

Integrated AI–Physics based End-to-End Framework for Coastal Prediction i-GCOAST

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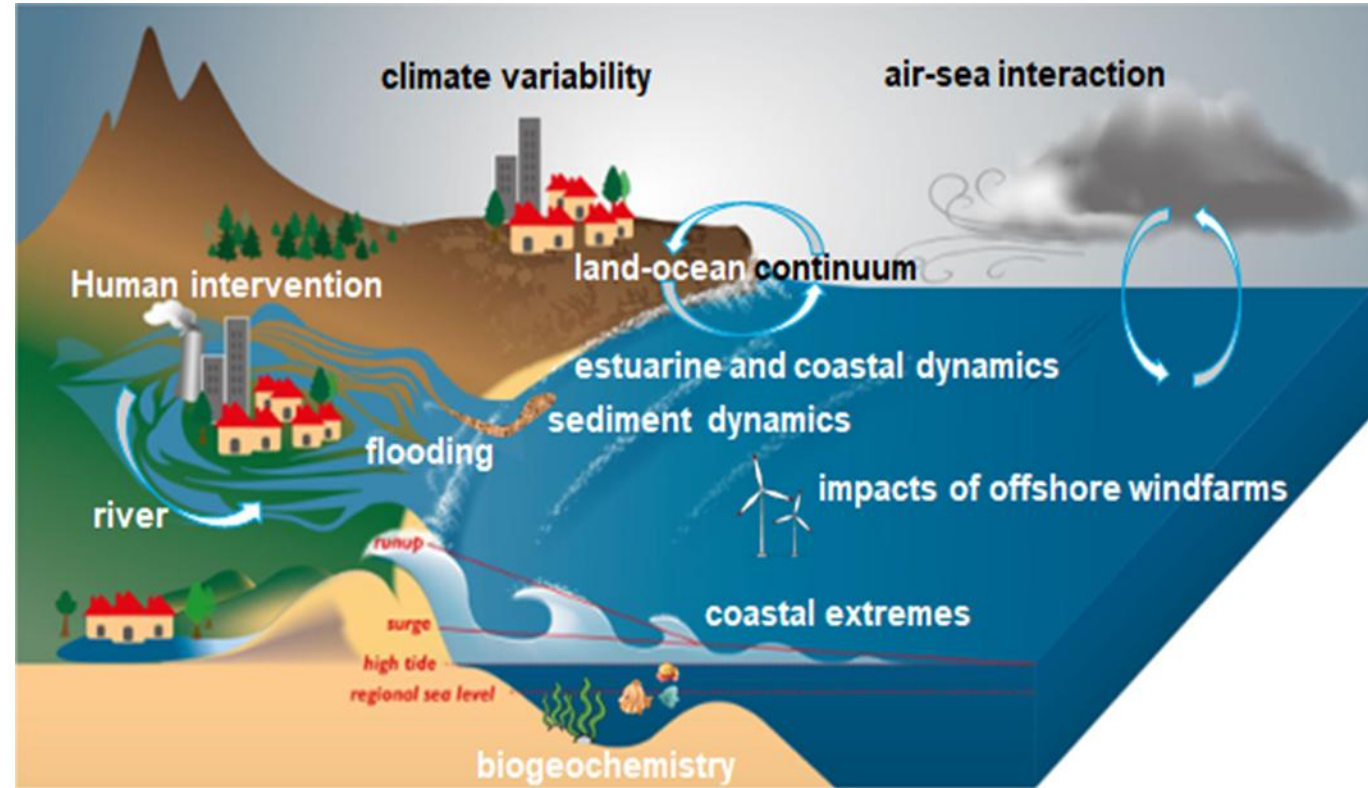
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Why Coastal Prediction is Challenging

- Strong nonlinearity & multi-scale dynamics
- Sparse and heterogeneous observations
- Uncertainty in forcing and boundary conditions
- Need for improved, integrated prediction systems

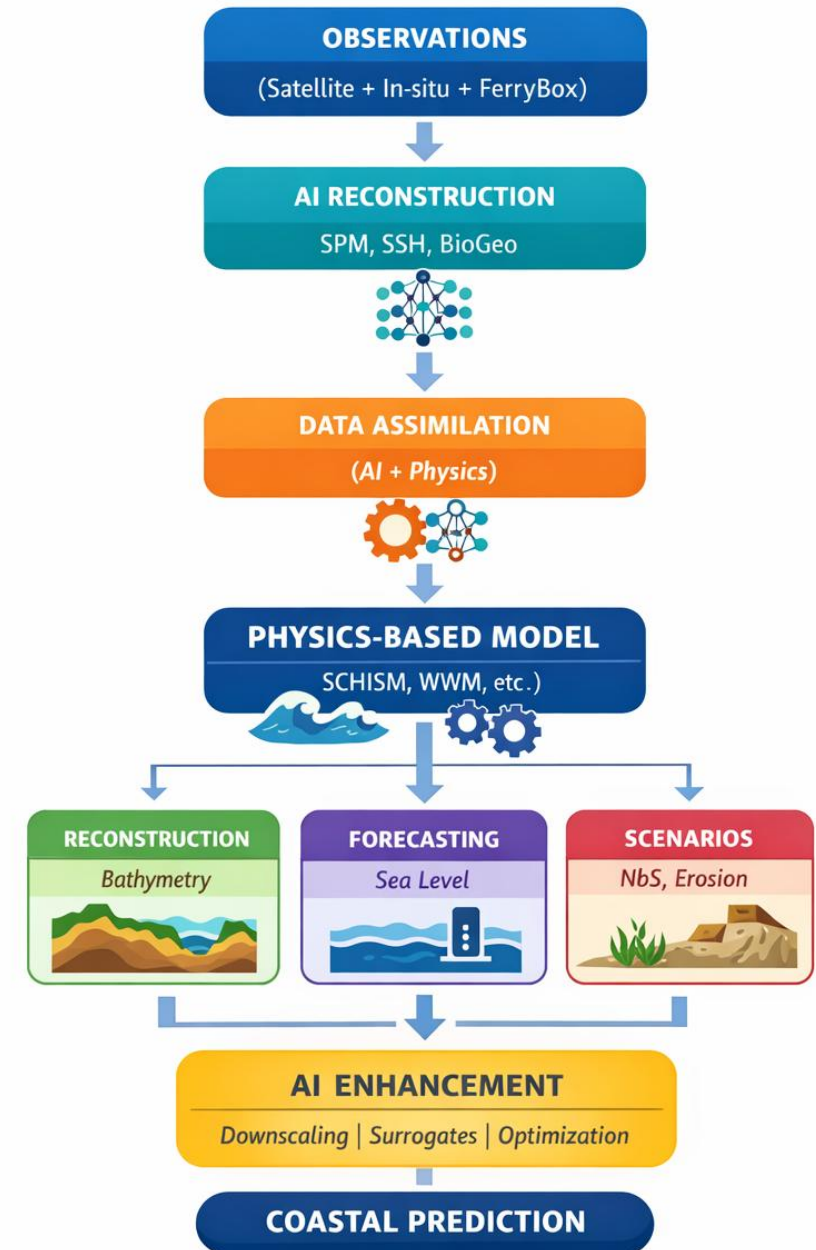


I-GCOAST

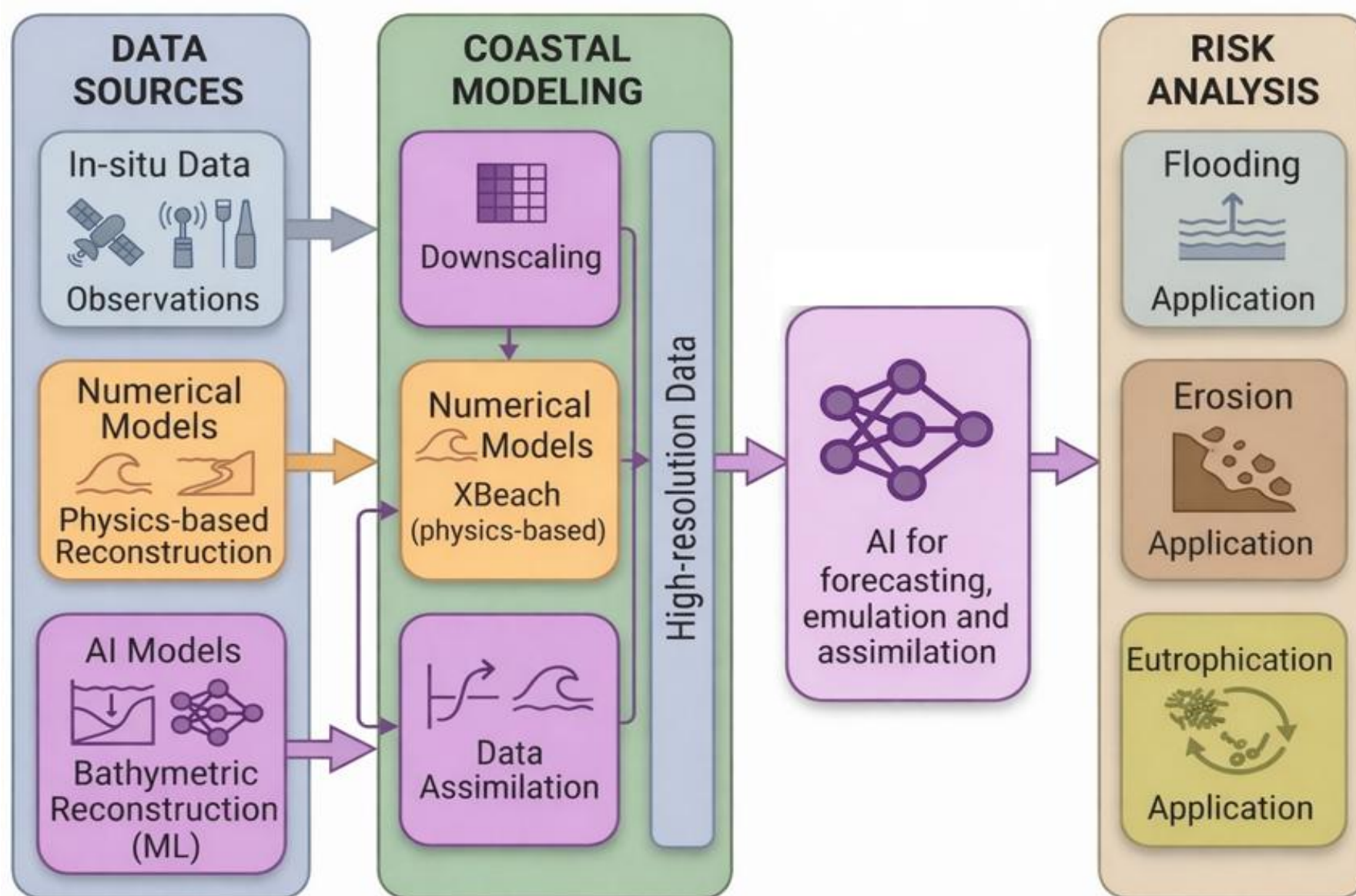
AI-Physics based Coastal Prediction Framework

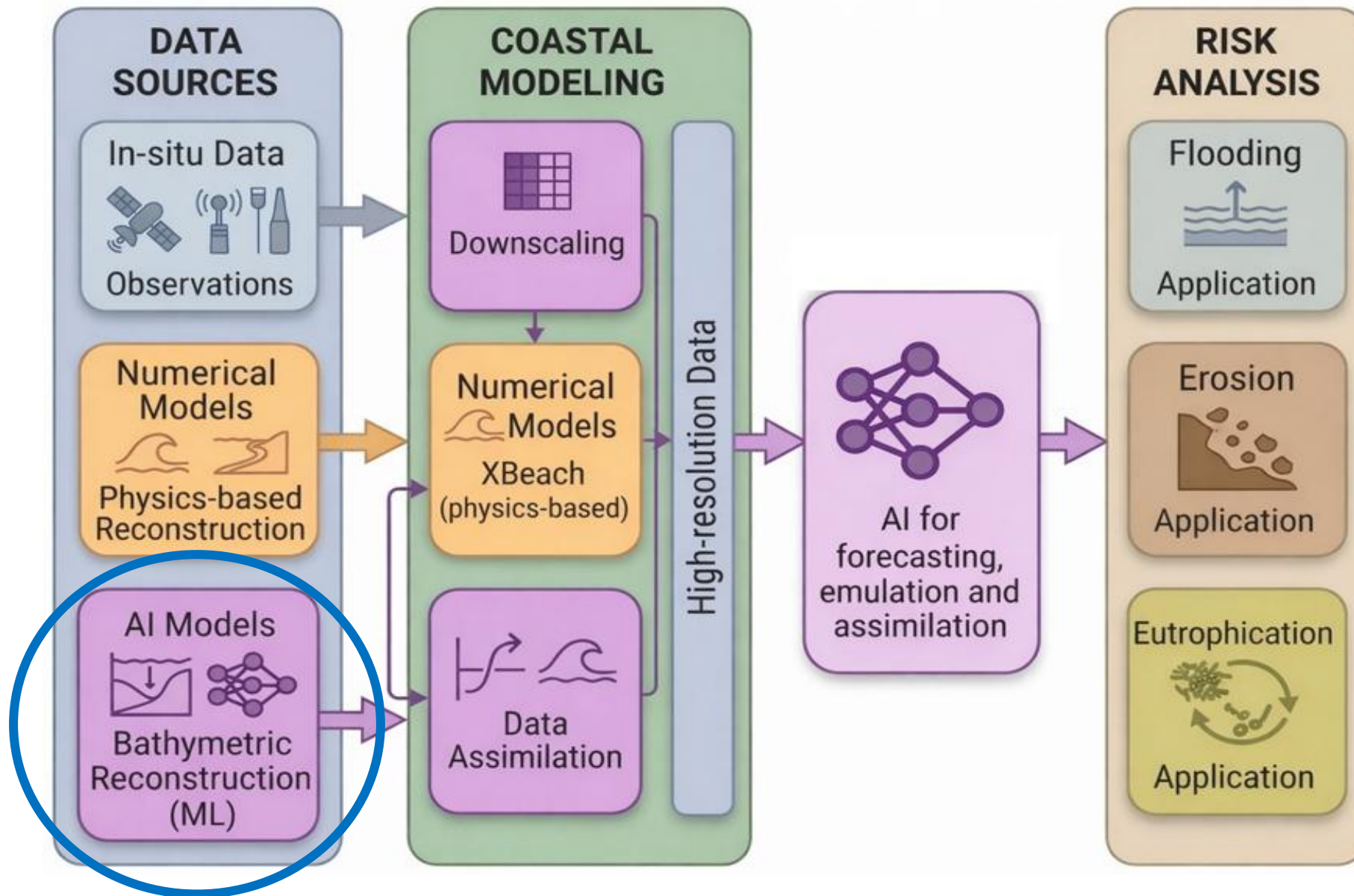
- Observations → AI Reconstruction → Data Assimilation
- → Physics-based Models → Forecasting / Scenarios
- → AI enhancement (downscaling, optimization)
- → Coastal Prediction

AI-Physics Coastal Prediction Framework



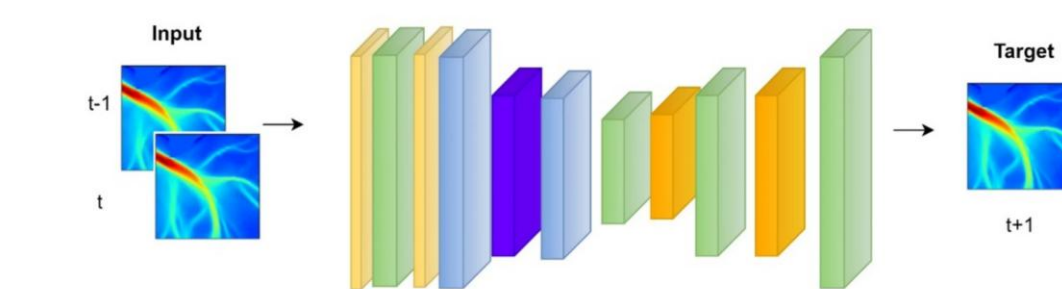
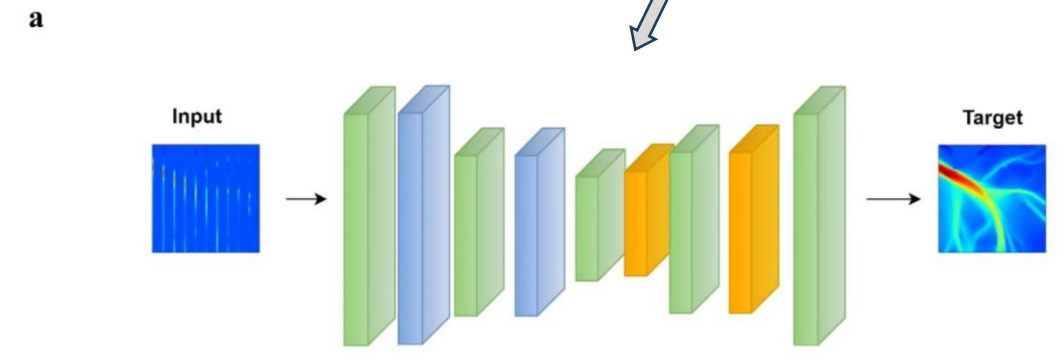
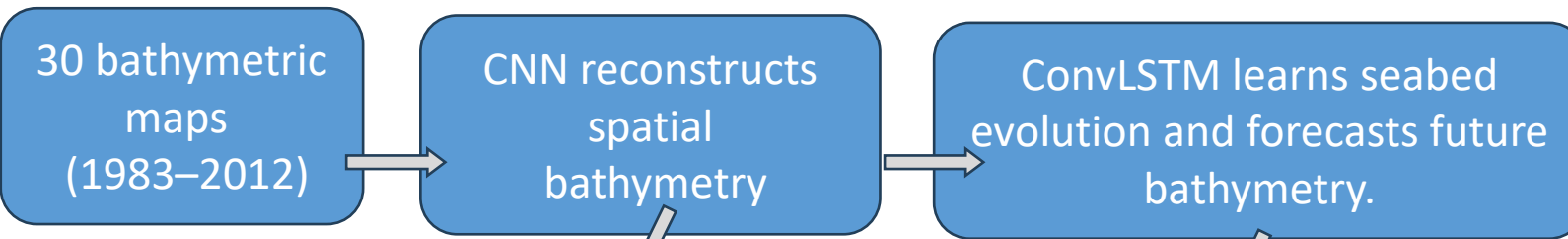
i-GCOAST – Overall workflow prototype





Bathymetric reconstruction and forecasting using deep learning

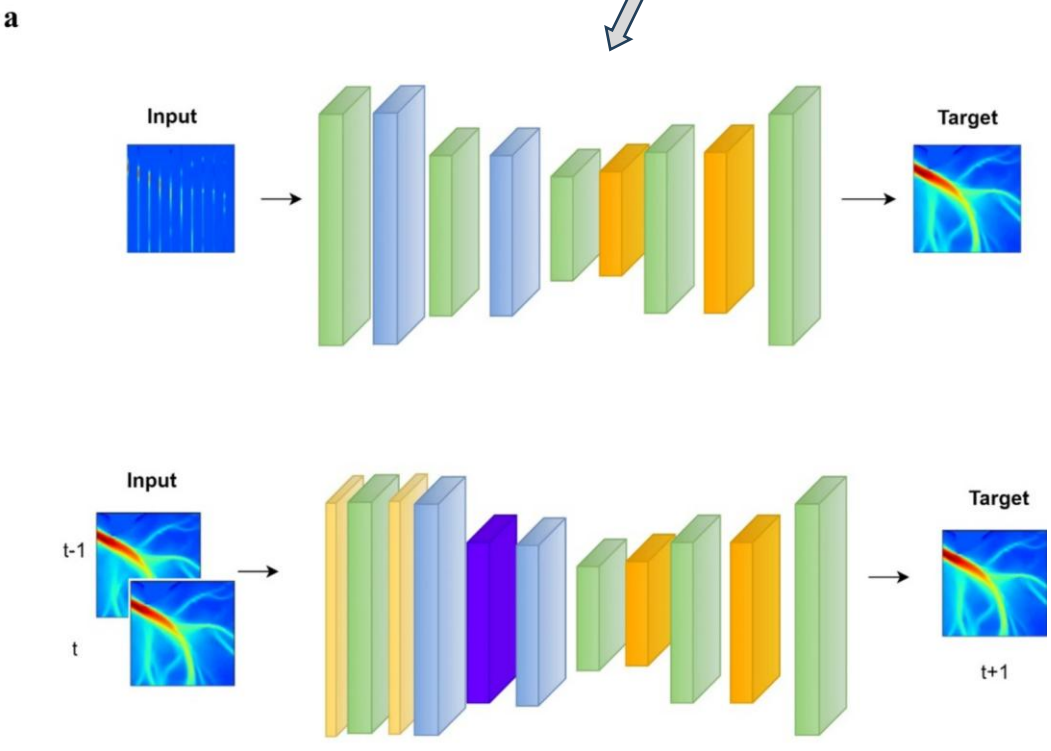
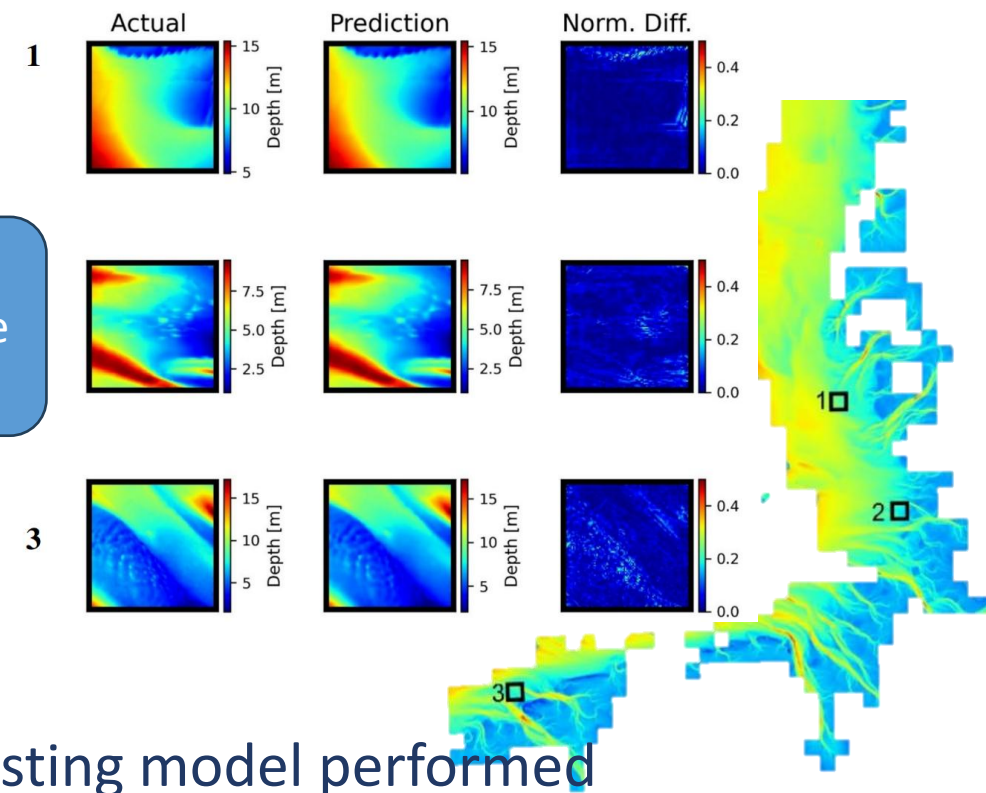
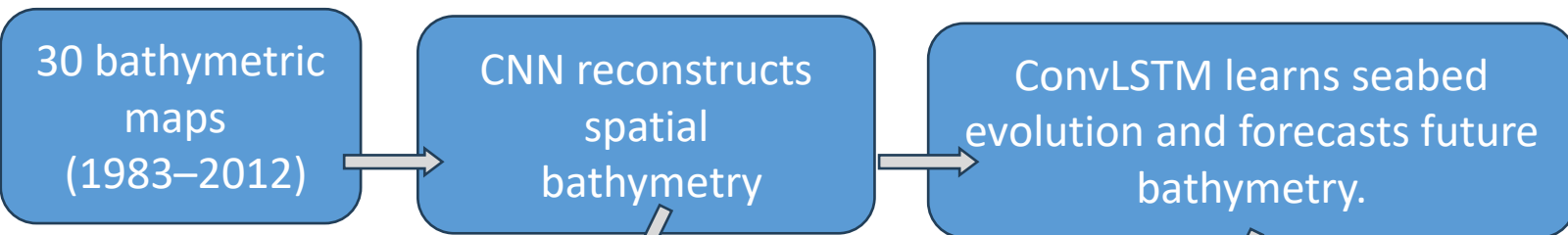
- Coastal models lack high-resolution time-series bathymetry.



Yildiz, I., Stanev, E.V. & Staneva, J. Advancing bathymetric reconstruction and forecasting using deep learning. *Ocean Dynamics* 75, 36 (2025). <https://doi.org/10.1007/s10236-025-01679-2>



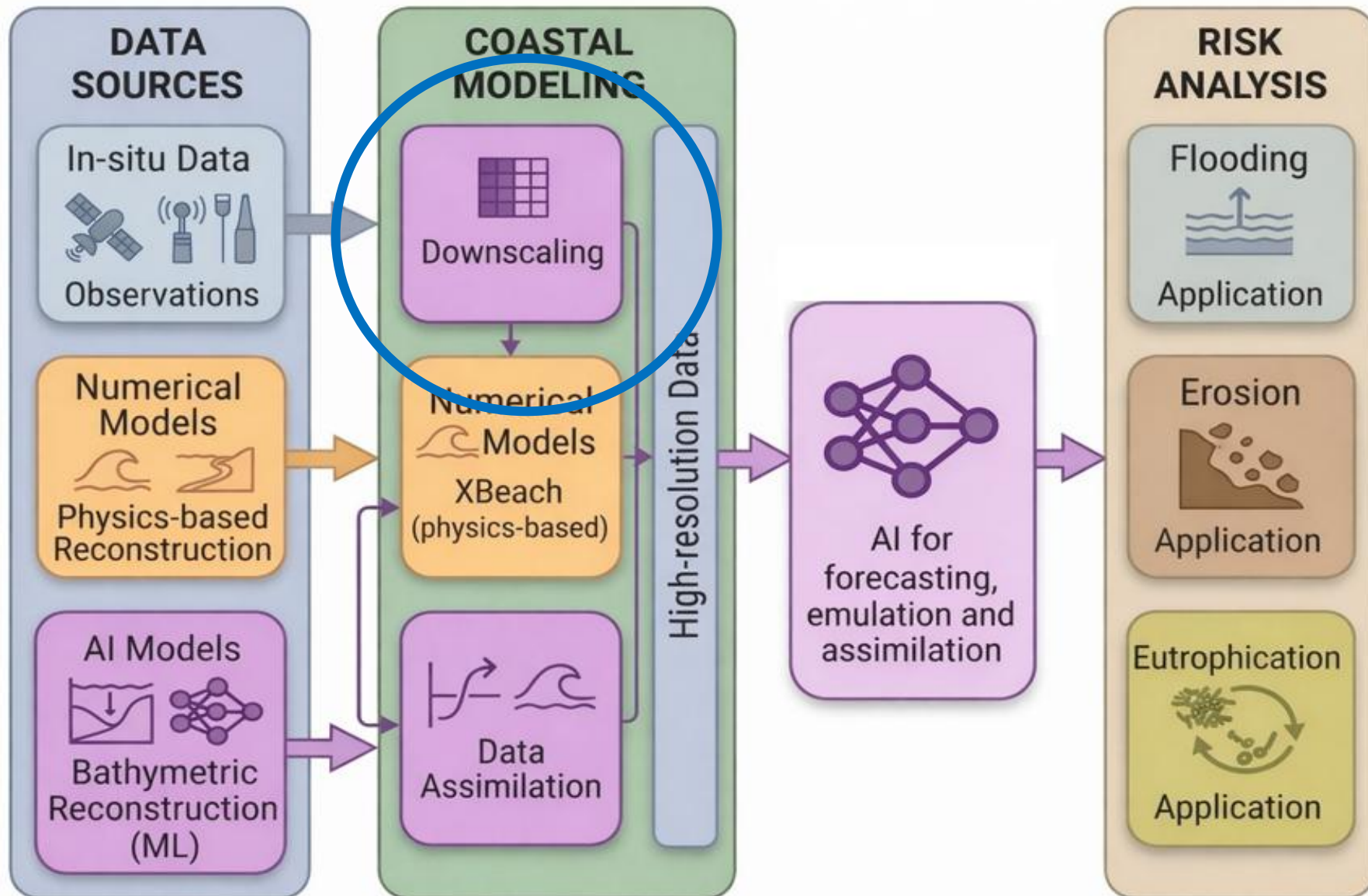
Bathymetric reconstruction and forecasting using deep learning



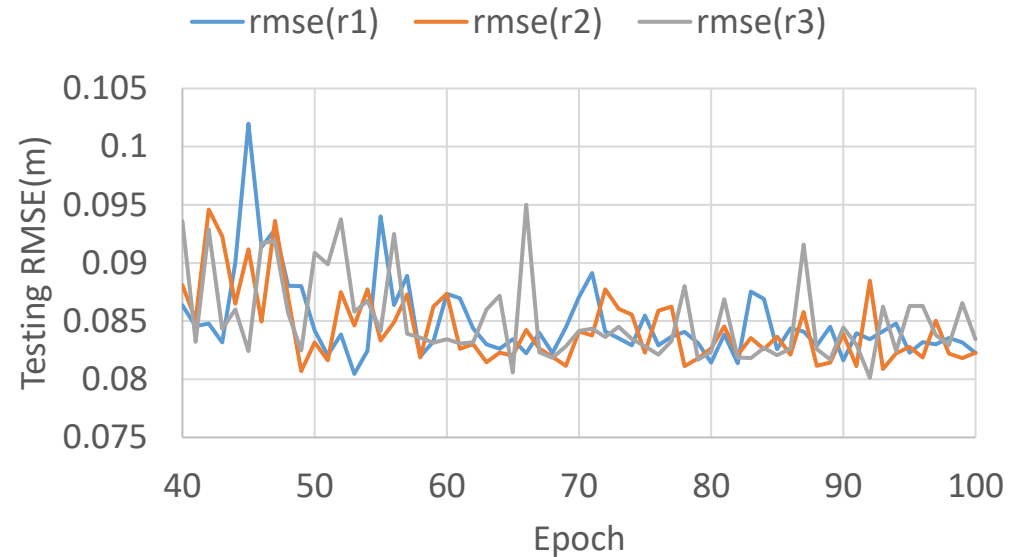
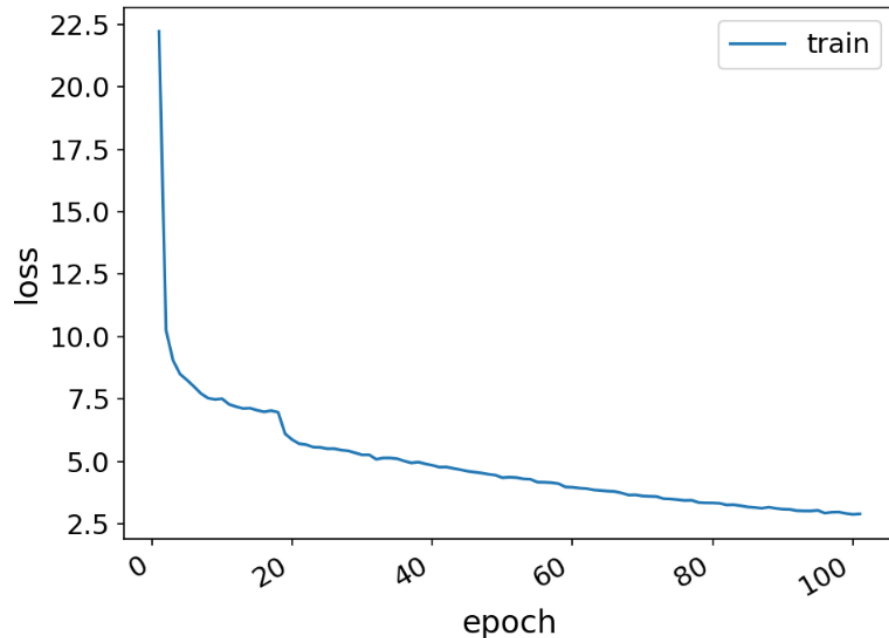
- The forecasting model performed consistently well over the analyzed period, with an average RMSE of 0.139 m
- Index of agreement between observations and forecasts higher than 0.994.

Yildiz, I., Stanev, E.V. & Staneva, J. Advancing bathymetric reconstruction and forecasting using deep learning. *Ocean Dynamics* 75, 36 (2025). <https://doi.org/10.1007/s10236-025-01679-2>





Introduction: Statistical downscaling



- **Randomness** (initialization & shuffling etc.) -> **Instability in model prediction:**
 - Trained model from which epoch/run to use for prediction?
- **Ensemble method:** combine predictions from epochs/runs/NN models

Unclear in the selection of trained model in studies using NN; and how to reduce **instability** in NN model prediction?
What about traditional deterministic model like **linear regression**?

Aim of the research

We propose an **ensemble CNN-based model** and a **linear regression** model for **spatial SWH downscaling** from publicly available global ERA5 dataset to regional model output.

Both **self-variable** and **cross-variable** (using **wind**) SWH downscaling are explored.

Questions:

- (i) How **effectively** can an **ensemble method** reduce the **prediction instability** of CNN-based models for spatial SWH downscaling?
- (ii) Does the **nonlinear** CNN-based model outperform the **linear** regression model in spatial wave downscaling with both **self-variable** and **cross-variable** approaches?

Material and methods

- Super-resolution residual network (**SRResNet**), based on Ledig et al. (2017)
- Ensemble method: combine multiple predictions from different NNs/runs/epochs etc.

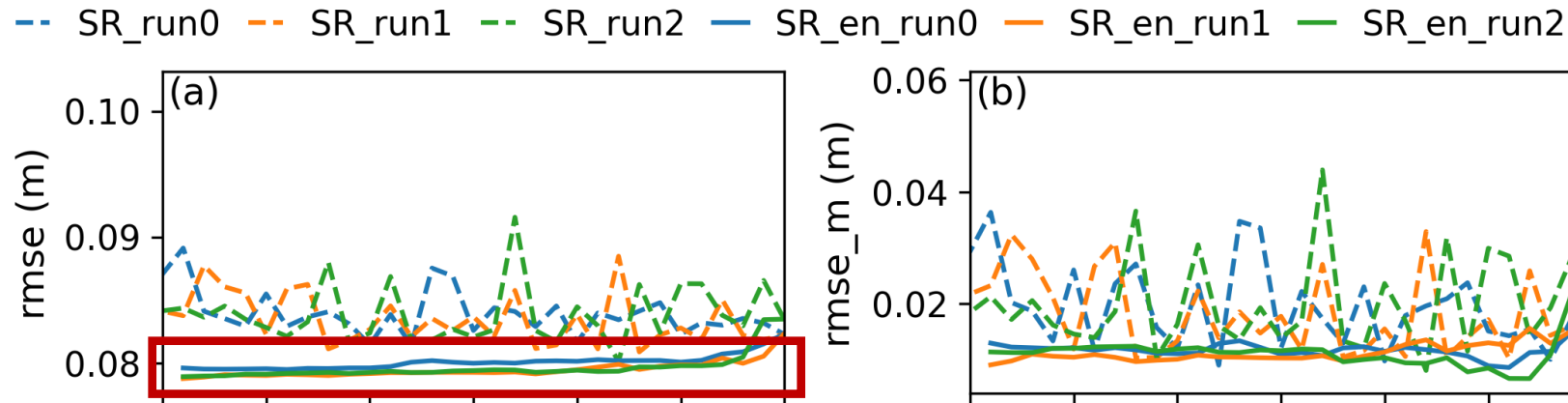
What we use:

- average epoch predictions after training loss is approximately stabilized, e.g., average predictions from the last few epochs.
 - No need to train multiple NNs
 - Directly applicable to other NNs

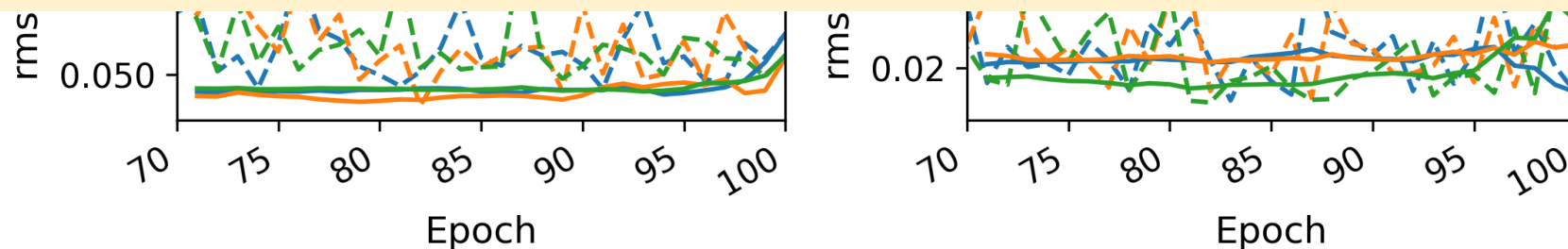
Material and methods

- Default setting for the experiment:
- **Loss function:** f -prediction, y -target (ground truth)
 - $L_G = \|f - y\|_2$
- **Input:**
 - self-variable: low-resolution SWH data; cross-variable: low-resolution wind components U&V
 - normalized using a range cover the maximum & minimum values of the variables
 - NaN value set to 0
- **Output:** high resolution data (e.g. SWH)
- **Scale factor:** self-variable: 20 (12*12->240*240 grid points); cross-variable 10.

Results: ensemble vs original SRResNet



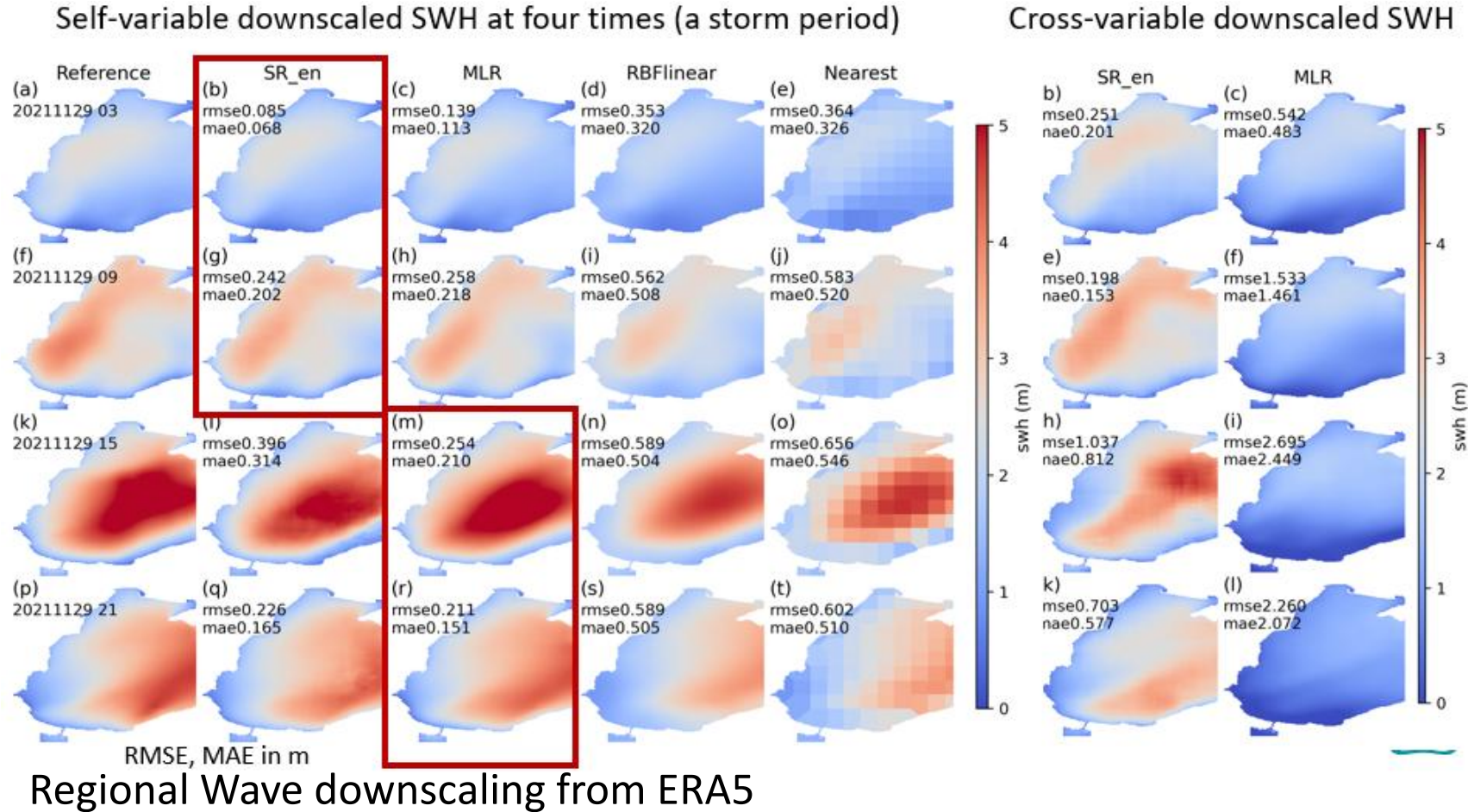
- Ensemble method reduces instability of NN model predictions and improves performance in terms of global RMSE. (select the last 20 epochs from run0 as ensemble to present the results)



Comparison of error metrics between SRResNet and the ensemble SRResNet for multiple runs in self-variable SWH downscaling. For the ensemble model, the error value at an epoch number is obtained by using the averaged prediction from that epoch to the last epoch 100.

AI coastal downscaling from global reanalysis, projections forecast

- Ensemble SRResNet and MLR have similar performance in self-variable SWH downscaling in the Black Sea;
- In cross-variable downscaling, the former still works, while the latter fails.

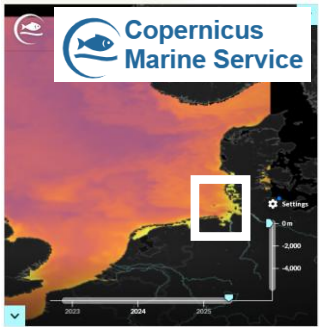


Yuan et al., Ocean Eng. (2025)



Efficient high-resolution prediction/
predictions without full models

Interoperability: AI downscaling



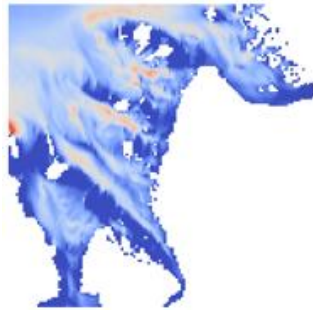
Low-resolution data from CMEMS, ECMWF CMIPs
Regional-coastal

Coastal fields downscaling

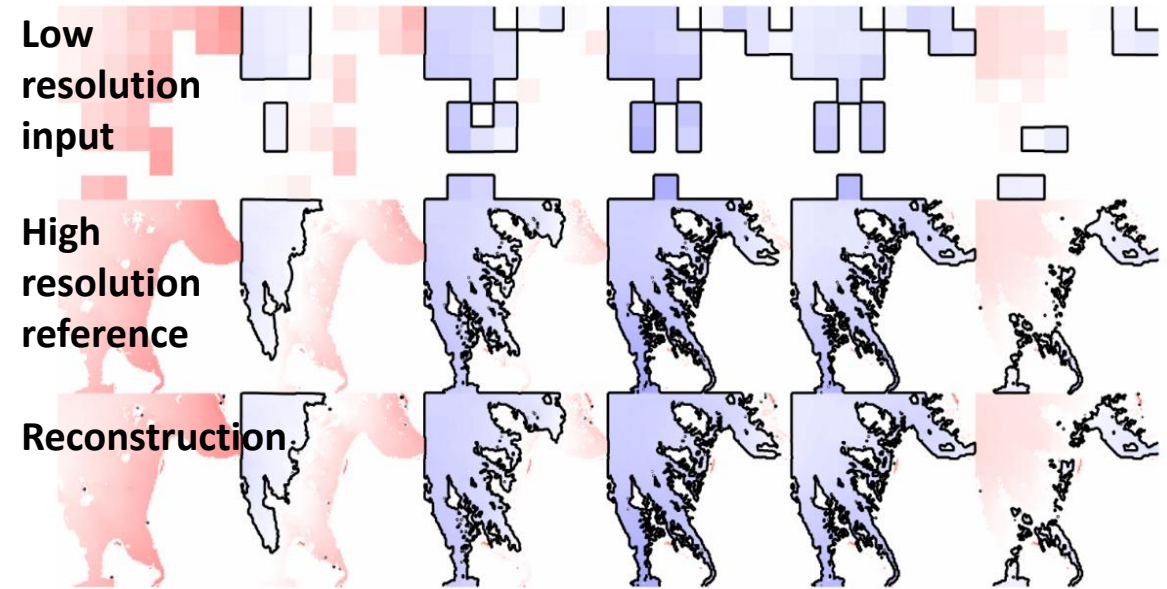
AI models



Inputs:
Time, variables (e.g., velocity)



High-resolution regional coastal fields

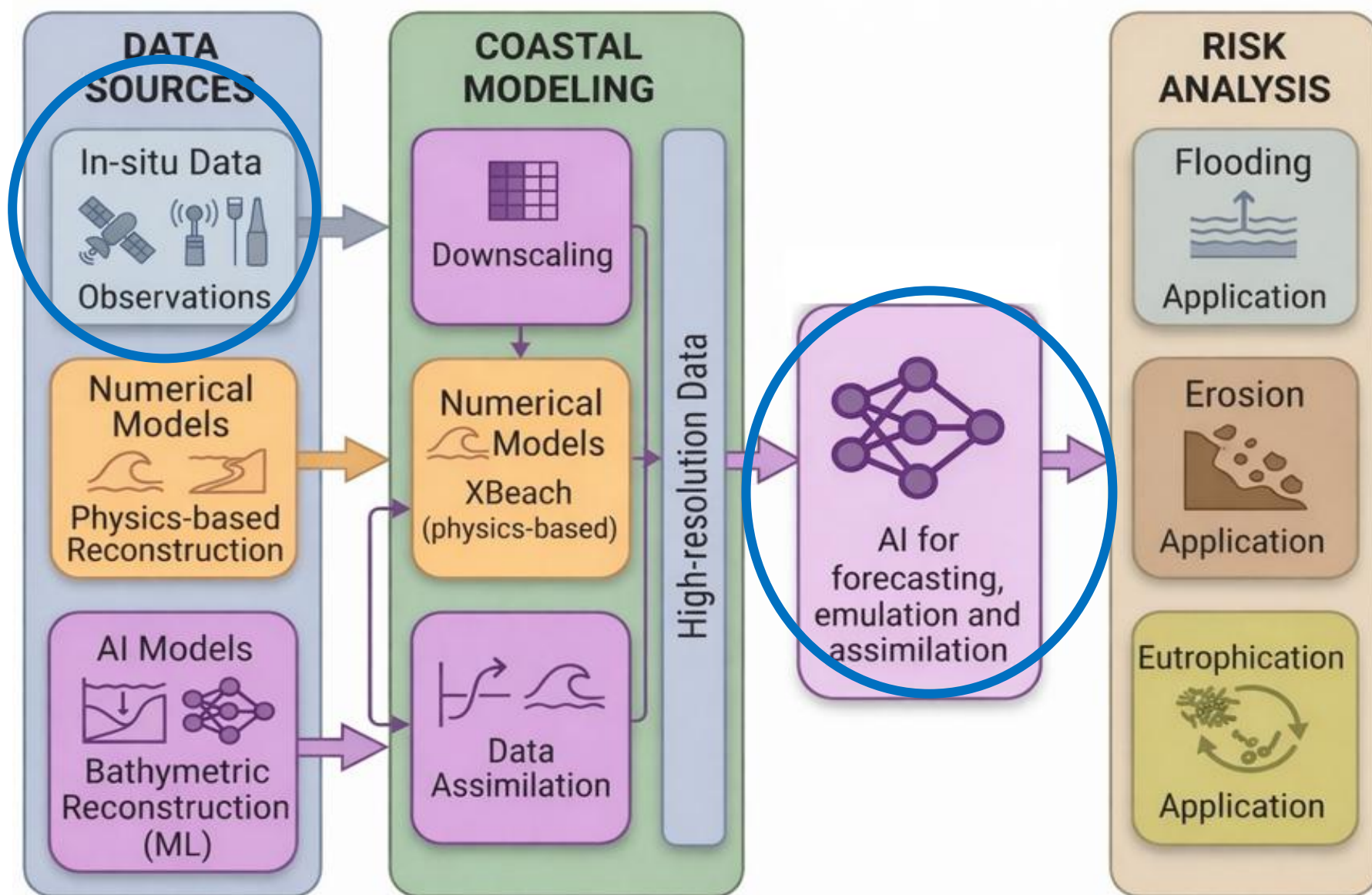


Coastal fields downscaling (SSH, scale up to 64)

Capability of downscale 10-km resolution data to 100-m scale regional hydro-data.



Yuan et al., Appl. Ocean Res. (2024);



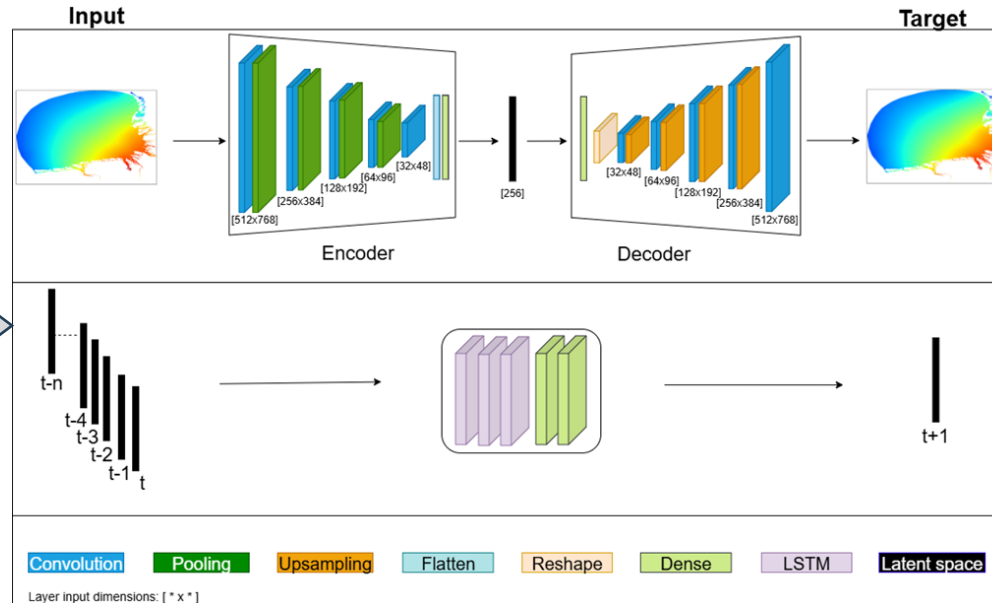
AI: reconstruction and forecasting of coastal sea level

Coastal observations in German Bight

CNN - LSTM hybrid architecture

reconstruct basin-wide sea level from limited observations

forecast short-term tidal variability in sea level



CNN Encoder–Decoder (spatial reconstruction)

LSTM (temporal forecasting)



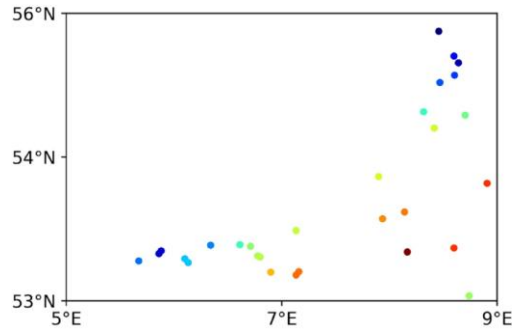
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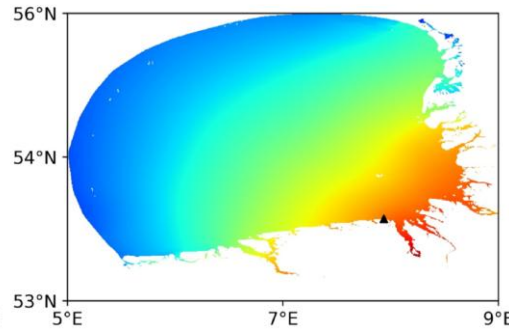
reconstruct basin-wide sea level from limited observations

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a

INOPUT



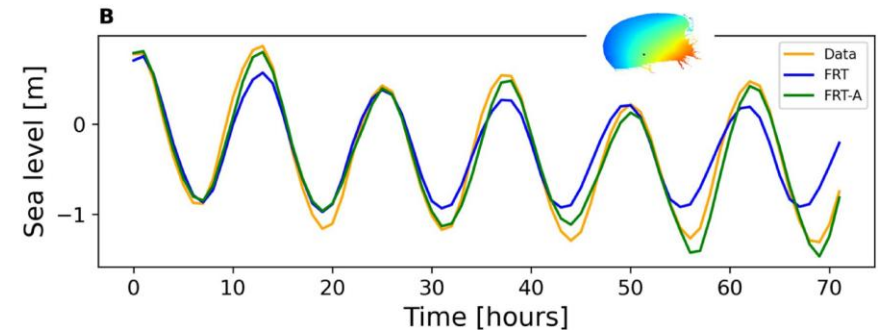
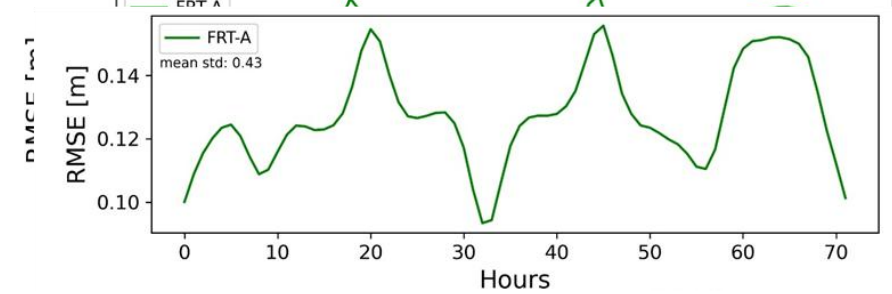
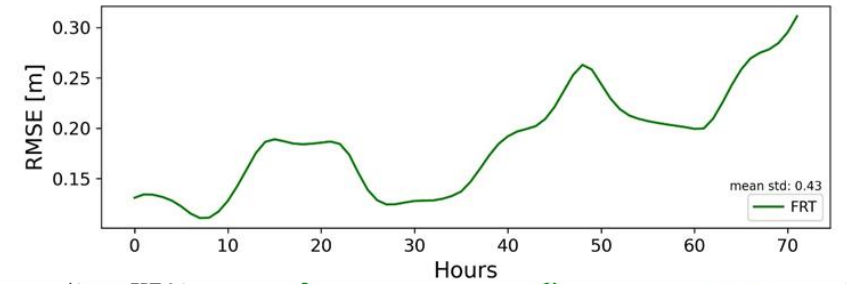
b

TARGET

FRT: Realistic sea level scenario

FRT-A: Realistic sea level scenario **with coastal observation**

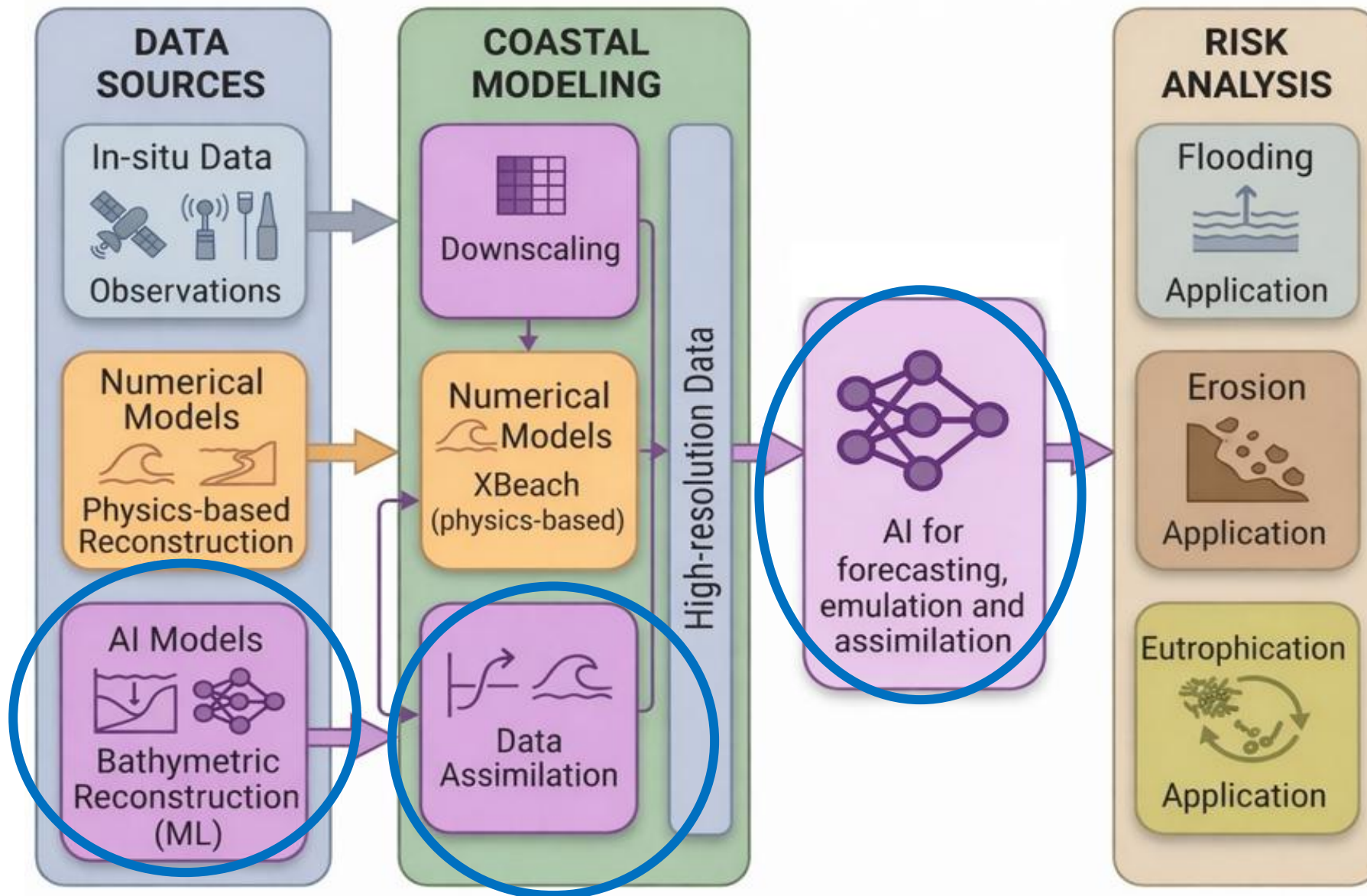
Predictive performance in FRT (first row) and FRT-A (second row)



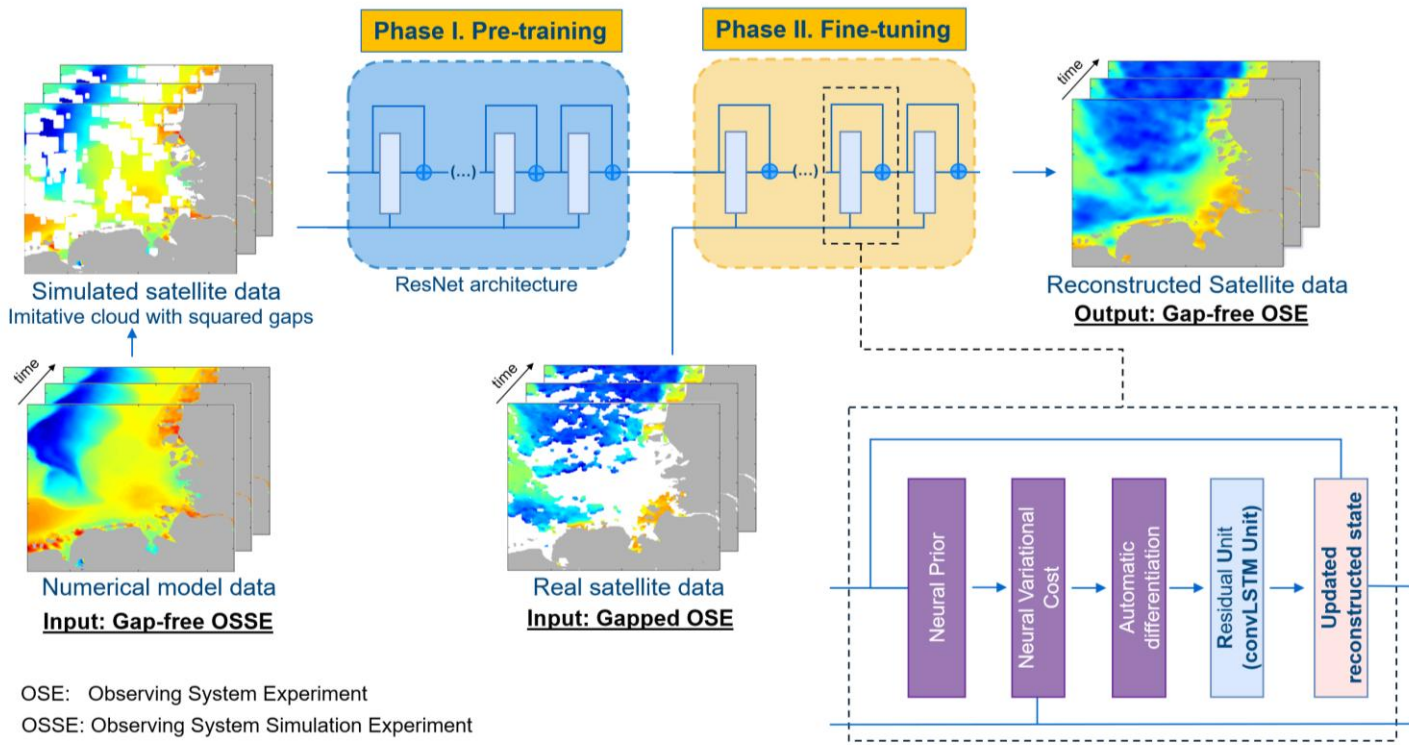
Yildiz, I., Stanev, E.V. & Staneva, J. From monochromatic waves to realistic tides: deep learning for short-term forecasting of coastal ocean. *Sci Rep* 15, 44229 (2025). <https://doi.org/10.1038/s41598-025-31670-2>



Improved prediction skill for short-term variability



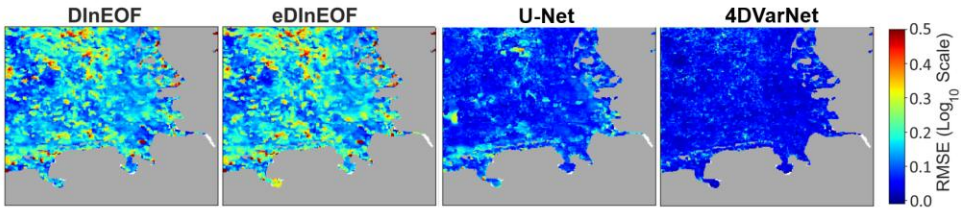
End-to-end AI reconstruction / prediction of SPM



- The approach employs a novel two-phase transfer learning strategy: (1) pre-training on OSSEs and (2) fine-tuning on OSEs.

Compare to DInEOF, 4DVarNet improved performance with a 70% reduction in RMSE and 50% increase in SSIM.

Chen et al., Appl. Ocean Res., (2025)



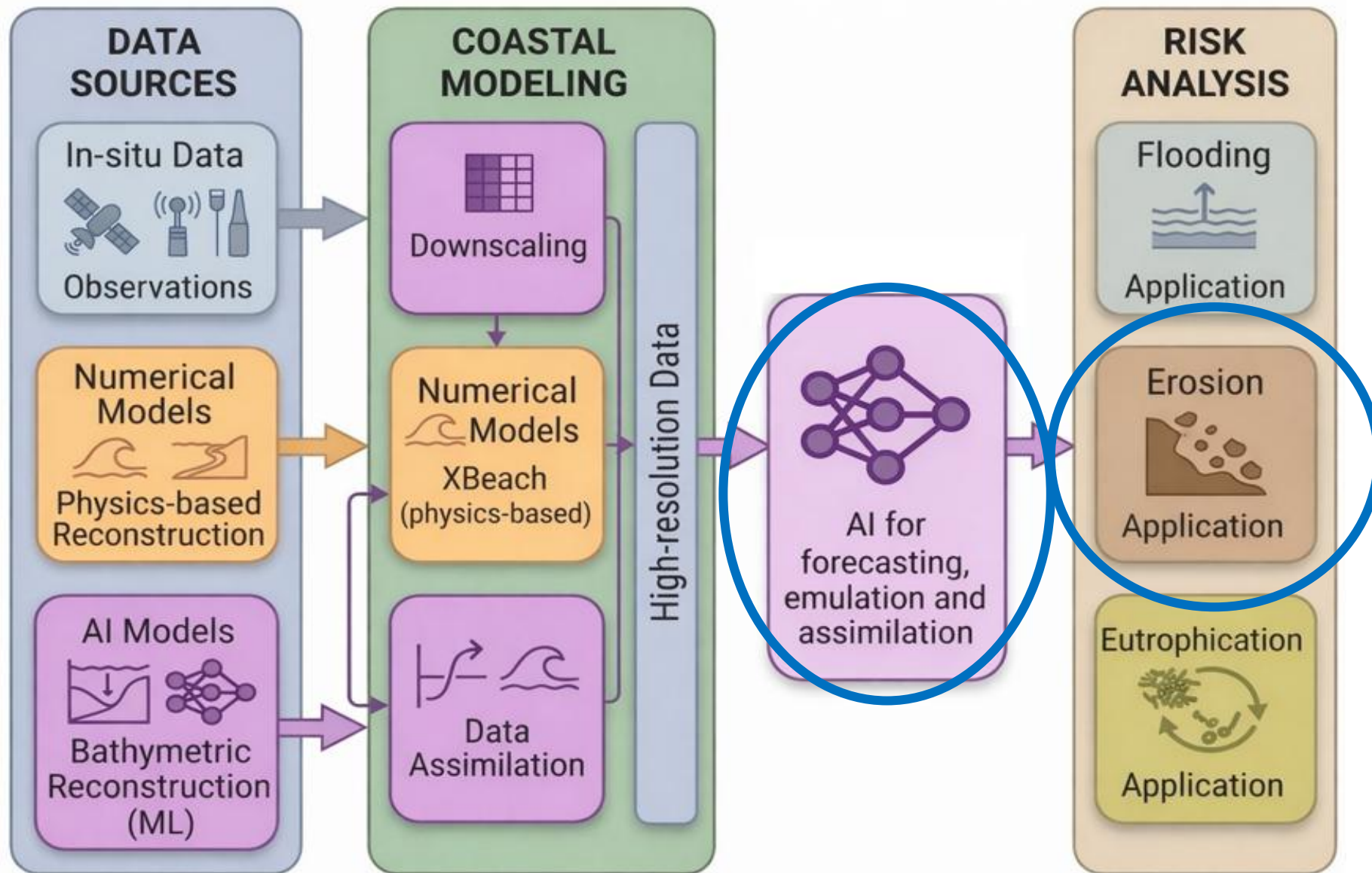
Algorithm	RMSE	RE (%)	MAE	SSIM
DInEOF	0.184	37.452	0.129	0.610
eDInEOF	0.192	39.943	0.135	0.611
UNet	0.098	14.754	0.062	0.905
4DVarNet	0.063	9.315	0.038	0.916

70%

50%

Chen, W., Nguyen, T.T.N., Pein, J., Jourdin, F., Fablet, R., Staneva, J. (2025): [Physics-informed neural data assimilation for high-resolution coastal SPM reconstruction from model and satellite data. Applied Ocean Research, Vol 165, 104871. https://doi.org/10.1016/j.apor.2025.104871](https://doi.org/10.1016/j.apor.2025.104871)





AI for Scenario Optimization

- Main Challenge

A transferable modeling and framework for coastal risk analysis (erosion) that simulates the complex multi-compartment system.



- **How can the optimal seagrass meadow (What-if different location, size) be determined regarding the model management strategies?**

Model and methods



Hydro-model
(SCHISM-WWM)

Hydrodynamics

Provides water level,
wave spectrum as
boundary forcing

Morph-model
(XBeach)

Morphodynamics

What-if Scenarios (WiS)

Without
seagrass

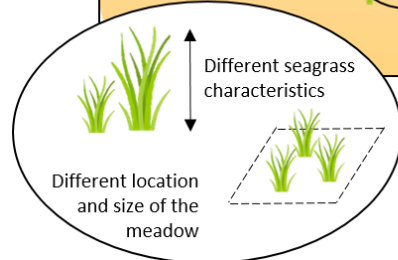
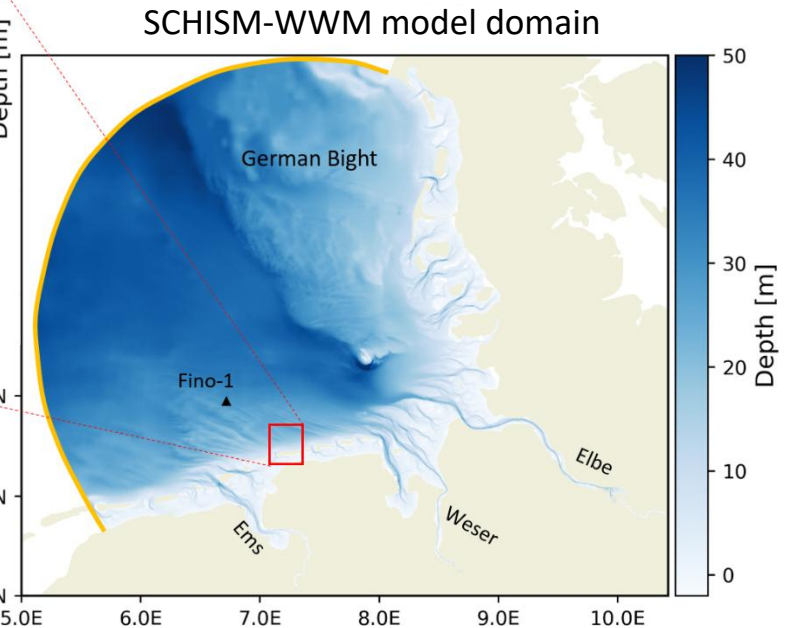
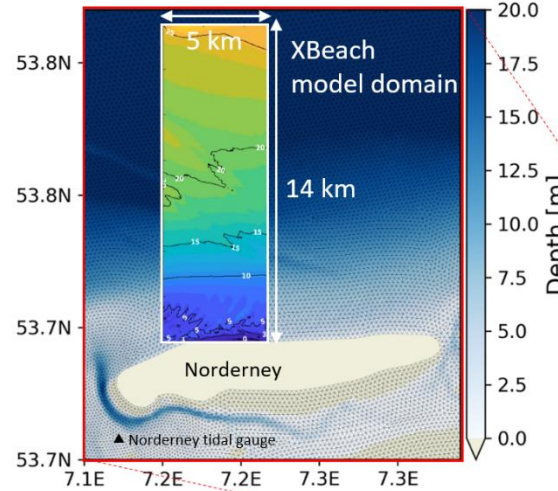
With
seagrass

Different
experiment
scenarios

Evaluation of
Coastal Erosion

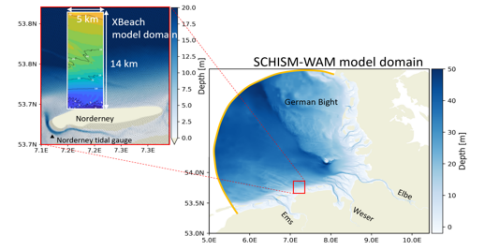
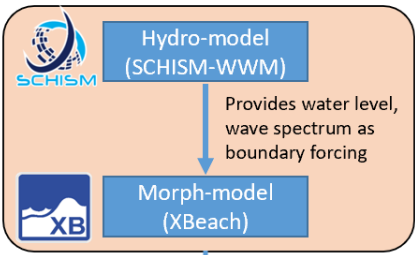


1280 cores
+
896 cores

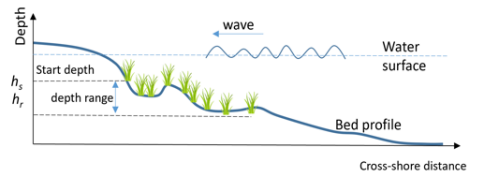
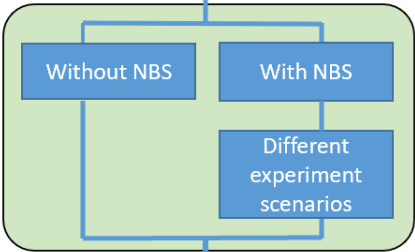


How to effectively find the best
seagrass meadow layout out of
hundreds of WiS?

Numerical model block

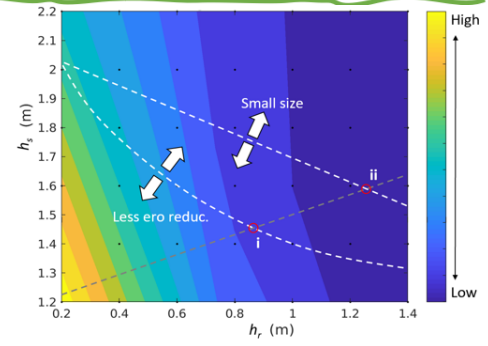


Experiments block

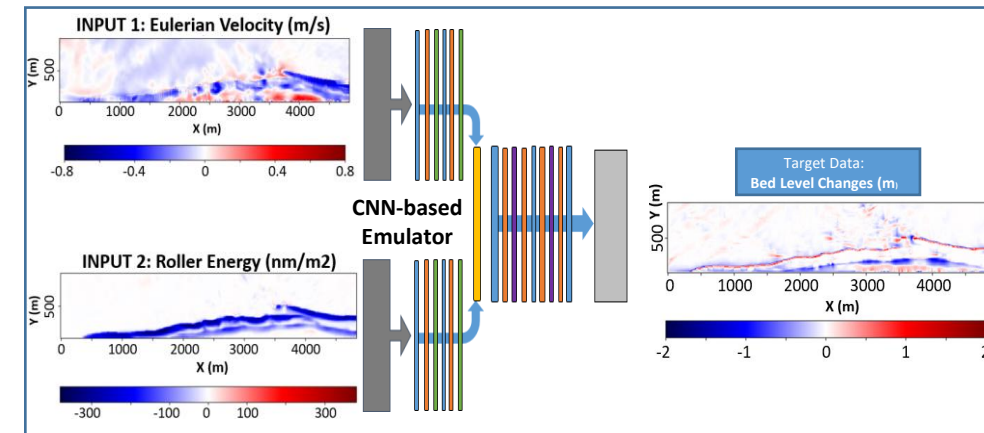
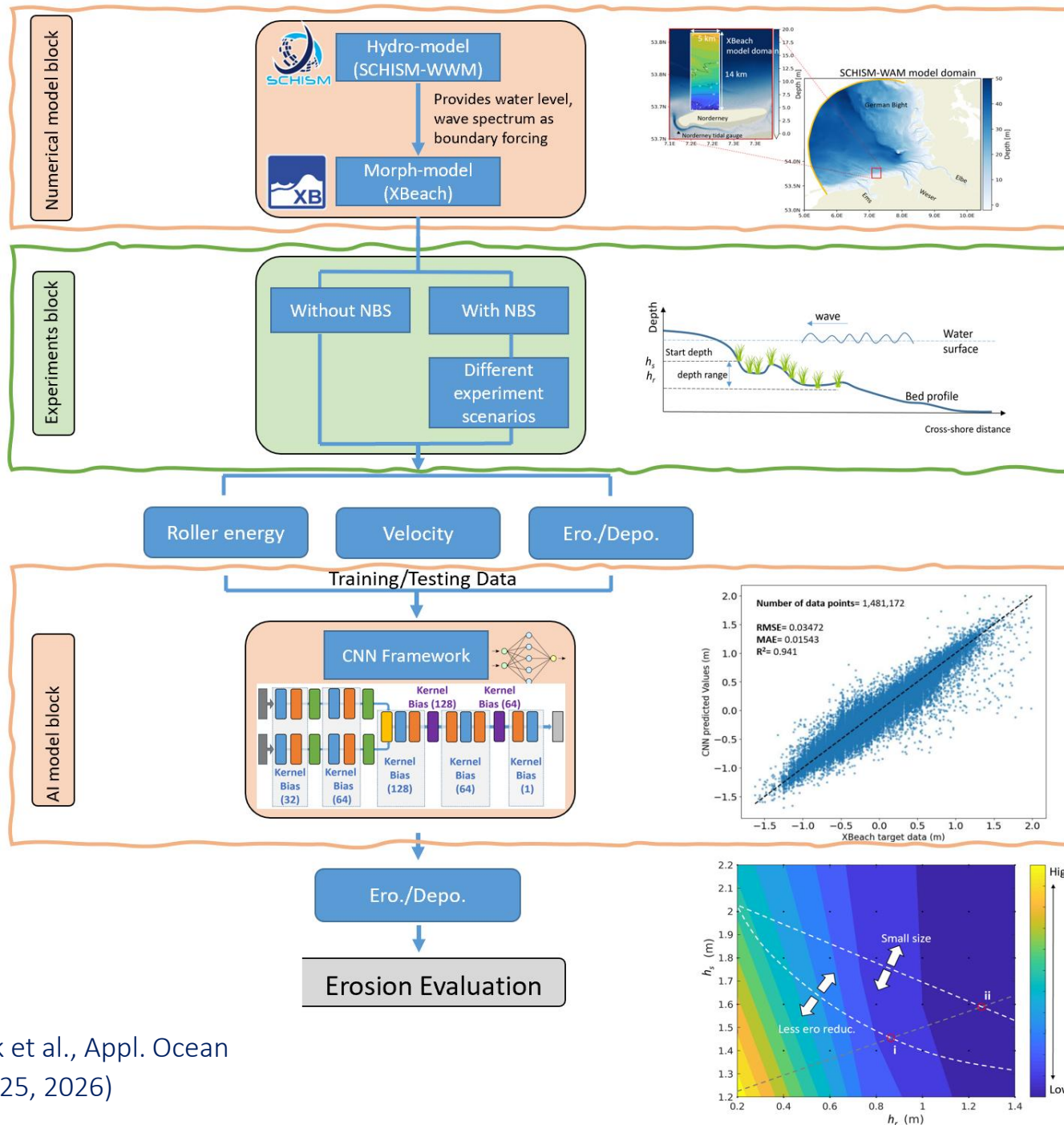


Ero./Depo.

Erosion Evaluation



AI & Physics-based numerical hybrid model framework

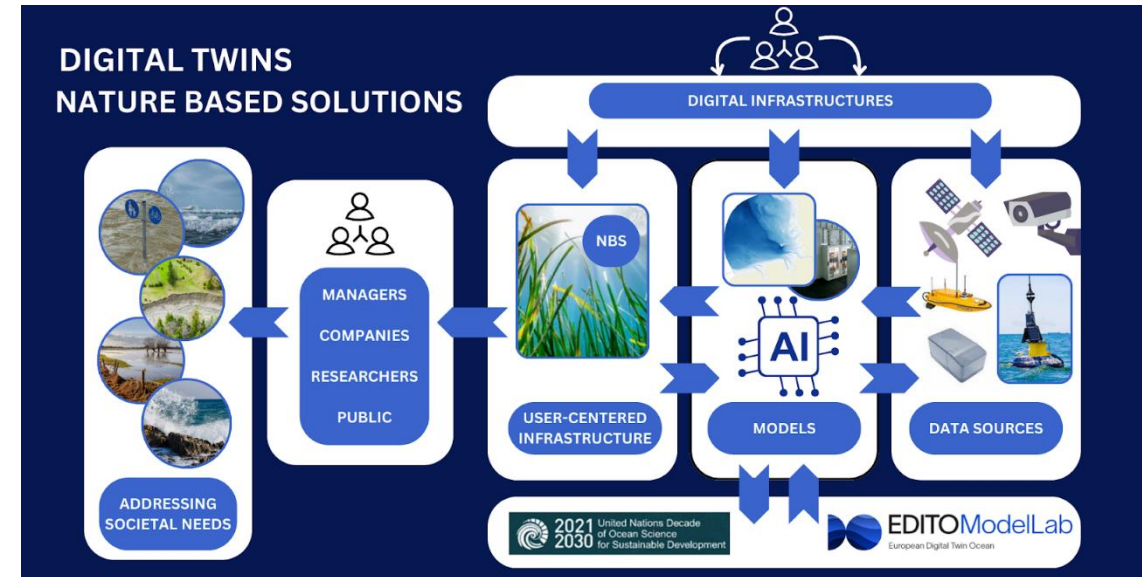


- A high level of precision in the AI model's prediction
- We can reduce experiment size by 70% while keep a sufficient accuracy!

Conclusions & Outlook iGCOAST Framework

- AI enhances reconstruction, forecasting, and downscaling
- Hybrid AI–Physics systems improve accuracy and efficiency
- Integration of observations and models is essential
- Towards operational Coastal AI systems
i-GCOAST

Integrated AI–Physics Approaches for Coastal Prediction



Main references

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Thank you!