Machine learning improvements to WindCube turbulence intensity measurements at five sites in Northern Europe

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Motivation

- Lidar turbulence intensity (TI) measurements generally show ~10% high biases compared to cup anemometers, and lower R2 than for wind speed.
- In wind energy development, Site Suitability analysis today requires cup anemometer TI measurements to estimate the fatigue loads on the turbines.
- Lidar TI measurements are not generally accepted for this analysis today.
- If we can correct lidar TI measurements and demonstrate good agreement with cup TI, this will allow for complete wind energy development with “standalone” lidar: both Energy Yield Assessment (EYA) and Site Suitability analysis.
- Industry groups such as CFARS and the DNV-JIP are hard at work on this topic.

Approach

To test whether a pure machine learning approach can adjust WindCube TI adequately for use with Site Suitability, you need a sufficient dataset.

What makes a dataset sufficient?

1. Training and testing data must be drawn from similar distributions.
2. Training data must cover as wide a range of conditions as is to be expected in model's application to future data.

Planetary boundary layer wind turbulence, in flat terrain, measured by Class 1 anemometry on IEC-complaint met masts and by collocated, identical wind lidars, with sufficient seasonality to include representative ranges of atmospheric parameters such as wind speed, wind shear, temperature, and stability

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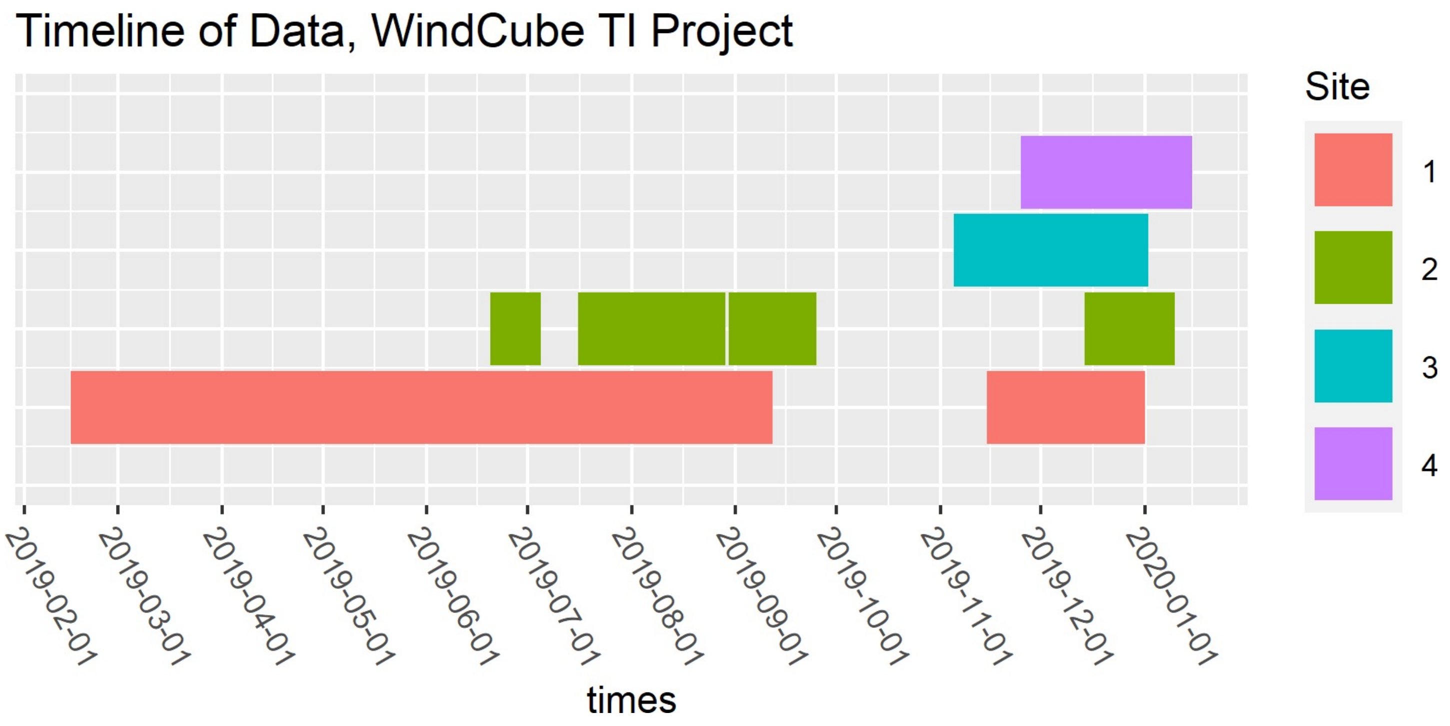
Dataset



- 14 WindCube lidars
- 4 flat terrain sites in Northern Europe (1 screened out)
- Class 1 anemometry
- IEC-compliant towers
- Good seasonal distribution
- All devices WindCube v2.1
- Line-of-sight (LOS) 1Hz data reprocessed with scalar, vector, hybrid wind field reconstruction
- Additional LOS statistics generated for all five beam directions
- 221K samples, ~5.5 years of data

Machine learning model : XGBoost

The XGBoost model is:

- **Supervised**: the features are trained using an objective function (RMSE in our case) to the mast TI (“labels” or “targets”).
- **Ensemble**: hundreds of weak learners are combined to make the prediction.
- **Bootstrap aggregated (“bagged”)**: only a random subset of the data is used to train each weak learner.
- **Gradient-boosted**: each tree is trained sequentially, with the poorest performing predictions given higher weighting (boosted) in each new, weak learner. The weights are determined by the (gradient) of the loss function.
- **Classification and Regression Tree (CART)**: each weak learner in the ensemble is a decision tree.

Feature + label engineering

Features

- Vector, Scalar, and Hybrid WFR wind speeds
- Vector, Scalar, Hybrid WFR turbulence intensity
- Normalized vertical LOS standard deviation (θ_{∞})
- Other LOS statistical data
- Standard deviation of wind direction
- Wind shear, wind veer

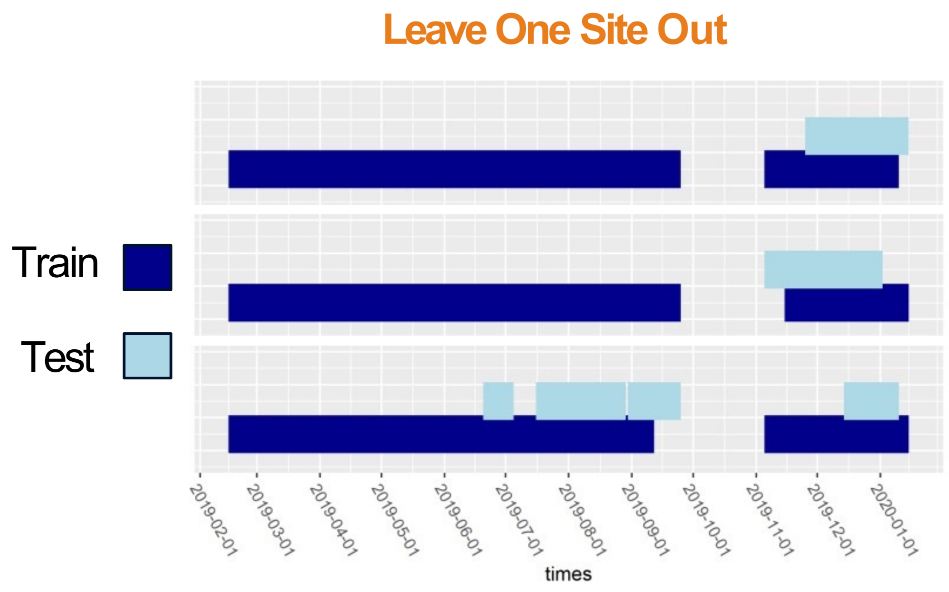
Labels

- TI Error, Percent
- TI Error, Difference
- **Standard Deviation Error, Percent**
- Standard Deviation Error, Difference
- Mast Standard Deviation

Cross validation

Leave one site out

- All results presented are from cross validation
- Each site weighted equally in training
- 75%/25% split for each test site



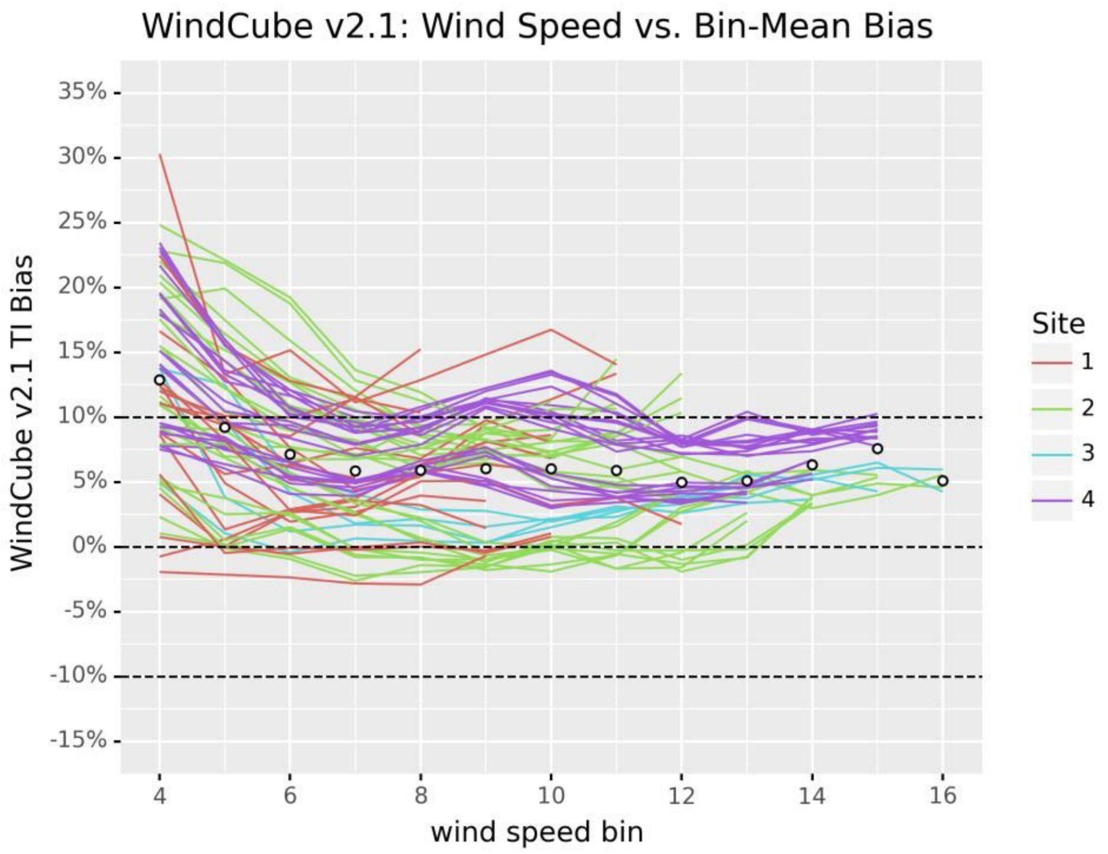
Various KPI results

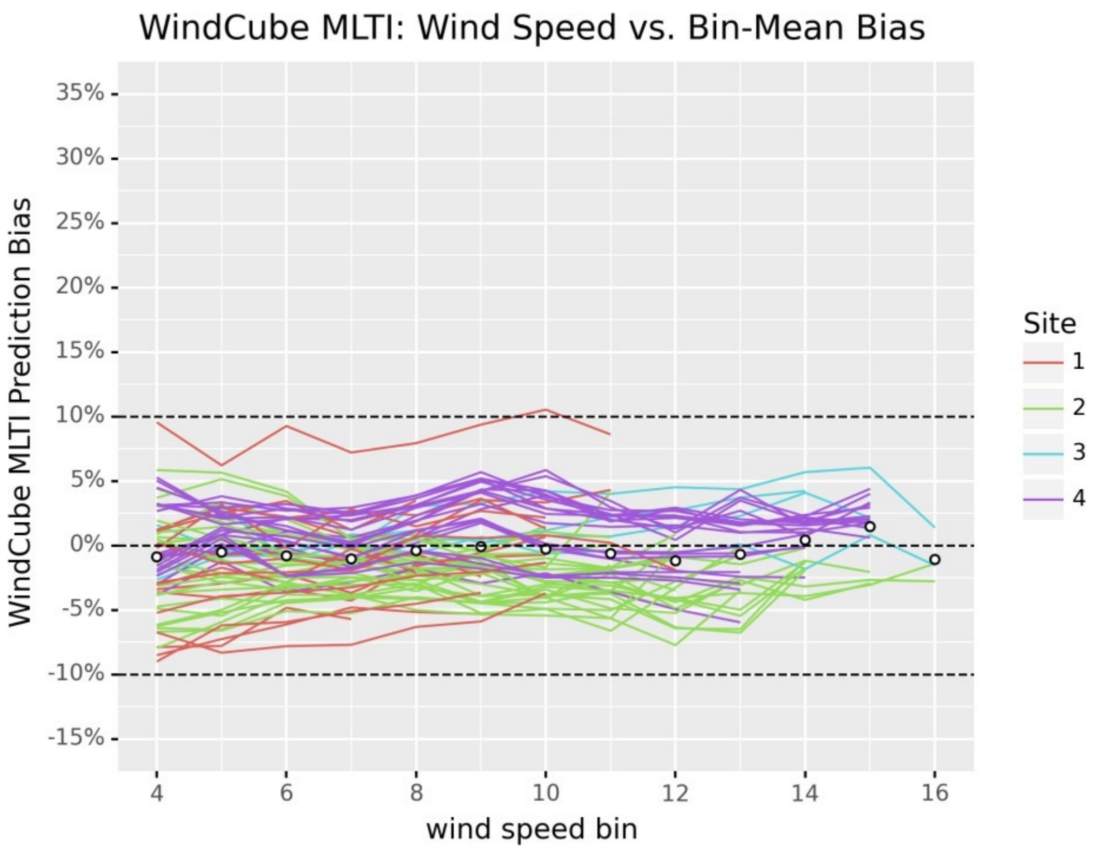
Linear regression	Slope	Intercept	Bias	R2
WindCube MLTI	0.988	0.003	1.007	0.901
WindCube v2.1	0.854	0.010	0.928	0.884

Wind speed binned TI	Average: relative mean bias error	RMS: relative mean bias error	% within ±5%
WindCube MLTI	-0.5%	3.2%	89.0%
WindCube v2.1	7.0%	8.7%	35.8%

Average TI	Average: relative mean bias error	RMS: relative mean bias error	% within ±5%
WindCube MLTI	-0.7%	3.0%	90.8%
WindCube v2.1	7.0%	8.4%	33.8%

Wind speed binned relative mean bias error





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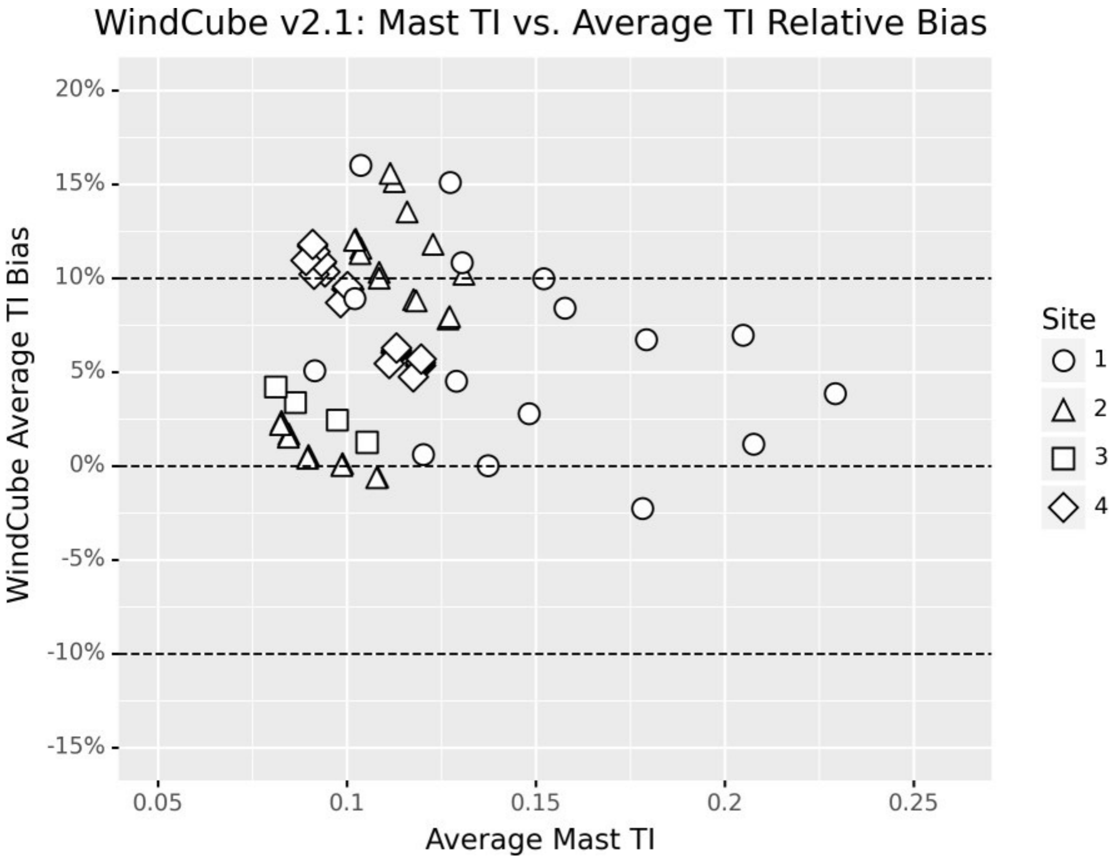
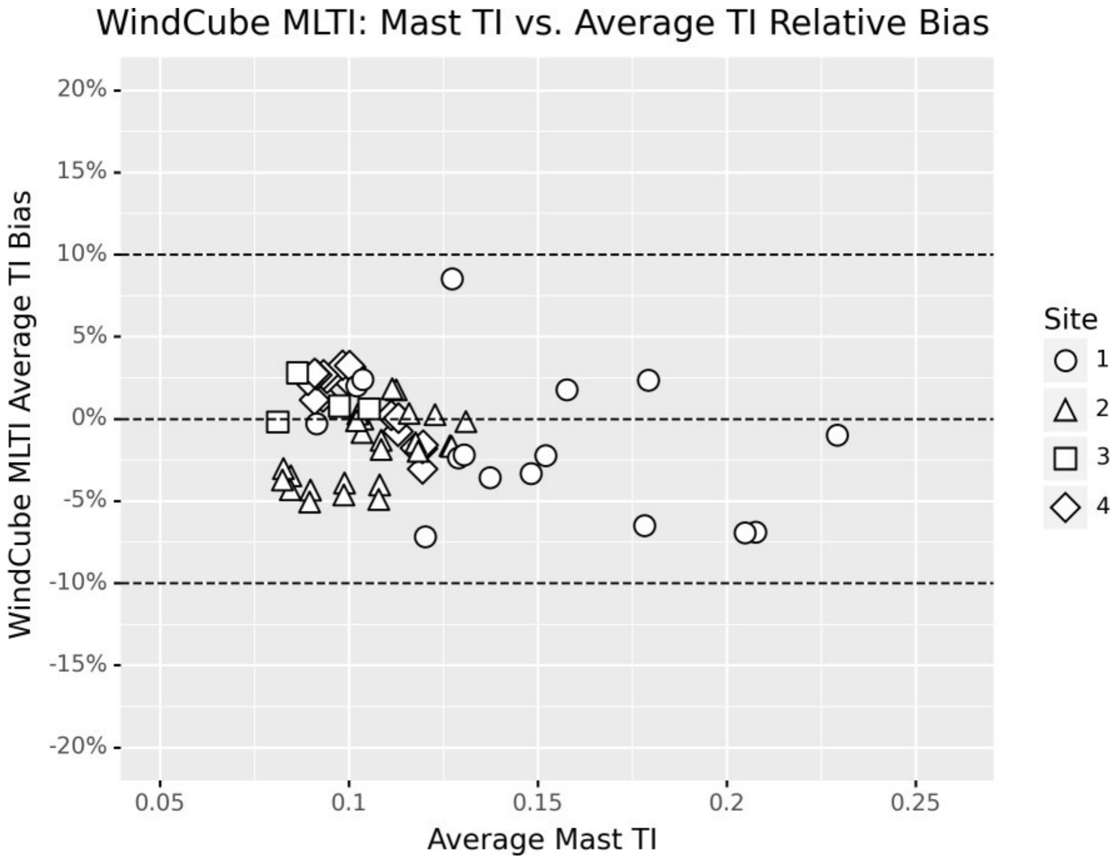
Average TI relative mean bias error by average mast TI





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Average TI relative mean bias error by average mast TI

- Proof of concept successful:
  - **Machine learning can be used to greatly improve lidar TI**
- All KPIs show substantial improvement:
  - **Regression slopes and R^2, average TI error, wind speed bin mean TI error**
- What are the limits of this model's applicability?
  - **Sites are on the lower end of global TI distributions How does it perform in the American Midwest?**
- Apply machine learning to different site distributions:
  - **Complex terrain, offshore, forested, high TI, cold climate, et al**
- Ongoing industry collaborations CFARS and DNV-JIP to further validate model
  - **Test + improve model according Turbine OEM, IE, and developer consensus KPIs**

Thank you

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