Aspects on remote sensing assisted minute scale forecasting

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WEPROG

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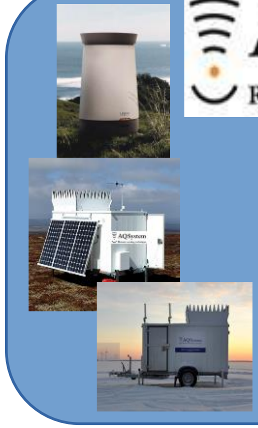
EARS4WindEnergy

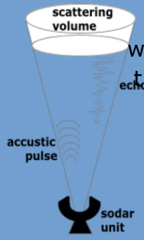
Ensemble-based Approach utilizing a Refined SODAR
for Wind Energy Applications

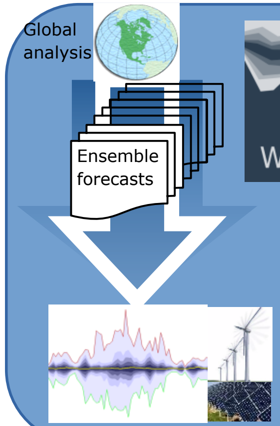
www.aqsystem.se

AQSystem
Remote sensing technique



started in 1989 to produce SODARs to monitor wind and turbulence for the wind energy market. Today the AQ510 is a robust self-sufficient life-cycle instrument for all climate conditions…





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..started in 2003 to generate ensemble w eather and energy forecasts for the energy market.

Today, the 75 ensemble member MSEPS system is run world-wide to serve efficient renewables integration and to assist in "dealing with uncertainties"..

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Uppsala University has long experience working with wind power as well as observations and analysis of measurements in the atmospheric boundary layer

Risø Campus & Test facilities

DTU

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Wind power minute scale forecasting

- The importance of minute scale prediction is increasing
  - New market rules
  - Larger VRE share in the system
- Machine learning have driven a methodology focused revolution
  - Less focus on theoretical limits and drivers of predictability

Meteorological model.

Lacks information from the recent hours.

Initialization lag time 6-30 hours

→

Statistical model.

Fed with meteorological variables + site observation.

Initialization lag time 15-60 minutes

→

Decision model.

Determines balancing actions or optimal market bids

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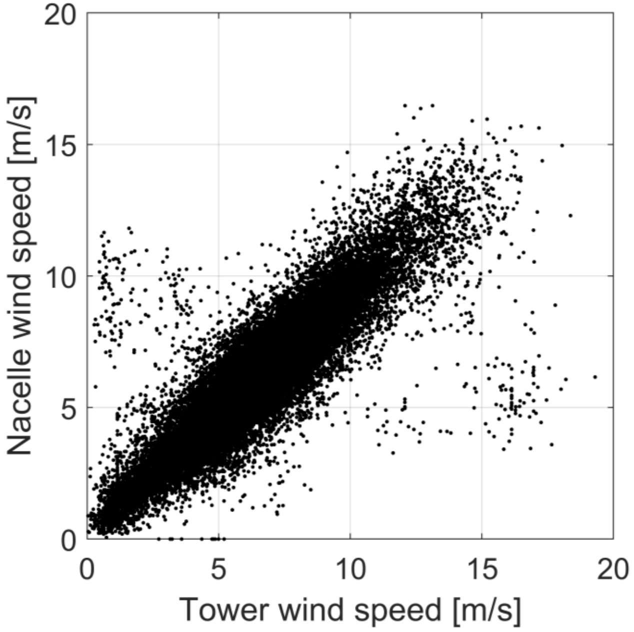
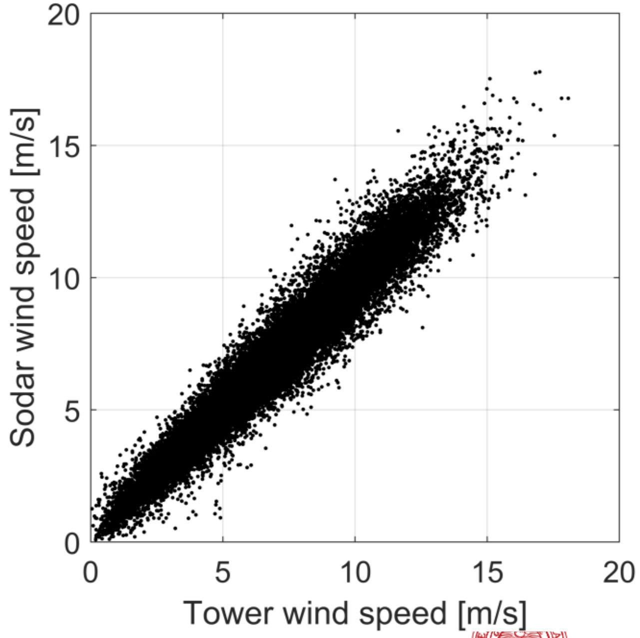
How can a ground based profiler assist in minute scale wind power prediction?

- The NWP product inevitably lacks skill on small scales
  - Initialization lag time
  - Resolution
  - Rapid error growth for 3-dimensional motions
- Onsite observations is <u>crucial</u> to improve skill
- Turbine observations are not always useful
  - Curtailed production
  - Data quality issues

Tower 200 m from turbine



Sodar 400 m from turbine



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Forecast error partitioning

$$\tilde{u}_p(x,t) = f(\tilde{u}_m(x,t), \tilde{u}(x+r, t-\delta t), ..., \tilde{u}(x+r_i, t-n\delta t))$$

Predicted wind speed is a function of *NWP forecast* and previously *observed wind speeds* at various locations

$$\langle[\tilde{u}_o - \tilde{u}_p]^2\rangle = 2\sigma_{\tilde{u}_o}\sigma_{\tilde{u}_p}\left(\frac{1}{2}\frac{\sigma^2_{\tilde{u}_o}}{\sigma_{\tilde{u}_o}\sigma_{\tilde{u}_p}} + \frac{1}{2}\frac{\sigma^2_{\tilde{u}_p}}{\sigma_{\tilde{u}_o}\sigma_{\tilde{u}_p}} - R(\tilde{u}_o, \tilde{u}_p)\right)$$

Prediction error =

= Correlated + uncorrelated observational variance + and model variance - Correlated large scales =

uncorrelated observational variance

+ uncorrelated model variance

Includes decorrelation from time lag and distance

Includes model errors, forecast errors and uncorrelated small scales

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Objective

- Establish how the distance between observation and target impacts the value of the observation
- Establish how different lag times impacts the value of the observation

Method

- 7 AQ510 Sodars and a 180 m met tower
- A 5 member high resolution, 1.5 km, NWP ensemble
  - 1.5 km resolution, 8 s timestep, 10 minute average output
  - Perturbed model physics which ensure immediate spread
- Investigate the scales of correlation between NWP forecast and target
  - Spectral analysis
- Investigate how correlation between observations decrease with distance
  - Cross correlation function and cross spectra
- Partition the contribution to forecast skill for different initialization lag times
  - RMSE of a simplified forecast

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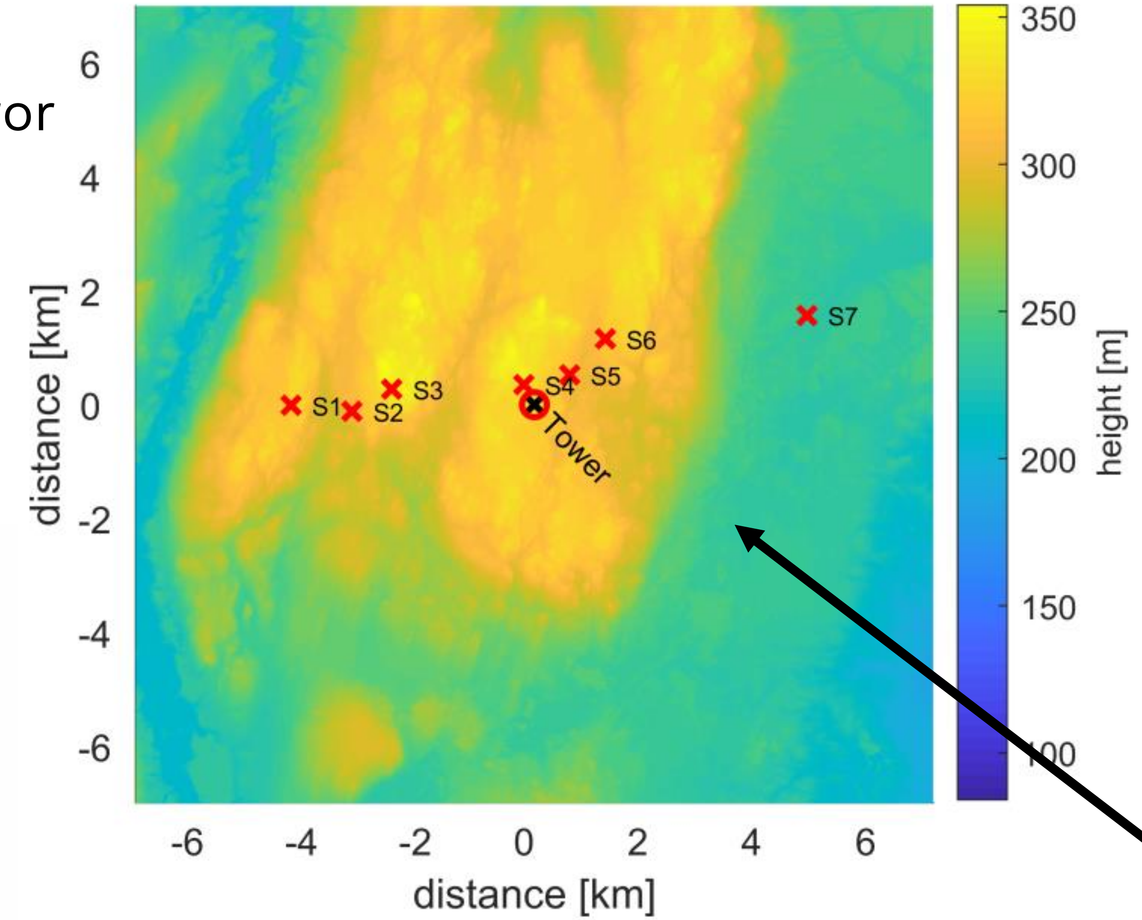
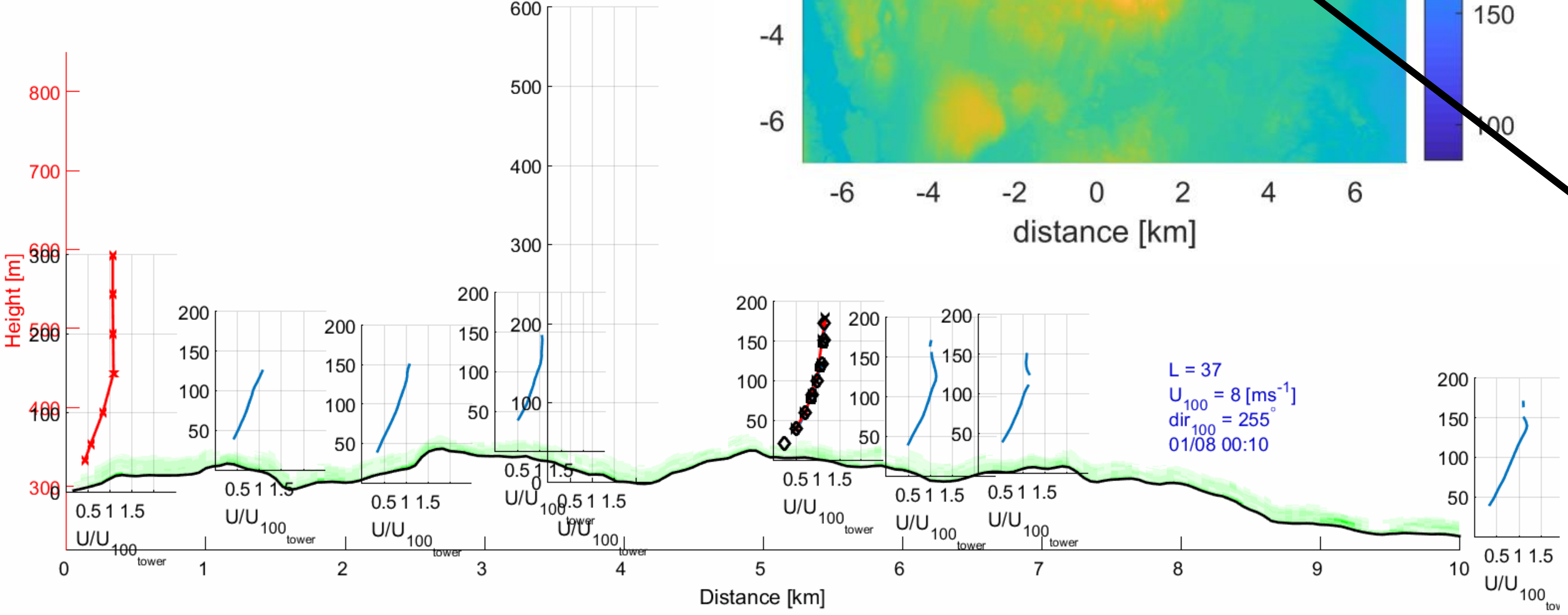
Important to consider random error when comparing measurements from two positions





The site

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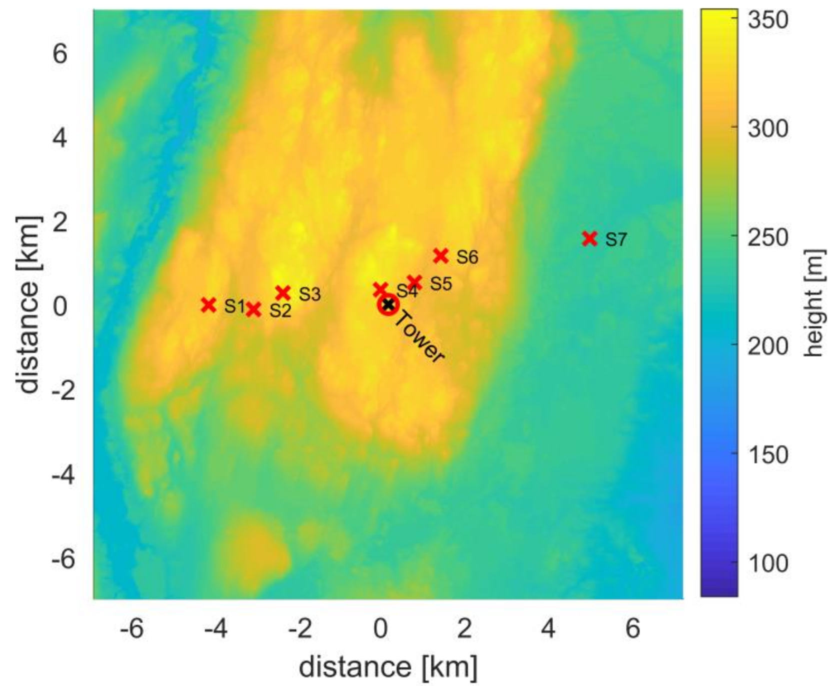
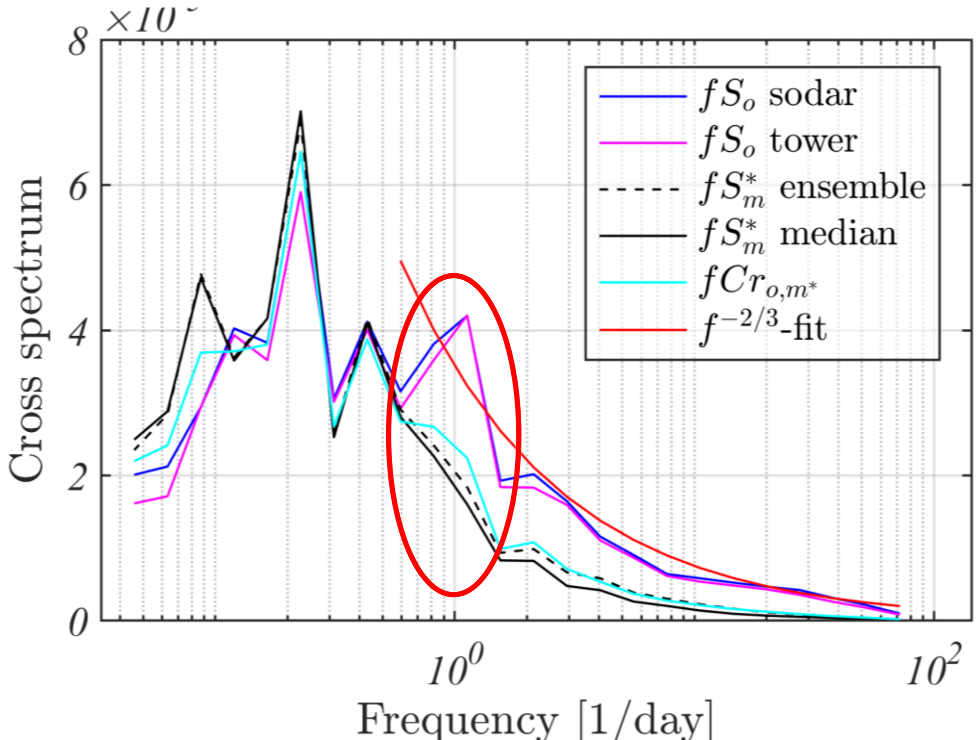
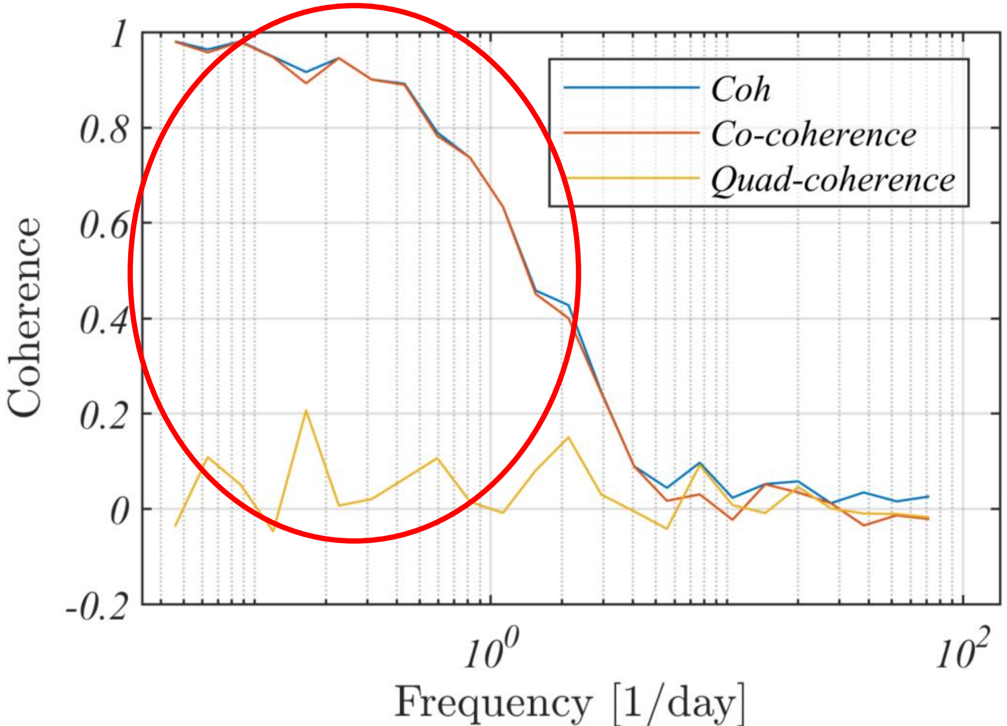
Spectral analysis



- The skill of the NWP comes predominately from time scales > 12 h
- The diurnal cycle is underpredicted by the NWP
- No systematic (average) phase difference between NWP and observations





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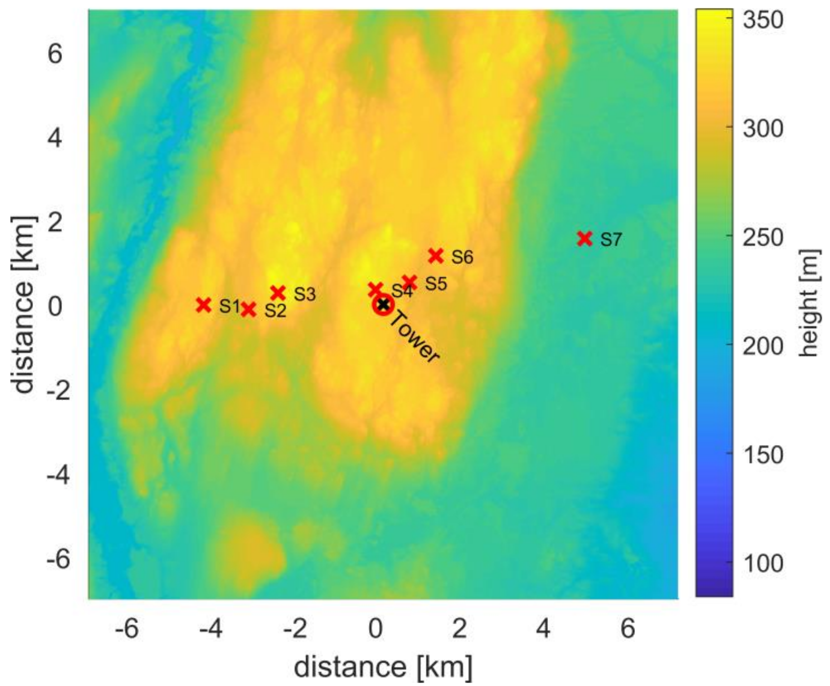
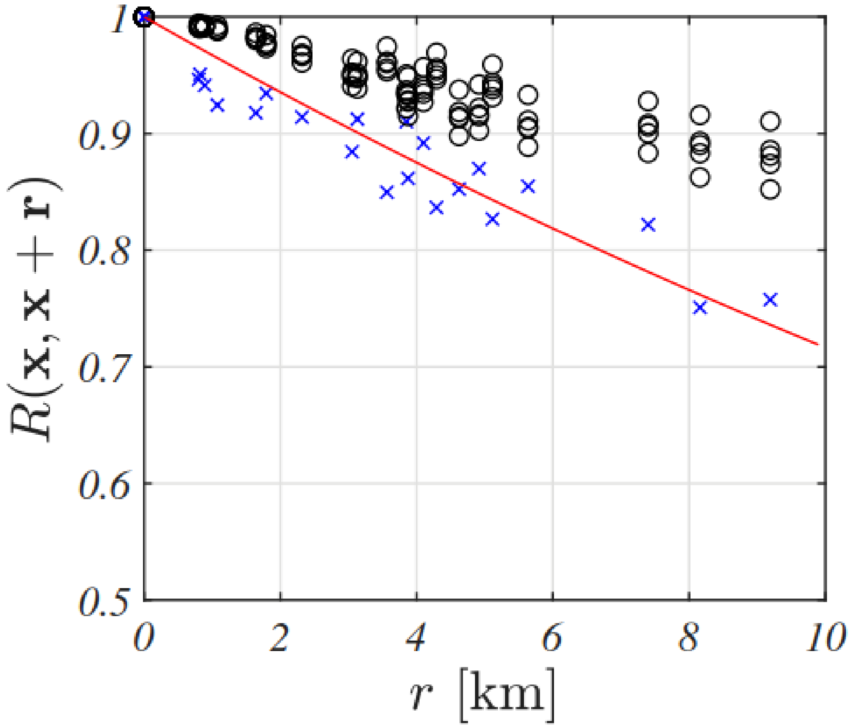
Cross-correlation

- The NWP is more homogeneous than the observations (expected due to resolution)
- The loss in correlation with distance is driven by smalls scales
- The value of the observations comes predominately at scales between 1 day and 4 h

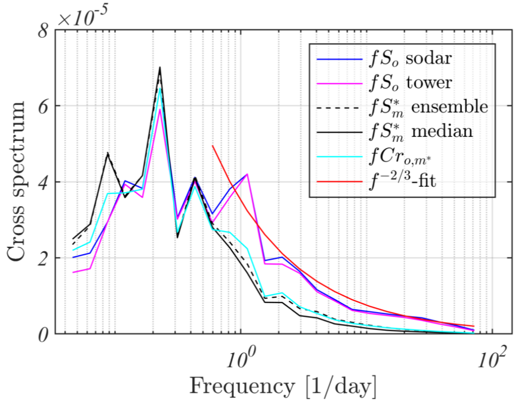


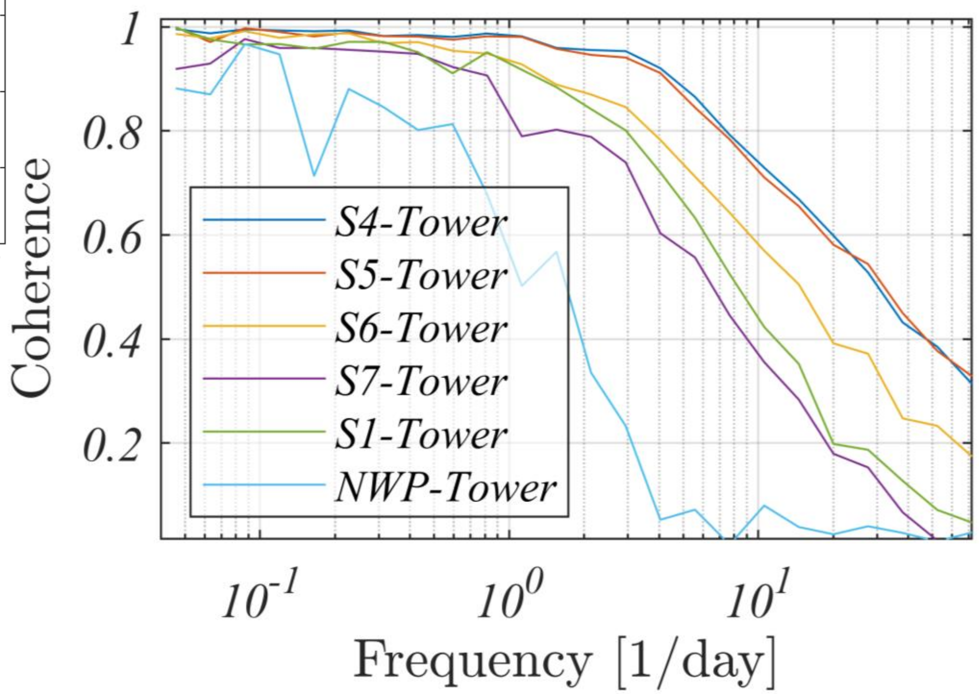


Observations

NWP model

Exponential fit to observations

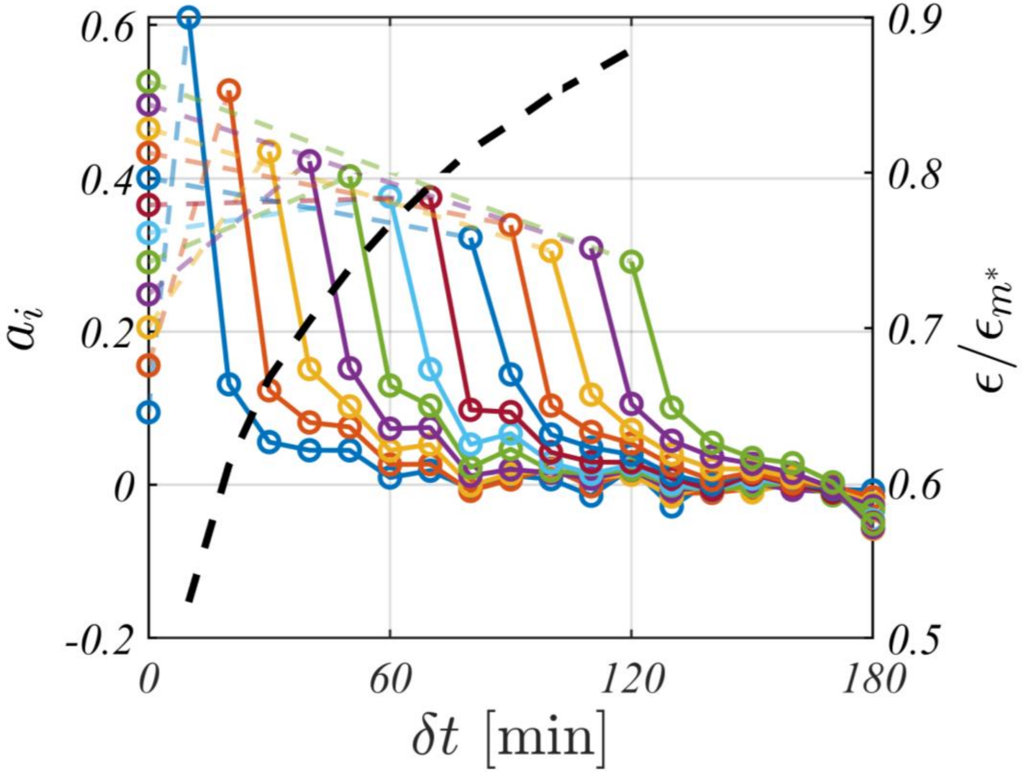




Error dependence on lag time

$$\overline{u}_p(\mathbf{x},t) = a_0\overline{u}_{m^*}(\mathbf{x},t) + \sum_{n=n_1}^{N} a_i\overline{u}_o(\mathbf{x}+r, t-n\delta t)$$

The prediction is a linear combination of NWP and observations with different lag times



- For lag times larger than 1 hour NWP becomes the leading order term
- Weighted observations from the last available hour contribute with skill
- Reducing the lag time is key to minimizing error
- The error ϵ grows asymptotically to the NWP error ϵ_{m*}.

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Conclusions

- Model and observations are only correlated on longer time scales
- Smoothing the observations is necessary to reduce the impact of uncorrelated scales
- Smoothing of model data is necessery and preferably done with ensembles to facilitate high resolution
- The value of the observations are largest at scales between 4 h to 24 h → the exact position of the remote sensor is not crucial

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Thank you for listening
Questions?

Acknowledgements

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