

Referee's comments are in **red**, our reply in black, quotes in the revised manuscript in **blue**.

## **Referee 1's comments**

### **General comments**

Wang et al. presents an interesting study about comparison between two downscaling approaches i.e. statistical downscaling (ISIMIP) and dynamical downscaling (WRF) combined with bias correction of the future projection of ESM scenarios (i.e. RCP4.5, RCP8.5, G4) over Beijing provincial region. The idea of comparing statistical with dynamical downscaling is a novel path of research. The authors focus on mean temperature, humidity, and wind speed, which are all relevant for climate impacts. The manuscript is generally clearly written and well structured, and the analysis is done in an organized way. However, some parts need to be clarified to easily understand some contents of the manuscript. I think the manuscript is scientifically sound and merits publication after some minor revisions based on my specific comments below.

Reply: We thank the reviewer for their overall positive and very constructive response, along with their helpful suggestions for improving the manuscript. Our response is given below.

### **Specific comments:**

1. In table 1, assessment on the performance of ISIMIP and WRF with bias correction is done only through RCP4.5 scenario. Is there any reason why RCP8.5 is excluded in this part?

Reply: In the assessment part, we only want to see the performance of QDM methods. So we choose the RCP4.5 scenario during 2008-2017 as our reference to simulate. There is no statistical difference between RCP4.5 and RCP8.5 in the 2007-2017 period so it does not matter whether we use RCP4.5 or RCP8.5.

2. This research used ERA5 reanalysis data as the proxy of observation. The authors need strong justification of choosing ERA5 reanalysis in this research as reanalysis data itself might contain some degree of bias.

Reply: Thanks for your comment. Choosing a reanalysis data is an important thing. ERA5 has a finer temporal resolution (hourly) and spatial resolution (0.25°). We add these sentences in Section 2.1

Here we use ERA5 reanalysis data as our reference. This fifth generation ECMWF atmospheric reanalysis of global climate combining huge amounts of historical observations into global estimates by advanced modelling and data assimilation

systems (Hersbach et al., 2020) has been widely used for meteorological data analysis (Chen et al., 2021; Huo et al., 2021; Lee et al., 2022; Zhang et al., 2022). The performance of ERA5 for temperature (Gong et al., 2020), relative humidity (Zhang et al., 2021) and wind speed (Yu et al., 2019) analyzed over China suggests it well reproduces the observed meteorological data in climatology and interannual variations.

## References

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Gong, Y., Yang, S., Yin, J., Wang, S., Pan, X., Li, D., and Yi, X.: Validation of the Reproducibility of Warm-Season Northeast China Cold Vortices for ERA5 and MERRA-2 Reanalysis, 61 (9), 1349-1366, <https://doi.org/10.1175/JAMC-D-22-0052.1>, 2022.

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Yu, J., Zhou, T., Jiang, Z., and Zou, L.: Evaluation of Near-surface Wind Speed Changes during 1979 to 2011 over China Based on Five Reanalysis Datasets, *Atmosphere*, 10, 804, <https://doi.org/10.3390/atmos10120804>, 2019.

3. Step 1 of ISIMIP statistical downscaling and bias correction is simplified and make it unclear. Please provide a more detailed description of it.

Reply: Done. We have changed sentences in Section 2.3.

### 2.3 ISIMIP statistical downscaling and bias correction

This method corrects daily variability on the premise that the monthly trend of the modeled variable is unchanged (Hempel et al., 2013). Here, we take the data from one grid point and for some single month as an example to illustrate the procedure. It includes three steps:

Step 1: We firstly bilinearly interpolate the model data to the same grid points of reanalysis data before bias correction.

Step 2: Monthly bias corrected data are found by multi-year averaged difference between the model output and reanalysis data in our referenced period.

$$M_m^* = \overline{R_m} - \overline{M_m} + M_m \quad (2)$$

The  $M_m^*$  is the bias-corrected monthly data,  $\overline{R_m}$  and  $\overline{M_m}$  are the multi-year averaged values in this month from reanalysis data and model data during the reference period, respectively.  $M_m$  is the modeled monthly data. The subscript  $m$  represents monthly. In this step, ISIMIP does not correct the daily variability of modeled data.

Step 3: Correct the modeled daily variability to a linear regression residual.

$$\Delta M_d^* = \overline{B} \times (M_d - M_m) \quad (3)$$

The  $\Delta M_d^*$  is the bias-corrected residual daily data from model.  $M_d$  is the modeled daily data. The subscript  $d$  represents daily.  $(M_d - M_m)$  represents the modeled daily residual values in this month, and residual of reanalysis data can be obtained in the same way.  $\overline{B}$  is the linear regression coefficient of daily residual values between reanalysis data and model data during our referenced period. Then, we can get the bias-corrected modeled daily data:

$$M_d^* = M_m^* + \Delta M_d^* \quad (4)$$

The  $M_d^*$  is the bias-corrected daily data of model. Therefore ISIMIP corrects the monthly mean and its daily variability. Here, we use the ERA5 reanalysis data as reanalysis data in our study. For convenience we use the term ISIMIP-ESM to denote the output from the ESMs after applying the ISIMIP statistical downscaling and bias correction methodology.

4. The statement “QDM is similar to QM but is non-stationary”. In what sense it is non-stationary?

Reply: Non-stationary means that the mean value or the probability density function (pdf) of a time series changes over time. QM is used to correct the pdf of model data under any scenario to be consistent with the pdf of observed data in the reference period. But the pdf in the future scenario is not the same as in the historical reference period. Therefore, QDM takes the difference between the pdf of model data and observed data in the reference period into account, and applies this difference to the

model data in the future scenario. In this sentence, what we want to express is that QM assumes that the pdf of model data does not change over time (under different scenarios).

5. From figure 3i we see that the WRF simulations have spatial patterns very different from ERA5. Moreover, figure 4 also shows that the pdf of WRF deviates from ERA5 significantly. Are there any reasons behind these findings?

Reply: From the figure 3i and 4, we can see that WRF overestimates the wind speed. In our paper discussion part (line 402-403 and 408-411), we only mentioned the reason for distribution of wind speed from WRF results. A new surface drag parameterization scheme was launched after WRFv3.4, although we chose not to use it here. Zheng et al. (2016) evaluated the effect of two surface drag parameterization schemes on the surface wind speed in Beijing, and found that terrain correction can improve the simulation of wind speed in valley areas. However, WRF still has a systematic overestimation of wind speed. We add the following sentence in the discussion section.

Overestimated surface wind speed in WRF is caused by using smoothed topography in the model (Jimenez and Dudhia, 2012).

#### References

Jimenez, P., and Dudhia, J.: Improving the representation of resolved and unresolved topographic effects on surface wind in the WRF model, *J. Appl. Meteorol. Climatol.*, 51 (2), 300-316, 2012.

Zheng, Y., Liu, S., Miao, Y., and Wang, S.: Effects of different topographic correction methods on the simulation of surface wind speed and temperature in parameterization scheme of YSU boundary layer, *Chinese Journal of Geophysics*, 59 (3), 803-815, 2016.

6. Authors use three different terms for ensemble i.e., “ensemble-mean”, “multi-ensemble mean”, “multi-model ensemble mean”. Are they referring to the same metric?

Reply: Yes. We have changed each usage to “ensemble mean”, which means the ensemble mean of four downscaled ESMs results.

7. In Figure 5, the caption states “labelled as ERA5”, but in the figure we cannot find the label “ERA5”. Do you mean the “observed” label? Figure 8 seems correct. Please make it consistent.

Reply: Yes. We have changed the “observed” label to the “ERA5” in the revised figure 5.

8.It is stated that “wind speed of all four ESMs outputs have correlation coefficients <0.1 with ERA5”. I would suggest that authors describe in the discussion section the consequence of this low value to the results of the analysis.

Reply: Done. We add some sentences after line 404.

Correlation coefficients of wind speed between WRF downscaling results and ERA5 for all four ESM raw results are all < 0.1. Zha et al. (2020) and Jiang et al. (2017) also found similar low correlations. Zha et al. (2020) projects the near-surface wind speed over eastern China based on a CMIP5 dataset, and found that 18 of the 24 ESMs analyzed show negative correlations with observed wind speed during 1979-2005. The low correlations are to be expected when considering variability in simulated weather at high temporal resolution. Jiang et al. (2017) found that differences in CMIP5 model wind responses to the East Asian monsoon in China are related to model parameterization and horizontal resolution.

#### References

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9.The statement “Humidity and windspeed anomalies from ISIMIP appear somewhat spatially anti-correlated, while for WRF there are no particular patterns” need to be clarified. What does the term “anti-correlated” mean? Is it a negative correlation?

Reply: This sentence is based on the G4-RCP8.5. This sentence has been rewritten.

Humidity anomalies from ISIMIP have a difference under G4 relative to RCP8.5 in the southwest of the domain, where windspeed anomalies show an obvious positive change, while for WRF there are no particular patterns.

10.In Table 3, I would suggest using Asterisk sign to indicate that the differences are significant, instead of writing the number in bold.

Reply: Sorry we prefer to use bold – as is the case on many articles. But perhaps it can be left to the journal style and editor decision on what approach to take.