Bias Correction, Historical Evaluations and Future Projections of Climate Simulations in the Wei River Basin Using CORDEX-EA

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

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10

11 **Abstract**

12 The utilization of Regional Climate Methods (RCMs) to predict future regional climate is an important study under the
13 changing environment. The primary objective of the paper is to correct the temperature and precipitation simulations for
14 the period of 1980-2005 and 2026-2098 in the Wei River Basin (WRB), to evaluate the performance of RCMs for the
15 period of 1980-2005, and further, to analyze the future changes of projected temperature and precipitation during
16 2026-2098. In this paper, the linear scaling method was used to correct the temperature simulations. Quantile mapping,
17 local intensity scaling method and hybrid method were used to correct the precipitation simulations. The future changes
18 of projected temperature and precipitation for the near-term (2026-2050), mid-term (2051-2075) and far-term
19 (2076-2098), relative to the period of 1980-2005, were investigated under RCP 2.6 and RCP 8.5. Results indicate that:
20 (1) The temperature biases were different spatial distributions, and the precipitation wet biases were detected in the
21 WRB. After correction, HadGEM2-ES driven by RegCM4-4 had the best temperature reproducibility, and
22 NCC-NorESM1-M driven by RegCM4-4 had the best precipitation reproducibility. (2) Under RCP 2.6, the projected
23 annual, winter and spring temperature showed decreasing trends. The temperature was higher than that for the period of
24 1980-2005 except for the spring temperature decreases in the Beiluo River Basin. Under RCP 8.5, the temperature
25 showed significantly increasing trends. The temperature for the near-term was similar to the period of 1980-2005, while
26 the temperature increased significantly for the mid-term and far-term. (3) Under RCP 2.6, the precipitation had
27 decreasing trends. Under RCP 8.5, precipitation trends were also spatially distributed. The relative deviation of winter
28 precipitation was the largest. Relative to the period of 1980-2005, the light and moderate rain days showed little change
29 for the period of 2026-2098, while the extreme rain days showed significantly increasing trends. (4) The results could
30 be beneficial to the future climate projection, which provide references for the water resources management, the future
31 hydrological process changes and attribution analysis in the WRB.

32 **Keywords** Climate projection · Bias correction · Temperature and precipitation · CORDEX-EA

33 1. Introduction

34 Climate change could be recognized as one of the most important challenges that has ever
35 faced, with increasingly severe adverse effects (e.g., climate warming, extreme weather events) at
36 different spatial and temporal scales (Ozturk et al. 2018; Almagro et al. 2020). According to the
37 Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC 2021),
38 human-induced climate change has already affected the temperature and precipitation in every
39 region across the globe. Further, climate change and human activity are expected to affect the
40 balance of the climate system, and the circulation tare of renewable freshwater resources is
41 determined by the climate system (Oki and Kanae 2006), posing a certain threat to human water
42 supply. In order to ensure appropriate climate change planning and water resources policies, it is
43 necessary to continuously access the spatial and temporal climatic characteristics to investigate the
44 evolving trends of the hydrological cycle at different spatial and temporal scales (McNutt 2013;
45 Almagro et al. 2020).

46 Over the years, Global Climate Models (GCMs) are usually used to assess the global future
47 climate projections (Maidment et al. 2015; Ayugi et al. 2020). GCM is an important tool to simulate
48 global climate response to changes in greenhouse gas concentrations, which have been widely
49 recognized in the fifth phase of the Coupled Model Intercomparison Project (CMIP5) (Almagro et
50 al. 2020). However, the resolution of current GCMs are 100-200 km, respectively (Ngai et al. 2020),
51 which makes them impossible to obtain the mesospheric processes and the dynamics driving such
52 physical process, and also limits their direct application in regional scale hydrological impact
53 assessment (Giorgi 1990; Fowler et al. 2007; Maraun et al. 2017). High resolution and dynamically
54 downscaling Regional Climate Models (RCMs) might provide more information for the climate
55 change detection (Giorgi and Gutowski 2015). RCMs, with the resolution of approximately 12-50
56 km (Dong et al. 2018), have been widely used to predict regional climate information and simulate
57 the regional hydrological processes (Leung et al. 2004; Niu et al. 2020). Indeed, previous studies
58 have demonstrated that RCMs have advantages over GCMs in terms of regional climate
59 characteristics detection (Gao et al. 2012; Zou and Zhou 2016).

60 The initiative to the Coordinated Regional Climate Downscaling Experiment (CORDEX) was
61 proposed by the World Climate Research Programme (WCRP) in 2009 to further advance the
62 development and application of RCMs (Giorgi et al. 2009). The CORDEX has been created or is in

63 progress for a number of regions around the world, with a total of 14 domains, which is the
64 ensemble of models driven by multiple CMIP5 GCMs (Li et al. 2018). Currently, it has the second
65 phase. The Wei River Basin (WRB) is located in the CORDEX-EA domain. A number of previous
66 studies have evaluated the performance of RCMs in CORDEX-EA. On the one hand, RCMs are
67 used to predict the future change of climate factors, such as precipitation (Hui et al. 2019),
68 temperature (Yu et al. 2020) and evapotranspiration (Yang et al. 2020), as well as extreme climate
69 events (Yang et al. 2019), heat wave (Wang et al. 2019) and wind resources (Gao et al. 2019), etc.
70 On the other hand, RCMs, combining with hydrological models, are used to simulate hydrological
71 impacts induced by climate (Dong et al. 2019; Hu et al. 2020).

72 Although RCMs could make up for the deficiency of coarse resolution of GCMs, there are still
73 systematic errors from the initial conditions, the driving GCMs process and the physical
74 parameterization schemes. It makes the direct utilization of RCMs in the regional climate studies
75 have a certain impact on the simulation results (Au-Yeung and Chan 2012; Shen et al. 2020).
76 Therefore, from the perspective of necessity rather than validity (Ehret et al. 2012), a number of
77 post-processing techniques have been applied to RCMs to eliminate systematic errors in climate
78 prediction studies. These methods include the local intensity scaling (Themessl et al. 2011), the
79 histogram equalization method (Dong et al. 2019), quantile mapping (Ngai et al. 2017), linear
80 scaling method (Dong et al. 2019), the multivariate 3 dimensional bias correction method (Hu et al.
81 2020) and so on. These post-processing methods could make future climate simulation projections
82 better by adjusting the RCMs output based on the observations characteristics.

83 In previous studies, the downscaling GCMs (Zuo et al. 2015) and corrected GCMs (Zhao et al.
84 2019) have been used to project the regional climate in the WRB. However, the RCMs are rarely
85 used to the future climate projections in the WRB. In this study, we aimed at correcting the RCMs
86 over WRB in CORDEX-EA, evaluating the performance of RCMs, and investigating projected
87 temperature and precipitation changes under RCP 2.6 and RCP 8.5. The paper is organized as
88 follows: the study area, the datasets, bias correction methods and evaluation metric used in this
89 study are described in Section 2. In Section 3, the results and discussion are presented, including
90 that: (1) relative to the observations, the reproducibility of RCMs to temperature and precipitation
91 are evaluated in the WRB during the period of 1980-2005 (base period, BAP) in Section 3.1, (2) the
92 different bias correction methods are used to calibrate simulations, and the applicability of different

methods are evaluated in Section 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 Section 3.3. The last Section summarizes the conclusions.

2. Material 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 $1.34 \times 10^5 \text{ km}^2$. 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 the main stream of WRB, Jing River Basin (JRB), 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

122 CORDEX-EA. Two RCMs were used in the study: (1) RegCM4-4 developed by the International
123 Centre for Theoretical Physics; (2) REMO2015 developed by the Climate Service Center Germany.
124 Both are the hydrostatic regional climate model. The dynamic model of the former is the same as
125 that of the hydrostatic version of the fifth generation Penn State/NCAR Mesoscale Model (Giorgi et
126 al. 2012), the latter uses physical parameterizations from European Centre Hamburg Version 4
127 (Roeckner et al. 1996) and a dynamical framework from the weather forecast model of the German
128 Weather Service Europa-Modell (Wang et al. 2021). The RegCM4-4 and REMO2015 have
129 successfully applied to multiple domains (i.e. America, Europe, Asia, Africa, and the Mediterranean)
130 in long-term climate simulations and climate change studies over the last two decades (Ozturk et al.
131 2018; Top et al. 2021). Both simulate most climate types relatively well, with high skill scores.

132 The atmospheric boundary conditions used for RegCM4-4 come from three widely used
133 GCMs available from the CMIP5 experiment: the Hadley Centre Global Environmental Model
134 version 2 Earth system model (HadGEM2-ES) (Collins et al. 2011), the Max Planck Institute for
135 Meteorology-Earth system model - mixed resolution (MPI-ESM-MR) (Jungclaus et al. 2013), and
136 the Norwegian Climate Center's Earth System Model (NCC-NorESM1-M) (Bentsen et al. 2013).
137 HadGEM2-ES, the Max Planck Institute for Meteorology - Earth system model-low resolution
138 (MPI-ESM-LR) (Jungclaus et al. 2013), and NCC-NorESM1-M were used in REMO2015. The
139 spatial resolution of RegCM4-4 is 25km, and REMO2015 is 0.22°. The detailed information is
140 shown in Table 1. We selected RegCM4-4 and REMO2015 simulations available from the
141 CORDEX experiment for the East Asia domain.

142 **2.3 Bias correction methods**

143 Although RCMs use complex physical parameterization to detail processes in the
144 land-atmosphere continuum, there are still systematic biases for the simulation data, which justifies
145 the use of bias correction (Dong et al. 2019). Considering the time dependence of the model biases
146 and relative short time sequence of historical simulations, cross validation was used to calibrate and
147 validate the performance of the RCMs (Shen et al. 2020). The 26-year period 1980-2005 is used as
148 the base period (BAP). For calibration, 20 years were randomly selected out of the BAP as the
149 reference period, and the remaining 6 years were used for validation as the validation period. The
150 whole cross-validation process was repeated 30 times to overcome the limitation of insufficient
151 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. 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 Eq1 (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.

$$P_o = TF(P_m) = F_o^{-1}(F_m(P_m)) \quad (1)$$

Empirical quantile mapping method is used to solve Eq1 using the empirical cumulative distributions function (ecdf) of observed and simulated values instead of theoretical cumulative distribution functions. It is one of non-parametric methods. By adjusting the quantiles of the RCMs data ($P_{hst,m,d}$ and $P_{rcp,m,d}$) to those of the observed data ($P_{obs,m,d}$), the bias-corrected distribution of $P_{hst,m,d}$ and $P_{rcp,m,d}$ could match the distribution of $P_{obs,m,d}$ (Vormoor et al. 2015). The transformation function is given as follows:

$$P_{BAP,m,d}^{cor} = ecdf_{obs,m}^{-1}(ecdf_{BAP,m}(P_{BAP,m,d})) \quad (2)$$

$$P_{RCP,m,d}^{cor} = ecdf_{obs,m}^{-1}(ecdf_{BAP,m}(P_{RCP,m,d})) \quad (3)$$

Where $P_{BAP,m,d}$ and $P_{BAP,m,d}^{cor}$ denote the simulated precipitation before and after correction in the BAP. $P_{RCP,m,d}$ and $P_{RCP,m,d}^{cor}$ 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. $ecdf_{obs,m}$ and $ecdf_{BAP,m}$ denote the empirical cumulative distribution function of observations and simulations in the BAP

179 especially. $ecdf_{obs,m}^{-1}$ represents the inverse of $ecdf_{obs,m}$.

180 2.3.2 Local intensity scaling

181 LOCI is a bias-correction method based on the mean values, which directly correct GCMs or
182 RCMs outputs for the observations. LOCI was developed by Widmann and Bretherton (2000). It
183 corrects the wet-day frequency and intensity on a monthly basis by a scaling factor calculated from
184 observations and simulations in the reference period, then expands to the scenarios data (Fang et al.
185 2015). LOCI normally includes three steps (Li et al. 2019):

186 (1) The wet-day threshold for the observations and simulations are determined from the
187 observed and simulated daily precipitation series for each month to ensure that the threshold
188 exceedance of simulations is equal to the observed precipitation frequency for the reference period
189 (Eq4).

$$190 \quad Fre(P^m \geq P_t^m) = Fre(P^o \geq P_t^o) \quad (4)$$

191 Where P^m and P^o denote the simulated and observed precipitation for the reference period,
192 especially. P_t^m and P_t^o are the monthly thresholds of simulations and observations. Themessl et
193 al. (2011) found that the observation thresholds had no significant differences on the correction
194 results.

195 (2) A scaling factor (s) is calculated to ensure that the mean of simulations and observations
196 are equal for each month (Eq5).

$$197 \quad s = \frac{\overline{P^o : P^o \geq P_t^o} - P_t^o}{\overline{P^m : P^m \geq P_t^m} - P_t^m} \quad (5)$$

198 (3) The monthly thresholds and scaling factors determined in the reference period are further
199 used to correct precipitation simulations in the validation period and WTP (Eq6).

$$200 \quad \hat{P}(t) = \max(P_t^o + s \times (P^m(t) - P_t^m), 0) \quad (6)$$

201 Where $P^m(t)$ and $\hat{P}(t)$ denote the simulated precipitation before and after correction in the
202 validation period and WTP.

203 2.3.3 Hybrid method

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

212 **2.4 Model simulation evaluation**

213 To facilitate bias correction, temperature and precipitation were interpolated to a common grid
214 of $0.22^\circ \times 0.22^\circ$ latitude/longitude using bilinear interpolation (Dong et al. 2019). The performance
215 of RCMs were evaluated on annual, winter (December-January-February, DJF), spring
216 (March-April-May, MAM), summer (June-July-August, JJA), autumn
217 (September-October-November, SON) and monthly time scales. The performance of different bias
218 correction methods and RCMs were also evaluated based on the cross-validation results. In order to
219 evaluate the correction results of different methods for precipitation under the same model, 39
220 indicators were analyzed based on the mean and standard deviation of annual, seasonal and monthly
221 scales, as well as the quantiles of 25%, 50%, 75%, 90% and 99%.

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

228 **3. Results and discussion**

229 **3.1 Evaluation of different models driven by RegCM4-4 and REMO2015**

230 The annual and four seasons biases in the different GCMs simulated temperature and
231 precipitation driven by RegCM4-4 and REMO2015 for the BAP are analyzed relative to

232 observations, to evaluate the ability of RCMs to reproduce the regional climate in the WRB. Fig. 3
233 shows the temperature observations, and differences between the simulations and observations in
234 the BAP. Fig. 4 is the same as Fig. 3, but for precipitation. It can be seen from Fig. 3a and Fig. 4a
235 that the spatial distribution trends of annual and seasonal temperature in the WRB are similar, and
236 the same for precipitation. Temperature and precipitation decrease from the southeast to the
237 northwest. Further, the spatial distributions of temperature biases for C1, C3 and C5 are mostly
238 similar, while those of C2, C4 and C6 are similar. It shows that the spatial distributions of biases
239 between the simulations and observations are same for the same RCM, and different RCMs produce
240 quite different spatial distributions of temperature biases in the WRB (Yu et al. 2020) (Fig. 3b-g).
241 The above analysis is also consistent for the precipitation (Fig. 4b-g).

242 There are cold biases in annual and seasonal temperature in the WRB for the RegCM4-4.
243 Except for JJA, there are cold biases in the annual and seasonal temperature in the upstream of the
244 WRB for the REMO2015, while there are warm biases over the rest of simulated area. For the cold
245 biases in the WRB, they may be caused by the cold biases of simulations or the warm biases of
246 observations. The former may be inherited from the GCMs (Wang et al. 2021), and be attributed to
247 inadequate representation of physical processes, such as overestimated topographic forcing and
248 snow cover (Tapiador et al. 2020; Pang et al. 2021). The latter may be connected with the fact that
249 most meteorological stations are located in valleys, making the observations include warm biases
250 for high altitude areas (Wang et al. 2016). For the warm biases in the WRB, they may be caused by
251 the overestimation of downward long-wave radiation (Pang et al. 2021).

252 There are significant wet biases in annual and seasonal precipitation for the RegCM4-4 and
253 REMO2015 with the exception of the REMO2015 which show the mixture of wet and dry biases in
254 the JJA and SON. Precipitation includes large scale precipitation and convective precipitation
255 (Wang et al. 2016), and precipitation simulations are preponderantly affected by atmosphere forcing
256 and cumulus parameterization scheme (Niu et al. 2020). The wet biases may be caused by the
257 overestimation of large scale precipitation (Pang et al. 2021). From the perspective of simulations
258 and observations, the wet biases may be caused by the overestimation of simulations or the
259 underestimation of observations. The former stems from overestimated precipitation in the GCMs
260 (Wang et al. 2021). The latter may be due to lack of correction for rain gauge measurements,
261 particularly for solid precipitation in the cold season (Wu and Gao 2013).

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

272 **3.2 RCMs evaluation after different bias correction methods**

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

280 The applicable bias correction method for the RCMs is obtained through the results of relative
281 deviation difference. Additionally, the relative deviation between the corrected precipitation
282 simulations and observations are analyzed by using 34 indicators based on precipitation mean and
283 standard deviation. The smaller the relative deviation is, the closer the corrected simulations is to
284 the observations. As can be seen from Fig. 6, the relative deviation of the six models range from
285 -8.12% to 15.94% for the average annual precipitation, and from -5.58% to 34.79% for the annual
286 standard deviation. The relative deviation are larger in SON and DJF for the mean seasonal
287 precipitation, while the relative deviation are larger in MAM and SON for the seasonal standard
288 deviation. The relative deviation of mean monthly precipitation for six models are smaller from
289 May to August, ranging from -17.49% to 35.39%, which is consistent with the result in section 3.1.
290 The relative deviation of precipitation is small in JJA. In general, the C5 corrected by M2 is closer
291 to the observations among the corrected simulations.

292 For a more quantitative and systematic evaluation, Taylor diagram is used to illustrate the
293 performance of the RCMs. Fig. 7 demonstrates the Taylor diagrams for the spatial distributions of
294 the annual and seasonal temperature and precipitation in the WRB. All RegCM4-4 and REMO2015
295 simulations successfully reproduce the spatial distribution of temperature with correlation
296 coefficients greater than 0.95 with the exception of DJF. Compared with six models, the C1 perform
297 much better, as indicated by higher correlation coefficients and smaller RMSEs in all seasons. For
298 the precipitation, the RegCM4-4 and REMO2015 simulate precipitation with greater skill for the
299 wet season, particularly in JJA. The C5 reproduce precipitation with the greatest skill, which is the
300 same result as Fig. 6.

301 **3.3 Climate projections under RCP 2.6 and RCP 8.5**

302 **3.3.1 Changes in projected temperature for the period of 2026-2098**

303 Fig. 8a and 8b show the spatial distributions of predicted future trends of temperature under
304 RCP 2.6 and RCP 8.5 in the WTP. As shown in Fig. 8a, the future temperature of JJA and SON
305 show increasing trends, while the temperature of DJF and MAM show decreasing trends under RCP
306 2.6. It can be seen from Fig. 8b that the future annual and seasonal temperature have statistically
307 decreasing trend at 5% significant level in the WRB under RCP 8.5 for the period of 2026-2098.

308 Annual and seasonal temperature differences between three periods and the BAP are shown in
309 Fig. 9a-c under RCP 2.6. From the perspective of annual temperature, the temperature of NTP, MTP
310 and FTP in the WRB are higher than that of BAP. Relative to temperatures in the BAP, the increase
311 is greatest for the MTP, which is the same result as Wang et al. (2021). Similarly, the temperature in
312 DJF, JJA and SON increase compared to the BAP. Notably, the DJF temperature increases are more
313 significant in the main stream of WRB, while the JJA temperature increases are spatially uniform in
314 the WRB. It can be clearly seen that the MAM temperature decreases are mainly in the BRB for
315 NTP, MTP and FTP.

316 Annual and seasonal temperature differences between RCP 2.6 and RCP 8.5 in three periods
317 are shown in Fig. 9d-f. For the NTP, the temperature increases under RCP 8.5 are similar to RCP
318 2.6 in the WRB, with differences between them ranging from -0.38 °C to 0.15 °C. Relative to
319 temperatures under RCP 2.6, the temperature increases of NTP, MTP and FTP increase accordingly.
320 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 RCP 2.6, ranging from 3.23 °C 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 twenty first century under RCP 8.5. Apparently, the largest temperature increase is in SON in the FTP.

Fig. 10a 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 trend of temperature differences in the three periods are 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 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 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 °C to 4.11 °C, and that between FTP and MTP range from 0.67 °C 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 that 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

Fig. 8c and 8d 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. 8c, the future annual precipitation show decreasing trends in the WRB, mainly from DJF, JJA and SON under RCP 2.6. Especially, the projected precipitation have 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 show

351 an increasing trend for MAM in the WRB. It can be seen from Fig. 8d that the future annual
352 precipitation show an increasing trend in the WRB except for the upstream and downstream, mainly
353 from DJF, MAM and SON under RCP 8.5. Especially, the projected precipitation have statistically
354 increasing trends at 5% significant level for DJF in the WRB upstream, JRB and BRB. Moreover,
355 the projected precipitation show decreasing trends for JJA in the WRB. In summary, the projected
356 precipitation show increasing trends for DJF under RCP 2.6 and RCP 8.5, while JJA show
357 decreasing trends.

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

368 Annual and seasonal precipitation relative deviation between RCP 2.6 and RCP 8.5 in three
369 periods are shown in Fig. 11d-f. The results show that the relative deviation between RCP 2.6 and
370 RCP 8.5 for the NTP, MTP and FTP will be -4.71%, -2.57% and 4.06% respectively, ranging from
371 -10.84% to 3.02%, from -9.80% to 4.13%, from -9.03% to 13.99%. In DJF and SON, the relative
372 deviation of seasonal precipitation will increase for three periods, especially in DJF. Under RCP 8.5,
373 the precipitation in DJF will be 55.49% higher than under RCP 2.6 by the end of the century, and
374 could be 70.91% higher than in the BAP, although the precipitation remain small. The precipitation
375 of MAM will be higher than under RCP 2.6 in the NTP, MTP and FTP. The relative deviation
376 between RCP 8.5 and BAP will be twice than that between RCP 2.6 and RCP 8.5 by the middle of
377 the century, while it will increase to three times by the end of the century. The precipitation of JJA
378 will be similar to that under RCP 2.6.

379 Fig. 10b shows the monthly precipitation in the BAP and the precipitation relative deviation
380 between three periods and BAP under RCP 2.6 and RCP 8.5. Under RCP 2.6 and RCP 8.5, relative

381 to the BAP, the precipitation from May to September for the NTP, MTP and FTP is not projected to
382 increase significantly, and even the precipitation for the MTP is slightly lower than in the BAP for
383 July under RCP 2.6 and August under RCP 8.5, while precipitation is projected to increase strongly
384 for winter and spring, which is agree with results discussed above. These suggest that the annual
385 cycle of precipitation will be likely to decrease because of the significant increase of precipitation in
386 the dry season rather than wet season.

387 Fig. 12 show the scatter plot between projected annual and seasonal precipitation (mm/decade)
388 and temperature trends ($^{\circ}\text{C}/\text{decade}$) under RCP 2.6 and RCP 8.5, respectively. The projected
389 precipitation have the similar variation tendency to the temperature, mainly in the NTP and FTP
390 under RCP 2.6. In the NTP, except the temperature of MAM decrease slightly, both temperature and
391 precipitation show increasing trends. On the contrary, the temperature and precipitation show
392 decreasing trends except that the temperature of DJF and the annual precipitation increase slightly
393 in the FTP. In the WTP, the trends for projected temperature and precipitation are not significant. In
394 the MTP, the projected temperature show decreasing trends, and the precipitation of DJF and MAM
395 decrease slightly, while the annual, JJA and SON precipitation increase significantly. Under RCP
396 8.5, the DJF and SON precipitation have similar variations to the temperature with the increasing
397 trends, except that the SON precipitation in the MTP show decreasing trends. For JJA and MAM,
398 the projected temperature increase and the precipitation decrease except that the JJA precipitation in
399 the MTP and the MAM precipitation in the NTP show increasing trends. The trends of annual
400 temperature and precipitation trends are not significant.

401 Under RCP 2.6, the JJA precipitation in the MTP is projected to the largest increasing trend
402 (0.345 mm/decade), while the SON precipitation in the FTP is projected to the largest decreasing
403 trend (0.149 mm/decade). The JJA temperature in the NTP is projected to the largest increasing
404 trend (0.903 $^{\circ}\text{C}/\text{decade}$), while the DJF temperature in the MTP is projected to the largest
405 decreasing trend (0.299 $^{\circ}\text{C}/\text{decade}$). Under RCP 8.5, the SON precipitation in the NTP is projected
406 to the largest increasing trend (0.163 mm/decade), while the JJA precipitation in the NTP is
407 projected to the largest decreasing trend (0.202 mm/decade). The projected temperature show
408 increasing trends, especially the SON temperature in the MTP is projected to the largest increasing
409 trend (0.893 $^{\circ}\text{C}/\text{decade}$). In conclusion, the projected precipitation in the WRB will change slightly
410 under RCP 2.6 and RCP 8.5, while the projected JJA temperature increase could be close to 9°C by

411 the middle of the century under RCP 2.6. Furthermore, the projected JJA temperature increase will
412 probably be 6.5°C, and SON will exceed 7.3°C by the end of the century.

413 In order to further analyze the future precipitation, the daily rain rates at the grid were
414 classified into four grades of intensity from light ($0.1 \leq R < 10$ mm/day), moderate ($10 \leq R < 25$
415 mm/day), heavy ($25 \leq R < 50$ mm/day), to extreme ($50 \leq R < 100$ mm/day) rains (Qian et al. 2007). Fig.
416 13a shows the future trends of rain days for light, moderate, heavy and extreme rains in the WTP
417 under RCP 2.6, and Fig.13b for RCP 8.5. The results show that the future light rain days will
418 decrease at 5% significant level in the WRB under RCP 2.6, while it will increase at 5% significant
419 level under RCP 8.5. For the moderate rain days, 19.56% of the grids show increase trends, while
420 79.11% of the grids show decrease trends under RCP 2.6. Half of the grids have increasing and
421 decreasing trends under RCP 8.5, respectively. For heavy rain days, the grids with decreasing trends
422 will be twice as much as that with increasing trends under RCP 2.6, and further, the grids with
423 decreasing trends will be nearly three times that with increasing trends under RCP 8.5. For extreme
424 rain days, half of the grids show increasing trends and half of the grids show decreasing trends
425 under RCP 2.6, and one-third of the grids show increasing trends and two-thirds of the grids show
426 decreasing trends under RCP 8.5. In summary, the grids with increasing trends for heavy rain days
427 will be the most, and the grids with decreasing trends for light rain days will be the least under RCP
428 2.6, while the grids with increasing trends for light rain days will be the most, and the grids with
429 decreasing trends for heavy rain days will be the least under RCP 8.5.

430 Fig. 13c and 13d show the spatial distribution of the relative deviation between WTP and BAP
431 for the light, moderate, heavy and extreme rain days in the WRB under RCP 2.6 and RCP 8.5,
432 respectively. As can be seen from Fig. 13c-d, the spatial distributions under RCP 2.6 will be similar
433 to RCP 8.5. The spatial distributions of mean relation deviation between WTP and BAP are
434 different under different rain types. For light and moderate rain days, the spatial distributions of
435 WTP and BAP are similar. Relative to the BAP, the heavy rain days in WTP will decrease slightly
436 except for the upstream of WRB. However, with the exception of upstream and midstream of WRB ,
437 the extreme rain days will increase significantly. The mean relative deviation between WTP and
438 BAP for the extreme rain days in the WRB will be 174.77% and 177.77% under RCP 2.6 and RCP
439 8.5, respectively. Fig. 13 shows that the spatial distributions of WTP under RCP 2.6 and RCP 8.5
440 are similar, and the extreme rain days in the future will increase significantly.

441 4. Conclusions

442 Based on six regional climate models driven by RegCM4-4 and REMO2015, this paper
443 investigated the ability of CORDEX-EA to reproduce the regional climate at annual and seasonal
444 scales during 1980-2005 in the WRB. Then, the temperature and precipitation simulations were
445 corrected by different correction methods, and the performance of RCMs corrected by different
446 methods were compared and analyzed. Finally, the changes of projected temperature and
447 precipitation for the period of 2026-2098 in the WRB under RCP 2.6 and RCP 8.5 were analyzed
448 based on the corrected simulations. The results are summarized as follows:

449 (1) By calculating biases between simulations and observations in the BAP, the results showed
450 that the temperature biases had the spatial difference, while the precipitation wet biases existed in
451 the WRB. As expected, the biases spatial distribution was similar for models driven by the same
452 RCM, but the distribution difference was relatively large for models driven by different RCMs (Fig.
453 3 and Fig. 4). The corrected simulations reproduced the spatial pattern of temperature and
454 precipitation in the WRB reasonably well, and there was some over-correction phenomenon in the
455 simulations inevitably. Further, the 39 indicators and Taylor diagram were used to analyze the
456 reproducing ability of models driven by RegCM4-4 and REMO2015. The results showed that
457 HadGEM2-ES driven by RegCM4-4 had the best temperature reproducibility, and
458 NCC-NorESM1-M driven by RegCM4-4 had the best precipitation reproducibility (Fig. 5 -Fig. 7).

459 (2) Based on the projected temperature after correction under RCP 2.6 and RCP 8.5, the
460 change trend for the WTP was analyzed by Mann-Kendall method. It can be seen that the projected
461 annual, DJF and MAM temperature showed decreasing trends, while increasing trends in JJA and
462 SON under RCP 2.6 (Fig. 8a). The temperature showed significantly increasing trends under RCP
463 8.5 (Fig. 8b). And then, the temperature changes for the NTP, MTP and FTP were analyzed relative
464 to the BAP. Under RCP 2.6, the temperature was higher than that for the BAP except for the MAM
465 temperature decreases in the BRB. Projected temperature may increase to a peak for the NTP and
466 MTP, and then it will decrease slightly for the FTP. Under RCP 8.5, the temperature for the NTP
467 was similar to the BAP, while the temperature increased significantly for the MTP and FTP, until
468 the end of twenty first century, the regional average temperature will significantly increase by
469 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
470 temperatures in the BAP (Fig. 9). Finally, the monthly average temperature changes were analyzed

471 under RCP 2.6 and RCP 8.5, respectively. As expected, the monthly temperature increases for the
472 NTP, MTP and FTP under RCP 2.6 were smaller than that under RCP 8.5 (Fig. 10a).

473 (3) Using Mann-Kendall method, the projected precipitation trends for the WTP were analyzed
474 based on the corrected precipitation under RCP 2.6 and RCP 8.5. It can be seen that the
475 precipitation had decreasing trends under RCP 2.6 (Fig. 8c), while the precipitation trends were
476 spatially distributed under RCP 8.5 (Fig. 8d). And then, the precipitation changes for the NTP, MTP
477 and FTP were analyzed relative to the BAP. There were precipitation wet biases in the WRB under
478 RCP 2.6. Under RCP 8.5, DJF projected precipitation had the largest relative deviation, with
479 55.49% more than RCP 2.6 and 70.91% more than the BAP at the end of the century (Fig. 11).
480 Although the relative deviation of DJF precipitation was the largest, its precipitation was still very
481 small, which was also confirmed by the monthly precipitation changes (Fig. 10b). Next, the
482 projected daily rain rates was classified into four grades. The light rain days decreased at the 5%
483 significant level under RCP 2.6, while increased at the 5% significant level under RCP 8.5.
484 Relatively to the BAP, the light and moderate rain days showed little changes for the WTP, NTP,
485 MTP and FTP, while the extreme rain days showed a significant increase (Fig. 13).

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

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499 **Declarations**

500 The authors have no conflicts of interest to declare that are relevant to the content of this
501 article.

502 **Availability of data and material**

503 The daily temperature and precipitation data were obtained from the China Meteorological
504 Data Sharing Service System at <http://cdc.nmic.cn>. The RCMs data were obtained from
505 <https://esg-dn1.nsc.liu.se/projects/cordex/>. All simulation outputs can be accessed by contacting
506 corresponding author.

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Figures

Figure 1

Locations of study area.

Figure 2

The flow chart of the study framework.

Figure 3

a Temperature from observations, and differences between the simulations and observations in the WRB for the period of 1980-2005; b–g The regional mean difference is marked at each upper right corner of the panel. The black dots denote differences statistically significant at the 5% significant level according to the two-tailed t test.

Figure 4

a Precipitation from observations, and differences between the simulations and observations in the WRB for the period 1980-2005; b–g The regional mean difference is marked at each upper right corner of the panel. The black dots denote differences statistically significant at the 5% significant level according to the two-tailed t test.

(a) RegCM4-4

(b) REMO2015

Figure 5

a The relative deviation difference of 39 indicators calculated from the simulations driven by RegCM4-4. The relative deviation difference is the difference between the relative deviation of the simulations before and after correction and the observations. b As Fig. 5 a, but for the simulations driven by REMO2015.

Figure 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.

Figure 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.

Figure 8

The spatial distributions of predicted future trends of temperature and precipitation under RCP 2.6 and RCP 8.5 for the period of 2026-2098.

Figure 9

Projected changes in annual and seasonal temperature for the NTP (2026-2050), MTP (2051-2075), and FTP (2076-2098), relative to the BAP (1980-2005) under RCP 2.6 and differences in temperature between RCP 2.6 and RCP 8.5 for the same periods.

(a) temperature

(b) precipitation

Legend: BAP (red), NTP (blue), MTP (yellow), FTP (green), NTP-BAP (solid blue), MTP-BAP (solid red), FTP-BAP (solid green), FTP-NTP (dashed blue), FTP-MTP (dashed green).

Figure 10

Boxplots of the spatially averaged monthly a temperature and b precipitation (left axis) for the BAP, NTP, MTP, and FTP under RCP 2.6 and RCP 8.5. The monthly changes (right axis) in a temperature and b precipitation for the NTP, MTP, and FTP, relative to the BAP under RCP2.6 and RCP8.5 (solid lines). The monthly changes (right axis) in a temperature and b precipitation for the FTP, relative to the NTP and

MTP under RCP 2.6 and RCP 8.5 (dash lines). the black dashed line denotes the zero-references line corresponding to the right axis.

Figure 11

Projected changes in annual and seasonal precipitation for the NTP (2026-2050), MTP (2051-2075), and FTP (2076-2098), relative to the BAP (1980-2005) under RCP 2.6 and differences in precipitation between RCP 8.5 and RCP 2.6 for the same periods.

Figure 12

The scatter plot between projected annual, DJF, MAM, JJA and SON temperature trends (°C/decade) and precipitation (mm/decade) in the WTP, NTP, MTP and FTP under RCP 2.6 and RCP 8.5.

Figure 13

a and b The trend changes of rain days for light, moderate, heavy and extreme rain days in the WTP under RCP 2.6 and RCP 8.5. c and d 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.