How Robust are Neural Network Emulations of Model Physics with Respect to Changes in Model Phase Space?

Alexei Belochitski[1,2], Vladimir Krasnopolsky[2]

[1]IMSG, [2]NOAA/NWS/NCEP/EMC

email: **alexei.a.belochitski@noaa.gov**

1 Neural Network Emulations of Model Physics

One of the main difficulties in developing and implementing high-resolution environmental models is the complexity of the physical processes involved. For example, the calculation of radiative transfer in a GCM often takes a significant part of the total model computation and is necessarily a trade-off between accuracy and computational efficiency. Very accurate methods exist, such as line-by-line procedures, that are, however, too computationally prohibitive to be used in GCMs, and, therefore, radiative transfer is parameterized, for example, by the correlated-k method. Nevertheless, even further computational cost reductions are needed and thus radiation calculations are usually made at lower temporal and/or spatial resolutions than the rest of the model followed by an interpolation of the results to an original finer grid. Such approaches reduce the horizontal, or vertical, or temporal variability of radiation fields and their consistency with other parts of model physics and with dynamics, which may, in turn, negatively affect the accuracy of climate simulations and weather prediction. For example, in the pre-operational version of NCEP FV3 GFS radiative transfer calculations are performed once per model hour and are interpolated on the much finer physical time step of 225 s when the rest of model's physical parameterizations are called. One approach addressing these issues is based on using neural networks to "emulate" existing physical parameterizations.

Any parameterization of model physics is a mapping (continuous or almost continuous) between two vectors: a vector of the input variables of parameterization and a vector of its output variables. A neural network (NN) is a generic approximation for any continuous or almost continuous mapping given by a set of its input and output records. Existence of the approximation is guaranteed, and its error bound is independent of the dimensionality of the mapping (e.g., Krasnopolsky (2013)). NNs are very accurate, fast, and convenient statistical models able to approximate numerical model components, which in essence are complex nonlinear input/output relationships. Finding the analytical expression for the approximation (or "training" the NN) is a complicated and time consuming nonlinear optimization procedure; however, training should be done only once for a particular application.

An NN emulation of a model physics parameterization is a functional imitation of this parameterization in the sense that the results of model calculations with the original parameterization and with its NN emulation are physically identical. It is accomplished by using the data for NN training simulated by running the original model with the original parameterization, which allows to achieve a very high accuracy of approximation because simulated data are free of the problems typical of empirical data.

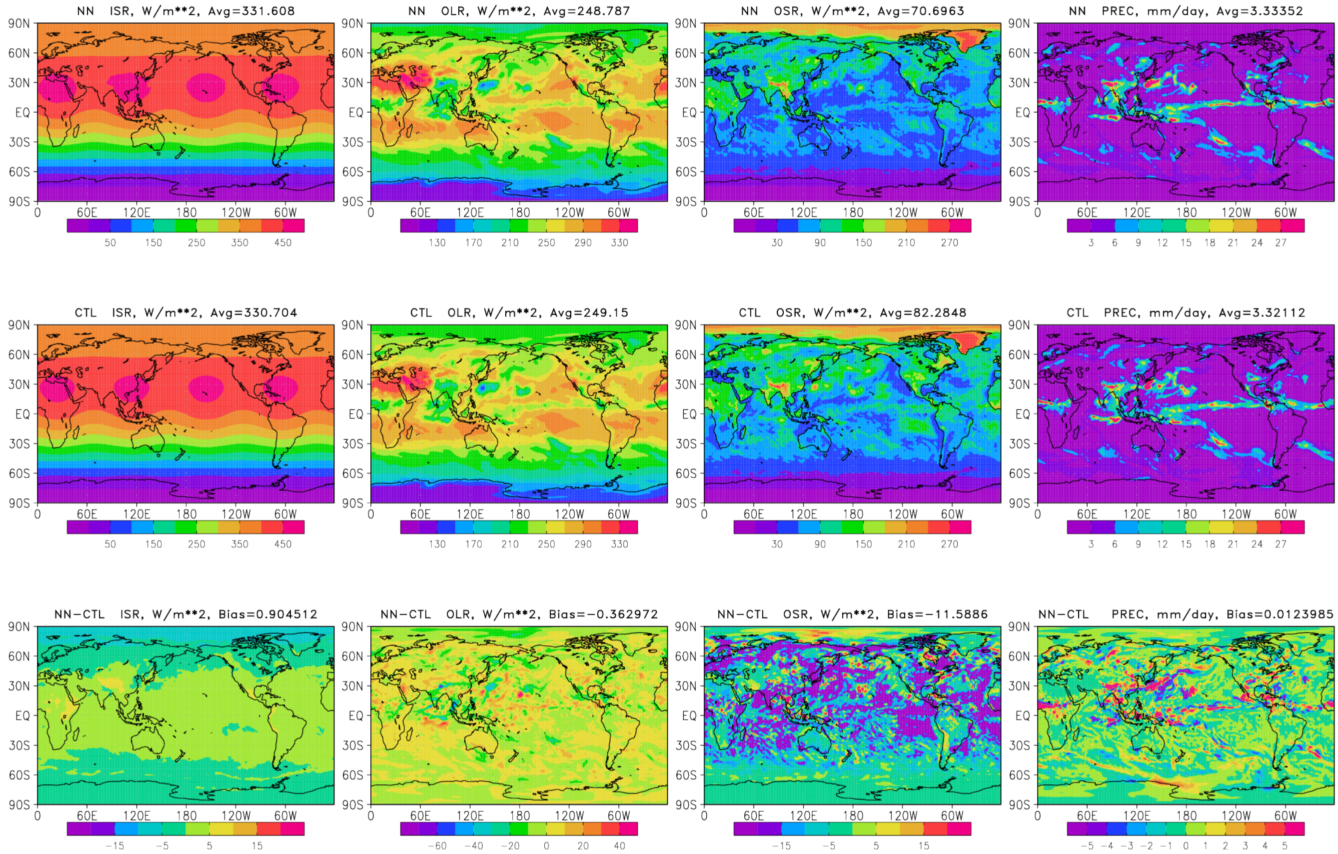
Previous work has demonstrated the practical possibility of using highly efficient NN emulations for the full (long- and short-wave) model radiation for decadal climate simulations in a coupled climate model with prescribed time dependent CO_2 and aerosols (NCEP CFS T126L64) by Krasnopolsky et al. (2010), and a high resolution short- to medium- range weather forecasting model (NCEP GFS T574L64) by Krasnopolsky et al. (2012). A very high accuracy and up to two orders of magnitude increase in speed as compared to the original parameterization for both NCEP CFS and GFS full radiation has been achieved. The systematic errors introduced by NN emulations of full model radiation are negligible and do not accumulate during the decadal model simulation. The random errors of NN emulations are also small. Almost identical results have been obtained for the parallel multi-decadal climate runs of the models using the NN and the original parameterization, and in limited testing in the medium-range forecasting mode.

The mapping approximated by an NN is defined not only by the parameterization that is being emulated, but by the entirety of the atmospheric model environment: the dynamical core, the suit of physical parameterizations, and the set of configuration parameters for both. Once any of these is modified, the set of possible model states is modified as well, possibly now including states that were absent in the NN's training data set. It is natural to ask how much of a change in the model's phase space can a statistical model like the NN tolerate? The answer will also provide an insight into how an NN emulation might fare under a change in boundary conditions, such as a change in greenhouse gas concentrations.

2 FV3 GFS experiments with 2011 GFS LW and SW NN Radiation

NN emulations of the LW and SW radiative transfer parameterizations, originally developed within the framework of the 2011 versions of GFS and CFS, were incorporated into the preoperational version of FV3 GFS. They can be used in place of the default RRTMG LW v4.82 and SW v3.8.

FV3 GFS differs from the 2011 version of GFS in a number of ways, most significant of which are the new dynamical core (FV3), microphysical parameterization (GFDL MP), PBL scheme (Hybrid EDMF), and a different set of values of tuning parameters. The most consequential change appears to be the replacement of the Zhao-Carr microphysics with the GFDL scheme. The reasons for this are twofold. The most important is a design choice made during development of the LW NN. Inputs to the RRTMG LW parameterization include, among others, vertical profiles of temperature, specific humidity, cloud fraction, liquid water path, ice water path, effective radius of liquid droplets, and effective radius of ice crystals. The last five profiles are calculated by the microphysical parameterization from the first two and are correlated with one another. Since profiles of specific humidity and temperature are already inputs to the LW NN, inclusion of only one cloud-related profile (cloud fraction) allows the NN to emulate the remaining four. In effect, LW NN emulates not only the radiative transfer parameterization, but also calculations of cloud properties by microphysics.



(a) Incoming SW , W/m^2 (b) OLR, W/m^2 (c) OSR, W/m^2 (d) Precipitation rate, mm/day

Figure 1: Full NN radiation vs control, Zhao-Carr MP, day 3-10 average of a C96 forecast initialized at 00Z on 8/1/17.

Consequently, when the microphysical parameterization is replaced, the internal representation of cloud properties in the NN is no longer consistent with the rest of the model.

Another possible contributing factor is that the change in microphysical parameterization leads to the near doubling of the model's prognostic variables from 7 to 12, and to the proportional increase in dimensionality of the physical phase space of the model. As a result, the set of possible model states in FV3 GFS is very different from a mathematical standpoint from the 2011 model version. Even though the vectors of inputs to the radiative transfer parameterizations remain the same, they are obtained by mapping from a very different mathematical object, potentially increasing the probability that a given input vector lies outside of the NNs original training data set.

These fundamental physical and mathematical inconsistencies between the 2011 GFS NN and FV3 GFS environment have led us to replace the GFDL microphysics with the Zhao-Carr scheme that was used to generate the 2011 NN training set. It is possible or even likely that the choice of tuning parameters in Zhao-Carr microphysics is different in FV3 GFS then what was used in the 2011 model (and what is implicitly built in into the NN). Therefore, we tune the value of the dimensionless coefficient of autoconversion of ice to snow, doubling it from 8e-4 to 16e-4 in the NN run, but keep it unchanged in the control.

Figure 1 shows averages over days 3-10 of a 10-day forecast initialized at 00Z on 08/01/17 at C96L64 resolution ($\sim$ 100 km horizontal grid size) produced by the current pre-operational FV3 GFS with Zhao-Carr MP (control) and the same model using both LW and SW NNs. The largest discrepancy is in outgoing SW at TOA (Fig. 1c), while discrepancies in incoming SW (Fig. 1a) and outgoing LW (Fig. 1b) at TOA are within observational uncertainties, as are the rest of radiative fluxes (not shown). Precipitation (Fig. 1d) is to the first order determined by the atmospheric energy balance, and differs only by 0.01 mm/day between the two runs. Overall, these results indicate significant robustness in the NN emulations with respect to the changes in the model, at least in the limited number of experiments. The NN performs like a plausible physical parameterization, tolerating the aforementioned significant changes in the model, provided that fundamental assumptions about the host model (like cloud properties) made during NN design did not change significantly.

The next step in our project is to generate the NN training data set using the FV3 GFS (including GFDL MP and all other upgrades) with the goal of calling NN emulations of the radiative transfer parameterizations at every physical time step.

References

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