

Interactive comment on “Weather and climate forecasting with neural networks: using GCMs with different complexity as study-ground” by Sebastian Scher and Gabriele Messori

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Dear Reviewer,

Thanks for your comments and suggestions. We will reply in detail once we have received all reviews and prepared a new manuscript. Here I outline how we plan to address your main points and add some clarifications following your minor points.

“1. As far as I can tell, the same network as was applied to the simple GCM PUMA is applied to the more comprehensive GCM PLASIM. In particular, the variables used are horizontal winds, geopotential height and temperature. This is surprising since

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PLASIM presumably has a hydrological cycle, and specific humidity is presumably a prognostic variables. Therefore, the state of the atmosphere in PLASIM at a given time is not described with the 4 variables used. The choice to not include humidity in the network should be justified. Presumably a network with humidity included would do better (?)”

You are right, we used the same architecture for PUMA and PLASIM, thus not including moisture, which is indeed part of PLASIM. This choice was made to keep the architecture the same across all models. However, we agree that adding moisture as variable might improve the neural network forecasts trained on PLASIM. In the revised version, we will include a new section where we explore changes/additions to our method. Here we will also include tests with moisture as additional in- and output of our network.

“2. It is difficult to assess how well the networks are doing in their forecasts in figure 3 because they are not compared to anything else. In the preceding work, comparison was made to ‘persistence’. But a more informative choice would be to plot RMSE and ACC for a ‘perfect model’ forecast in which the same GCM is used to make the forecast with a small perturbation in the initial conditions (or alternatively in the tuned constants in the model physics). Comparing to a perfect model forecast would allow the reader to assess the skill of the neural net forecast - it can’t be expected to do better than a perfect model prediction (given any error and the chaotic nature of the atmosphere). This will help the paper have more impact since the neural net will ultimately have to compete with traditional NWP, albeit in terms of both accuracy and speed and not just accuracy.”

We agree that a baseline forecast would help to aid the reader. In the revised version, we will include the skill of persistence forecasts. We will also explore the possibility of making perfect-model forecasts with PUMA/PLASIM. Additionally, we are planning to include some tests on coarse-grained reanalysis data (as in Dueben and Bauer 2018), which will allow to put our forecast skill in context of the IFS forecasts that Dueben and Bauer used as comparison.

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“ Another possibility to consider for why the climate prediction with a seasonal cycle does not work well is that you are forecasting over a short time frame (1 day) in which diabatic effects that vary seasonally such as changes in insolation are not very important compared to the dynamical initial condition. Perhaps training using a longer forecast lead time (e.g. 5 days) would work better for the climate simulations with a seasonal cycle”

Thanks for this suggestion. We will add a test with 5-day forecasts in the additional section on changes/additions to our method we plan to include in a revised manuscript.

1. “The neural net architecture is described as an autoencoder. My understanding of the nomenclature is that it is an encoder-decoder but not an autoencoder (since the output is not the same as the input).”

You are right, our architecture is indeed more correctly described as an encoder-decoder. Thanks for pointing this out, we will change the naming in our revised manuscript

2. “A few more lines description is needed for each GCM in section 2.1. How is the dry dynamical core of PUMA forced? (e.g. is it a Held-Suarez setup?) What makes PLASIM an ‘intermediate complexity’ GCM? (e.g. how exactly does it differ from a standard GCM aside from the lack of a dynamical ocean).”

PUMA uses Newtonian cooling for diabatic heating/cooling. The main difference between PLASIM and standard GCMs is that all included sub-systems of the Earth system except for the atmosphere (like the ocean, sea-ice and soil) are reduced to systems of low complexity.

We will include a more detailed description of PUMA and PLASIM in the revised manuscript.

“3. Figure 2 is helpful but not fully described in the caption. In particular the caption should say what the numbers are - does None, 64, 128, 40 refer to ?, lat, lon, chan-

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nels.What does 'None' refer to here?"

None, 64,128,40 is the typical notation in Keras and refers to time(or samples), lat, lon, channels. We agree that the notation is confusing to the reader not familiar with the Keras library. We will remove the "None"- that it is not necessary to understand the architecture -in our revised manuscript, and update the caption to better explain the figure.

"4. Appendix A1: do you use all times t_1 before and after t in the calculation"

yes, exactly. For computing the local dimension at time t , the distances of the field at t with the fields at all other timesteps are computed.

We will try to make this clearer in the revised manuscript.

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