Bias correction, historical evaluations, and future projections of climate simulations in the Wei River Basin using CORDEX-EA

Yinping Wang¹ · Rengui Jiang¹ · Jiancang Xie¹ · Jiwei Zhu¹ · Yong Zhao² · Xixi Lu³ · Fawen Li⁴

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Abstract

The utilization of regional climate methods (RCMs) to predict future climate is an important study under the changing environment. The primary objective of the paper is to correct the temperature and precipitation simulations for the period of 1980–2005 and 2026–2098 in the Wei River Basin (WRB), to evaluate the performance of RCMs for the period of 1980–2005, and further, to analyze the future changes of projected temperature and precipitation during 2026–2098. In this paper, the linear scaling method was used to correct the temperature simulations. Quantile mapping, local intensity scaling method, and hybrid method were used to correct the precipitation simulations. The future changes of projected temperature and precipitation for the near term (2026–2050), mid-term (2051–2075), and far term (2076–2098), relative to the period of 1980–2005, were investigated under RCP 2.6 and RCP 8.5. Results indicate that (1) the temperature biases were either warm or cold in the spatial scale, and the precipitation wet biases were detected. After correction, HadGEM2-ES driven by RegCM4-4 had the best temperature reproducibility, and NCC-NorESM1-M driven by RegCM4-4 had the best precipitation reproducibility. (2) Under RCP 2.6, the projected annual, winter, and spring temperature showed decreasing trends. The temperature was higher than that for the period of 1980–2005 except for the spring temperature decreases in the Beiluo River Basin. Under RCP 8.5, the temperature showed significantly increasing trends. The temperature for the near term was similar to that of the period of 1980–2005, while the temperature increased significantly for the mid-term and far term. (3) Under RCP 2.6, the precipitation had decreasing trends. Under RCP 8.5, precipitation trends were also spatially distributed. The relative deviation of winter precipitation was the largest. Relative to the period of 1980–2005, the light- and moderate-rain days showed little change for the period of 2026–2098, while the extreme-rain days showed significantly increasing trends.

Keywords Precipitation and temperature variability · Future climate projection · Bias correction · High-resolution RCMs · CORDEX-EA · Wei River Basin

1 Introduction

Climate change could be recognized as one of the most important challenges that we have ever faced, with increasingly severe adverse effects (e.g., climate warming, extreme weather events) at different spatial and temporal scales (Ozturk et al. 2018; Almagro et al. 2020). According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC 2021), global surface temperature will continue to increase until at least the mid-century, and global warming of 1.5 °C relative to 1850–1900 would be exceeded during the twenty-first century. Adaptation to the projected climate is challenging because of the uncertainty and complexity of the climate system (Ahmed et al. 2020). Several studies have documented the magnitude of projected increase in temperature varies with altitude, and the
projected change in precipitation is also different between wet and dry regions (Pepin et al. 2015; Pang et al. 2021). Studying the characteristics of the history of climate change can play an important role in understanding the future of climate change. It is necessary for ensuring appropriate climate change planning and water resources policies to improve the reliability of projected change in temperature and precipitation.

Over the years, global climate models (GCMs) are usually used to assess the global future climate projections (Maidment et al. 2015; Ayugi et al. 2020). A GCM is an important tool to simulate global climate response to changes in greenhouse gas concentrations, which has been widely recognized in the fifth phase of the Coupled Model Inter-comparison Project (CMIP5) (Almagro et al. 2020). However, the resolution of current GCMs is 100–200 km (Ngai et al. 2020), which makes it impossible for them to obtain the mesospheric processes and the dynamics driving such physical process, and also limits their direct application in regional-scale hydrological impact assessment (Giorgi 1990; Fowler et al. 2007; Maran et al. 2017). High-resolution and dynamically downscaling regional climate models (RCMs) might provide more information for climate change detection (Giorgi and Gutowski 2015). RCMs, with a resolution of approximately 12–50 km (Dong et al. 2018), have been widely used to predict regional climate information and simulate the regional hydrological processes (Leung et al. 2004; Niu et al. 2020). Indeed, previous studies have demonstrated that RCMs have advantages over GCMs in terms of regional climate characteristic detection (Gao et al. 2012; Zou and Zhou 2016).

Although RCMs could make up for the deficiency of coarse resolution of GCMs, there are still systematic errors from the initial conditions, the driving GCMs process, and the physical parameterization schemes. It makes the direct utilization of RCMs in the regional climate studies have a certain impact on the simulation results (Au-Yeung and Chan 2012; Shen et al. 2020). Therefore, from the perspective of necessity rather than validity (Ehret et al. 2012), a number of post-processing techniques have been applied to RCMs to eliminate systematic errors in climate prediction studies. These methods include local intensity scaling (Themessl et al. 2011), the histogram equalization method (Dong et al. 2019), quantile mapping (Ngai et al. 2017), linear scaling method (Dong et al. 2019), the multivariate 3-dimensional bias-correction method (Hu et al. 2020), and so on. These post-processing methods could make future climate simulation projections better by adjusting the RCMs’ output based on the observation characteristics.

The initiative to the Coordinated Regional Climate Downscaling Experiment (CORDEX) was proposed by the World Climate Research Programme in 2009 to further advance the development and application of RCMs (Giorgi et al. 2009). The CORDEX has been created or is in progress for a number of regions around the world, with a total of 14 domains, which is the ensemble of models driven by multiple CMIP5 GCMs (Li et al. 2018). Currently, it has the second phase. The Wei River Basin (WRB) is located in the CORDEX-EA domain. A number of previous studies have evaluated the performance of RCMs in CORDEX-EA. On the one hand, RCMs are used to predict the future change of climate factors, such as precipitation (Hui et al. 2019), temperature (Yu et al. 2020), and evapotranspiration (Yang et al. 2020), as well as extreme climate events (Yang et al. 2019), heat wave (Wang et al. 2019), and wind resources (Gao et al. 2019), etc. On the other hand, RCMs, combining with hydrological models, are used to simulate hydrological impacts caused by climate (Dong et al. 2019; Hu et al. 2020).

As the global climate changes, it is essential to understand how the projected climate will change in the WRB. In previous studies, too little work has been devoted to the projected temperature and precipitation change in the WRB. Zuo et al. (2015) studies the response of runoff to future climate change using downsampling GCMs in the WRB. Zhao et al. (2019) investigates the change of hydrological droughts using the bias-corrected climate projections from GCMs in the WRB. However, the low accuracy of GCMs cannot better adapt to the future climate change of projections in some little areas in the WRB. In this study, we aimed at correcting the RCMs of CORDEX-EA using different bias-correction methods over WRB, evaluating the performance of RCMs, and investigating projected temperature and precipitation changes of the most adaptable RCM under RCP 2.6 and RCP 8.5.

The paper is organized as follows: the study area, the datasets, the bias-correction methods, and the evaluation metric used in this study are described in Sect. 2. In Sect. 3, the results and discussion are presented, including that (1) relative to the observations, the reproducibility of RCMs to temperature and precipitation is evaluated in the WRB during the period of 1980–2005 (base period, BAP) in Sect. 3.1; (2) the different bias-correction methods are used to calibrate simulations, and the applicability of different methods is evaluated in Sect. 3.2; (3) the projected temperature and precipitation trends are analyzed during the period of 2026–2098 (whole-term period, WTP), and the projected annual and seasonal temperature and precipitation changes during the periods of 2026–2050 (near-term period, NTP), 2051–2075 (mid-term period, MTP), 2076–2098 (far-term period, FTP) relative to the BAP are investigated under RCP 2.6 and RCP 8.5 in Sect. 3.3. The last section summarizes the conclusions.
Materials and methods

2.1 Study area

The WRB is the largest tributary of the Yellow River Basin, with a total length of 818 km and a drainage area of $1.34 \times 10^5$ km$^2$. The northern part of the WRB is the Loess Plateau, the central part is Guanzhong Plain, and the southern part is the Qinling Mountains (Zhang et al. 2021). Topographically, the elevation of the western WRB is higher. The WRB is located in the continental monsoon climate zone, and the climatic conditions of the whole year are obviously different. The WRB consists of the main stream of WRB, the Jing River Basin (JRB), and the Beiluo River Basin (BRB), which are two tributaries of the WRB (Fig. 1). Among the tributaries, the JRB has the largest area, accounting for 33.7% of the WRB, while the BRB is the longest with a total length of 680 km (Zuo et al. 2014). According to the river morphology, the main stream of the WRB could be divided into three parts. The upstream of the WRB rises from the Qin Mountains. The midstream of the WRB is located from Baoji Gorge to Xianyang. The downstream of the WRB runs from Xianyang to Tongguan, where it flows into the Yellow River Basin (Jiang et al. 2019). The WRB provides water resources for domestic, industrial and agricultural purposes in the Guanzhong Plain, and promotes economic and social development in western China. Therefore, under the policy of high-quality development of the Yellow River Basin, the management of water resources in the WRB still needs to be strengthened. The projection of future temperature and precipitation in the WRB can provide preferences for water resources management in the WRB.

2.2 Climate data

The gridded daily temperature and precipitation observations at a spatial resolution of $0.5^\circ \times 0.5^\circ$ were obtained from the Chinese Meteorological Administration in this study. The data from 1980 to 2005 were used for bias correction in the study, to coincide with the historic period of CORDEX-EA. Two RCMs were used in the study: (1) RegCM4-4 developed by the International Centre for Theoretical Physics and (2) REMO2015 developed by the Climate Service Center Germany. Both are the hydrostatic regional climate models. The dynamic model of the former is the same as that of the hydrostatic version of the fifth generation of the Penn State/NCAR Mesoscale Model (Giorgi et al. 2012), the latter uses physical parameterizations from European Centre Hamburg Version 4 (Roeckner et al. 1996) and a dynamical framework from the weather forecast model of the German Weather Service Europa-Modell (Wang et al. 2021). The RegCM4-4 and REMO2015 have successfully applied to multiple domains (i.e., America, Europe, Asia, Africa, and the Mediterranean) in long-term climate simulations and climate change studies over the last two decades (Builes-Jaramillo and Pantano 2021; Pang et al. 2021; Ozturk et al. 2018; Top et al. 2021; Velikou et al. 2019). Both simulate most climate types relatively well, with high skill scores (Remedio et al. 2019).

Fig. 1 Locations of study area
The atmospheric boundary conditions used for RegCM4-4 come from three widely used GCMs available from the CMIP5 experiment: the Hadley Centre Global Environmental Model version 2 Earth system model (HadGEM2-ES) (Collins et al. 2011), the Max Planck Institute for Meteorology-Earth system model-mixed resolution (MPI-ESM-MR) (Jungclaus et al. 2013), and the Norwegian Climate Center’s Earth System Model (NCC-NorESM1-M) (Bentsen et al. 2013). HadGEM2-ES, the Max Planck Institute for Meteorology-Earth system model-low resolution (MPI-ESM-LR) (Jungclaus et al. 2013), and NCC-NorESM1-M were used in REMO2015. The spatial resolution of RegCM4-4 is 25 km, and that of REMO2015 is 0.22°. The detailed information is shown in Table 1. We used RegCM4-4 and REMO2015 simulations available from the CORDEX experiment for the East Asia domain. To facilitate bias correction, temperature and precipitation were interpolated to a common grid of 0.22° × 0.22° latitude/longitude using bilinear interpolation (Dong et al. 2019).

2.3 Bias-correction methods

Although RCMs use complex physical parameterization to detail processes in the land–atmosphere continuum, there are still systematic biases for the simulation data, which justifies the use of bias correction (Dong et al. 2019). Considering the time dependence of the model biases and relative short time sequence of historical simulations, cross validation was used to calibrate and validate the performance of the RCMs (Shen et al. 2020). The 26-year period 1980–2005 is used as the base period (BAP). For calibration, 20 years was randomly selected out of the BAP as the reference period, and the remaining 6 years was used for validation as the validation period. The whole cross-validation process was repeated 30 times to overcome the limitation of insufficient sample sizes and enhance the robustness of the validation results. In the study, the quantile mapping method (QM), the local intensity scaling method (LOCI), the QM-LOCI method, and the LOCI-QM method are chosen to correct precipitation, and the temperature is corrected using the linear scaling method. The correction methods were used to get the bias-correction factors in the reference period, and the bias-correction factors were applied in the validation period and WTP.

2.3.1 Quantile mapping

The QM derived from the statistical transformation was developed by Panofsky and Brier (1968). It has been widely used in the bias correction of both GCMs and RCMs. The QM method focuses not only on the average values and standard deviations of the distribution but also on correcting the quantiles of the distribution. The transformation is defined as Eq. 1 (Ngai et al. 2017). The statistical transformation implementation of QM can be classified into (1) distribution-based transformations, (2) parametric transformations, and (3) non-parametric transformations. Gudmundsson et al. (2012) found that non-parametric transformations usually produced a better performance compared with the distribution-based transformations and parametric transformations when using QM for deviation correction.

\[
P_o = TF(P_m) = F_o^{-1}(F_m(P_m))
\]

where \(P_o\) and \(P_m\) denote the observation and simulation. \(F_m\) is the cumulative distribution functions of \(P_m\) and \(F_o^{-1}\) is the inverse cumulative distribution functions of \(P_o\).

The empirical quantile mapping method is used to solve Eq. 1 using the empirical cumulative distributions function (ecdf) of observed and simulated values instead of theoretical cumulative distribution functions. It is one of the non-parametric methods. Taking month as the application window of the QM, by adjusting the quantiles of the RCM data \(P_{\text{hist},m,d}\) and \(P_{\text{rcp},m,d}\) to those of the observed data \(P_{\text{obs},m,d}\), the bias-corrected distribution of \(P_{\text{hist},m,d}\) and \(P_{\text{rcp},m,d}\) could match the distribution of \(P_{\text{obs},m,d}\) (Vormoor et al. 2015). The transformation function is given as follows:

\[
P_{\text{BAP},m,d}^{\text{cor}} = ecdf_{\text{obs},m}^{-1}(ecdf_{\text{BAP},m}(P_{\text{BAP},m,d}))
\]

\[
P_{\text{rcp},m,d}^{\text{cor}} = ecdf_{\text{obs},m}^{-1}(ecdf_{\text{BAP},m}(P_{\text{rcp},m,d}))
\]

where \(P_{\text{BAP},m,d}\) and \(P_{\text{rcp},m,d}\) denote the simulated precipitation before and after correction in the BAP. \(P_{\text{rcp},m,d}\) and \(P_{\text{BAP},m,d}\) denote the simulated precipitation before and after correction in the WTP under RCP 2.6 and RCP 8.5. \(m\) and \(d\) denote the month and day. \(ecdf_{\text{obs},m}\) and \(ecdf_{\text{BAP},m}\) denote the empirical cumulative distribution function of observations and simulations in the BAP especially. \(ecdf_{\text{obs},m}^{-1}\) represents the inverse of \(ecdf_{\text{obs},m}\).

2.3.2 Local intensity scaling

LOCI is a bias-correction method based on the mean values, which directly correct GCMs’ or RCMs’ outputs for

| Abbreviated name | GCM name         | RCM name       | Resolution |
|------------------|-----------------|----------------|------------|
| C1               | HadGEM2-ES      | RegCM4-4       | 25 km      |
| C2               |                  | REMO2015       | 0.22°      |
| C3               | MPI-ESM-MR      | RegCM4-4       | 25 km      |
| C4               | MPI-ESM-LR      | REMO2015       | 0.22°      |
| C5               | NCC-NorESM1-M   | RegCM4-4       | 25 km      |
| C6               |                  | REMO2015       | 0.22°      |
the observations. LOCI was developed by Widmann and Bretherton (2000). It corrects the wet-day frequency and intensity on a monthly basis by a scaling factor calculated from observations and simulations in the reference period, then expands to the scenario data (Fang et al. 2015). LOCI normally includes three steps (Li et al. 2019):

1. The wet-day threshold for the observations and simulations is determined from the observed and simulated daily precipitation series for each month to ensure that the threshold exceedance of simulations is equal to the observed precipitation frequency for the reference period (Eq. 4).

\[ F_{\text{wet}}(P_s^m \geq P_t^m) = F_{\text{wet}}(P_o^m \geq P_t^o) \]  

(4)

where \( P_s^m \) and \( P_o^m \) denote the simulated and observed precipitation for the reference period, especially. \( P_t^s \) and \( P_t^o \) are the monthly thresholds of simulations and observations. Themessl et al. (2011) found that the observation thresholds had no significant differences on the correction results.

2. A scaling factor \((s)\) is calculated to ensure that the means of simulations and observations are equal for each month (Eq. 5).

\[ S = \frac{P_o^m}{P_s^m} \times \frac{P_s^o \geq P_t^s - P_t^o}{P_o^m \geq P_t^o} \]  

(5)

3. The monthly thresholds and scaling factors determined in the reference period are further used to correct precipitation simulations in the validation period and WTP (Eq. 6).

\[ \hat{P}(t) = \max (P_o^s(t) + s \times (P_s^m(t) - P_s^o), 0) \]  

(6)

where \( P_s^o(t) \) and \( \hat{P}(t) \) denote the simulated precipitation before and after correction in the validation period and WTP.

2.3.3 Hybrid method

Similar to the daily bias-correction method, both LOCI-QM and QM-LOCI are obtained by combing QM and LOCI. The daily bias-correction method is a hybrid method combining the daily translation and LOCI method. Both QM and daily translation are quantile-based correction methods (Chen et al. 2013). LOCI-QM first uses the LOCI method to insure the frequency of precipitation occurrence for a month of corrected data which is equal to that of the observed data, and then uses the QM method to correct the frequency distribution of precipitation. On the contrary, QM-LOCI uses the QM method first and then the LOCI method. QM, LOCI, QM-LOCI, and LOCI-QM are hereafter referred to as M1, M2, M3, and M4.

2.4 Model simulation evaluation

The performance of the RCMs was evaluated on annual, winter (December-January-February, DJF), spring (March-April-May, MAM), summer (June-July-August, JJA), autumn (September-October-November, SON), and monthly time scales. The performance of different bias-correction methods and RCMs was also evaluated based on the cross-validation results. In order to evaluate the correction results of different methods for precipitation under the same RCM, 39 indicators were analyzed based on the mean and standard deviation of the annual, seasonal, and monthly scales, as well as the quantiles of 25%, 50%, 75%, 90%, and 99%.

The evaluation of different model performances makes use of the standard deviation, the spatial correlation coefficient, and the root-mean-square error (RMSE). A Taylor diagram was used to assess the differences between RCM simulations and observations to evaluate the performance of different models. A Taylor diagram (Taylor 2001) shows the ratio of the standard deviations for the simulations and observations, and the correlation coefficient and the RMSE between the simulations and observations. The overall framework of the study is shown in Fig. 2.

3 Results

3.1 Evaluation of different models driven by RegCM4-4 and REMO2015

The annual and four seasons’ biases in the different GCMs’ simulated temperature and precipitation driven by RegCM4-4 and REMO2015 for the BAP are analyzed relative to observations, to evaluate the ability of RCMs to reproduce the regional climate in the WRB. Figure 3 shows the temperature observations, and differences between the simulations and observations, in the BAP. Figure 4 is the same as Fig. 3, but for precipitation. It can be seen from Fig. 3(a) and Fig. 4(a) that the spatial distribution trends of annual and seasonal temperatures in the WRB are similar, and the same for precipitation. Temperature and precipitation decrease from the southeast to the northwest. Further, the spatial distributions of temperature biases for C1, C3, and C5 are mostly similar, while those of C2, C4, and C6 are similar. It shows that the spatial distributions of biases between the simulations and observations are same for the same RCM, and different RCMs produce quite different spatial distributions of temperature biases in the WRB (Yu et al.
The above analysis is also consistent for the precipitation (Fig. 4(b–g)). There are cold biases in annual and seasonal temperatures in the WRB for the RegCM4-4. Except for JJA, there are cold biases in the annual and seasonal temperatures in the upstream of the WRB for the REMO2015, while there are warm biases over the rest of the simulated area. For the cold biases in the WRB, they may be caused by the cold biases of simulations or the warm biases of observations. The former may be inherited from the GCMs (Wang et al. 2021), and be attributed to inadequate representation of physical processes, such as overestimated topographic forcing and snow cover (Tapiador et al. 2020; Pang et al. 2021). The latter may be connected with the fact that most meteorological stations are located in valleys, making the observations include warm biases for high-altitude areas (Wang et al. 2016). For the warm biases in the WRB, they may be caused by the overestimation of downward long-wave radiation (Pang et al. 2021). There are significant wet biases in annual and seasonal precipitation for the RegCM4-4 and REMO2015 with the exception of the REMO2015 which show the mixture of wet and dry biases in the JJA and SON. Precipitation includes large-scale precipitation and convective precipitation (Wang et al. 2016), and precipitation simulations are preponderantly affected by atmosphere forcing and the cumulus parameterization scheme (Niu et al. 2020). The wet biases may be caused by the overestimation of large-scale precipitation (Pang et al. 2021). From the perspective of simulations and observations, the wet biases may be caused by the overestimation of simulations or the underestimation of observations. The former stems from overestimated precipitation in the GCMs (Wang et al. 2021). The latter may be due to lack of correction for rain gauge measurements, particularly for solid precipitation in the cold season (Wu and Gao 2013).

Although the spatial distributions under the same RCM are similar, there are differences between the biases for each GCM relative to the observations. According to the comprehensive evaluation of the maximum, minimum, and mean value of temperature difference between simulations and observations in the spatial grid, the annual and seasonal temperature biases of HadGEM2-ES are relatively small, and the precipitation biases of MPI-ESM-MR and MPI-ESM-LR are relatively small. The biases are found for all seasons, but vary from season to season. The DJF temperature biases of simulations driven by RegCM4-4 are smaller than those of JJA, while those driven by REMO2015 are the opposite. The relatively larger biases in the winter are possibly caused by the poor representation of land surface processes (Ozturk et al. 2012; Yu et al. 2020). The absolute bias of JJA precipitation simulations is the largest, but the relative bias is the largest in DJF.

### 3.2 RCM evaluation after different bias-correction methods

Based on the 39 indicators, the relative deviations between the uncorrected simulations and observations, as well as between the corrected simulations and observations, are calculated respectively. The relative deviation difference is used to represent the difference between the above two relative deviations. The larger the absolute value of the relative deviation difference is, the closer the corrected simulation is to the observation. Therefore, the applicability of the bias-correction method for the RCMs is better. As shown in Fig. 5, M3 has a better correction performance on C1.
C3, and C6, while M2 has a better correction effect on C2, C4, and C5.

The applicable bias-correction method for the RCMs is obtained through the results of relative deviation difference. Additionally, the relative deviation between the corrected precipitation simulations and observations is analyzed by using 34 indicators based on precipitation mean and standard deviation. The smaller the relative deviation is, the closer the corrected simulations are to the observations. As can be seen from Fig. 6, the relative deviation of the six models range from $-8.12$ to $15.94\%$ for the average annual precipitation, and from $-5.58$ to $34.79\%$ for the annual standard deviation. The relative deviation is larger in SON and DJF for the mean seasonal precipitation, while it is larger in MAM and SON for the seasonal standard deviation. The relative deviation of the mean monthly precipitation for the six models is smaller from May to August, ranging from $-17.49$ to $35.39\%$, which is consistent with the result in Sect. 3.1. The relative deviation of precipitation is small in JJA. In general, the C5 corrected
by M2 is closer to the observations among the corrected simulations.

For a more quantitative and systematic evaluation, the Taylor diagram is used to illustrate the performance of the RCMs. Figure 7 demonstrates the Taylor diagrams for the spatial distributions of the annual and seasonal temperature and precipitation in the WRB. All RegCM4-4 and REMO2015 simulations successfully reproduce the spatial distribution of temperature with correlation coefficients greater than 0.95 with the exception of DJF. Compared with the six models, the C1 performs much better, as indicated by higher correlation coefficients and smaller RMSEs in all seasons. For the precipitation, the RegCM4-4 and REMO2015 simulate precipitation with greater skill for the wet season, particularly in JJA. The C5 reproduces precipitation with the greatest skill, which is the same result as Fig. 6.
3.3 Climate projections under RCP 2.6 and RCP 8.5

3.3.1 Changes in projected temperature for the period of 2026–2098

Considering the performance of different corrected RCMs, the corrected C1 was used to analyze the projected temperature. Figure 8 shows the spatial distributions of predicted future trends of temperature under RCP 2.6 and RCP 8.5 in the WTP. As shown in Fig. 8(a), the future temperature of JJA and SON shows increasing trends, while the temperature of DJF and MAM shows decreasing trends under RCP 2.6. It can be seen from Fig. 8(b) that the future annual and seasonal temperatures have statistically decreasing trend at 5% significant level in the WRB under RCP 8.5 for the period of 2026–2098.

Annual and seasonal temperature differences between three periods and the BAP are shown in Fig. 9(a–c) under RCP 2.6. From the perspective of annual temperature, the temperature of NTP, MTP, and FTP in the WRB is higher than that of BAP. Relative to temperatures in the BAP, the increase is greatest for the MTP, which is the same result as that of Wang et al. (2021). Similarly, the temperature in DJF, JJA, and SON increases compared to the BAP. Notably, the DJF temperature increases are more significant in the main stream of WRB, while the JJA temperature increases are spatially uniform in the WRB. It can
Fig. 6 (a) The relative deviation between the corrected mean precipitation and observations on the annual, seasonal, and monthly scales. (b) As Fig. 6(a), but for the precipitation standard deviation. The interpretation of C1 to C6 is shown in Table 1. M1 to M4 represents quantile mapping, local intensity scaling, quantile mapping-local intensity scaling, and local intensity scaling-quantile mapping. avg and SD represent the mean and standard deviation of annual, seasonal, and monthly scales.

Fig. 7 Taylor diagram for the spatial variability of annual and seasonal mean (a) temperature and (b) precipitation simulated by six models. The radial distance from the origin is the ratio between the simulated and observed standard deviation of the temperature and precipitation during the validation period. The azimuthal position is the correlation coefficient between the simulation and observation. The distance from the Obs point demonstrates the normalized centered RMSE. Obs is the observations. The interpretation of C1 to C6 is shown in Table 1.
be clearly seen that the MAM temperature decreases are mainly in the BRB for NTP, MTP, and FTP.

Annual and seasonal temperature differences between RCP 2.6 and RCP 8.5 in three periods are shown in Fig. 9(d-f). For the NTP, the temperature increases under RCP 8.5 are similar to those under RCP 2.6 in the WRB, with differences between them ranging from −0.38 to 0.15 °C. Relative to temperatures under RCP 2.6, the temperature increases of NTP, MTP, and FTP increase accordingly. Unsurprisingly, a significant rise in projected temperature is due to the increase in greenhouse gas emissions under RCP 8.5. In the FTP, mean annual temperatures under high-emissions scenario RCP 8.5 will be 3.76 °C higher than those of RCP 2.6, ranging from 3.23 to 4.19 °C. Furthermore, it will be 4.40 °C higher on average than the BAP, with a spread of 3.23–5.19 °C. Compared to temperatures under RCP 2.6, the temperature increase of MAM is the largest in the NTP and MTP, and the largest temperature increase is detected in SON in the FTP. Compared with temperatures in the BAP, the regional average temperature will significantly increase by 4.66 °C in DJF, by 3.27 °C in MAM, by 4.36 °C in JJA, and by 5.58 °C in SON by the end of the twenty-first century under RCP 8.5. Apparently, the largest temperature increase is in SON in the FTP.

Figure 10(a) shows the monthly temperature in the BAP and the temperature difference between three periods and BAP under RCP 2.6 and RCP 8.5. Under high-emissions scenario RCP 8.5, the temperature increases
are the greatest in the FTP and the smallest in the NTP. However, the interannual variation trends of temperature differences in the three periods are the same, with the maximum in November and the minimum in May. There are temperature increases and temperature decreases for monthly temperature difference in the three periods under low-emissions scenario RCP 2.6. Meanwhile, the interannual variation trend of temperature differences in the three periods are the same, with the maximum in November and the minimum in April. On the whole, monthly temperature increases under RCP 2.6 are less rapid than those under RCP 8.5 for the three future periods. For the temperature difference of the future three periods, the temperature increases between FTP and NTP range from 1.98 to 4.11 °C, and those between FTP and MTP range from 0.67 to 2.09 °C under RCP 8.5. Under RCP 2.6, the temperature differences between FTP and NTP except from July to October and those between FTP and MTP except for August and December decrease. In summary, the temperature differences among the three future periods follow the trajectory of the CO₂ concentrations and the total radiative forcing in RCP 2.6 and RCP 8.5 (Meinshausen et al. 2011; Wang et al. 2021).

3.3.2 Changes in projected precipitation for the period of 2026–2098

Considering the performance of different RCMs corrected by different bias-correction methods, the C5 corrected by M2 was used to analyze the projected precipitation. Figure 8(c) and (d) show the spatial distributions of predicted future trends of precipitation under RCP 2.6 and RCP 8.5 for the WTP. As shown in Fig. 8(c), the future annual precipitation shows decreasing trends in the WRB, mainly from DJF, JJA, and SON under RCP 2.6. Especially, the projected precipitation has statistically decreasing trends at 5% significant level for DJF in the WRB except for the upstream and for SON in the JRB and BRB. The projected precipitation shows an increasing trend for MAM in the WRB. It can be seen from Fig. 8(d) that the future annual precipitation shows an increasing trend in the WRB except for the upstream and downstream, mainly from DJF, MAM, and SON under RCP 8.5. Especially, the projected precipitation has statistically increasing trends at 5% significant level for DJF in the WRB upstream, JRB, and BRB. Moreover, the projected precipitation shows decreasing trends for JJA in the WRB. In summary, the projected precipitation shows increasing
trends for DJF under RCP 2.6 and RCP 8.5, while JJA shows decreasing trends.

Annual and seasonal precipitation relative deviations between three periods and the BAP are shown in Fig. 11(a–c) under RCP 2.6. The annual precipitation in the three periods will be higher than that in the BAP, and the mean relative deviations are 23.00%, 17.39%, and 13.00%, respectively. Then, the seasonal precipitation in the NTP, MTP, and FTP under RCP 2.6 is analyzed. With the exception of MAM, the mean relative deviation will be the greatest by the middle of the century, which is consistent with the results of Fig. 9. In DJF and SON, the precipitation for the three periods will be higher than that for the FTP except for the precipitation in the WRB downstream for the FTP. In MAM, the precipitation for the three periods will be higher than that for the BAP. In JJA, the precipitation for the three periods will be higher than that for the BAP except for the precipitation in the WRB midstream and downstream for the three periods.

Annual and seasonal precipitation relative deviations between RCP 2.6 and RCP 8.5 in three periods are shown in Fig. 11(d–f). The results show that the relative deviation between RCP 2.6 and RCP 8.5 for the FTP will be $-4.71\%$, $-2.57\%$, and $4.06\%$, respectively, ranging from $-10.84$ to $3.02\%$, from $-9.80$ to $4.13\%$, and from $-9.03$ to $13.99\%$. In DJF and SON, the relative deviation of the seasonal precipitation will increase for three periods, especially in DJF. Under RCP 8.5, the precipitation in DJF will be 55.49% higher than under RCP 2.6 by the end of the century, and could be 70.91% higher than in the BAP,
although the precipitation remains small. The precipitation of MAM will be higher than under RCP 2.6 in the NTP, MTP, and FTP. The relative deviation between RCP 8.5 and BAP will be twice that between RCP 2.6 and RCP 8.5 by the middle of the century, while it will increase to three times by the end of the century. The precipitation of JJA will be similar to that under RCP 2.6.

Figure 10(b) shows the monthly precipitation in the BAP and the precipitation relative deviation between three periods and BAP under RCP 2.6 and RCP 8.5. Under RCP 2.6 and RCP 8.5, relative to the BAP, the precipitation from May to September for the NTP, MTP, and FTP is not projected to increase significantly, and even the precipitation for the MTP is slightly lower than in the BAP for July under RCP 2.6 and August under RCP 8.5, while precipitation is projected to increase strongly for winter and spring, which agrees with results discussed above. These suggest that the annual cycle of precipitation will be likely to decrease because of the significant increase of precipitation in the dry season rather than in the wet season.

Figure 12 shows the scatterplot between projected annual and seasonal precipitation (mm/decade) and temperature (°C/
decade) trends under RCP 2.6 and RCP 8.5, respectively. The projected precipitation has a similar variation tendency to the temperature, mainly in the NTP and FTP under RCP 2.6. In the NTP, except for the temperature of MAM which decreases slightly, both temperature and precipitation show increasing trends. On the contrary, the temperature and precipitation show decreasing trends except that the temperature of DJF and the annual precipitation increase slightly in the FTP. In the WTP, the trends for projected temperature and precipitation are not significant. In the MTP, the projected temperature shows decreasing trends, and the precipitation of DJF and MAM decreases slightly, while the annual, JJA, and SON precipitation increases significantly. Under RCP 8.5, the DJF and SON precipitation has similar variations to the temperature with the increasing trends, except that the SON precipitation in the MTP shows decreasing trends. For JJA and MAM, the projected temperature increases and the precipitation decreases except that the JJA precipitation in the MTP and the MAM precipitation in the NTP show increasing trends. The trends of annual temperature and precipitation trends are not significant.

Under RCP 2.6, the JJA precipitation in the MTP is projected to the largest increasing trend (0.345 mm/decade), while the SON precipitation in the FTP is projected to be the largest decreasing trend (0.149 mm/decade). The JJA temperature in the NTP is projected to be the largest increasing trend (0.903 °C/decade), while the DJF temperature in the MTP is projected to be the largest decreasing trend (0.299 °C/decade). Under RCP 8.5, the SON precipitation in the NTP is projected to be the largest increasing trend (0.163 mm/decade), while the JJA precipitation in the NTP is projected to be the largest decreasing trend (0.202 mm/decade). The projected temperature shows increasing trends, especially the SON temperature in the MTP is projected to be the largest increasing trend (0.893 °C/decade). In conclusion, the projected precipitation in the WRB will change slightly under RCP 2.6 and RCP 8.5, while the projected JJA temperature increase could be close to 9°C by the middle of the century under RCP 2.6. Furthermore, the projected JJA temperature increase will probably be 6.5°C, and SON will exceed 7.3°C by the end of the century.

In order to further analyze the future precipitation, the daily rain rates at the grid were classified into four grades of intensity from light (0.1 ≤ R < 10 mm/day), moderate (10 ≤ R < 25 mm/day), heavy (25 ≤ R < 50 mm/day), to extreme (50 ≤ R < 100 mm/day) rains (Qian et al. 2007). Figure 13(a) shows the future trends of rain days for light, moderate, heavy, and extreme rains in the WTP under RCP 2.6, and Fig. 13(b) for RCP 8.5. The results show that the future light-rain days will decrease at 5% significant level in the WRB under RCP 2.6, while it will increase at 5% significant level under RCP 8.5. For the moderate-rain days, 19.56% of the grids show increasing trends, while 79.11% of the grids show decreasing trends under RCP 2.6. Half of the grids have increasing and decreasing trends under RCP 8.5, respectively. For heavy-rain days, the grids with decreasing trends will be twice as much as those with increasing trends under RCP 2.6, and further, the grids with decreasing trends will be nearly three times those with increasing trends under RCP 8.5. For extreme-rain days, half of the grids show increasing trends and half of the grids show decreasing trends under RCP 2.6, and one-third of the grids show increasing trends and two-thirds of the grids show decreasing trends under RCP 8.5. In summary, the grids with increasing trends for heavy-rain days will be the most, and the grids with decreasing trends for light-rain days will be the least under RCP 2.6, while the grids with increasing trends for light-rain days will be the most, and the grids with decreasing trends for heavy-rain days will be the least under RCP 8.5.

Figure 13 (c) and (d) show the spatial distribution of the relative deviation between WTP and BAP for the light-, moderate-, heavy-, and extreme-rain days in the WRB under RCP 2.6 and RCP 8.5, respectively. As can be seen from Fig. 13(c and d), the spatial distributions under RCP 2.6 will be similar to those under RCP 8.5. The spatial distributions of mean relation deviation between WTP and BAP are different under different rain types. For light- and moderate-rain days, the spatial distributions of WTP and BAP are similar. Relative to the BAP, the heavy-rain days in WTP will decrease slightly except for the upstream of WRB. However, with the exception of upstream and midstream of WRB, the extreme-rain days will increase significantly. The mean relative deviation between WTP and BAP for the extreme-rain days in the WRB will be 174.77% and 177.77% under RCP 2.6 and RCP 8.5, respectively. Figure 13 shows that the spatial distributions of WTP under RCP 2.6 and RCP 8.5 are similar, and the extreme-rain days in the future will increase significantly.

4 Conclusions

Based on six regional climate models driven by RegCM4-4 and REMO2015, this paper investigated the ability of CORDEX-EA to reproduce the regional climate at annual and seasonal scales during 1980–2005 in the WRB. Then, the temperature and precipitation simulations were corrected by different correction methods, and the performances of RCMs corrected by different methods were compared and analyzed. Finally, the changes of projected temperature and precipitation for the period of 2026–2098 in the WRB under RCP 2.6 and RCP 8.5 were analyzed based on the corrected simulations. The results are summarized as follows:
By calculating biases between simulations and observations in the BAP, the results showed that the temperature biases had the spatial difference, while the precipitation wet biases existed in the WRB. As expected, the biases’ spatial distribution was similar for models driven by the same RCM, but the distribution difference was relatively large for models driven by different RCMs (Fig. 3 and Fig. 4). The corrected simulations reproduced the spatial pattern of temperature and precipitation in the WRB reasonably well, and there was some over-correction phenomenon in the simulations inevitably. Further, the 39 indicators and Taylor diagram were used to analyze the reproducing ability of models driven by RegCM4-4 and REMO2015. The results showed that HadGEM2-ES driven by RegCM4-4 had the best temperature reproducibility, and NCC-NorESM1-M driven by RegCM4-4 had the best precipitation reproducibility (Figs. 5, 6 and 7).

Based on the projected temperature after correction under RCP 2.6 and RCP 8.5, the change trend for the WTP was analyzed by Mann–Kendall method. It can be seen that the projected annual, DJF, and MAM temperatures showed decreasing trends, while increasing trends in JJA and SON under RCP 2.6 (Fig. 8(a)). The temperature showed significantly increasing trends under RCP 8.5 (Fig. 8(b)). And then, the temperature changes for the NTP, MTP, and FTP were analyzed relative to the BAP. Under RCP 2.6, the temperature was higher than that for the BAP except for the MAM temperature decreases in the BRB. Projected temperature may increase to a peak for the NTP and MTP, and then it will decrease slightly for the FTP. Under RCP 8.5, the temperature for the NTP was similar to that of the BAP, while the temperature increased significantly for the MTP and FTP, until the end of the twenty-first century; the regional average temperature will signifi-
cantly increase by 4.66 °C in DJF, by 3.27 °C in MAM, by 4.36 °C in JJA, and by 5.58 °C in SON compared to temperatures in the BAP (Fig. 9). Finally, the monthly average temperature changes were analyzed under RCP 2.6 and RCP 8.5, respectively. As expected, the monthly temperature increases for the NTP, MTP, and FTP under RCP 2.6 were smaller than those under RCP 8.5 (Fig. 10(a)).

(3) Using the Mann–Kendall method, the projected precipitation trends for the WTP were analyzed based on the corrected precipitation under RCP 2.6 and RCP 8.5. It can be seen that the precipitation had decreasing trends under RCP 2.6 (Fig. 8(c)), while the precipitation trends were spatially distributed under RCP 8.5 (Fig. 8(d)). And then, the precipitation changes for the NTP, MTP, and FTP were analyzed relative to the BAP. There were precipitation wet biases in the WRB under RCP 2.6. Under RCP 8.5, the DJF projected precipitation had the largest relative deviation, with 55.49% more than that of RCP 2.6 and 70.91% more than that of the BAP at the end of the century (Fig. 11). Although the relative deviation of DJF precipitation was the largest, its precipitation was still very small, which was also confirmed by the monthly precipitation changes (Fig. 10(b)). Next, the projected daily rain rates were classified into four grades. The light-rain days decreased at the 5% significant level under RCP 2.6, while they increased at the 5% significant level under RCP 8.5. Relatively to the BAP, the light- and moderate-rain days showed little changes for the WTP, NTP, FTP, while the extreme-rain days showed a significant increase (Fig. 13).

The results of this study provide the performance of RCMs of CORDEX-EA in the WRB under a changing environment, which would be useful for water resource planning and management. In particular, we further investigated the reproduction ability of the different RCM simulations after correction, which expands our knowledge on future climate change and its impacts in the WRB. Our future work will focus on attribution analysis of future climate change and future hydrological process changes.

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Author contribution Yinpang Wang and Rengui Jiang conceived and designed the study. Yinpang Wang analyzed the data. Jiancang Xie, Jiwei Zhu, Yong Zhao, Xixi Lu, and Fawen Li provided critical insights on the results and conclusions. Yinpang Wang drafted the manuscript, with a substantial contribution from all authors.

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Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication All authors gave their consent for the publication in the journal.

Competing interests The authors declare no competing interests.

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