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U.S. DEPARTMENT OF ENERGY

Generalizable Implicit Neural Representations via Parameterized Latent Dynamics for Baroclinic Ocean Forecasting

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Introduction

Mesoscale ocean dynamics drive key climate processes like:

- Heat transport
- Hurricane genesis
- Drought patterns

But simulating these dynamics at high resolution is computationally expensive due to their nonlinear, multiscale nature.

Opportunity with AI

Recent advances in Implicit Neural Representations (INRs) enable:

- Learning continuous spatiotemporal fields
- Operating on unstructured, coordinate-based data

But most INRs struggle with many-query tasks — needing separate models for each scenario.

Our Solution – PINROD

We introduce Parameterized Implicit Neural Representations for Ocean Dynamics (PINROD) — A unified AI framework for ocean dynamics that integrates:

- INRs for continuous spatial prediction
- Parameterized Neural ODEs (PNODEs) for modeling latent dynamics over time

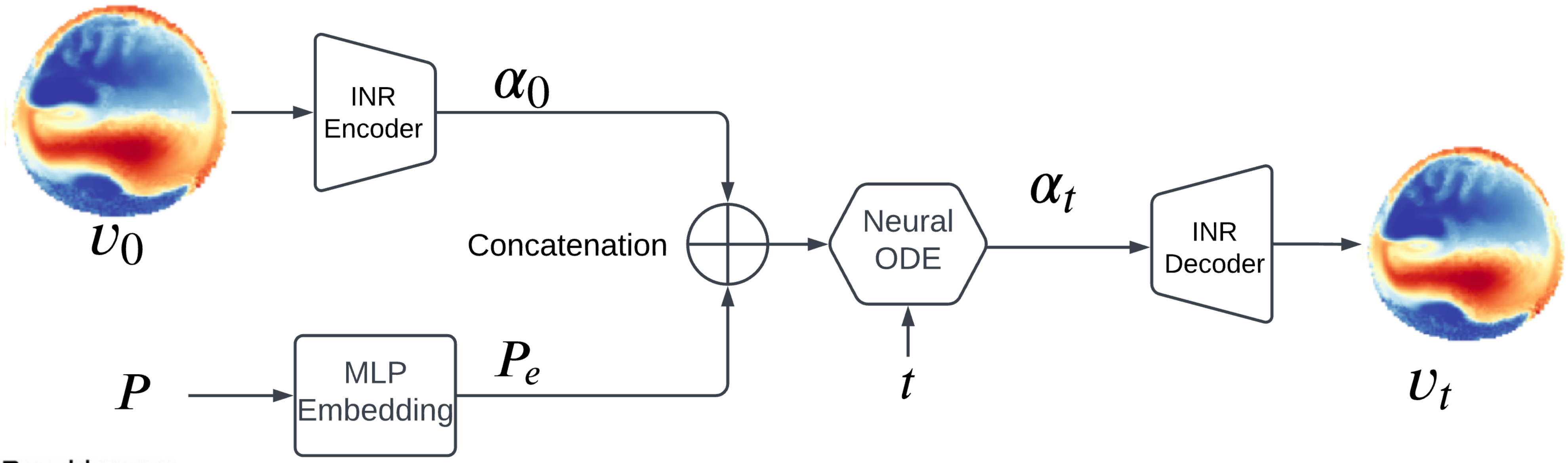
Delivering fast and accurate ocean forecasting across diverse physical conditions — all from a single, generalizable model.

Framework Overview

Encoder: Compress continuous ocean fields into latent vectors.

PNODE: Capture the continuous temporal evolution of latent states.

Decoder: Reconstruct the original continuous fields .



Training strategy

Encoder–Decoder Pretraining:

Jointly train encoder, decoder to minimize reconstruction error.

PNODE Training

Fix encoder/decoder and train PNODE on latent trajectories using physical parameters.

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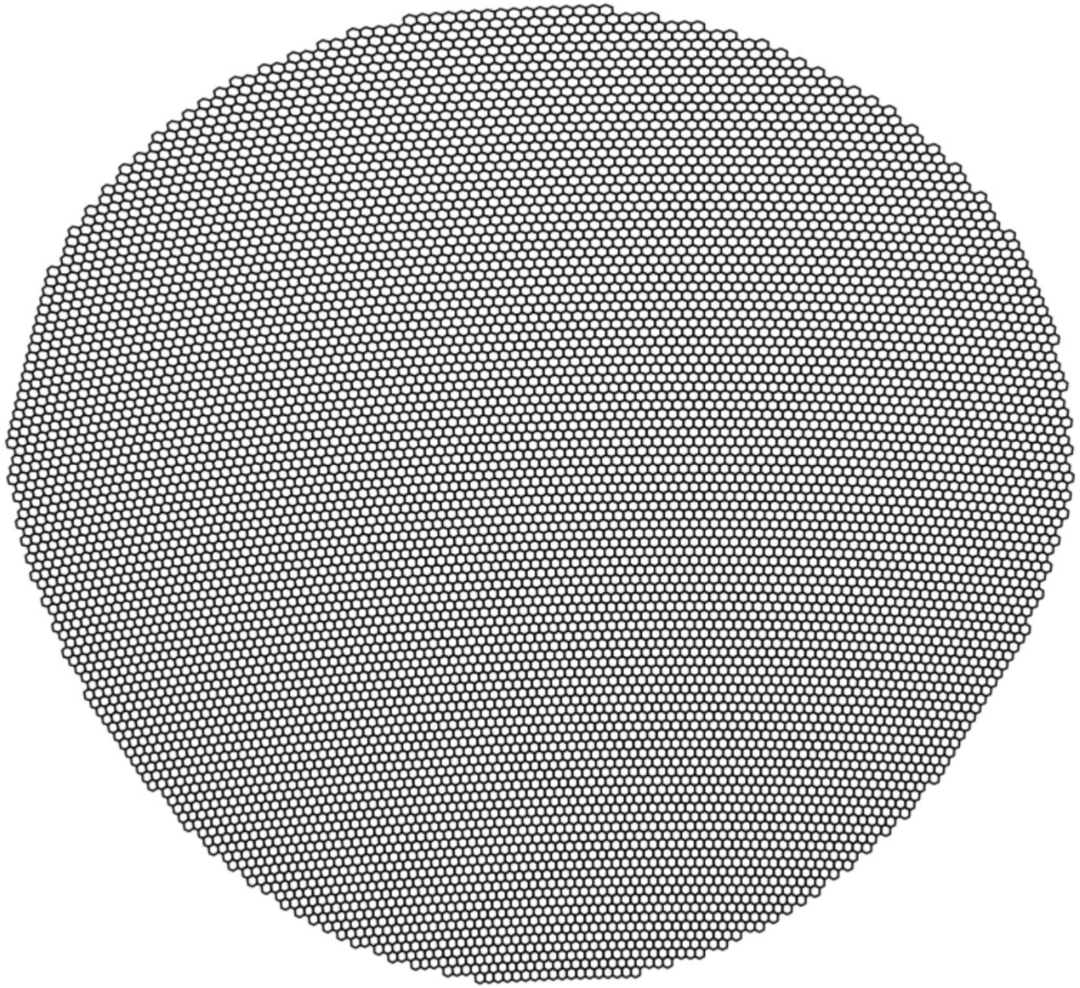
SOMA Testbed

Realistic midlatitude ocean simulation with:

- Hex mesh: 8,521 cells × 60 layers
- Perturbation: bottom drag coefficient

Task: Predict 29-day ocean evolution from Day 0 state + drag coefficient.



Adapted from: Sun et al., *Parametric Sensitivities of a Wind-driven Baroclinic Ocean using Neural Surrogates*

Baselines

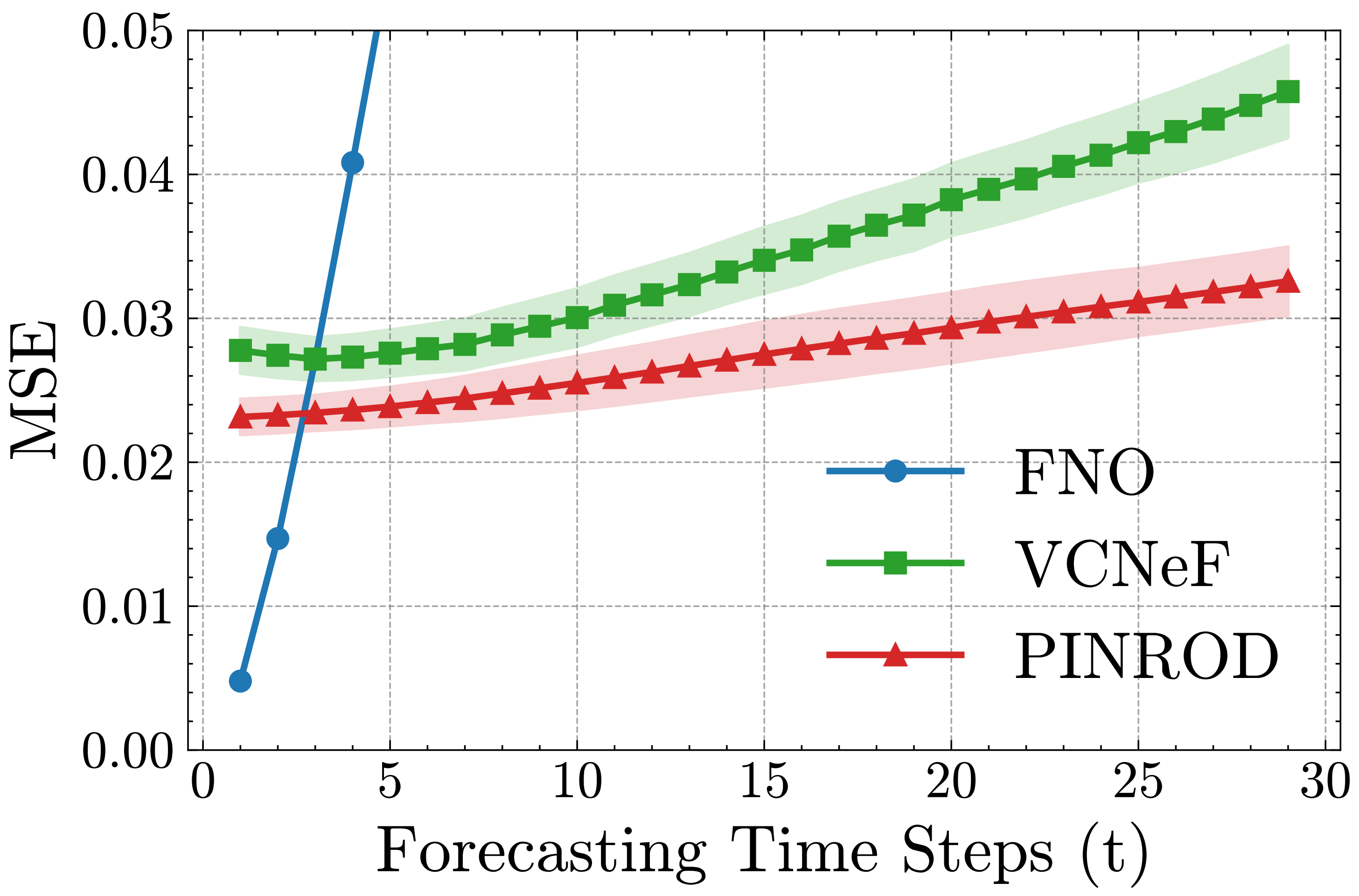
We compare against two strong baseline surrogates:

- FNO (Fourier Neural Operator)
  Learns in frequency domain, uses autoregressive time stepping.
- VCNeF (Vectorized Conditional Neural Field)
  Vision Transformer-based model, requires interpolation onto regular grids

PINROD is evaluated directly on unstructured data, avoiding interpolation artifacts.

Error Stability Across Time Steps

PINROD maintains more stable error.



Temperature MSE vs. time.

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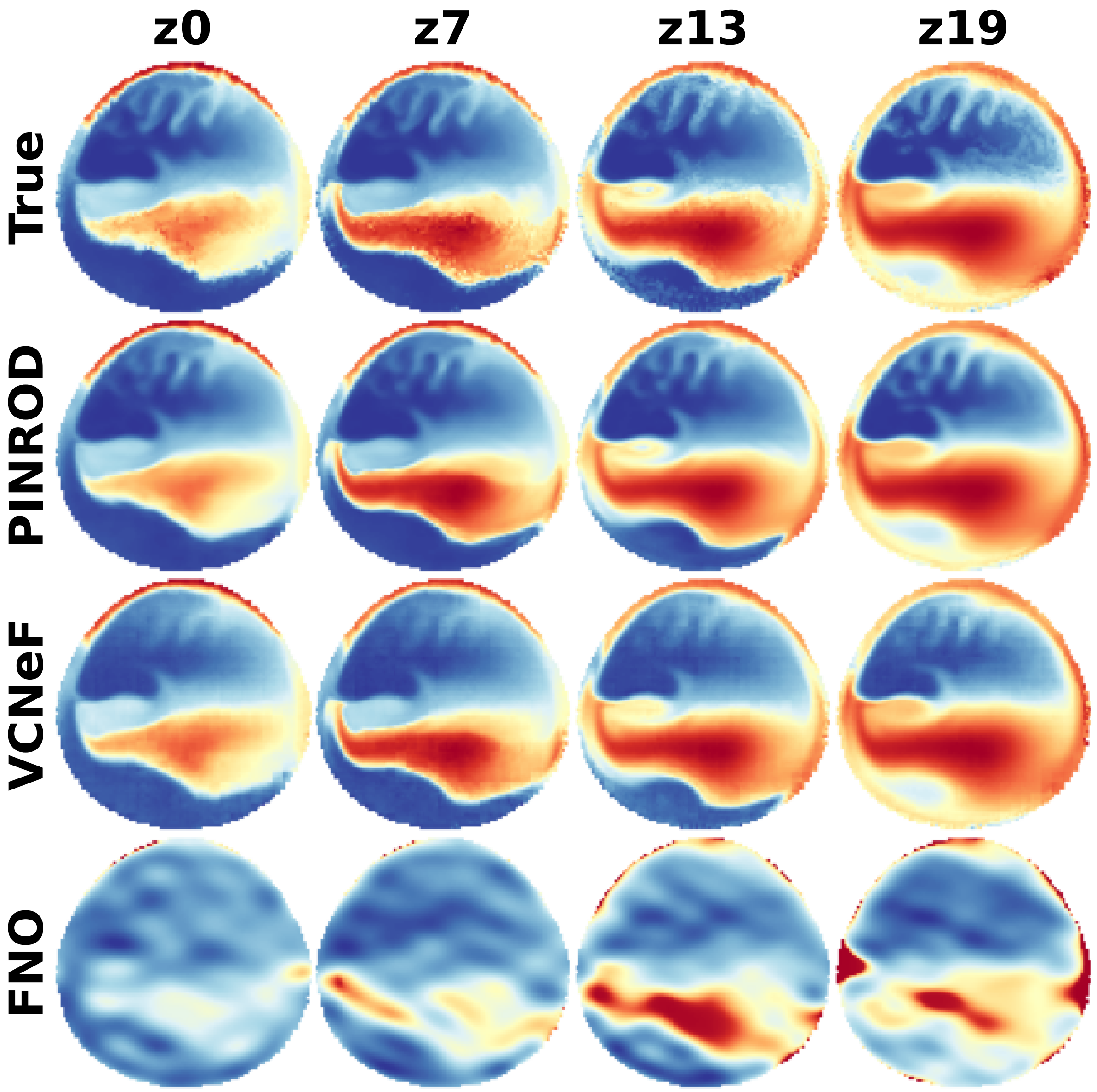
Qualitative result

PINROD preserves fine-scale structures more accurately than FNO/VCNeF



Temperature fields at day 29 (depths z=0, 7, 13, 19).

Conclusion

We presented PINROD a novel framework combining INRs with PNODEs for ocean forecasting. The method:

- Handles high-dimensional, nonlinear, and parameter-dependent ocean dynamics.
- Supports continuous-time, coordinate-based prediction.
- Achieves state-of-the-art accuracy on the SOMA dataset.

Thank you

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