LETTER

Multivariate bias corrections of CMIP6 model simulations of compound dry and hot events across China

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Abstract
Climate model simulations provide useful information to assess changes in climate extremes (e.g. droughts and hot extremes) under global warming for climate policies and mitigation measures. Due to systematic biases in climate model simulations, bias correction (BC) methods have been employed to improve simulations of climate variables such as precipitation and temperature. Previous studies mostly focus on individual variables while the correction of precipitation-temperature (P-T) dependence, which is closely related to compound dry and hot events (CDHEs) that may lead to amplified impacts, is still limited. In this study, we evaluated the performance of the multivariate BC (MBC) approach (i.e. MBCn and MBCr) for adjusting P-T dependence and associated likelihoods of CDHEs in China based on 20 Coupled Model Intercomparison Project Phase 6 (CMIP6) models with observations from CN05.1. Data for the period 1961–1987 were used for model calibrations and those for 1988–2014 were used for model validations. Overall, the MBC can improve the simulation of P-T dependence and associated CDHEs with large regional variations. For P-T dependence, the median values of root mean squared error (RMSE) for corrected simulations show a decreased bias of 5.0% and 4.3% for MBCn and MBCr, respectively, compared with those of raw CMIP6 models. For the likelihood of CDHEs, a decrease of 1.0% and 7.2% in RMSE is shown based on the MBCn and MBCr, respectively. At the regional scale, the performance of the MBC varies substantially, with the reduced RMSE up to 34.8% and 18.7% for P-T dependence and likelihood of CDHEs, respectively, depending on regions and MBC methods. This study can provide useful insights for improving model simulations of compound weather and climate extremes for impact studies and mitigation measures.

1. Introduction
Climate extremes have remarkable impacts on water resources, agricultural production, and terrestrial ecosystems. Climate model simulations, such as those from Phase 5 and Phase 6 of the Coupled Model Intercomparison Project (CMIP5 and CMIP6), have been employed to understand climate extremes (e.g. droughts, hot extremes) and their impacts under global warming (Coumou and Robinson 2013, Betts et al 2018, Hao et al 2019, Vogel et al 2020). However, systematic bias exists in climate models, which may lead to inaccurate evaluation and projection of hazardous extremes and impacts. Previous studies have evaluated the performance of CMIP5/CMIP6 models in simulating precipitation and temperature at different time scales and revealed biases across different regions (Di Luca et al 2020, Fan et al 2020). For example, a detailed assessment of daily temperature extremes by Di Luca et al (2020) revealed the exaggeration of magnitudes in temperature anomalies in CMIP5 and CMIP6 models at the global scale. Precipitation is more heterogeneous than temperature and displays large deviations in climate models. Abdelmoaty et al (2021) assessed the performance of CMIP6 models in simulating the annual maximum
of daily precipitation and found several regions, such as the tropics, showed large biases in precipitation simulations. Thus, bias correction (BC) of climate model simulations is important for improving variability assessments and impact studies of climate extremes.

Previous studies have demonstrated univariate BC methods could improve the simulation of the mean, variance, and quantiles of individual climate variables, such as precipitation and temperature (Teutschbein and Seibert 2012, Räty et al. 2014). Commonly used BC approaches, such as quantile mapping, have been utilized to correct biases of precipitation and temperature. For example, based on the quantile mapping methods, Piao et al. (2022) adjust monthly precipitation and surface temperature from CMIP6 model simulations for the monsoon transitional zone in China and found dramatically decreased bias with respect to uncorrected model simulations. However, univariate BC methods correct climate variables independently without consideration of the relationships among variables, which may not perform well in assessments of weather and climate extremes triggered by multiple factors (Zscheischler et al. 2019).

Due to the interaction of multiple climate variables, such as precipitation-temperature (P-T) dependence, the multivariate BC (MBC) of climate variables has been developed to address the deficiencies in preserving multivariate dependence structures (Piani and Haerter 2012, Li et al. 2014, Cannon et al. 2015, Vrac and Friederichs 2015, Mehrotra and Sharma 2016, Vrac 2018, Guo et al. 2019, 2020, Whan et al. 2021). For example, a two dimensional BC method based on copulas has been developed by Piani and Haerter (2012), which was shown to capture the P-T dependence over six weather stations in Germany. Besides, Li et al. (2014) developed a joint BC method by adjusting one variable (i.e. precipitation or temperature) before correcting the other one, and demonstrated the improvement in simulating individual variables (e.g. precipitation, temperature) and P-T dependence in CMIP5 models. Recently, the MBC methods with three variants (i.e. MBCp, MBCr, MBCn) have been proposed for post-processing multiple variables from climate models, such as precipitation and temperature series (Cannon 2016, 2018). Among three variants, MBCp and MBCr combines the quantile mapping and multivariate linear rescaling (correcting the dependence based on Pearson correlation coefficients and Spearman rank correlation coefficients, respectively), while the MBCn combines the quantile mapping and image processing techniques. For example, compared with univariate BC methods, the MBCn method introduced by Cannon (2018) has been shown to successfully reduce biases in the multivariate dependence structure among variables related to the Canadian Forest Fire Weather Index (e.g. relative humidity, temperature, wind speed, precipitation).

The interaction of multiple variables is closely related to the concurrent or consecutive occurrences of multiple events, which are commonly termed compound events (Zscheischler et al. 2018, Hao 2022). Specifically, the P-T dependence is closely related to the occurrence of compound dry and hot events (CDHEs) with a stronger negative P-T correlation likely associated with a higher occurrence of CDHEs (Hao et al. 2013, Zscheischler and Seneviratne 2017), which may lead to amplified impacts on ecosystems and socioeconomics (Zscheischler et al. 2018). To understand their risk under global warming, some studies have evaluated changes in the P-T dependence (and CDHEs) in historical and future periods (Zscheischler and Seneviratne 2017, Hao et al. 2019, Wang et al. 2021). The development of CMIP6 models has inspired increasing studies to evaluate how climate models perform in simulating the P-T dependence and compound events (Wu et al. 2013, Hao et al. 2019, Ridder et al. 2021). However, the performance of MBC in correcting simulations of historical P-T dependence and the associated likelihood of CDHEs is still limited.

The objective of this study is to assess if the MBC methods can improve CMIP6 simulations of the P-T dependence and CDHEs in China. There are two questions to answer in this study: (a) How do CMIP6 models simulate historical P-T dependence and likelihoods of CDHEs in China? (b) Can MBC methods improve simulations of P-T dependence and likelihoods of CDHEs in China? Discussions on the implications and limitations of this study are also provided.

2. Data and methods

2.1. Climatic data

For observations, we use monthly precipitation and temperature during the period 1961–2020 from CN05.1 (Wu and Gao 2013), which provides gridded climate variables (i.e. precipitation, mean, maximum and minimum temperature, humidity, wind speed, and surface evaporation) with a resolution of 0.25° × 0.25° and has been widely used in regional climate research (Wu et al. 2017). Historical simulations of monthly precipitation and temperature from 20 CMIP6 models are selected for this study (Eyring et al. 2016). The monthly data from CN05.1 and CMIP6 from 1961 to 2014 are used for this study and are re-gridded to a 1° × 1° resolution. The detailed information of CMIP6 models is provided in table S1.

2.2. Multivariate bias correction

Two variants of MBC methods, including MBCn and MBCr (Cannon 2016, 2018), are employed to correct precipitation, temperature, and P-T dependence in CMIP6 simulations. These approaches have been
used in previous studies to correct the inter-variable correlation in climate model outputs (François et al 2020, Whan et al 2021). The MBC (with two algorithms including MBCr and MBCn) in this study is conducted based on the MBC package in R (https://cran.r-project.org/web/packages/MBC/). Observations and simulations from 1961 to 1987 are used for calibrations and those from 1988–2014 are used for validations. By applying MBCn and MBCr, we generate two datasets of corrected precipitation and temperature during 1988–2014 across China. We then compare the difference between observed, simulated, and corrected P-T dependence and CDHEs likelihoods during the validation period.

2.3. P-T dependence and CDHEs

We compute Spearman’s rank correlation coefficients to measure P-T dependence during the summer seasons (June–July–August, JJA). The threshold-based methods are used to define occurrences of CDHEs during JJA at each grid based on the combination \( P < P_{50} \) and \( T > T_{50} \), in which \( P_{50} \) and \( T_{50} \) are the 50th percentiles of precipitation and temperature, respectively. The CDHEs likelihood is defined as the number of occurrences for a specific period divided by the total seasons for each grid. The P-T dependence and CDHEs likelihood based on the multi-model mean from CMIP6 models is used to assess the performance of MBC results.

2.4. Statistical measure

The root mean squared error (RMSE) is used as the measure to assess the performance of MBC methods in this study (Li et al 2014, Cannon 2016). The RMSE can be expressed as:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{\text{obs},i} - X_{\text{mod},i})^2}{n}}
\]

where \( X \) can be correlation coefficients, likelihoods of CDHEs, mean and standard deviation of precipitation (or temperature) at each grid; \( n \) stands for the number of grids across specific regions; ‘obs’ and ‘mod’ in the subscript represent observations (i.e. CN05.1) and model simulations (i.e. raw CMIP6, MBCn, MBCr), respectively. The measure is computed to assess the performance of MBC for the mainland of China and seven sub-regions (shown in figure S1).

3. Results

3.1. Comparison of P-T dependence in CMIP6 and observations

The comparisons of the P-T dependence (measured by Spearman’s rank correlation coefficients) of CN05.1 observations, raw CMIP6 simulations, and corrections during the validation period from 1988 to 2014 are shown in figure 1. Observations (figure 1(a)) display a negative P-T dependence during summers in most land regions except for certain areas (e.g. parts of the Tibetan Plateau), which is consistent with previous studies (Wu et al 2019). The negative P-T correlation during boreal summers can be attributed to the land-atmospheric feedbacks and synoptic processes (Berg et al 2016, Zscheischler and Seneviratne 2017, Vogel et al 2018). The simulations based on the multi-model ensemble (MME) of CMIP6 models indicate that the overall negative P-T dependence in observations across China can be captured (figure 1(c)). However, a large bias in the P-T dependence exists in certain regions such as parts of northwest China, which might be related to the deficiency of climate model simulations for complex topography (Xin et al 2020). Besides, the magnitudes of negative P-T dependence in CMIP6 simulations differ from observations in certain areas (figures 1(a) and (c)). For example, the negative P-T dependence in north China is underestimated compared with that of observations.

The boxplot of P-T dependence of CN05.1 and CMIP6 simulations during JJA is shown in figure 2. The median of the P-T dependence is \(-0.40\) and \(-0.28\) for CN05.1 and raw CMIP6 simulations, respectively. The P-T dependence over China is underestimated compared with observations (figure 2(a)). The difference in Spearman correlation coefficients between precipitation and temperature is computed based on the MME of CMIP6 simulations minus that of observations, as shown in figure 3(a). This further demonstrates that the negative P-T relationship is underestimated for large areas, particularly in parts of southwest, north, east, and south China. The P-T dependence in parts of northwest China (e.g. parts of the Tibetan Plateau) is overestimated by CMIP6 models from 1988 to 2014. In summary, CMIP6 models capture general spatial patterns in the relationship between precipitation and temperature in China, albeit with a discrepancy in certain regions.

3.2. Performance of MBC in P-T dependence

We then assess the performance of MBC in correcting the P-T dependence, as shown in figures 1(e) and (g). Both MBCn and MBCr reproduce the overall spatial pattern of the P-T dependence across China with improved simulations in several regions. For example, the P-T dependence in the northeast of the Tibetan Plateau is improved by the MBC. However, some overcorrections are induced in certain regions such as the far west of southwest China. From the boxplot of the P-T dependence between observations and corrections in figure 2(a), the P-T dependence from MBCr shows a better performance with a median
Figure 1. The spatial distribution of P-T dependence and likelihood of CDHEs based on CN05.1, CMIP6, MBCn, and MBCr over the validation period from 1988 to 2014. Dots indicate the regions where P-T dependence and likelihoods of CDHEs fall within the 10th to 90th percentile range of model simulations.

Figure 2. The boxplot of P-T dependence and likelihood of CDHEs based on CN05.1, raw CMIP6 models, MBCn, and MBCr during the validation period from 1988 to 2014.
Figure 3. The difference in P-T dependence (a), (c), (e) and likelihood of CDHEs (b), (d), (f) between CN05.1 and simulations/corrections (raw CMIP6, MBCn, and MBCr) during the validation period from 1988 to 2014. The marked grids are the same as those in figure 1.

of −0.37, which is closer to observations (−0.40). However, MBCn does not perform as well as the MBCr with marginal improvement.

Figures 3(c) and (e) quantify the difference between corrected simulations and CN05.1, which demonstrates the heterogeneity in BC across different regions. For example, large parts of the southwest, central, south, and east China witness reduced bias of P-T dependence for the two MBC methods. However, large biases remain in some regions, such as north China. Following Li et al (2014), the box-plot of the RMSE of raw and corrected CMIP6 simulations is shown in figure 4(a). The RMSE of P-T dependence from MBCn and MBCr falls within the range of 0.30–0.33 (25th and 75th percentile), which demonstrates certain decreases in model uncertainty compared with raw model simulations (ranging from 0.32 to 0.35). Specifically, based on the relative bias of median RMSE between CMIP6 and MBC methods, the reduced RMSE of P-T dependence is 5.0% and 4.3% for MBCn and MBCr, respectively. The changed RMSE of P-T dependence after MBC in seven sub-regions across China is shown in figure 5. The regional results indicate that MBC methods greatly contribute to the reduced bias in southwest, central, south, and east China, but do not perform well in north China. In particular, the MBC performs better in the south (with decreased RMSE of 15.6% and 34.8% for MBCn and MBCr, respectively) and east China (with decreased RMSE of 17.4% in MBCn and 17.9% in MBCr, respectively). These results indicate the overall improvements of MBC in
correcting the P-T dependence with large regional variations.

3.3. Comparison of CDHEs in CMIP6 and observations

We then extend our analysis to the performance of CMIP6 models in simulating the likelihood of CDHEs. The likelihood of CDHEs from observations and raw CMIP6 simulations during summers from 1988 to 2014 is shown in figures 1(b) and (d). In general, some underestimation of the likelihoods of CDHEs is shown in large regions. The boxplot of likelihoods of CDHEs from observations and simulations is shown in figure 2(b). This result further indicates that raw CMIP6 model simulations underestimate CDHEs likelihoods compared with observations (0.30 and 0.28 for CN05.1 and raw CMIP6, respectively).

A large discrepancy exists in the magnitude of the likelihood of CDHEs from observations and model simulations, as shown in figure 3(b). For example, the difference between CMIP6 and CN05.1 indicates

![Figure 4](image_url)  
**Figure 4:** Boxplots of the RMSE of P-T dependence and CDHEs likelihood between CN05.1 and simulations/corrections (i.e. raw CMIP6, MBCn, and MBCr) from 20 CMIP6 models.

![Figure 5](image_url)  
**Figure 5:** Boxplots of the changed RMSE of P-T dependence between CN05.1 and model simulations/corrections (i.e. raw CMIP6, MBCn, and MBCr) for seven sub-regions. The positive (negative) numbers indicate reduced (increased) RMSE for MBC compared with raw CMIP6 models.
underestimations in the likelihood of CDHEs in north, east, and south China. This is likely related to the underestimation of the negative P-T dependence, as shown in figure 1. By contrast, overestimations of CDHEs likelihood are shown in the part of northwest China in figure 3(b). Overall, CMIP6 simulations capture the general spatial distribution of likelihoods of CDHEs but deficiencies exist in simulating the magnitude of likelihoods.

3.4. Performance of MBC in CDHEs
The performance of MBCn and MBCr algorithms in correcting the likelihood of CDHEs is then explored. The spatial distribution of CDHEs likelihood is improved after MBC for several regions (e.g. south and east China), as shown in figures 1(f) and (h). This improvement is also shown from the boxplot of likelihoods of CDHEs in figure 2(b). For example, the median value of CDHEs likelihood captured by MBCr (0.30) is closer to that of observations (0.30), compared with the likelihood of 0.28 for raw CMIP6 simulations.

The difference in the likelihood of CDHEs from corrected simulations and observations is shown in figures 3(d) and (f). These results demonstrate the likelihood of CDHEs in raw CMIP6 simulations is improved in corrected simulations in large regions, including parts of southwest (e.g. the Tibetan Plateau), east, and south China; however, some over-corrections are shown in north China. Based on the MME, we find that MBC methods can generally reduce RMSE of CDHEs likelihood, which is displayed in figure 4(b). Specifically, the range of RMSE for MBCn and MBCr is 0.078–0.082 and 0.071–0.079 (25th and 75th percentile), respectively, while that for raw CMIP6 models is from 0.078 to 0.083 (25th and 75th percentile). The median RMSE of the simulated likelihood of CDHEs in raw CMIP6 models is reduced by 1.0% and 7.2% for MBCn and MBCr, respectively. Moreover, the changed RMSE of CDHEs likelihood after MBC across seven sub-regions in China is provided in figure 6. Except for north and northeast China, the rest regions witness reduced biases, with pronounced decreases in central China (8.4% and 13.9% for MBCn and MBCr, respectively) and south China (5.2% and 18.7% for MBCn and MBCr, respectively). These results indicate the improved simulation of CDHEs likelihoods from CMIP6 models after MBC.

4. Discussion
4.1. Performance for individual variables
Our findings demonstrate the usefulness of MBC in improving simulations of P-T dependence and the likelihoods of CDHEs from CMIP6. A remaining question is whether the bias in individual precipitation and temperature can also be improved. To answer this question, the difference between observations and raw simulations/corrections of mean precipitation and temperature during JJA from 1988 to 2014 is then assessed, as shown in figure S2. Before MBC, the wet bias in precipitation between CMIP6 simulations and observations is shown in the Tibetan Plateau and southwest China, which is consistent with previous studies (Cui et al 2021, Yang et al 2021) (figure S2(a)). For temperature, there is a large cold bias in the Tibetan Plateau, as shown in figure S2(b), which is consistent with You et al (2020). After MBCn and MBCr, we find remarkable improvement in the mean precipitation and temperature, as shown in figures S2(c)–(f).

On top of that, we calculate the RMSE between CN05.1 and simulations/corrections for precipitation and temperature, as shown in figure S3. A consistent improvement in precipitation and temperature is
shown across China. Specifically, the RMSE between CN05.1 and raw CMIP6 simulations shows that the inter-model variability for mean precipitation falls within the range of 2.0–3.0 (mm d$^{-1}$), which reduces to approximately 0.52 (mm d$^{-1}$) after MBCn and MBCr, as shown in figure 3(a). For mean temperature, the median value of RMSE for 20 raw CMIP6 models and corrected models is around 2.7 (K) and 0.39 (K), respectively, which demonstrates a substantial reduction of bias (figure S3(b)). Furthermore, a decrease in the RMSE of the standardized deviation of precipitation and temperature from corrected simulations is also demonstrated (figures 3(c) and (d)). These results show that MBC methods not only correct the P-T dependence but also perform well in improving the simulations of individual precipitation and temperature.

4.2. Implications

Results from this study indicate strong regional variations in the performance of MBC. Since global climate models with coarse spatial resolution have difficulties in simulating regional/local climate phenomena (Kim et al. 2021), the performance of bias correction for simulations from regional climate models (RCMs) have been assessed (Meyer et al. 2019, Nguyen et al. 2020). Further research on the performance of MBC in simulating CDHEs and their impacts from RCMs should also be explored at regional scales. For the detrimental impacts of climate extremes (e.g. droughts, floods, heatwaves) on water resources, ecosystems, and socioeconomics, it is of great importance to evaluate the performance of model-simulation of these impacts (usually with an impact model, such as a hydrological model or crop model). For example, the meteorological forcing data from CMIP5 or CMIP6 can be employed as inputs of hydrological models or crop models to understand the impacts and risks in the future (Eum et al. 2020, François et al. 2020, Chen et al. 2021, Lemus-Canovas and Lopez-Bustins 2021, Miralha et al. 2021, Whan et al. 2021, Feng et al. 2022). In this case, bias adjustments of the dependence among climate variables can be of particular importance since the impacts may be related to the interaction of meteorological forcing variables. Multiple studies provide several lines of evidence of a better performance of MBC on impact studies. For example, based on the comparison between univariate BC and MBC, Meyer et al. (2019) found simulated snowfall by MBC showed higher consistency with reference data and found that inter-variable relationships between precipitation and temperature affected hydrological responses in snow-dominated catchments in Alpine, which provides useful information for water resources management. It should be noted that certain studies did not find improved performance of MBC in simulating hydroclimate variables (Räty et al. 2018). Nevertheless, MBC is still a useful tool for the impact studies related to multivariate contributing variables (or compound extremes) at regional scales.

4.3. Limitations

There are some limitations in our studies. The inherent drawback of MBC (i.e. the disruption of temporal consistency) cannot guarantee the correction of inter-annual variability (Cannon 2016). We focus on the P-T dependence and CDHEs at the seasonal scales. The variations and impacts of CDHEs at daily or weekly time scales are also of particular interest (Weber et al. 2020, Mukherjee and Mishra 2021). Evaluating the performance of MBC in the likelihood of CDHEs at finer time scales may provide useful insights for impact studies. In addition, inadequate sample sizes may lead to potential uncertainties in the estimation of P-T dependence and the likelihood of CDHEs. Moreover, the P-T dependence between the calibration period and validation period may change and this can affect the performance of MBC. Last but not the least, there are still limitations in correcting the biases triggered by misrepresented physical processes (e.g. atmospheric circulations), which may limit the assessment of droughts and heatwaves at regional and global scales (Dosio and Paruolo 2011, Maraun et al. 2021).

5. Conclusion

This study evaluates the performance of CMIP6 models in simulating the P-T dependence and likelihoods of CDHEs during JJA from 1988 to 2014 in China based on comparisons with CN05.1 as observations. The multi-model mean of CMIP6 models shows that CMIP6 simulations underestimate the negative P-T correlation in parts of north, east, and south China (contributing to the 2012 underestimation of CDHEs likelihoods) and overestimate the negative P-T dependence in parts of northwest China (contributing to overestimation of CDHEs likelihoods). Corrections of CMIP6 simulations based on MBC show improvements in capturing the P-T dependence and likelihoods of CDHEs in China, particularly in southwest, central, east, and south China. After the BC, the RMSE of raw CMIP6 is reduced by 5.0% and 4.3% for MBCn and MBCr, respectively. In addition, the RMSE of the likelihood of CDHEs is reduced by 1.0% and 7.2% based on MBCn and MBCr, respectively. The performance of the MBC methods varies substantially at regional scales, with dramatic decreases in the RMSE of P-T dependence in south (15.6% and 34.8% for MBCn and MBCr, respectively) and east China (17.4% in MBCn and 17.9% in MBCr) for P-T dependence. Reduced RMSE of the likelihood of CDHEs is also shown in central (8.4% and 13.9% for MBCn and MBCr, respectively) and south China (5.2% and 18.7% for MBCn and MBCr, respectively).
The results of this study are useful for impact studies of compound extremes based on climate model simulations and the development of mitigation measures under a changing climate.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://esgf-node.llnl.gov/projects/cmip6/.

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