Improving Remote Sensor Accuracy and Uncertainty in Complex Terrain

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Abstract

Flow curvature bias remains the leading impediment to widespread adoption of remote sensing for wind resource assessment in complex terrain. Previous studies have shown that the flow pattern can be predicted with CFD modeling, yielding a correction to compensate for the flow-induced bias in horizontal wind speed measurements[1]. This paper demonstrates a systematic approach to correcting this bias and introduces a new method for assessing uncertainty in the computed corrections.

Twenty sites were selected, spanning a wide range of terrain complexity, and with concurrent remote sensor / tower data. The WindSim CFD modeling software was used to predict 3D wind flow at the tower location and in the vicinity of the remote sensing device (RSD). Model results were analyzed to predict flow curvature above the remote sensor, and from the curvature, compute RSD bias as a function of wind direction and measurement height. The mean-wind-speed site-calibration between the RSD and tower was also computed from the model results and applied to the data, so the remaining discrepancy in the measured data could be compared to the predicted RSD bias.

Objectives

- Predict RSD bias **without** using site measurements (wind, stability, etc.)
- Predict the uncertainty of the computed bias correction
- Correct RSD data to improve accuracy and AEP uncertainty
  - Use for past/present RSD sites with historical data
  - Use for future sites to improve RSD site selection

Background

Curved flow between sampling volumes cannot be detected by ground-based remote sensors using Doppler processing of multiple beams diverging from a single origin. Instruments typically assume the wind to be homogeneous, e.g. not curved, throughout their conical sampling volume. In complex sites, terrain-induced flow curvature breaks the homogeneity assumption and gives rise to a measurement bias that changes with wind direction. The bias is negative for hilltop sites and can be 10% or more in the most affected direction sector for complex terrain sites[2]. When integrated over the wind rose, the mean wind speed measured by remote sensors can be up to 5% low at hilly sites.

The bias affects any RSD (LiDAR or SoDAR) that uses a divergent beam profiling strategy, and can be approximated by the formula:

$$Bias \approx \frac{-h}{R} \cdot 100\%$$

where R is flow curvature radius, and h is measurement height.

Methods

CFD Simulations

WindSim CFD model computes flow curvature information by solving the Reynolds-averaged Navier-Stokes Equations for 16 wind directions. The wind flow is represented as 3D velocity vectors for each grid point around and above the RSD. The innermost, highest resolution part of the grid is 400 m x 400 m. It has a grid spacing of 5 m in the horizontal plane, and is centered on the RSD location. In the height dimension, the lower part of the grid (encompassing the measurement height range of the remote sensor) has 20 m vertical grid spacing.

Virtual RSD Measurement

For each measurement height, a subset of grid points is selected to approximate the sample volume of typical RSD Doppler beams. These points are used to compute the horizontal wind speed, U_{RSD}, of the virtual RSD. The curvature bias may be computed as a ratio to the mean CFD wind speed at the selected grid points.

$$bias\ ratio = \frac{U_{RSD}}{\overline{U_{CFD}}}$$

$$correction\ factor = \frac{1}{bias\ ratio}$$

The computation is performed for each wind direction sector and height.
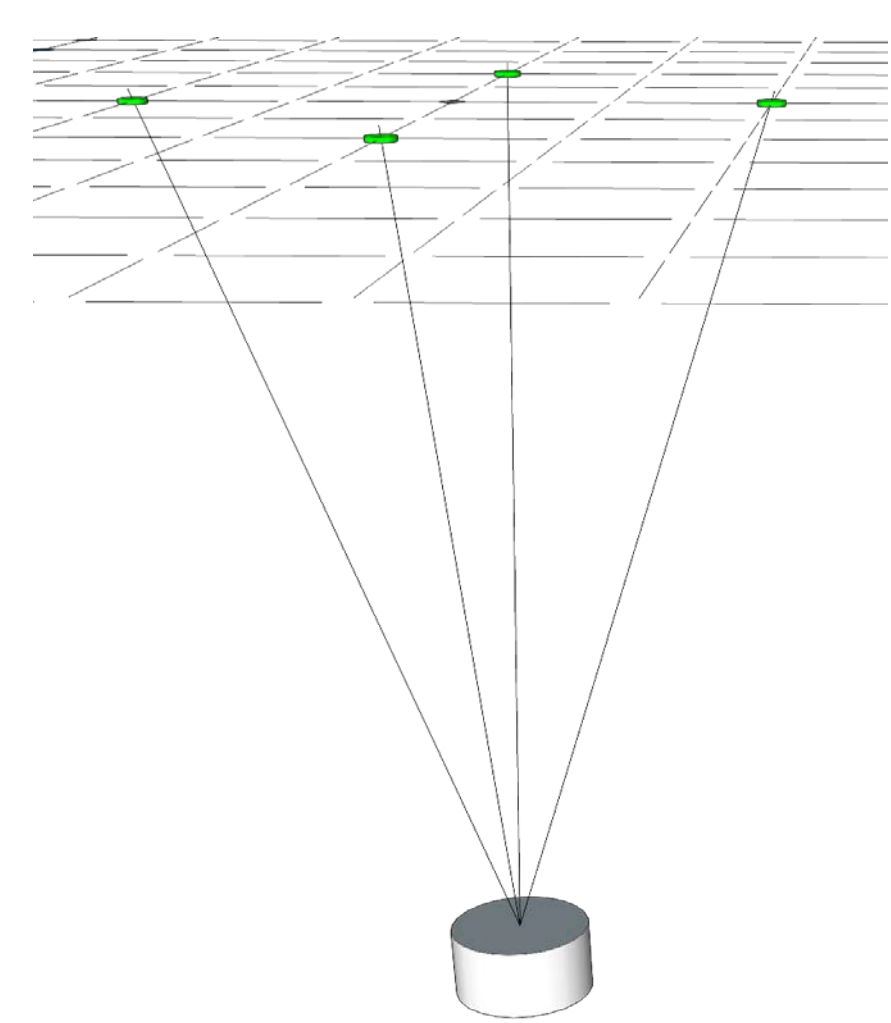
Methods (continued)

Uncertainty Estimate

If the predicted flow curvature radius is uniform, then the bias ratio will be independent of the choice of grid points used as virtual RSD beams. However, if the CFD predicts changing curvature within a neighborhood of points over the RSD, then the choice of grid points matters. The extent to which the bias depends on grid point selection is assessed as uncertainty in the correction methodology for the following reasons:

1. The true location of RSD beams is not precisely known
2. The true location of the RSD may not be precisely known
3. The terrain and complicating surface features aren't precisely known
4. The CFD model results may not be as accurate if second order complexity is present (detached flow, stability effects).

The correction uncertainty is composed of three components, which are assumed to be roughly independent and added in quadrature. The quadrature sum is evaluated over all wind directions to find the maximum, or worst-case correction uncertainty, for each measurement height.

1. Change in predicted bias with beam spread, U_{BS}
2. Change in predicted bias by moving 30m North or South, U_{NS}
3. Change in predicted bias by moving 30m East or West, U_{EW}

For each measurement height:

$$Correction\ Uncertainty = \max(\sqrt{U_{BS}^2 + UNS^2 + UEW^2})$$

Note: Correction uncertainty is not a good measure of total uncertainty.

Verification

Site Calibration

Terrain complexity may cause significant wind speed differences between nearby locations at a site. The differences are not related to RSD flow curvature bias, but need to be considered when comparing RSD and tower measurements. A site calibration evaluates the mean wind speed differences at each anemometer height as a function of wind direction. Comparison data is then scaled according to wind direction to eliminate (calibrate out) the difference.

In this study, the site calibration was computed from CFD-predicted wind speed differences between the tower and RSD locations. The predicted site calibration is shown along with the predicted flow curvature bias, and the total predicted difference is then compared to the measured difference, binned by wind direction.

Data and Quality Control

We identified pairs of collocated Triton® Wind Profiler SoDARs and met towers in terrain ranging from flat to very complex. The data include 20 pairs, and 57 separate met tower speed sensor / height pairs. Data from both the met towers and the Tritons were quality controlled following standard industry practices.

Results

Bias by Direction

The following example shows the comparison between predicted and measured biases from one site in the study. Plots show site calibration, flow curvature bias, and the total bias, as predicted by the CFD-based method. These are compared to the measured difference, expressed as a percentage, between the Triton and met tower measurements for all anemometer heights, and for all wind direction sectors with sufficient data (minimum 60 data points per wind direction bin).
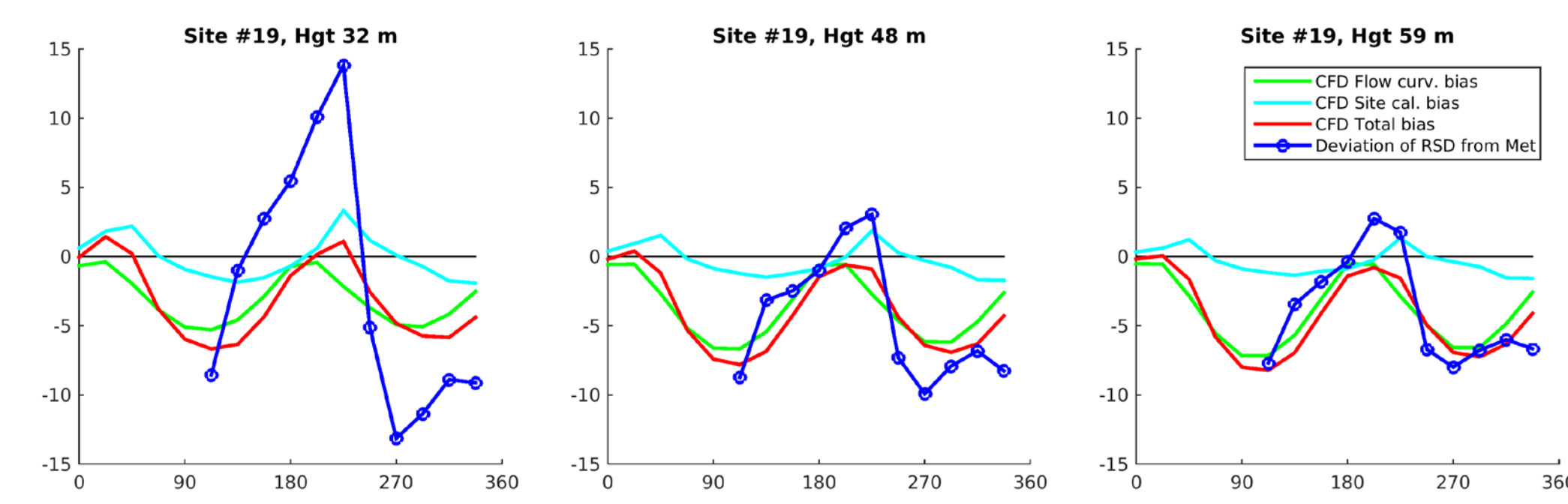

Figure 1. Bias by direction, for one example site, with separate graphs for the different speed sensor heights on the tower. Within each plot, x-axis is wind direction, and y-axis is bias. Separate curves show CFD-predicted flow curvature bias (green); CFD-predicted site calibration bias (cyan); CFD-predicted total bias (red); and observed deviation (Triton minus met tower, blue, as percentage).

Correction Uncertainty by Height

30m	50m	70m	90m	110m	130m	150m	170m	190m
5.6%	2.2%	1.5%	1.0%	0.8%	0.8%	0.7%	0.7%	0.8%

Table 1. Correction uncertainty for the example site at CFD grid heights. These are the maximum, over all wind directions, of the combined uncertainty components for beam spread, north/south position, and east/west position.

Results

Summary Statistics

Using uncorrected data from all sites and measurement heights, the performance of the correction methodology is measured by looking at improvements to R2 and the regression slope after the site calibration and flow curvature correction is applied. The following before-and-after histograms summarize the results for all 57 sensor height pairs in the study.
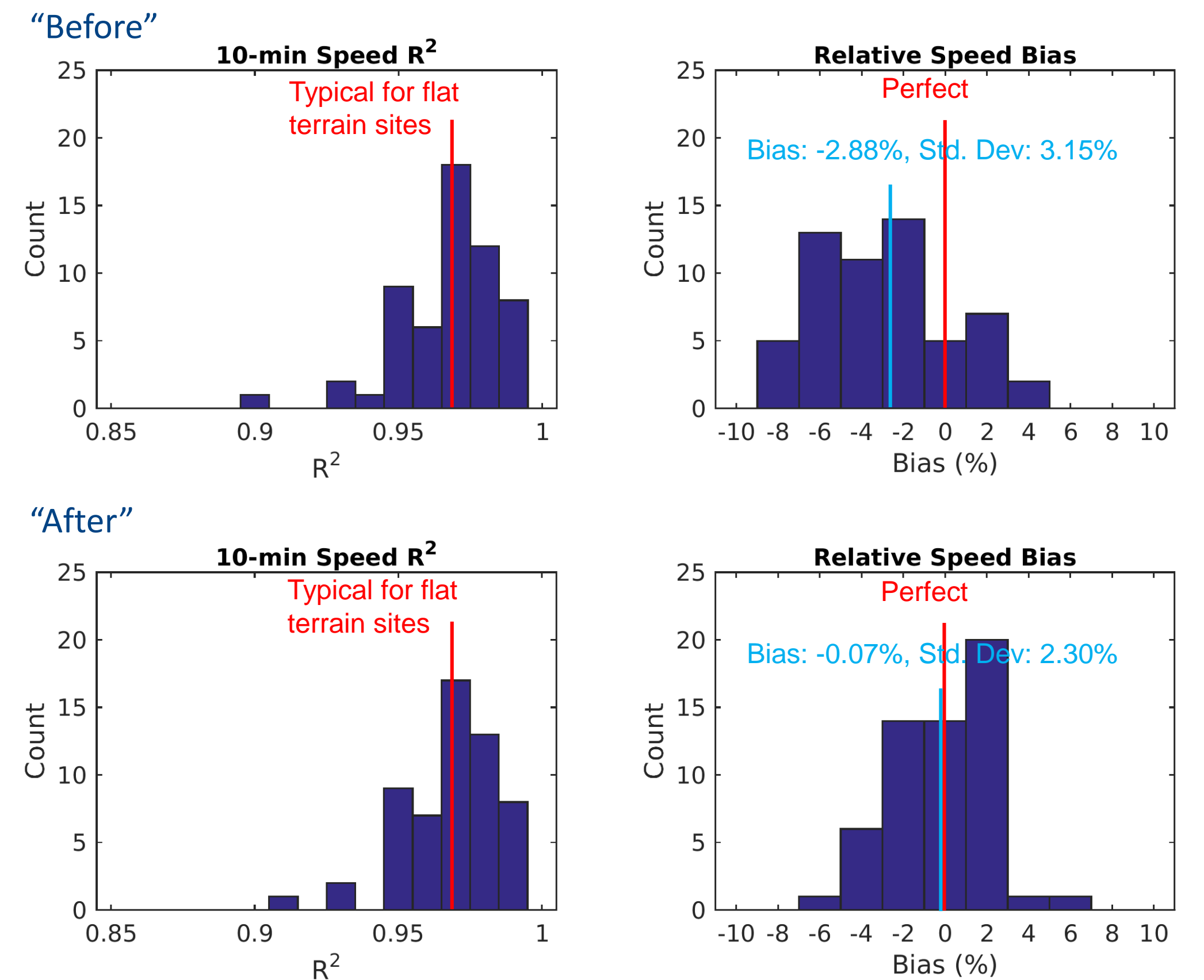

Figure 2. Summary histograms for entire dataset, comprised of 57 separate wind sensor heights on 20 different Triton / met tower pairings. The relative speed bias is the deviation of the regression slope from 1.0, expressed in percent.

While the improvement in R^2 statistics is small, many sites did show improvement in correlation. The relative speed biases, based on regression slope, were greatly improved. Not only did the spread of biases, over all datasets, go down significantly, but the mean bias improved from −2.9% to −0.1%, which is a substantial improvement, on average.

Correction uncertainty is higher near the ground at all sites. The range of uncertainties varies by site, indicating the degree to which terrain induced flow curvature variations limit correction accuracy.
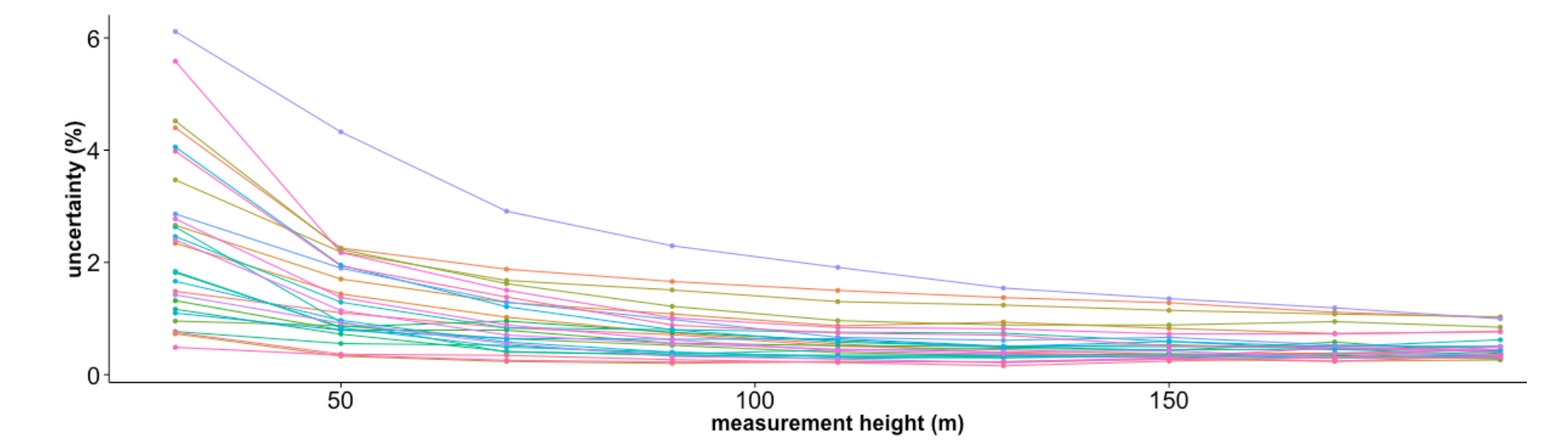

Figure 3. Correction uncertainty vs. height for all sites in the entire dataset

Conclusions

On a site by site basis, the CFD-predicted bias combining both flow curvature and site calibration effects generally captured the correct sign of the observed difference between the Triton and met-measured wind speeds. It captured the correct magnitude in most cases. Capturing the pattern of the bias with wind direction was more challenging, although in some cases was captured very well.

Unfortunately, the site calibration and flow curvature biases cannot be separated in the comparison data. The CFD methodology was used to compute both bias corrections, and the results we see reflect the combined improvement. It is not possible to evaluate the improvement from flow curvature correction by itself.

Overall, application of the correction factors (by height and direction) to the time series of Triton-measured winds resulted in an improvement in bias across all measurement pairs, from −2.9% to −0.1%. The root mean square, across all 57 Triton met/sensor pairs, of mean wind speed difference, was reduced from 3.2% to 2.3%.

These results indicate that correction factors derived from a relatively simply configured CFD model can significantly reduce the flow-induced errors inherent in wind speed measurements from divergent beam-based remote sensing devices. The uncertainty metric provides an indication of how site specific flow curvature limits accuracy in the computed corrections.

References

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