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Reconstructing Global Ocean Deoxygenation Over a Century with Deep Learning

Bin Lu[1], Ze Zhao[1], Luyu Han[2], Xiaoying Gan[1], Yuntao Zhou[2], Lei Zhou[2], Luoyi Fu[1], Xinbing Wang[1], Jing Zhang[2], and Chenghu Zhou[3]

[1]Department of Electronic Engineering, Shanghai Jiao Tong University, Shanghai, China
[2]School of Oceanography, Shanghai Jiao Tong University, Shanghai, China
[3]Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China

Oxygen is fundamentally essential for all life. Unfortunately, recent research has shown that global ocean deoxygenation has significantly increased over the past 50 years, and the stock of dissolved oxygen (DO) in the ocean has been continuously decreasing. Breathless ocean has led to large-scale death of fish, seriously affecting the marine ecosystem. Moreover, global warming and human activities have further intensified the expansion of dead zones (low-oxygen area) in the ocean.

Hence, it is of vital importance to quantitatively understand and predict the trend of global ocean deoxygenation. However, despite of the accumulation of in-situ DO observation in recent years, global and long-term observation data is still severely sparse, leading to a critical challenge in reconstructing global ocean deoxygenation over a century. Existing works can be categorized into two ways: (1) Physics-informed numerical models. These methods simulate the DO concentration based on climate models without utilizing in-situ observations, e.g., Coupled Model Intercomparison Project Phase 6 (CMIP6). However, these models fail to adjust biased simulation results based on temporal DO observations and cause error propagation. (2) Spatial interpolation methods. These methods reconstruct the global deoxygenation through available observations by geostatistical regression, Kriging, etc. But these ways are unable to capture the complex spatiotemporal heterogeneity and physical-biogeochemical properties, showing inconsistent performance in different areas.

To this end, we propose a knowledge-infused deep graph learning method called 4D Spatio-Temporal Graph HyperNetwork (4D-STGHN) to reconstruct four-dimensional (including time, latitude, longitude, and depth) global ocean deoxygenation from 1920 till now. To capture the spatio-temporal heterogeneity in different regions, 4D-STGHN utilize hypernetwork to generate non-shared parameters by fusing 4D geographic information and observations. Moreover, we design a chemistry-informed gradient norm mechanism as the loss function by integrating the observation of nitrate and phosphate, hereby further improving the performance of DO reconstruction. 4D-STGHN shows promising reconstruction with mean absolute percentage error (MAPE) of only 5.39%, largely outperforming three CMIP6 experiments (CESM2-omip1,

CESM2-omip2 and GFDL-ESM4-historical) on dissolved oxygen and other machine learning methods. Further analysis on the global oxygen minimum zones, as well as regional analysis are conducted to evaluate the effectiveness of our proposed methods.