RAIN RADAR MEASUREMENT ERROR ESTIMATION USING DATA ASSIMILATION IN AN ADVECTION-BASED NOWCASTING SYSTEM

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The Idea

This work presents a method to combine precipitation data from different sources through ensemble data assimilation. The aim is to obtain

- an areal precipitation product,
- spatially and temporally variable uncertainty information.

By using nowcasting, the uncertainty information evolves consistently in time and space and is flow dependent. Areal uncertainty information is valuable for e.g.

- probabilistic hydrological modeling,
- data assimilation...

Data and Ensemble Forecast

Areal precipitation data:

- Four X-band radars in a network north-west of Hamburg, Germany
- Single radar data with 30 s temporal, 60 m and 1° spatial resolution (Fig. 1)
- Network composite product on a 250x250 m Cartesian grid (Fig. 2)

Probabilistic precipitation nowcasting:

- Forecast of composite data by advection
- Motion vectors computed through correlation analysis (Fig. 3)
- Ensemble generation by perturbation of the motion vector field with spatially correlated random noise (Fig. 4)

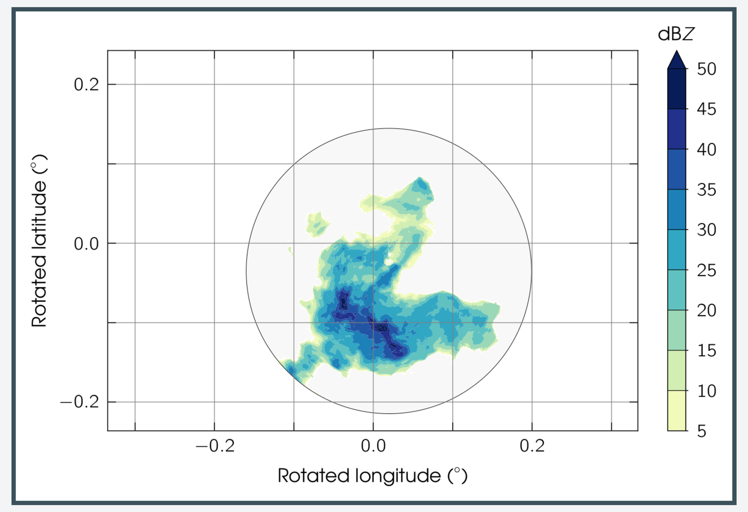

Figure 1: Single radar precipitation data (03.07.2013 15:32:00 UTC).

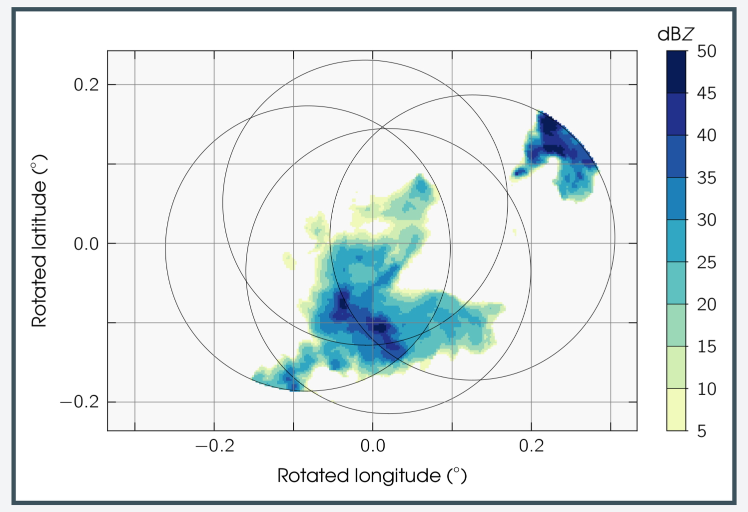

Figure 2: Composite network precipitation data (03.07.2013 15:32:00 UTC).

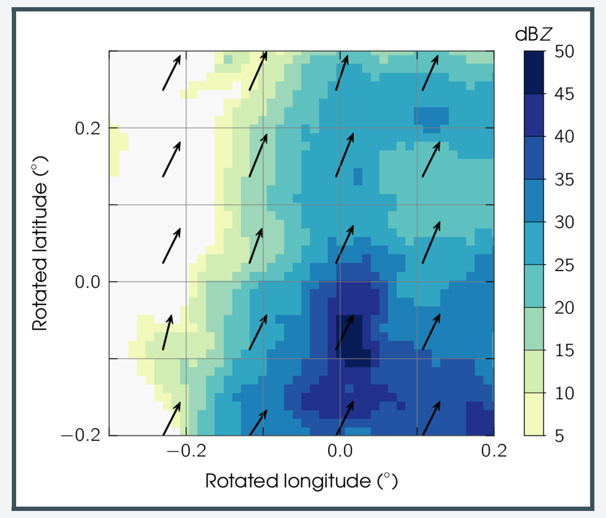

Figure 3: Nowcasting motion vectors for a region of the network domain.

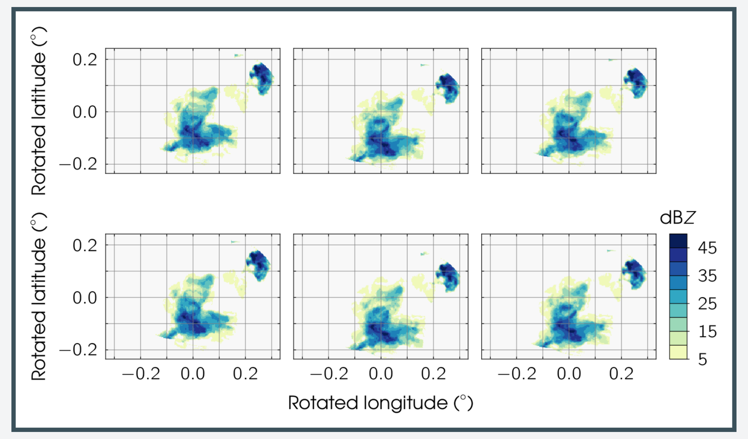

Figure 4: Example of members from the ensemble precipitation forecast (03.07.2013 15:32:00 UTC).

Experiment

Data assimilation

- combines forecast and observation
- under consideration of the uncertainty of both information sources (Fig. 5).

Data for assimilation and verification:

- Single radar data observations
- 40x40 km grid with 5 km thinning length, shifted grids for independent verification data (Fig. 6)

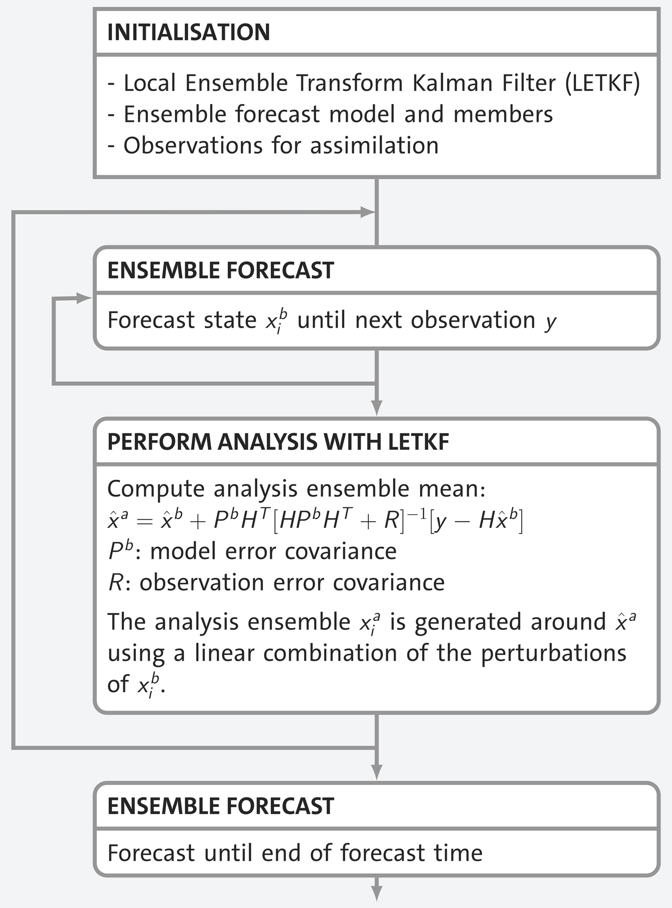

Figure 5: Main steps of data assimilation cycle.

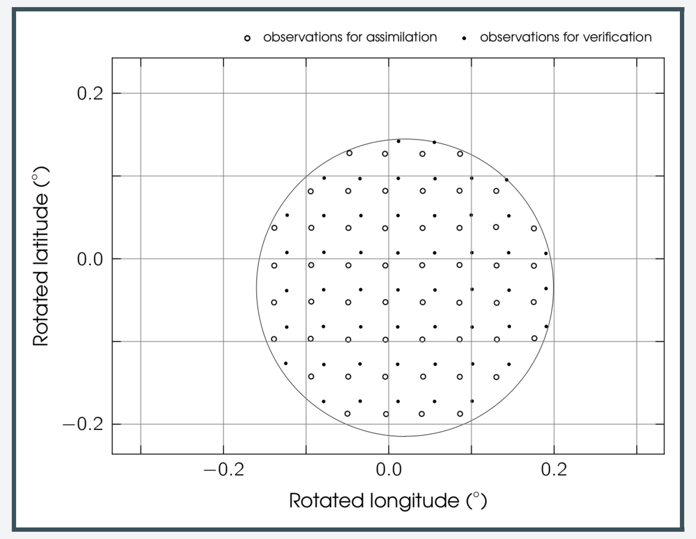

Figure 6: Assimilation and verification locations.

The experiment is run with

- 30 min precipitation forecast starting at 15:26:00 UTC (03.07.2013),
- 2 min time step and
- assimilation of observations every 4 min.

The ensemble comprises 50 members. Fig. 7 shows a time series of the precipitation forecast at one location, demonstrating the forecast-assimilation cycle. The ensemble mean at the end of the forecasting time is in good agreement with the observation (Fig. 8).

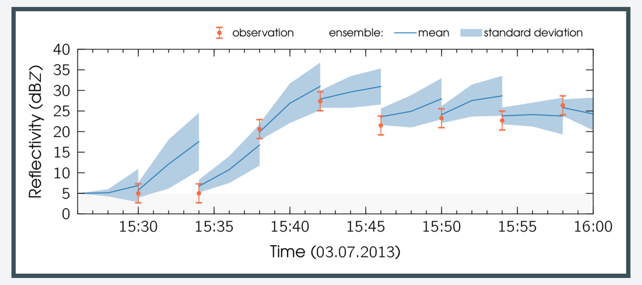

Figure 7: Data assimilation cycle at an observation location.

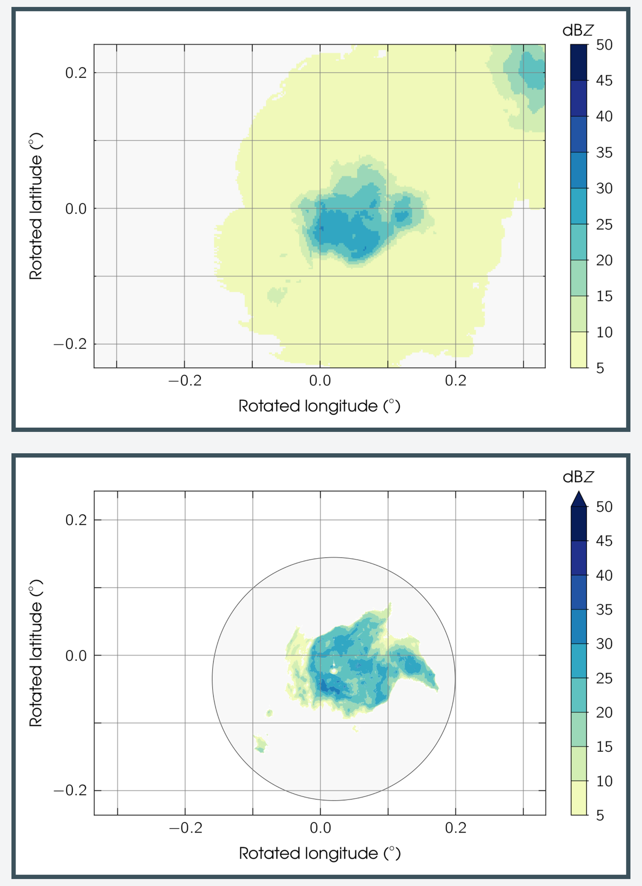

Figure 8: Ensemble mean after 30 min forecast (top) and corresponding single radar observation (bottom).

Results

The ensemble spread (here standard deviation σ) is a description of the forecast uncertainty. Through the forecast-assimilation cycle, the ensemble spread σ_v evolves according to the flow and taking into account additional information that reduces uncertainty (Fig. 9). The ensemble spread σ_v yields a spatially and temporally variable uncertainty field. Its potential is analysed by comparison to a constant spread, the mean spread of the system $\sigma_c = 3.45$ dB. Statistically, the absolute model mean error ϵ must be equal to the predicted model uncertainty σ (Fig. 10). Three scores are used to analyse the skill of the system and its ability to predict an improved system uncertainty.

Forecast skill: Performance of ensemble mean μ:

$$S_{\text{mean}} = \sqrt{\tfrac{1}{n}\textstyle\sum_n(\mu - \text{obs})^2} = 2.78\ \text{dB}$$

Uncertainty prediction skill: Deviation from the perfect spread-skill relation:

$$S_{\text{spread}} = \sqrt{\tfrac{1}{n}\textstyle\sum_n(\sigma_n - \epsilon_n)^2}$$

Percentage of hits: Amount of model error values within the predicted uncertainty range:

$$HITS = \tfrac{100}{n}\textstyle\sum_n(\epsilon_n \leq \sigma_n)$$

Results (Tab. 1) show that the variable spread σ_v yields a better uncertainty forecast than the constant spread σ_v. It shows a smaller deviation from the theoretical spread-skill relation and model errors fall more frequently into the predicted uncertainty range.

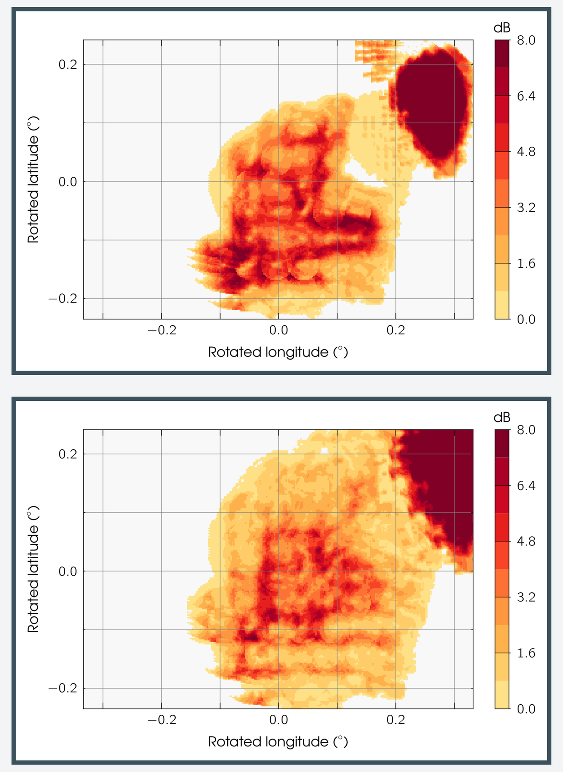

Figure 9: Ensemble spread σ_v after 8 min (top) and 25 min (bottom) forecast.

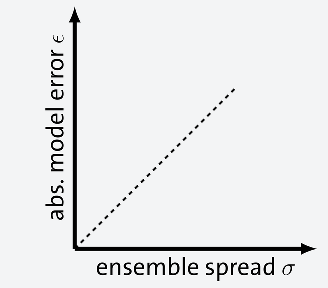

Figure 10: Theoretical spread-skill relation.

Table 1: Results for uncertainty prediction assessment.

Score	σ_c	σ_v
S_{spread} (dB)	2.35	2.06
$HITS$ (%)	78.19	85.54

Conclusions and Outlook

This study presents a framework

- combining precipitation data and
- providing a flow dependent, spatially and temporally variable and consistent uncertainty description.

The uncertainty field obtained by this method yields better error estimation than constant uncertainty information. To further study the potential of the method, it should be applied

- in a more realistic setup,
- with more observation sources (rain gauges, micro rain radars...),
- and using a longer time period.

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