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Understanding Pulsed Lidar Data Availability

Simulating with Reanalysis Data and Boosting with Convolutional Neural Networks

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Abstract

As wind energy development accelerates worldwide, many more campaigns are using profiling and scanning lidar, and more campaigns are occurring in locations with low aerosol density ("clean air" or "clear sky"). Lidar backscatter signal quality depends on the presence of aerosols advecting in the wind: clean air sites reduce lidar range and data availability and can lead to increased project uncertainties. Large scale deployment of wind lidar requires **(1) simulators that can reliably predict lidar data availability (2) novel techniques to improve range and availability to reduce energy yield assessment uncertainties.** Here we present:

- New range data availability simulator using satellite and reanalysis data,
- Technique to maximize profiling lidar data availability with traditional algorithms via detailed study of lidar metrology and uncertainty, and
- MosquitoNet, a new lidar range boosting technique based on a convolutional neural network that can recover low CNR data.

Data Availability and Range Estimator

Why is it important to simulate the availability of a lidar before the campaign? Successful measurement campaigns require careful planning. The expected data availability of the sensors in your observation network is a key detail in allocating field engineering resources, sizing power supplies, and choosing the right sensors for your application's requirements. Vaisala's Data Availability and Range Estimator allows WindCube lidar users to simulate the performance of their devices based on historical weather and reanalysis data at the proposed measurement campaign site

Atmospheric Function

$$F_{atmo}(r) = \beta_\lambda(r)e^{-2\int_0^r \alpha_\lambda(r')dr'}$$

β = backscatter coefficient at λ (1540 nm)
- 180° backscatter cross section

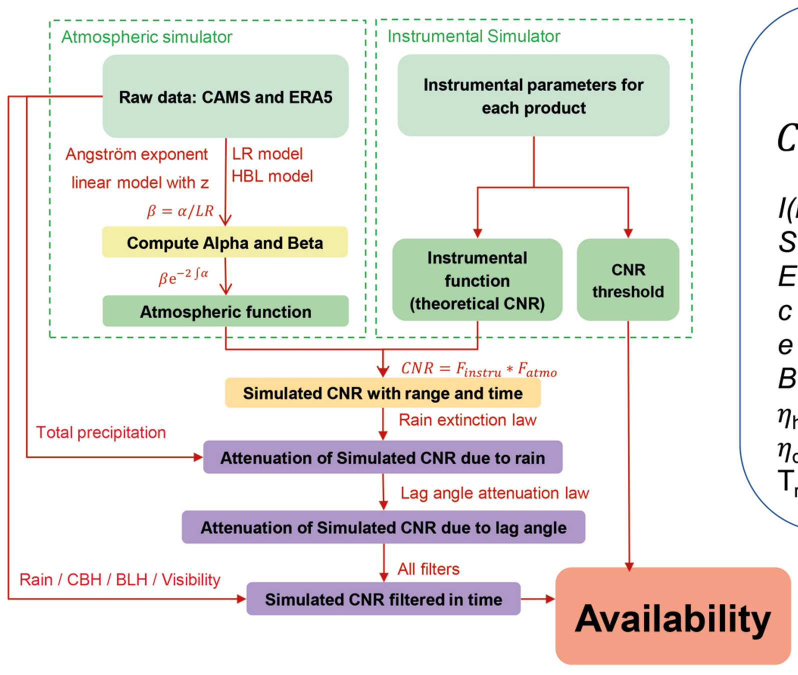
r = distance from lidar
α = extinction coefficient at 1540 nm (units)
- Signal attenuation due to scattering
- Function of aerosol optical depth (AOD), a measure of aerosols above the lidar
- AOD is modulated by the boundary layer height, where aerosol concentrations are highest

Data Sources

ECMWF provides ERA5 global reanalysis data. From ERA5, the Boundary Later height is derived
Resolution: 0.25° and 1h

ECMWF Copernicus Europe's eyes on Earth

Copernicus Atmospheric Monitoring Service provides global satellite measurements of AOD for various particulates, and rainfall rate
Resolution: 0.125° and 3h



Instrumental Function

$$CNR(r) = \eta_h \eta_q T_{rt}(r)\frac{\lambda\, S\, E_T\, c}{2eB}\beta(r)I(r)$$

$I(r)$ = Lorentzian shape, symmetry about r_0
S = detector sensitivity
E_T = pulse energy
c = speed of light
e = electron charge
B = noise bandwidth
η_h = heterodyne efficiency
η_q = detector quantum efficiency
T_{rt} = round trip transmission

WindCube Scan
Variable instrument parameters, highly application specific

WindCube
Fixed instrument parameters, V2 and V2.1 have same instrumental function for CNR purposes

WindCube Offshore
Same parameters as onshore V2 or V2.1 with respect to CNR

WindCube Nacelle
Short Range, Long Range and Turbine Control variants

Optimizing Traditional Filtering Thresholds

Lidar device uncertainty, independent of atmospheric sensitivities, can be derived by measuring the uncertainties of LOS measurements in the laboratory using Vaisala's Simulation of the Atmosphere with Fiber Optics (SAFO) test bench, and then propagating the measured uncertainties through the wind field reconstruction algorithm, and combining the uncertainties of N measurements in a 10-minute period, following the GUM (1995).

WindCube Device Uncertainty

$$\delta Vh_{10min} = \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\sqrt{\left(\frac{\sqrt{2}\,\delta V_{r,i}}{2\sin\theta}\right)^2 + cov[\delta V_{r,i,j}]}$$

N = number of 1 Hz wind speeds in average
$\delta V_{r,i}$ = Uncertainty of LOS wind speed
θ = lidar elevation angle from vertical
cov = covariance of 1 Hz with neighboring samples

Using this description of lidar uncertainty, to maintain 0.1 m/s precision, a **50% availability threshold can be used to boost data availability in bankable campaigns.**

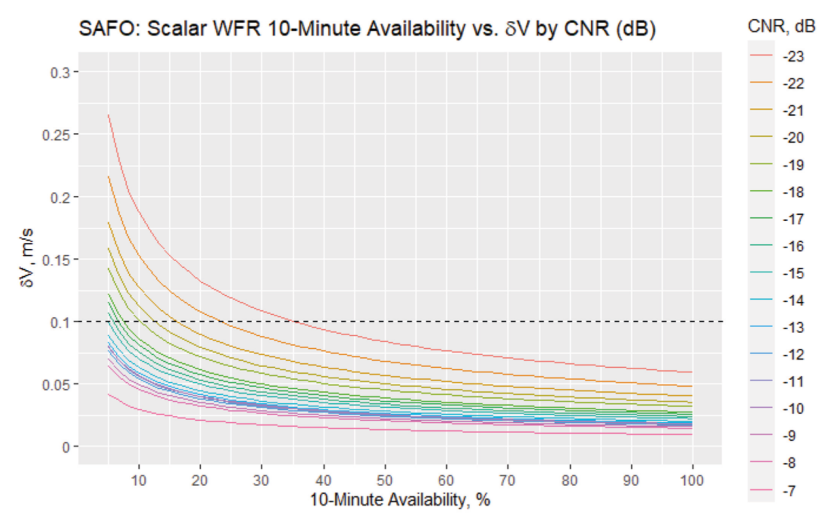


Figure 1: WindCube uncertainties as a function of CNR and 10-minute data availability

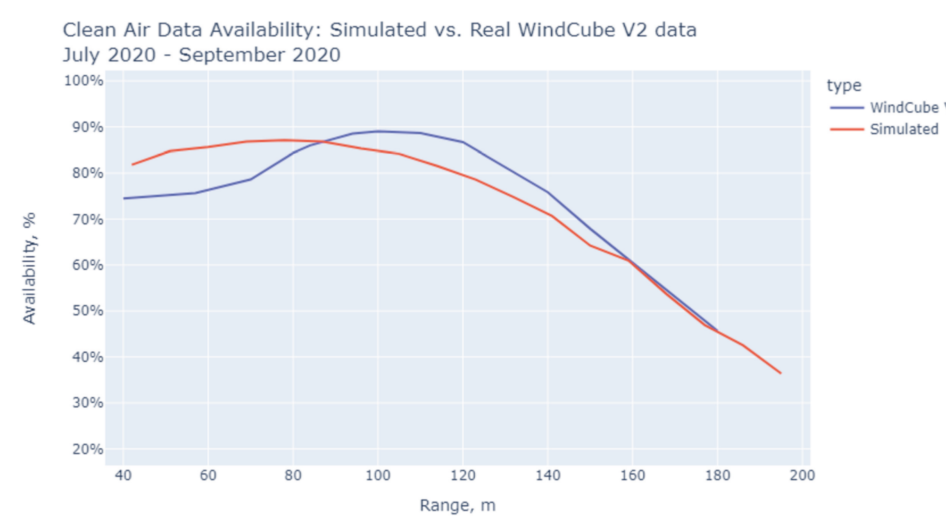


Figure 2: Simulated data availability for WindCube V2 profiling lidar compared to data availability observed in real measurement campaign. WindCube Data Availability filter threshold of 80% 10-minute availability

MosquitoNet – a Deep Learning Range Booster

Vaisala has developed an experimental **new filtering technique using a convolutional neural network** to perform semantic segmentation on LOS time series images, classifying pixel data into categories "wind", "hard target", or "outlier". After labeling, the CNR threshold is reduced from -23 dB to -26 dB and wind speeds are recalculated using only "wind" data. Validation of biases and uncertainties of these recaptured data is ongoing.

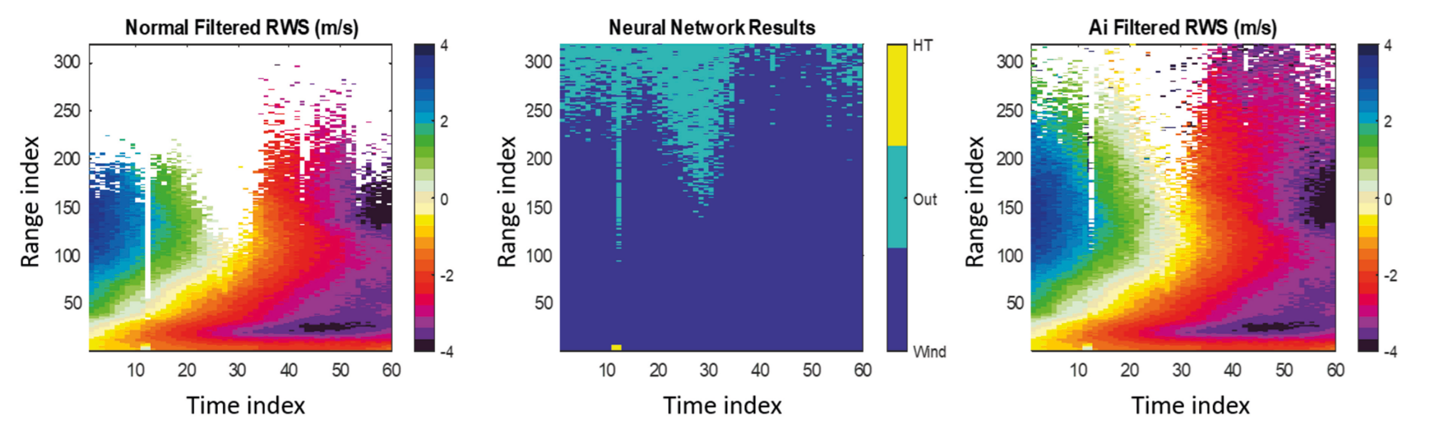


Figure 3: (A) Time series of one LOS, all heights, -23 dB threshold. (B) MosquitoNet semantic segmentation results. (C) Time series of same LOS, all heights, -26 dB threshold including only pixels classified as wind

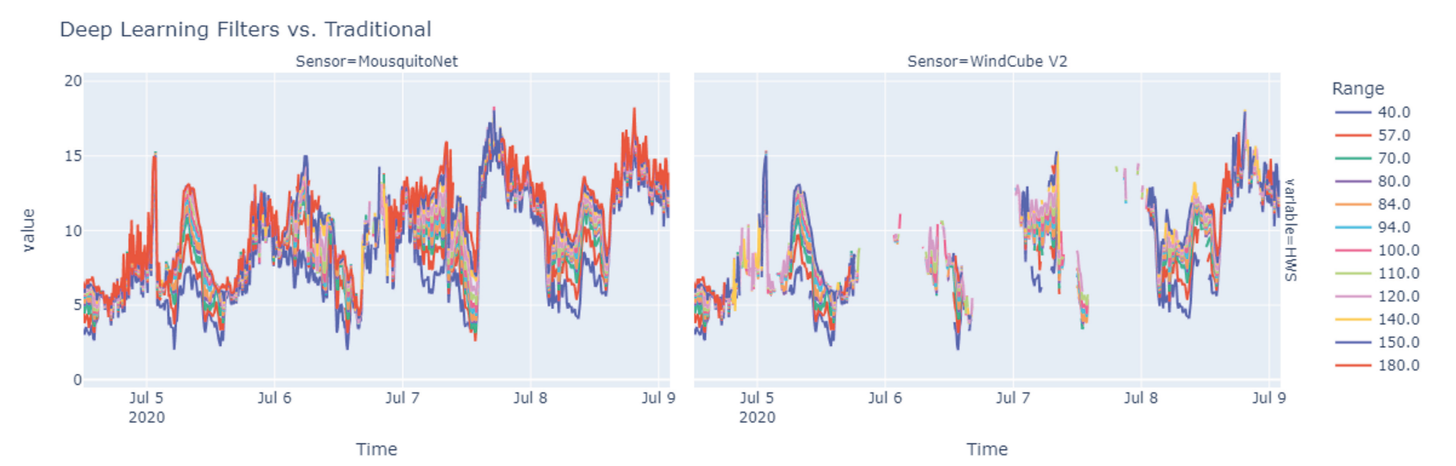


Figure 4: (A) Time series of horizontal wind speed, all heights, -26 dB threshold, all "wind" classified LOS data included, 50% 10-minute availability threshold (B) Traditional threshold filter, -23 dB, 50% 10-minute Availability

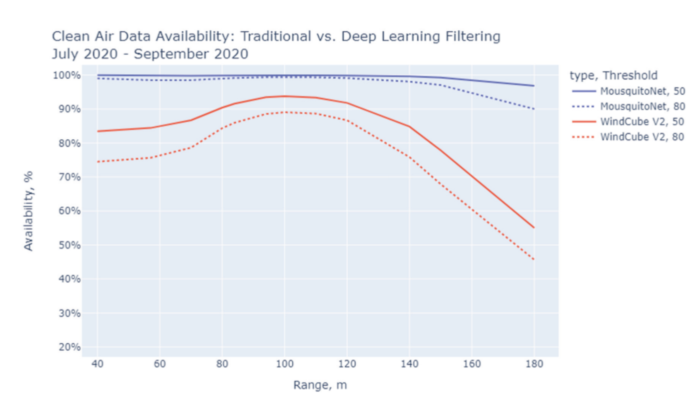


Figure 5: Comparison of -23 dB, 80% filters, -23 dB, 50% filters, and -26 dB 50% filters data availability

Conclusions

Clean air conditions can be predicted with sufficient accuracy for lidar met campaign planning. Precise application of traditional filtering techniques enable 5-10% improvements in campaign availability. Deep learning-based filters can boost availability by up to 40%.

References

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4. Machta et al. Boosting Lidar Range using Convolutional Neural Network. CLRC (2022)

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