Graph Neural Networks versus Reduced-Order Models for Surrogate-Based Coastal Forecasting on Unstructured Meshes

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Motivation

Emulating trusted numerical models by embedding domain expertise and local knowledge into data-driven surrogates.

Augmenting slow traditional models with fast, operational alternatives for time critical decision-making.

Facilitating ensemble generation and uncertainty quantification on lightweight hardware.

Objective

Comparative analysis of two surrogate architectures to evaluate technical trade-offs and performance constraints.

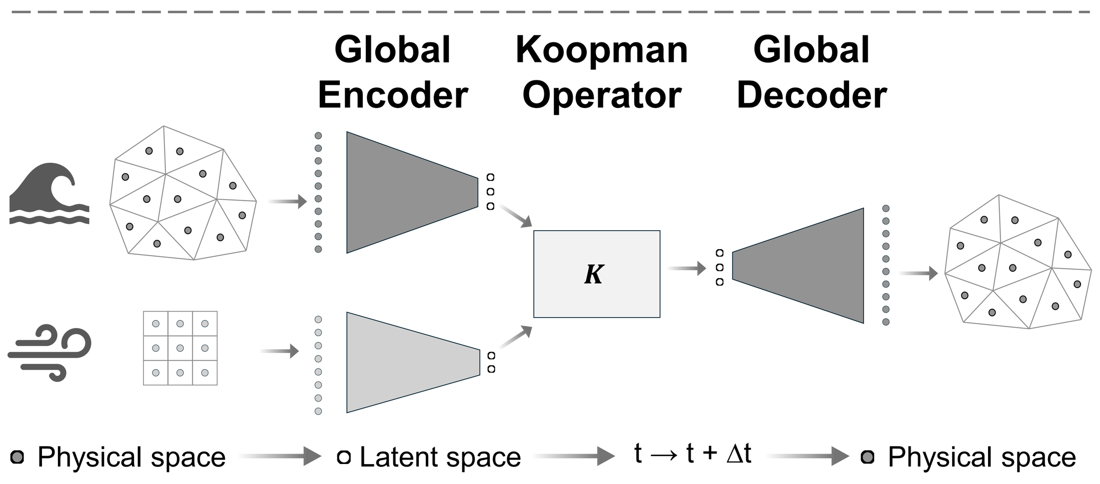
Lead time
24h

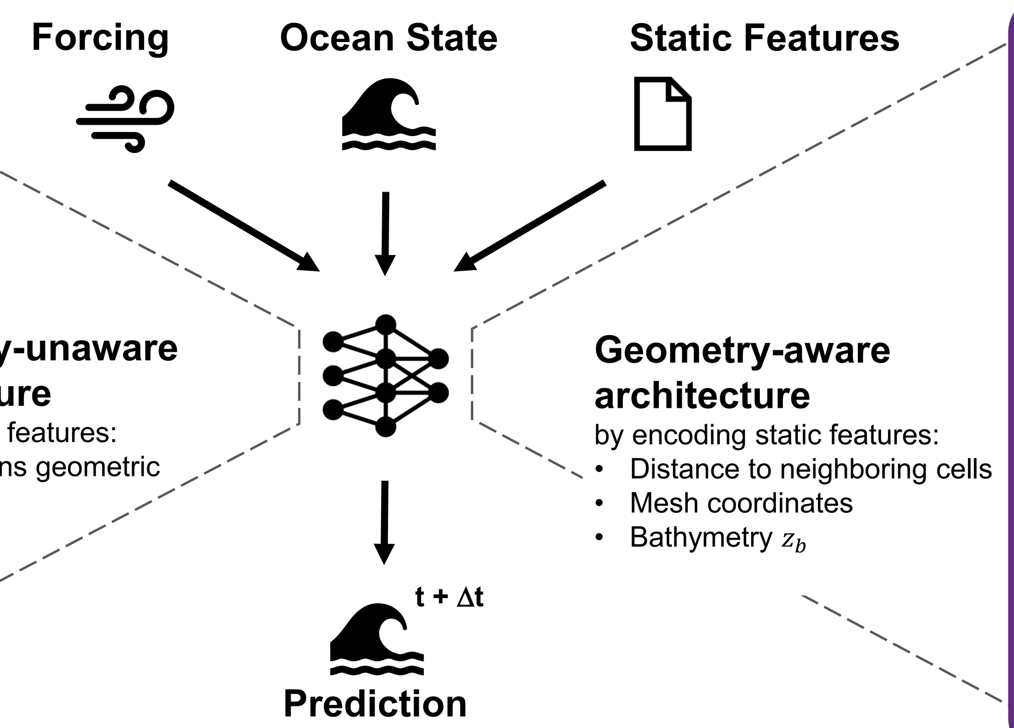
Prediction variables
Surface elevation η
Eastward velocity u
Northward velocity v

Architectures

Reduced-Order Model (ROM)

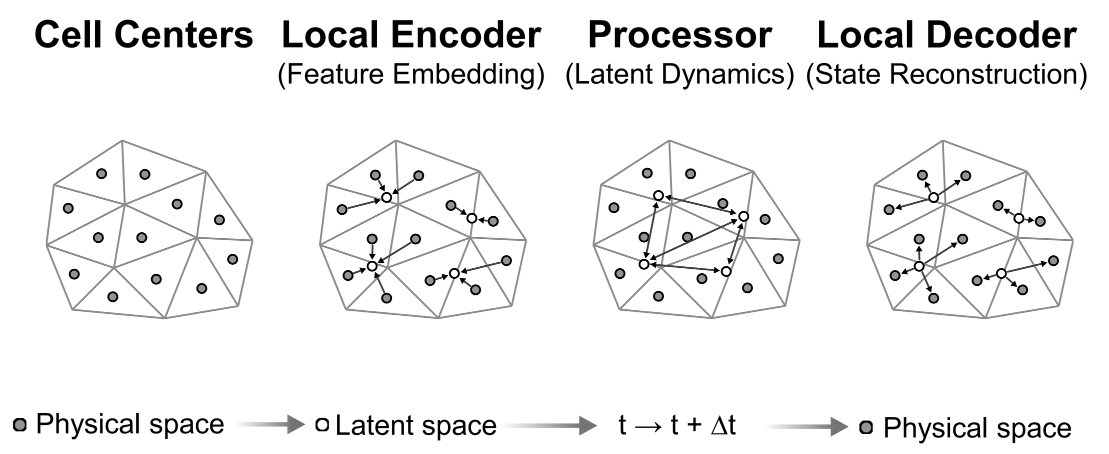
Koopman autoencoder [1]
Autoencoder with linear Koopman operator for externally forced systems. Developed as part of a PhD project at DHI with focus on light-weight training and fast inference.





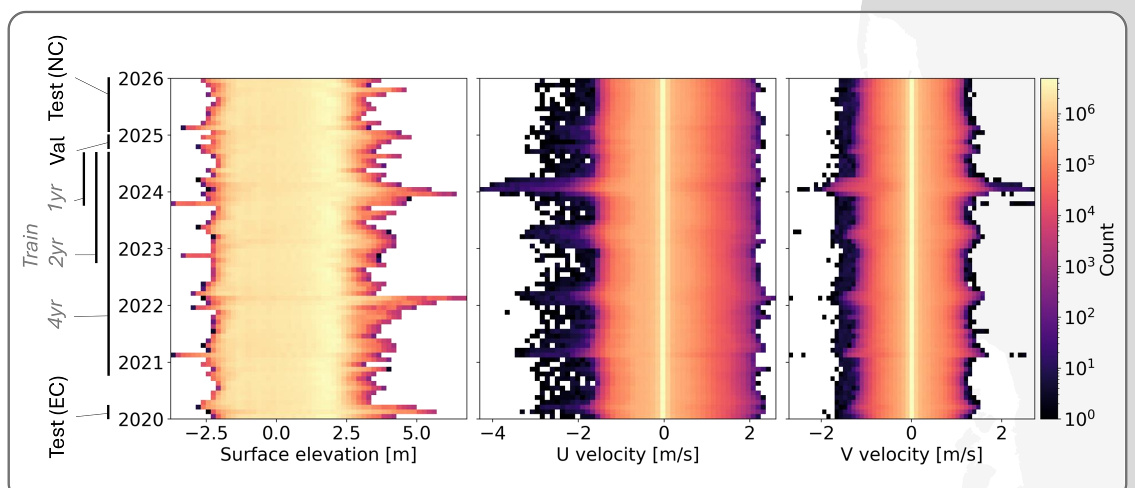
Graph Neural Network (GNN)

Framework *ML-LAM* [2]
Adapted version of an open-source weather modelling GNN framework, extended for ocean forecasting on unstructured data.



Case Studies

Data Distribution



Hamburg

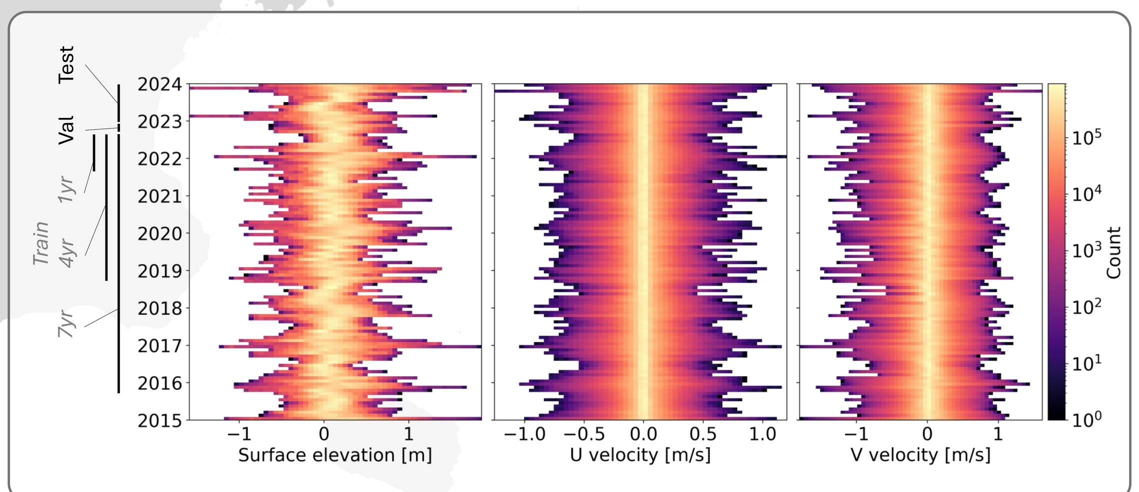
Primary Use
Current information system for pilot boats and storm surge forecasting in the port area

Forcing
River discharge and tidal dynamics on boundaries

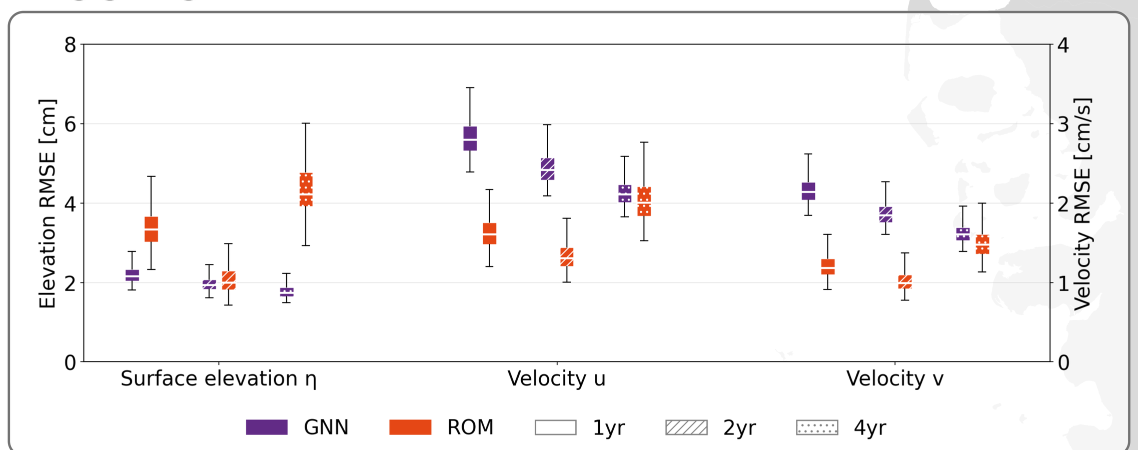
Mesh
~8200 triangular and quadrilateral elements

Training Data
6 years of hourly training data generated with Mike21FM

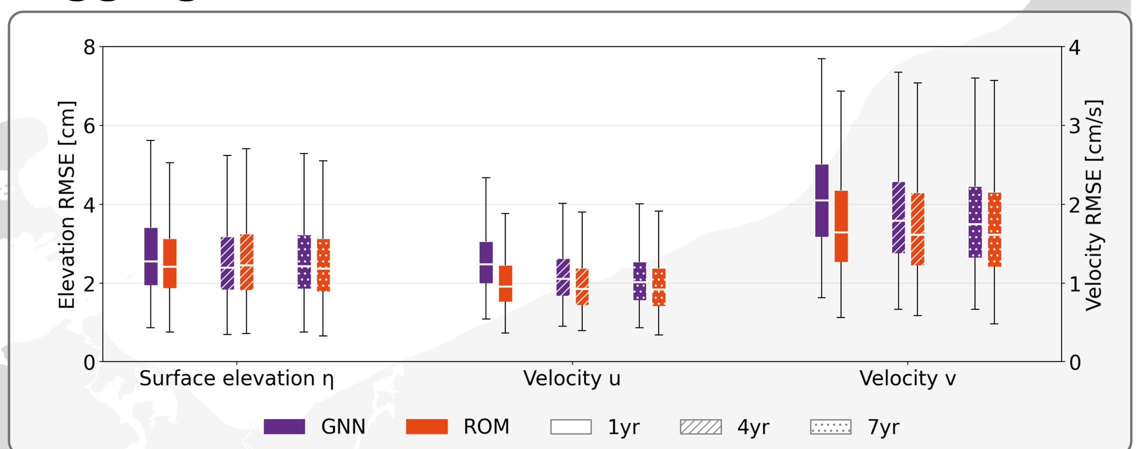
Data Distribution



Aggregated RMSE



Aggregated RMSE



Øresund

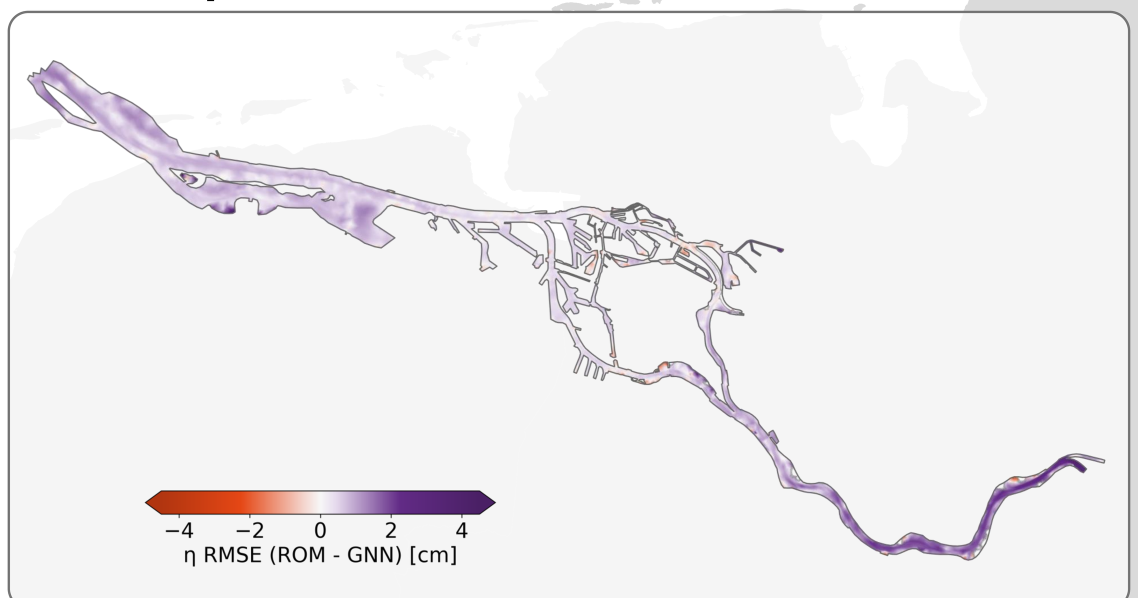
Primary Use
Cut out of a North-Sea Baltic model used for design studies and storm surge forecasting

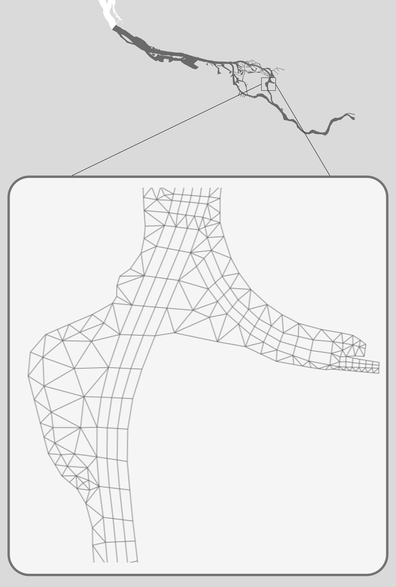
Forcing
Tidal dynamics on boundaries and wind

Mesh
~3300 triangular elements

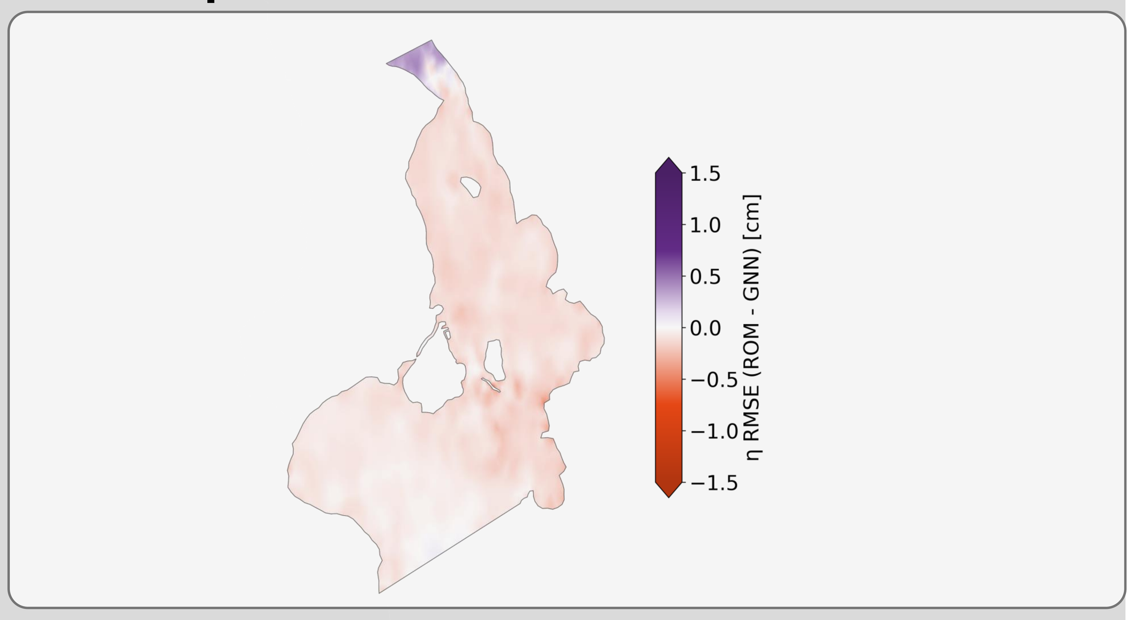
Training Data
10 years of hourly training data generated with Mike21FM

Mean Spatial RMSE Difference





Mean Spatial RMSE Difference



Challenges

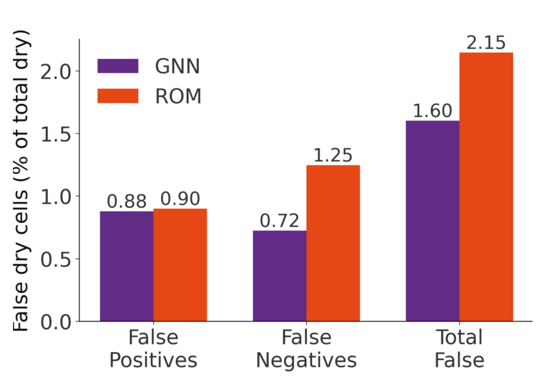
Dry Cells

Challenge: Numerical solvers produce NaNs in dry cells, leading to spurious propagation in ML training.

Approach:

1. Pre-training: Map *NaN* values to defaults
   $\eta \rightarrow z_b$ and $u, v \rightarrow 0$
2. Post-training: Re-identify dry cells
   $|\eta - z_b| < threshold$ or $\eta < z_b$

Outcome:

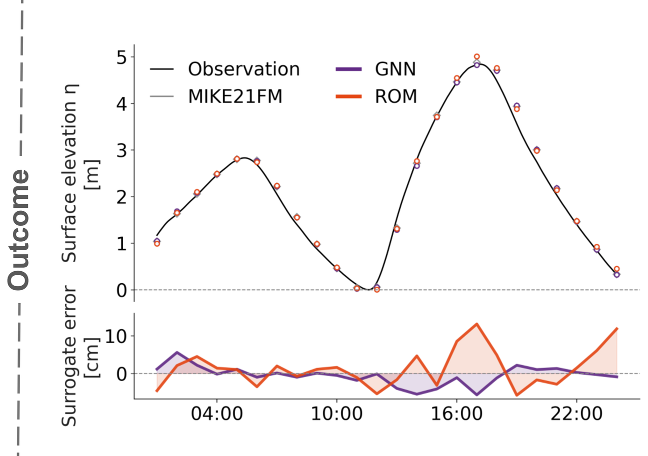


Extreme Events

Challenge: Uncertain model generalization under rare extremes.

Approach: Augment normal-condition (NC) testing with extreme-condition (EC) testing and evaluate on a severe storm surge event on 10th Feb 2022 (Hamburg).

Outcome:



Temporal Unrolling

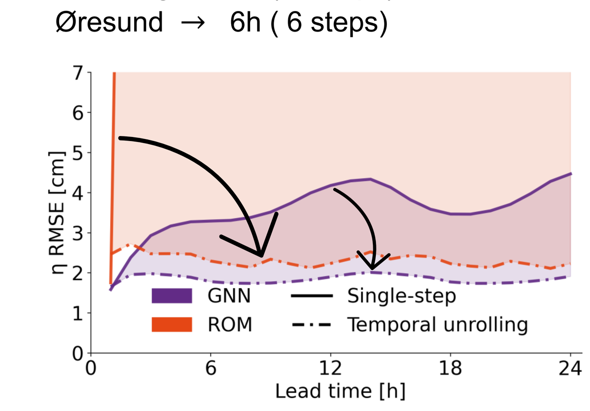
Challenge: Autoregressive rollout of single-step model causes error growth over long lead times.

Approach:

1. Initial training: Single-step loss
2. Fine-tuning: Multi-step loss

Grid search over rollout length reveals:
Optimal rollout ≈ multiple of half tidal-cycle
Hamburg → 13h (13 steps)
Øresund → 6h (6 steps)

Outcome:



Key Take Aways

	Accuracy	Scalability	Training	Inference	Strength
GNN	Hamburg: 95% Øresund: 79%	Clear correlation: Training data size ↑ Model performance ↑	Hours	x100 speed-up	Complex geometries
ROM	Hamburg: 90% Øresund: 80%	Unclear correlation: Training data size ↑ Model performance ?	Minutes	x1000 speed-up	Easy set-up

[1] Petersen, F.H., Mariegaard, J.S., Palmitessa, R., Engsig-Karup, A.P. (2026) Reduced-Order Surrogates for Forced Flexible Mesh Coastal-Ocean Models. arXiv:2602.05416 [Preprint]

[2] Adamov, S., Oskarsson, J., Denby, L., et al. (2025). Building Machine Learning Limited Area Models: Kilometer-Scale Weather Forecasting in Realistic Settings. arXiv:2504.09340 [Preprint]

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