Abstract:

The ocean surface boundary layer (OSBL) plays a crucial role in the ocean by modulating the exchange of mass and energy between the atmosphere and ocean interior via vertical turbulent mixing. The processes driving this mixing cannot be resolved in ocean climate models, necessitating the use of numerous ad hoc components for their parameterizations. These ad hoc components contribute to uncertainty in climate projections.

In this talk, I will describe improvements in an existing energetics based parameterization of vertical mixing for the OSBL in the NOAA-Geophysical Fluid Dynamics Laboratory’s ocean model (MOM6). I will demonstrate how neural networks, trained to predict the eddy diffusivity profile from a high-fidelity and expensive second moment closure scheme, enhances the vertical mixing scheme in MOM6. These networks replace ad hoc components while maintaining the conservation principles of the standard ocean model equations. This is crucial for their effective use in climate simulations. The enhanced scheme outperforms its predecessor by reducing biases in the mixed-layer depth and modestly improving the tropical upper ocean stratification in ocean-only global simulations. Motivated by the success of neural networks, I will describe how the “black box” neural networks were replaced with interpretable models using equation discovery and empirical fitting techniques. The transparent and interpretable model of eddy diffusivity performs comparably to neural networks, yet at a lower computational cost. Due to its transparency, it also aids in understanding (and fixing) the structural deficiency in the baseline parameterization. This work is one of the first few demonstrations of successfully applying machine learning to target improvements in a sub-grid parameterization of mixing used in ocean climate models.