

Observational network design and the forecast error variance reduction due to observations

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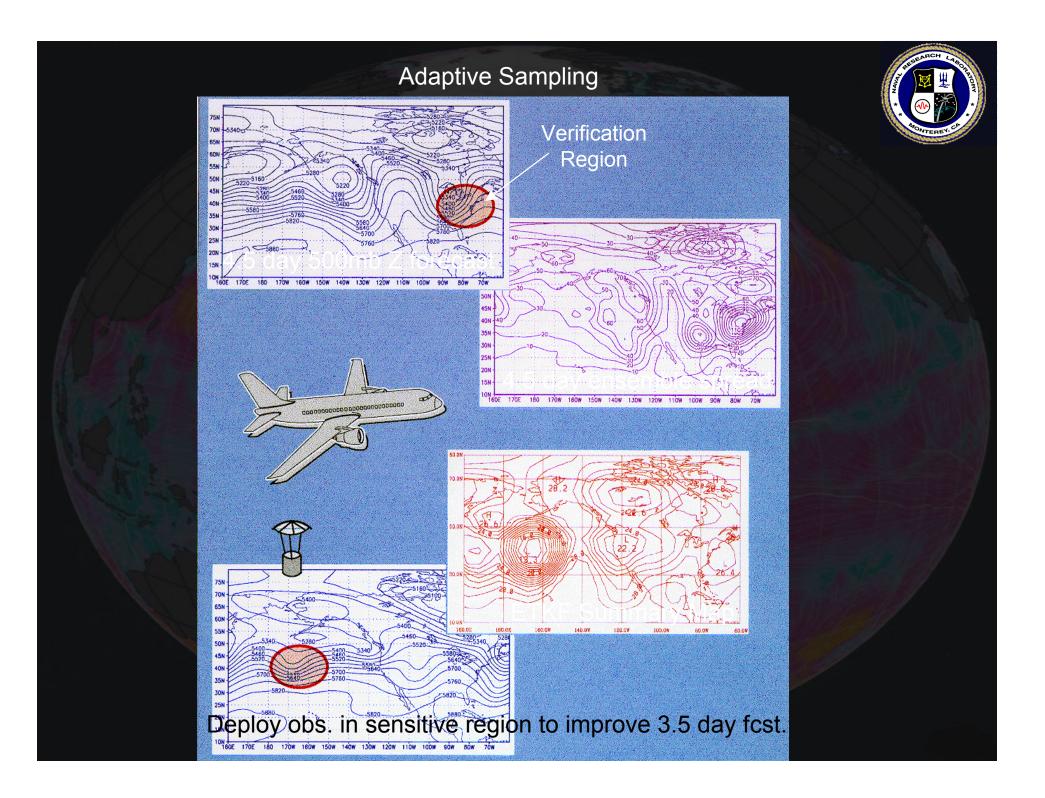
Acknowledgements: Istvan Szunyogh (Texas, A&M), Zoltan Toth (ERL, NOAA), Brian Etherton (ERL, NOAA)

BIRS workshop, July 2011

Overview



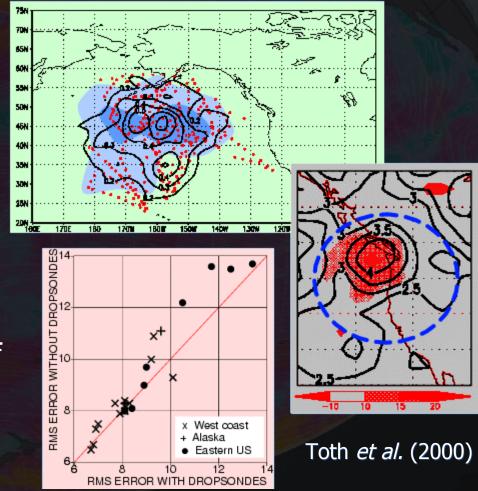
- Effect of targeted observations on forecast error variance and signal variance.
- Effect of observations on analysis error variance in the presence of strong nonlinearity



Main results from WSR programs

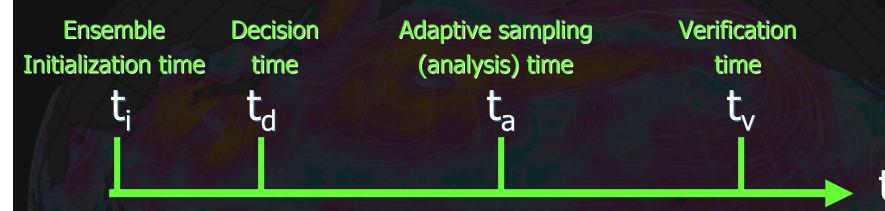
(based on data from winters 1998-2002)

- 60-80% of forecasts improved because of targeted observations
- 12-hour gain in forecast lead time
- RMS forecast errors reduced by 10-20%
- Improvement similar to that achieved in last 20 years of advances in numerical modeling and data acquisition





How the ETKF works



ETKF attempts to predict the "signal covariance" Sq: reduction in error covariance for any deployment q of adaptive observations:

 $S^{q} = P^{N} - P^{q} = M P^{N}(t_{a}) H^{qT} (H^{q}P^{N}(t_{a})H^{qT})^{-1} H^{q} P^{N}(t_{a}) M^{T}$ $= Z^{N}(t_{v}) T^{N} C^{q} \Gamma^{q} (\Gamma^{q+1})^{-1} C^{qT} T^{NT} Z^{NT}(t_{v})$ "Signal variance" = diagonal of S^q, calculated rapidly



ETKF targeting approach

Definitions:

 \mathbf{Z}^{f} is matrix of ensemble perts divided by $\sqrt{K-1}$ at the targeting time $\mathbf{Z}^{f}(t^{v})$ is matrix of ensemble perts divided by $\sqrt{K-1}$ at the verification time Step 1: Get square root of routine analysis error covariance matrix at targeting time using ETKF or ET $\mathbf{Z}_{r}^{a} = \mathbf{Z}^{f}\mathbf{C}_{r}(\Gamma_{r}+\mathbf{I})^{-1/2}\mathbf{C}_{r}^{T}$, from svd $\mathbf{Z}^{fT}\mathbf{H}_{r}^{T}\mathbf{R}_{r}^{-1}\mathbf{H}_{r}\mathbf{Z}^{f} = \mathbf{C}_{r}\Gamma_{r}\mathbf{C}_{r}^{T}$

Step 2: Find square root of analysis error covariance matrix associated with qth feasible deployment of adaptive observations.

$$\mathbf{Z}_{q}^{a} = \mathbf{Z}_{r}^{a} \mathbf{C}_{q} \left(\boldsymbol{\Gamma}_{q} + \mathbf{I} \right)^{-1/2} \mathbf{C}_{q}^{T}, \text{ from svd } \mathbf{Z}_{r}^{aT} \mathbf{H}_{q}^{T} \mathbf{R}_{q}^{-1} \mathbf{H}_{q} \mathbf{Z}_{r}^{a} = \mathbf{C}_{q} \boldsymbol{\Gamma}_{q} \mathbf{C}_{q}^{T}$$

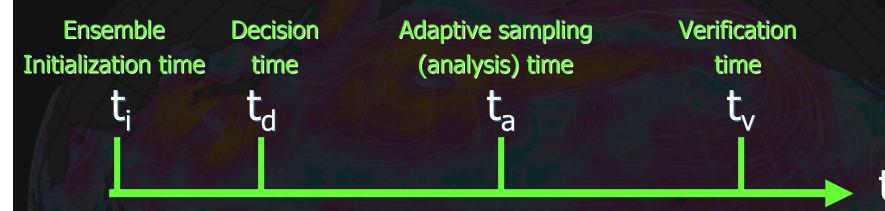
Step 3: Propagate square root of analysis error covariance matrix from q th feasible observational network to the verification time. Linear propagation would be $(Q^{1/2} \text{ is model error})$

$$\mathbf{Z}_{q}^{v} = \mathbf{M}\mathbf{Z}_{q}^{a} + \mathbf{Q}^{1/2} = \mathbf{M}\mathbf{Z}_{r}^{a}\mathbf{C}_{q}\left(\Gamma_{q} + \mathbf{I}\right)^{-1/2}\mathbf{C}_{q}^{T} + \mathbf{Q}^{1/2} = \mathbf{M}\mathbf{Z}^{f}\left[\mathbf{C}_{r}\left(\Gamma_{r} + \mathbf{I}\right)^{-1/2}\mathbf{C}_{r}^{T}\right]\left[\mathbf{C}_{q}\left(\Gamma_{q} + \mathbf{I}\right)^{-1/2}\mathbf{C}_{q}^{T}\right] + \mathbf{Q}^{1/2}$$

But $\mathbf{Z}^{f}\left(t^{v}\right)$ is the non-linear equivalent of $\mathbf{Z}^{f}\left(t^{v}\right)$, hence ETKF sets
$$\mathbf{Z}_{q}^{v} = \mathbf{Z}^{f}\left(t^{v}\right)\left[\mathbf{C}_{r}\left(\Gamma_{r} + \mathbf{I}\right)^{-1/2}\mathbf{C}_{r}^{T}\right]\left[\mathbf{C}_{q}\left(\Gamma_{q} + \mathbf{I}\right)^{-1/2}\mathbf{C}_{q}^{T}\right] + \mathbf{Q}^{1/2}$$



How the ETKF works

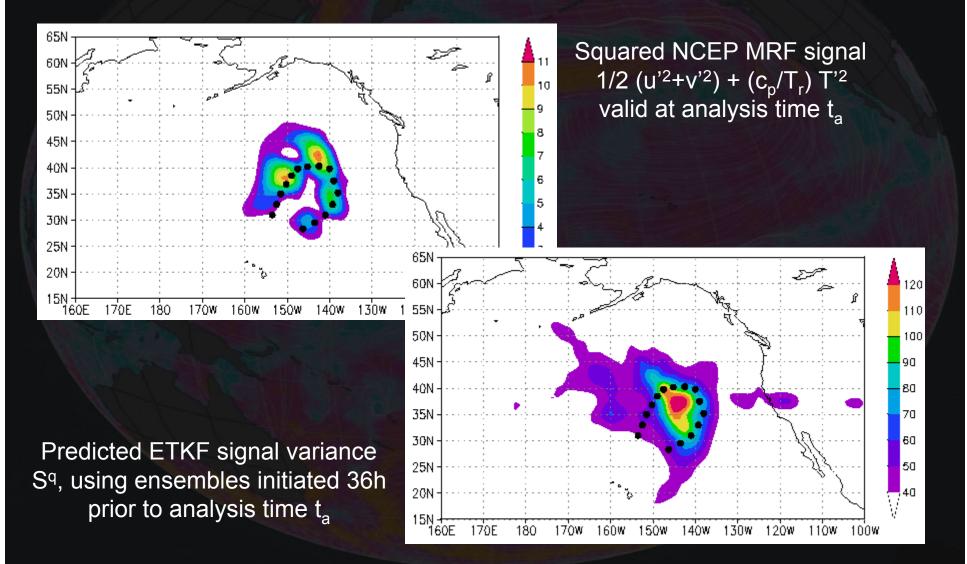


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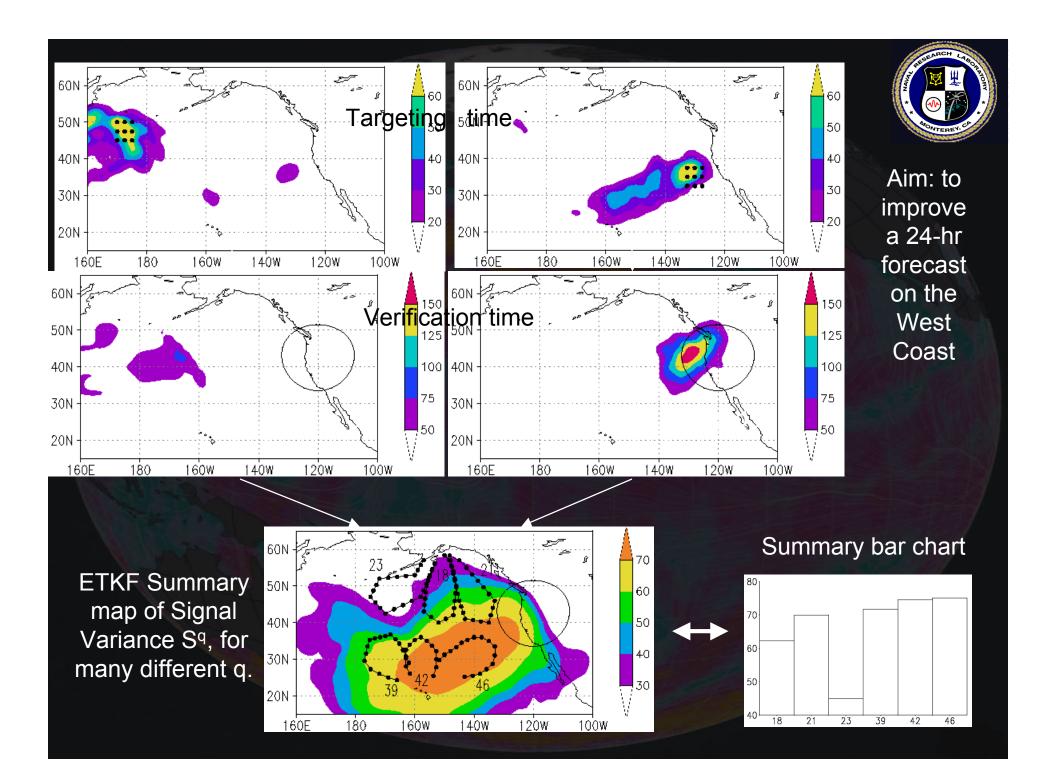
Signals and Signal Variance



Summary Maps of Signal Variance

ETKF predicts signal variance (reduction in forecast error variance) for all feasible deployments of targeted observations.

Summarize these predictions in the form of a map or bar chart.

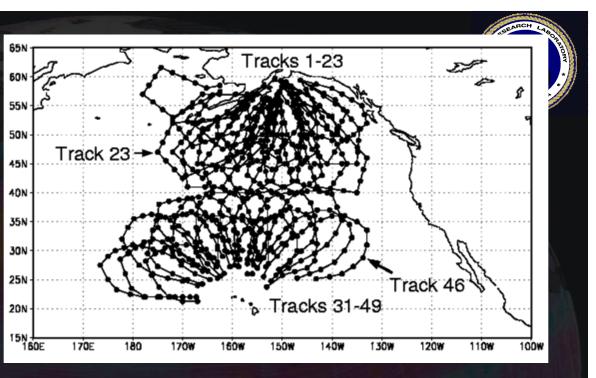


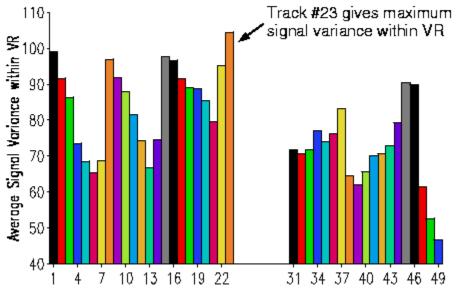


Serial adaptive sampling

- Many combinations and permutations of adaptive observations are available.
- Suppose that two sets of observations can be deployed simultaneously.
- First, find the optimal first deployment. Next, calculate the best second deployment given that the first set of observations are to be assimilated by the ETKF at the same time.
- Reduces observational redundancy.

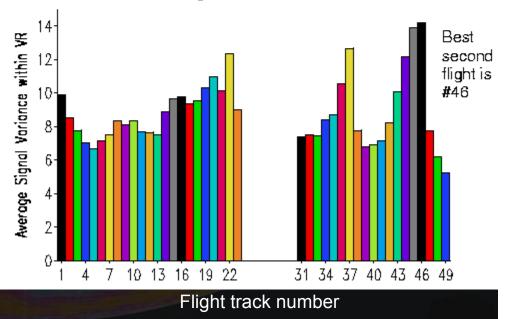
Serial adaptive sampling during WSR 2000





Flight track number

Observations from flight track #23 have been assimilated

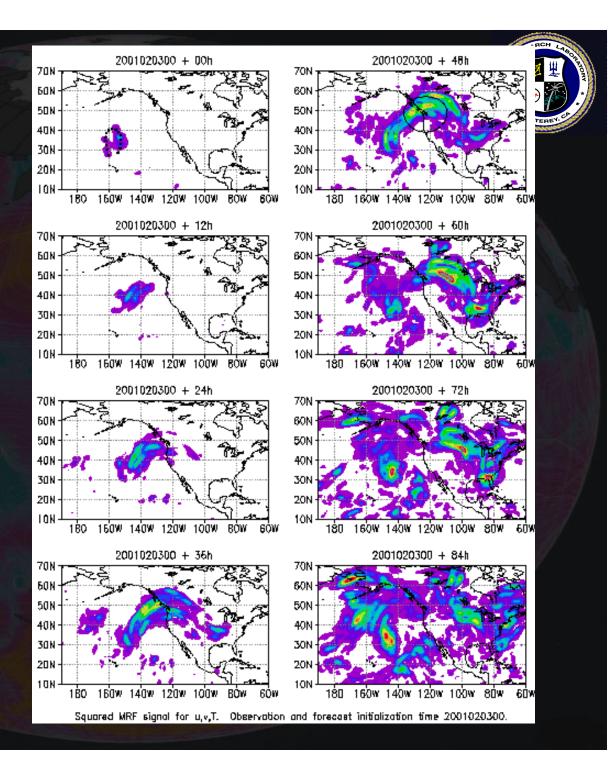


Question

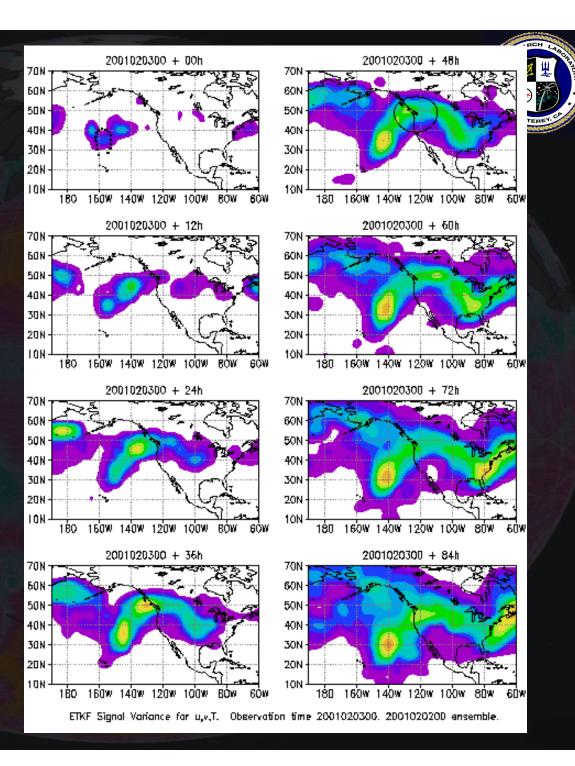


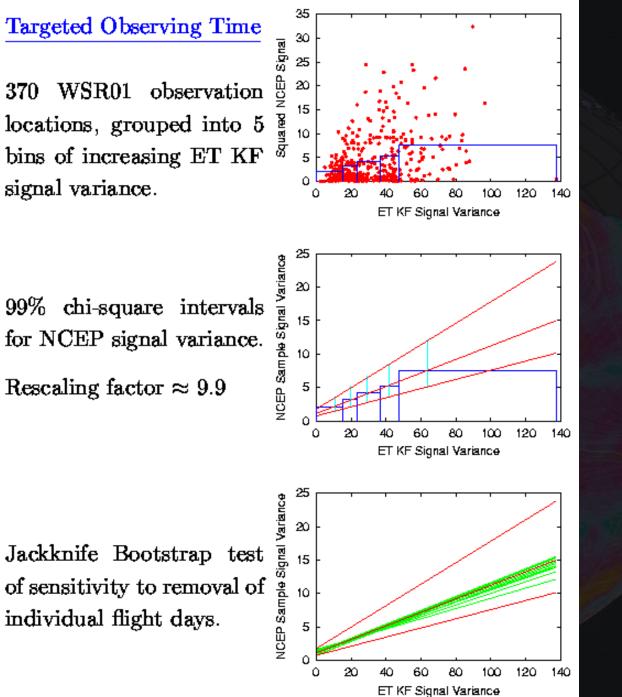
 Can an ETKF predict signal variance for any deployment of targeted observations?

Evolution of operational signal over 84h



Evolution of predicted ETKF signal variance over 84h

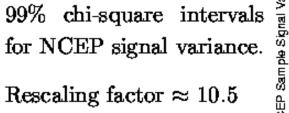




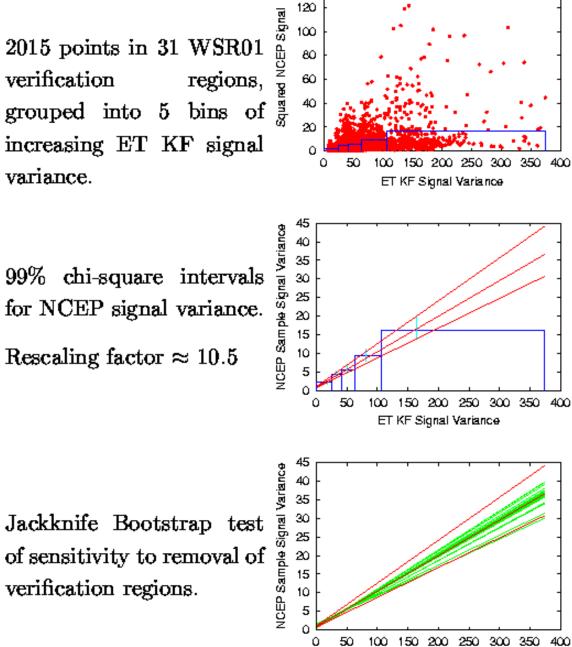


Verification Time

2015 points in 31 WSR01 verification regions, grouped into 5 bins of increasing ET KF signal variance.

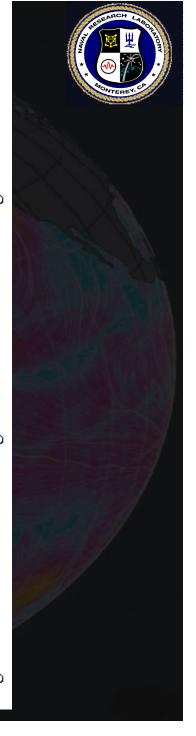


verification regions.



ET KF Signal Variance

140



Conclusions



- The Kalman filter provides a rigorous means for quantitatively predicting the reduction in analysis and forecast error variance due to assimilating observations.
- The Ensemble Transform Kalman Filter enables the reduction in forecast error variance due to targeted observations to be rapidly estimated for a large number of feasible deployments of observational resources.
- Proved useful in the Winter Storms Reconnaissance Program
- More quantitative testing of accuracy of predictions is required.



Talk based on following papers

• See

- Bishop, C.H., B.J., Etherton and S.J. Majumdar, 2001: Adaptive Sampling with the Ensemble Transform Kalman Filter. Part I: Theoretical Aspects. *Mon. Wea. Rev.* **129**, 420-436.
- Majumdar, S.J., C.H. Bishop, I. Szunyogh and Z. Toth, 2001: Can an Ensemble Transform Kalman Filter predict the reduction in forecast error variance produced by targeted observations? *Quart. J. Roy. Met. Soc.* **127**, 2803-2820.
- Bishop, C.H., C.A. Reynolds and M.K. Tippett, 2003: Optimization of the Fixed Observing Network in a Simple Model. *J. Atmos. Sci.*, 60, 1471-1489.

In short,

- Majumdar et al. (2001, QJRMS)
- Bishop et al. (2003, JAS)