Estimation of the benefits of remote- sensing profilers for sustainable energy applications

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PROBE COST ACTION

Motivation

- Networks of ground-based instruments planned
- Model output with 1000 ensembles available for sensitivity analysis
- No real observations are required
- Impact on short-term forecast for renewable energy applications?
- Our first attempt: wind lidar network for low-level wind forecast

Question for this study

- How much improvement can a Doppler wind lidar network add relative to conventionally assimilated surface observations?

Input data

Model

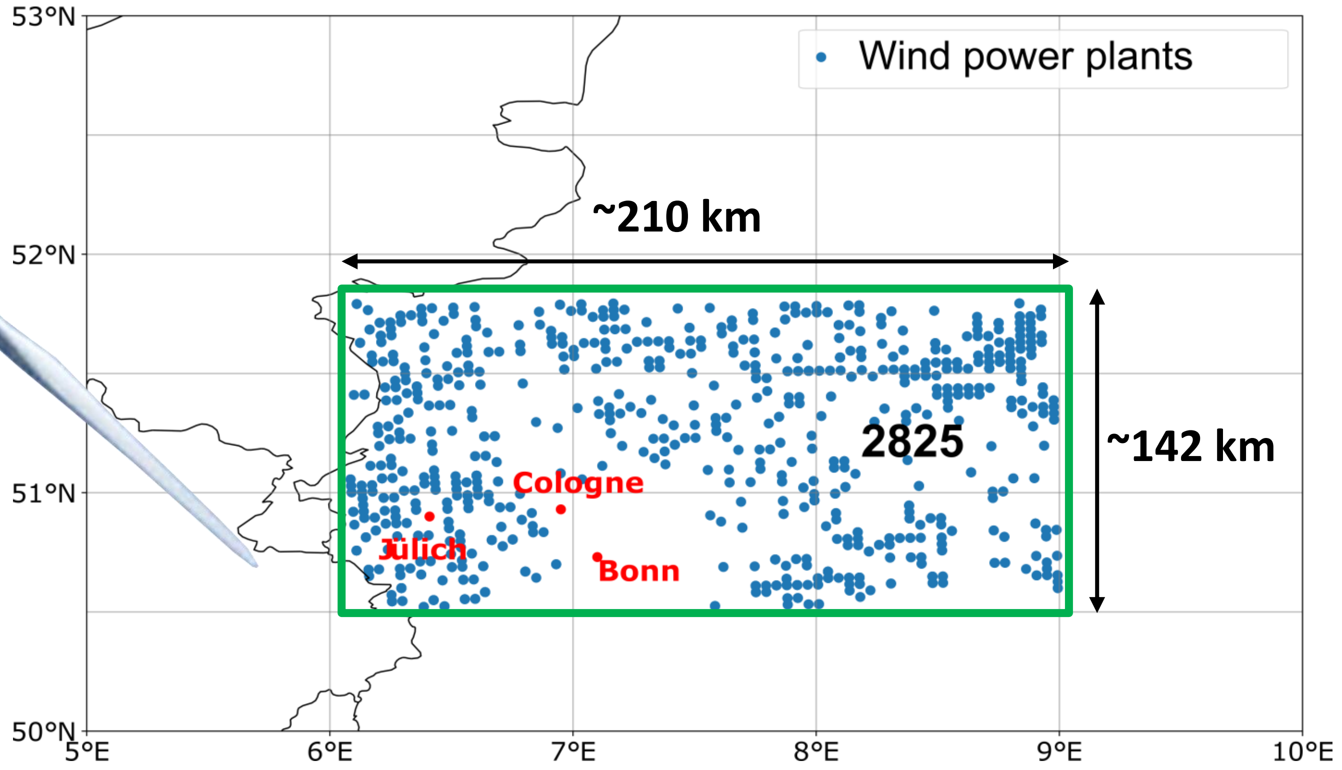
- Regional climate / weather forecasting model **SCALE-RM**
- **1000-member ensemble** (Necker et. al, 2020)
- Over Germany, space resolution **3 km**
- **Model domain:** 352 x 250 grid points centered over Germany
- **Every 10th grid point** of model-output used for the analysis to reduce the state space

Simulated observations

- **Wind profiles** from hypothetical **Doppler lidars**
- Analysis of **5 levels** (model output): (80, 429, 1062, 1853, and 2845 m)

https://w3.windfair.net/wind-energy/product/403-windcube-v2

Focus of the experiment: RRA with wind parks



Wind power parks (2019):

2825 wind power plants within RRA

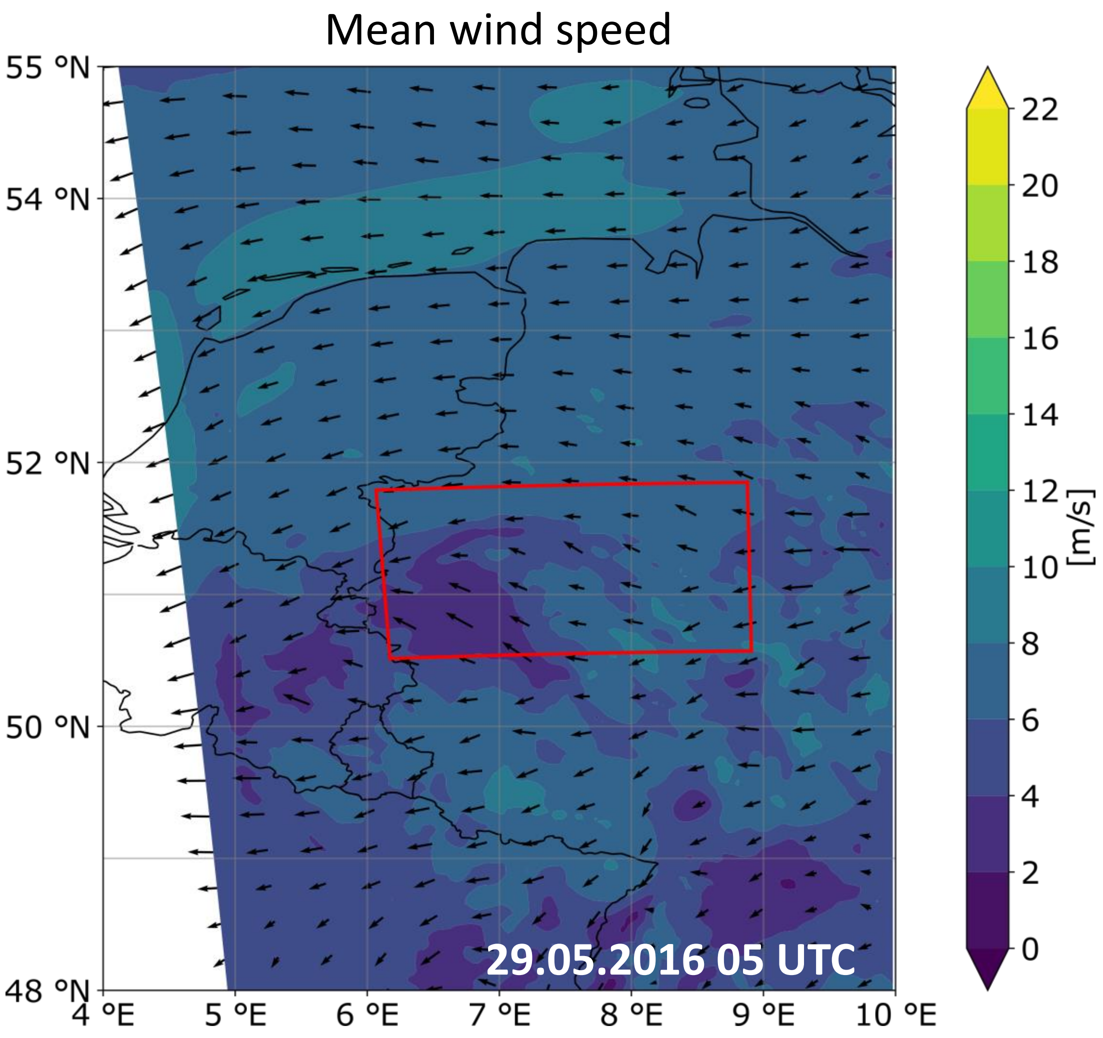
Maximum output of **RRA** power stations:

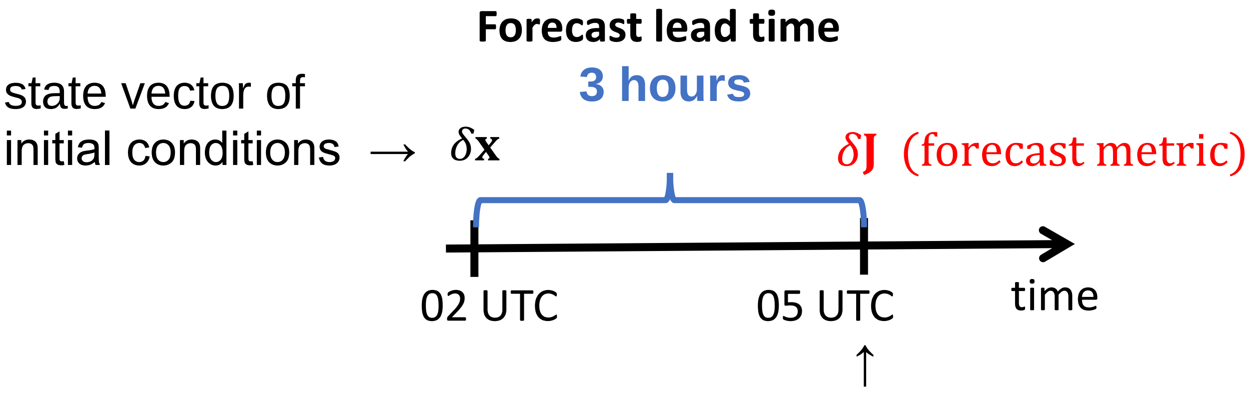
~5.1 GW (7.4 %)

Total wind power in Germany ~ **69.23 GW**

Data of wind power location were obtained by personal communication with Lukas Schmidt and https://github.com/OpenEnergyPlatform/open-MaStR

Forecast metric over RRA: wind speed at 80 m





Domain averaged wind speed over RRA at 80 m
(typical hub-height of wind turbines)

$$\textbf{Sensitivity} = \mathrm{cov}(\delta\mathbf{J}, \delta\mathbf{x})\ \mathbf{B}^{-1}$$

$$\mathbf{B} = \{\delta\mathbf{x}\ \delta\mathbf{x}^{\mathrm{T}}\}$$

Ancell and Hakim, 2007

Method: ensemble sensitivity to estimate variance reduction

1) Forecast variance reduction: $\delta\sigma^2 = \text{Sensitivity}\,\boxed{(\mathbf{A}_{\mathbf{updated}} - \mathbf{B})}\,(\text{Sensitivity})^{\mathrm{T}}$

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2) Reduction of background covariance matrixes (Ancell and Hakim, 2007):

$$\boxed{(\mathbf{A}_{\mathbf{updated}} - \mathbf{B})} = -\mathbf{KHB} = -\underbrace{\boxed{(\mathbf{L} \circ \mathbf{B})\,\mathbf{H}^{\mathrm{T}}\left(\mathbf{H}\,(\mathbf{L} \circ \mathbf{B})\,\mathbf{H}^{\mathrm{T}} + \boldsymbol{R}\right)^{-1}}}_{\text{Kalman gain (K)}}\,\mathbf{H}\,\mathbf{B}\,,$$

$\mathbf{B}$ – state covariance matrix before added wind lidars; $\mathbf{A}_{\mathbf{updated}}$ – updated state covariance matrix;
H – forward operator; **R** – error covariance matrix; $\circ$ Schur product; **L** – localization matrix

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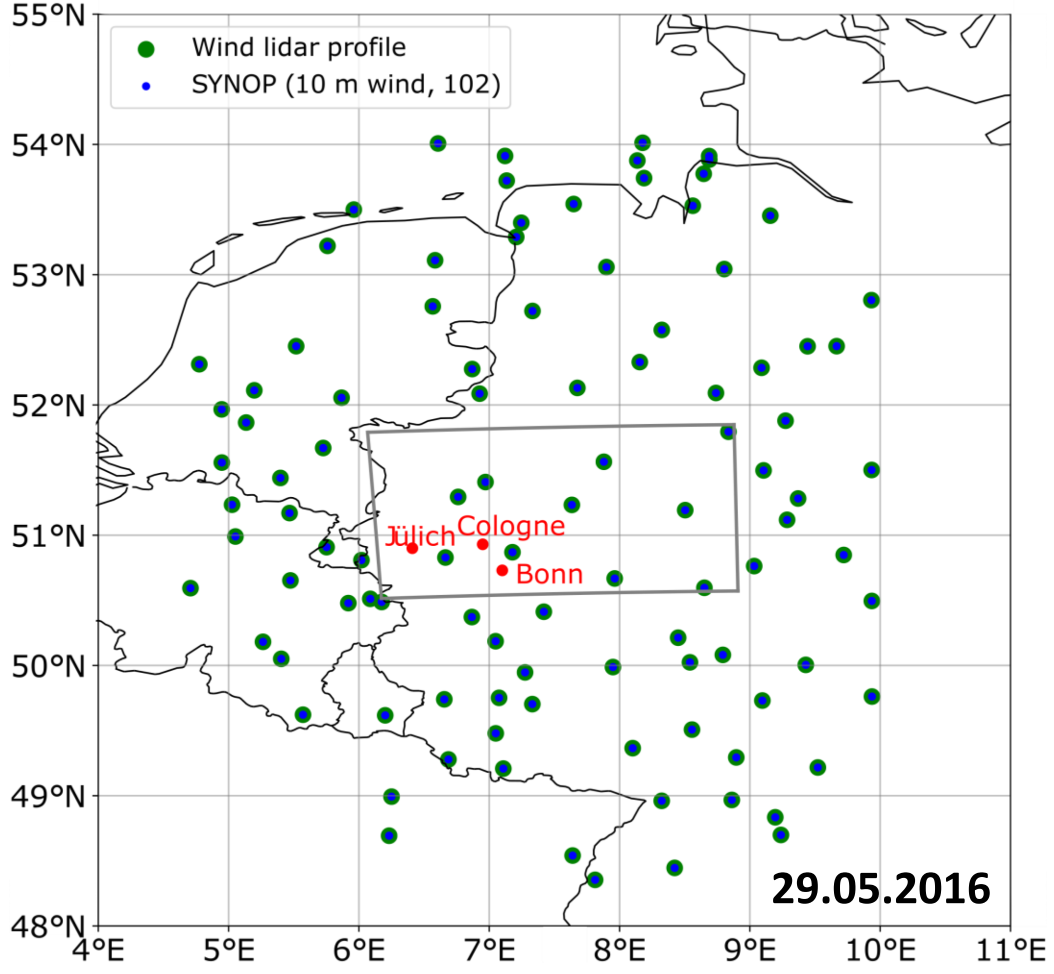
3) $\text{Sensitivity} = \left(\mathbf{B}^{\mathrm{T}}\,\mathbf{B} + \alpha^2\,\mathbf{I}\right)^{-1}\mathbf{B}^{\mathrm{T}}\left(\mathrm{cov}\left(\delta\mathbf{J}, \delta\mathbf{x}^{\mathrm{T}}\right)\right)^{\mathrm{T}}$

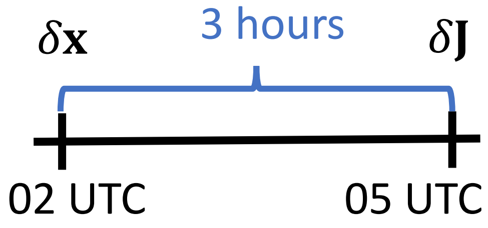
$\delta\mathbf{J}$ – forecast metric,
$\delta\mathbf{x}$ – state vector of initial conditions

Sensitivity is regularized by Tikhonov method ($\alpha = 0.1$)

Experimental setup based on SCALE-RM 1000 ensemble

Potential wind lidar network to improve 3-hour forecasted low-level wind (at 05 UTC):





1) Target: domain averaged 80 m wind speed over RRA

(typical hub-height of wind turbines)

2) Incorporated observations:

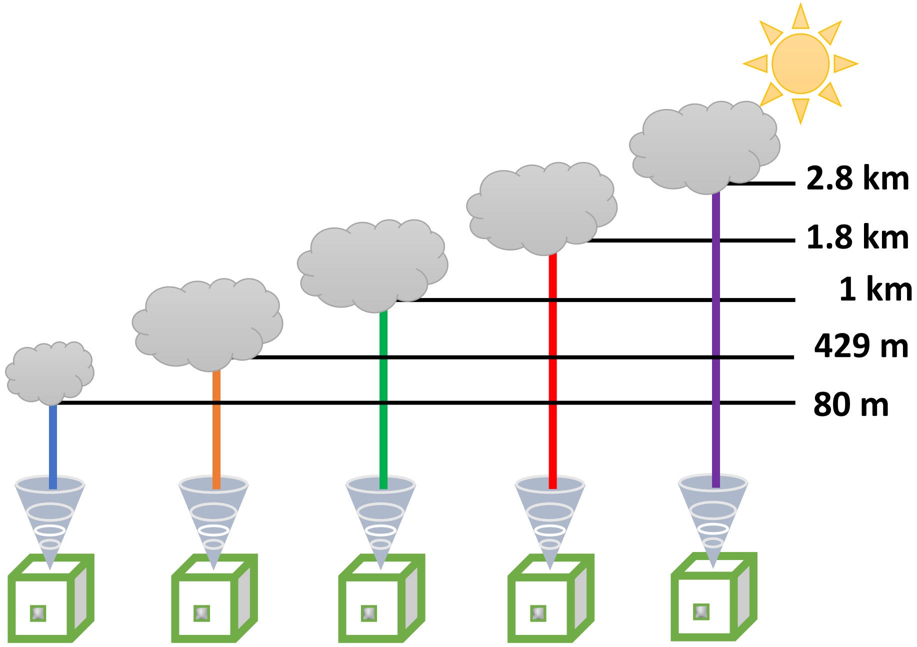
- **wind speed at 10 m** (SYNOP stations)
- **wind speed profiles** (up to **25 random stations**)
- **1 to 5 levels** included: **80, 429, 1062, 1853, 2845 m**
- **50 repetitions** (random choice of stations)

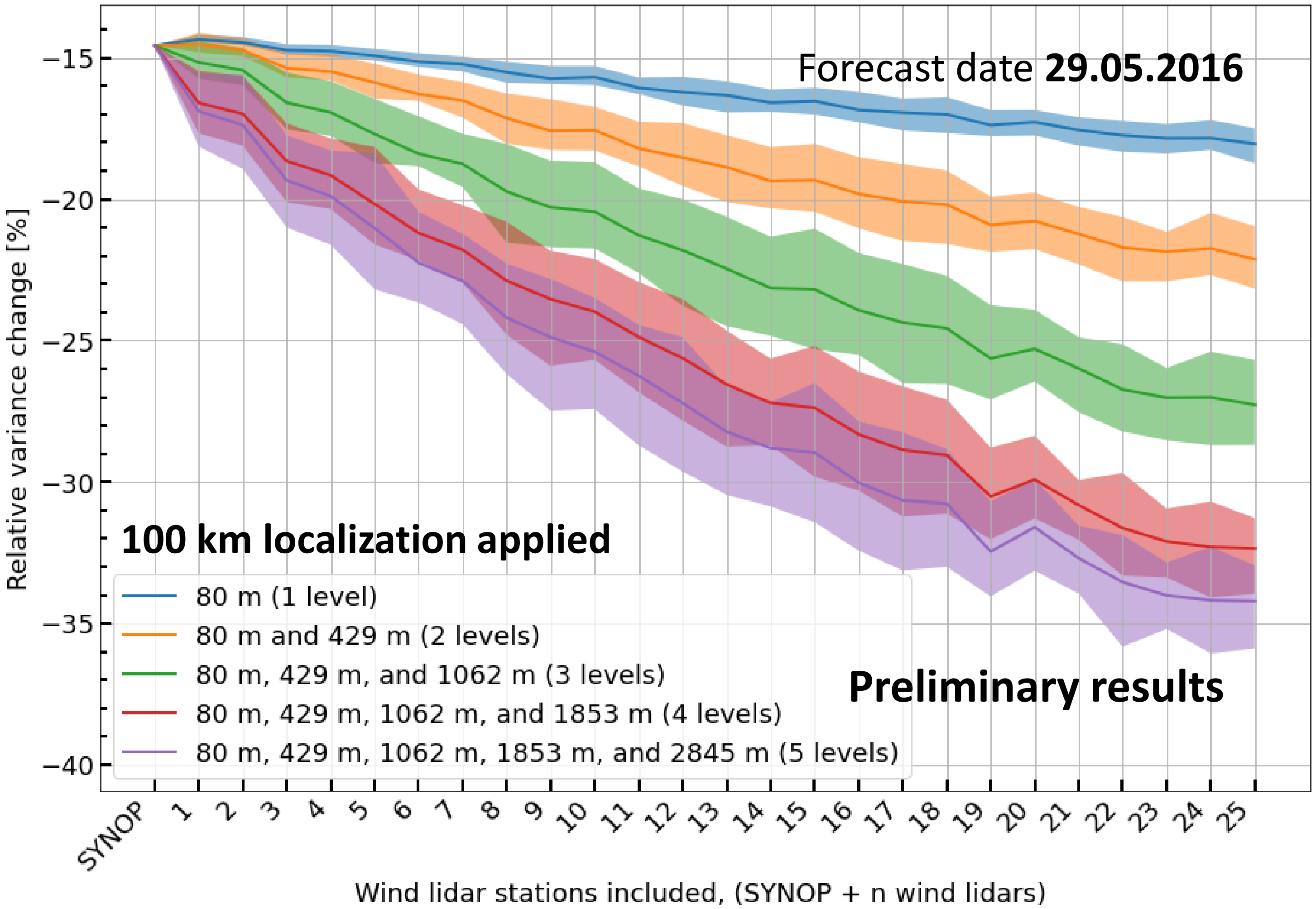
NOTE: this study considers only one day (29.05.2016)

Coordinates of the SYNOP stations were provided by
Elisabeth Bauernschubert

Variance reduction: with applied localizations of 100 km

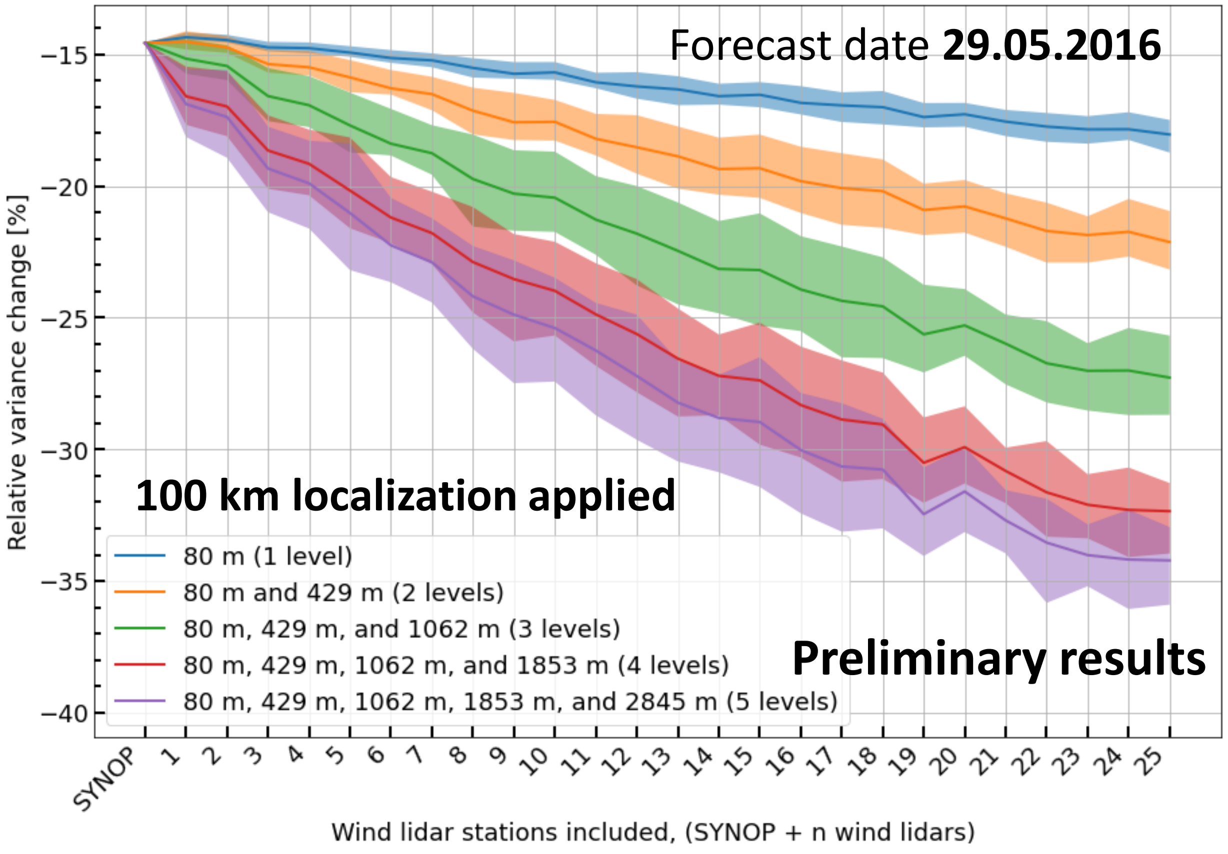
Potential wind lidar observations:

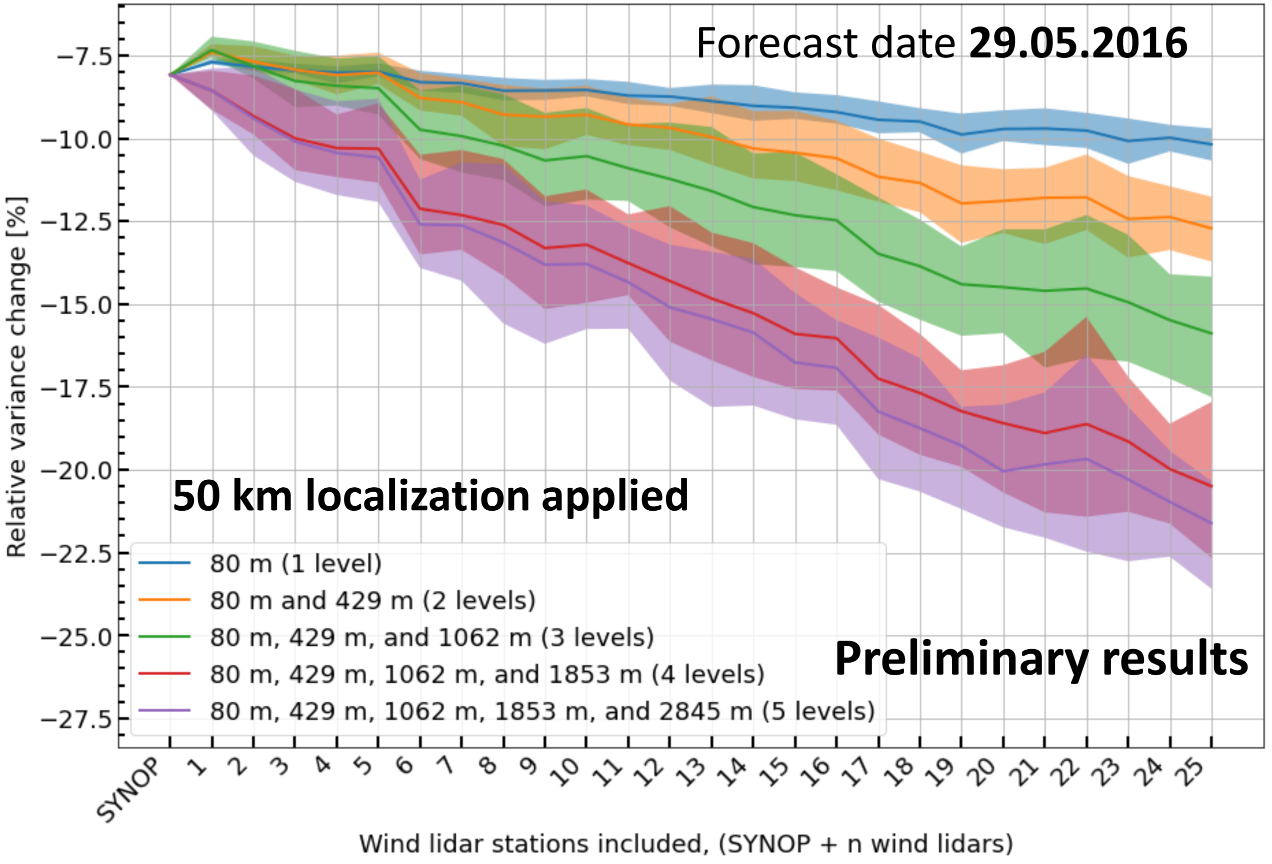




- **25 wind lidars → 1.2** - **2.5x** improvement
- The benefit depends on different wind lidar ranges, influenced by ABL conditions

Variance reduction: with applied localizations of 100 and 50 km



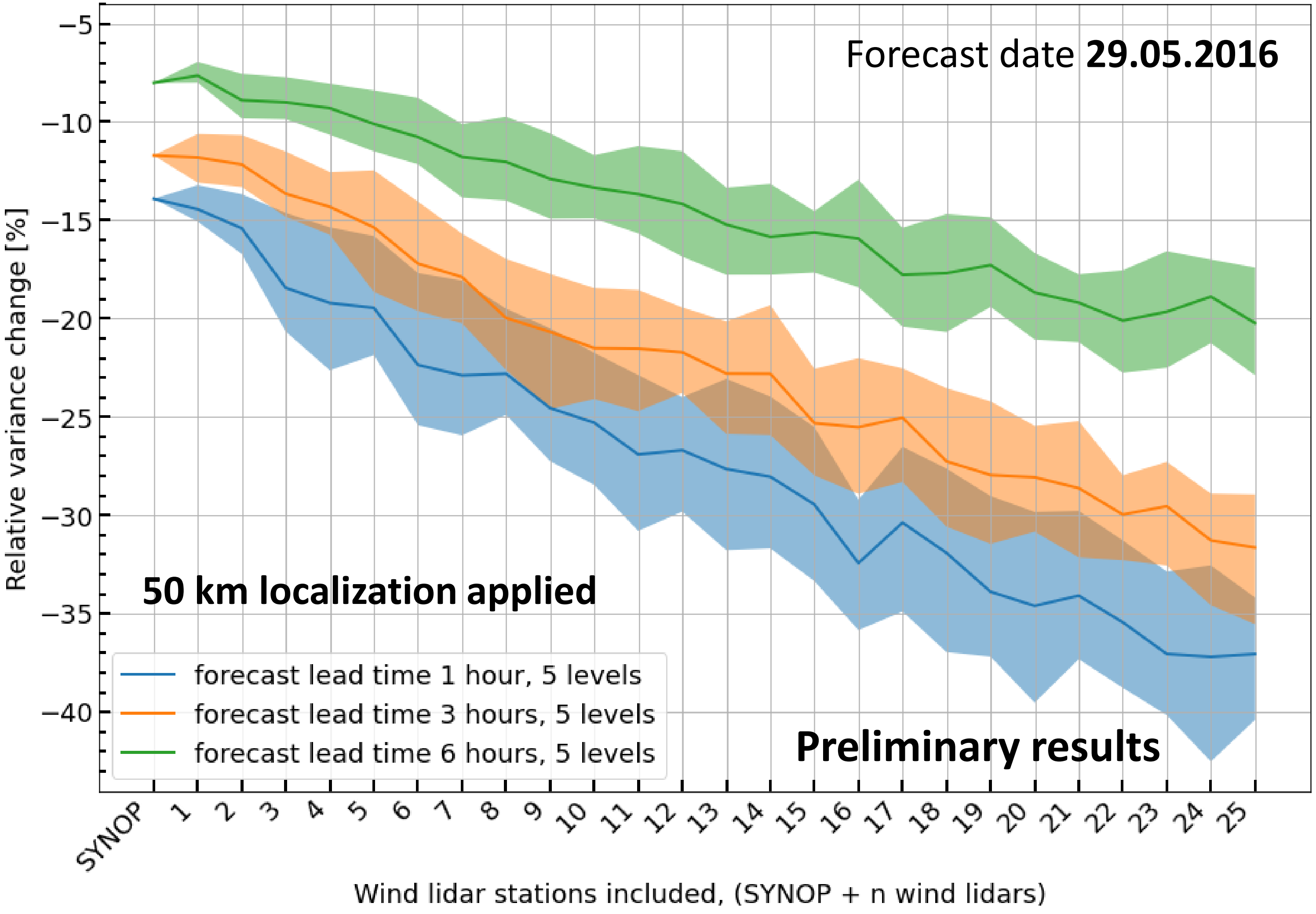


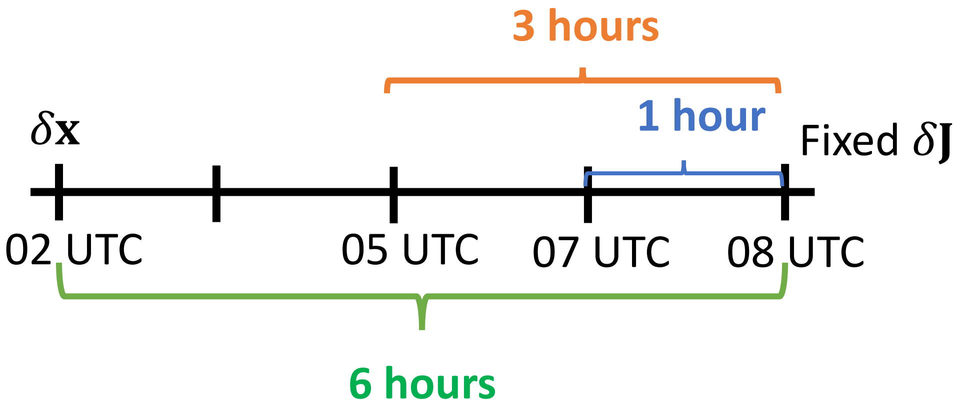
An additional relative change with respect to SYNOP:

25 wind lidars → 1.2 - 2.5x improvement (**L = 100 km**)

25 wind lidars → 1.5 - 3x improvement (**L = 50 km**)

Variance reduction: for different lead time (localization 50 km)





- As expected more improvements for the smaller lead time (**25 wind lidars** → **3x** improvement with respect to SYNOP)
- Benefits from Doppler lidar network even for a **6 hour** lead time (**25 wind lidars** → **2.8x** improvement with respect to SYNOP)

Summary

- Doppler wind lidars (spread out inside and around RRA) show the potential to improve the low-level wind forecast
- **25 wind lidars** → **1.2** - **3x** improvement (with respect to SYNOP stations only) depending on localization value and different wind lidar ranges, influenced by ABL conditions
- As expected more improvements for the smaller lead time (**25 wind lidars** → **3x** improvement with respect to SYNOP). Benefits from Doppler wind lidar network even for a 6 hour lead time

Outlook

- Extend the analysis to include more available forecasts and days
- Investigate potential impact of ground-based microwave radiometers on cloud cover and predicted solar power production