Geoscientific Model Development Discussions

Geosci. Model Dev. Discuss., author comment AC4
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Reply on RC4

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-AC4, 2022

The article is well written and easy to understand. I have the following comments for the authors to consider.

- L55. Single image super-resolution approaches have attracted much attention for precipitation downscaling. In Vandal et al. 2019 cited here, the authors first coarsened a precip dataset and then tried to recover the original fine scale precip data. While that exercise had pedagogical meanings, it is not exactly very practical. Sun and Tang (2020) focused on a 3-deg study area in Texas and demonstrated downscaling and bias correction using multiple coarse-resolution satellite data and Attention GAN superresolution. That work is especially relevant to this study, as it focused local and fine features for an area near Gulf of Mexico. It can be added to the list of references here.

Response: Thank you for your comments. We have added the reference of Sun and Tang (2020) in the introduction section of the updated manuscript.

- MERRA2 is reanalysis data. I wonder if near real time data from, e.g., GPM, should be used to demonstrate operational aspect of this algorithm.

Response: Thank you for your comments. MERRA2 is a state-of-the-art global reanalysis product and it incorporates new satellite observations through data assimilation and benefits from advances in the GEOS-5, which also includes relevant atmospheric variables that can assist in estimating precipitation at fine scale as indicated by Scenario4 to Scenario6 in this study. Besides climate reanalysis, this algorithm can be potentially integrated with precipitation data from the Global Precipitation Measurement (GPM) mission to generate more accurate operational precipitation data at a finer resolution. We have added the following information in the discussion section 5 of the updated manuscript "While this study explored bias correcting and downscaling hourly precipitation from climate reanalysis data, this algorithm with customized loss function can be potentially integrated with precipitation data from the Global Precipitation Measurement (GPM) mission to generate more accurate operational precipitation data at a finer resolution."

- Most deep learning studies adopt some baseline. The authors may want to show a comparison to baseline. A meaningful baseline here can be bilinear interpolation.

Response: Thank you for your comments. We compared the deep learning models with Quantile delta mapping with bilinear interpolation (QDM_BI) as the baseline approach. QDM was applied at a coarse resolution to correct biases between MERRA2 and Stage IV precipitation and then used bilinear interpolation (BI) to increase the resolution. Please see a detailed description of QDM_BI in Section 3.2 of the updated manuscript.

- Figure 3. The downscaled maps seem to be smooth and lacking many details shown in Stage IV. Here the authors mainly considered climate covariates from MERRA2. I think adding static covariates such as DEM may help to resolve some local details.

Response: Thank you for your comments. We agree with you that adding static variables could be helpful for resolving local details. We include a discussion about the potential room for improving the performance by incorporating static variables as follows "Furthermore, static variables, such as elevations, long-term climatology (Sha et al., 2020a), soil texture and land cover, could be helpful for resolving local details. However, our study region has little topographic variations and therefore including elevation data cannot add any additional information to the model."

References

Sha, Y., Gagne II, D. J., West, G., and Stull, R.: Deep-learning-based gridded downscaling of surface meteorological variables in complex terrain. Part II: Daily precipitation, Journal of Applied Meteorology and Climatology, 59, 2075-2092, 2020a.

Sun, A. Y., & Tang, G. (2020). Downscaling satellite and reanalysis precipitation products using attention-based deep convolutional neural nets. Frontiers in Water, 2, 536743.