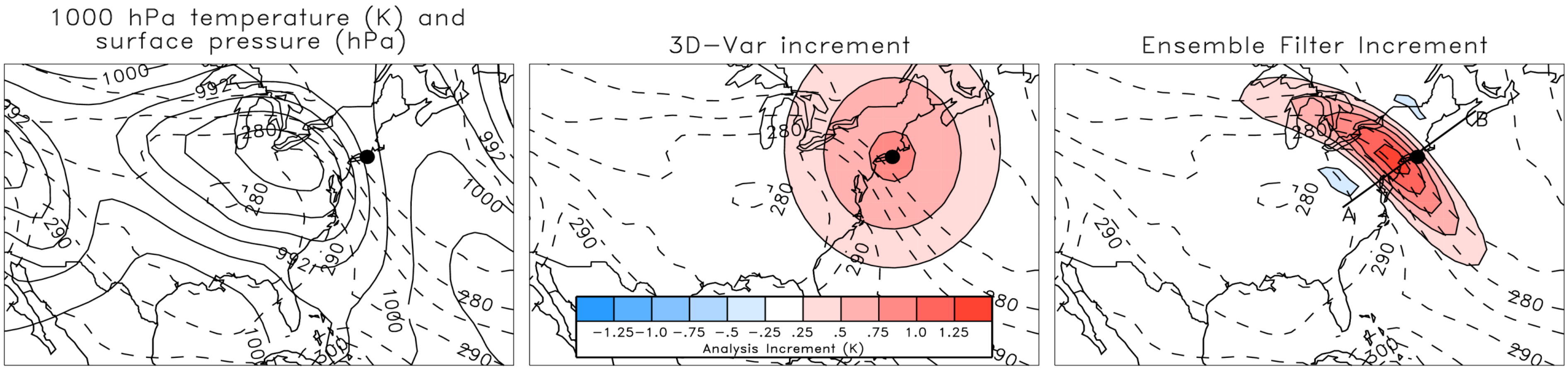
Ensemble Data Assimilation with the NCEP Global Forecasting System

Jeff Whitaker and Tom Hamill

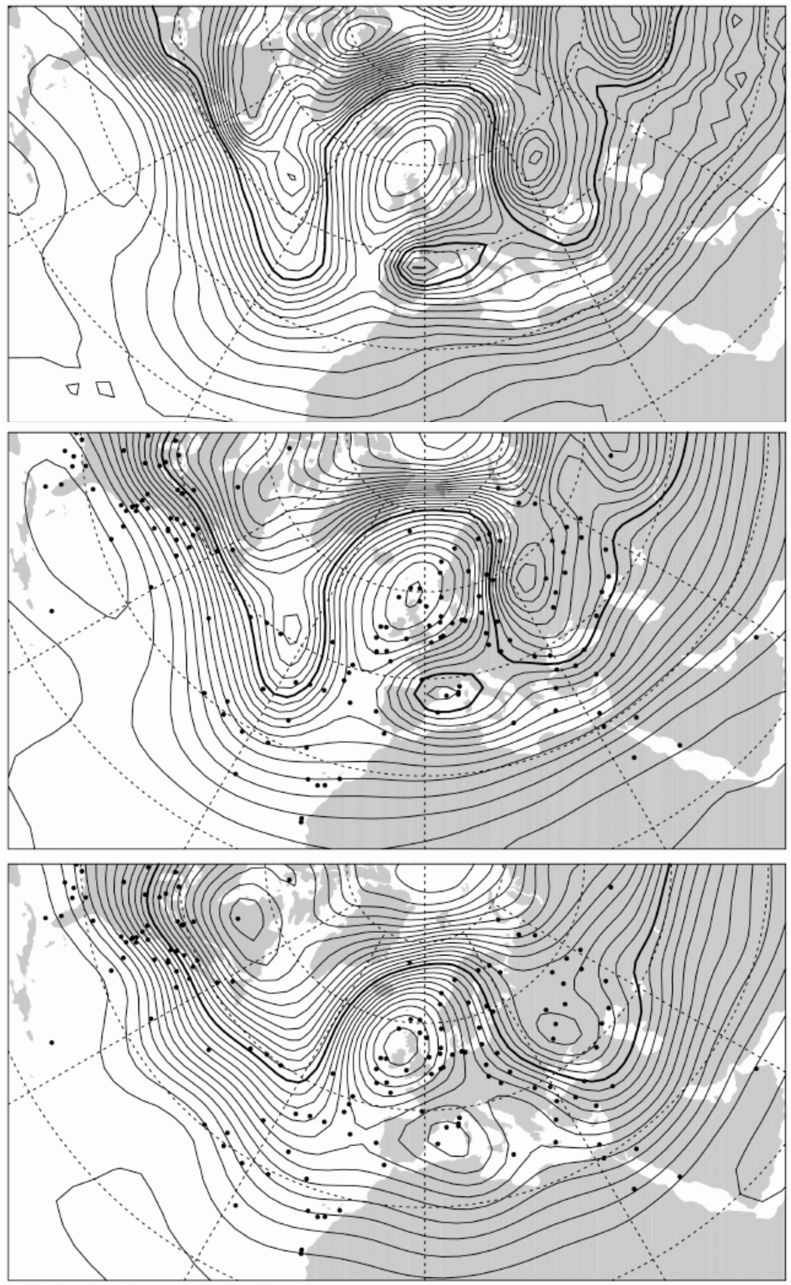
(jeffrey.s.whitaker@noaa.gov and tom.hamill@noaa.gov)

Ensemble-based data assimilation



- Parallel forecast and analysis cycles
- Ensemble of forecasts is used to estimate forecast-error statistics during the data assimilation
- Theoretically appealing: proper initialization of ensemble forecasts, targeting applications

Prior results: 500 hPa height analyses assimilating only SfcP obs



Full NCEP-NCAR Reanalysis (3DVar)
(120,000+ obs)

Ensemble Filter
(214 surface pressure obs)

Black dots show pressure ob locations

RMS = 39.8 m

Optimal Interpolation
(214 surface pressure obs)

RMS = 82.4 m
(3D-Var worse)

The Question

- Are ensemble-based data assimilation algorithms competitive with / superior to existing NCEP 3D-Var with *full current observational data set*?
- **Problem**: Most ensemble-based data assimilation algorithms scale with
  - number of elements in the state vector,
  - size of the ensemble,
  - number of observations.

  (i.e., it's too expensive right now to run a high-res., large ensemble experiment with full observation data set)
- **Compromise**: compare against 3D-Var in reduced-resolution model with ~full set of observations (except satellite radiances).

Experiment Design

- **Model**: NCEP GFS, T62 L28, March 2004 physics. 100 members.
- **Observations**: *Almost all non-radiance data*; raobs, ACARS, profilers, cloud-drift winds, surface observations.
  - 145K observations @ 1200 UTC, 60K@ 1500 UTC
  - No humidity data assimilated.
  - Surface pressure observations adjusted to model's orography
  - No ACARS temperatures (not virtual temp).
  - No non-surface pressure observations below $\sigma = 0.9$
  - Same observation error statistics as NCEP 3D-Var
  - Assimilate every 3 h; no "FGAT"
- **Period of test**: January 2004.
- **Compare against short-range forecasts from**:
  - NCEP-NCAR T62 reanalysis (includes TOVS retrievals, but uses older model).
  - Operational T254 3D-Var analysis with all data
  - Soon, we hope: T62 3D-Var with March 2004 GFS, data specified above.
- **Grid and timing**: 128*64*L28 grid; analysis parallelized over 42 processors. @1200 UTC, 37 minutes to do analysis.

Ensemble Square-Root Filter (EnSRF; Whitaker and Hamill, MWR '02)

$$\mathbf{X} = (\mathbf{x}_1^b - \overline{\mathbf{x}^b}, \ldots, \mathbf{x}_n^b - \overline{\mathbf{x}^b})$$
$$\mathbf{P}^b = \rho \circ \frac{1}{n-1}\mathbf{X}\mathbf{X}^{\mathrm{T}}$$

background-error covariances estimated from ensemble, with "covariance localization"

$$\mathbf{K} = \mathbf{P}^b\mathbf{H}^{\mathrm{T}}(\mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}} + \mathbf{R})^{-1}$$
$$\bar{\mathbf{x}}^a = \bar{\mathbf{x}}^b + \mathbf{K}\big(\mathbf{y} - H(\bar{\mathbf{x}}^b)\big).$$

Mean state updated, correcting background to new observations, weighted by **K**, the Kalman gain

$$\widetilde{\mathbf{K}} = \left(1 + \sqrt{\frac{\mathbf{R}}{\mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}} + \mathbf{R}}}\right)^{-1}\mathbf{K}.$$
$$\mathbf{x}_i'^a = \mathbf{x}_i'^b + \widetilde{\mathbf{K}}\big(H(\mathbf{x}_\mathbf{i}'^\mathbf{b})\big).$$

"reduced" Kalman gain calculated to update perturbations around mean

$$\mathbf{x}_i^b(t+1) = M(\mathbf{x}_i^b(t)) + e, \qquad e \sim N(0, \mathbf{Q})$$

Forecast forward to the next time when data is available. Add noise in some fashion to simulate model error.

EnKF?

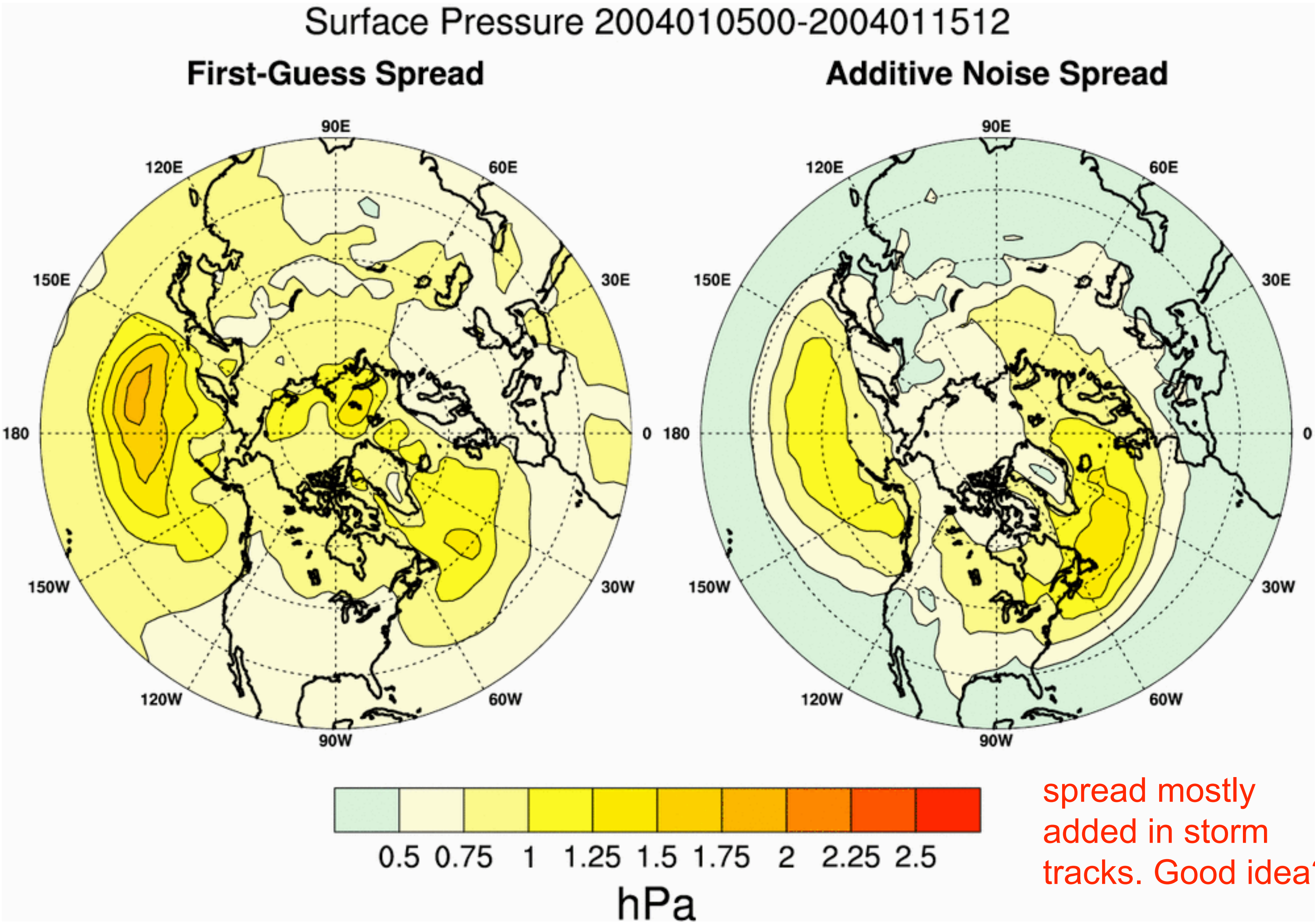
Implementation details

- **Covariance localization**
  - ***Horizontal***: Gaspari and Cohn, tapers to zero at 2800 km
  - ***Vertical***: Zero at 2 scale heights [σ such that $-\ln(\sigma)=2$]; surface observation has no influence above ~ 135 hPa
- **Lynch filter** to control gravity-wave noise (3h forecast Gaussian-weighted average of 0-6 h forecast)
- **Background Check**: Throw out observation when

$$|\mathbf{y}-\mathbf{H}\bar{\mathbf{x}}^b| > 5\left(\sqrt{\mathbf{H}\mathbf{P}^b\mathbf{H}^T} + \sqrt{\mathbf{R}}\right)$$

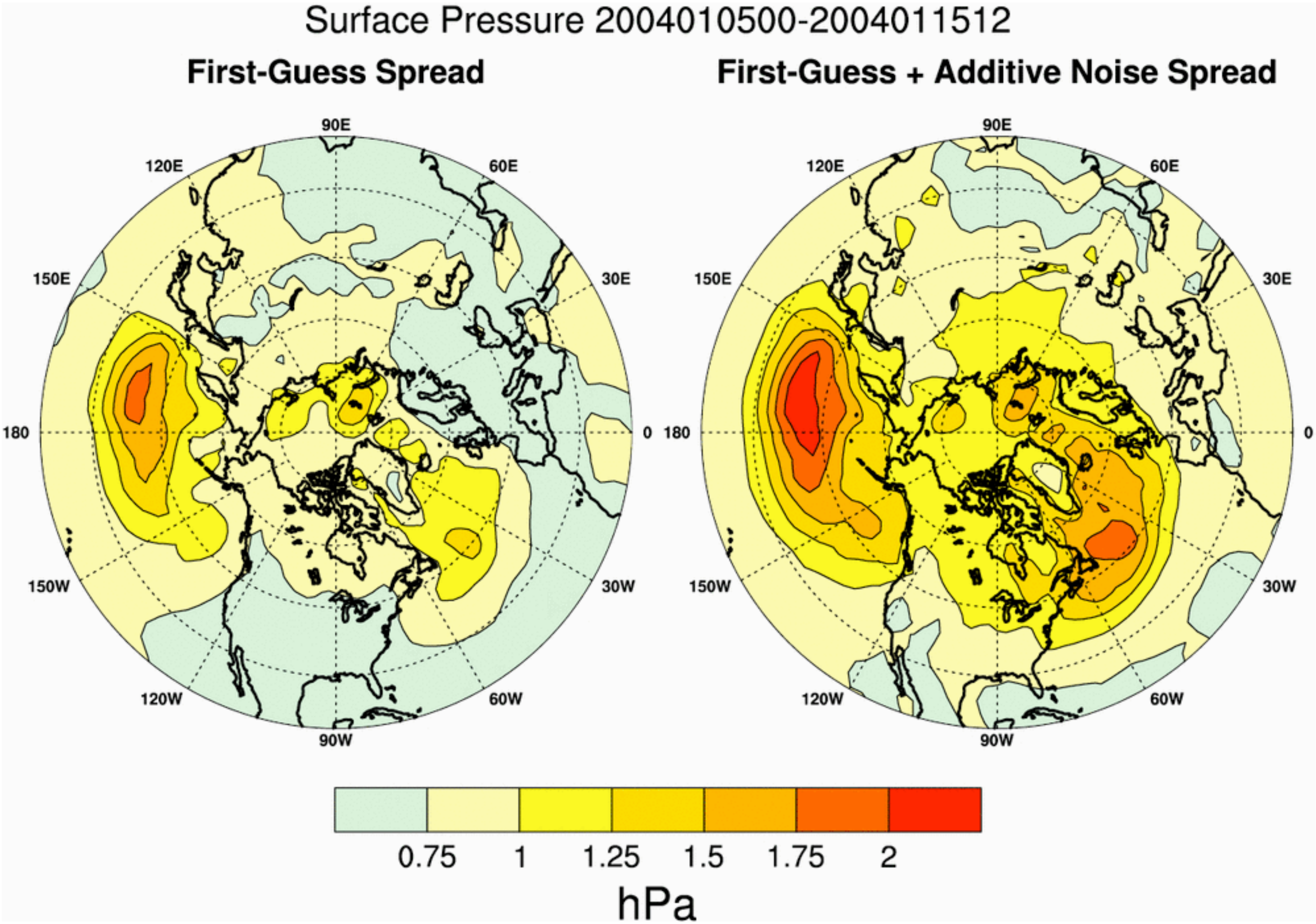
- **Model Error**:
  - ***Covariance inflation***, 30% NH, 20% SH, taper in between. Inflation amount tapers in vertical to 0.0 at 6 scale heights (problem with top boundary).
  - ***Relaxation to prior***: Snyder and Zhang (MWR, 2003), relax analysis ensemble back toward prior (40% analysis, 60% prior).
  - ***Additive errors***, random 6-h model tendencies scaled by 25 %. Samples from NCEP-NCAR reanalysis, '71-'00, for similar time of the year.

Additive “model” errors from 6-h tendencies



spread mostly added in storm tracks. Good idea?

Additive “model” errors from 6-h tendencies



Analysis, forecast, and model-error spread statistics for surface pressure

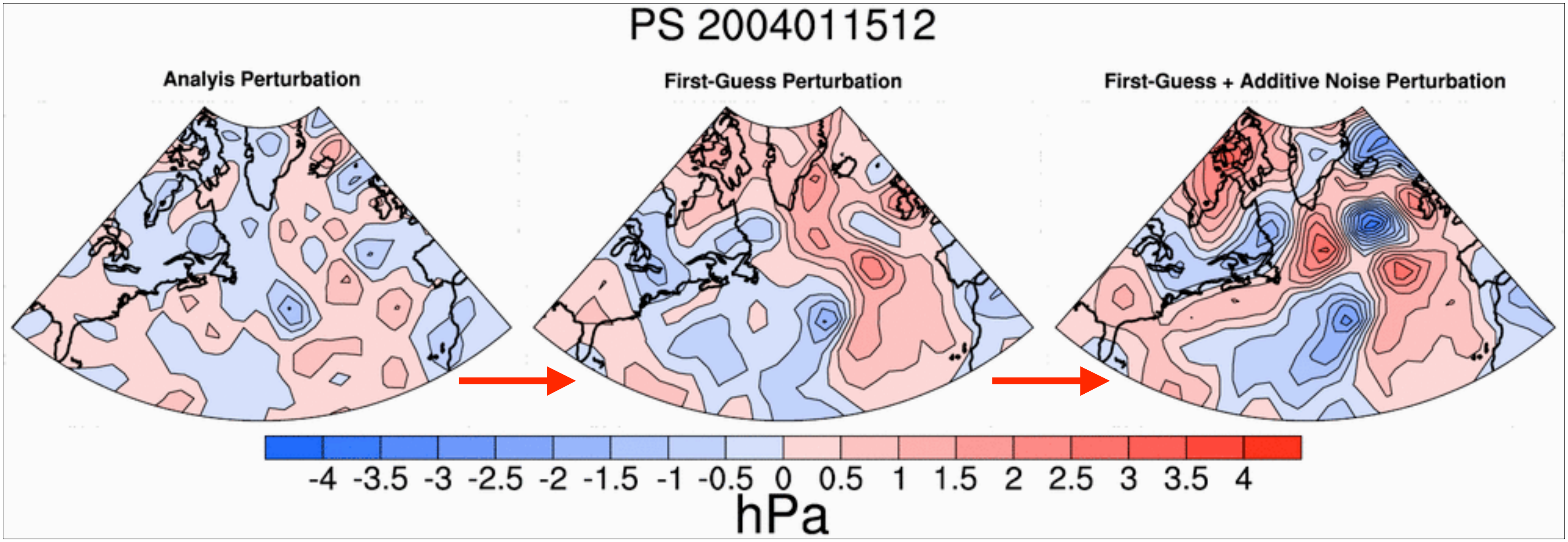
Variances from additive error run, 0000 and 1200 UTC cycles, 0000 UTC 5 Jan 2004 - 0000 UTC 15 Jan 2004

Analysis :	0.50 mb^2	(σ = 0.707 mb)
Background (3 h later): (w/o additive error)	0.87 mb^2	(σ = 0.932 mb)
Background (with additive error)	1.09 mb^2	(σ = 1.044 mb)

[**Observation, R** = 1.0 hPa^2 over land, 1.6 hPa^2 for ships]

Our spread DOES increase during forecast, unlike previous results of H&M. Due to the chosen additive error strategy?

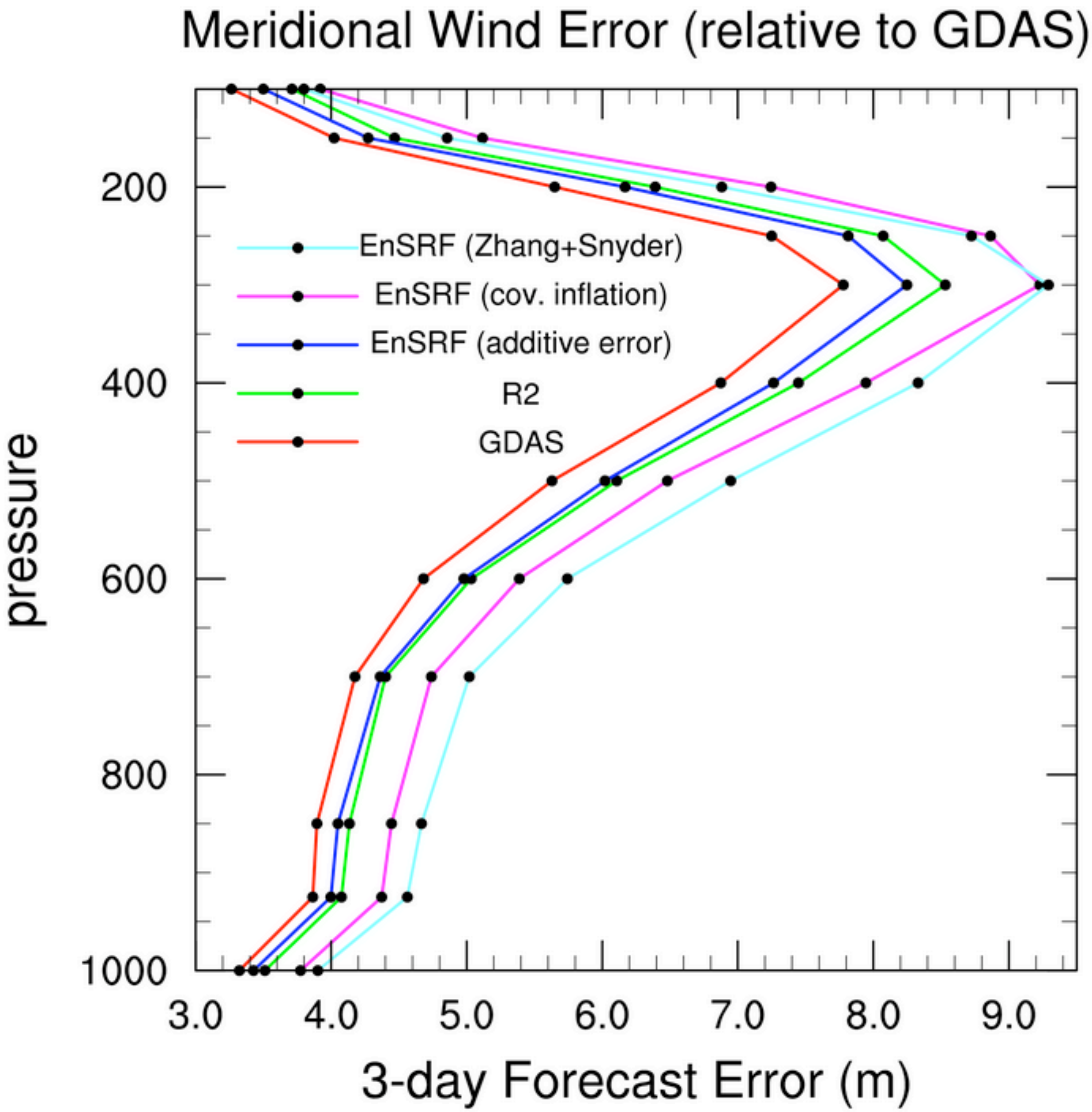
Example: structure of perturbations



(errors grow during the 3-h forecast)

(fairly large amount of noise added, especially in storm tracks)

3-day N Hem. forecast errors from analyses

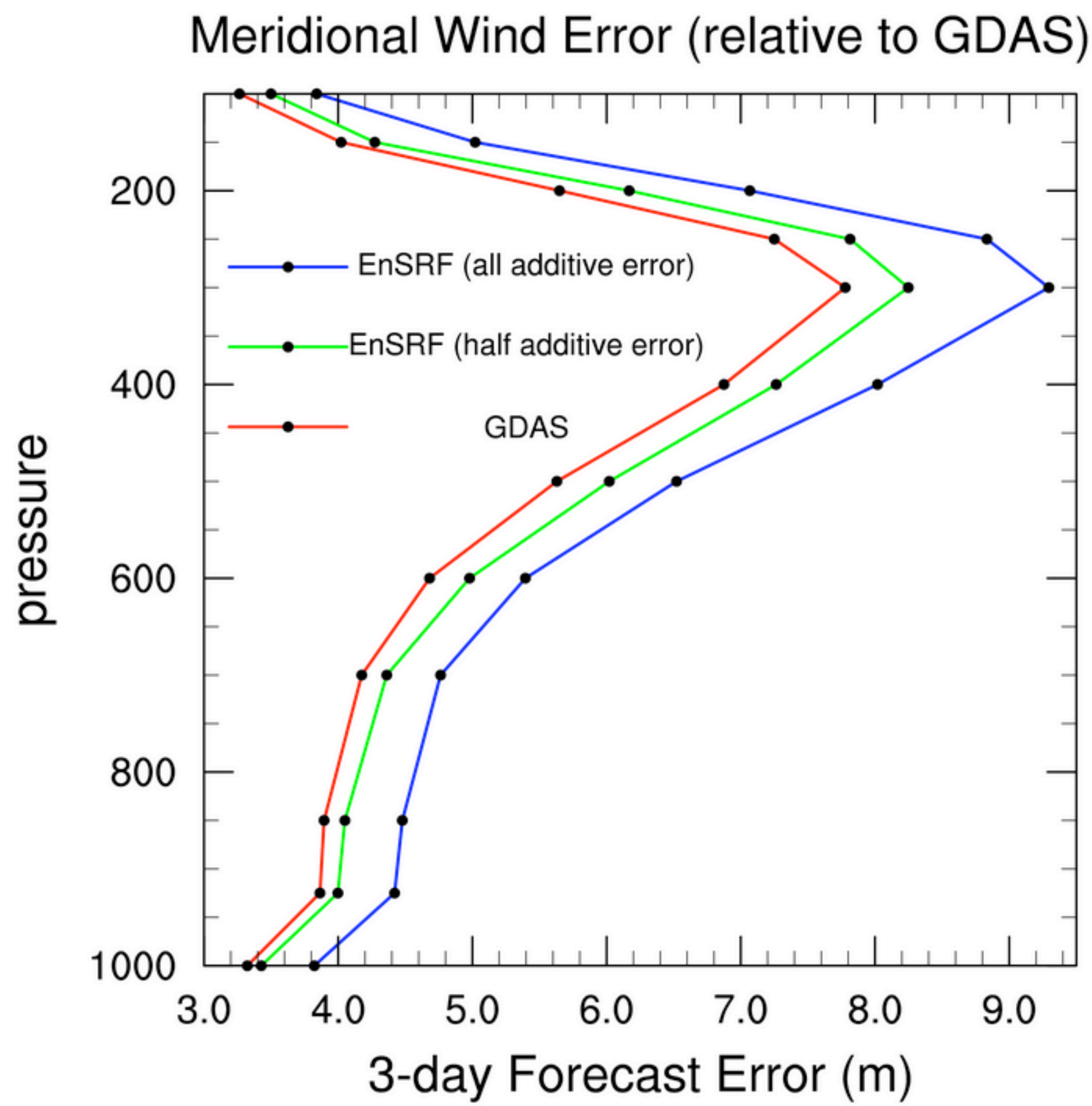


- Additive error the best of the filters (not true in sparse sfc. pres. expt's).

- Additive errors comparable to NCEP/NCAR reanalysis (uses older model but utilizes extra TOVs retrievals).

- Additive produces larger errors than operational T255 3D-Var including radiances (equivalent to 3-6 h of forecast lead).

Do flow-dependent covariances from ensemble have positive influence?

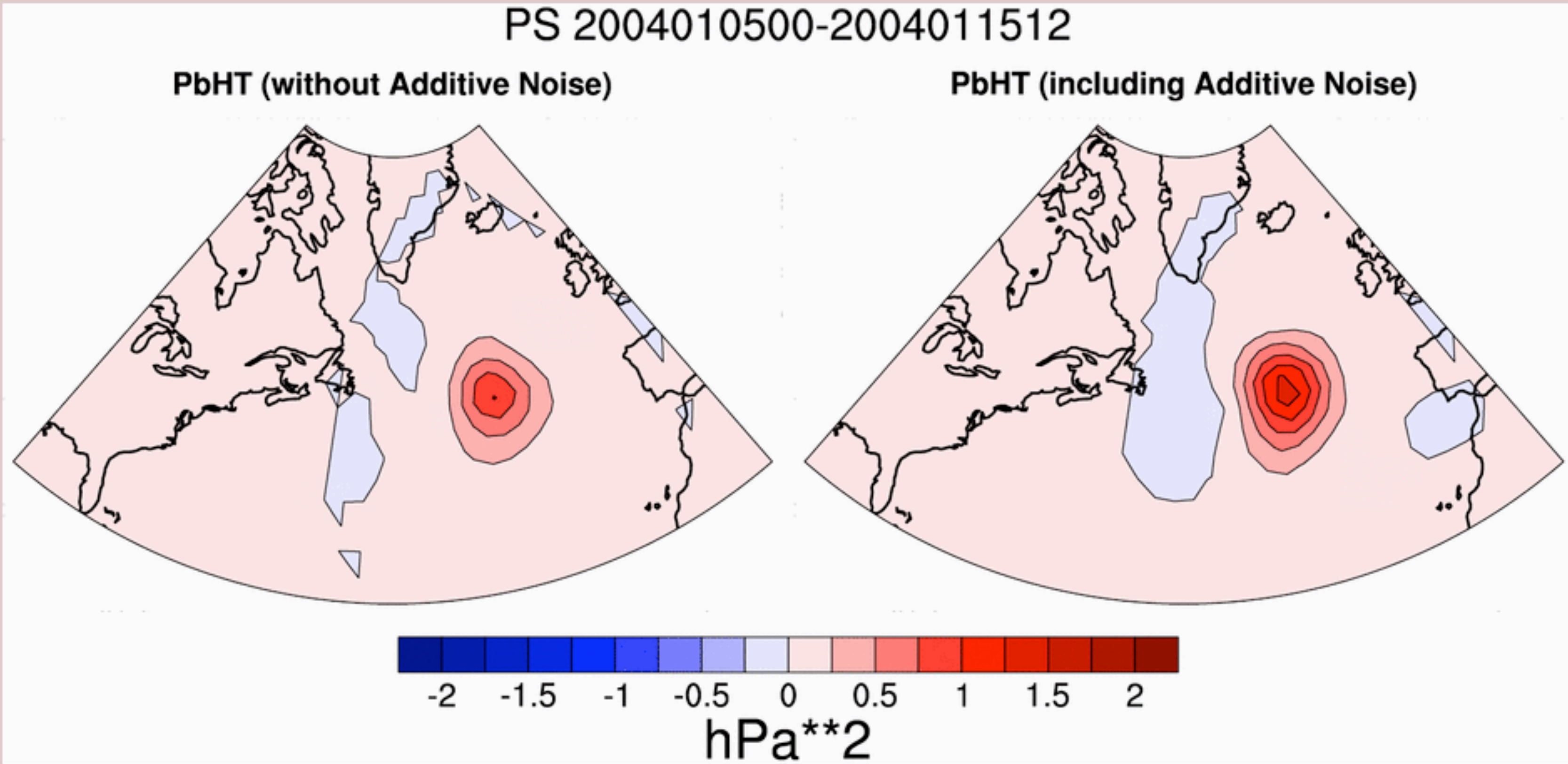


Here, another version of the filter was run where the background ensemble perturbations from the background mean were fully replaced by additive error noise. This decreased the analysis accuracy, Indicating that ensemble did provide useful information.

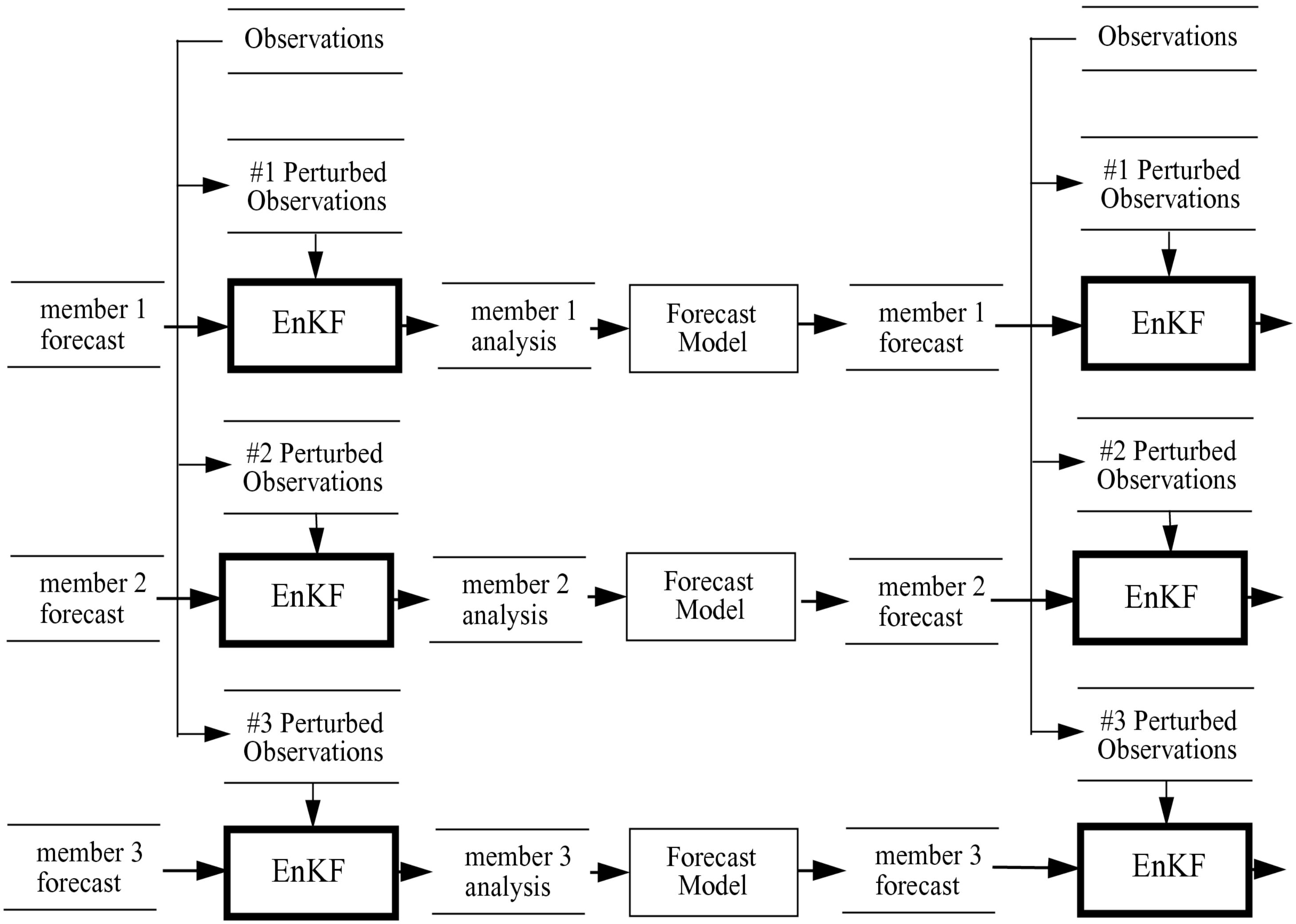
Conclusions

- Generally positive initial results from EnSRF
  - additive error implementation of filter competitive with similar-resolution reanalysis with more observations, older model.
  - worse than T255 3D-Var with radiances (3-6 h forecast lead @ 72h).
  - need closer standard for comparison (NCEP committed to run T62 3D-Var using Mar 2004 model, same observations).
- Mostly ad-hoc experimentation with model error so far. Don’t know if our 6-h tendency approach is a good one. Most of model-error noise is added in storm tracks.
- Issues:
  - Need to better quantify model and observation errors.
  - Higher-res. forecasts would be preferable to increase internal error growth.
  - Test other ways to improve computational efficiency (hybrid 3D-Var / ETKF following Hamill and Snyder ‘00, Etherton and Bishop ‘04?)

Does background-error covariance model change much with time?

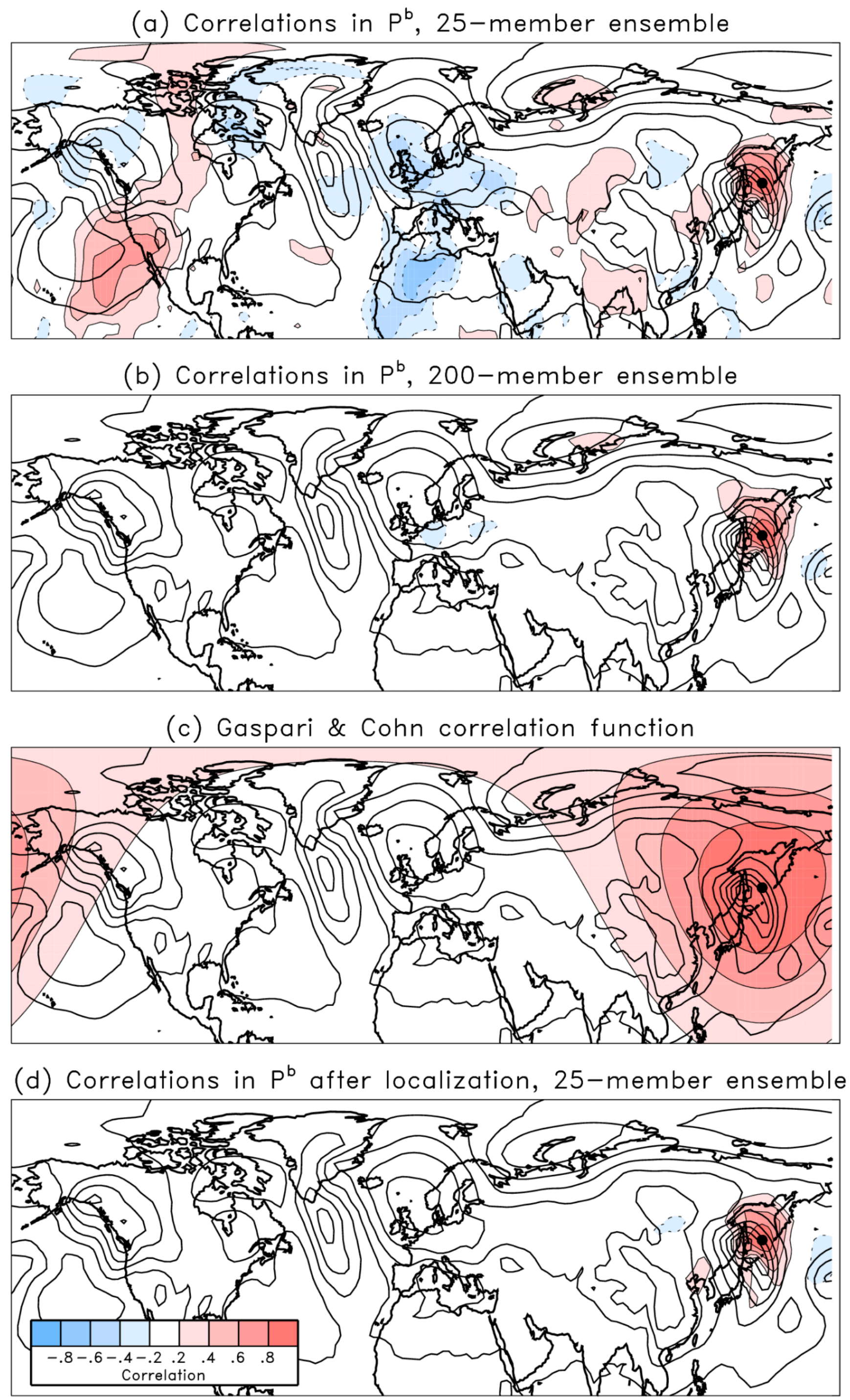


The ensemble Kalman filter: a schematic



(This schematic is a bit of an inappropriate simplification, for EnKF uses every member to estimate background-error covariances)

Covariance localization: a way of dealing with inappropriate covariance estimates due to small ensemble size.



from Hamill review paper, to appear in upcoming Cambridge Press book. See also Houtekamer and Mitchell, MWR, March 1998