Machine Learning For Low-Cost Offshore Modelling

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Supergen ORE Hub Annual Assembly
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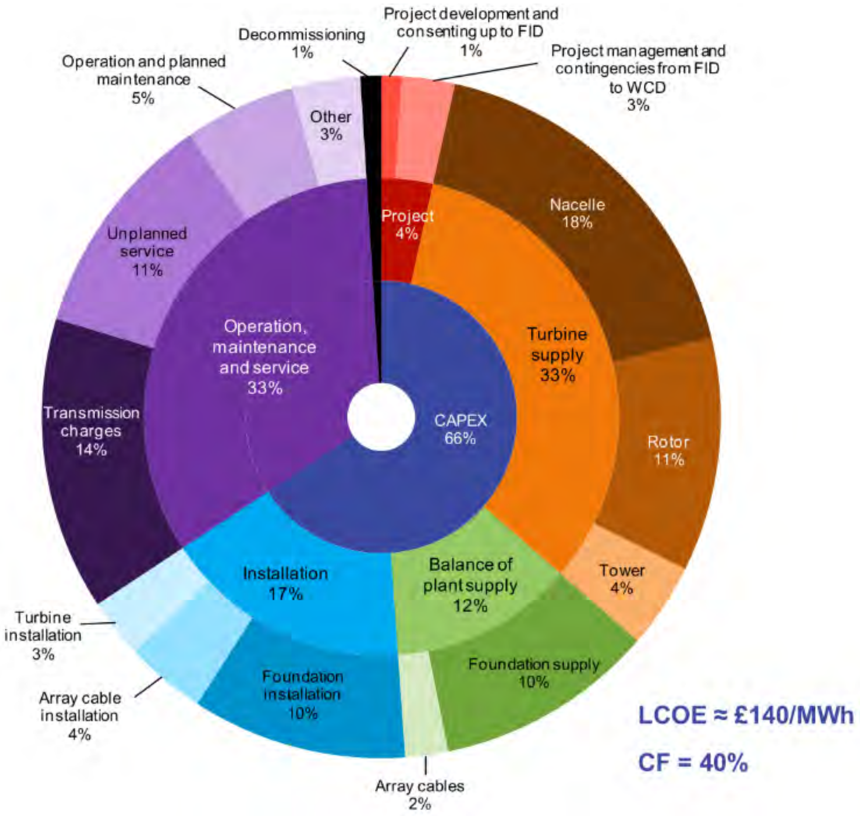
Background



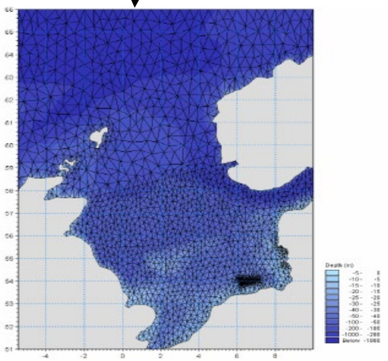
- Installation, inspection, operation, and maintenance activities at offshore renewable energy sites are governed by **strict weather limits**
- Weather delays have significant impacts:
  - Wikinger Wind Farm: **£17 million** additional cost due to inaccurate forecasts during installation
- Weather forecasts used in decision making currently provided by numerical models
- **More accurate, short-term forecasts can provide improved decision-making during installation, operation, and maintenance processes**

Aims and Objectives

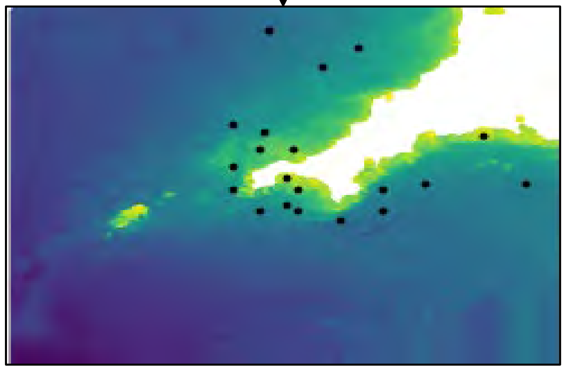
To develop a **Machine Learning model framework** that can **integrate metocean sensor networks** and **physical models**, to **improve** the provision of metocean data

Spatiotemporal wave distribution

Physics-based models | **In-situ Observations**



High-fidelity
High-computational cost

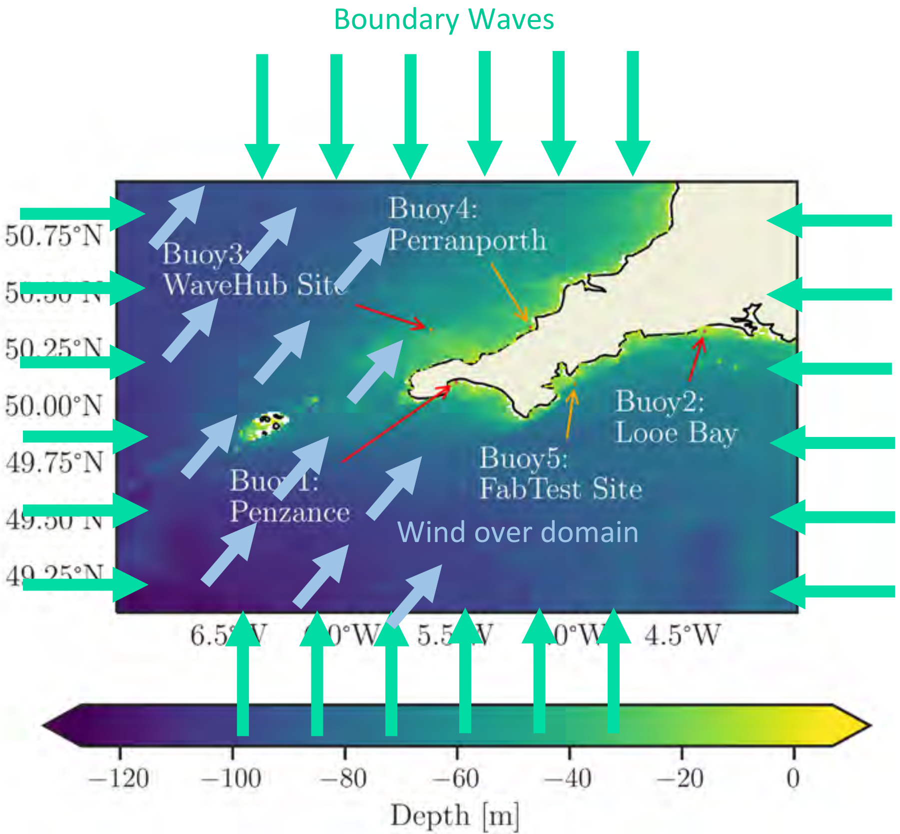


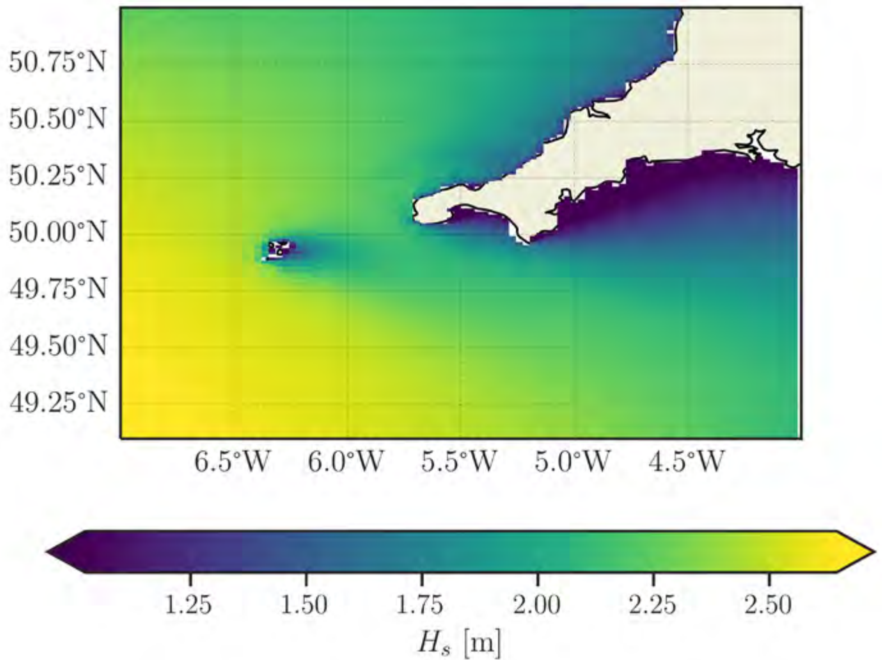
Relatively reliable
Sparse data set

Objective: Develop **machine learning** surrogates that represent the **nonlinear mapping** from fixed points to spatially distributed wave data across a region; enable **observation-based forecasting**

Traditional Modelling Approach

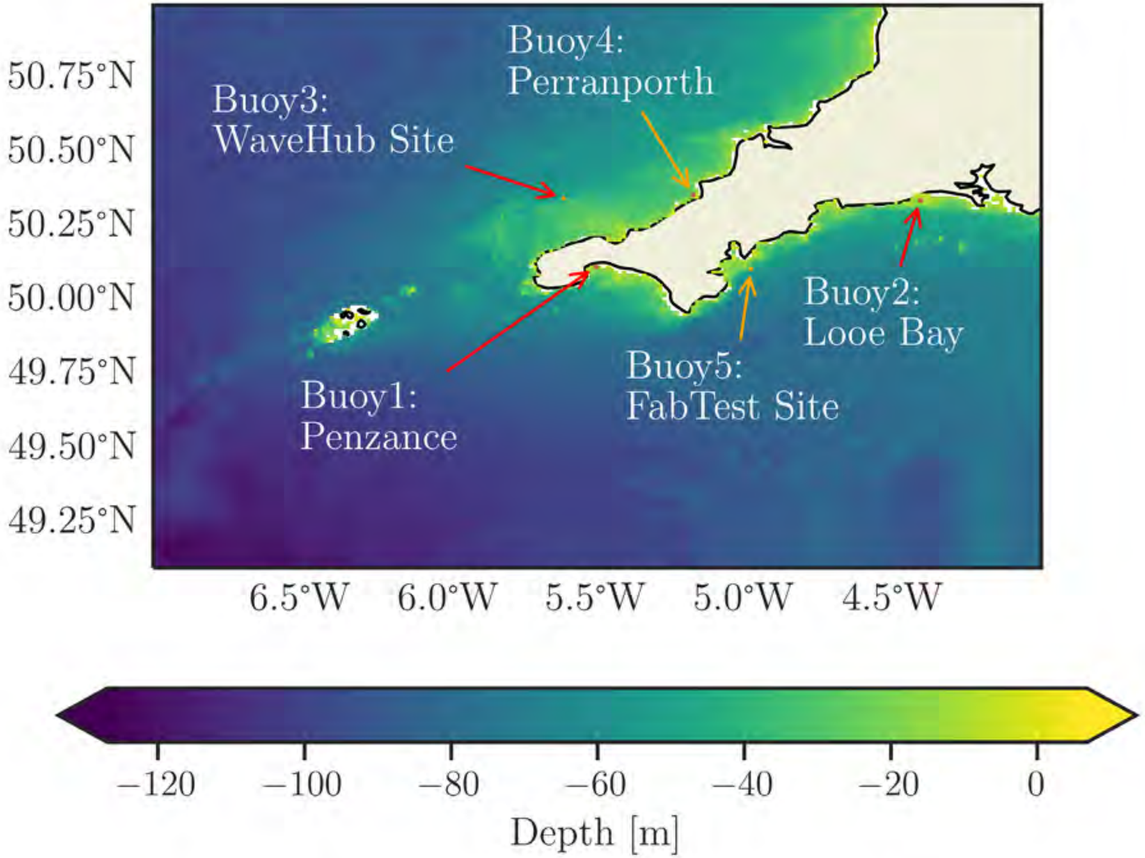
- Basic wave model includes a mesh and bathymetry data
- Input wave conditions from the boundary drive model
- Wind generally applied over entire domain
- Physics modelled throughout the region including bathymetric effects, refraction, triad, etc.
- Characterized by high computational cost/expense

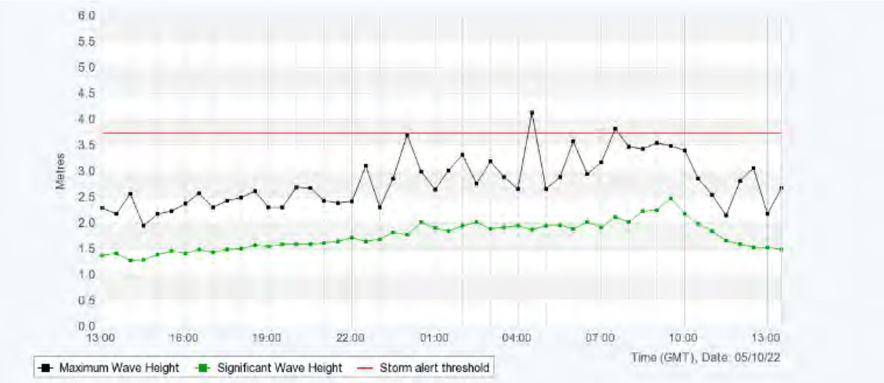




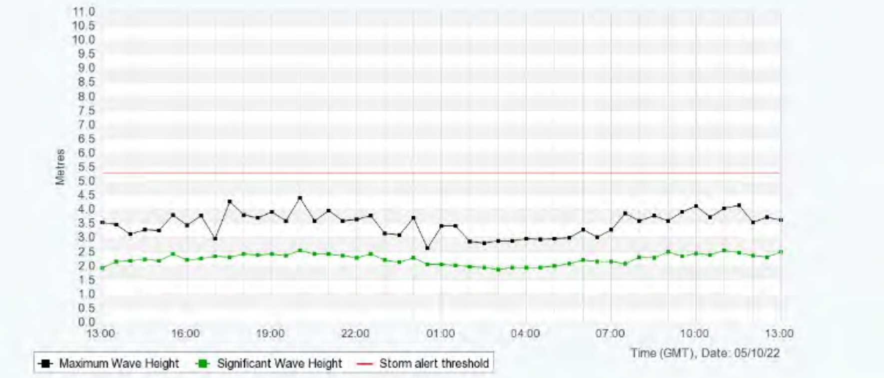
Traditional Measurement Approach

- Coastal wave buoys provide timeseries data at specific locations
- Provide an accurate representation of the waves at point locations



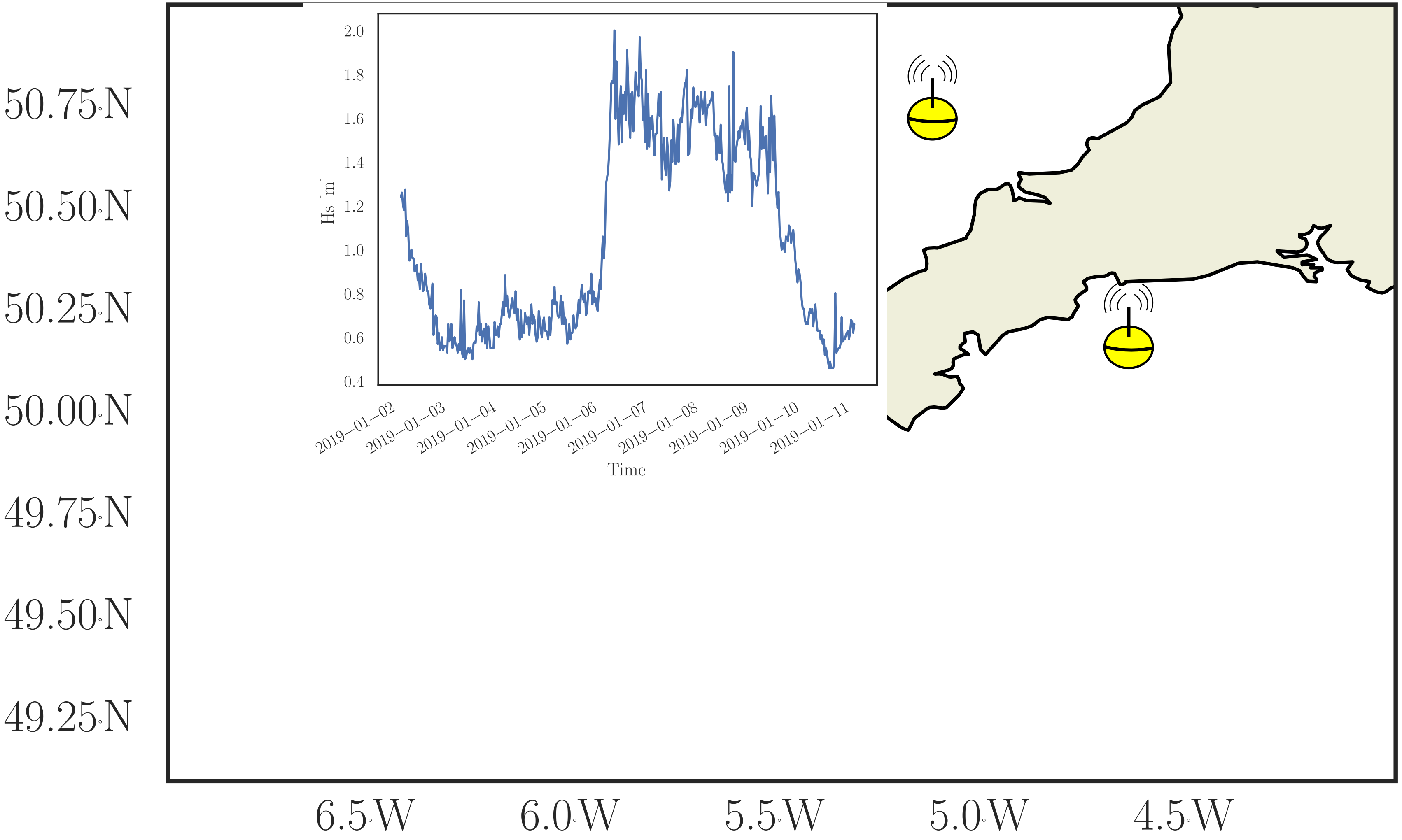


Looe Bay

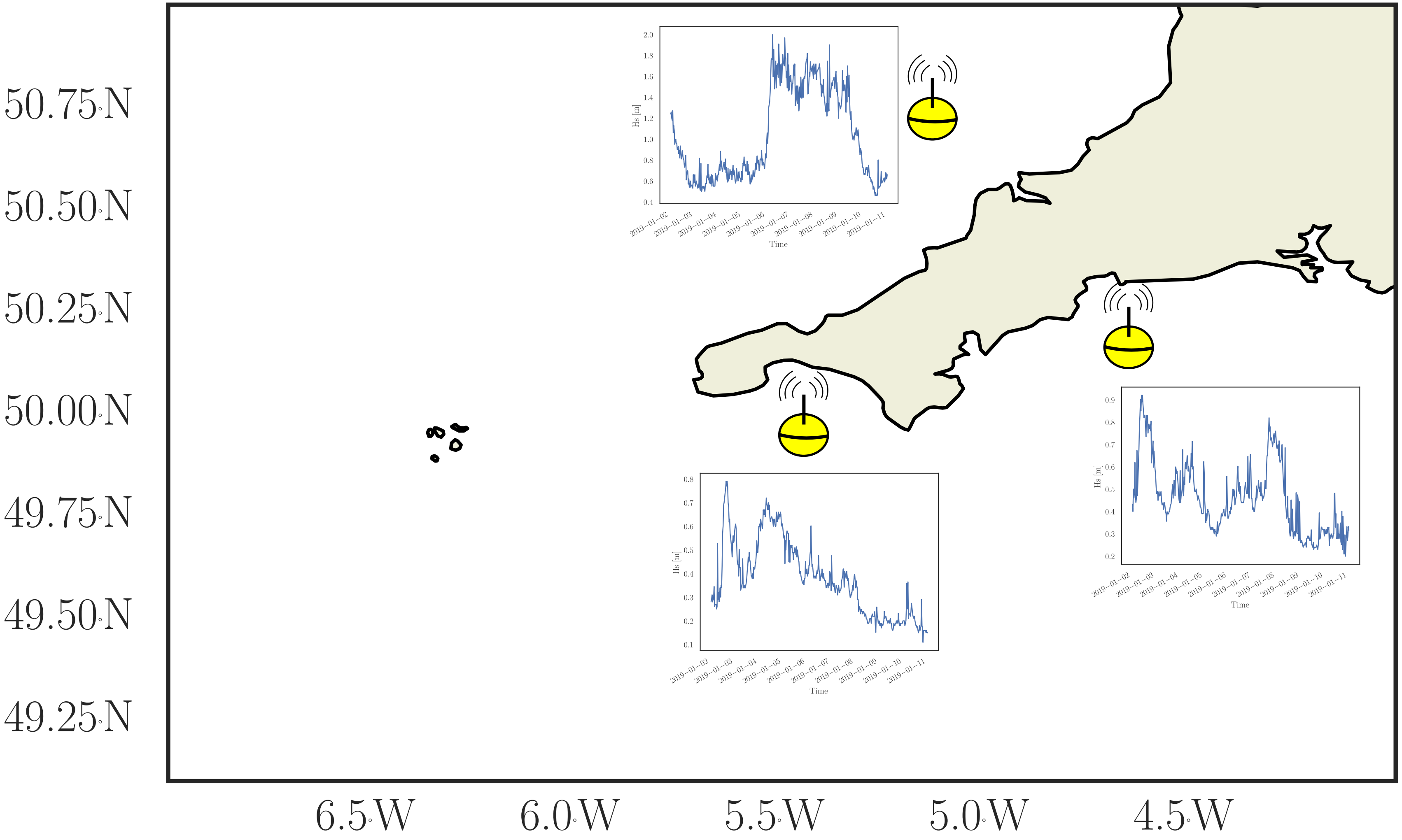


Perranporth

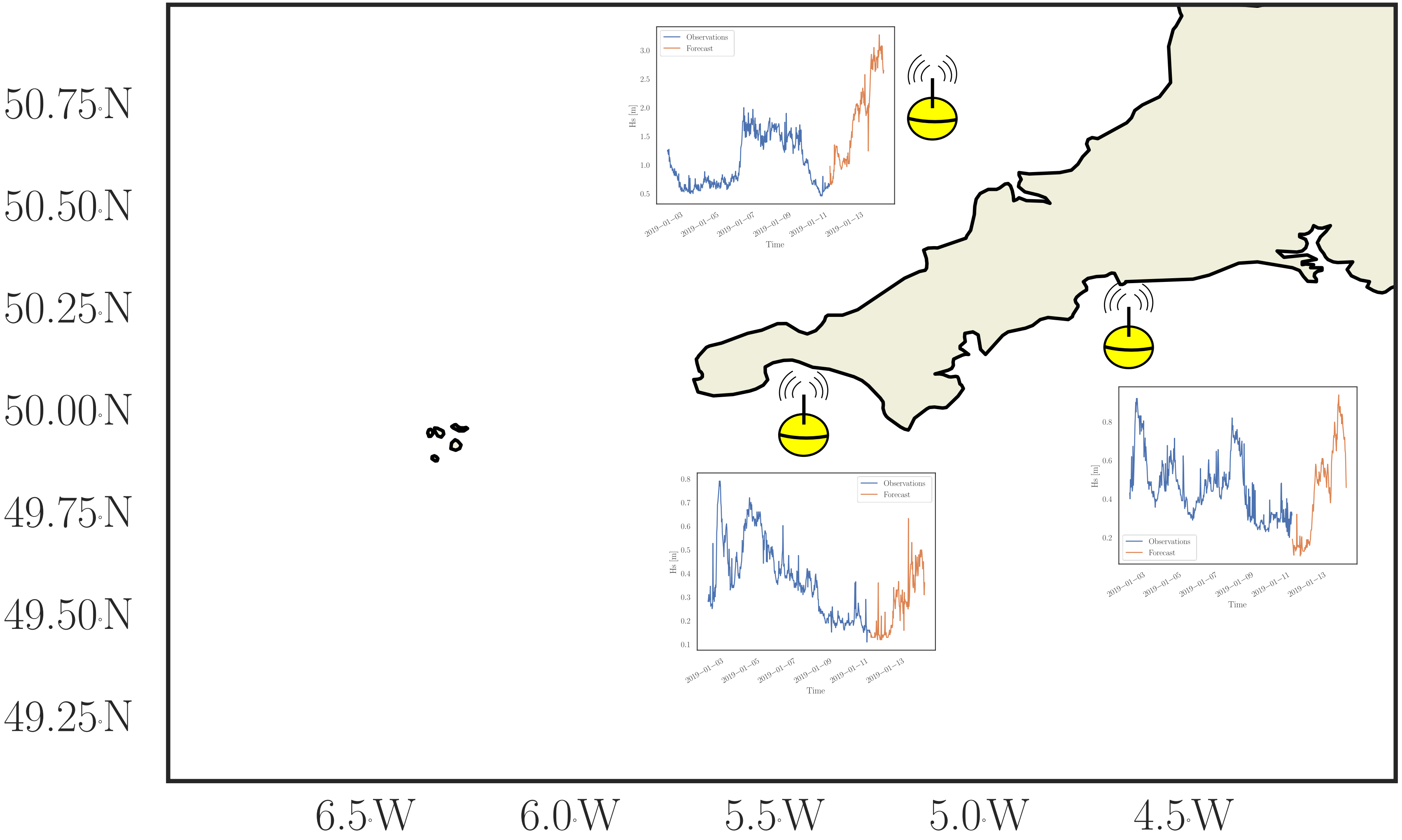
Observation-Based Forecasts



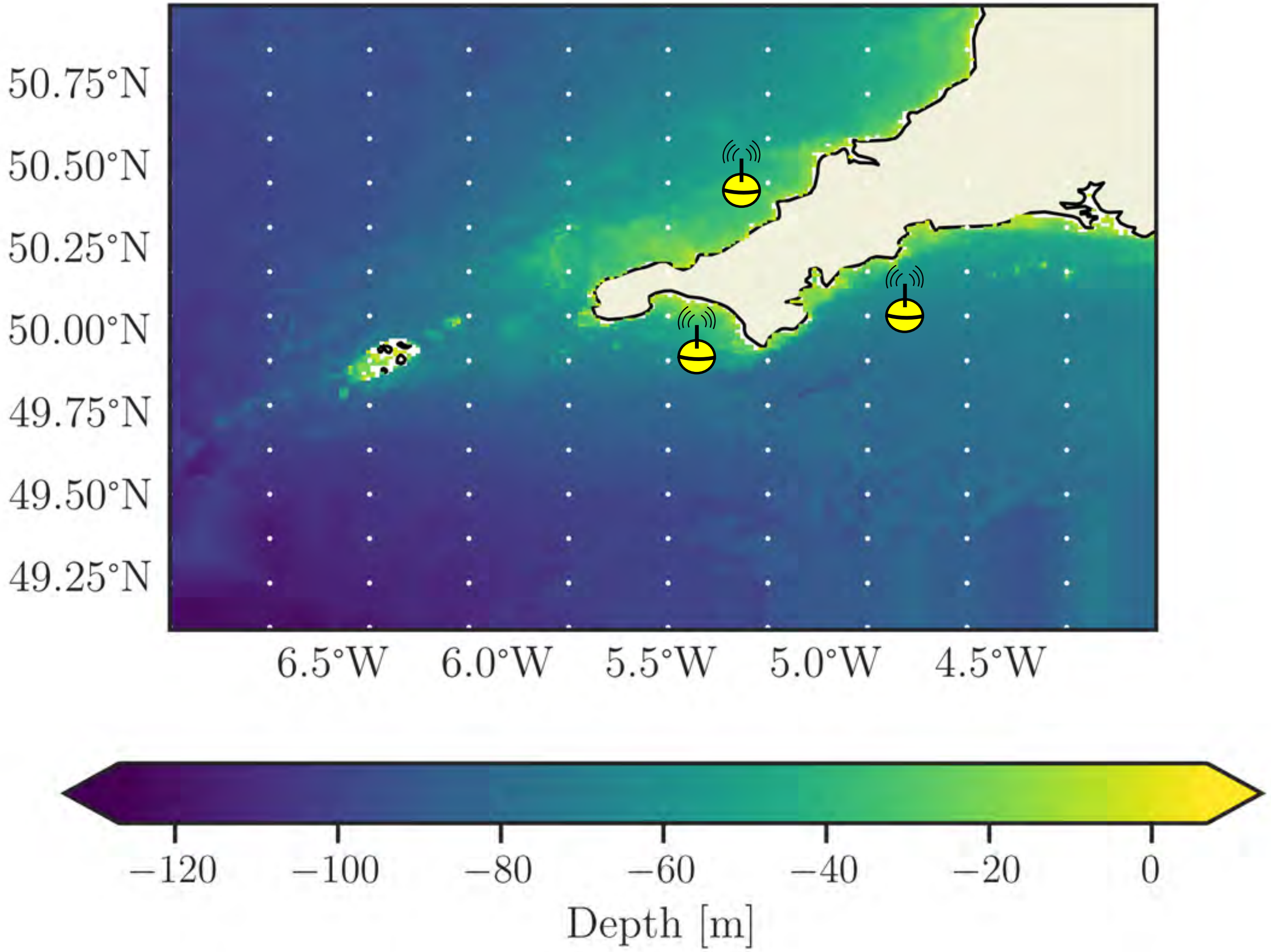
Observation-Based Forecasts



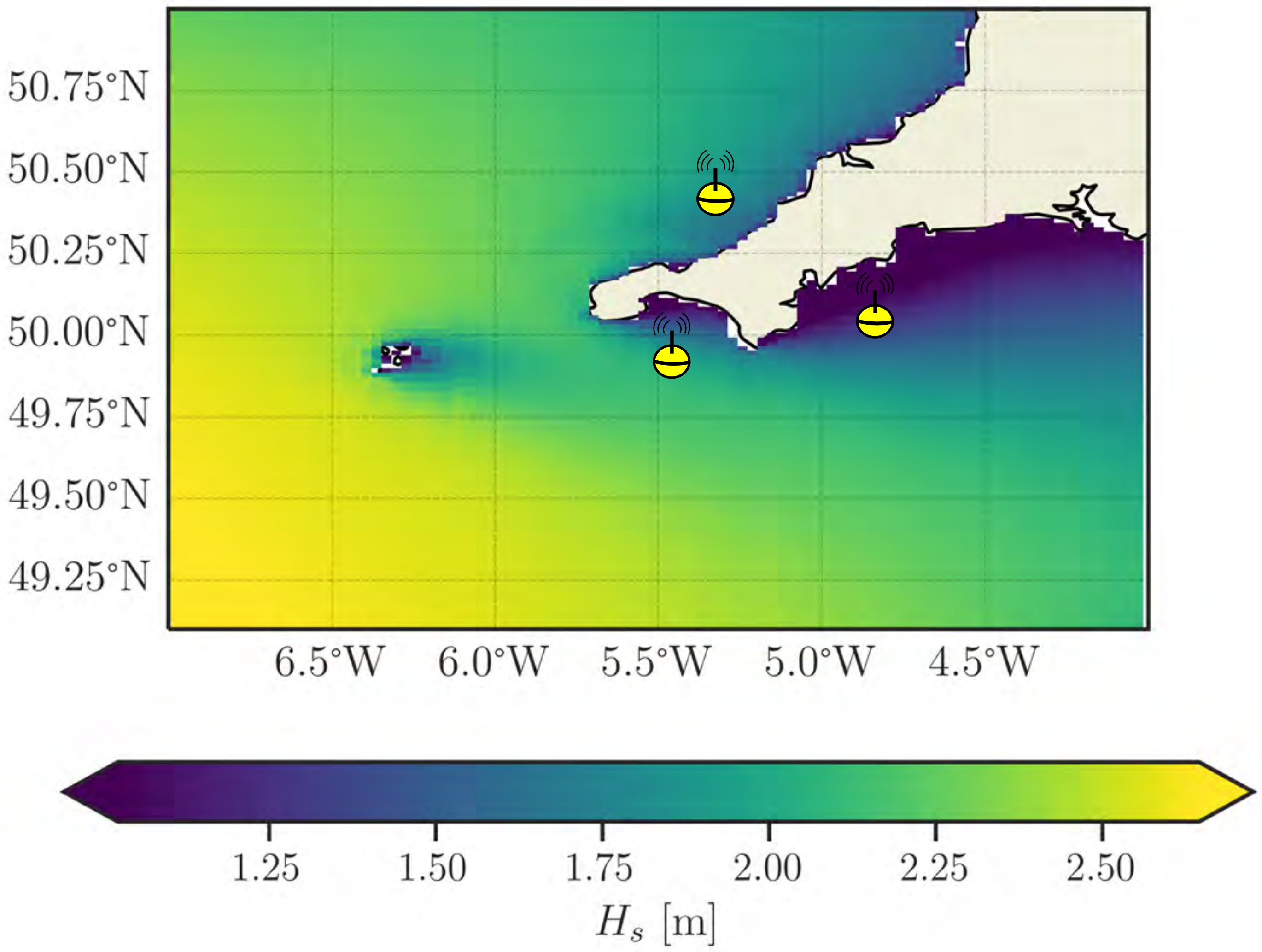
Observation-Based Forecasts



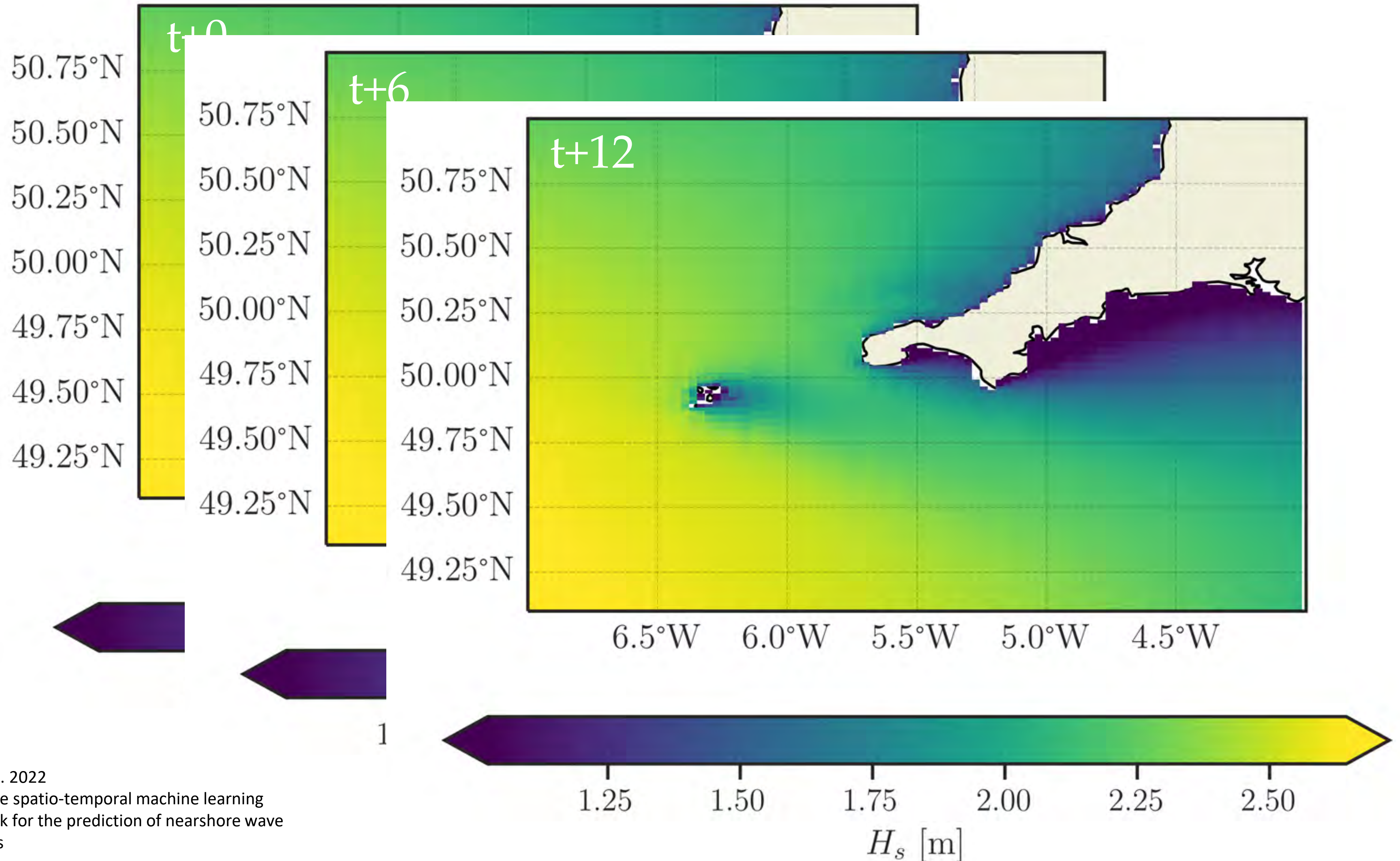
Spatial Observation-Based Forecast



Spatial Observation-Based Nowcast



Spatial Observation-Based Forecast



Chen et al. 2022
A real-time spatio-temporal machine learning framework for the prediction of nearshore wave conditions

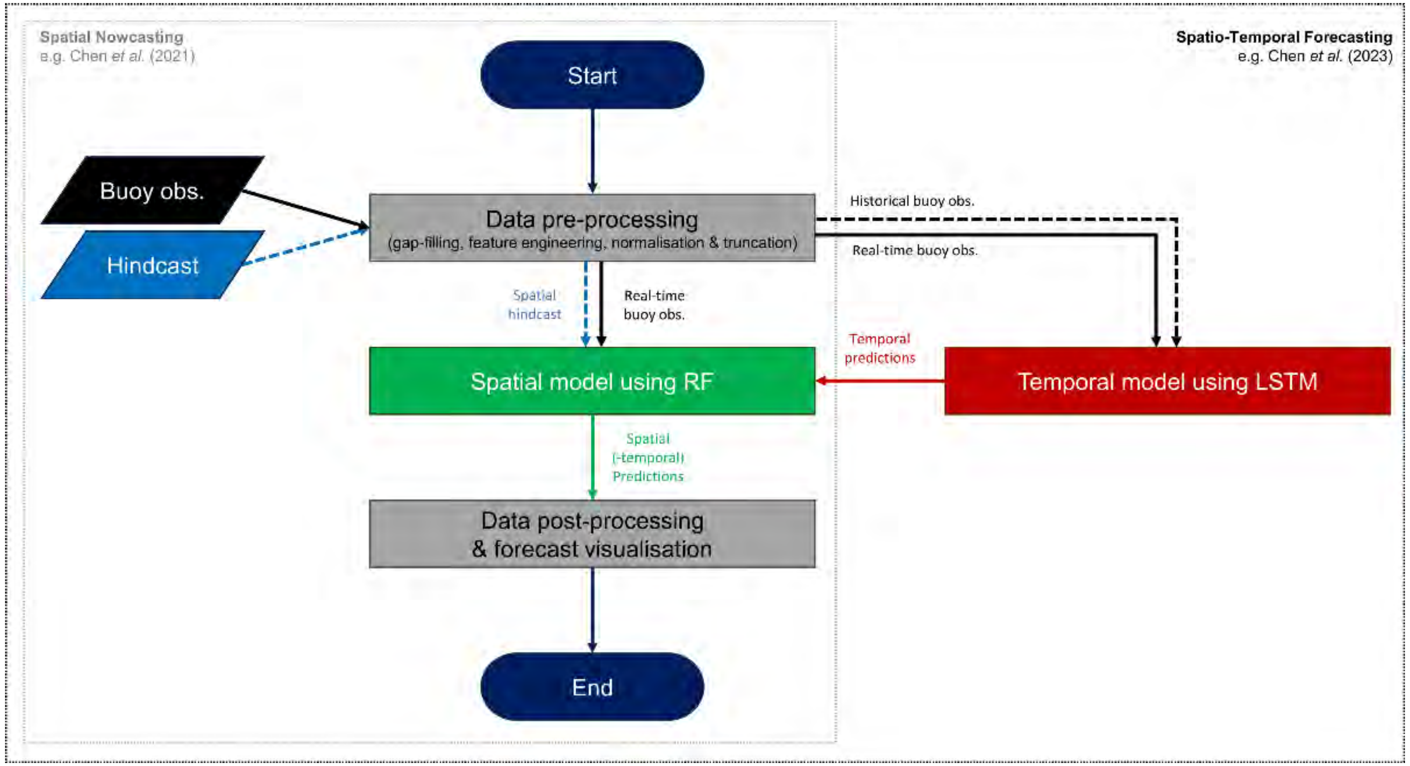
Model Framework Overview

- Forecasting methodology divided into two models that are coupled:

  1. Spatial Nowcasting
     - Relate the conditions at point locations to the conditions throughout the model domain

  2. Temporal Forecasting at a Point
     - Use the conditions at the in-situ measurement locations to forecast future conditions at the same location

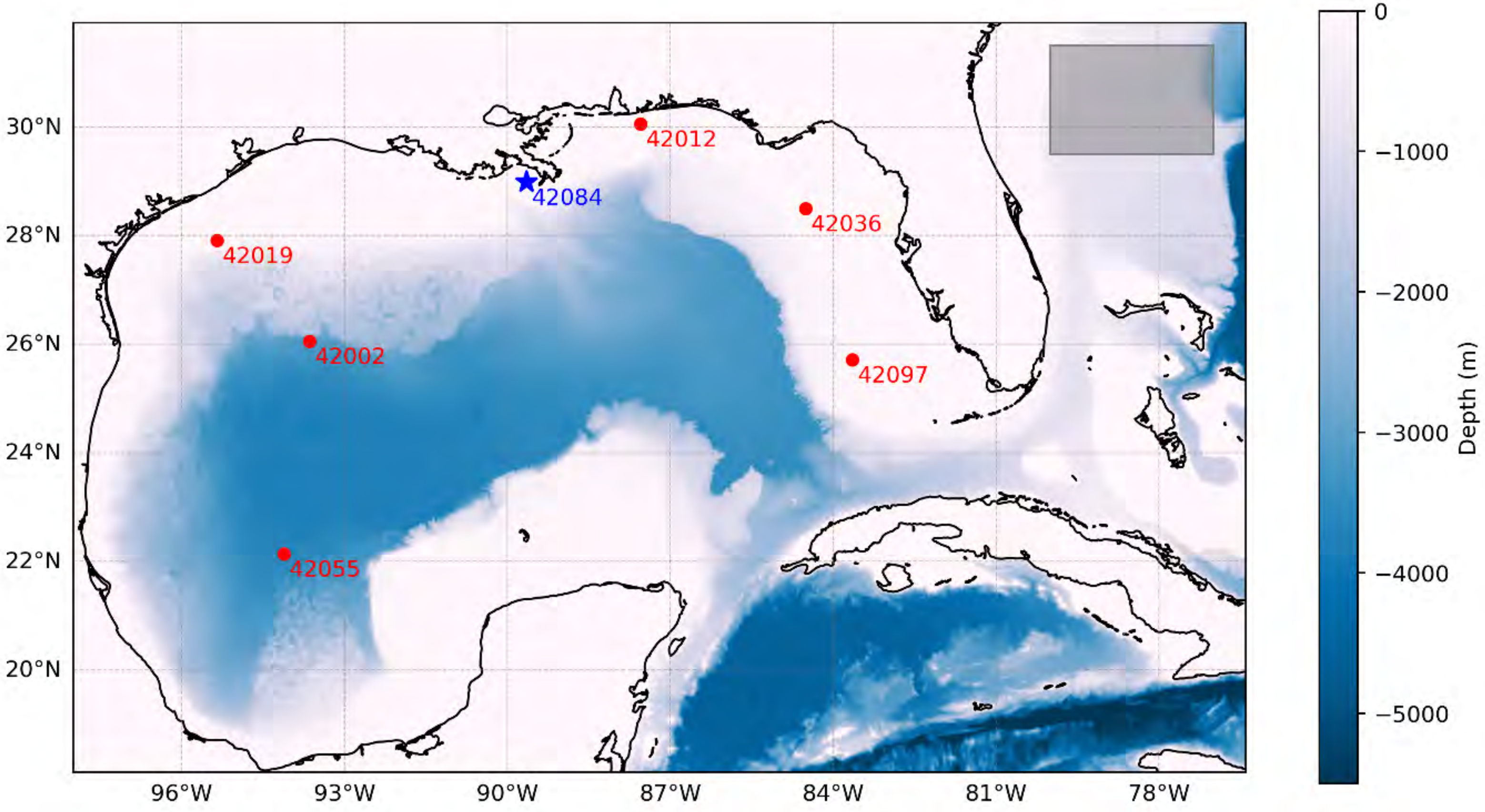
- Coupling models enables spatial forecasting



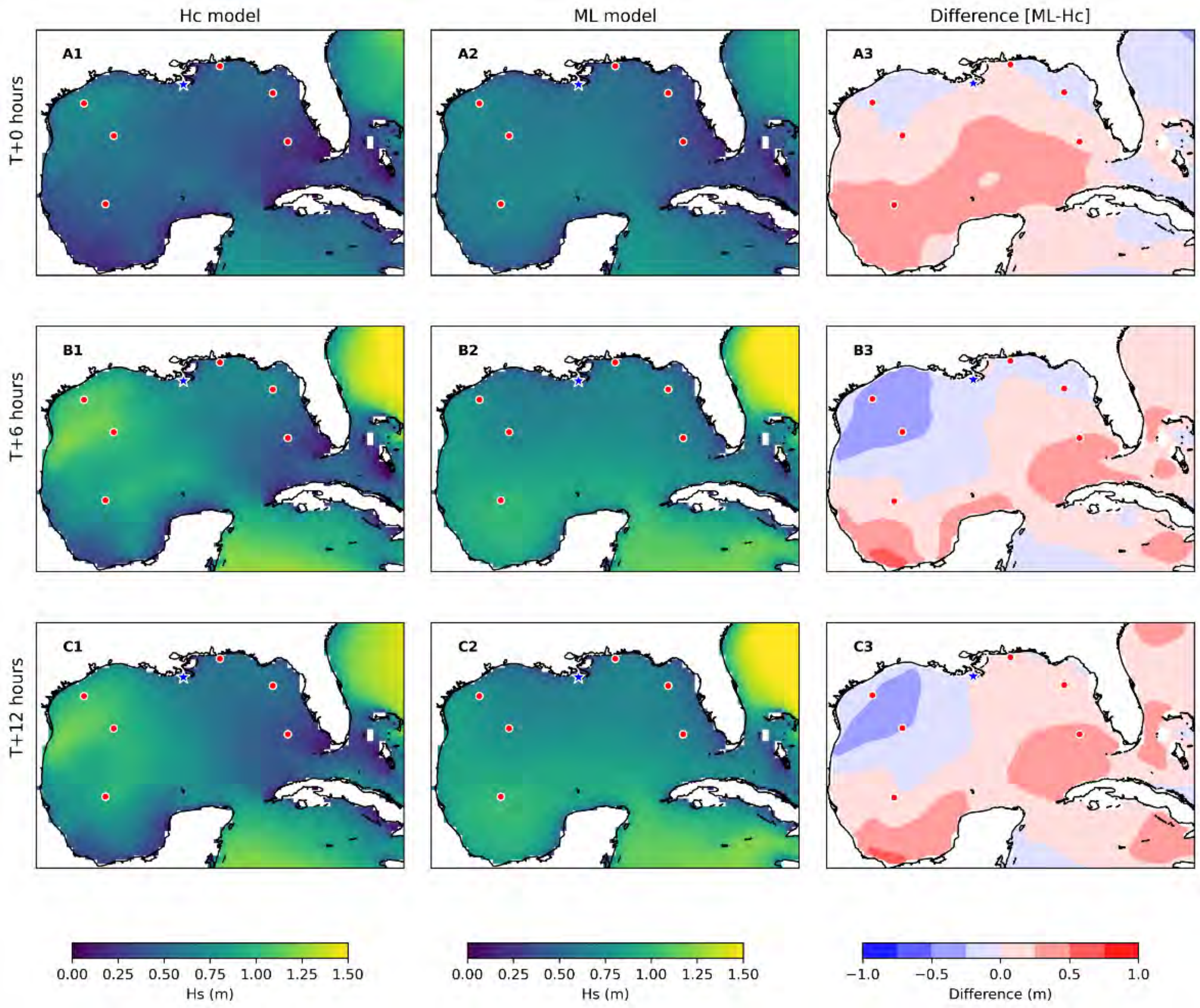
Steele et al. 2024
A Spatiotemporal Machine Learning Framework for the Prediction of Metocean Conditions in the Gulf of Mexico

Case Study Description

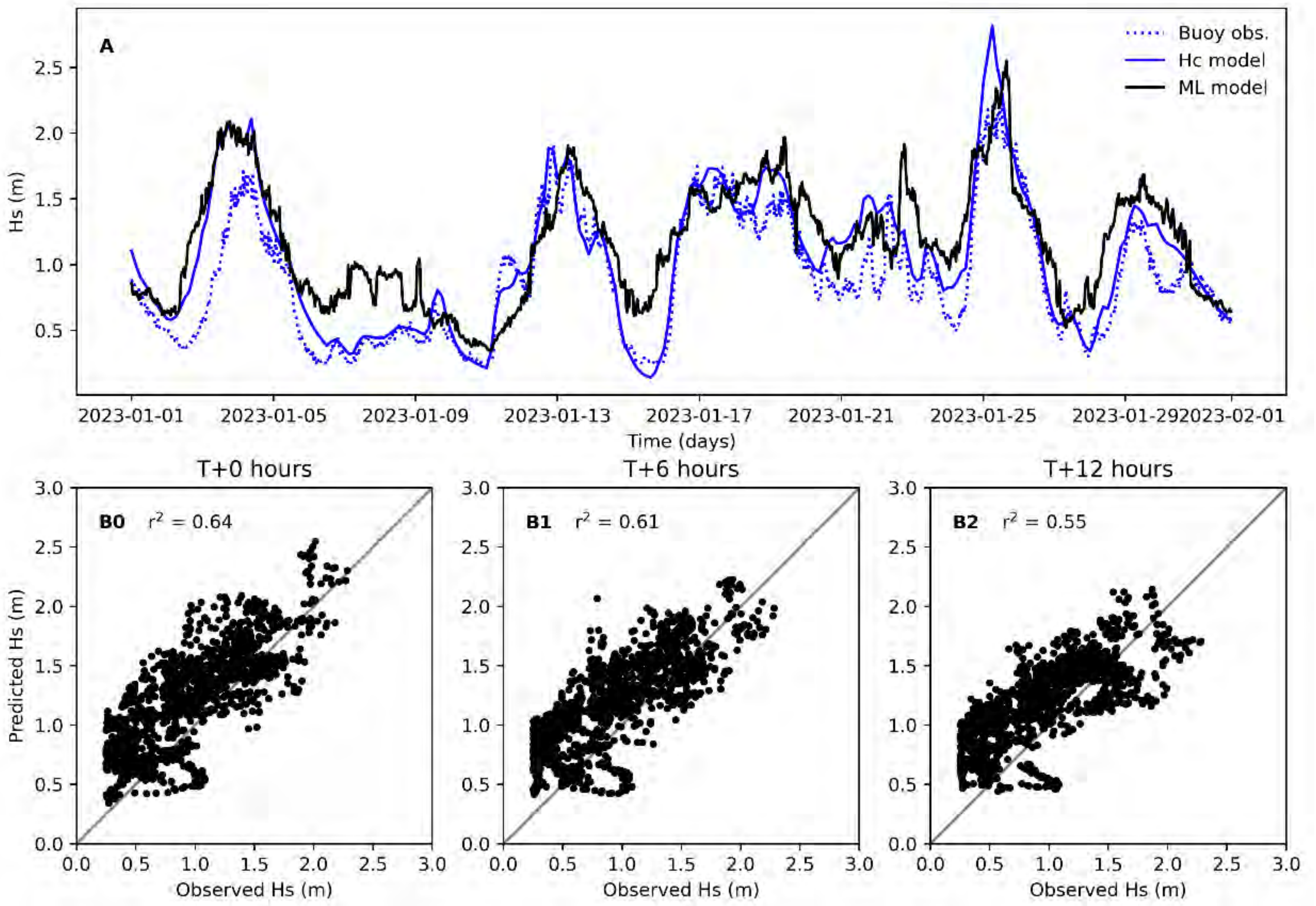
- Application of same method in Gulf of Mexico
- Test in a far more complex oceanographic area
- Test system for extreme data sparsity
  - 2 years of concurrent buoy measurements for training temporal model
  - 2 years of hindcast outputs to train spatial model
- More than **30 times larger** than Southwest Approaches domain



Results


Hc model
ML model
Difference [ML-Hc]
T+0 hours
T+6 hours
T+12 hours
A1
A2
A3
B1
B2
B3
C1
C2
C3
0.00 0.25 0.50 0.75 1.00 1.25 1.50
Hs (m)
0.00 0.25 0.50 0.75 1.00 1.25 1.50
Hs (m)
−1.0 −0.5 0.0 0.5 1.0
Difference (m)

Results



- Useful tool for improved offshore planning & workabilitity
- Promising results with very limited training data
- Potential extensions to currents for prediction of complex Loop Current and Loop Current Eddy dynamics

Summary

- A **machine learning** forecasting framework integrating **in-situ buoy observations** and a **surrogate regional numerical wave model** has been developed

- De-couples dependency on boundary data, and errors in boundary data in traditional physics-based models; leverages in-situ measurements

- The framework has similar levels of accuracy with physics-based forecasting model, but requires only much less computational resources in operation

Next Steps and Concluding Remarks

University of Exeter

Surrogate spatial model enables **improvements** compared to a hindcast both in respect to accuracy and time efficiency

Chen et al. 2021: Using machine learning to derive spatial wave data: A case study for a marine energy site

The spatiotemporal model can achieve equivalently accuracy with advanced numerical model

Chen et al. 2022: A real-time spatio-temporal machine learning framework for the prediction of nearshore wave conditions

- Industrial case studies considering turbine access
- Work with partners to develop an optimized system
- Design for operation with autonomous systems

- Incorporating alternate data sets (satellite, vessel motions, etc.)
- Consider other applications for accurate nowcast wave data
- Improve historical data

University of Exeter

Thank you.