EGUsphere, author comment AC3
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Reply on EC1

Adrian Rojas-Campos et al.

Author comment on "Deep learning models for generation of precipitation maps based on Numerical Weather Prediction" by Adrian Rojas-Campos et al., EGUsphere, https://doi.org/10.5194/egusphere-2022-648-AC3, 2022

Dear Editor:

We appreciate your comments and observations about our paper. In the following, we respond to each of the points enumerated.

Best regards,

- 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.

The 143 variables correspond to the ensemble statistics (mean and standard deviation) of the 20 ensemble members of the COSMO-DE-EPS, which represent simulations for several atmospherical variables (wind speed, temperature, pressure, etc.) and soil and surface variables (water vapor on the surface, amount of snow, etc.). As you correctly guessed, we provide the different variables as input channels for the DL model (we tried to illustrate this in Figure 2). The DL models combined the input channels in a non-linear fashion using the deconvolutional kernels to generate the high-definition precipitation map. Additional information about the input variables will be added to the paper following this consideration.

- 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.

This is a very important point. Our approach was to include sufficient input information about the atmospherical state (143 channels), together with a sufficiently complex model, and let the model automatically discover the relevant patterns in the input data that improve precipitation. This means that the complex DL models learn the relevant non-linear interactions between the input information for each type of precipitation, without an explicit classification from our side.

Given the improvement in the performance obtained by our models, we could assume that the DL algorithms learned to differentiate between the different types of precipitation and use the proper and filter out the unimportant information in each case. We consider it essential to include enough information about the meteorological state so that the right mapping can be performed. Additional consideration about this will be included as part of the discussion.

- 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 EGUsphere.

We will adapt our methodology section and code to meet the standard guidelines.