30-second-cycle convection-resolving data assimilation of dense phased array weather radar data

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Data Assimilation Seminar
Introduction

- The resolution of advanced radar observation data is higher than that a typical NWP system can use.
  - In particular, **Phased Array Weather Radar (PAWR)**.

- With the powerful K computer resources, we explore radar data assimilation
  - with a **30-sec rapid-update cycle**
  - at **1-km – 100-m model resolution**
  - comparable to the spatial and temporal resolution of PAWR observations.
Key investigation

- Development of a high-performance regional data assimilation system, targeted for rapid update cycle and big observation data.
  - SCALE-LETKF (Lien et al. 2017; Miyoshi et al. 2016)

- Techniques for assimilating high-resolution, dense data.
  - Radar data quality control (Ruiz et al. 2015)
  - Super-observation
  - Relaxation-to-prior-spread (RTPS)
  - Implicit thinning and localization

- Better use of both raining and clear reflectivity data to initiate and suppress the convections.
  - Clear reflectivity shift
  - Reject data based on background ensemble conditions
SCALE-LETKF

SCALE-LETKF  (Lien et al. 2017)

https://github.com/gylien/scale-letkf

A regional Local Ensemble Transform Kalman Filter (LETKF) data assimilation system for SCALE-RM (Lien et al. 2016)

- Highly configurable
- Highly scalable
Flowchart of ensemble DA cycles in the SCALE-LETKF

- Creating job script
- Boundary file preparation
- Ensemble Forecasts
- Observation Operator
- LETKF Stage-out

- One MPI program for ensemble
- Scripts called within MPI programs
- Entire DA cycle in a single job

- Member #1
- Member #2
- Member #3
- Mean/spread

- Data conversion removed
- Use local disks for parallel I/O
Computational time
– Local disk vs. global disk

“Other (Fortran)” includes:
1. Initialization/finalization of MPI communicators.
2. Copying/moving files before and after programs.

“Other (Shell)” includes:
1. Initialization/finalization of programs.
2. Collecting the standard output/errors.
Computational time
– Test with up to 72,720 nodes

TEST1: January, 2016
TEST2: February, 2016
TEST3: June, 2016
TEST4: September, 2016
TEST5: January, 2017

- No data
- No detailed items

- LETKF - Shellscript
- LETKF - Init+final
- LETKF - I/O (in Fortran)
- LETKF - Comp+MPI
- OBSOPE - Shellscript
- OBSOPE - Init+final
- OBSOPE - I/O (in Fortran)
- OBSOPE - Comp+MPI
- SCALE - Shellscript
- SCALE - Init+final
- SCALE - I/O (in Fortran)
- SCALE - Comp+MPI
Settings of the PAWR assimilation

<table>
<thead>
<tr>
<th>Resolution</th>
<th>Size</th>
<th>Observation</th>
<th>Cycle length</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>15 km</td>
<td>5760 x 4320 km</td>
<td>PREPBUFR</td>
</tr>
<tr>
<td>D2</td>
<td>5 km</td>
<td>1280 x 1280 km</td>
<td>PREPBUFR</td>
</tr>
<tr>
<td>D3</td>
<td>1 km</td>
<td>180 x 180 km</td>
<td>PAWR</td>
</tr>
<tr>
<td>D4</td>
<td>1 km</td>
<td>120 x 120 km</td>
<td>PAWR</td>
</tr>
</tbody>
</table>

Ensemble size: **100**

State variables: $U$, $V$, $W$, $P$, $T$, $Q$, $Qc$, $Qr$, $Qs$, $Qi$, $Qg$

Observations superobed to model resolution

Assimilate PAWR data every 30 seconds in D4:
Reflectivity ($Ref$) +
Radial velocity ($Vr$)

00:00Z July 1 00:00Z July 12

02:00Z July 13

06:00Z July 13 (15:00L)

30-min forecasts
Observation pre-processing

Raw data

Radar quality control:
Remove ground clutter and attenuated data
(Ruiz et al. 2015)

QCed data

Superobing:
Average observations within a model grid

Data for LETKF
250M super-obs for LETKF assimilation

250-m superobs

Radar reflectivity \([Z = 3000\text{m}]\) [06:00:00 UTC]

Data counts in a single 30-sec cycle:

Original data (in polar coordinates):
- 600 radial points (every 100 m)
- 300 azimuthal angles (every 1.2 deg)
- 98 elevation angles (every ~ 1 deg)

Superobed data:
- Ref : \(~3,100,000\)
- Vr : \(~170,000\)

Assimilated data:
- Ref : \(~280,000\)
- Vr : \(~160,000\)

Mostly rejected because both the model and observations are clear-sky (< 10 dBZ)
Raining / clear reflectivity

- **Ref\_rain**: raw Ref $\geq$ 10 dBZ
  - **Ref\_clear**: raw Ref $<$ 10 dBZ

- **“Clear reflectivity shift”**: 
  - Set all Ref\_clear (both observation and background) to 5 dBZ
    (Similar to Aksoy et al. 2009, but leave a 5-dBZ gap between minimum Ref\_rain and Ref\_clear)

- Reject data when there are too few raining (Ref\_rain) background members:
  - For Ref\_rain obs, require $\geq$ 1 (out of 100) background members having Ref\_rain
  - For Ref\_clear obs, require $\geq$ 20 (out of 100) background members having Ref\_rain
    (Similar to Lien et al. 2013, 2016 for precipitation assimilation)
Impact of clear-reflectivity shift (I)

Threat scores (1KM)
(6-forecast average)

[10 dBZ]

All Ref_clear (Ref < 10 dBZ) → 10 dBZ (no gap)

[30 dBZ]

All Ref_clear (Ref < 10 dBZ) → 5 dBZ
All Ref_clear (Ref < 10 dBZ) → 0 dBZ
Impact of clear-reflectivity shift (II)

10-min analyses and 30-min forecasts (1KM)

OBS

Ref_clear (Ref<10 dBZ) → 10 dBZ (no shift)

Ref_clear (Ref<10 dBZ) → 5 dBZ
Covariance inflation

- “Relaxation” methods:
  - Relax the analysis members (covariance) back to the background members
  - Easy to compute
  - (Almost) Do not need “spin-up” time
  - Adaptive to observation density

- Relaxation to prior perturbation (RTPP; Zhang et al. 2004) vs. Relaxation to prior spread (RTPS; Whitaker and Hamill 2012)

- In the LETKF, can be done by relax the weight matrix ($W$):
  
  **RTPP:** $W \leftarrow (1 - \alpha)W + \alpha I$
  
  **RTPS:** $W \leftarrow \left( \alpha \frac{\sigma^b - \sigma^a}{\sigma^a} + 1 \right)W = \left( \alpha \sqrt{\frac{X^b X^{bT}}{(k-1)X^b \tilde{P}^a X^{bT}}} - \alpha + 1 \right)W$

- Can be more adaptive:
  - Adaptively determine the $\alpha$ parameter (Kotsuki et al. 2017)
Impact of relaxation method

Threat scores (1KM)
(6-forecast average)

[10 dBZ]

[30 dBZ]

RTPS: $\alpha = 0.95$

RTPP: $\alpha = 0.95$
RTPP: $\alpha = 0.9$
RTPP: $\alpha = 0.85$
RTPP: $\alpha = 0.8$
RTPP: $\alpha = 0.7$
Thinning and covariance localization

- **Thinning**, because of:
  - Observation error correlation
  - Representativeness errors
  - Reduce the observation number *compared to the degree of freedoms of the analysis* (i.e., ensemble size)
  - Computational costs

- **Covariance localization**, because of:
  - Sampling errors with a limited ensemble size
  - Reduce the observation number in local areas *compared to the degree of freedoms of the analysis* (i.e., ensemble size)
  - Computational costs

- With **very dense observations**, the last two reasons become much more important.

- Thinning unavoidably decreases the resolution of the observation data!

Lorenc 2003, QJRMS
Tsyrulnikov 2010, COSMO News Letters
Hotta 2017, RISDA 2017
An alternative way: Observation number limit in the LETKF (I)

- **Hamrud et al. 2015** (ECMWF global model): Limit the number of observations used at each grid point for each combination of different report types (e.g., radiosonde) and variables (e.g., U-wind).
  - $\#OBS = 30$ per report types and variables; Ens size $= 60\sim 240$

- **Schraff et al. 2016** (DWD regional model: KENDA-COSMO): Keep a constant of the “effective number of observations” used at each grid point by adjusting the localization radius.
  - Effective $\#OBS = 100$; Ens size $= 40$

- Observations **spatially closest to the analyzed grid** are selected.
An alternative way: Observation number limit in the LETKF (II)

- Advantages of the observation number limit:
  - (Significantly) improve the analysis and forecasts! (Hamrud et al. 2015)
  - Save the computational time.

- We implement and test this technique in our regional data assimilation system (SCALE-LETKF), assimilating dense radar data.
  - Not new, but we test it with very dense data and very high model resolution.
Observation number limit vs. thinning

- Observations
Observation number limit vs. thinning

- Model grids
- Observations
- Observations picked by thinning

Thinning mesh
Observation number limit vs. thinning

Thinning

- Model grids
- Observations
- Observations picked by thinning
- Observations assimilated at grid A, B, C
- Localization cut-off radius
Observation number limit vs. thinning

Observation number limit = 10

- Model grids
- Observations

Observations assimilated at grid A, B, C

Localization cut-off radius
# Experimental design

<table>
<thead>
<tr>
<th>Experiment name</th>
<th>Ensemble size</th>
<th>#OBS limit (for each obs type)</th>
<th>Thinning (pick up one every XxYxZ grids)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M100-#OBS&lt;XX&gt;</td>
<td>100</td>
<td>&lt;XX&gt;</td>
<td>---</td>
</tr>
<tr>
<td>M100-Unlmt</td>
<td>100</td>
<td>Unlimited</td>
<td>---</td>
</tr>
<tr>
<td>M25-#OBS&lt;XX&gt;</td>
<td>25</td>
<td>&lt;XX&gt;</td>
<td>---</td>
</tr>
<tr>
<td>M25-Unlmt</td>
<td>25</td>
<td>Unlimited</td>
<td>---</td>
</tr>
<tr>
<td>THIN4x4</td>
<td>100</td>
<td>100</td>
<td>4x4x2</td>
</tr>
<tr>
<td>THIN16x16</td>
<td>100</td>
<td>100</td>
<td>16x16x8</td>
</tr>
</tbody>
</table>

* Observations are first superobed to the model resolution (250 m) in all experiments.
M100-Unlmt  (2-fcst average)

**Threat score**
- Threshold = 15 dBZ

**Bias score**
- Threshold = 15 dBZ

TS and BS are verified against the 3-D reflectivity observations, averaged onto 1-km grids.
M100-#OBS<XX>  (2-fcst average)

**Threat score**

Threshold = 15 dBZ

**Bias score**

Threshold = 15 dBZ

TS and BS are verified against the 3-D reflectivity observations, averaged onto 1-km grids.
M25-#OBS<XX>  (2-fcst average)

Threat score
Threshold = 15 dBZ

Bias score
Threshold = 15 dBZ

TS and BS are verified against the 3-D reflectivity observations, averaged onto 1-km grids.
Mean 5-min and 30-min forecast TS

Mean threat score (threshold = 15 dBZ)

Solid lines: Mean TS for the first 5-min forecasts

Dashed lines: Mean TS for 30-min forecasts

Red: 100 members
Blue: 25 members
Unlimited

#OBS for each obs type

24  50  100  200  400  800 for total
# observations assimilated at each grid (first cycle)

- **M100-#OBS25**: 50
- **M100-#OBS100**: 200
- **M100-Unlmt**: > 100,000

Localization cut-off area
Real localization cutoff radius (km) (first cycle)

M100-#OBS25
~0.5 km

M100-#OBS100
~0.9 km

M100-Unlmt
~15 km

Localization adaptive to the observation density
Analysis increment: Reflectivity (dBZ) (first cycle)

Very similar!
# observations assimilated at each grid (first cycle)

M100-#OBS25

M100-#OBS100

M100-Unlmt

THIN4x4 (1 km)

THIN16x16 (4 km)
Analysis increment: Reflectivity (dBZ) (first cycle)

M100-#OBS25

M100-#OBS100

M100-Unlmt

THIN4x4 (1 km)

THIN16x16 (4 km)

Increments change with thinning
**Thinning** (2-forecast average)

**Threat score**
Threshold = 15 dBZ

![Graph showing threat score over forecast time with different thinning methods: M100-#OBS100, M100-Unlmt, THIN4x4, THIN16x16.]
Computational time

LETKF main computation (3672 nodes)

#OBS for each obs type

Time (s)

M100-
#OBS25  M100-
#OBS50  M100-
#OBS100  M100-
#OBS200  M100-
Unlmt
Discussion: observation number limit (I)

- The number of observations that can be effectively assimilated by the EnKF is limited by (a few times of) the ensemble size, due to the limited degree of freedoms of the analysis (e.g., Lorenc 2003, QJRMS; Tsyrlinikov 2010, COSMO News Letters; Talk [8-2]: Daisuke Hotta)

- In the situation of assimilating dense mesoscale observation data, this may be the dominant reason for thinning, and also an important reason for localization.

- If we can only assimilate a limited number of observations, we should choose the most important ones!
Discussion: observation number limit (II)

- This method provides a simple way to perform both “implicit thinning” and “adaptive localization” in the LETKF.
- Suggested strategies of assimilating dense observation data with the LETKF:
  - 1) Mitigate the issues of observation error correlation and representativeness errors by, e.g.,
     - Thinning
     - Superobing
     - Considering the full R matrix
   - 2) Assimilate with the observation number limit.
     - #OBS ≈ a few times of the ensemble size
   Not as strong as if not using the observation number limit
PAWR assimilation results with different model resolutions

<table>
<thead>
<tr>
<th>Experiments</th>
<th>Model resolution</th>
<th>Observation resolution</th>
<th>Cycle length</th>
<th>Assimilation period</th>
<th># forecast cases (every 10 min)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1 KM (D3)</strong></td>
<td>1 km</td>
<td>1 km</td>
<td>5 min</td>
<td>4 hour</td>
<td>--</td>
</tr>
<tr>
<td><strong>1 KM (D4)</strong></td>
<td>1 km</td>
<td>1 km</td>
<td>30 sec</td>
<td>60 min</td>
<td>6</td>
</tr>
<tr>
<td><strong>500 M (D4)</strong></td>
<td>500 m</td>
<td>500 m</td>
<td>30 sec</td>
<td>60 min</td>
<td>6</td>
</tr>
<tr>
<td><strong>250 M (D4)</strong></td>
<td>250 m</td>
<td>250 m</td>
<td>30 sec</td>
<td>60 min</td>
<td>6</td>
</tr>
<tr>
<td><strong>100 M (D4)</strong></td>
<td>100 m</td>
<td>100 m</td>
<td>30 sec</td>
<td><strong>20 min</strong></td>
<td>2</td>
</tr>
</tbody>
</table>

Provide ensemble boundary conditions
12:00L–15:00L: 3-hr analysis at 1KM with 5-min cycles (not shown)

15:00L–15:20L: 20-min analysis (gray background)

15:20L–15:50L: 30-min forecast (purple background)
30-min forecasts at 250-m model resolution

Initial time: 15:10L
Radar reflectivity [Z = 3068m] [06:10:00 UTC]

15:20L
Radar reflectivity [Z = 3068m] [06:20:00 UTC]

15:30L
Radar reflectivity [Z = 3068m] [06:30:00 UTC]

15:40L
Radar reflectivity [Z = 3068m] [06:40:00 UTC]

15:50L
Radar reflectivity [Z = 3068m] [06:50:00 UTC]

16:00L
Radar reflectivity [Z = 3068m] [07:00:00 UTC]

Observation: 
- 10 dBZ
- 40 dBZ
Fractions Skill Score (FSS)  
(Roberts and Lean 2008)

- Verify fractions in neighbor areas
- Changeable parameters:
  - Threshold
  - Verification length scale

Asymptotic value related to bias

Skill increases with length scales

Better than “uniform” forecasts when FSS > ~0.5

Less skillful

More skillful

FSS = \( \frac{2f_s f_m}{f_s^2 + f_m^2} \)

(=1 if no bias)
30-min forecasts
Fractions Skill Score (FSS)

Threshold = 15 dBZ (6-fcst average)

Solid lines: Analysis
Dashed lines: 10-min forecast
(Better than “uniform”)

Dotted lines: 30-min forecast
“Skillful” 10-min forecasts in all scales including the finest grid scale
“Skillful” 30-min forecasts at scale > ~10 km
Higher resolution forecasts become worse in longer forecast time

Horizontal length scale (km)
30-min forecasts
Fractions Skill Score (FSS)

Threshold = 15 dBZ (6-fcst average)

Solid lines:
Hori. length scale = 1 km

Dashed lines:
Hori. length scale = 10 km

(Better than “uniform”)

Forecast time (min)

1KM
500M
250M
30-min forecasts
Fractions Skill Score (FSS)

[2013-07-13 06:10:00] Threshold = 15 dBZ

Solid lines:
Hori. length scale = 1 km

Dashed lines:
Hori. length scale = 10 km

(Better than “uniform”)

Forecast skill differs much run by run:
Need to conduct more forecasts?
Summary

- We assimilate phased array weather radar data with a **30-second rapid-update cycle** at **sub-kilometer resolution**.
  - The analyses are very close to observation.
  - Skillful 10-min forecasts and acceptable 10- to 30-min forecasts are obtained.
  - Higher-resolution model forecasts need to be improved.
- Studies on the techniques for assimilating high-resolution radar data, e.g.,
  - Implicit thinning and localization by observation number limit.
  - Clear reflectivity shift.
- Next step:
  - Longer assimilation period (> days).
**Additional topic:** Deterministic run

- Perform an independent update of a deterministic run (Schraff et al. 2016; KENDA-COSMO).

- Ensemble mean update:

\[
\bar{x}^a = \bar{x}^b + X^b \bar{w}^a \\
= \bar{x}^b + X^b \tilde{P}^a (Y^b)^T R^{-1} [y^o - H(x^b)]
\]

- (Mean) Deterministic run update:

\[
\hat{x}^a = \hat{x}^b + X^b \tilde{P}^a (Y^b)^T R^{-1} [y^o - H(\hat{x}^b)]
\]

(From Schraff et al. 2016)
Impact of deterministic run (I)

Threat scores (1KM)
(5-forecast average)

Threshold = 10 dBZ

Threshold = 20 dBZ
Impact of deterministic run (II)

**Imbalance**: Domain-averaged $|dP_s/dt|$
Potential key use: Typhoon data assimilation

Big differences in typhoon intensity between ensemble mean and deterministic run

(Courtesy of Honda)
Ongoing work: Random additive noises

- Proposed by Dowell and Wicker (2009) and has been used in a number of radar data assimilation studies afterwards.
- Add **spatially correlated** random noises on $U$, $V$, $T$ and $T_d$ (in order to perturb $Q$) onto the analysis every cycle.
  - Horizontal scale = 4 km; Vertical scale = 2 km
  - Only apply to the area with observed reflectivity
- My modifications:
  - Add the noises **only on $Q$**, by relative amounts to its original analysis value.
  - Done as “additive inflation” in the LETKF.
  - Prepare samples with the same number as the ensemble size and **randomly shuffle** them every cycle.
  - Horizontal scale = 1 km; Vertical scale = 500 m
  - (Tentatively) Apply to the entire domain
A sample of random additive noises
Impact of additive noise on spreads (I)

- Standard deviation = 3% to the original Q values
- After 3-h DA cycle every 5 minutes (36 cycles)
- Also apply RTPS = 0.9 for the entire period
Impact of additive noise on spreads (II)

- Standard deviation = 3% to the original Q values
- After 3-h DA cycle every 5 minutes (36 cycles)
- Also apply RTPS = 0.9 for the entire period

Q (g/kg)  U (m/s)  T (K)

No noise  Additive Q noise

Domain maximum  Domain average  Domain minimum
Impact of additive noise on spreads (III) 30-min-forecast FSS

Threshold = 15 dBZ (6-fcst average)

Solid lines: Hori. length scale = 1 km
Dashed lines: Hori. length scale = 10 km

(Better than “uniform”)

No noise
Additive Q noise

Lines: forecasts from deterministic run
Dots: forecast from ensemble mean