Chesapeake Bay assimilation using Local Ensemble Transform Kalman Filter in the presence of forcing errors

Chesapeake Bay Modelng Symposium
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Project Outline

Long Term Goal: create a Chesapeake Bay reanalysis and operational assimilation system

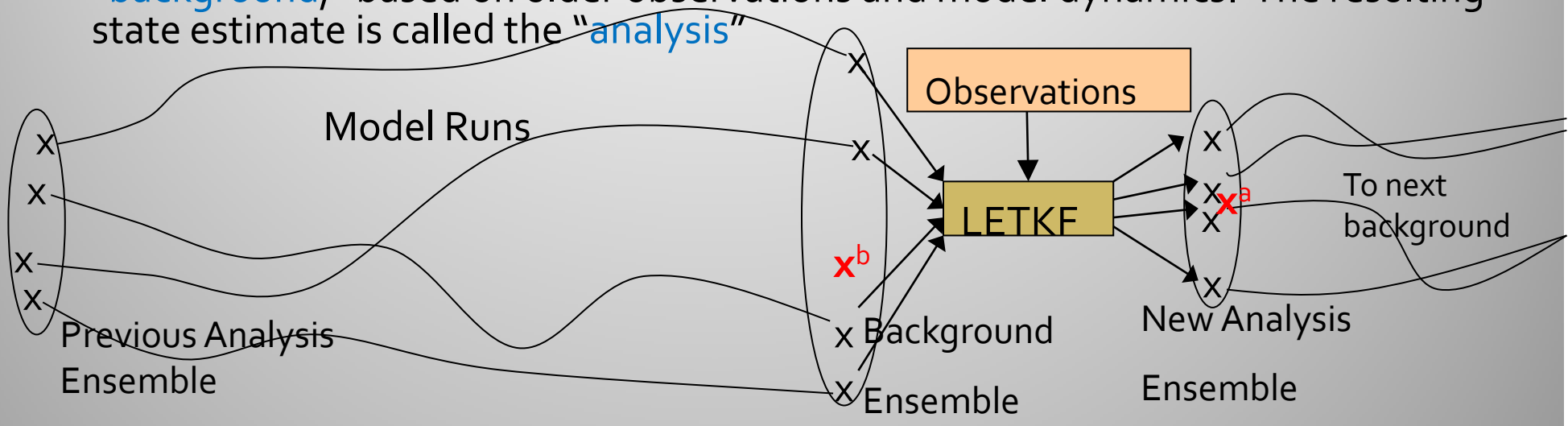
- assimilate satellite SST observations, in situ temperature and salinity observation, and any others
- ChesROMS model
- Local ensemble transform Kalman filter (LETKF)

Current Results: observing system simulation experiments (OSSEs)

- assimilating synthetic observations
- Correcting errors in wind forcing

LETKF

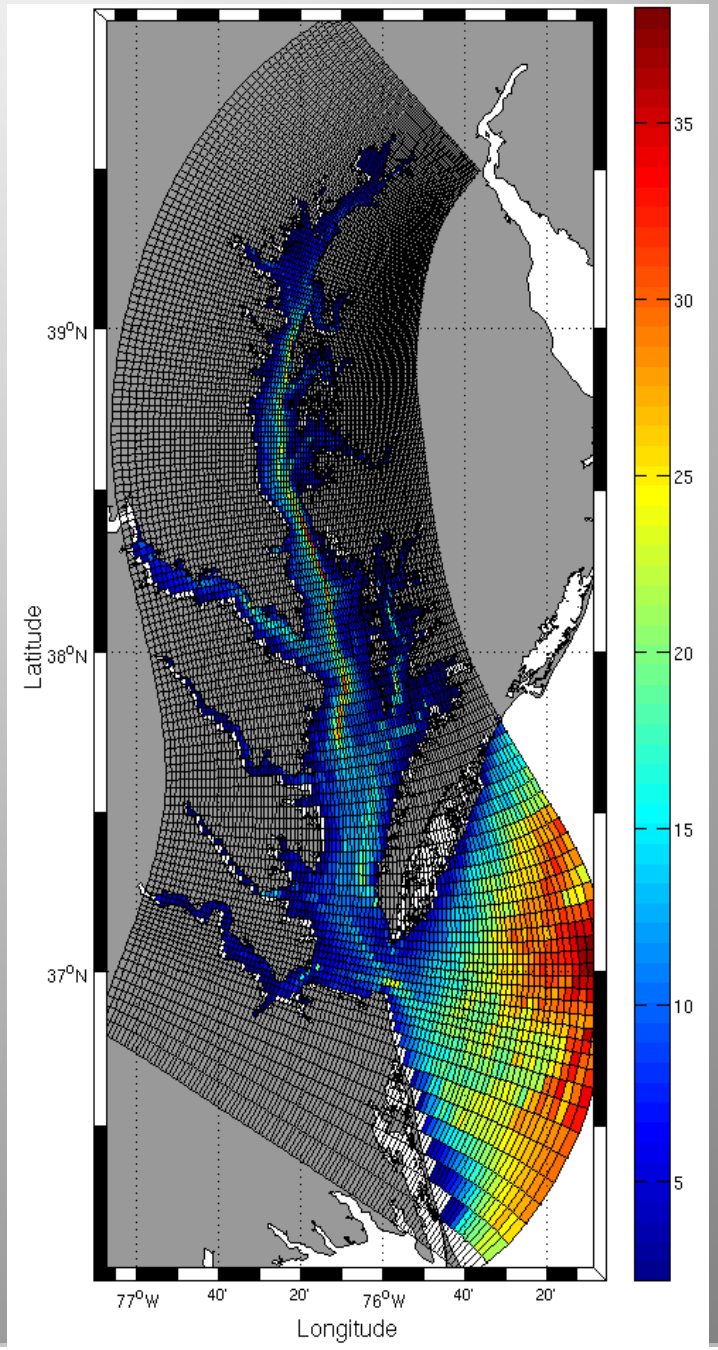
- Data assimilation combines observations with a previous state estimate, called the "background," based on older observations and model dynamics. The resulting state estimate is called the "analysis"



- The ensemble characterizes the uncertainty: $\tilde{\mathbf{P}}^a = \left[(k-1)\mathbf{I} + \mathbf{Y}^{b^T}\mathbf{R}^{-1}\mathbf{Y}^b\right]^{-1}$
- New analysis is created: $\mathbf{x}^a = \mathbf{x}^b + \mathbf{X}^b\tilde{\mathbf{P}}^a\mathbf{Y}^{b^T}\mathbf{R}^{-1}\left(\mathbf{y}^o - \mathbf{y}^b\right)$
- Along with an analysis ensemble: $\mathbf{X}^a = \mathbf{X}^b\left[(k-1)\tilde{\mathbf{P}}^a\right]^{1/2}$
- Analysis is local—analysis is performed independently at each grid point using observations in a neighborhood of that point
- In practice the covariance is artificially inflated to account for underestimation.

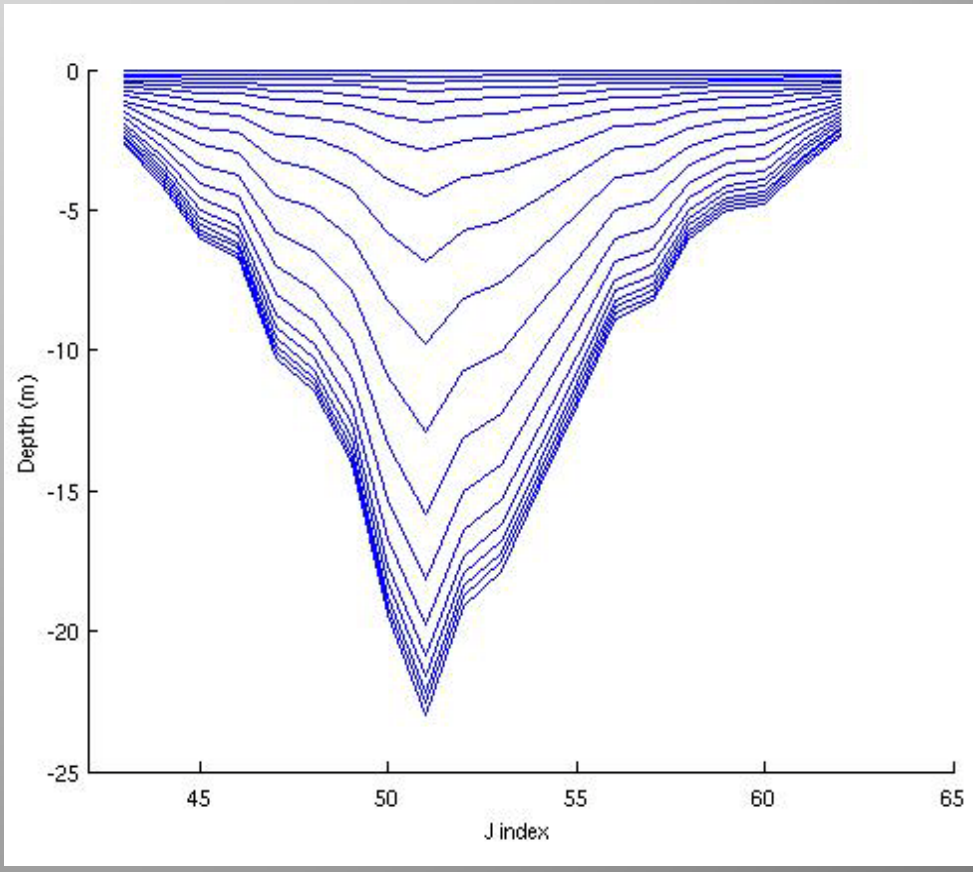
ChesROMS

- Numerics are from the Regional Ocean Modeling System (ROMS)
- Curvilinear grid with 100x150x20 resolution
- Same bathymetry and forcing as ChesROMS (Xu et al., 2009)



ChesROMS

- Numerics are from the Regional Ocean Modeling System (ROMS)
- Curvilinear grid with 100x150x20 resolution
- Same bathymetry and forcing as ChesROMS (Xu et al., 2009)
- Terrain following sigma coordinate



from Xu et al., 2009

Experiment Setup

Truth: given by a year long model run for 1999

Synthetic Observations: created from the truth

- Adding random Gaussian error with prescribed standard deviation

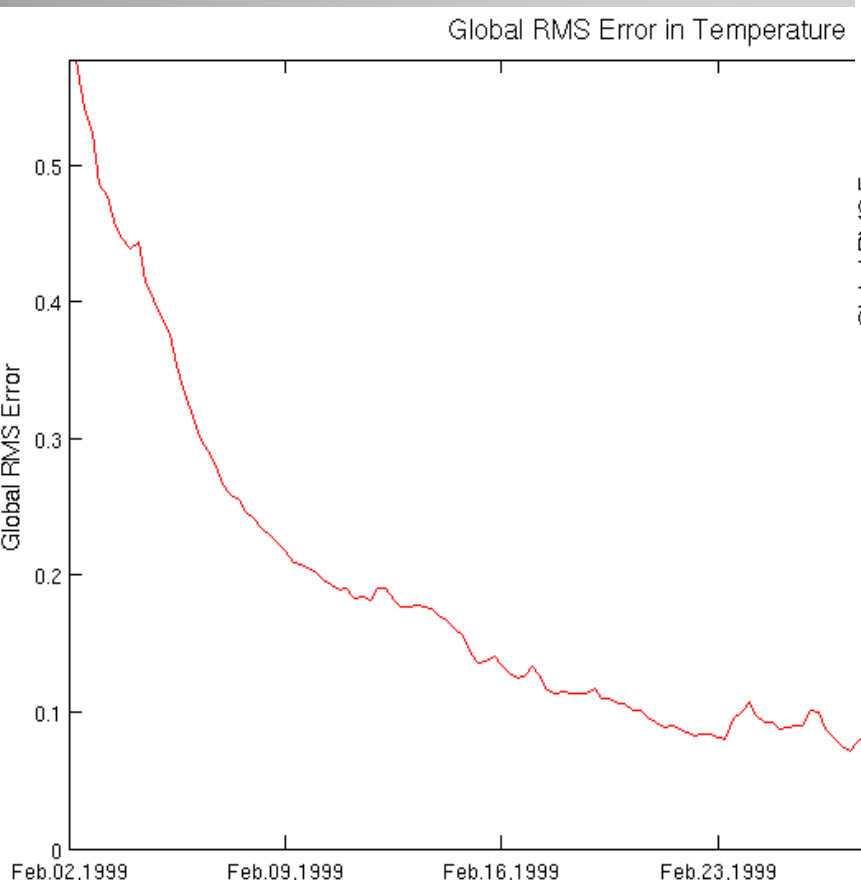
Initial Ensemble: 40 member ensemble is formed from the 40 states of the spinup

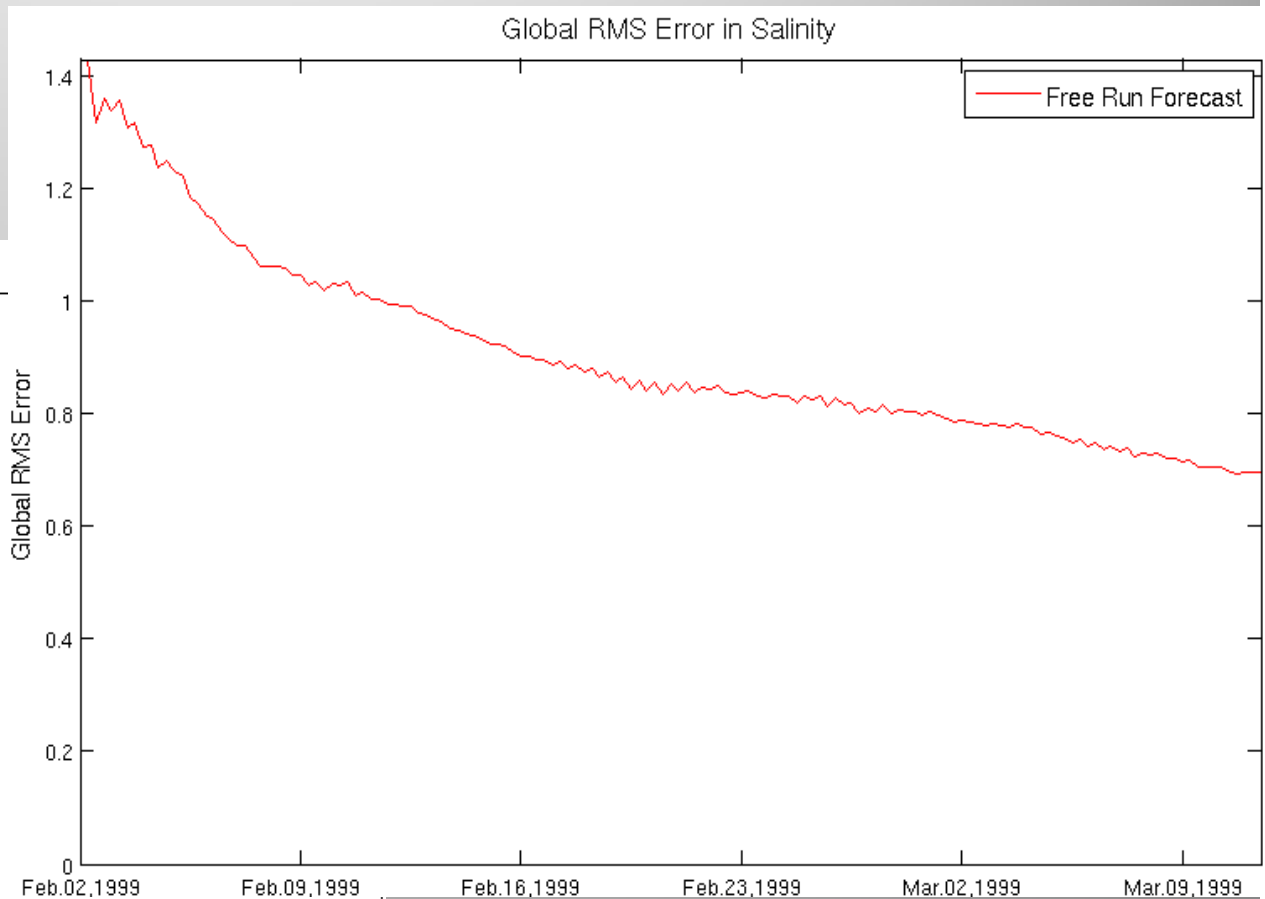
Free Run Forecast: model run without data assimilation from the initial ensemble average used as a benchmark

Assimilation Interval: 6 hours (4 assimilations/day)

Perfect Model Convergence

- With a perfect model (including perfect forcing) the Chesapeake Bay model converges even with incorrect initial conditions

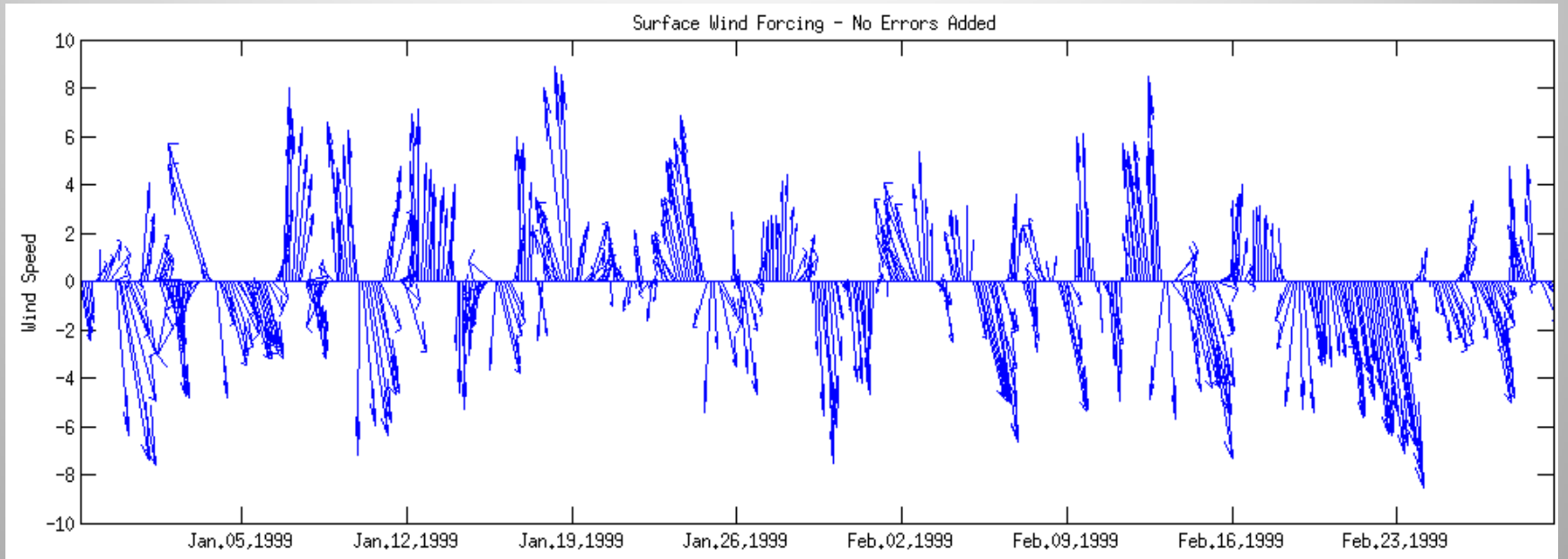


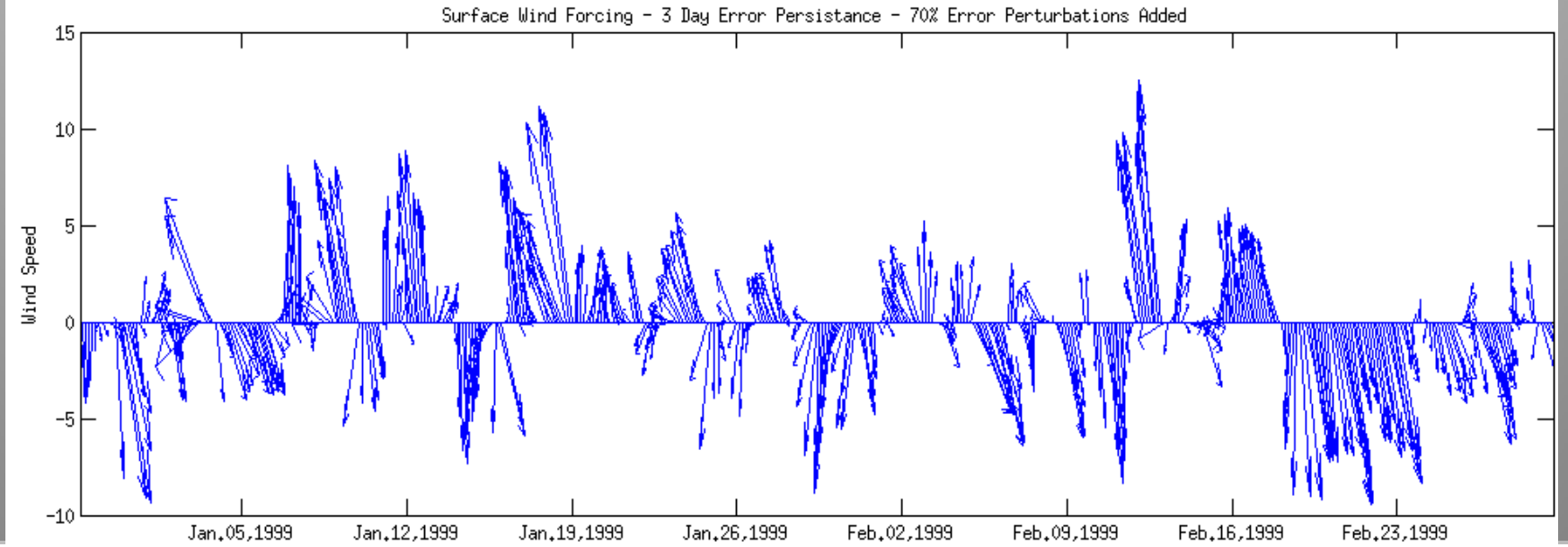


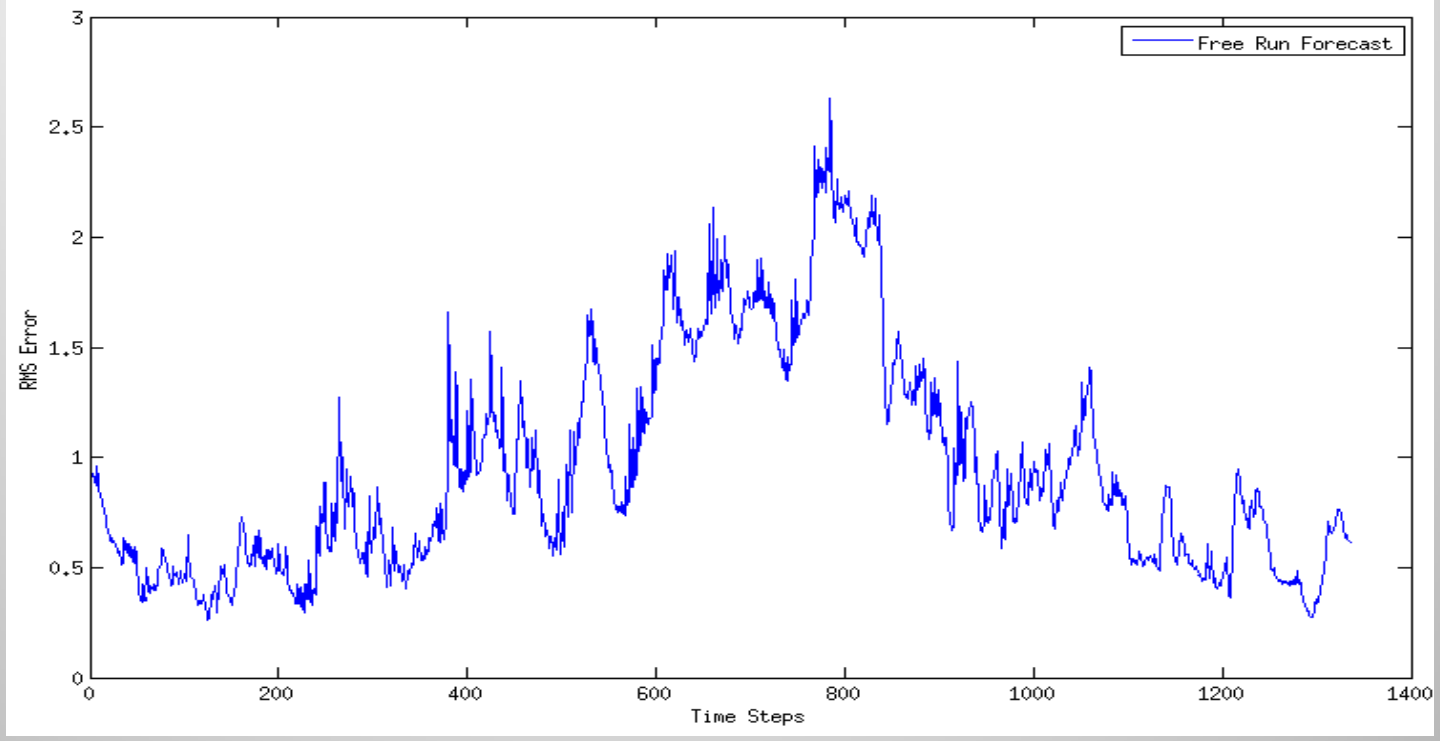
Imperfect Forcing

- In practice, the forcing fields are not perfect
- To visualize these errors, surface winds and pressure are perturbed
  - -A forcing field is randomly selected from within 30 days of the year-long forcing field
  - -The mean is subtracted out, leaving just the perturbation
  - -70% of this perturbation is added to the original forcing
  - -This perturbation is allowed to persist for 3 days

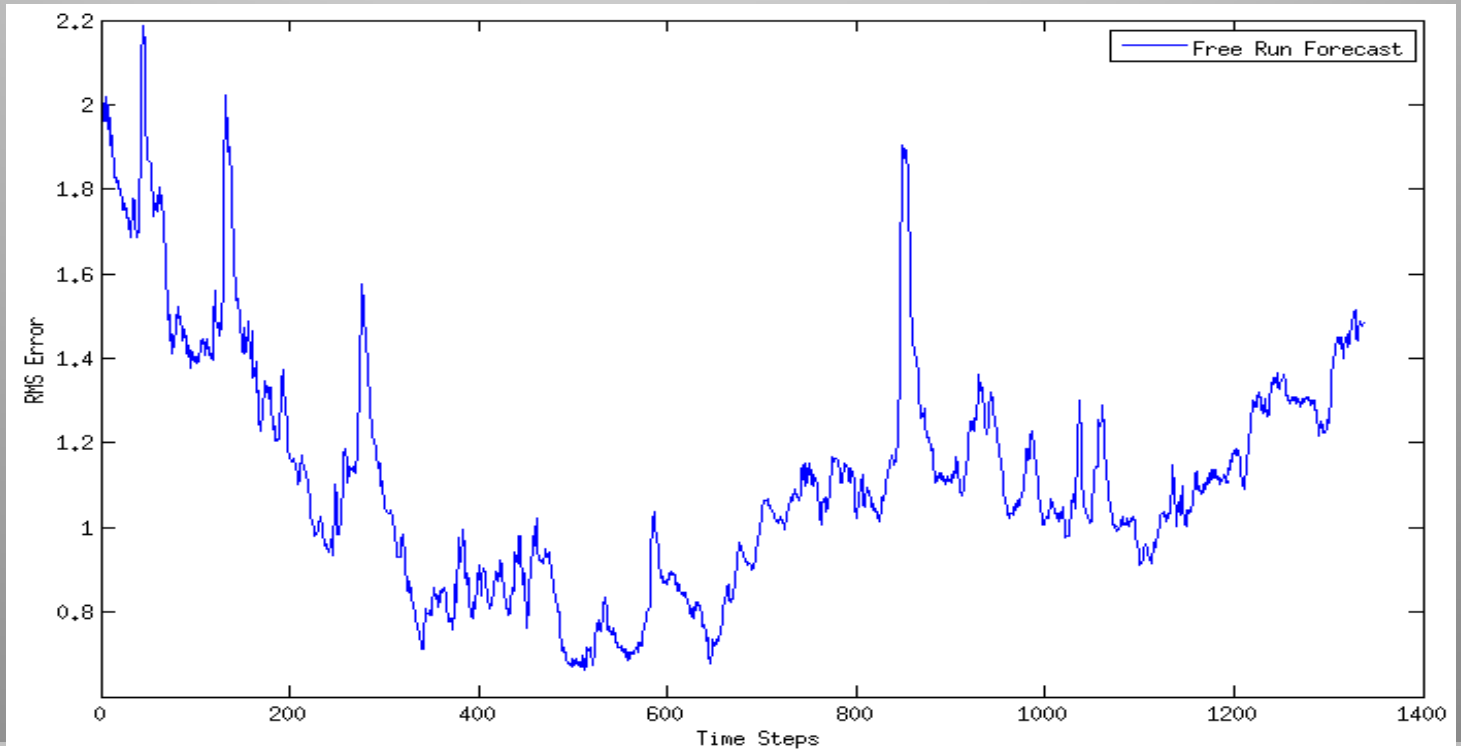
Imperfect Forcing







Both temperature and salinity fields now do not converge to the true state



Experiment Setup

Synthetic Observations: temperature, salinity, and current observations every 5 grid points in horizontal and every level

Observation Errors: 0.1C, 0.1 psu, 0.01 m/s

Inflation: 4% multiplicative

Forcing: Same for each ensemble member

Localization: σ is 3 grid points in horizontal and 1 in vertical (out to 3 σ is used)

Assimilation Interval: 6 hours (4 assimilations per day)

Imperfect Single Forcing

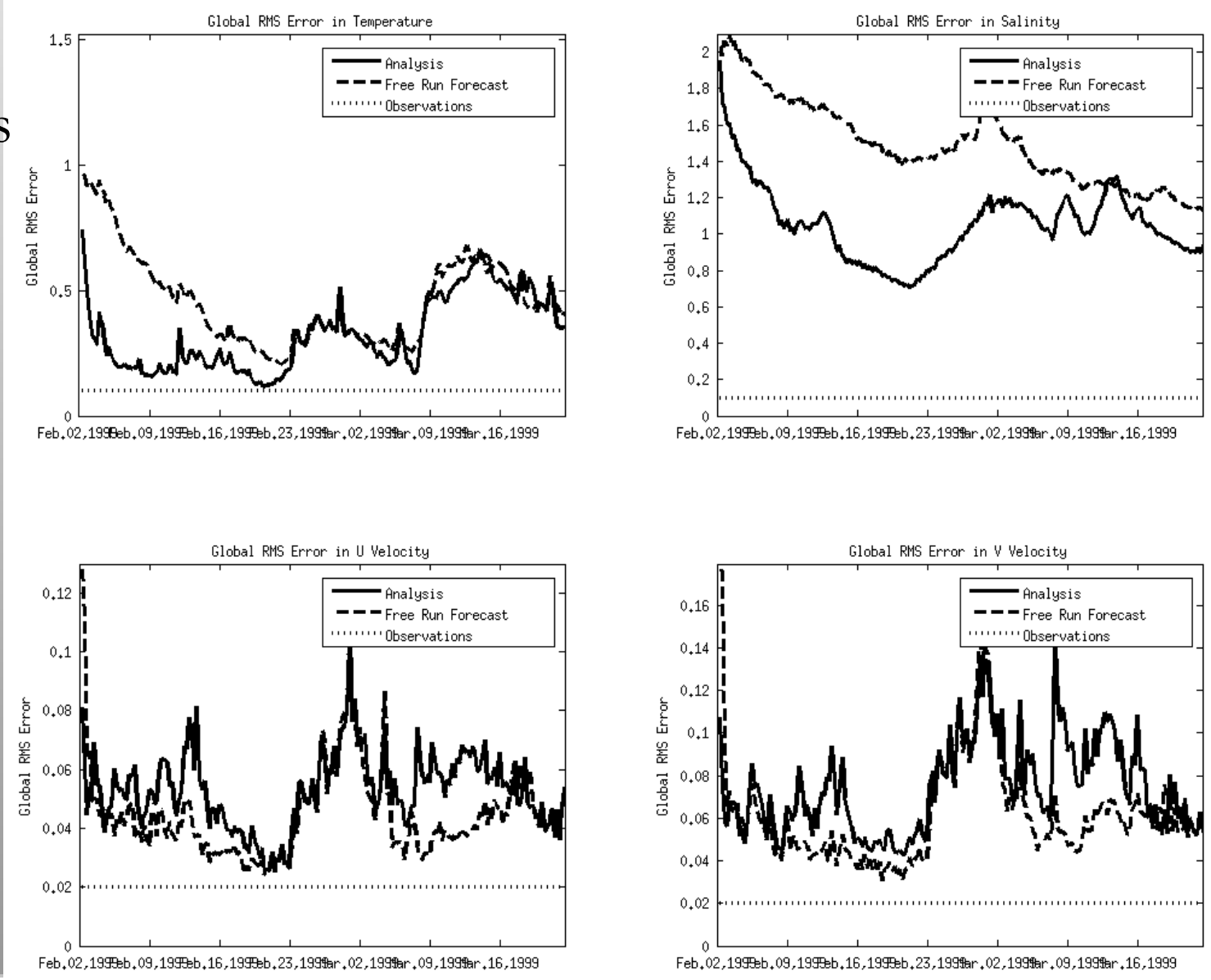
- However, the ensemble must contain information about the background uncertainty
- If only one forcing is used for the ensemble, the filter cannot make the proper adjustments
- For example, consider a 40 member ensemble, each with the same surface, river, and OBC forcing fields
- Initial ensemble comes from 40 states selected as every 12 hours from the spin-up
- 4% inflation is used, analysis every 6 hours

Imperfect Single Forcing

- 40 member ensemble, each with the same surface, river, and OBC forcing fields

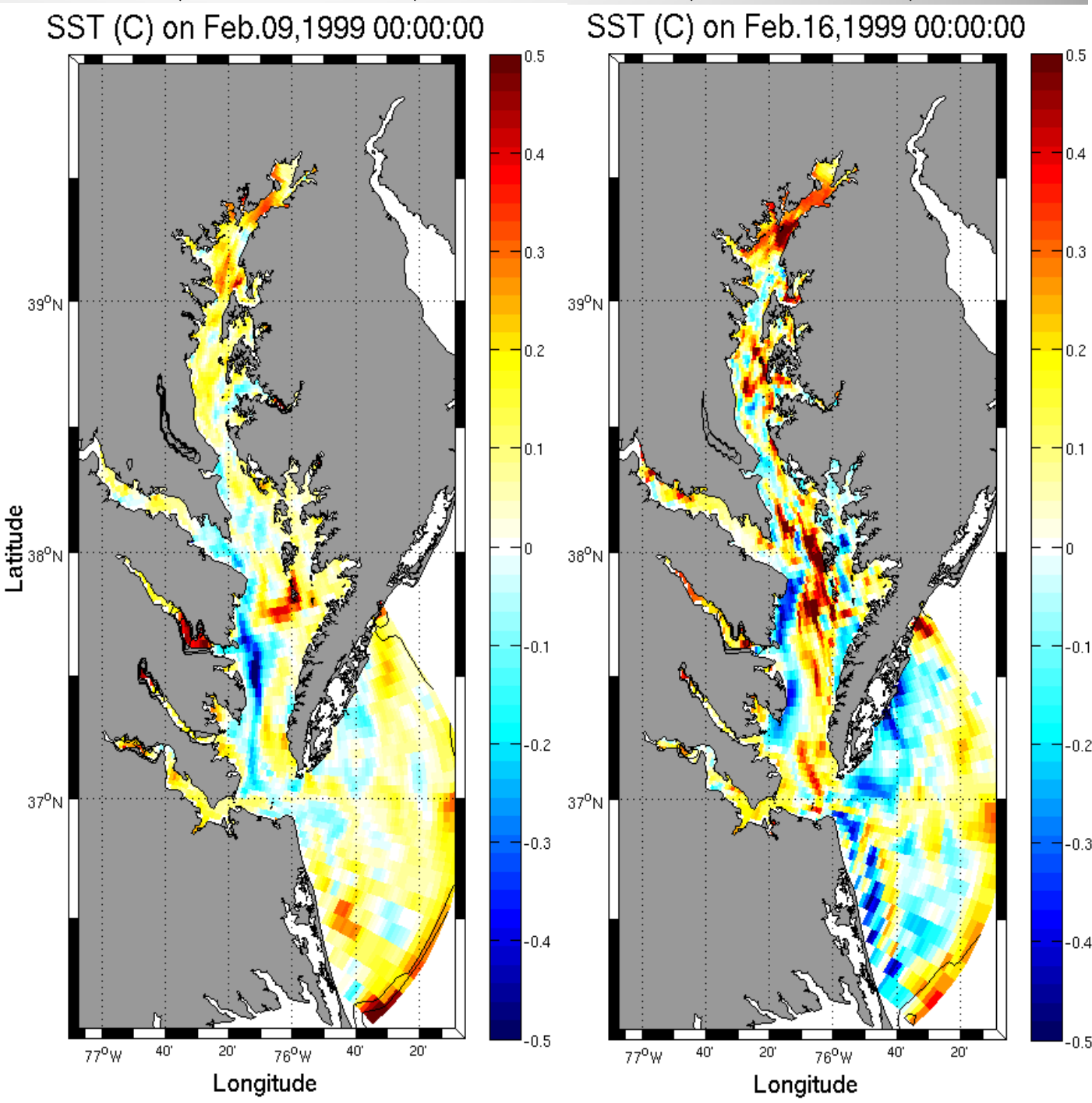
- This analysis does not converge to the true state

- After about 2 weeks, the analysis is converging to the free run



Background Spread (contour) vs Error (shaded)

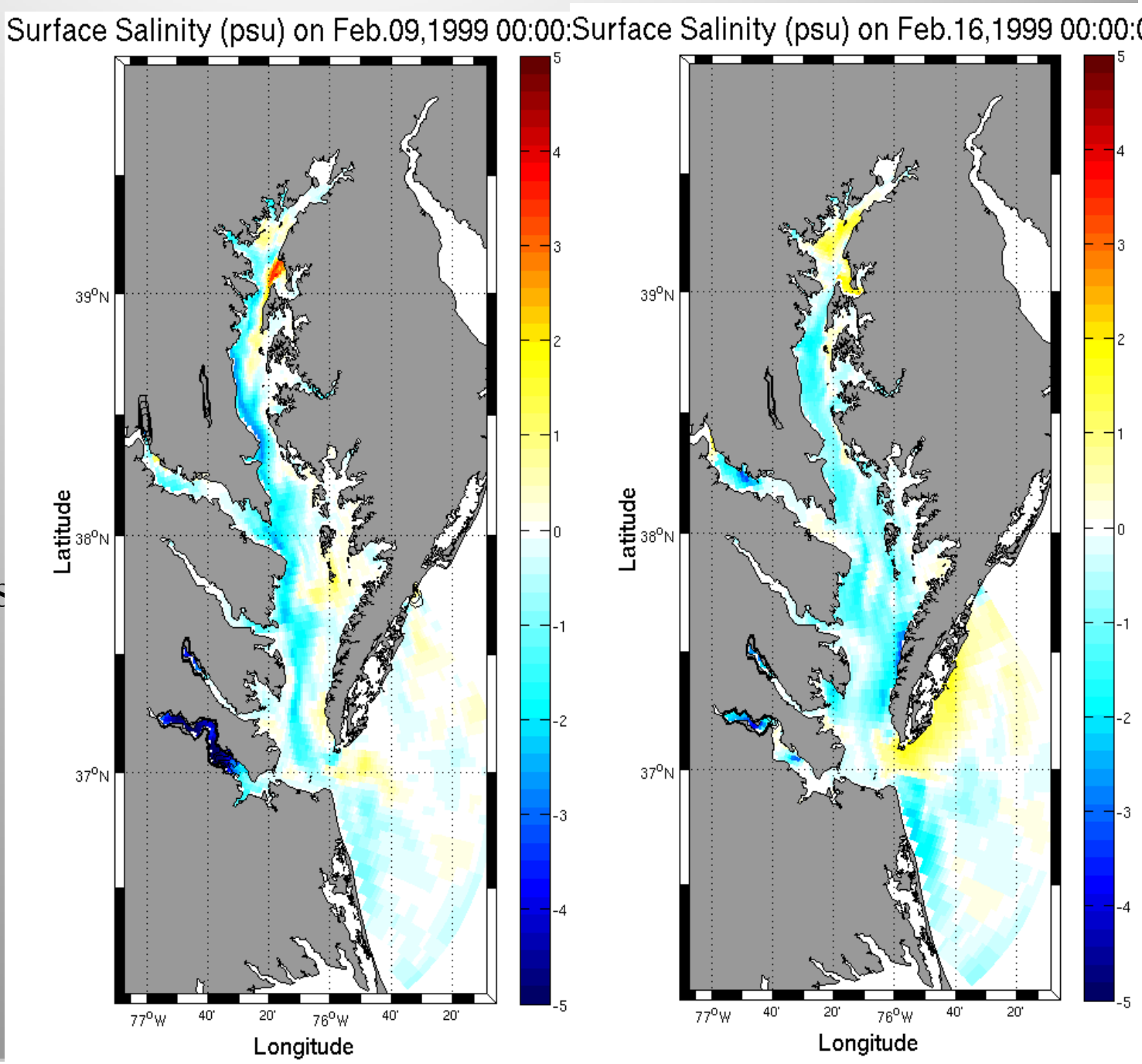
- Ensemble is not representing the error
- There is essentially no ensemble spread in temperature (smallest contour is 0.1)



Background Spread (contour) vs Error (shaded)

- Same is true in salinity (smallest contour is 0.4)

- Although error appears to be captured in the James river

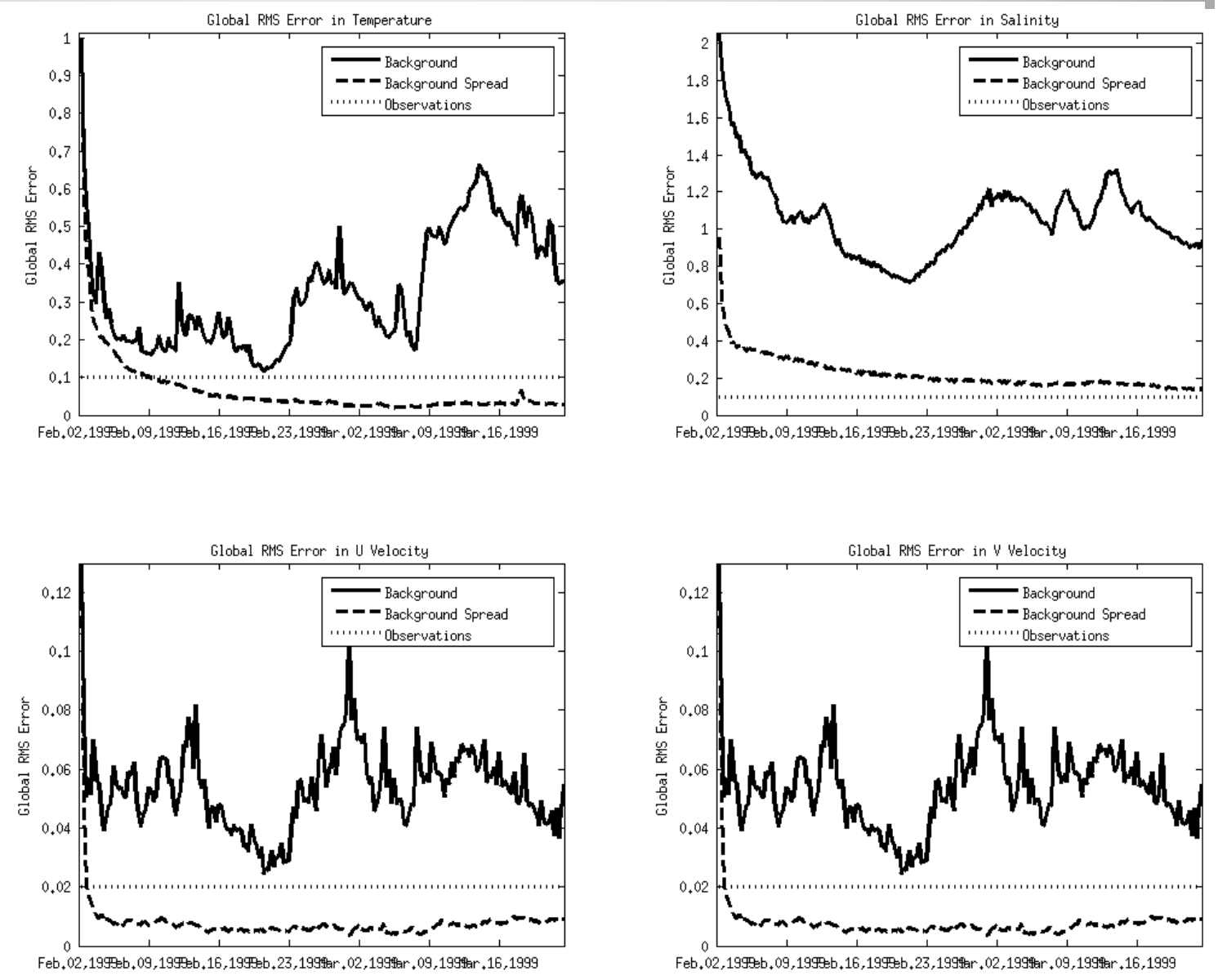


Imperfect Single Forcing

- The problem is that the ensemble spread is not accurately characterizing the uncertainty in the background

- Instead, it converges to the free run state

- Then the filter is no longer able to make adjustments to the observations



Ensemble Forcing Setup

Synthetic Observations: temperature and salinity every 5 grid points in horizontal and every level

Observation Errors: 0.3C, 0.5 psu

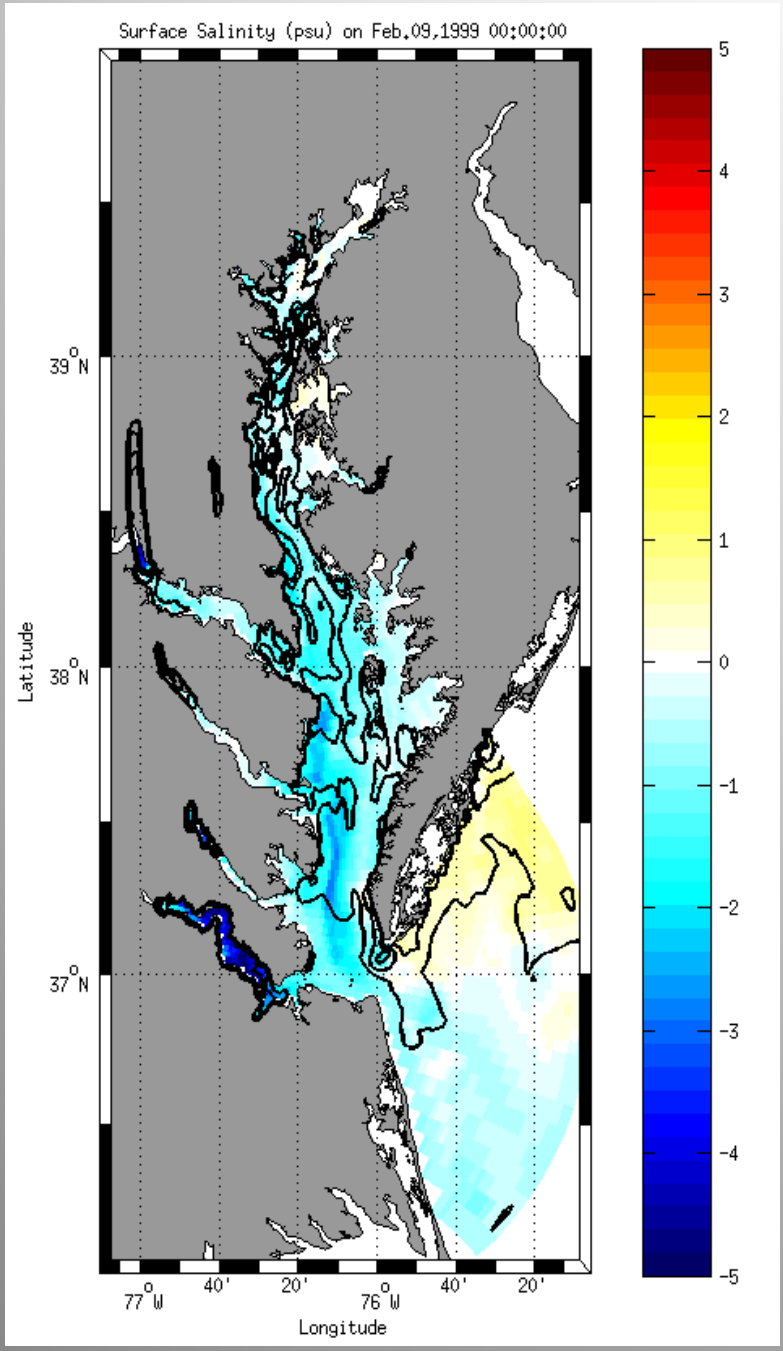
Inflation: 4% multiplicative

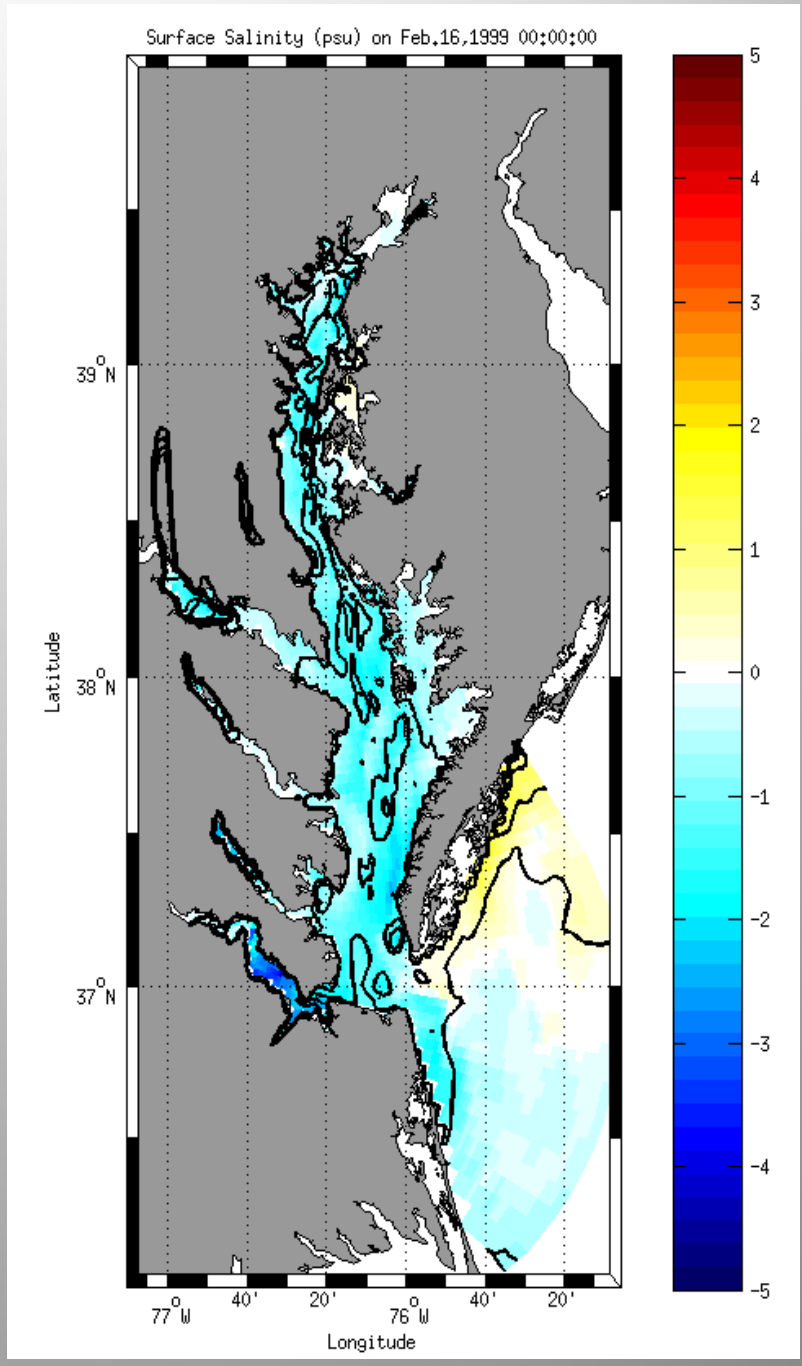
Forcing: Different wind forcing for each ensemble member

Localization: σ is 3 grid points in horizontal and 1 in vertical (out to 3 σ is used)

Assimilation Interval: 6 hours (4 assimilations per day)

Background Spread (contour) vs Error (shaded)





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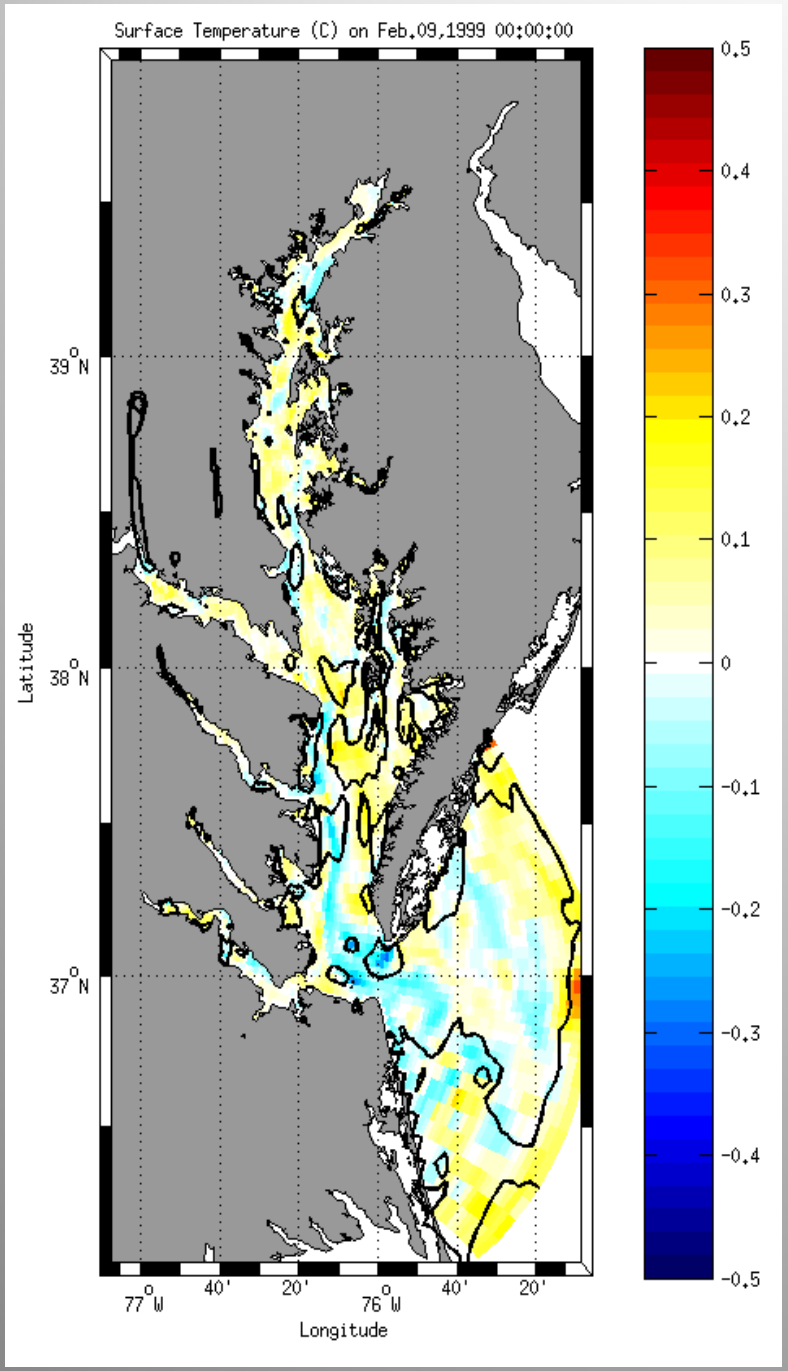
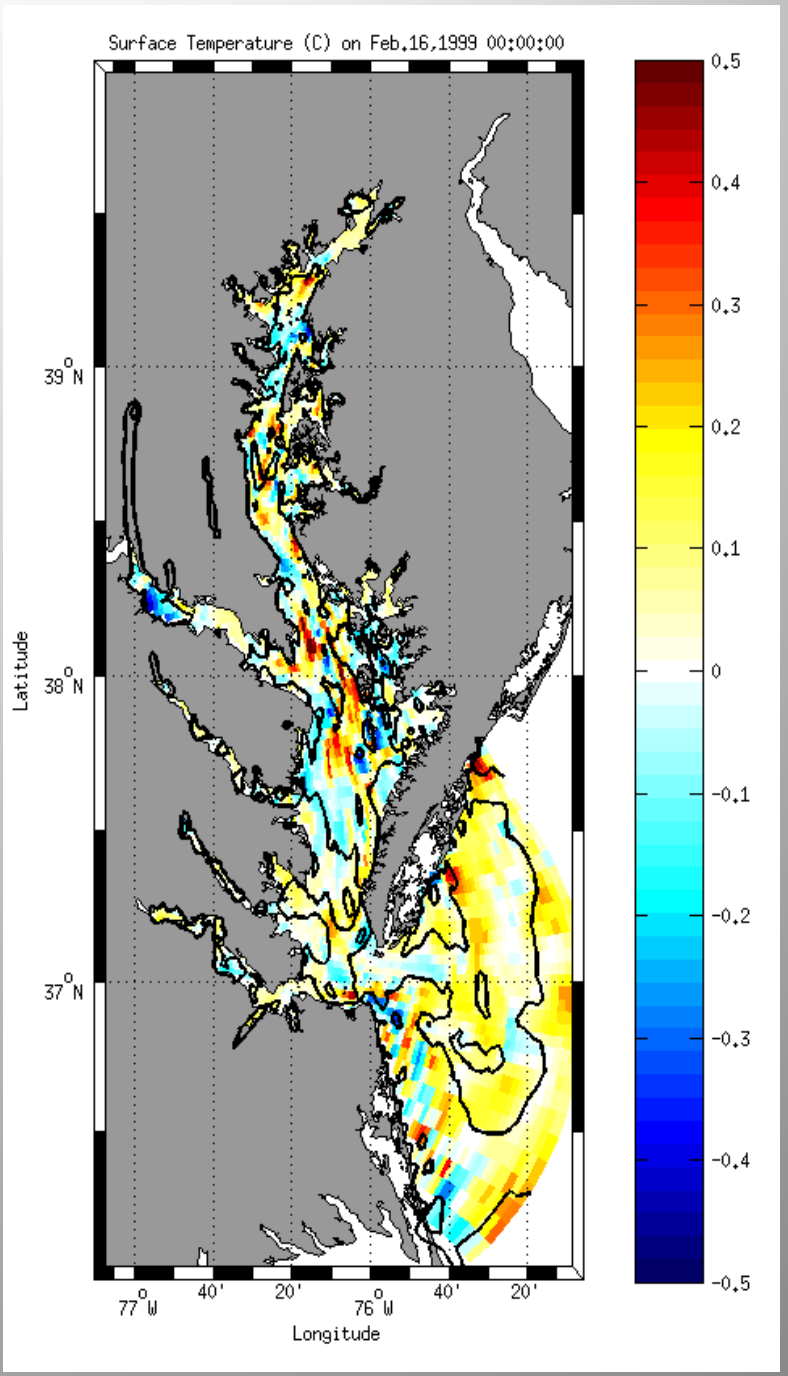
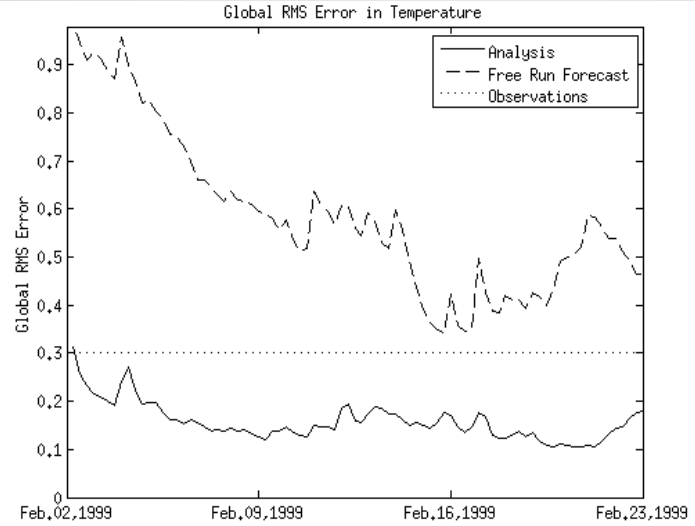


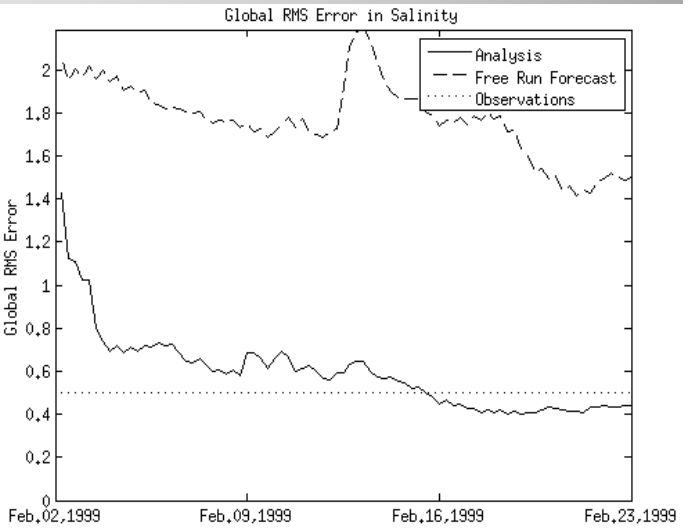


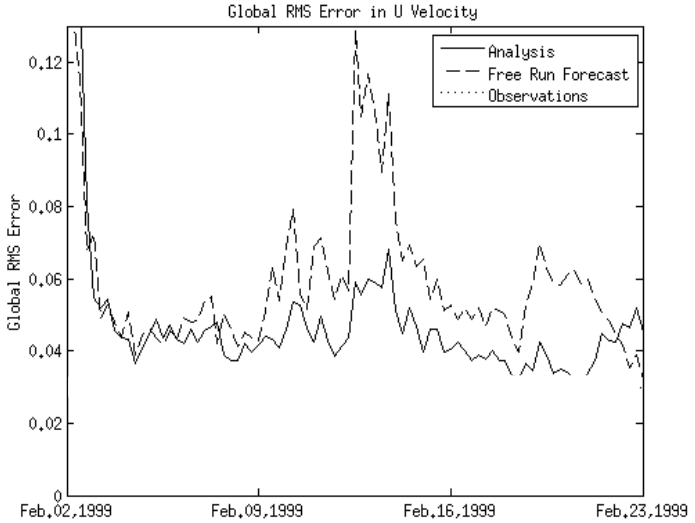
Ensemble Forcing

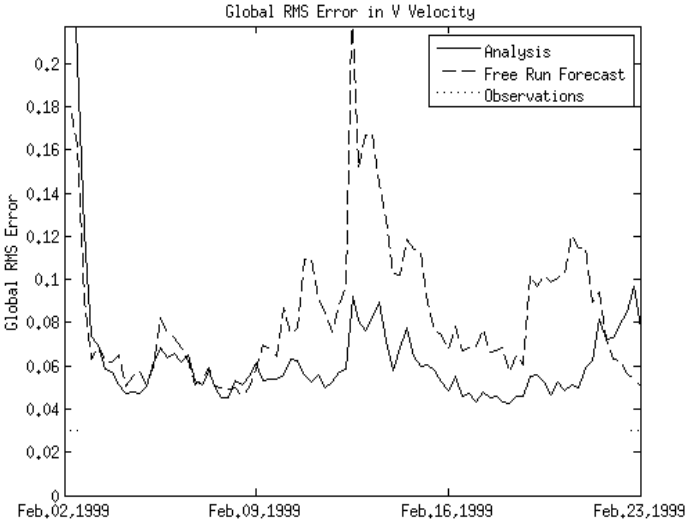
- The temperature and salinity converge to below the observation error

- The currents, which have no obs, are still corrected and improved



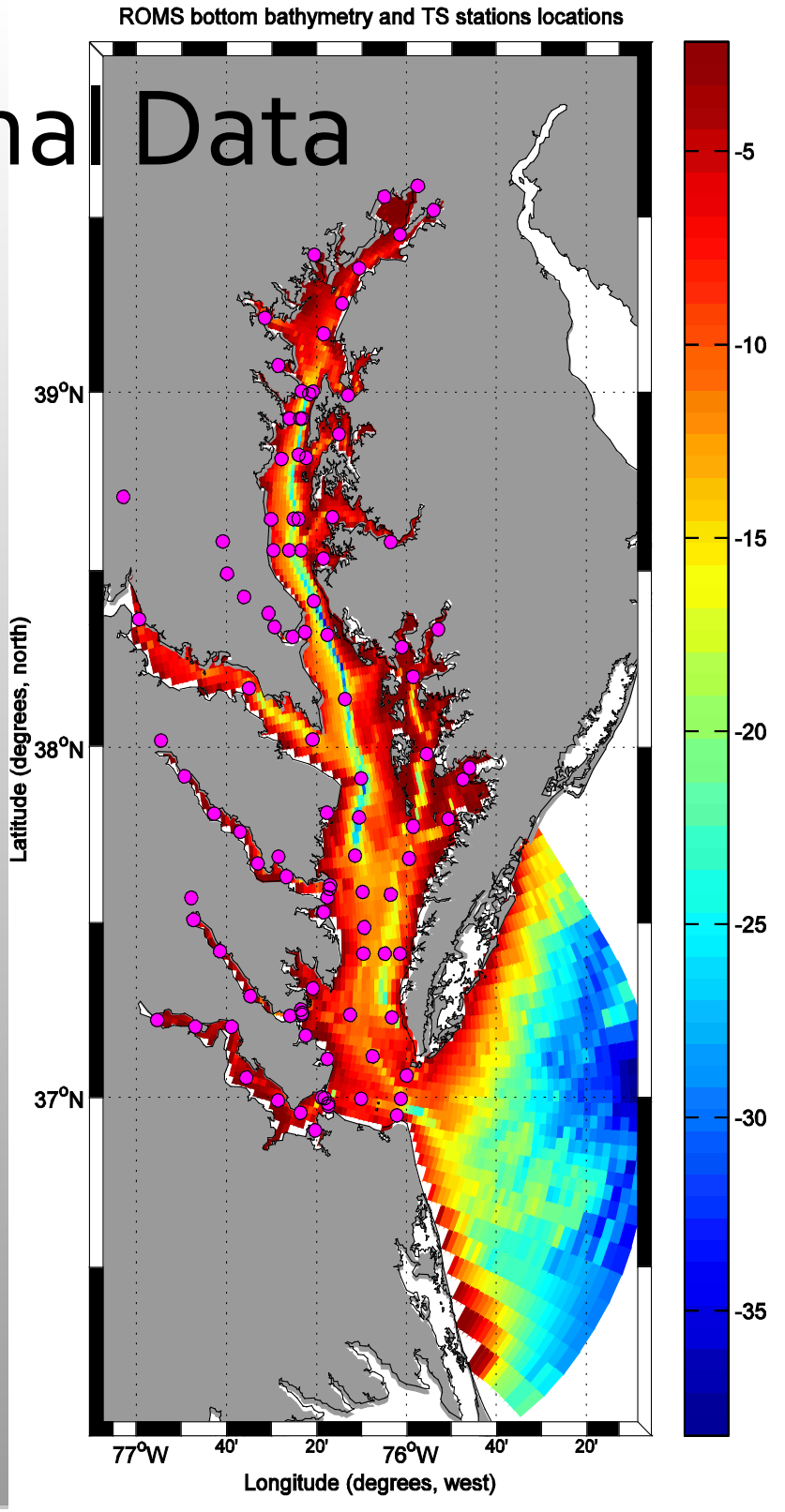






Real Observational Data

- Buoy observations are available from the Chesapeake Bay Program (CBP) and the Chesapeake Bay Observing System (CBOS)
- 6 CBOS and 120+ CBP stations report temp. and salt. profiles



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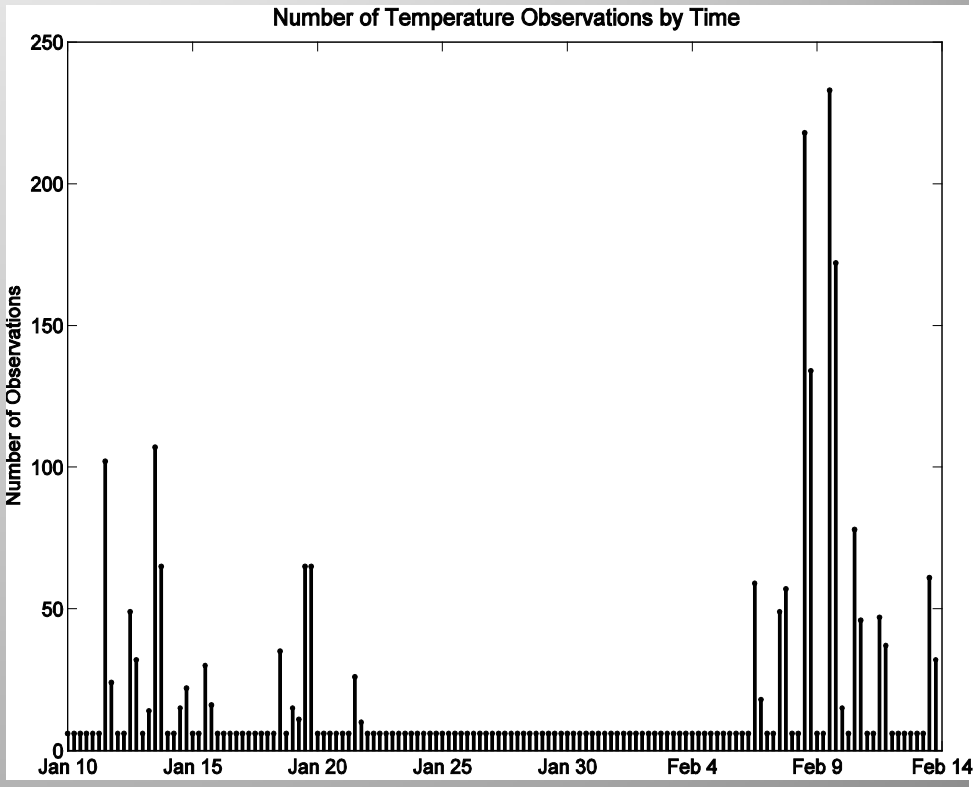

Real Observational Data

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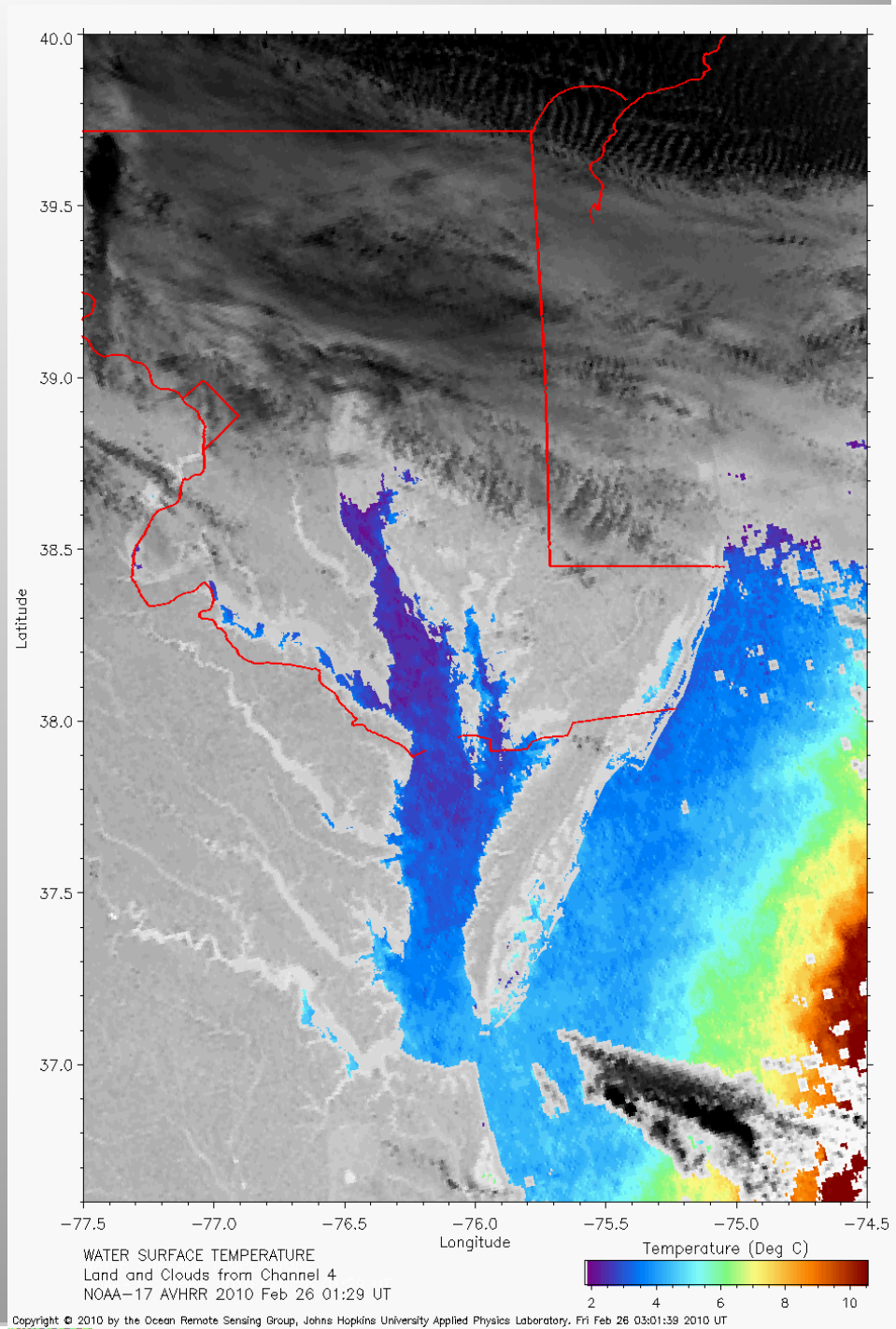
- 6 CBOS and 120+ CBP stations report temp. and salt. profiles
- CBOS stations report every 6-30 minutes, CBP report every 2 weeks-1 month
- AVHRR gives 1.1km SST obs daily or better at an error of 0.5°C



Experiment Setup

Synthetic Observations: SST at every grid point, salinity at closest grid point to station observations

Observation Errors: 0.5 C, 0.6 psu

Inflation: 4% multiplicative

Forcing: Different wind forcing for each ensemble member

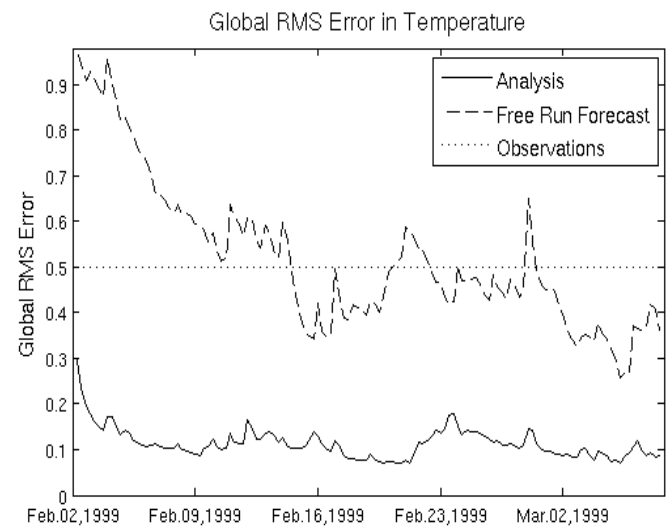
Localization: σ is 3 grid points in horizontal and 7 in vertical (out to 3 σ is used)

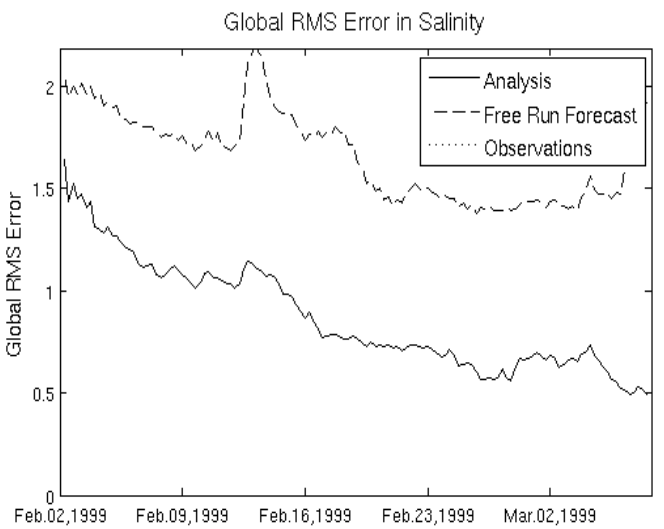
Assimilation Interval: 6 hours (4 assimilations per day)

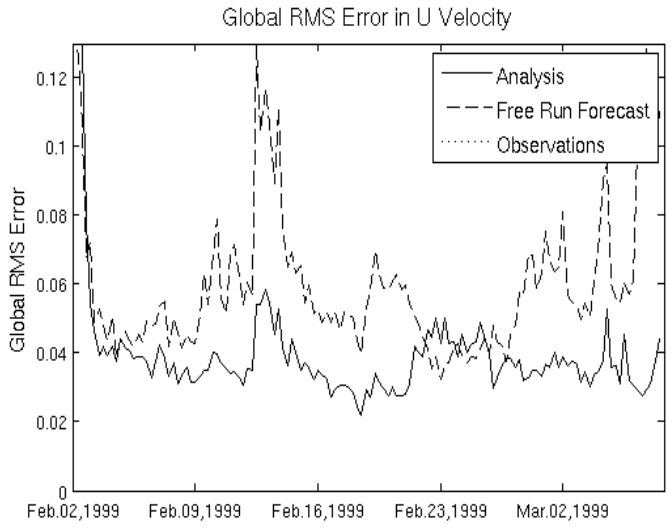
Only SST Observations

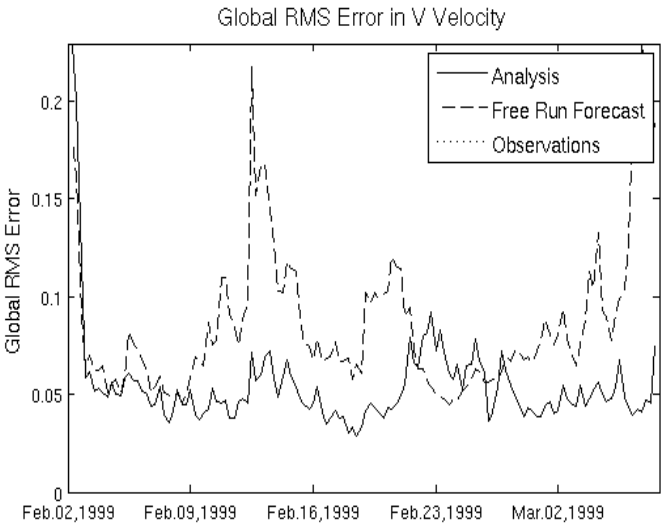
- Only assimilating synthetic satellite SST observations (which dominate the station data) improves all of the prognostic variables

- This is very promising for starting the assimilation of real data





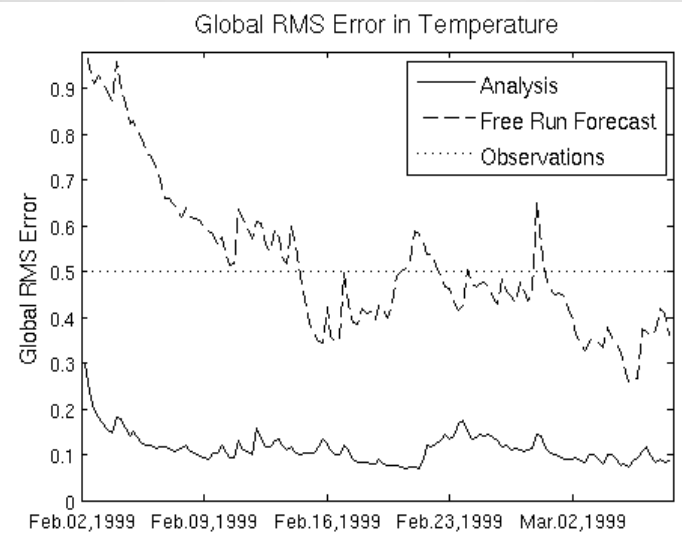


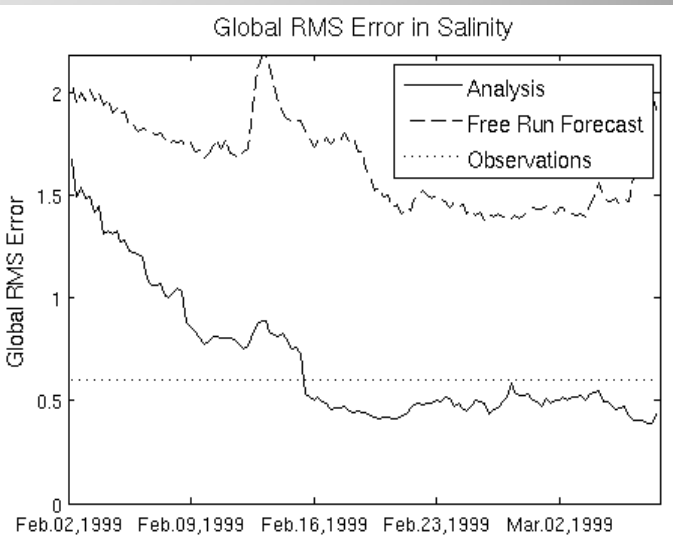


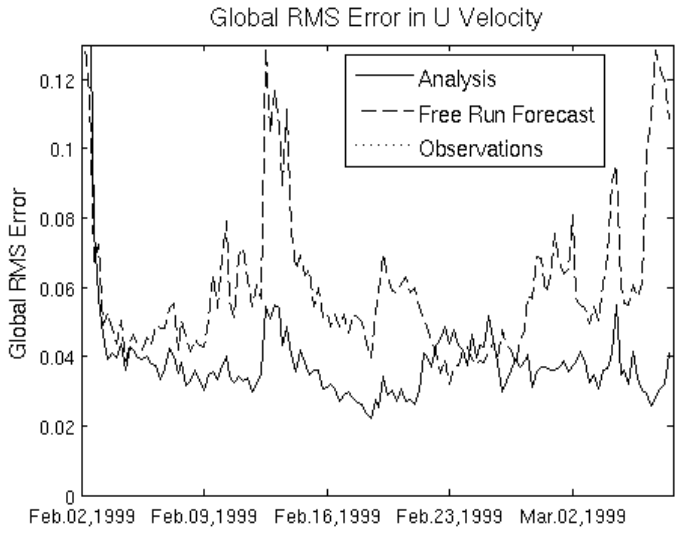
SST+Station Salinity Observations

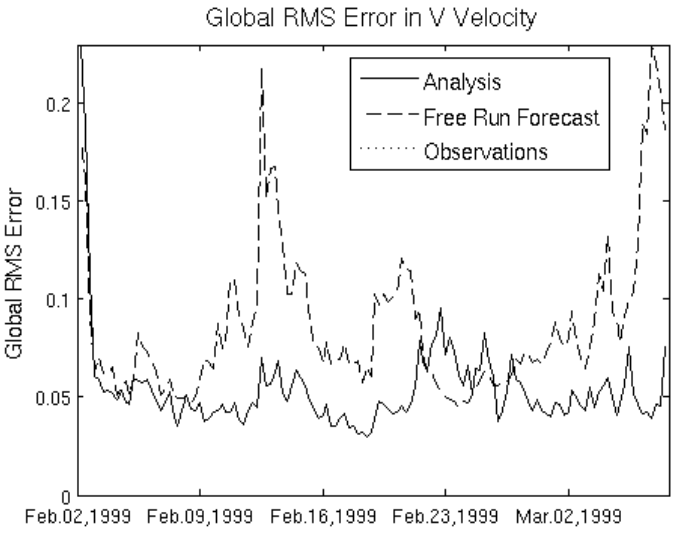
- The addition of salinity observations causes a sharp drop in salinity RMS at the time of the injection of data

- There is little change in the temperature RMSE and a small improvement in currents as well.



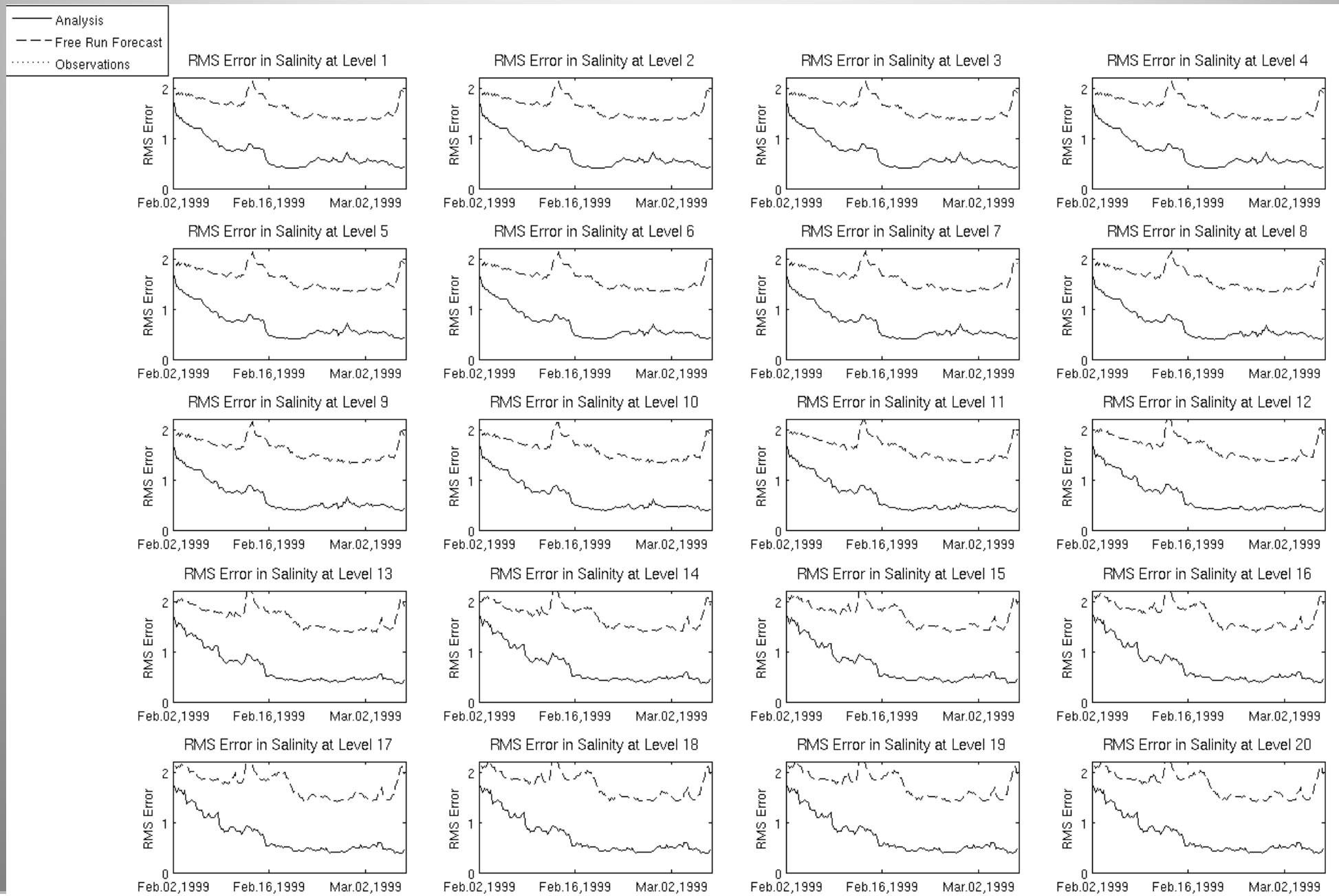






Realistic Observations

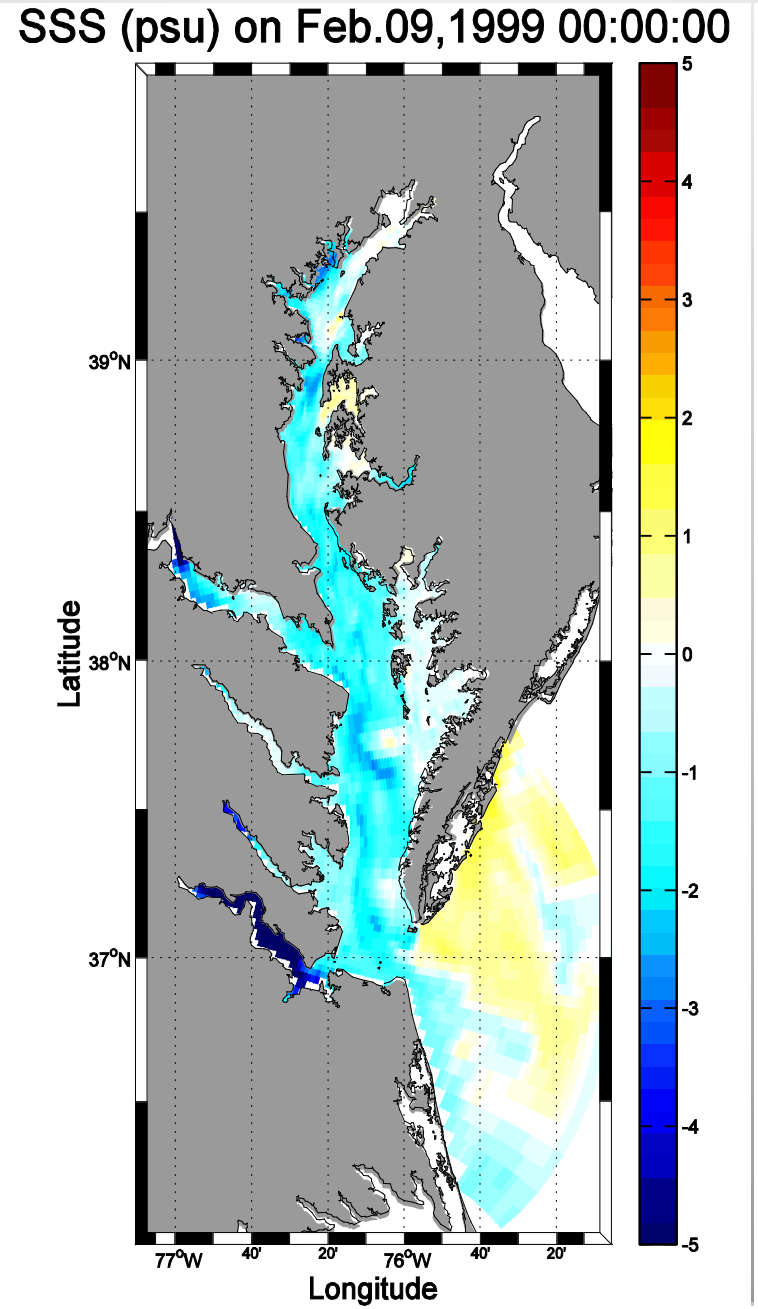
- RMSE at all levels shows similar improvement



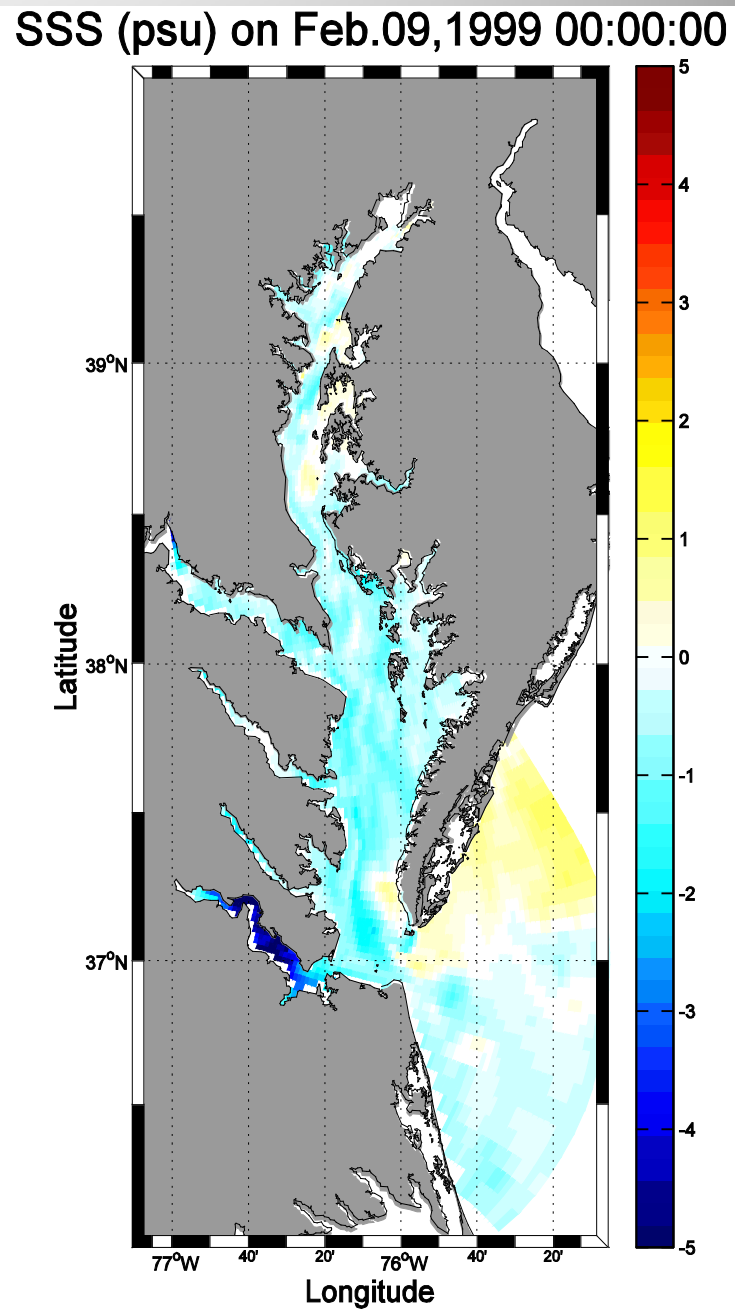
Realistic Observations

- Error is lower in the main stem of the Bay after 1 week in salinity

Freerun



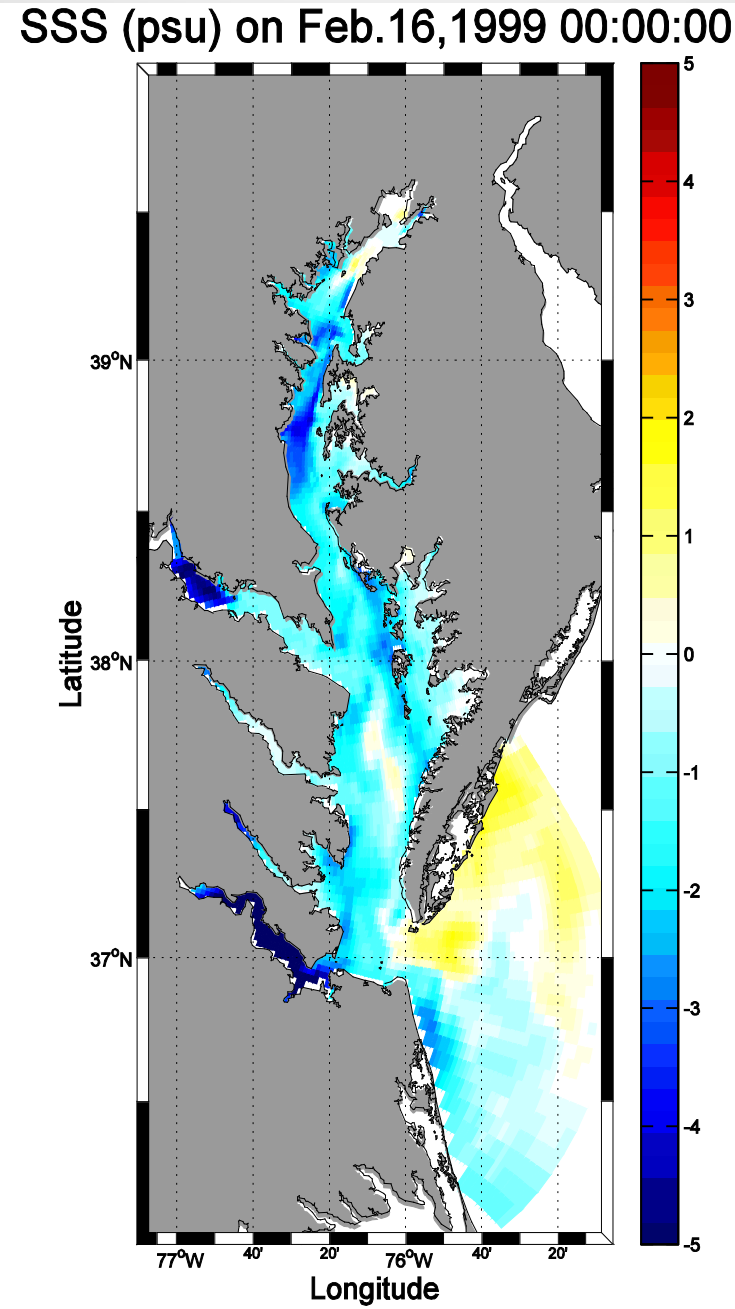
Analysis



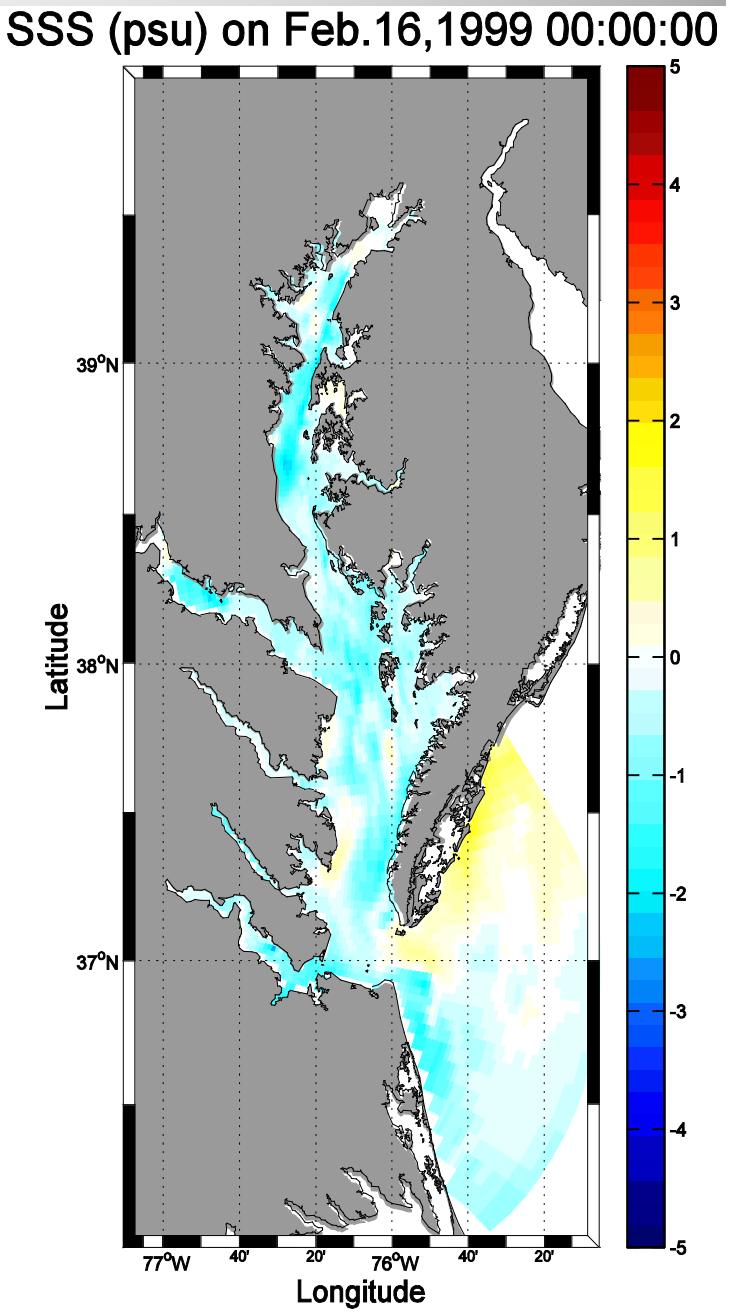
Realistic Observations

- After 2 weeks difference in error is more dramatic

Freerun



Analysis



Summary

- Forcing fields are a very important source of error in the Chesapeake
- The LETKF (when modified slightly) is able to correct errors caused by imperfect forcing using idealized observations
- Improvement is also seen with a realistic distribution of observations, which is promising for the switch over to real data
- We are starting with a reanalysis of the year 2003, but hope to move on to a reanalysis covering the data record and also see how the physical assimilation improves biological and chemical tracer fields
- We also can investigate the impact of new observations as well

END