A METHOD TO ESTIMATE THE UNCERTAINTY OF AREAL PRECIPITATION USING DATA ASSIMILATION

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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.

Data and Ensemble Forecast

Areal precipitation measurements:

- four X-band radars in a network
- data with 30 s temporal, 60 m and 1° spatial resolution (Fig. 1)
- network composite product on a 250x250 m Cartesian grid (Fig. 1)

Probabilistic precipitation nowcasting:

- forecast of composite data by advection
- motion vectors computed through correlation analysis (Fig. 2)
- ensemble generation by perturbation of the motion vector field with spatially correlated random noise (Fig. 3)

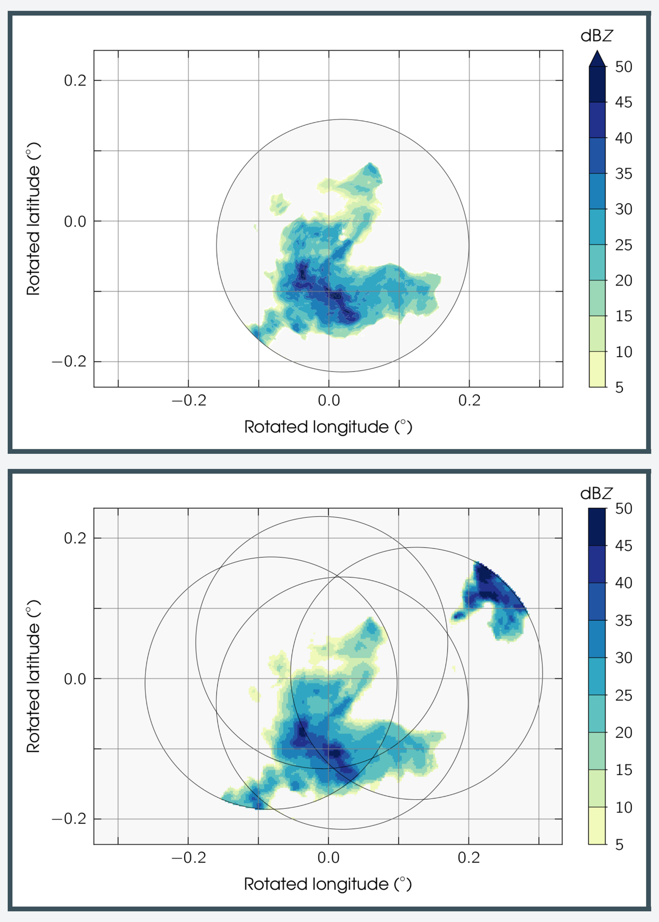

FIG. 1: Single radar (top) and composite network (bottom) precipitation data for 03.07.2013 15:32 UTC.

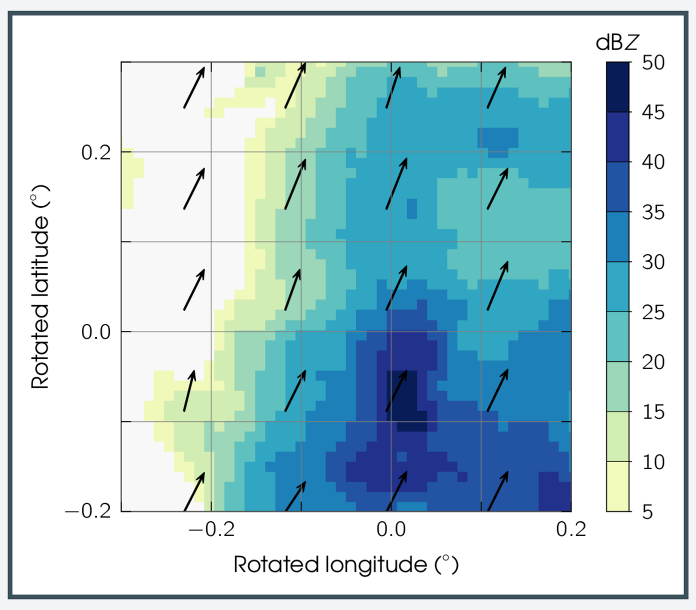

FIG. 2: Nowcasting motion vectors for a region of the network domain.

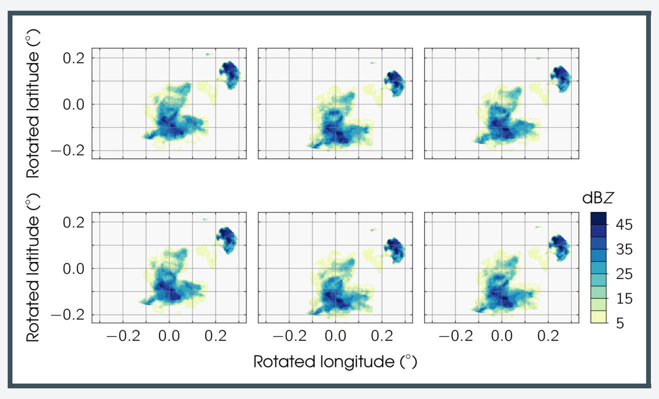

FIG. 3: Example of members from the ensemble precipitation nowcasting.

Experiment

Data assimilation

- combines forecast and observation
- statistically weights the respective uncertainties (Fig. 4).

Data for assimilation and verification:

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

The experiment is run with

- 50 ensemble members
- 30 min precipitation forecast starting at 15:26:00 UTC (03.07.2013)
- 2 min time step
- assimilation of obs. every 4 min

Fig. 6 demonstrates the forecast-assimilation cycle at one location. The ensemble mean at the end of the forecasting time shows as smooth, smeared cell, probabilistic information confines the most probable location of the precipitation cell (Fig. 7).

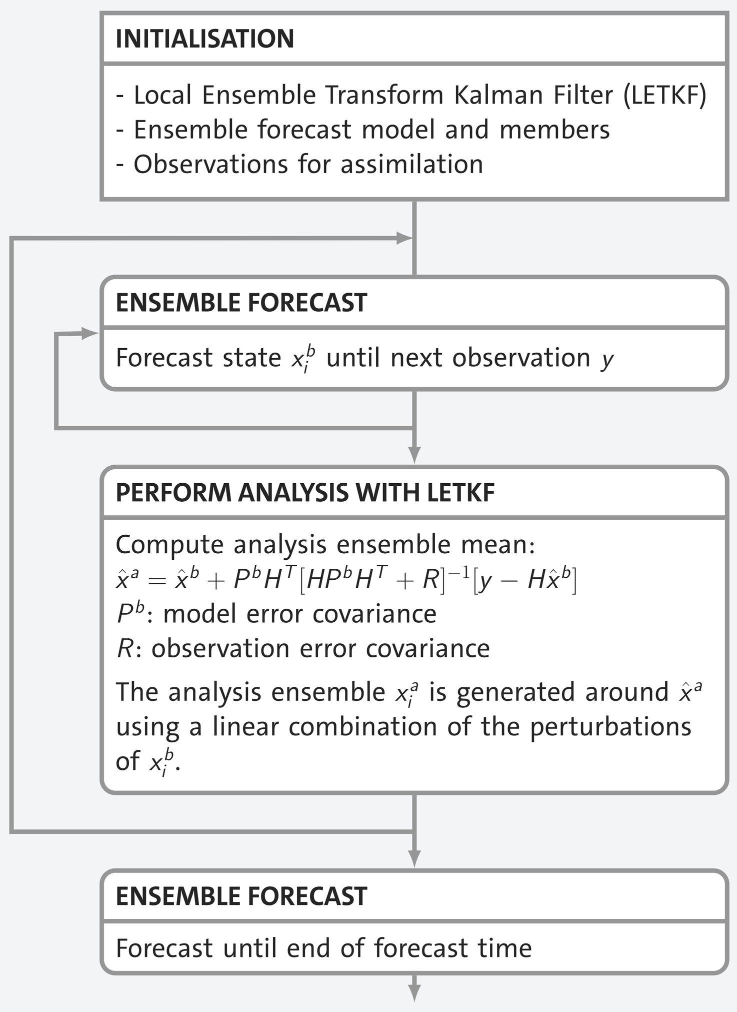

FIG. 4: Main steps of data assimilation cycle.

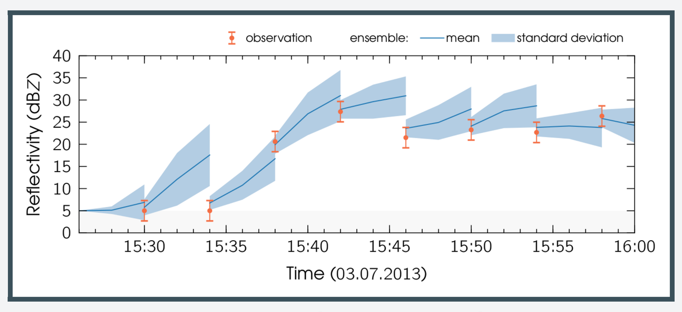

FIG. 6: Data assimilation cycle at an observation location.

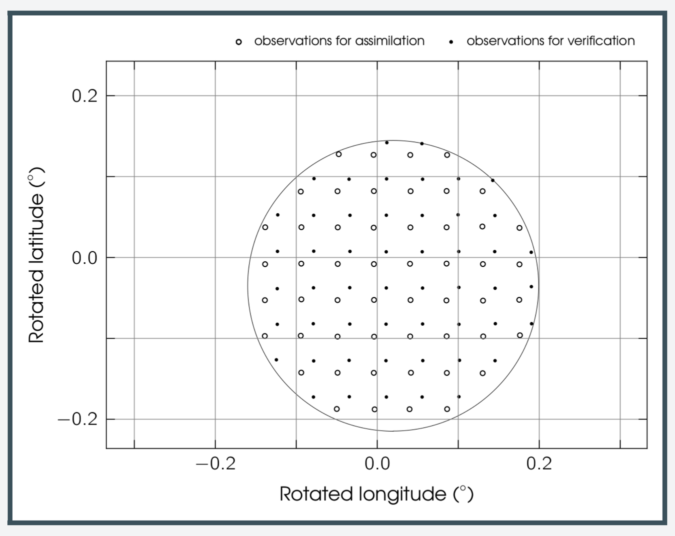

FIG. 5: Assimilation and verification locations.

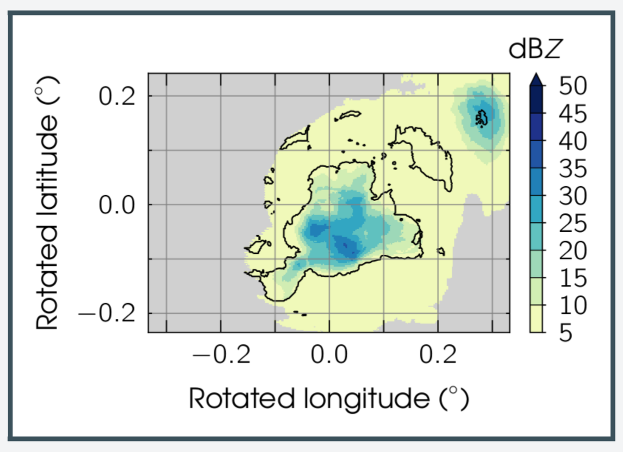

FIG. 7: Ensemble mean and 80% precipitation probability contour after 18 min forecast.

Results

The ensemble spread (standard deviation σ_v) describes the forecast uncertainty. Through the forecast-assimilation cycle, σ_v is variable and flow-dependent (Fig. 8). It evolves according to all available information (observations and situation).

Evaluation: Concept of statistical spread-skill relation (Fig. 9)

spatially and temporally variable uncertainty field σ_v	against	constant benchmark, mean spread of the system $\sigma_c = 1.63$ dB

Scores: Ability to improve the prediction of the system's error ε

- Reliability: percentage of hits

$$REL = \frac{100}{N} \sum \begin{cases} 1, & \text{if } \varepsilon \leq \sigma \\ 0, & \text{otherwise} \end{cases}$$

- Spread-skill deviation: deviation from the perfect spread-skill relation (RMSE)

$$DEV = \sqrt{\frac{1}{N} \sum (\varepsilon - \sigma)^2}$$

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

TAB. 1: Results for uncertainty prediction assessment.

Score	σ_c	σ_v
REL (%)	56.38	77.13
DEV (dB)	3.17	1.25

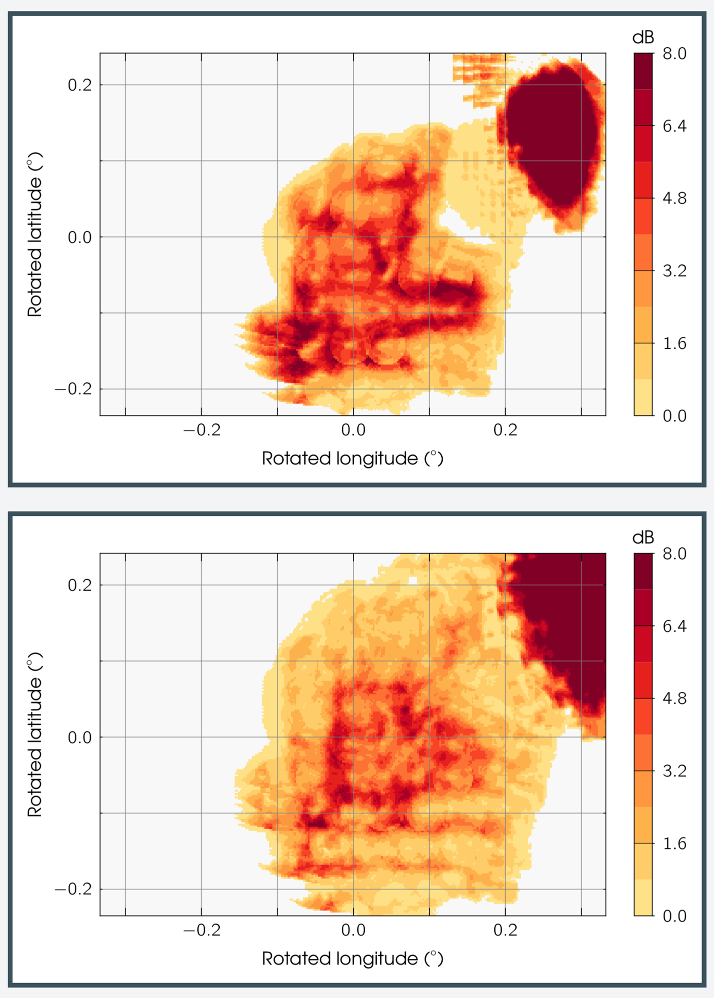

FIG. 8: Ensemble spread σ_v after 8 min (top) and 25 min (bottom) forecast.

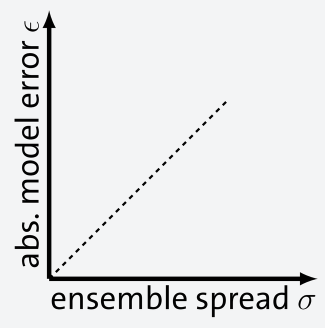

FIG. 9: Theoretical spread-skill relation.

Summary 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.

The method has great potential for

- flow-dependent, statistical combination of different observations under consideration of respective information uncertainty
- generation of precipitation ensembles
- seamless probabilistic analysis combining observations and model forecasts

For details on the implementation, have a look at the poster: pyenda - The Python Ensemble Data Assimilaton framework (10.2)

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