Geoscientific Model Development Discussions

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Reply on RC5

Fang Wang et al.

Author comment on "Customized deep learning for precipitation bias correction and downscaling" by Fang Wang et al., Geosci. Model Dev. Discuss., https://doi.org/10.5194/gmd-2022-213-AC5, 2022

The paper presents a customized deep learning methodology that incorporates customized loss functions, multitask learning, and physically relevant covariates for bias correction and downscaling of precipitation data, starting from the hourly time scale. This is a very difficult task, due to the complexity of the precipitation characteristics. Improvements in the generation of temporal and spatial high-resolution data for practical applications and for scientific tasks, as validation of very high resolution nonhydrostatic atmospheric models. The bias correction procedure reflects one of the weakness of this kind of methodology: it relays on the estimation of climate trends based on the differences between the training and test periods. These differences could be related to low frequency climate variability and the bias correction procedure can be influenced for this variability.

The methodology is evaluated using six different scenarios to systematically evaluate the added values of weighted loss functions, multitask learning, and atmospheric covariates and compare its performance to the regular deep learning and statistical approaches, pointing to the usefulness of considering physical relationships in choosing the atmospheric covariates. This fact points to the necessity of the consideration of physical variables related to precipitation relationships for a better bias correction and downscaling.

The authors show that using atmospheric covariates also helps to improve the performance of the methodology for capturing extreme events. One important result is the ability that customized deep learning to improve downscaling and bias correction of precipitation estimates of gridded precipitation datasets with respect to more standard deep learning and statistical methods.

I consider this paper an important step forward in the task of the improvement of bias correction and downscaling of gridded data. It is especially important for the downscaling and bias correction of climate data generated for climate change impact studies, as there is a strong need in a good bias correction (taking caution about the low frequency variability problem) and downscaling for impact studies. The paper deserves to be published after some corrections

Some questions:

- Will the use of a different interpolation method in the upsampling layers would influence the downscaling? Which is the limit for the downscaling factor?

Response: Thank you for your comments. We did not explore other interpolation methods in the upsampling layers except the default nearest neighbor method, while using different approaches may impact the result. We added an explanation in Section 3.1.1 as follows: "effects of different interpolation methods were not explored in this study". The downscaling factor in this study is 12. In our previous study based on synthetic experiments (Wang et al. 2021), we indicated that the downscaling factor of 24 still worked better than the traditional statistical downscaling method.

- Which criteria do you use to choose the atmospheric covariates? The fact that despite the use of covariates still is not enough and you heavily need the precipitation for training the model reflects the necessity of considering other covariates?

Response: Thank you for your comments. The covariates are chosen based on precipitation formation theory as well as findings from studies on estimating precipitation as listed in Section 3.1.4 of the revised manuscript. We have added the following explanation in Section 3.1.4 of the updated manuscript "We chose these variables based on precipitation formation theory (cloud mass movements and thermodynamics) as well as findings from previous studies as indicated above." We did not explore the importance among those covariates in this study and we have made a note in the discussion section 5 of the updated manuscript as follows: "Note that we did not evaluate the importance ranking among these covariates in improving the model performance in this study, which can be a potential avenue for future work."

- In Baño-Medina et al(2022) deep learning was used for downscaling the EUROCORDEX CMIP5 simulations. Could your methodology be used for a similar task?

Response: Yes, the regular SRDRN has been investigated to downscale daily temperature from CMIP6 GCM outputs in the historical run (Wang et al., 2022). The SRDRN architecture can be further customized to downscale different gridded precipitation including downscaling precipitation from GCM projections, which can be a future study. We have added this information to the discussion (section 5) of the updated manuscript.

Manuscript

- Line 27: correct "experiencing" with "experience"

Response: Thank you for your comments. We have fixed it.

- Line 36 correct "data" with "datasets"

Response: Thank you for your comments. We have fixed it.

- Line 325. It also can be related to natural climate variability.

Response: Thank you for your comments. We have added "climate variability" in Section 4.2 of the updated manuscript.

- Line 401. Please, elaborate on this "The DL models treated hourly spatial P data independently and did not explicitly account for temporal dependence. However, the DL models could potentially well reduce temporal biases if spatial P data for each hour can be well corrected and downscaled"

Response: Thank you for your comments. We agree with you. In this study, the DL

models considered each hourly P spatial data as a 2D image and did not explicitly account for temporal dependence among images. However, we can argue if the DL models are perfectly bias-corrected and downscaled each 2D image, the temporal biases can then be reduced. Therefore we have modified this statement in Section 4.4 of the updated manuscript as follows: "The DL models treated each hourly P spatial data as a 2D image and did not explicitly account for temporal dependence between images. We assumed that the DL models could potentially preserve the temporal dependence of observations if the DL models well bias-corrected and downscaled each 2D image."

- Line 474. Please, elaborate on this. Precipitation events can have different nature and can behave distinctly, depending on atmospheric conditions. How far and under which conditions can be results for the training in one place can used to estimate hourly P in other places where high resolution data are not available

Response: Thank you for your comments. Using transfer learning to estimate hourly P in other places where high-resolution data are not available deserves a separate study since precipitation types are different at different locations. For example, if we train the DL model for bias correcting and downscaling precipitation at a coastal area where convective precipitation is the main type, the trained model may have difficulties downscaling and bias correcting precipitation events at locations where dynamic precipitation is the main type. Adding local information into the trained model may improve the model performance of transfer learning. There are many questions that need to be explored under this topic about transferability under various climate zones and the impact of spatial distance, which deserves a separate study. We have included a discussion in Section 5 of the updated manuscript.

References

Wang, F., Tian, D., Lowe, L., Kalin, L., and Lehrter, J.: Deep learning for daily precipitation and temperature downscaling, Water Resources Research, 57, e2020WR029308, 2021.

Wang, F. and Tian, D.: On deep learning-based bias correction and downscaling of multiple climate models simulations, Climate Dynamics, 1-18, 2022.

Baño-Medina, J., Manzanas, R., Cimadevilla, E., Fernández, J., González-Abad, J., Cofiño, A. S., and Gutiérrez, J. M.: Downscaling multi-model climate projection ensembles with deep learning (DeepESD): contribution to CORDEX EUR-44, Geosci. Model Dev., 15, 6747–6758, https://doi.org/10.5194/gmd-15-6747-2022, 2022.