Response to Referee #1,

The comments of reviewers are posted in **black**; our answers are posted in **blue.**

Q1: The authors should emphasize this work's main novelty or contribution more clearly.

Thank you for your kind advice which helps improve our work.

In this study, we applied three machine learning methods (OLS, DT and DNN) to produce ensembled datasets during the time period of 2015-2100 under three SSP scenarios (SSP1-2.6, SSP2-4.5 and SSP5-8.5), to project changes in temperature and precipitation over the global continent.

Previous studies mainly project future climate changes through single GCMs or multi-model ensemble (MME) datasets. MME is also the ensemble method that shows generally good performance in terms of various variables or indices (e.g., Massoud et al, 2019; Zhang et al, 2022). We compared the accuracy of single GCM, MME and our new ensemble datasets. The accuracy assessment showed that the credibility of new datasets has improved compared with single GCMs and MME.

Former studies mainly focus on regional climate changes (Gaitán et al. 2019; Lee et al. 2022). The optimized datasets were applied to capture future climate change at continental and global scales. The climate characteristics at the global and continental scales in the future were proposed as follows.

(1) Aisa, Europe and North America continents contributed more to global warming than Oceania, Africa and South America continents under the studied three SSPs scenarios.

(2) The slopes of Asia under three SSPs are the largest among six continents, which are 0.165 °C·10a^{-1}、0.439 °C·10a^{-1} and 0.961 °C·10a^{-1} under SSP1-2.6, SSP2-4.5 and SSP5-8.5.

(3) Precipitation will aggregate during July and August over the global continent. April and September to subsequent February can be categorized as dry months under selected SSPs.

(4) SSP5-8.5 scenario will accelerate global precipitation polarization ($p < 0.05$).

Refer

Gaitán, E., Monjo, R., Pórtoles, J., et al. Projection of temperatures and heat and cold waves for Aragón (Spain) using a two-step statistical downscaling of CMIP5 model outputs. Science of The Total Environment, 2019, 650, 2778-279.

Massoud E C, Espinoza V, Guan B, et al. Global climate model ensemble approaches for future projections of atmospheric rivers. Earth's Future, 2019, 7(10): 1136-1151.

Lee, Y., Paek, J., Park, J.-S., et al. Changes in temperature and rainfall extremes across East Asia in the CMIP5 ensemble. Theoretical and Applied Climatology, 2022, 141, 143-15.

Zhang M Z, Xu Z, Han Y, et al. Evaluation of CMIP6 models toward dynamical downscaling over 14 CORDEX domains. Climate Dynamics, 2022, 1-15.

Q2: Though ML methods were successfully applied in the precious regional studies, regionalized models were just suitable for specified periods or regions. How can the authors promise the suitability of the ML methods at the global scale?

Thank you for your question. The climate projection in this study is at a global scale. The accuracy assessment is also based on the observed, GCM and ensemble datasets which contain climate information of the global continent. Due to the missing of the observed dataset in the future, we verified the accuracy of the models in the historical period. The training time period of ensemble models is1965-1994 and the validation time period is 1995-2014. Thackeray et al. (2022) demonstrate that there exists a relationship between the future increased occurrence of precipitation extremes aggregated over the globe and the observable change over recent decades. Moreover, Thackeray et al. (2022) also proposed that model errors in the historical climate can be used to inform the best estimate of future change. Many studies assess the accuracy of GCMs in reproducing observed temperatures in historical periods and then employed multi-model ensembles to simulate climate changes (Boberg et al., 2012; Aloysius et al., 2017; Jia et al., 2019; Shiru et al., 2020).

Refer

Boberg F, Christensen J H. Overestimation of Mediterranean summer temperature projections due to model deficiencies. Nature Climate Change, 2012, 2(6): 433-436.

Aloysius N, Saiers J. Simulated hydrologic response to projected changes in precipitation and temperature in the Congo River basin. Hydrology and Earth System Sciences, 2017, 21(8): 4115-4130.

Jia K, Ruan Y, Yang Y, et al. Assessment of CMIP5 GCM simulation performance for temperature projection in the Tibetan Plateau. Earth and Space Science, 2019, 6(12): 2362-2378.

Shiru M S, Chung E S, Shahid S, et al. GCM selection and temperature projection of Nigeria under different RCPs of the CMIP5 GCMS. Theoretical and Applied Climatology, 2020, 141(3): 1611-1627.

Thackeray C W, Hall A, Norris J, et al. Constraining the increased frequency of global precipitation extremes under warming. Nature Climate Change, 2022, 12(5): 441-448.

Q3: By using the OLS model, did each GCM represent a dimension of space? How to set the weights for each GCM?

Thank you for your questions. Each GCM represents a dimension of space in a certain month.

To calculate the weight of each GCM in the i^{th} month, Residual standard error (RSS) needs to be minimized, which can be described as follow.

$$RSS^i = \sum_{s}^{k=1} \left(Y^{(i,k)'} - Y^{(i,k)}\right)^2 \tag{3}$$

where $Y^{(i,k)'}$ and $Y^{(i,k)}$ denote the values of single kth pixel value in the CRU TS4.5 image and the ensemble image according to the temporal-spatial correspondence, respectively; s which equals to 2022600(67420*30) denotes the sum of pixels of the CRU TS4.5 (or ensemble) images during the period of 1965-1994.

Take the first derivative of Eq. (3) equal to 0 after substituting $Y^{(i,k)}$ in Eq. (2) into Eq. (3). The weight in the i^{th} month can be determined as follows.

$$\begin{bmatrix} \beta_1^i \\ \vdots \\ \beta_{16}^i \end{bmatrix} = \left(X_i^T X_i\right)^{-1} X_i^T Y_i \tag{4-1}$$

$$X_i = \begin{bmatrix} pixel_1^{(1,1965,i)} & \cdots & pixel_{15}^{(1,1965,i)} & pixel_{16}^{(1,1965,i)} \\ \vdots & \ddots & \vdots & \vdots \\ pixel_1^{(67420,1965,i)} & \cdots & pixel_{15}^{(67420,1965,i)} & pixel_{16}^{(67420,1965,i)} \\ \vdots & \ddots & \vdots & \vdots \\ pixel_1^{(67420,1994,i)} & \cdots & pixel_{15}^{(67420,1994,i)} & pixel_{16}^{(67420,1994,i)} \end{bmatrix} \tag{4-2}$$

$$Y_i = \begin{bmatrix} y^{(1,1965,i)} \\ \vdots \\ y^{(67420,1965,i)} \\ \vdots \\ y^{(67420,1994,i)} \end{bmatrix} \tag{4-3}$$

where β_k^i denotes the weight of the kth model in the i^{th} month; $pixel_k^{(p,q,i)}$ and $y_k^{(p,q,i)}$ denote the value of the p^{th} pixel in the q^{th} year from the image of the kth model and CRU TS4.5, respectively.

Q4: Does the sum of $\beta11$, $\beta21$, …, $\beta16$ equal 1?

Thank you for raising this question. Considering the overestimation of models, the sum of βs doesn't equal 1. Constraining the sum equal to 1 may lead to overestimation. Paul (2022) proposed that GCMs exaggerate the impacts of global warming. Chai. et al. (2022) demonstrated the projected precipitation increase in the future is overestimated by CMIP6 over Asia.

Refer

Voosen Paul. "Hot" climate models exaggerate Earth impacts. Science, 2022, 376

Chai, Y., Yue, Y., Slater, L.J. et al. Constrained CMIP6 projections indicate less warming and a slower increase in water availability across Asia. Nature Communication, 2022, 13, 4124.

Q5: Please make the code of this paper available for authors if possible.

Thank you for your kind advice. The code is available via https://doi.org/10.5281/zenodo.7104329.

Refer

Piaoyin, Zhang, Jianzhong Lu: Machine Learning-GCM-WHU (1.0). Zenodo [code], https://doi.org/10.5281/zenodo.7104329

Q6: Different GCMs have different spatial resolutions; how do you simultaneously set them as the input? Did the authors downscale the GCMs to the same spatial resolution?

Thank you for raising this point. All GCM simulations and CRU data are re-gridded into a common $0.5° \times 0.5°$ resolution by the bilinear interpolation, which is a widely used method (Aloysius et al. (2016); Abbasian et al. (2018); Thackeray et al. (2022)). We have added related details to the revision.

Refer

Aloysius N R, Sheffield J, Saiers J E, et al. Evaluation of historical and future simulations of precipitation and temperature in central Africa from CMIP5 climate models. Journal of Geophysical Research: Atmospheres, 2016, 121(1): 130-152.

Abbasian, M., Moghim, S. and Abrishamchi, A. Performance of the general circulation models in simulating temperature and precipitation over Iran. Theoretical and Applied Climatology, 2018, 135, 1465–1483.

Thackeray C W, Hall A, Norris J, et al. Constraining the increased frequency of global precipitation extremes under warming. Nature Climate Change, 2022, 12(5): 441-448.

Q7: The authors should improve image resolution.

Thank you for your advice which improves our work. We have improved the resolution to 600dpi in the revision.

There are also some tiny mistakes:

1) In Figure 1, the 30 CRU images in February should be changed to 196502

Thank you raising this typo. We have corrected it in the revision as follows:

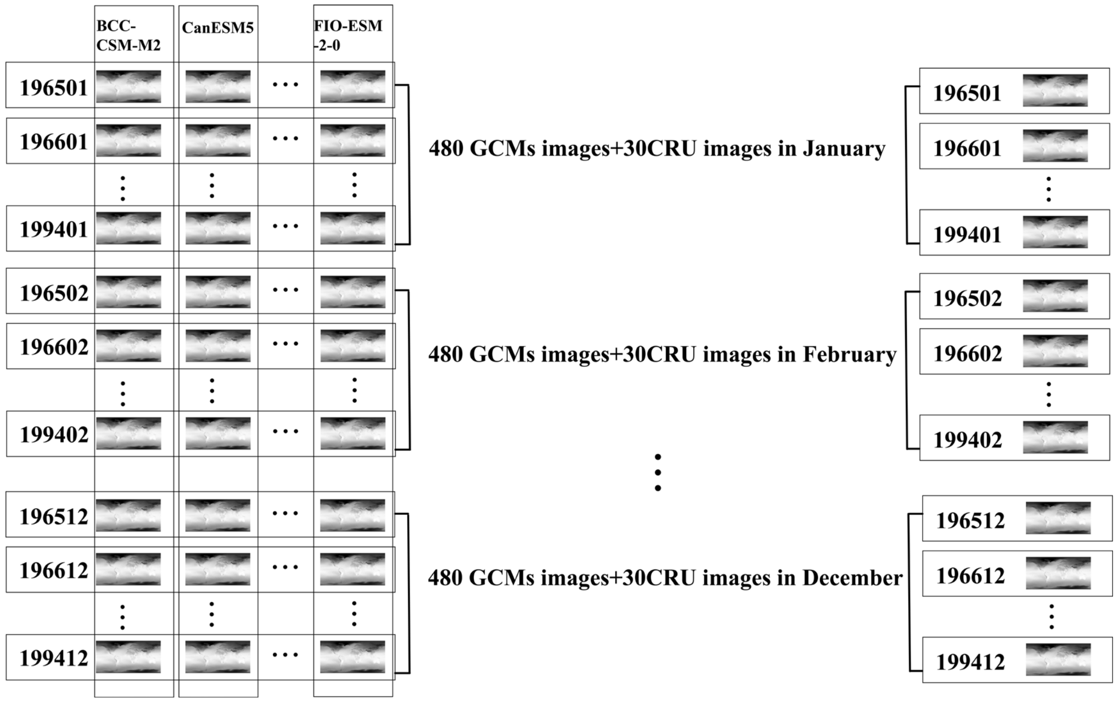

Fig. 1. Weight assignment of 16 GCMs on a time scale

2) In line 165, "The process can be described as four steps in detail:" but only three steps are presented.

Thank you for raising this typo. This sentence has been modified.

3) In line 173, it should be equation 5.

Thanks. We have made corrections according to your comments.