Potential impact of Ground-based remote sensing observations

- **Renewable energy applications**

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- **Atmospheric stability application**

ARON project

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Ensemble sensitivity analysis to estimate the potential impact of ground-based observations

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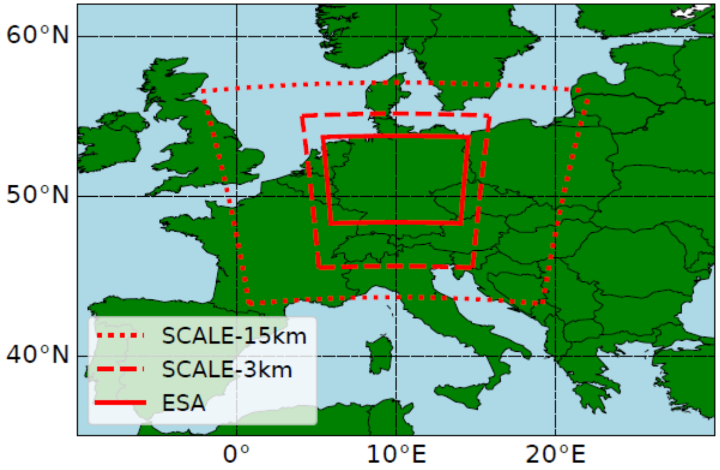
Research questions

- Can we improve short-term forecasts of meteorological variables important for renewable energy applications (e.g. cloudiness and low-level wind) using ground-based observations?
- Which instruments fit better for which forecasted variables?
- How many observations do we need to get an optimal improvements of short-term forecasts? What would be an optimal position for additional remote sensing observations?
- How dense should the station network be to get an optimal improvements of short-term forecasts?

INSTRUMENT VARIABLES AND PRODUCTS

- SCALE-RM model data output over Germany
- Convective-scale 1000-member ensemble

  (Necker et al, 2020) (focus over Germany, 3 km)



Necker et al., 2020

Variables for potential improvements of a short-term forecast:

- Brightness temperature (simulated) for MWR frequencies
- Wind at different levels from hypothetical observations of Doppler lidar

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

Ensemble sensitivity analysis, variance reduction

1) The forecast metric **J** and a state vector of initial conditions **x**:

For example, **x** is a current **wind speed** at certain height

J is the **low level wind speed** in **3 hours**

2) Variance of the forecast metric **J**:

$$\boldsymbol{\Sigma}^2 = \{\delta\mathbf{J}\delta\mathbf{J}^{\mathrm{T}}\} \approx \left[\frac{\partial\mathbf{J}}{\partial\mathbf{x}}\right]^{\mathrm{T}} \mathbf{A} \left[\frac{\partial\mathbf{J}}{\partial\mathbf{x}}\right],$$

3) Sensitivity of the forecast metric **J** to the state vector **x** of initial conditions:

$$S = \left[\frac{\partial\mathbf{J}}{\partial\mathbf{x}}\right]^{\mathrm{T}}$$

4) Initial-time state covariance matrix:

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

Ensemble sensitivity analysis, variance reduction

+ new observation:

4) δ**x** and **A'** updated using hypothetical observations

$$\delta\mathbf{x}^a = \delta\mathbf{x}^p - \tilde{\mathbf{K}}\mathbf{H}\delta\mathbf{x}^p = (\mathbf{I} - \tilde{\mathbf{K}}\mathbf{H})\delta\mathbf{x}^p$$

$$\mathbf{A}' = \left\{\delta\mathbf{x}^a \delta\mathbf{x}^{a^T}\right\}$$

K is a Kalman gain,
K → 1 (accurate observations),
K → 0 observation errors are much larger with respect to the model.

5) $\delta\Sigma^2$ change in the covariance matrix due to added hypothetical observations

$$\delta\mathbf{\Sigma}^2 = \left[\frac{\partial\mathbf{J}}{\partial\mathbf{x}}\right]^{\mathrm{T}} (\mathbf{A}' - \mathbf{A}) \left[\frac{\partial\mathbf{J}}{\partial\mathbf{x}}\right]$$

Limitations of ensemble sensitivity methods

Size of the state covariance matrix

- A large size of the covariance matrix leads to time consuming calculations
- Solution: Application on a model or observation space

Correlated inputs

- Some methods use an assumption of independency between model inputs

Problem with inverse covariance matrix

- Reduction of the resolution
- Get pseudoinverse matrix

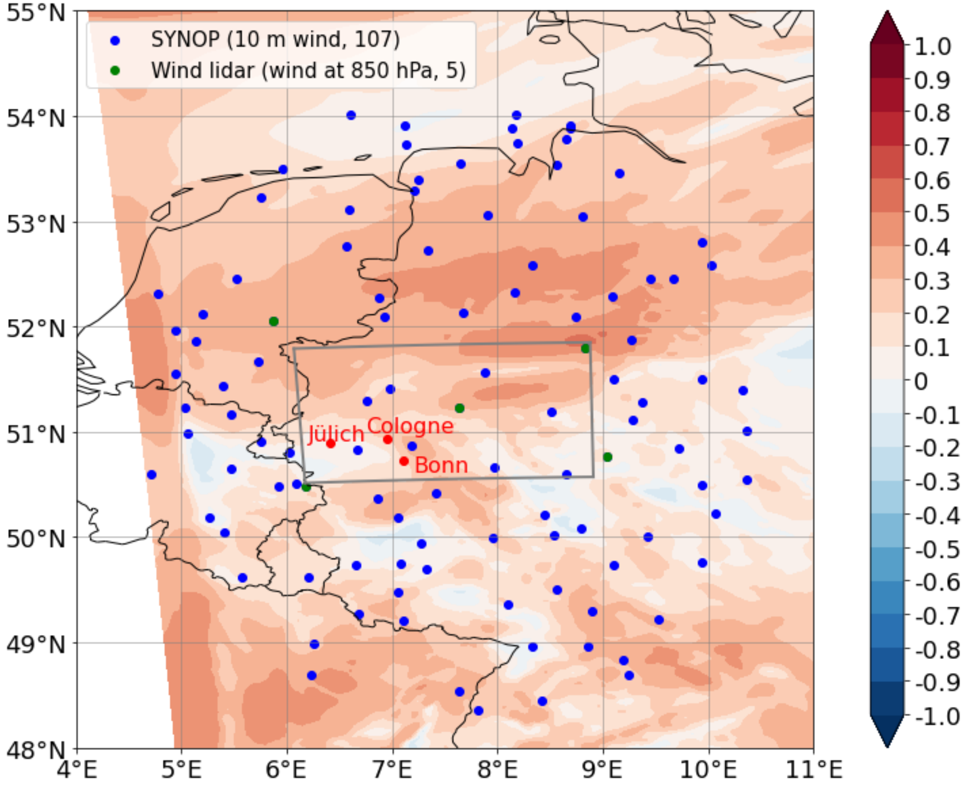
Nonlinearity

- Some methods based on linear regression while the model response is nonlinear with respect to its inputs

Sampling spurious correlations

- Less effect in a large number of ensemble members

Modal data (SCALE-RM 1000 ens)



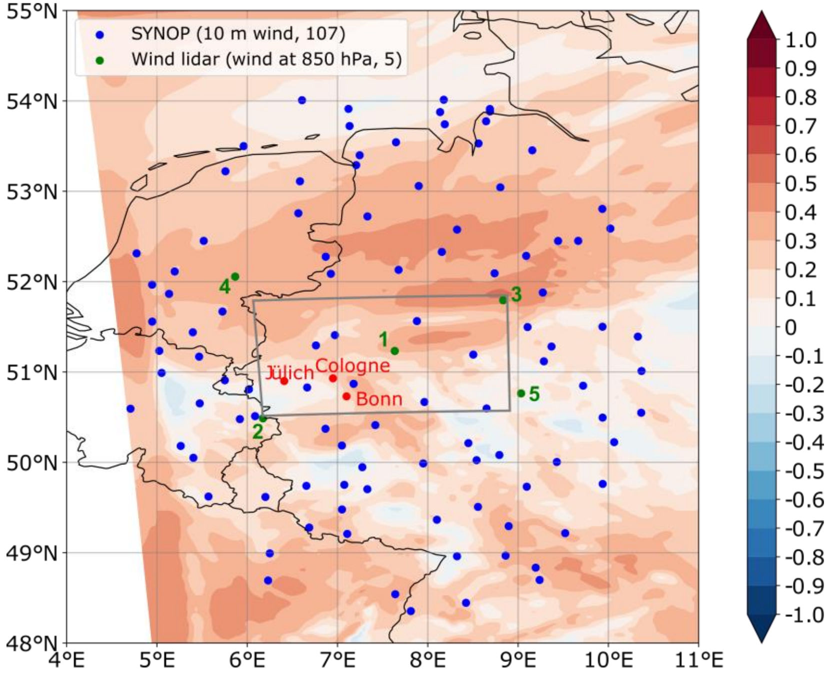
01.06.2016

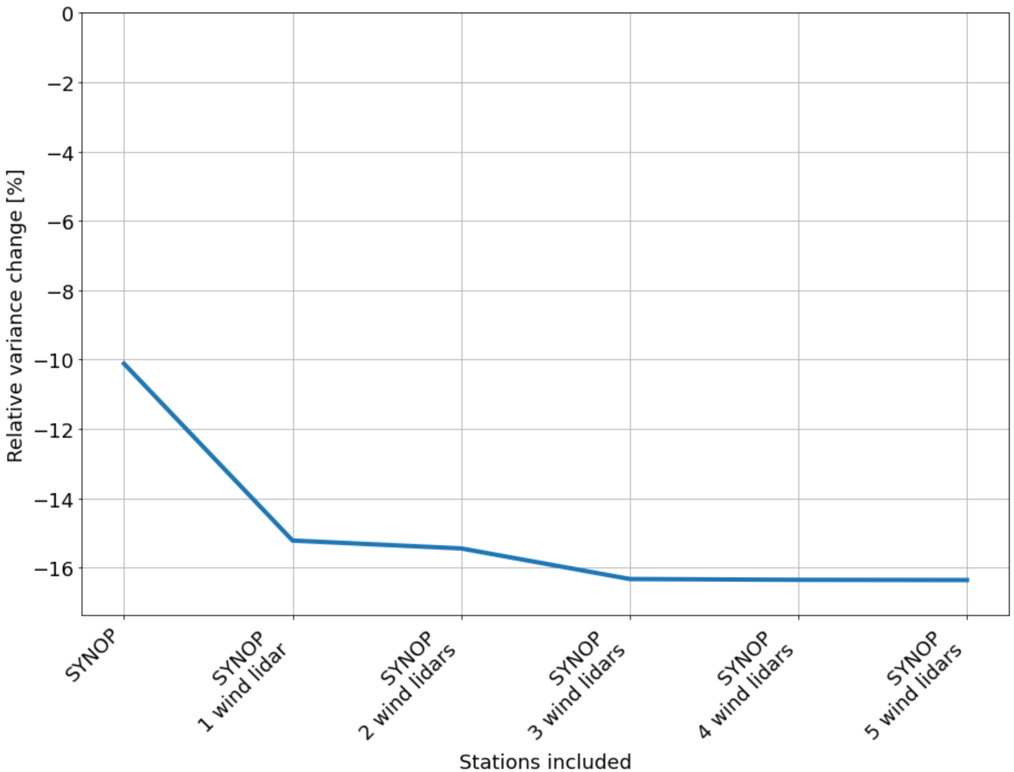
Initial conditions (14 UTC)
State vector **X** [1000 x Lat x Lon]
10 m wind speed

Response function **J [1000 x 1]**
averaged over RRA of state vector **X**
wind speed at 925 hPa
Forecast 3 hour (17 UTC)

Incorporated observations:
wind speed at 10 m (shown in blue)
wind speed at 850 hPa (shown in green)

Modal data (SCALE-RM 1000 ens)





Current status

Extracted the data from the model files to get wind at original height levels (30 model levels)

Further step

Apply the method to improve low level wind including wind profiles extracted from the original model files