Comparison between Local Ensemble Transform Kalman Filter and PSAS in NASA finite volume GCM

Perfect model experiments

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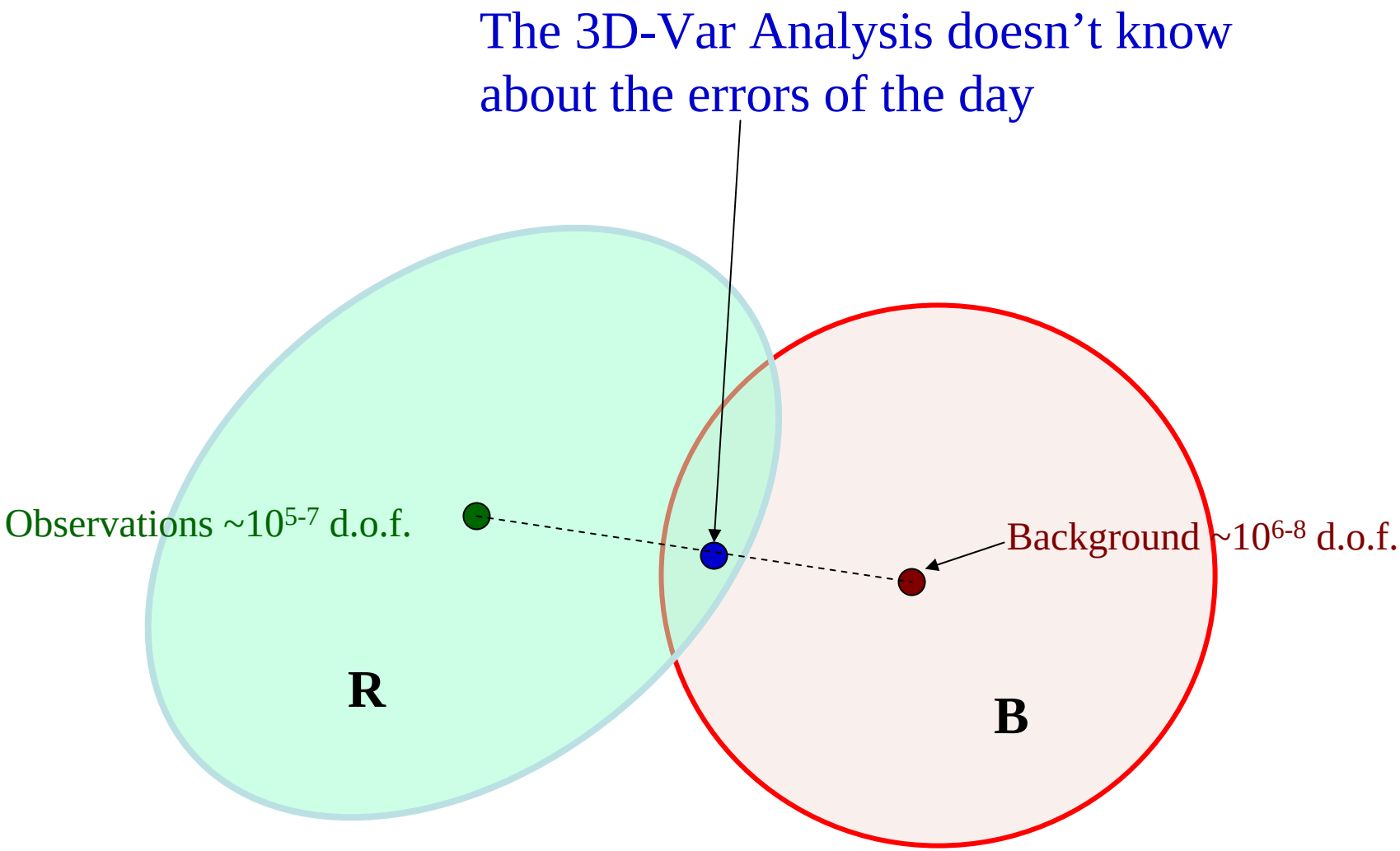
Outline

- Introduction
  - Physical-space Statistical Analysis System (PSAS)
  - Local Ensemble Transform Kalman Filter (LETKF)
  - NASA finite volume GCM (fvGCM)
- Experimental Design
  - Assimilate simulated rawinsonde observations
  - Comparison of PSAS and LETKF for perfect model
- Results
  - Using small ensemble (40 members), LETKF can capture fvGCM background uncertainty
  - LETKF obtains a superior analysis than PSAS
- Diagnostics
  - LETKF better captures the errors of the day
- Conclusions and Future Plans
  - Running experiments with real rawinsonde observations
  - Preparing to assimilate AIRS retrievals
  - Will assimilate AIRS radiances
- Challenges: Computer access and infrastructure

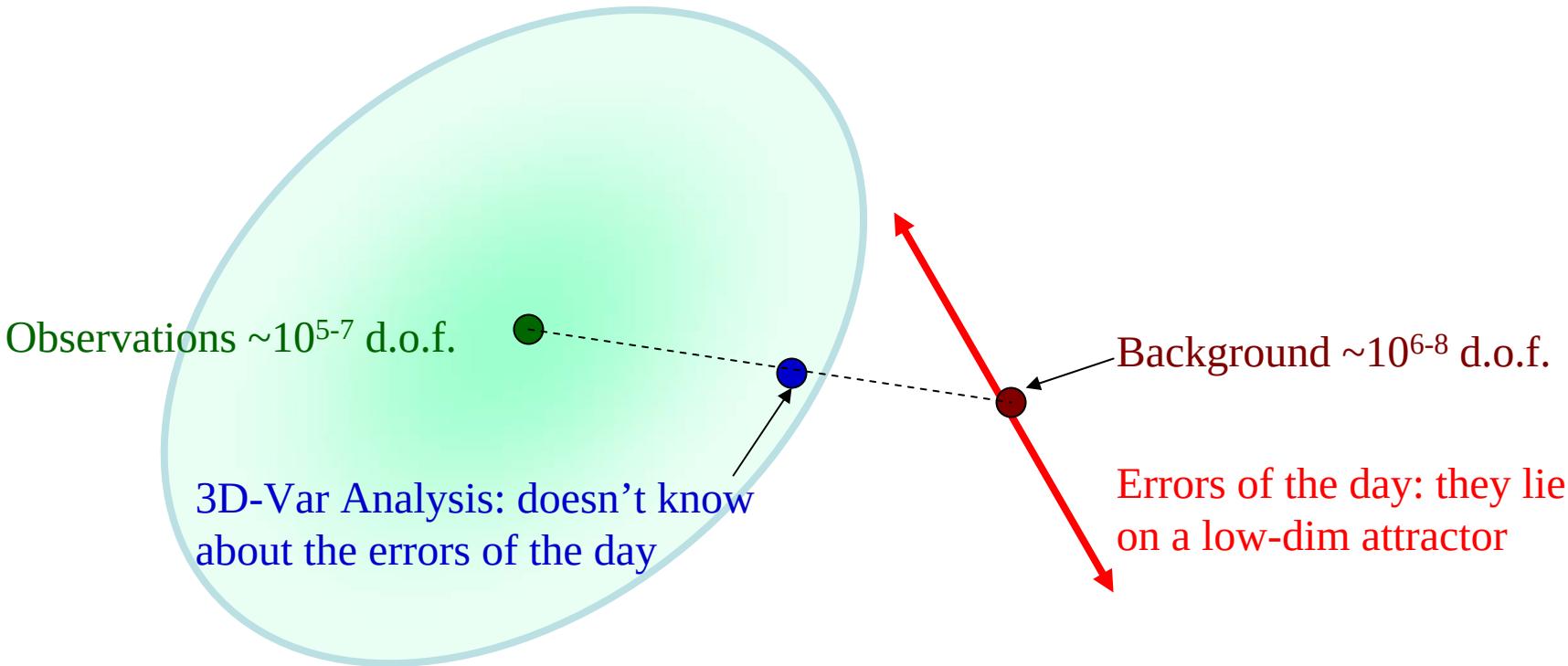
Introduction and Experimental Design

Hong Li

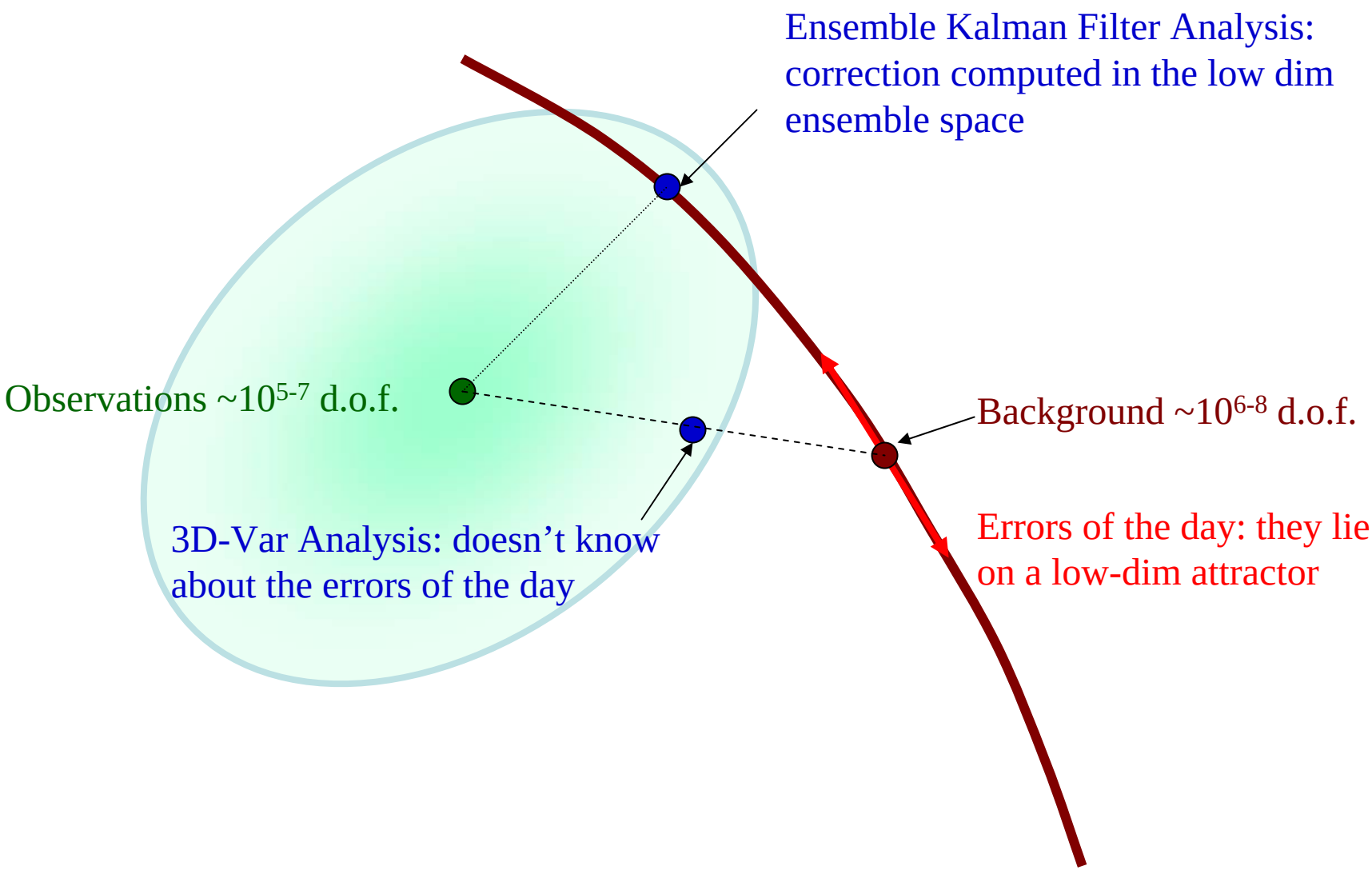
Suppose we have a 6hr forecast (background) and new observations



With Ensemble Kalman Filtering we get perturbations pointing to the directions of the "errors of the day"



Ensemble Kalman Filtering is efficient because matrix operations are performed in the low-dimensional space of the ensemble perturbations



Attributes of PSAS

- Until recently, the operational 3DVAR scheme used at NASA.
- User-friendly infrastructure
- Matrix computations are done in observation space, which has a lower dimension than the model state.

Local Ensemble Transform Kalman Filter (LETKF, Hunt 2006)

- Forecast step

$$\mathbf{x}_t^f = m\mathbf{x}_{t-1}^a$$

$$\mathbf{P}_t^f = \mathbf{M}_{x_{t-1}^a}\mathbf{P}_{t-1}^a\mathbf{M}_{x_{t-1}^a}^T + \mathbf{Q}$$

- Analysis step

$$\mathbf{x}_i^a = \mathbf{x}_i^f + \mathbf{K}_i(\mathbf{y}_i^o - h(\mathbf{x}_i^f))$$

$$\mathbf{K}_i = \mathbf{P}_i^f\mathbf{H}^T[\mathbf{H}\mathbf{P}_i^f\mathbf{H}^T + \mathbf{R}]^{-1}$$

$$\mathbf{P}_{i\ n\times n}^a = [\mathbf{I} - \mathbf{K}_i\mathbf{H}]\mathbf{P}_i^f$$

- LETKF is an ensemble based Kalman Filter

$$\mathbf{P}_i \approx \frac{1}{k-1}\sum_{i=1}^{K}(x_i^f - \overline{x^f})(x_i^f - \overline{x^f})^T$$

$$= \frac{1}{k-1}\mathbf{X}^f \bullet \mathbf{X}^{fT}$$

- Compute matrix inverse in space spanned by ensemble

$$\mathbf{K} = \mathbf{X}^f\tilde{\mathbf{P}}^a(\mathbf{H}\mathbf{X}^f)^{\mathbf{T}}\mathbf{R}^{-1}$$

$$\mathbf{X}^a = \mathbf{X}^f\left(\tilde{\mathbf{P}}^a\right)^{1/2}$$

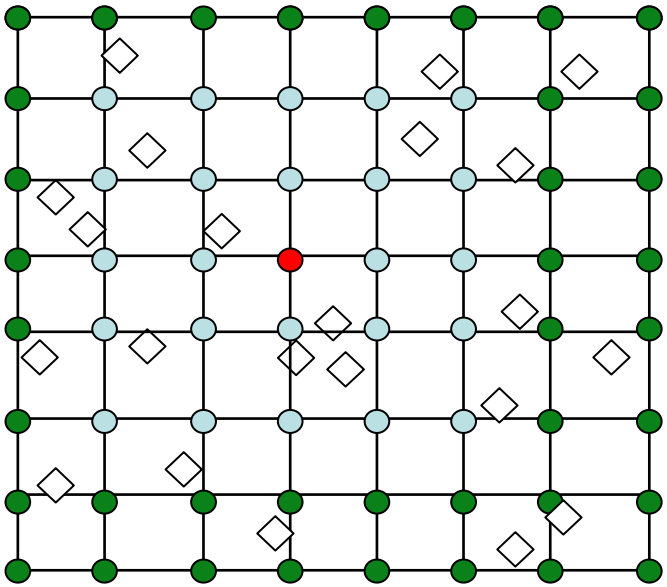
$$\tilde{\mathbf{P}}^a = \left[(k-1)\mathbf{I}_{\mathbf{kxk}} + \left(\mathbf{H}\mathbf{X}^f\right)^{\mathbf{T}}\mathbf{R}^{-1}\mathbf{H}\mathbf{X}^f\right]^{-1}$$

Local Ensemble Transform Kalman Filter

Perform Data Assimilation in local patch (3D-window)

- The state estimate is updated at the central grid red dot

- All observations (purple diamonds) within the local region are assimilated



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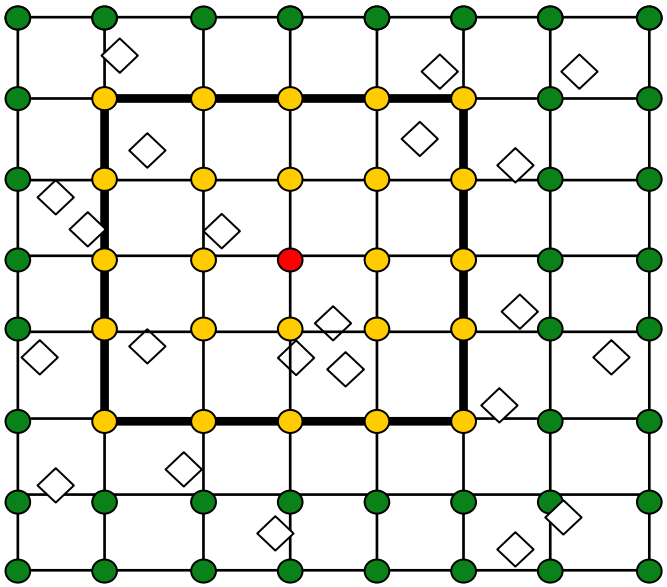

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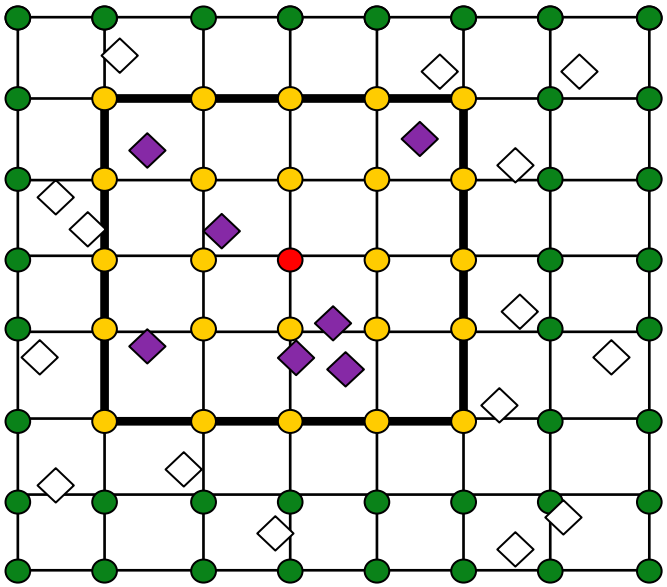
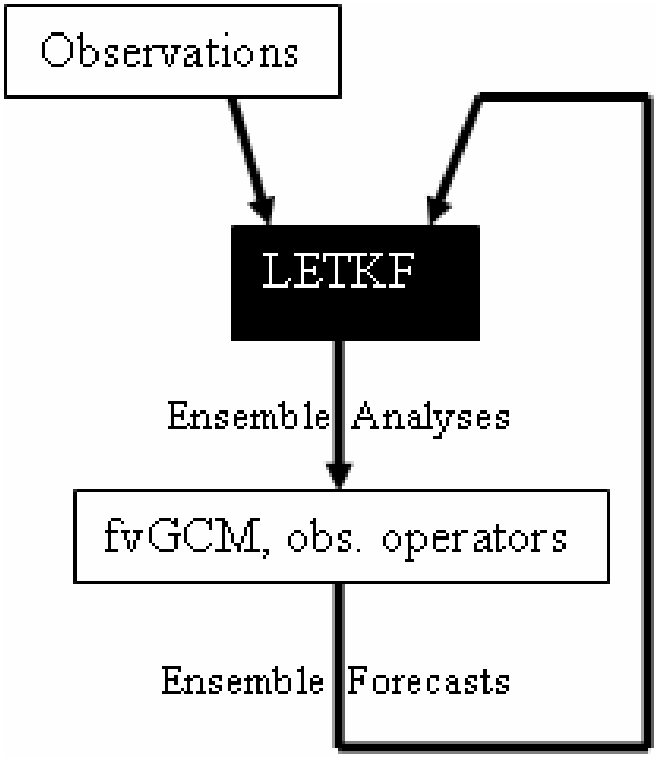


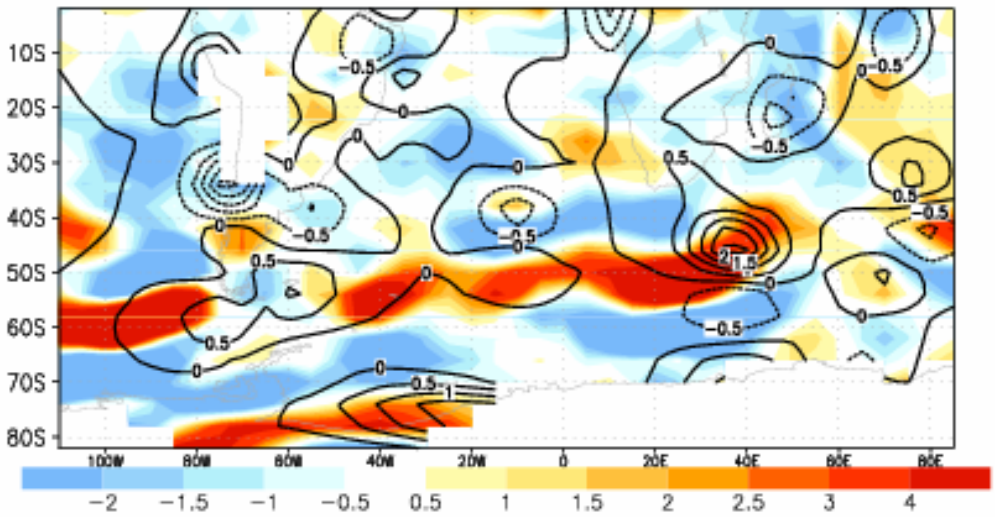
Advantages of LETKF

- Matrix computations are done in a very low-dimensional space: both accurate and efficient, needs small ensemble.
- The analysis is computed independently at each grid point, it is 100% parallel!
- Very fast! 5 minutes in a 20 PC cluster with 40 ensemble members.
- Model independent, and also do not require adjoint of the model.
- Can use full nonlinear observation operator, do not require its adjoint or Jacobian.
- It knows about the "errors of the day" through P^f.



Errors of the Day

PSAS



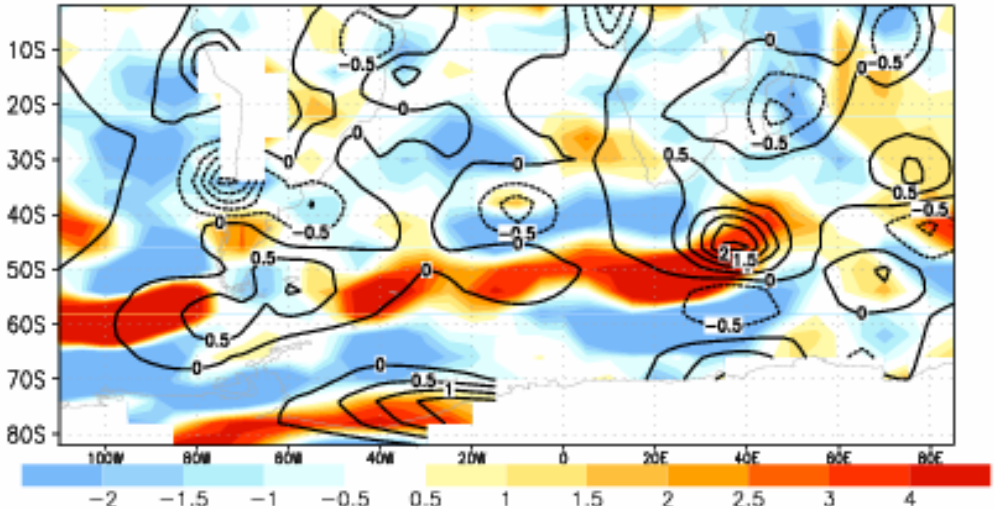
PSAS cannot account for the errors of the day!!

Snapshot of background error (colored area)

and analysis increment (contour)

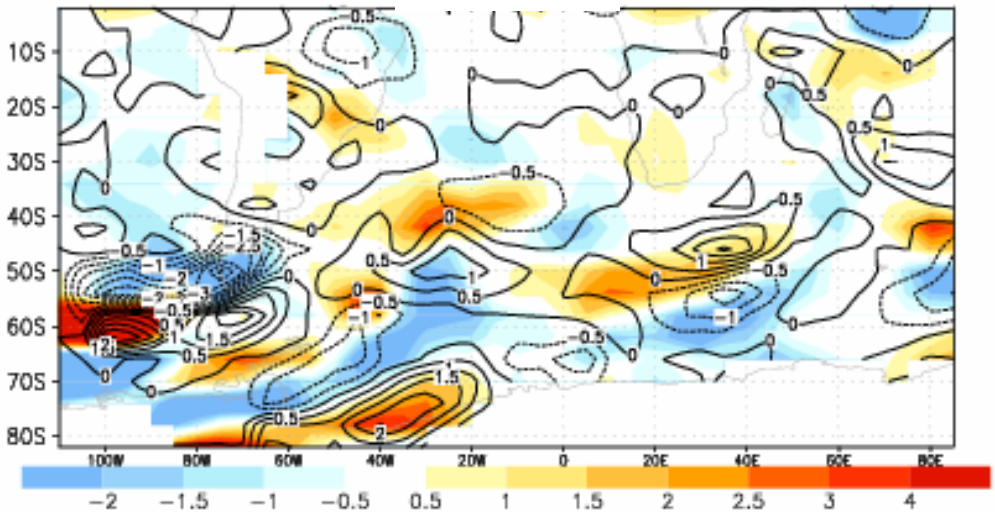
Errors of the Day

PSAS



PSAS cannot account for the errors of the day!!

LETKF



LETKF does account for the errors of the day!!

NASA finite-volume GCM

The NASA finite-volume GCM(fvGCM) is a quasi-operational weather forecasting model.

It has 72 zonal, 46 meridional grid-points and 55 levels.

It has highly accurate numerics but it is very different from other models (e.g., surface pressure is not a prognostic variable)

Data Assimilation on NASA fvGCM with LETKF

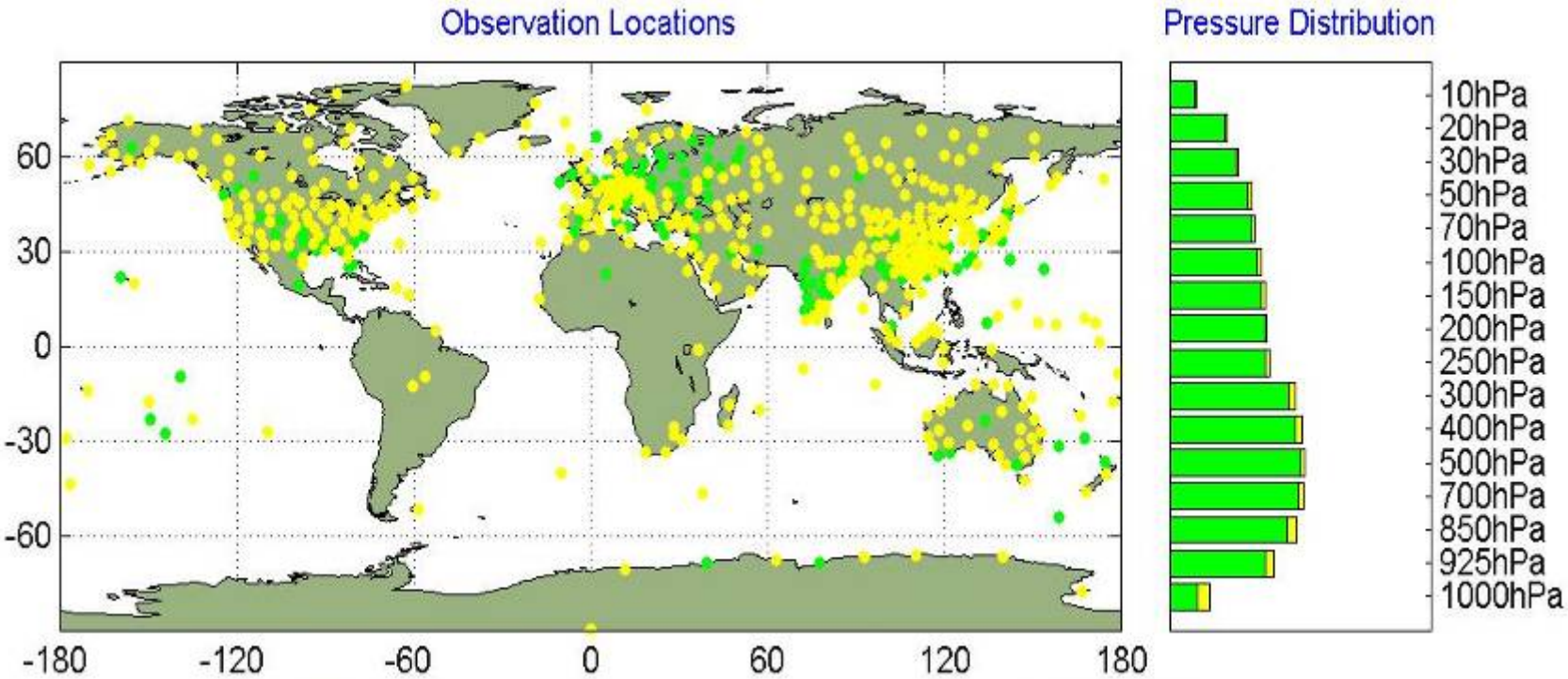
Experimental Design:

Perfect model scenario: A “true” trajectory is generated by integrating the fvGCM model for several months.

Simulated rawinsonde observations: The observations are the truth plus observational error as operational one. They are at rawinsonde locations. We have two sets of observation types.

1) zonal wind(u), meridional wind (v), and geopotential height (H)
2) zonal wind(u), meridional wind (v), temperature (T), and surface pressure(ps)

Real rawinsonde observation locations



horizontal distribution

relative vertical distribution

00Z rawinsonde observation distribution

Data Assimilation on NASA fvGCM with LETKF

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1) zonal wind(u), meridional wind (v), and geopotential height (H)
2) zonal wind(u), meridional wind (v), temperature (T), and surface pressure(ps)

Local patch size : Change with latitude based on the observation coverage and physical distance between grid points.

Inflation scheme : Multiplicative inflation is used.

Results

Junjie Liu

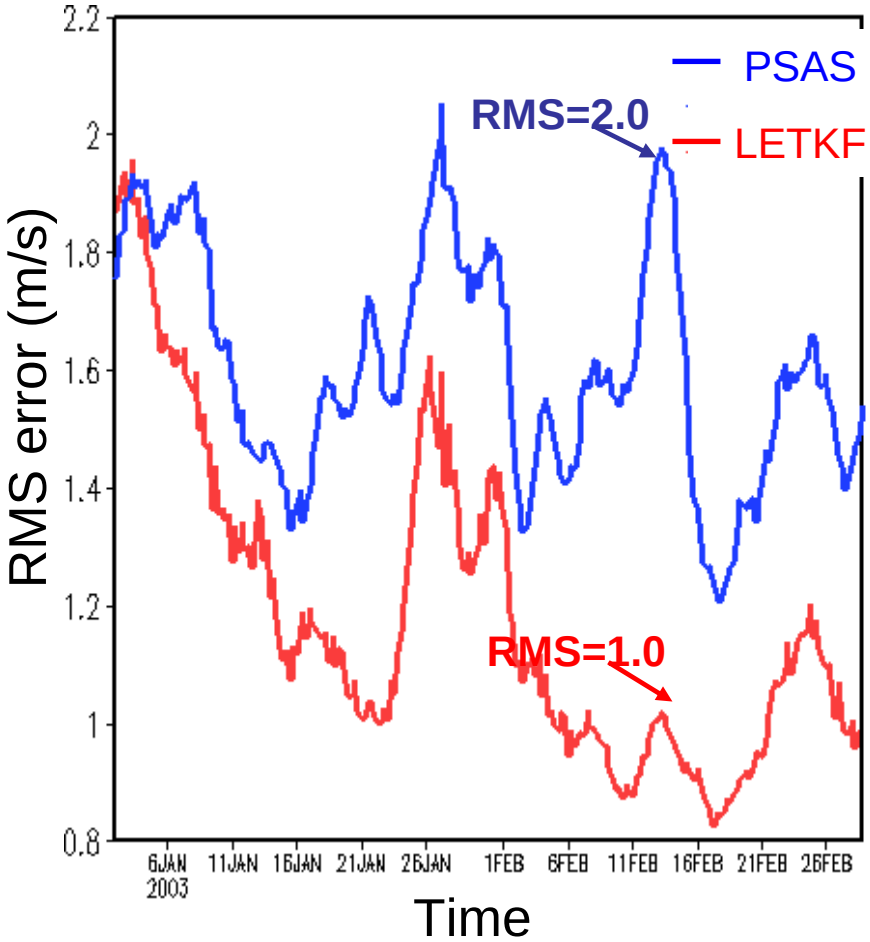
First set of observation experiments

- Observed variable: U, V, H

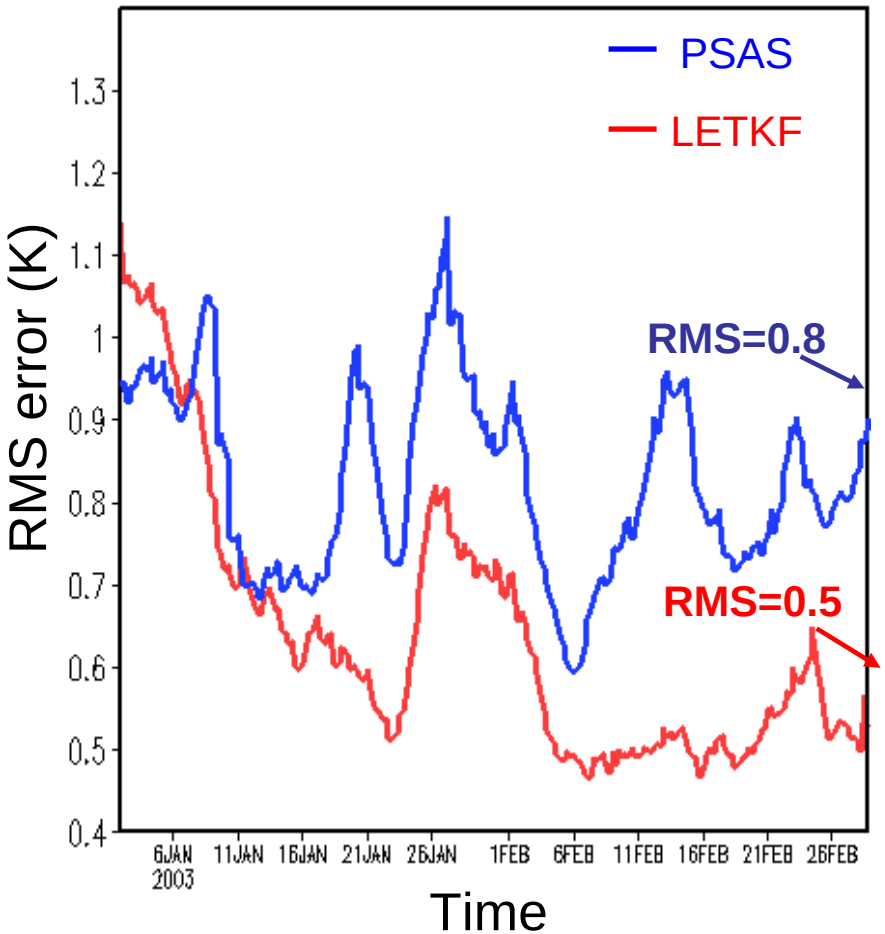
- Updated dynamical variable (eta coordinate): U, V, scaled potential T, and Ps

- Plotted variable: U, T (related with scaled potential T, and pressure thickness (delp))

500hPa analysis RMS error (Global average)

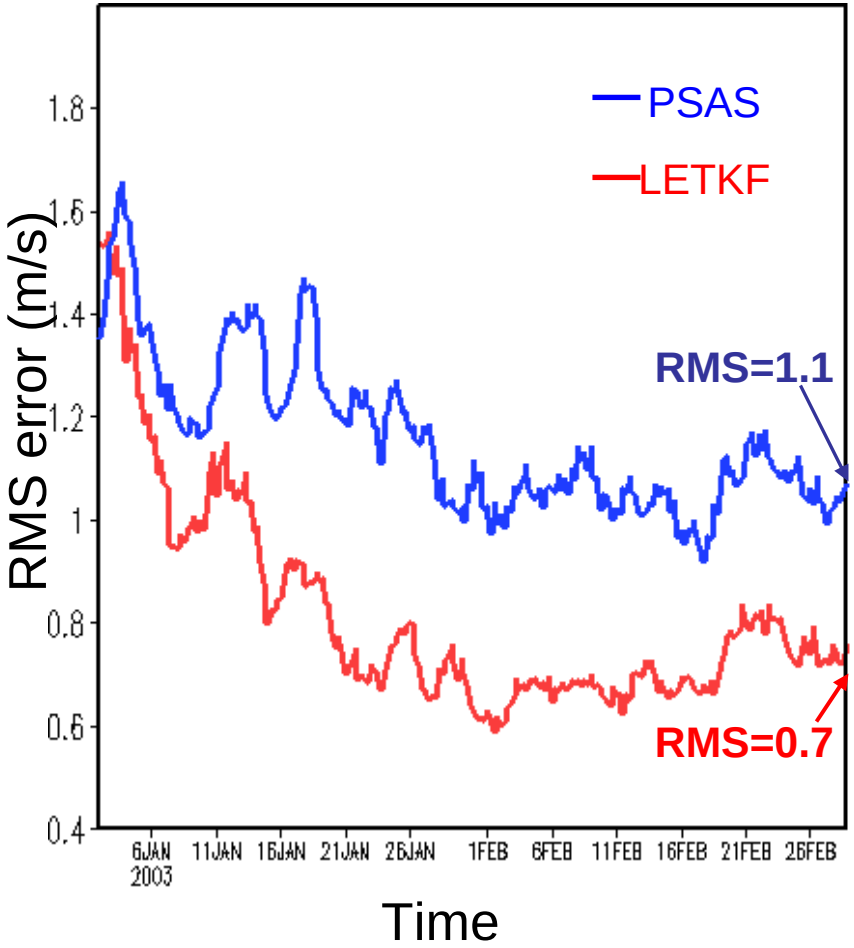


Zonal Wind

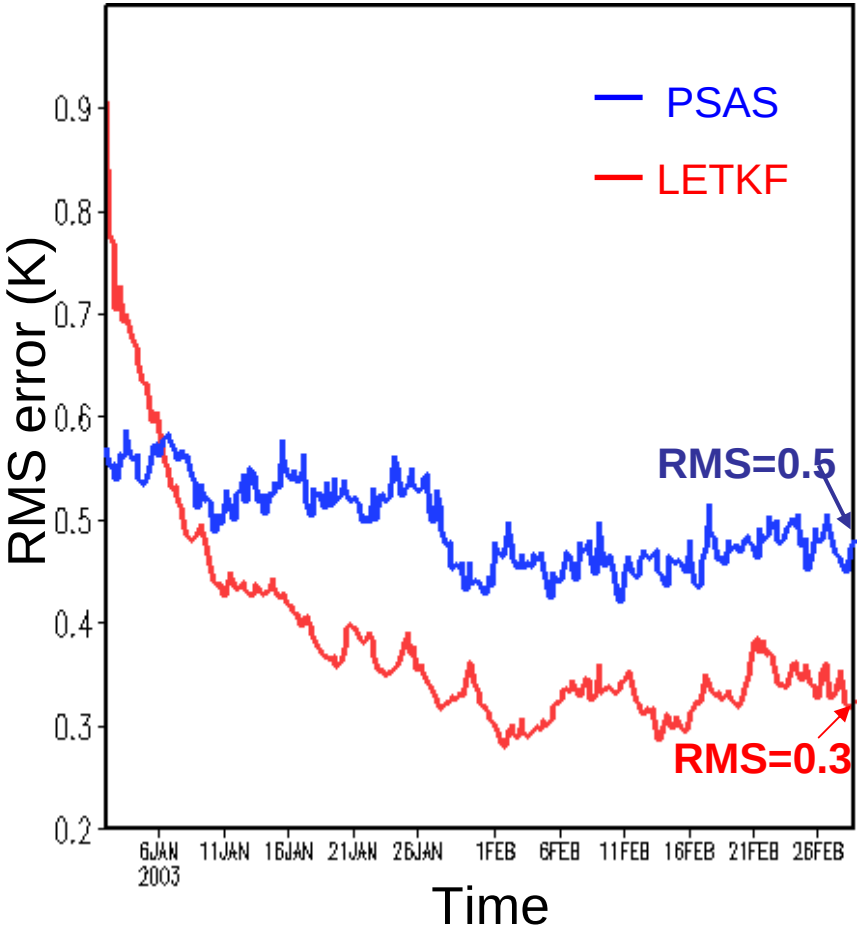


Temperature

500hPa analysis RMS error (Northern Hemisphere average)

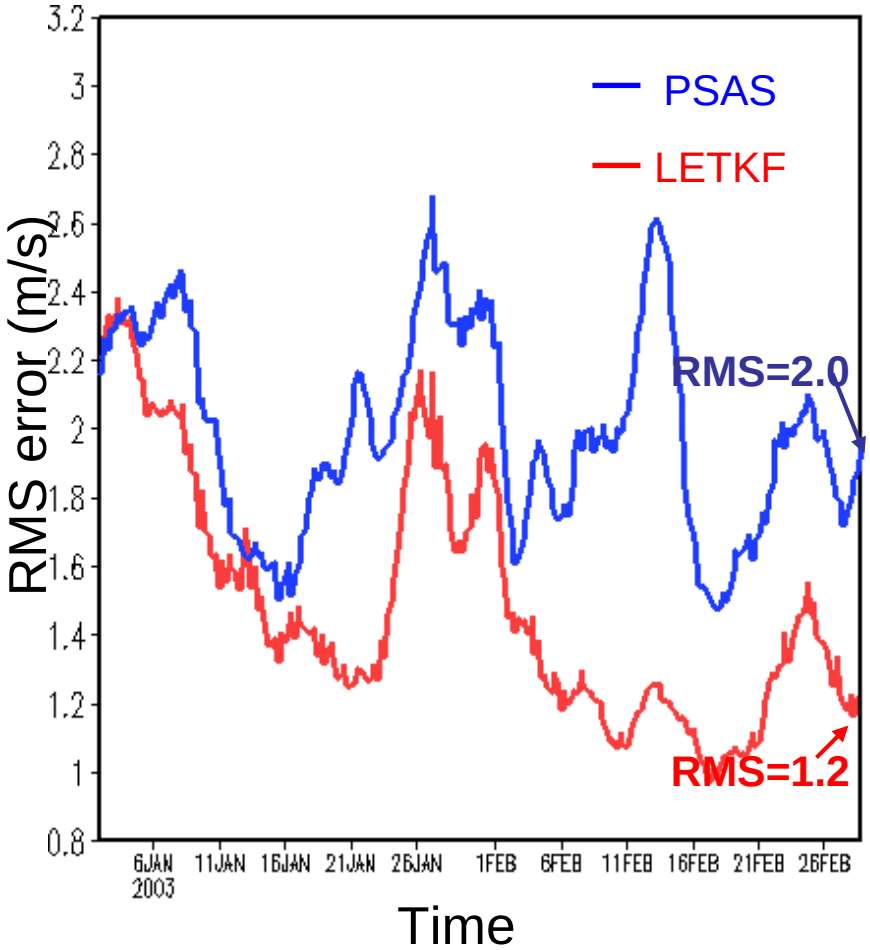


Zonal Wind

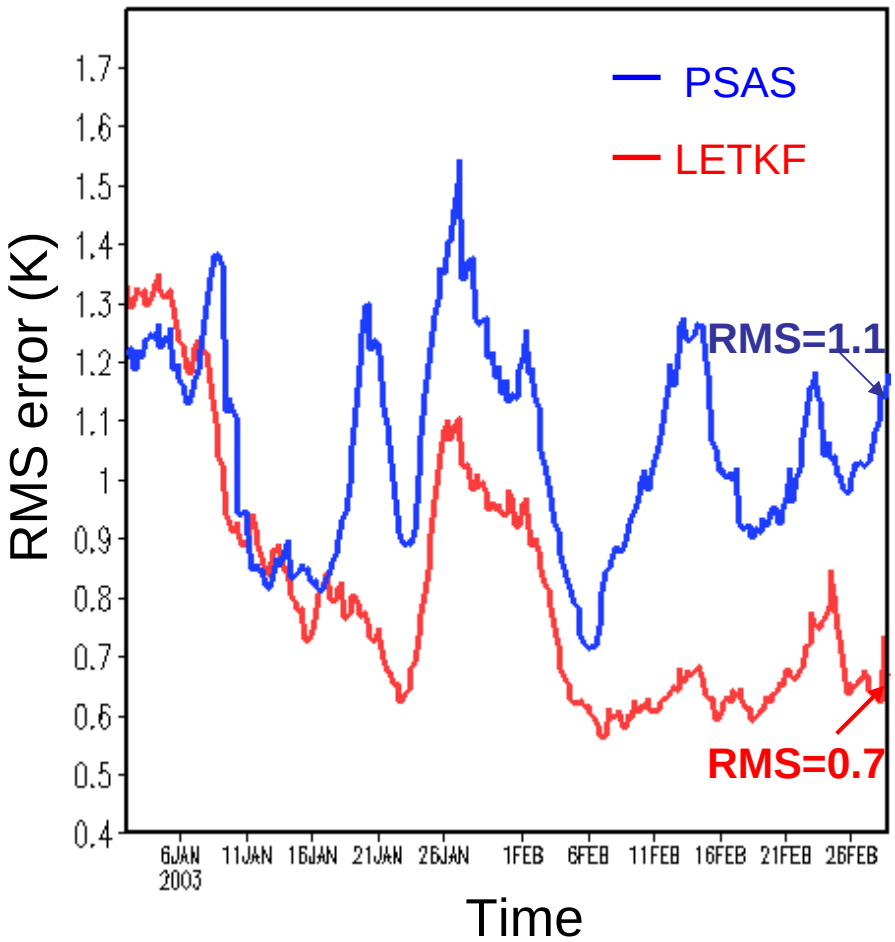


Temperature

500hPa analysis RMS error (Southern Hemisphere average)

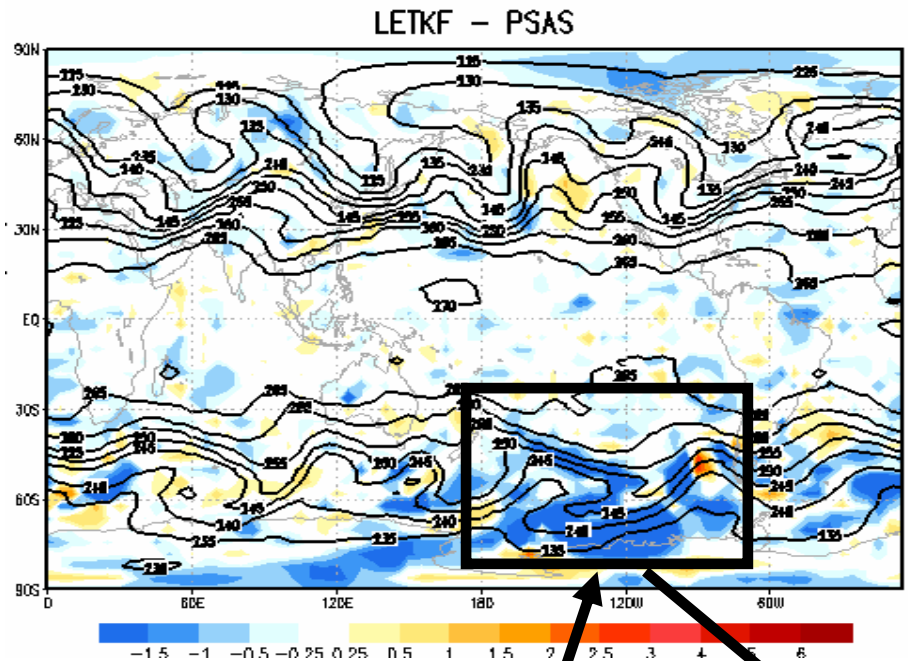


Zonal Wind



Temperature

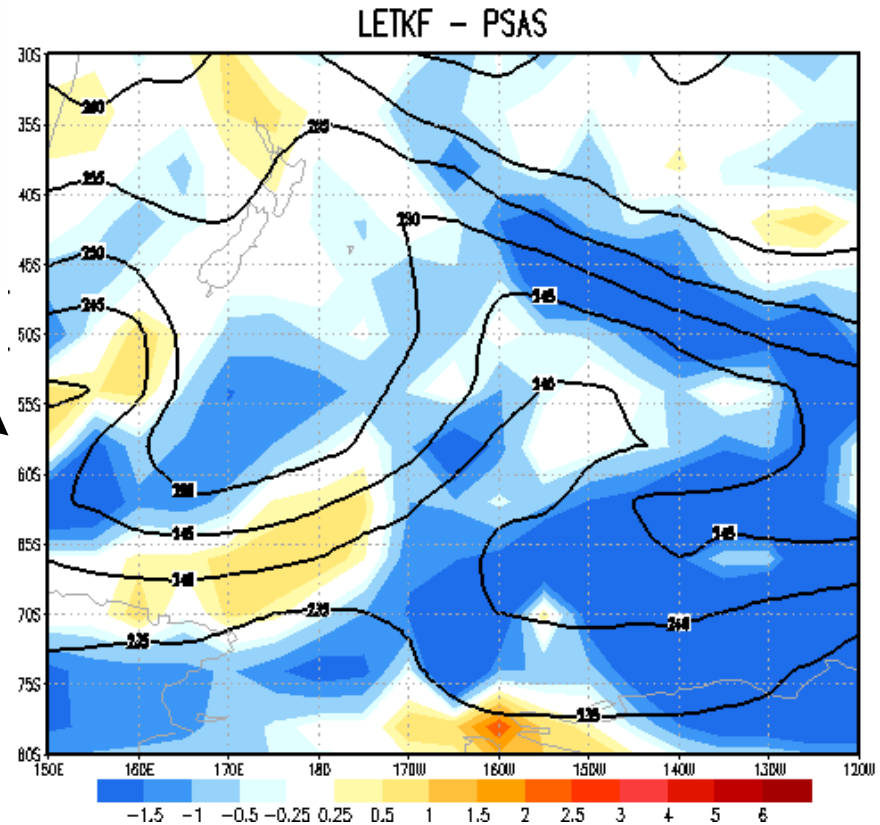
Exploring large RMS analysis error on 06Z Feb12



500 hPa temperature

RMS error difference between LETKF and PSAS analysis (**color**)

True atmospheric state (**contour**)

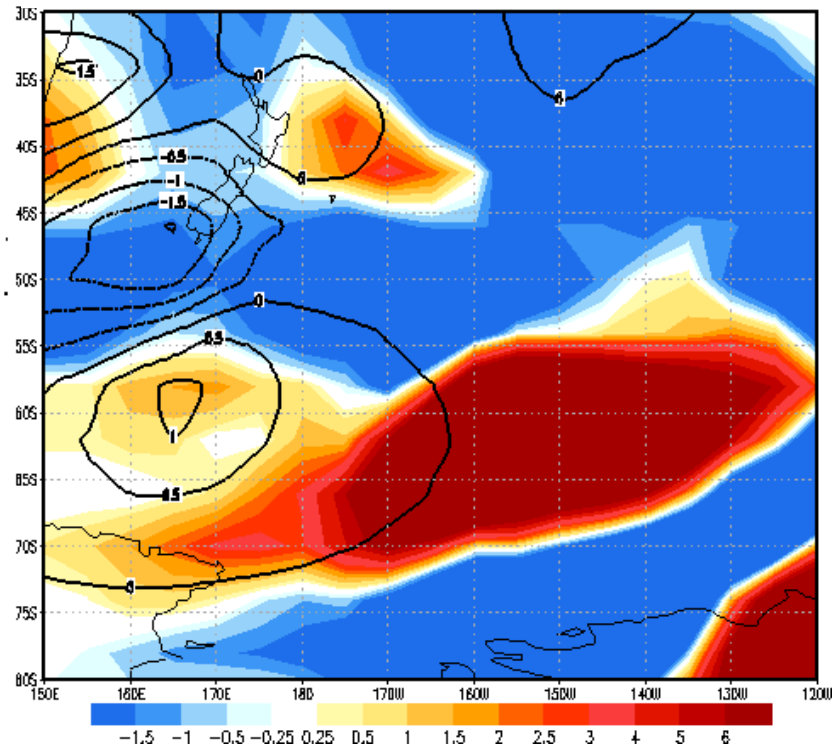


Error difference between LETKF and PSAS most significant in this region

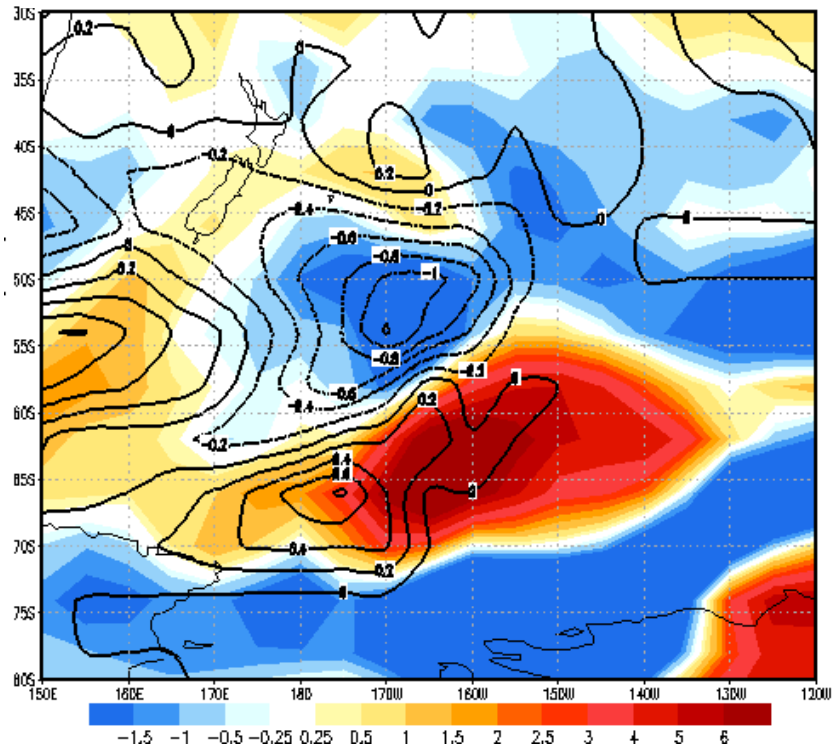
Exploring large RMS analysis error on 06Z Feb12

Background Error (**color**)
Analysis Increment (**contour**)
500 hPa temperature

PSAS

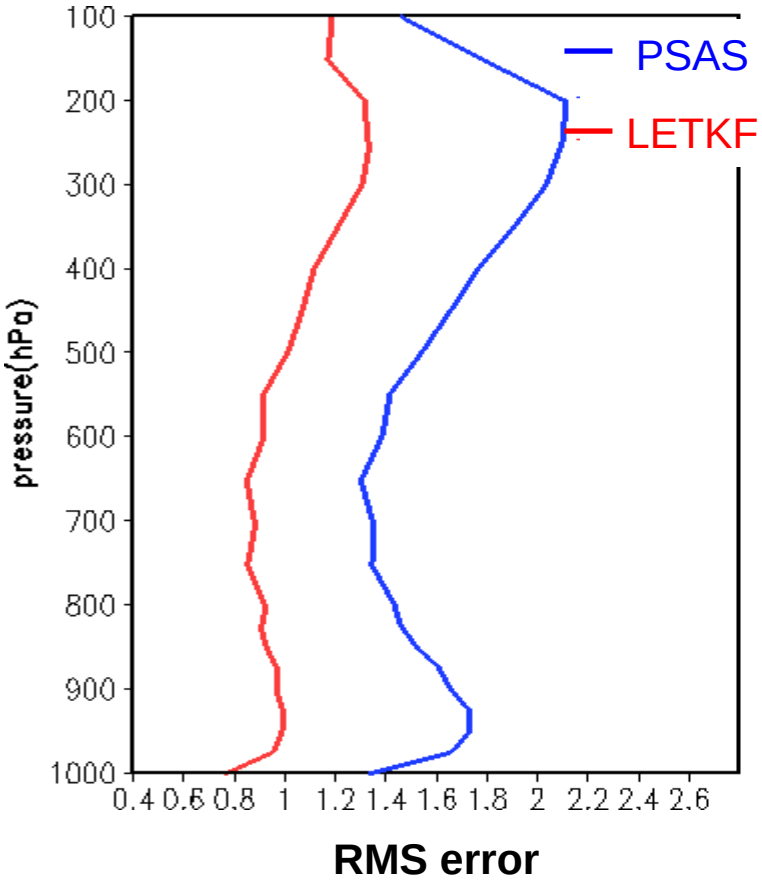


LETKF

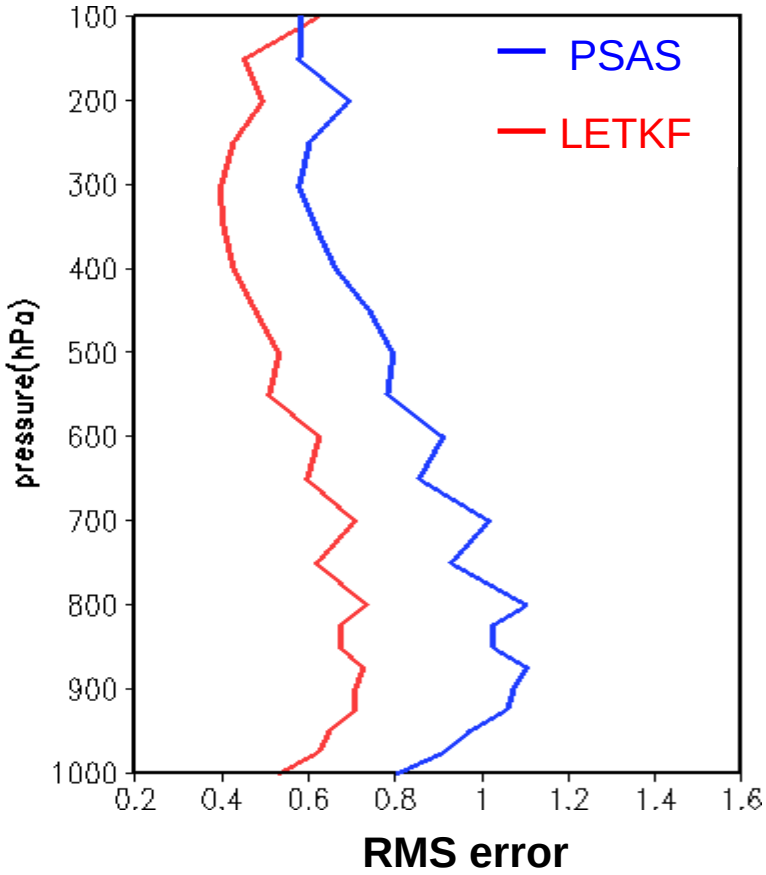


LETKF captures the errors of the day while PSAS cannot

Feb. average analysis RMS error at different levels (Global average)



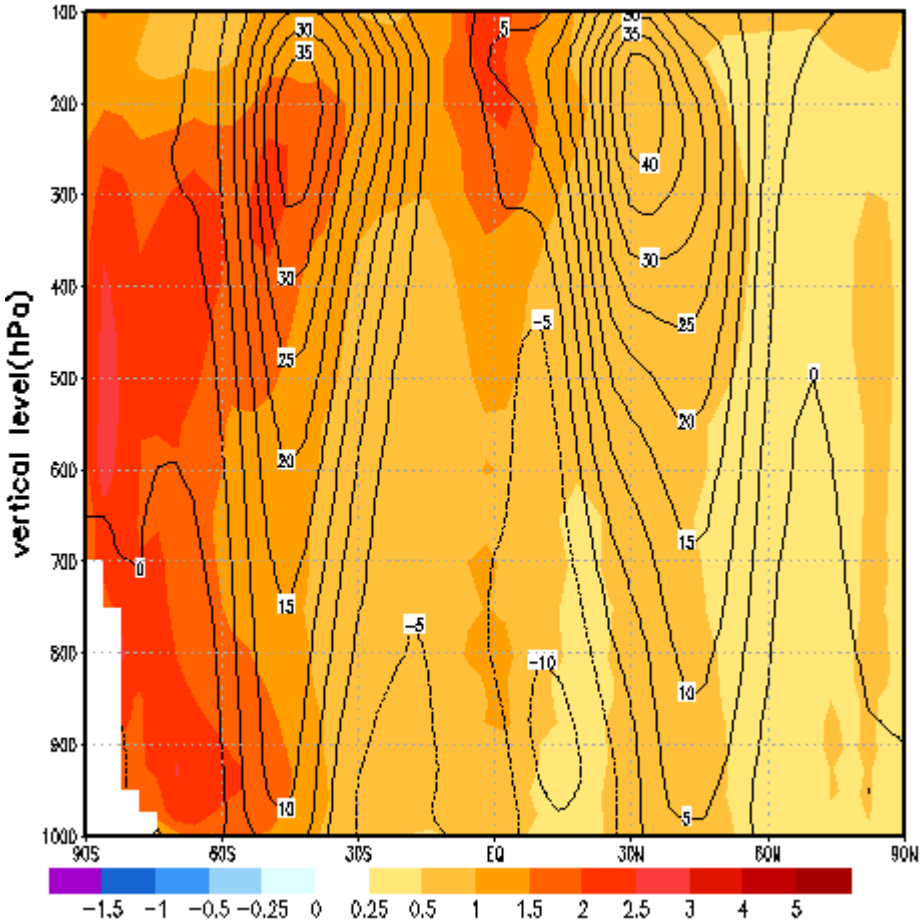
Zonal Wind



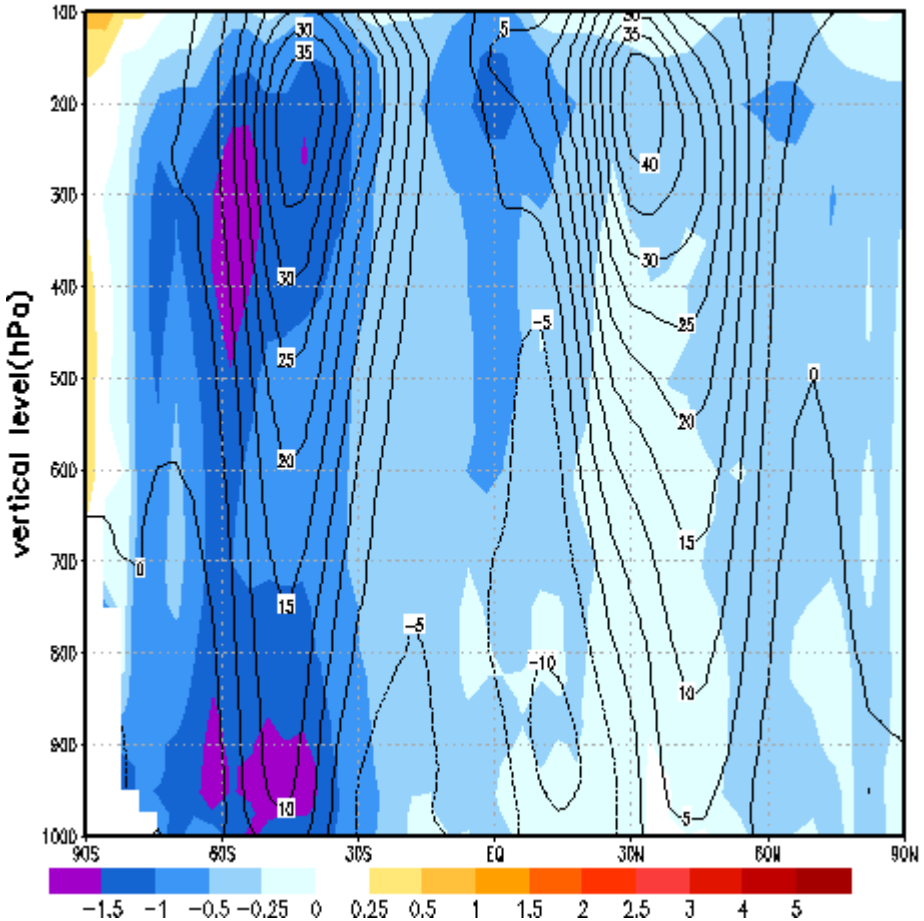
Temperature

Time mean of zonal mean analysis RMS error (averaged over February) and dynamical state (contour)

Zonal Wind

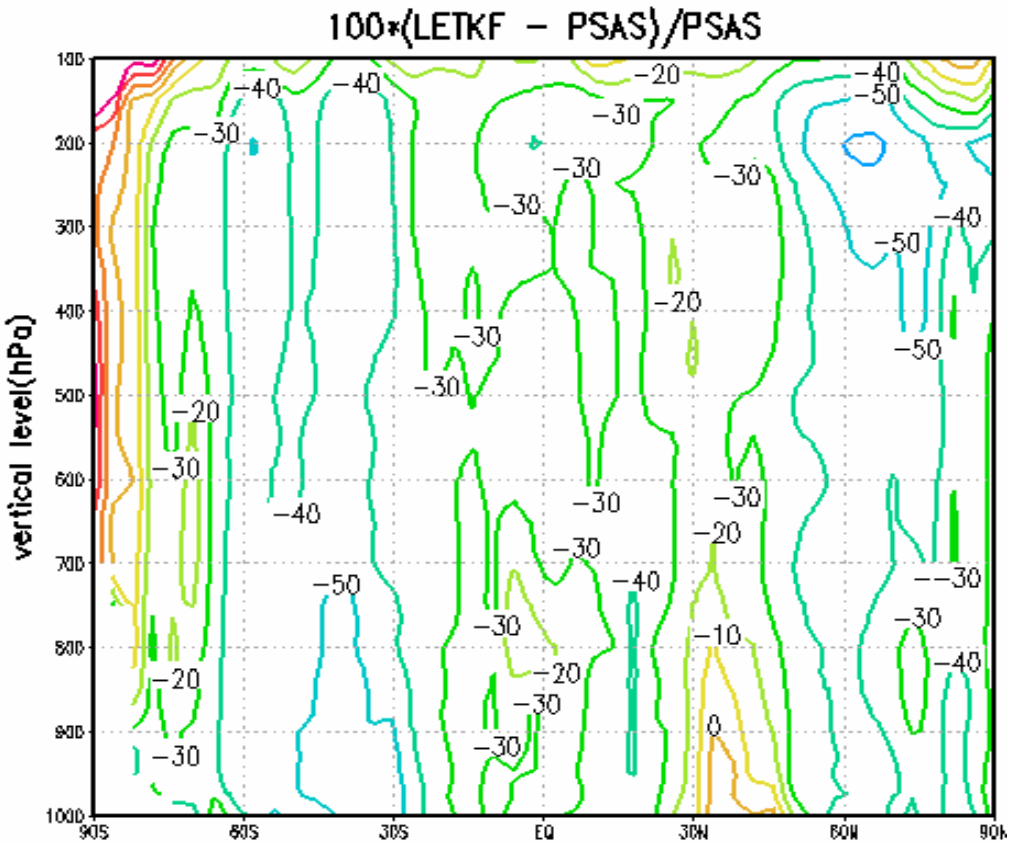


RMS error of LETKF



RMS error difference between LETKF and PSAS

Zonal wind average analysis RMS error relative improvement

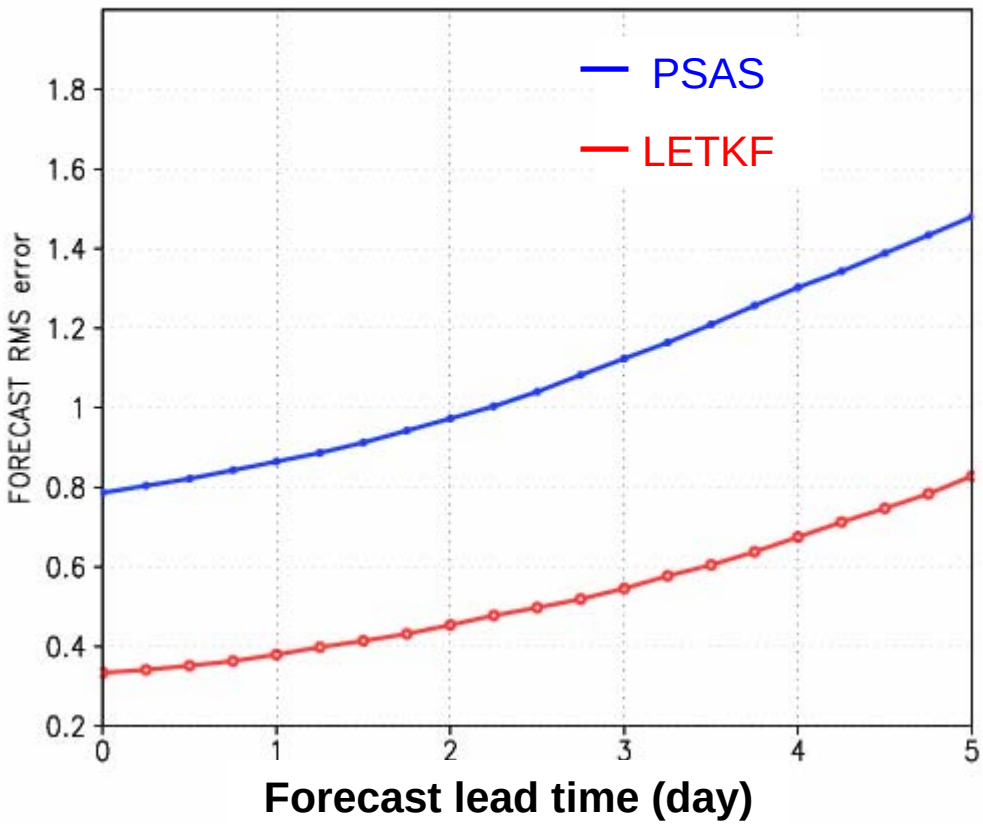


Southern Hemisphere **Northern Hemisphere**

percentage improvement

500hPa Feb. average RMS forecast (Global average)

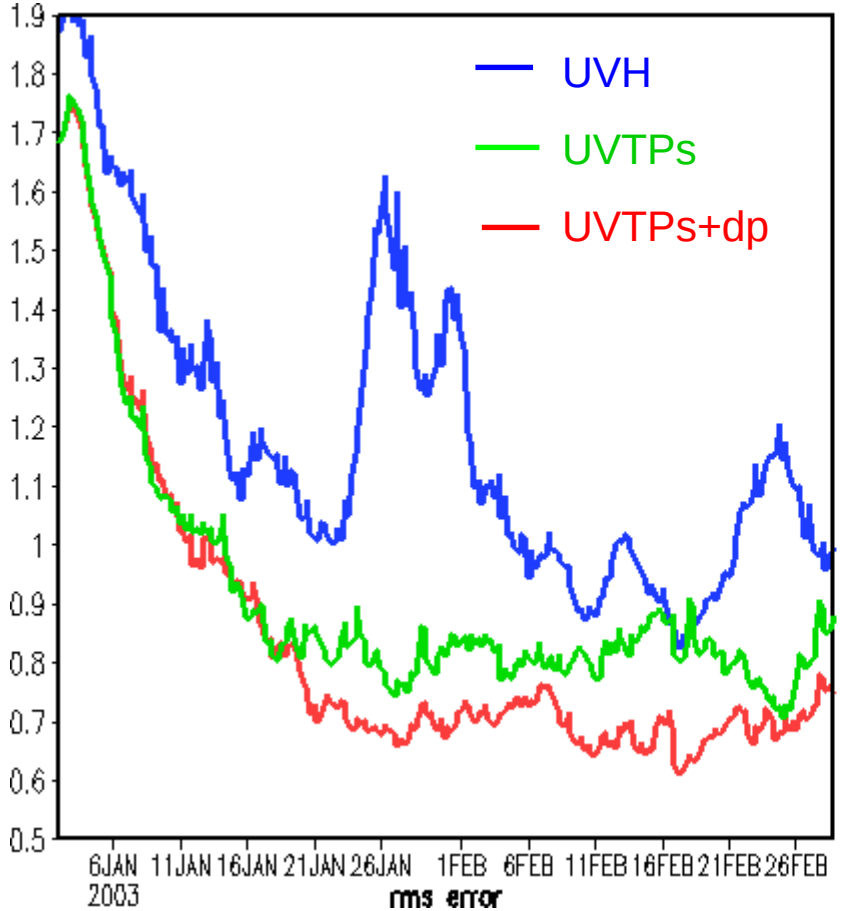
Zonal Wind



LETKF retains its advantage over PSAS

throughout the entire 5 day period

500hPa analysis RMS error (Global average)



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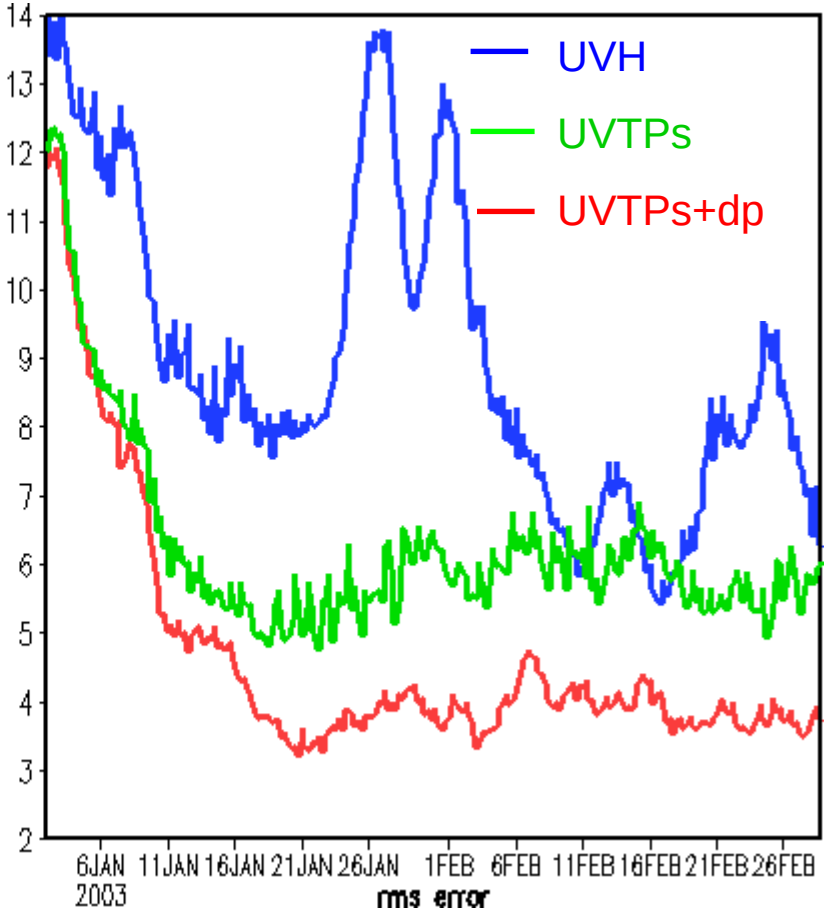


Geopotential Height

Analysis is further improved by assimilating operational data types T & Ps.

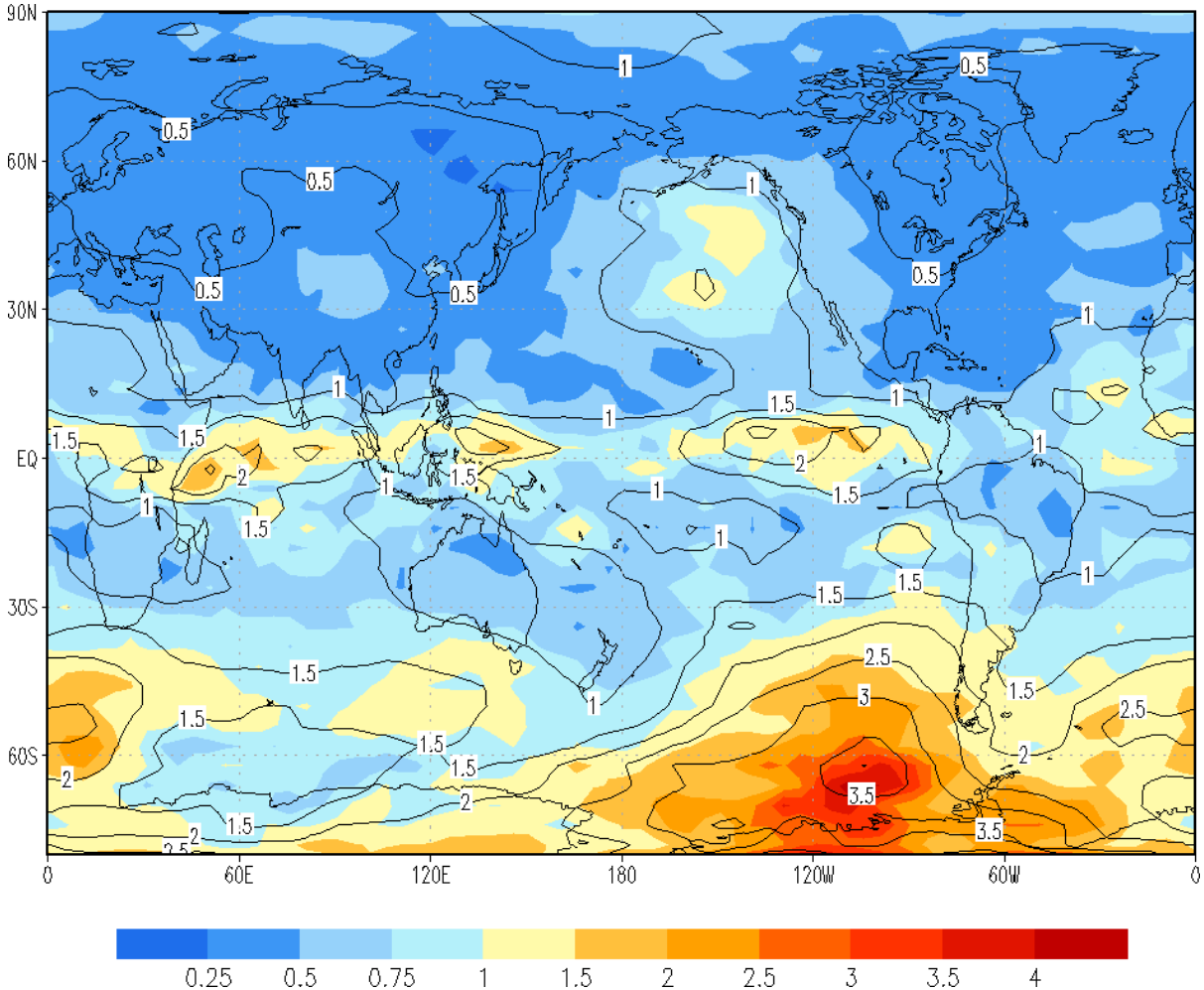
Updating pressure thickness further improves analysis.

Diagnostics

Elana Fertig

Structure of 6hr forecast ensemble spread and error variance (averaged over February)

500 hPa Zonal Wind



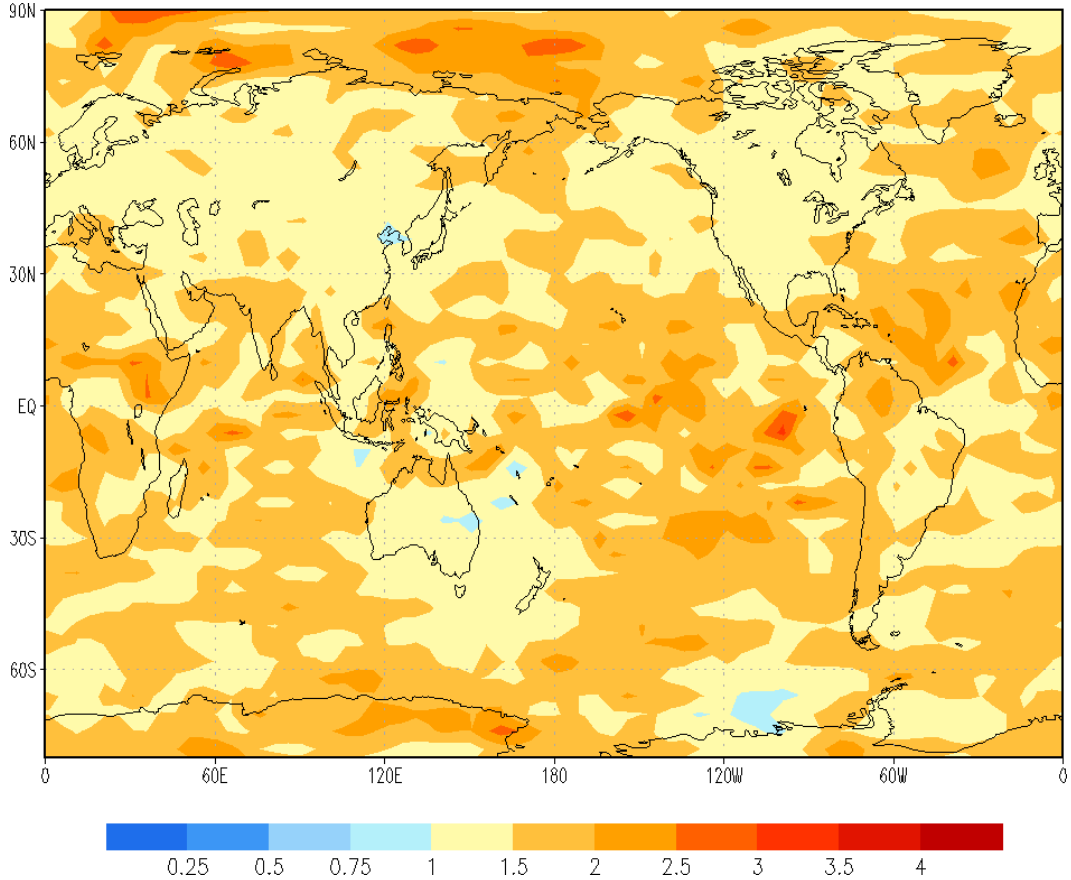
Ensemble Spread is the average distance between the ensemble members and the mean forecast state (**contour**)

Ensemble Variance is the average distance between the ensemble members and the truth (**color**)

Structure of ensemble spread and variance agree.

Ratio of ensemble spread to ensemble variance (averaged over February)

500 hPa Zonal Wind



In general, the ensemble spread over estimates the forecast error.

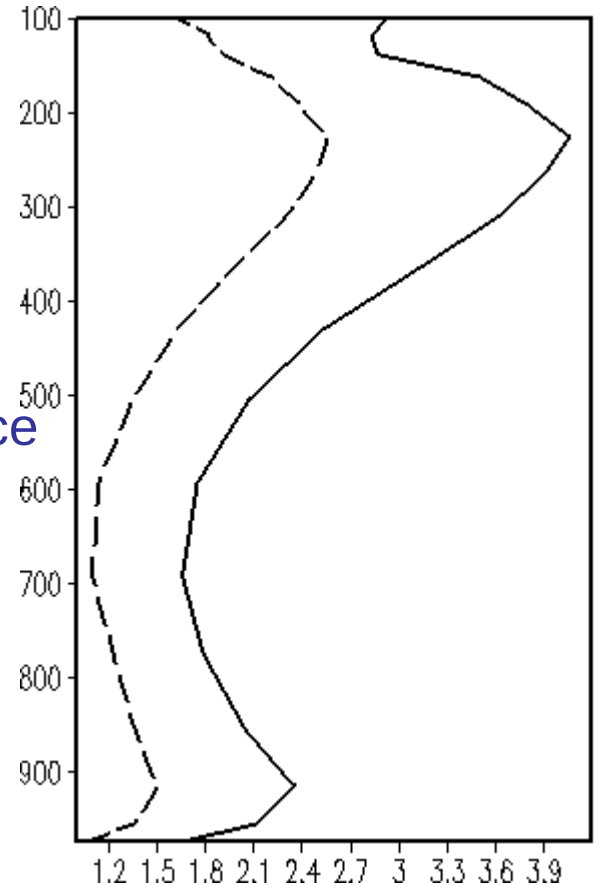
This is more prominent over data sparse regions.

Vertical structure of ensemble spread and variance (averaged over February)

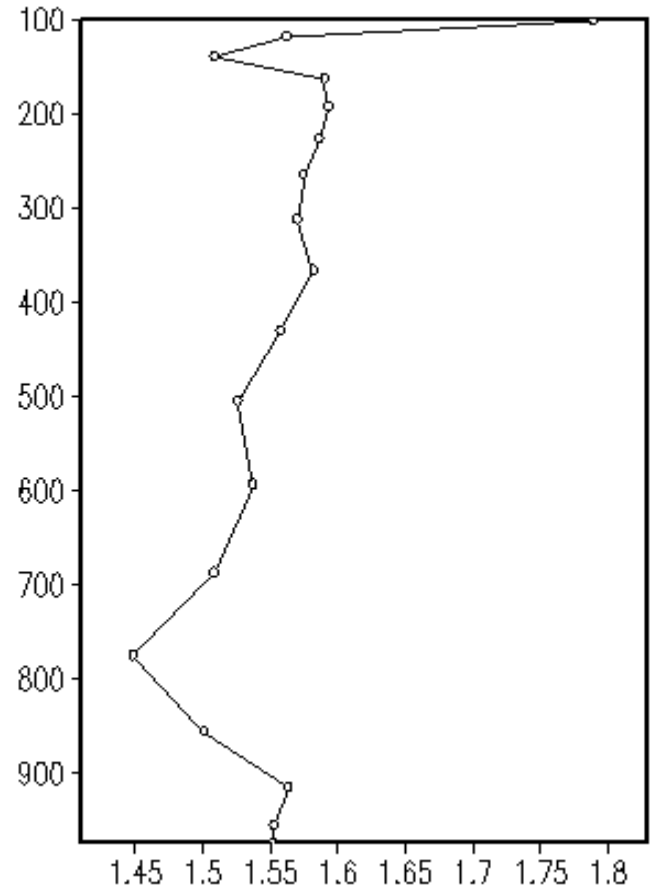
Ensemble Spread
(**solid line**)

Ensemble Variance
(**dashed line**)

Zonal Wind



Ratio of
spread to variance



Structure of ensemble spread and variance agree.

Ensemble spread is larger than the ensemble variance.

Online Variance Inflation

Variance inflation is a tunable parameter.
Can be estimated online as part of the data assimilation at low cost by augmenting state vector to include inflation parameter
(Miyoshi, 2005)

Observation of inflation factor:

$$\delta^o = 1 - \frac{\mathbf{tr}\left(\mathbf{dd}^{\mathbf{T}}\right) - \mathbf{tr}(\mathbf{R})}{\mathbf{tr}(\mathbf{HP}^f\mathbf{H}^{\mathbf{T}})}$$

Forecast of inflation factor:

$$\delta^f = \delta^a$$

d is the observation innovation

Update inflation parameter using normal Kalman Filter Equations.

E-dimension: are there enough ensemble members?

The E-dimension represents the number

of uncertainty directions captured by the ensemble.

(Patil et al., 2001)

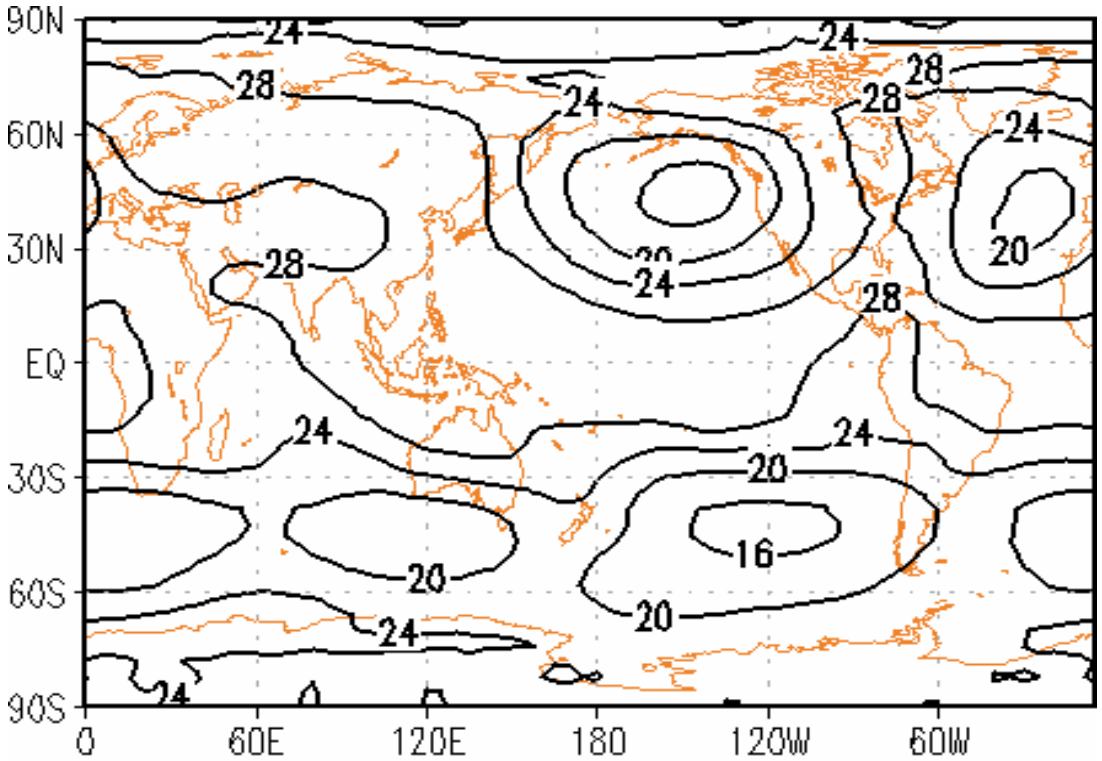
$$E = \frac{\left(\sum_{j=1}^{j=K} \lambda^{(j)}\right)^2}{\sum_{j=1}^{j=K} \lambda^{(j)\,2}}$$

$\lambda^{(j)}$ is the jth eigenvalue of the background error covariance

Minimum value 1: all the uncertainty is in one direction

Maximum value k: the total uncertainty is in at least as many directions as ensemble members

Vertical Average of E-dimension (Feb. Average)



E-dimension is well below the number of ensemble members (40) everywhere.

Therefore, 40 ensemble members seem to be sufficient to capture dynamics.

Smaller E-dimension over midlatitude oceans.

Conclusions

- For simulated rawinsonde observations, with operational possible ensemble member(40), LETKF is much better than NASA PSAS analyses after the spin-up time. The percentage improvement is up to 50% in Southern Hemisphere, most areas is between 30% and 40%.

- LETKF captures the error of the day, while PSAS cannot.

- LETKF is an efficient and parallel method of data assimilation. 5 minutes in a 20 PC cluster with 40 ensemble members.

- Analysis is improved by assimilating T and Ps instead of H.

- 40 ensemble members can capture the directions of uncertainty.

- Ensemble spread and variance structures agree. These fields indicate the ability to further improve the LETKF analysis.

LETKF Implementation Challenges

- **Very limited computational resources (shared cluster of 20 PC's)**
- fvGCM has a very high top and strong instabilities at the top
- Must tune parameters of scheme
- Adaptation of existing forward operators to our scheme

Future Plans

Eugenia Kalnay

Plans for this AIRS project

1) Real rawinsonde observations: u, v, T, q and SLP. We are starting now.

2) Add AIRS retrievals: T, q with high density coverage

3) Rawinsondes plus clear AIRS radiances

(Compare with L. Strow forward model?)

4) AIRS data impact:

* Estimate the impact of AIRS.

* Compare clear radiances with retrievals (less accurate but more coverage)

Funded by NASA/AIRS Project.

Miyoshi and Yamane (2006): LETKF at the Japan Earth Simulator, T159/L48

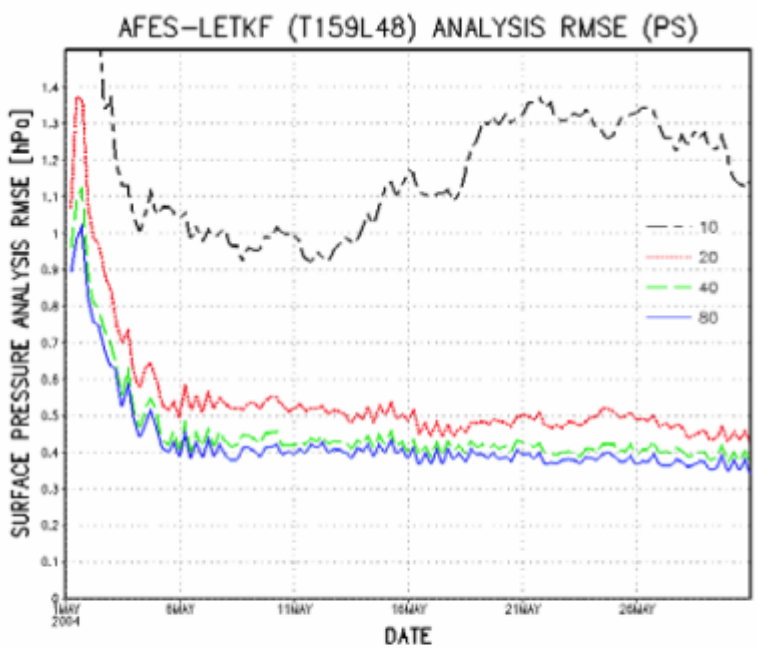


Figure 1. Time series of the analysis errors of LETKF for 30 days with 10 (black long-short-dashed line), 20 (red broken line), 40 (green dashed line), and 80 (blue solid line) ensemble members. The errors are measured by the RMSE of the surface pressure.

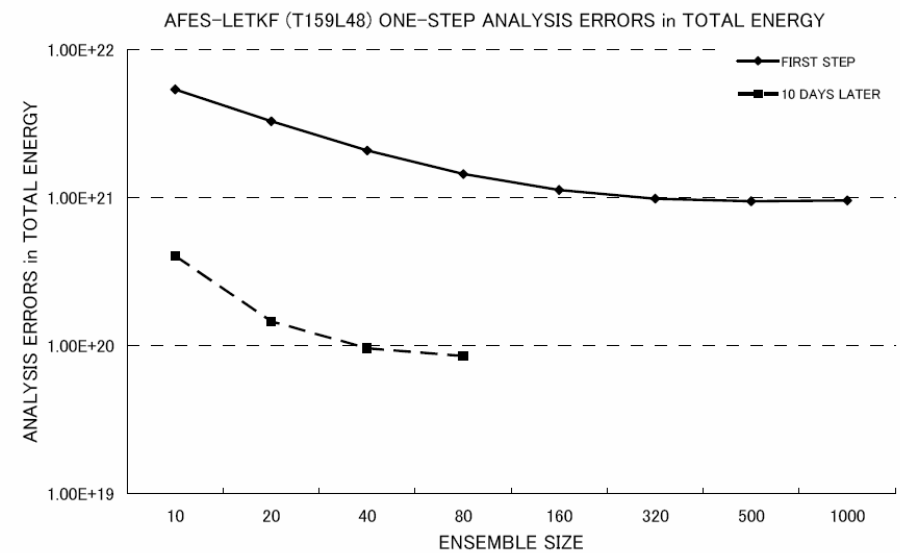
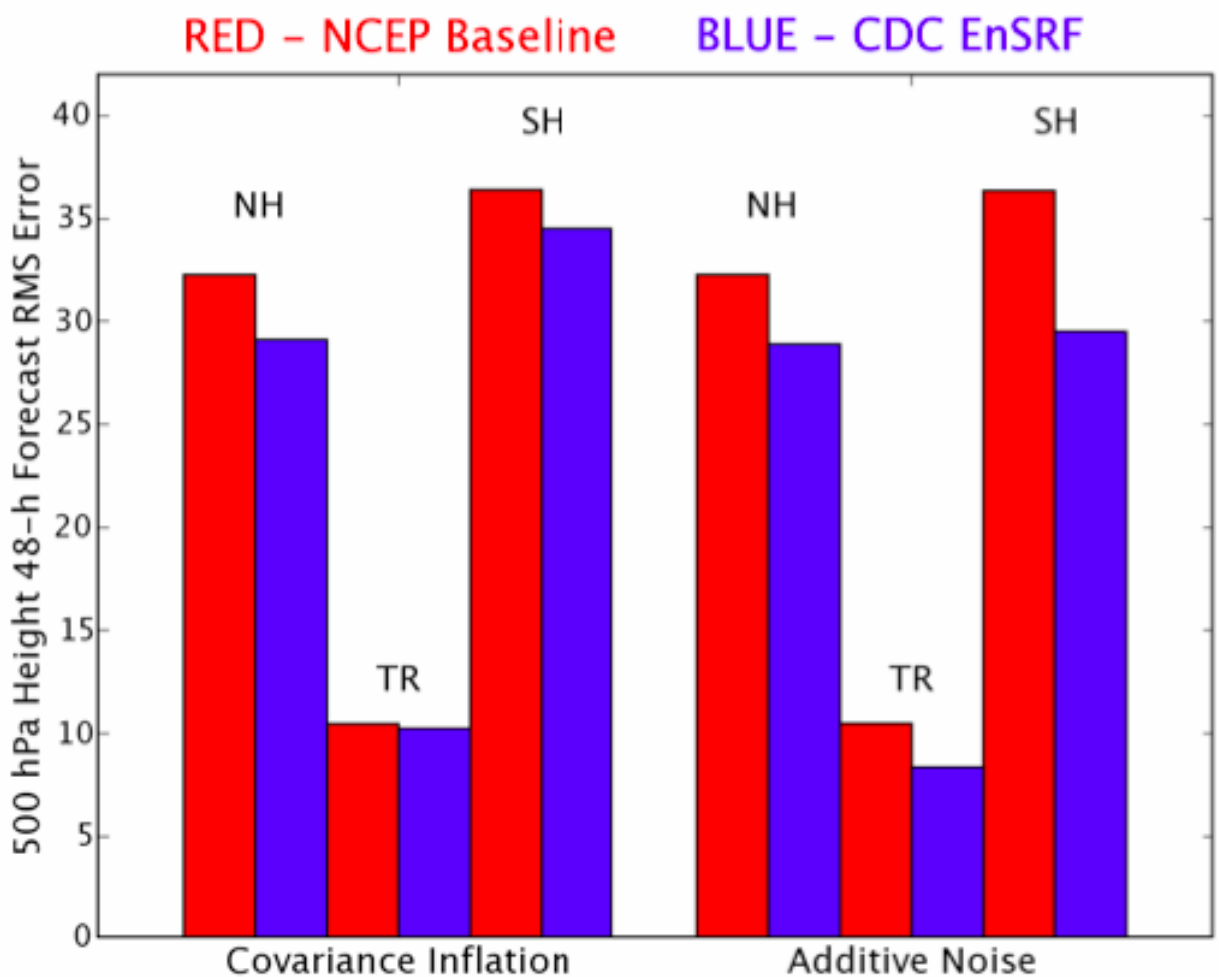


Figure 2. Analysis errors in the total energy norm at one-step analyses of LETKF with changing the ensemble size. Solid and dashed lines show the analyses at the first-step and 10 days later from the first-step, respectively.

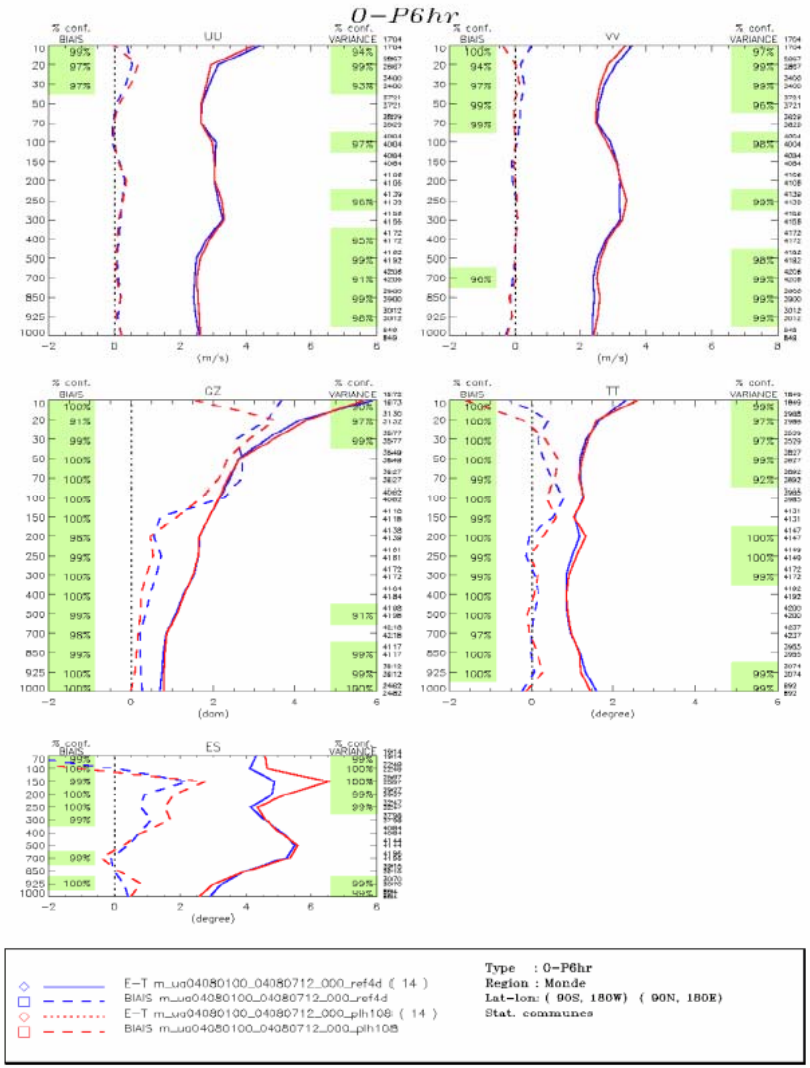
With 80 ensemble members and 80 processors it takes only 4 minutes

Whitaker and Hamill (2005)

500 hPa Z 48-h Forecast Errors



Verifying the EnKF and 4D-Var against radiosonde data



panels for u,v, height, T and T-Td

Period: 1-10 August 2004.

Blue curves: the pre-implementation 4D-Var

Red curves: The EnKF on a 400 $\times$ 200 grid with time interpolation for H but a "synoptic" data selection

The EnKF is inferior for winds below 400 hPa, for temperature at 200 hPa and humidity above 300 hPa.

The EnKF is superior for winds above 100 hPa, for the bias of the geopotential height and for temperature and humidity at the surface.

Houtekamer (2006): 4D-Var and EnKF about the same!

Final Comments

1) LETKF is fast, parallel and mature

2) It is ready for testing in an operational testbed

3) It produces optimal initial perturbations for ensemble forecasting

4) It has a few tuning parameters (inflation, local patch size)

5) 4DLETKF assimilates satellite obs at their right time, like 4D-Var

6) It can be combined with Purser et al ideas for flow dependent 3D-Var in the selection of data, which is now isotropic in LETKF