Learning UFS State-Dependent Systematic Errors from the Analysis Increments

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Abstract

Systematic errors in the state-of-the-art NWP models degrade the accuracy of forecasts made with these models. Past studies showed that a running average of analysis increments from data assimilation can reveal part of these systematic errors in seasonal and diurnal time scales. Applying corrections based on these simple estimates improves the model forecast skill.
However, in addition to stationary seasonal and diurnal time scales, the analysis increments also contain information about state-dependent errors. Using the GFSv16b parallel runs, a variety of Neural Networks (NN) are trained to predict the corresponding increment from a forecast, with the goal to capture the underlying state-dependent systematic model errors. We will show that in addition to the obvious diurnal and seasonal signals in the analysis increments (accounting for 30% of the total variation) the NNs can predict on average more than 50% of the signal in the increments at any given point, using only the model forecast as an input. Adding both neighboring points from the forecast and background fields from the previous DA cycles further improves the skill of the NNs in predicting the analysis increments. We will also demonstrate a sensitivity measure of the NN prediction to the input information.

Keywords: Machine Learning, Neural Network, Systematic Error, Model Bias Correction, UFS

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