Neural-ROM: A Graph Neural Network for Probabilistic Regional Ocean Forecasting in the Baltic Sea

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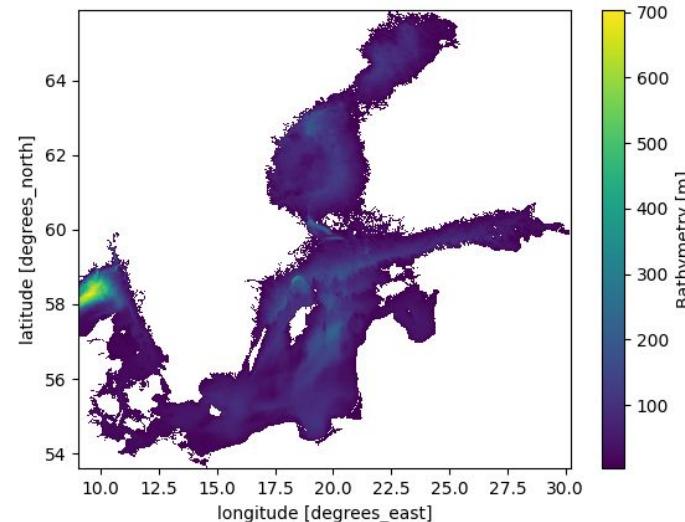
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# Standard Baltic Sea modeling
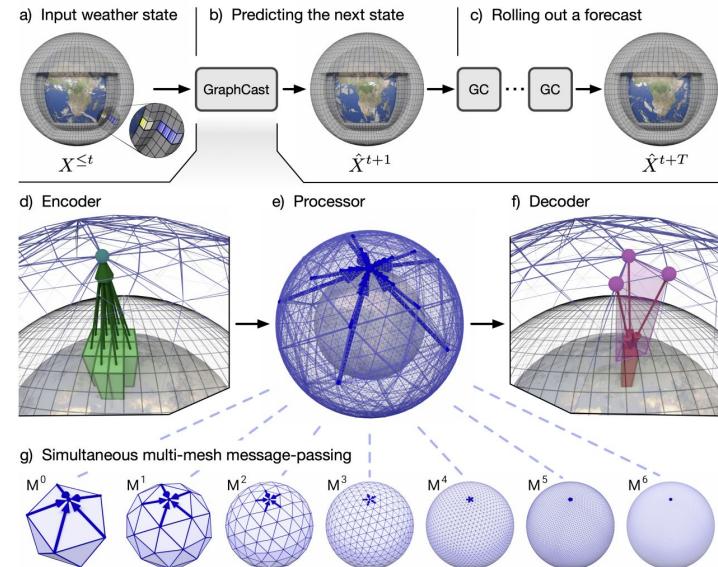
- Physical ocean processes such as currents, temperature, and salinity are simulated numerically using Nucleus for European Modelling of the Ocean (*Nemo*).

- Incorporates observations using variational ocean data assimilation (*OceanVar*).

- Operates on high-resolution 1/48° grid with 56 vertical levels.

- Open boundary to the North Sea.

- Forced with surface atmospheric quantities.

Proposed method
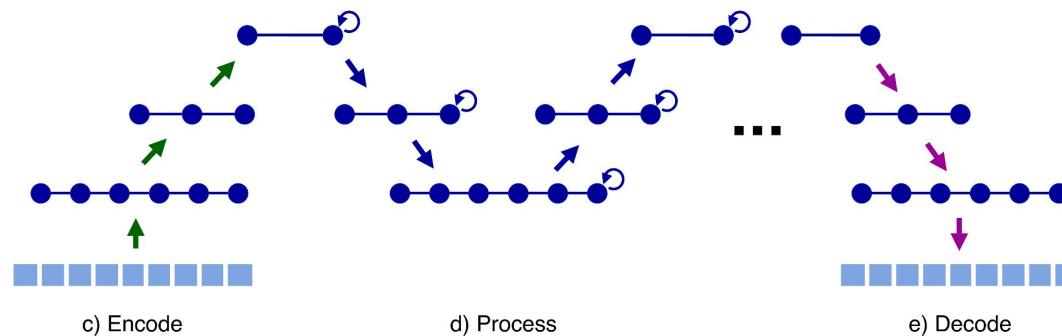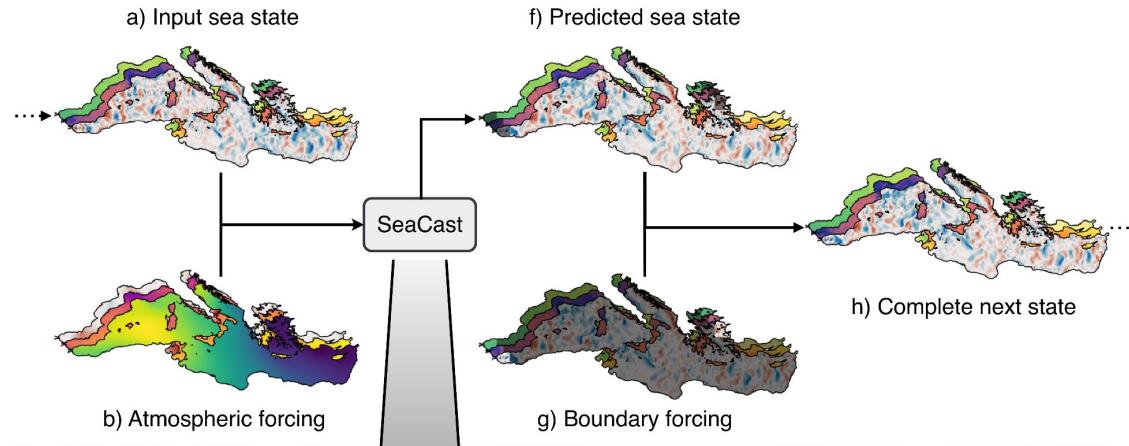
- Train a graph neural network (GNN) to *autoregressively* predict next simulation step. Meaning, predicted state is used as input to predict the following state after that.

- Produces a *cumulative error*, and smoothening as time goes on.

- However, for ocean forecasting the method is promising: reasonable amount of rollout steps.

- *Large advantage in terms of prediction speed* vs numerical simulations.

- Modern generative models open the doors for fast ensemble forecasts and *uncertainty quantification*.


a) Input weather state b) Predicting the next state c) Rolling out a forecast

$X^{\leq t}$ $\hat{X}^{t+1}$ $\hat{X}^{t+T}$

d) Encoder e) Processor f) Decoder

g) Simultaneous multi-mesh message-passing

M^0 M^1 M^2 M^3 M^4 M^5 M^6

Remi Lam et al., Learning skillful medium-range global weather forecasting. Science (2023)
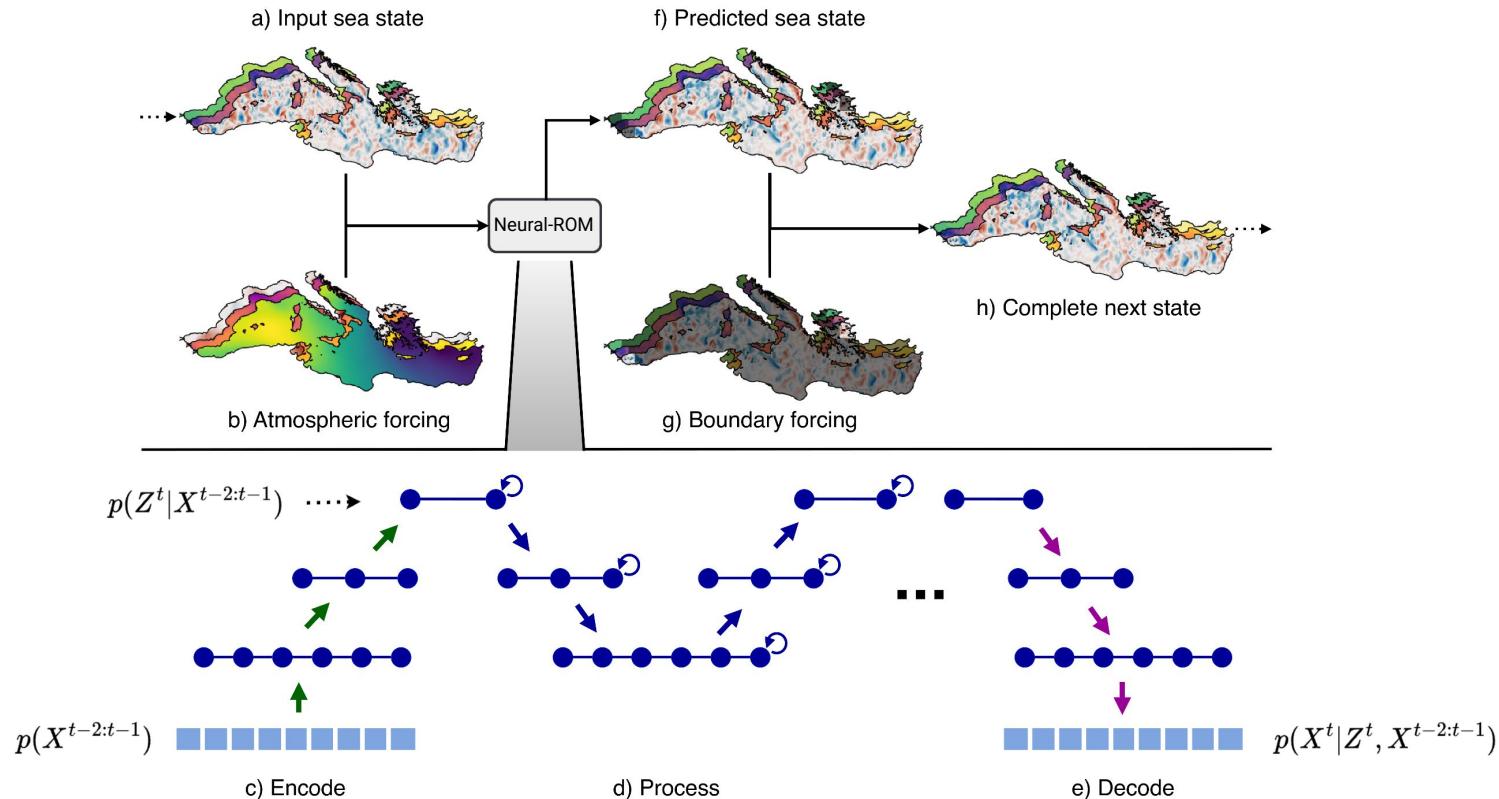
Deterministic model overview (https://arxiv.org/abs/2506.23900)

a) Input sea state

f) Predicted sea state

SeaCast

b) Atmospheric forcing

g) Boundary forcing

h) Complete next state

c) Encode

d) Process

e) Decode
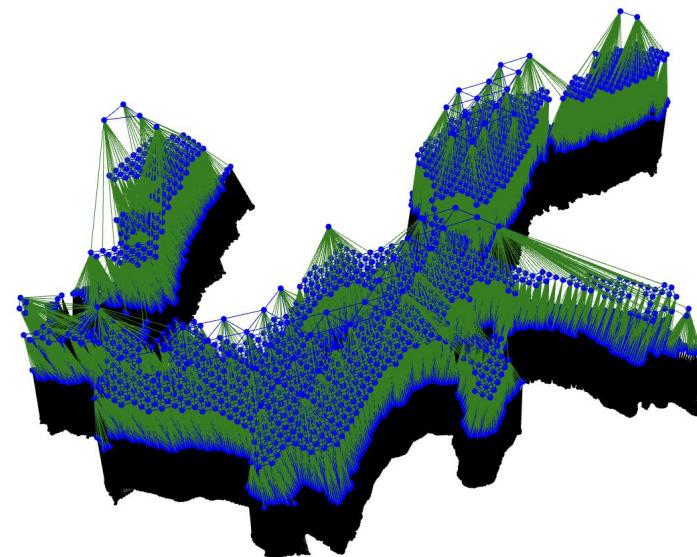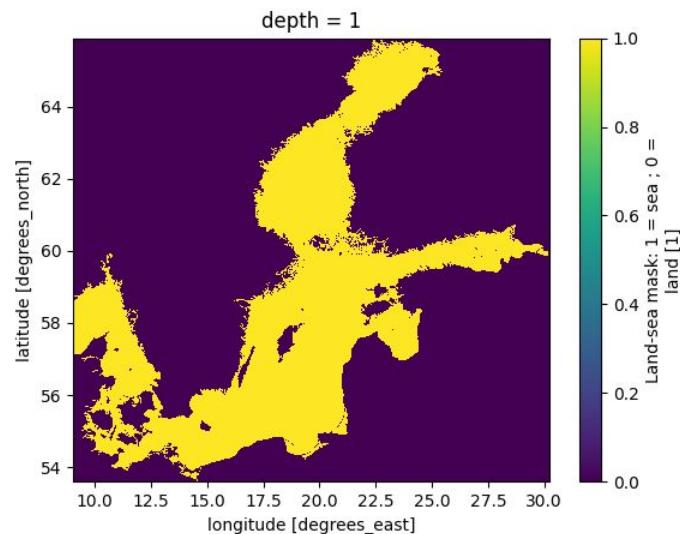
Probabilistic model overview

a) Input sea state

f) Predicted sea state

Neural-ROM

b) Atmospheric forcing

g) Boundary forcing

h) Complete next state

$p(Z^t|X^{t-2:t-1})$ $\cdots\blacktriangleright$

$p(X^{t-2:t-1})$

$p(X^t|Z^t, X^{t-2:t-1})$

c) Encode

d) Process

e) Decode
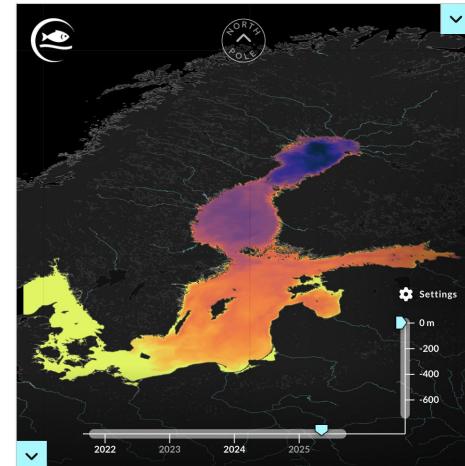
Baltic Sea surface mask and hierarchical graph

Baltic Sea dataset
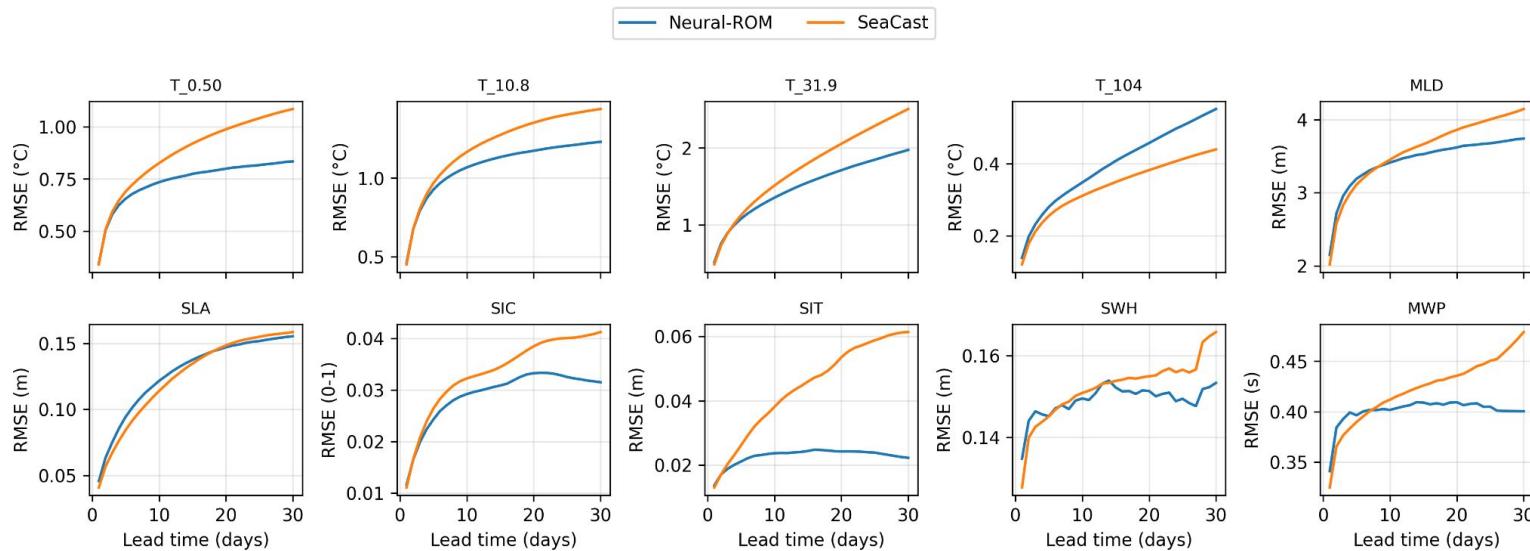
- Here we model temperature (T), sea level anomaly (SLA), sea ice concentration (SIC), sea ice thickness (SIT), mixed layer depth (MLD), significant wave- height (SWH), and significant wave period (SWP).

  - From Nemo-Nordic reanalysis and WAM hindcast.

- Atmospheric forcing: 2m temperature, 10m wind components, mean sea level pressure from ERA5 reanalysis.

- *Training* on 2010–2015.

- *Validation* 2016 Jan–March

- *Testing* on 2016 April–December.


https://marine.copernicus.eu/
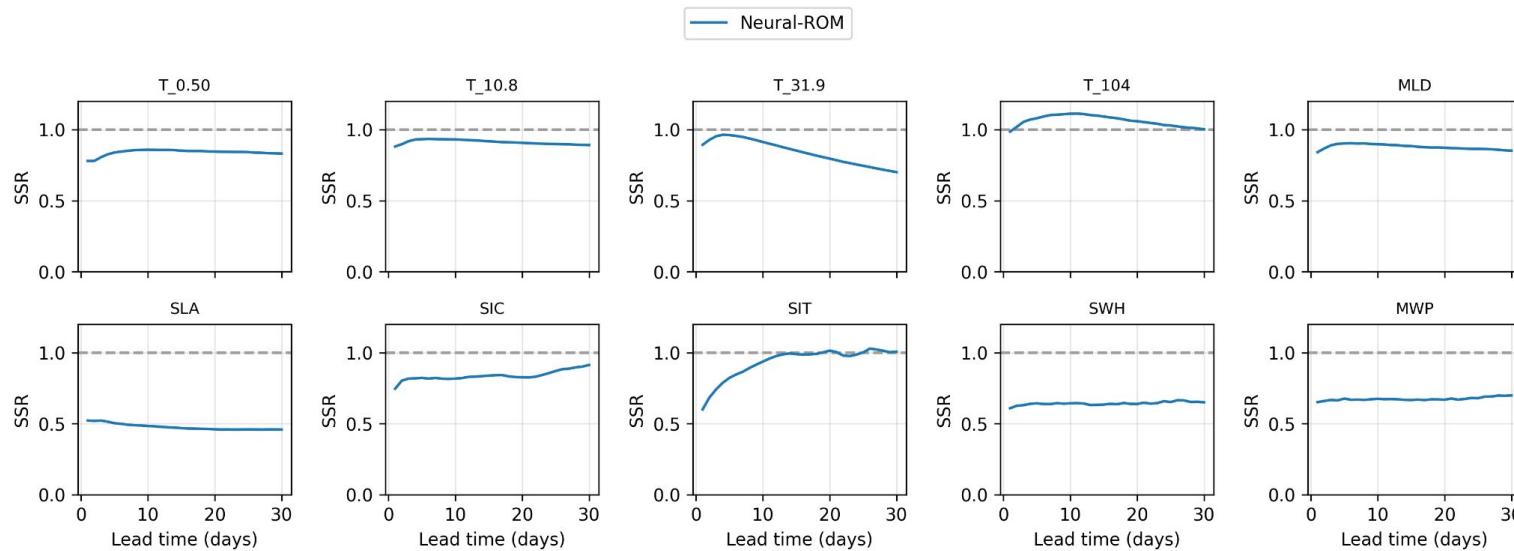
Forecast root mean squared error
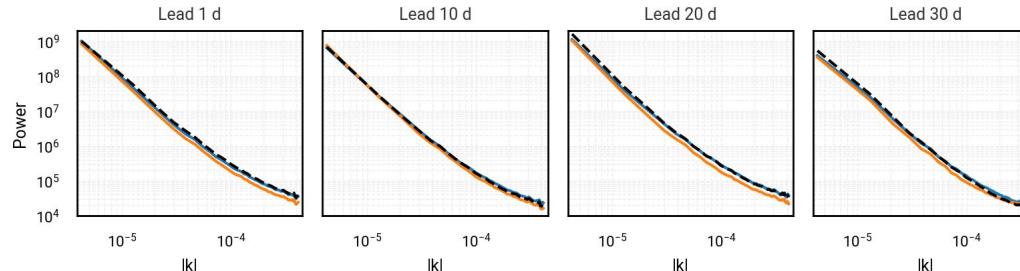
Forecast spread-skill-ratio
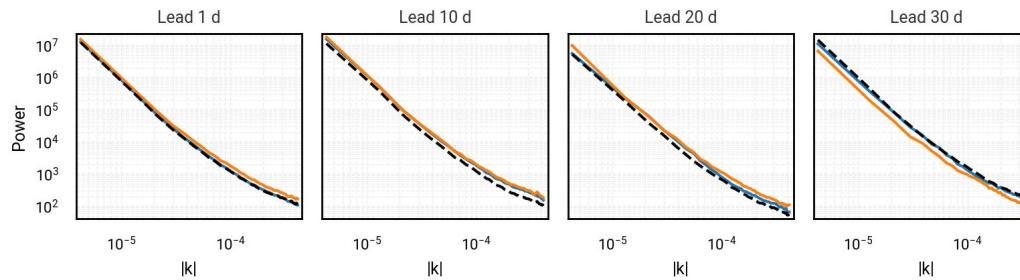
Forecast power spectra

Mean wave period

Sea level anomaly
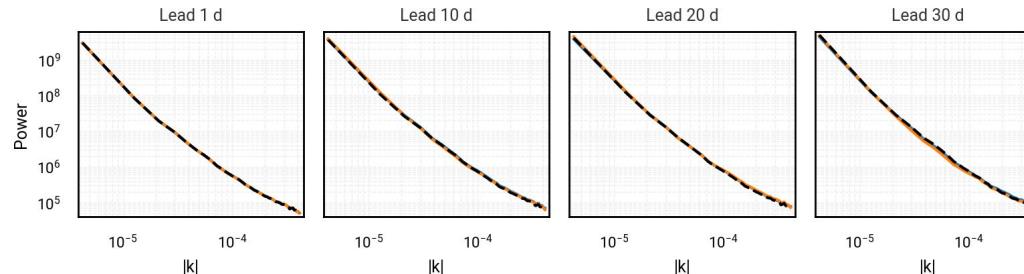
Legend: Neural-ROM — SeaCast — NEMO-Nordic Reanalysis
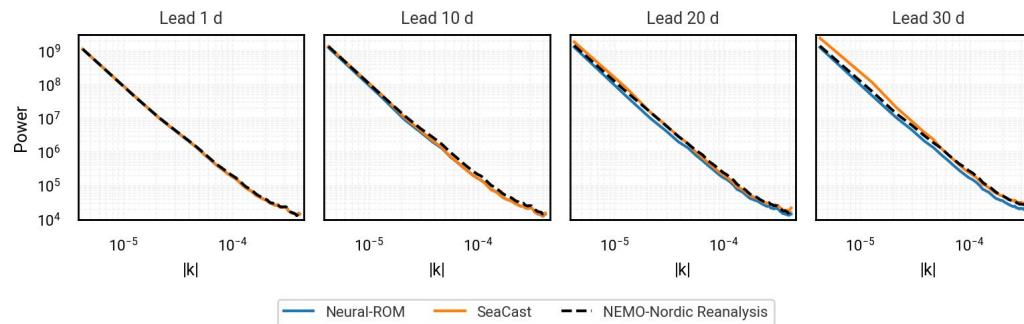
Forecast power spectra

Temperature at 0.5 m

Temperature at 31.9 m

Neural-ROM — SeaCast — NEMO-Nordic Reanalysis

Example forecast

Mixed layer depth, lead time 1 (2016-04-03)
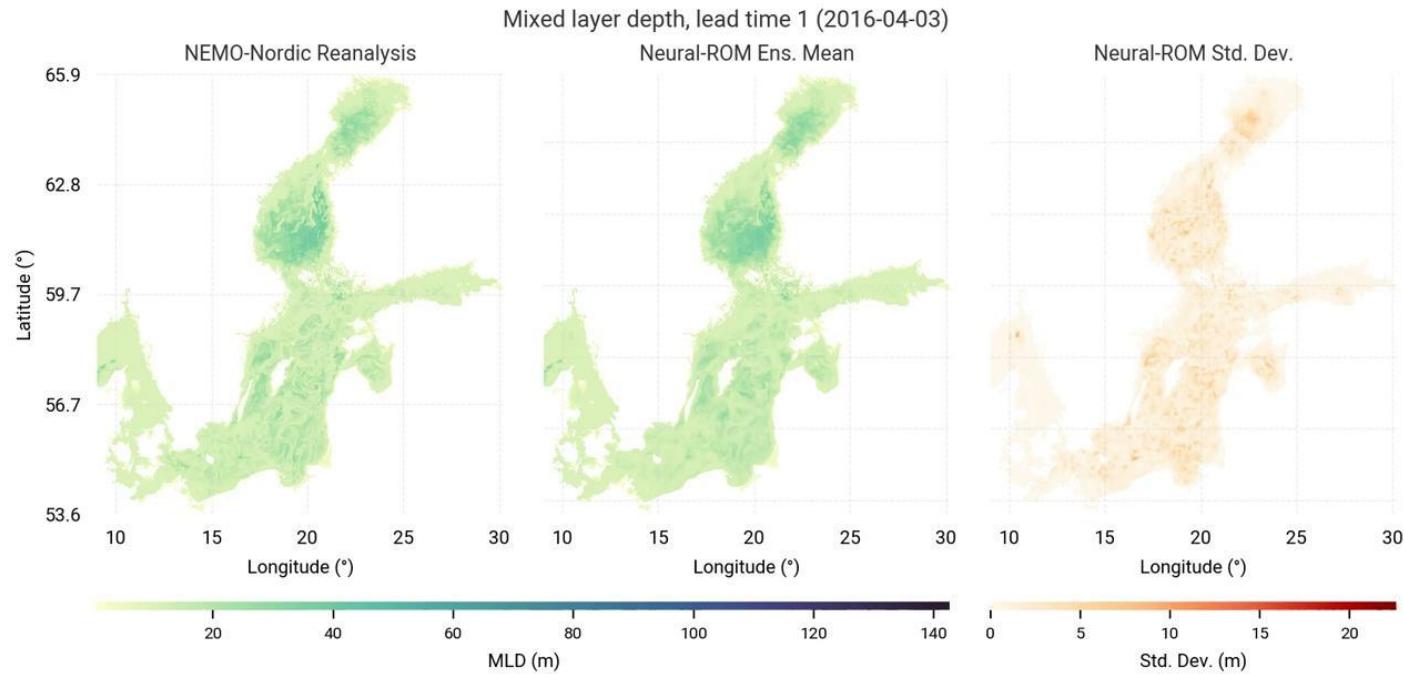
Outlook

- Compare to the Nemo-Nordic operational forecast.

- Atmospheric data from ERA5 → should use ECMW *forecasts* for evaluation.

- Could adapt Neural-ROM to model irregular grids, such as high-res costal simulation.

- Include more variables/depths, e.g. biogeochemistry.

- See SeaCast article for an operational comparison and impact of numerical and data-driven atmospheric forcings.

SeaCast paper