and observed precipitation data from the meteorological stations, the temporal and spatial change characteristics of precipitation in the whole UYRB and five sub-basins are analyzed. The major conclusions are as follows:

(1) The BCSD method is used to reduce the systematic error of CMIP6 models, and it improves the spatial resolution, and the performance of CMIP6 models on spatial accuracy and interannual variability improves.

(2) Under SSP1-2.6, SSP2-4.5 and SSP5-8.5 scenarios, relative to that in the historical period (1988–2014), the mean annual precipitation over the UYRB increases during 2015–2064, and it increases more in the long term (2040–2064) than that in the near term (2015–2039). Interdecadal precipitation variability is more intense than interannual precipitation variability. Therefore, under the background of global warming, the precipitation will have increasing trend in the UYRB, and the increasing trend is more obvious in the long term (2040–2064).

(3) Three extreme precipitation indices, including R95p, Rx1day and R10 mm, generally increase in the whole UYRB and five sub-basins. R95p and Rx1day increase more in WR and YBYCR basins with relatively high mean annual precipitation than that in other three sub-basins, especially for R95p. R10 mm changes slightly in all sub-basins. The lower region of the UYRB may face greater risk of extreme precipitation.

(4) Under the scenario of lower radiative forcing, the precipitation will increase more significantly, which means lower emission of aerosols and greenhouse gases may increase the risk of flood disaster in the future in the UYRB.

Acknowledgments

This work was supported by the Open Research Fund Program of State key Laboratory of Hydroscience and Engineering (sklhe–2021–A-05), National Natural Science Foundation (No. 51922063) and the scientific project of China Three Gorges Corporation (Grant No. 202003098). The authors are grateful to the anonymous reviewers for their invaluable comments and for editing a previous draft of the manuscript.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.
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