



EGUsphere, editor comment EC1
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Comment on egusphere-2022-648

Chanh Kieu (Editor)

Editor comment on "Deep learning models for generation of precipitation maps based on Numerical Weather Prediction" by Adrian Rojas-Campos et al., EGU sphere, <https://doi.org/10.5194/egusphere-2022-648-EC1>, 2022

In this study, the authors attempt to enhance low-resolution precipitation forecast maps from the NWP model by using deep learning models. Several deep learning models used in this study are examined, which include UNet, 2 deconvolution networks, CGANs, and a baseline. Their results demonstrate that direct mapping between physical simulations and precipitation maps can be achieved by DL models. However, the accuracy of predicting precipitation maps using their ML methods is still a challenge.

Overall, both the merit and the approach used in this study are interesting and worth consideration for publication on EGU sphere. I have only a few minor questions to help readers better follow the significance and methodology presented in this study.

1. It is mentioned in this study that 143 forecast variables are used as input for the deep learning models in this study. However, there is nowhere in the text mentioning what are these variables and why are they relevant to precipitation augmentation. I am wondering what are the possible 143 different variables that a NWP model can produce, and how these variables are handled in your DL approach. Are they treated as different channels of input? If not, how are they combined and/or fed in your DL designs? It would be useful for readers to know more details about what these variables are and how are they used as input for your DL models.

2. Precipitation is generally a subtle variable, which is an end product of many processes and scales in a numerical model. While the overall objective of this work is to enhance the model precipitation output by using ML, the characteristics of different types of precipitation such as stratiform or convective precipitation are very different. I am not sure if the ML models can help distinguish these different types of precipitation, which is in fact related to my comment # 1 above on the use of 143 forecast variables as input. There is no discussion of how many of these variables are essential for different types of precipitation. One could of course combine all possible input and see what potential outcome from an ML model could be. However, more input channels do not generally lead to a better outcome, since some bad channels could degrade the ML performance. Any discussion on the relative importance of different input variables for different types of precipitation would be helpful here.

3. As a "model description paper", the manuscript is expected to be detailed and accessible for a wide range of geophysical communities as described here

https://www.geoscientific-model-development.net/about/manuscript_types.html#item1. However, the current methodology section (section 3) is too brief for readers to follow and appreciate your ML model settings and approach. Please provide additional information as instructed in the link above to meet the standard guideline of EGU sphere.