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How should machine learning be successfully used for wind speed vertical extrapolation?

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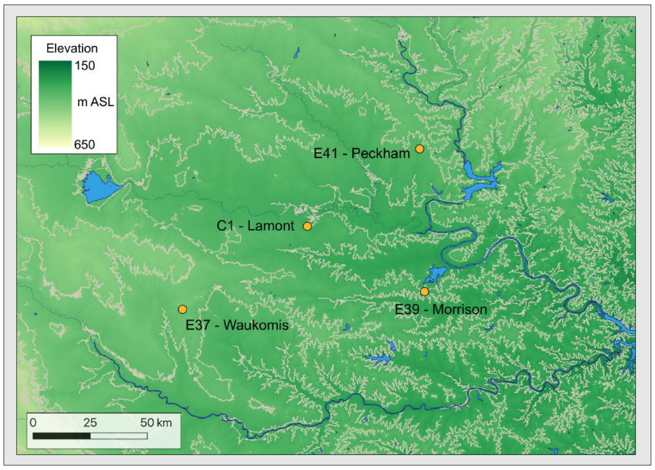


Goal

Machine learning (ML) has recently been proposed [1] to overcome the limits [2] of conventional wind extrapolation methods (power law, logarithmic profile). However, for it to be recommended for real-world applications, ML needs to be tested under a round-robin approach, where wind is extrapolated at a site different from the training one.

Data and Methods

We use 20 months of observations (as 30-min averages) collected by lidars and sonic anemometers at four sites at the Southern Great Plains (SGP) atmospheric observatory. We train and test a random forest to extrapolate wind speed at 143 m AGL using a set of atmospheric variables as input, and compare the results with extrapolation from the conventional power law and logarithmic profile (+ stability corrections).

Testing *MAE* ($m\,s^{-1}$)

Testing site	Site C1	Site E37	Site E39	Site E41
Logarithmic law	0.84	0.94	0.92	0.92
Power law	0.86	1.18	0.97	0.92
Random forest, trained and tested at same site	0.66	0.75	0.71	0.69
Random forest, round robin approach	0.75	0.83	0.79	0.77

Comparing extrapolation methods

When evaluated at a single site, we find that the random-forest approach achieves, on average, a 23% reduction in mean absolute error (MAE) compared to the logarithmic law and a 28% reduction compared to the power law.

When the round-robin validation is used, the ML approach still outperforms the conventional extrapolation techniques, with a reduction in MAE that decreases to 14% for the log law and 20% for the power law.

We find that ML leads to the largest benefits in strongly stable conditions.

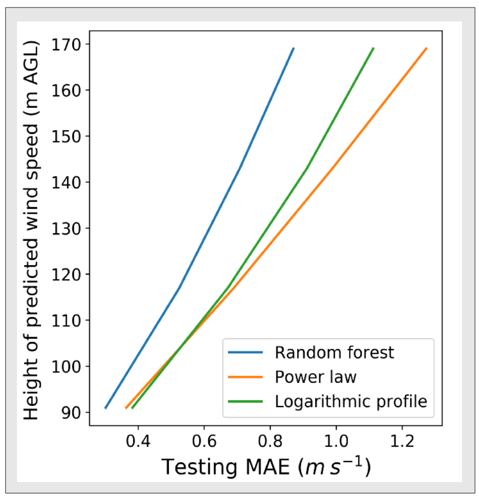
(b) Testing *MAE* ($m\,s^{-1}$)

	WS 65m	+WS 4m	+time	+L	+TKE
Site C1	0.94	0.79	0.69	0.66	0.65
Site E37	1.12	0.97	0.85	0.76	0.75
Site E39	1.06	0.87	0.79	0.75	0.72
Site E41	1.03	0.83	0.75	0.72	0.69
AVERAGE	1.04	0.86	0.77	0.72	0.70

ML performance

Wind speed at 65 m AGL (i.e. the height closest to the extrapolation level) is the most important feature for the ML prediction. However, adding as additional inputs surface wind speed, time of day, Obukhov length and TKE improves the ML performance by over 20%.

Finally, the performance of the random forest degrades more slowly with height than the conventional methods, highlighting the limitations of these conventional approaches over large vertical extrapolation ranges.



More in Bodini and Optis, Wind Energy Science 2020

References & Copyright

1. Mohandes, M. A. and Rehman, S.: Wind Speed Extrapolation Using Machine Learning Methods and LiDAR Measurements, IEEE Access, 2018.
2. Optis, M., Monahan, A., and Bosveld, F. C.: Moving Beyond Monin–Obukhov Similarity Theory in Modelling Wind-Speed Profiles in the Lower Atmospheric Boundary Layer under Stable Stratification, Bound.-Lay. Meteorol., 2014.

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