On the Benefits of a High-Resolution Analysis for Convective Data Assimilation of Radar Observations using a Local Ensemble Kalman Filter

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(Hendrik Reich, Andreas Rhodin)

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Limited predictability, scale-dependent

Obstacles of forecasts:

- Forecasts tainted by model error
- Predictability limited by error growth in the chaotic atmospheric system
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*Is an ensemble forecast (a) from a fine EnKF analysis better than (b) from a coarse analysis?*

Forecast window: 3 hours
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OSSE: Fine vs. Coarse Assimilation

Local analyses of storm systems using LETKF (Hunt et al, 2007)

Nature Run
single cells of an elongated squall line

Fine Analysis R4
single cells taken from best fitting member(s)
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Local analyses of storm systems using LETKF (*Hunt et al, 2007*)

- **Nature Run**: single cells of an elongated squall line
- **Fine Analysis R4**: single cells taken from best fitting member(s)
- **Coarse Analysis R16**: coarse fit from coarsely fitting member(s)
### COSMO model setup

**Domain:** 198 x 198 x 50 gridpoints  
periodic lateral boundaries conditions

**Resolution:** 2 km horizontally
Nature Run and Ensemble

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- **Initial state:** Horizontally homogenous sounding,
  \[ \text{CAPE} = 2200 \, \text{J/kg} \]
  random white noise on T (0.02 K) and W (0.02 m/s)
  in the boundary layer
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- **Model:** Full COSMO physics with active radiation scheme

- **Forecast:** 8 hour spinup until convection evolves:
  - long-lived cells, lifetime \( \geq 6 \) h
  - horizontal position *fully random* in ensemble
Fine vs. Coarse Assimilation

Assimilation setup

- 50 member ensemble (perfect model)
- simulated observations of *radial wind* and *(no)-reflectivity*
- analysis produced by LETKF (*Hunt et al, 2007*) in KENDA\(^a\)

\(^a\) Kilometre-scale ENsemble Data Assimilation, developed at DWD Offenbach (Hendrik Reich, Andreas Rhodin)
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- Fine assimilation scheme R4
- Coarse assimilation scheme R16

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Fine Analysis Scheme (R4)

- Convergence of analysis onto observed clouds
- Spurious clouds suppressed
- Small error and variance

Coarse Analysis Scheme (R16)
Fine vs. Coarse Assimilation Scheme: Setup

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- Position of clouds roughly coincident with observations
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- Larger error and variance
**Fine vs. Coarse Assimilation Scheme: Setup**

<table>
<thead>
<tr>
<th>Fine Analysis Scheme (R4)</th>
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</tr>
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<tbody>
<tr>
<td><strong>1</strong> 4 km Localization length</td>
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<tr>
<td><strong>2</strong> 2 km Observations</td>
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</table>
| **3** $R$-matrix:  
  $R_{\text{wind-obs}} = (5 \text{ m/s})^2$  
  $R_{\text{refl-obs}} = (20 \text{ dBZ})^2$ | **Larger error and variance** |
| **4** 5 min assimilation interval | |

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### Fine vs. Coarse Analysis Scheme: Setup

#### Fine Analysis Scheme (R4)
1. 4 km Localization length
2. 2 km Observations
3. \( R \)-matrix:
   - \( R_{\text{wind-obs}} = (5 \frac{m}{s})^2 \)
   - \( R_{\text{refl-obs}} = (20 \text{ dBZ})^2 \)
4. 5 min assimilation interval

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- Spurious clouds suppressed
- Small error and variance

#### Coarse Analysis Scheme (R16)
1. 16 km Localization length
2. 8 km SuperObservations
3. Inflated \( R \)-matrix:
   - \( R_{\text{wind-SuperObs}} = (5 \frac{m}{s})^2 \)
   - \( R_{\text{refl-SuperObs}} = (20 \text{ dBZ})^2 \)
4. 20 min assimilation interval

- Position of clouds roughly coincident with observations
- Spurious clouds allowed
- Larger error and variance
Assimilation Results: Nature vs. Analysis Ensemble Means

Nature Run 01, 14 UTC
R4 Analysis EnsMean
R16 Analysis EnsMean

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Assimilation Results: Nature vs. Analysis Ensemble Means

Nature Run 01, 15 UTC
R4 Analysis EnsMean
R16 Analysis EnsMean

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Assimilation Results: Nature vs. Analysis Ensemble Means

Nature Run 01, 16 UTC
R4 Analysis EnsMean
R16 Analysis EnsMean

Ref Max (dBZ)

T (K), z = 150m

W (m/s), z = 3500m
**Assimilation Results: Nature vs. Analysis Ensemble Means**

- **Nature Run 01, 17 UTC**
- **R4 Analysis EnsMean**
- **R16 Analysis EnsMean**

**Ref Max (dBZ)**

**T (K), z = 150m**

**W (m/s), z = 3500m**

[Images of data visualizations showing temperature and wind fields at different heights and distances.]
Fine Analysis R4, Realization 01, t = 17 UTC

Nature Run   Member 001   Member 013

Member 025   Member 037   Member 050

Distance (km)
Analysis Members R16

Coarse Analysis R16, Realization 01, t = 17 UTC

Nature Run

Member 001

Member 013

Member 025

Member 037

Member 050

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Fine vs. Coarse Storm Assimilation
Analysis Ensemble Distributions

Ensemble distribution where $\text{Refl}_{\text{nature}} = 40 \pm 0.5 \text{ dBZ}$

- **R4**
- **R16**
Fine vs. Coarse EnKF Analyses

Experimental Setup of OSSE

Results

Cycled Assimilation

Ensemble Forecasts

RMSE-Statistics: U, W

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Fine vs. Coarse Storm Assimilation 10 / 14
Forecast Results: Nature vs. Forecast Ensemble Means

Nature Run 01, 20 UTC

R4 Forecast EnsMean

R16 Forecast EnsMean

Refl Max (dBZ)
DAS-DIS Displacement Score

Displacement of forecast field with respect to observations, measured by the amplitude of the morphing vector field:

![Graph showing DAS-DIS of Refl_Max (Mean Score of Ensemble Members)]
Methods:

- Successful assimilation of long-lived convection by LETKF using only radar observations of radial wind and reflectivity.
- 3 hours of cycled assimilation followed by 3-h forecast.
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Fine scheme R4
- precise fit onto observed clouds
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Coarse scheme R16

- initializes equally good 3-h forecasts
- needs much less computational power
Conclusions, Outlook

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- coarse analysis possibly closer to model climatology
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Outlook
- radar assimilation schemes in KENDA of COSMO-DE and COSMO-MUC
- predictability horizons of convection in real-world model
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References

Hunt et al 2007
Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter

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*Monthly Weather Review*, to be submitted
Rigorous Convergence vs. Relaxation

(a) $\sigma_o = 5$ dBZ

(b) $\sigma_o = 20$ dBZ