

# 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.

### The 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:

A unified AI framework that combines:

- Dynamics-aware Implicit Neural Representations (INRs)
- Parameterized Neural ODEs (PNODEs)

Delivering fast, accurate ocean forecasting across varying physical conditions — using a single, generalizable model.

## PINROD Framework

PINROD (Parameterized Implicit Neural Representation for Ocean Dynamics): a physics-aware AI framework that learns generalizable ocean dynamics from a single model.

It combines:

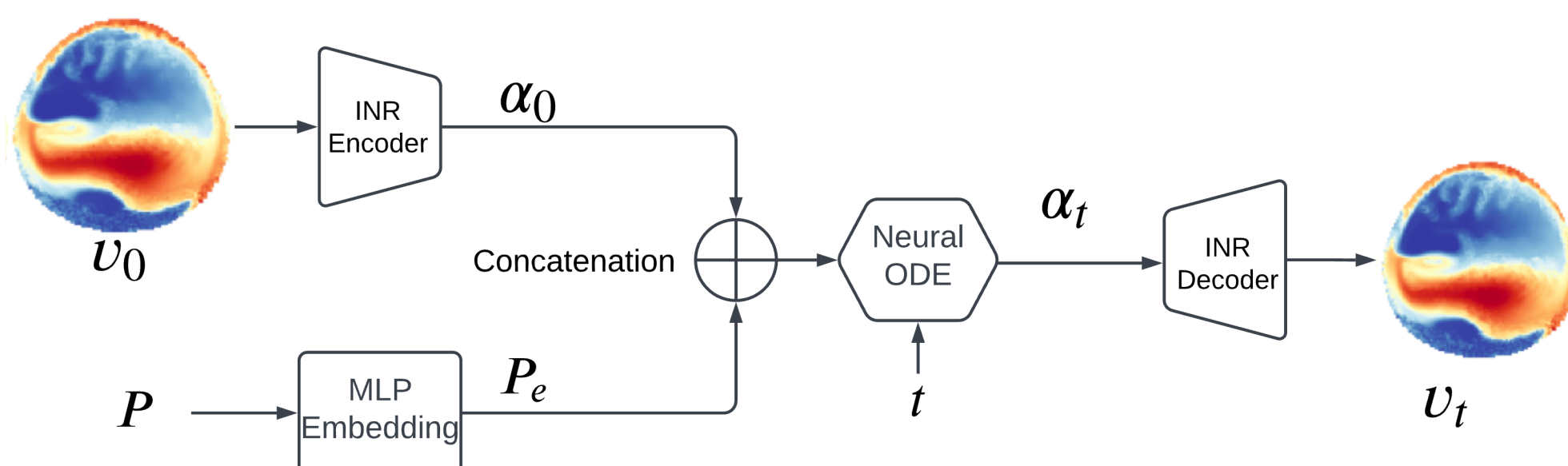
- Implicit Neural Representations (INRs) for continuous spatial prediction
- Parameterized Neural ODEs (PNODEs) for modeling latent dynamics over time

### Framework Overview:

**Encoder:** Compress continuous ocean fields into low-dimensional 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.

## Experimental Results

**Testbed:** SOMA (Simulating Ocean Mesoscale Activity) a realistic simulation of midlatitude ocean basin with:

- Unstructured hexagonal mesh (8521 cells × 60 vertical layers)
- Physical perturbations: bottom drag coefficient

**Task:** given the initial state (day 0) and bottom drag coefficient, forecast ocean states for the next 29 days.

### Baselines:

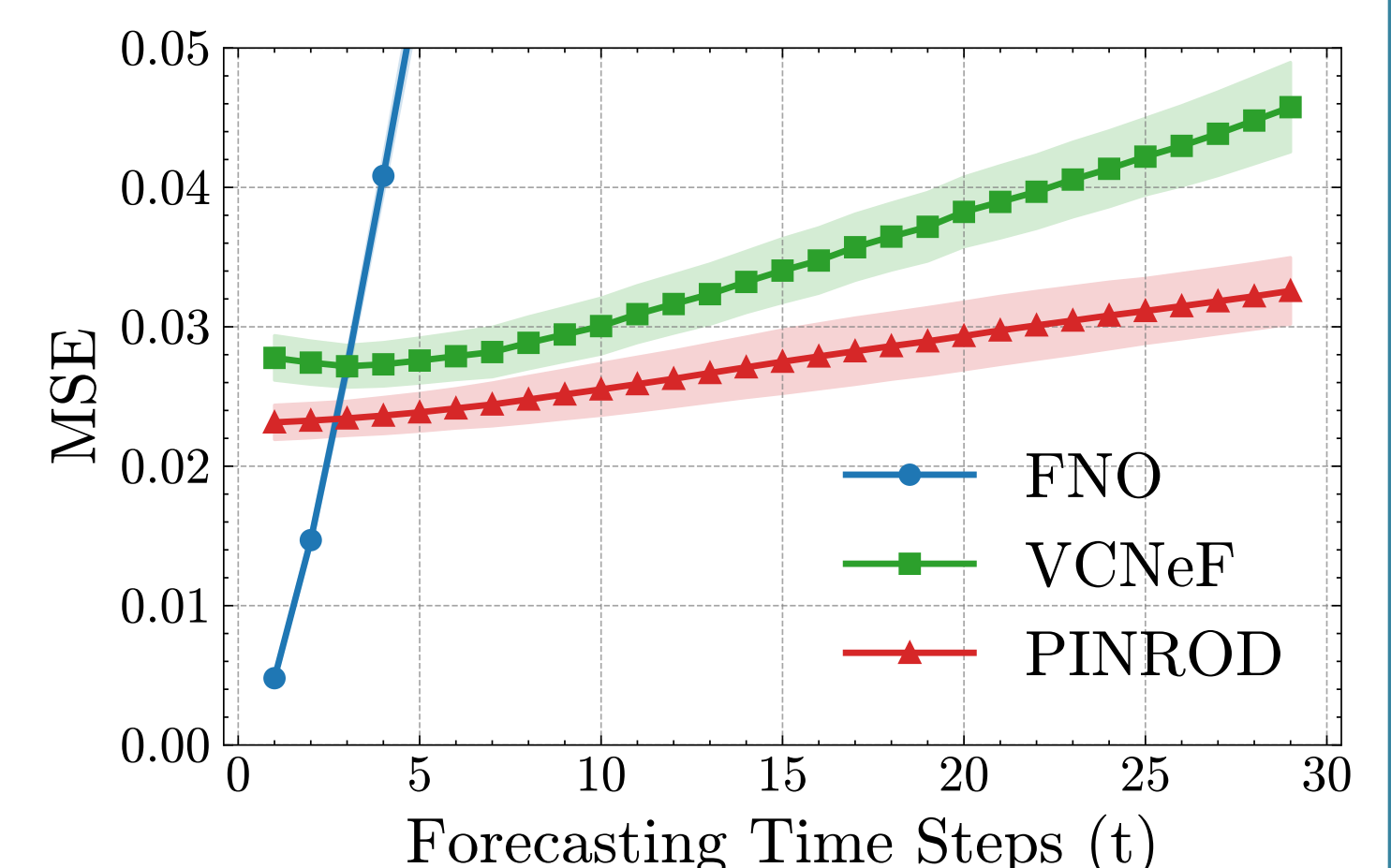
**FNO:** Fourier Neural Operator

**VCNeF:** Vectorized Conditional Neural Field

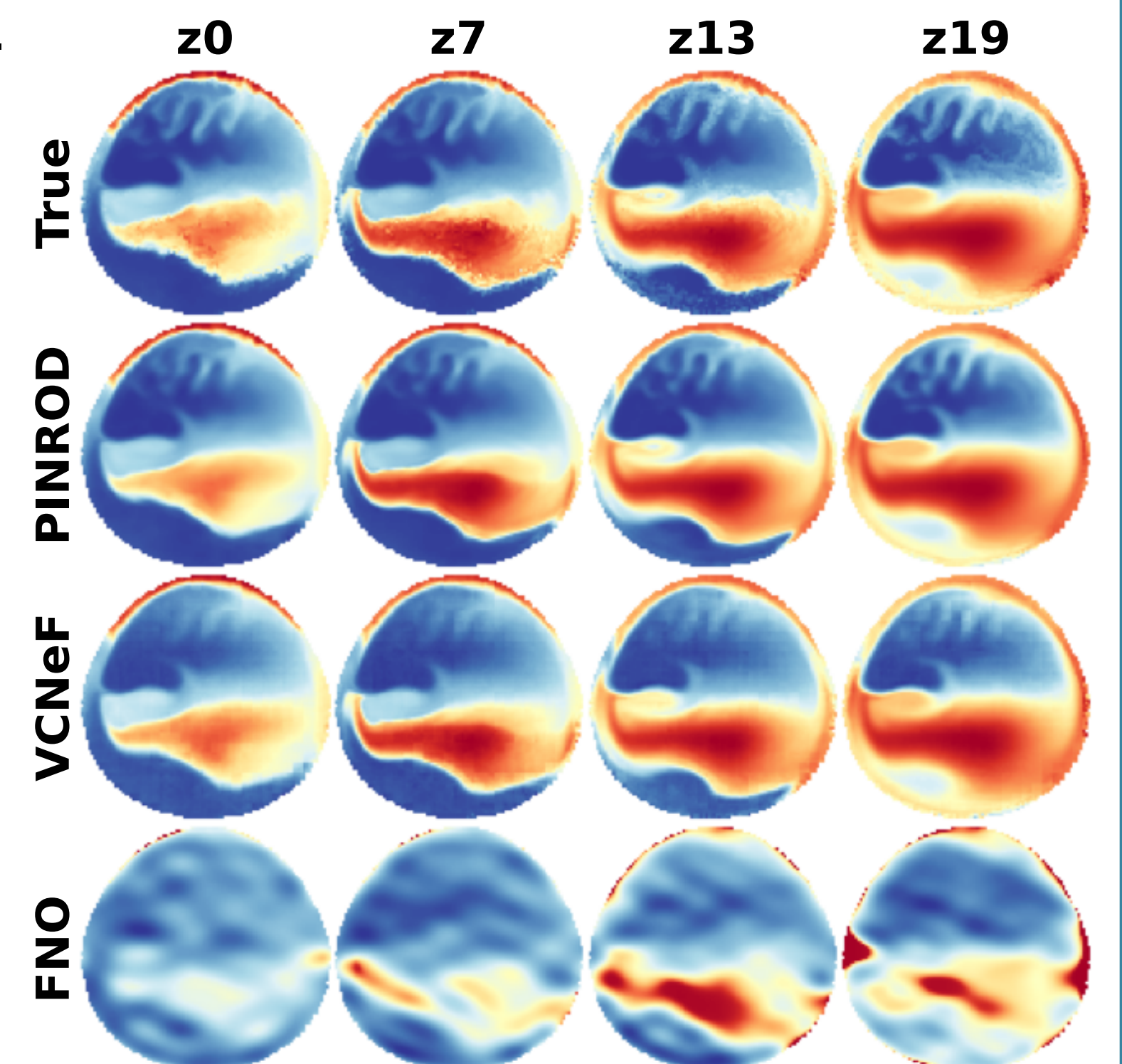
**PINROD:** Our method

### Results:

Temperature MSE vs. time. PINROD maintains more stable error.



Temperature fields at day 29 (depths  $z=0, 7, 13, 19$ ). PINROD preserves fine-scale structures more accurately than FNO/VCNeF.



## 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.