PO.261

Evaluation of performance of machine learning-adjusted WindCube v2.1 turbulence measurements

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Summary

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 Site Suitability, you need a sufficient dataset.

What makes a dataset sufficient?

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

Machine Learning Model

The XGBoost model is: Supervised, Ensemble, Bootstrap-aggregated, Gradient-boosted Classification and Regression Tree (CART).

Feature Engineering

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

Cross Validation

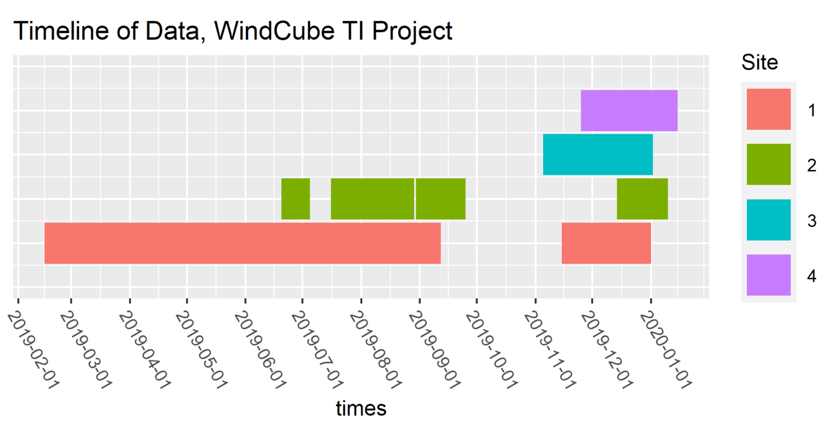
- Leave One Site Out
- All results presented are from CV
- Each site weighted equally in training
- 75% / 25% split for each test site

Results + Next Steps

All KPIs show substantial improvement, the regression slopes and R2, average TI error, and wind speed bin mean TI error. The training sites are on the lower end of global TI distributions, with average TI around 10%. Further research must be carried out to probe the applicability of this model on other TI ~ 10% sites, and as well this framework of testing and training on seemingly similar sites. How does it perform in high turbulence environments? In complex terrain? In mid-latitudes? Wind energy stakeholders and collaborative groups such as CFARS are in the process of determining the acceptability of machine-learning adjusted lidar TI for specific applications such as Energy Yield Assessment and Site Suitability.

Machine learning can significantly improve correlation between lidar and cup anemometer turbulence intensity measurements

Additional Graphs and Tables

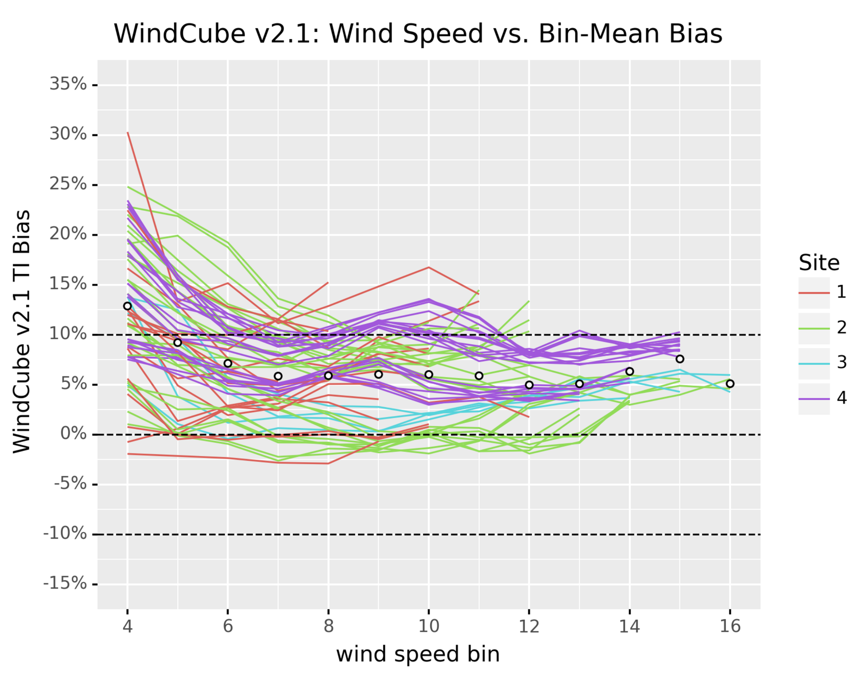


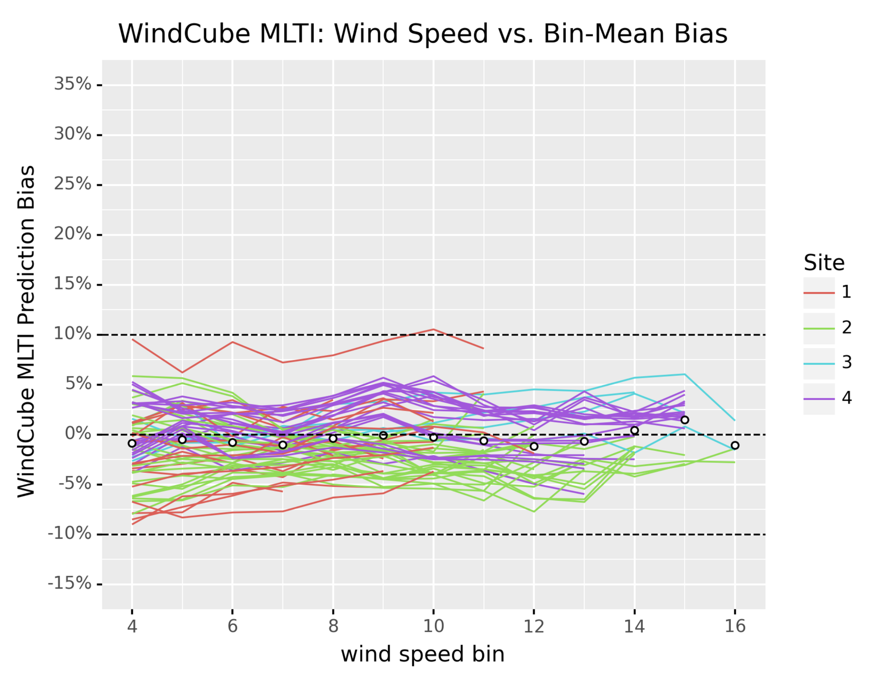
- 14 WindCubes
- 4 flat terrain sites in Northern Europe
- Class 1 anemometry
- IEC-compliant towers
- Good seasonal distribution
- All devices WindCube v2.1
- Line-of-sight (LOS) 1Hz data reprocessed with scalar, vector, hybrid wind field reconstruction
- Additional LOS statistics generated
- 221k samples,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

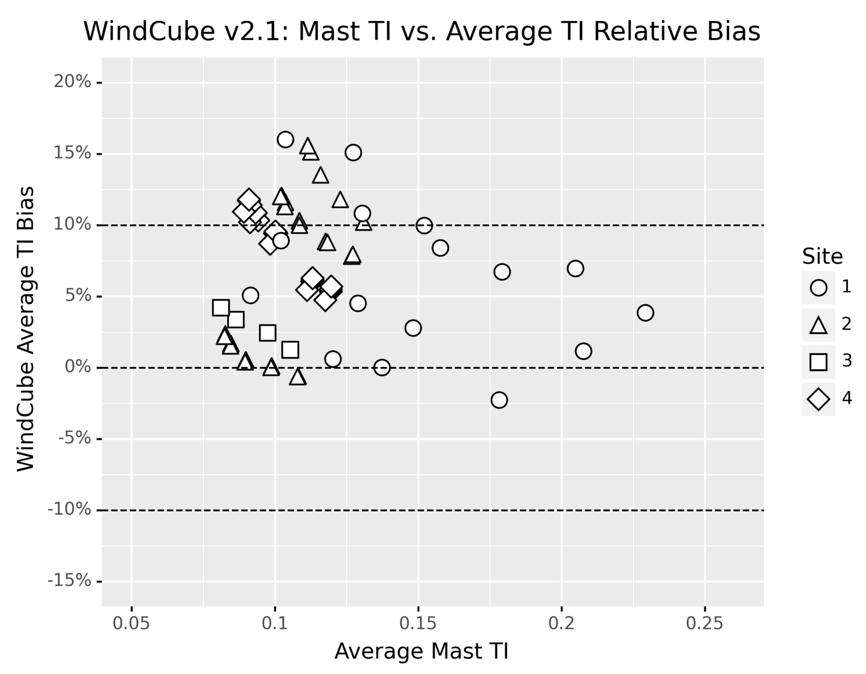
Linear Regression	slope	intercept	bias	R2
WindCube MLTI	0.988	0.003	1.007	0.901
WindCube v2.1	0.854	0.010	0.928	0.884

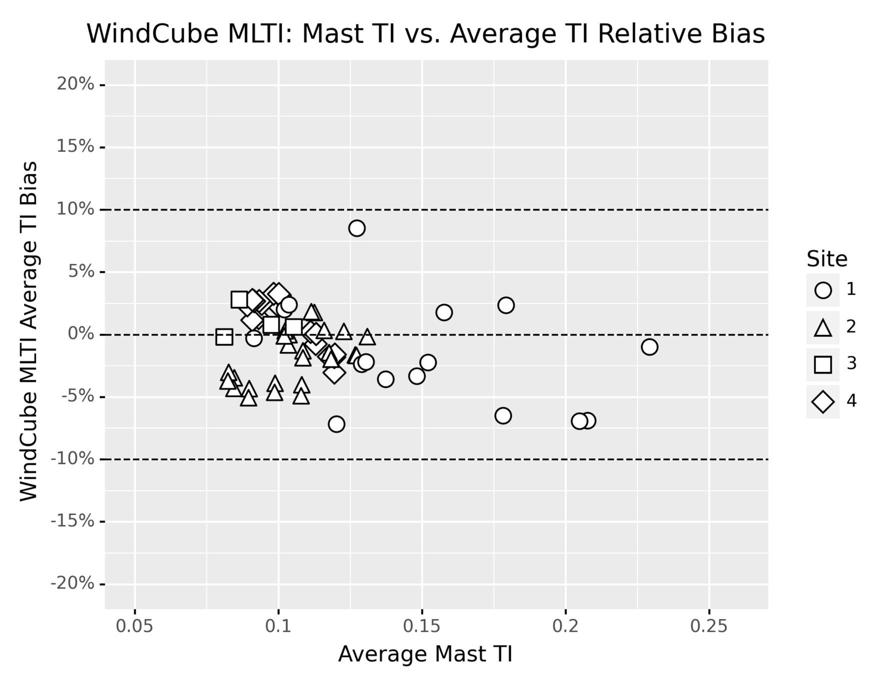
Average TI	Average: relative mean bias error	RMS: relative mean bias error	% within ±5%
WindCube MLTI	-0.7%	3.0%	90.8%
WindCube v2.1	7.0%	8.4%	33.8%

Wind Speed Binned 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%









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