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

Heiner Lange and George C. Craig

Hans-Ertel-Centre for Weather Research, Data Assimilation Branch
LMU Munich
in Co-Operation with DWD, Offenbach
(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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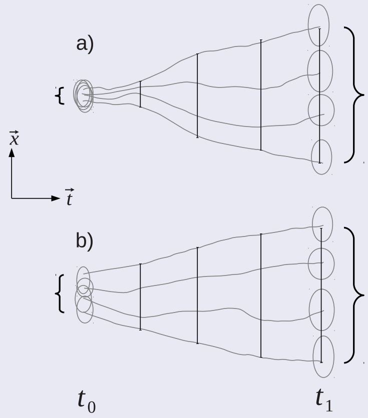
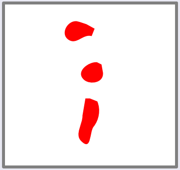
Expected behavior:

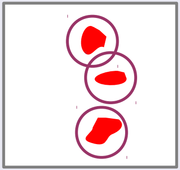


OSSE: Fine vs. Coarse Assimilation

Local analyses of storm systems using LETKF (*Hunt el 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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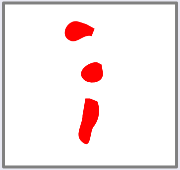

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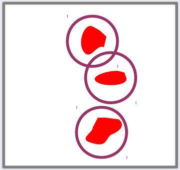

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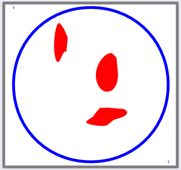

Coarse Analysis R16
coarse fit from coarsely fitting member(s)

Nature Run and Ensemble

COSMO model setup

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

Resolution: 2 km horizontally

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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 el 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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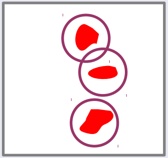
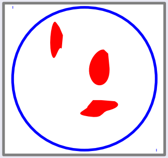
Fine vs. Coarse Assimilation Scheme: Setup

Fine Analysis Scheme (R4)



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

Coarse Analysis Scheme (R16)



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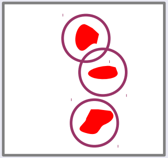

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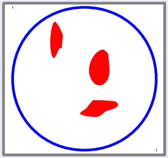

- *Position of clouds roughly coincident with observations*
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Fine vs. Coarse Assimilation Scheme: Setup

Fine Analysis Scheme (R4)

1. 4 km Localization length
2. 2 km Observations
3. **R**-matrix:
   $\mathbf{R}_{wind\text{-}obs} = (5\frac{m}{s})^2$
   $\mathbf{R}_{refl\text{-}obs} = (20\ \mathrm{dBZ})^2$
4. 5 min assimilation interval

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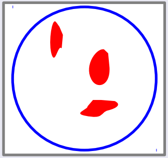

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Coarse Analysis Scheme (R16)

1. 16 km Localization length
2. 8 km SuperObservations
3. *Inflated* **R**-matrix:
   $\mathbf{R}_{\textit{wind-SuperObs}} = (5\frac{\mathrm{m}}{\mathrm{s}})^2$
   $\mathbf{R}_{\textit{refl-SuperObs}} = (20\ \mathrm{dBZ})^2$
4. 20 min assimilation interval

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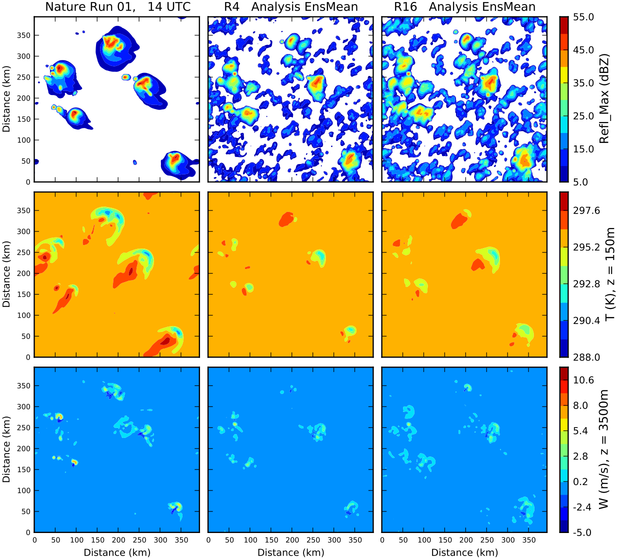
Assimilation Results: Nature vs. Analysis Ensemble Means



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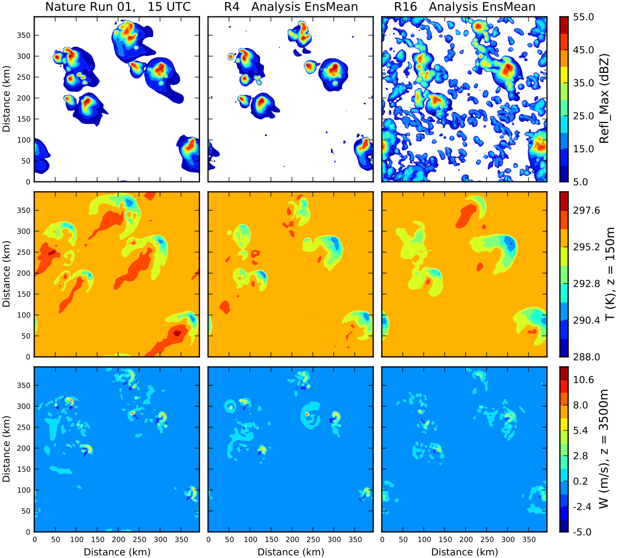

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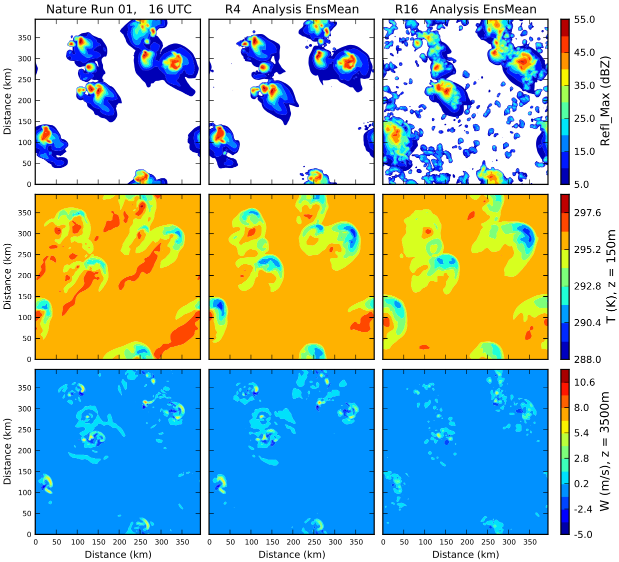

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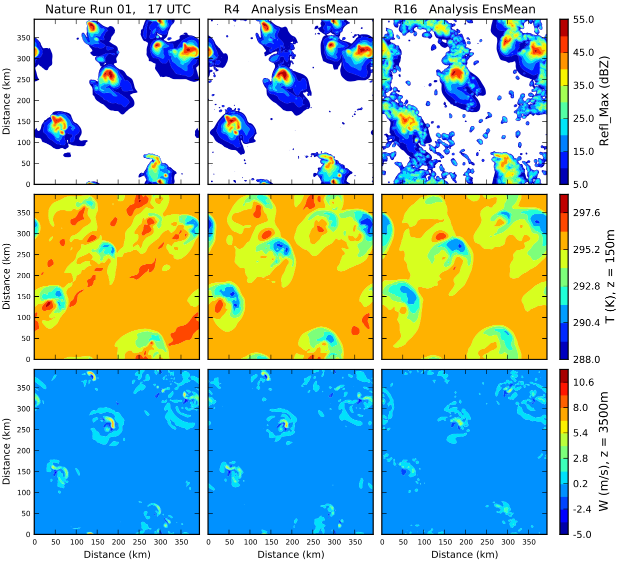
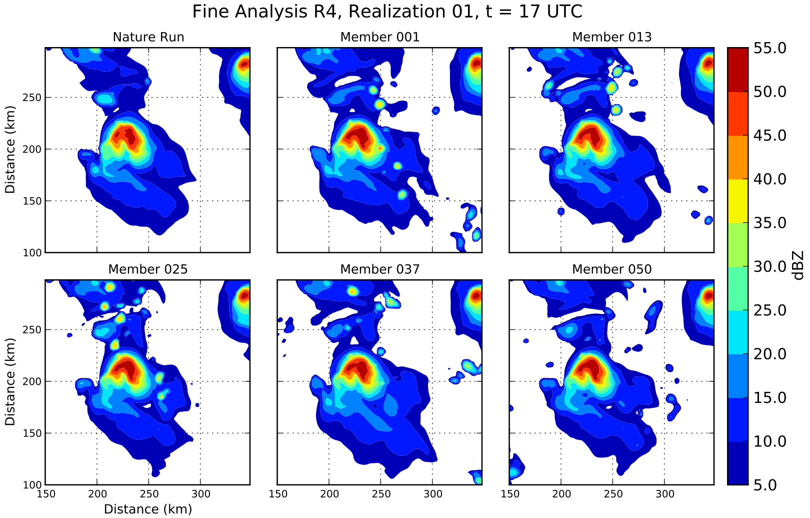


Analysis Members R4



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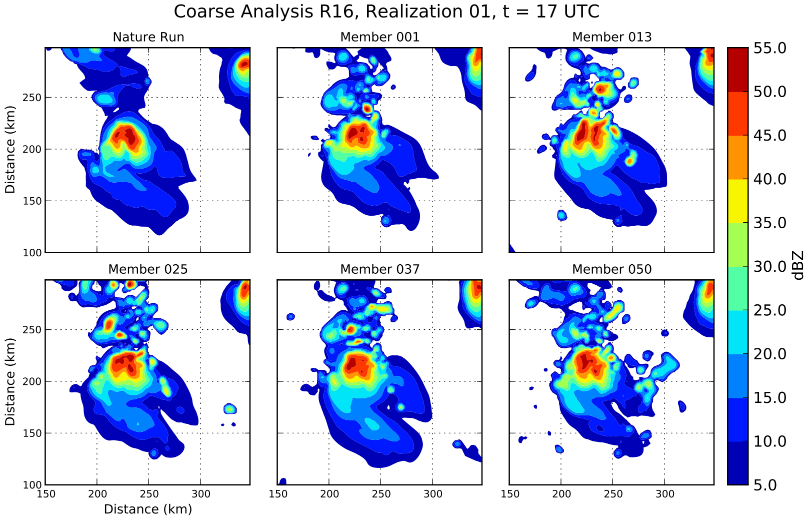
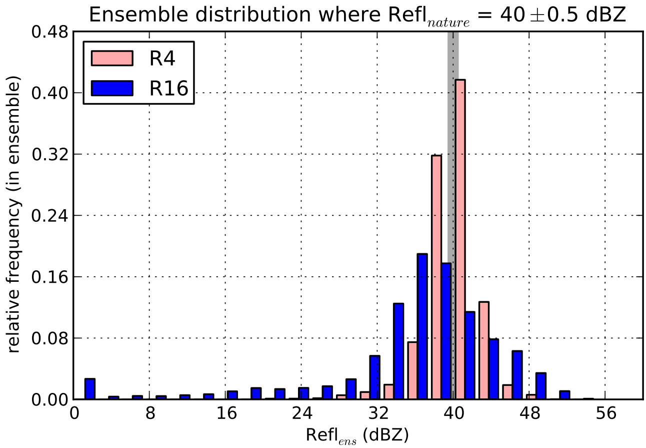
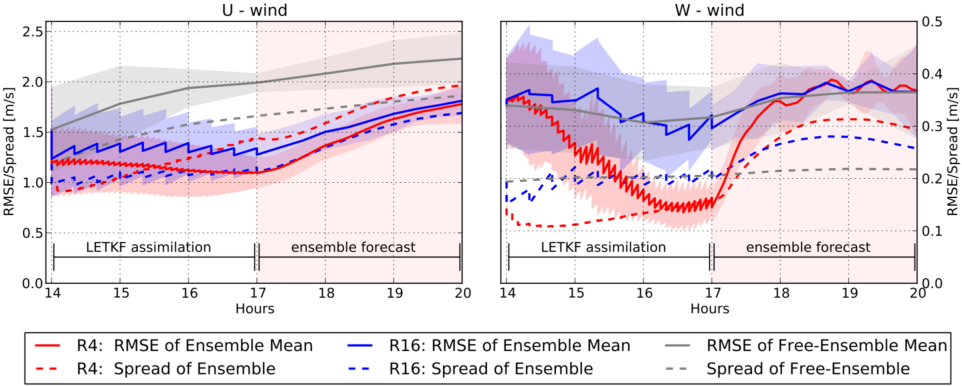


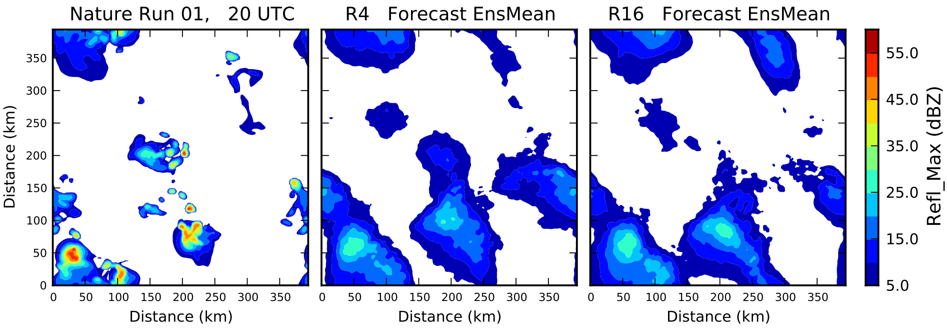
Analysis Ensemble Distributions



RMSE-Statistics: U, W

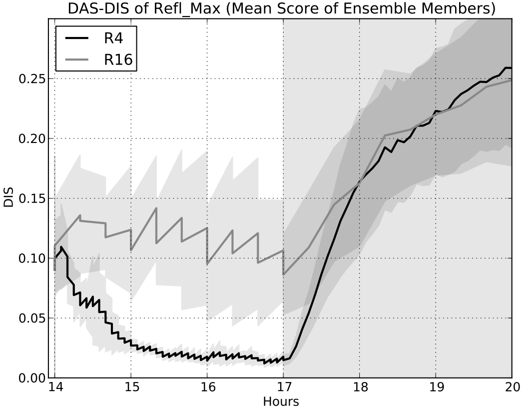


Forecast Results: Nature vs. Forecast Ensemble Means



DAS-DIS Displacement Score

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



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Methods:

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Coarse scheme R16

- initializes equally good 3-h forecasts
- needs *much less* computational power

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References

Hunt et al 2007
Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter
Physica D, 230, 112-126, 2007

H. Lange and G.C. Craig 2013
On the Benefits of a High-Resolution Analysis for Convective Data Assimilation of Radar Observations using a Local Ensemble Kalman Filter
Monthly Weather Review, to be submitted

Rigourous Convergence vs. Relaxation