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Ocean bias correction in coupled model predictions: ocean tendency adjustment based on data assimilation and machine learning

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Initialized coupled model prediction, ranging from subseasonal to decadal timescales, is a key use case of coupled climate models and central to operational climate services. Coupled model biases lead to the emergence of prediction biases and, in most cases, the deterioration of prediction skills. A posteriori bias correction based on climatological model drift is widely used in coupled predictions, but it is inadequate in dealing with nonlinear dynamics, especially coupled dynamics between model components.
In this presentation, we will discuss prognostic coupled model bias correction based on both data assimilation (DA) and machine learning (ML) methods. A new bias correction technique, ocean tendency adjustment (OTA), was implemented in GFDL's SPEAR real time seasonal prediction system. OTA applies the climatological DA increments to the model prognostically as tendency terms to reduce model bias. While the idea of OTA resembles other bias correction methods used in some reanalysis products, the tendency correction terms for OTA are produced in such a manner that they can be applied to initialized coupled model predictions to prevent model drift of the ocean component, which in turn reduces model drift in other model components such as atmosphere and sea ice. In SPEAR, OTA improves the coupled model's ability to predict the observed climatology, which leads to improved prediction skill in certain seasonal climate variability.
Despite the effectiveness of OTA in SPEAR, the tendency terms are currently only climatological averages. As part of an international collaborative effort, we used ML models, trained on Argo-era ocean state estimation and DA increments, to improve upon the existing OTA. The goal is to predict flow-dependent tendency terms that can minimize ocean model drift in a coupled model simulation. We will also discuss how learning from DA increments connects to and complements ML-based physical parameterization.

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Authors: LU, Feiyu (Princeton University and NOAA/GFDL); DELWORTH, Thomas (NOAA/GFDL); VERMA, Tarun (Princeton University and NOAA/GFDL); ADCROFT, Alistair (Princeton University and NOAA/GFDL); JIA, Liwei (UCAR and NOAA/GFDL); ROSATI, Anthony (UCAR and NOAA/GFDL)

Presenter: LU, Feiyu (Princeton University and NOAA/GFDL)

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