2D to 3D Wind Speed Data Reconstruction for Development of Low-Cost Monitoring Systems

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Motivation and objectives

1. Spatiotemporal in-situ measurements are essential to achieving reliable simulations of atmospheric boundary layer flows.
2. To obtain high-fidelity predictions of wind behavior on the regional scale, a monitoring system should be comprised of a large number of measurement points.
3. Using 2D anemometers instead of 3D sensors significantly reduces costs and allows a denser monitoring network with additional stations.
4. To make this substitution possible, it is necessary to reconstruct the vertical component of the wind velocity, *w*, from the measured horizontal velocity vector (*u*, *v*).
5. The present study aimed to develop a machine-learning-based reconstruction of vertical wind velocity *w* to facilitate the reliability of 2D anemometers in the field.

Methodology

Field data collection

A ten-foot tower was deployed on the roof of the Mudd Building to collect boundary layer wind data. The tower contained a 2D anemometer measuring at 1Hz, a 3D anemometer measuring at 20Hz, and other sensors measuring solar radiation, temperature, and relative humidity at 1Hz. Data was collected over ten days.

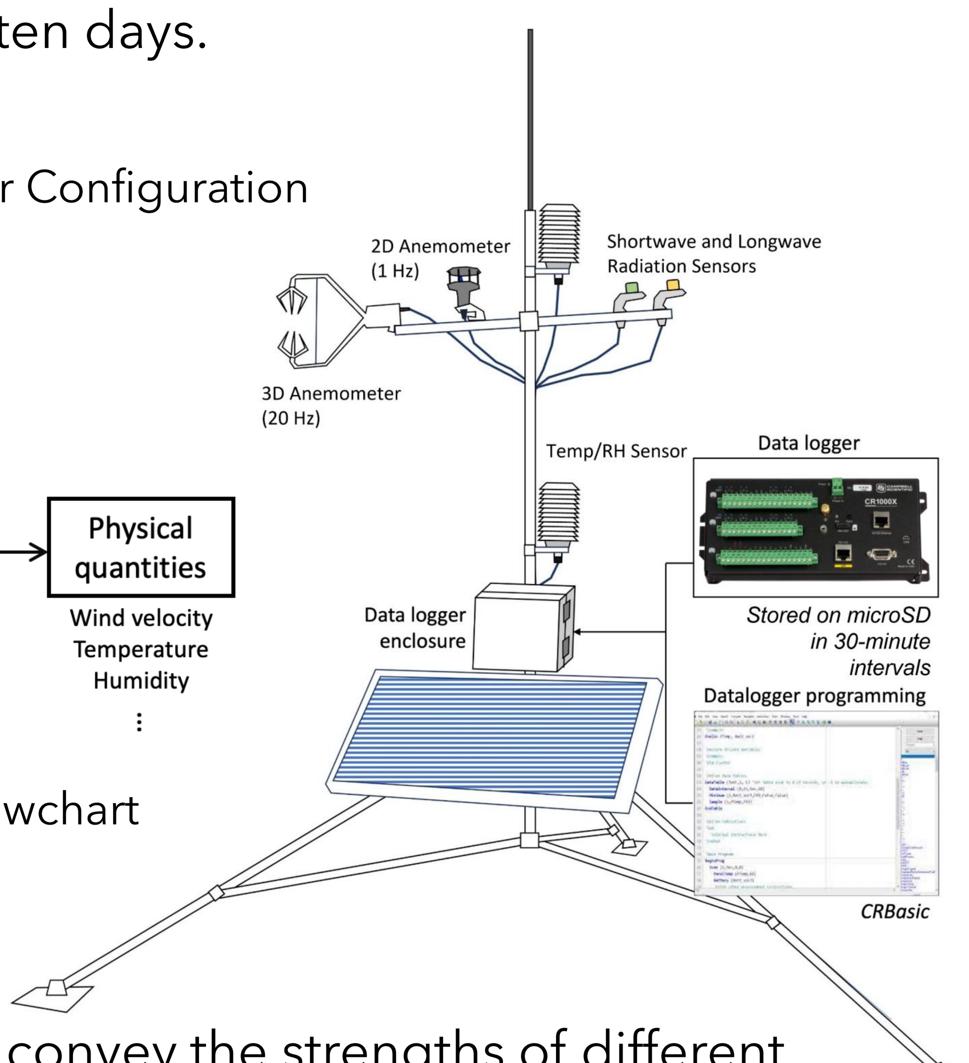

Figure 1. Weather Tower Configuration

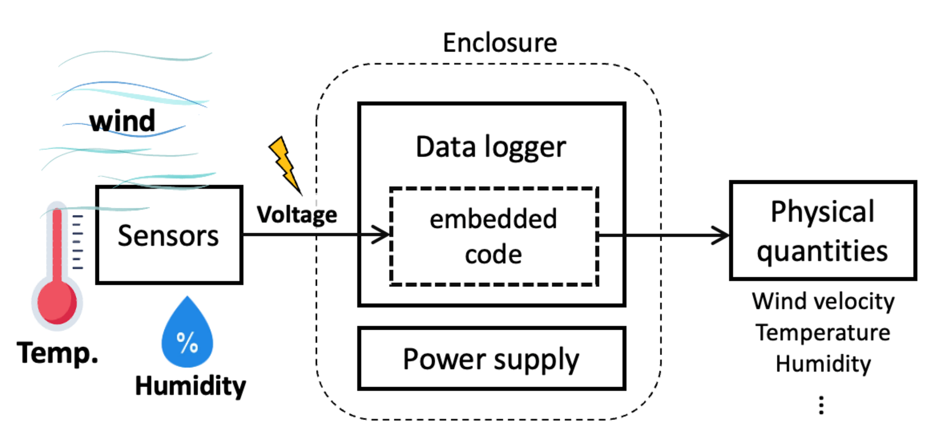

Figure 2. Data Processing Flowchart

Data Postprocessing

Power density spectrums that convey the strengths of different wavelengths within the timeseries were derived using fast Fourier transforms

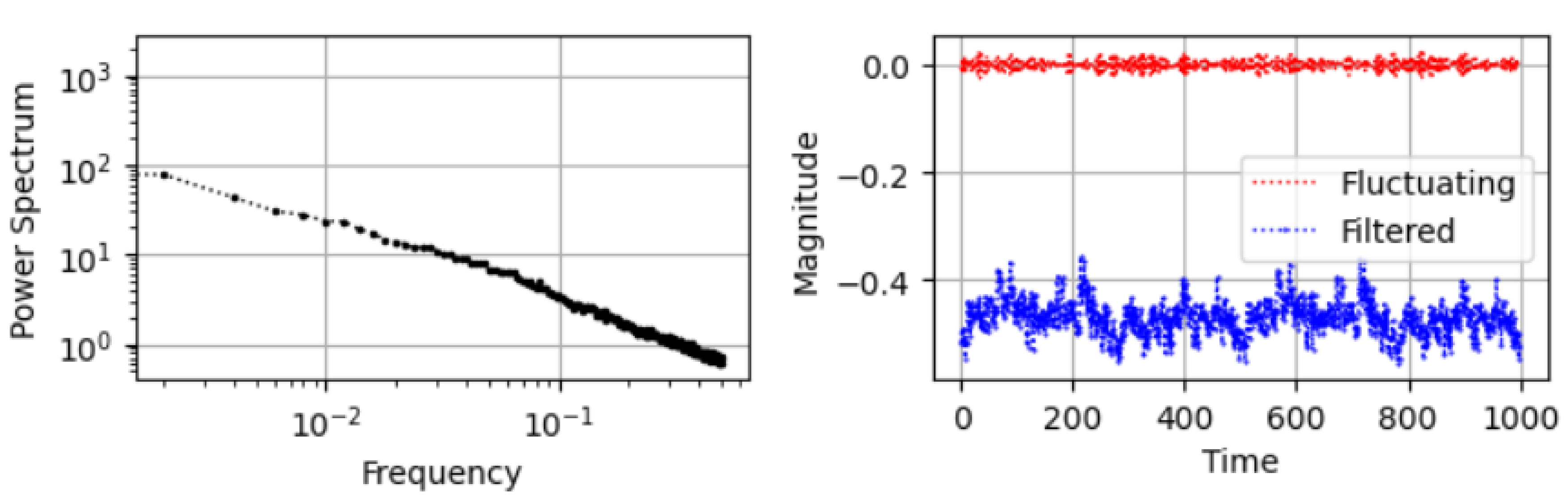

Figure 3. Power Spectrum Density Plot with Corresponding Timeseries

Statistical analyses of data and prediction proof of concept

To inform predictive models for the reconstruction of vertical velocity component, several statistical factors were examined:

1. Relationships based on meteorological principles[1]
   - Fluctuations of u, v, w wind velocity components
   - Reynolds Shear Stress values
   - Turbulent Kinetic Energy
   - Temperature and humidity gradients and buoyancy
   - Correlations between means and standard deviations of timeseries data.
2. Trends within timeseries data
   - Fractal Dimension Analysis[2], which utilizes structures within timeseries data to characterize variability

Results

Observed Physical Relationships and Prediction Results

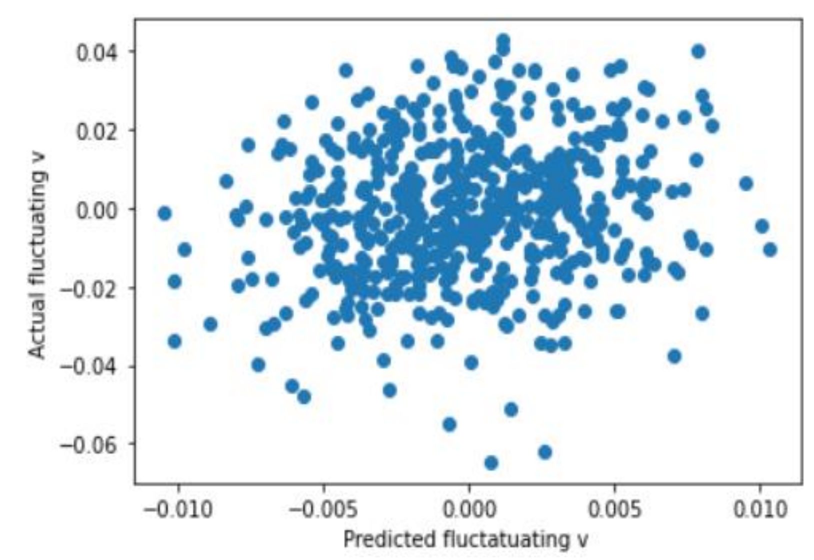

Figure 4. Scatterplot between Reconstructed vs. Observed Vertical Velocity Points

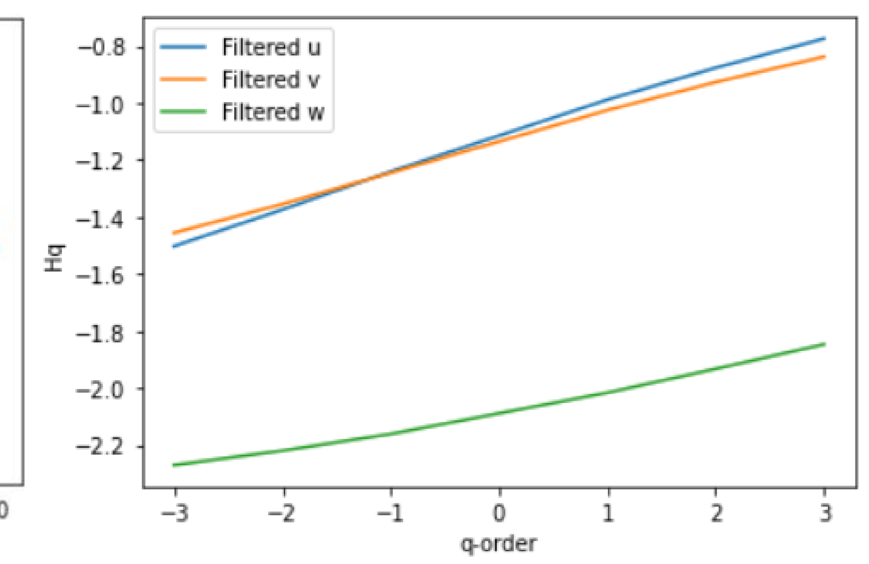

Figure 5. Hurst Exponent (Scaling Descriptor) vs. Order of Fluctuation Function

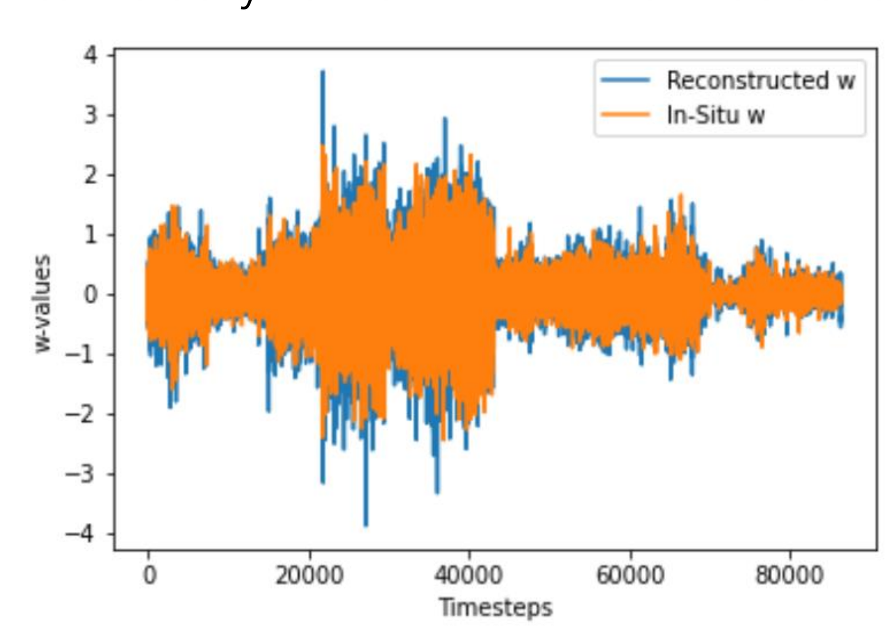

Figure 6. Reconstructed vs. In-Situ Vertical Velocity Timeseries

Mean Data	In-Situ Value	3D Reconstruction	Absolute Difference
w	6.51E-04	5.65E-06	6.45E-04
w*u	5.07E-07	-2.11E-05	2.16E-05
w*v	-4.63E-07	-2.74E-05	2.69E-05
w*w	1.4E-04	9.19E-06	1.34E-04
w*T	-2.20E-08	2.14E-07	-2.36E-07

Table 1. Fluctuation Relationships with Reconstructed and In-Situ Vertical Velocity Components

	U + V + TG + HG	U	V	TG	HG
6 Hours					
MAE	0.1034197841	0.2080996097	0.2059620111	0.4215034516	0.5646423564
MSE	0.2069948121	0.1069610787	0.1021330392	1.144410875	2.864737871
12 Hours					
MAE	0.17926211	0.2989972023	0.3086607209	0.4862633809	0.5514125054
MSE	0.3050101502	0.1658877835	0.1843832961	0.7428145829	1.085585993
24 Hours					
MAE	0.2166757766	0.3164810573	0.3312290081	4.24E-01	0.6299452074
MSE	0.3243184471	0.1995352387	0.227479091	3.91E-01	1.256116781

Table 2. MAE and MSE Values for Vertical Velocity Reconstruction

Conclusions

- Horizontal wind velocities show strongest consistent relationships with vertical velocity
- As time chunk length decreases, accuracy increases for reconstruction
- A combination of variables as input is optimal for reconstruction
- Confirmed reconstruction as a proof of concept

Future Study

Use of more sophisticated machine learning models/tuning parameters

Models like transformers and other temporally dependent models will be well-suited to this application

Specific topographical analysis

Another possible way to improve predictions is by considering each sensor's surrounding topography and using basic simulations to check and correct extrapolated values

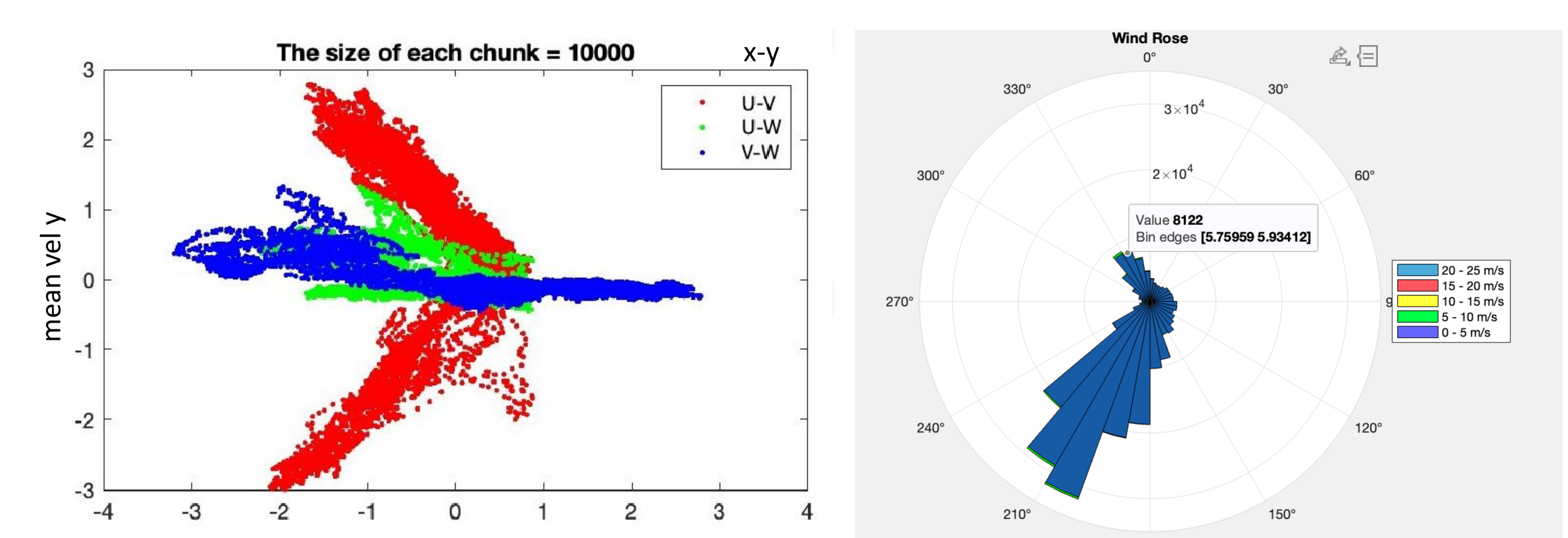

Figure 7. Example Spatial Dependencies. Left: Horizontal Wind Interactions due to Obstruction. Right: Wind Rose Showing Dominant Wind Directions

References

[1] Stull, R. B. (1988). *An introduction to boundary layer meteorology* (Vol. 13). Springer Science & Business Media.

[2] Shu, Z. R., Chan, P. W., Li, Q. S., He, Y. C., Yan, B. W., Li, L., ... & Yang, H. L. (2021). Characterization of vertical wind velocity variability based on fractal dimension analysis. *Journal of Wind Engineering and Industrial Aerodynamics*, 213, 104608.

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