

Title: Towards Hybrid Climate Models: Offline Testing of New Data-driven Parameterizations for Atmospheric Gravity Waves to Reduce Climate Model Biases

Abstract:

Global climate models are the primary tools for climate change prediction. They typically operate at a grid resolution of 100-200 km and employ physical parameterizations to approximately represent sub-grid processes (like deep convection, gravity waves, and turbulence). These sub-grid processes play an important role in shaping the climate but are not explicitly resolved. Such approximations are the leading source of uncertainty in future climate projections. Targeting one such unresolved process, atmospheric gravity waves, this work proposes a set of neural networks (NNs) trained on observations to re-envision and replace their existing simplified parameterizations. Gravity waves are ubiquitous waves in the atmosphere-ocean, generated around thunderstorms, fronts, and mountain flow, and are among the key drivers of the middle atmospheric circulation. Their improved representation in climate models will eliminate the stubborn cold-pole bias and improve the simulation of the global circulation.

The work introduces a set of three neural networks (NNs) that learn gravity wave momentum fluxes from multiple years of global reanalysis. The three NNs: a 1×1 ANN (M1), a 3×3 ANN-CNN (M2), and an Attention UNet (M3), embed different levels of horizontal nonlocality in the ML architecture to represent nonlocal GW effects, i.e., their horizontal propagation, which is missing from current parameterizations. The (fully nonlocal) M3 predicts the transient evolution and seasonal distribution of GWs over prominent hotspots more skillfully than M1 and M2. Since reanalysis too does not fully resolve all the atmospheric gravity waves, the NNs are further improved through transfer learning of the pre-trained models over a 1.4 km global forecast model. Transfer learning both preserves the learning from reanalysis and appropriately corrects the predicted fluxes. The findings establish the need for nonlocal parameterizations to climate model sub-grid scales and the promise of data-driven methods. Ongoing work that aims to couple these Python-based NNs to existing Fortran-based climate models will also be discussed briefly.