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The influence of atmospheric stability on floating-lidar-observed turbulence intensity and its correction via machine learning

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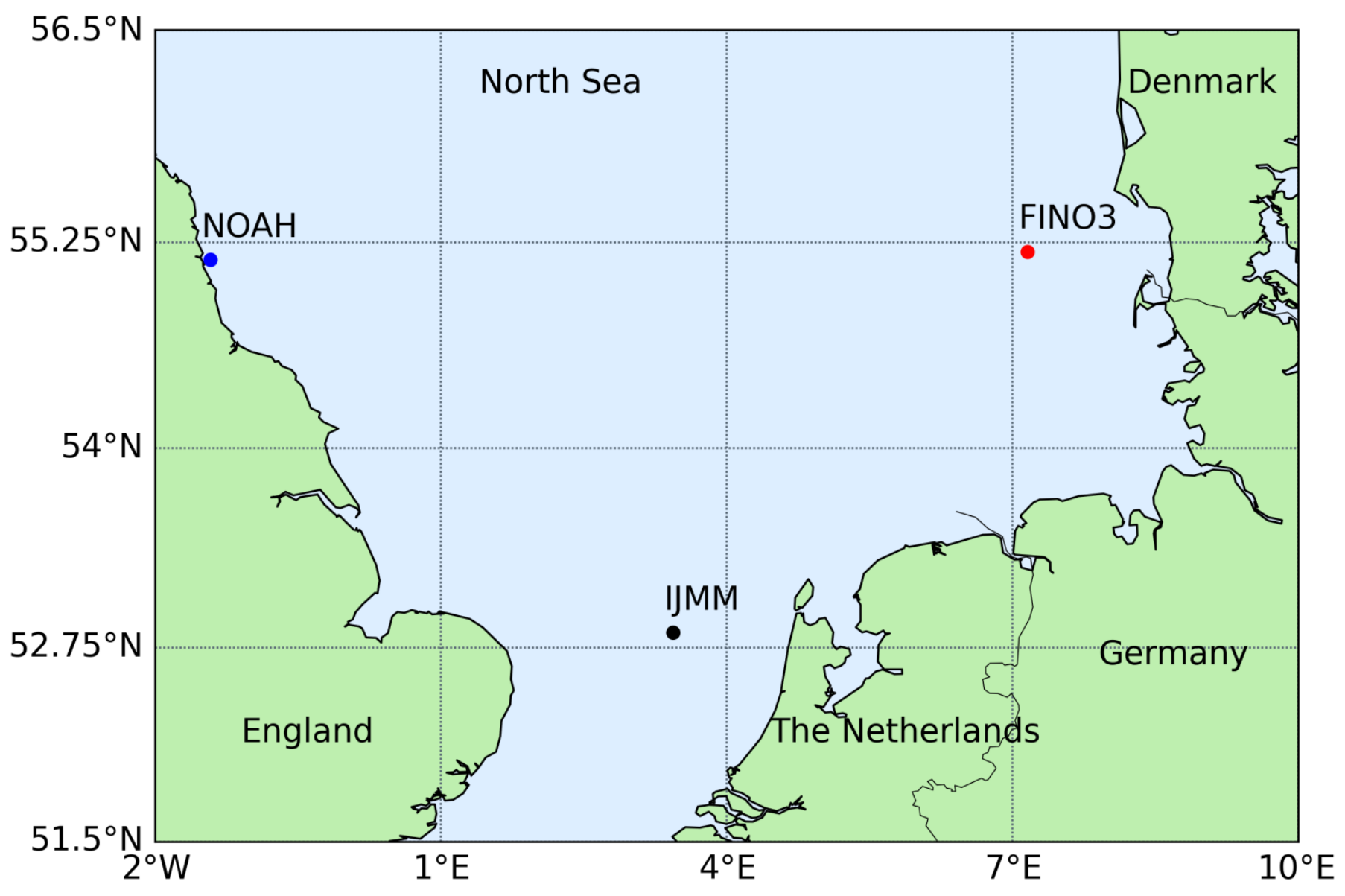
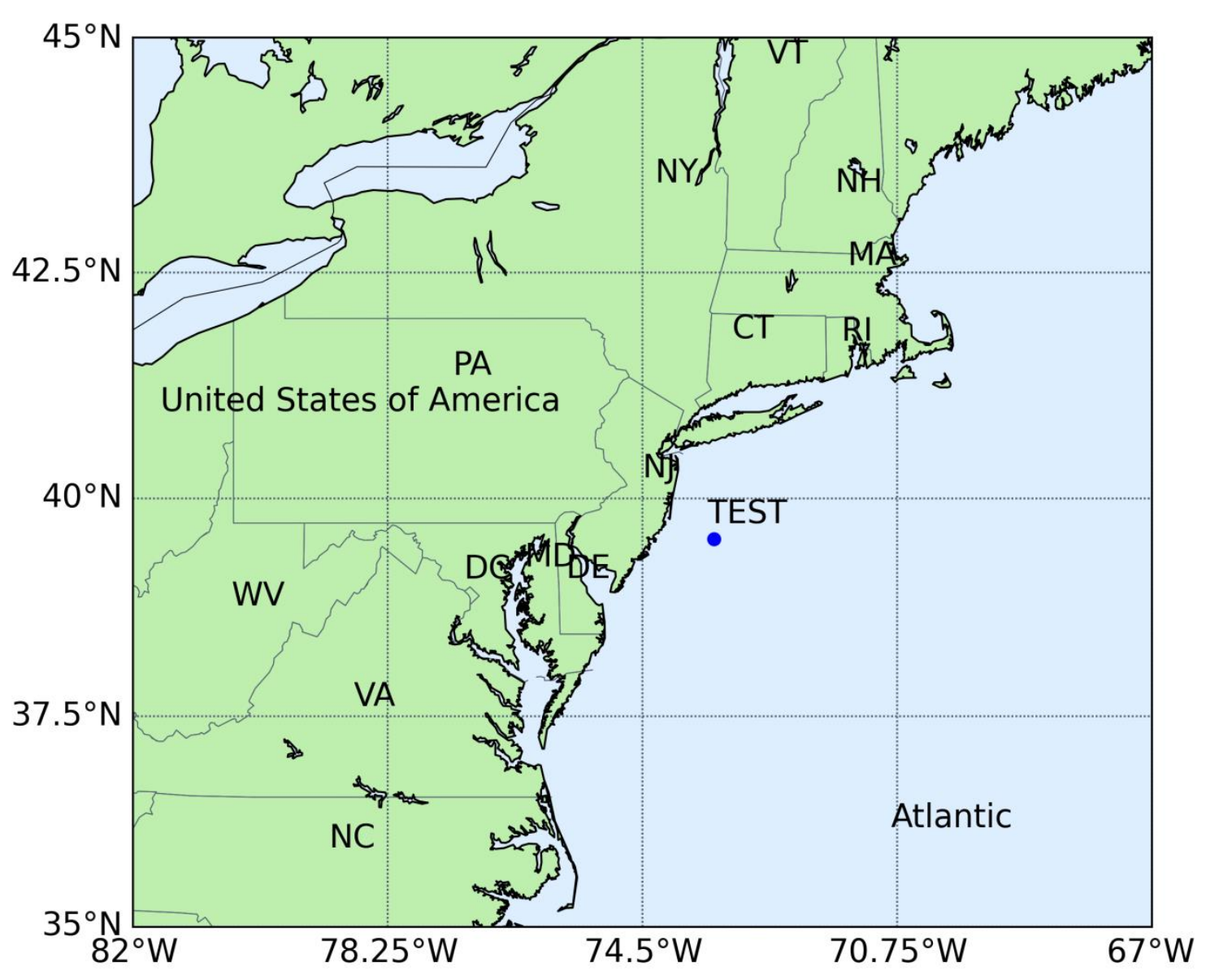
Measurement campaigns

This work tackles the influence of atmospheric stability on floating-lidar-observed turbulence intensity in the context of its correction with respect to metmast reference using a decision-tree-based machine-learning algorithm developed by Rapisardi et al (2024). The algorithm is tested using data from a measurement campaign financed by NYSERDA, in which the EOLOS FLS200-E06 was installed in the Atlantic from August 2019 to August 2022.

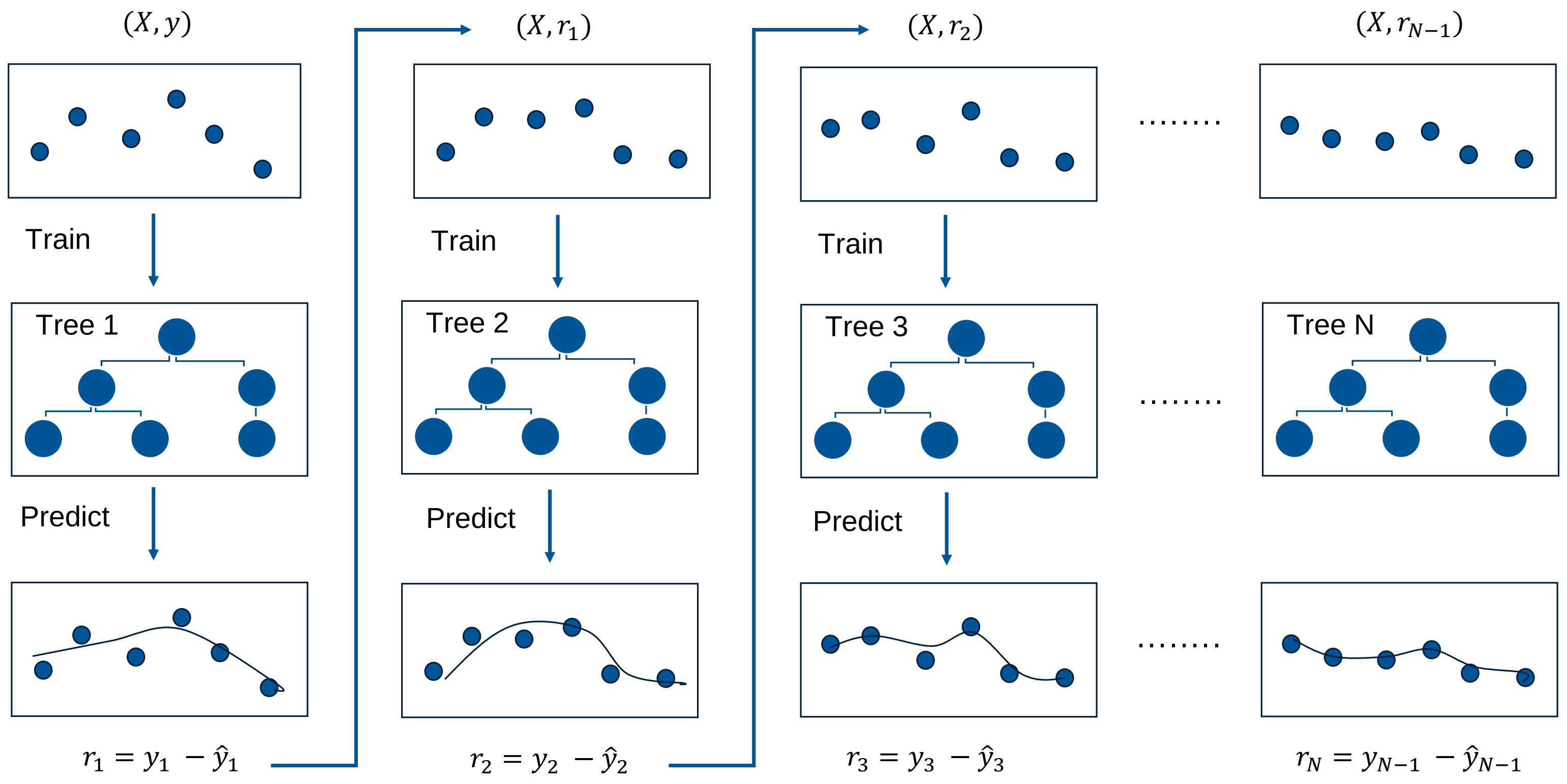


Training sites in the North Sea

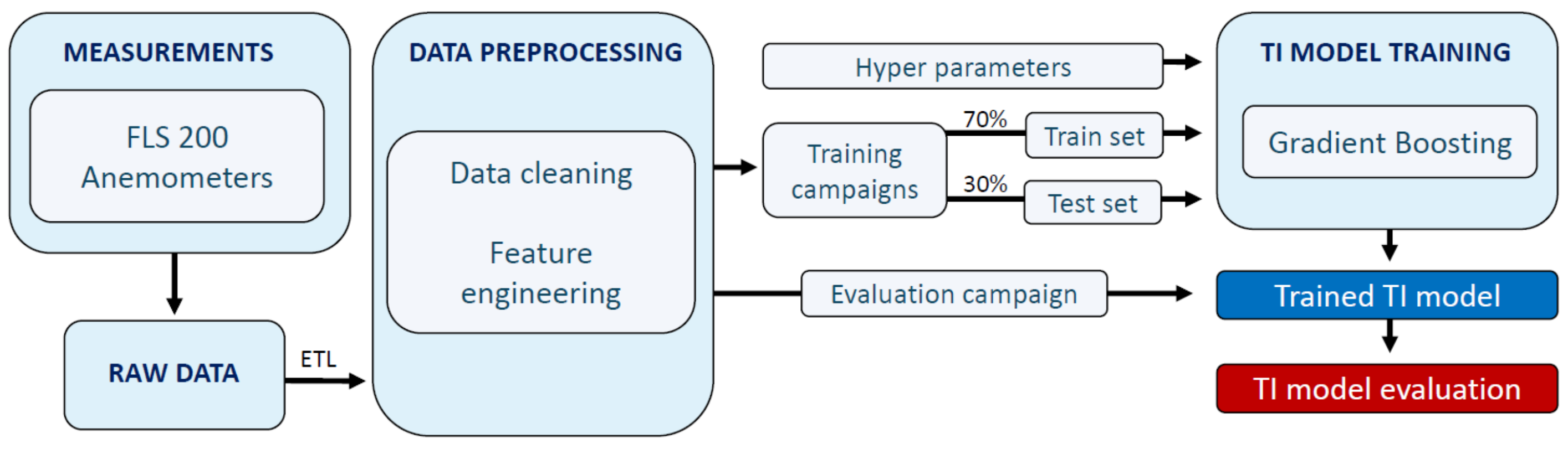


Test site in the Atlantic

Feature	NOAH	IJMM	FINO3	TEST
Total of campaigns	20	1	1	1
Distance to shore [km]	5.42	82.45	81.5	62.21
Total of 10-min records	131,228	31,392	5,894	78,768



Gradient boosting decision tree


MEASUREMENTS

FLS 200 Anemometers

RAW DATA

ETL

DATA PREPROCESSING

Data cleaning

Feature engineering

Hyper parameters

Training campaigns

70%

Train set

30%

Test set

Evaluation campaign

TI MODEL TRAINING

Gradient Boosting

Trained TI model

TI model evaluation

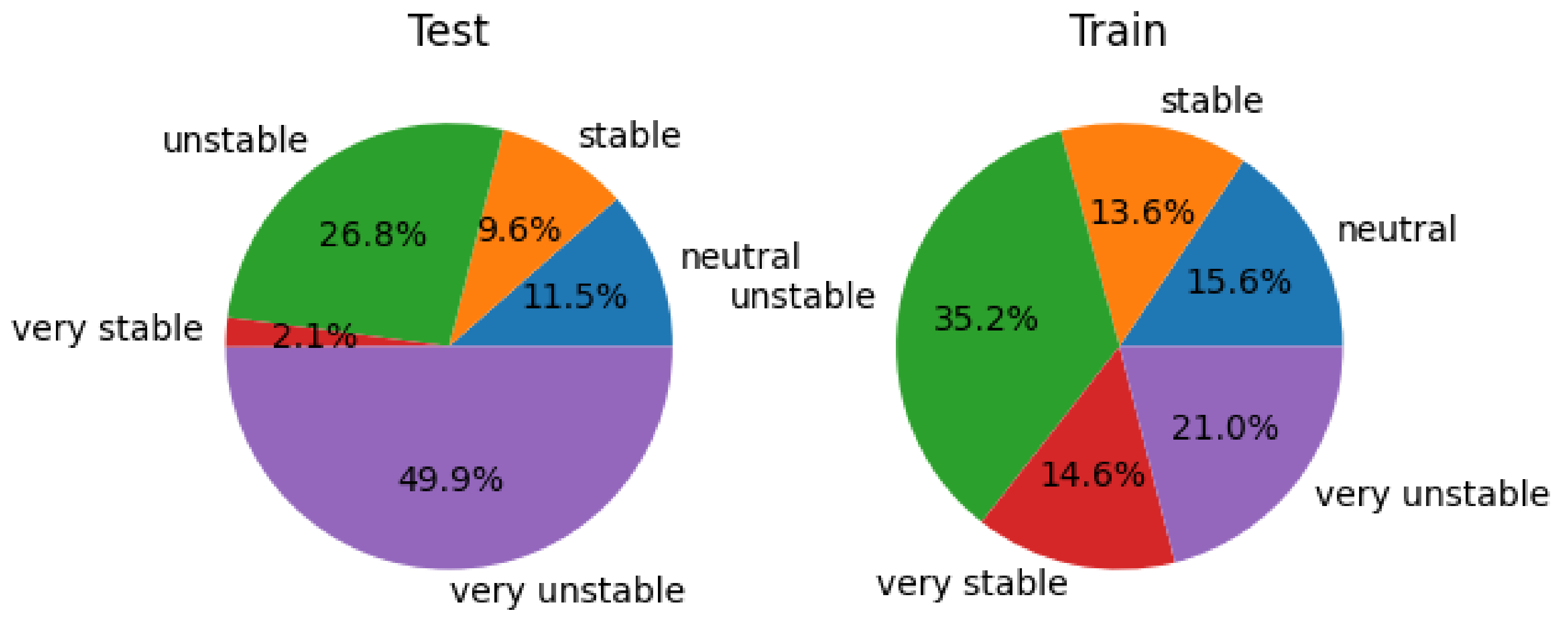
Model workflow

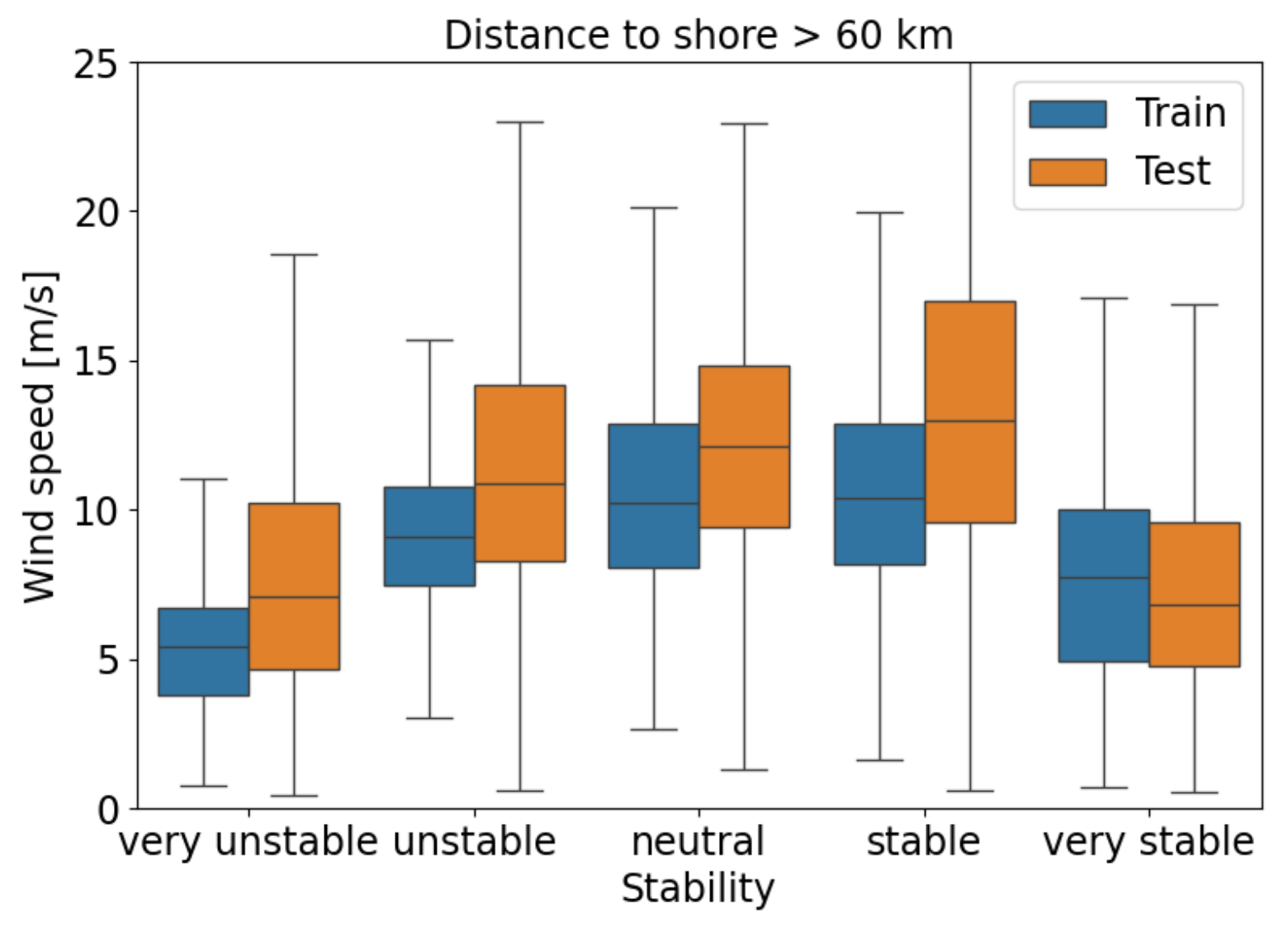
Results

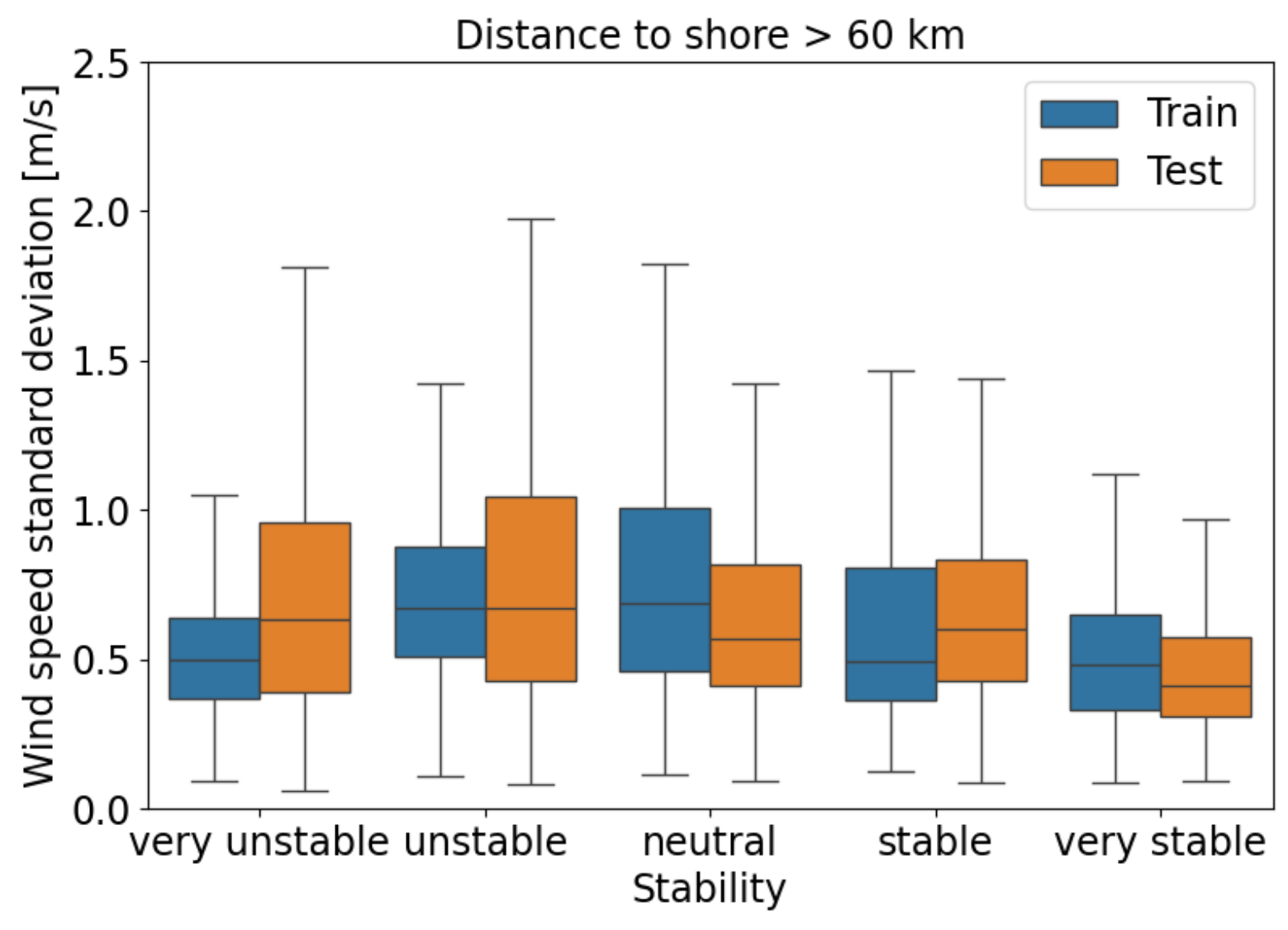
The atmospheric stability was assessed via Obukhov length derived from bulk Richardson number computed from floating-lidar-measured metocean parameters (Hatfield et al., 2023).

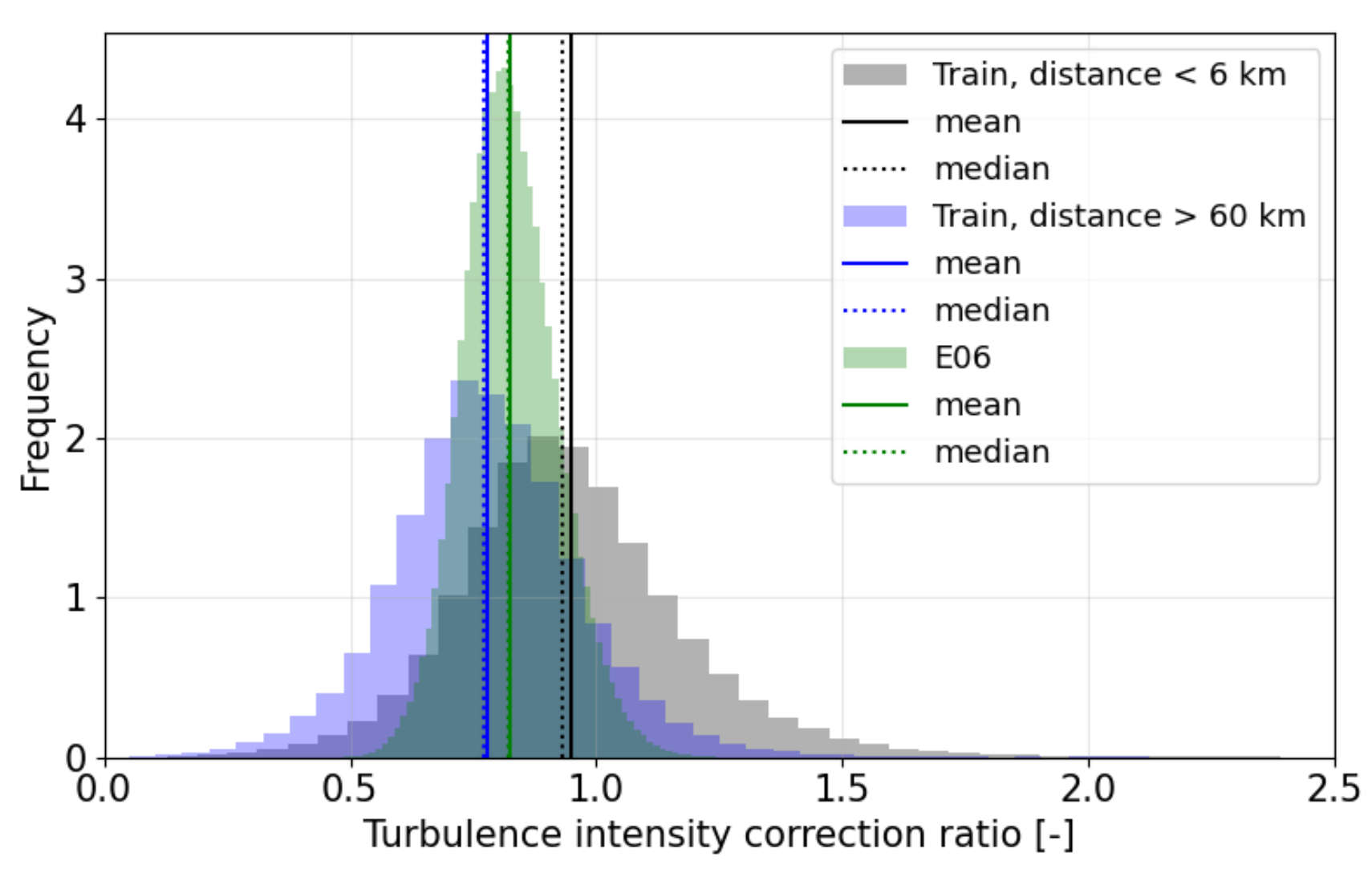
Stability is classified based on ranges of Obukhov length, L: very unstable (-100 <= L < 0), unstable (-500 < L < -100), neutral (L >= |500|), stable (100 < L < 500), and very unstable (0 < L <= 100)

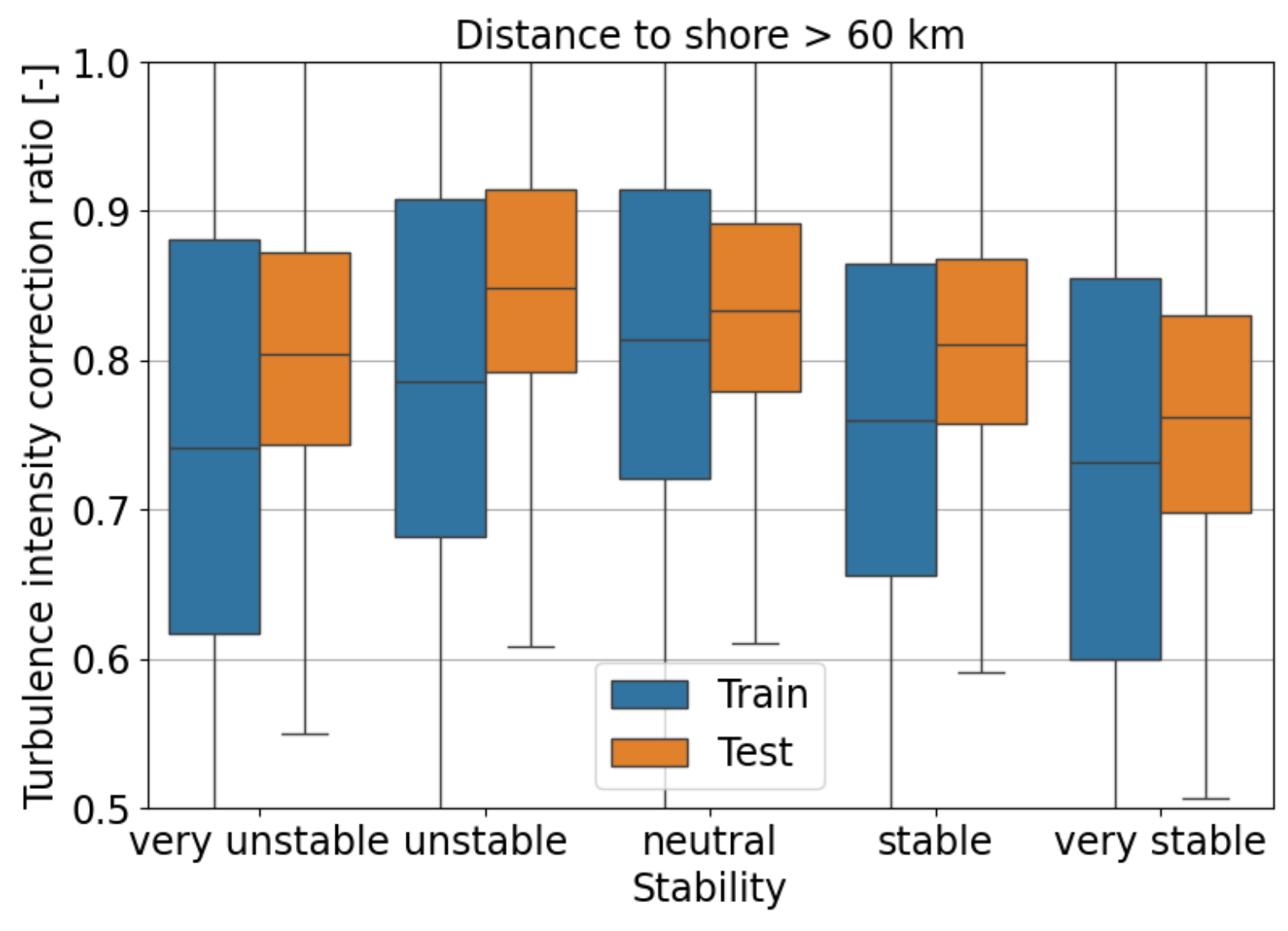
- The higher the distance to shore, the lower the average turbulence-intensity correction factor.
- Turbulence-intensity relative error with respect to mast reference tend to increase out of the neutral stability.
- Accordingly, the model compensates more when the atmosphere is not in neutral regime (e.g., very unstable and very stable regimes have the lowest correction ratios).











References

Rapisardi, G., da Silva, M. P. A., & Miquel, A. (2024, June). A Machine Learning Approach to Correct Turbulence Intensity measured by Floating Lidars. In Journal of Physics: Conference Series (Vol. 2767, No. 9, p. 092050). IOP Publishing.

Hatfield, D., Hasager, C. B., & Karagali, I. (2023). Vertical extrapolation of Advanced Scatterometer (ASCAT) ocean surface winds using machine-learning techniques. Wind Energy Science, 8(4), 621-637.