Convective-scale data assimilation in the Weather Research and Forecasting model using a nonlinear ensemble filter

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Data assimilation in weather models

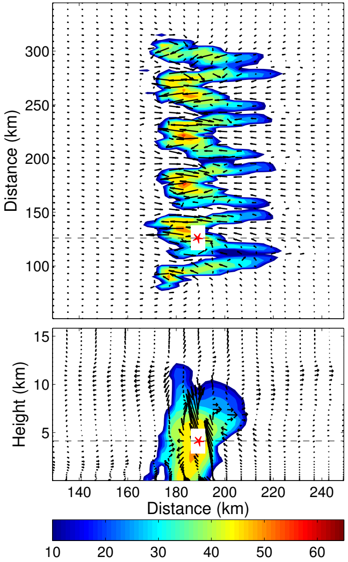
Filters and smoothers are applied regularly for data assimilation in geophysics.

Current methods are based on variational approaches (**3DVar** and **4DVar**), Ensemble Kalman filters (**EnKFs**), or combinations of the two.

Assumptions:

- The model dynamics are linear.
- Observations relate linearly to the model state variables.
- The model state and observation errors are Gaussian.

Example problem



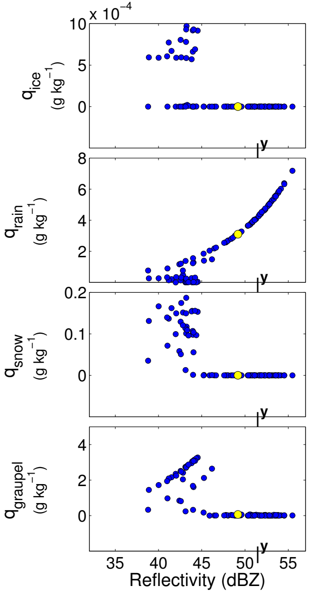
Given:

- 100-member ensemble forecasts are samples from prior error distribution $p(\mathbf{x})$
- Radar reflectivity measurement at $\star$ (denoted $\mathbf{y}$).

Top and bottom panels show cross sections through true storm at observation location.

Reflectivity and storm-relative winds are plotted.

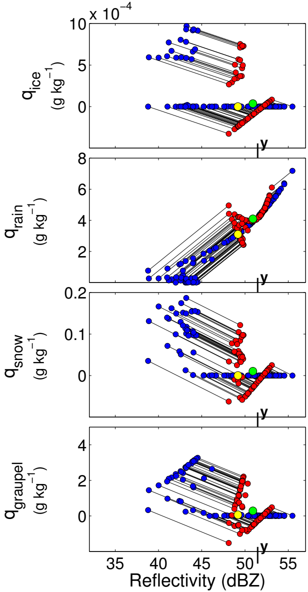
Prior ensemble at $\star$



$$p(\mathbf{x}|\mathbf{y}) \propto p(\mathbf{y}|\mathbf{x})p(\mathbf{x})$$

- **Blue markers**: prior samples from joint probability distribution of reflectivity and microphysics variables
- **Yellow markers**: true state
- **Black tickmarks**: observed reflectivity

EnKF update at ⋆



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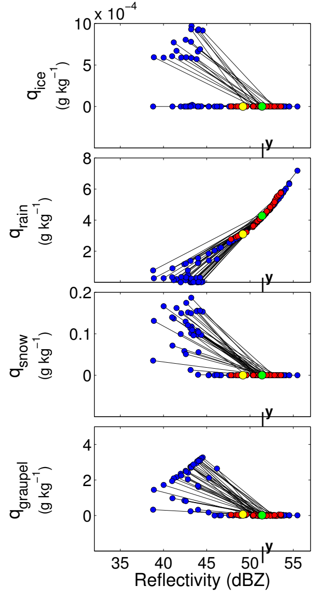
- **Red markers**: posterior samples
- **Green markers**: posterior mean

Particle filter update at ⋆



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Particle filters as a practical solution?

Challenges:

- PFs have known limitations for high-dimensional systems (e.g., Bengtsson et al. 2008; Bickel et al. 2008; Snyder et al. 2008).
- They may also be inappropriate for models containing error sources that are represented poorly or ignored.

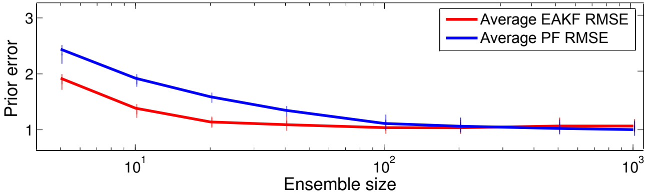
Several attempts have been made to circumvent these issues: van Leeuwen (2010), Frei and Kunsch (2013), Majda et al. (2014), Cheng and Reich (2015), etc.

The local PF

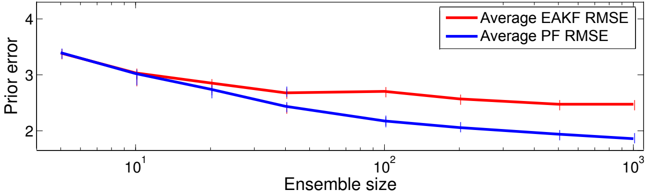
Poterjoy (MWR, 2016) and Poterjoy and Anderson (MWR, 2016) introduce the local PF for data assimilation.

Local PF vs. EAKF (Anderson, 2001) using 40-variable Lorenz (1996) model:

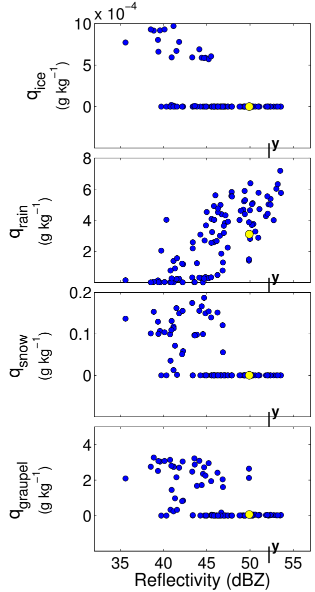
Linear measurement operator:
$H(x) = x$



Nonlinear measurement operator:
$H(x) = \ln(|x|)$



Prior with ob located 2 km lower



$$p(\mathbf{x}|\mathbf{y}) \propto p(\mathbf{y}|\mathbf{x})p(\mathbf{x})$$

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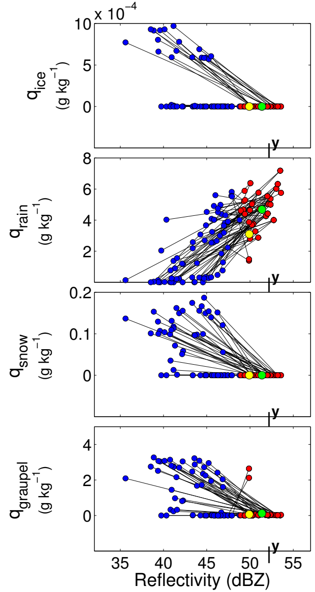
PF update



$$p(\mathbf{x}|\mathbf{y}) \propto p(\mathbf{y}|\mathbf{x})p(\mathbf{x})$$

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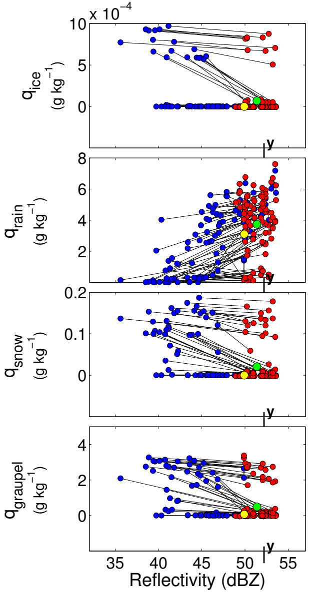
Local PF update



$$\color{red}{p(\mathbf{x}|\mathbf{y})} \propto p(\mathbf{y}|\mathbf{x})p(\mathbf{x})$$

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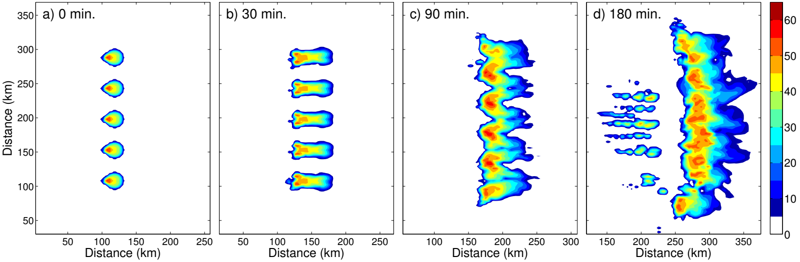
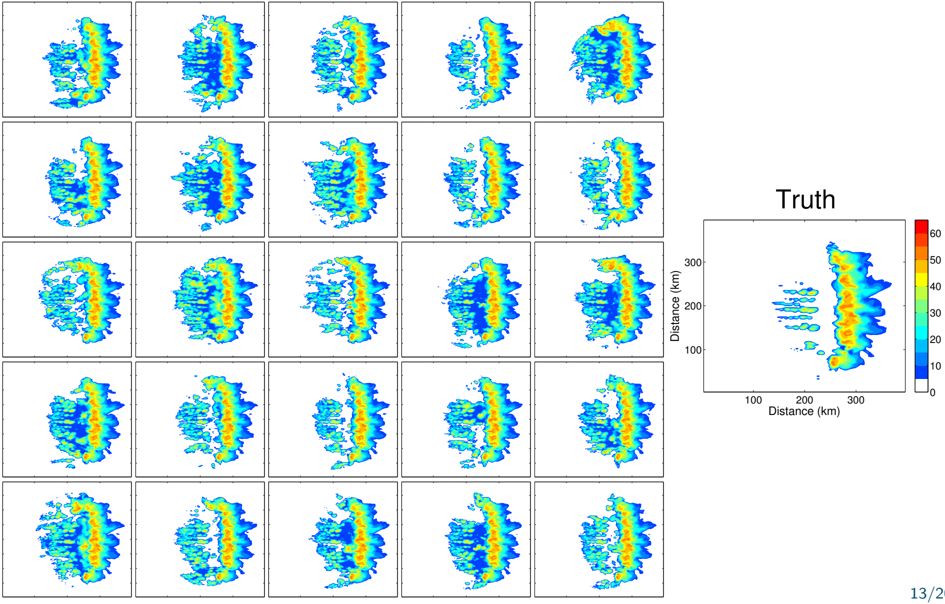
Case study: idealized MCS



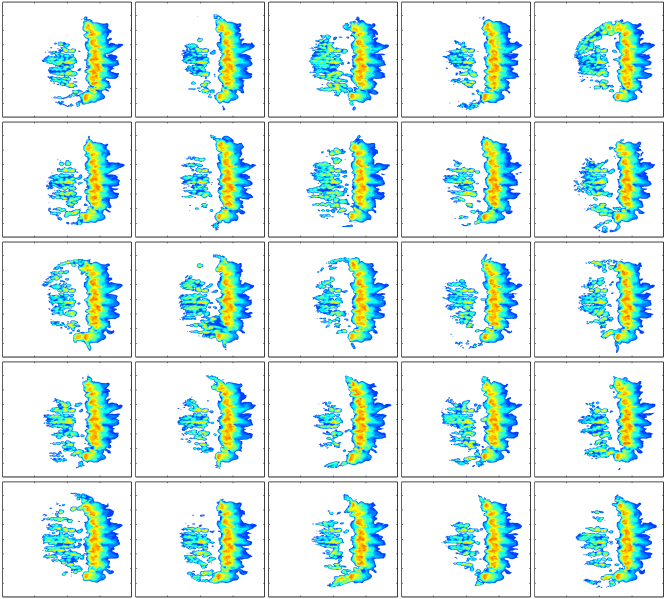
- **Model**: NCAR Weather Research and Forecasting model (3-km grid spacing with 40 vertical levels)
- **Observations**: radar velocity and reflectivity every 5 minutes
- **Data assimilation**: Local PF and EAKF in DART framework using 100 members

See Sobash and Stensrud (2013) for details

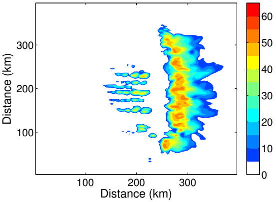
EAKF members (180 min)



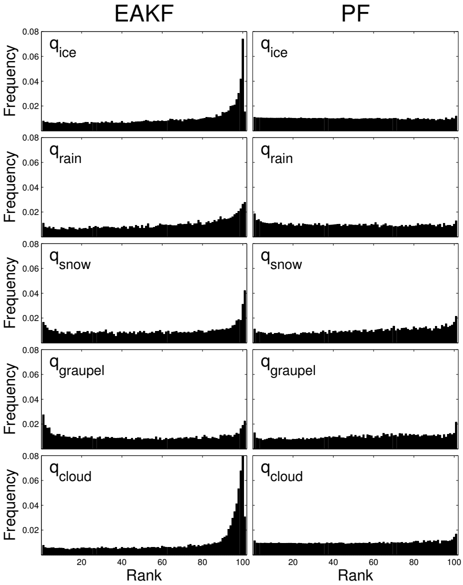
Local PF members (180 min)



Truth

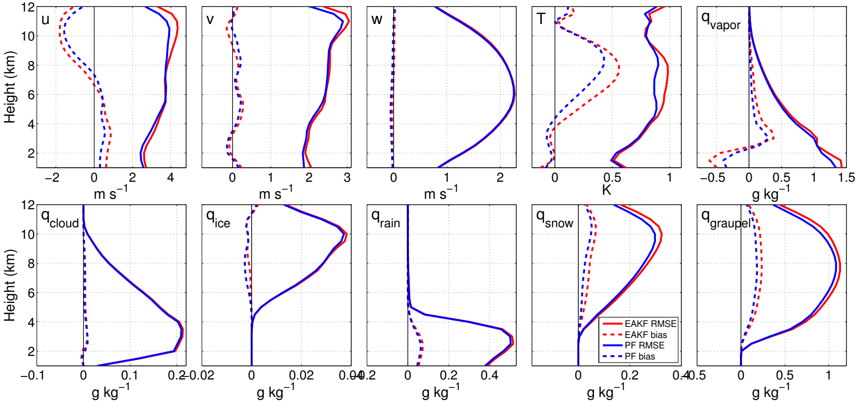


Probabilistic verification



- Rank histograms calculated from prior members every 10 min in convective cells within leading edge of squall line.
- Grid points where true reflectivity $>$ 0 dBZ are used for verification, assuming no spatial and temporal correlations between variables.

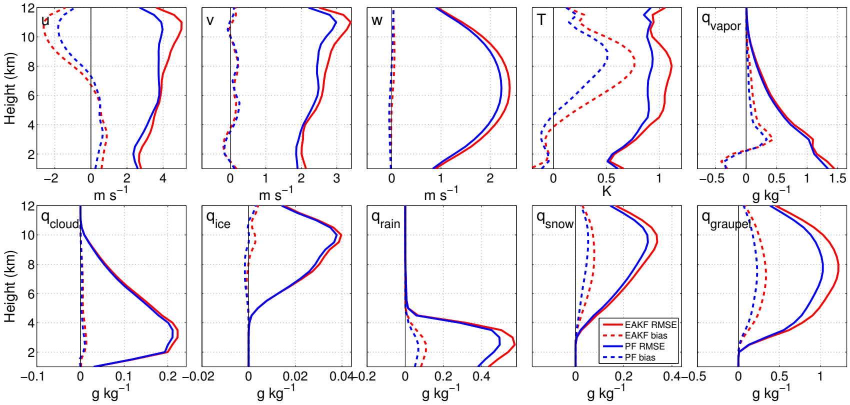
RMSE and bias (5-min cycling)



- Horizontal mean RMSEs (solid) and bias (dashed) from 60-min forecasts.
- Values are averaged in vicinity of squall line.

RMSE and bias (20-min cycling)

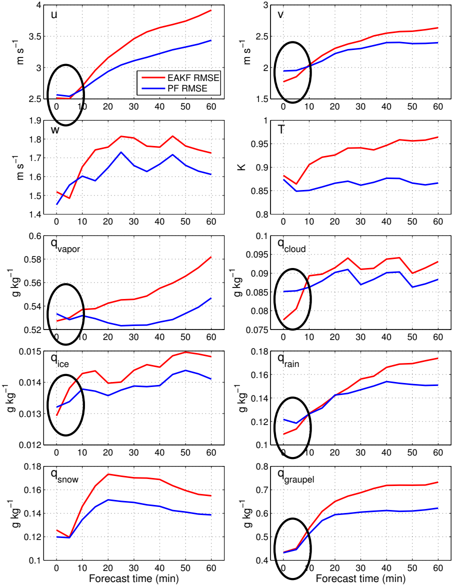
NCAR



- Horizontal mean RMSEs (solid) and bias (dashed) from 60-min forecasts.
- Values are averaged in vicinity of squall line.

Forecast error evolution

- Mean forecast RMSEs as a function of time.
- Values are averaged in vicinity of squall line from 20-min obs frequency experiment.
- Initial error growth in EAKF forecasts is much more rapid than in PF forecasts.



Summary

NCAR

Particle filters provide a means of assimilating observations for applications that are difficult for linear/Gaussian filters.

A new data assimilation system is developed that approximates the particle filter within local neighborhoods of observations (Poterjoy 2016).

The local PF is computationally affordable—with a cost comparable to the NCAR DART EAKF.

Recent testing of the local PF in the WRF model provide an incentive to explore real applications.

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