
Ensemble Filtering at NCAR

The Importance of Four-Dimensional Localization

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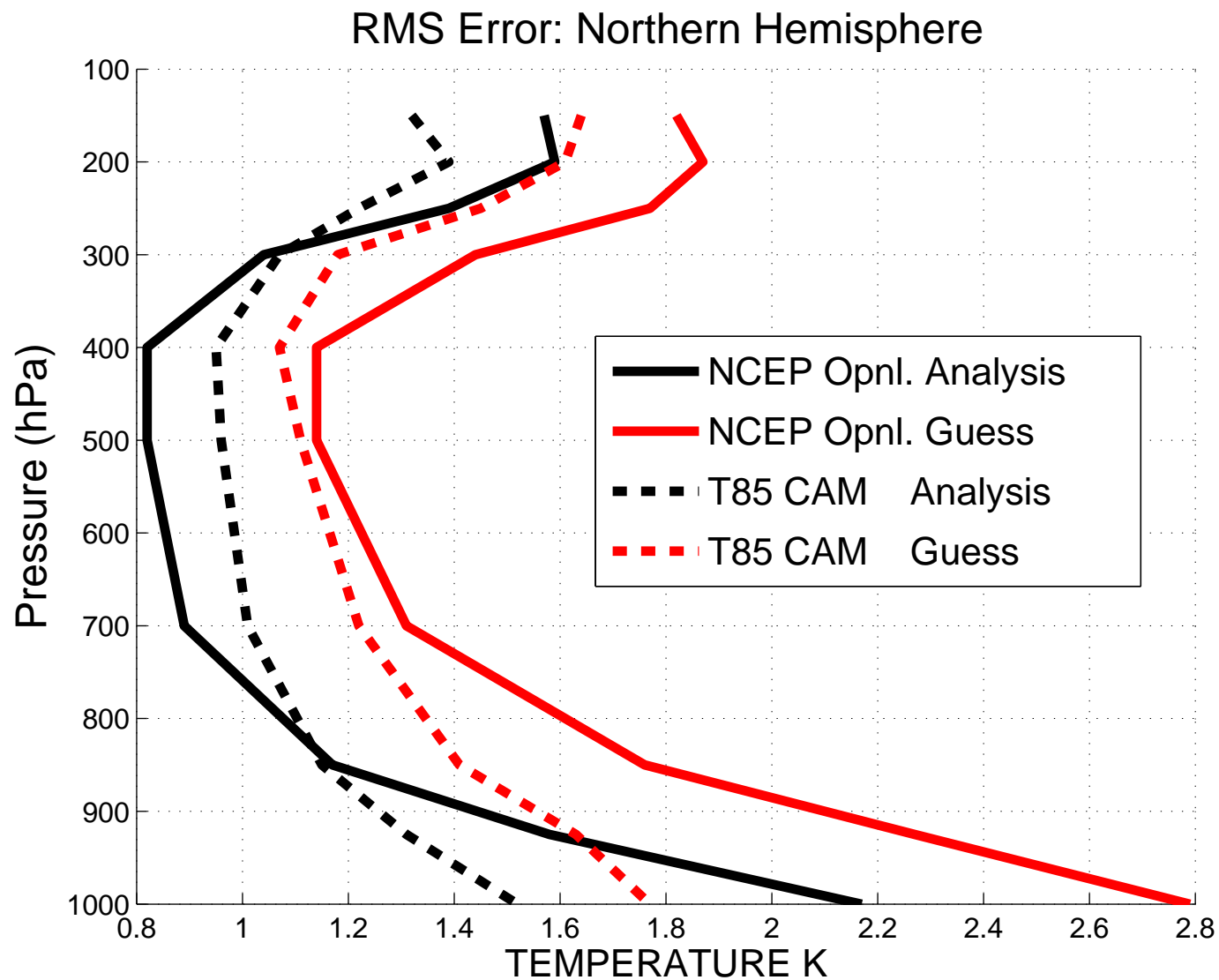
Talk Outline

- **1. Ensemble Filtering at NCAR - Comparisons to the NCEP Operational System of Jan 2003**
- **2. Four-Dimensional Localization**
- **3. Routine Network Design**
- **4. Ensemble Smoothers**

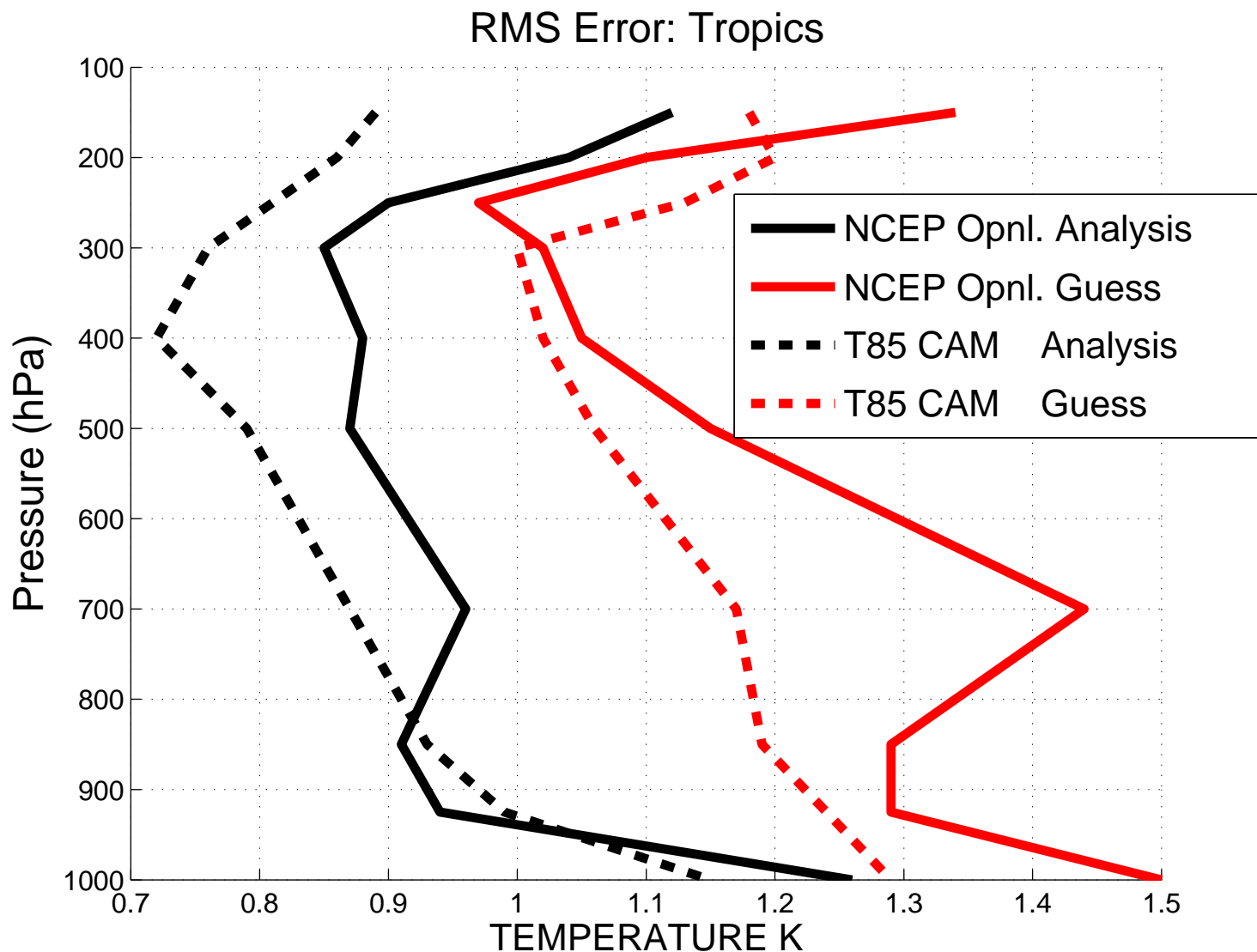
CAM Assimilation - Jan 2003

- CAM 3.1 T85L26
 - U, V, T, Q and PS state variables impacted by observations
 - Land model (CLM 2.0) not impacted by observations
 - Climatological SSTs
- Assimilation/Prediction Experiments
 - 80 member ensemble divided into 4 equal groups
 - Adaptive error correction algorithm
 - Initialized from climatological distribution (huge spread)
 - Uses most observations used in reanalysis (Radiosondes, ACARS, Sat.Winds ..., **no surface obs. or retrievals**)
 - Assimilated every 6 hours; +/- 1.5 hour windows for obs
- Results generated by **KEVIN RAEDER**

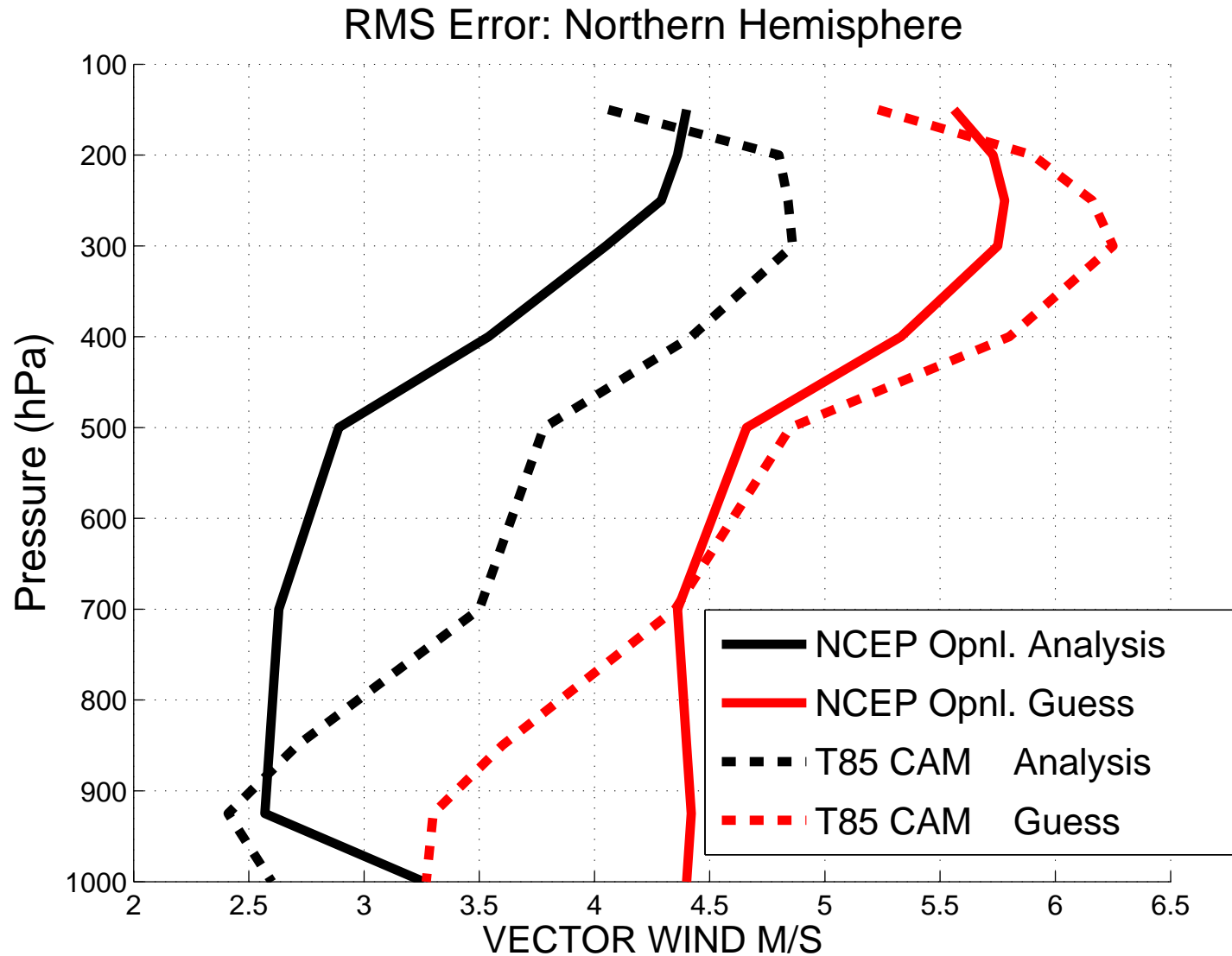
Observation Space Temperature RMS: NH



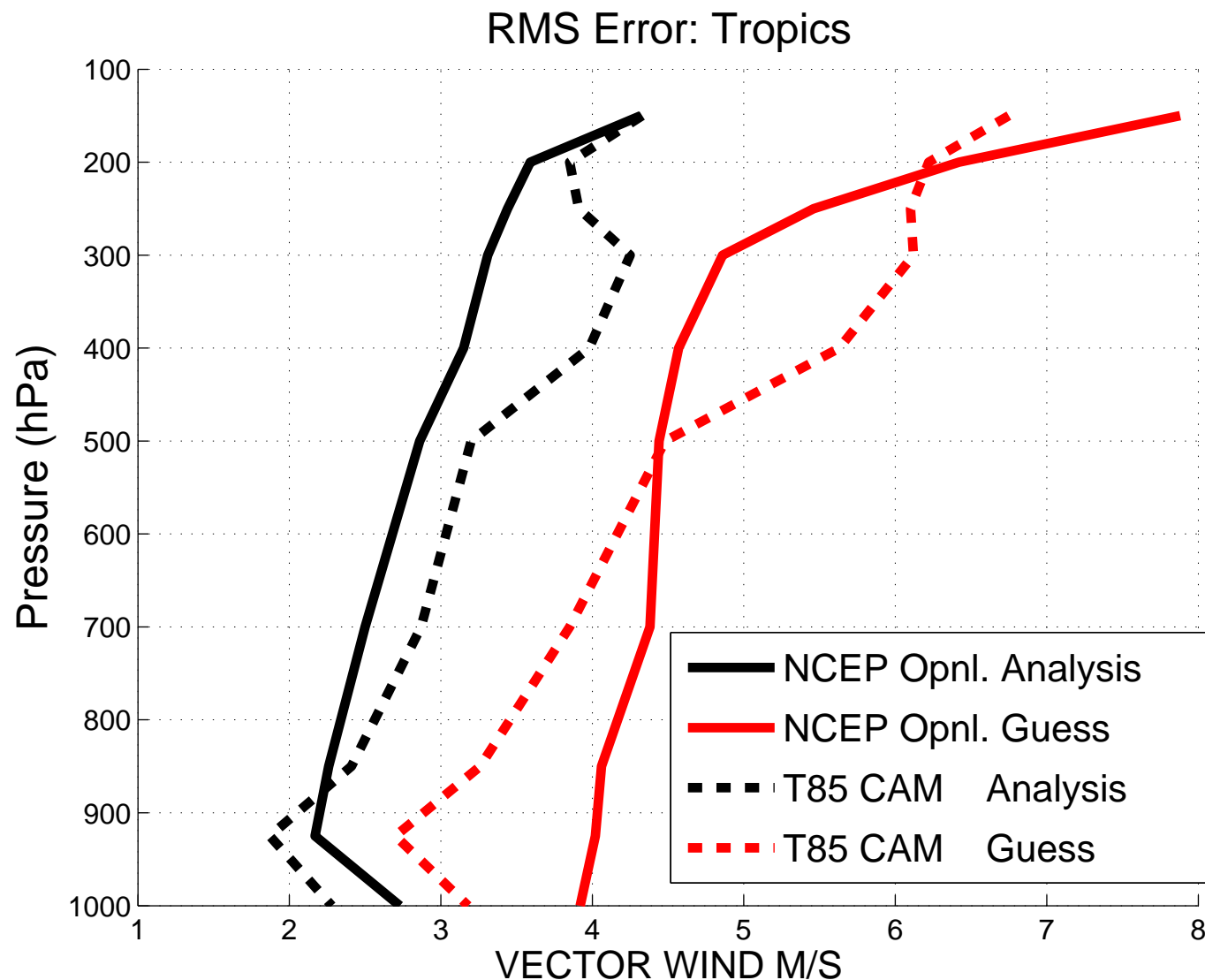
Observation Space Temperature RMS: TROPICS



Observation Space Wind RMS: NH



Observation Space Wind RMS: TROPICS



Next ...

- 1. Ensemble Filtering at NCAR - - Comparisons to the NCEP Operational System of Jan 2003
- 2. **Four-Dimensional Localization**
- 3. Routine Network Design
- 4. Ensemble Smoothers

Four-Dimensional Localization

- Ensemble Filters - Advantage: Adaptive Observations (ETKF), Routine Network Design (RDA) and Ensemble Smoothers

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- Adaptive Observations, Routine Network Design, Ensemble Smoothers: Calculations in **extended state space**

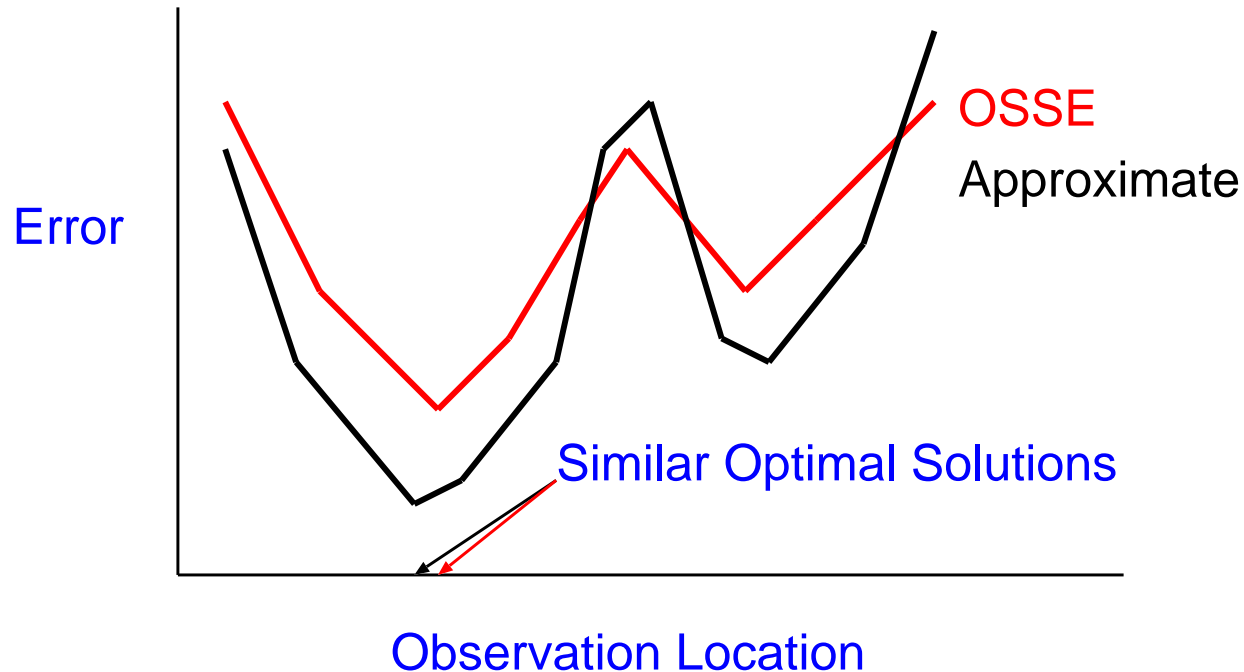
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- Adaptive Observations, Routine Network Design, Ensemble Smoothers: Calculations in **extended state space**
- Consider $corr(x_1(t), x_2(\tilde{t}))$ where $t \neq \tilde{t}$

Next ...

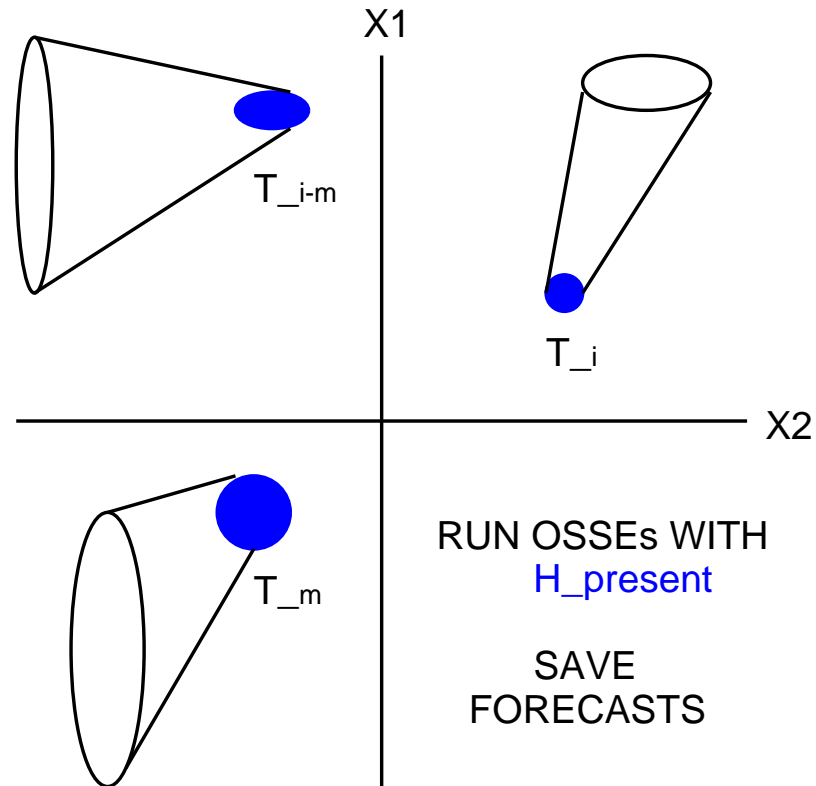
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Approximating Information Derived from OSSEs



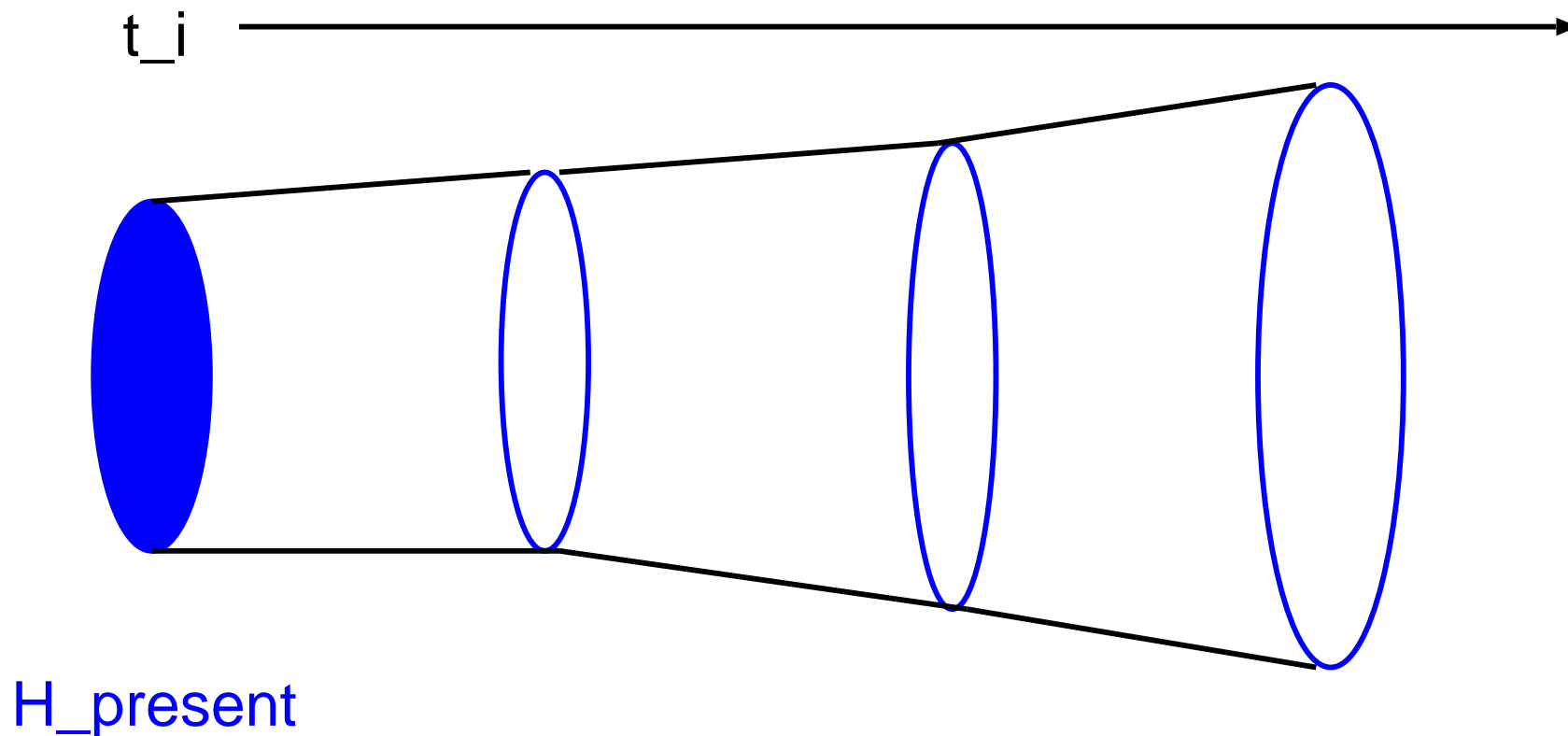
- How can we obtain a statistically and dynamically significant approximation of information derived from OSSEs?

Retrospective Design Algorithm



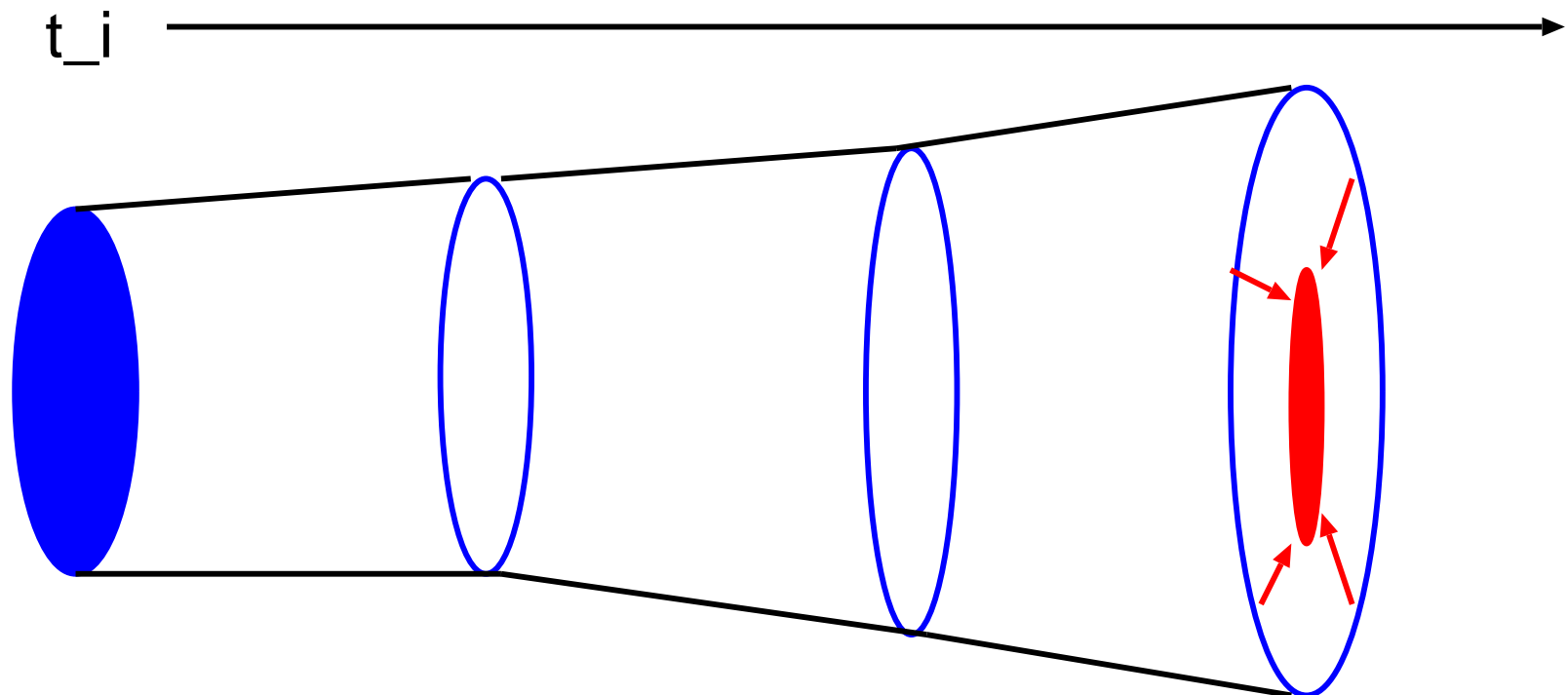
• Trial network $H_{trial} = [H_{present}; H_{additional}]$

Retrospective Design Algorithm



An ensemble forecast generated at t_i during
the OSSE with H_{present}

Retrospective Design Algorithm

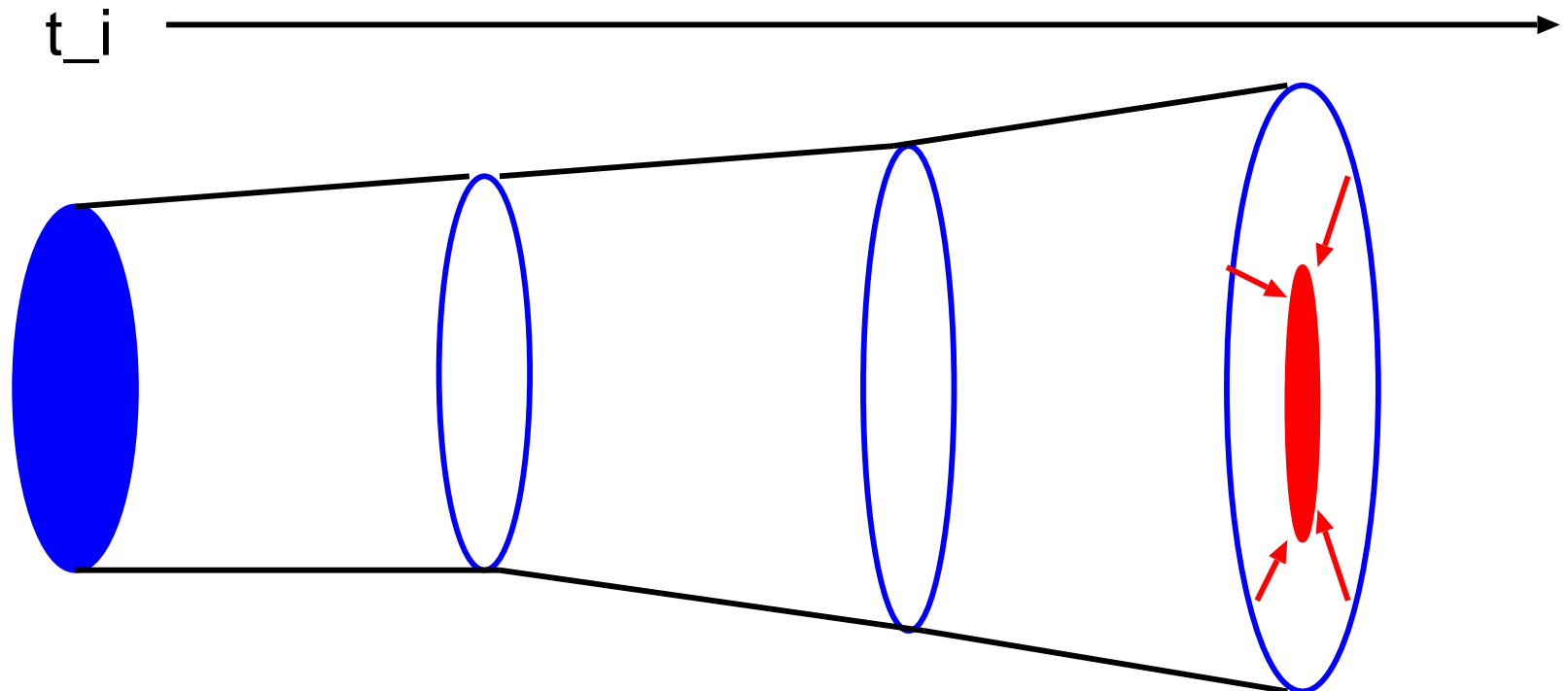


$$H_{\text{present}} \quad H_{\text{trial}} = H_{\text{present}} + H_{\text{additional}}$$

From t_{i+1} onward, assume the observing network is H_{trial} - the trial network

Want to compute the covariance of the atmosphere given H_{trial} for some time $t > t_i$

Retrospective Design Algorithm

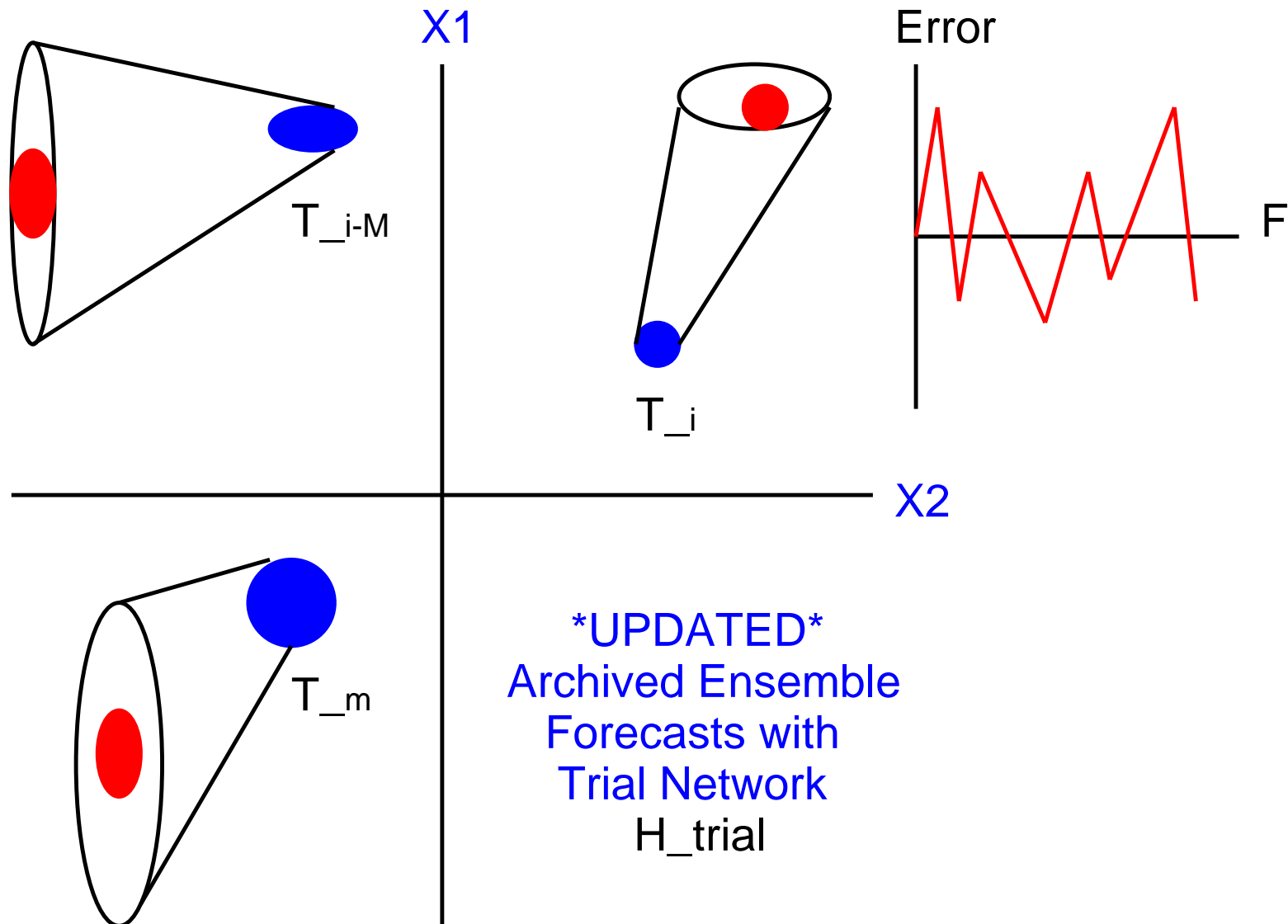


$$H_{\text{present}} \quad H_{\text{trial}} = H_{\text{present}} + H_{\text{additional}}$$

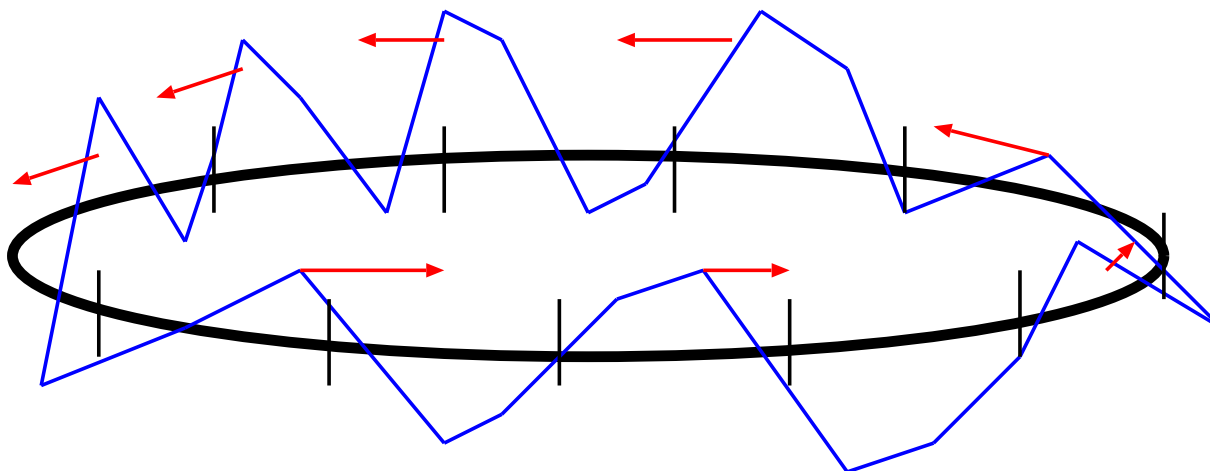
Without re-running the forecast model - an EnKF based algorithm exists for computing the atmosphere's covariance at $t > t_i$ given trial network

$$H_{\text{trial}} = H_{\text{present}} + H_{\text{additional}} - \text{KEY POINT}$$

Evaluate the Objective Function using the RDA



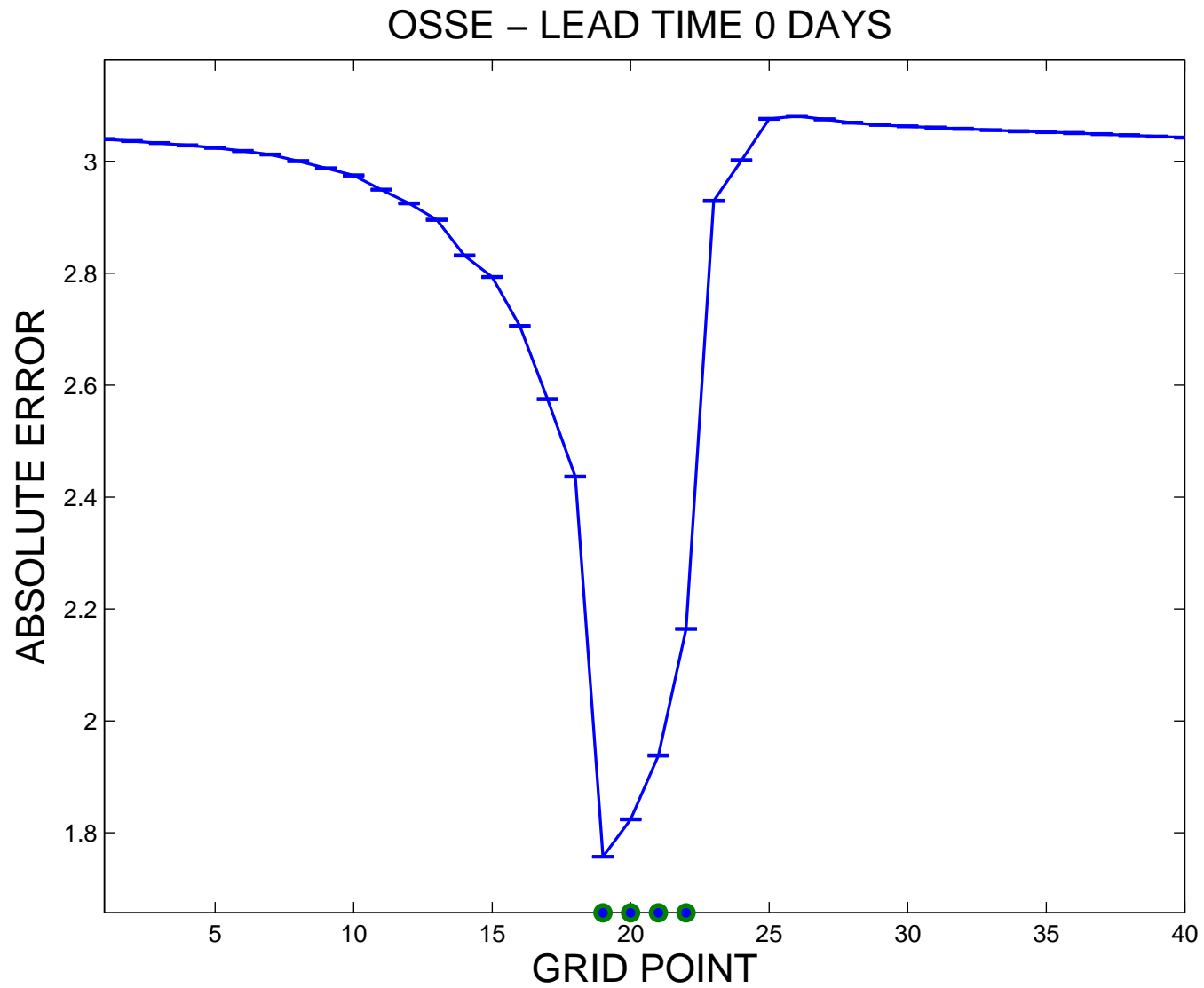
Experiments in an Atmospheric 'Toy Model'



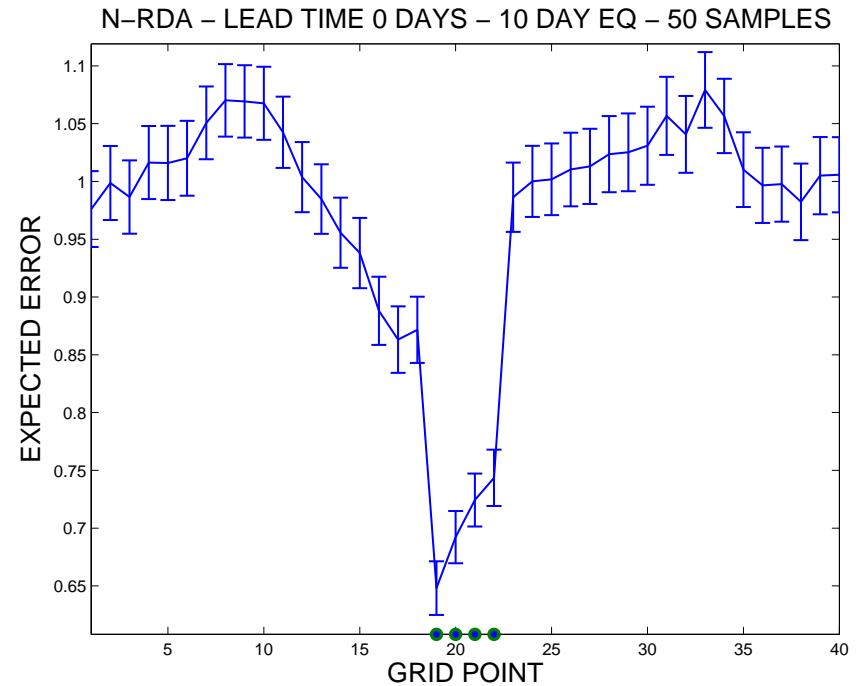
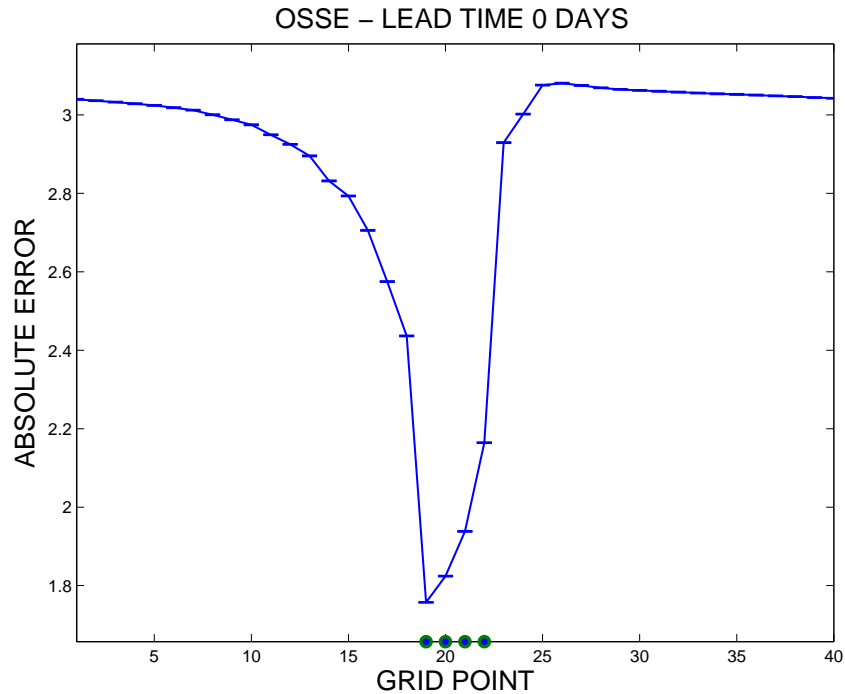
$$\frac{dx_j}{dt} = -x_{j-2}x_{j-1} + x_{j-1}x_{j+1} - x_j + F$$

- Non-linear advection, forcing, linear dissipation, energy conservation $E = (x_1^2 + \dots + x_{40}^2)$
- $F = 8$ sensitive dependence on IC's, $j = 1, \dots, 40$, cyclic
- Climatology $\sqrt{\sigma_{climate}} = 3.6$ and $\bar{x} = 2.3$

OSSEs in Lorenz 1996

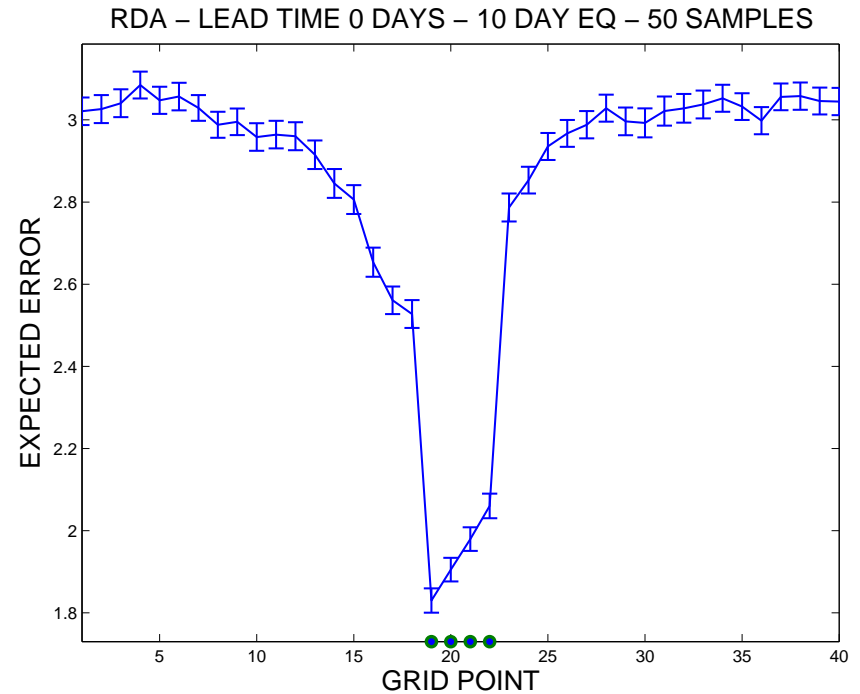
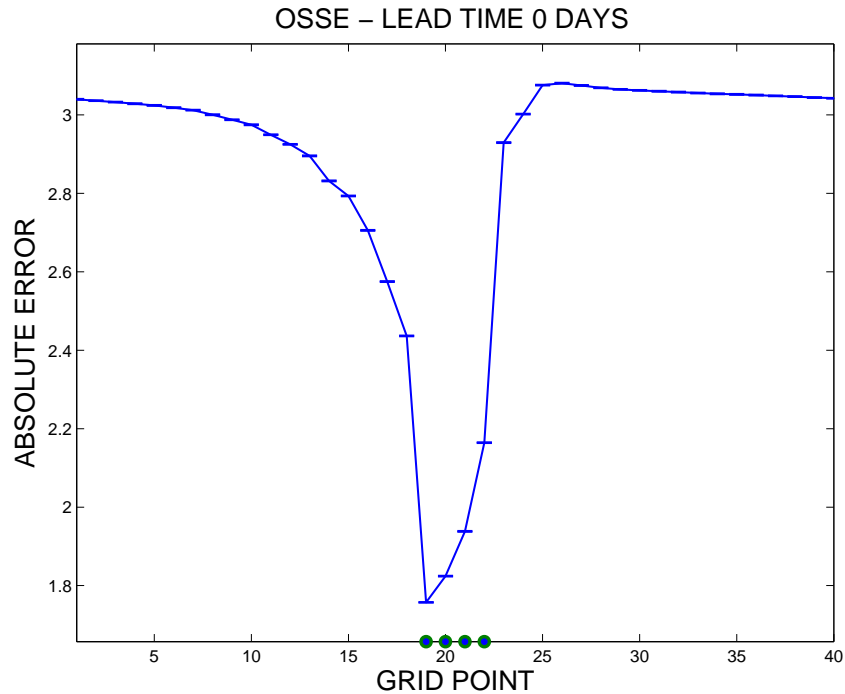


OSSEs vs. RDA (No Localization)



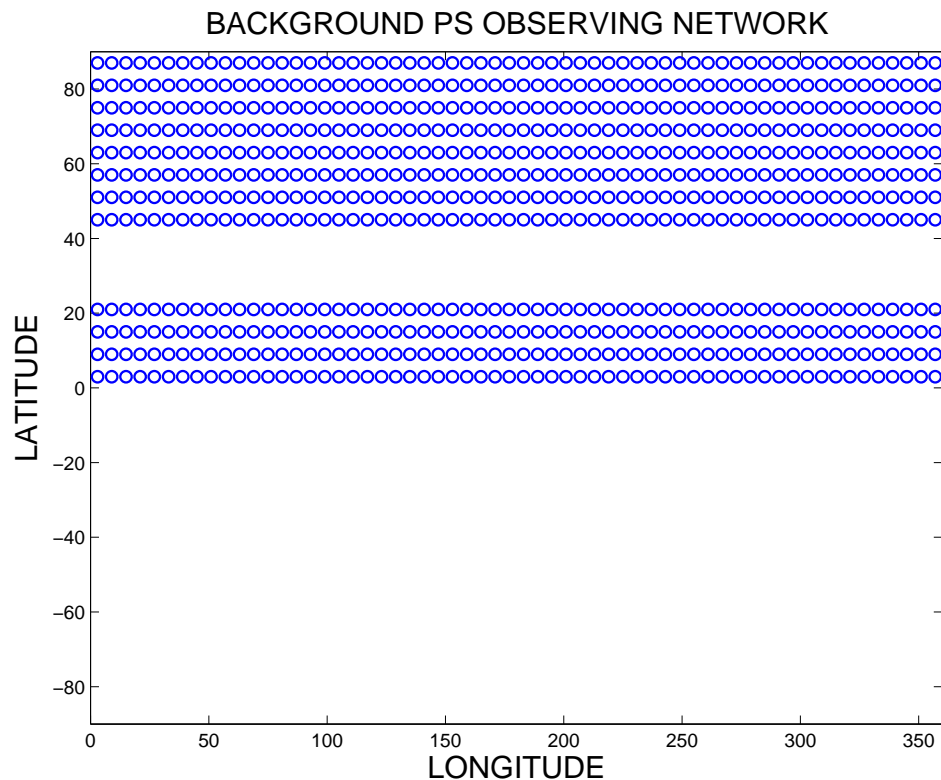
- Verification region - continuous
- Forecast lead time - 0 days
- 50 independent samples - noisy

OSSEs vs. RDA (With Localization)



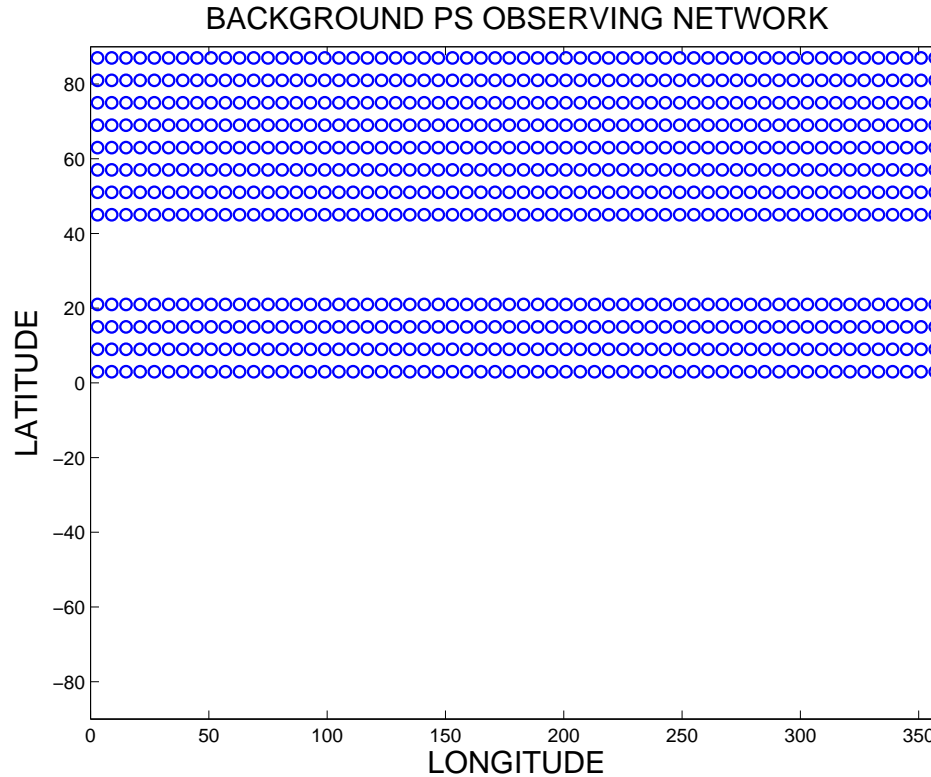
- Verification region - continuous
- Forecast lead time - 0 days
- 50 independent samples - reduced noise

PS Network Design in a GCM



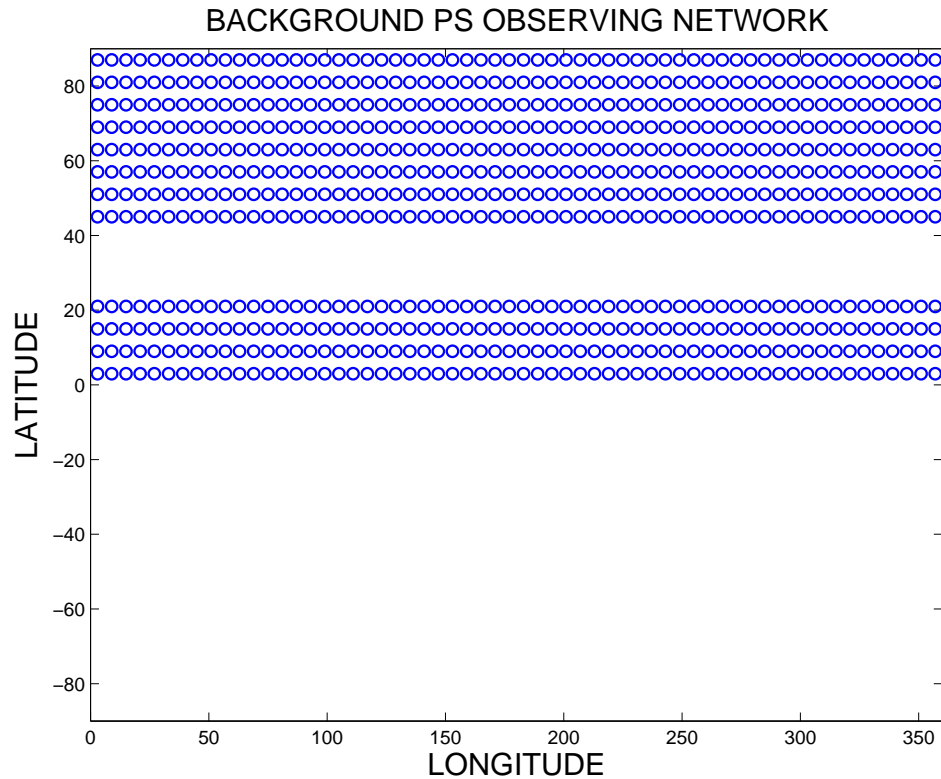
- FIXED network of surface pressure observations - 7 mb observational standard deviation - assimilate every 12 hours

PS Network Design in a GCM



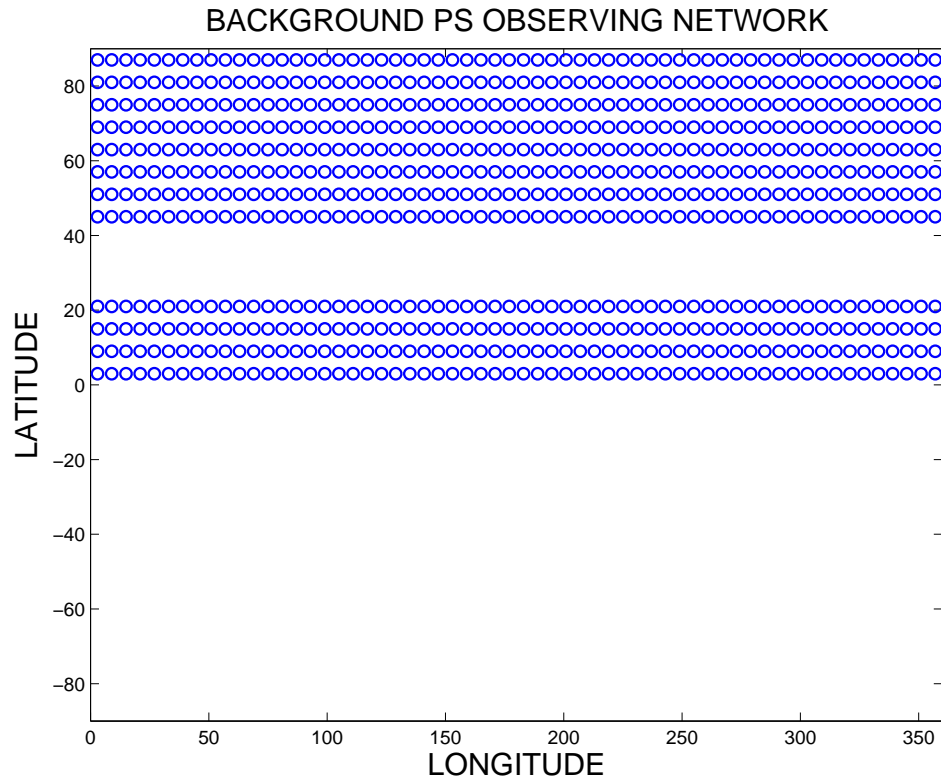
- Run an EAKF with $N = 20$ ensemble members (with localization and no inflation)

PS Network Design in a GCM



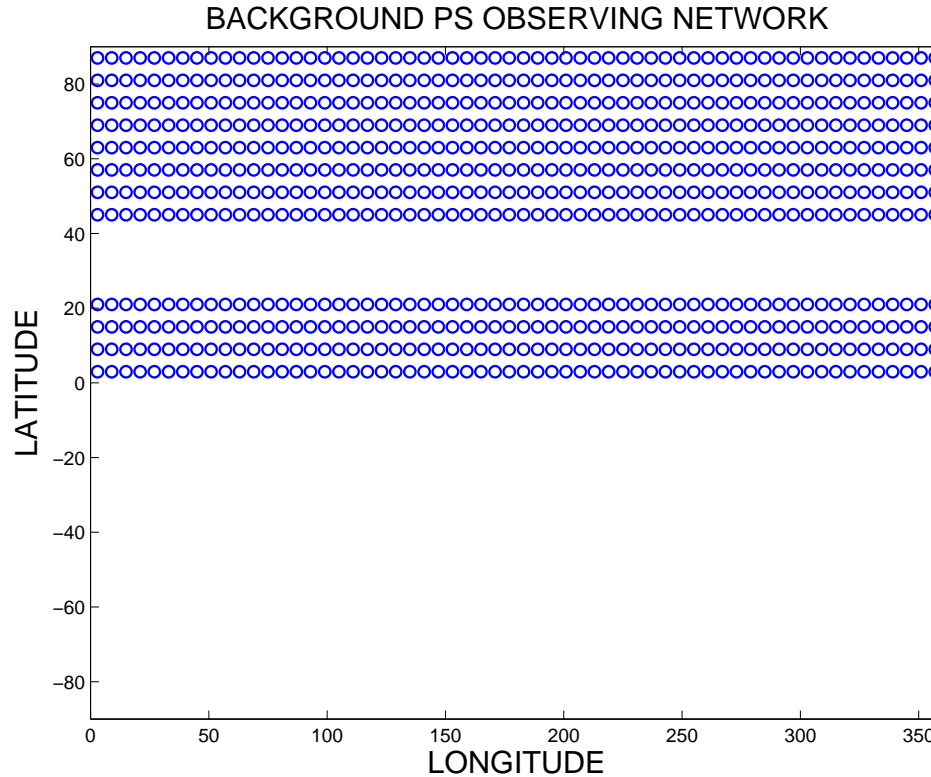
- Zonally symmetric Held-Suarez forcing

PS Network Design in a GCM



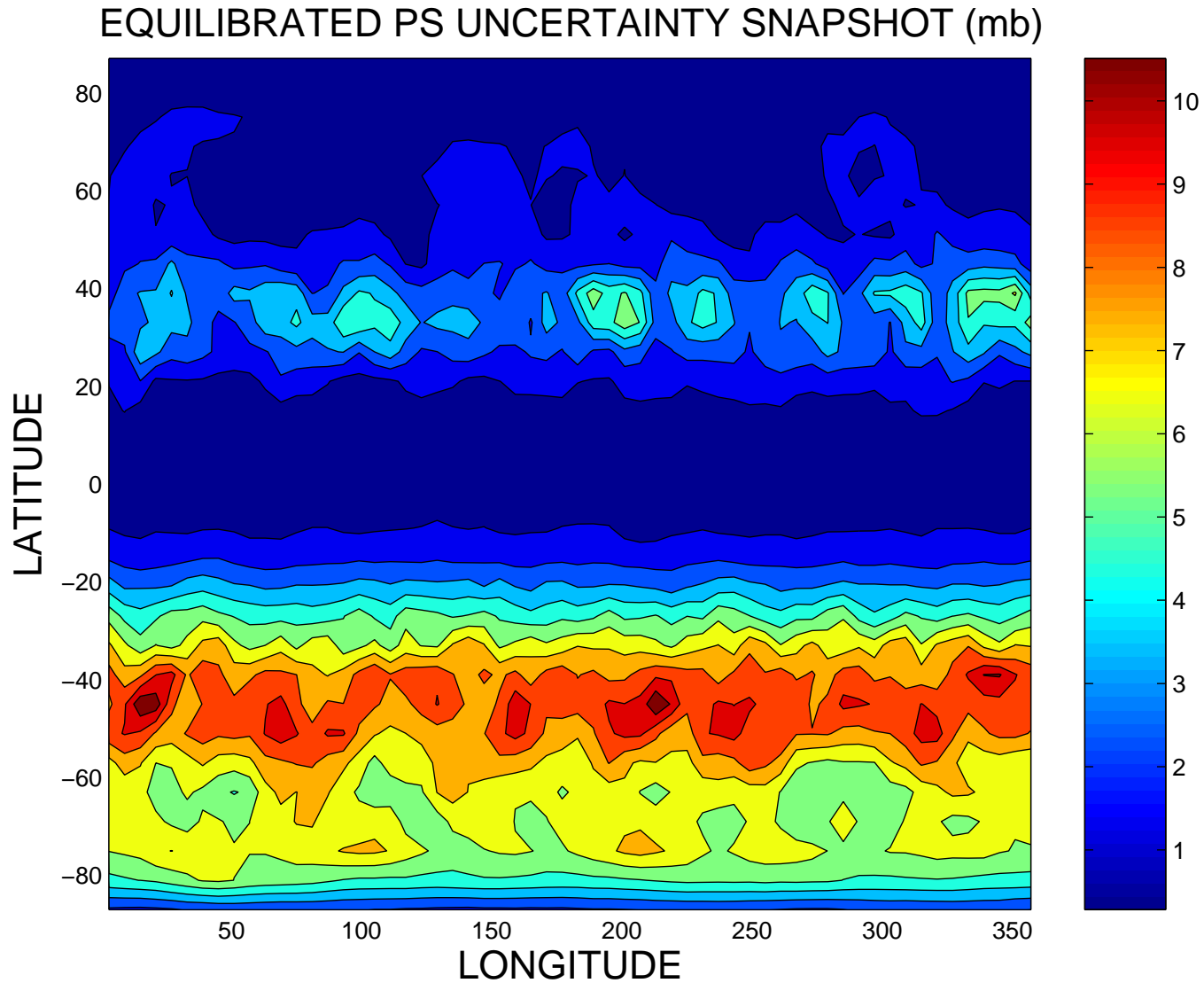
- 6 degrees horizontal resolution (60×30) - 5 vertical levels

PS Network Design in a GCM

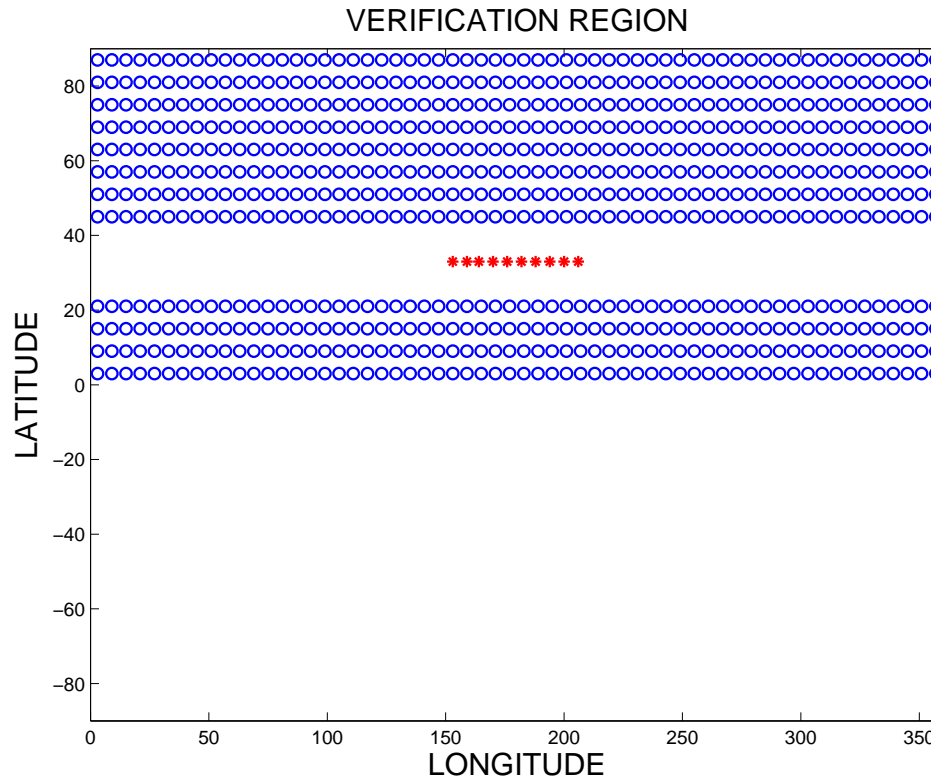


- Temperature gradient drives a baroclinically unstable flow in the mid-latitudes

Assimilation Results: Posterior PS Uncertainty

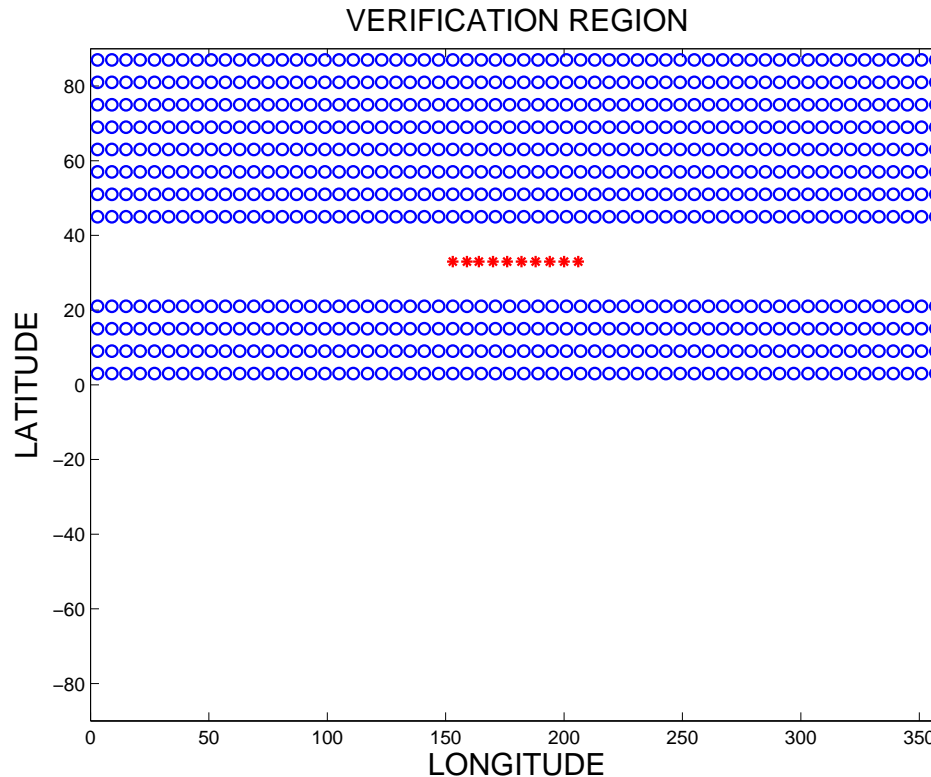


The Experiment



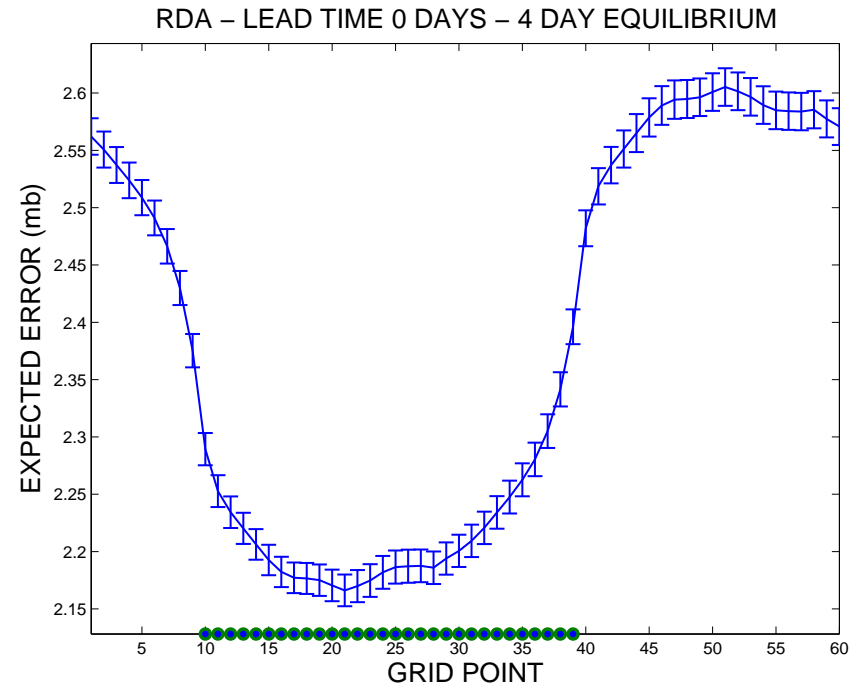
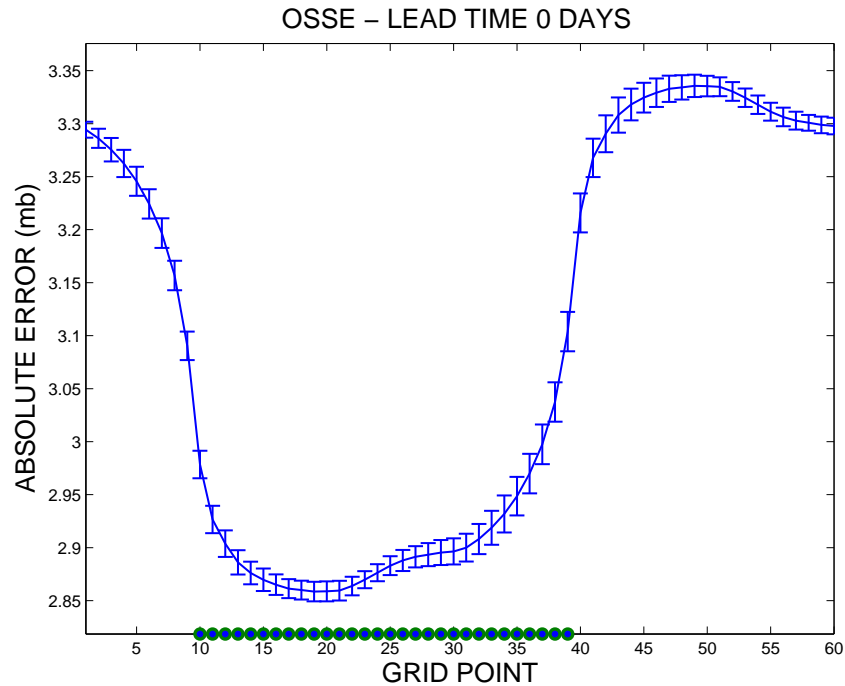
- Find the optimal placement of one *additional* accurate PS observation along the 33 degree latitude band

The Experiment



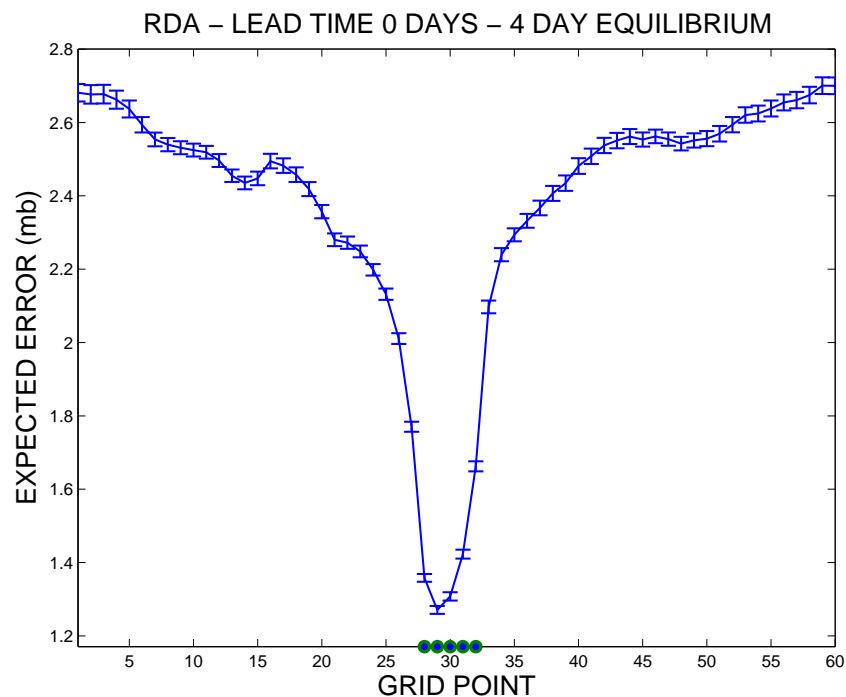
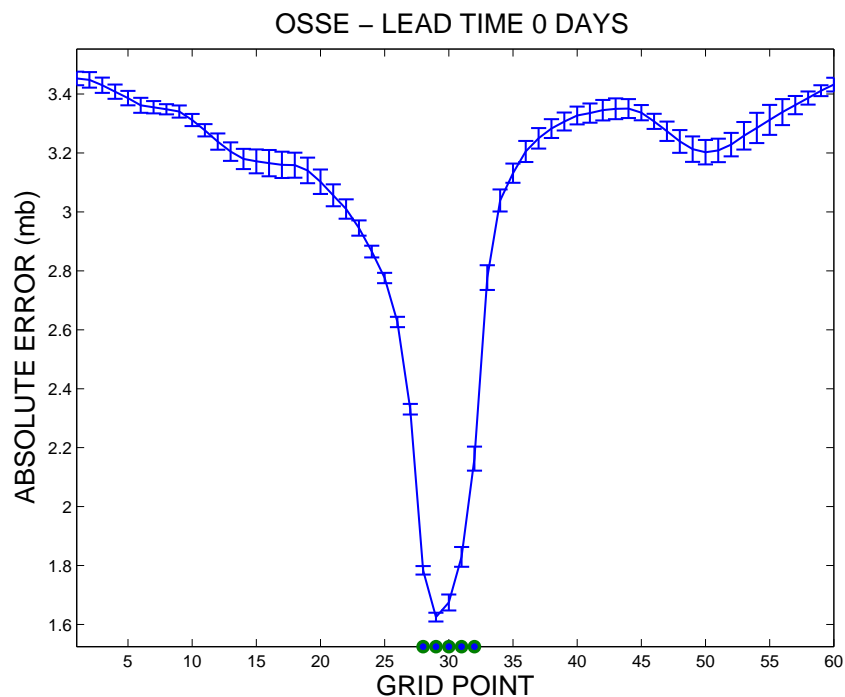
- Strong time mean winds at 33 degrees lat. ensures a strong dynamical signal in this problem

Comparison of Cost Functions I



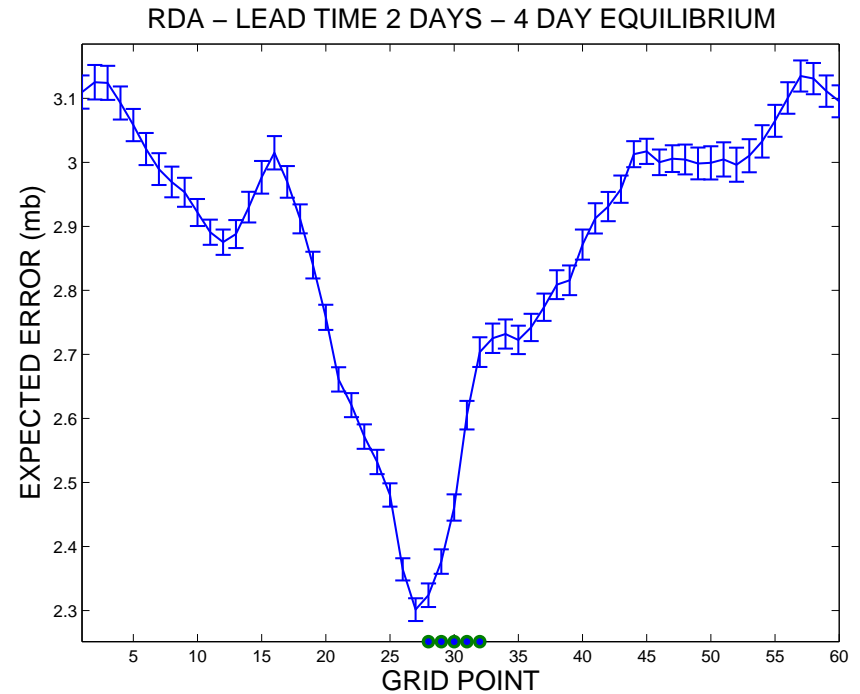
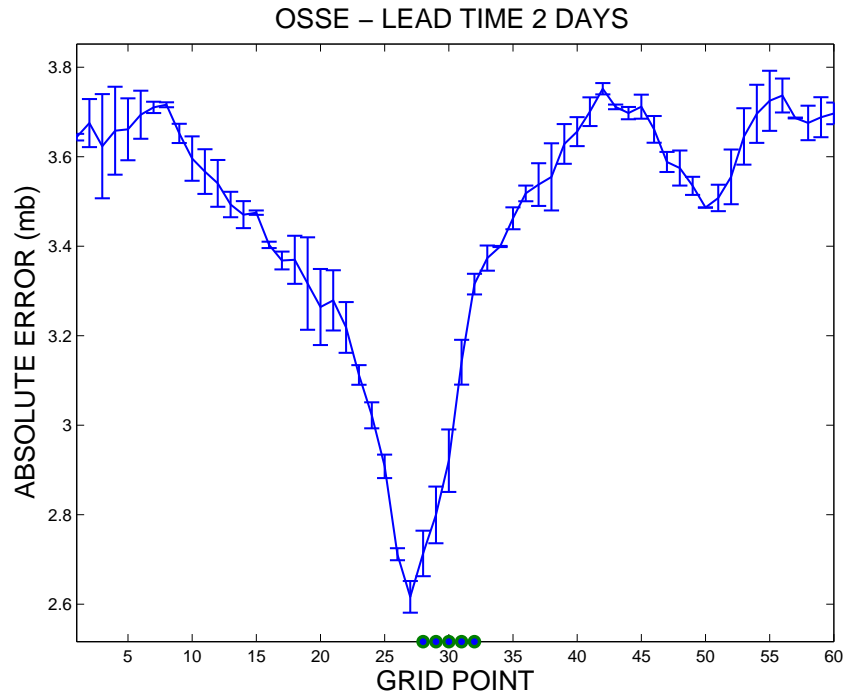
- Verification region - half the latitude band
- Forecast lead time - 0 days
- 1000 independent samples

Comparison of Cost Functions II



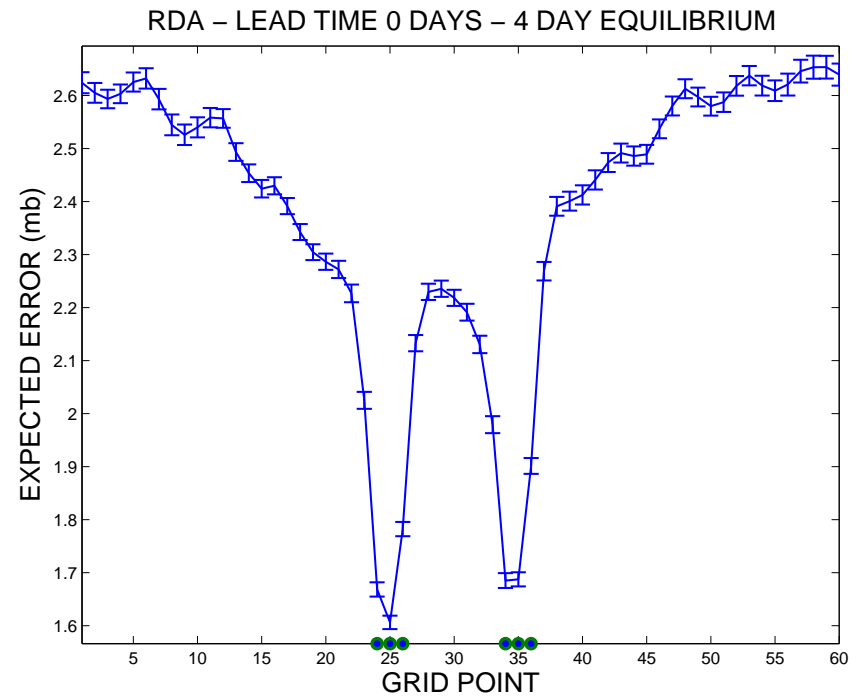
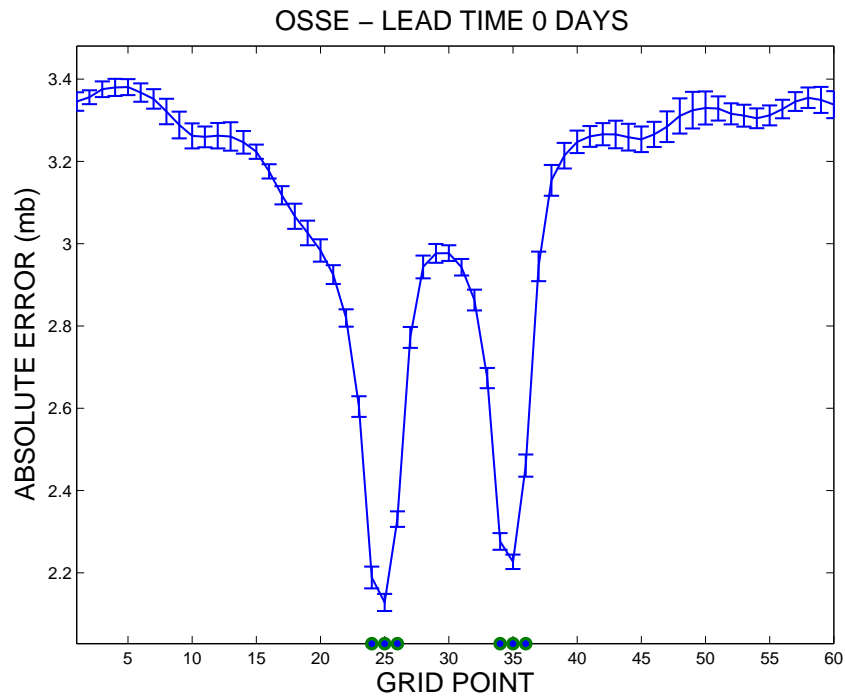
- Verification region - 5 consecutive grid points
- Forecast lead time - 0 days
- 1000 independent samples

Comparison of Cost Functions III



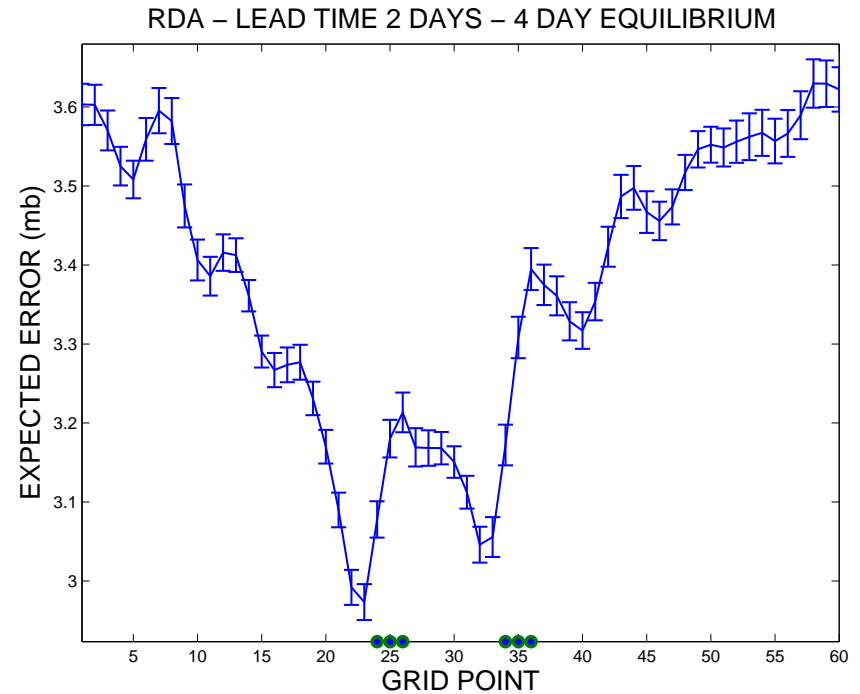
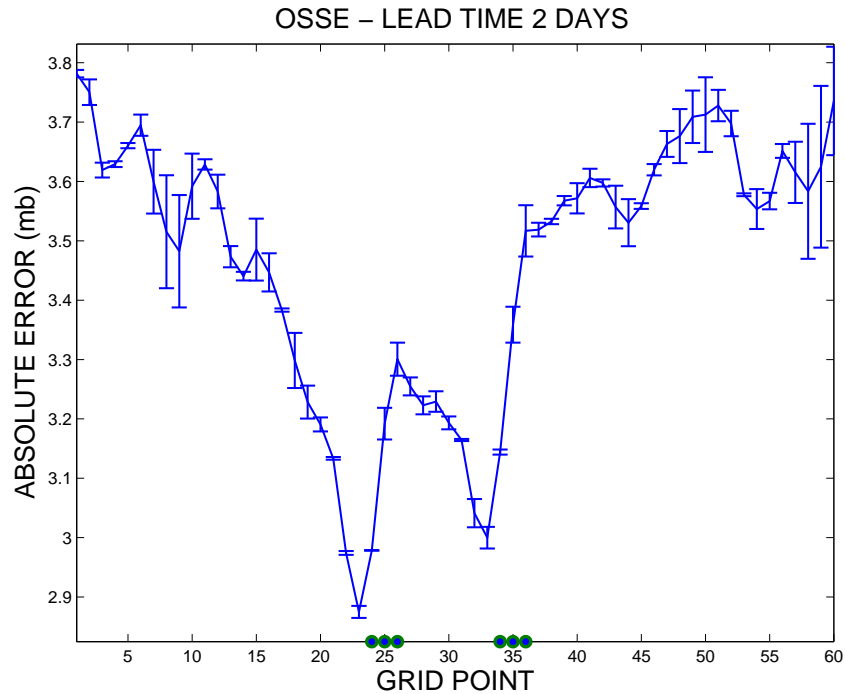
- Verification region - 5 consecutive grid points
- Forecast lead time - 2 days
- 1000 independent samples

Comparison of Cost Functions IV



- Verification region - discontinuous
- Forecast lead time - 0 days
- 1000 independent samples

Comparison of Cost Functions V



- Verification region - discontinuous
- Forecast lead time - 2 days
- 1000 independent samples

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Lag k Smoother for State x_o

- $p(x_o|y_o, \dots, y_k, \mathbf{Y}_o) = \int p(x_o, \dots, x_k|y_o, \dots, y_k, \mathbf{Y}_o) dx_1 \dots dx_k$

Lag k Smoother for State x_o

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- Start with: $p(x_o|y_o) \xrightarrow{M} p(x_1|y_o, x_o)$

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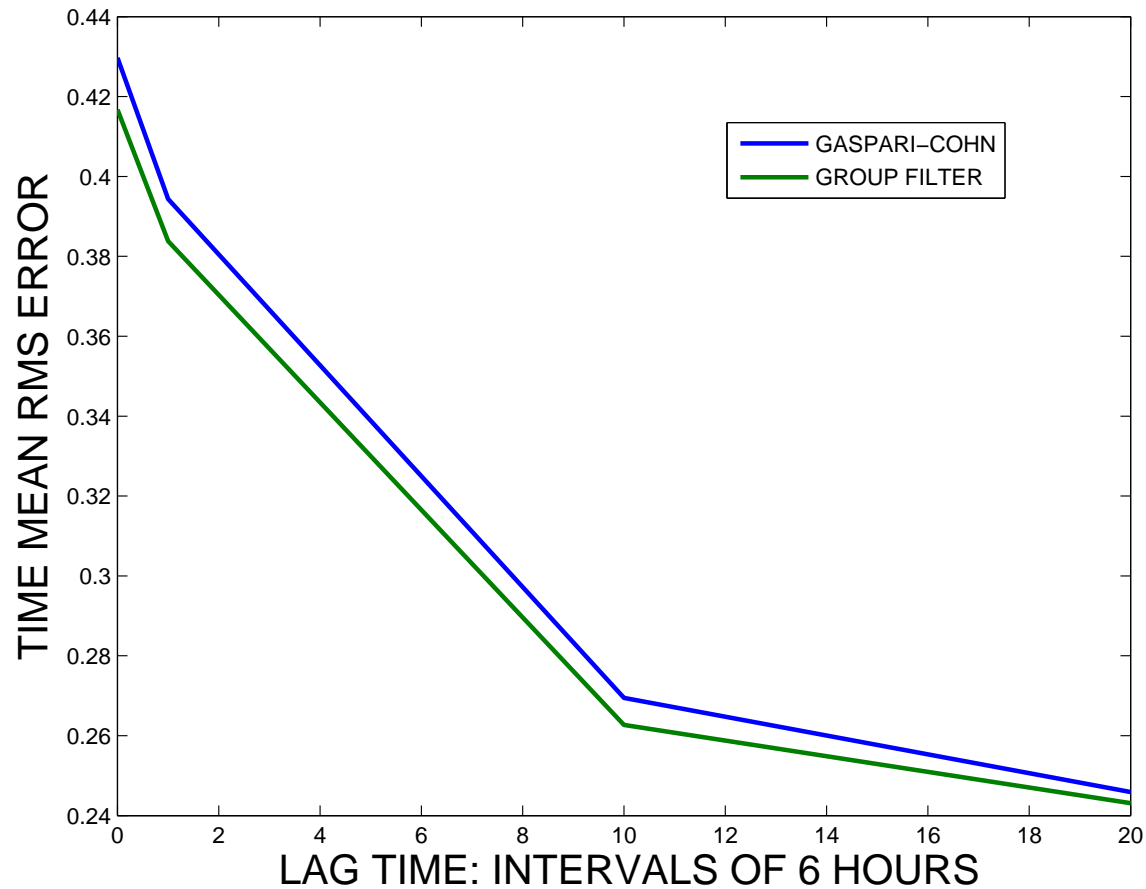
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- Replace distributions with samples: use EnKF based update method: **Extended state space localization**

Ensemble Smoother in DART: Lorenz 1996



• $N = 40, \gamma = \sqrt{1.04}, c = 0.25, \mathbf{H} = \mathbf{I}, \mathbf{R}_{i,i} = 1.0$