Reconstructing the Breathless Ocean with Spatio-Temporal Graph Learning

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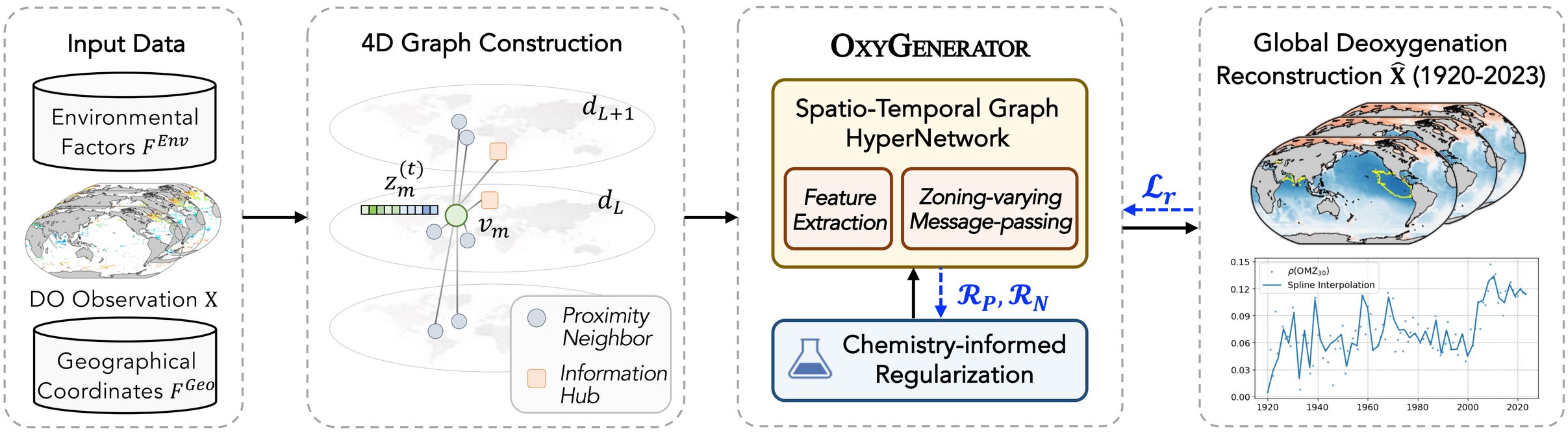
🤔 **Research Question**: Can deep learning methods more accurately reconstruct global ocean deoxygenation over a century under sparse dissolved oxygen observations?

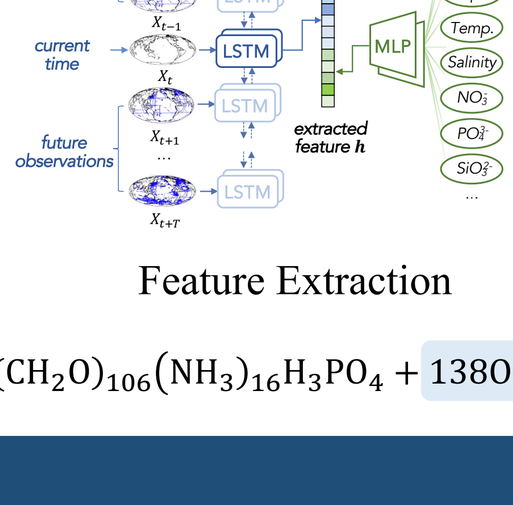


Background & Introduction

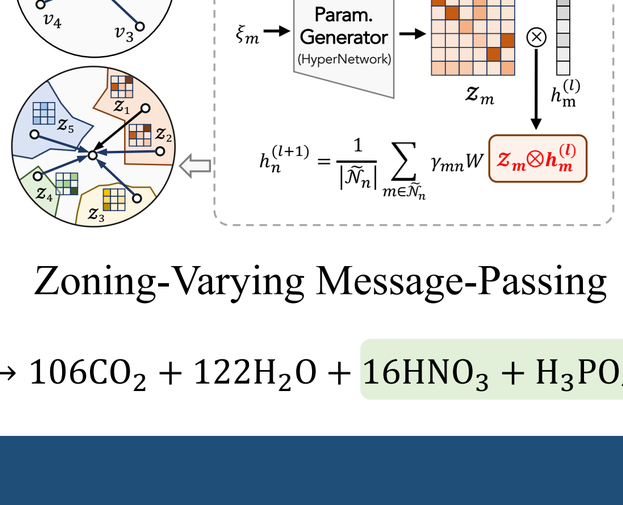
- Oxygen is fundamentally essential for all life. Unfortunately, dissolved oxygen (DO) in the ocean has been steadily decreasing over the past 50 years, indicating the acceleration of global ocean deoxygenation.
- To quantitatively understand the long-term trend of global ocean deoxygenation, oceanographers simulate the DO concentration based on numerical simulations, e.g., CMIP6, without utilizing in-situ DO observations.
- However, these models are unable to adjust for DO simulation biases caused by global warming and human activities, leading to error propagation and showing large discrepancies with in-situ observations.

Data-Driven Method: OxyGenerator

- Graph-based Modeling: Connect both local and remote observations in irregular four-dimension space.
- Spatio-Temporal Graph HyperNetwork: Inspired by the zoning strategy in oceanography, we propose zoning-varying graph message-passing to capture the heterogeneity.
- Chemistry-informed regularization: To fuse the knowledge of physical-biogeochemical properties.



Feature Extraction



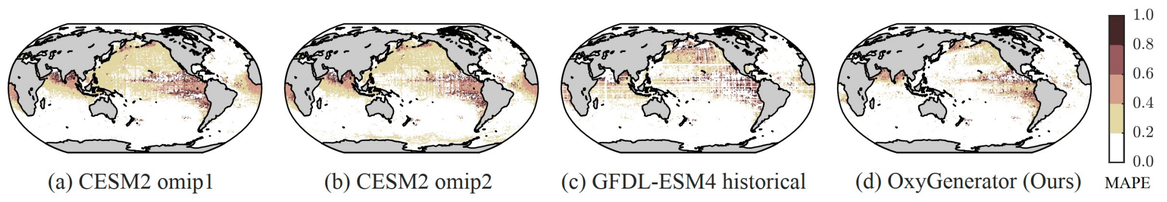
Zoning-Varying Message-Passing

$$(CH_2O)_{106}(NH_3)_{16}H_3PO_4 + 138O_2 \rightarrow 106CO_2 + 122H_2O + 16HNO_3 + H_3PO_4$$

Experiments

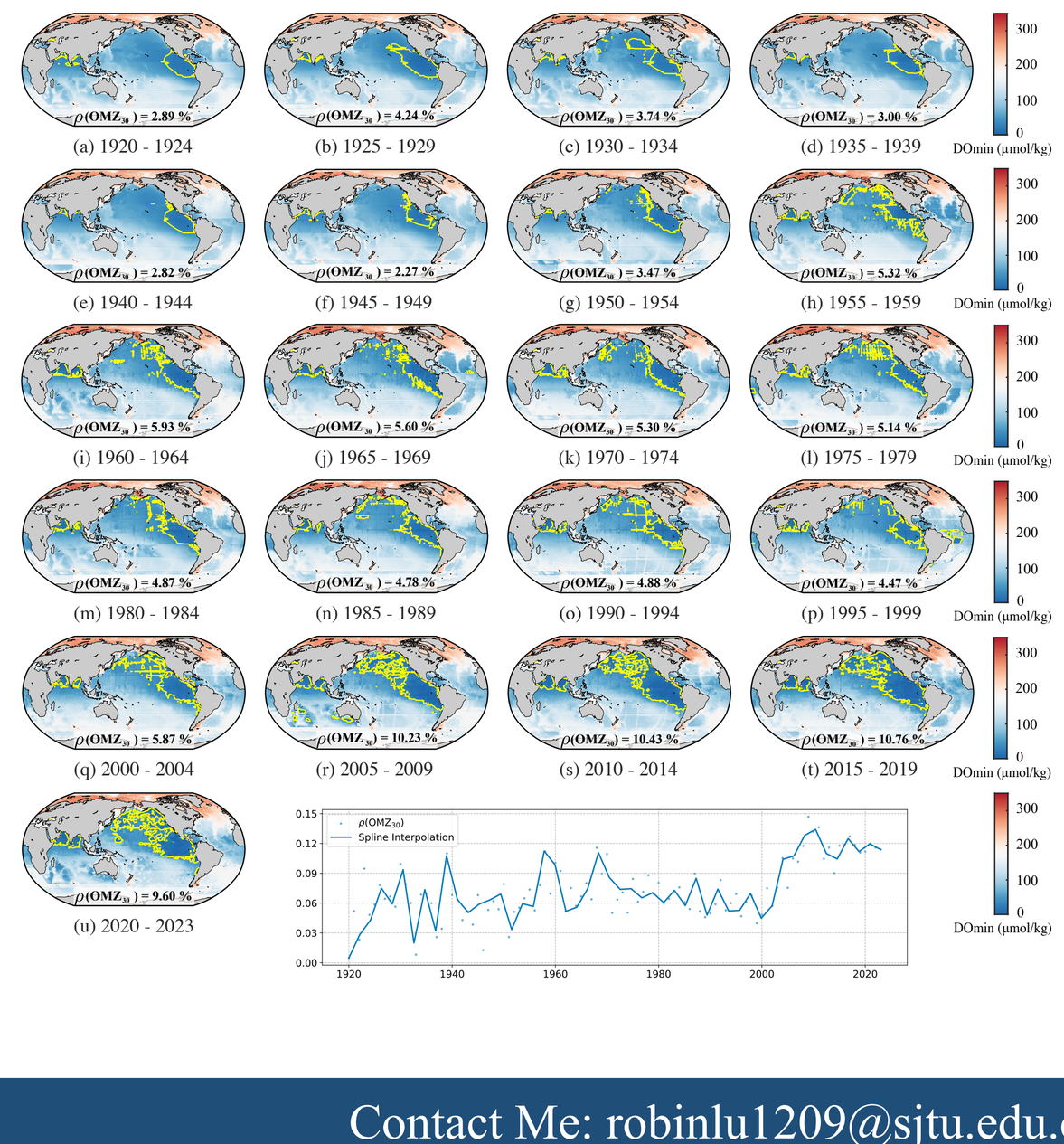
- Performance Comparison

Benchmark	$k=1$	$k=2$	$k=3$	$k=4$	Average Performance			
	MAPE	MAPE	MAPE	MAPE	MAPE	R2	RMSE	MAE
CESM2 omip1	23.63	23.15	23.67	22.87	23.32±0.38	0.7966±0.0064	37.37±0.34	25.98±0.31
CESM2 omip2	23.62	23.00	24.60	23.13	23.58±0.72	0.7947±0.0096	38.22±0.55	27.12±0.32
GFDL-ESM4 historical	26.13	24.01	26.68	24.33	25.28±1.31	0.8228±0.0051	35.45±0.65	23.69±0.38
OxyGenerator (Ours)	**14.72**	**13.48**	**15.72**	**13.20**	**14.28**±1.16	**0.9026**±0.0072	**26.31**±1.23	**17.57**±1.10
Improvement	37.67%	41.38%	33.59%	42.28%	38.77%	9.70%	25.78%	25.83%



(a) CESM2 omip1 (b) CESM2 omip2 (c) GFDL-ESM4 historical (d) OxyGenerator (Ours)

- Reconstruction Results



(a) 1920 - 1924 (b) 1925 - 1929 (c) 1930 - 1934 (d) 1935 - 1939
(e) 1940 - 1944 (f) 1945 - 1949 (g) 1950 - 1954 (h) 1955 - 1959
(i) 1960 - 1964 (j) 1965 - 1969 (k) 1970 - 1974 (l) 1975 - 1979
(m) 1980 - 1984 (n) 1985 - 1989 (o) 1990 - 1994 (p) 1995 - 1999
(q) 2000 - 2004 (r) 2005 - 2009 (s) 2010 - 2014 (t) 2015 - 2019
(u) 2020 - 2023

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