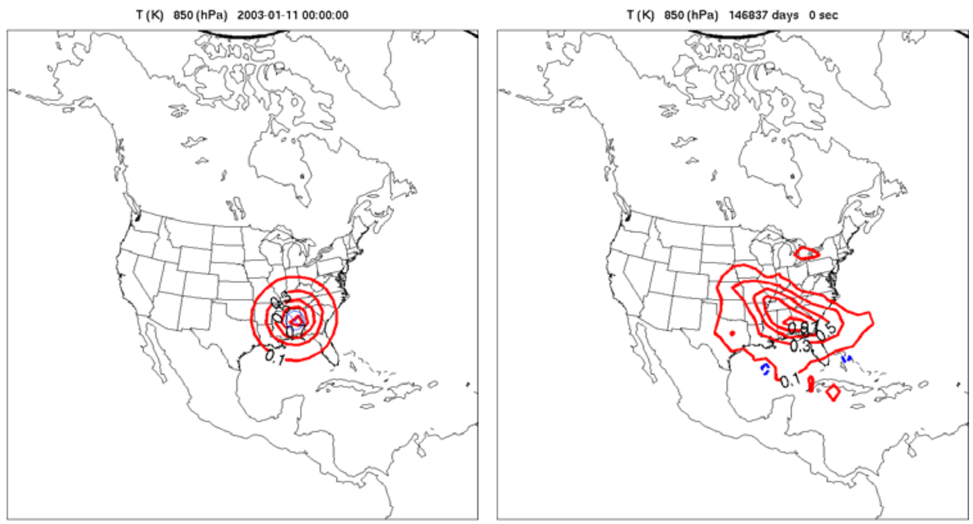
An ensemble Kalman filter for WRF and a comparison with the WRF 3DVar



- Alain Caya (IMAGe, NCAR)
- Chris Snyder (MMM and IMAGe)
- Dale Barker (MMM, NCAR)
- Bill Skamarock (MMM, NCAR)
- Jeff Anderson (IMAGe, NCAR)

What is an Ensemble Kalman Filter (EnKF)?

Given forecast ensemble, valid at some t

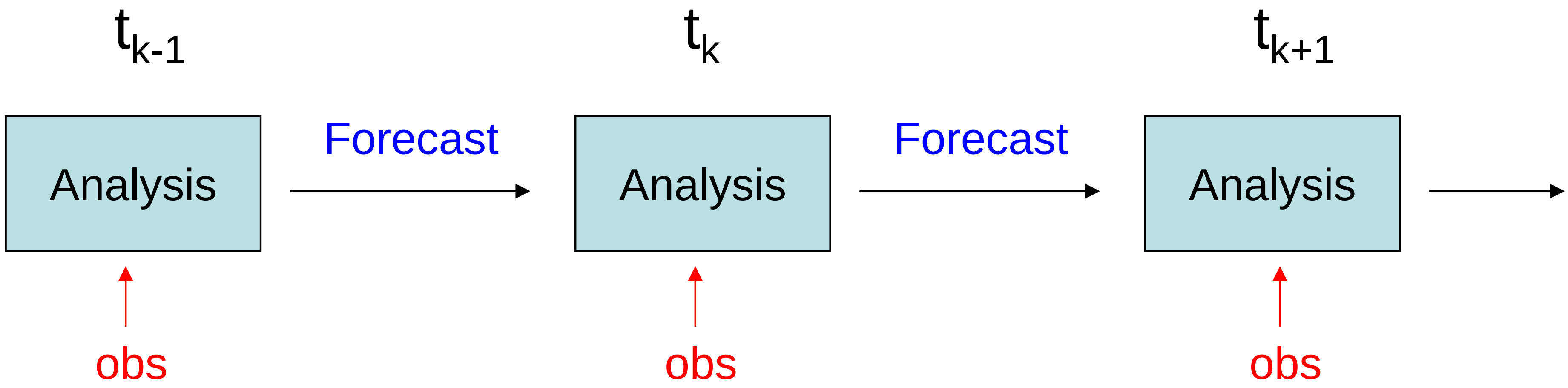
- estimate forecast-error covariances needed for DA using sample covariance of ensemble
- perform analysis for each member based on obs available at t
  $\Rightarrow$ analysis ensemble
- integrate forecasts from analysis ensemble to the time of next observations

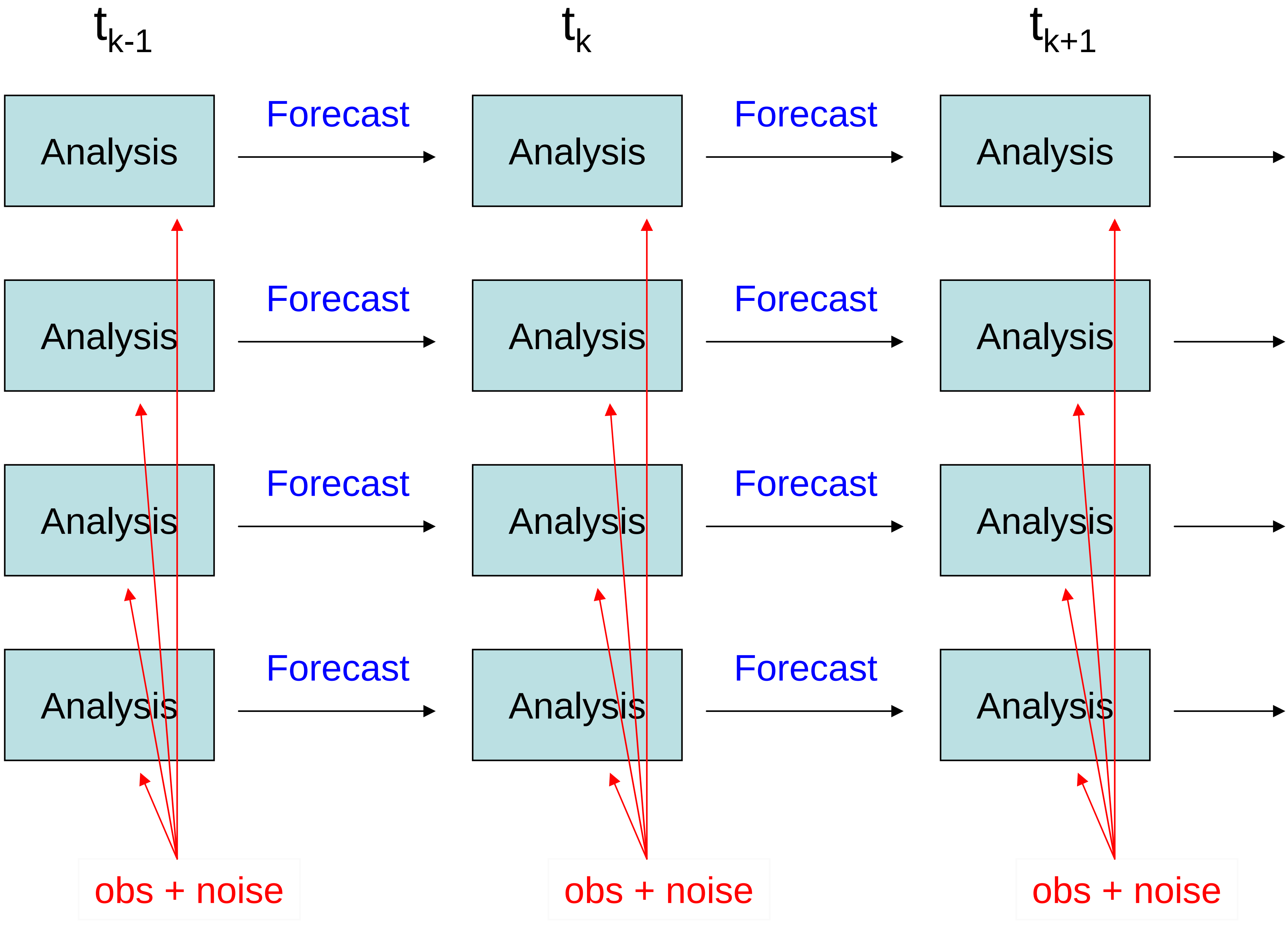
Combines data assimilation and ensemble forecasting

- analyses $plus$ their uncertainty

Uses "flow dependent" forecast-error covariances

- 3DVar covariances (typically) assumed stationary, isotropic, homogeneous


t_{k-1}
t_k
t_{k+1}
Analysis
Forecast
Analysis
Forecast
Analysis
obs
obs
obs



t_{k-1}
t_k
t_{k+1}
Analysis
Forecast
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Forecast
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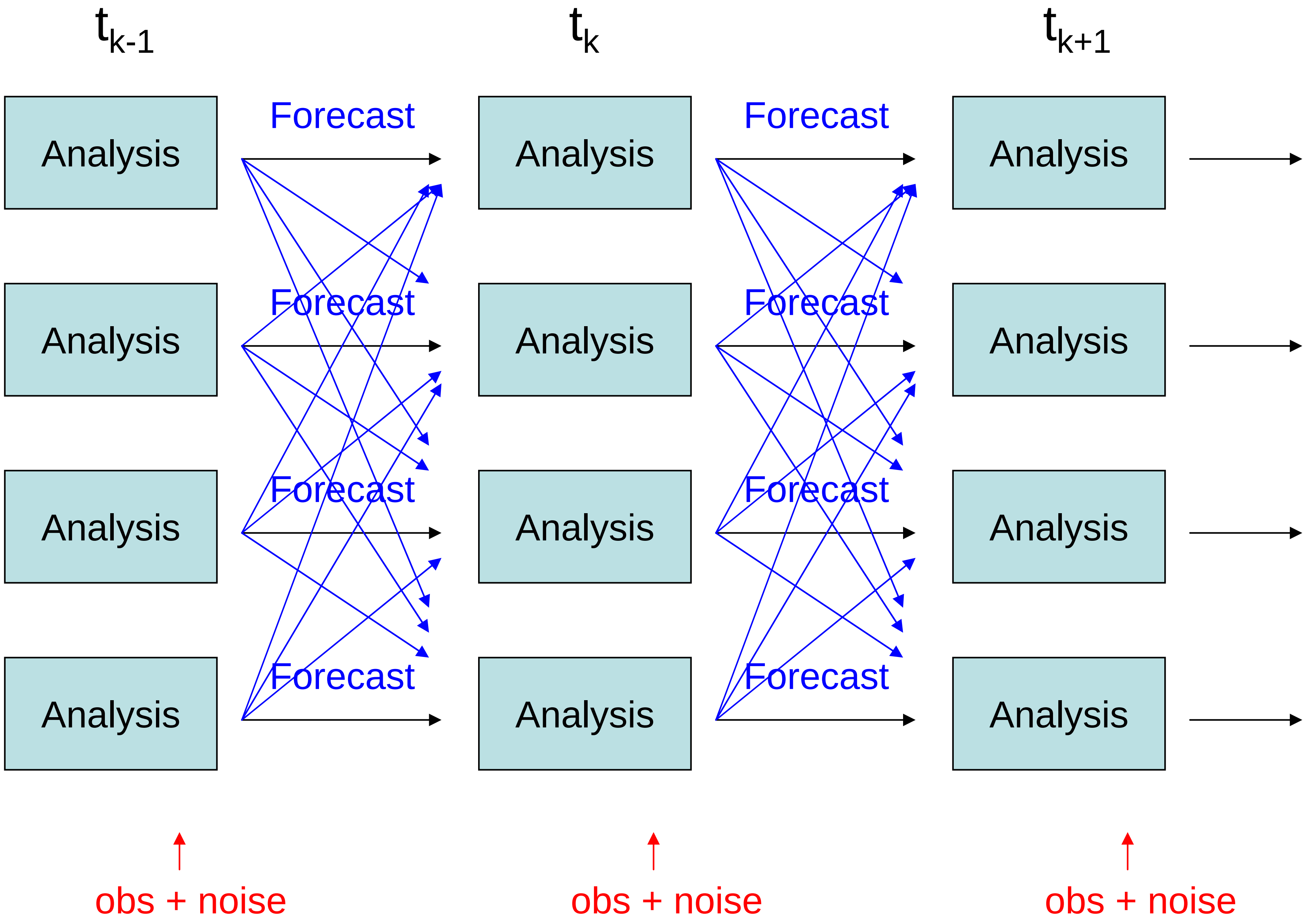
obs + noise
obs + noise
obs + noise



t_{k-1}
t_k
t_{k+1}
Analysis
Analysis
Analysis
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Analysis
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Forecast
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Forecast
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Forecast
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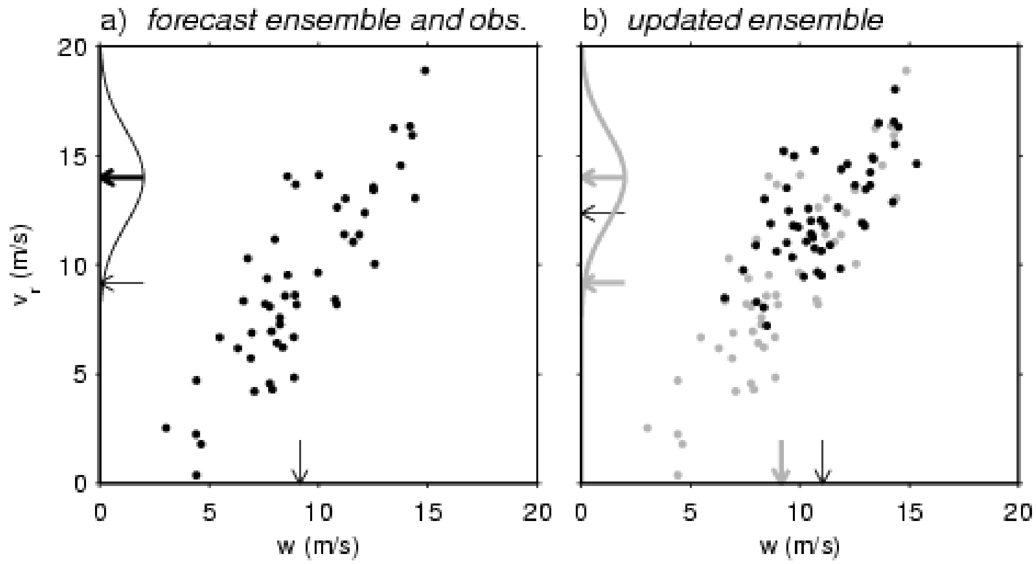
Forecast
obs + noise
obs + noise
obs + noise

Update Step: Schematic Radar Example

Update w given an observation of v_r



- let $v_r^f = \mathbf{Hx}^f$; compute for each member
- For each grid point i, estimate from ensemble

$$c_i = (\mathbf{P}^f\mathbf{H}^T)_i = \text{Cov}(w_i^f, v_r^f), \quad d = \mathbf{HP}^f\mathbf{H}^T + \mathbf{R} = \text{Var}(v_r^f) + \mathbf{R}$$

- update each member at ith grid point,

$$w_i^a = w_i^f + (\hat{c}_i/\hat{d})(v_r - v_r^f + \epsilon) \quad \epsilon \sim N(0, \mathbf{R})$$

EnKFs for WRF

Presently, 3 implementations at different institutions

- typically, 20–100 members
- deterministic/square-root versions of EnKF
- serial processing of observations, with covariance localization
- parallel computations on linux clusters with slow interconnect

Real-time implementation at UW

- http://www.atmos.washington.edu/~enkf/enkfpy.cgi

At NCAR, use the Data Assimilation Research Testbed (DART)

- http://www.cgd.ucar.edu/DAI/hawaii_release.html

Initial issues

- Lateral BCs in forecast step?
- Are EnKF analysis increments balanced?
- How does EnKF compare with 3DVar?

Lateral BCs

In limited-area model, lateral BCs a source of uncertainty

- ensemble forecasts require ensemble of lateral BCs
- global ensemble schemes not designed/tuned for very short range

Approaches for ensemble BCs

- preferred: ensemble from EnKF on larger domain
- ad hoc: draw BC perturbations from Gaussian with 3DVar covariances or from (scaled) perturbations from climatology

Ad-hoc approaches inferior, but not horrible

- Torn et al. (2005), http://www.atmos.washington.edu/~hakim/papers/torn_etal_2005.pdf

EnKF/3DVar Comparison

Performance of EnKF for LAM?

- ▷ WRF 3DVar as benchmark

Importance of EnKF's 'flow dependent' covariances?

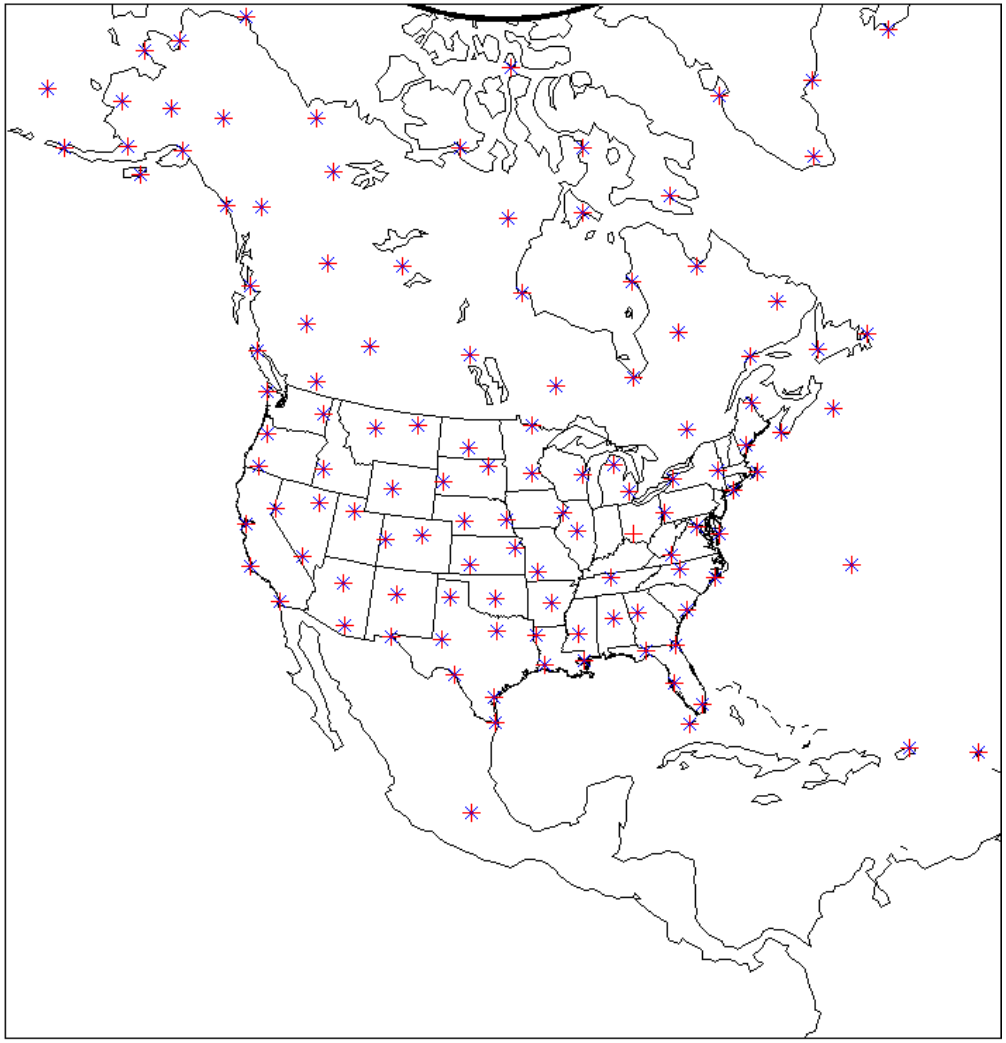
- ▷ in LAM, benefits suppressed by ad hoc treatment of BC uncertainty
- ▷ enhanced by local effects (e.g. orography)?

Consider synoptic scales, CONUS domain

- ▷ balances assumed in 3DVar best suited to such flows
- ▷ degree of imbalance in EnKF, 3Dvar analyses?

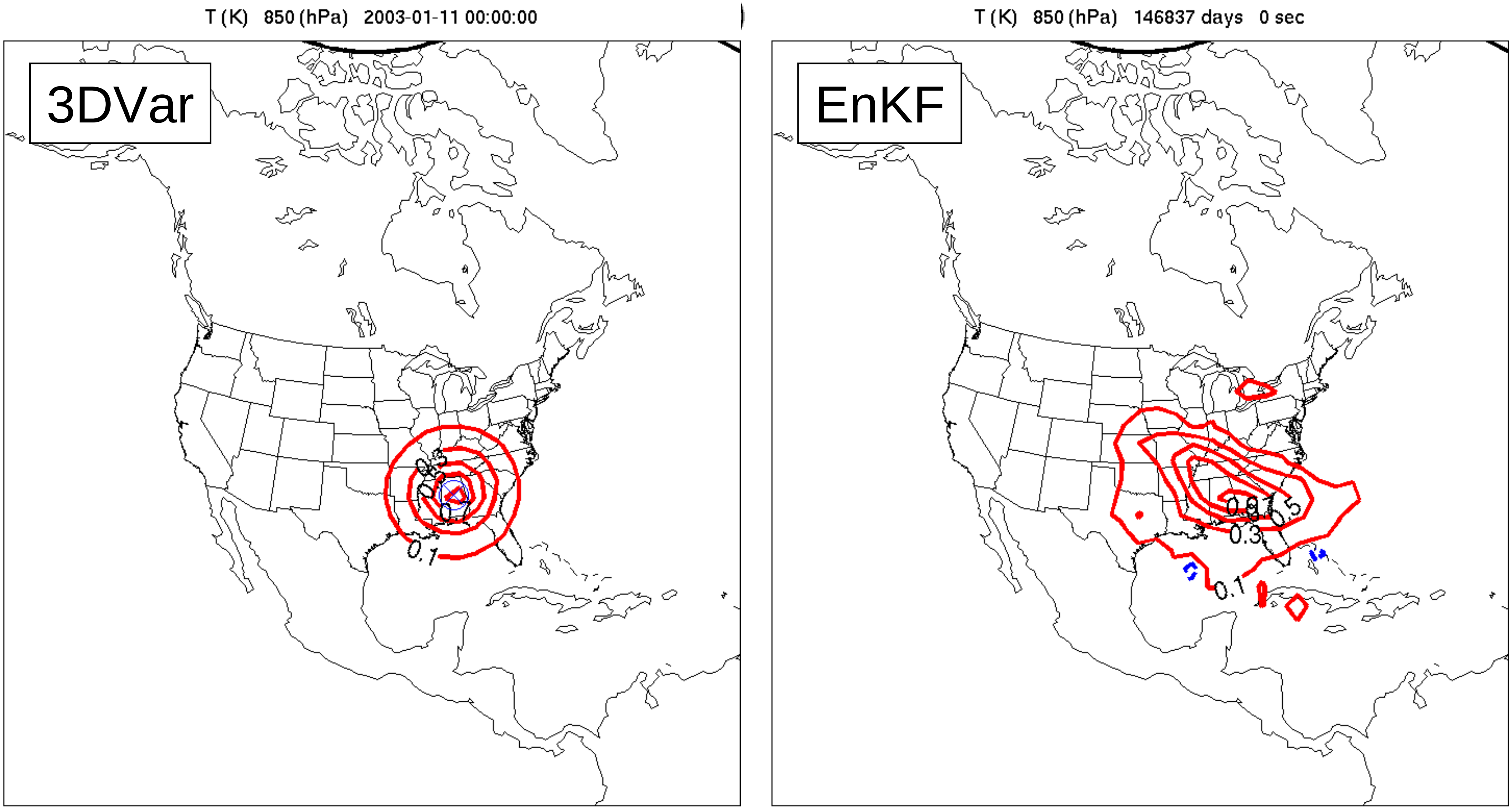
Experimental Design

- obs from NA rawinsonde network
- domain (200 km) and obs locations shown
- assimilate u, v, T every $12\,\mathrm{h}$
- LBCs from GFS analyses
- cycle for Jan 2003

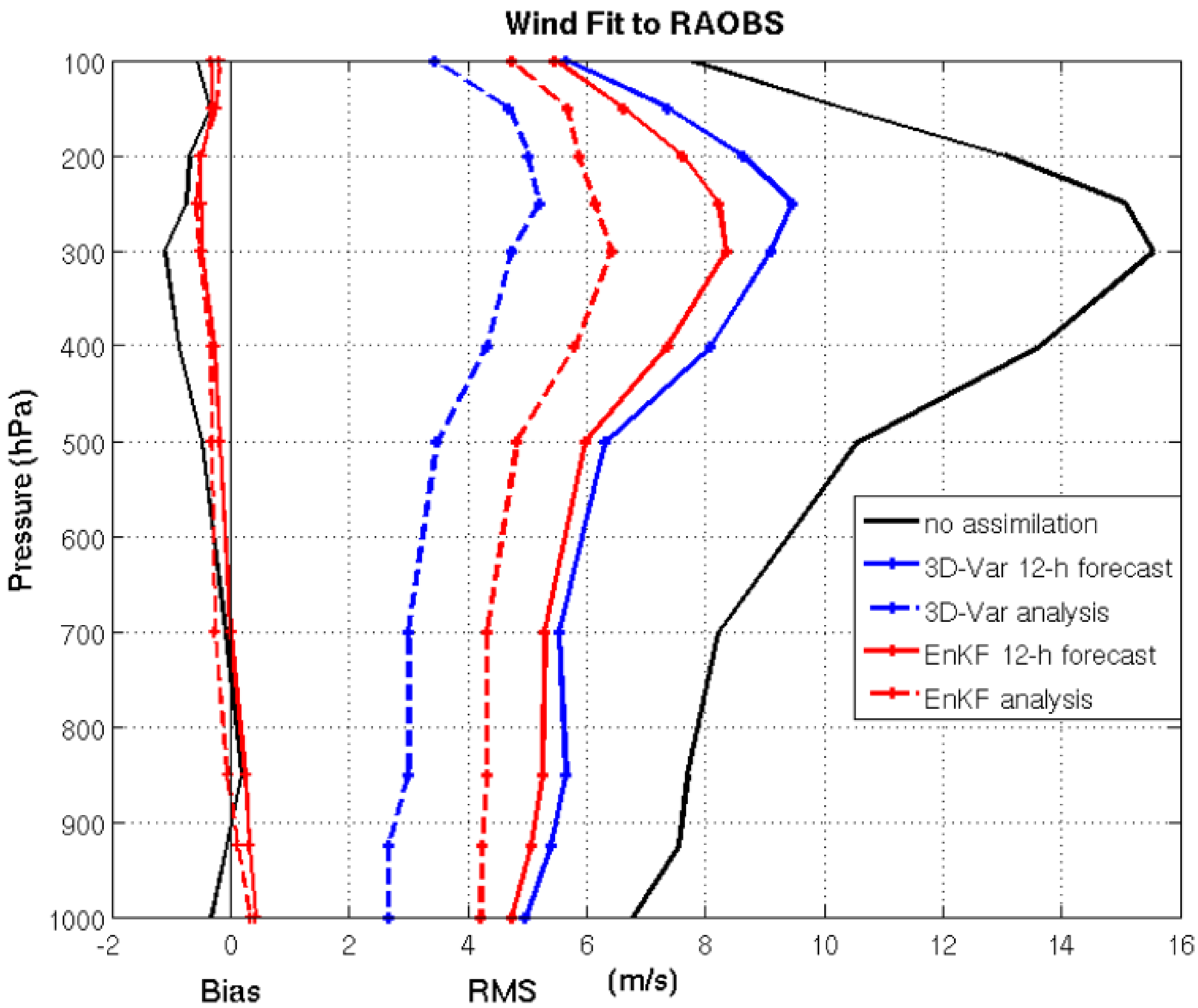


EnKF/3DVar Comparison

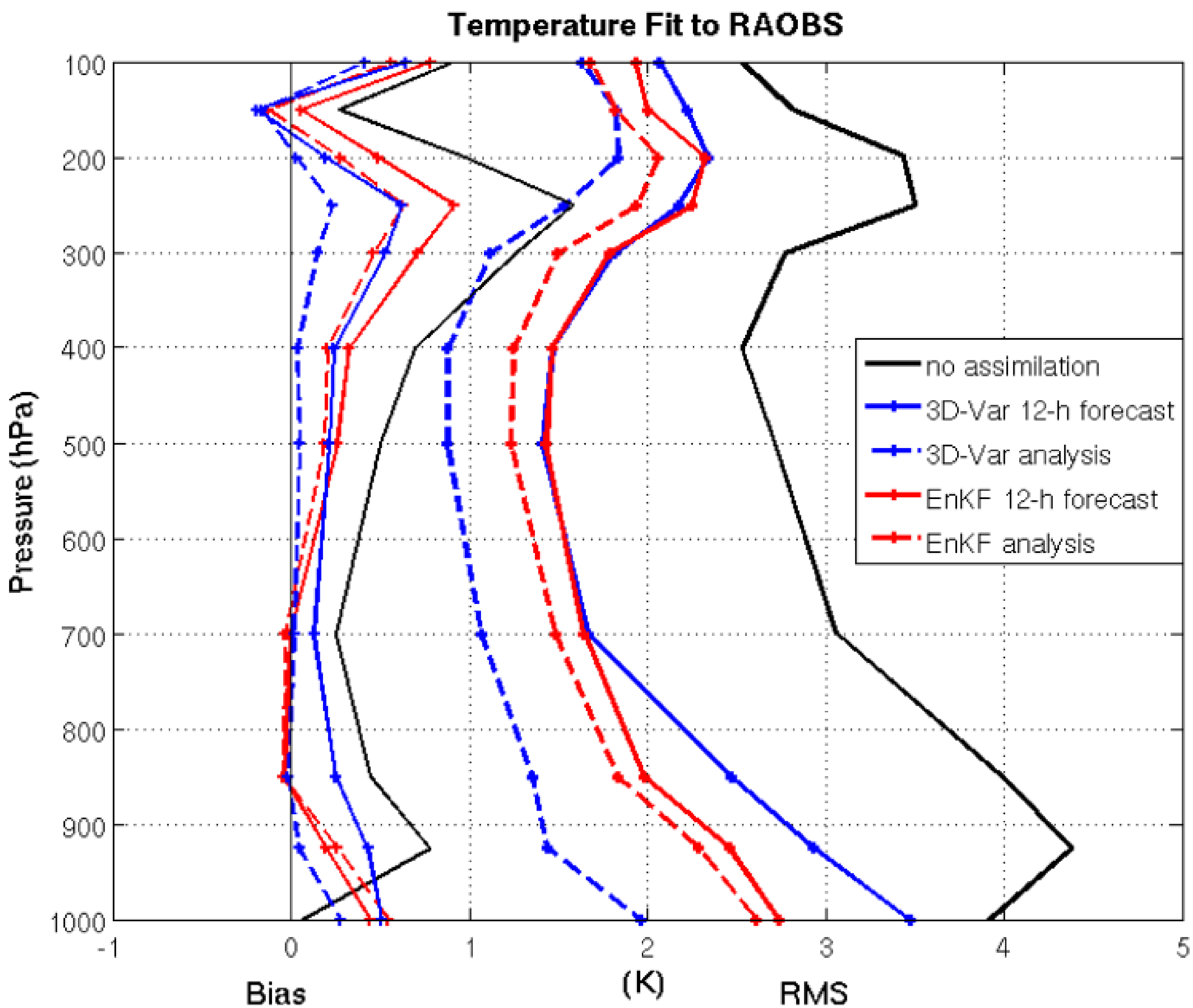
- T analysis increment, day 10, single T observation at $850\,\mathrm{mb}$



EnKF/3DVar Comparison

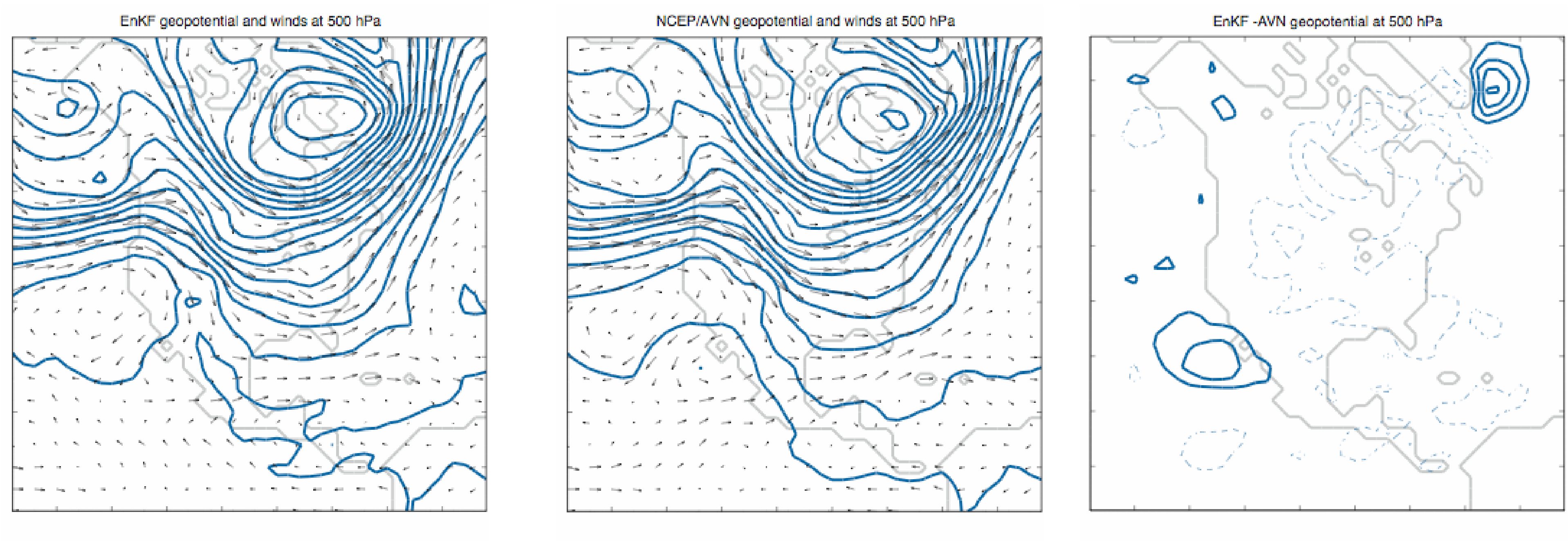


EnKF/3DVar Comparison



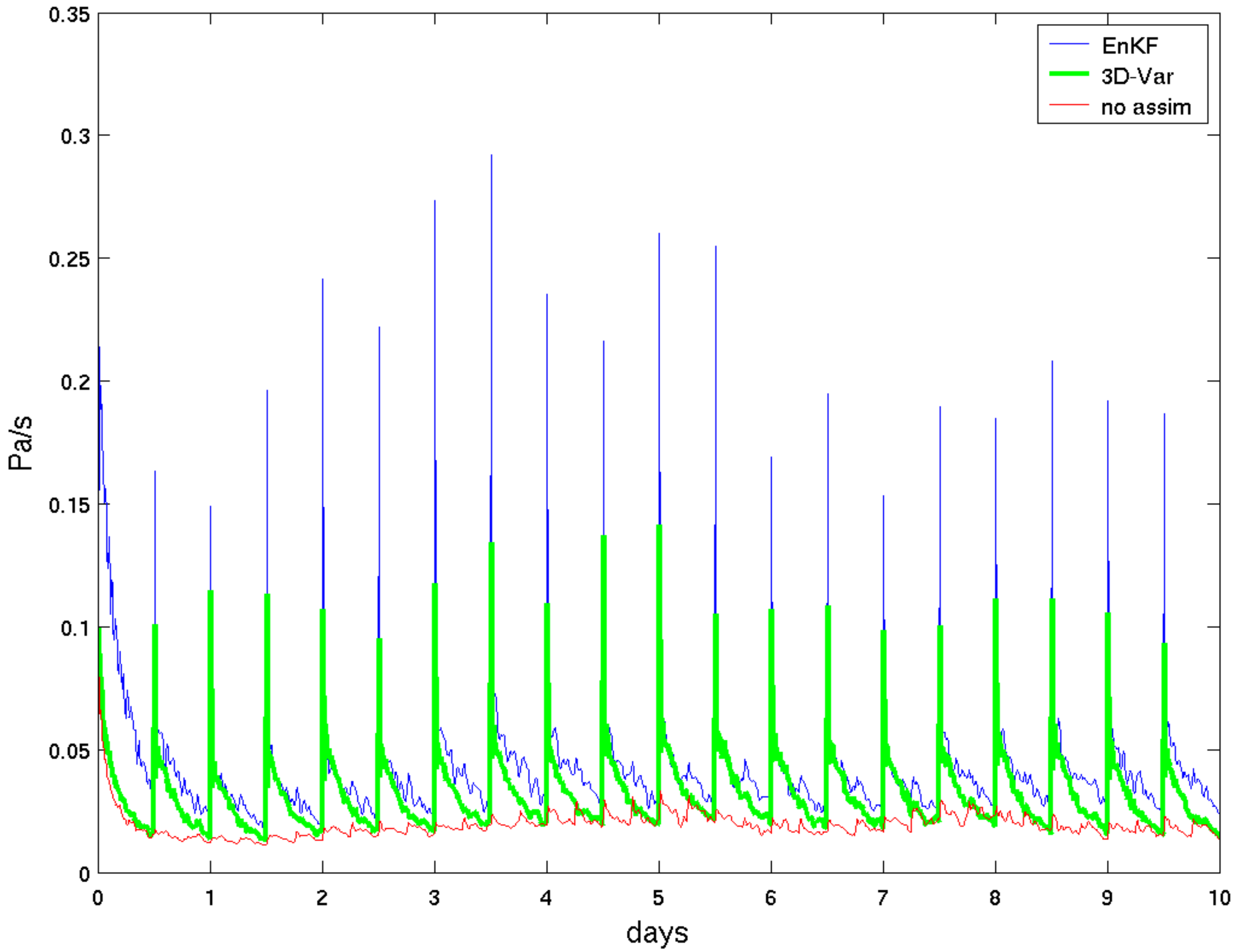
Comparison with GFS Analysis

- 500-hPa heights and winds, 00UTC 31 January
- EnKF (left; $\Delta = 60$ m), GFS (center), difference (right; $\Delta = 20$ m)



EnKF/3DVar Comparison

- rms $\partial p_s/\partial t$ as function of t



Conclusions

Lateral boundary conditions

- BC perturbations from ‘exterior’ EnKF preferred, but not essential
- scaled perturbations drawn (randomly) from 3DVar background covariances and from climatology both perform acceptably

Comparison with 3DVar

- in OSSEs, EnKF analysis errors 20–30% smaller than for 3DVar
- for real obs, EnKF obs-minus-forecast diffs noticeably smaller
- balance of increments comparable to 3DVar

Why the EnKF?

Ensemble-based covariance model requires few assumptions

- appears to be applicable to variety of scales and domains with relatively little tuning
- e.g. convective scales (Snyder and Zhang 2003; Dowell et al. 2004; Caya et al. 2005)

A flexible research tool

- easy to implement and maintain—no adjoints needed for model or obs operators
- basic parallelization is straightforward
- easily accomodates nested-grid models
- facilitates use of unconventional obs

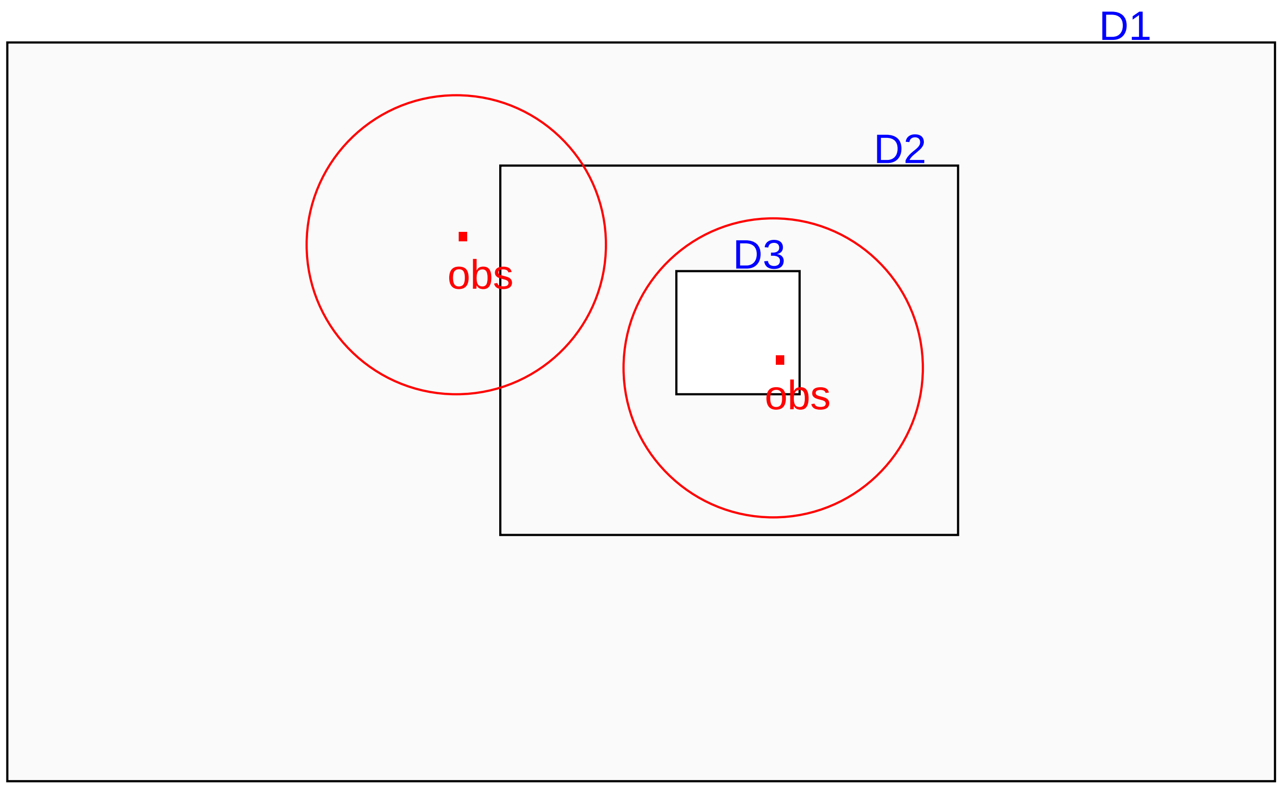
Basis for a unified EF/DA system

- provides estimates of analysis and forecast uncertainty

EnKF Analyses Across Multiple Domains

Have implemented EnKF for multiple, nested domains

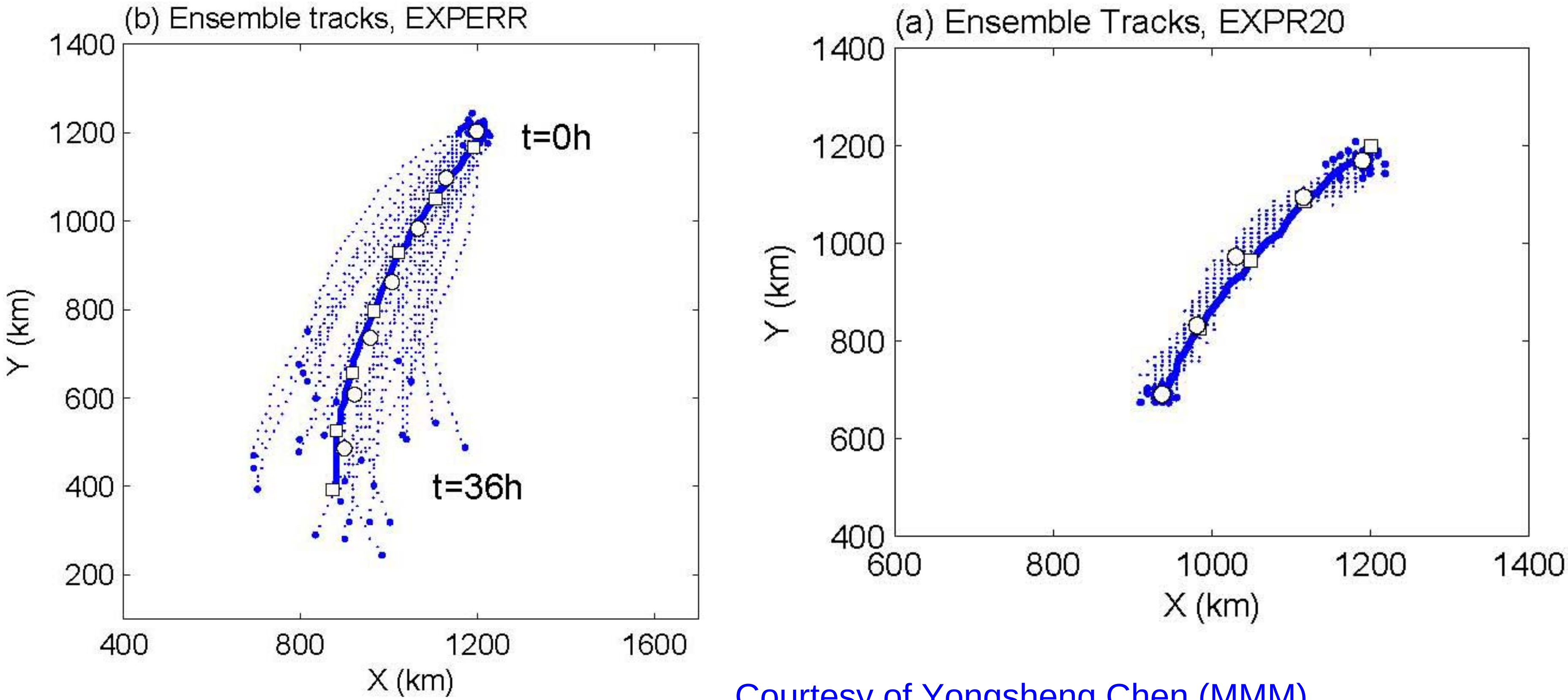
- innovations calculated using finest available grid
- all grid points w/in localization radius are updated
- minor extension to code



Assimilation of Vortex Position

Have frequent obs of hurricane position

- ▷ analyzed vortex should be consistent with these
- ▷ to use in EnKF, simply need "position" operator



Courtesy of Yongsheng Chen (MMM)
http://box.mmm.ucar.edu/individual/snyder/Papers/ChenSnyder2005.pdf

References

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Bengtsson T., C. Snyder, and D. Nychka, 2003: Toward a nonlinear ensemble filter for high-dimensional systems. *J. Geophys. Research*, **108(D24)**, 8775–8785.

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Dowell, D., F. Zhang, L. Wicker, C. Snyder and N. A. Crook, 2004: Wind and thermodynamic retrievals in the 17 May 1981 Arcadia, Oklahoma supercell: Ensemble Kalman filter experiments. *Mon. Wea. Rev.*, **132**, 1982–2005.

Caya, A., J. Sun and C. Snyder, 2005: A comparison between the 4D-Var and the ensemble Kalman filter techniques for radar data assimilation. *Mon. Wea. Rev.*, accepted.

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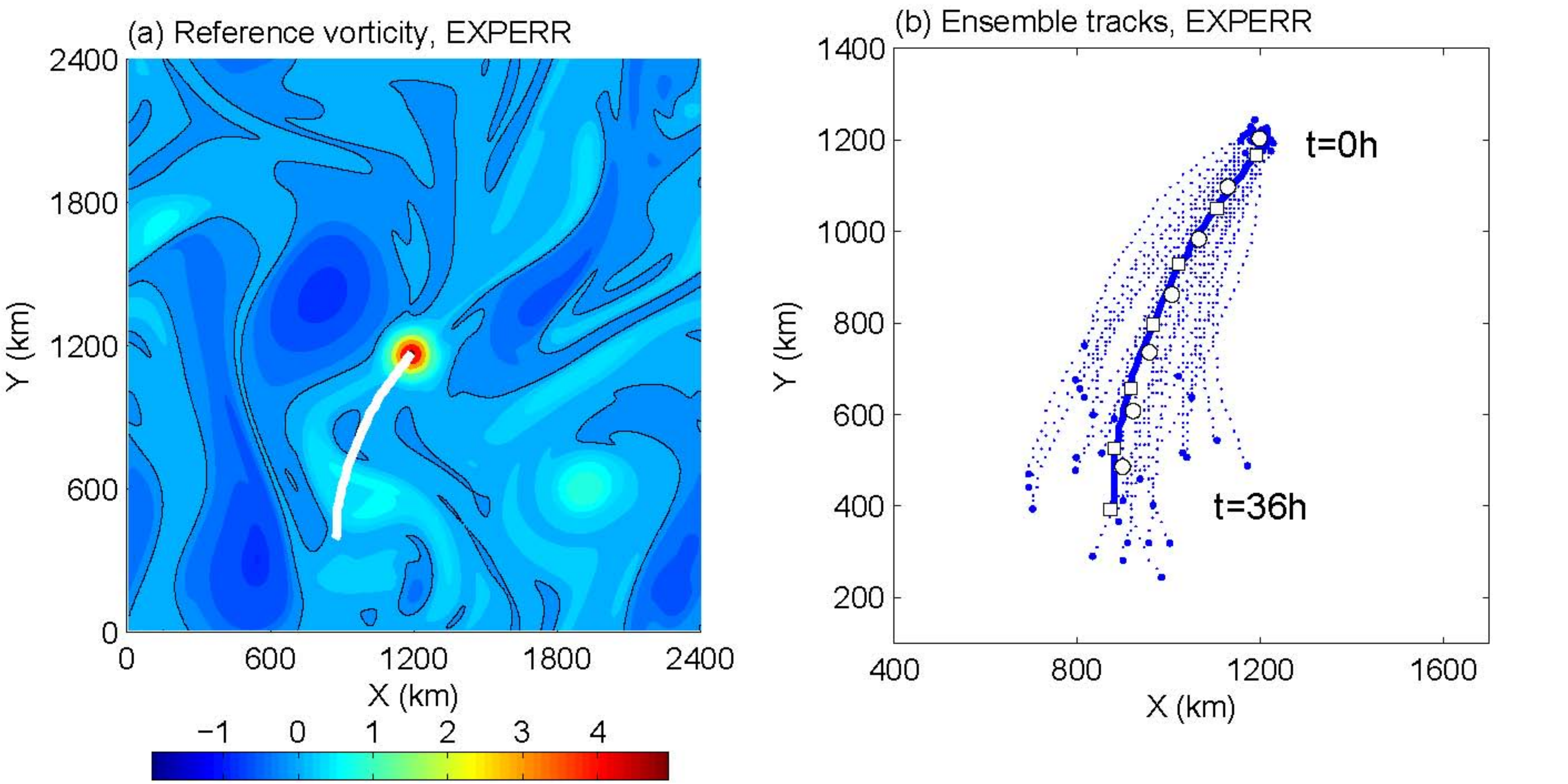
Chen, Y., and C. Snyder, 2005: Assimilating vortex position with an ensemble Kalman filter. *Mon. Wea. Rev.*, to be submitted.



(a) Reference vorticity, EXPERR
2400
1800
1200
600
0
Y (km)
0
600
1200
1800
2400
X (km)
−1
0
1
2
3
4
(b) Ensemble tracks, EXPERR
1400
1200
1000
800
600
400
200
Y (km)
400
800
1200
1600
X (km)
t=0h
t=36h

Testing of Lateral BC schemes

Assimilate simulated observations, assume perfect model

- CONUS domain
- observations of column dry-air mass ($\sim p_s$)

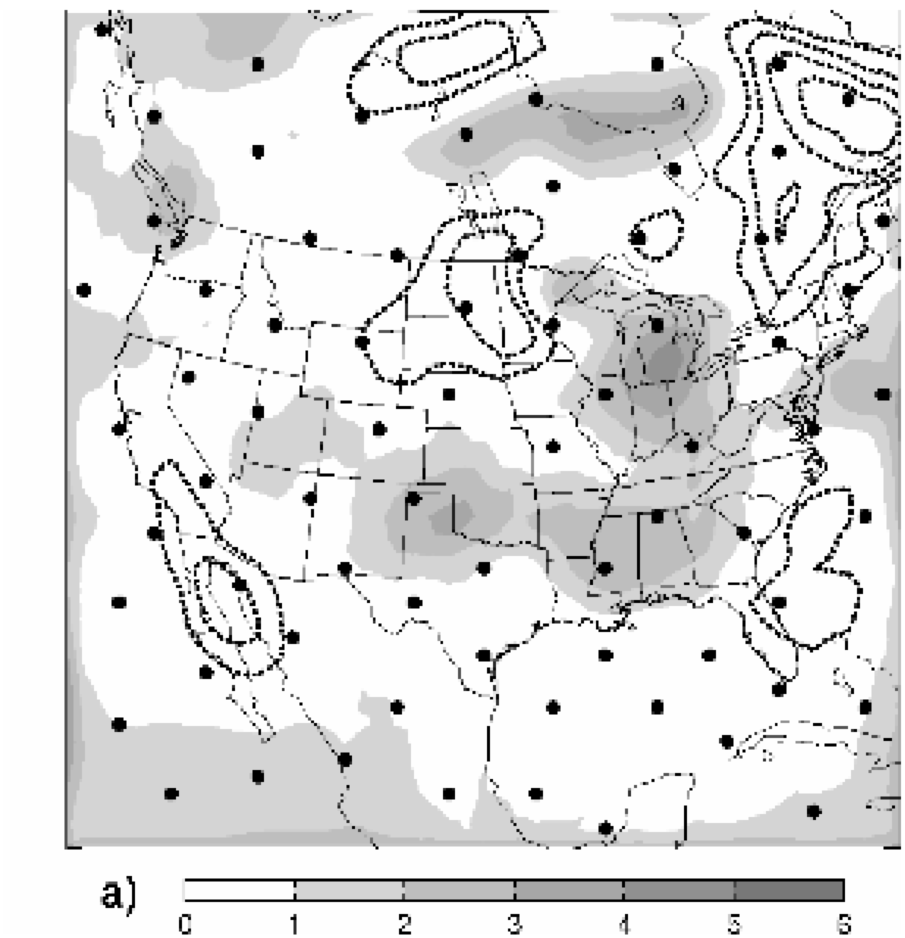
EnKF on larger domain provides standard of reference

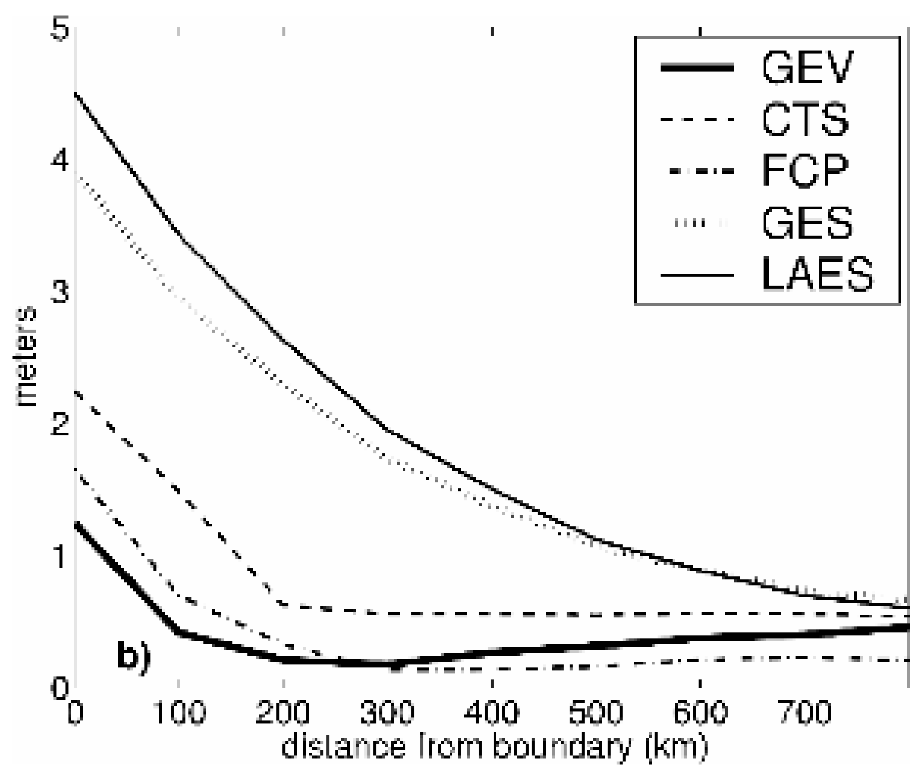
Compare: ensemble BCs from larger-domain EnKF, from 3DVar perturbations, and from climatological perturbations

See Torn, Hakim and Snyder (2005)

Testing of Lateral BC schemes

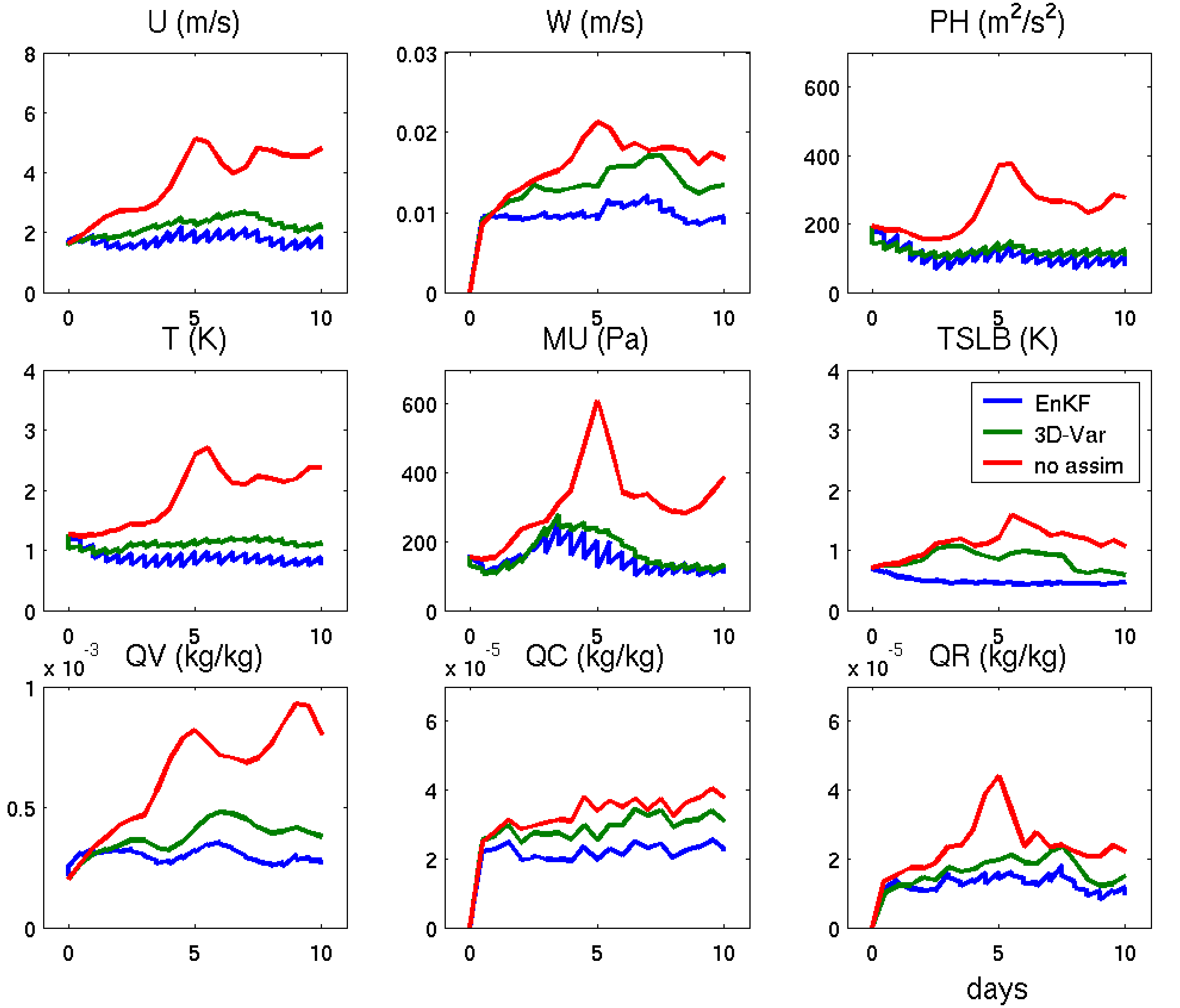
- (left) Difference in time-averaged, rms height error at 500 mb between large-domain EnKF and EnKF with 3DVar LBC perturbations
- (right) As above, but summed over all grid points a given distance from the boundary and for various LBC schemes





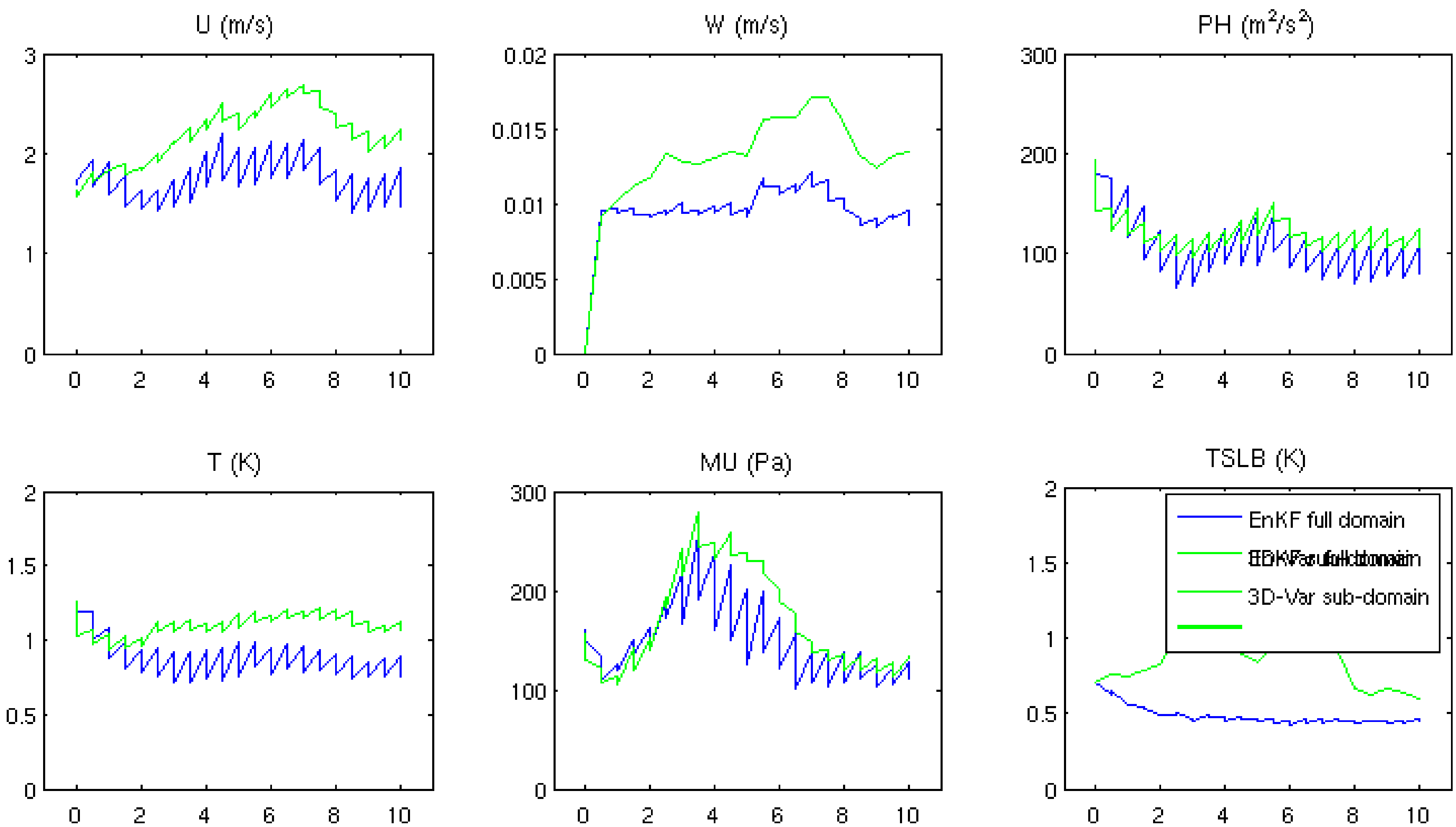
EnKF/3DVar Comparison

- rms errors (both first guess and analysis) over entire domain



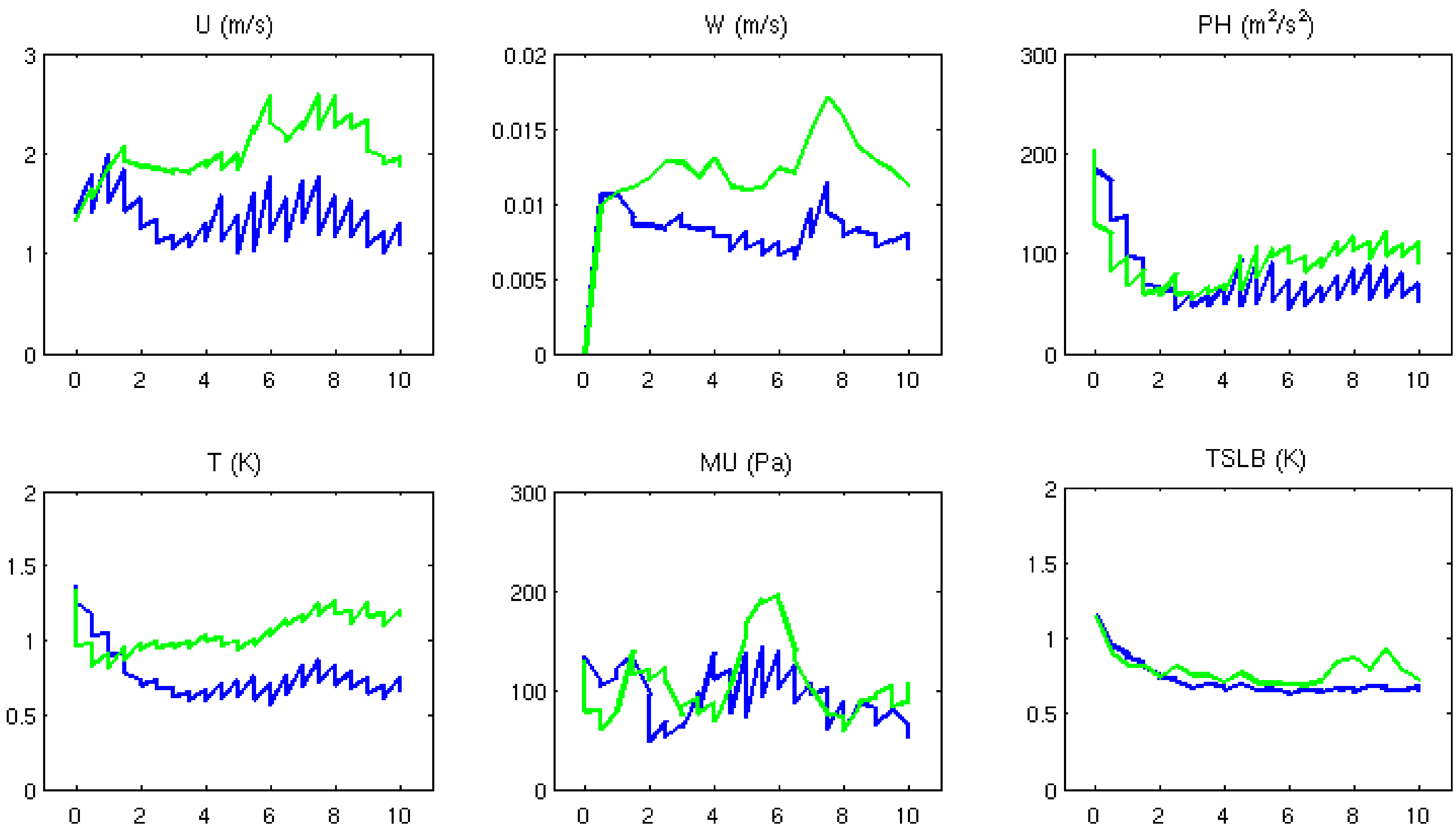
EnKF/3DVar Comparison

- ▷ rms errors on inner 1/4 of domain



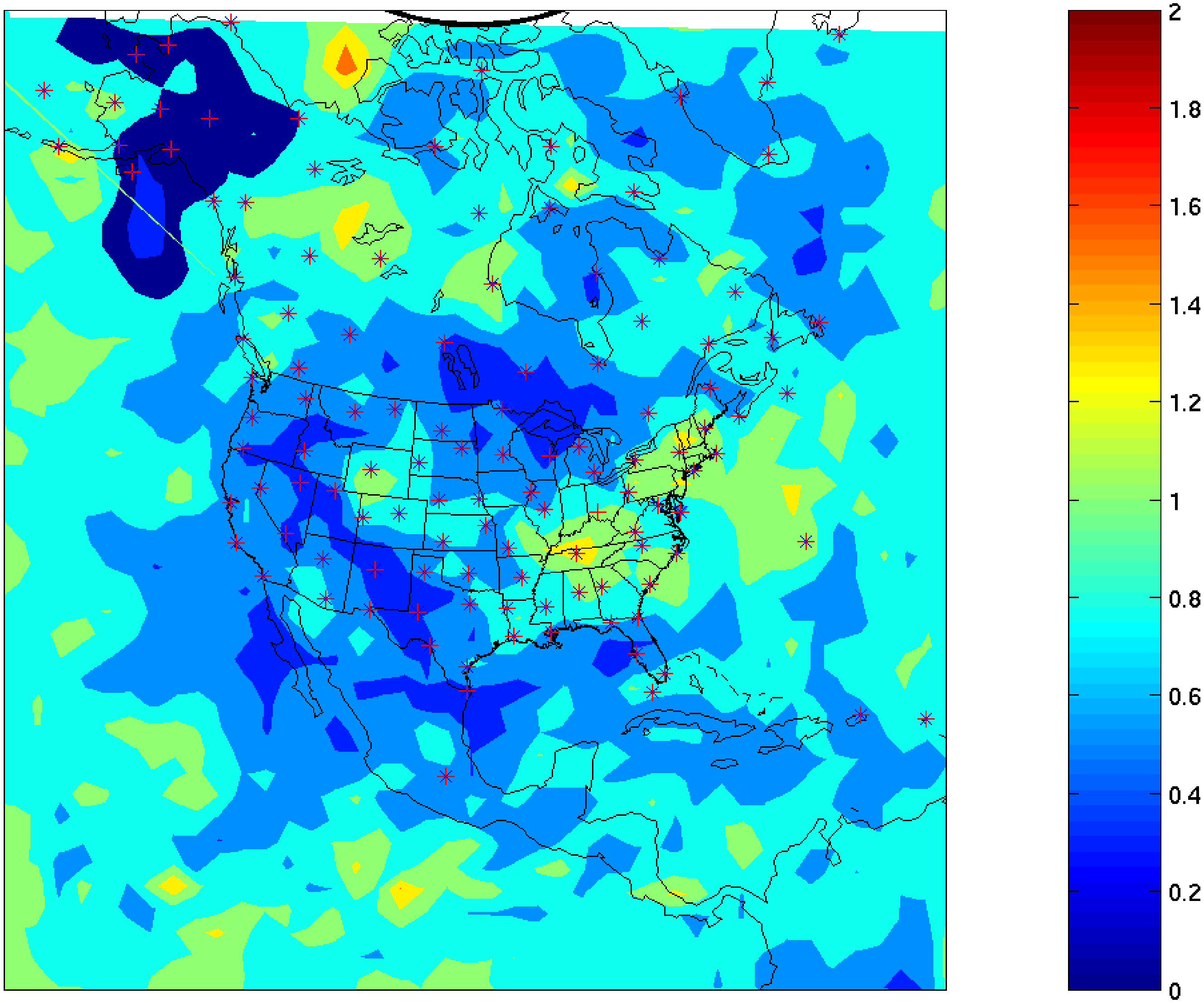
EnKF/3DVar Comparison

- rms errors on inner 1/4 of domain



EnKF/3DVar Comparison

- Ratio of time-av'd EnKF rms T error to that of 3DVar at 500 mb



Details

Lateral BC experiments

- experiment extends over 15 days
- 100 km grid spacing
- 250 μ obs, spaced roughly every 500 km
- obs assimilated every 6 h
- truth run initialized with NCEP GFS analysis from 18 UTC 18 March 2003, and uses lateral BCs from subsequent GFS analyses
- 100 members in EnKF
- covariance localization of 3000 km

Details

3DVar comparisons

- experiment extends over 10 days
- 200 km grid spacing
- obs are columns of u, v, T at locations of NA radiosondes, every 12 h
- 40 members in EnKF
- covariance localization of 2500 km
- construct ICs for 41 ensemble members by adding 3DVar perturbations to GFS analysis from 00 UTC 1 January 2003; thus, 1st EnKF analysis approximates 1st 3DVar analysis.
- construct ensemble of 41 lateral BCs by adding climatological perturbations scaled by 0.2 to subsequent GFS analyses
- truth run uses 41st IC and lateral BCs

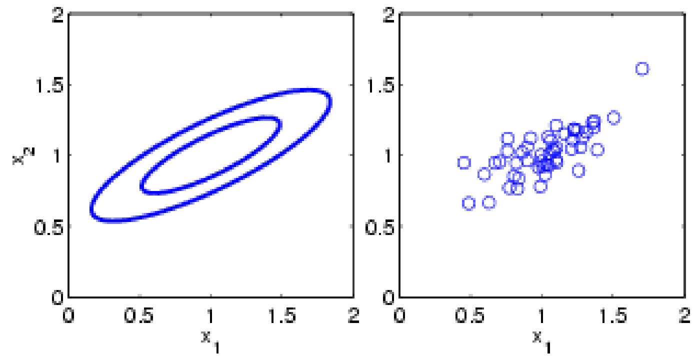
Initializing “True” State and Ensemble

- Construct N+1 initial states
  - AVN analysis (1 Jan 03) + perturbations drawn randomly from 3DVar covariances
- Construct N+1 lateral BC’s
  - AVN analyses (1-10 Jan 03) + perturbations
  - Perturbations are deviations from Jan climatology, scaled by 0.2
- EnKF uses first N initial states and LBCs; true state use N+1st
  - Ensemble and true state drawn from same pdf

The Ensemble Kalman Filter (EnKF)

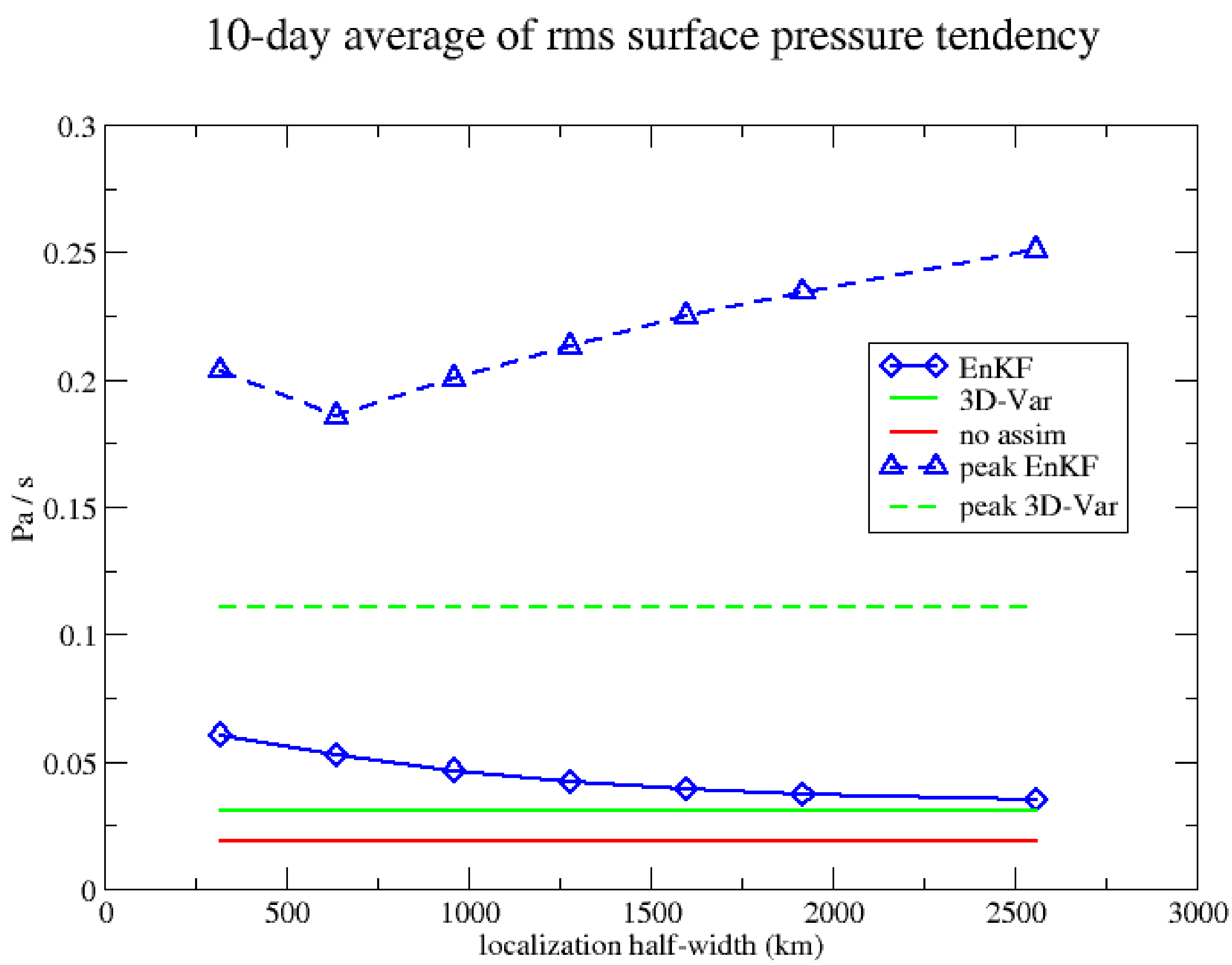
Monte-Carlo approach

- work with samples rather distributions



Sequential method: given ensemble at $t = t_k$,

- forecast each member to t_{k+1}, time of next observations
- update each member at t_{k+1}
- continue as above, from $t = t_{k+1}$



10-day average of rms surface pressure tendency
0.3
0.25
0.2
0.15
0.1
0.05
0
Pa / s
0
500
1000
1500
2000
2500
3000
localization half-width (km)
EnKF
3D-Var
no assim
peak EnKF
peak 3D-Var