Contribution ID: **4** Type: **Oral**

Enhance Ocean Reanalysis in Regions with Limited Observations using a Time-Guided Physics-Informed Machine Learning Approach

Friday, April 12, 2024 1:50 PM (20 minutes)

Observing subsurface temperatures in the ocean can be challenging due to their natural sparsity, leading to considerable uncertainties in model-based estimates. As a result, historical assessments of ocean heat content (OHC) often suffer from distortions and biases. In this research, we explore the feasibility of employing physics-informed neural networks (PINNs) to reconstruct subsurface temperature data, with a specific focus on the North Atlantic Subpolar Gyre.

We train our neural network using a time period abundant in observations to capture authentic physical patterns. Subsequently, we assess the network's ability to apply these learned patterns to time periods characterized by significantly fewer observations within a consistent data assimilation framework. Our goal is to enhance historical OHC estimates in such scenarios. Our findings demonstrate the efficacy of this PINN approach in both learning and transferring realistic physical patterns from its training data. Consequently, when dealing with limited observational input, the PINN-generated reconstructions display more faithful representations of physical structures compared to current state-of-the-art data assimilation methods.

This improvement is particularly evident in the enhanced estimation of the North Atlantic Current's flow. Our technique is able to represent the North West Corner even in the early days with very sparse observational information, where pure Ensemble Kalman Filter fails to show this physical pattern. Thus, we provide evidence that time-guided physics-informed machine learning has the potential to significantly improve monthly reanalyses, especially in regions and time periods where observations are sparse. Furthermore, by rectifying historical biases and misrepresentations, these techniques offer the prospect of greatly impacting the initialization and assessment of forecast models.

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Session Classification: Conference