Machine learning correction of parameterized physics in coarse-resolution FV3GFS across a range of climates

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Over the past three years, AI2, in collaboration with GFDL, has developed a 'corrective machinelearning (ML)' methodology that aims to improve weather forecast skill and reduce climate biases in a coarse-grid climate model. The corrective ML is trained by nudging the 3D temperature, humidity and wind fields forecast by the coarse-grid model to a reference simulation, in this case a finer-grid version of the same model, and learning the 'nudging tendencies' as a function of the column state of the model. The ML is interpreted as a correction to the combined physics parameterization of the coarse-grid model.

We use four two-year reference FV3GFS with 25 km grids, with realistic geography, an interactive land surface, and specified sea-surface temperatures that are incremented - 4K, 0K, 4K and 8K from a present-day climatology. We aim to improve a coarse 200 km grid version of FV3GFS across this same range of climates. The ML is trained from nudged runs in all four climates. When added to prognostic simulations, it can run stably for many years and reduce the geographic biases of the seasonal cycle of precipitation and near-surface temperature by 10-30% in all climates relative to the fine-grid reference.