Data Assimilation Technique Development in and related to the Warn-on-Forecast Project

Warn-on-Forecast Workshop

February 8, 2012

Norman Oklahoma

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Data Assimilation Tools in WoF Toolbox

- WRF DART (for WRF and NCOMMAS)
- ARPS EnKF System (for ARPS and WRF)
- ARPS 3DVAR/Cloud Analysis
- WRF 3DVAR and 3DVAR-Hybrid
- GSI-based EnKF/EnKF-Hybrid (for WRF and others)

DA Technique Development in WoF

- CAPS's multi-scale parallel EnKF system
  - Hybrid OpenMP/MPI parallelization
  - Multiple data types, especially high-density radar data
  - 4D asynchronous filter (4DEnSRF), and iterative procedure (iEnSRF) for faster convergence/spin up
  - Interface with both ARPS and WRF
  - Support for 2-moment microphysics, perturbed physics and multi-physics ensemble, build-in attenuation correction
  - Microphysical parameter estimation
  - Polarimetric radar data assimilation
  - Adaptive covariance inflation, successive spatial localization
  - EnKF-3DVAR hybrid and LETKF algorithms (under development)
  - En4DVAR (planned)

DA Technique Development in WoF

- Enhancements to ARPS 3DVAR/Cloud Analysis System
  - Added diagnostic pressure equation constraint
  - Direct assimilation of reflectivity data with hydrometeor classification
  - Vertical correlation scale defined in terms of height
  - 2-moment MP scheme support and use of dual-pol data in cloud analysis (under development)

- WRF 3DVAR/Hybrid System
  - Applied to radar radial velocity assimilation of a hurricane case

- GSI-based EnKF and EnKF-Hybrid
  - Tested for Rapid Refresh configurations including all operational data at a 40 km grid spacing,
  - Developed dual-resolution capabilities for EnKF
  - One-way and two-interactive EnKF-Hybrid

Posters on EnKF Algorithms (algorithm development)

- 14) Doppler Radar Data Assimilation using a Local Ensemble Transform Kalman Filter (LETKF, Therese Thompson)
- 22) Implementation of LETKF with ARPS model and some preliminary results of OSSE (Gang Zhao)
- 19) Multi-scale EnKF data assimilation and forecasts of the 10 May 2010 tornado case in the central US domain (Youngsun Jung)
- 20) A four-dimensional asynchronous ensemble square-root filter (4DEnSRF) algorithm and tests with the 10 May 2010 tornado case (Shizhang Wang)

Posters on EnKF Analyses Coupled with Multi-moment Microphysics

- 7) The Impact of Single and Double Moment Microphysics Schemes on Ensemble Kalman Filter Analyses and Forecasts of the 8 May 2003 Tornadic Supercell Storm (Nusrat Yussouf)

- 10) Multi-Moment and Multi-Phase Ice Microphysics in Storm-scale EnKF (Ted Mansell)

- 15) Ensemble prediction of the 4 May 2007 Greensburg, KS tornadic supercell: Impact of microphysics (Daniel Dawson)

- 21) The analysis and prediction of microphysical states and polarimetric variables in a mesoscale convective system using double-moment microphysics, multi-network radar data, and the ensemble Kalman filter (Bryan Putnam)

Posters on GSI-based EnKF/Hybrid, 3DVAR Analysis of Reflectivity, etc.

- 23) GSI-based EnKF and EnKF-hybrid development and testing for Rapid Refresh configurations (Kefeng Zhu et al.)
- 24) The impact of covariance inflation methods on the spread of ensemble simulations (Tim Supinie)
- 25) Assimilation of attenuated data from an X-band radar network for a quasi-linear storm using the ensemble Kalman filter (Jing Cheng)
- 6) Assimilation of reflectivity data in a convective-scale, cycled 3DVAR framework with hydrometeor classification (Jidong Gao)

An Iterative Ensemble Square Root Filter (iEnSRF)

- Use radar data multiple times at the beginning of assimilation cycles when state estimation and ensemble covariance are poor.
- Serve to accelerate filter convergence/storm spin up
- Similar to ‘Running-in-Place’ idea for LETKF (Kalnay and Yang 2010)
- Tests with Simulated Radar Data for Storm Scale Data Assimilation

Wang et al. (2012 QJ)

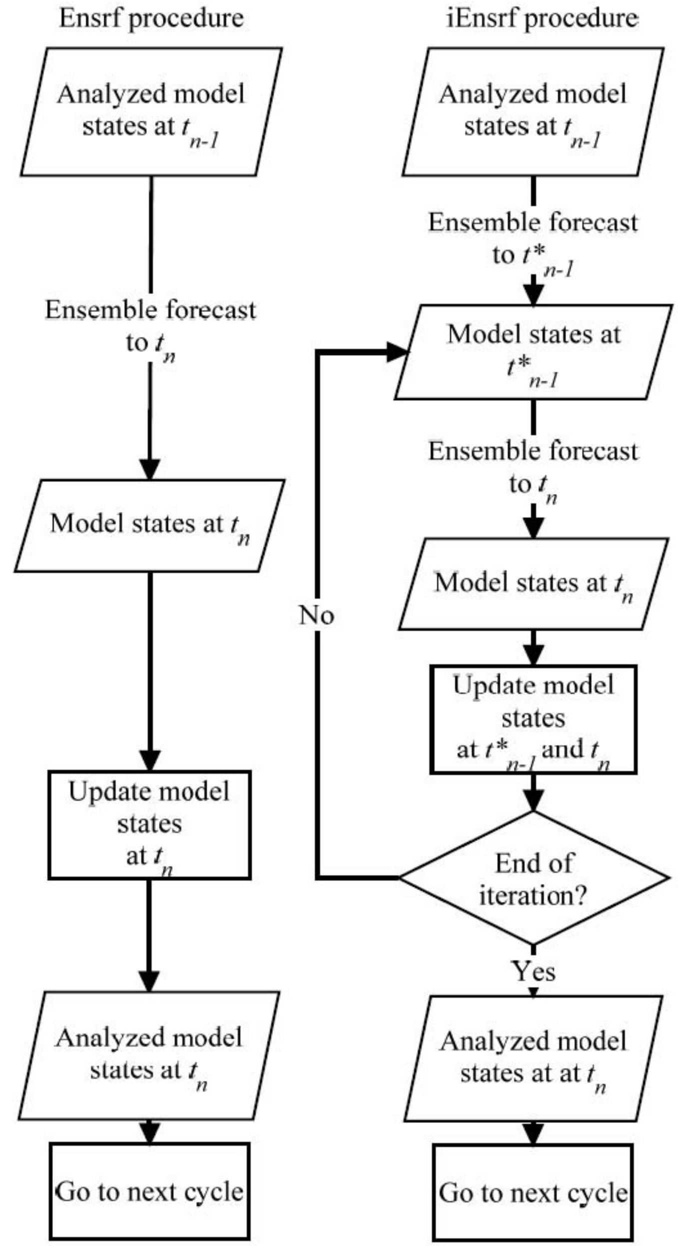


Figure 1.The Flow chart for EnSRF and iEnSRF procedure in each cycle, where the t^*_{n-1} is an arbitrarily intermediate time between t_{n-1} and t_n.

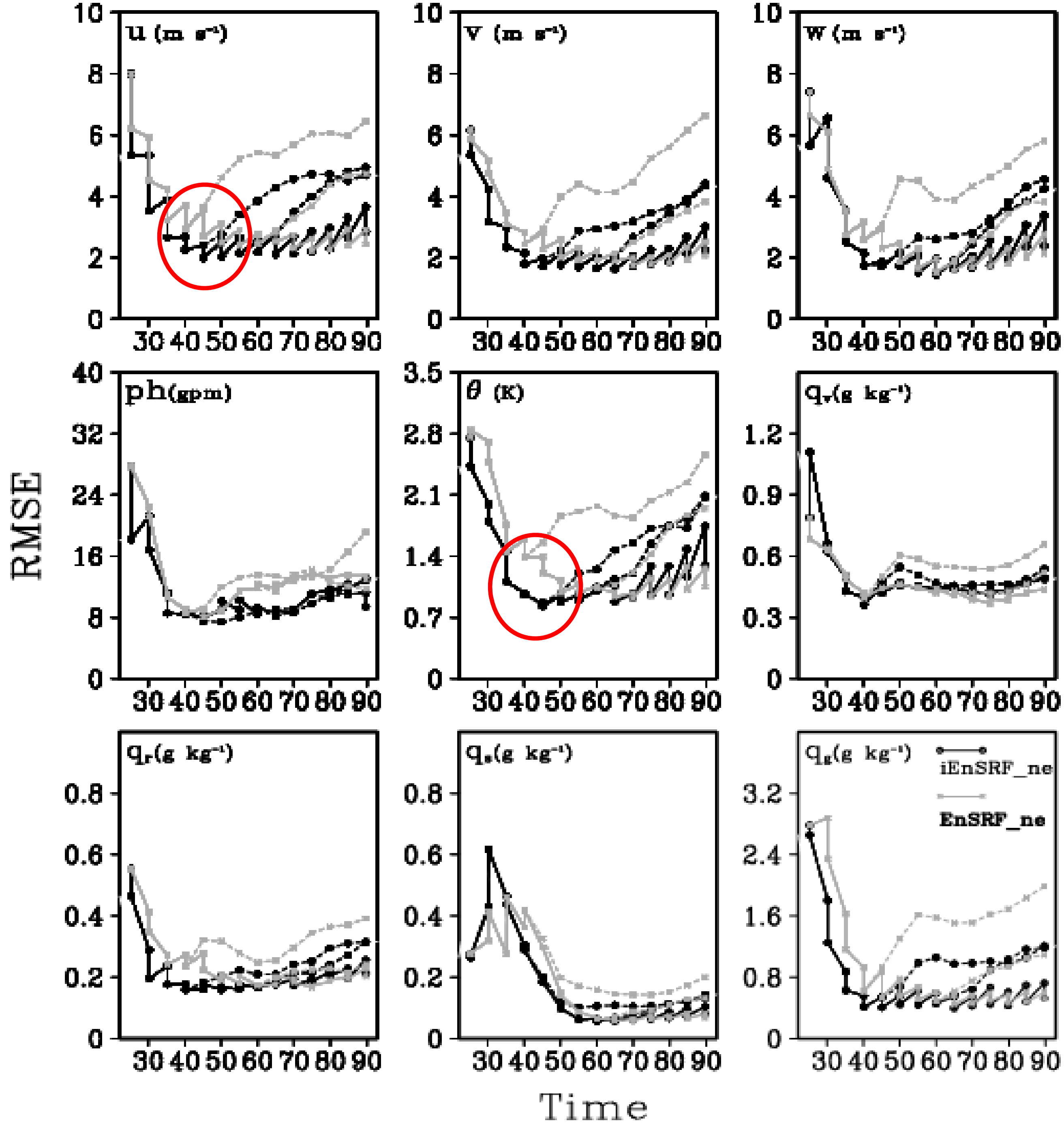
Supercell OSSE Tests with WRF

Analysis and Forecast Errors

Gray: EnSRF

Black: iEnSRF

Free forecasts launched after 4 analysis cycles



4D Asynchronous EnSRF (4DEnSRF)

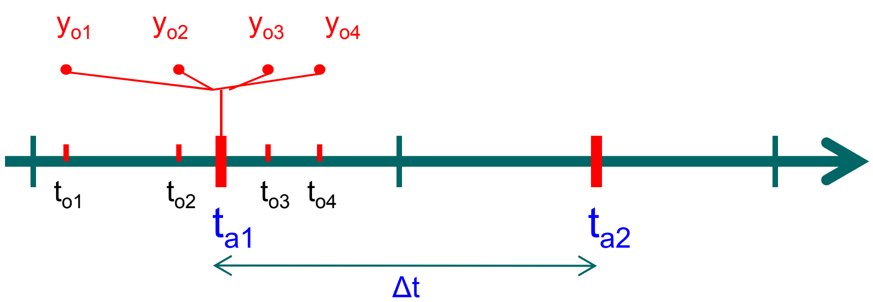
- Motivation
  - High-frequency EnKF DA is costly, given that data I/O can cost >80% overall (reading and writing of ensembles).
  - 4D extension of EnKF requires fewer cycles while still using obs at their correct times
  - Implemented based on the serial EnSRF algorithm in the ARPS EnKF framework – 4DEnSRF

Poster 20: (Shizhang Wang)

Wang, Xue and Min (2012)

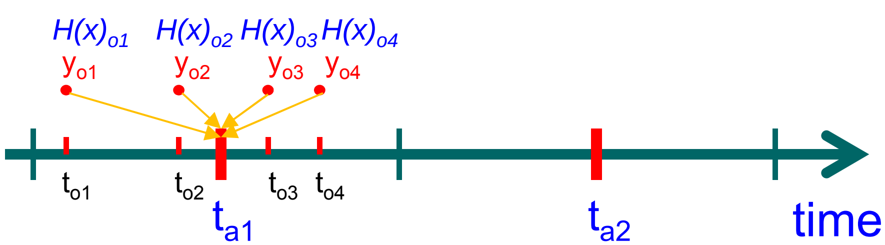
4DEnKF vs. Regular EnKF

EnKF: Observation are assumed to be taken at the assimilation time, like 3DVAR.



t_a: time of analysis, Δt: analysis time interval,
t_o: time of observation

4DEnKF: Observation can be assimilated at the times they are taken – no timing error, like 4DVAR

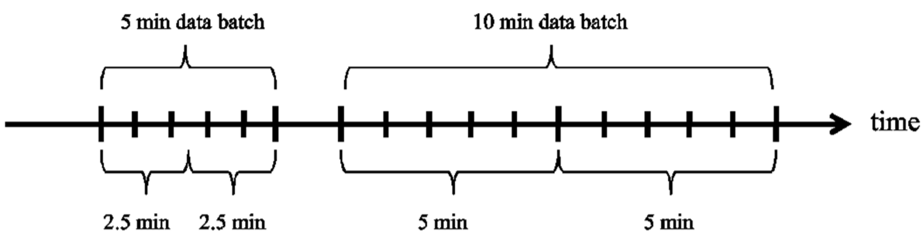


- Existing 4D ensemble algorithms include 4D-LETKF, En4DVAR.
- 4D EnSRF algorithm requires special treatment due to its serial nature.
- 4DEnSRF computes and update observation priors at the observations times.
- 4DEnSRF has been tested with simulated radar data for both WRF and ARPS, and with real data and ARPS.

H(x) can be calculated within the numerical model – added to ARPS.

Asynchronous EnSRF (AEnSRF) assimilation of radar data OSSE with WRF

- Following Sakov et al (2010), an asynchronous ensemble square-root filter (AEnSRF) has been developed in the WRF framework.
- The performance of AEnSRF and EnSRF for radar DA is tested with OSSEs



Radar observations are grouped into batches with different time spans (5 min and 10 min).

Performance evaluation

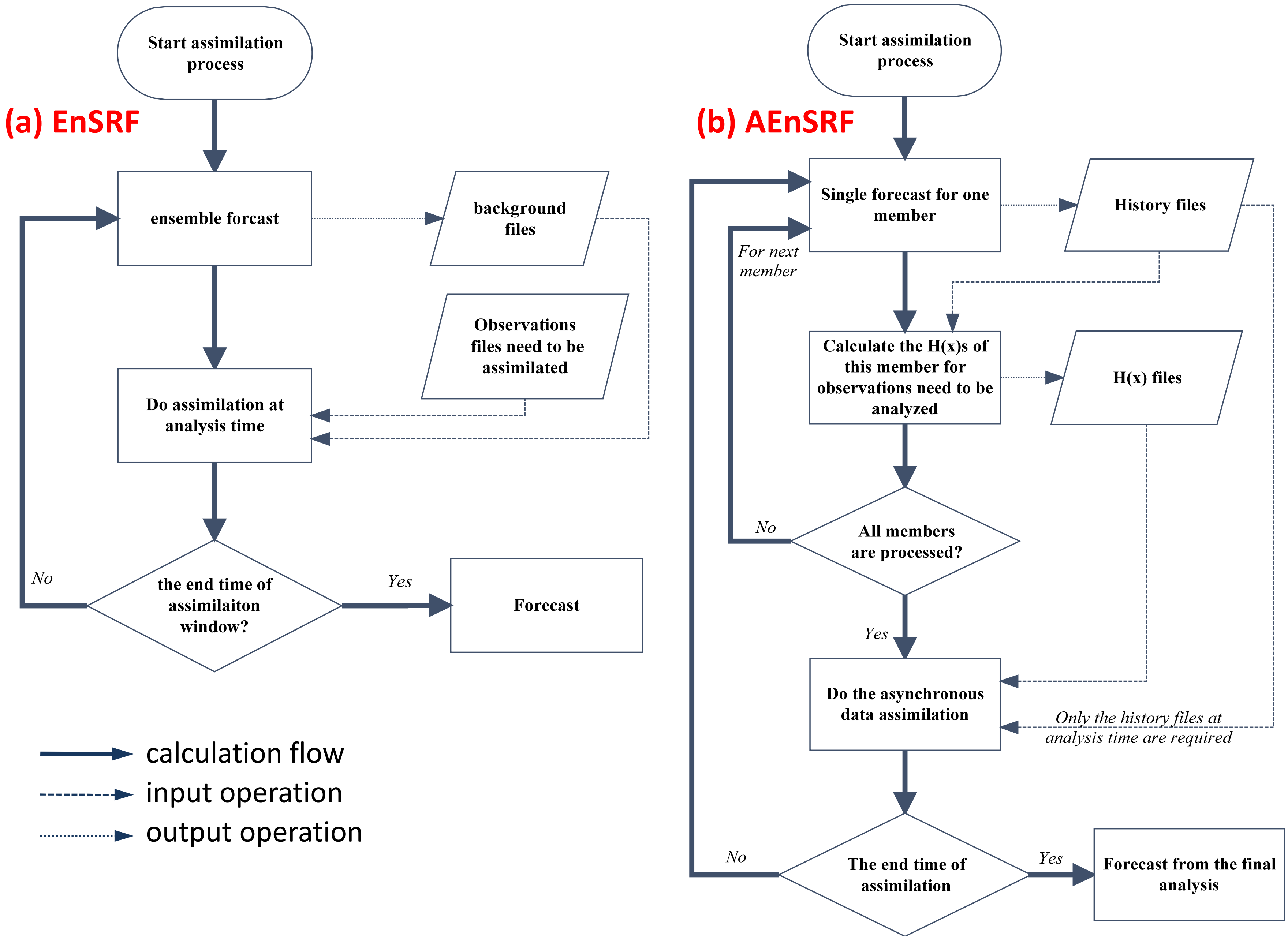
- Difference Total Energy (DTE) (Meng and Zhang 2007)

$$DTE = 0.5(u'u' + v'v' + w'w' + kT'T')$$

- HydroDTE for variables associated with water

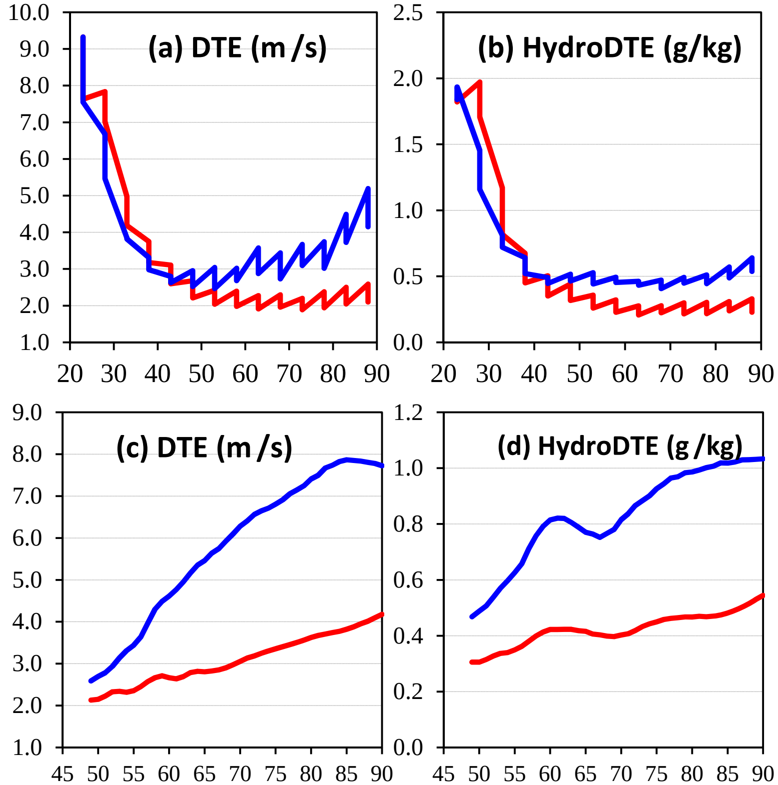
$$HydroDTE = 0.5(q_v'q_v' + q_r'q_r' + q_s'q_s' + q_g'q_g')$$

Process Flowchart of AEnSRF and EnSRF



EnSRF and 4DEnSRF Analysis and Forecast Errors: OSSEs for a Supercell with WRF

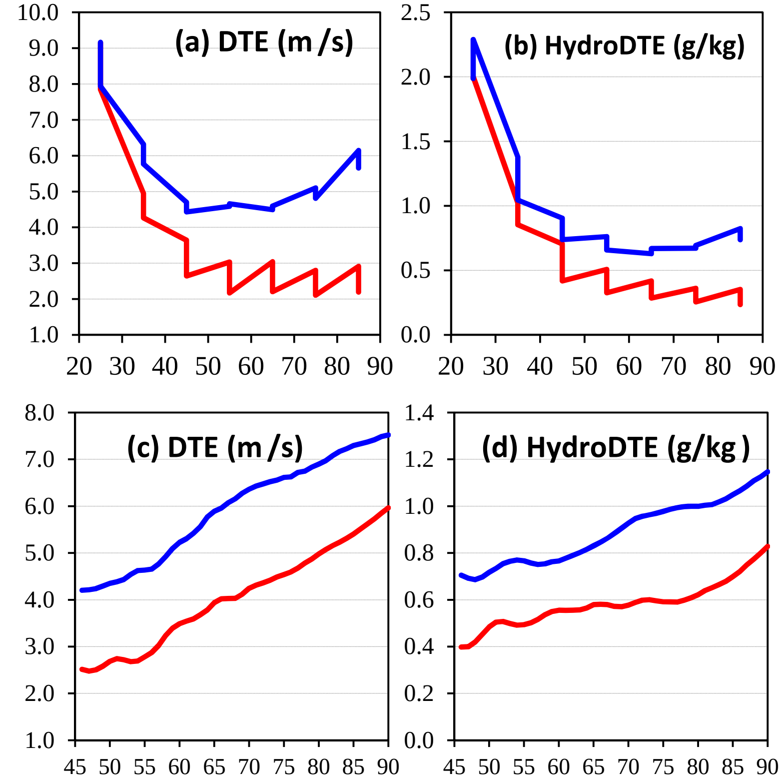
Blue: EnSRF Red: 4DEnSRF



5 min data batch

during analysis

during forecast

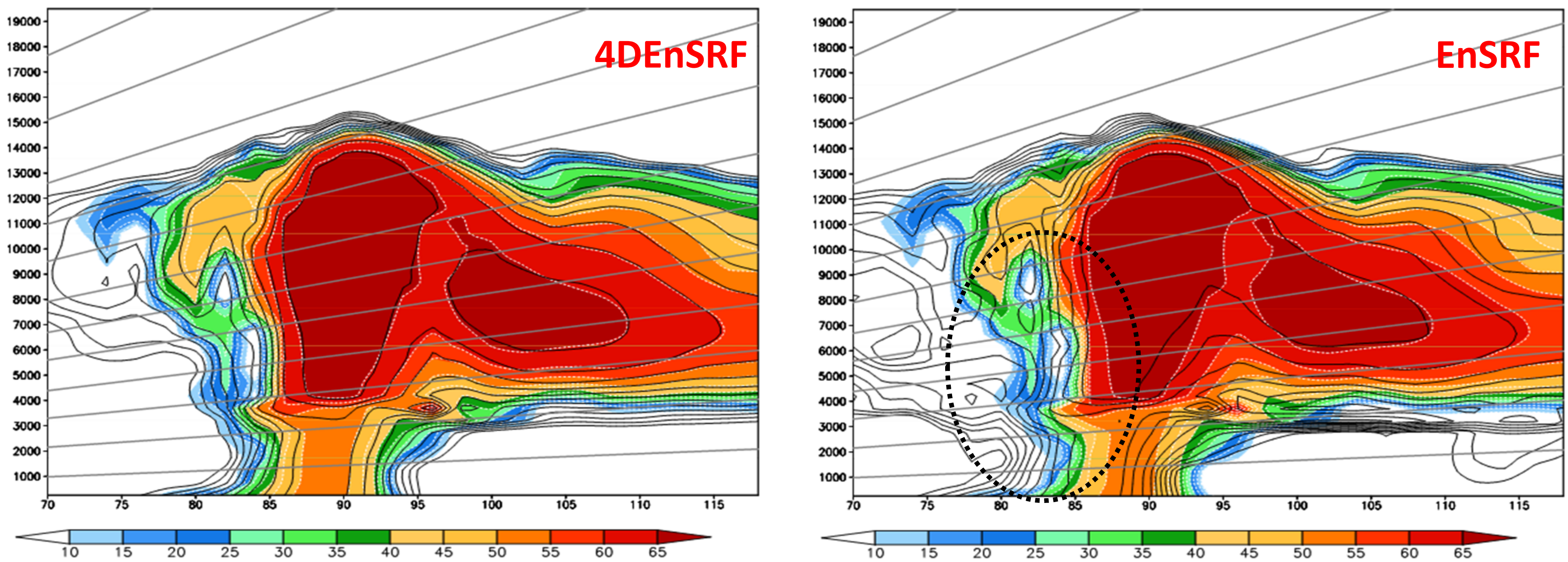


10 min data batch

- The RMS errors of 4DEnSRF are lower than those of EnSRF.
- The advantage of 4DEnSRF is more when analysis interval is longer (10 min or longer).
- Forecast error with 4DEnSRF grow faster for 10 min data batches than the 5 min case, while the growth rates for EnSRF are fast in both cases.

4DEnSRF v.s. EnSRF with 5 min data batches

Reflectivity

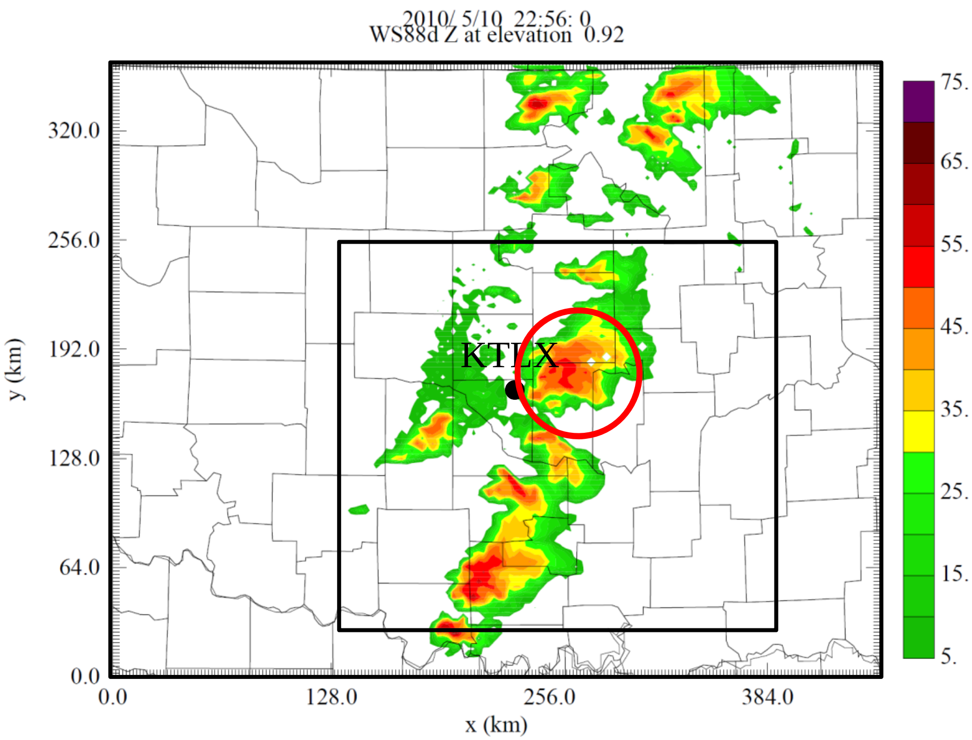


Color shade: Truth   Black contours: Analysis

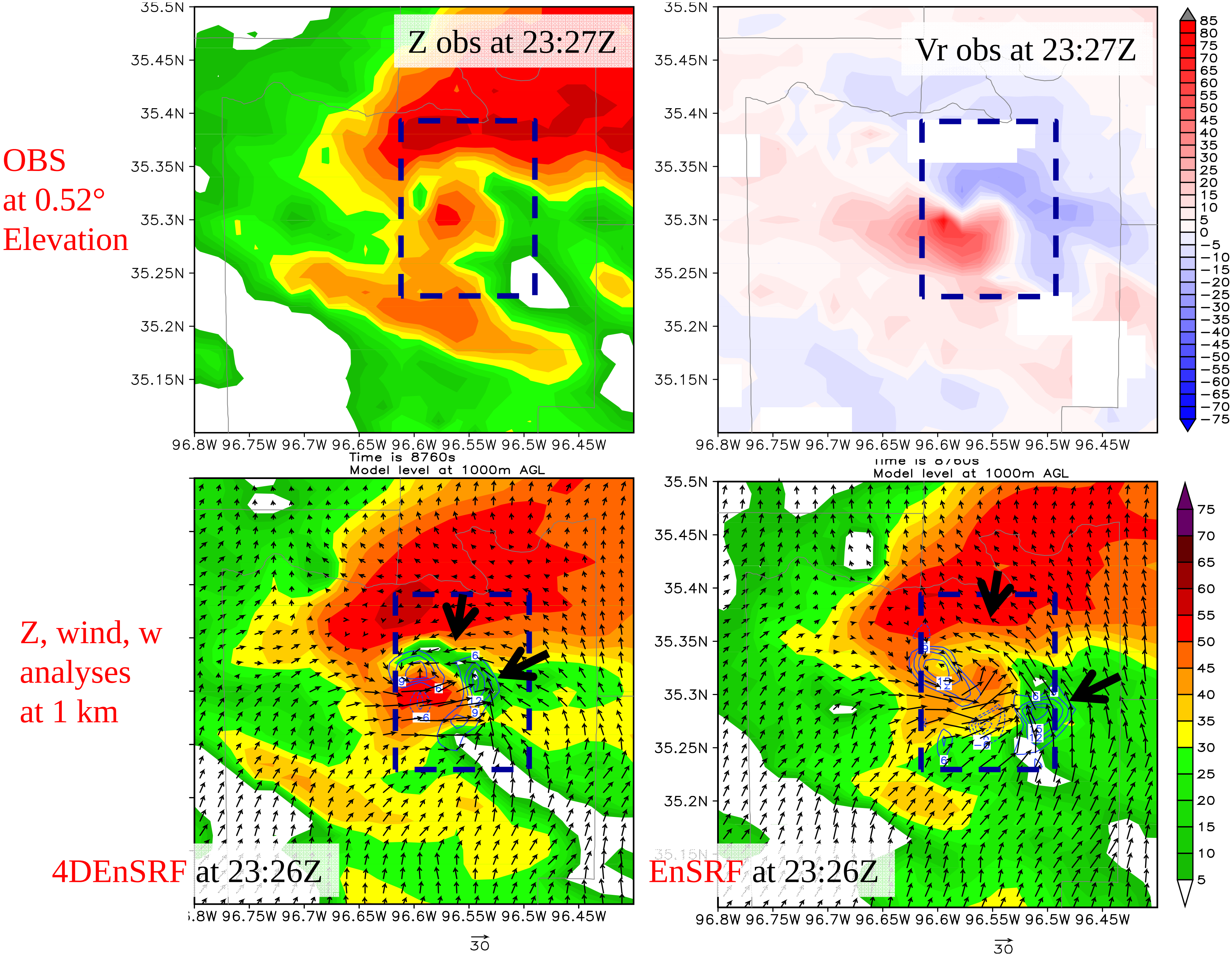
- Analyzed reflectivity with EnSRF exhibits larger errors due to timing error

- Analysis of a tornadic supercell on May 10, 2010
- EnSRF v.s. 4DEnSRF

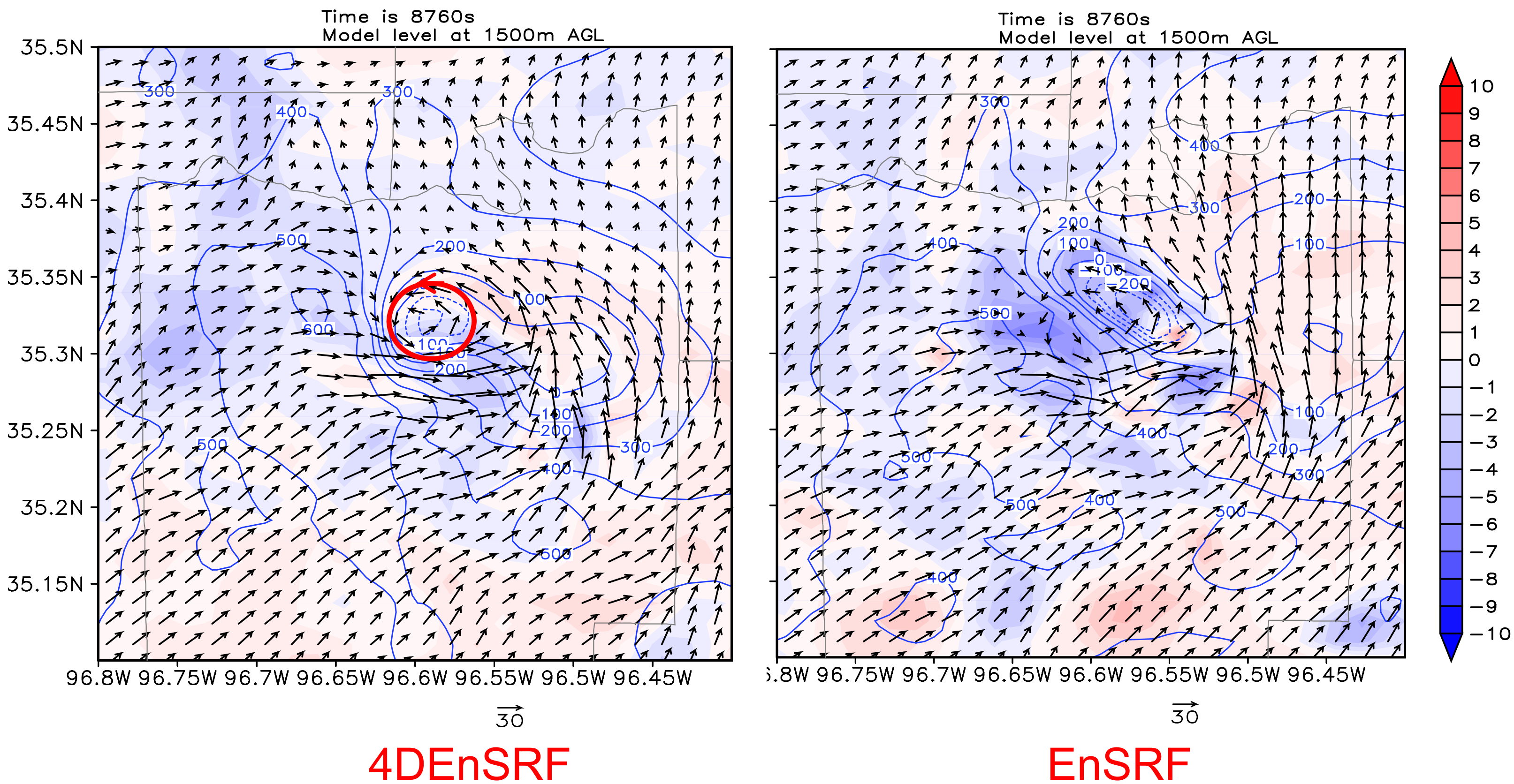
1.5 km grid nested within a 3 km grid



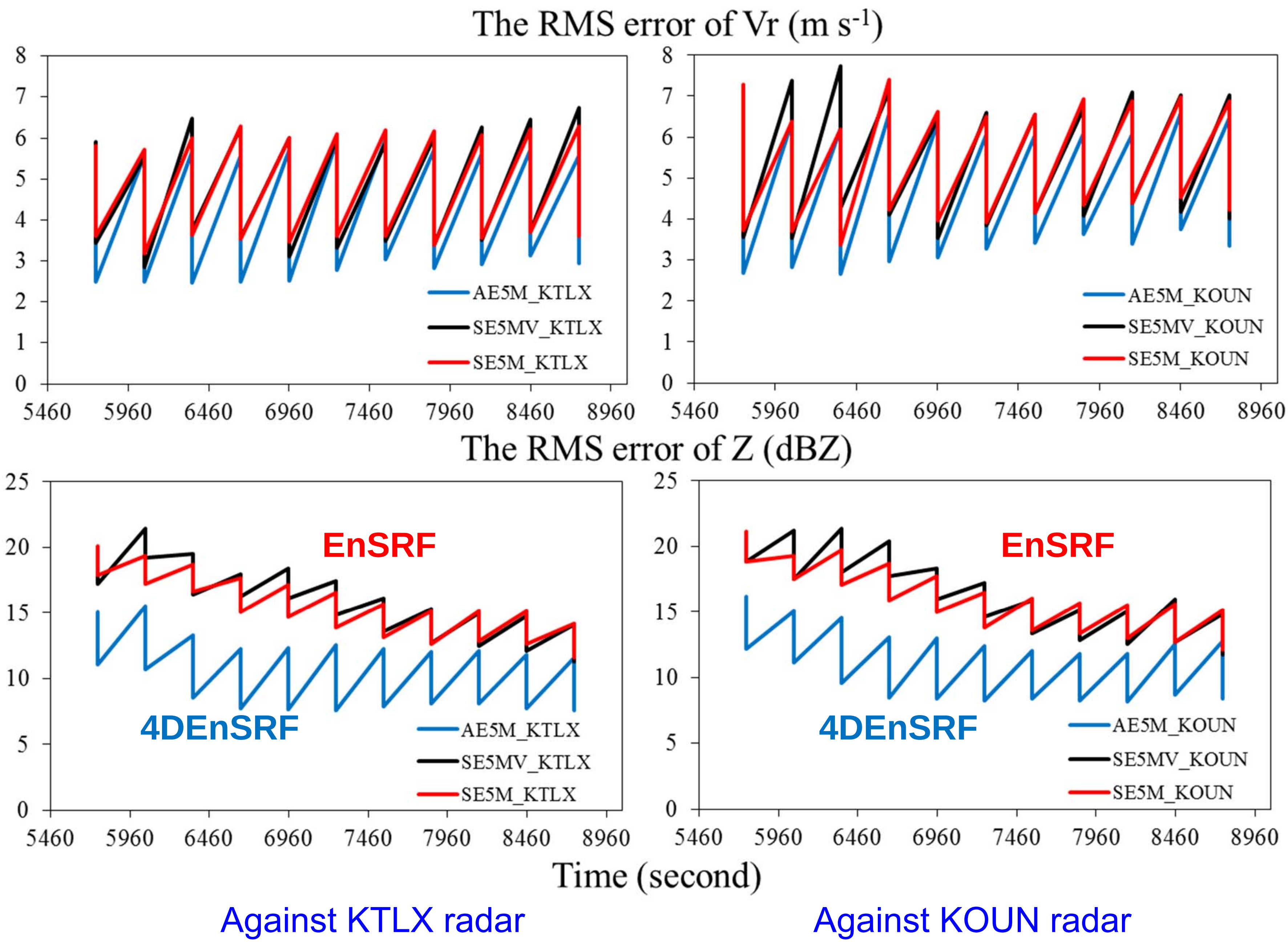
(See Poster 20)


OBS
at 0.52°
Elevation
Z obs at 23:27Z
Vr obs at 23:27Z
Z, wind, w
analyses
at 1 km
Time is 8760s
Model level at 1000m AGL
4DEnSRF at 23:26Z
EnSRF at 23:26Z
35.5N
35.45N
35.4N
35.35N
35.3N
35.25N
35.2N
35.15N
96.8W 96.75W 96.7W 96.65W 96.6W 96.55W 96.5W 96.45W
30

Analyzed T' (shaded), Pressure (contours) and Wind Vectors at 1.5 km AGL



- Much better organization of low-level mesocyclone with 4DEnSRF
- Better dynamical consistency between wind, pressure and temperature fields



The RMS error of Vr (m s-1)
AE5M_KTLX
SE5MV_KTLX
SE5M_KTLX
AE5M_KOUN
SE5MV_KOUN
SE5M_KOUN
The RMS error of Z (dBZ)
EnSRF
4DEnSRF
EnSRF
4DEnSRF
AE5M_KTLX
SE5MV_KTLX
SE5M_KTLX
AE5M_KOUN
SE5MV_KOUN
SE5M_KOUN
Time (second)
Against KTLX radar
Against KOUN radar

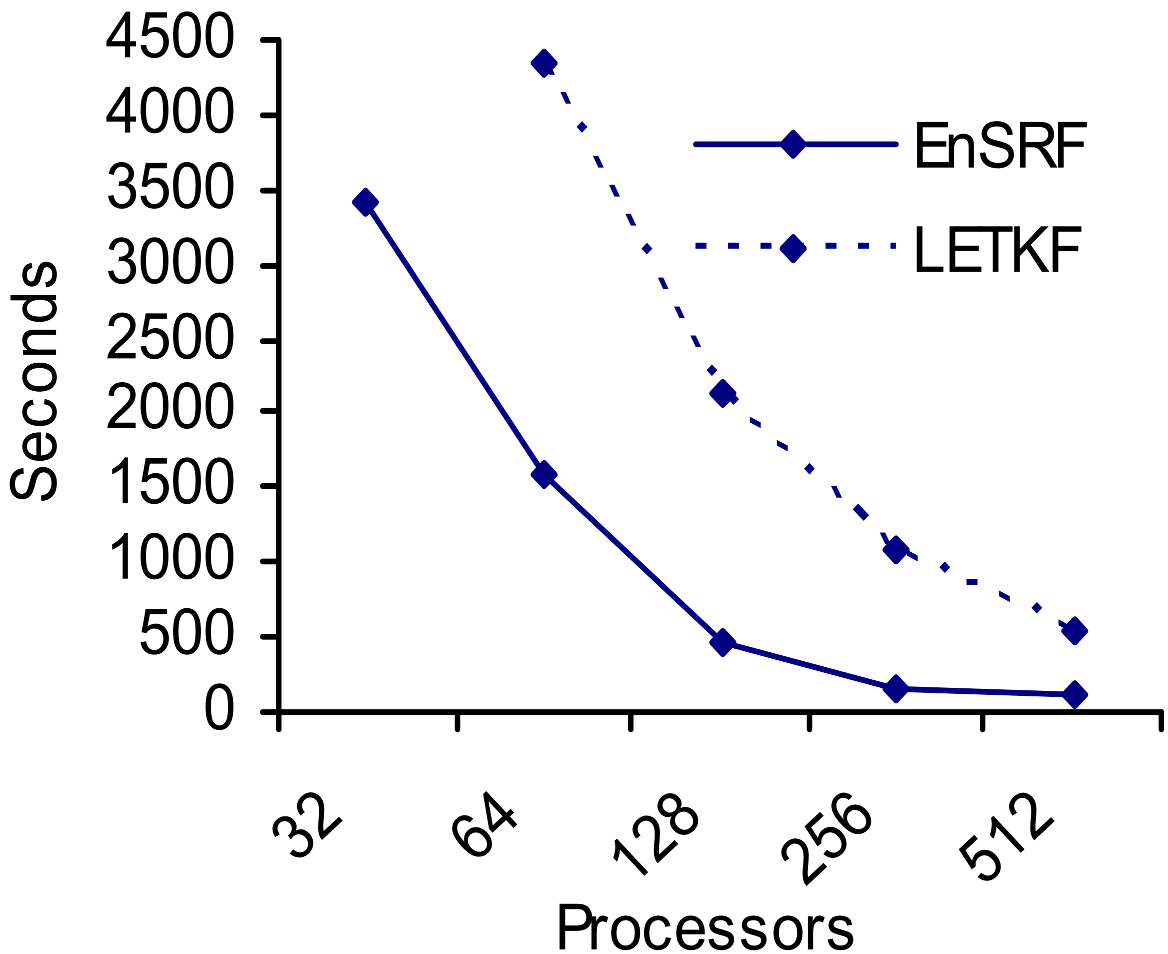
Development of a Scalable Parallel EnSRF DA System suitable for Very-high-density Observations (e.g., WSR-88D network)

- Commonly used EnSRF is serial – observations affecting common grid points cannot be assimilated simultaneously
- Current parallel algorithms (e.g., Anderson and Collins JTech 2007, as used in DART) assimilate obs one after another, updating state variables in parallel – the algorithm is not very scalable to millions of dense obs.
- The LETKF algorithm is easier to parallelize, but the algorithm itself is more expensive.
- We employ a domain-decomposition-based hybrid OpenMP-MPI (SMP-DMP) approach for achieve better scalability for very dense observations.

(Wang, Jung, Supinie and Xue 2012) Also Poster 19.

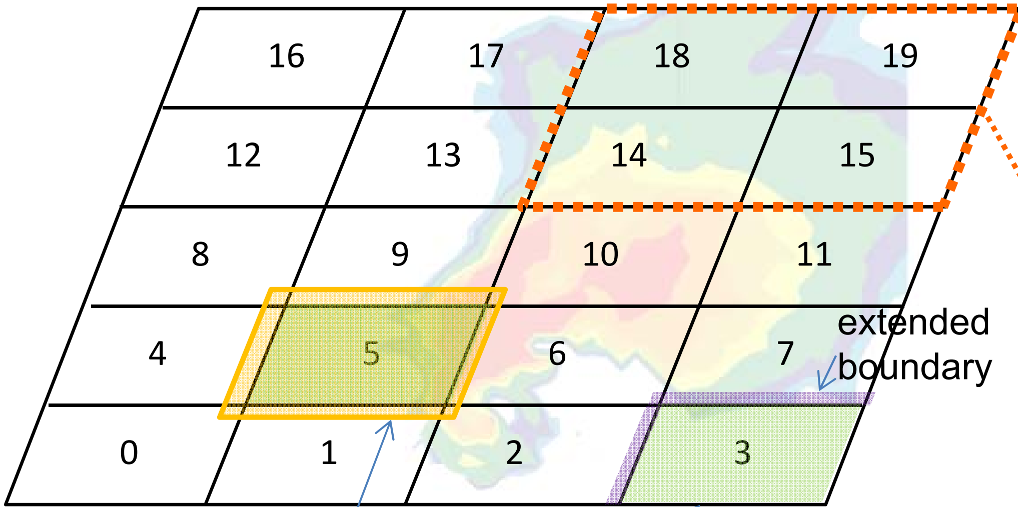
Timing statistics of parallel EnSRF and LETKF algorithms for a global model test problem of moderate resolution

(courtesy of Jeffrey Whitaker).



Here, the EnSRF parallelization is at the state vector level – observations are still assimilated on after another.

Hybrid MPI/OpenMP Algorithm for EnSRF



14, 15, 18, 19: physical domains

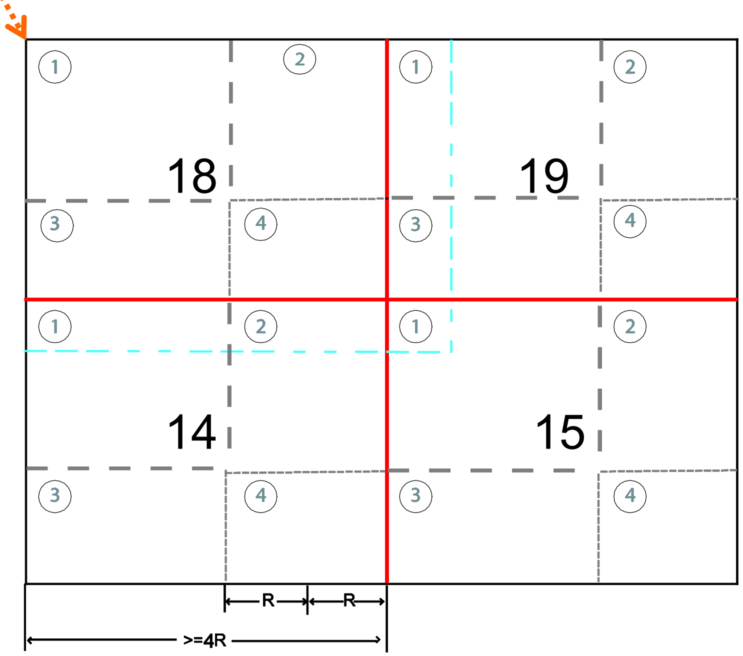
①, ②, ③, ④: sub-patches

Red: physical domain boundaries

Blue: extended boundaries

Gray: sub-patch boundaries

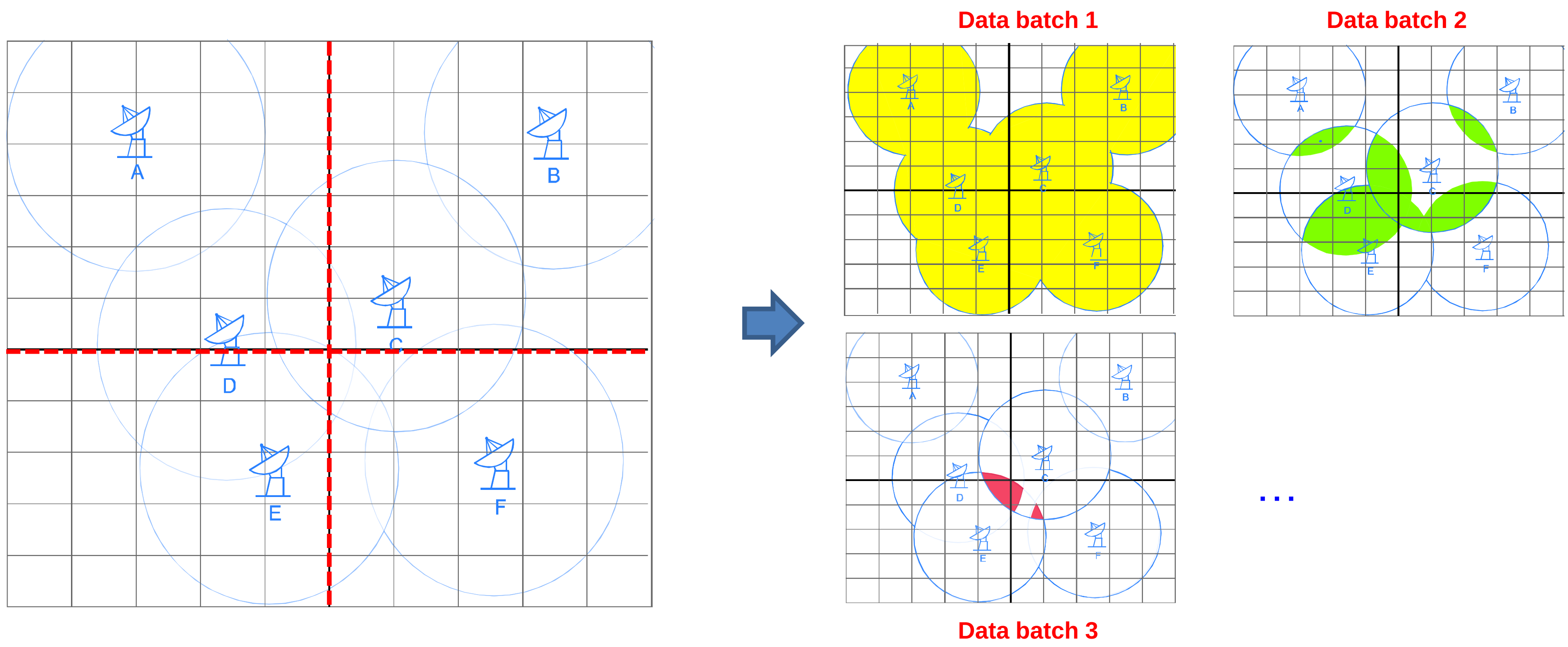
R: covariance localization radius



e.g.) Parallel algorithm for radar data

- Hybrid Parallel EnKF system has been developed based on domain decomposition strategy.
- Each decomposed domain can use multiple cores on shared memory nodes via OpenMP parallelization.
- For radar data, each domain is further divided into 4 uneven-sized patches to ensure maximum parallelism.
- For conventional data, state variables within the influence radius of each observation are updated across multiple processors.

Radar data reorganization

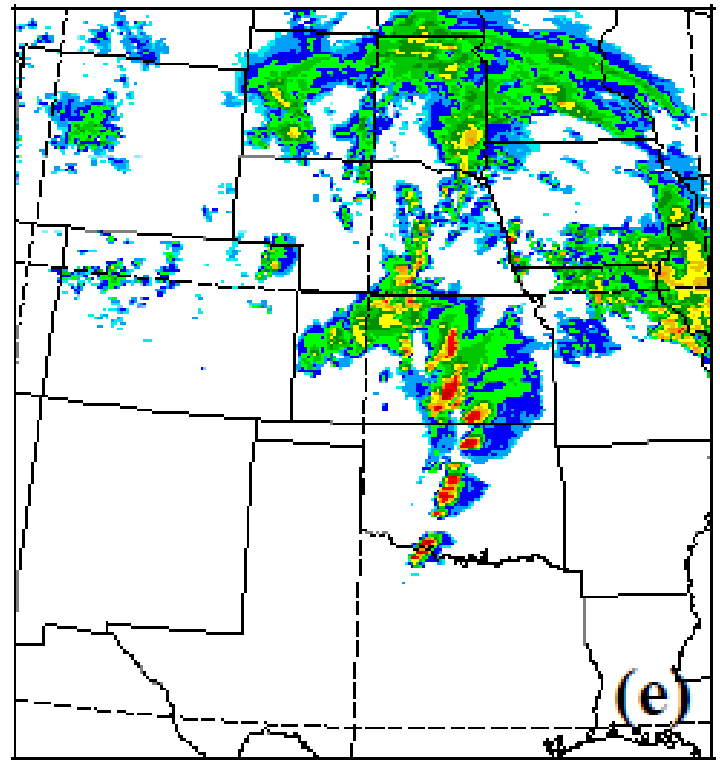


- Radar data are grouped into several batches such that no more than one column of data exists for each column of grid within each batch.
- The load imbalance issue is significantly improved for radar networks designed to maximize spatial coverage, such as the WSR-88D network.
- Suitable for very dense radar observations.

Performance Analysis of MPI EnKF Algorithms (test with the May 10 OK-KS Tornado Outbreak)

Model configurations

- Forecast model: ARPS
- DA scheme: parallel EnSRF
- Microphysics scheme: LFO83
- Grid configurations: 4 km grid
- Nested inside 40 km RR ensemble
- Physical domain: 443x483x53
- 40 ensemble members
- Observations
  - conventional data : surface, sounding, profiler (3,841 observations)
  - radar: 35 WSR-88D radars (788,145 observations)



Performance analysis of MPI and MPI/OpenMP hybrid EnKF algorithms

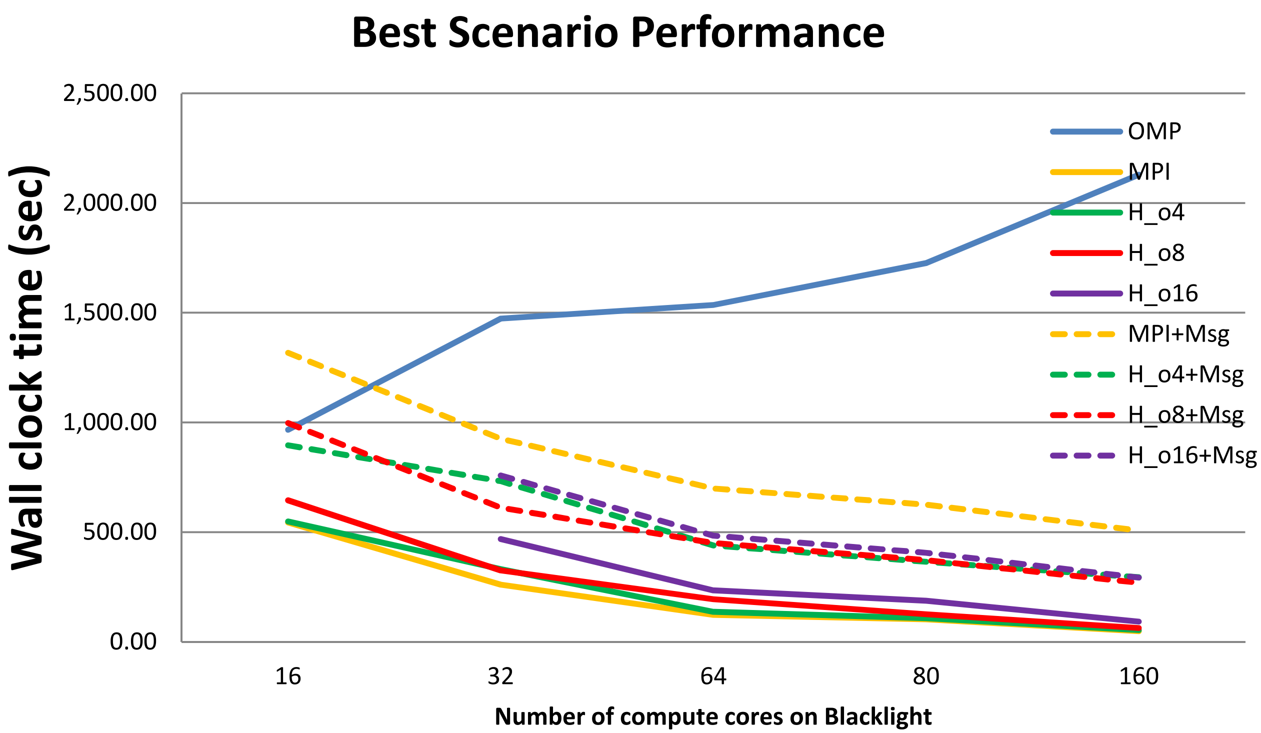
Table 3. Comparison of minimum time taken in hybrid mode with that in MPI mode using the same amount of cores on 4 compute nodes

Number of cores	Hybrid case	Minimum time	MPI case	Minimum time	Improvement
8	HYB_01x04_01_2	1,471	MPI_02x04_02_1	2169	698
16	HYB_01x04_01_4	1,129	MPI_04x04_04_1	1327	198
24	HYB_01x04_01_6	831	MPI_03x08_06_1	880	49
40	HYB_02x10_05_2	635	MPI_04x10_10_1	637	2
48	HYB_03x08_06_2	604	MPI_06x08_12_1	606	2

- Performance tests on National Institute for computational Science (NICS) supercomputer.
- The hybrid mode is usually faster than MPI mode with optimal setting.
- The hybrid and MPI wall clock time is sensitive to the domain partitioning and # of core/node configurations.
- Case-dependent and system-dependent.
- The hybrid distributed-shared-memory parallel mode helps reduce explicit data communication within a node and improve load balance across nodes.

Performance analysis of MPI EnKF algorithms

- PSC Blacklight
  - SGI UV 1000 cc-NUMA shared-memory system
  - 2 Intel Xeon X7569 eight-core processors per node
  - Radar assimilation: 48 sec excluding I/O and message passing (10 x 16 subdomains)



"H" stands for hybrid, "_ox" for the number of OMP threads, dashed: I/O and message.

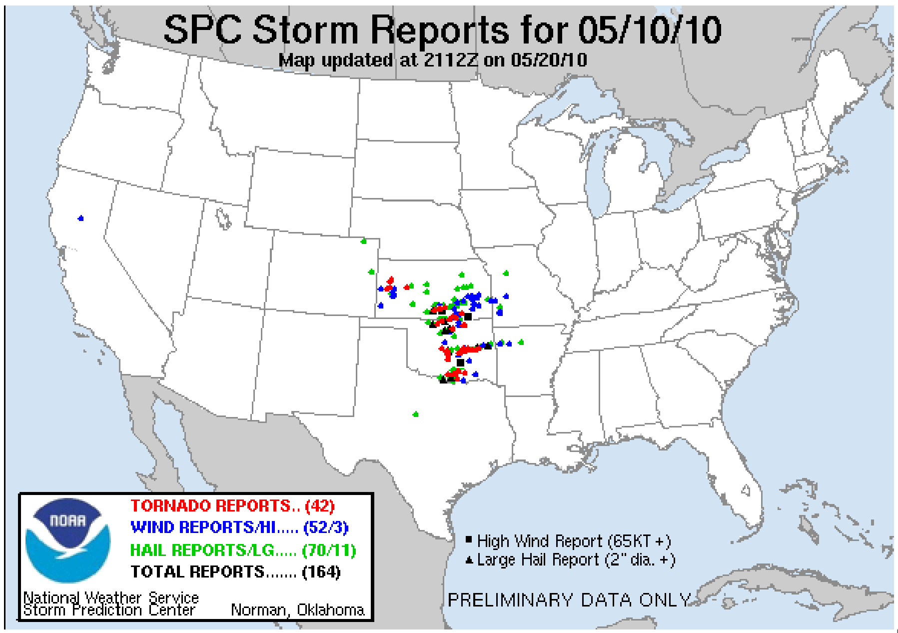
Performance analysis of MPI EnKF algorithms

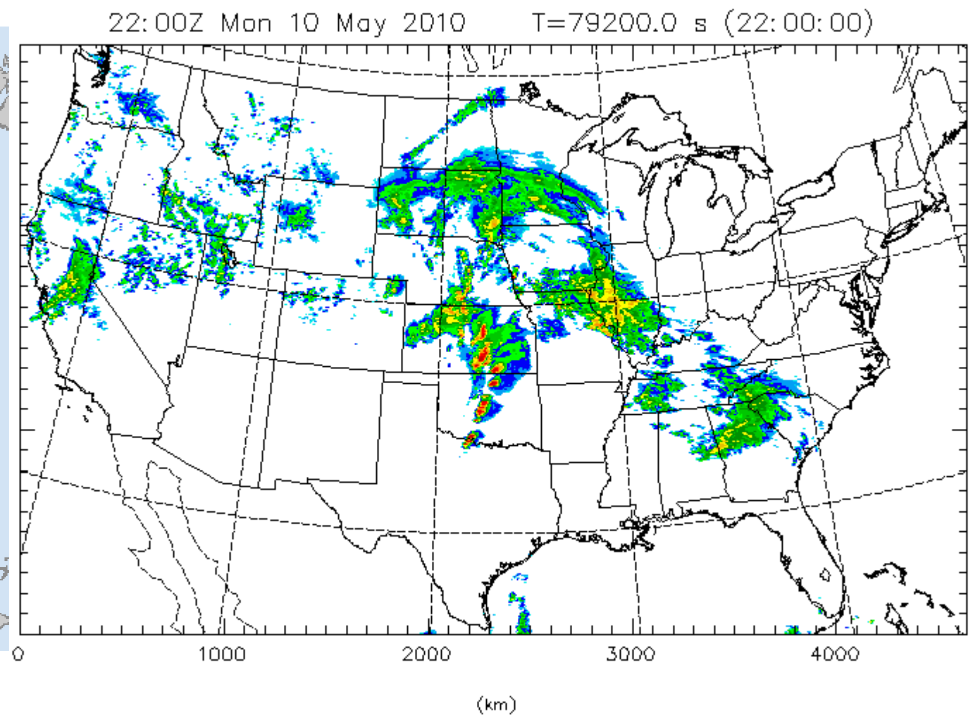
- Kraken (4 x 6 PEs x 3 threads)
  - Two 2.6 GHZ six-core-AMD Opteron processors
  - Peak performance: 1.17 Pflops
  - Radar assimilation: 1.99 min excluding only IO (4x6 subdomains)

- Sooner (4 x 8 PEs x 8 threads)
  - Pentium5 Xeon EM64T quad core “Harpertown” E5405 2.0 GHz
  - Peak performance: 34 Tflops
  - Radar assimilation: 4.18 min
  - Conventional (surface, sounding, profiler) data assimilation: 2.11 min
  - Radar + conventional data: 6.96 min (4x8 subdomains)

10 May 2010 Oklahoma-Kansas tornado outbreak

- Over 40 tornadoes, with up to EF4 intensity in OK and KS

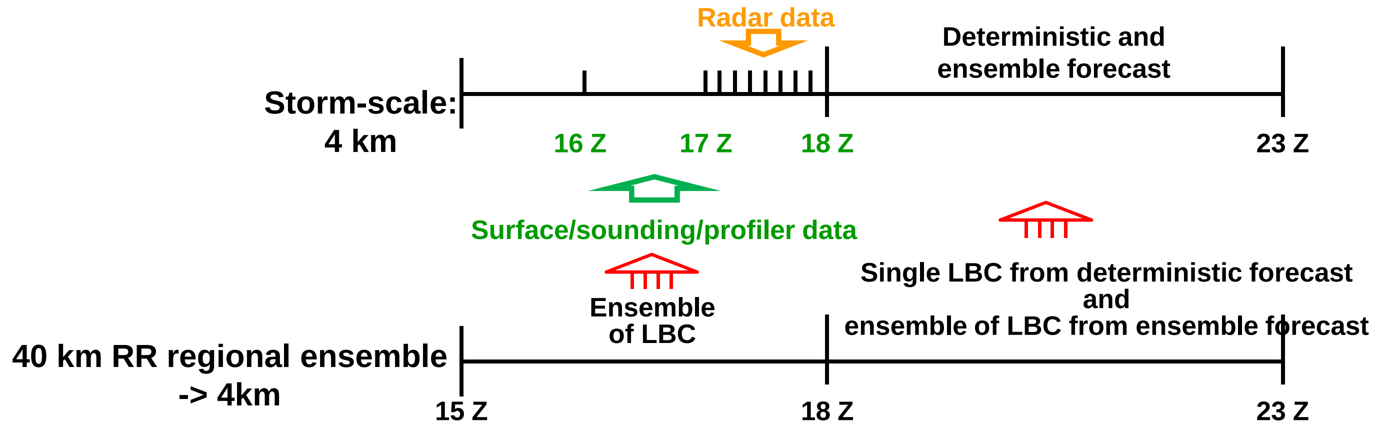




CAPS 4km 22h realtime forecast using WRF

Poster 19, Jung et al.

Experiments

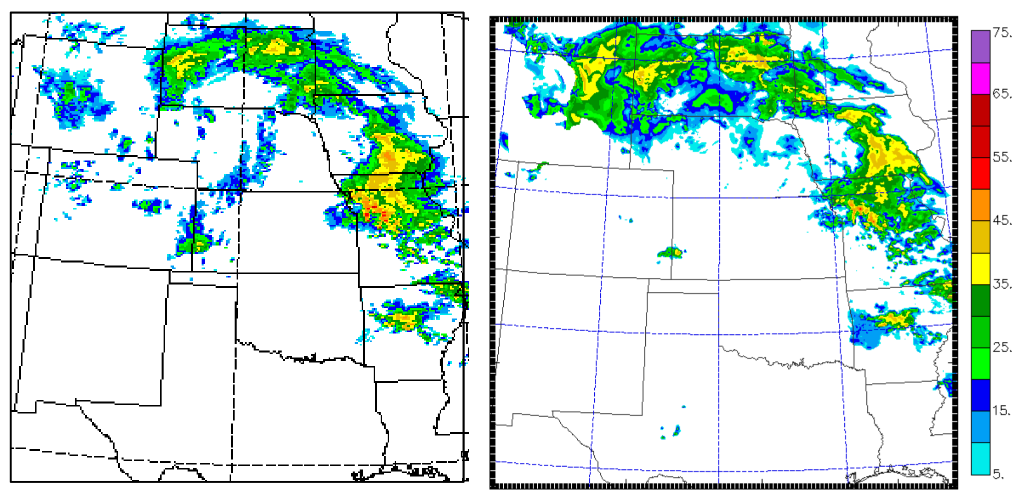


- noDA: no additional data
  - Start from 40 km RR regional ensemble interpolated to 4 km at 1500 UTC

- CNTL
  - Conventional data: 1600, 1700, 1800 UTC
  - Radar data: 1705 – 1800 UTC (5 min. interval)

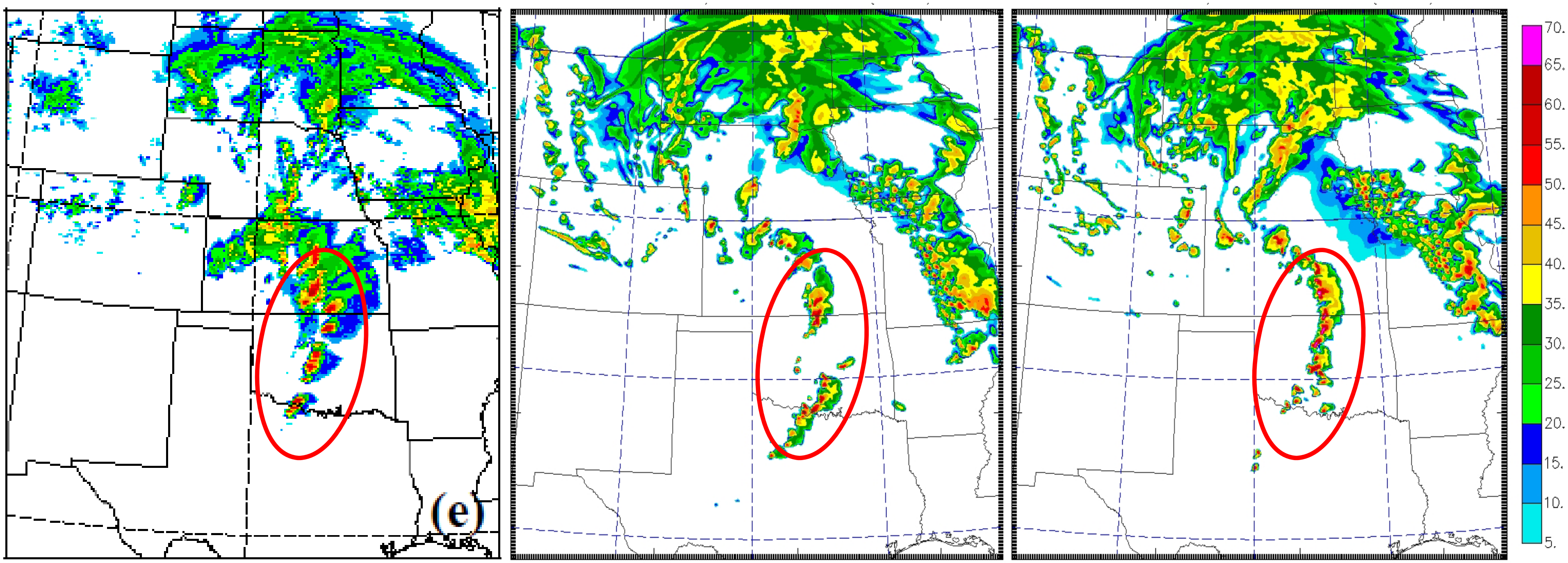
Observation (composite)

EnKF analysis (grid level 10)
valid at 1800 UTC



Ensemble forecasts valid at 2200 UTC

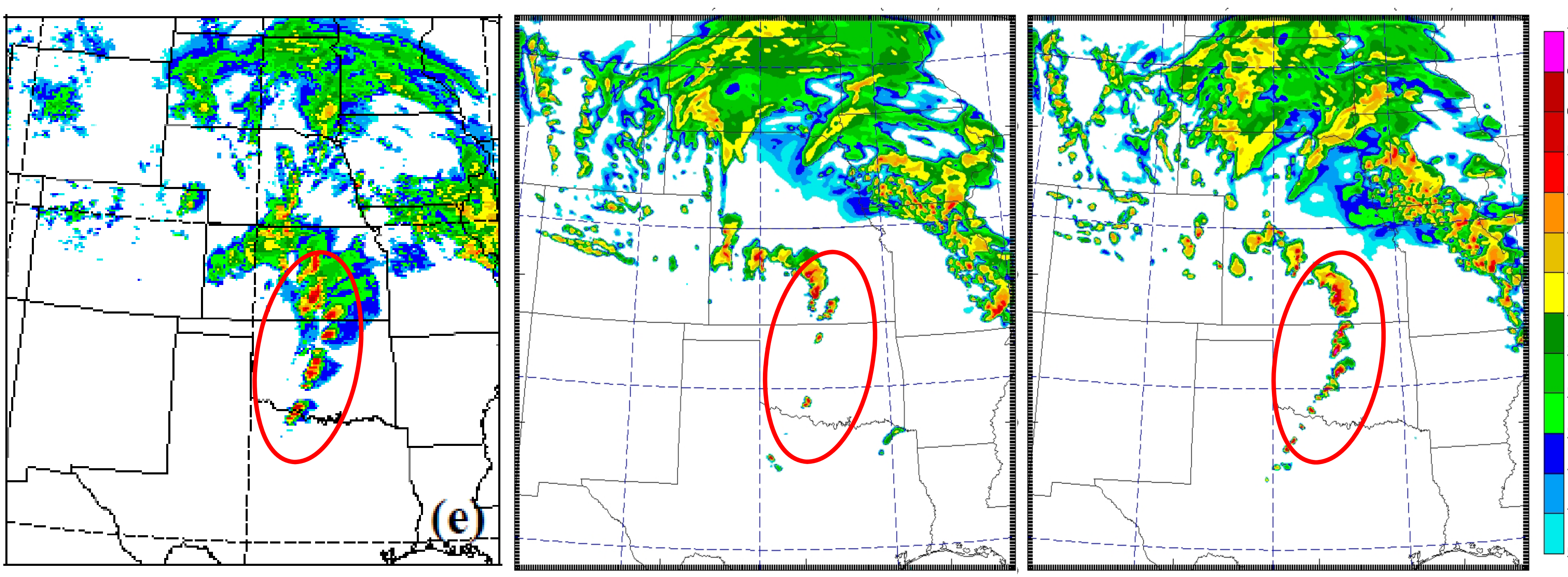
Observation | No DA | with DA



Member 2

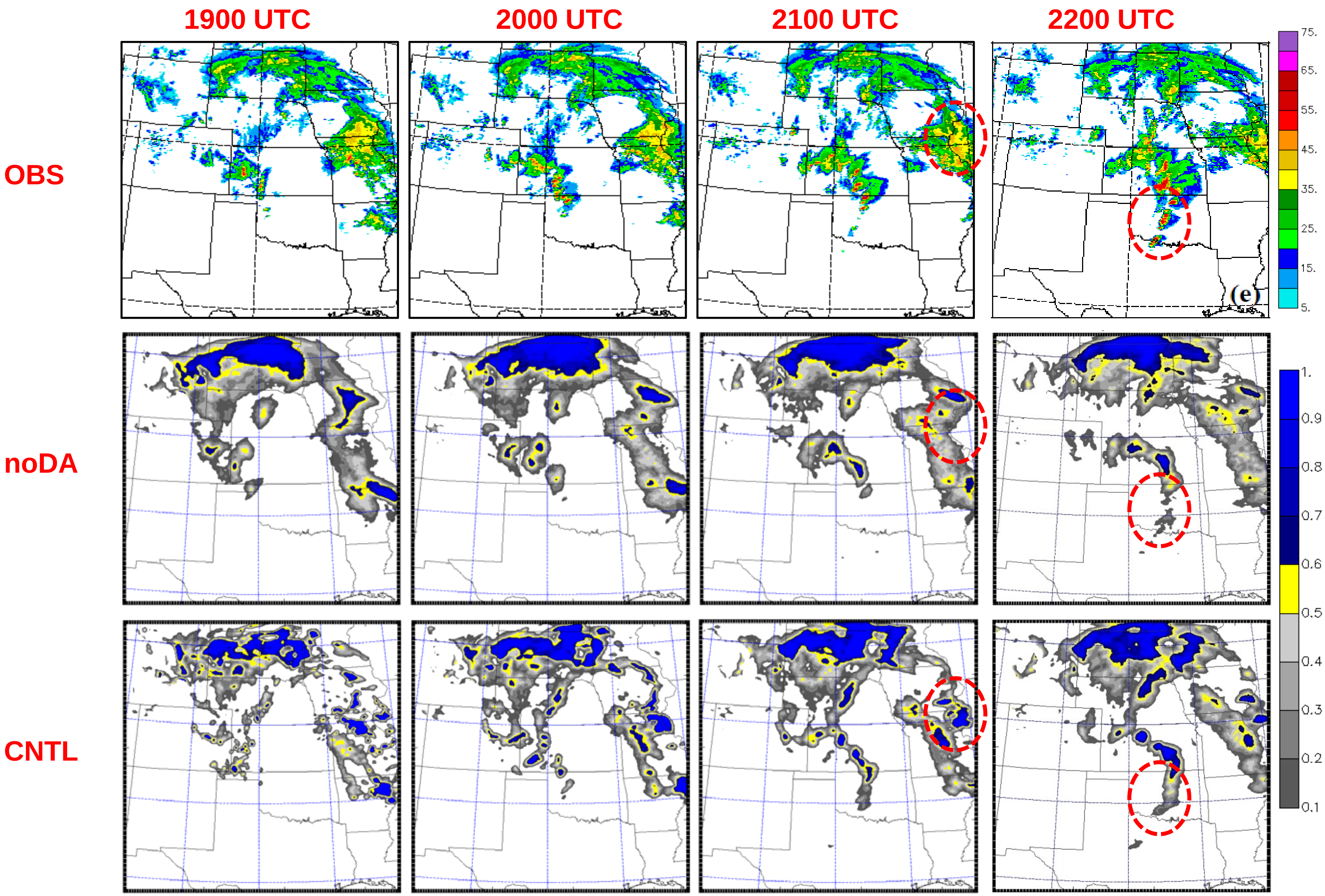
Ensemble forecasts valid at 2200 UTC

Observation | No DA | with DA

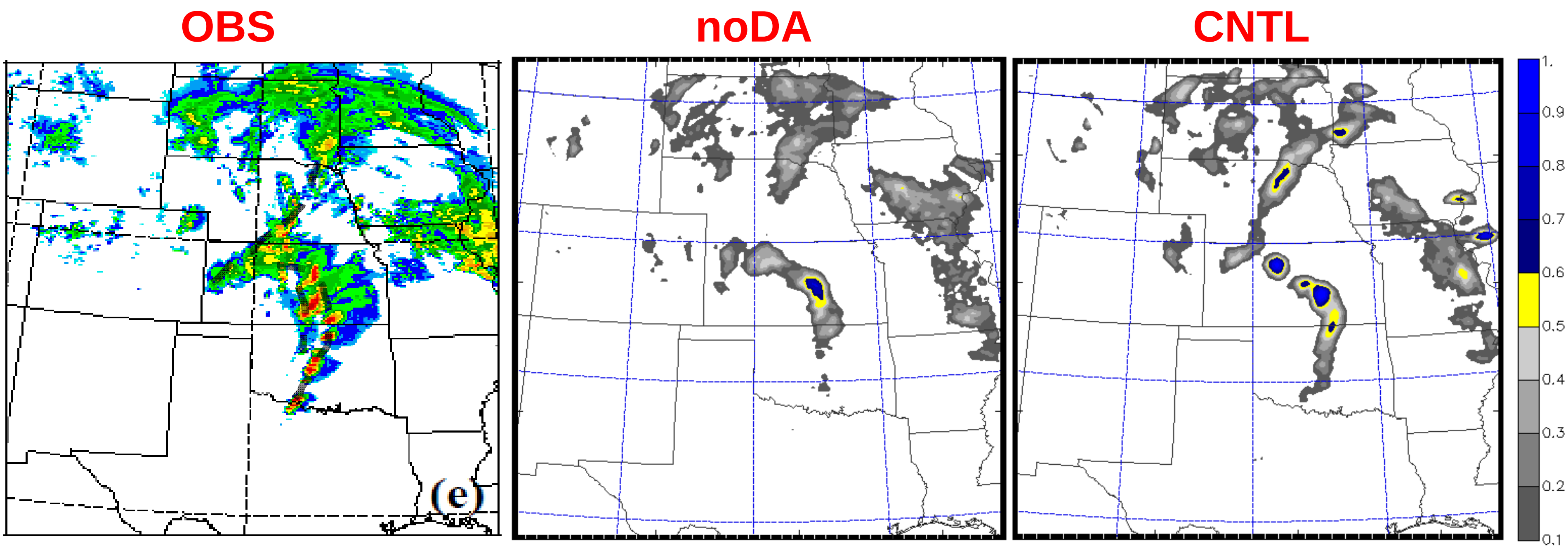


Member 12

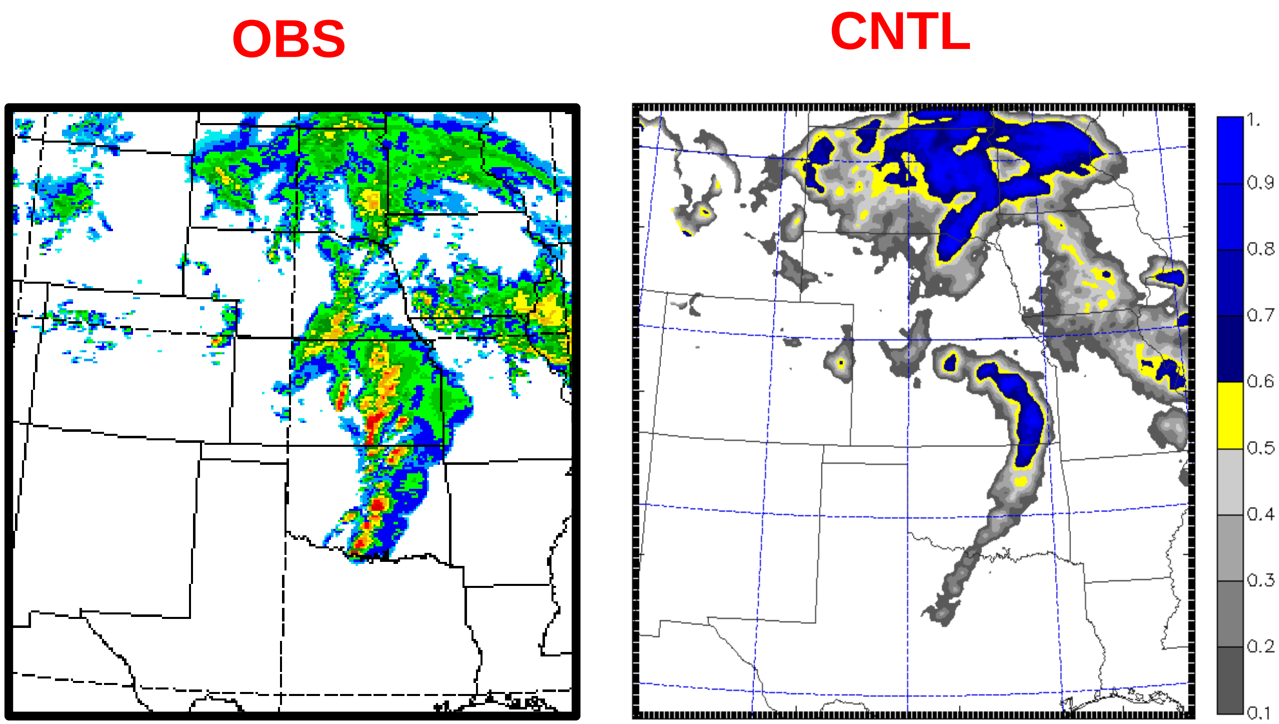
Ensemble forecast probability for Z_H > 25 dBZ at z = 2km



Ensemble forecast probability for Z_H > 35 dBZ valid at 2200 UTC (t=4 h) at z = 2km



Ensemble forecasts probability for Z_H > 25 dBZ valid at 2300 UTC (t=5 h) at z = 2km



LETKF for Doppler Radar Data

Local Ensemble Transform Kalman Filter (LETKF)

- Update for each state variable can be done in parallel (Hunt et al 2007).
- Scales to high-dimensional systems and large numbers of observations.
- LETKF has not been applied to applied to storm-scale radar DA before

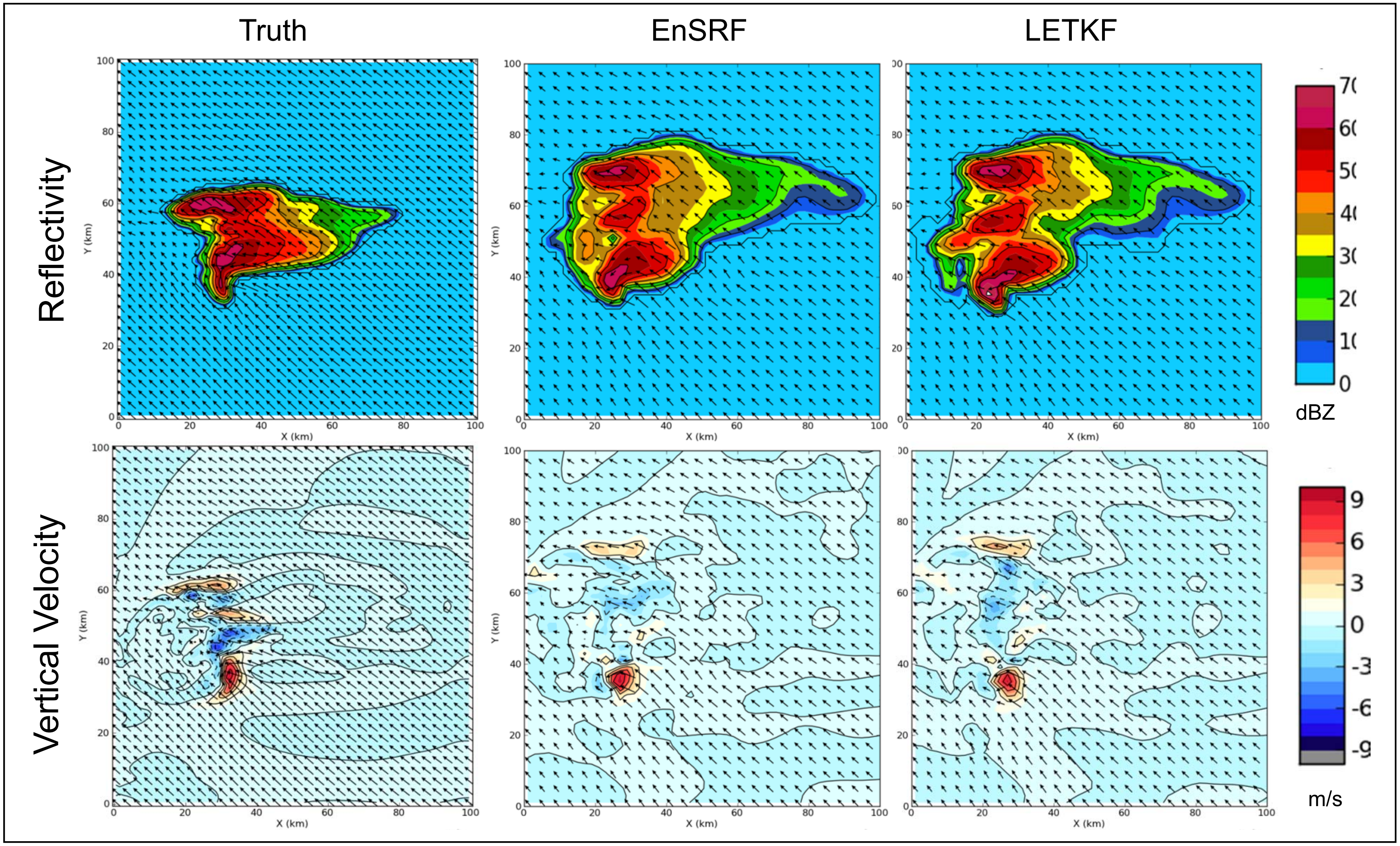
Poster 14: Doppler Radar Data Assimilation Using a LETKF (Terra Thompson)
Poster 22: Implementation of LETKF with ARPS model and some preliminary results of OSSE (Gang Zhao)

LETKF Implementation (NSSL Version)

- Built upon the LETKF kernel/core Fortran code by Takemasa Miyoshi (2010).
- LETKF is developed for the cloud model, NCOMMAS.
- System is a Python-Fortran hybrid.

- OSSE experiments: supercell environment, 2 km horizontal grid, 15 ensemble members, assimilation of radial velocity observations every 2 minutes for 40 minutes.

Preliminary Results (work in progress)



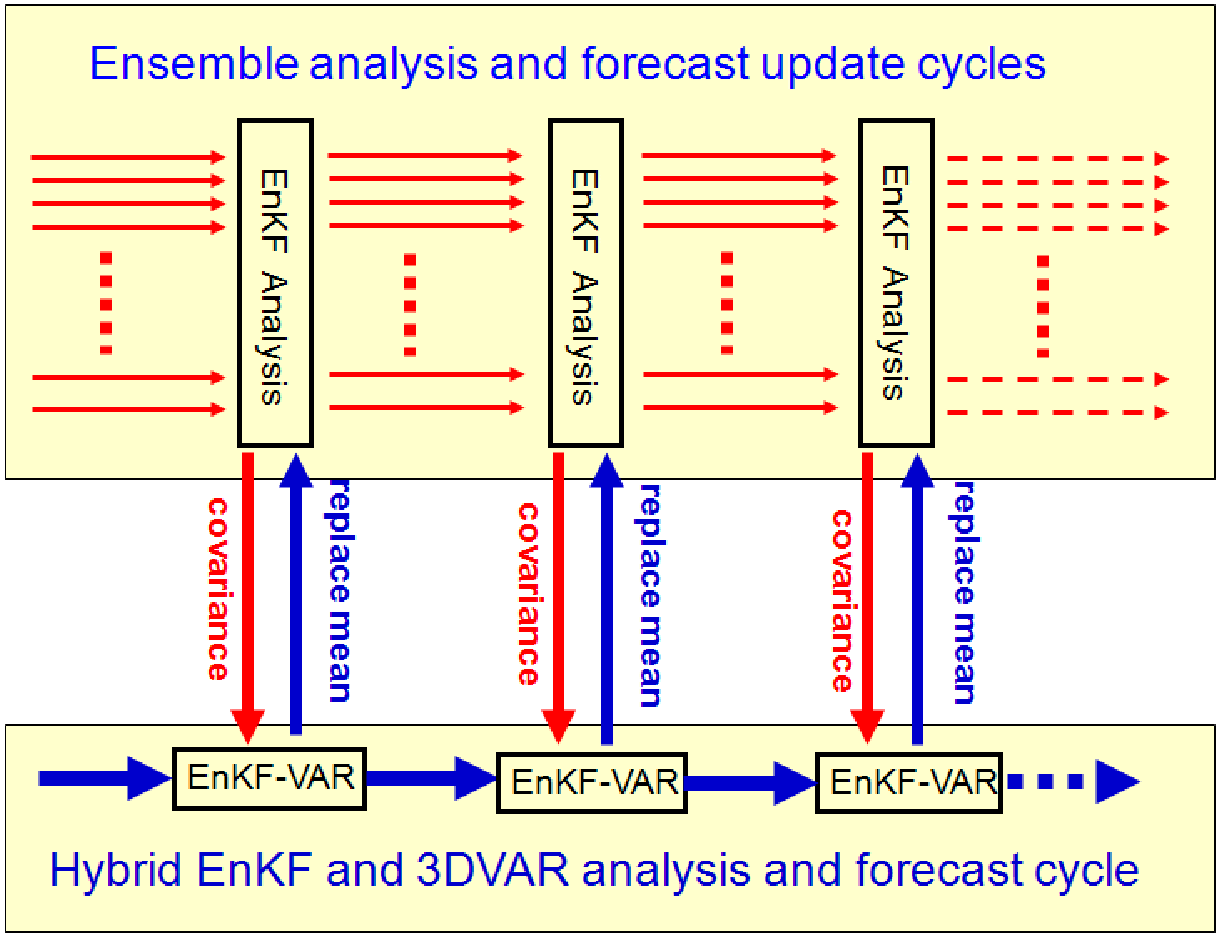
For more details see "Doppler Radar Data Assimilation Using a LETKF" poster by Terra Thompson, Lou Wicker, Xuguang Wang.

Analyses after 40 min of 2 min cycles, only Vr data were used

Hybrid Variational-Ensemble DA

- Combines the strengths of variational (VAR) and ensemble DA methods
- Allows VAR to use flow-dependent background error covariance P.
- Allows the inclusion/use of equation constraints (including full model equations in 4DVAR)
- Allows model-space localization for correctly handling non-local observations (e.g., radiance, attenuated reflectivity)
- For small ensembles, combination of static B and P promises to give better results then P alone.
- Ease the transition from currently operational 3DVAR to eventual ensemble-4DVAR hybrid.
- Direction that NCEP, UK Met Office, Env. Canada, etc. are taking.

ARPS Hybrid 3DVAR-EnKF Data Assimilation System

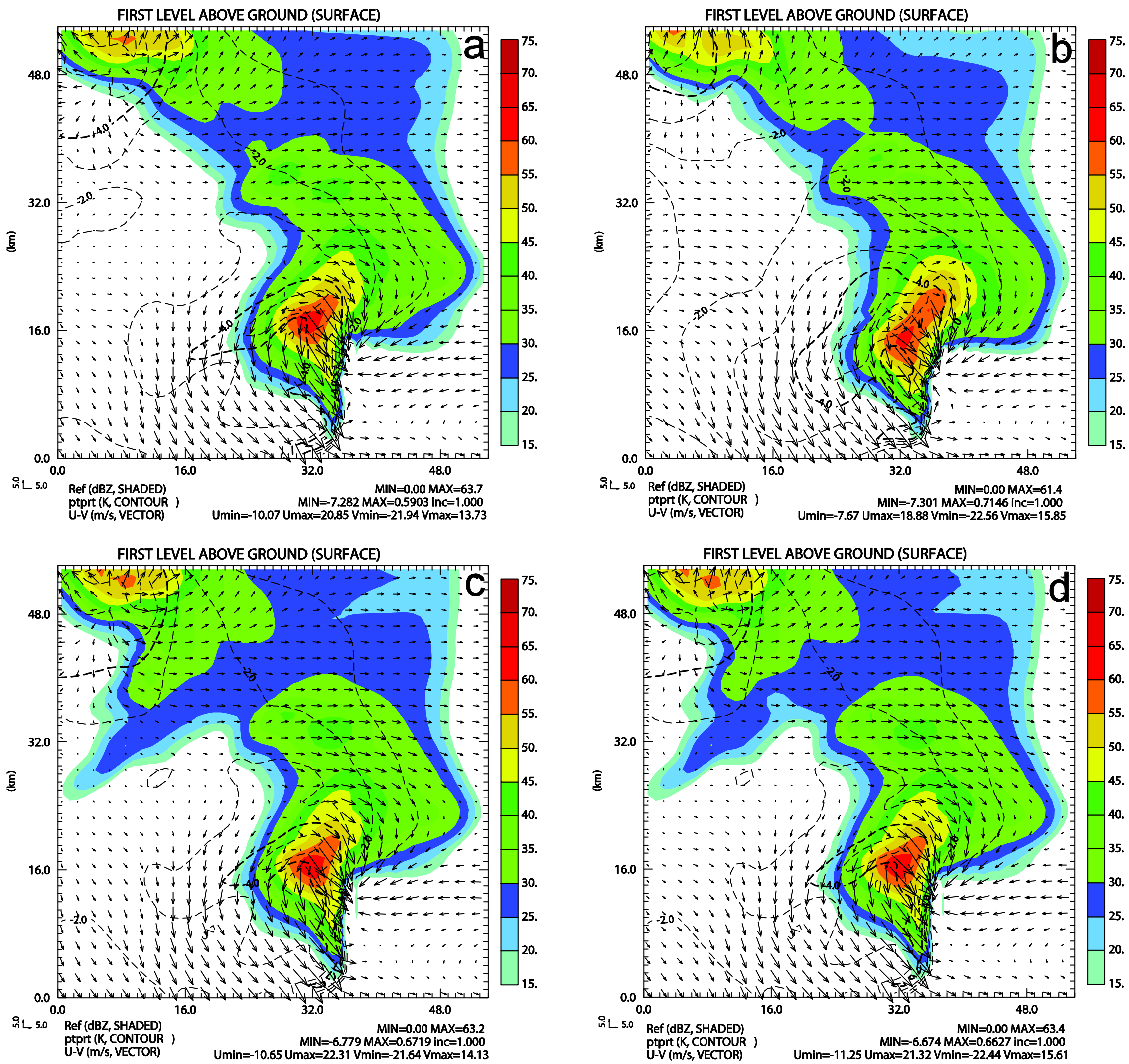


Gao, Xue and Stensrud (2010 SLS)

θ'(contours), Z(color shades) and V_h (vectors) at Surface at the End of the 80 Min. DA Cycles with single radar

Truth

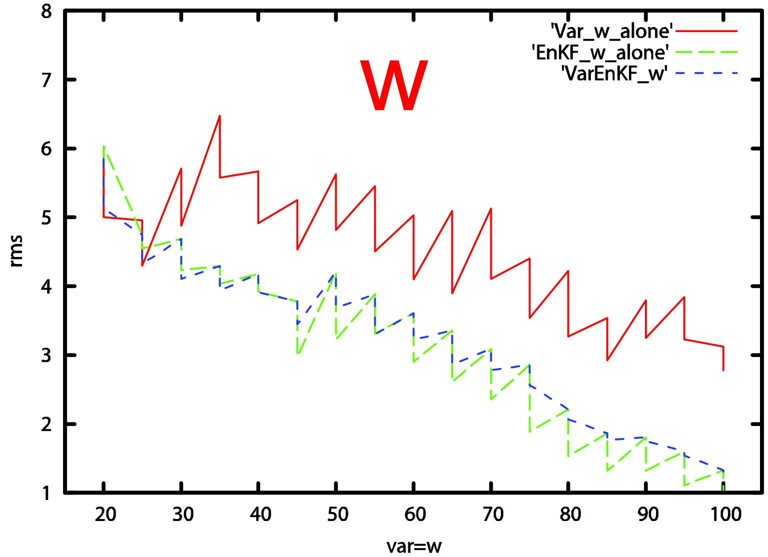
3DVAR

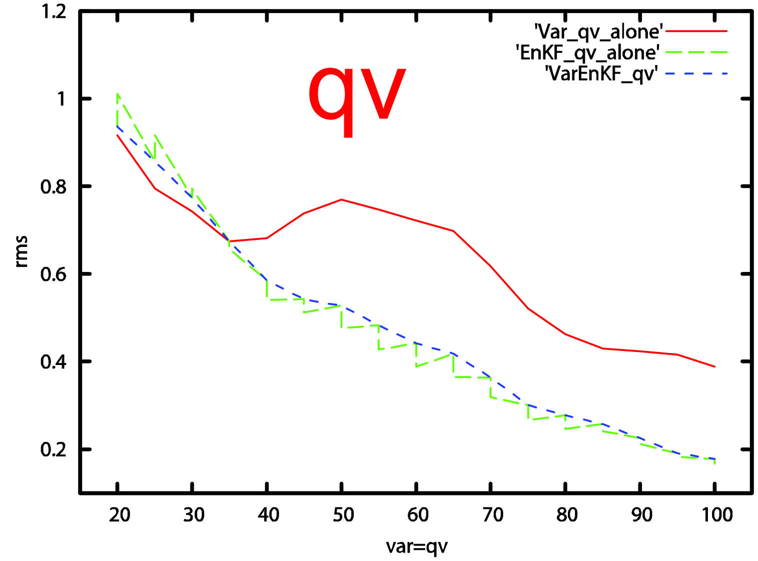


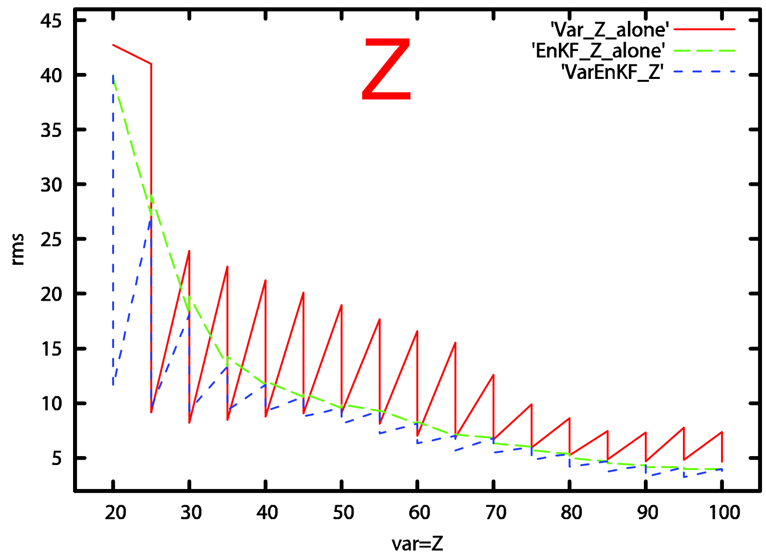
Pure EnKF

Hybrid

Analysis RMS Errors with Radar from One Radar







Red: 3DVAR

Green: Pure EnKF

Blue: 3DVAR-EnKF hybrid,
100% flow-dependent P

Assimilating Reflectivity Within a 3DVAR Framework

Previous research:

> 4DVAR technique (Sun and Crook 1997;1998);

> EnKF (Tong and Xue 2005; Dowell, Wicker and Synder, 2011);

> Cloud Analysis method (Alber et al. 1996; Brewster et al. 2005; Hu et al. 2006; Weygandt and Benjamin et al. 2008);

> MM5 3DVAR (Xiao et al. 2005), 3.5VAR (Zhao et al. 2008)

This study is trying to assimilate reflectivity in a unified 3DVAR framework by including ice hydrometeors and partition of hydrometeors using temperature field from NWP model.

(Gao and Stensrud, 2011, *J. Atmos. Sci.* Accepted).

Assimilating Reflectivity Within a 3DVAR Framework

- First method (1)

  - total reflectivity computed as

$$Z_e = Z_{er}(q_r) + Z_{es}(q_s) + Z_{eh}(q_h)\,, \qquad (1)$$

- Second method (2)

  – partition reflectivity via temperature from NWP model output.

  • T > +5 C: all rain

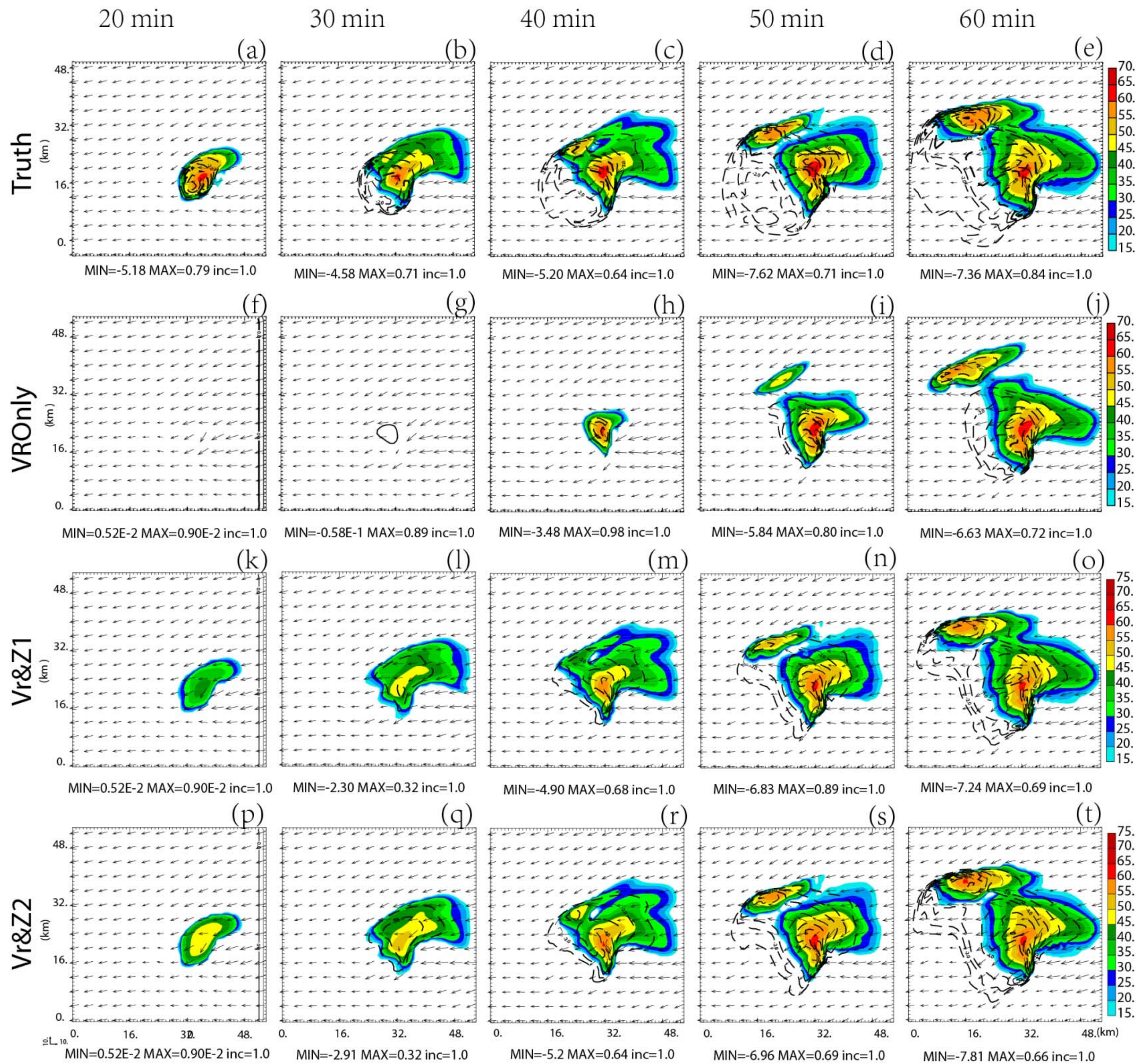
  • T < - 5 C: all snow and hail

  • 5 C > T > -5 C: mixed phase

  - linearly partition reflectivity between rain and ice

$$\boxed{Z_e = \begin{cases} Z_{er}(q_r) & T_b > 5^oC \\ Z_{es}(q_s) + Z_{eh}(q_h) & T_b > -5^oC \\ \alpha Z_{er}(q_r) + (1-\alpha)\left[Z_{es}(q) + Z_{eh}(q)\right] & -5^oC < T_b < 5^oC \end{cases}} \qquad (2)$$

(Gao and Stensrud, 2012, *JAS*) Poster 6



5 min cycled 3dvar analysis

For an idealized Case

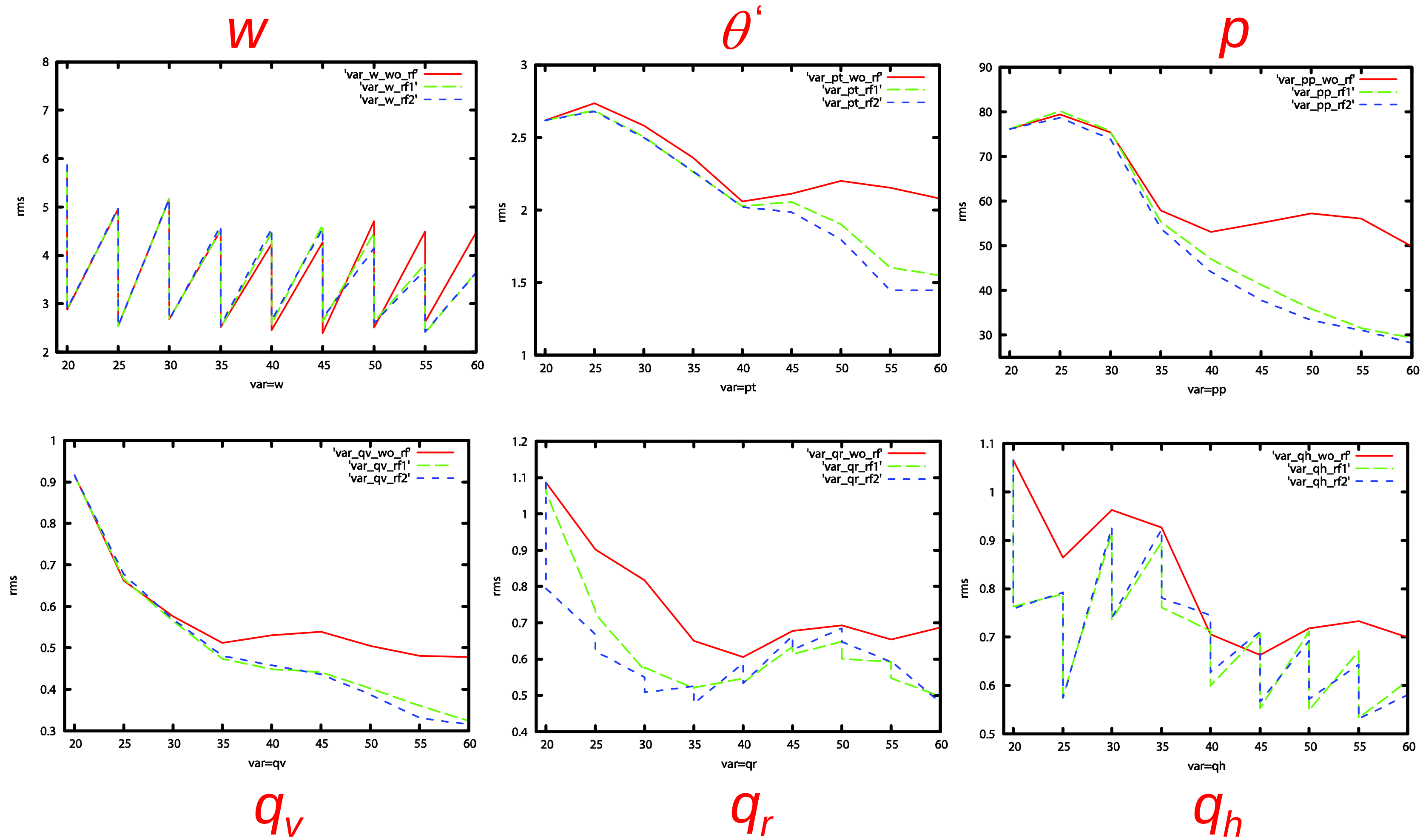
Z (shaded)

V (vectors)

θ (contours)

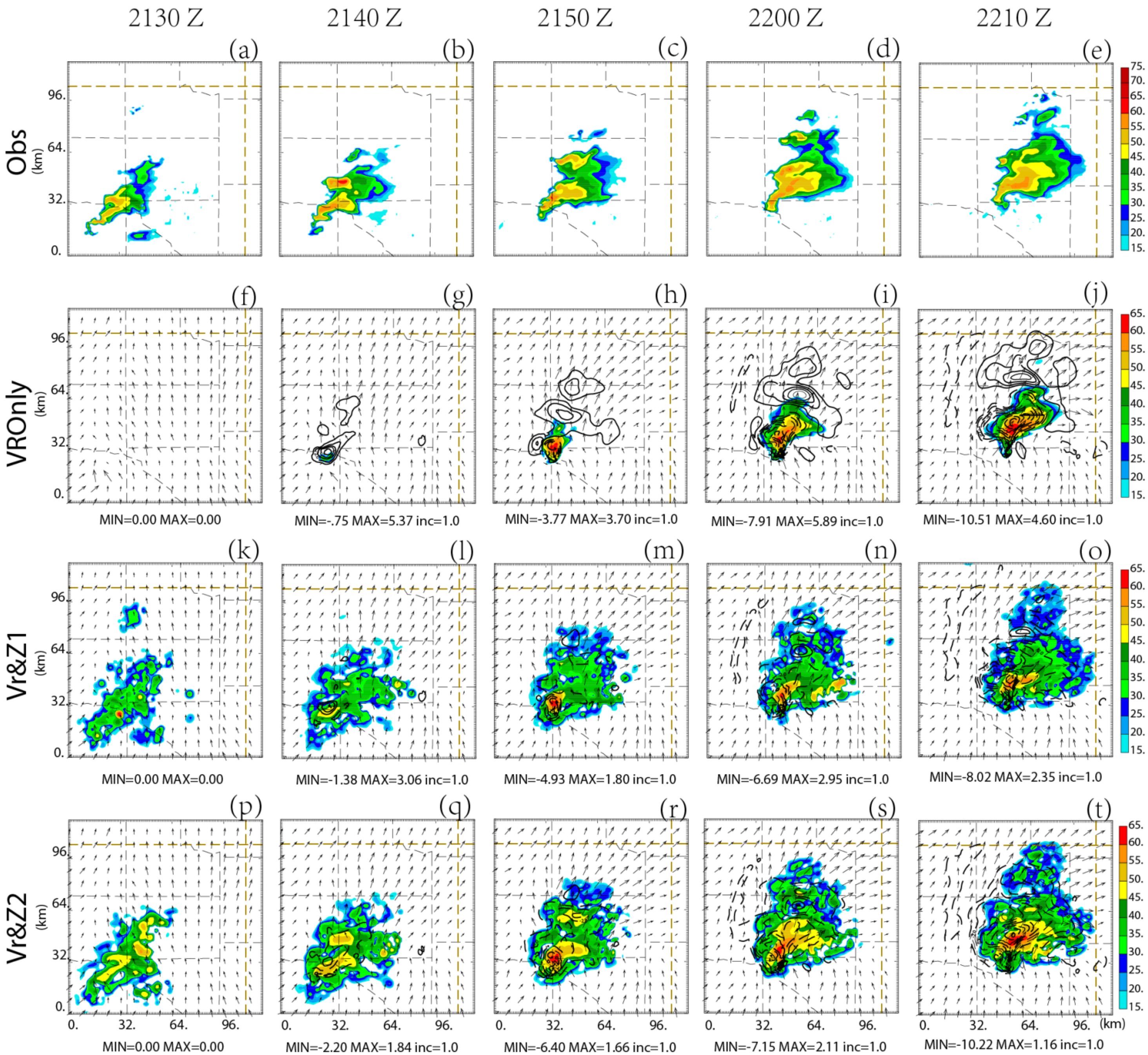
(Gao and Stensrud, 2012, *JAS*)

RMS Errors of the Analyses for 6 model variables



Red real line is for Vr only; dashed green is for Vr&Z(1) and the dashed blue is for Vr&Z(2)

May 8, 2003 OKC Tornadic Supercell case



Z (shaded)

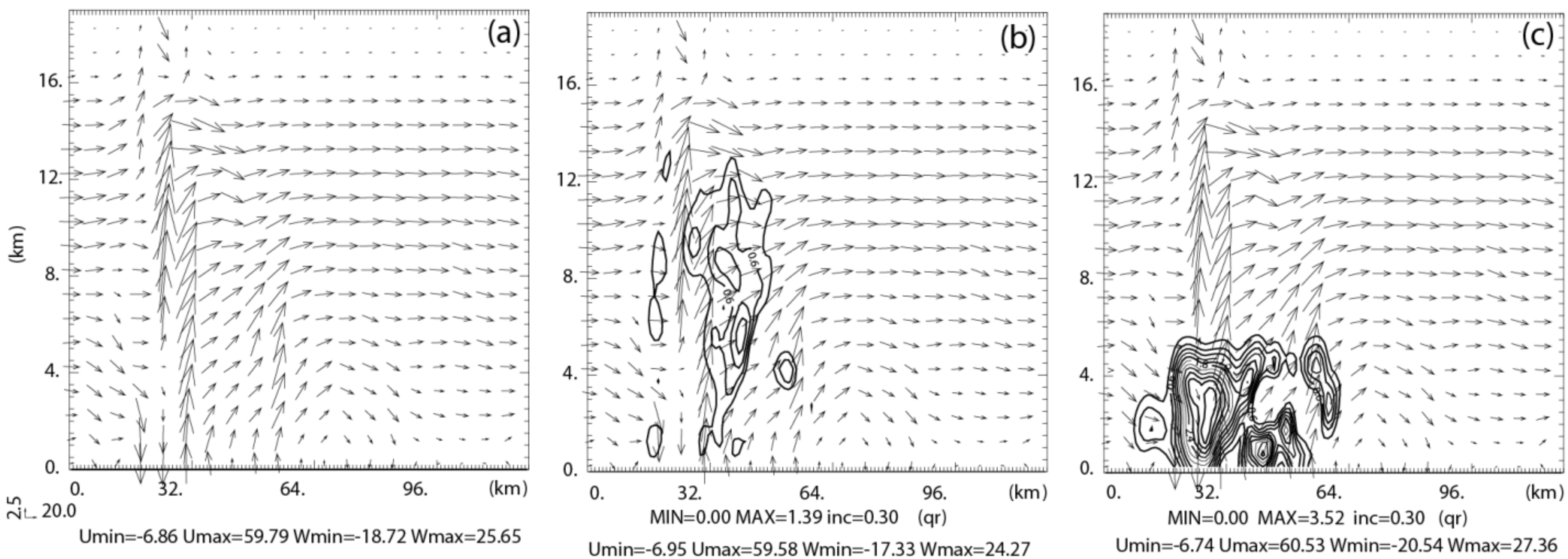
V (vectors)

θ (contours)

Poster 6

(Gao and Stensrud, 2012, *JAS*)

Vr Only | Vr & Z (1) | Vr & Z (2)



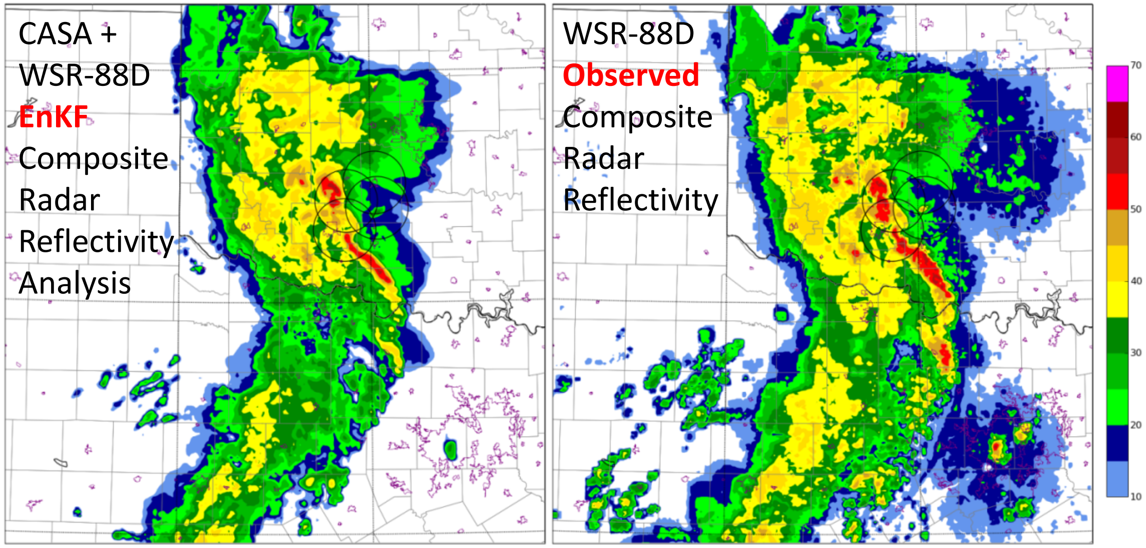
A x-z vertical slice for V (m s^{-1}), qr (contours)

At 2130 UTC, 8 May 2003 OKC supercell storm

Assimilation of CASA and 88D radar data using mixed-microphysics ensemble: Results of EnKF Analysis using dx=2km

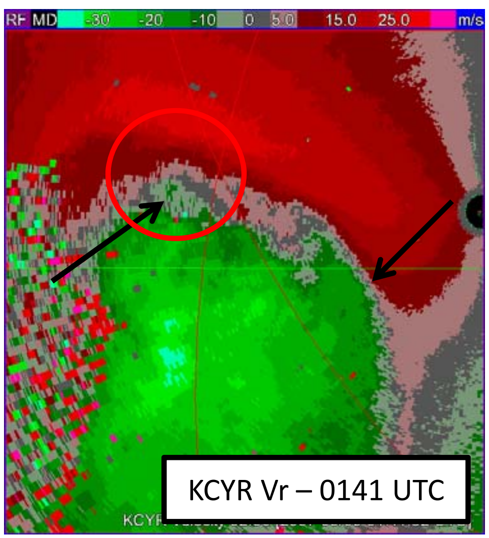
Nathan Snook Talk Thursday

Final analysis (0200 UTC) Reflectivity

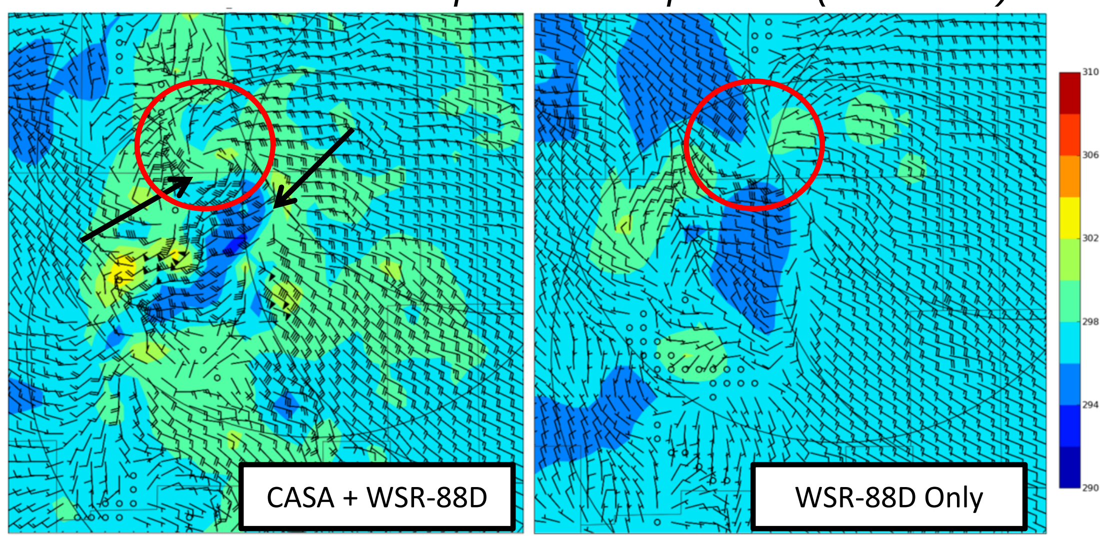


Snook et al (MWR 2011)

See also Snook's Talk



Near-surface winds and potential temperature (0140 UTC)

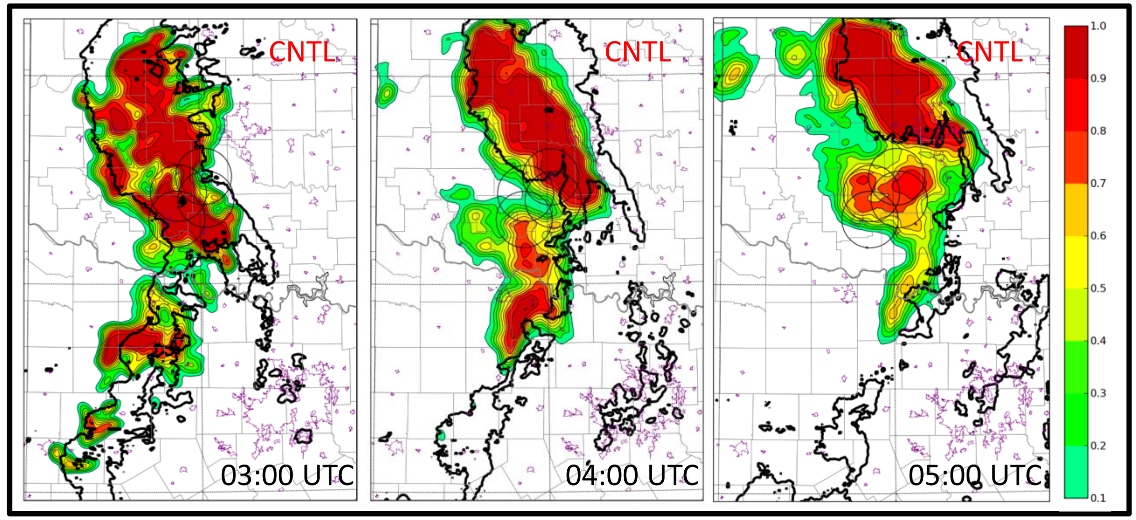


Effects of assimilated CASA data and mixed-microphysics ensemble

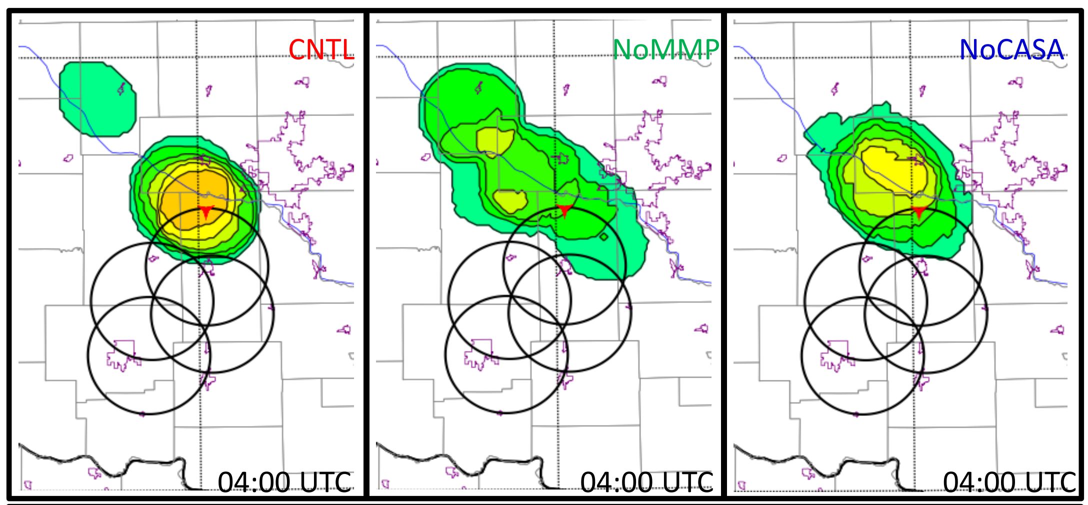
Ensemble-based Probabilistic Convective-scale Forecasts

- Probabilistic ensemble forecasts were generated from the final analysis state at 0200 UTC.
- For probabilstic prediction of radar reflectivity, areas of highest probability match well in placement and motion compared with observed 25 dBZ threshold.
- Assimilation of CASA radar data and use of a mixed-microphysics ensemble improved probabilistic vortex prediction; promising results were obtained predicting tornadic meso-vortices on timescales of 0-3 hours.

1, 2, and 3-Hour Probabilistic Forecasts for P[Z > 25 dBZ]



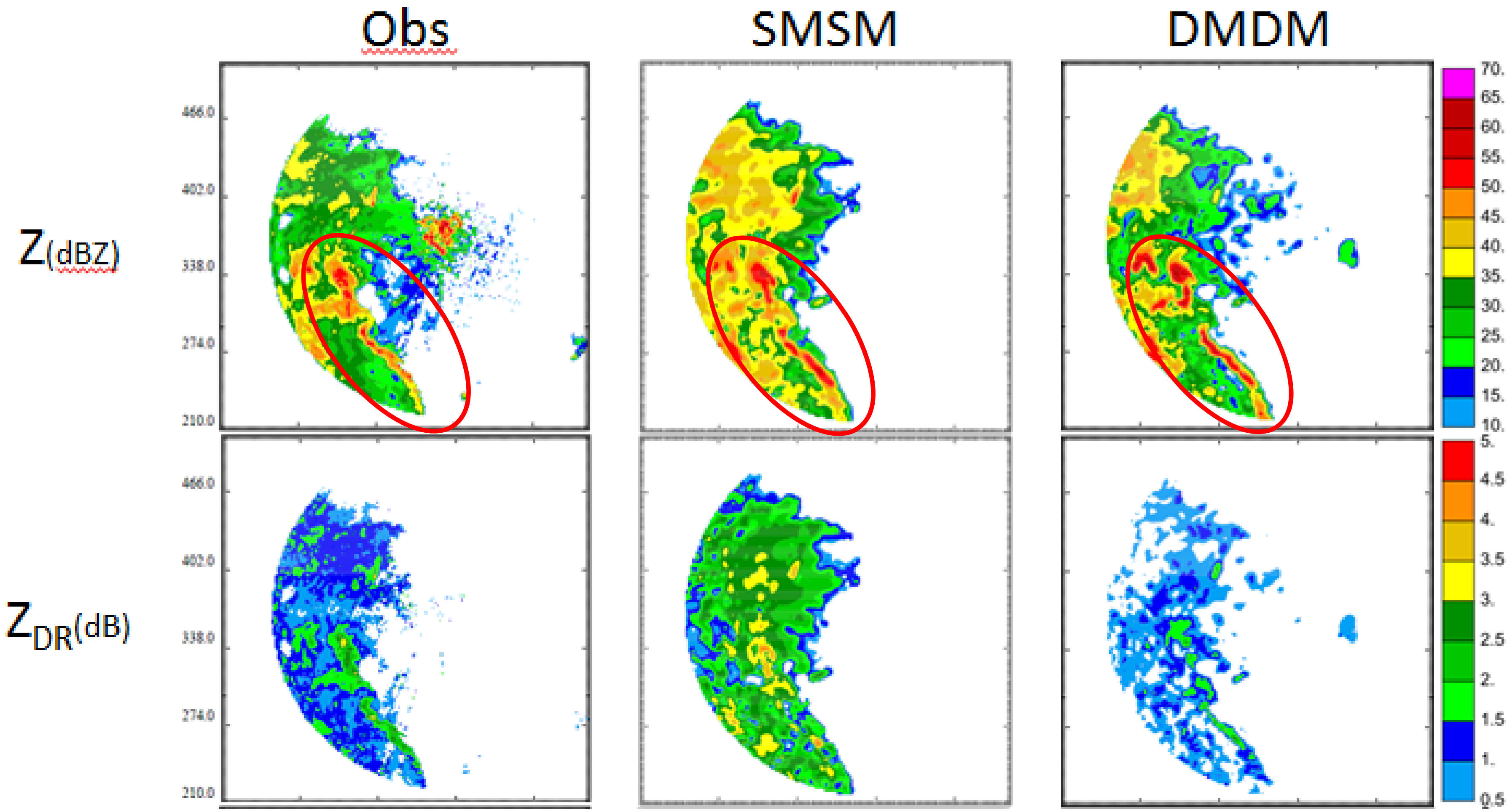
2-Hour Probabilistic Forecasts for Presence of Near-surface Vortices



CNTL: 0.65 NoMMP: 0.35 NoCASA:0.43

Single- and Dual-Moment Microphysical State Estimation With EnKF Direct Comparison with Radar Reflectivity

Simulated dual-pol signatures at the final analyses at 0.5 tilt

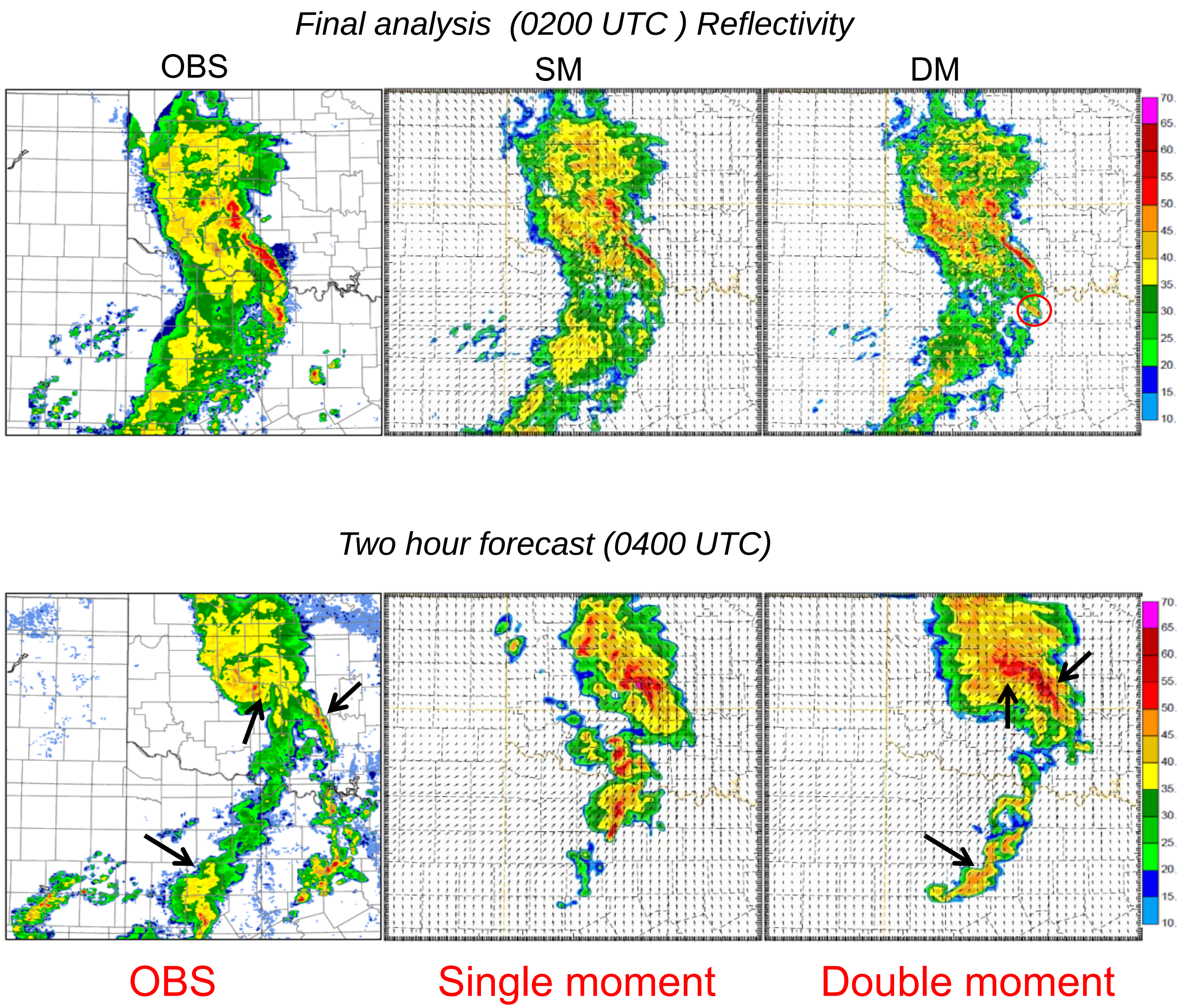


Single- and Dual-Moment Microphysical State Estimation With EnKF

Direct Comparison with Radar Reflectivity

- The analyzed reflectivity fields in both 1-moment and 2-moment experiments compare well with radar observations (shown at top).
- However, 2-moment forecast show significant improvement over the 1-moment experiment (shown at bottom).
- The structure and evolution of the forecast MCS, LEV and leading and trailing convective lines is remarkably better with a 2-moment scheme throughout the forecast period than with a 1-moment scheme.

Poster 21.



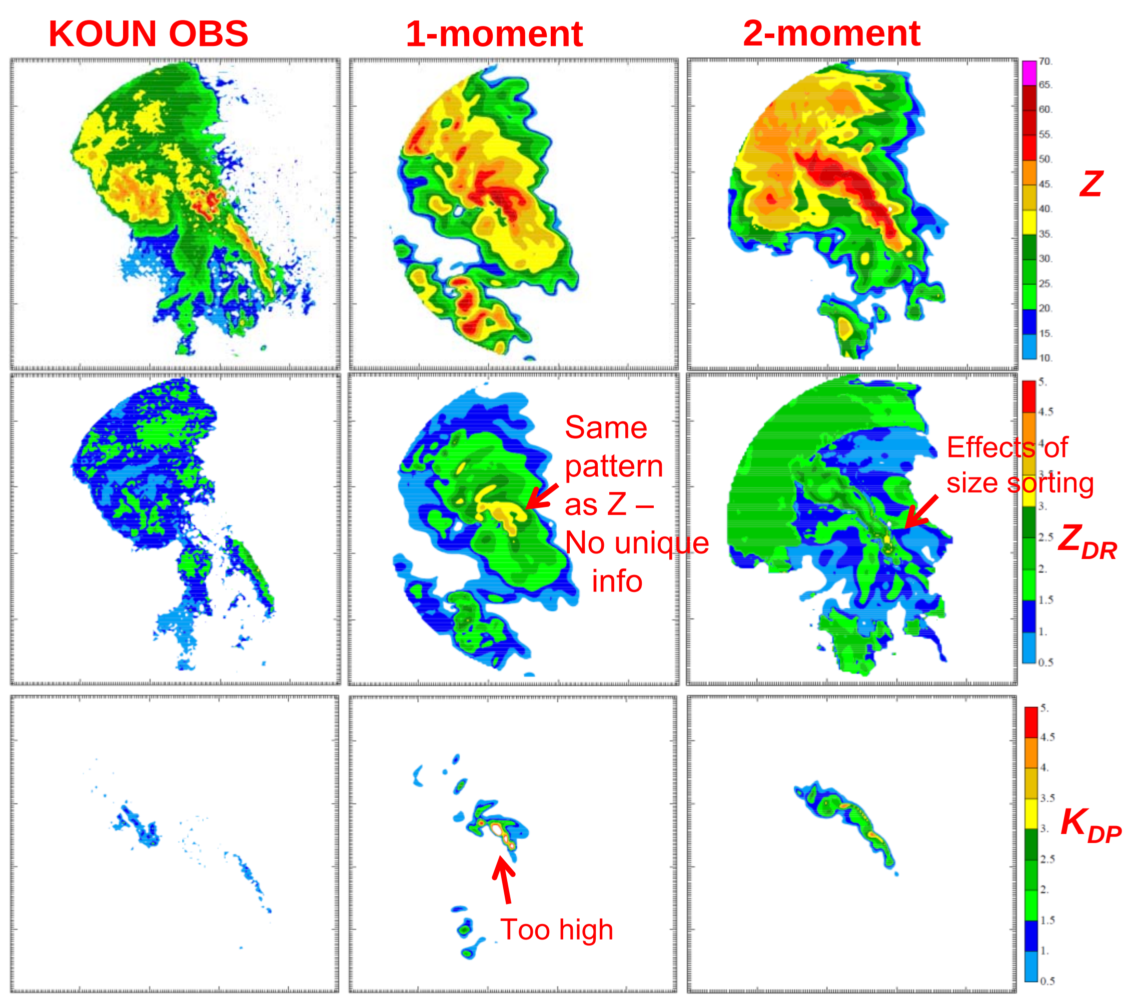
Single- and Dual-Moment Microphysical State Estimation With EnKF

Direct Comparison with Polarimetric Variables

(Putnam, et al.)

- Polarimetric variables on .5 tilt as seen by KOUN using polarimetric radar data simulator (Jung et al. 2010)
- The polarimetric signatures are more realistic in the 2-moment results in general.
- Specifically, there is evidence of size sorting of hydrometeors on the leading edge of the system indicated by increased Z_{DR}. The reduction of Z_{DR} in the center of the line in 2-moment experiment is due to hail while observations show no sign of hail.
- K_{DP} is unrealistically high in the 1-moment scheme (maximum ~ 11 deg/km), suggesting an excess of rain drops. As with Z_{DR} , the 2-moment scheme values are also higher than observed, but the results are in a closer agreement with observations.

Two hour Forecast (0400 UTC)

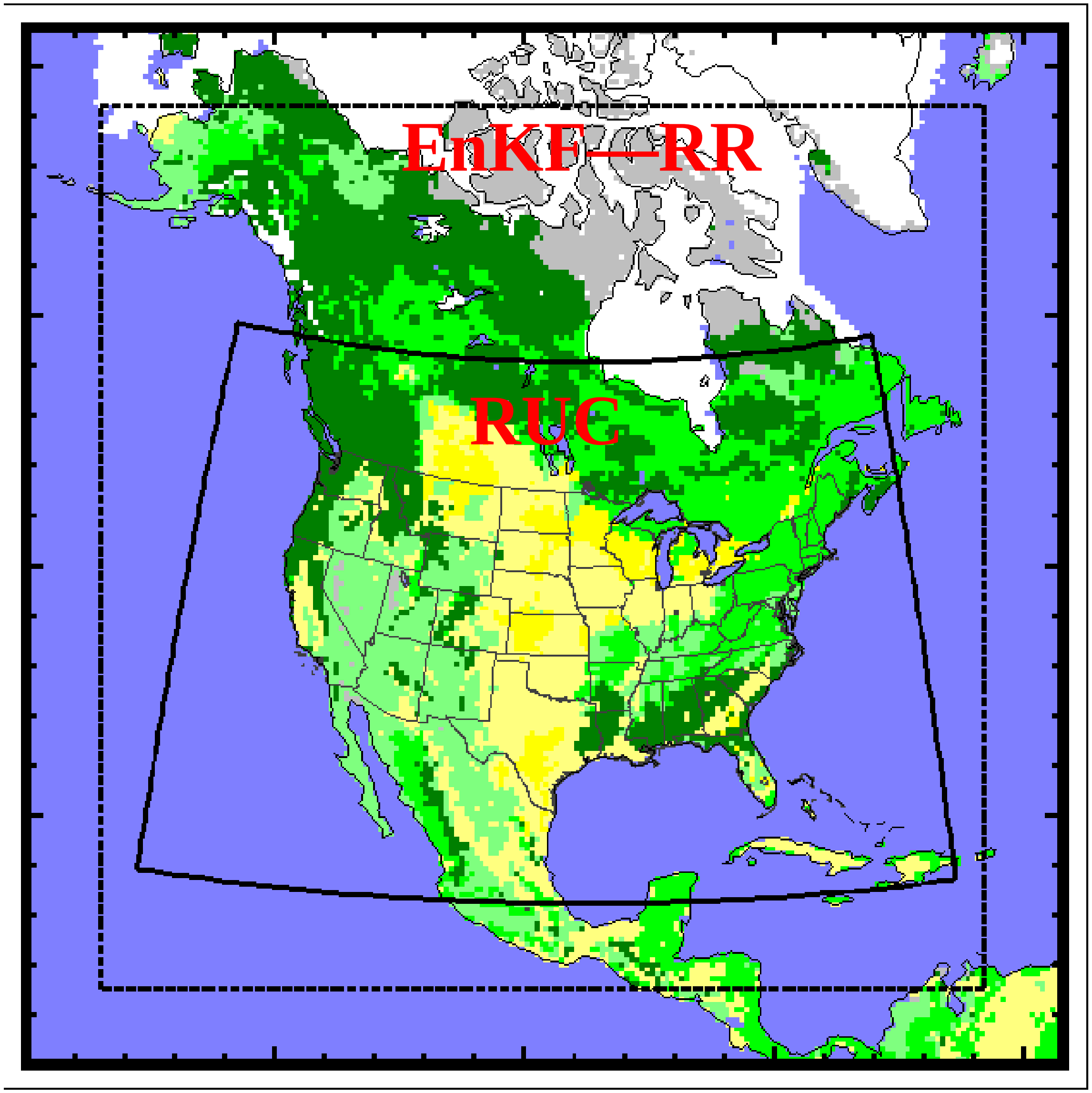


Development and Testing of GSI-based EnKF and EnKF-Hybrid for Rapid Refresh Configurations

Kefeng Zhu, Yejie Pan, Ming Xue, Xuguang Wang
Center for Analysis and Prediction of Storm

Jeffrey Whitaker, Stephen Weygandt, Stanley Benjamin, Ming Hu
NOAA/ESRL

FAA-Supported EnKF/Hybrid work for RR



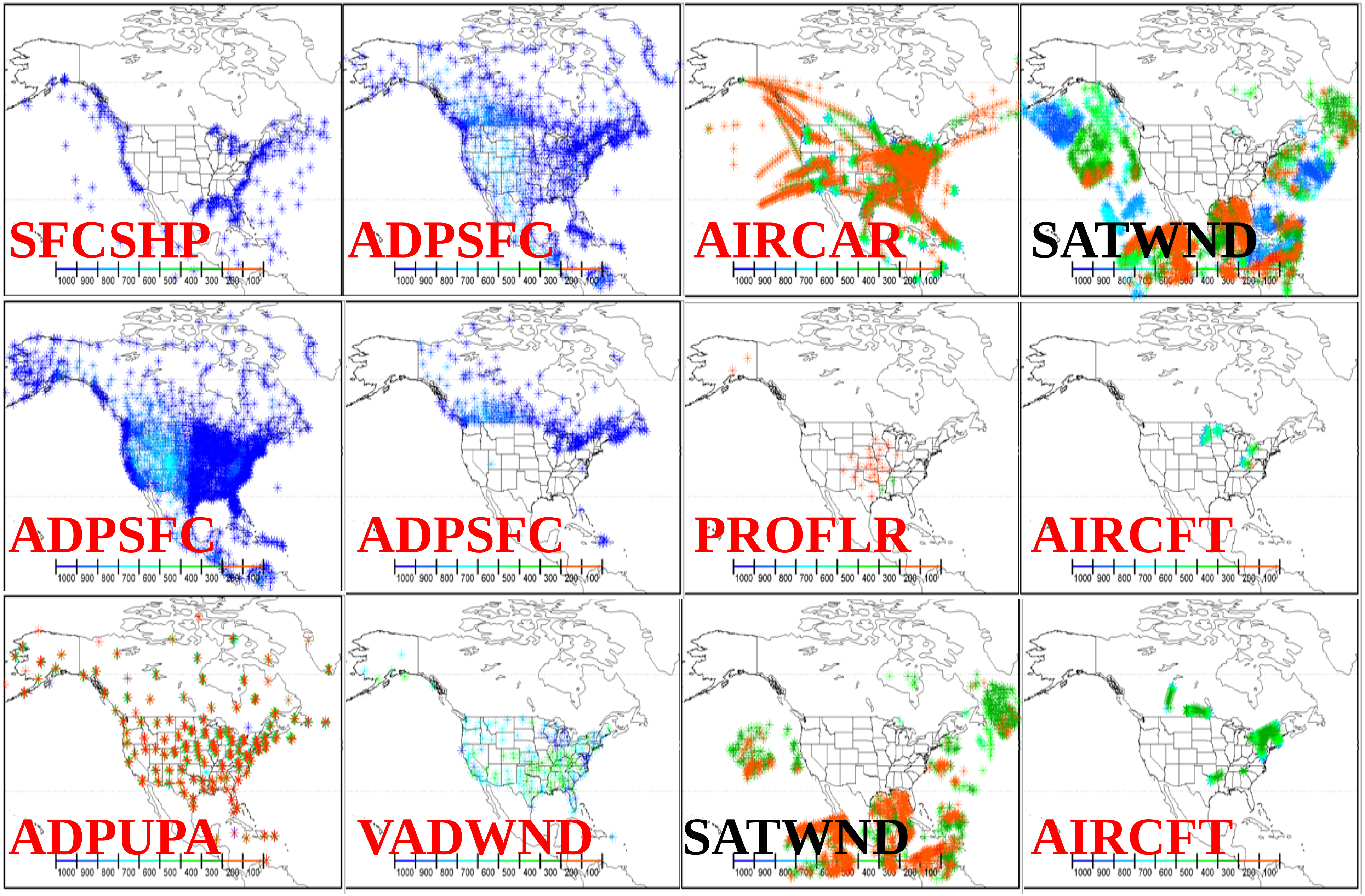
EnKF Test Domain
207x207 grid points
~40 km, 51 levels

The 13 km RR-like forecast Domain
532x532 grid points
~13 km, 51 levels

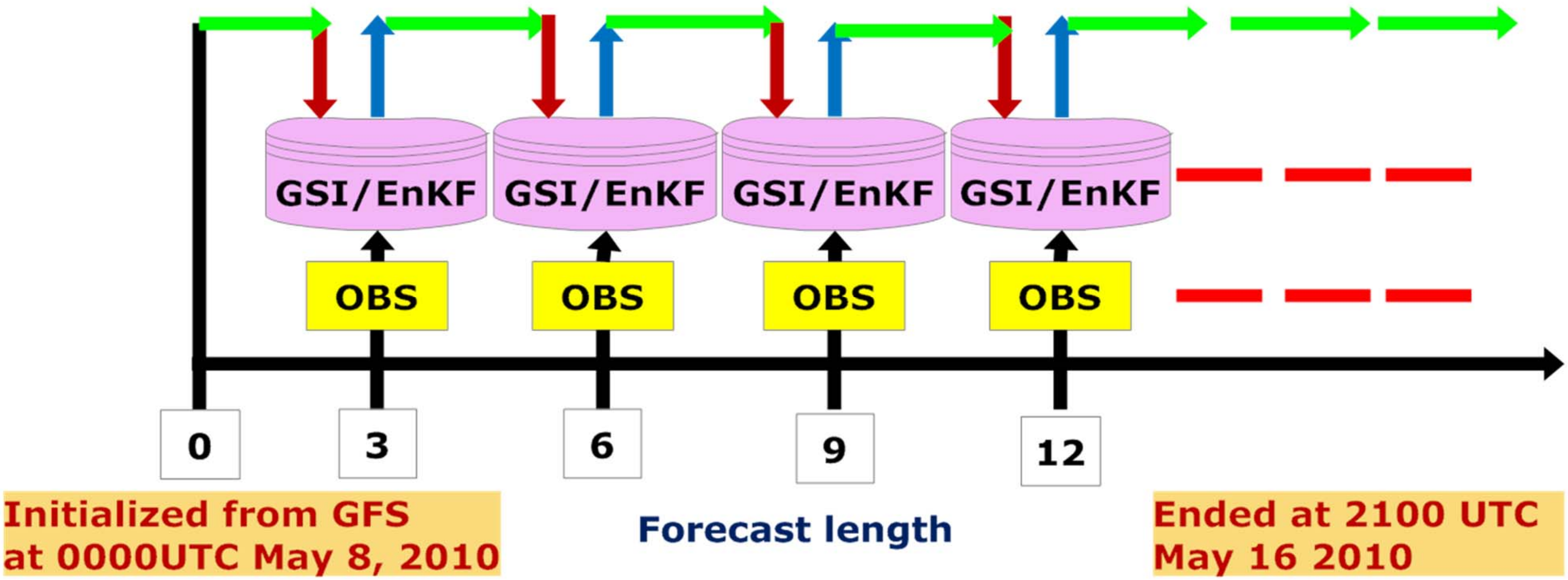
Current RUC Domain as indicated

Started working on GSI-based hybrid

Observation Distribution Valid at 2010051412

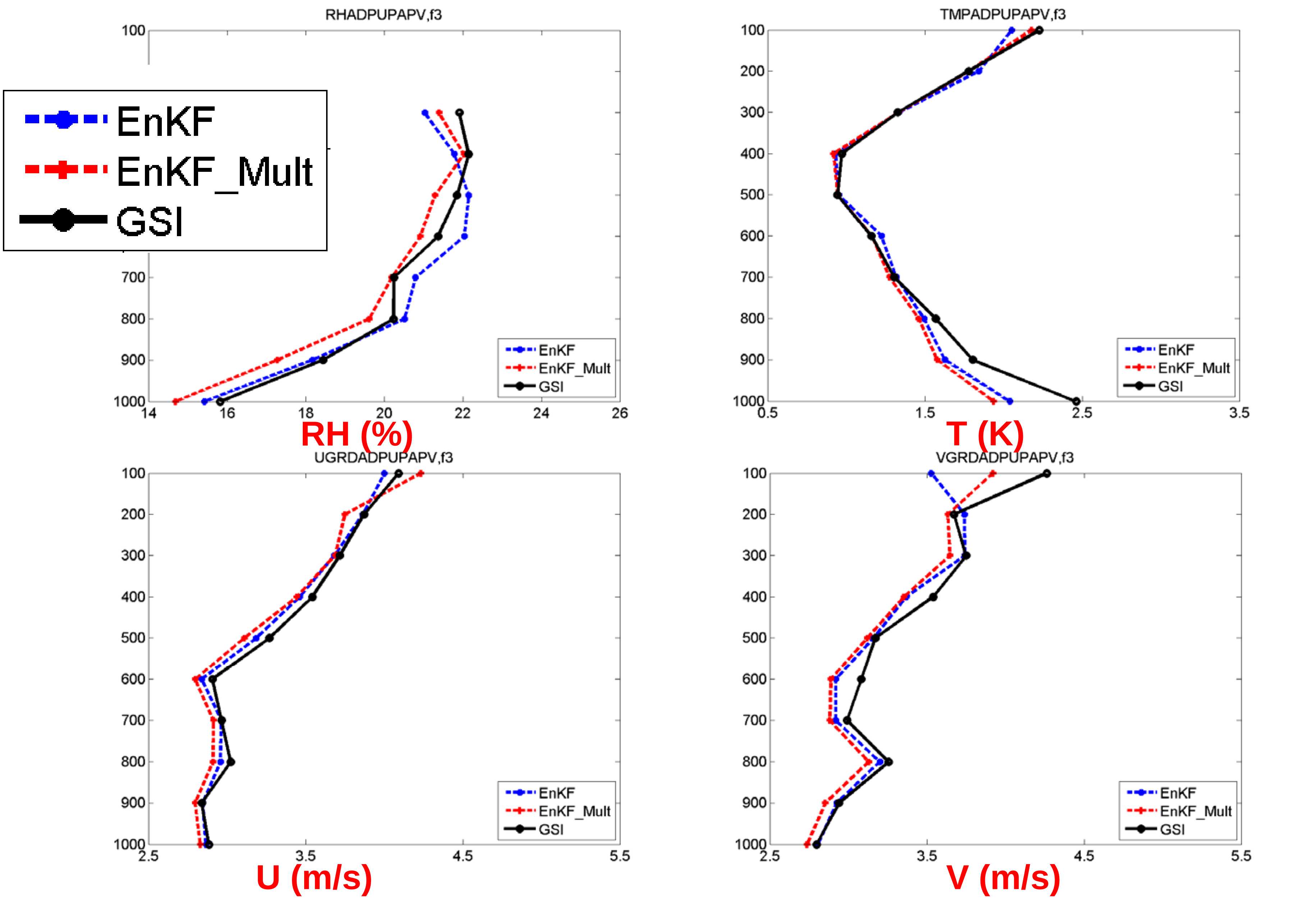


Flowchart of EnKF/GSI

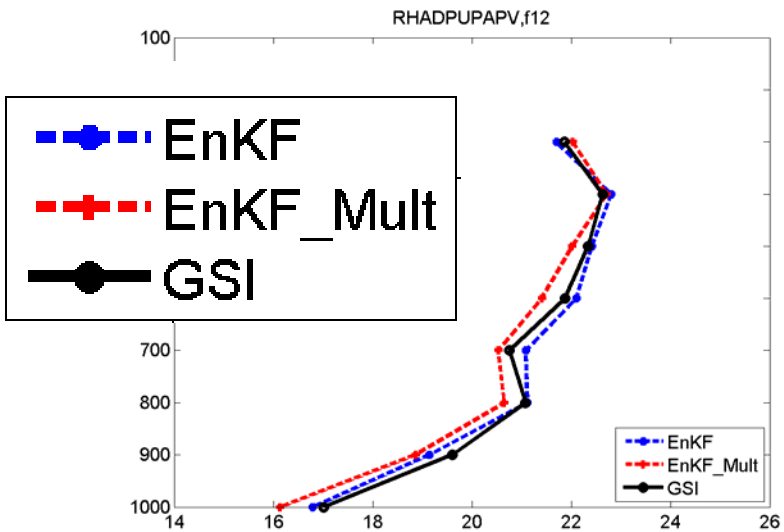


Both EnKF and GSI were run with 3-hourly assimilation cycles for a one-week-long test period starting at 00 UTC, May 8 2010.

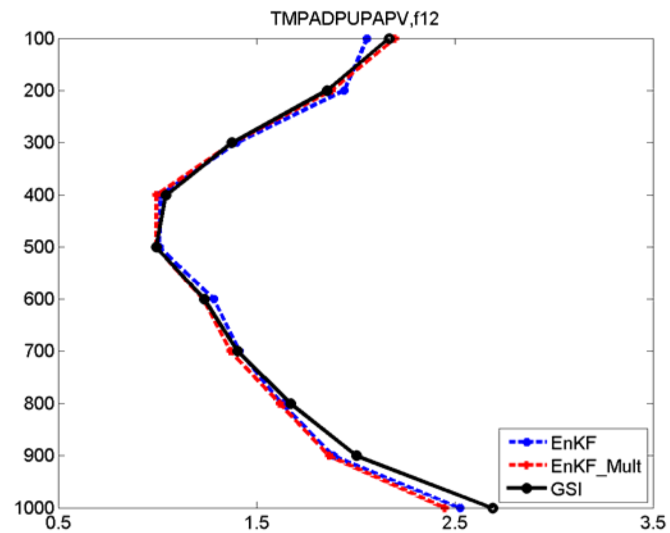
3-h forecasts verified against sounding (EnKF v.s. GSI)



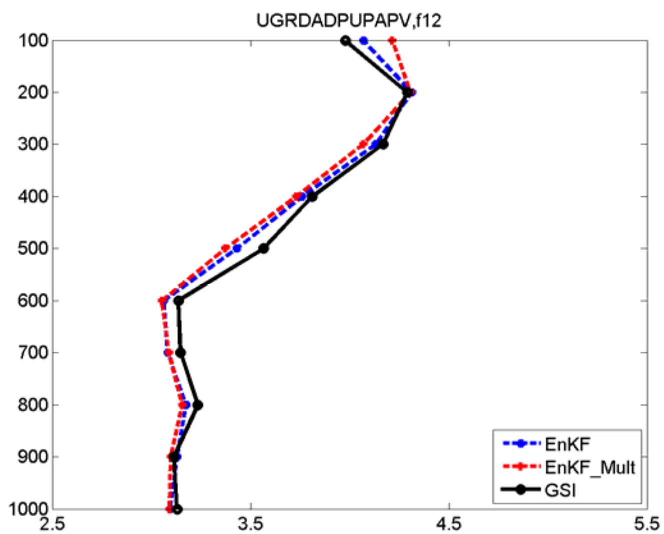
12-h forecasts verified against sounding (EnKF v.s. GSI)



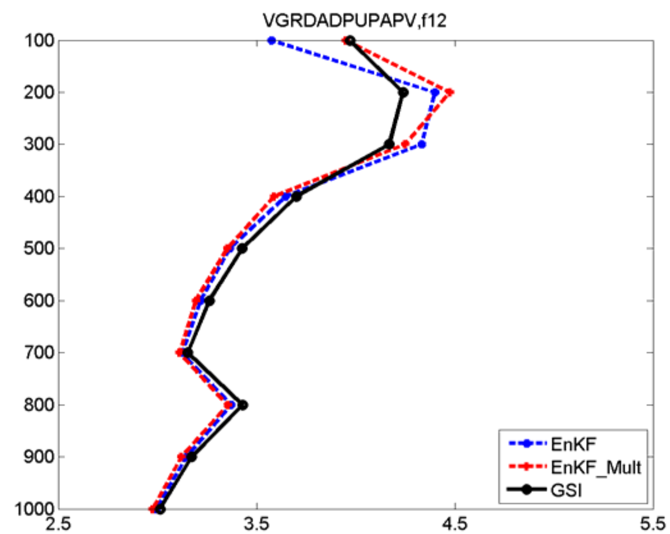
RH (%)



T (K)

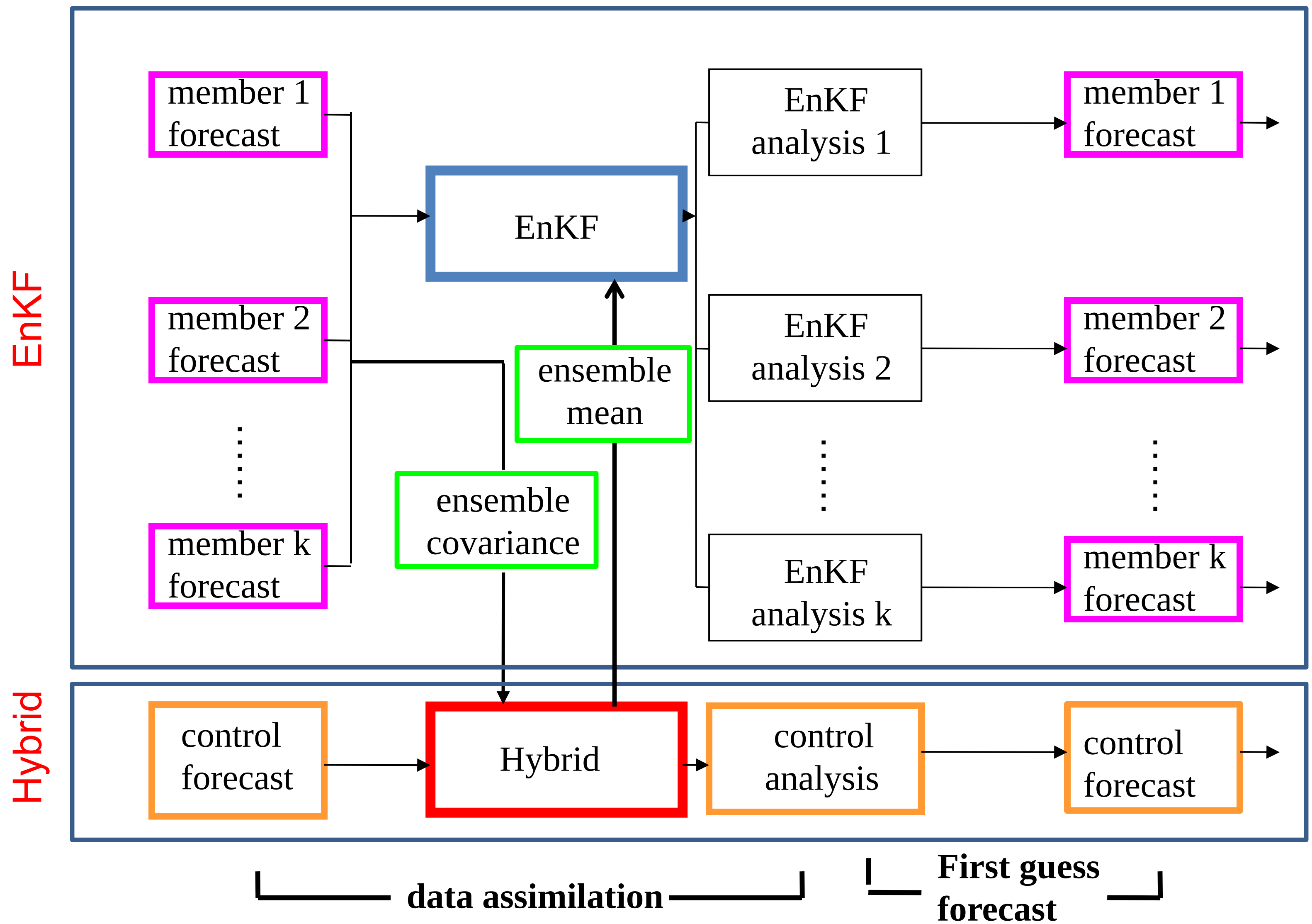


U (m/s)



V (m/s)

EnKF-Hybrid DA System



How to incorporate ensemble in GSI?

- Ensemble covariance is included in the VAR cost function through augmentation of control variables (Lorenc 2003; Buehner 2005; Wang et al. 2007a, 2008a, Wang 2010) .
- Hybrid formula (Wang 2010 -- formula for GSI with B preconditioning):

$$J(\mathbf{x}_1', \boldsymbol{\alpha}) = \beta_1 J_1 + \beta_2 J_e + J_o$$

$$= \beta_1 \frac{1}{2} \mathbf{x}_1'^T \mathbf{B}^{-1} \mathbf{x}_1' + \beta_2 \underbrace{\frac{1}{2} \boldsymbol{\alpha}^T \mathbf{C}^{-1} \boldsymbol{\alpha}} + \frac{1}{2} \left(\mathbf{y}^{o'} - \mathbf{H}\mathbf{x}'\right)^T \mathbf{R}^{-1} \left(\mathbf{y}^{o'} - \mathbf{H}\mathbf{x}'\right)$$

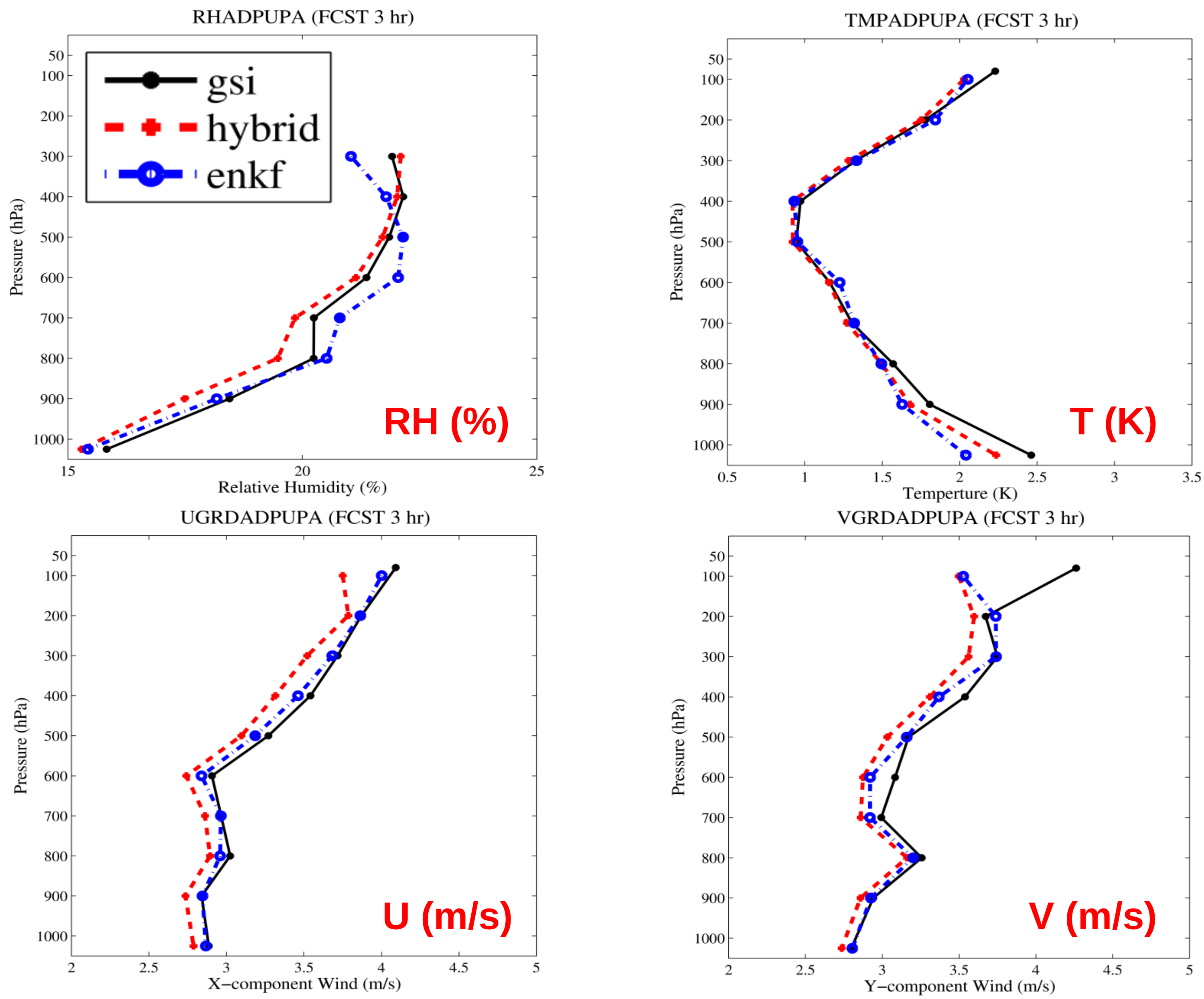
Extra term associated with extended control variable

$$\mathbf{x}' = \mathbf{x}_1' + \underbrace{\sum_{k=1}^{K} \left(\boldsymbol{\alpha}_k \circ \mathbf{x}_k^e\right)}$$

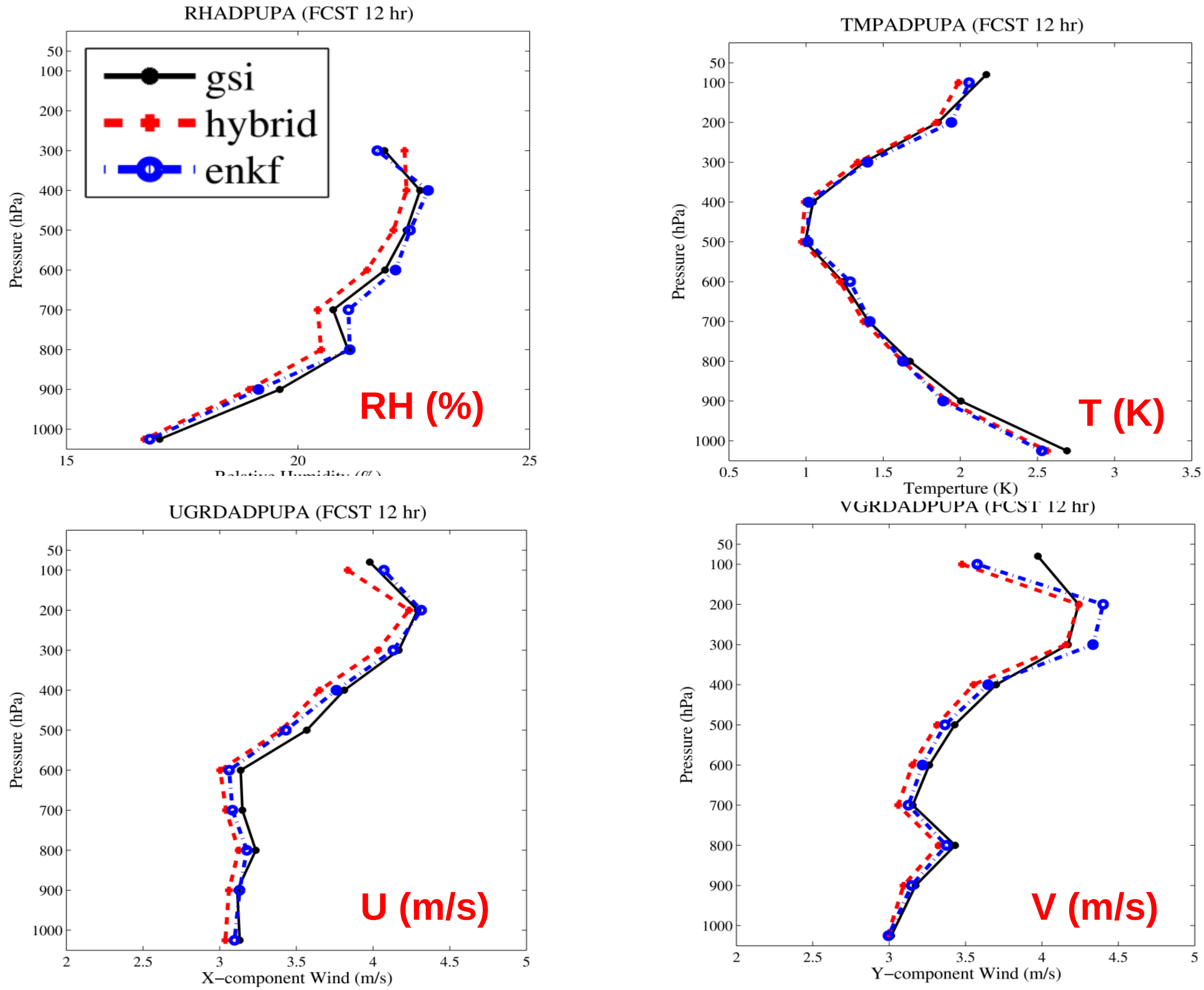
Extra increment associated with ensemble

$\mathbf{B}$ 3DVAR static covariance; $\mathbf{R}$ observation error covariance; K ensemble size;
$\mathbf{C}$ correlation matrix for ensemble covariance localization; $\mathbf{x}_k^e$ kth ensemble perturbation;
$\mathbf{x}_1'$ 3DVAR increment; $\mathbf{x}'$ total (hybrid) increment; $\mathbf{y}^{o'}$ innovation vector;
$\mathbf{H}$ linearized observation operator; β_1 weighting coefficient for static covariance;
β_2 weighting coefficient for ensemble covariance; $\boldsymbol{\alpha}$ extended control variable.

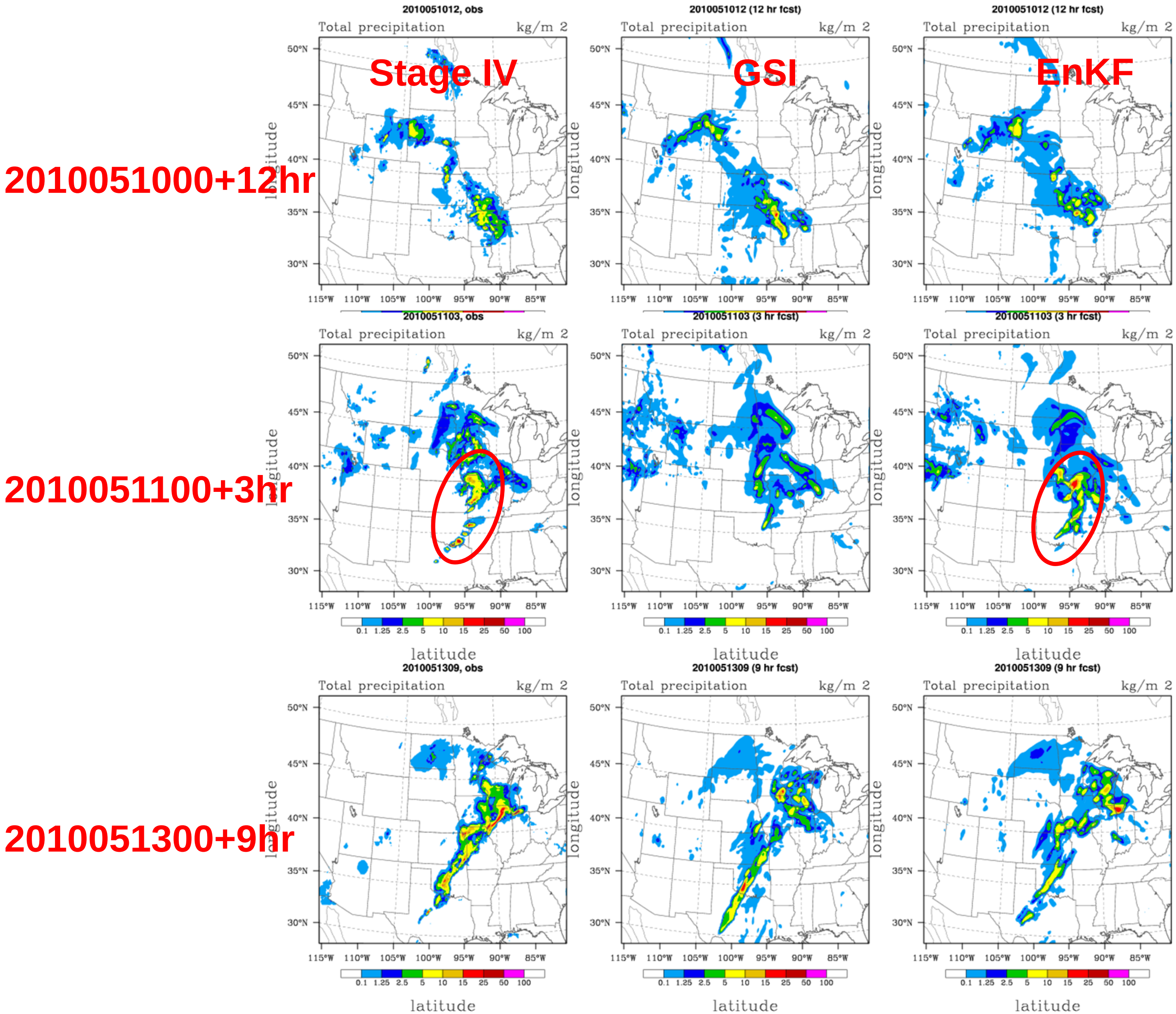
3-h fcsts verified against sounding (EnKF v.s. Hybrid v.s. GSI)



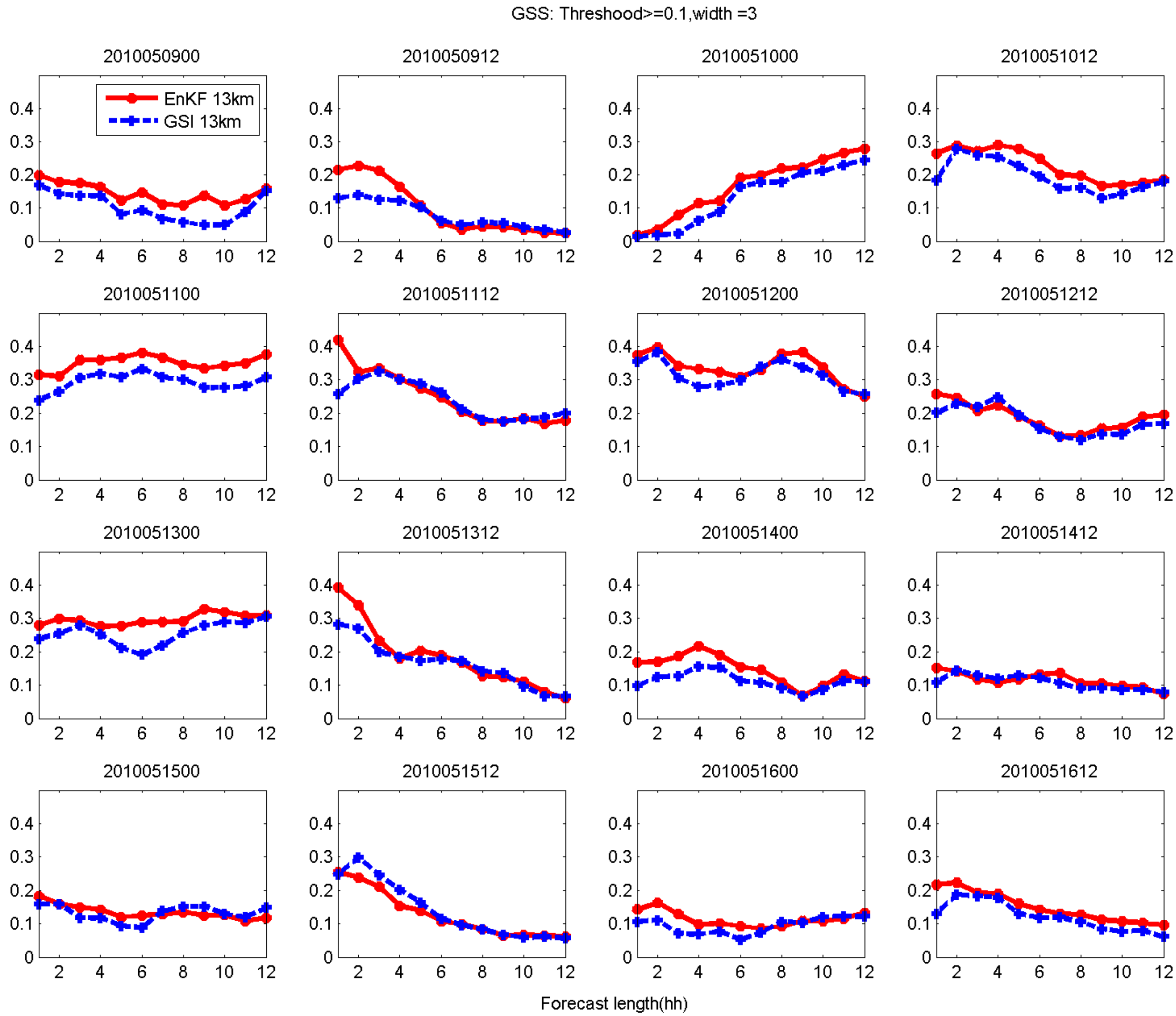
12-h fcsts verified against sounding (EnKF v.s. Hybrid v.s. GSI)



1 hour accumulated precipitation forecasts on 13 km grid

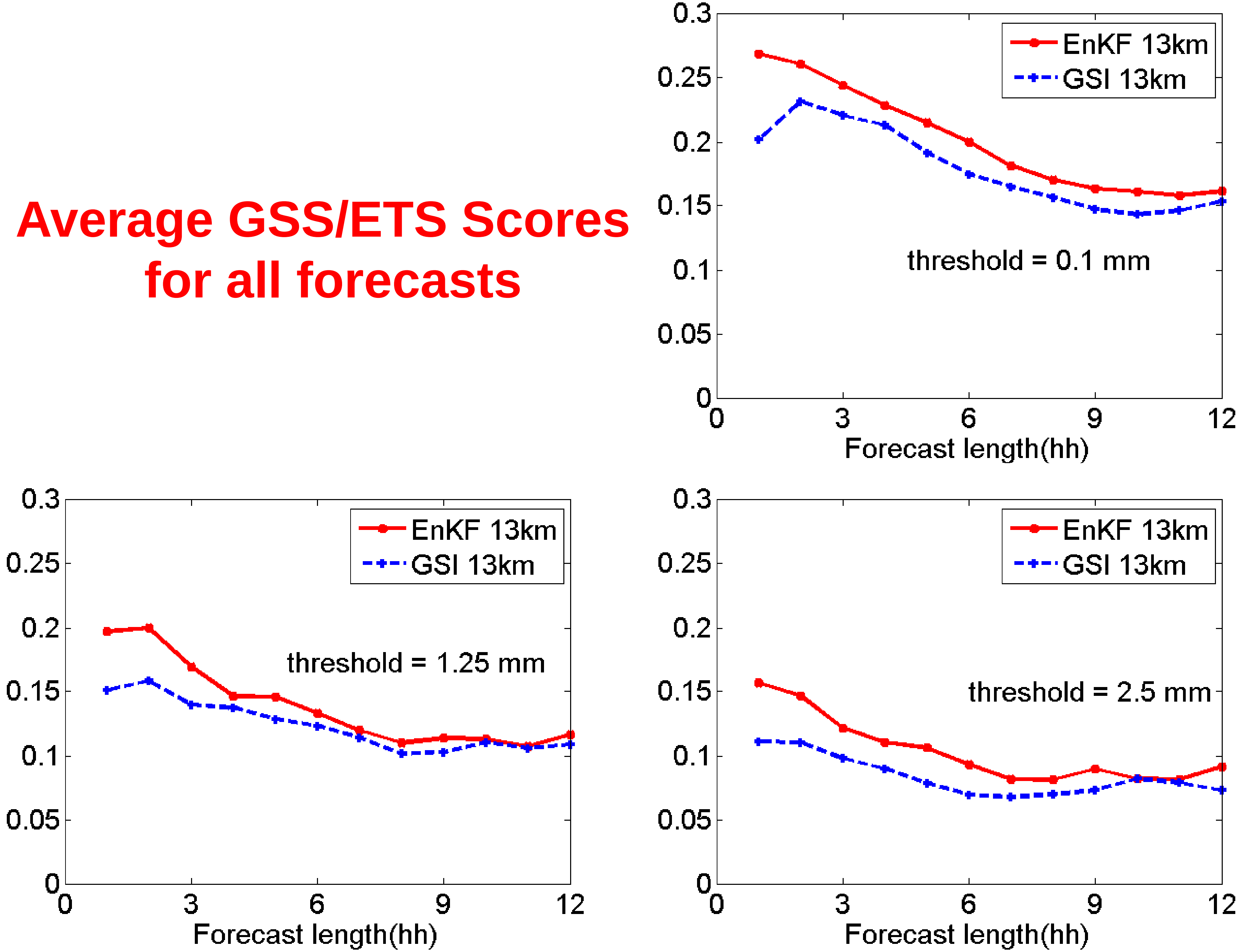


13 km hourly QPF verification (ETS scores)



GSS/ETS, Threshold=0.1mm/h

Average GSS/ETS Scores for all forecasts

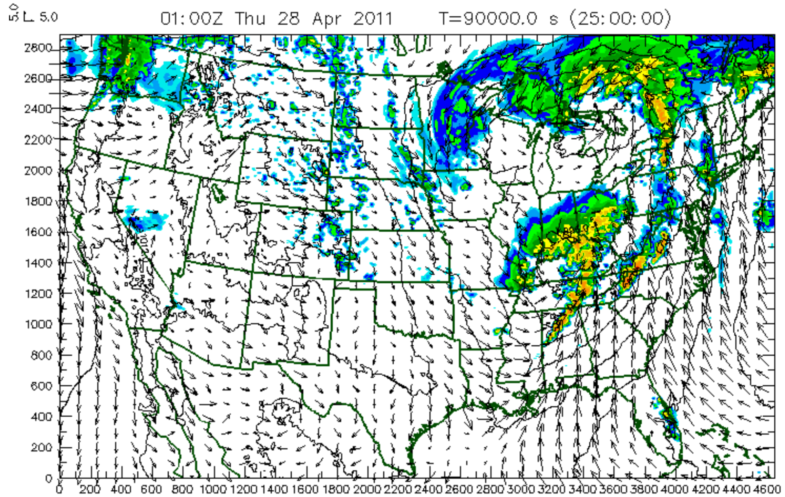


Ambition for the next few years

- Central Great Plain ~4 km domain continuous EnKF cycles including all radar data in realtime, nesting inside RR EnKF/hybrid ensemble
- CONUS-domain ~4 km EnKF/hybrid cycles including all data (including satellite) used in Rapid Refresh GSI plus all radar data
- Sub-km cycled EnKF with 88D and CASA-type high-resolution radars.
- Use EnKF analyses to initialize convection-resolving ensemble probabilistic forecasting

CAPS CRTM Simulation –Preliminary Results

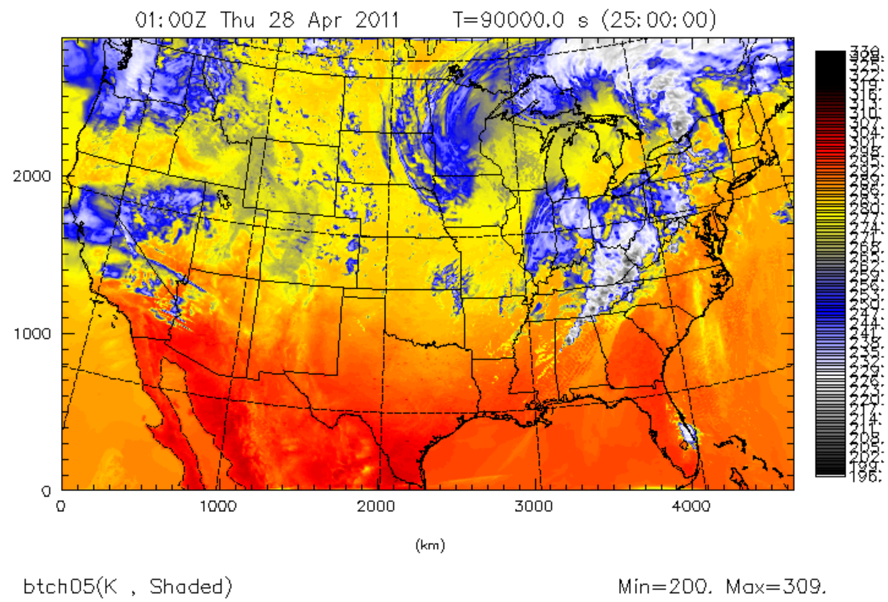
Composite Reflectivity



25-h 4 km WRF forecast with WSM6

01 UTC, April 28, 2011

8.5 µm



From Jason Otkin ABI 8.5 µm

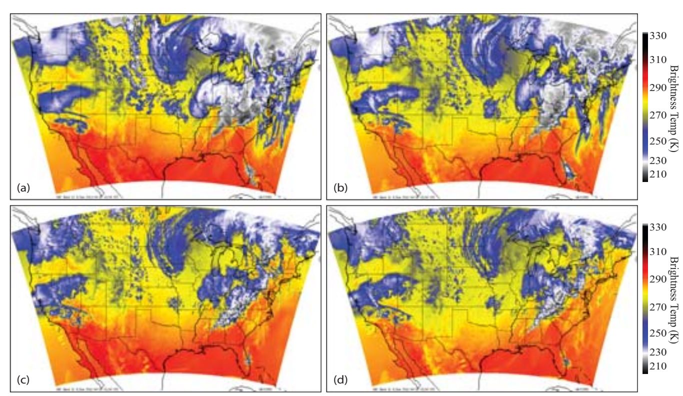


Fig. 1. Simulated ABI 8.5 µm brightness temperatures (K) valid at 0100 UTC on 28 April 2011 for four CAPS ensemble members.