

Global assimilation with Ensemble Kalman filter (EnKF) method

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- What is the EnKF?
 - Advantages
 - Applications

The Data Assimilation problem ...

Given a prior estimate (first-guess) and new observations, create an analysis that is as close to the 'true' state as possible.

Kalman Filter is the least-square solution ..

$$\mathbf{x}_a = \mathbf{K}\mathbf{y} + (\mathbf{I}-\mathbf{K})\mathbf{x}_b$$

analysis → \mathbf{x}_a ← prior
obs → \mathbf{y} ← Kalman Gain

Interp. between observations and prior, with weights

$$\mathbf{K} = \mathbf{B}(\mathbf{B} + \mathbf{R})^{-1}$$

Background error → \mathbf{B}
Obs.error → \mathbf{R}

GSI (3DVar): Assume \mathbf{B} given (constant), solve problem iteratively (as a minimization problem).

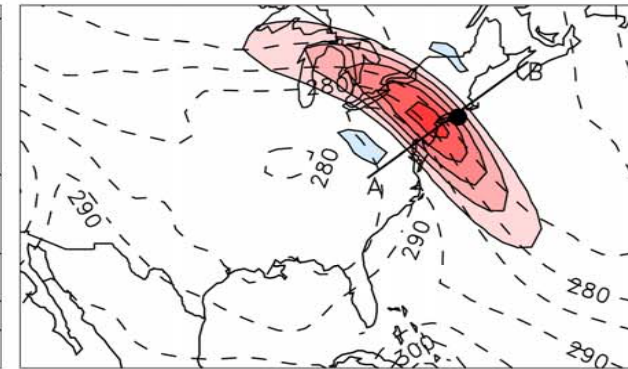
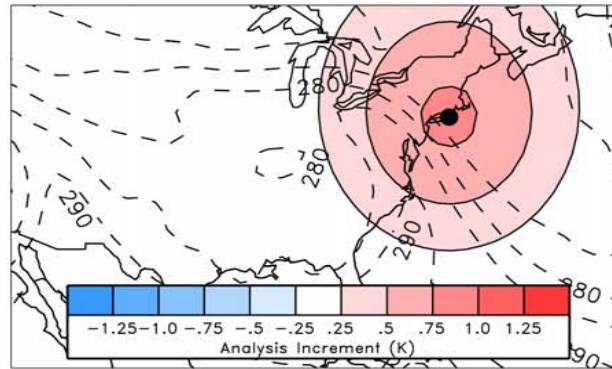
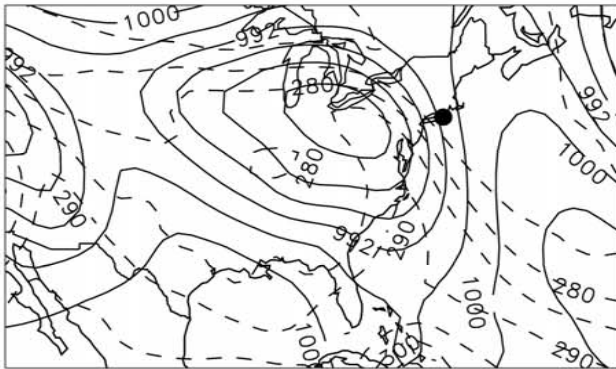
EnKF: Solve problem directly, with \mathbf{B} estimated from an ensemble.

Benefits of Flow-Dependent Background Errors: Example 1 (Front)

1000 hPa temperature (K) and
surface pressure (hPa)

3D-Var increment

Ensemble Filter Increment



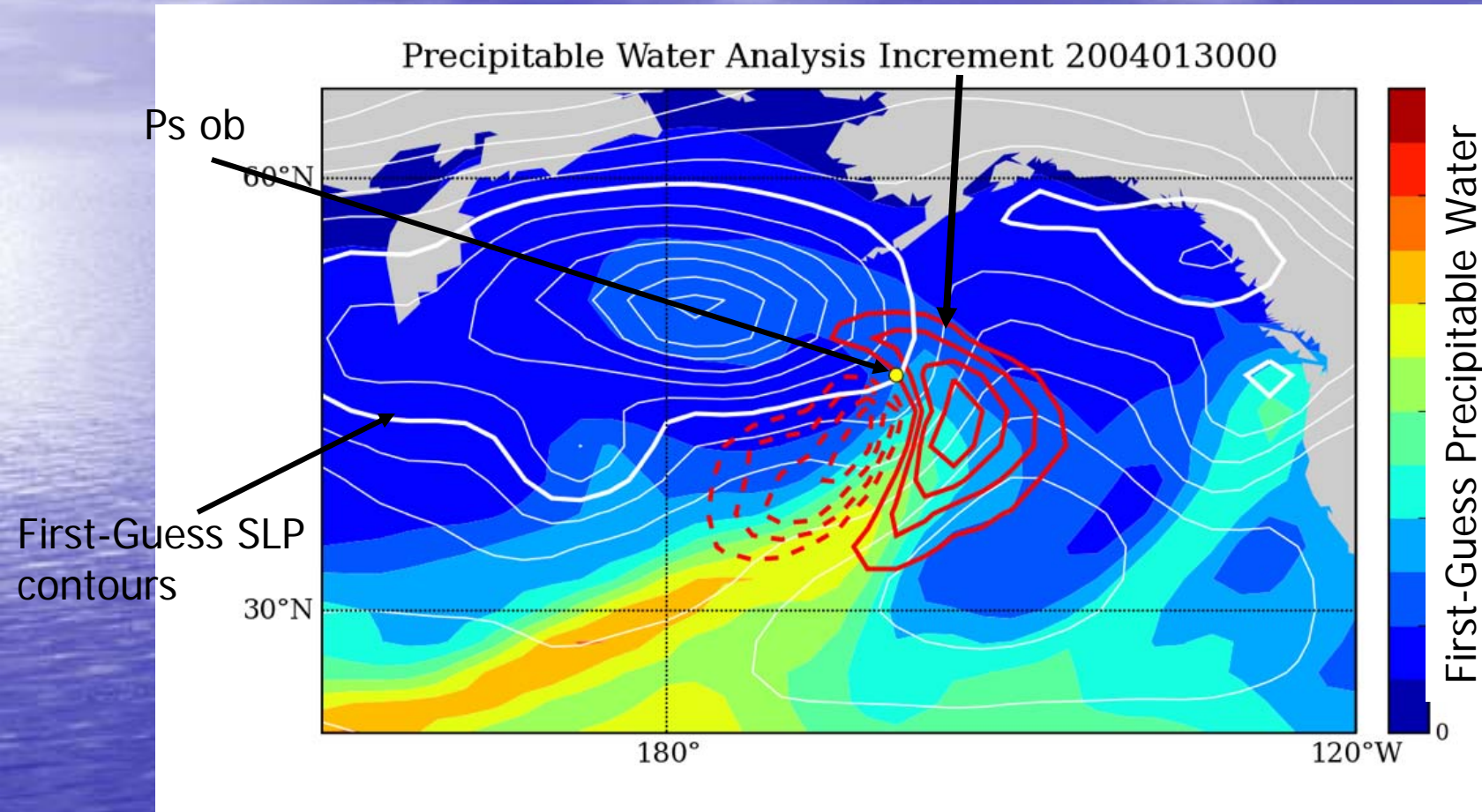
First Guess + Ob location

3DVar Increment

EnKF Increment

*Structure of background-error covariances can adapt to
flow situation.*

Benefits of Flow-Dependent Background Errors: Example 2 (Atmospheric River)



*Surface pressure observation can improve analysis of integrated water vapor (cross-variable covariance in **B**).*

Why we like the EnKF ...

- *Simple to implement - no need for adjoint and TLM, iterative minimization algorithm, specification of B .*
- *Provides uncertainty estimate! (ensemble).*

Outstanding issues ...

- *Sampling error due to small ensemble size. [example](#)*
- *Representing model uncertainty.*
 - Stochastic/dynamic model .
 - Covariance inflation.
 - add noise to analysis ensemble
 - multimodel ensemble.

Current Applications ...

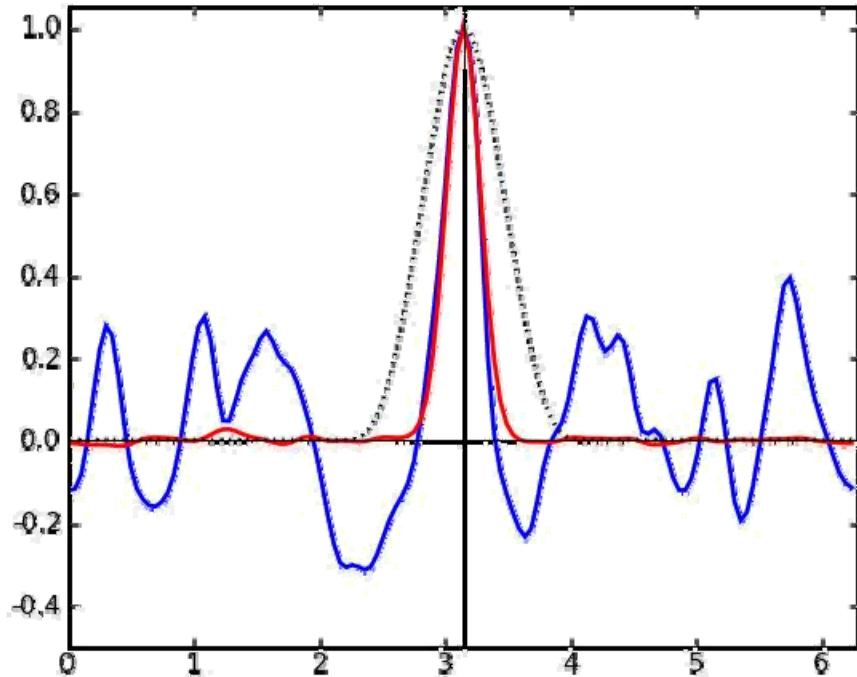
- Reanalysis: 20th Century Reanalysis Project (1892 - present, surface pressure obs only, see poster)
- Operational NWP: prototype operational system for NCEP (candidate to replace GSI).
- Carbon Tracker.

Future Applications ...

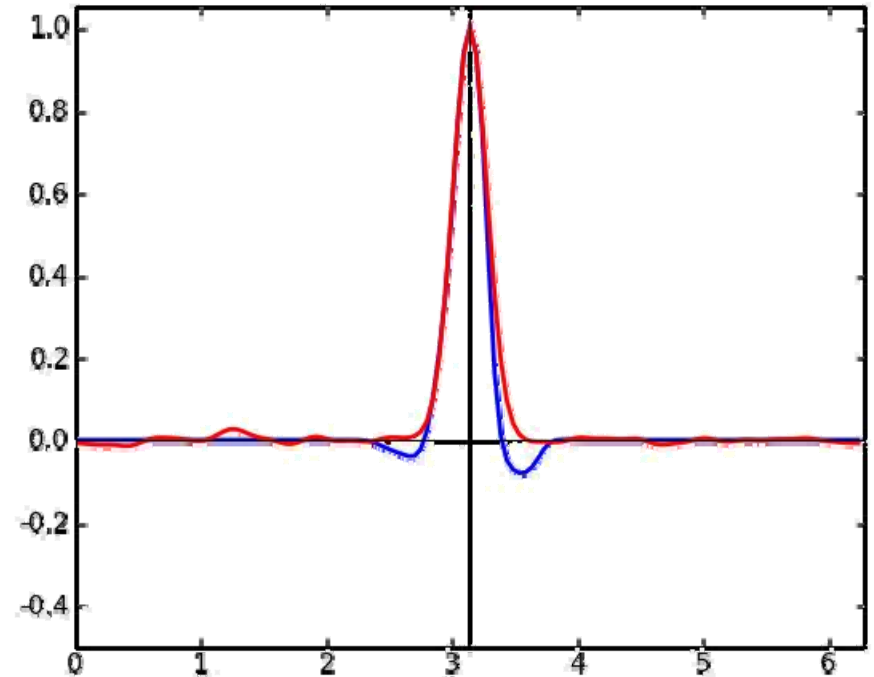
- Online CO₂ assimilation (next-gen Carbon Tracker).
- EnKF for FIM/NIM.
- Hurricane data assimilation.
- ???

Problem: *Noise in variances should decrease like $1/N^{1/2}$, maybe slower for covariances.*

true and sample correlation



true and modulated sample correlation



Red: true correlation
Blue: sample correlation
Dotted: Localization function

[back](#)

Global modeling and assimilation

– Earth System Modeling

ESRL Theme Presentation

2:00 – 3:30 PM, Wed 7 May 2008

- 2:00 Intro to Earth System modeling, FIM – Stan Benjamin
- 2:15 Icosahedral grid in FIM, NIM – Jin Lee
- 2:30 FIM real-data tests – John Brown
- 2:40 Global observations for assimilation, NCEP Gridpoint
Statistical Interpolation – Dezso Devenyi
- 2:55 Global assimilation with ensemble Kalman filter
– Jeff Whitaker
- 3:10 Panel discussion – presenters, Andy Jacobson,
Georg Grell, Tom Schlatter

Questions to prime the discussion

What are the biggest goals for global modeling and assimilation over the next 20 years for NOAA Research?

How should ESRL proceed on ESRL Chemical/Earth System reanalysis?

How can ESRL design OSSEs including those for chemistry observations?

Treatment of B

- *In 3DVar (GSI) B is specified and time invariant.*
- *In 4DVar minimization over a time window, 3DVar minimization is done for a single time.*
- *In 4DVar B is specified at beginning of window, but evolved implicitly by TLM.*
- *In EnKF, a sample of B evolved via an ensemble. Adjusts to dynamics, observing network.*
- *Minimization gives you mean, but not second moment (A). EnKF gives you both.*