MACHINE LEARNING FOR LOW-COST OFFSHORE MODELLING (MALCOM)

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Supergen ORE Hub FlexFund Project – Final Results

Overview

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- Project Aims & Objectives

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- Nowcasting results
- Forecasting methodology
- Forecasting & benchmarking results

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- Case Study at an ORE Site

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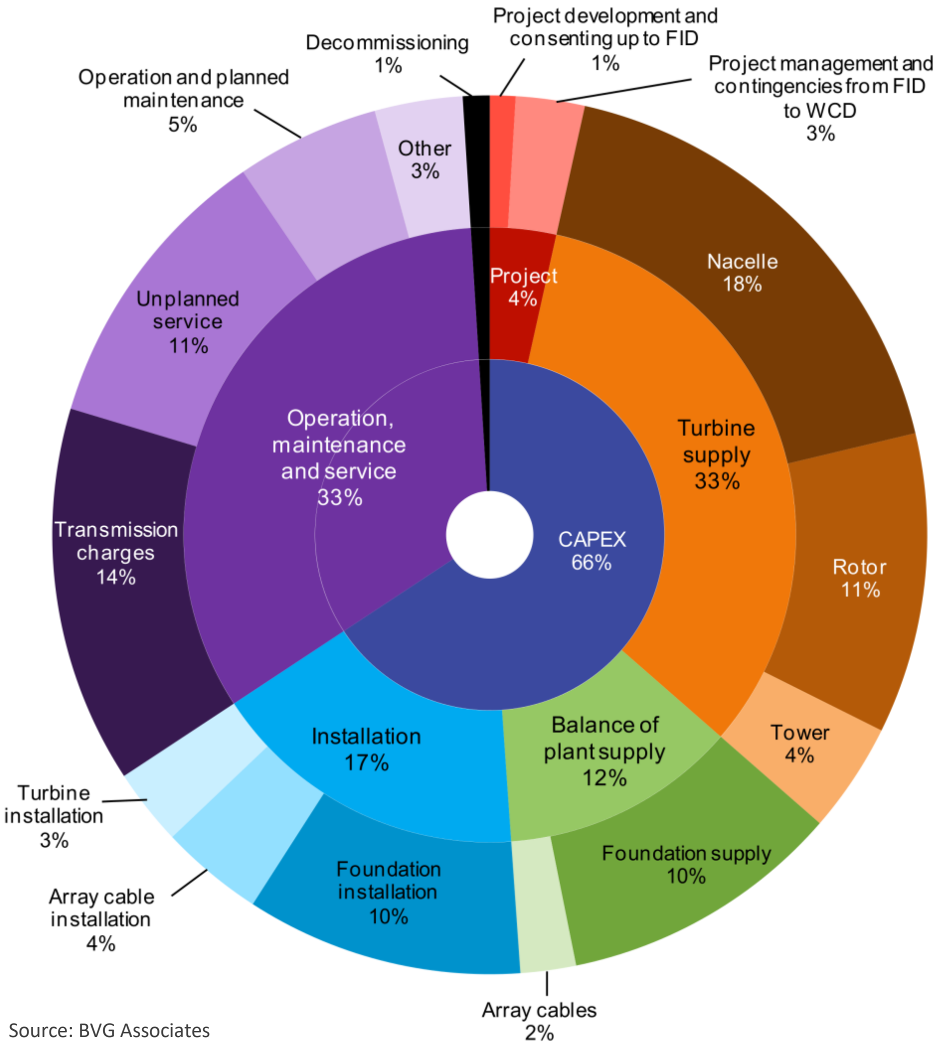
BACKGROUND



Source: BVG Associates

- Installation, inspection, operation, and maintenance activities at ORE 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, turbine-specific forecasts can provide improved decision-making during installation, operation, and maintenance processes**

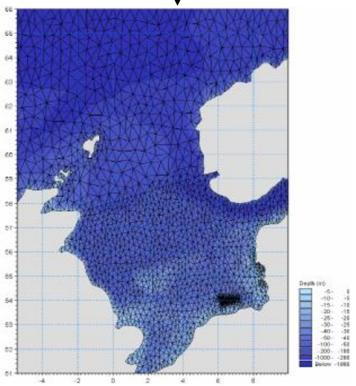
Aims and Objectives

- MaLCOM aims to demonstrate a **machine learning system** that can **integrate metocean sensor networks** and **physical models**, to **improve** the provision of met-ocean data
- Aims:
  - Develop low computational cost machine learning methods using hindcast model runs and real-time in-situ measurements to:
    - Provide spatial nowcasts
    - Provide short-term forecasts

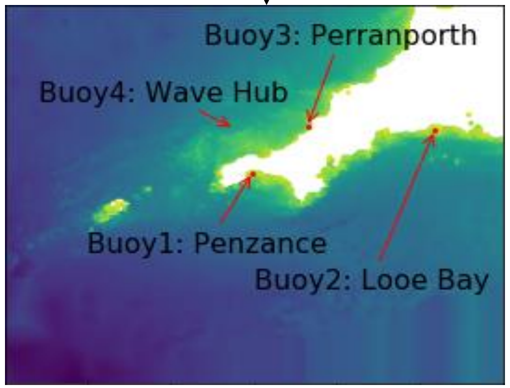
Motivation and Objective

Temporal-spatial wave distribution

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



High-fidelity
High-computational cost



Relatively reliable
Sparse data set

Objective: Develop **machine learning** models to act as surrogates that learn the **nonlinear mapping** from fixed points to spatially distributed wave data across a region

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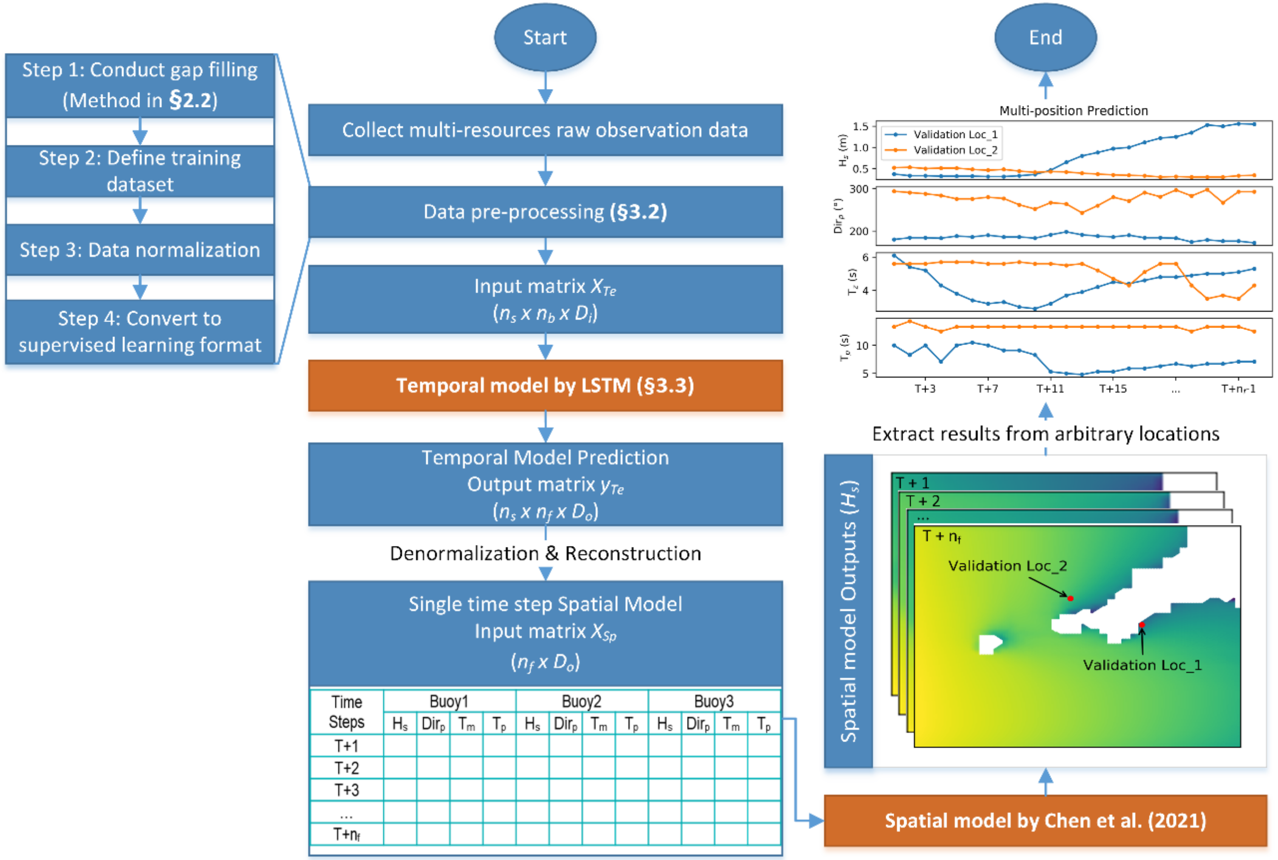
SYSTEM OVERVIEW

- 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 Point Forecasting*
     Use the conditions at the in-situ measurement locations to forecast future conditions at the same location

- Coupling models enables spatial forecasting



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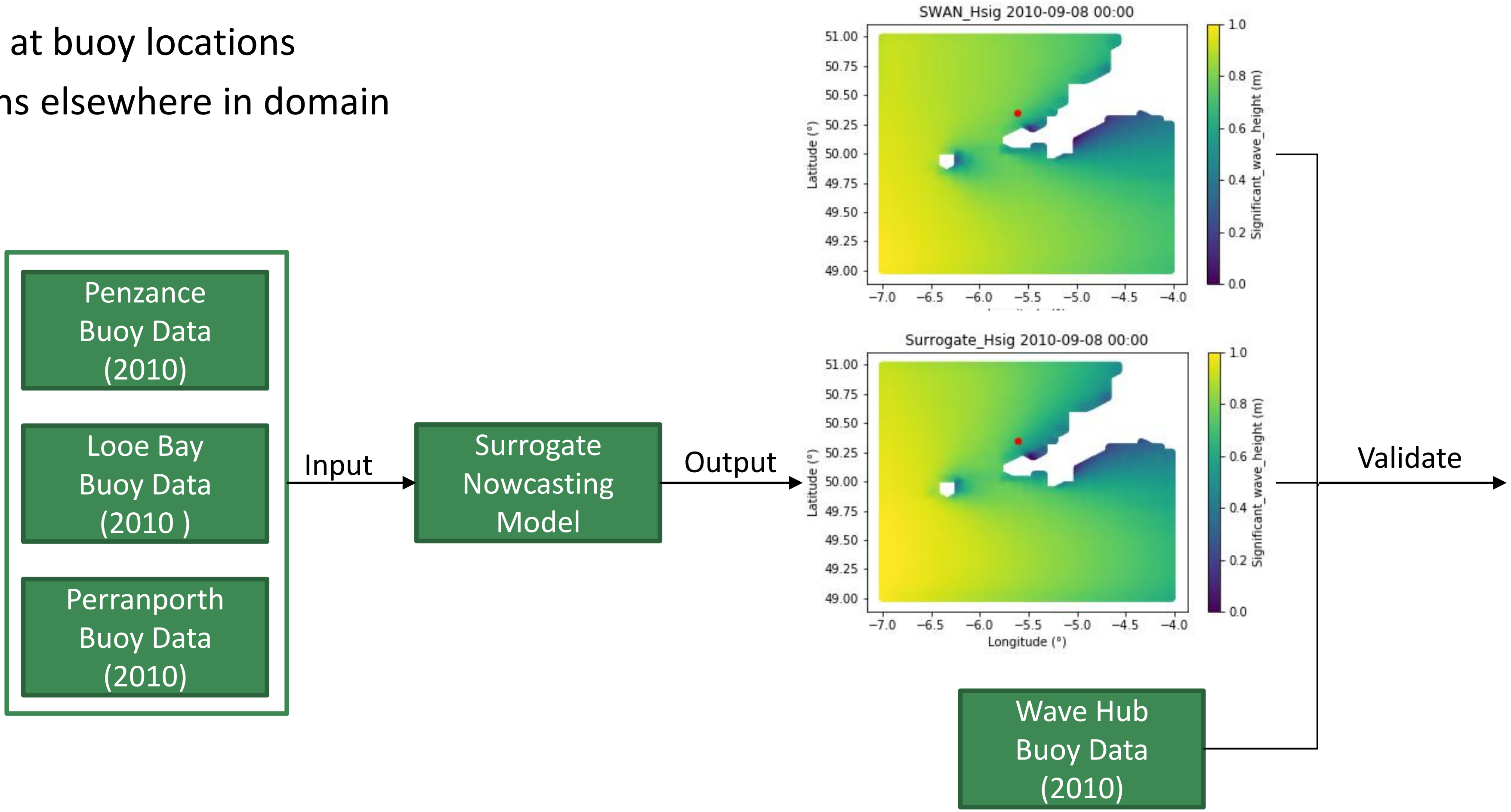
Surrogate Model Development (Spatial Nowcasting)

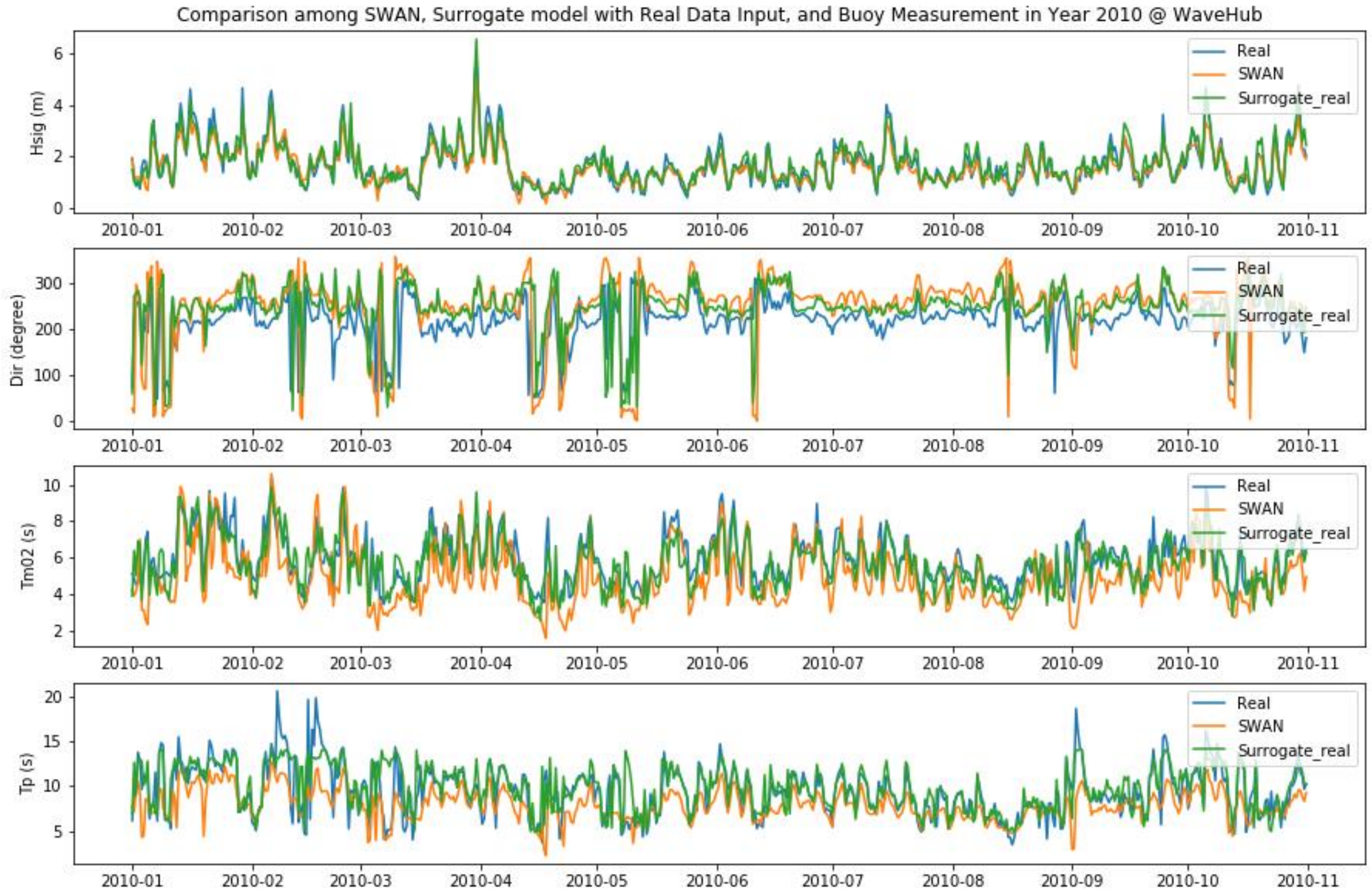
- **Model training**
  - *Inputs*: SWAN conditions at buoy locations
  - *Outputs*: SWAN conditions elsewhere in domain

- **Model “operational mode”**
  - *Inputs*: Buoy measurements
  - *Outputs*: Estimated nowcast conditions elsewhere in domain
  - *Validation Outputs*: Wave Hub



J. Chen, A. C. Pillai, L. Johanning, and I. Ashton, “Using Machine Learning to Derive Spatial Wave Data: A Case Study for a Marine Energy Site,” Environmental Modelling & Software, vol. 142, no. April, p. 105066, 2021, doi: 10.1016/j.envsoft.2021.105066.

NOWCASTING RESULTS: SURROGATE MODEL ACCURACY

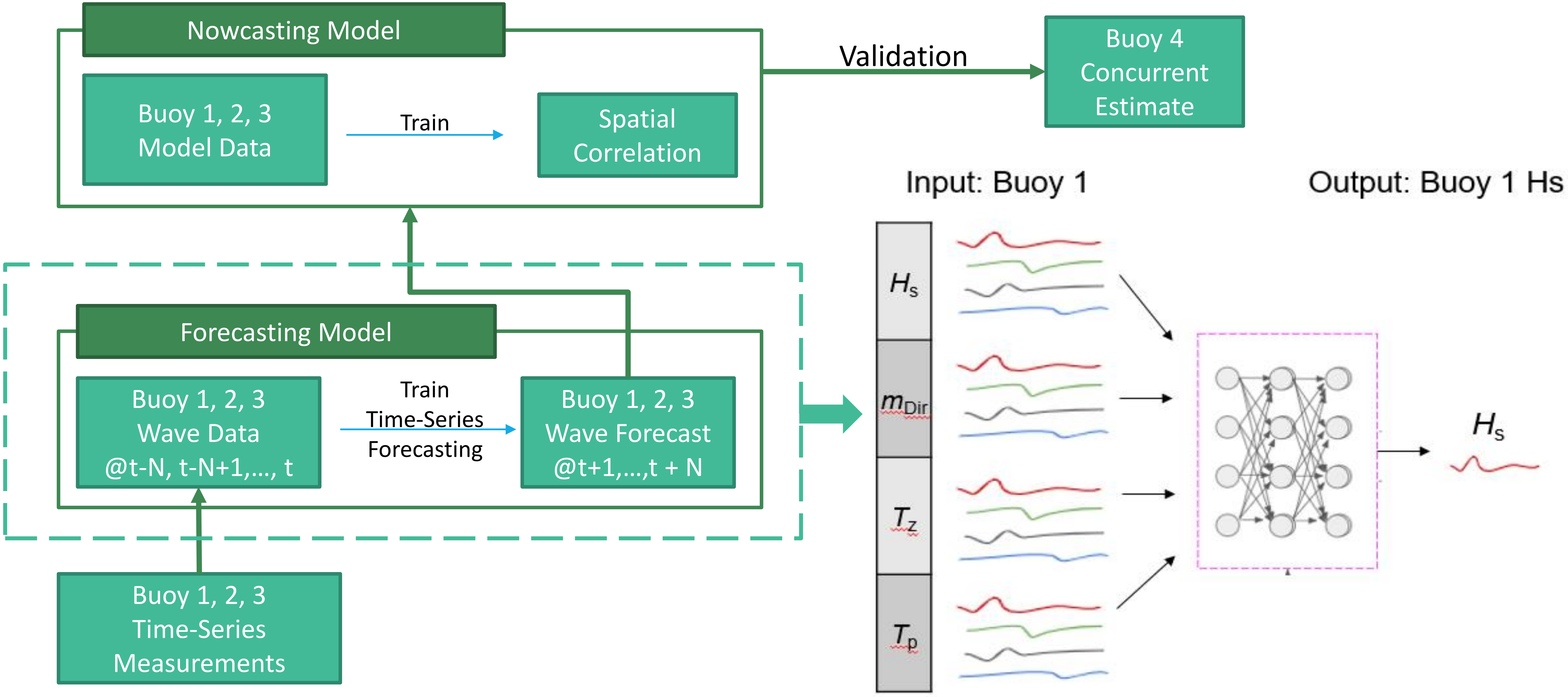


- The surrogate model consistently matches the real data better than the hindcast
- T_{m02} has a dramatic improvement
- Surrogate model captures the spatial correlation across the site

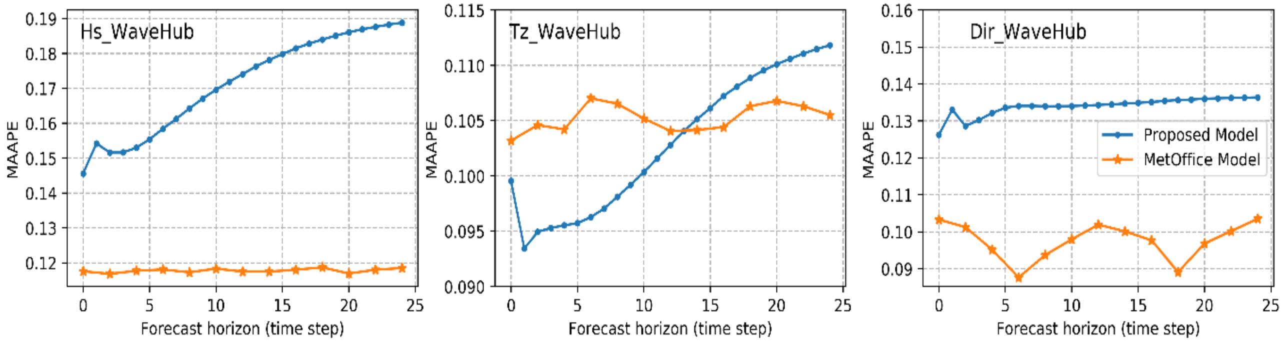
		R2	RMSE	RMSE/AVG
H_s	SWAN	0.8521	0.3218	0.1901
	Surrogate	**0.9074**	**0.2547**	**0.1504**
mDir	SWAN	-0.8043	68.1254	0.3114
	Surrogate	**-0.1473**	**54.3238**	**0.2483**
T_{m02}	SWAN	-0.0257	1.3903	0.2371
	Surrogate	**0.7144**	**0.7336**	**0.1251**
T_p	SWAN	0.2263	2.4852	0.2626
	Surrogate	**0.5537**	**1.8876**	**0.1994**

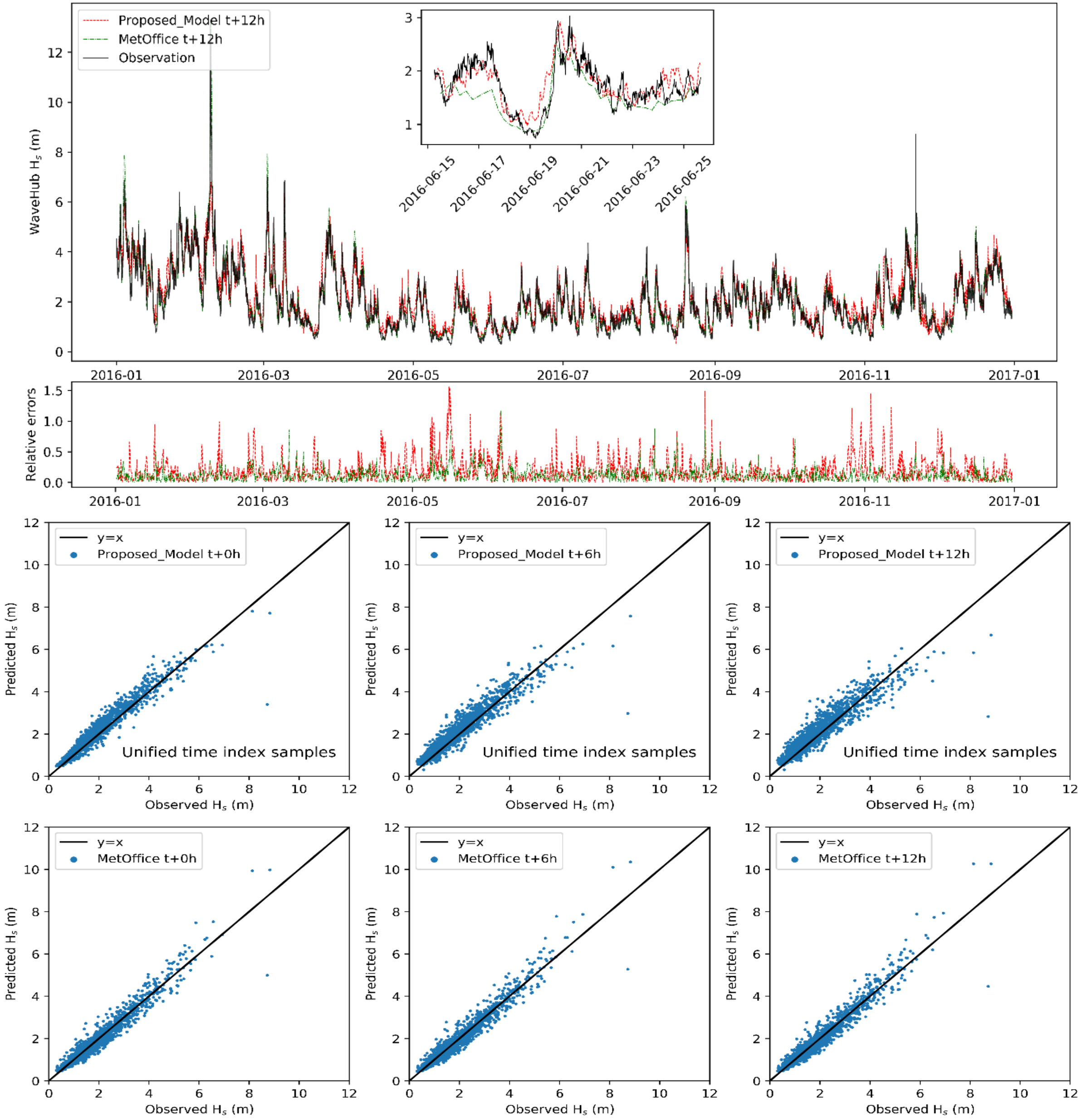
J. Chen, A. C. Pillai, L. Johanning, and I. Ashton, “Using Machine Learning to Derive Spatial Wave Data: A Case Study for a Marine Energy Site,” Environmental Modelling & Software, vol. 142, no. April, p. 105066, 2021, doi: 10.1016/j.envsoft.2021.105066.

FORECASTING FRAMEWORK



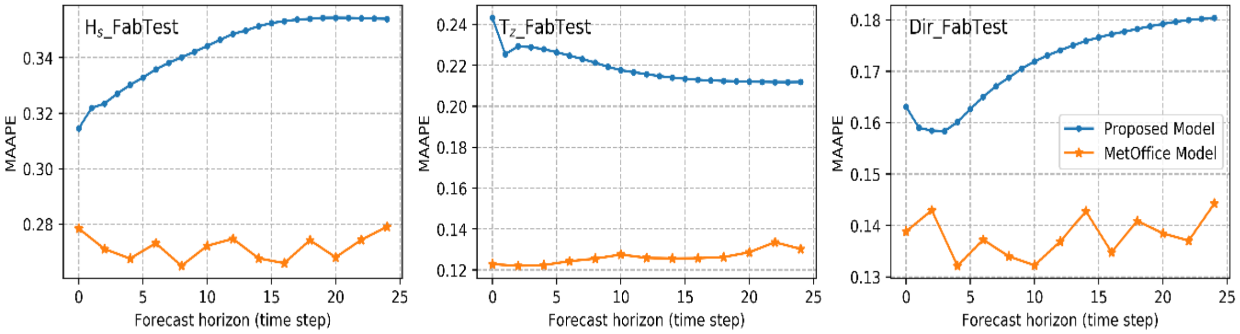
Spatio-Temporal Model Performance - WaveHub



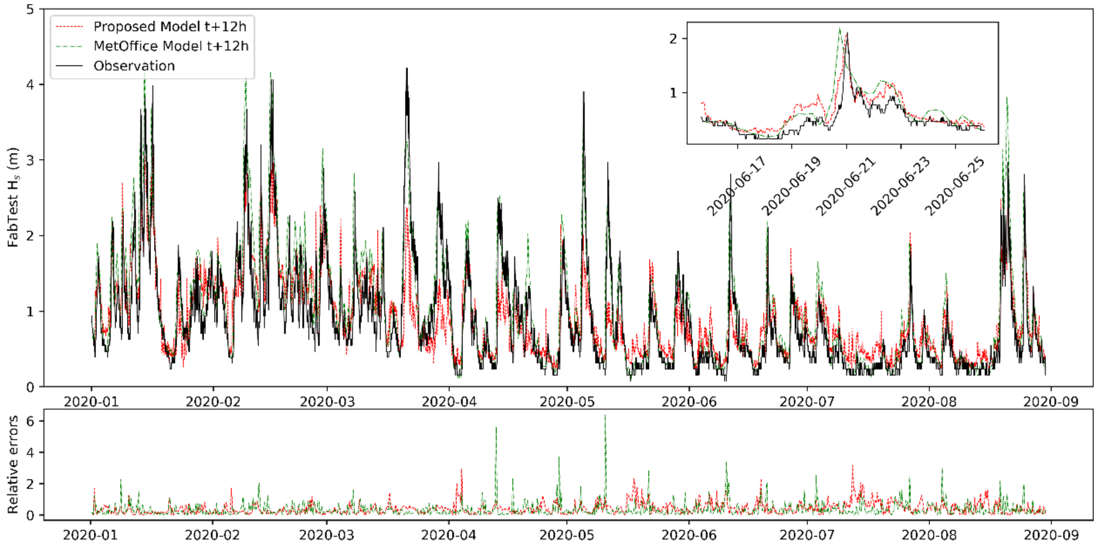


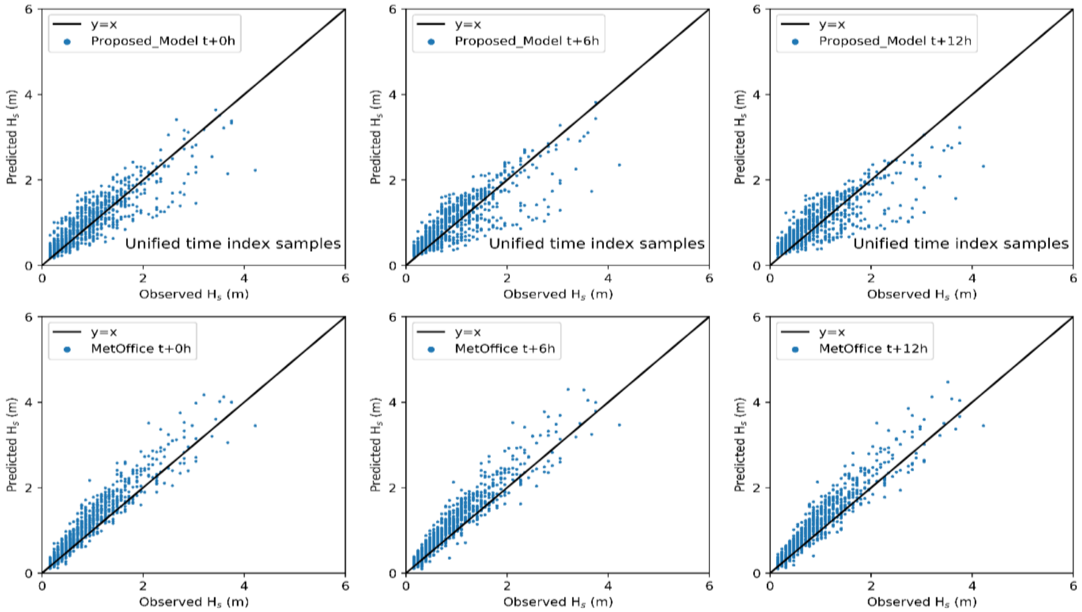
- The proposed model framework has a similar level of accuracy as the UKMO model across all the wave parameters.
- Scatter plots of the proposed model framework show increased scatter with increased forecast lead time, while not apparent for UKMO model.
- For both Tz and Hs, the UKMO model appears to slightly over-predict at large values while the proposed model framework under-predicts.

SPATIO-TEMPORAL MODEL PERFORMANCE - FABTEST

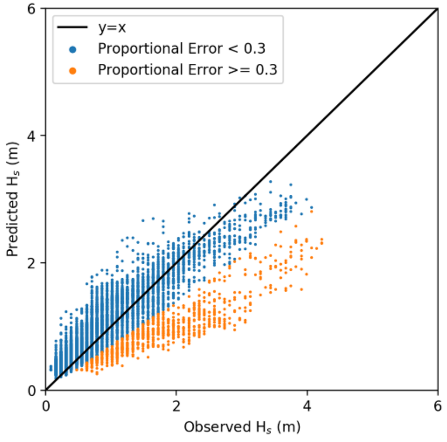


- The proposed model framework and the UKMO model are less accurate at FabTest than at WaveHub.
- The proposed model framework is consistently less accurate (i.e. higher errors) and the UKMO model is more accurate in all statistics for Hs and Tz over the forecast time horizon.
- The proposed model framework shows a group of results with consistent under-prediction of Hs.

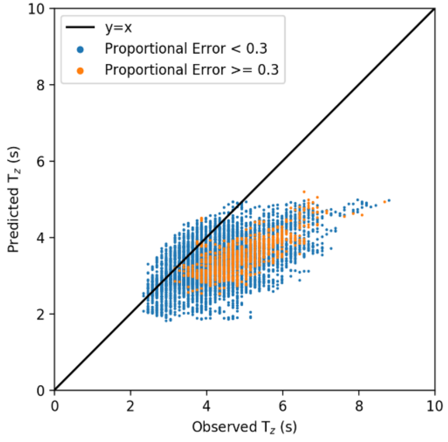




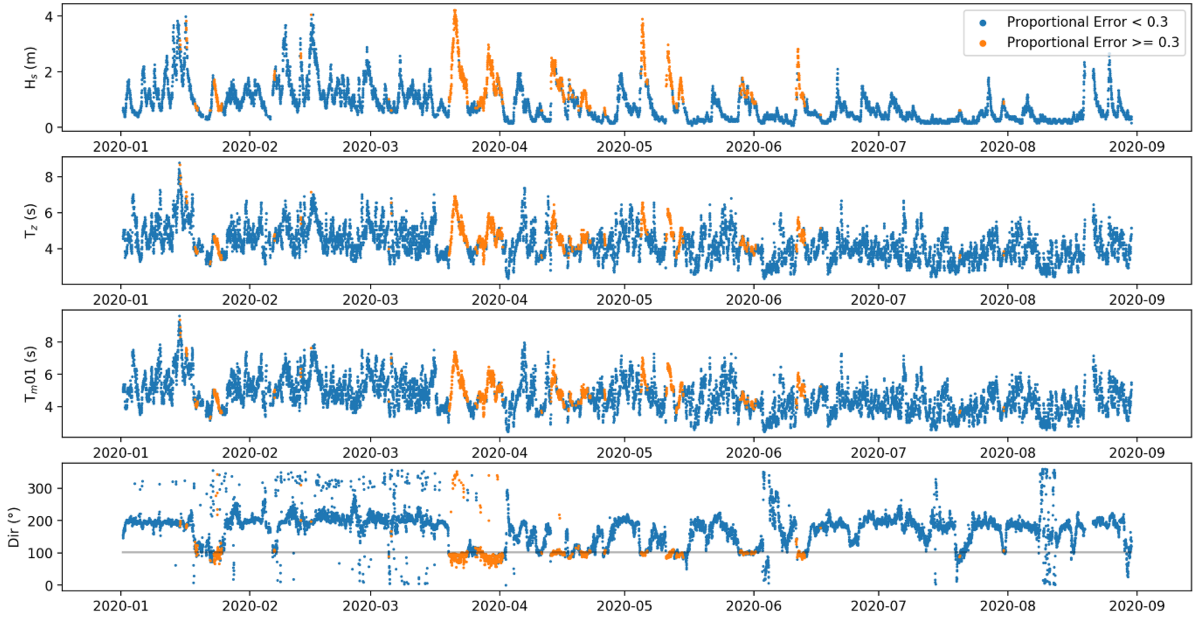
Spatio-Temporal Model Performance - FabTest



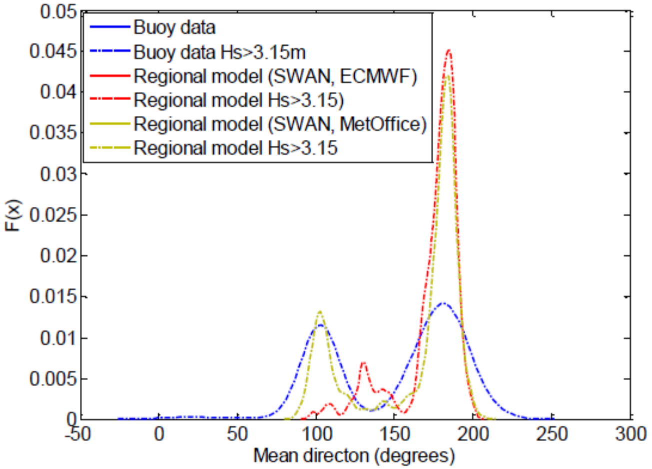
(a)



(b)



(c)



Empirical distribution of SWAN model shows waves from SE are omitted from boundary conditions.

- At the FaBTest buoy, the surrogate model has a subset with clear errors
- Errors when waves arrive from the South East is consistent with the original wave model

Conclusion

Key Points:

- A new multivariate spatio-temporal machine learning framework is proposed for real-time forecasting of waves across a region.
- The temporal forecast uses the Long Short-Term Memory neural network, while highlighting the importance of feature selection.
- Our wave forecasts up to 12 hours ahead are found to have very similar errors to traditional physics-based models such as those used by UK Met Office, but require far less computational power.

Future work:

- The framework is of immediately interest to wind farm operators, autonomous marine systems and for coastal applications, to give instant access to spatial wave data.
- Further ahead, this system could be used as part of more autonomous operations such as site management systems or mobile autonomous measurements.

CONCLUSIONS

- Preliminary results indicate that the surrogate modelling method enables **improvements** compared to a hindcast both in respect to accuracy and time efficiency

- Spatial nowcasting methodology is able to leverage real-time in-situ measurements to estimate entire domain

- Forecasting methodology is shown to have similar errors to physics-based forecast, though requires significantly less computational effort

Project Publications:

[1] Nowcasting model: J. Chen, A. C. Pillai, L. Johanning, and I. Ashton, "Using Machine Learning to Derive Spatial Wave Data: A Case Study for a Marine Energy Site," Environmental Modelling & Software, vol. 142, no. April, p. 105066, 2021, doi: 10.1016/j.envsoft.2021.105066.

[2] Full spatio-temporal forecasting model: J. Chen, I. Ashton, E. Steele, A. C. Pillai, "A Real-Time Spatio-Temporal Machine Learning Framework for the Prediction of Nearshore Wave Conditions" (Submitted)

[3] Gap filling: Chen, J., Ashton, I. G. C., & Pillai, A. C. (2022). Wave record gap-filling using a low-rank tensor completion model. *ASME 41st International Conference on Ocean, Offshore and Arctic Engineering (OMAE2022)*.

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ONGOING AND FUTURE WORK

- Several studies with UKMO to augment and improve forecasts
- Deploy considering other regions and hindcast models
- Extending these methods to estimate and possibly correct model bias
- Industrial case studies with partners considering turbine access, weather windows, and vessel planning