VAISALA

WindCube Pure TI™

Performance Report

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Nomenclature

Table 1: Nomenclature Table

Symbol / Metric	Description	Unit	Formula
HWS	Average Horizontal wind speed 10min	m/s	-
stdHWS	Standard deviation of wind speed 10min	m/s	-
TI	Turbulence Intensity	%	$\frac{stdHWS}{HWS}$
MBE	Mean bias (absolute)	-	$\frac{1}{N}\sum_{i=0}^{N}(\hat{y}_i - y_i)$
RMBE	Relative mean bias	%	$\frac{1}{N}\sum_{i=0}^{N}\frac{\hat{y}_i - y_i}{y_i}$
MAE	Mean absolute error	-	$\frac{1}{N}\sum_{i=0}^{N}\lvert\hat{y}_i - y_i\rvert$
RMAE	Relative mean absolute error	%	$\sum_{i=0}^{N}\left\lvert\frac{\hat{y}_i - y_i}{y_i}\right\rvert$
RMSE	Root mean square error	-	$\sqrt{\frac{1}{N}\sum_{i=0}^{N}(\hat{y}_i - y_i)^2}$
RRMSE	Relative RMSE	%	$\sqrt{\frac{1}{N}\sum_{i=0}^{N}(\frac{\hat{y}_i - y_i}{y_i})^2}$
Slope (m)	Slope of linear fit y = m x + b	-	$\frac{\sum_{i=0}^{N}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sum_{i=0}^{N}(\hat{y}_i - \bar{y})^2}$
Intercept (b)	Intercept of linear fit y = m x + b	-	$\bar{\hat{y}} - m\bar{y}$

Wasserstein distance	1-D Earth-Mover distance between TI distributions, computed by sorting the values and taking the mean absolute difference between corresponding elements.	-	$\frac{1}{N}\sum_{i=0}^{N}\lvert\hat{y}_{sorted\_i} - y_{sorted\_i}\rvert$
i90	Characteristic TI upper bound per IEC (binwise), calculated using the mean TI $\mu_{TI,i}$ and the standard deviation $\sigma_{TI,i}$ for each windspeed bin	-	$\mu_{TI,i} + 1.28 \times \sigma_{TI,i}$

Background: turbulence intensity in wind measurements

Turbulence Intensity (TI) is a key parameter in wind resource assessment. It is defined as the standard deviation of wind speed divided by its mean value over a given averaging period. It quantifies the degree to which wind speed fluctuates around its average and has a direct impact on structural loading, fatigue damage, and turbine lifetime.

TI measurements are used in the development of wind farms to select the most appropriate wind turbine based on the assessed turbulence conditions at a site. This application is commonly referred to as turbine site suitability. Another application is estimating the structural loads of a wind turbine using TI measurements, which is referred to as load validation. Today, this application is mostly carried out using cup anemometers mounted on meteorological masts.

Challenges of measuring tubulence with lidar

Doppler wind lidars are commonly used to measure average wind speed and wind direction. However, for TI, lidars are not yet widely trusted. The main reason is that, in contrast to cup and sonic anemometers, which measure at (approximately) a single point in space, vertical profilers sample a finite volume of air. This volume averaging is not problematic for accurately determining mean wind speed and direction, but it is critical for TI.

Depending on the specific lidar technology, this averaging effect could lead to an under-estimation or an over-estimation of TI. Profiling, pulsed lidars are widely shown to overestimate turbulence intensity when compared to co-located meteorological masts. Until now, there has not been a general solution to this limitation, and cup anemometers remain a necessary instrument for applications such as site suitability and load validation.

The Windcube Pure TI™ methodology

Vaisala has developed and evaluated a range of post-processing algorithms for TI reconstruction, including both machine-learning-based and physics-based approaches, and on this basis has chosen a physics-based method. This choice is motivated by the fact that the dominant physical sources of lidar-related uncertainty are reasonably well understood and can be treated through targeted, explicitly defined correction steps, rather than relying on a purely data-driven model. Machine learning is generally more appropriate when the governing mechanisms are not sufficiently known or cannot be represented in a tractable physical model. In the present context, however, the generalization performance of a regression-type machine-learning model outside its training domain would be difficult to guarantee, and such models tend to regress predictions toward the mean, potentially distorting the underlying TI distribution. Moreover, any systematic bias present in the training reference data (here, cup-anemometer measurements) would be inherited by the machine-learning model.

The algorithm is called **WindCube P**hysically **U**nified **RE**construction of **T**urbulence **I**ntensity or **WindCube Pure TI**.

It's physical: derived from first-principles of lidar measurement in turbulent flow.

It's unified: it combines multiple sub-algorithms, each addressing different error sources that affect lidar turbulence measurements.

It's a reconstruction (not a model): it uses the 1 Hz line-of-sight radial wind speed data to generate the 10-minute standard deviation of horizontal wind speed.

Vaisala's research covered almost every lidar turbulence methodology in the scientific and industry literature. Along the way, we discovered new phenomena and their solutions, included in Pure-TI for the first time.

While met mast data was used to validate WindCube Pure TI, the cup reference instruments are not used to train a model following a machine learning approach. The algorithm **does not inherit anemometer flaws**: it is based only on lidar and atmospheric physics, and outputs the best estimate of standard deviation of horizontal wind speed.

A detailed physical understanding of error mechanisms and a scientific approach enabled us to understand and systematically eliminate lidar biases. Vaisala studies over the last 5 years show the steady progress towards a comprehensive solution:

- 2021, ACP Resource Assessment, *Machine Learning Improvements to WindCube Turbulence Intensity Measurements at Five Sites in Northern Europe*
- 2022, WindEurope, *Evaluation of performance of machine learning-adjusted WindCube v2.1 turbulence measurements*
- 2023, Wind Energy Science Conference, *Development of a Generalized Framework for Point and Lidar Measurement Sensitivities in Turbulent, Complex Flow*
- 2024, WindEurope Tech Workshop, *Comparing 5Hz and 1Hz floating LiDAR system measurements against an offshore met mast*
- 2024, TORQUE, *Behavior and mechanisms of Doppler wind lidar error in complex terrain: stable flow case study at Perdigão*
- 2024, PhD Thesis, *Practical uncertainty estimation for turbulence from ground-based lidar*
- 2025, WindEurope, *Benchmarking Pulsed Lidar TI Solutions*
- 2025, ACP Peak, *Untangling turbulence profiles with new lidar algorithms*

- 2026, ACP Peak, *Reproducibility and uncertainty estimation of new lidar turbulence algorithm at North American sites*
  2026, WindEurope, *Repeatability, reproducibility, and uncertainty estimation of a new lidar turbulence algorithm in varying wind conditions around the world*

Validation and key results

Validation Database:

As of today, the algorithm has been validated on **104 systems across 48 sites worldwide and counting.** The map below shows the current distribution of the validation database across the globe. Most deployments are in Europe (73 systems, 22 sites), with additional validation in Asia (15 systems, 13 sites), North America (14 systems, 12 sites), and Australia (2 systems, one site).

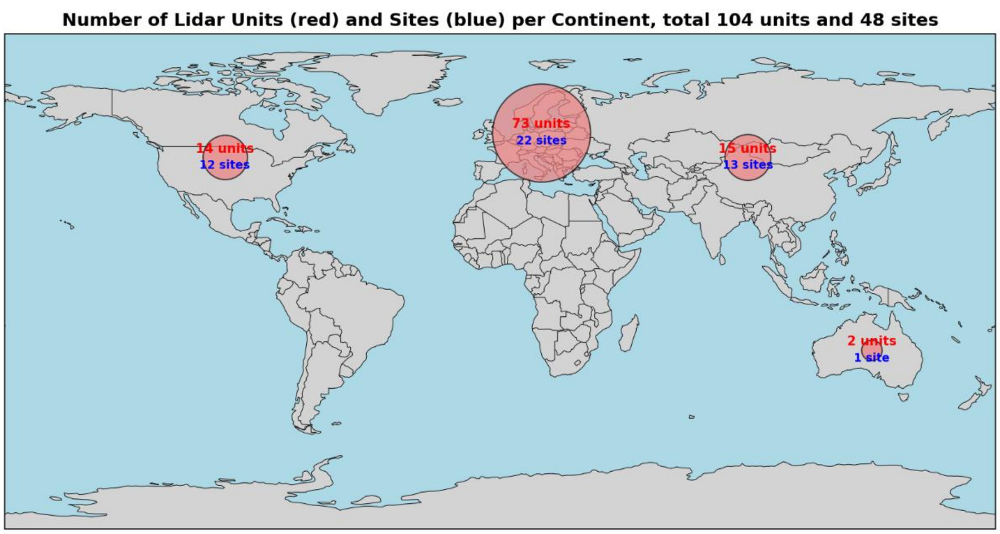


Figure 1: Validation database

WindCube Pure TI has now been validated across a large international database (103 systems at 48 sites). The present paper reports results on a representative subset of that database: 48 lidar units at 34 sites (18 flat and 16 moderately-to-very-complex terrain). These results reflect WindCube Pure TI alone (no CFD corrections). The pooled, filtered dataset for analysis comprises 9.2 years of cleaned data. On average each site was validated at roughly four measurement heights, giving ~1.3 million quality-controlled 10-minute samples in total. The findings here are consistent with, and representative of, the full validation database.

We present the validation results of the algorithm. For all sites, the reference data is taken from meteorological masts equipped with cup or sonic anemometers.

Correlation of lidar TI with reference instruments

The simplest way to assess the overall performance is through a scatter plot (in black), ordinary least squares regression, and TI bin averages (in white). The data from different sites is here pooled together to a single database.

The figure below compares lidar TI to reference cup TI before (left) and after (right) applying the WindCube Pure TI algorithm, using the pooled validation database.

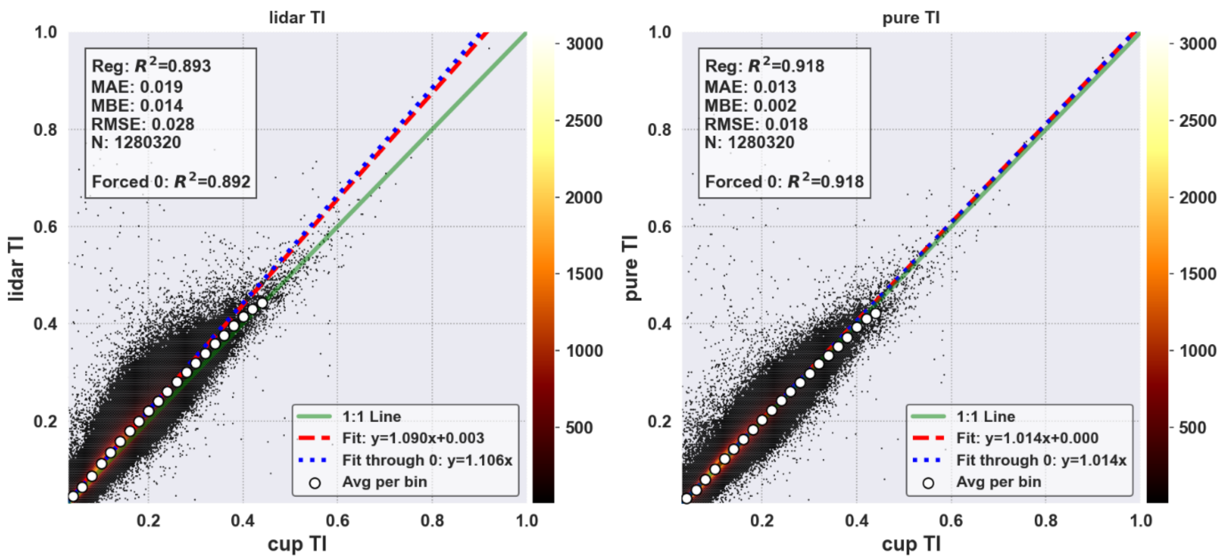


Figure 2: correlation between lidar-derived TI (y-axis) and met mast TI (x-axis) across the entire validation database

The original, uncorrected lidar reconstruction overestimates turbulence intensity shown by the mean bias error (MBE) of 0.014 and the regression slope of 1.105**.**

After applying the new algorithm, the agreement with the mast measurements improves substantially: the MBE is reduced to 0.002, regression slope of 1.014, large reductions in MAE and RMSE, and a higher R^2. Pure TI agrees closely with the reference TI over the full range with minimal systematic bias.

Performance at high heights:

lidar measurements at high altitudes cover a larger volume of air. This increase in measurement volume is a key difference between measurement heights, and suitable corrections should exhibit strong stability across all altitudes. The mean and standard deviation of the performance are shown below, grouped into 20 m bins between 40 and 200 m.

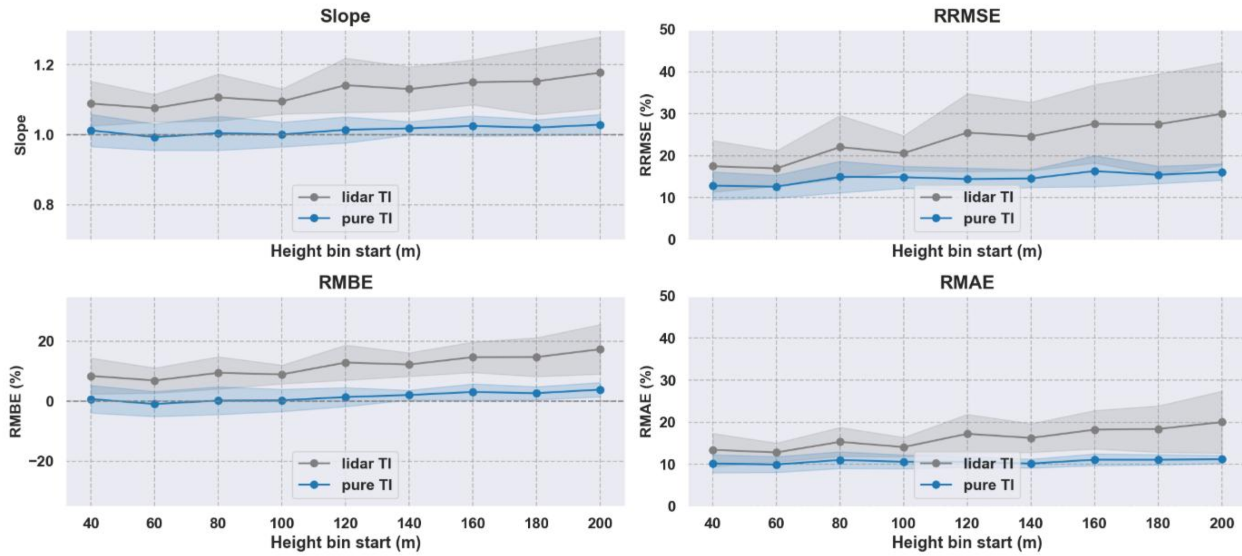


Figure 3: Average Performance Metrics by Height (mean ± 1 standard deviation across, forced slope) across all sites

For each metric, the shaded areas represent ±1 standard deviation. For Pure TI, these bands are narrow and height-independent, indicating low site-to-site and height variability, a robust reconstruction method in all conditions. This robustness shows that Pure TI not only improves the mean error statistics but also reduces variability across location and height.

Performance in complex terrain:

Metrics presented thus far have included all terrain types, including simple sites, moderately complex, complex, and very complex terrain. Here we divide the database by terrain complexity using roughness index (RIX). Terrain is classified as follows:

- 0 < **RIX** < 2: Simple terrain
- 2 < **RIX** < 5: Moderately complex terrain
- 5 < **RIX** < 20: Complex terrain
- 20 > **RIX**: Very Complex terrain

To assess the performance in function of terrain complexity, the graph below represents the distribution of TI mean bias error (MBE) per site and complexity class.

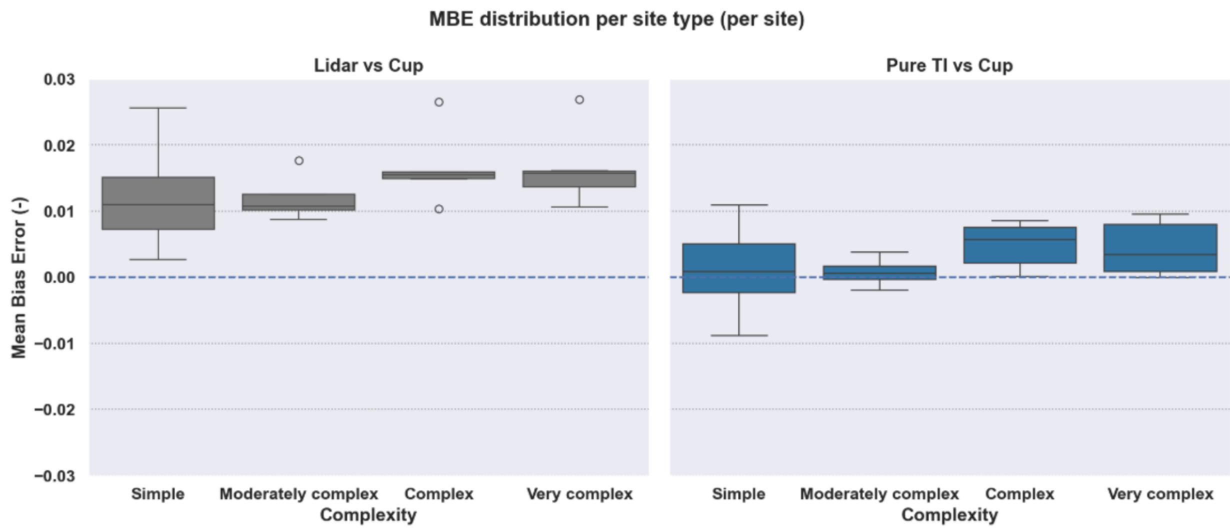


Figure 4: Mean bias error in function of terrain complexity. Left: original reconstruction; right: new reconstruction.

Uncorrected lidar TI measurements exhibit a systematic overestimation of turbulence intensity across all terrain classes, with a positive bias that shows only a weak dependence on site complexity. When applying the WindCube Pure TI reconstruction together with flow complexity recognition (FCR, without CFD-based corrections), this bias is greatly reduced: the median error is close to zero for all complexity classes. Across all terrain types, the inter-site medians lie within approximately ±0.01, indicating a consistent and terrain-robust reconstruction performance.

Key Performance Indicators – CFARS:

The **C**onsortium for the **A**dvancement of **R**emote **S**ensing (**CFARS**) Site Suitability Initiative whitepaper was adapted by Fugro and DNV in 2023 into key performance indicators (KPIs) for lidar turbulence. These KPIs consider mean bias error (MBE) and the difference between the 90th percentile of TI (P90) measured the lidar and the met mast, by wind speed bin.

Acceptance criteria are:

- TI MBE binned by HWS:
    - < 0.01 Best Practice; < 0.02 Minimum Practice
- P90 MBE binned by HWS:
    - < 0.015 Best Practice; < 0.03 Minimum Practice

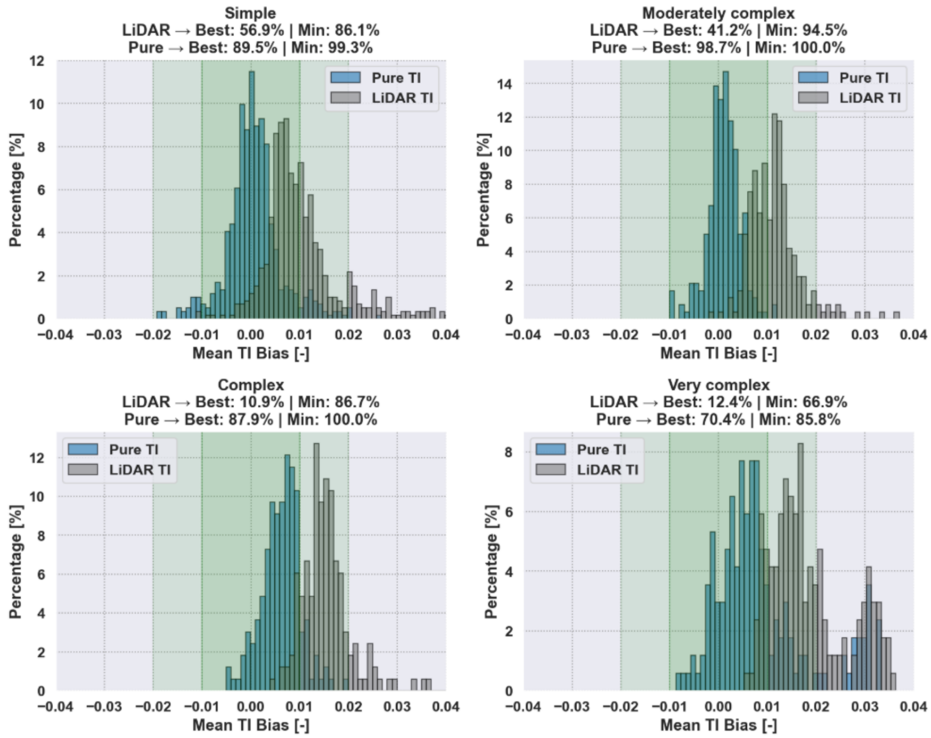


Figure 5: CFARS MBE metrics, gray: original reconstruction; blue: new reconstruction

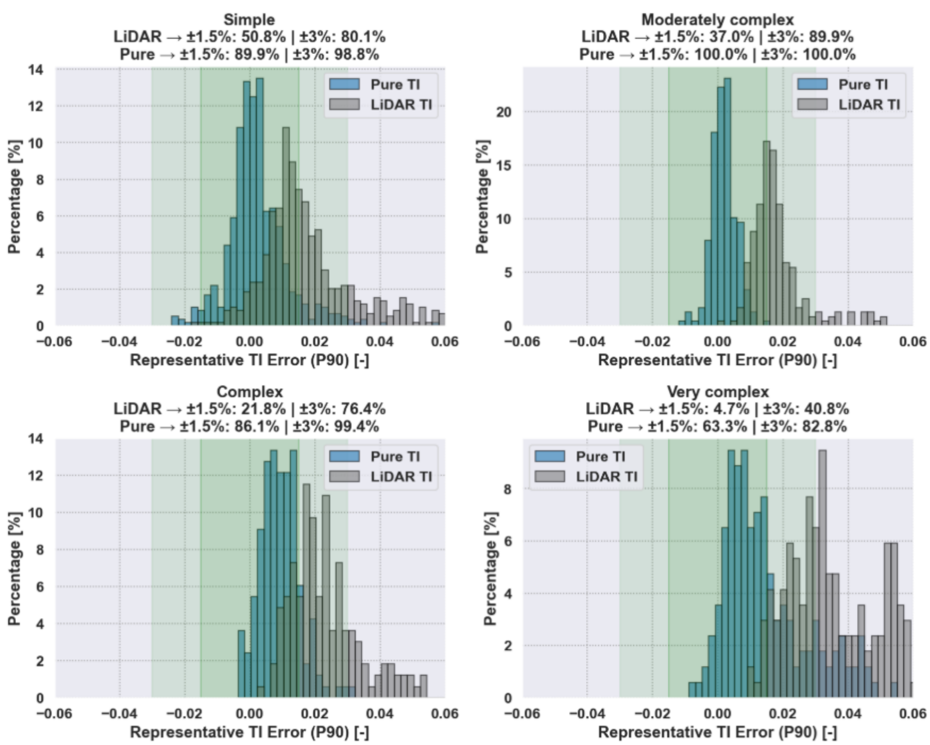


Figure 6: CFARS Representative TI error metrics, gray: original reconstruction; blue: new reconstruction

From simple to very complex terrain, WindCube Pure TI shows dramatic improvements compared to ordinary lidar TI reconstruction. For both mean TI and representative TI (P90), Pure TI meets the CFARS Best Practice thresholds in 64–100% of cases, without CFD correction, and satisfies the minimum-practice criteria in most cases. Taken together, these results indicate that the algorithm provides a robust and largely site-independent improvement in TI characterization suitable for CFARS-compliant site assessments.

Key Performance Indicators – DNV-RP 0661:

DNV-RP 0661 KPIs were developed in the DNV Joint Industry Project (DNV-JIP) of 2020-2022. The recommended practice defines two primary, wind-speed-binned metrics at hub height, Relative Mean Bias Error (RMBE) and Relative Root Mean Square Error (RRMSE)

These metrics quantify systematic bias and scatter between the reference and lidar TI. Acceptance thresholds are specified for different intended applications.

$\boldsymbol{TI}(\boldsymbol{V_{hub}})$ **RMBE** should meet passbands**:**

- **Energy Yield Assessment:** ±10%
- **Site Suitability:** -6% to +10% (WS < 7m/s) -3% to +10% (WS > 7m/s)
- **Loads Validation:** ±5%

$\boldsymbol{TI}(\boldsymbol{V_{hub}})$ **RRMSE** should meet passbands

- **Site Suitability:** ≤ 30% (WS < 7m/s) ≤ 15% (WS > 7m/s)
- **Loads Validation:** ≤ 15%

Results below are pooled across all sites, measurement heights, and windspeed bins.

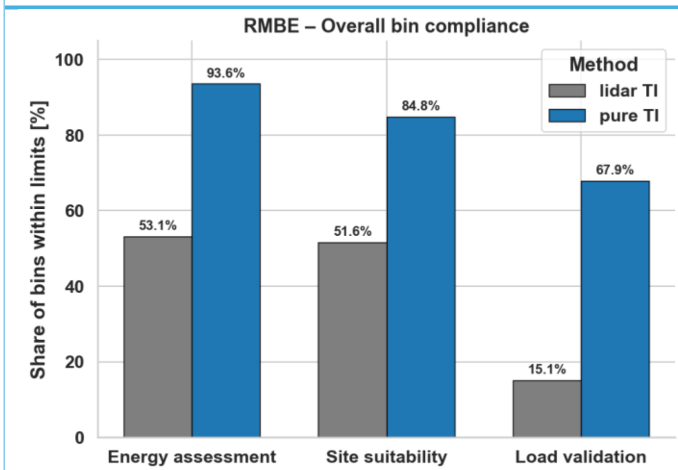
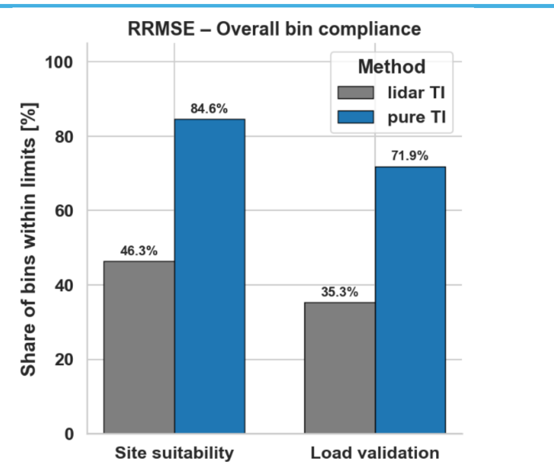
DNV RP RMBE	DNV RP RRMSE
	

Figure 7: Percentage of bin compliance by application. gray: original reconstruction; blue: new reconstruction

Evaluation following the DNV RP 0661 consistent improvement when using the WindCube Pure TI reconstruction. For the RMBE criterion, the share of wind speed bins within limits increases from 53.1% to 93.6% for energy assessment, from 51.6% to 84.8% for site suitability, and from 15.1% to 67.9% for load validation. For the RRMSE criterion, compliance for site suitability increases from 46.3% to 84.6%, and for load validation from 35.3% to 71.9%. Overall, WindCube Pure TI yields a substantially higher fraction of bins that satisfy the DNV RP 0661 passbands across all applications considered.

Turbulence distribution:

A reliable lidar TI algorithm should successfully replicate the reference TI *distribution*, not just the mean. To evaluate this property, we use the Wasserstein distance. This metric represents the minimum work required to transform one probability distribution into another. Also known as the earth mover's distance, it represents the agreement between two distributions without correlating the underlying data via regression or direct comparison of time series data.

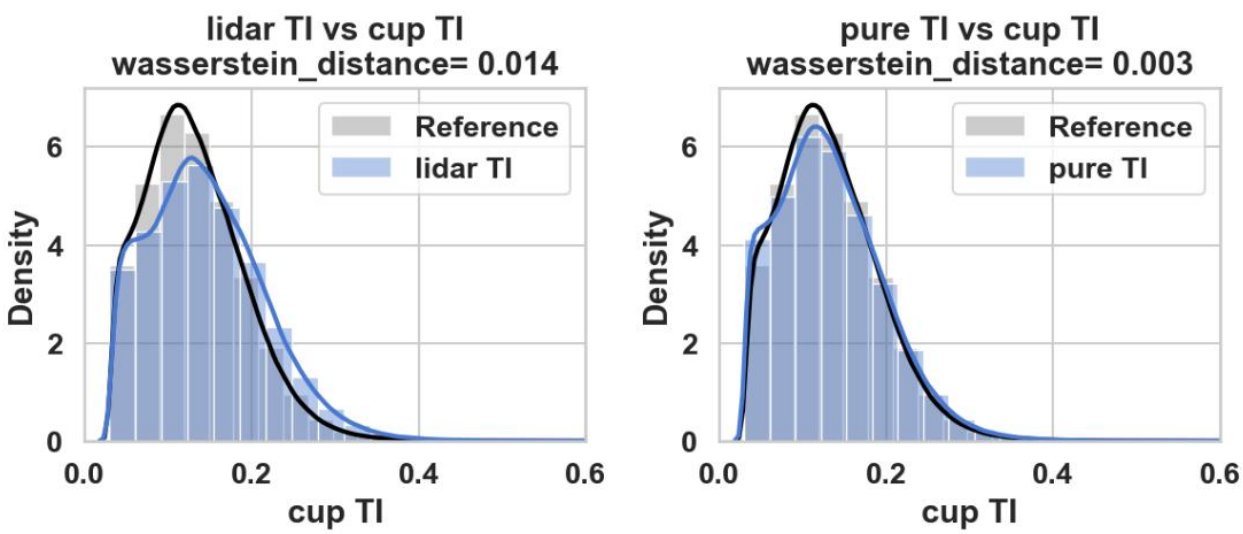


Figure 8: TI distributions: black = cup TI, blue = lidar TI. Left: original reconstruction; right: new reconstruction.

Using this metric, the WindCube Pure TI reconstruction clearly reproduces the reference TI distribution across the entire validation database. This validates the agreement shown via other KPIs, while removing dependence on precise spatial details of the validation sites.

Characteristic TI curves:

Characteristic or Representative TI curves are used to select wind turbines based on the upper distribution of bin-wise TI, defined in IEC 61400-1.

Characteristic TI provides a conservative estimate of the upper tail of the turbulence intensity distribution in each wind-speed bin, ensuring that turbine class selection is robust to any site variability or measurement uncertainty.

$$i90 = \mu_{TI,i} + 1.28 \times \sigma_{TI,i}, for\ each\ windspeed\ bin\ i$$

Lidar TI algorithms must accurately replicate Characteristic TI curves from reference instruments. The IEA Wind Task 52's Turbulence sub-group has proposed to build multi-site, multi-height databases to evaluate the performance of new approaches. The ratios between the lidar-based and mast-based Characteristic TI values are summarized as boxplots by wind-speed bin, shown in the figure below. Sites are grouped by terrain complexity (flat terrain on top, complex terrain on the bottom) and by algorithm (original reconstruction on the left, Pure TI on the right). The shaded band denotes the ±5% acceptance range.

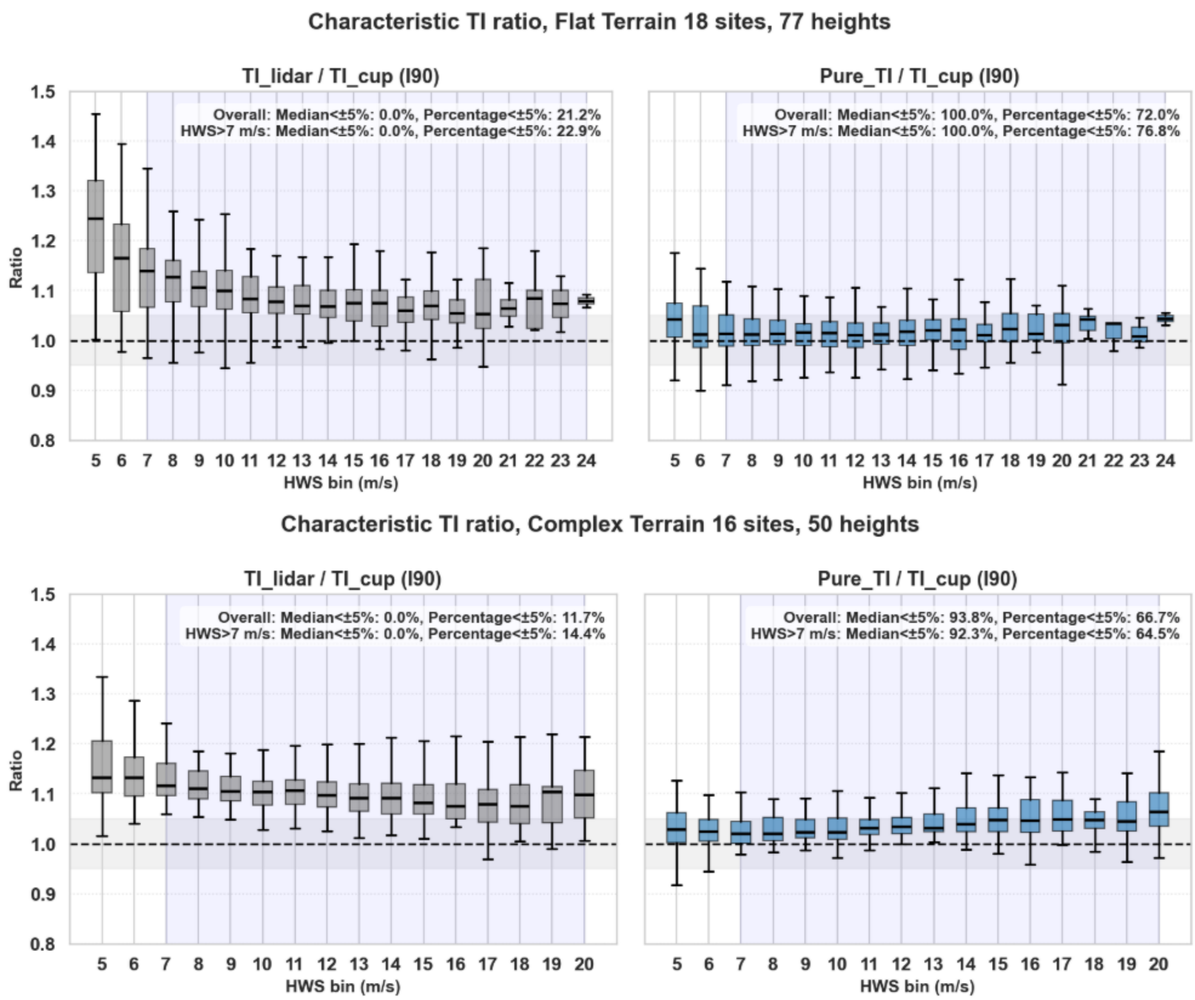


Figure 9: Characteristic TI curves ratios between lidar and mast box plot by site in function windspeed bins. Left is lidar TI, right is the new reconstruction algorithm.

From these plots, WindCube Pure TI substantially improves agreement with mast-derived Characteristic TI curves. In both flat and complex terrain, wind speed bin median ratios fall within ±5% increases from 0% for ordinary lidar reconstruction to nearly 100%, even without CFD corrections. For higher wind speeds (HWS > 7 m/s), the percentage of points that lie within ±5% rises from 22.9% to about 76.8% in flat terrain and from 14.4% to 64.5% in complex terrain. The boxplot widths are tighter, indicating lower scatter and a more consistent reproduction of Characteristic TI across sites and heights.

Conclusion

WindCube Pure TI reconstruction is a step change improvement compared to the traditional WindCube TI algorithm. In the global validation database having more than one million 10-minute records, WindCube Pure TI reduces mean bias in turbulence intensity from 0.014 to just 0.001. Residual bias at individual sites remains tightly constrained within ±0.01 TI units across 150 site-height combinations and all terrain classes - simple, moderately complex, and complex - demonstrating terrain-robust, bankable TI performance.

WindCube Pure TI distributions almost perfectly replicate those from cup measurements (Wasserstein distance improves from 0.014 to 0.002), and the error is constant with height from 40 m to 200 m. WindCube measurements with Pure TI exhibits outstanding accuracy from hub height to blade tip, and solve the problem range drift, typical of profiling remote sensors.

WindCube Pure TI meets or exceeds relevant industry KPIs in simple and complex terrain. Under the CFARS framework, more than 90% of bins satisfy the MBE Best Practice criterion and 99% meet the Minimum Practice. By the DNV-RP-0661, 83% of bins fall within the stricter, RMBE passbands for Site Suitability and 70% for Loads Validation. Followng the IEA Task 52 Characteristic TI metric, 75% of bins are within ±5% of the reference Characteristic TI curve. These results show that WindCube Pure TI improves absolute accuracy and delivers results consistent with industry requirements.