Response to Reviewer Comments

General comments

The article “Mapping the Future Afforestation Distribution of China Constrained by National Afforestation Plan and Climate Change” explored the distribution of future potential afforestation areas based on future high-resolution climate data from the WRF model and HLZ model. It is highlighted that the afforestation scenario is constrained by both the climatological suitability for tree and national afforestation plan. The climatology suitability for tree is decided by future climate conditions and determines the potentially available afforestation domain. The national afforestation plan determines the total afforestation area. The potential value is to provide the design framework for locations of future afforestation. Overall, the article is suitable for the scope of Biogeosciences, I recommend that the authors address the concerns below in a minor revision prior to publication.

Response: Thank you for your help in improving this manuscript. These comments are valuable and very helpful for revising and improving our paper. We have studied the comments and have made revisions carefully. I hope these major revisions meet with approval. The point-by-point responses to the reviewer’s comments are as follows:

Specific comments

Method: I'm confused about the spatial resolution of the article and please provide an explanation. Firstly, the authors emphasize the “high-resolution simulations” in this article. However, the spatial resolution is only 25 km. The other high-resolution climate dataset product (i.e., WorldClim data, https://www.worldclim.org/data/index.html.) is available at the ~1km spatial resolution. I'm confused if that description is appropriate, and please illustrate the advantages of WRF simulation in this study. L115: Why the spatial resolution of ERA5 reanalysis data is 1.0°×1.0°. In ECMWF, the highest resolution of the ERA5 product is 0.25°×0.25°, which is close to WRF simulation (25 km). In the HIS_ERA experiment, is downscaling 1.0° ERA5 data to 25 km necessary? L89: The spatial resolution of MCD12Q1 is 500m, which is different from the WRF simulation (25km). How do you match it well? Please give some detailed information.

Response: Thank you for your suggestion. In this study, the spatial resolution of the WRF simulation is 25- by 25-km, which is higher than the raw CMIP6 model, ranging from 2.8125°×2.8125° (CanESM5 model) to 0.6667°×0.5° (INM-CM5-0 model). This is the meaning of high-resolution simulation in this paper. Additionally, the WorldClim data is spatially interpolated global climate data, with a spatial resolution of 1- by 1-km. Compared to the WorldClim data, the dynamical downscaling climate data (i.e., the WRF model output) has the advantage of keeping physical consistency constraints among these variables such as the hydrostatic equilibrium and the geostrophic wind balance. The physically consistent variables are an important basis for this study.

Second, on the behalf of ERA5 reanalysis data, there are actually multiple resolutions of datasets from the ECMWF. The aim of downscaled ERA5 is to evaluate the accuracy of the downscaled MPI–ESM1–2–HR model. In order to enhance the comparability of downscaled ERA5 reanalysis data and the MPI–ESM1–2–HR model, we used ERA reanalysis data with a grid size closer to that of the MPI–ESM1–2–HR model.

Third, in this study, we filled the 500-meter resolution of the MODIS data into the 25-km resolution of the WRF model grids by aggregating the MODIS pixels within a 25x25 km grid cell and calculating the area fraction of each land use type within the 25x25 km grid cell.

L218: "Areas with high precipitation are allowed priority afforestation." In this study, precipitation is treated as a key meteorological factor that restricts forest distribution. Indeed, precipitation is critical for forest growth. However, a single climate variable is slightly simple rather than representing climatology suitability for tree. Multivariate comprehensive indicators affecting forest growth are more appropriate. In this study, the essence of the HLZ model is the distance to the three bioclimatic variables. I recommend considering the distance as a comprehensive indicator to quantify the climatology suitability for tree.

Response: We agree with this comment. In the revised manuscript, the HLZ value as a comprehensive indicator has been used to quantify the climatology suitability for afforestation. Areas with a low HLZ value are allowed priority afforestation. Because a low HLZ value means a greater opportunity to be potential forestlands. Following this new method, we find that the probable locations for future potential afforestation areas in China are around and to the east of the Hu Line.

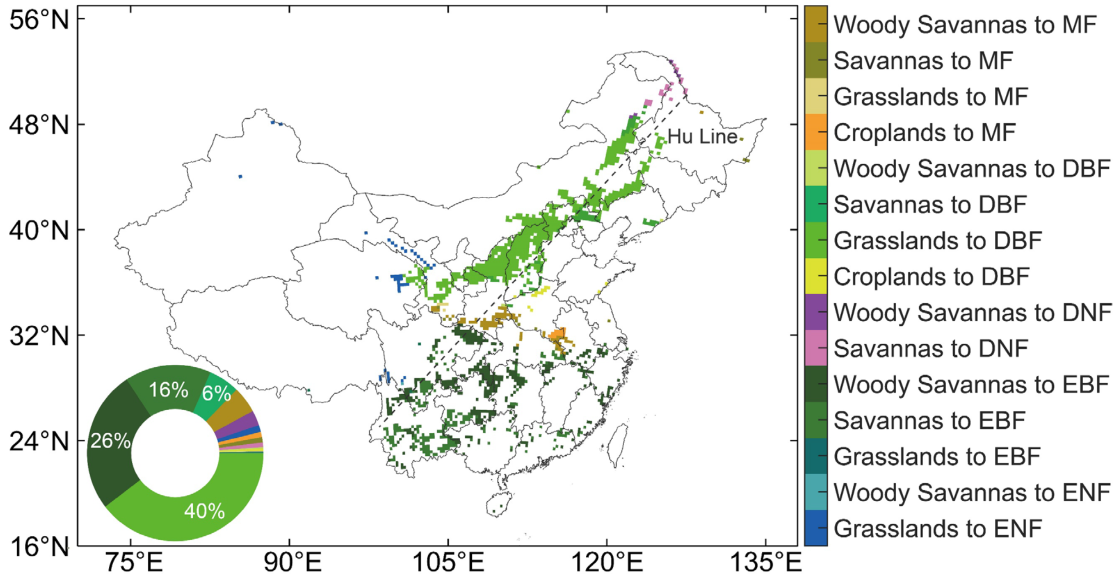

Figure 1: Map of future potential afforestation distribution under constraining of national afforestation planning total area and future climate changes and the afforestation-induced vegetation types conversions. Forest types from IGBP include Evergreen Needleleaf Forests (ENF), Evergreen Broadleaf Forests (EBF), Deciduous Needleleaf Forests (DNF), Deciduous Broadleaf Forests (DBF), and Mixed Forests (MF). The black dotted line indicates the Hu Line.

L204: In the section on the approach of the newly afforestation allocation, I'm confused about the definition of forest. Please clarify it. For the national afforestation plan (NFMP), the total afforestation area is 73.78×10^4 km^2. How to define the total afforestation area? I wonder whether the definition from the State Forestry Administration of China agrees with this study.

Response: This study remains consistent with the definition of forest of China's State Forestry Administration. In the statistical context of China's State Forestry Administration, the term "forest area" is essentially synonymous with "woodland area." This designation is based on the criterion that the fraction of tree canopy cover exceeds 20%. The total afforestation area of 73.78×10^4 km^2 implies that we will be planting trees across this area. It is anticipated that the trees would grow in health and the fraction of tree canopy cover could exceed 20%. Thereby, afforestation implicates that non-woodland would be replaced by woodland. Given the need to ensure food security, urban expansion, and ecological protection in the future, future afforestation cannot occupy cropland, urban, and wetlands (including water bodies). Therefore, the implementation of future afforestation in this study occurs mainly on the present grassland, savanna, and woody savanna.

L113: The authors use the SSP2–4.5 scenario (the middle-of-the-road development) to represent the climate future projections. However, this study only used one model projections rather than multiple model ensemble mean. Following the methodology of CMIP6 climate projection, scenario-based climate projection may have large uncertainties. It is suggested the revision to address this issue. It is also worthy to discuss effects of single model projection uncertainties on the research result of this study.

Response: Following this comment, we revised the discussion. In the revised manuscript, the model scenarios and uncertainties are discussed, as follows:

This study may have some limitations and uncertainties. Following the approach of existing studies (Ma et al., 2023; Qiu et al., 2022), we also utilized the bias-correction LBC in dynamical downscaling. However, the model uncertainty in the future climate projection is difficult to quantify because one GCM is used to nest into the WRF model. The projected result generally exhibits variations based on the choice of driving GCMs (Gao et al., 2022). This divergence can be attributed to the inherent configurations and physics parameterization of the GCMs, distinct radiative forcing scenarios, and varying equilibrium climate sensitivities found in CMIP6 models (Zuo et al., 2023; Bukovsky and Mearns, 2020). For instance, the high emissions scenario could lead to higher temperature and stronger precipitation in China (Yang et al., 2021). Consequently, the suitability of land for future forests may change accordingly. Exploring the impacts of different SSPs on the distribution of potential afforestation regions would be an intriguing avenue for future research.

To address the concerns about model uncertainty, exploring WRF forced by multiple bias-corrected CMIP6 models can help uncover the source of uncertainty. Utilizing ensemble means for downscaled climate simulation would contribute to a more robust projection. Additionally, the selection of different physics parameterization schemes in the WRF model can also influence the simulation performance (Gbode et al., 2019). Selecting the most suitable combination is beneficial to reduce the underlying bias.

Although the resolution of our dynamical downscaled simulation (25 km) is finer than raw GCMs (~100 km), it is difficult to meet the needs of afforestation planning in areas with complex topography. Convection-permitting climate modelling at the kilometre-scale has recently been developed to reproduce better mesoscale atmospheric processes (Prein et al., 2015; Lucas-Picher et al., 2021), and obviously improve the WRF simulation, especially precipitation (Knist et al., 2020). However, increasing the resolution of the simulation implies higher computational costs. In contrast, statistical downscaling methods are also known to obtain high-resolution climate data with fewer computational resources (Tang et al., 2016). It assumes that the historical relationship between local climate variables and the large-scale circulation remains fixed in the future term (Wilby and Dawson, 2013). The multi-model ensemble means from the CMIP6 statistical downscaling can significantly reduce the biases compared to individual models (Gebrechorkos et al., 2019). Thus, some statistical downscaled CMIP6 datasets (Gebrechorkos et al., 2023; Lin et al., 2023; Thrasher et al., 2022), with a resolution of 0.1°-0.25° covering the global land, can be applied to explore the future global potential afforestation area in following work. However, it is noted that the statistically downscaling data may have a limitation, as the covariance among the variables may not align with physical laws.

References

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Gebrechorkos, S., Hülsmann, S., & Bernhofer, C. (2019). Regional climate projections for impact assessment studies in East Africa. Environmental Research Letters, 14(4), 044031.

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Wilby, R. L., & Dawson, C. W. (2013). The statistical downscaling model: insights from one decade of application. International Journal of Climatology, 33(7), 1707-1719.

Gbode, I. E., Dudhia, J., Ogunjobi, K. O., & Ajayi, V. O. (2019). Sensitivity of different physics schemes in the WRF model during a West African monsoon regime. Theoretical and Applied Climatology, 136, 733-751.

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Lucas-Picher, P., Argüeso, D., Brisson, E., Tramblay, Y., Berg, P., Lemonsu, A., et al. (2021). Convection-permitting modeling with regional climate models: Latest developments and next steps. Wiley Interdisciplinary Reviews: Climate Change, 12(6), e731.

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Qiu, Y., Feng, J., Yan, Z., Wang, J., & Li, Z. (2022). High-resolution dynamical downscaling for regional climate projection in Central Asia based on bias-corrected multiple GCMs. Climate Dynamics, 58(3-4), 777-791.

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Bukovsky, M. S., & Mearns, L. O. (2020). Regional climate change projections from NA-CORDEX and their relation to climate sensitivity. Climatic Change, 162(2), 645-665.

Yang, X., Zhou, B., Xu, Y., & Han, Z. (2021). CMIP6 evaluation and projection of temperature and precipitation over China. Advances in Atmospheric Sciences, 38, 817-830.

L353: "Our findings indicated that future afforestation in China would mostly occur around and to the east of the Hu Line, consistent with Zhang et al. (2022)." The authors try to compare other similar studies on future potential afforestation distribution. More result differences should be discussed. I suggest to highlight the innovation and implications of the article by comparing with existing studies.

Response: In the revision, we discussed the innovation and implications of the article by comparing with existing studies, as follows:

The most probable geographical distribution of future potential afforestation regions in China has been investigated in this study. Compared with previous studies, the total afforestation area in this study is greater than theirs. For example, Zhang et al. (2022) reported future climate changes may lead to an increase in suitable forestation lands by 33.1×10^4 km^2 (2070s) through predicting the ecological niche of the forest using the machine learning approach. Xu et al. (2023) found that the area of prioritized potential forestation land was about 66.61×10^4 km^2 in 2020 through spatial overlay analysis by considering multiple factors including climate, transportation, topography, land use and so on. This study is oriented towards national afforestation plans to identify future potential afforestation regions referring to climate change scenarios and land use patterns. The overall result is a more realistic and plausible afforestation scenario. The dataset would be valuable for studying the effects of future afforestation on carbon budget, ecosystem service, water resources, and surface climate.

References

Zhang, L., Sun, P., Huettmann, F., & Liu, S. (2022). Where should China practice forestry in a warming world?. Global Change Biology, 28(7), 2461-2475.

Xu, J. (2023). Estimation of the spatial distribution of potential forestation land and its climatic potential productivity in China. Acta Geographica Sinica, 78(3), 677–693.

L180-186: Why the Holdridge life zone (HLZ) model is suitable for simulating the potential vegetation types in China. The author simply describes the extensive application of the HLZ model. I suggest validating the accuracy of the HLZ model. It is necessary to compare potential vegetation types with true vegetation types. Please add it to the Supplement Material.

Response: Following this suggestion, we included a comparison between potential vegetation from the HLZ model and the actual vegetation. The actual vegetation in the year 2005 refers to China's Land-Use/cover Datasets (CLUDs), which has a spatial resolution of 1- by 1 km and covers the entire China (Liu et al., 2014). The overall accuracy of CLUDs is above 90% (Liu et al., 2010). We find that the HLZ model can reproduce the potential forest distribution and grassland-forest geographical boundary well.

Reference

Liu, J., Kuang, W., Zhang, Z., Xu, X., Qin, Y., Ning, J., et al. (2014). Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. Journal of Geographical Sciences, 24, 195-210.

Liu, J., Zhang, Z., Xu, X., Kuang, W., Zhou, W., Zhang, S., et al. (2010). Spatial patterns and driving forces of land use change in China during the early 21st century. Journal of Geographical Sciences, 20, 483-494.

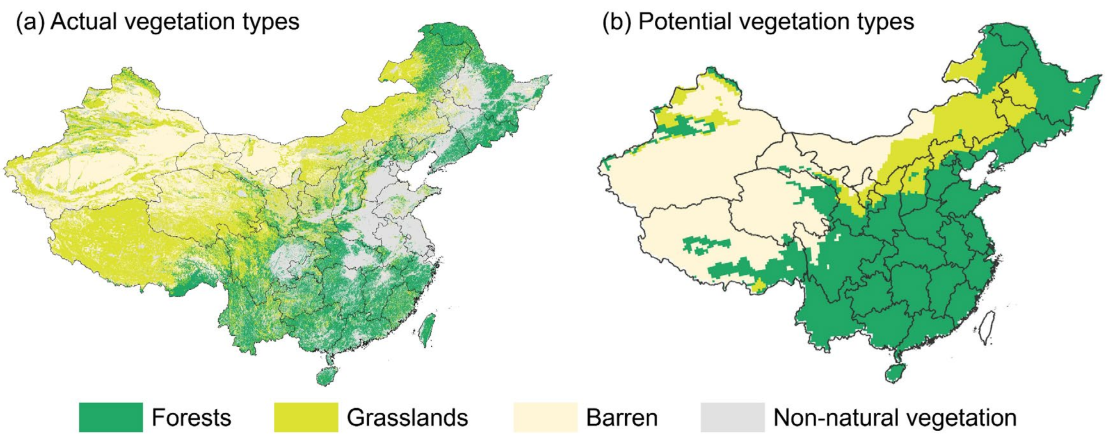

Figure 2. Comparison of actual (a) and potential (b) nature vegetation types. The actual vegetation types refer to China's Land-Use/cover Datasets (CLUDs) for the year 2005. The potential vegetation types derived from the HLZ model are based on the average of 1995-2014.

L125: The authors have done substantial work on numerical experiments. For example, the authors correct the lateral boundary conditions rather than the raw GCM before dynamic downscaling. It is a very good solution to reduce the underlying bias. I suggest adding the

comparison of raw GCM, bias-corrected GCM, and observation.

Response: To select the excellent performance of GCM, our previous (Song et al., 2023) studies comprehensively evaluated the performance of the GCM involved in CMIP6. It was reported that the MPI–ESM1–2–HR model from the Max Planck Institute outperforms all other GCMs in East Asia. We have added the comparison of the raw MPI–ESM1–2–HR model, bias-corrected MPI–ESM1–2–HR model, and the observation. The bias-corrected MPI–ESM1–2–HR model can reduce the underlying biases. The results are as follows:

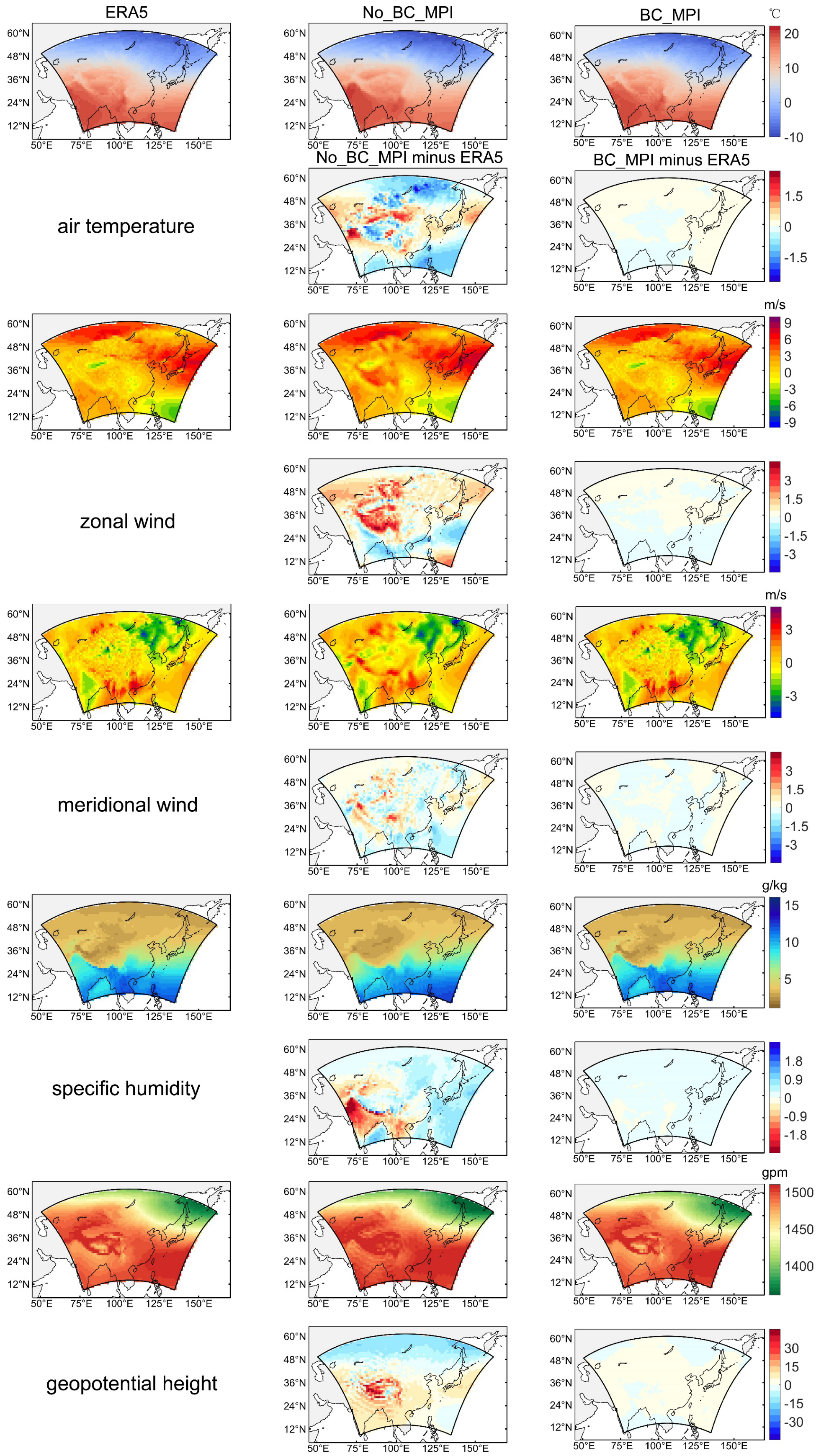

Figure 3: Comparison of ERA5 reanalysis data with raw (No_BC_MPI) and bias-corrected historical MPI–ESM1–2–HR model (BC_MPI) at the pressure of 850 hPa for the period 1995–2014.

The odd rows represent the spatial distribution of climatology, and the even rows represent the differences.

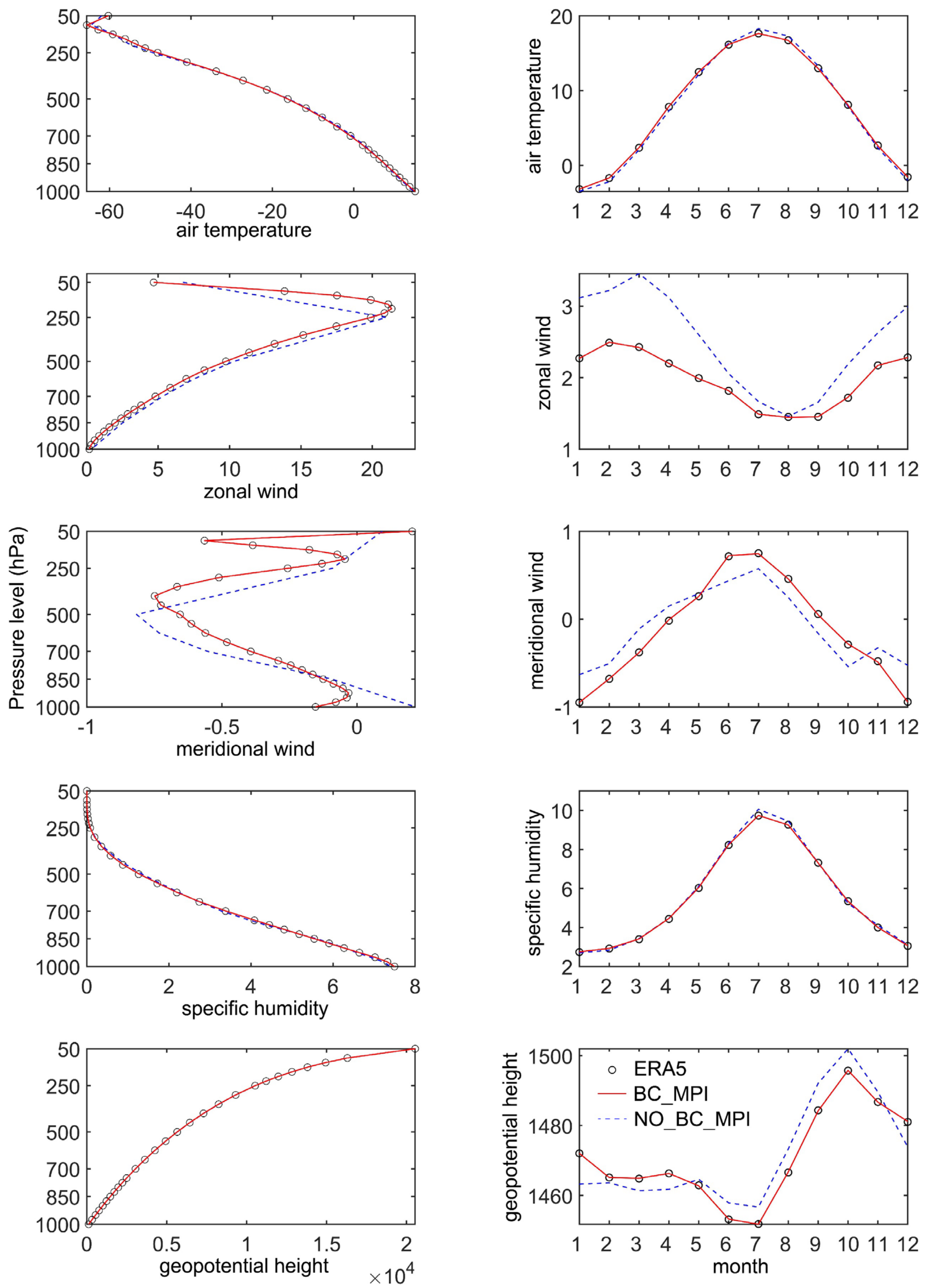

Figure 4: Comparison of ERA5 reanalysis data with raw (No_BC_MPI) and bias-corrected historical MPI–ESM1–2–HR model (BC_MPI) at the different pressure levels and months.

Reference

Song, S., Zhang, X., Gao, Z., & Yan, X. (2023). Evaluation of atmospheric circulations for dynamic downscaling in CMIP6 models over East Asia. Climate Dynamics, 60(7-8), 2437-2458.

L351: This article emphasizes "The dataset would be valuable for studying the effects of future afforestation on carbon budget, ecosystem service, water resources, surface climate". Would the data set be available to the public, especially in Figure 7?

Response: Yes. This dataset is available from the corresponding author upon request.

L234: "The WRF simulation generally overestimates TP in most regions with a national-average bias of 92.883 mm". According to Figure 3d-3f, the obvious overestimate is over the southeast Tibetan Plateau. It is suggested to explain the potential reasons of these bias in the revision.

Response: The southeastern Tibetan Plateau (TP) is characterized by complex terrain. Regional climate models (RCMs) generally overestimate precipitation over the TP (Wang et al., 2021; Liu, et al., 2023). The wet bias could be attributed to inappropriate parameterization schemes (Ou et al., 2020; Zhao et al., 2023), coarse horizontal resolution (Lin et al., 2018; Rahimi et al., 2019), and inappropriate land-surface processes associated with soil moisture and frozen–thawing (Fu et al., 2020; Yang et al., 2018). For example, a high-resolution simulation can reproduce more realistic terrain characteristics and reduce the wet bias because finer resolutions decrease the water vapour transport towards the TP due to improving resolving orographic drag (Lin et al., 2018). An improved cloud macrophysics scheme can increase low cloud cover and reduce latent heat flux and land surface temperature, which leads to a more stable atmosphere and less precipitation (Zhao et al., 2023).

References

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Ou, T., Chen, D., Chen, X., Lin, C., Yang, K., Lai, H. W., & Zhang, F. (2020). Simulation of summer precipitation diurnal cycles over the Tibetan Plateau at the gray-zone grid spacing for cumulus parameterization. Climate Dynamics, 54, 3525-3539.

Rahimi, S. R., Wu, C., Liu, X., & Brown, H. (2019). Exploring a variable-resolution approach for simulating regional climate over the Tibetan Plateau using VR-CESM. Journal of Geophysical Research: Atmospheres, 124(8), 4490-4513.

Fu, Y., Ma, Y., Zhong, L., Yang, Y., Guo, X., Wang, C., et al. (2020). Land-surface processes and summer-cloud-precipitation characteristics in the Tibetan Plateau and their effects on downstream weather: a review and perspective. National Science Review, 7(3), 500-515.

Yang, K., Wang, C., & Li, S. (2018). Improved simulation of frozen-thawing process in land surface model (CLM4. 5). Journal of Geophysical Research: Atmospheres, 123(23), 13-238.

Wang, X., Tolksdorf, V., Otto, M., & Scherer, D. (2021). WRF-based dynamical downscaling of ERA5 reanalysis data for High Mountain Asia: Towards a new version of the High Asia Refined analysis. International Journal of Climatology, 41(1), 743-762.

Liu, H., Zhao, X., Duan, K., Shang, W., Li, M., & Shi, P. (2023). Optimizing simulation of summer precipitation by weather research and forecasting model over the mountainous southern Tibetan Plateau. Atmospheric Research, 281, 106484.

Table 1: Why this parameterization scheme of the WRF model is appropriate in this study. Please give a specific reason or reference.

Response: The reference was included in the revision.

Reference

Hu, Y., Zhang, X. Z., Mao, R., Gong, D. Y., Liu, H. B., & Yang, J. (2015). Modeled responses of summer climate to realistic land use/cover changes from the 1980s to the 2000s over eastern China. Journal of Geophysical Research: Atmospheres, 120(1), 167-179.

L300: What is the meaning of "The corresponding annual total precipitation is over 353.6 mm among the selected grids"? How to obtain the value of 353.6 mm. Please clarify it.

Response: In the HLZ model, the minimum precipitation for forests is prescribed as 353.6 mm. In the revision, it is revised as:

Their annual precipitation is all above 353.6 mm, which is prescribed as a precipitation limitation for forests in the HLZ model.

L311: "It is generally common sense that afforestation is highly constrained by precipitation." Please add specific explanations or references.

Response: The references were included in the revision.

References

Harvey, J. E., Smiljanić, M., Scharnweber, T., Buras, A., Cedro, A., Cruz-García, R., et al. (2020). Tree growth is influenced by a warming winter climate and summer moisture availability in northern temperate forests. Global Change Biology, 26(4), 2505-2518.

Fang, J., Piao, S., Zhou, L., He, J., Wei, F., Myneni, R. B., et al. (2005). Precipitation patterns alter growth of temperate vegetation. Geophysical Research Letters, 32(21).

L275: To what does "total area" refer to? Is it the whole nation? Please clarify.

Response: The "total area" refers to the entire China land area.

Figure 5b: The flow diagrams are not clear, and please give specific values.

Response: The flow diagram was improved and specific values are included.

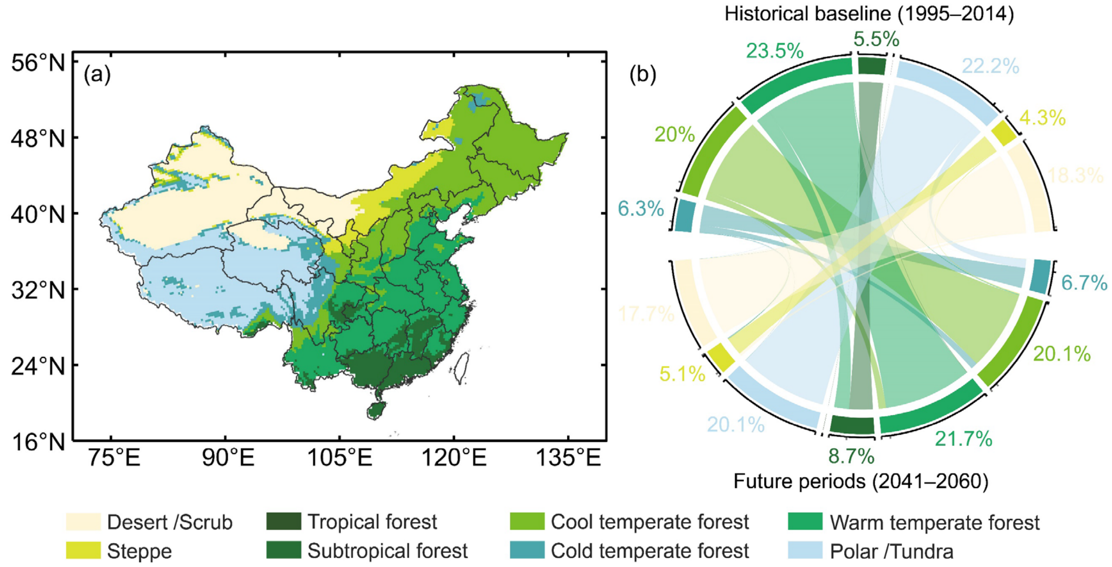

Figure 5: Projected spatial pattern of (a) potential vegetable types from HLZ model under the SSP2–4.5 scenario in the future periods (2041–2060) from the FUT_ MPI simulation, and (b) area changes across historical baseline (1995–2014) and future periods, where the calculations are based on FUT_ MPI simulation versus HIS_ MPI simulation.

Eq. (2): “ ,   , and ”. Please correct it.

Response: The Equation (2) was corrected in the revision.

$$F_{cor} = D_{GCM\_F} \times \frac{SD_{ERA}}{SD_{GCM}} + M_{ERA} + \left(M_{GCM\_F} - M_{GCM\_H}\right) \quad (2)$$

Figure 3 and Figure 4: For Figure 3 and Figure 4 captions, suggest not to use the abbreviations “HLZ”, “AT”, “TP”, and “PE”.

Response: The full names were included in the captions.

L208: “national afforestation plan” is redundant. Please use the “NFMP”.

Response: It is revised.

L98: “The total national afforestation area is about 73.78×10^4 km^2 from 2020 to 2050”. Please give specific forest cover.

Response: It was revised as follows:

The national afforestation plan shows a total afforestation area of about 73.78×10^4 km^2

(equivalent to an increase China's forest cover by 7.7%) from 2020 to 2050.

Figure 2: No citation for Figure 2 in the text.

Response: The citation of Figure 2 was included in the revision.

Figure 6: Please do not use the abbreviations in the figure captions.

Response: All full name is presented in the captions in revision.

L338: “woody savannas” replaces “Woody savannas”.

Response: It is revised.