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

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Data Assimilation Seminar

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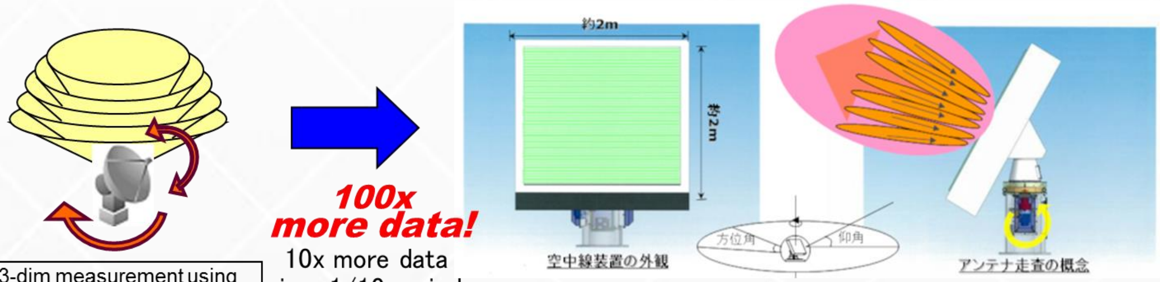
Introduction

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



3-dim measurement using a parabolic antenna (150 m, 15 EL angles in 5 min)

3-dim measurement using a phased array antenna (100 m, 100 EL angles in 30 sec)

- 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

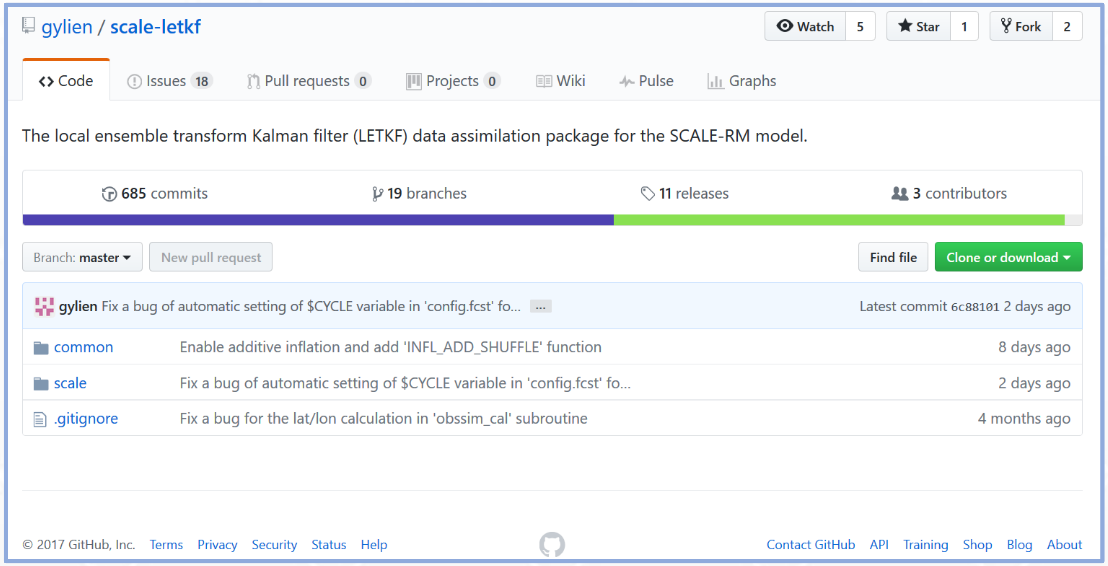
- Development of a high-performance regional data assimilation system, targeted for rapid update cycle and big observation data.
  - SCALE-LETKF (Lien et al. 2017; Miyoshi et al. 2016)
- Techniques for assimilating high-resolution, dense data.
  - Radar data quality control (Ruiz et al. 2015)
  - Super-observation
  - 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
Scalable Computing for Advanced Library and Environment

Scalable Computing for Advanced Library and Environment-Regional Model (SCALE-RM) (Nishizawa et al. 2015; Sato et al. 2015)

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

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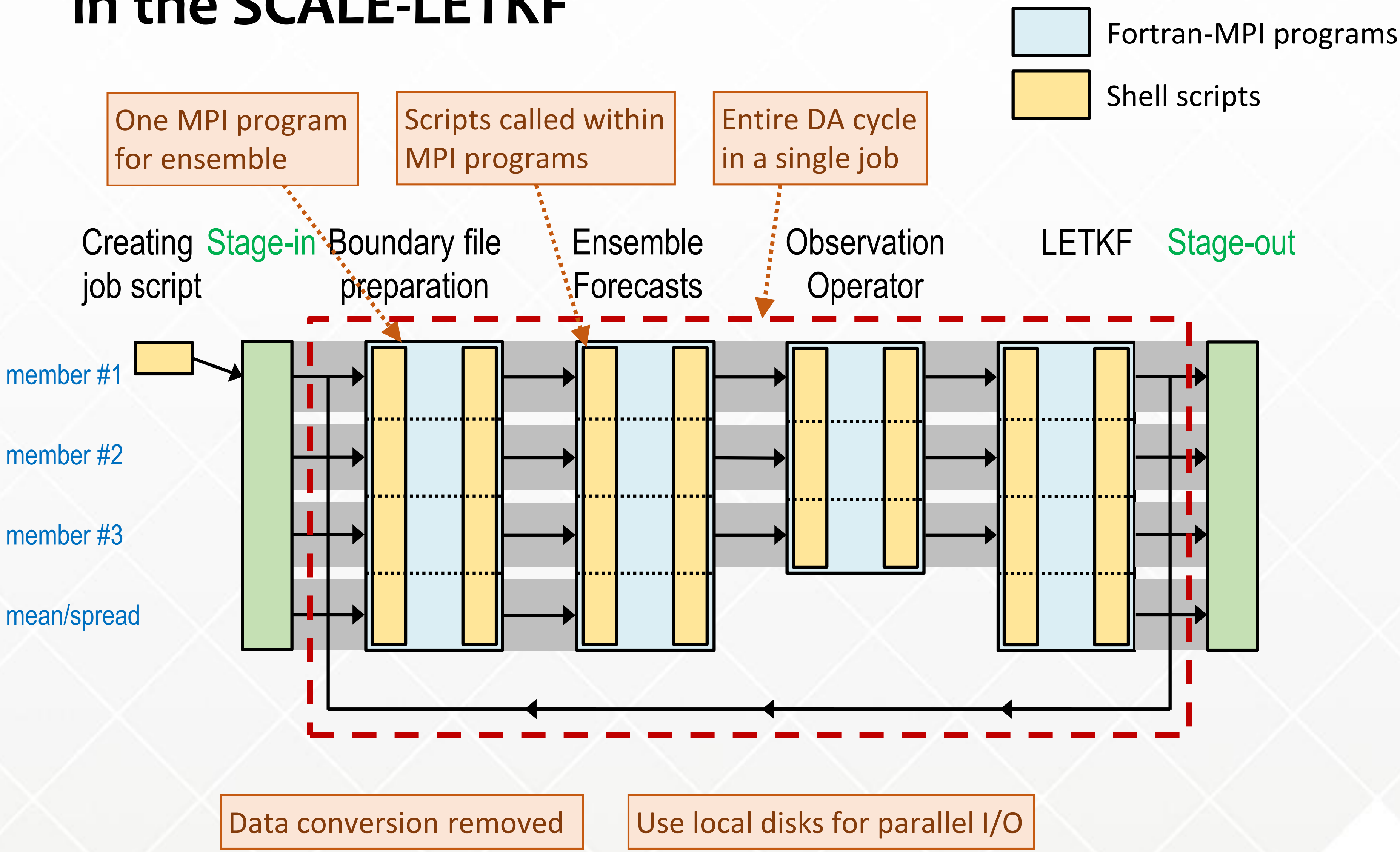
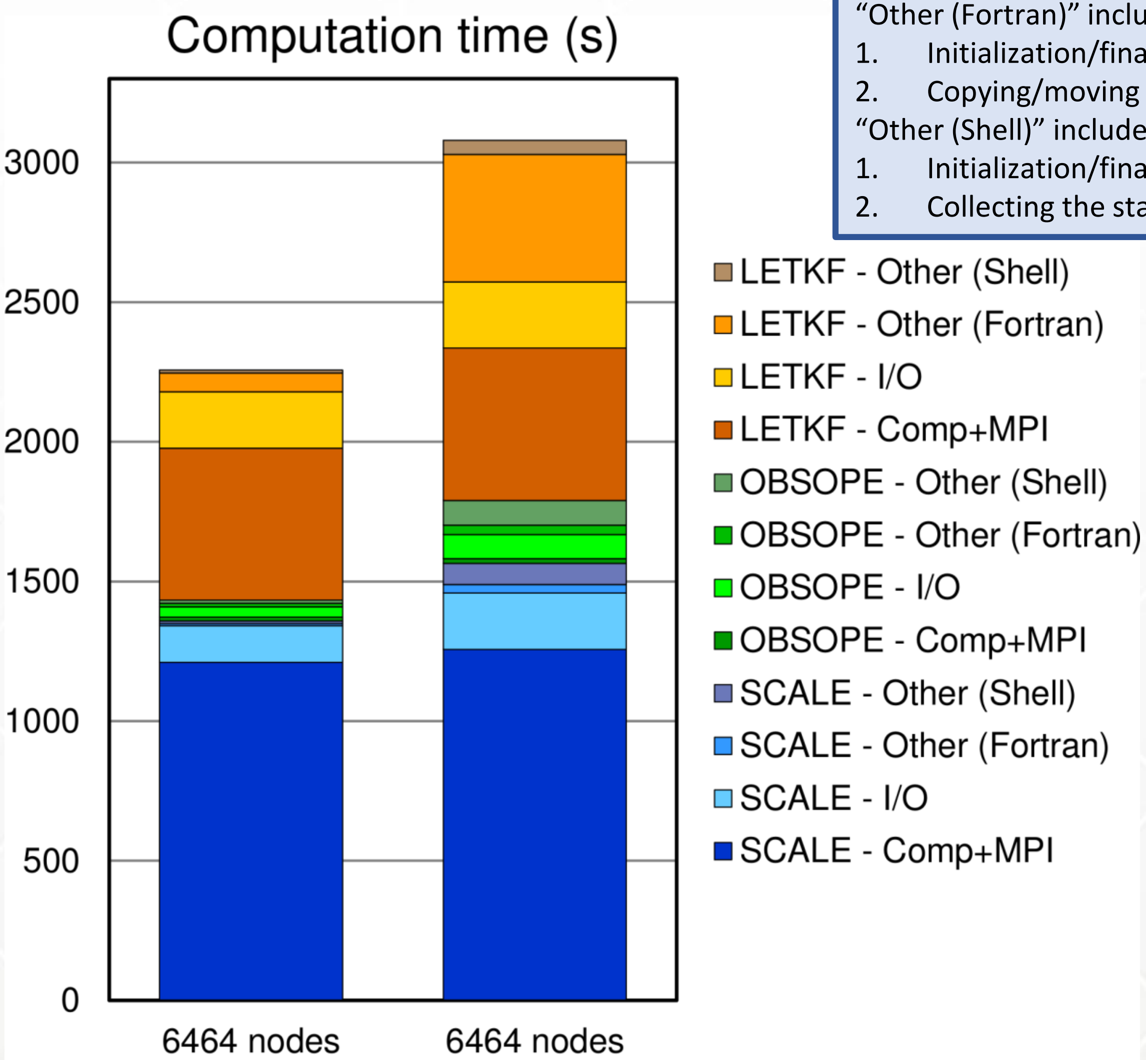


Computational time
– Local disk vs. global disk



Local disk (rank-directory)

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.

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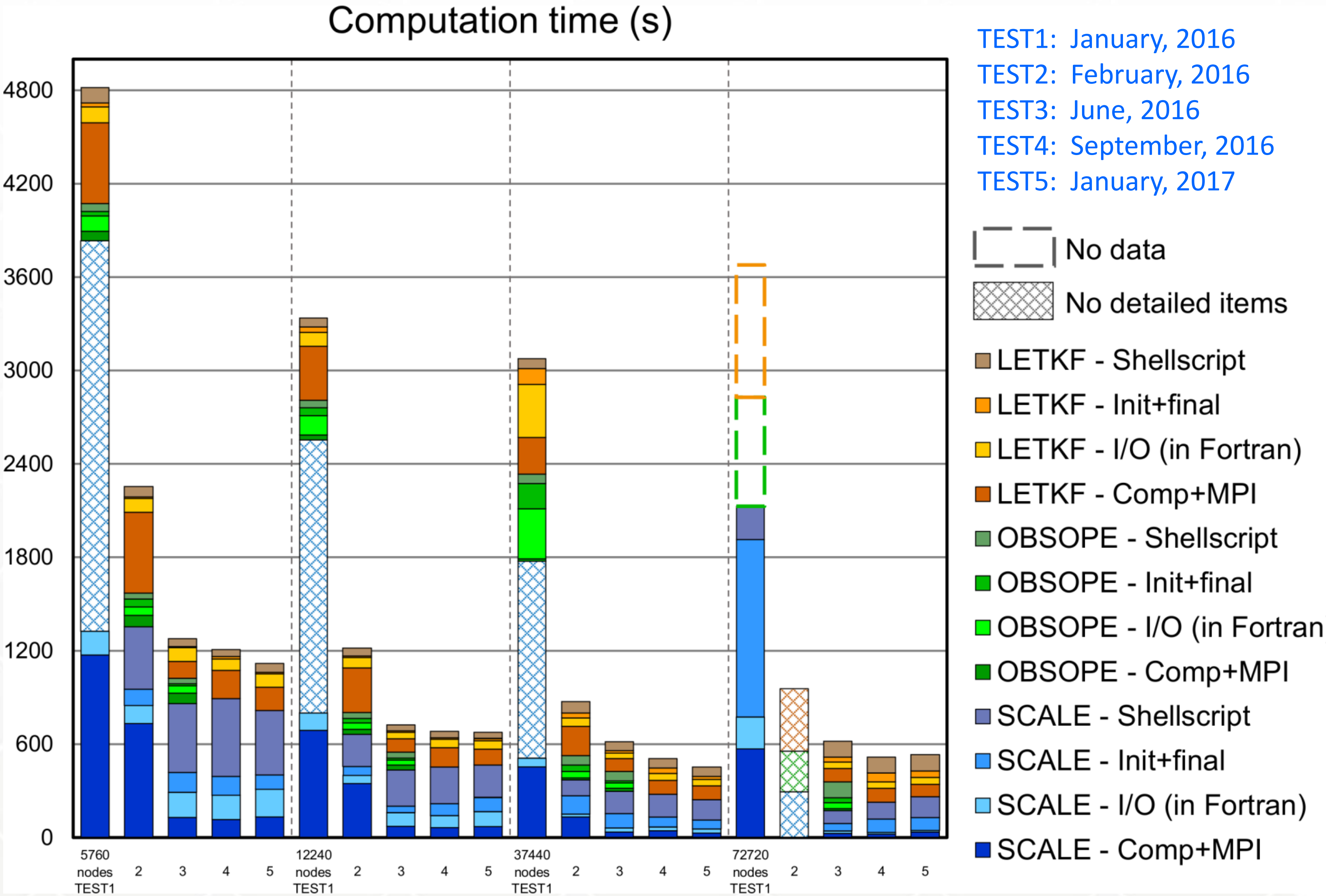
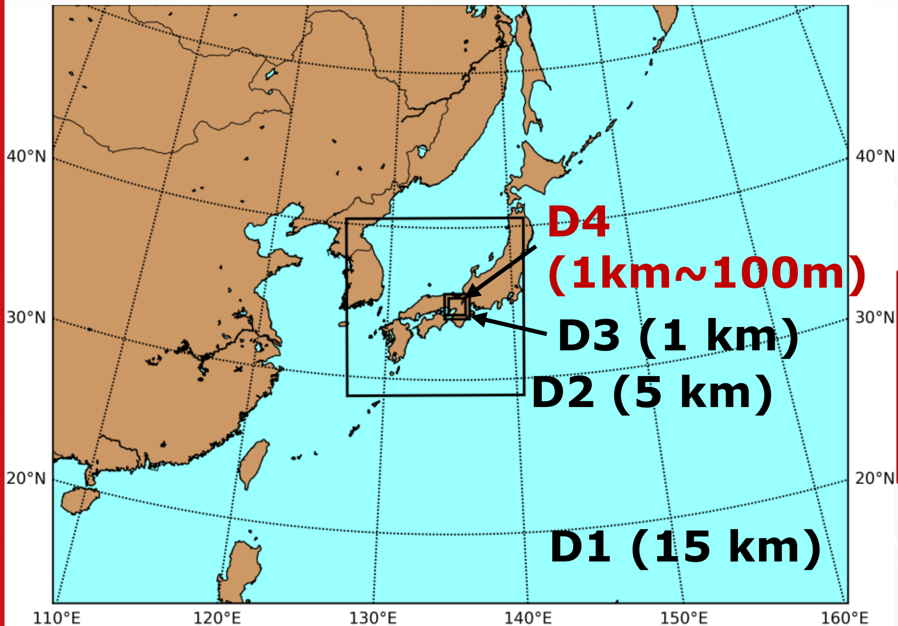
Computational time
– Test with up to 72,720 nodes



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

Settings of the PAWR assimilation

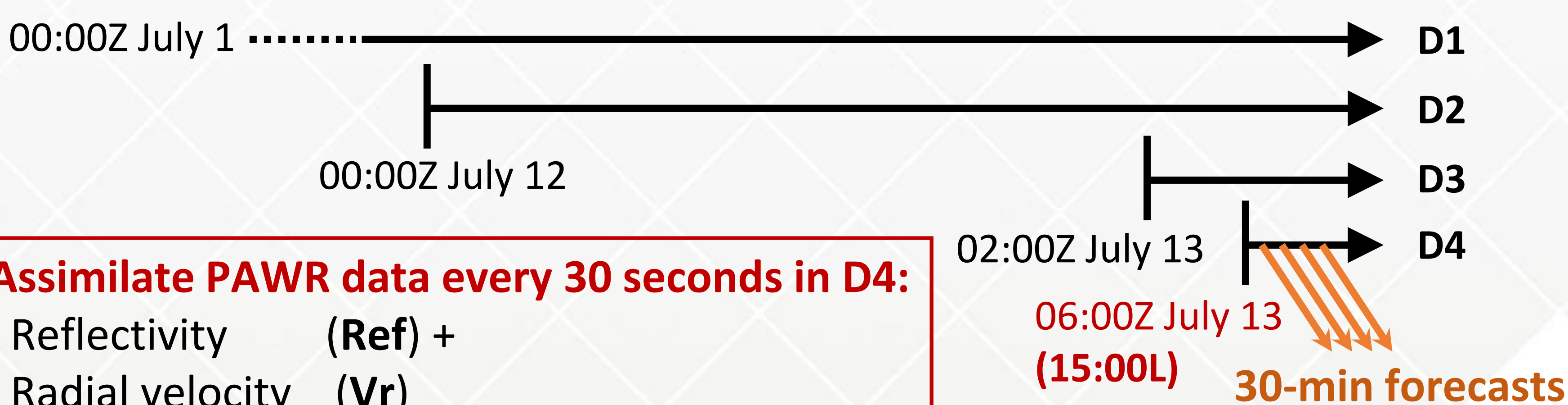


	Resolution	Size	Observation	Cycle length
D1	15 km	5760 x 4320 km	PREPBUFR	6 h
D2	5 km	1280 x 1280 km	PREPBUFR	6 h
D3	1 km	180 x 180 km	PAWR	5 m
D4	1 km 500 m 250 m 100 m	120 x 120 km	PAWR	30 s

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**)

Observation pre-processing

Raw data

↓

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

↓

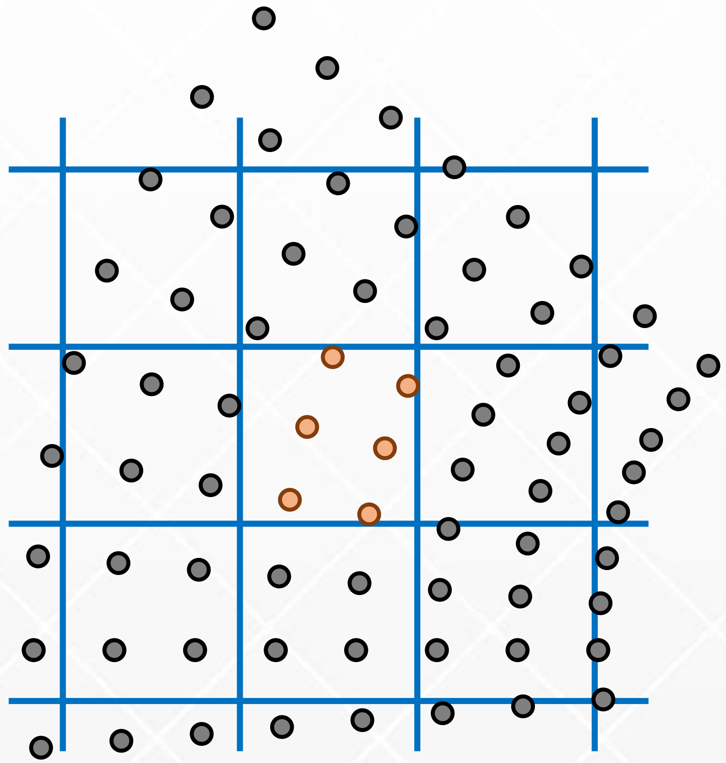
QCed data

↓

Superobing:
Average observations <u>within a model grid</u>

↓

Data for LETKF



250M super-obs for LETKF assimilation

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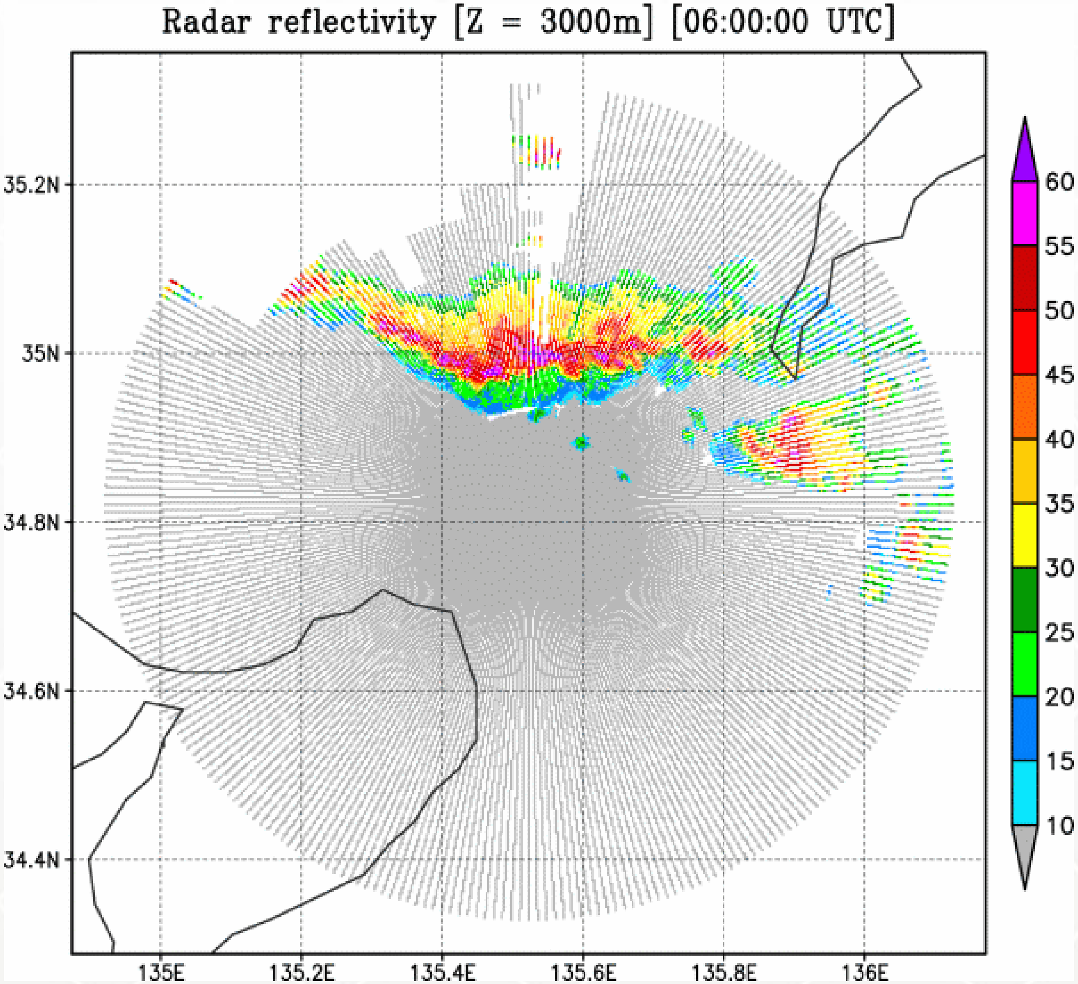
250-m superobs



<u>Data counts</u> 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

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

Assimilated data:

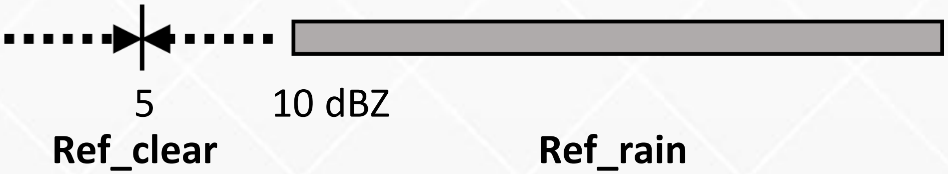
- **Ref** : ~ 280,000
- **Vr** : ~ 160,000

Raining / clear reflectivity

- **Ref_rain**: raw Ref >= 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 >= 1 (out of 100) background members having **Ref_rain**
  - For **Ref_clear** obs, require >= 20 (out of 100) background members having **Ref_rain**

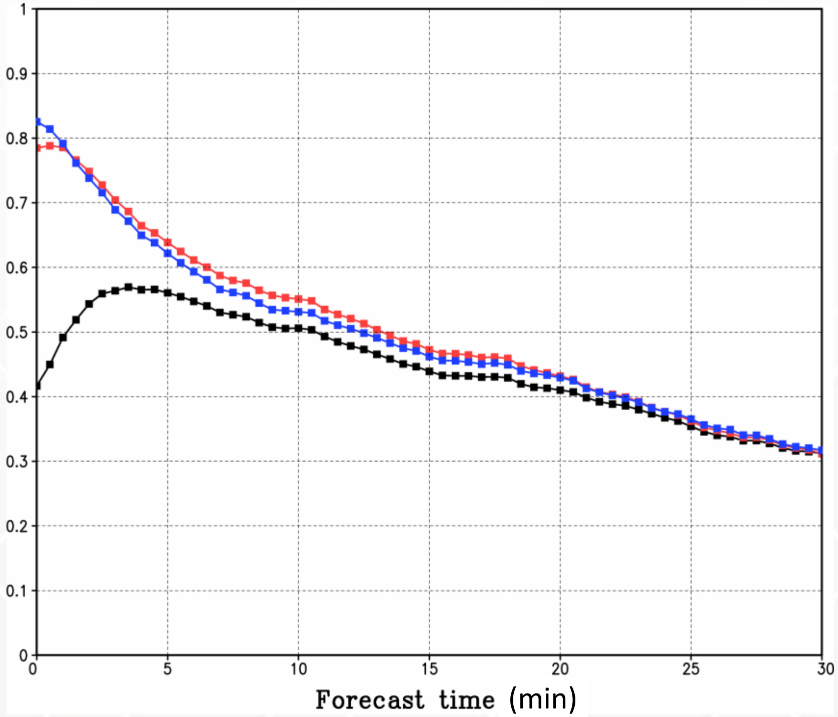
  (Similar to Lien et al. 2013, 2016 for precipitation assimilation)

Impact of clear-reflectivity shift (I)

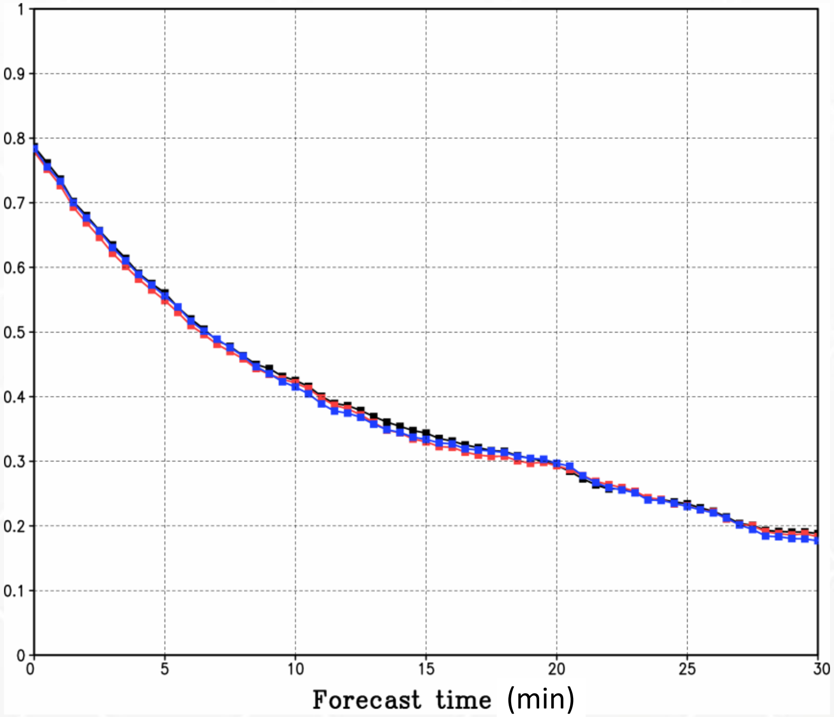
Threat scores (1KM)

(6-forecast average)

[10 dBZ]



[30 dBZ]



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

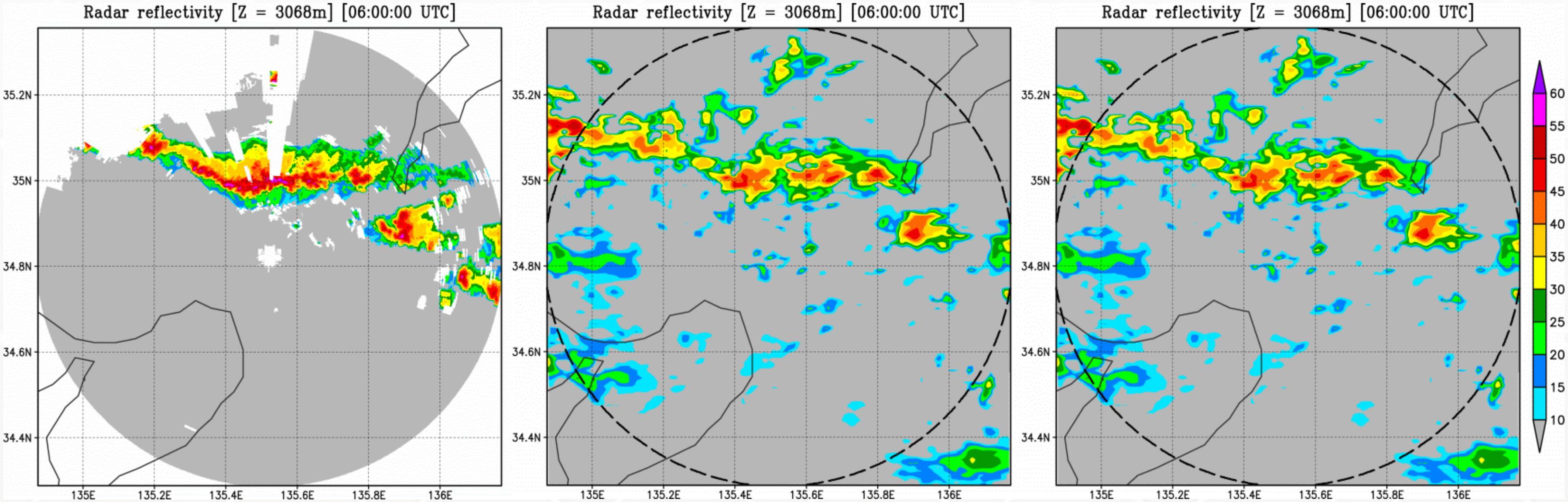
All Ref_clear (Ref < 10 dBZ) → 5 dBZ

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: $\mathbf{W} \leftarrow (1-\alpha)\mathbf{W} + \alpha\mathbf{I}$

RTPS: $\mathbf{W} \leftarrow \left(\alpha \frac{\sigma^b - \sigma^a}{\sigma^a} + 1\right)\mathbf{W} = \left(\alpha \sqrt{\frac{\mathbf{X}^b\mathbf{X}^{bT}}{(k-1)\mathbf{X}^b\tilde{\mathbf{P}}^a\mathbf{X}^{bT}}} - \alpha + 1\right)\mathbf{W}$

- Can be more adaptive:
  - Adaptively determine the α parameter (Kotsuki et al. 2017)

Impact of relaxation method

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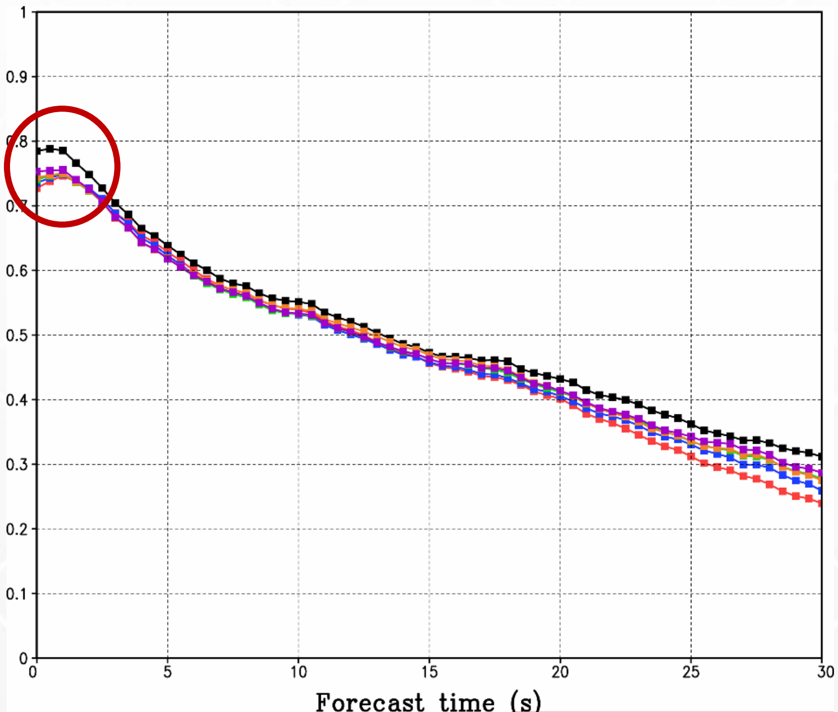
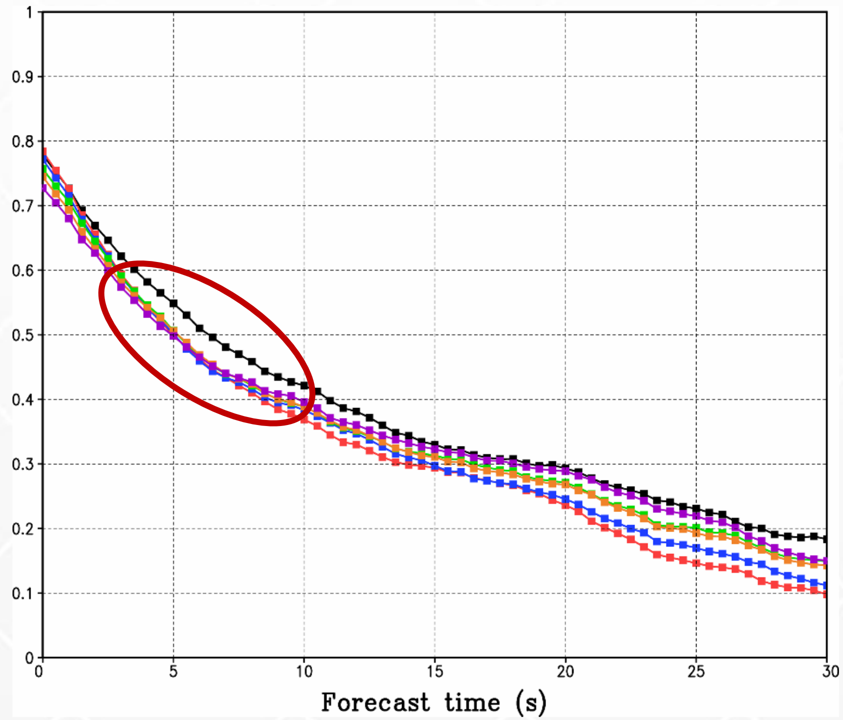
Threat scores (1KM)

(6-forecast average)

[10 dBZ]



[30 dBZ]



RTPS: α = 0.95

RTPP: α = 0.95
RTPP: α = 0.9
RTPP: α = 0.85
RTPP: α = 0.8
RTPP: α = 0.7

Thinning and covariance localization

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- **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

Lorenc 2003, QJRMS
Tsyrulnikov 2010, COSMO News Letters
Hotta 2017, RISDA 2017

- **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!

An alternative way: Observation number limit in the LETKF (I)

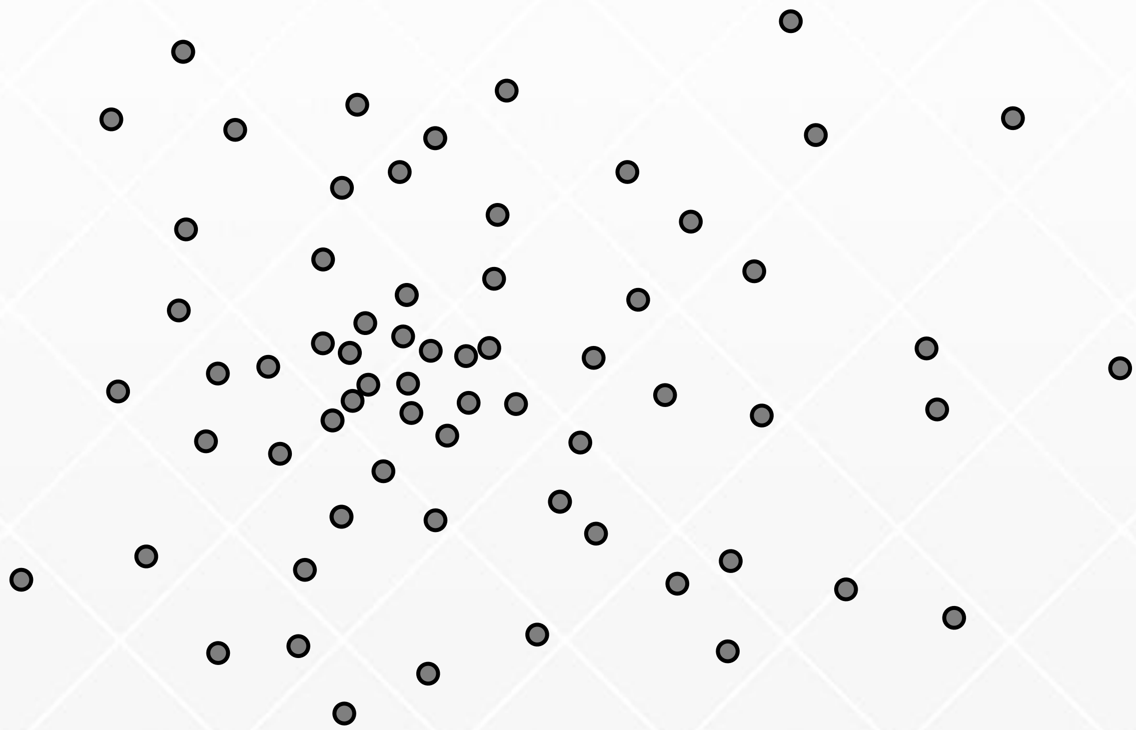
- Hamrud et al. 2015 (ECMWF global model): Limit the number of observations used at each grid point for each combination of different report types (e.g., radiosonde) and variables (e.g., U-wind).
  - **#OBS** = 30 per report types and variables; **Ens size** = 60~240
- Schraff et al. 2016 (DWD regional 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

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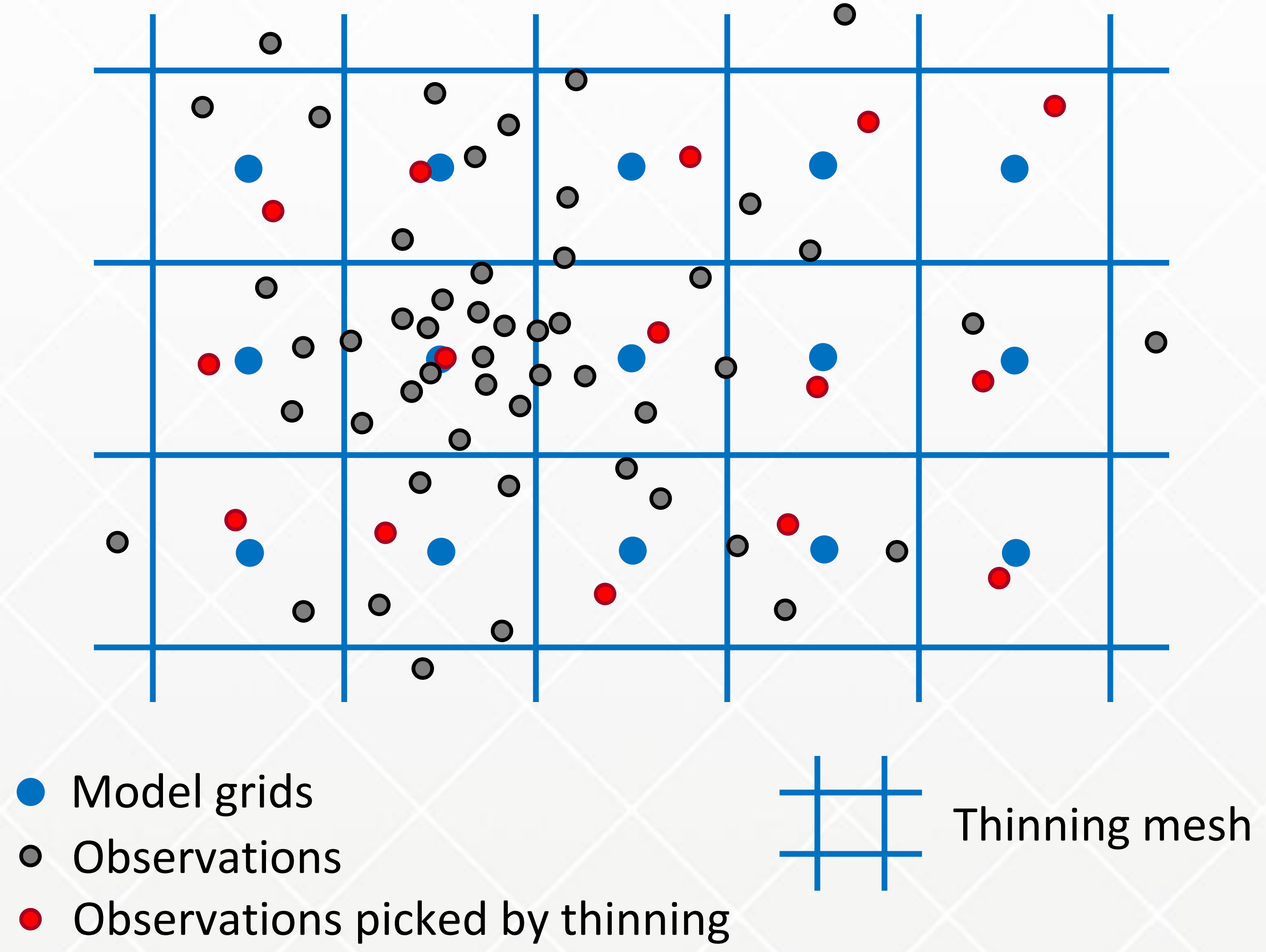
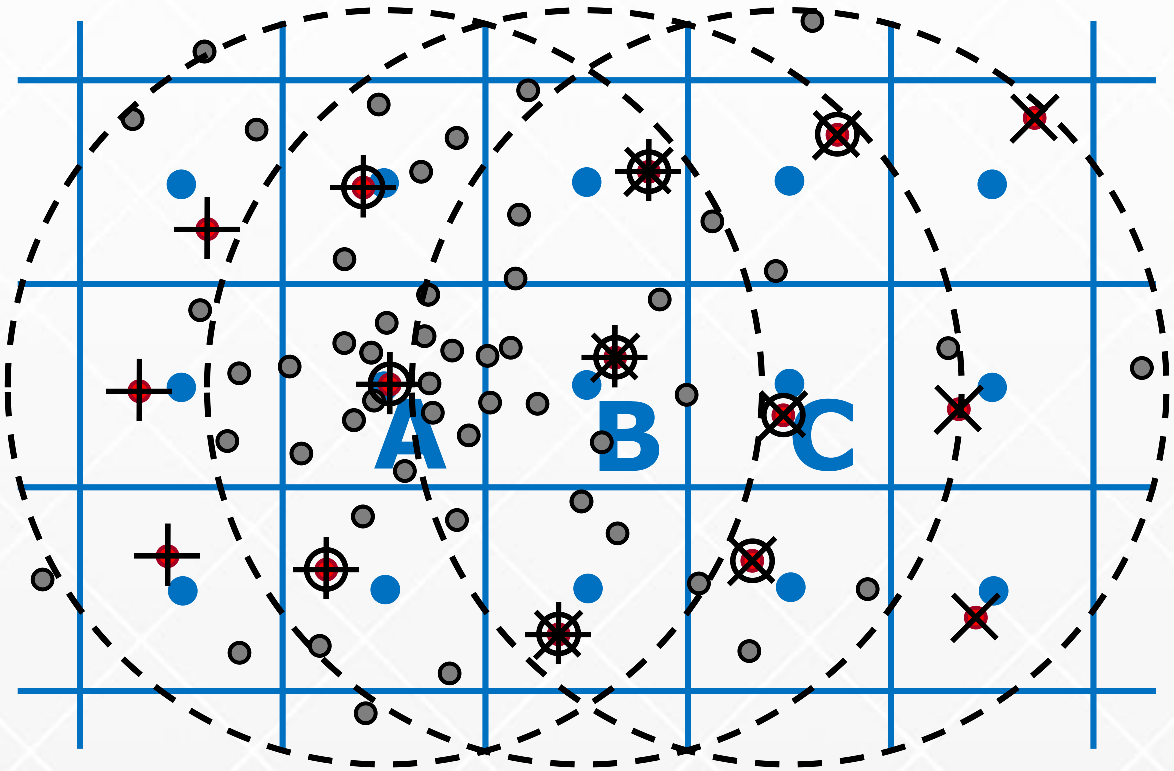
Thinning



Observation number limit vs. thinning

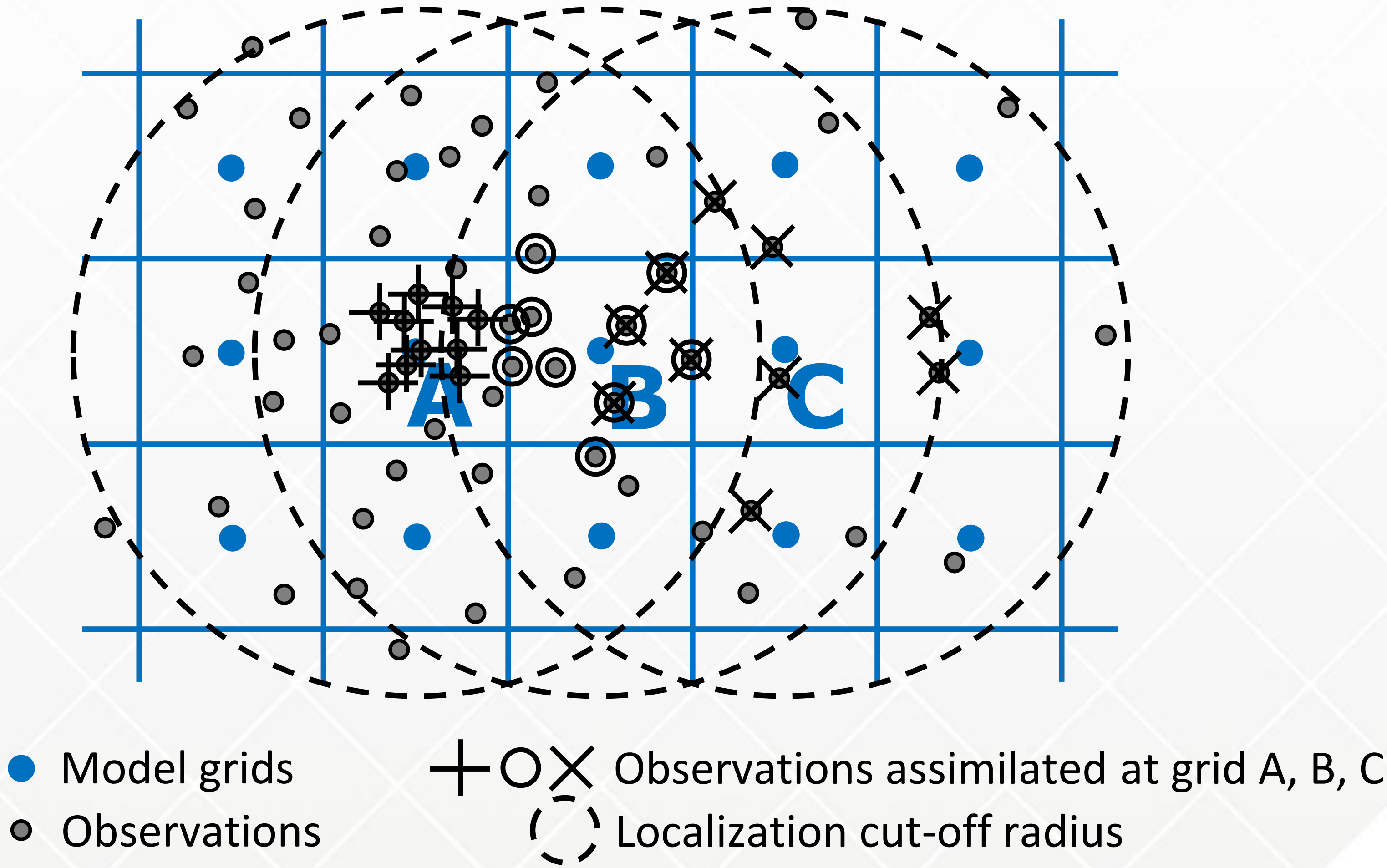
Thinning



- 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



Experimental design

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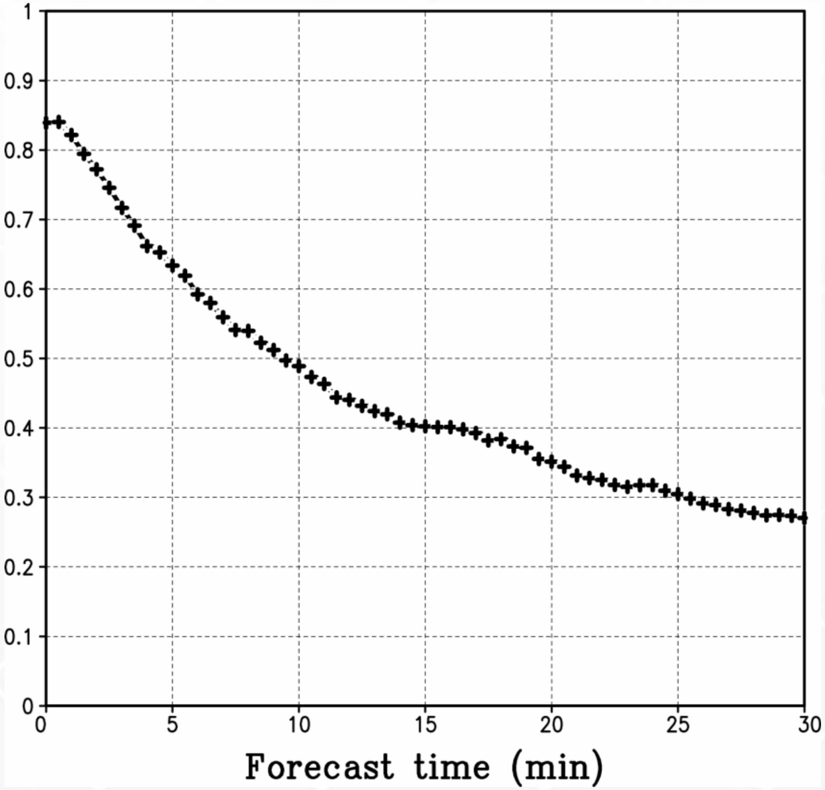
Experiment name	Ensemble size	#OBS limit (for each obs type)	Thinning (pick up one every XxYxZ grids)
M100-#OBS*<XX>*	100	*<XX>*	---
M100-Unlmt	100	Unlimited	---
M25-#OBS*<XX>*	25	*<XX>*	---
M25-Unlmt	25	Unlimited	---
THIN4x4	100	100	4x4x2
THIN16x16	100	100	16x16x8

* Observations are first superobed to the model resolution (250 m) in all experiments.

M100-Unlmt (2-fcst average)

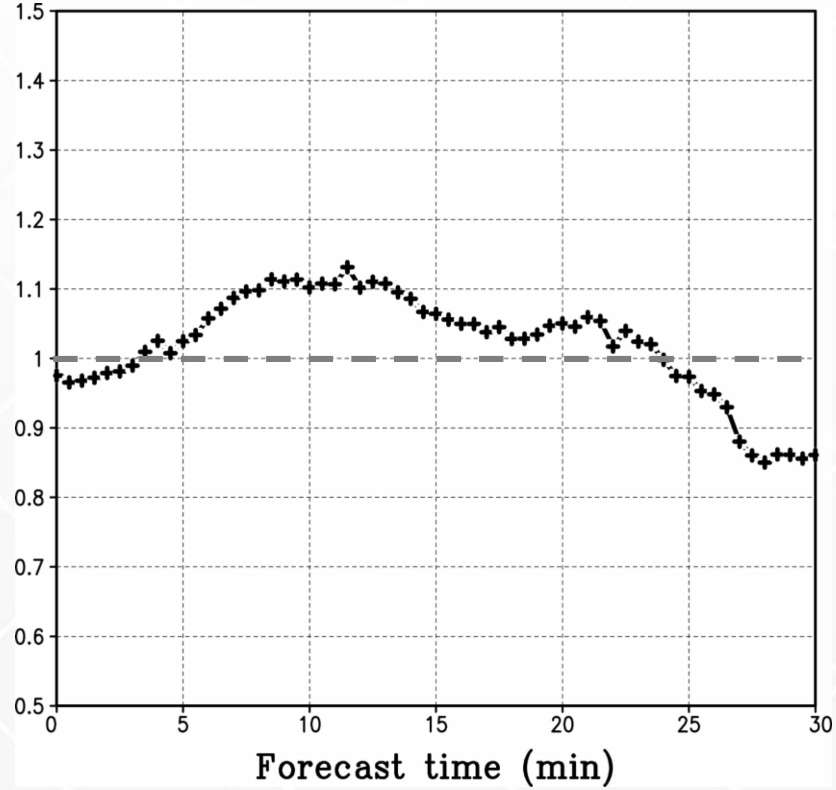
Threat score

Threshold = 15 dBZ



Bias score

Threshold = 15 dBZ



TS and BS are verified against the 3-D reflectivity observations, averaged onto 1-km grids

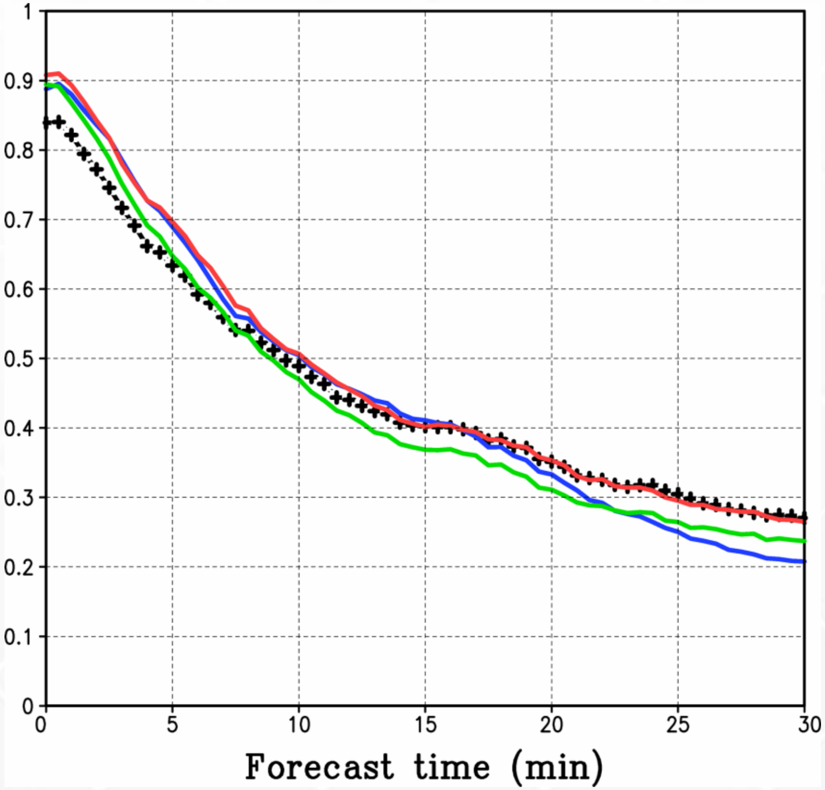
✚✚✚✚✚✚✚ **M100-Unlmt**

M100-#OBS<*XX*> (2-fcst average)

Computer simulations create the future

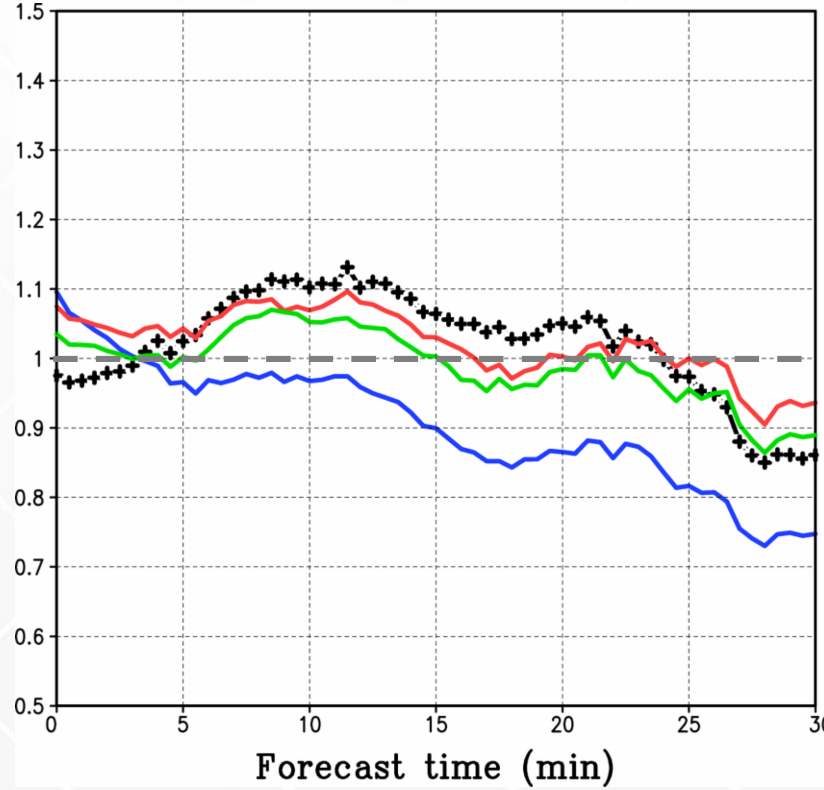
Threat score

Threshold = 15 dBZ



Bias score

Threshold = 15 dBZ



M100-#OBS25
M100-#OBS100
M100-#OBS400
M100-Unlmt

TS and BS are verified against the 3-D reflectivity observations, averaged onto 1-km grids

M25-#OBS<*XX*> (2-fcst average)

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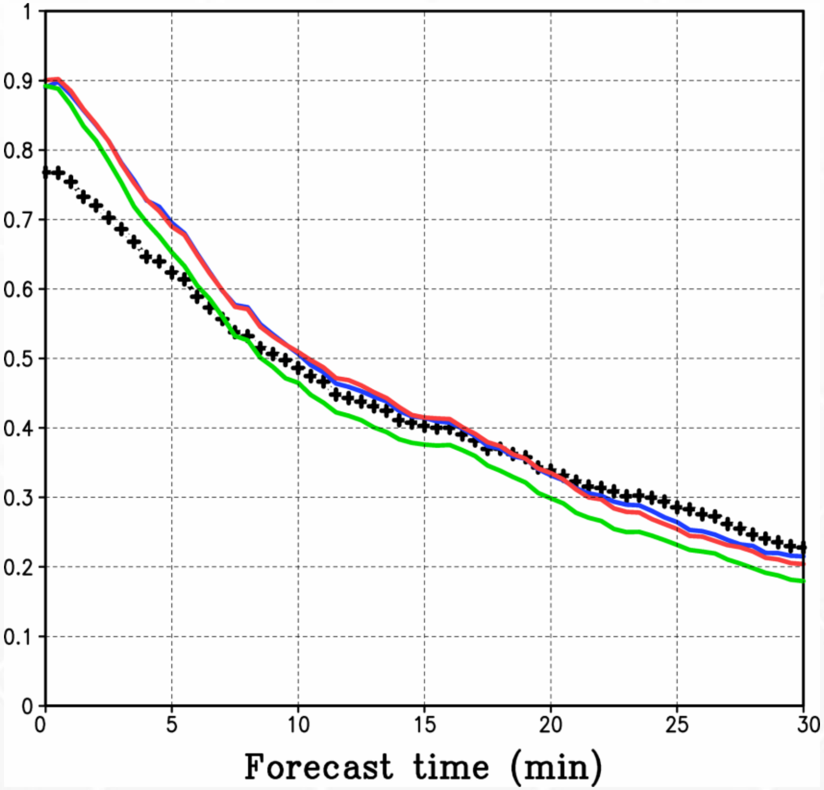
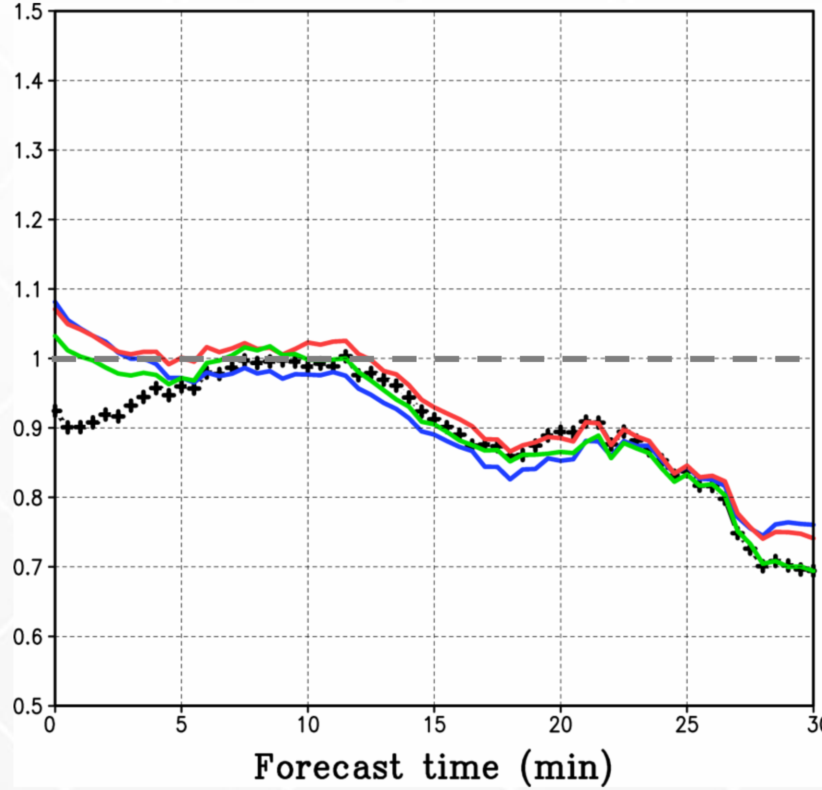
Threat score
Threshold = 15 dBZ



Bias score
Threshold = 15 dBZ



M25-#OBS12
M25-#OBS25
M25-#OBS100
M25-Unlmt

TS and BS are verified against the 3-D reflectivity observations, averaged onto 1-km grids

Mean 5-min and 30-min forecast TS

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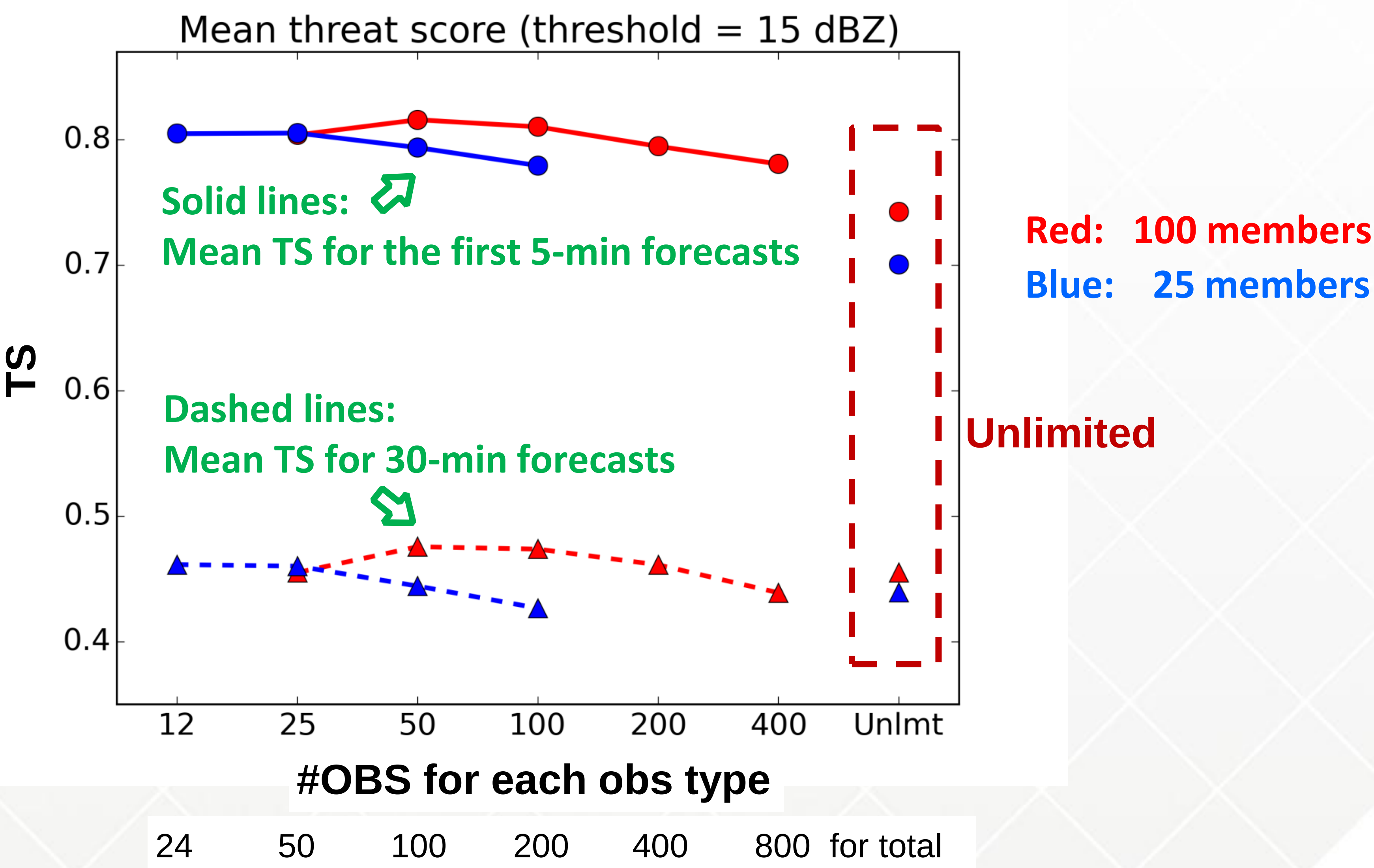

observations assimilated at each grid (first cycle)

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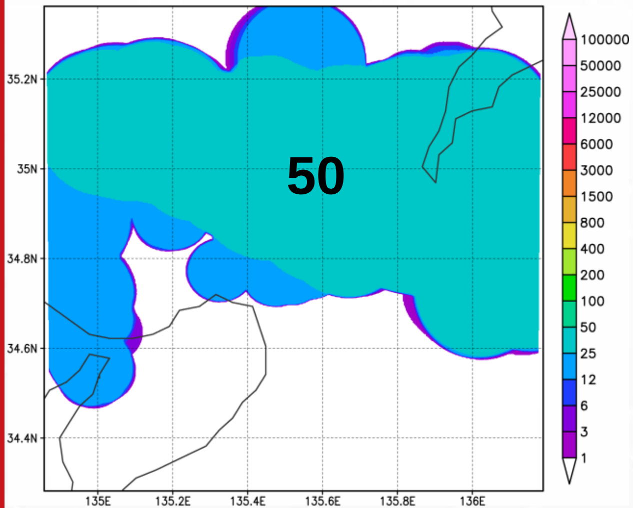
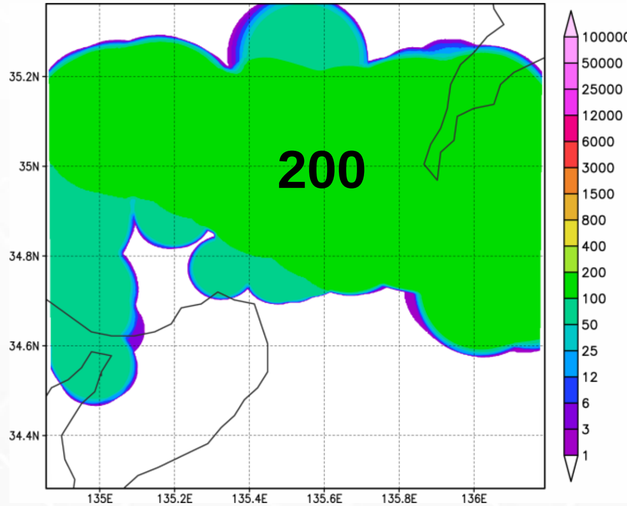
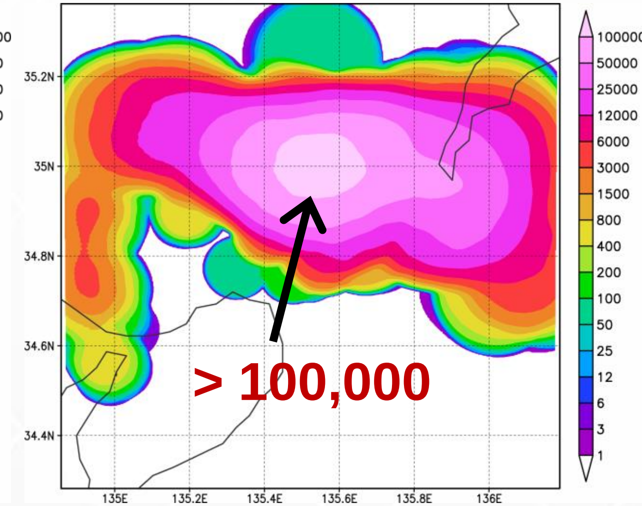
M100-#OBS25



M100-#OBS100



M100-Unlmt



Localization cut-off area

Real localization cutoff radius (km) (first cycle)

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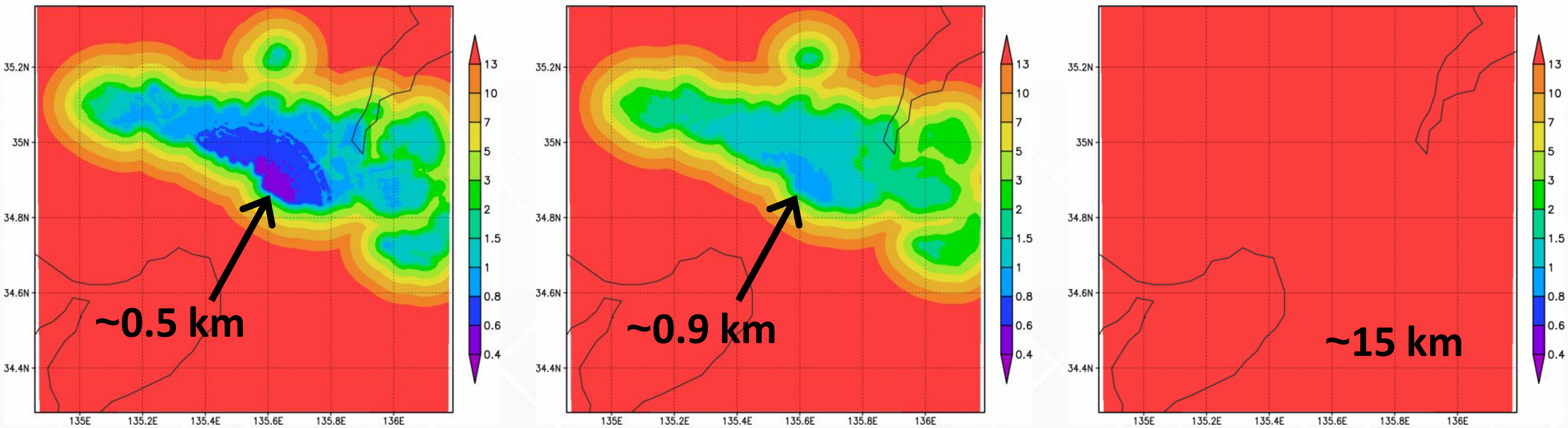
M100-#OBS25 | M100-#OBS100 | M100-Unlmt



Localization adaptive to the observation density

Analysis increment: Reflectivity (dBZ) (first cycle)

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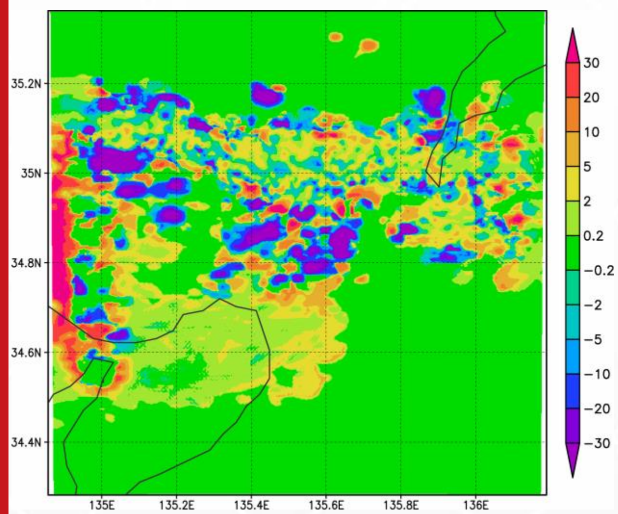
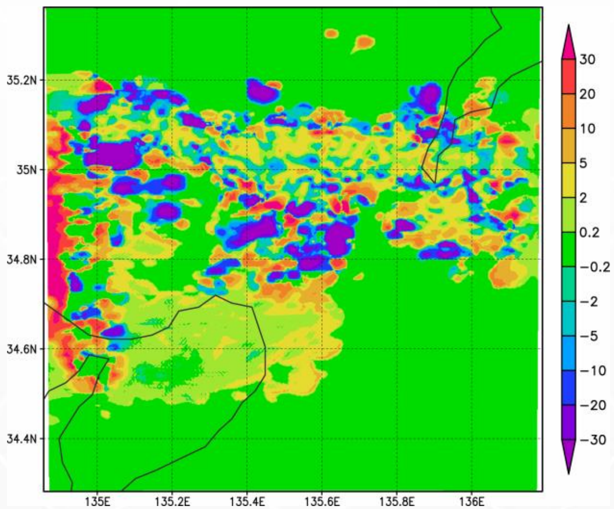
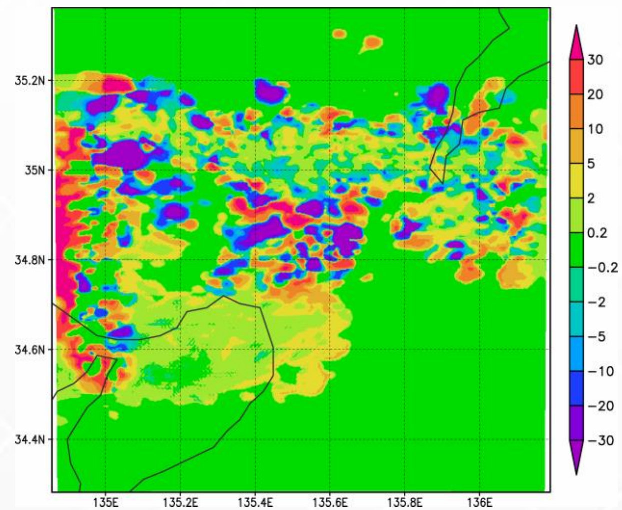
M100-#OBS25



M100-#OBS100



M100-Unlmt



Very similar !

observations assimilated at each grid (first cycle)

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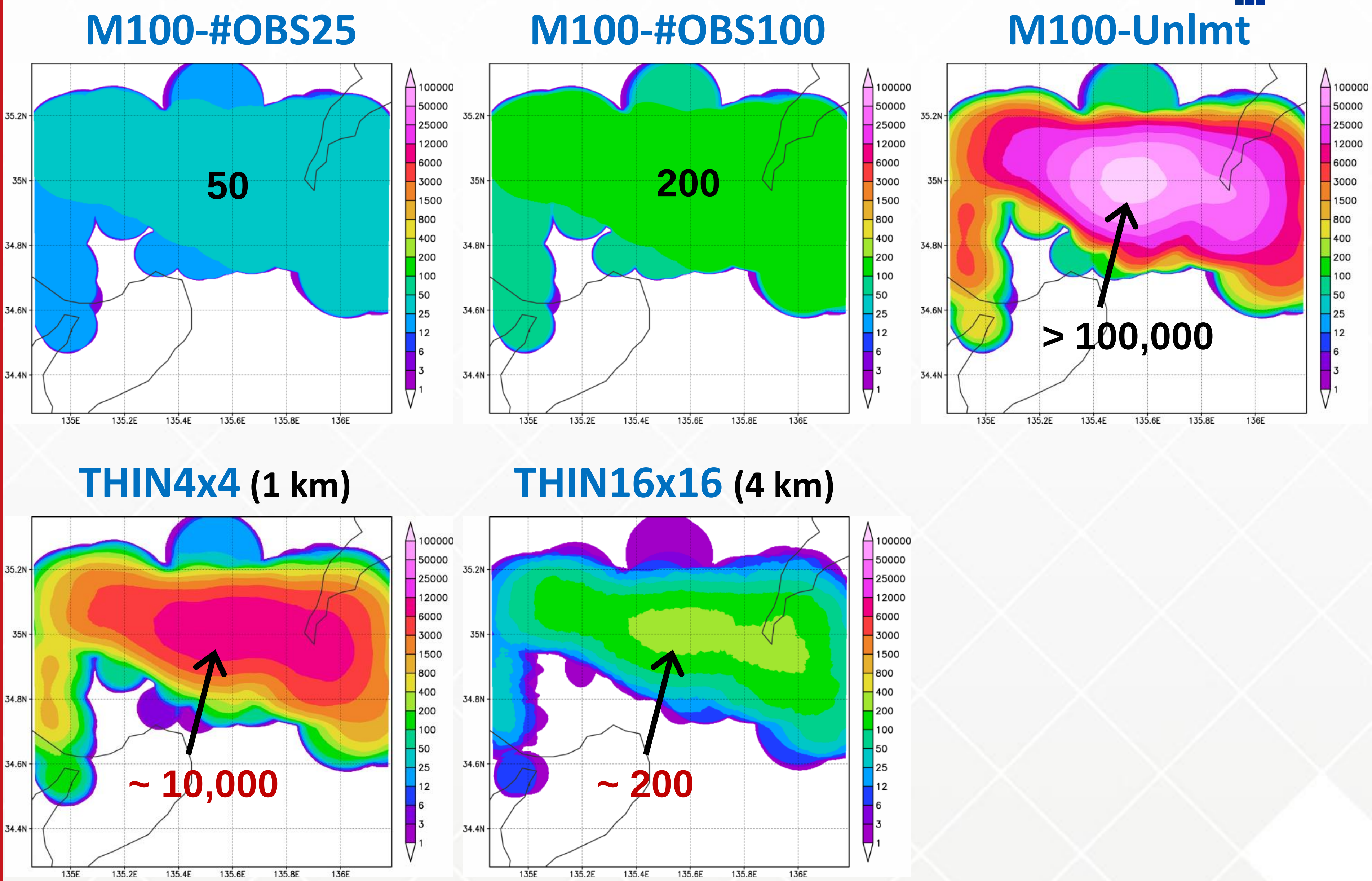

Analysis increment: Reflectivity (dBZ) (first cycle)

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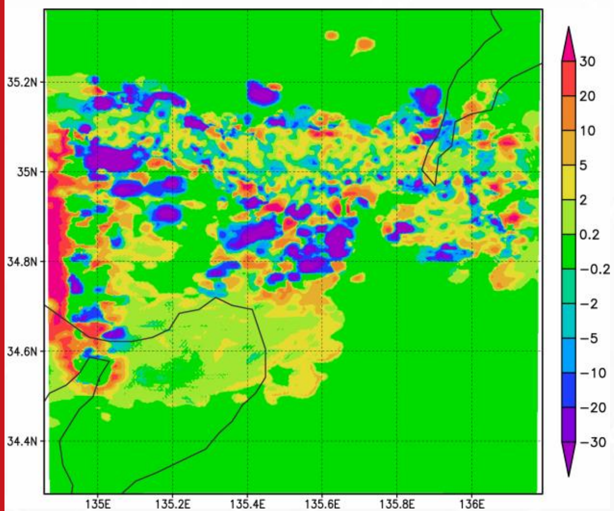
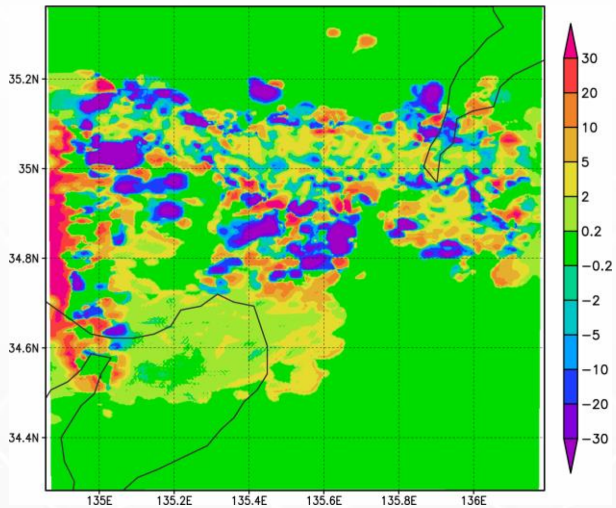
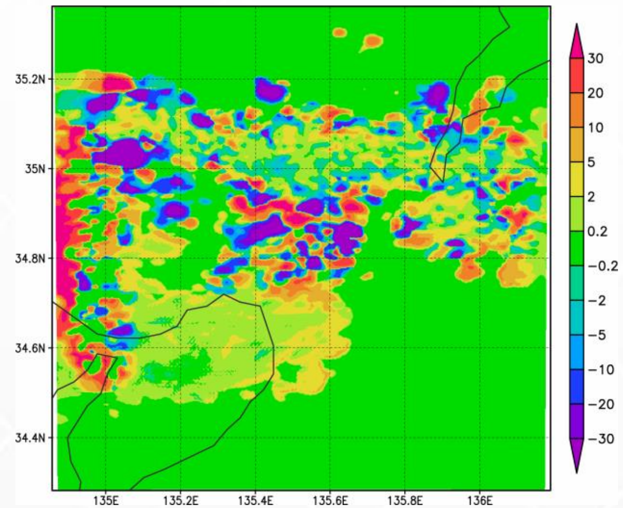
M100-#OBS25



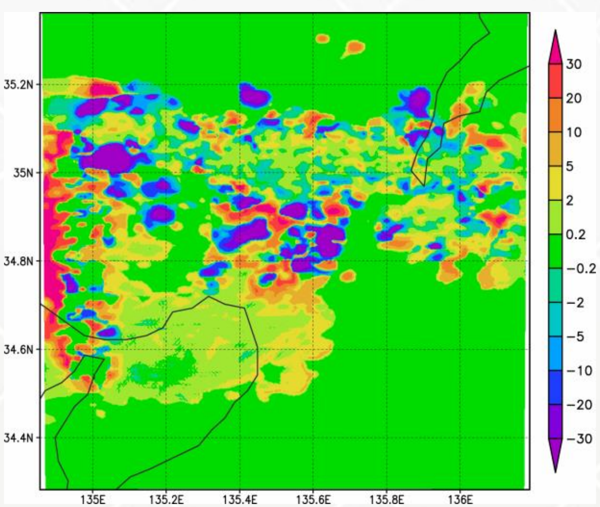
M100-#OBS100



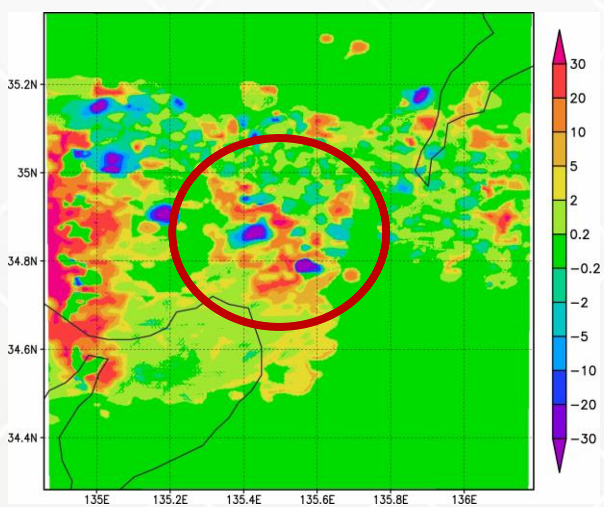
M100-Unlmt



THIN4x4 (1 km)



THIN16x16 (4 km)

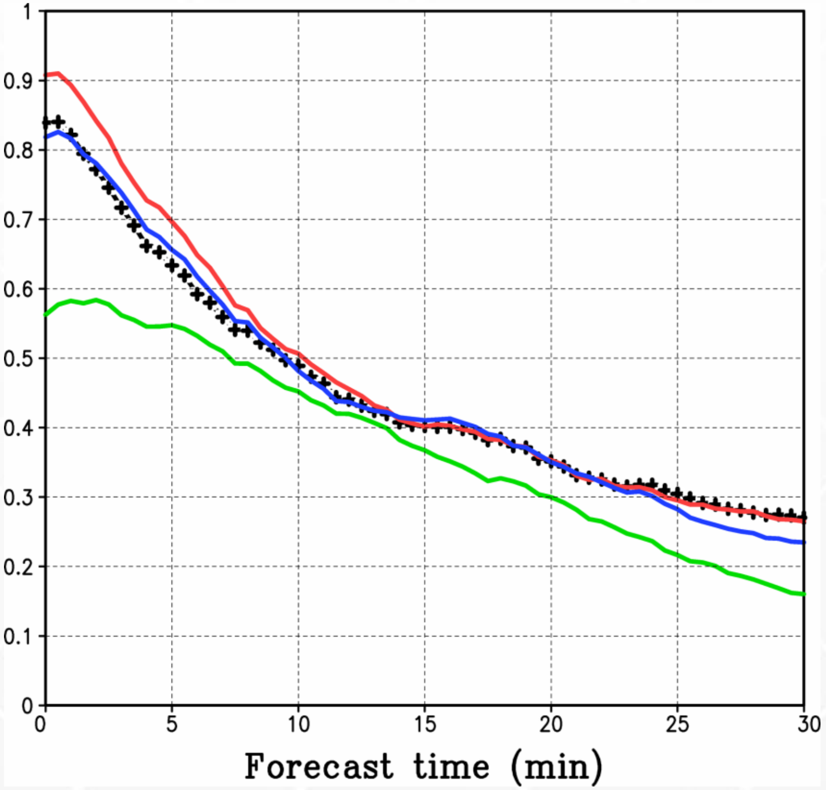


Increments change with thinning

Thinning (2-fcst average)

Threat score

Threshold = 15 dBZ



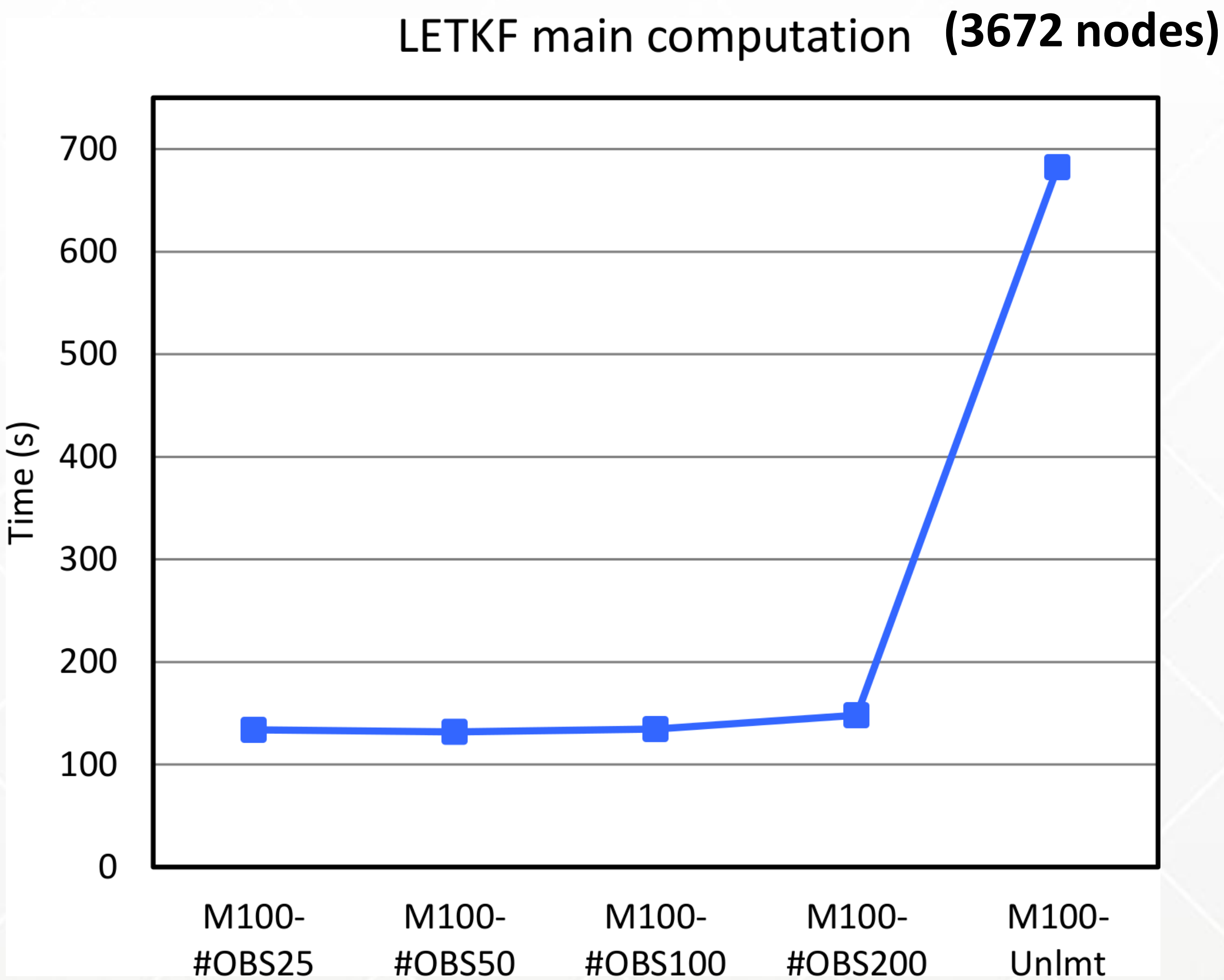
M100-#OBS100

M100-Unlmt

THIN4x4

THIN16x16

Computational time



#OBS for each obs type

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; Tsyrulnikov 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

    Not as strong as if not using the observation number limit
  - 2) Assimilate with the observation number limit.
    - #OBS ~ a few times of the ensemble size

PAWR assimilation results with different model resolutions

Experiments	Model resolution	Observation resolution	Cycle length	Assimilation period	# forecast cases (every 10 min)
1 KM (D3)	1 km	1 km	5 min	4 hour	--
1 KM (D4)	1 km	1 km	30 sec	60 min	6
500 M (D4)	500 m	500 m	30 sec	60 min	6
250 M (D4)	250 m	250 m	30 sec	60 min	6
100 M (D4)	100 m	100 m	30 sec	20 min	2

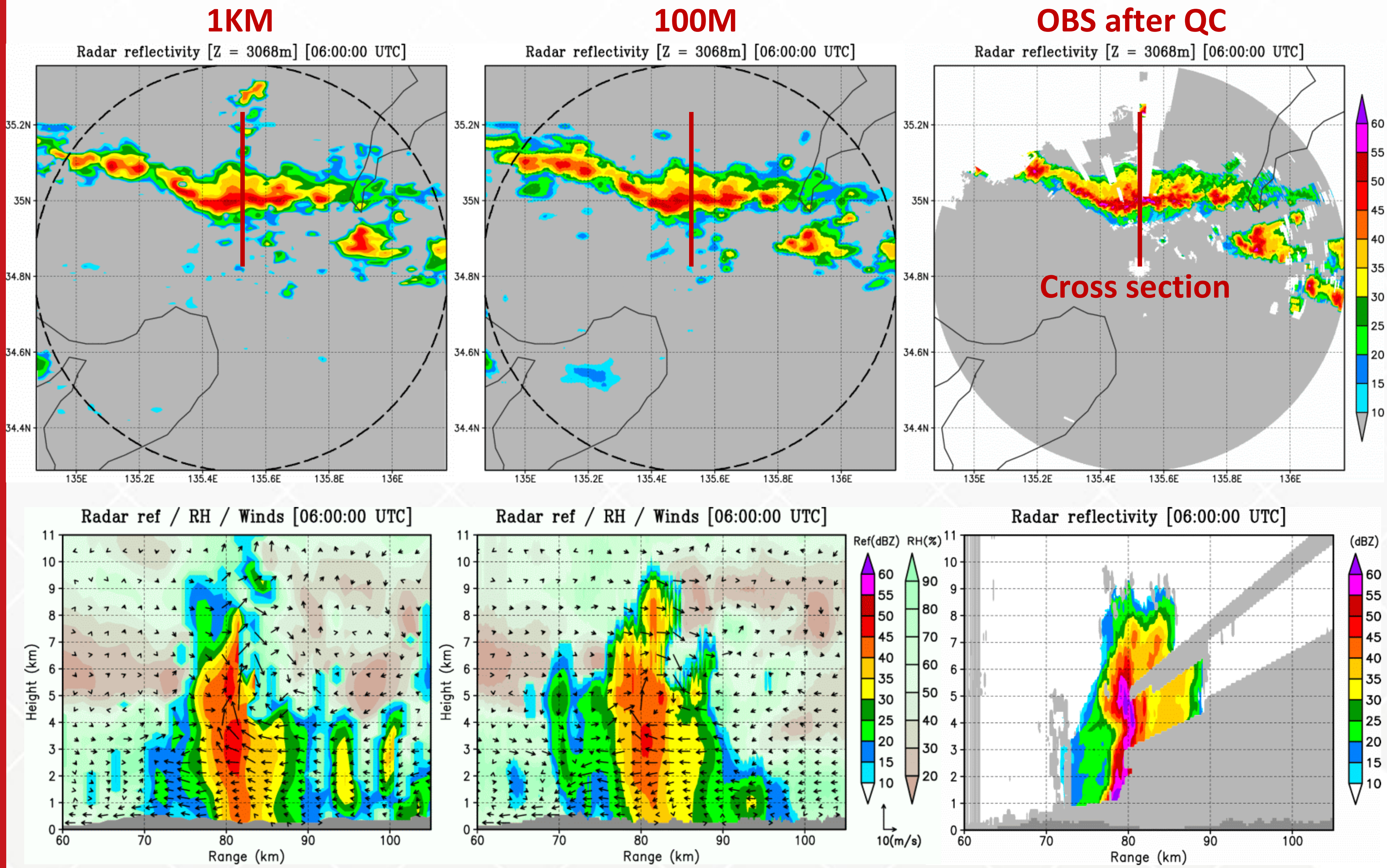
Provide ensemble boundary conditions

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

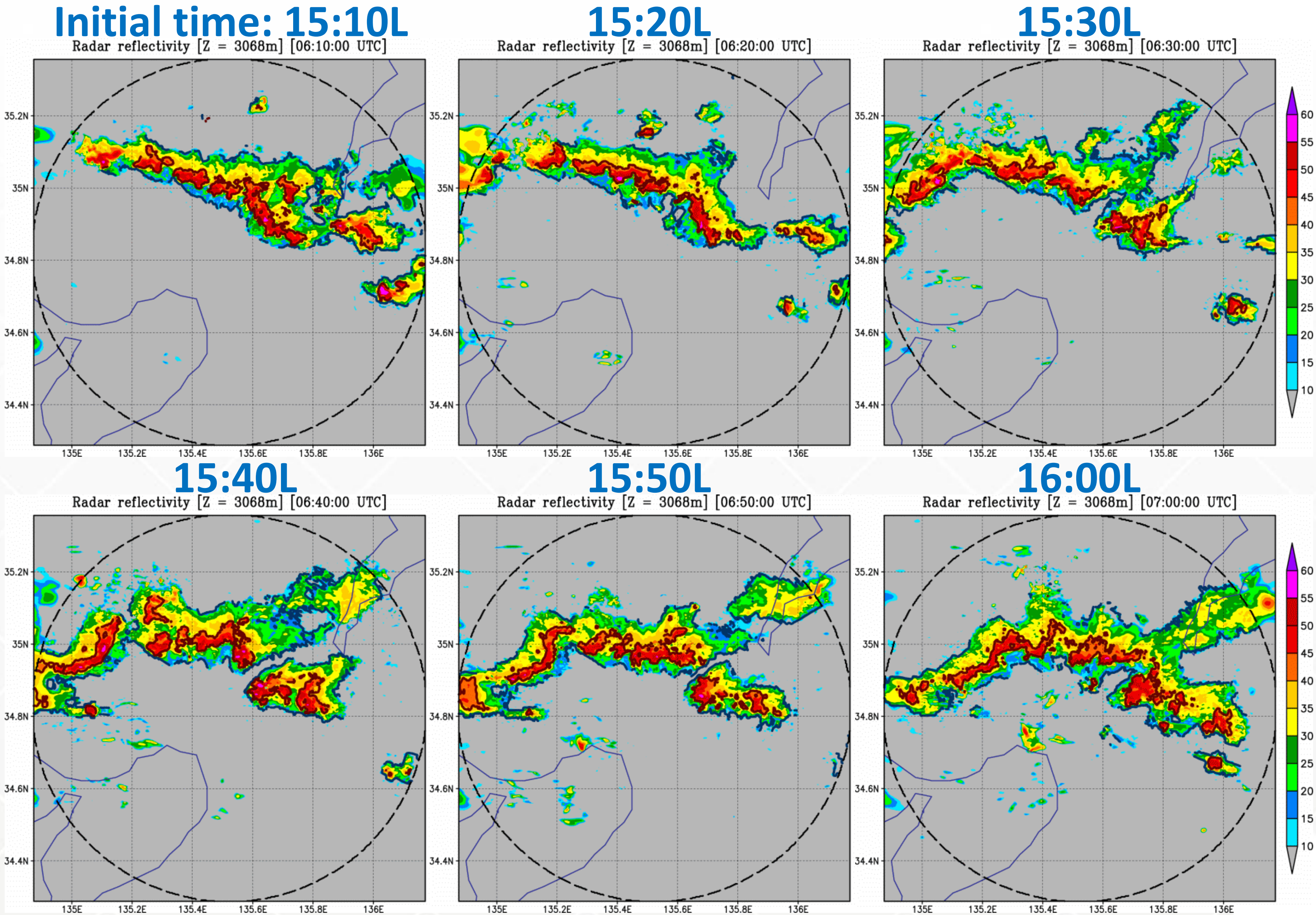
15:00L–15:20L : 20-min analysis (gray background)

15:20L–15:50L : 30-min forecast (purple background)

Computer simulations create the future



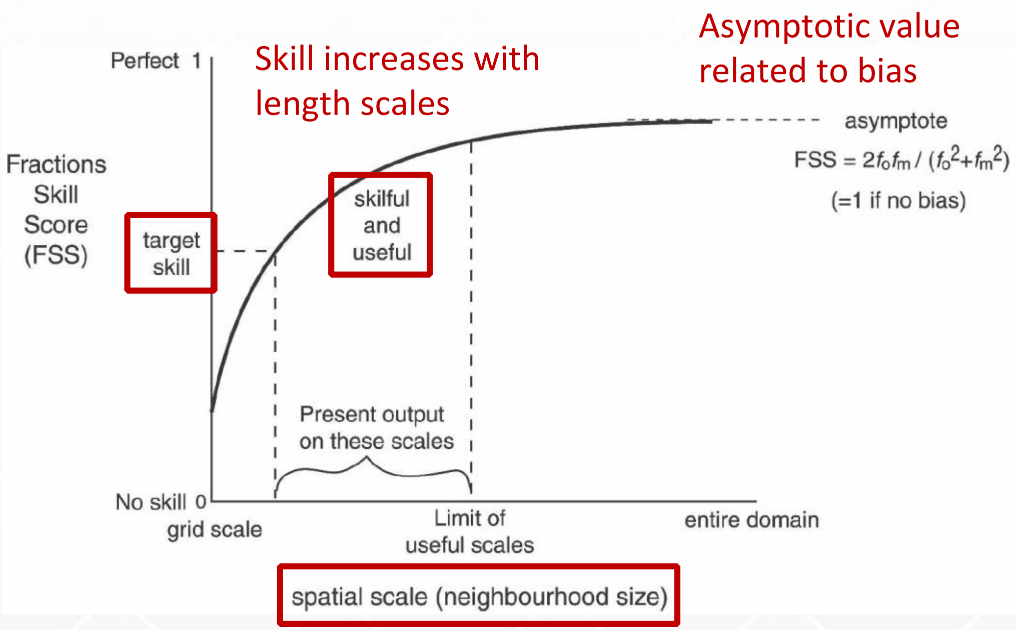
30-min forecasts at 250-m model resolution

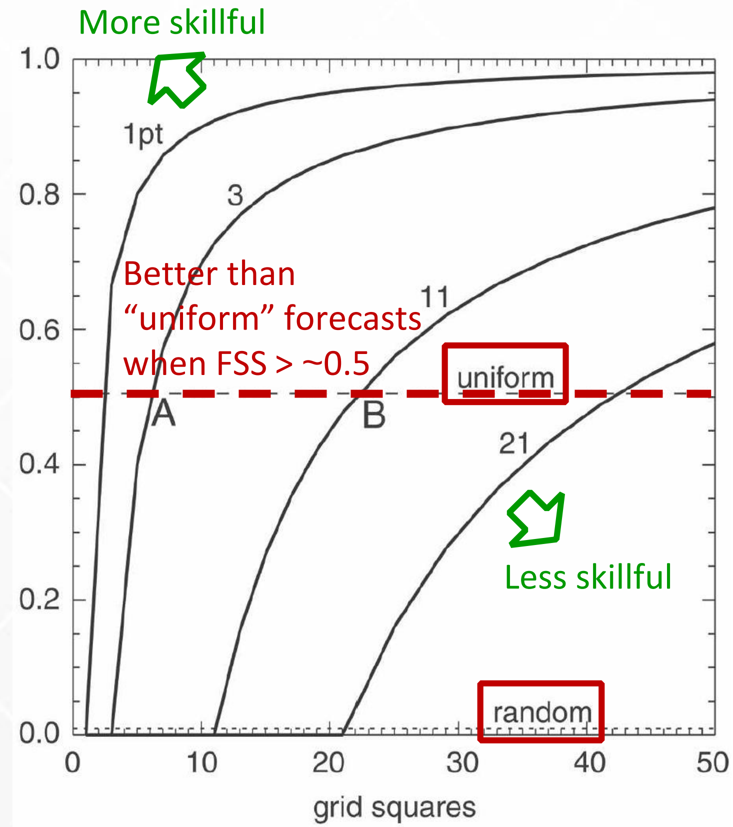


Observation: 10 dBZ 40 dBZ

Fractions Skill Score (FSS)

(Roberts and Lean 2008)

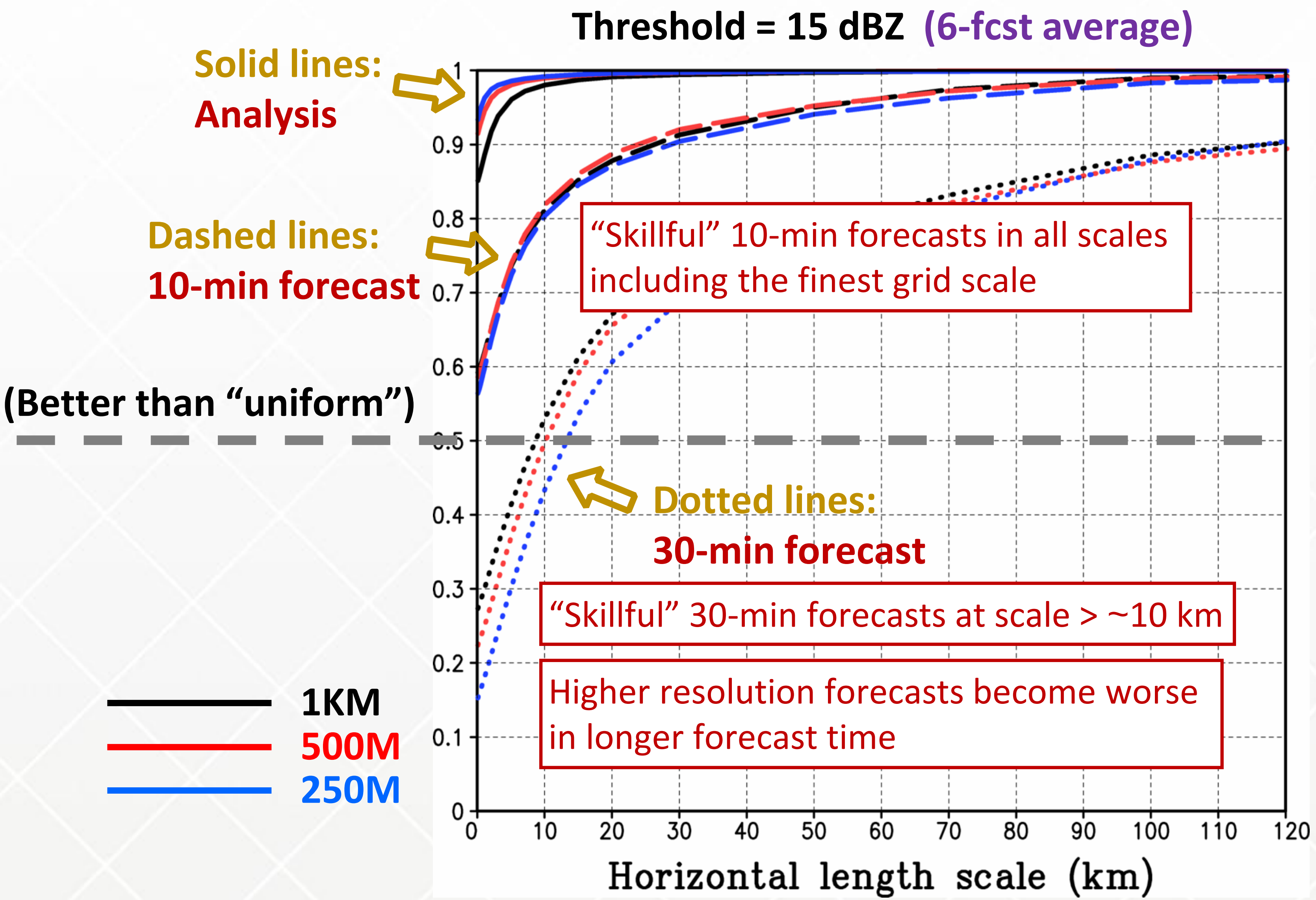




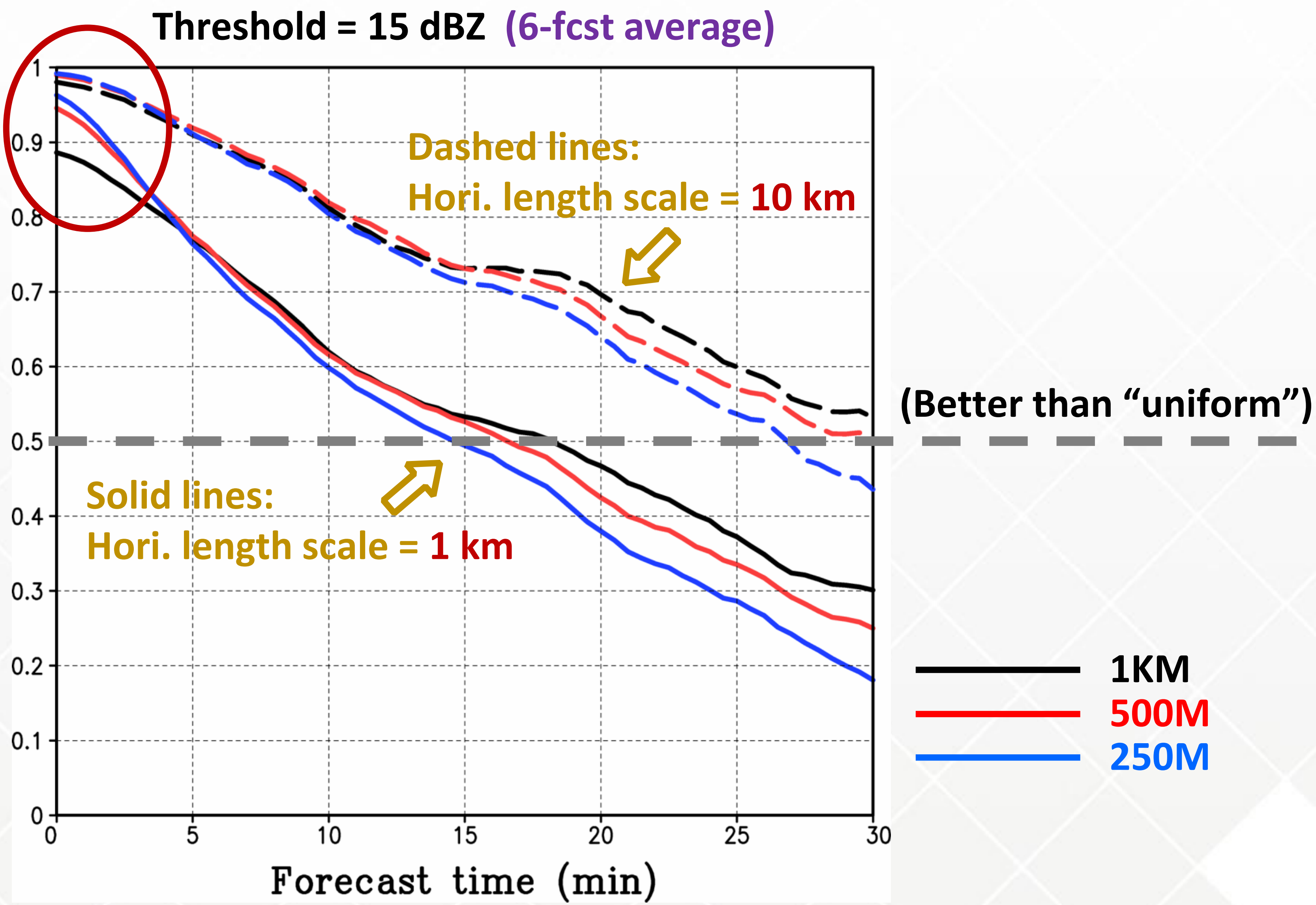
(from Roberts and Lean 2008)

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

30-min forecasts
Fractions Skill Score (FSS)

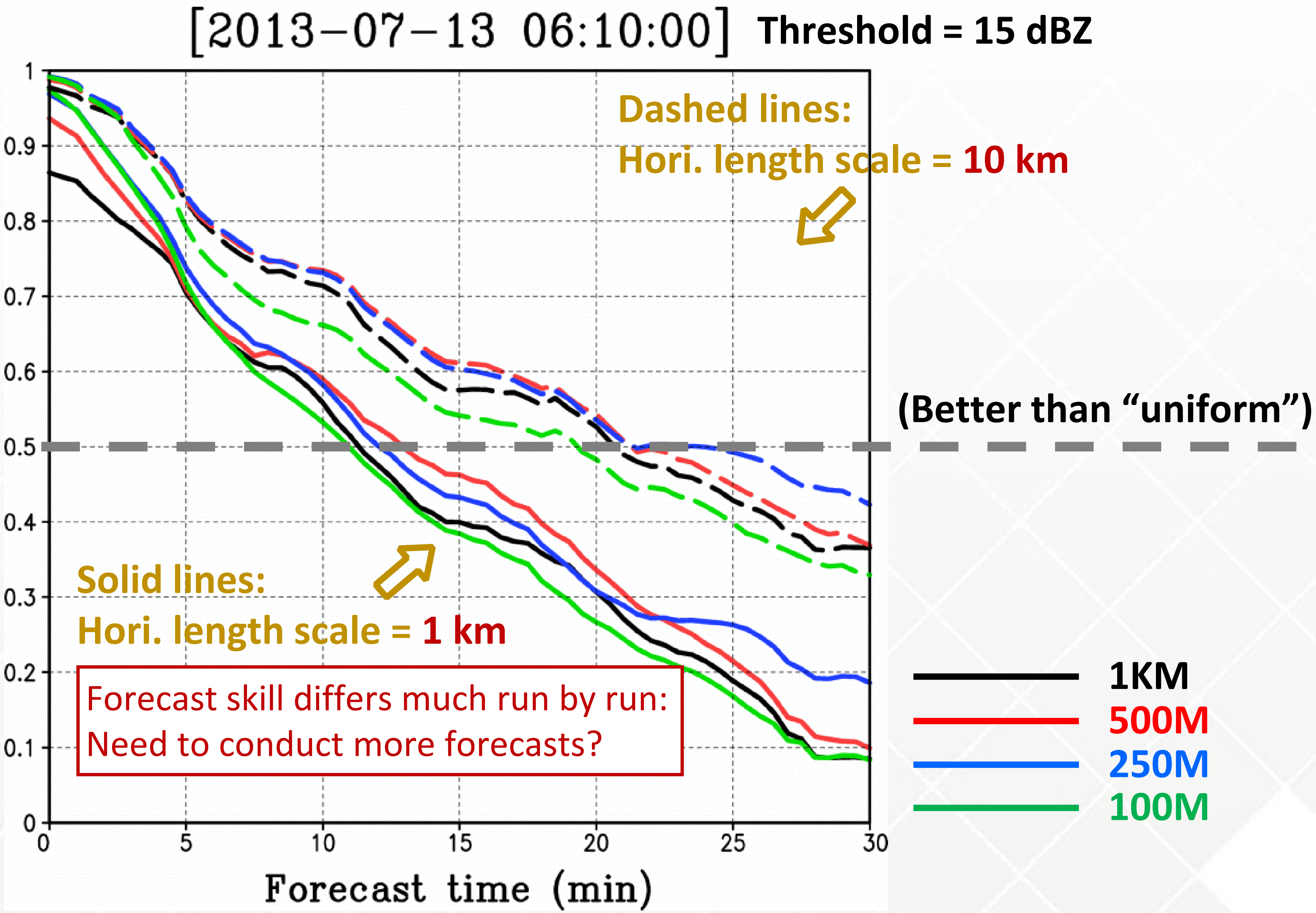


30-min forecasts
Fractions Skill Score (FSS)



30-min forecasts
Fractions Skill Score (FSS)

Computer simulations create the future
Data Assimilation Team



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

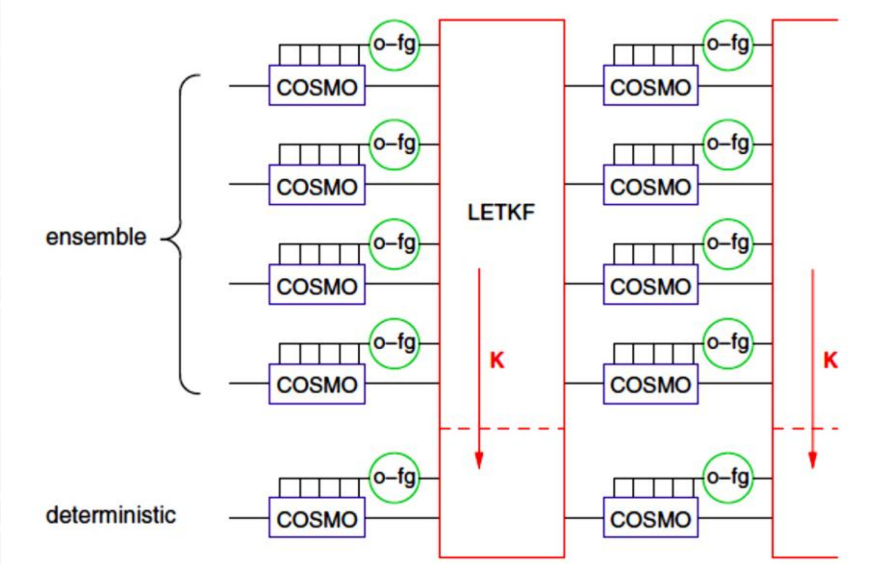
- Perform an independent update of a deterministic run (Schraff et al. 2016; KENDA-COSMO).
  - Ensemble mean update:

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

$\bar{\square}$: ensemble mean
$\hat{\square}$: deterministic run

  - (Mean) Deterministic run update:

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



(from Schraff et al. 2016)

Impact of deterministic run (I)

Computer simulations create the future

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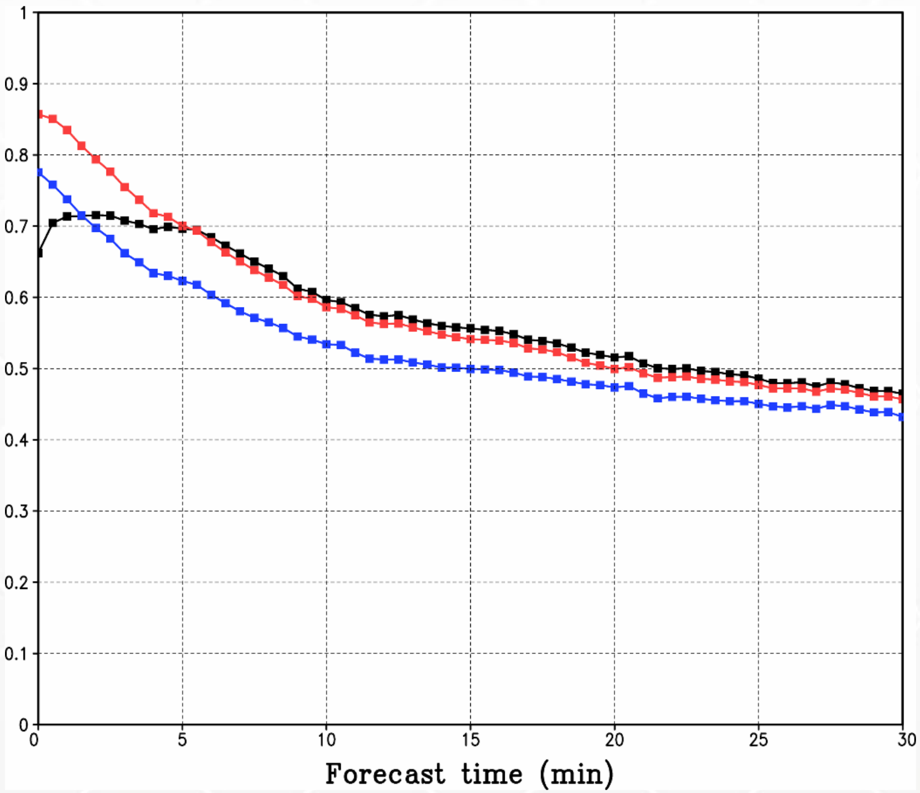
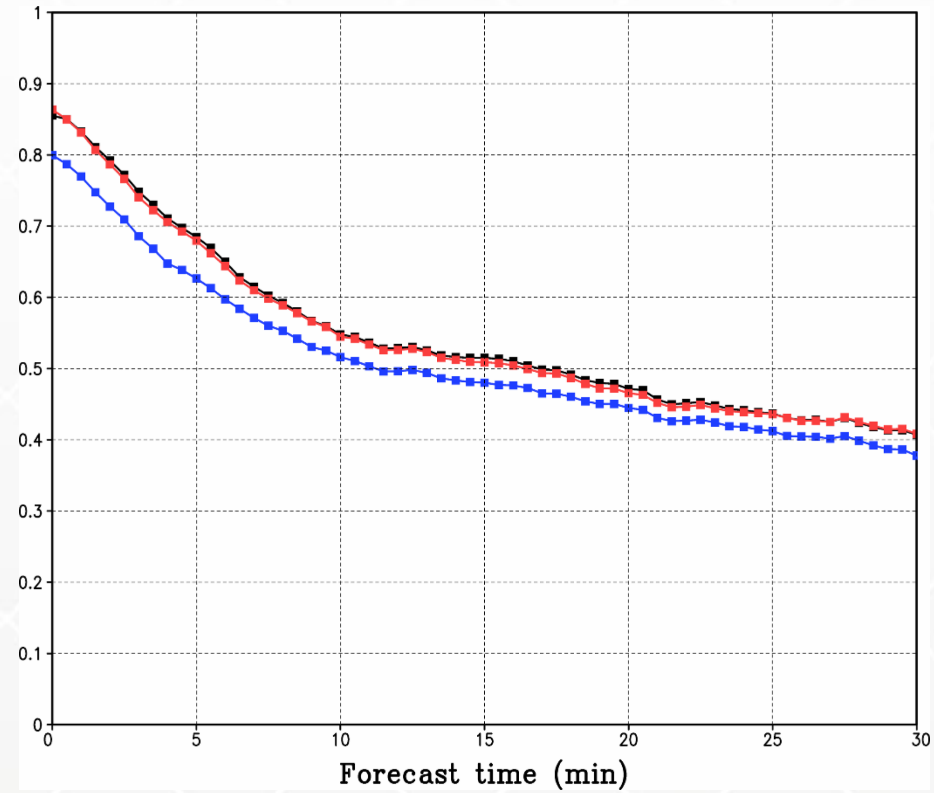
Threat scores (1KM)

(5-forecast average)

Threshold = 10 dBZ



Threshold = 20 dBZ



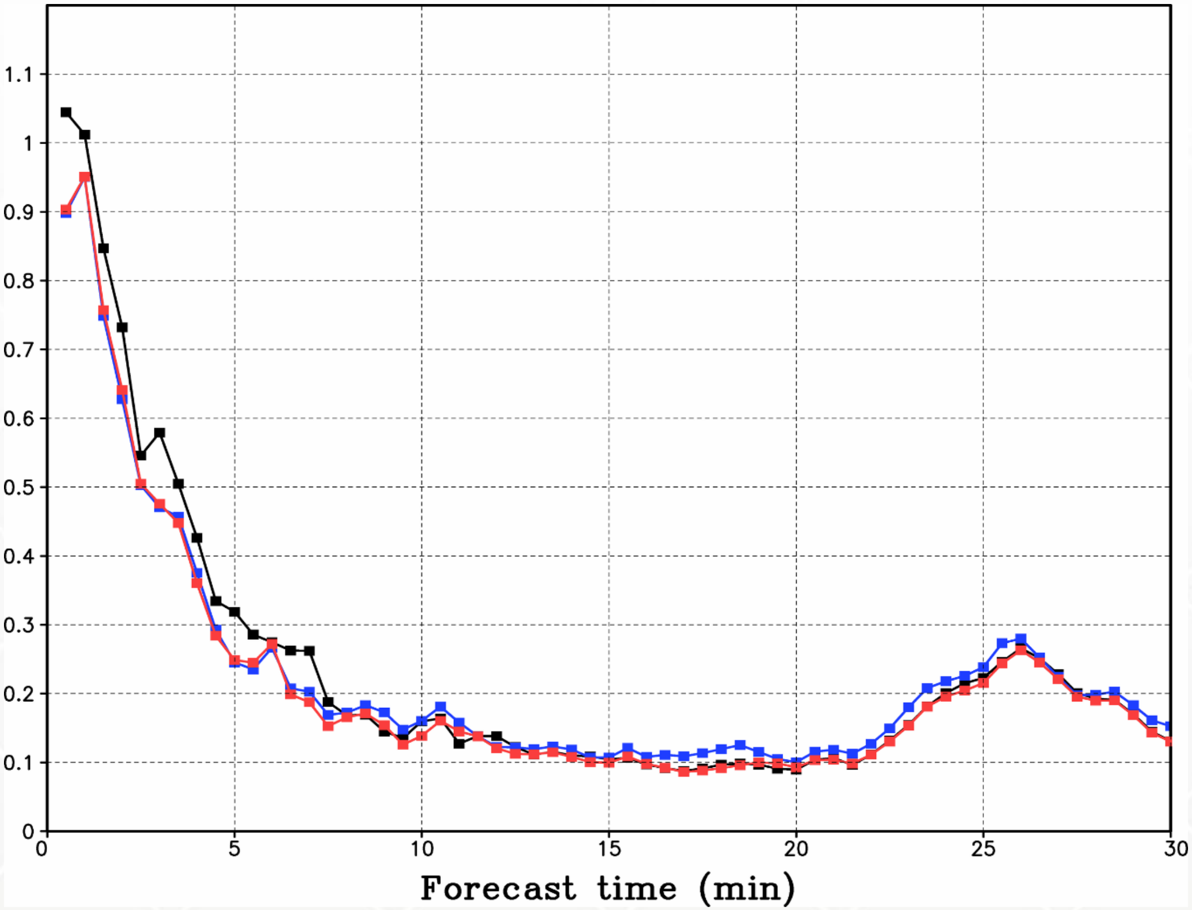
Ensemble mean

(Mean) Deterministic run

Member #1

Impact of deterministic run (II)

Imbalance: Domain-averaged |dPs/dt|

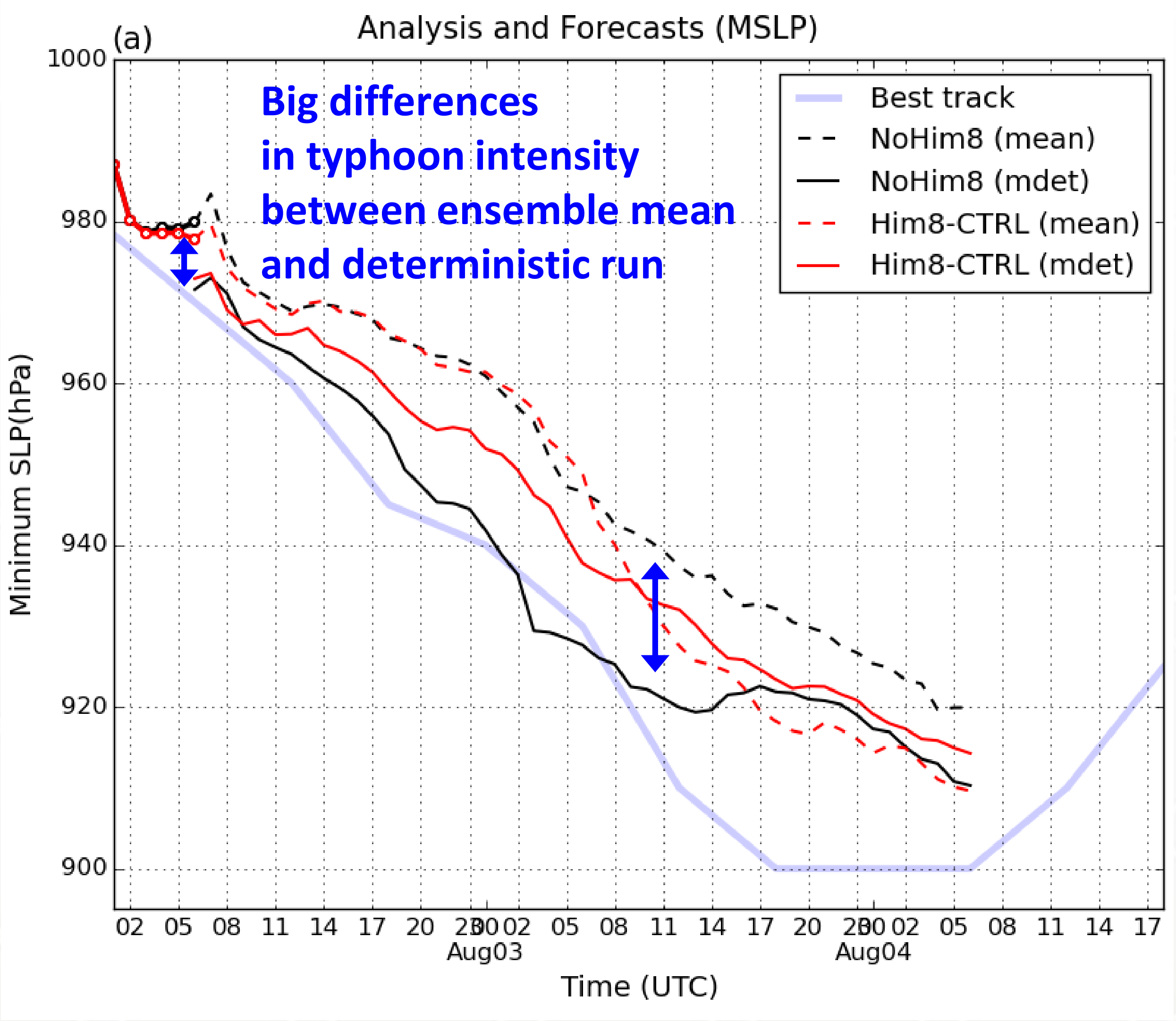


Ensemble mean

(Mean) Deterministic run

Member #1

Potential key use:
Typhoon data assimilation

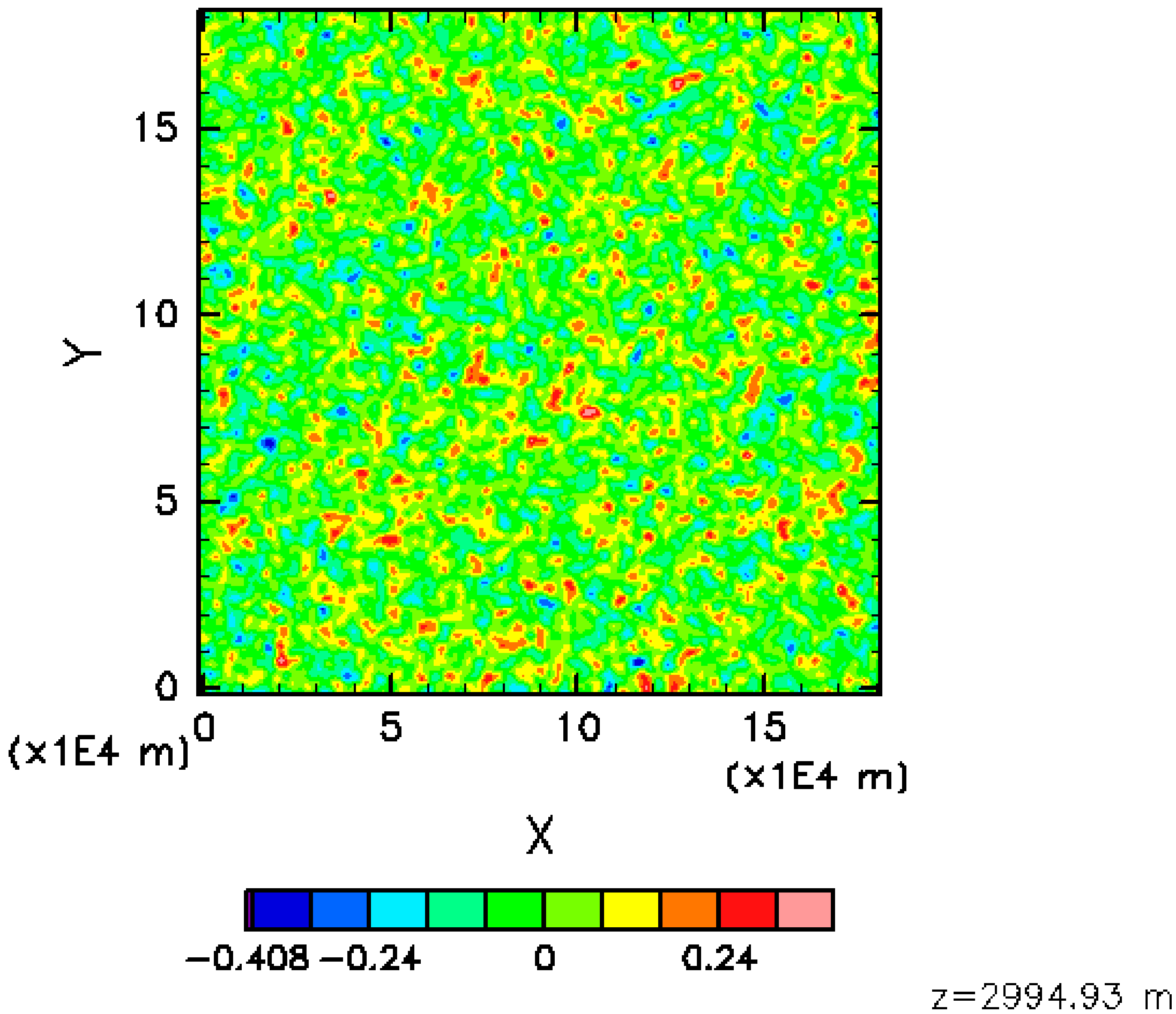


(Courtesy of Honda)

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)

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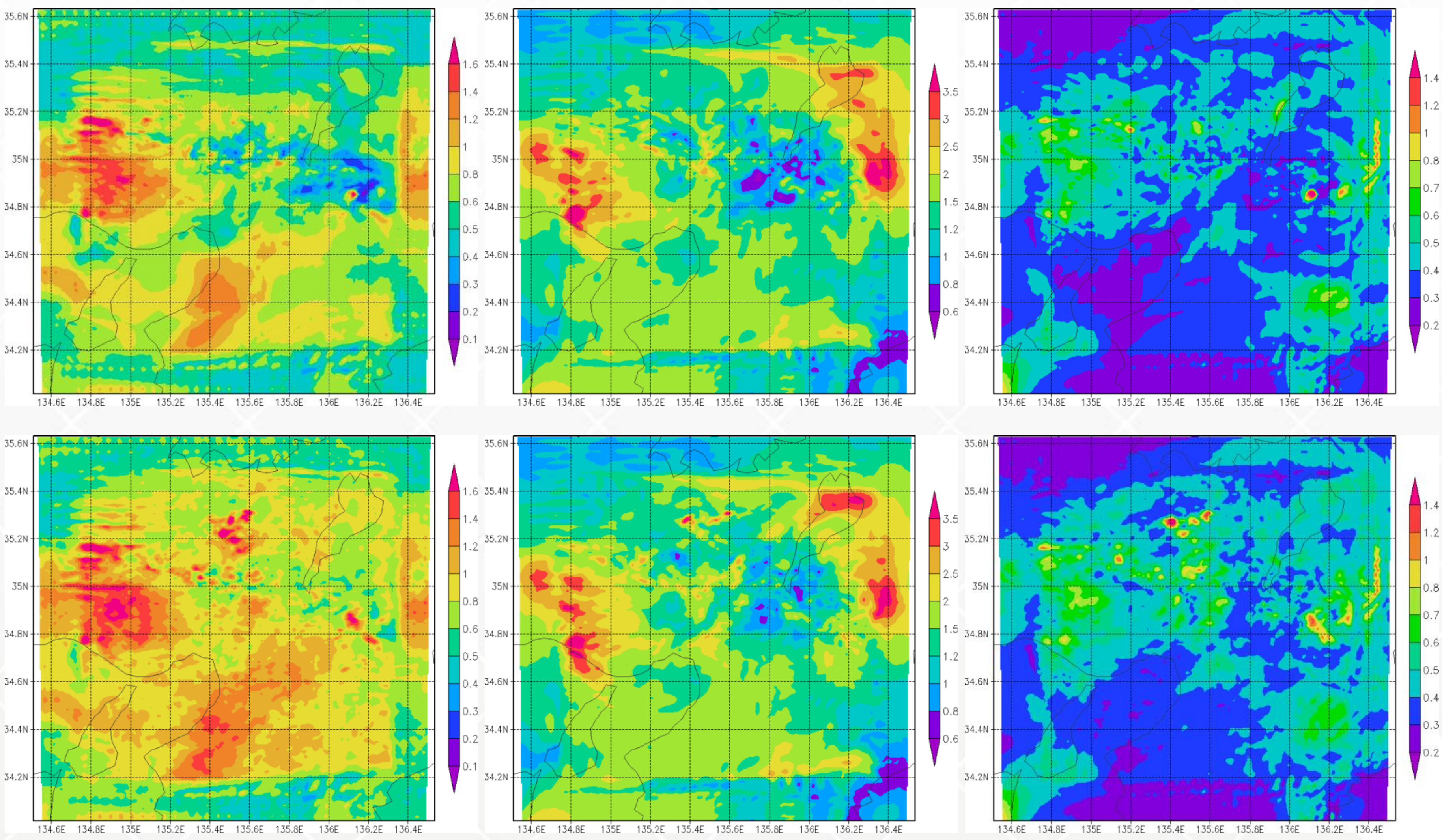
- Standard deviation = 3% to the original Q values
- After 3-h DA cycle every 5 minutes (36 cycles)
- Also apply RTPS = 0.9 for the entire period

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

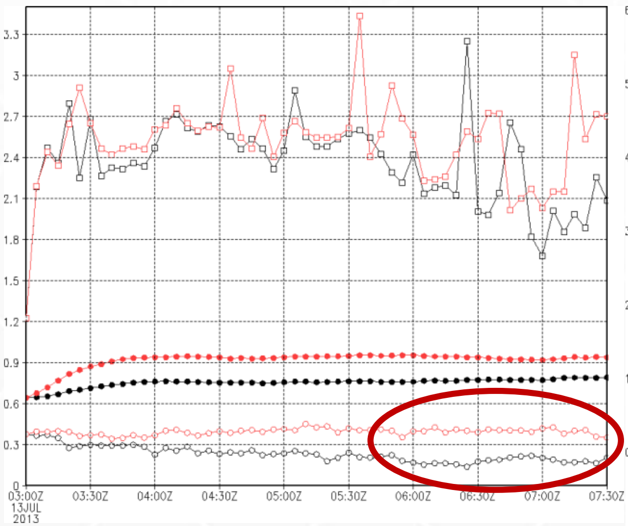
No noise / **Additive Q noise**



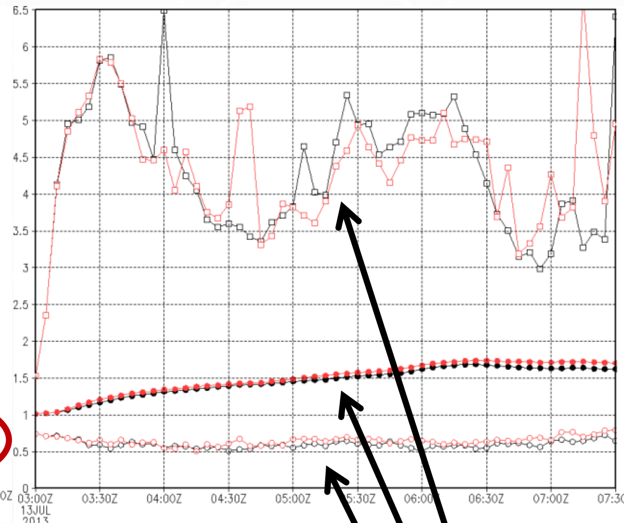
Impact of additive noise on spreads (II)

- 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

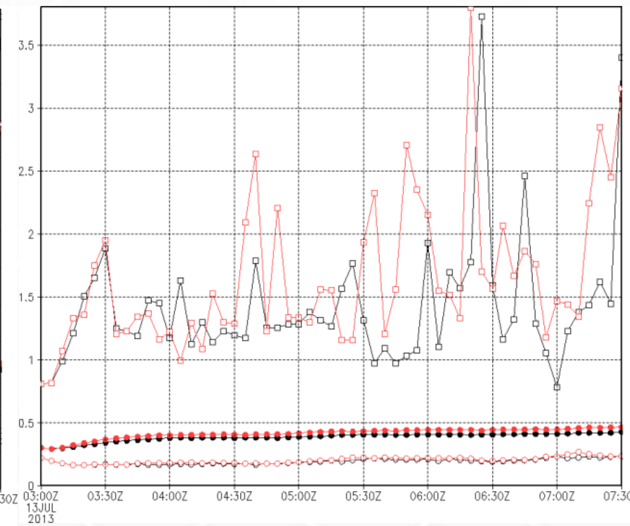
Q (g/kg)



U (m/s)



T (K)



No noise

Additive Q noise

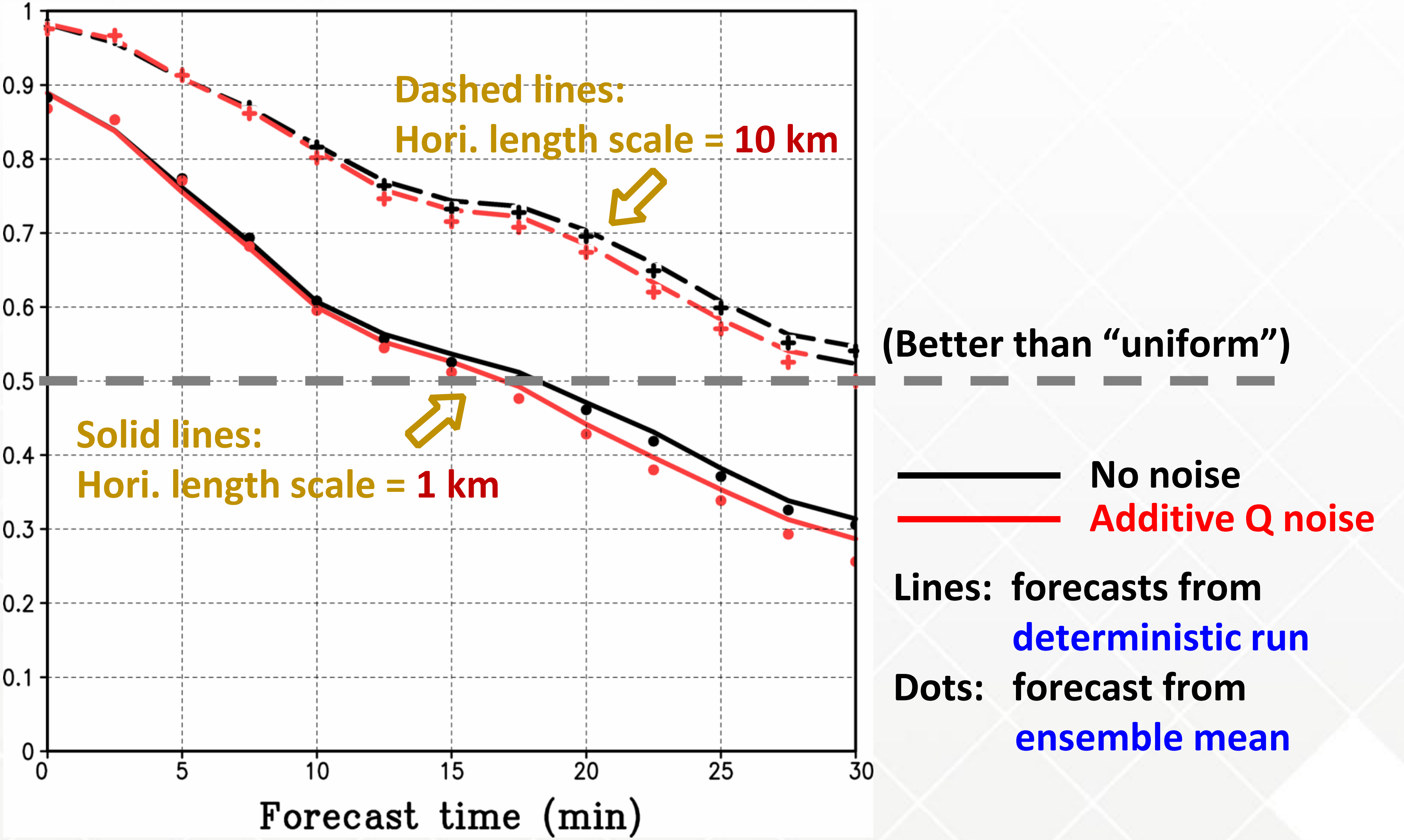
Domain maximum

Domain average

Domain minimum

Impact of additive noise on spreads (III)
30-min-forecast FSS

Threshold = 15 dBZ (6-fcst average)



Lines: forecasts from deterministic run

Dots: forecast from ensemble mean