Geoscientific Model Development Discussions

Geosci. Model Dev. Discuss., referee comment RC5
https://doi.org/10.5194/gmd-2022-213-RC5, 2022

Comment on gmd-2022-213

Anonymous Referee #5

Referee 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-RC5, 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 weakeness of this kind o 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?
- 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 ?
- 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?

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.

- Line 27: correct “experiencing” with “experience”
- Line 36 correct “data” with “datasets”
- Line 325. It also can be related to natural climate variability.
- 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”
- 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 results for the training in one place can used to estimate hourly P in other places where high resolution data are not available