Observing and data assimilation strategies to improve short-term low-level wind forecast for sustainable energy applications

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1. Introduction

In Germany, a large part of renewable energy generation is attributed to wind. Therefore, an accurate forecast of low-level wind is required. One of the solutions to improve the wind forecast is assimilation of new observations into a numerical weather prediction model.

In this study, we estimated the potential to improve the short-term forecast of low-level wind using a network of Doppler lidars (DL). This study addresses the following questions:

- What impact from DL to expect with respect to surface observations?
- How the impact depends on the number of DL in the network?
- How does the impact depend on the penetration of the lidar signal through the atmospheric boundary layer (ABL)?

2. Methodology

The methodology based on the ensemble sensitivity analysis (ESA) described in [1,2] is used.

In this study, we applied an improved ESA approach which includes an extension of existing ESA methods by accounting for a localization scale of the assimilation system.

The **variance of the forecast metric** can be found as follows [1]:

$$\sigma^2 = \boldsymbol{s}\mathbf{B}\boldsymbol{s}^T, \tag{1}$$

where **B** is the background covariance matrix, $\boldsymbol{s}$ is the sensitivity.

The **sensitivity** is regularized using the Tikhonov method [3]:

$$\mathbf{s} \approx \mathrm{cov}\left(\delta\boldsymbol{j}, \delta\mathbf{X}^{\mathrm{T}}\right)\mathbf{B}^{\mathrm{T}}\left(\mathbf{B}^{\mathrm{T}}\,\mathbf{B} + \alpha^2\,\mathbf{I}\right)^{-1}, \tag{2}$$

where $\delta\mathbf{j}$ is the deviation of the predicted quantity, $\delta\mathbf{X}$ is the deviation of the state vector from corresponding ensemble means, **I** is the identity matrix, α = 3 is the regularization coefficient, cov is the cross covariance matrix.

An **update of the state** δX due to the incorporation of observations:

$$\delta\mathbf{X}_u = \delta\mathbf{X} - \mathbf{KH}\delta\mathbf{X}, \tag{3}$$

where **H** is the linear forward operator, **K** is the **Kalman gain** matrix [4]:

$$\mathbf{K} = (\mathbf{L}\circ\mathbf{B})\,\mathbf{H}^{\mathrm{T}}\left[\left(\sqrt{\mathbf{H}\,(\mathbf{L}\circ\mathbf{B})\,\mathbf{H}^{\mathrm{T}} + \boldsymbol{R}}\right)^{-1}\right]^{T}\left[\sqrt{\mathbf{H}\,(\mathbf{L}\circ\mathbf{B})\,\mathbf{H}^{\mathrm{T}} + \boldsymbol{R}} + \sqrt{\boldsymbol{R}}\right]^{-1}, \tag{4}$$

where **L** is the localization matrix, ∘ is the Schur product, $\boldsymbol{R}$ is the observation error matrix.

The **change in the variance** of the forecast metric after the assimilation of observations:

$$\Delta\sigma^2 \approx \mathrm{var}\big(s(\delta\mathbf{X} - \mathbf{KH}\delta\mathbf{X})\big) - \mathrm{var}(s\delta\mathbf{X}), \tag{5}$$

The **relative variance change** is: $\Delta\sigma_r^2 = \Delta\sigma^2 / \sigma^2,$ (6)

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3. Experimental setup and model data

This study focused on the **Rhein-Ruhr area** (**RRA**, gray rectangle, Fig.1) and its surroundings. We used low-level wind components (80 m, typical hub-height of wind turbines) averaged over the RRA as the forecast metrics.

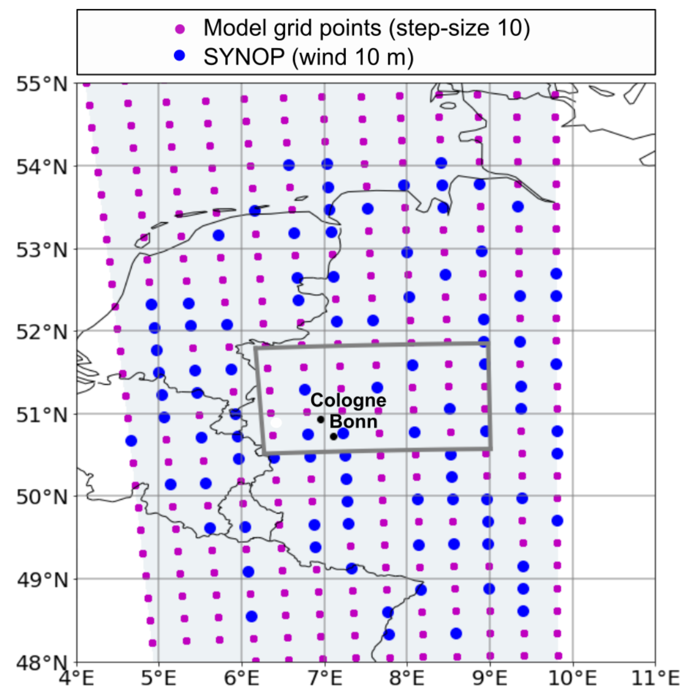


Fig.1: *Locations of SYNOP stations used in this work. SYNOP stations are located within a circle with the radius of 3° and the center in the middle of the RRA. Magenta dots denote the model grid used for the state vector. Figure adopted from Nomokonova et al., (2022)*

Model data and synthetic observations:

- Regional climate/weather forecasting model **SCALE-RM**
- **1000-member ensemble** [5] over Germany, space resolution **3 km**, 31 vertical levels
- **Model domain:** 352 x 250 grid points centered over Germany
- 16 initial times covering **8 days** in **May/June 2016**
- Every 10th grid point of the model output used for the state vector
- Wind profiles from hypothetical DL (**5 levels** of model output: **80, 429, 1062, 1853,** and **2845 m)**

4. Single case study: 29 May 2016, 00 UTC

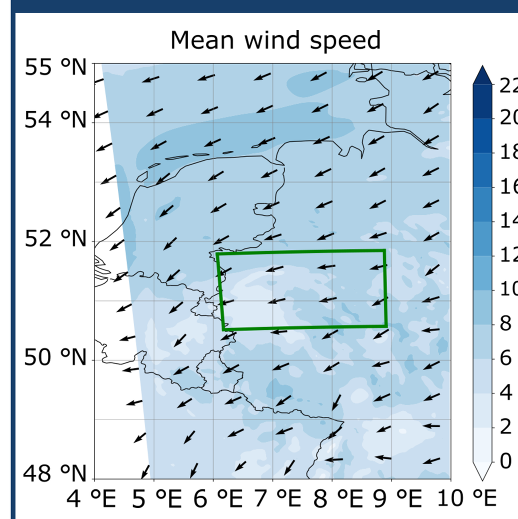


Fig.2: *Mean wind calculated over 1000 ensemble members at 80 m height on 29 May 2016 05 UTC. Black arrows indicate wind direction. Figure adopted from Nomokonova et al., (2022)*

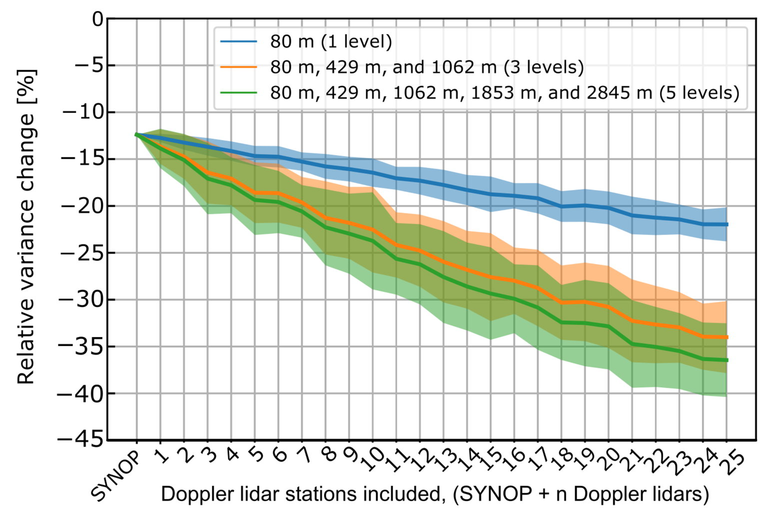
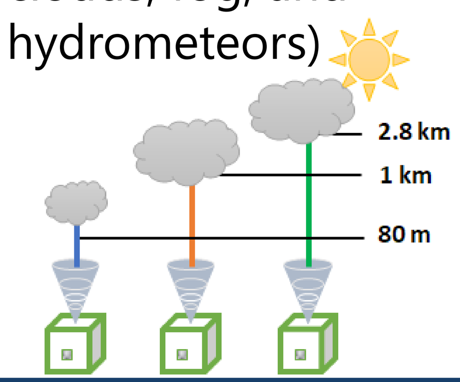


Fig.3: *Dependence of $\Delta\sigma_r^2$ on the number of DL in the network. The forecast metric is the u-component of 80 m wind, lead time 3 h. The solid lines show the mean values over the 50 repetitions. The shaded areas depict 25th and 75th percentiles. Figure adopted from Nomokonova et al., (2022)*

The benefit depends on different DL ranges, influenced by ABL (optically thick clouds, fog, and hydrometeors)



5. All cases: saturation effect

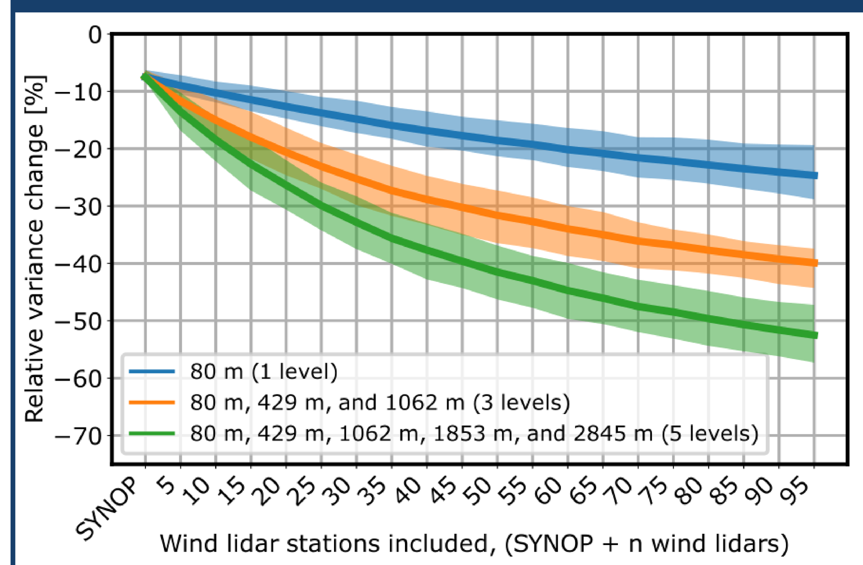


Fig.4: *$\Delta\sigma_r^2$ for different numbers of DL in the network. The forecast metric is the u-component of the 80 m wind, lead time 3 h. The solid lines show the mean values over the 50 random location sets of the DL. The shaded areas depict 25th and 75th percentiles. Figure adopted from Nomokonova et al., (2022).*

- Saturation effect in wind components starts at **20-30 instruments** when at least 3 levels are available
- Less pronounced saturation effect only for one level
- **Most cost-efficient** improvement of low-level wind in RRA achieved by a **network of 25 DL**
- On average 25 DL give **3 times** better $\Delta\sigma_r^2$ than SYNOP only

6. All cases: impact of 25 Doppler lidars in the network

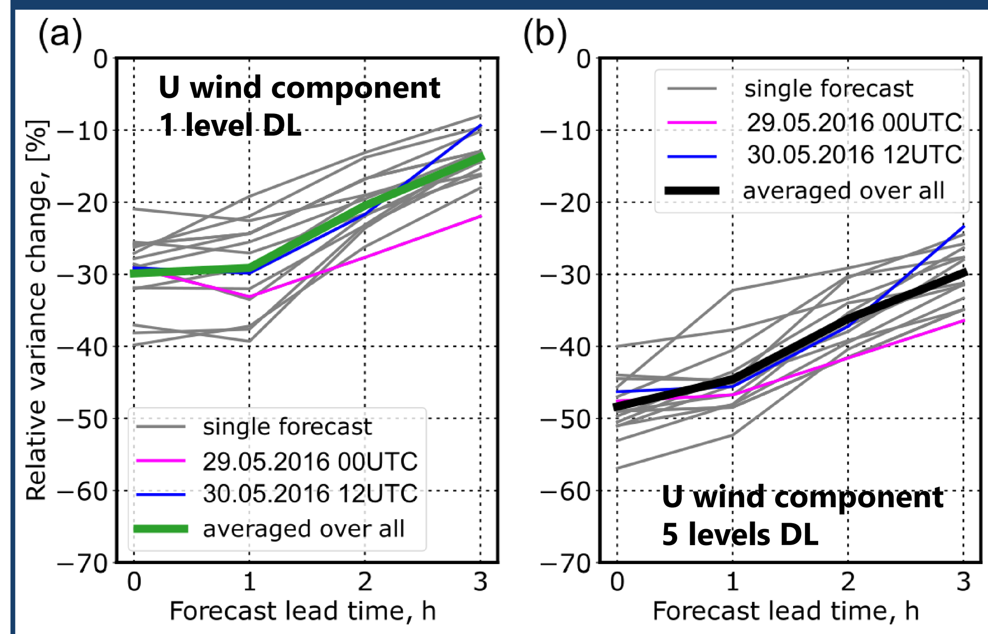


Fig. 5*: Dependence of $\Delta\sigma_r^2$ on the lead time. The forecast metrics are the u-component of the 80 m wind. The assimilation were performed for simulated data from 25 DL and 95 SYNOP stations. Gray lines correspond to values of $\Delta\sigma_r^2$ averaged over the 50 repetitions for a single case. Figure adopted from Nomokonova et al., (2022)*

- The analyzed period includes distinct weather patterns with both day and night-time cases
- **±8 – 15% variability** in the averaged values of $\Delta\sigma_r^2$

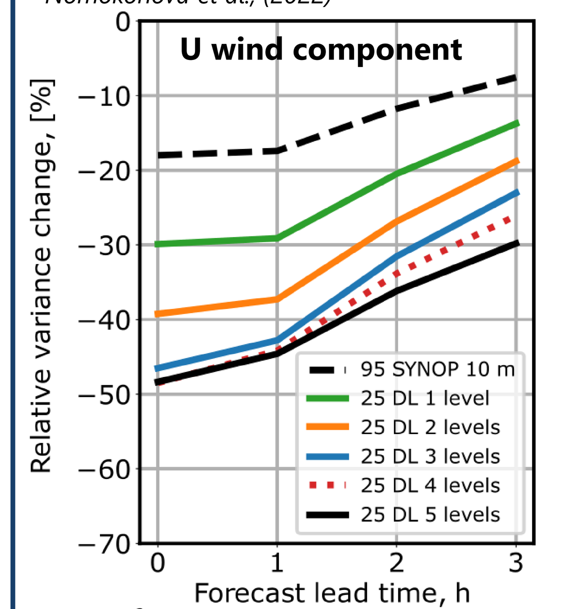


Fig. 6*: $\Delta\sigma_r^2$ for u-component of the 80 m wind averaged over 16 available cases for different lead times. Calculations were performed for 95 SYNOP stations only (dashed black lines), and for 25 DL in addition to the 95 SYNOP stations (other lines). Figure adopted from Nomokonova et al., (2022)*

- Assimilation of SYNOP only yields on average **18%** and **8%** for **1** and **3 h** lead time, respectively.
- 1 layer in DL wind profile leads to improvement of a factor of **1.6** for **1 h** lead time and **2** for the **3 h** lead time.
- 3 layers in DL wind profile (up to 1 km) lead to a factor of **2.3** improvements for **1 h** lead time and **2.7** for the **3 h** lead time.
- The contribution from wind observations >**1 km** does not lead to considerable improvements

7. Summary

- A network of DL is beneficial for the short-term forecast of low-level wind
- **Most cost-efficient improvement** of low-level wind in the RRA could be achieved by a network of **25 DL**
- For **1 layer (up to 80 m)** in wind profile, the expected improvements in $\Delta\sigma_r^2$ is only a factor of **1.6-2** better than SYNOP only
- Wind profiles up to **1 km (3 levels)** can lead to improvements of $\Delta\sigma_r^2$ by a factor of **2.3-2.7** with respect to SYNOP only.
- The impact of DL network strongly depends on the available range layers (limited by optically thick clouds, fog, and hydrometeors) in the wind profiles

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