Optimizing Global-Scale Seasonal Marine Biogeochemical Forecasting with Compact Neural Networks

Marine biogeochemical models are essential for understanding nutrient and carbon cycles and for predicting the impacts of climate change on marine ecosystems. Unfortunately, these models are often limited by their complexity and the computational power required to run them. In this study, we propose a resource-efficient, machine learning-based methodology for global, surface-level biogeochemical forecasting at a seasonal scale. We examine its application to chlorophyll-a, a key indicator of phytoplankton biomass and aquatic ecosystem productivity. By leveraging a compact variation of the UNet, we show that we can skillfully integrate sea surface temperature, salinity, height, and mixed layer depth forecasts to predict multiannual and seasonal chlorophyll levels. The neural network was trained on the Global Ocean Colour (GlobColour) dataset, a cloud-free, merged chlorophyll concentration output from various sensors, and the Global Ocean Physics Reanalysis (GLORYS12). Twelve six-month chlorophyll-a forecasts were generated for 2017-2023. Evaluation against GlobColour data from the corresponding period showcased the neural network's ability to accurately capture both spatial and temporal patterns. Seasonal performance was assessed for regions of interest, encompassing the Northern, Tropical and Southern Pacific Ocean, the Northern and Tropical Atlantic, and the Indian Ocean. The neural network is able to generate forecasts with accuracy that rivals that of numerical models and has the additional advantage of being less resource-intensive.

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