Emulation of a Full Suite of Atmospheric Physics Parameterizations in NCEP GFS using a Neural Network

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1 Introduction

Machine learning (ML) can be used in parameterization development at least in two different ways: 1) as an emulation technique for accelerating calculation of parameterizations developed previously, and 2) for development of new "empirical" parameterizations based on reanalysis/observed data or data simulated by high resolution models. An example of the former is the paper by Krasnopolsky et al. (2012) who have developed highly efficient neural network (NN) emulations of both long– and short-wave radiation parameterizations for a high resolution state-of-the-art short– to medium-range weather forecasting model. More recently, Gentine et al. (2018) have used a neural network to emulate $2D$ cloud resolving models (CRMs) embedded into columns of a "super-parameterized" general circulation model (GCM) in an aqua-planet configuration with prescribed invariant zonally symmetric SST, full diurnal cycle, and no annual cycle. An illustration of the latter is the work of Brenowitz and Bretherton (2019) who built an NN-based deep convection parameterization by up-scaling global CRM tendencies to the GCM scales using an aqua-planet global CRM in a tropical channel.

Building ML emulation of the entire block of atmospheric physics parameterizations in a state-of-the-art GCM is an attractive task: if successful, it could contribute to development of methodology for constructing new ML-based "empirical" parameterizations, in addition to the speedup of model calculations. This task may be aided by the fact that the full diabatic forcing profiles in atmospheric models are generally smoother than forcing profiles from individual processes, because the latter often balance each other. Krasnopolsky et al. (2009) discussed problems arising when emulating full atmospheric physics using NNs, and developed methods addressing some of those problems.

In this study we present preliminary results from a shallow NN-based emulator of a complete suite of atmospheric physics parameterizations in NOAA National Centers for Environmental Prediction's (NCEP) Global Forecast System (GFS) GCM.

2 NCEP Global Forecast System Configuration

The GFS version 16 is the foundation of NCEP's new production suite slated to to become operational in October of 2020. Dynamical core of the GFS is a finite volume cubed-sphere non-hydrostatic global model (FV^3) with spatial resolution of C768 ($\sim 13\ km$), and 127 fully Lagrangian layers on a hybrid sigma-pressure vertical coordinate. The GFS contains a comprehensive physics suite (Kain et al., 2020) that includes parameterizations of radiative transfer, planetary boundary layer processes, orographic and convective gravity wave drag, deep convection, shallow convection, and microphysics. In addition, effects of time varying carbon dioxide, trace gases, stratospheric and tropospheric aerosols, as well as ozone and H_2O photo-chemistry are included.

Our study is a proof of concept, so we reconfigure the GFS with the goal of substantially reducing the model's phase space while ensuring that in the new configuration it still remains a sophisticated GCM. To this end, we reduce the horizontal resolution to C96 ($\sim 100\ km$), and vertical resolution to 64 vertical layers. We also almost halve the number of the model's prognostic variables by replacing the six-category single-moment GFDL microphysics with a single-category single-moment Zhao-Carr scheme, and the prognostic-TKE-based PBL parameterization with a K-profile scheme. These modifications result in an atmospheric model state, as seen by the physics package, described by seven prognostic variables: zonal and meridional wind components, temperature, water vapor, total condensate, and ozone mixing ratios, as well as pressure. Only the first six of these variables are modified by physical parameterizations. The Noah Land Surface Model employed in GFS uses the following 3 prognostic variables, all defined on four soil layers: temperature, total moisture content, and liquid water content.

In the GFS, the radiative transfer parameterizations are invoked less frequently than the rest of model physics because of computational expense. For example, there are 8 calls to the physics block per single radiation call in the GFS using C96 horizontal resolution. Because full atmospheric physics NN will encompass both radiation and the atmospheric physics block, and because it is going to be invoked with the frequency of the physics block, we configure the GFS to call radiation as often as the rest of the model physics for the sake of consistency between experimental and control configurations.

3 Training Set Design and NN Architecture

The training data set is generated by running 24 10-day GFS forecasts initialized at 00Z on the 1^{st} and 15^{th} of each month of 2018 with instantaneous data saved three-hourly to capture diurnal and annual cycles. (See below what specifically is being saved). Note, that in GFS both the dynamical core and the full physics package operate on a globally quasi-uniform cubed sphere grid, while, for the sake of compatibility with other components of the forecasting system (e.g. DA, post-processing), the output of the model is saved on a full Gaussian grid that has resolution at the equator comparable to that of the native grid, but a higher resolution closer to the poles. Therefore, the number of columns on a given latitude that are included in the training set is proportional to the cosine of the latitude.

After taking into account latitudinal dependence, 1,500 profiles were randomly selected from each 3-hourly global field. As a result, three independent data sets have been created: 1) training set containing 414,000 records, 2) test set containing 414,000 records, and 3) validation set containing 250,000 records. A shallow NN with 522 inputs, 304 outputs, and 250 hidden neurons in the hidden layer was trained using a back-propagation algorithm with adjustable learning rate and other hyper-parameters, as well as with multiple exit conditions.

NN Input	**NN Input #**	**Layers**	**NN Input**	**NN Input #**	**Layers**
$\cos\frac{2\pi\times day}{366}$	1	-	Vertical velocity	266 : 329	1 : 64
$\sin\frac{2\pi\times day}{366}$	2	-	Temperature	330 : 393	1 : 64
$\cos\frac{2\pi\times month}{12}$	3	-	Specific humidity	394 : 430	1 : 37
$\sin\frac{2\pi\times month}{12}$	4	-	Cloud water mix. ratio	431 : 473	1 : 43
$Latitude$	5	-	Ozone mixing ratio	474 : 505	33 : 64
$\cos(Longitude)$	6	-	Total soil moisture	506 : 509	1 : 4
$\sin(Longitude)$	7	-	Soil liquid water	510 : 513	1 : 4
$\cos(Zenith\ angle)$	8	-	Soil temperature	514 : 517	1 : 4
Layer geop. height	9 : 72	1 : 64	Skin temperature	518	-
Layer pressure	73 : 136	1 : 64	Water in the canopy	519	-
Surface pressure	137	-	Sea ice thickness	520	-
U-wind	138 : 201	1 : 64	Surf. snow water equiv.	521	-
V-wind	202 : 265	1 : 64	Solar constant	522	-
NN Output	**NN Output #**	**Layers**	**NN Output**	**NN Output #**	**Layers**
U-wind increment	1 : 64	1 : 64	Specific humidity incr.	193 : 229	1 : 37
V-wind increment	65 : 128	1 : 64	Cloud water mix. ratio incr.	230 : 272	1 : 43
Temperature incr.	129 : 192	1 : 64	Ozone mixing ratio incr.	272 : 304	33 : 64

Table 1: Full Atmospheric Physics NN Inputs and Outputs

Table 1 shows inputs and outputs of the NN. Some input variables have zero values on the upper (e.g. water vapor) or lower (e.g. ozone) vertical layers. For CO_2, trace gases, and aerosols the entire profile is constant for a given month, and is obtained from climatology. Constant inputs (zero or nonzero) do not contribute to the functional input/output relationship and were removed. However, to capture the temporal and spatial variability of climatological greenhouse gas and aerosol forcings, we supply the NN with a periodic function of current month number and the geographical location of a given column. Position of said column on the globe with respect to the Sun is represented by the cosine of solar zenith angle. Location of Earth in orbit is captured by periodic functions of day and month, and variability of solar energy output is reflected in the solar constant. In addition to the full atmospheric state, NN receives full land-surface model (LSM) state to capture impact of surface boundary conditions. All NN outputs are increments of dynamical core's prognostic variables that the original atmospheric physics package modifies.

4 Hybrid Coupling of Full Atmospheric Physics NN to GFS

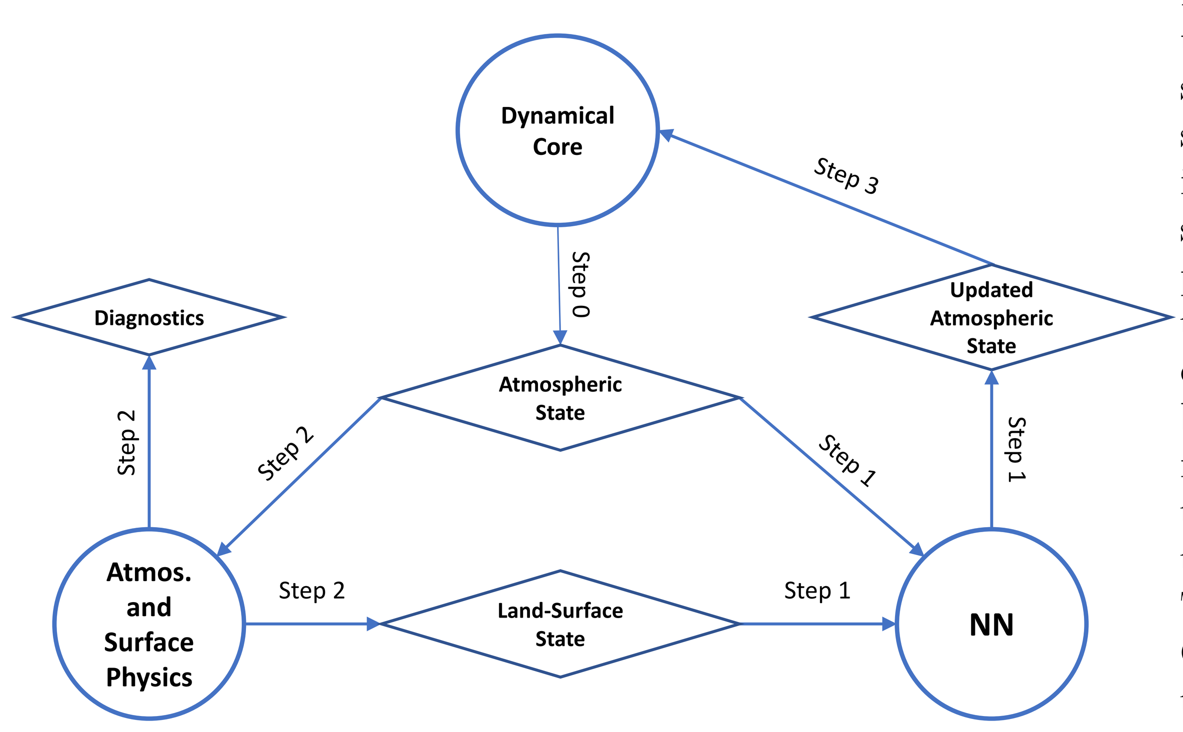


Figure 1: Hybrid Coupling of the NN to GFS

Full atmospheric physics NN only updates the state of the atmosphere and does not update the state of LSM. At the same time, it requires input from the land-surface model to capture the impact of surface boundary conditions on atmospheric physical processes. LSM, in turn, requires boundary conditions from the atmosphere (e.g. fluxes of precipitation and incident radiation etc) that the NN does not provide. Therefore, we couple the NN to GFS in a "hybrid" manner, illustrated on Figure 1, and described below.

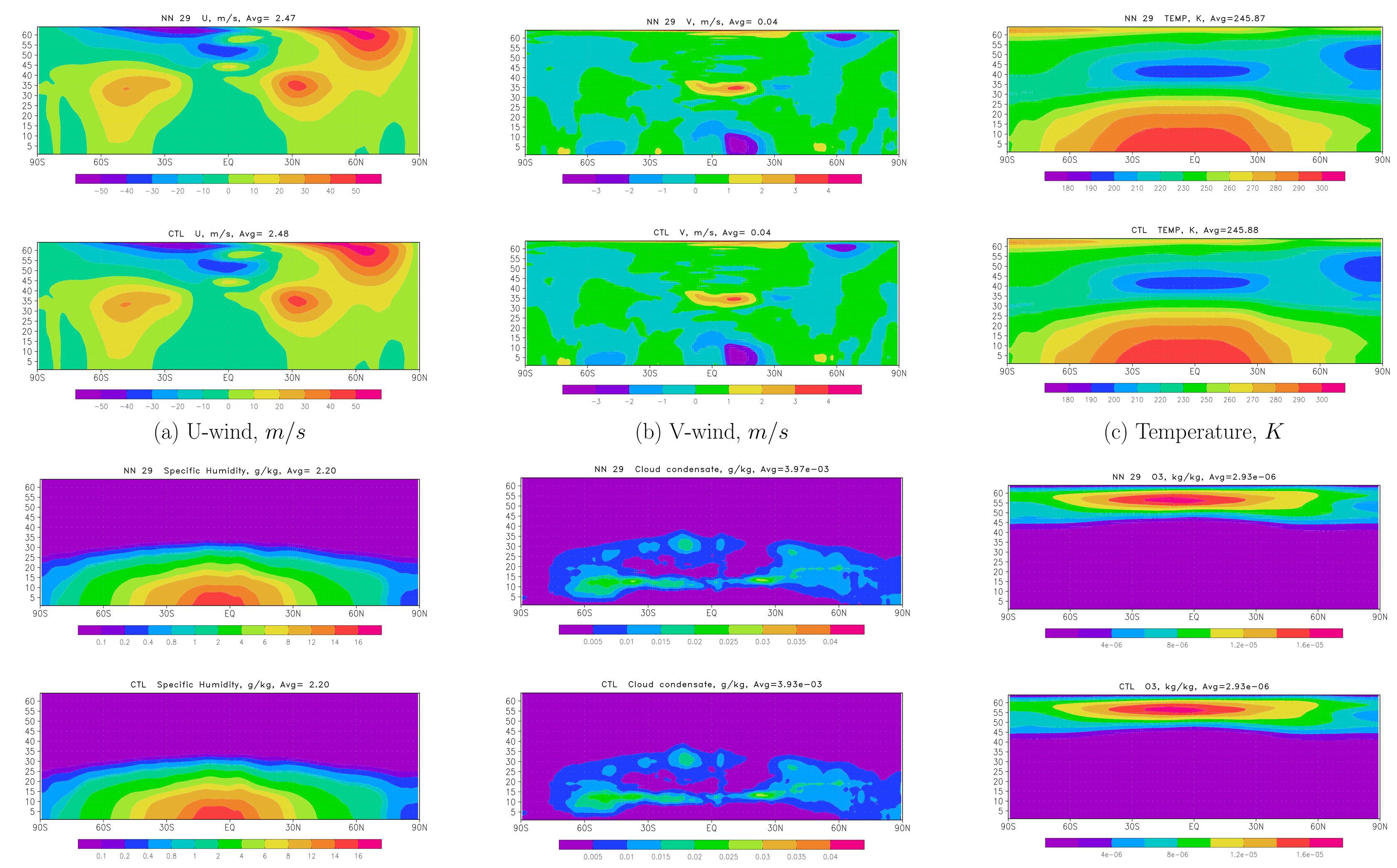
Updated atmospheric state from the dynamical core is supplied to both the NN and the original suite of atmospheric and land surface parameterizations. NN is called first, and calculates an update to the atmospheric state using the current state of LSM. This update is stored for later use. Original physics suite is ran after that. Its update to the atmospheric state is discarded, but the fluxes at the surface that it calculates are used to advance LSM forward in time. Various diagnostics are also calculated on this step. Atmospheric state is then modified by the update from the NN, and control is returned to the dynamical core.

5 GFS Experiments with Full Atmospheric Physics NN

Figure 2 shows an average over a 10-day forecast initialized at 00Z on 01/01/18 produced by GFS configured as described in Section 2 and the same model coupled to the full atmospheric physics NN. We concentrate on zonal means of variables directly modified by the neural network. All variables predicted by the NN compare well to the control. However, analysis of temporal evolution of biases show that they grow with time, with most biases emerging later in the forecast at higher latitudes (not shown). This may be related to the fact that higher latitudes is where the GFS output Gaussian grid used in generation of the training set differs most from the model's native cubed sphere grid.

We also performed 23 additional 10-day forecasts using the same initial conditions that were utilized in generation of the training data set, and obtained similar results in all of them (not shown). In all 24 forecasts carried out with the NN no signs of instability were observed. It's worth noting that even though initial conditions are the same, only 3% of all atmospheric states saved during creation of the data set were used in NN training. Moreover, internally, the GFS updates the atmospheric state on each physics time step, or every 450 s, resulting in 24 different global states per 3-hourly output cadence. As a result, the NN is almost exclusively exposed to the inputs that were not used in training.

NN-based emulation of the entire GFS atmospheric physics suite is three times as fast as the original physics block configured to calculate radiation with the same frequency as the rest of model physics.



(a) U-wind, m/s (b) V-wind, m/s (c) Temperature, K

(d) Specific Humidity, kg/kg (e) Cloud condensate, kg/kg (f) Ozone mixing ratio, kg/kg

Figure 2: Full atmospheric physics NN vs control, 10-day average of a forecast initialized at 00Z on 1/1/18.

6 Future Work

Potential next steps for our project are: 1) explore stability of the NN by performing longer-term runs, 2) explore generalization of the NN by using initial conditions outside of the time period spanned by the training data set, 3) if found necessary, generate a new version of training data set saved directly on the GFS's native cubed sphere grid, 4) perform cycled experiments with data assimilation to verify model with full atmospheric physics NN against its own analysis and to correctly assess RMSE errors.

References

Brenowitz, N. D., and C. S. Bretherton, 2019: Spatially extended tests of a neural network parametrization trained by coarse-graining. *Journal of Advances in Modeling Earth Systems*, **11 (8)**, 2728–2744.

Gentine, P., M. Pritchard, S. Rasp, G. Reinaudi, and G. Yacalis, 2018: Could machine learning break the convection parameterization deadlock? *Geophysical Research Letters*, **45 (11)**, 5742–5751.

Kain, J. S., and Coauthors, 2020: Advances in model physics for the next implementation of the GFS (GFSv16). *AMS Annual Meeting*, Boston, MA, 6A.3.

Krasnopolsky, V., A. A. Belochitski, Y.-T. Hou, S. Lord, and F. Yang, 2012: Accurate and fast neural network emulations of long and short wave radiation for the NCEP Global Forecast System model. *NCEP Office Note 471*, Camp Springs, MD.

Krasnopolsky, V., S. Lord, S. Moorthi, and T. Spindler, 2009: How to deal with inhomogeneous outputs and high dimensionality of neural network emulations of model physics in numerical climate and weather prediction models. *International Joint Conference on Neural Networks*, Atlanta, GA, 1668–1673.