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SPLASH
DIGITAL APPROACHES TO PREDICT WAVE OVERTOPPING HAZARDS

SPLASH: A Deployable AI-Based Tool for Coastal Overtopping Forecasting and Climate Resilience

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4th International workshop on waves, storm surges, and coastal hazards - Santander September 2025

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National Oceanography Centre

Coastal Processes Research Group

University of Plymouth

Context

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Dawlish 7 December 2021

- Coastal flooding poses a threat to human life, properties, services

Increased coastal resolution of large-scale numerical weather prediction models + the potential of Artificial Intelligence (AI) = Potential for real-time forecast of coastal flooding

Collapse of seawall at Dawlish (SW UK). Two-month closure cost the economy up to **£1.2bn**

Dawlish 7 February 2014

- Systems using process-based models are computationally demanding
- The necessity to include nested regional models restricts their application in operational forecasting
- Exploit measurements of wave-by-wave overtopping (NE/R014019/2). First time measured in W2018/19

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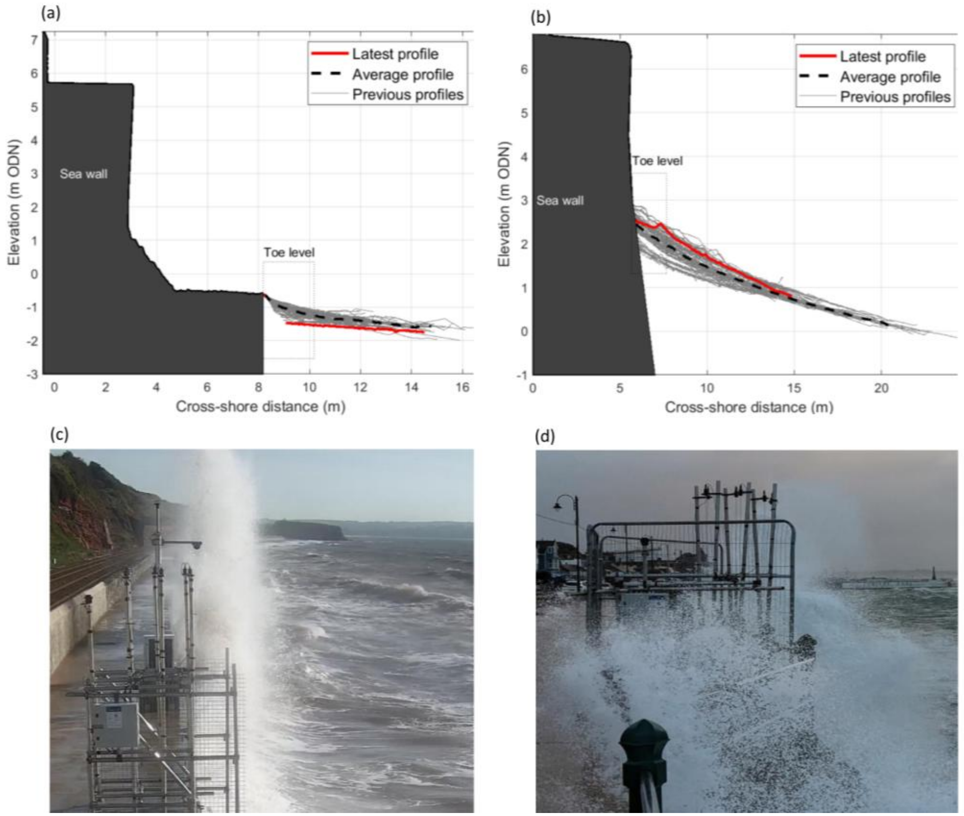
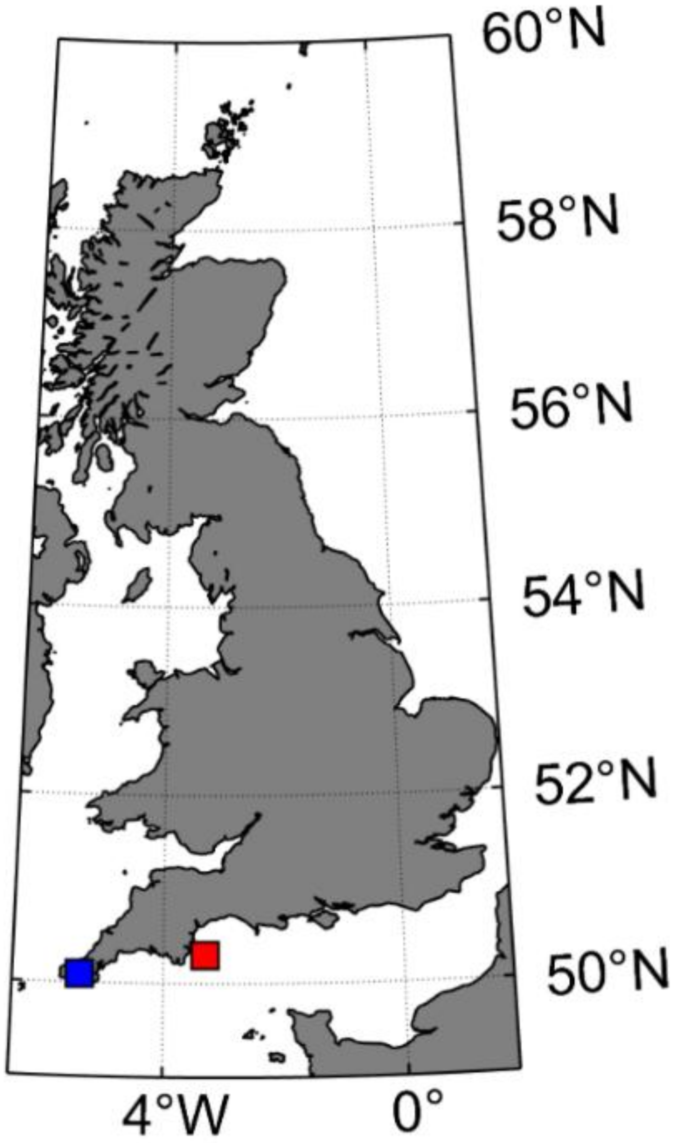
Methods

Observations - Pilot Sites

- Dawlish – cross-shore variability
- Penzance – alongshore variability





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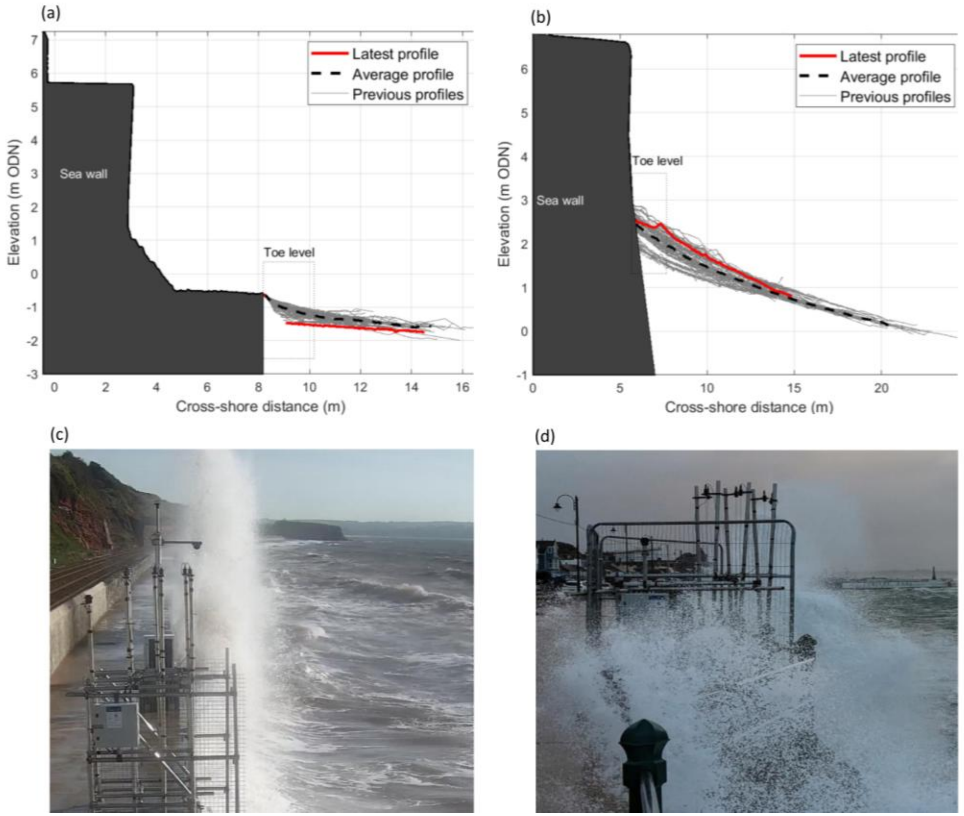

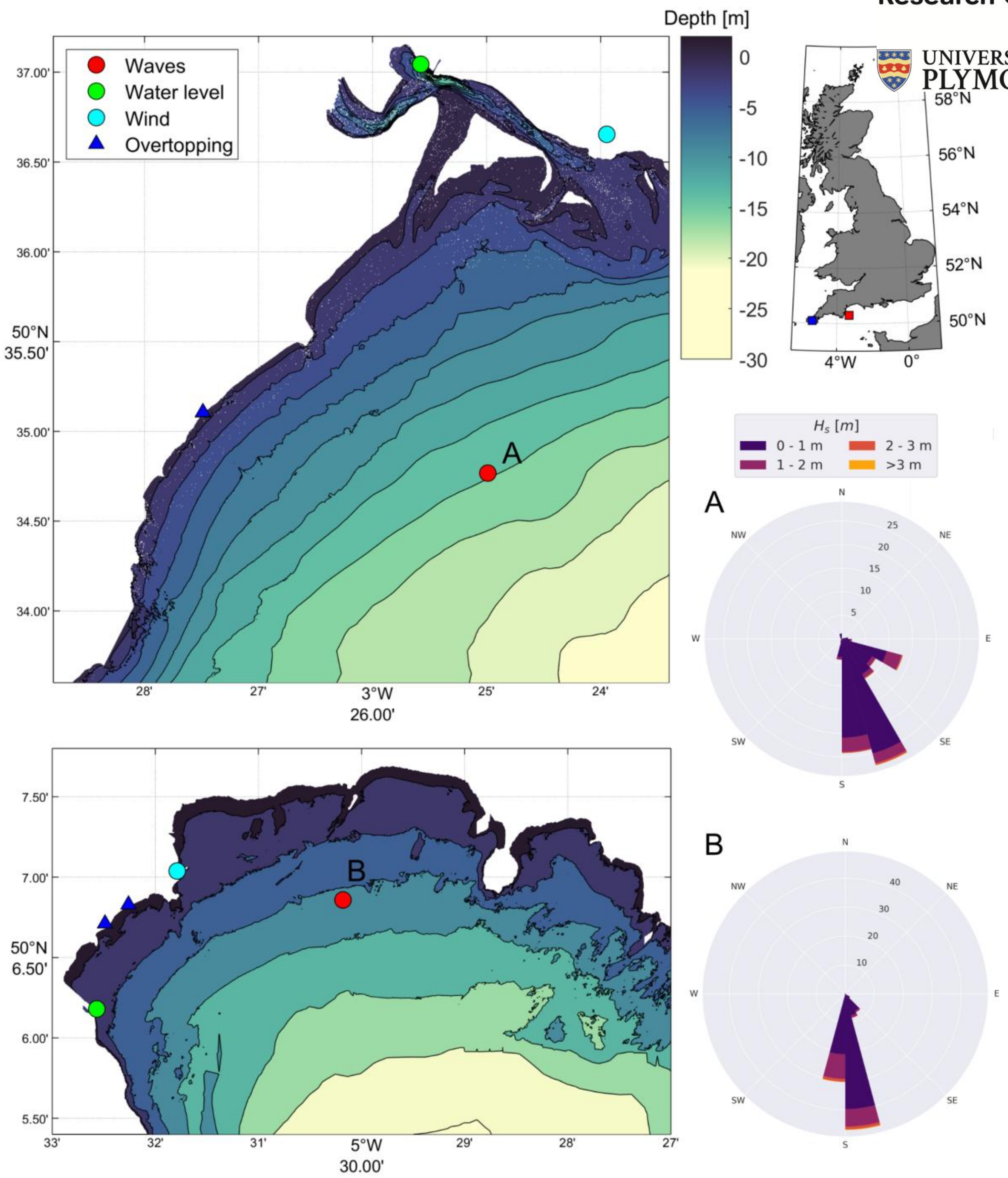

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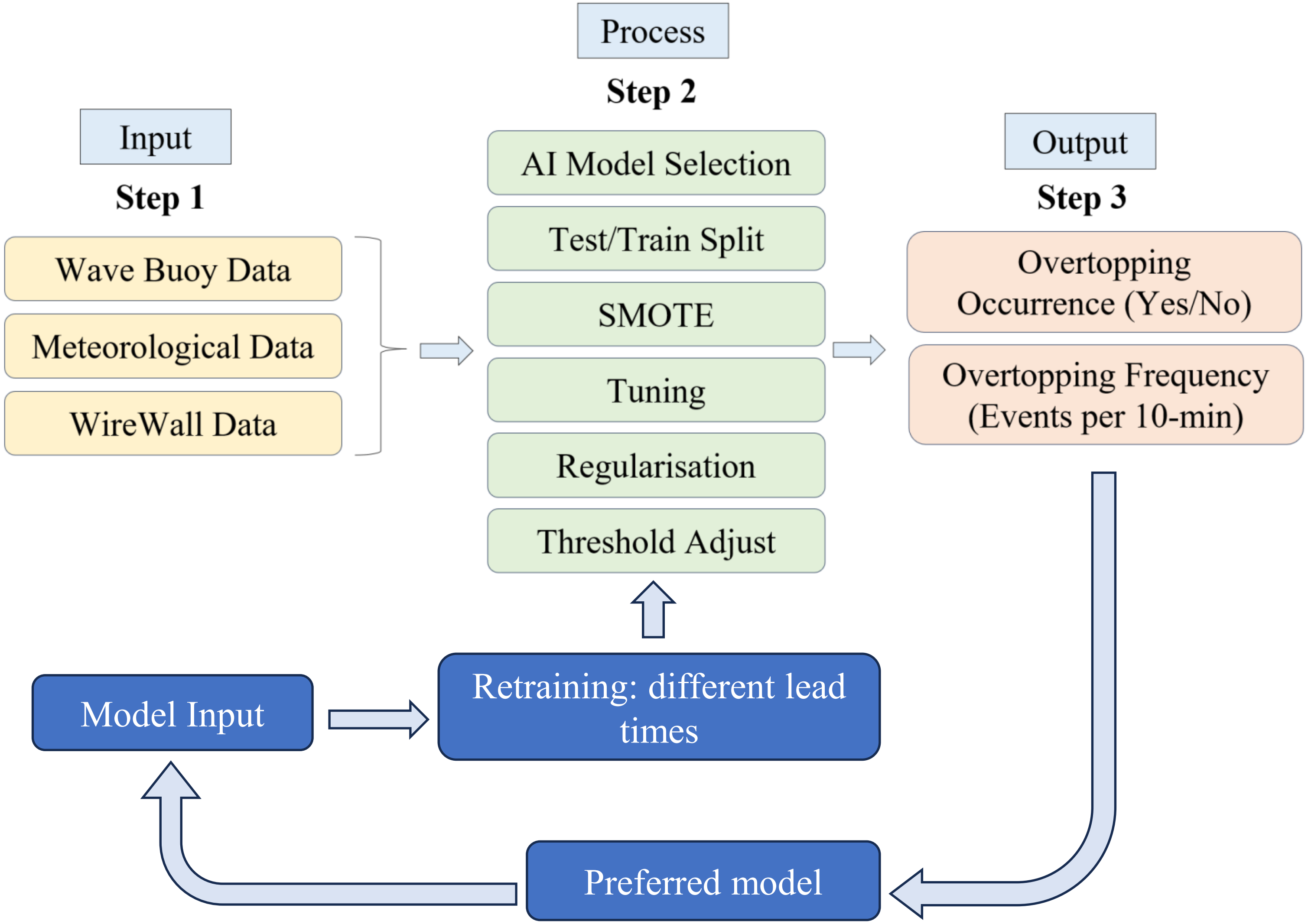
See McGlade et al. (2025). https://doi.org/10.1016/j.ocemod.2025.102510

AI workflow



AI workflow built based on observations and model data

1. Sensitivity to different AI models using observations as training and testing
    1. Random Forest (RF)
    2. Extreme Gradient Boosting
    3. Support Vector Machines
    4. Artificial neural Network
2. 80/20 training/testing
3. Model selection
4. Verification of selected AI model using metocean model data
5. “Retraining” and testing for different lead times (T+24, T+48, T>72)
6. Testing of operational overtopping model
7. Validation with video cameras

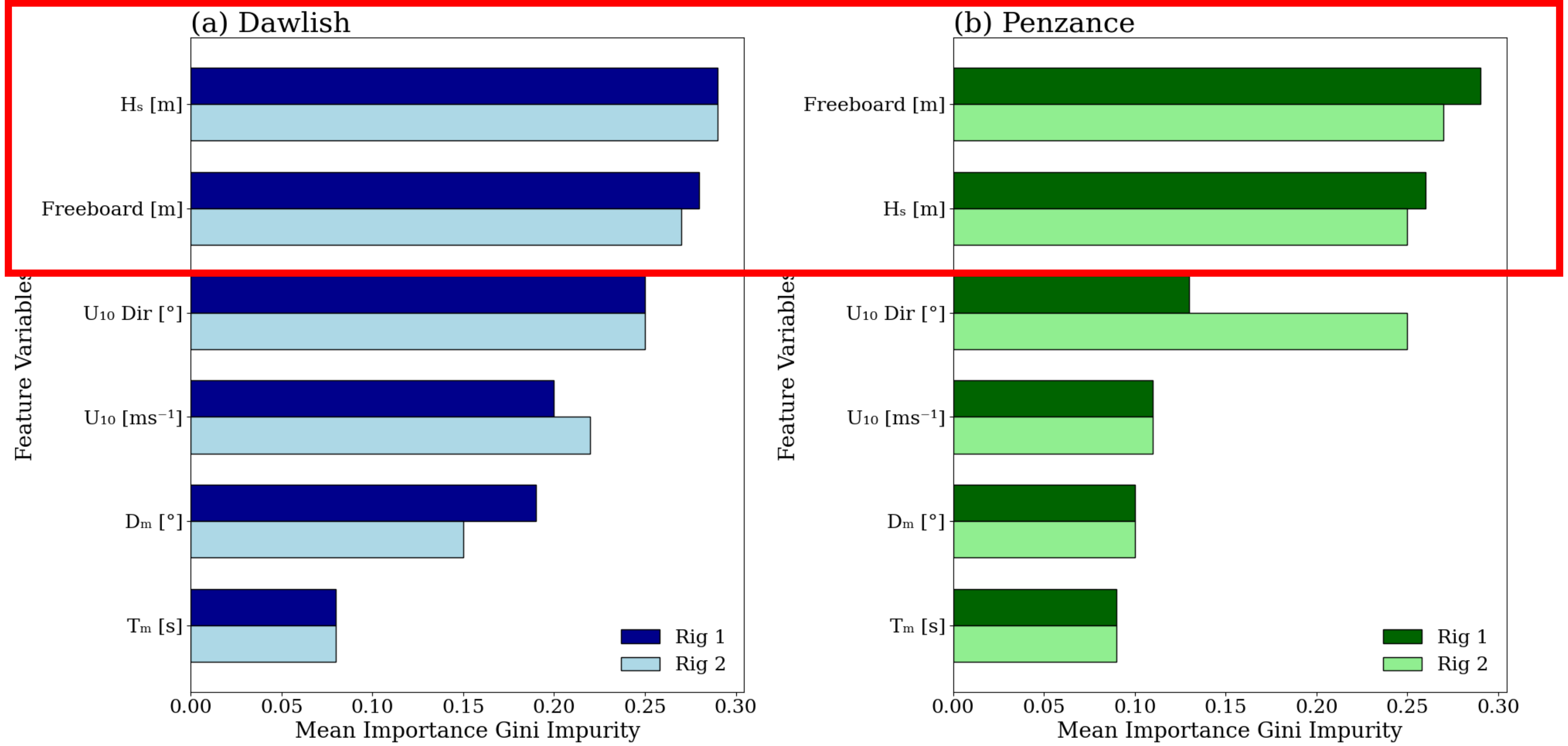
Results

Variables influencing wave overtopping

Variable importance metric by comparing and examining how each feature reduces the error

Freeboard and H_s are the most important feature variables influencing wave overtopping.

Most important at reducing Gini impurity



Low Gini Impurity = Data points more likely to belong to the same class

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Results

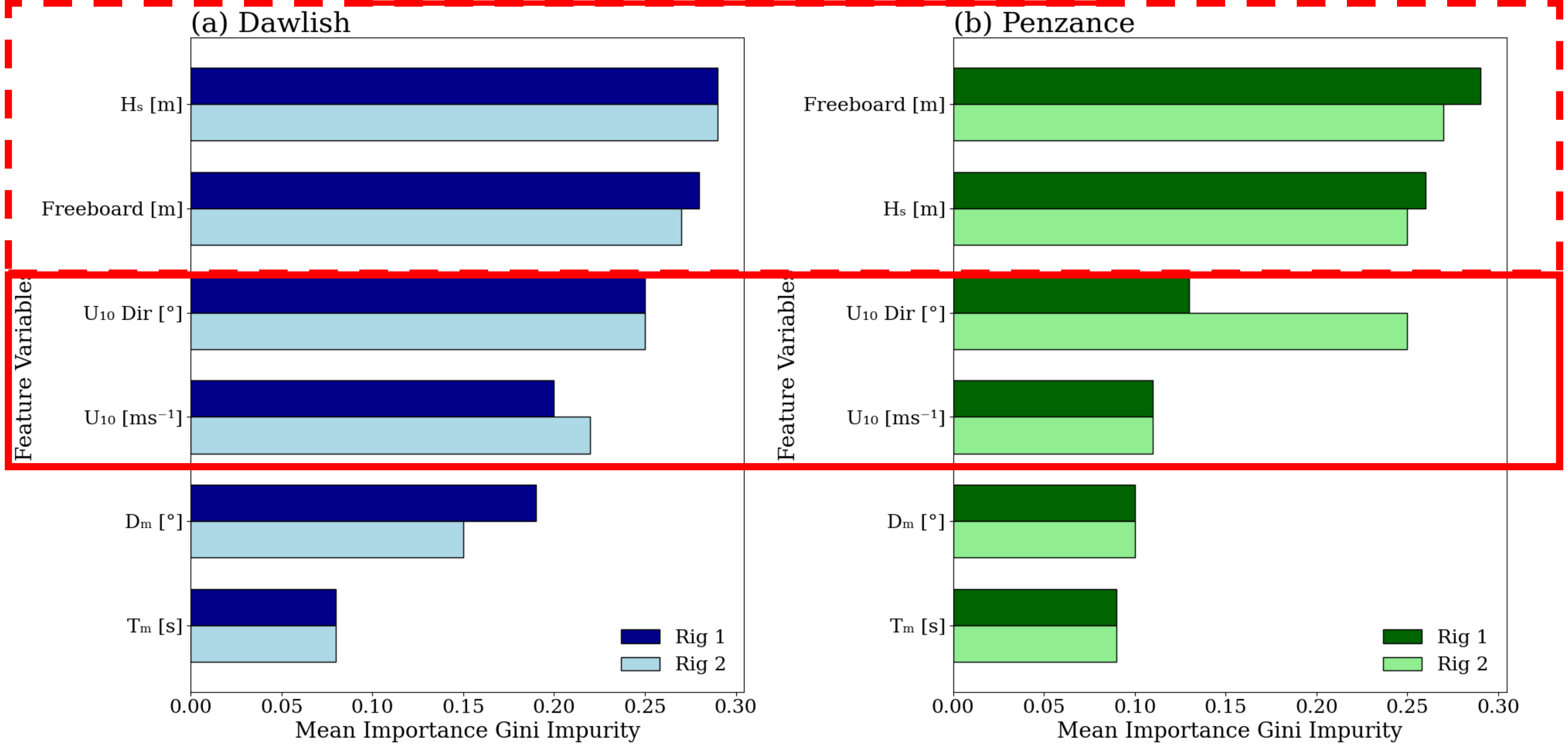
Variables influencing wave overtopping

Variable importance metric by comparing and examining how each feature reduces the error

Freeboard and H_s are the most important feature variables influencing wave overtopping.

Unlike EurOtop, AI models can also include wind and directional variables that will also clearly influence overtopping.

Most important at reducing Gini impurity



Low Gini Impurity = Data points more likely to belong to the same class

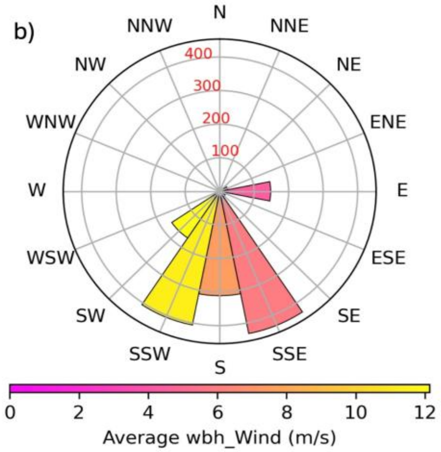
Variables influencing wave overtopping

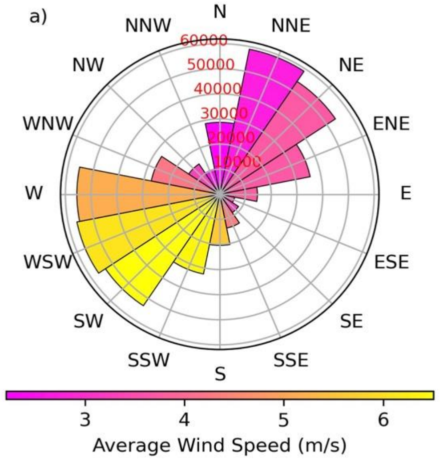
Effect of wind in overtopping

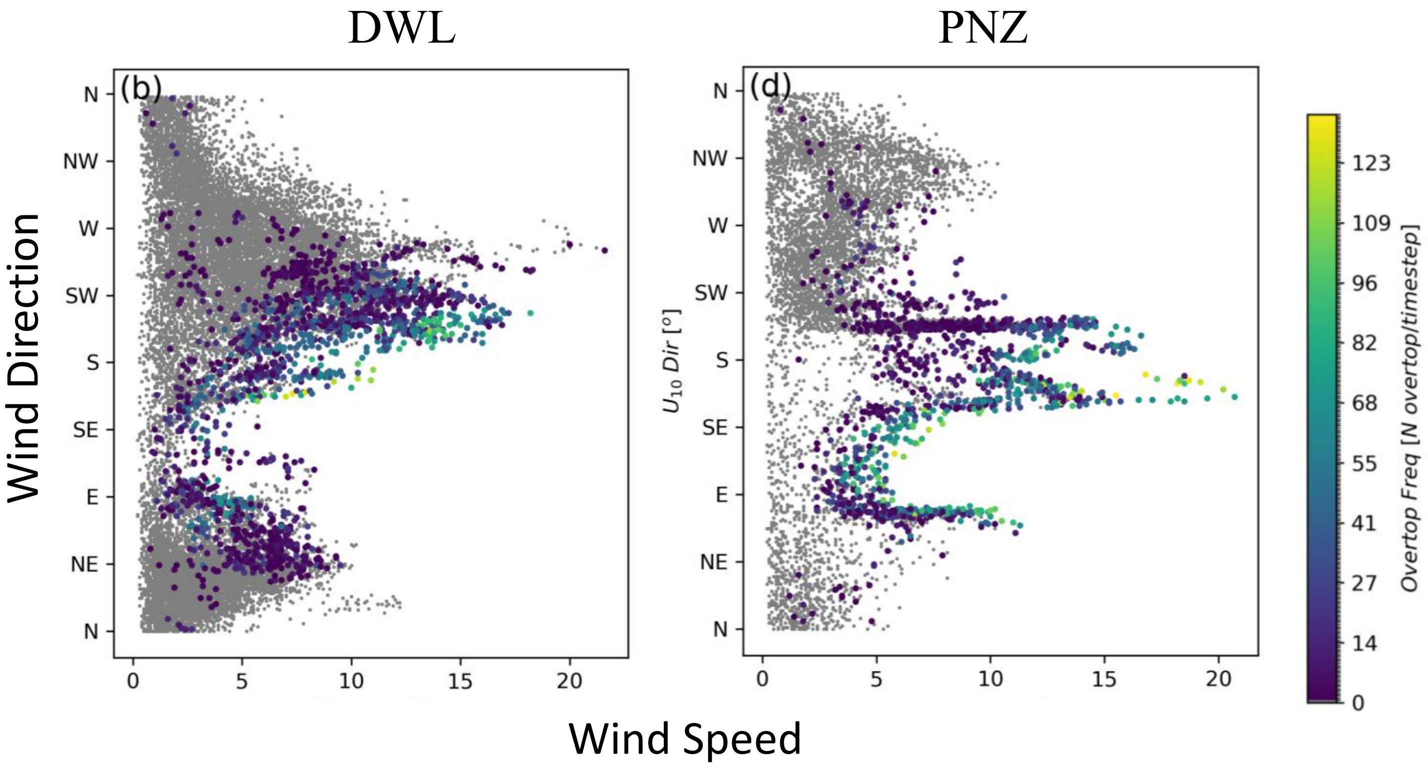
The model was retrained without wind features

Significant decrease in model skill when wind variables are neglected

U_{10} when overtopping occurs







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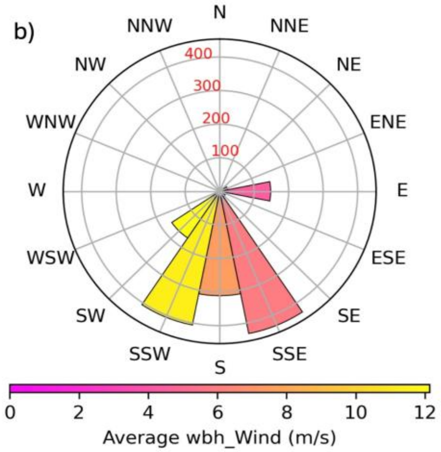

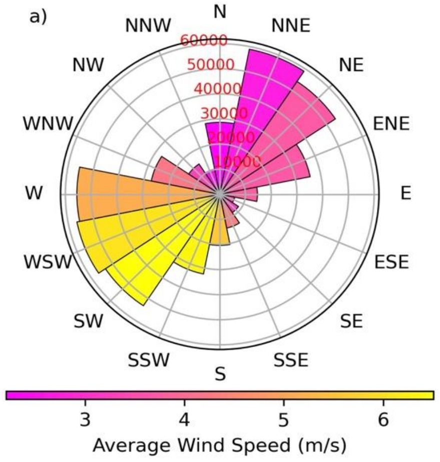

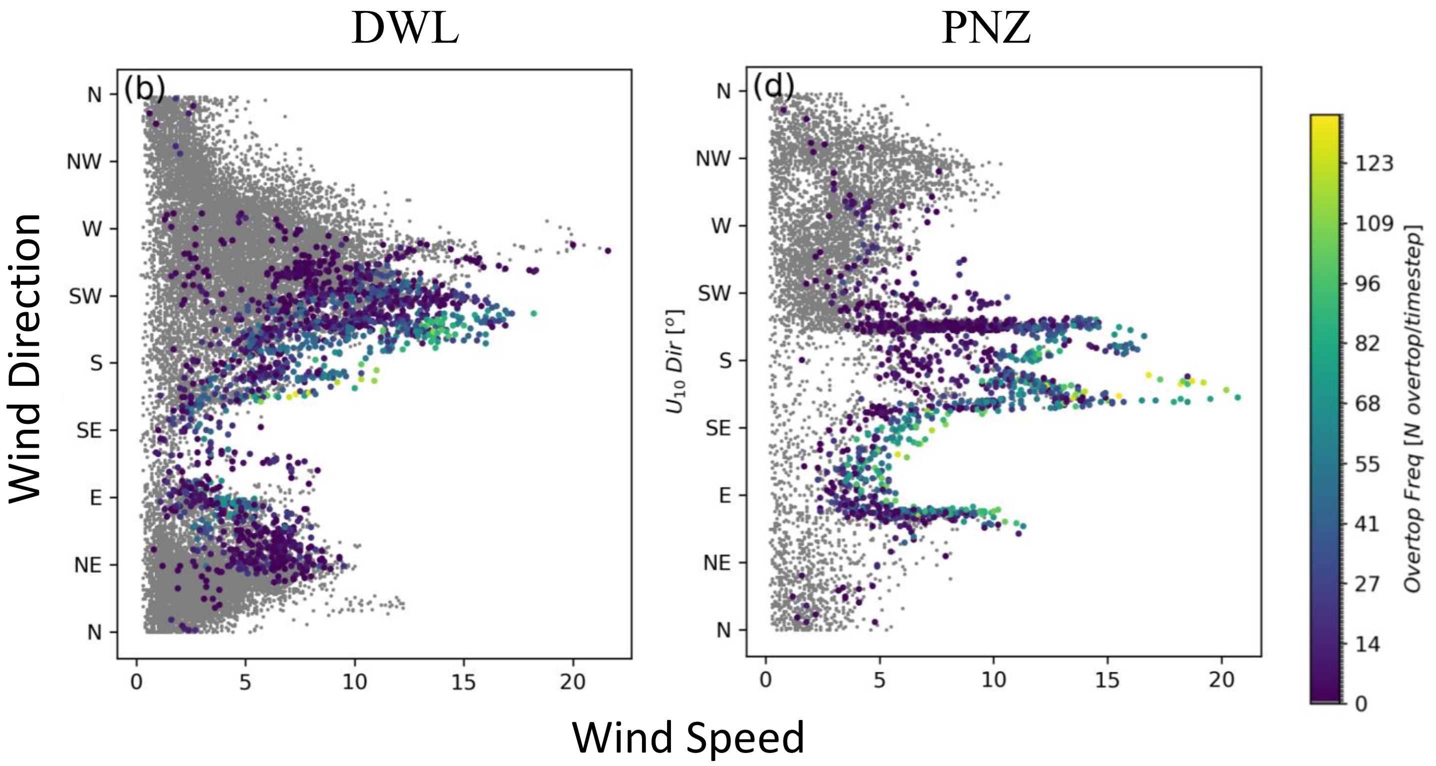

		Including U_{10}/U_{10} Dir				Excluding U_{10}/U_{10} Dir			
Rig	Location	R^2	MAE	RMSE	MSE	R^2	MAE	RMSE	MSE
1	Dawlish	0.81	0.66	3.05	9.28	0.65	0.87	4.07	16.6
2	Dawlish	0.76	0.23	1.90	3.62	0.19	0.40	3.48	12.1
1	Penzance	0.84	2.53	7.87	61.9	0.73	3.41	10.24	104
2	Penzance	0.84	1.18	1.53	2.33	0.25	1.70	5.37	29

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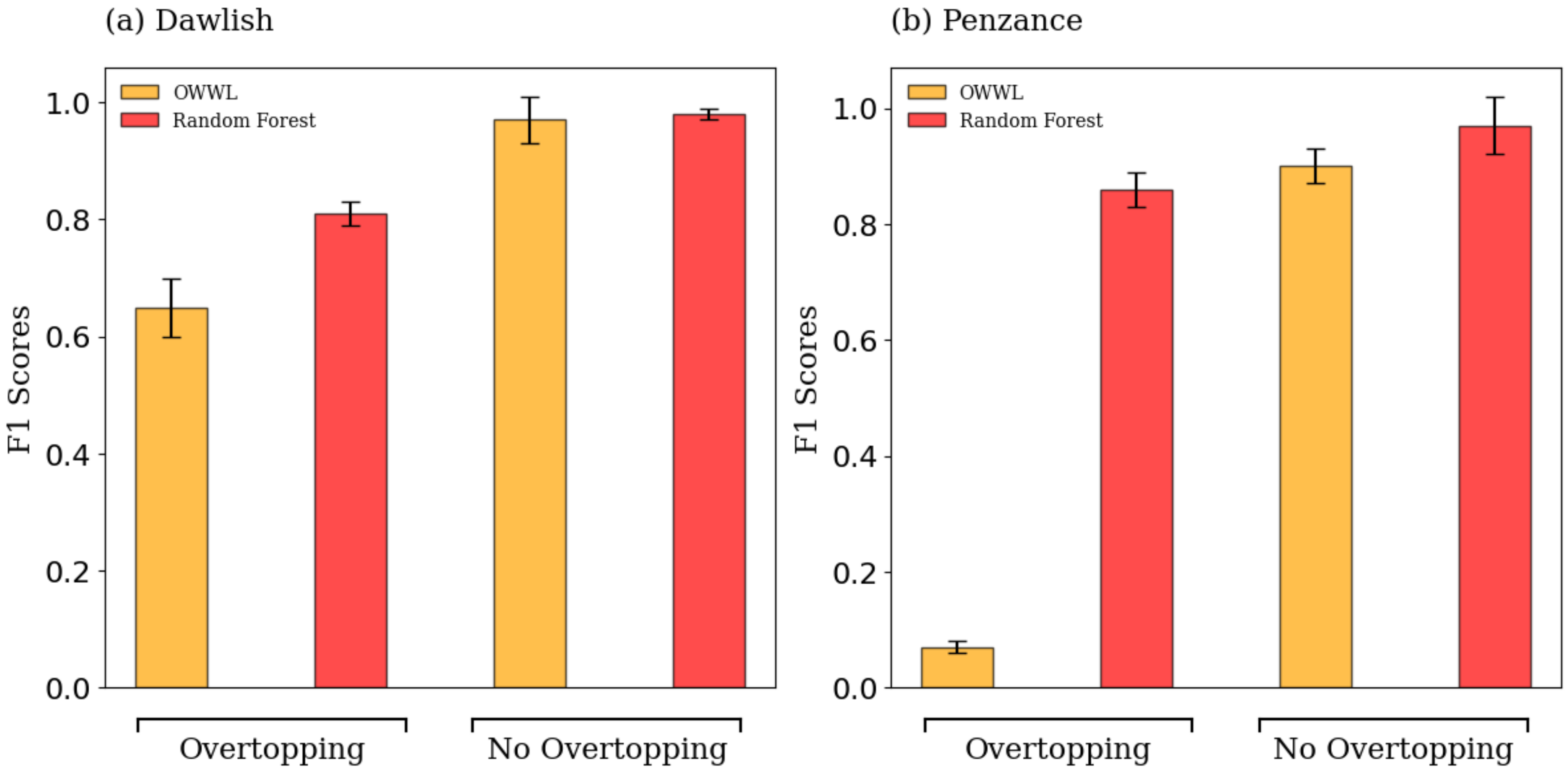
Comparison with OWWL (i.e. process based model + EurOtop)

$$\frac{Q}{\sqrt{gH_{m0}^3}} = a\exp\left[-\left(b\frac{R_c}{H_{m0}}\right)^c\right] \; for\ R_c \geq 0$$

Q < 0.1L/s/m → 0
Q > 0.1L/s/m → 1

$$\text{F1} = \frac{TP}{TP + 0.5(FP + FN)}$$



The random forest significantly outperforming OWWL for estimating overtopping.

Importance of incorporating U_{10} and U_{10} *Dir* when predicting the overtopping class. These are significantly important variables influencing overtopping, that the OWWL model (as well as most current empirical approaches) disregard.

McGlade, M., Valiente, N.G., Brown, J., Stokes, C., Poate, T. (2024). Investigating appropriate Artificial Intelligence approaches to reliably predict coastal wave overtopping and identify process contributions, *Ocean Modelling,* 194, 102510. https://doi.org/10.1016/j.ocemod.2025.102510

Deployable tool

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- Systems using process-based models are computationally demanding.
- The necessity to include nested regional models restricts their application in operational forecasting.

Observations:
Overtopping
Wind
Wave
Water level

Artificial Intelligence (AI):
80% events training
20% events testing

Camera Validation

Dawlish WireWall deployment

Overtopping predictions:
Daily update

AI tools

Operational forecast:
Met Office predictions 5 days in advance

Digital Twin:
User interface to explore uncertainty in inputs

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Deployable tool

- SPLASH DT hosted in https://coastalmonitoring.org/ccoresources/SPLASHDT
- User can play with input variables, re-run model and get updated overtopping

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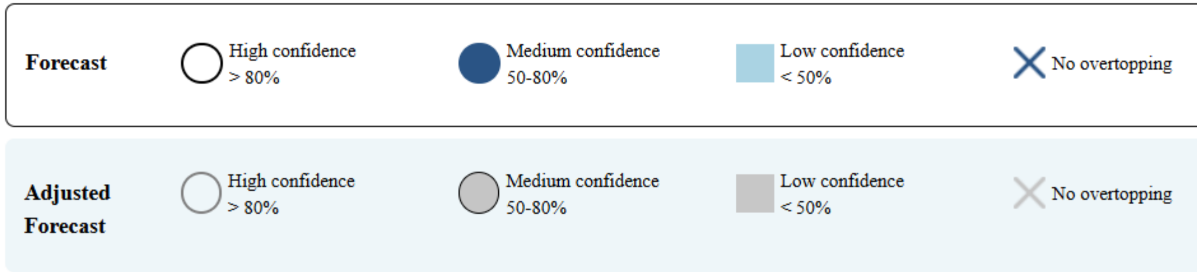

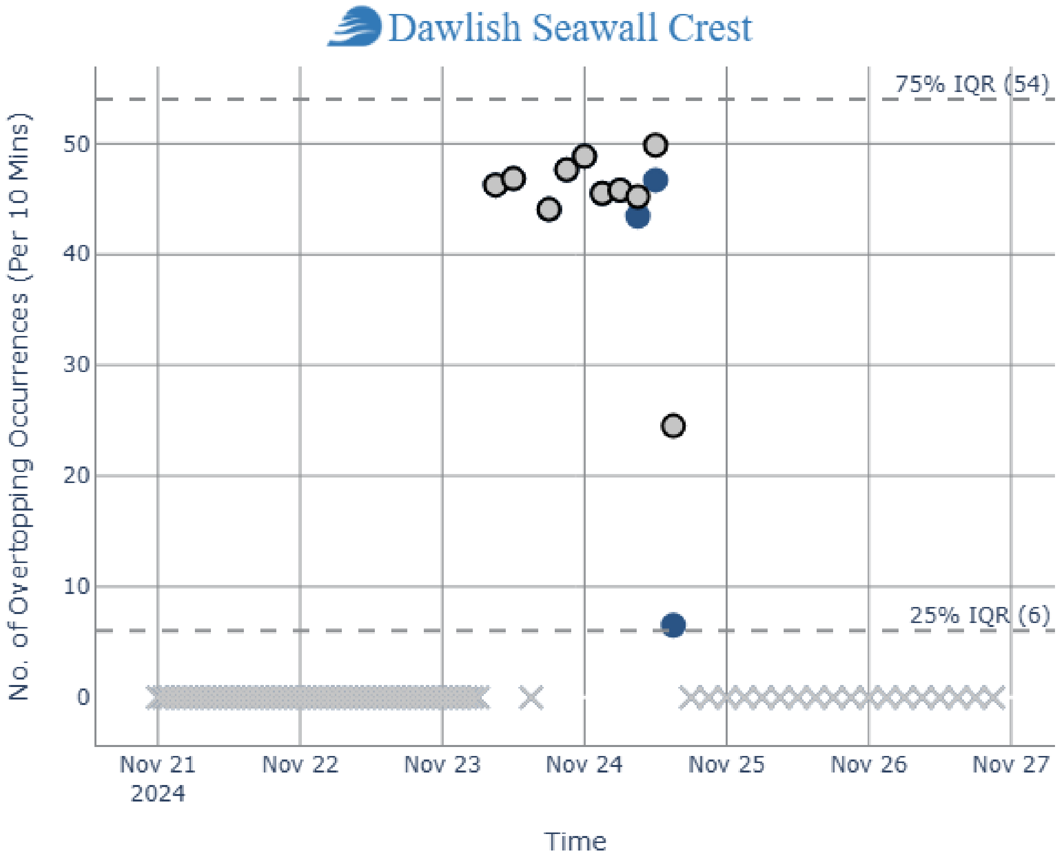

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There are **significant opportunities for using machine learning approaches to predict wave overtopping**: <u>good accuracy, potential for generalisation, and high speed and computational efficiency.</u>

Machine learning **random forests offer the highest predictive performance** even when comparing against very developed operational forecasting systems (nowcasting).

U_{10} and U_{10} *Dir* are significantly important variables influencing overtopping, that current empirical approaches disregard.

Opportunities to generalise these AI approaches to multiple locations across the UK **if overtopping observations are available**. Future testing to measure overtopping in #gravelbeach project using LiDAR 2D.

In progress: Variable importance in overtopping climate projections – using transformer models incorporating positional encoding, for enhancing the spatial and temporal predictions of wave overtopping.

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THANKS!

https://coastalmonitoring.org/ccoresources/SPLASHDT/

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Wave overtopping – binary

Example Dawlish – Overtopping: Yes or No

Rig	Model	F1	Precision	Recall	Accuracy	MCC	Brier Score
1	Random Forest	0.83	0.85	0.80	96%	0.79	0.031
	XGBoost	0.81	0.82	0.79	94%	0.77	0.032
	Neural Network	0.70	0.72	0.67	93%	0.77	0.032
2	Random Forest	0.80	0.79	0.81	97%	0.76	0.011
	XGBoost	0.78	0.74	0.80	95%	0.71	0.019
	Neural Network	0.72	0.70	0.74	93%	0.70	0.034

Random forest outperforms the other two models

- FN always when Hs = 0.7-1.1 m, low WL and low Tm
- FN always when overtopping freq is very low
- Most FN during summer (misclassification) – less training data during summer

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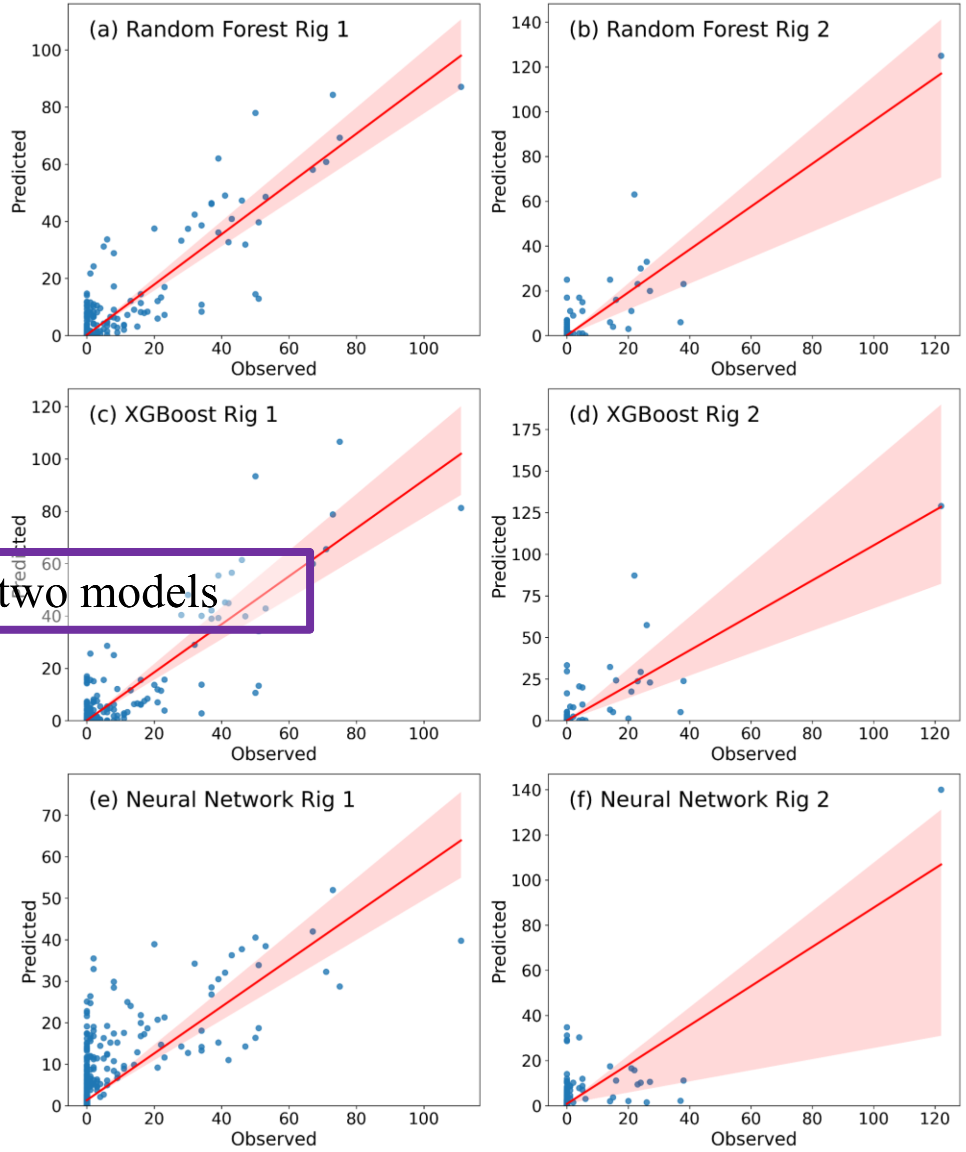
Wave overtopping – frequency of overtopping per 10min window

Example Dawlish – Overtopping Frequency

Rig	Model	R^2	RMSE	MSE	MAE	Mean Bias	T-Test
1	Random Forest	0.81	3.05	9.28	0.66	0.11%	t = 1.37; p = 0.17
	XGBoost	0.77	3.28	10.7	0.69	0.01%	t = 0.15; p = 0.88
	Neural Network	0.45	5.1	26	2.43	0.83%	t = 6.42; p = < 0.01
2	Random Forest	0.76	1.90	3.62	0.23	0.08%	t = 0.55; p = 0.58
	XGBoost	0.53	2.65	7	0.30	0.16%	t = 1.03; p = 0.30
	Neural Network	0.45	2.85	8.14	1.08	0.83%	t = 5.57; p = 0.675

Overall, random forest outperforms the other two models

- Good correlation coefficients for XGBoost and random forest modelling.
- The neural network performs well, but not as strongly as the decision tree learners.



Variables influencing wave overtopping

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D03 – DWL Rig 1
P03 – PNZ Rig 1

- WL – Asymmetry. Overtopping more freq 2h before HT
- Tidal modulation. Waves > when flooding tide
- Hs – overtopping occurs from Hs~1m, with low Hs in PNZ
- Wave steepness – overtopping more freq with steeper waves in DWL

H_s when overtopping occurs