Ocean Data Assimilation with DART[1] at LANL

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[1]Thanks to Nancy, Tim, and Jeff

Outline

Motivation
- POP-DART
- Data Assimilation

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POP-DART

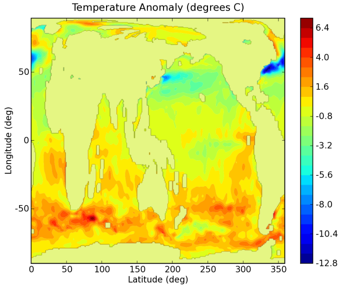
Data Assimilation

POP Setup

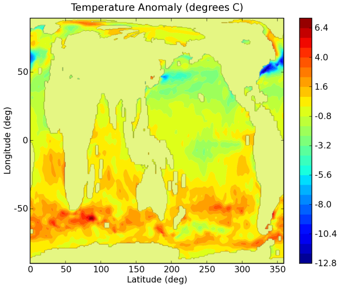
- 200 year spinup with NYF Core v2 with corrections
- Subsequent 1948-2006 IAF Core v2 with corrections
- Ensemble initialized about Jan 1, 1990
- Default 6 mth. weak salinity restoring
- Ensemble size of 20
- Assimilation of T & S

Diagnosis of Initial POP-DART Runs

Jan-Mar 1990; adaptive inflation (1.0,0.2)



- 20 member ensemble run. No assim.



- 20 member ensemble run with assim.

- Anomaly wrt Levitus
- Very slight improvement ($\approx 3\%$)

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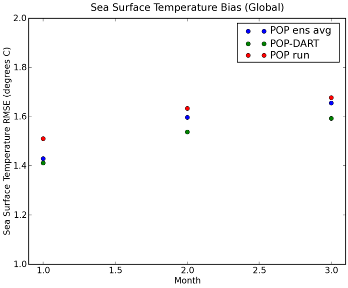

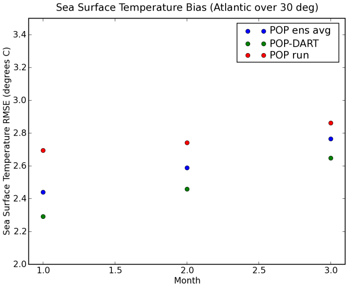

- Red: Single Free; Blue: Ensemble Free; Green: POP-DART
- 20 member ensemble
- Slight decrease of bias with assimilation (Blue-Green)
- 5% in N. Atl. vs. 3% globally
- Improvements are lower-bounds since computed with priors

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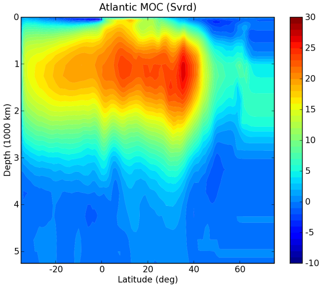

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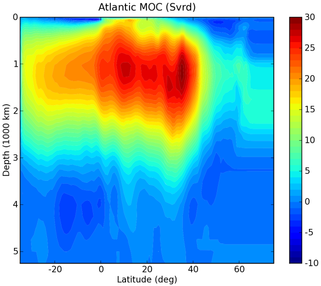
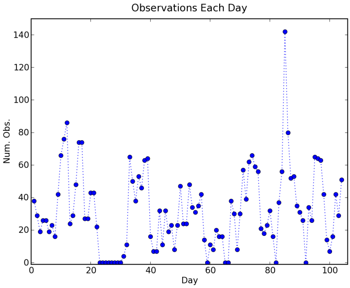


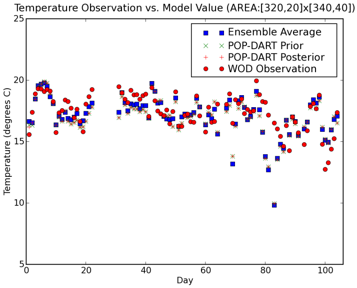
- 20 member ensemble run with assim.

- Maxima large for the 6 mth. weak salinity restoring.
- Significant differences in MOC (intensified with assim.)
- Implies significantly different subsurface T and/or S

Are the assimilations working?

Jan-Mar 1990; adaptive inflation (1.0,0.2)





- Observation space of a portion of N. Atlantic below 100m
- XBT Temperatures: About 40 a day
- Blue Symbols: Ensemble run with no assim.

Are the assimilations working?

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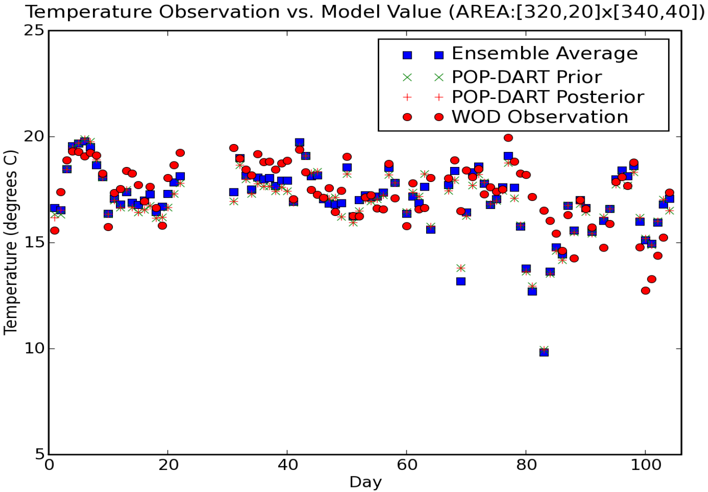

- Priors and posteriors same after 2 days
- Previously noted differences at upto 3 months due to changes over first 2 days!

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POP-DART

Data Assimilation

Two Main Points of This Talk

Atm. DA vs. Oceanic DA; Instabilites and Error Covariance

- There are differences between atmospheric data assimilation for short-range (weather) predictions and ocean data assimilation for long-range (climate) predictions.
- Taking into account flow-dependent forecast error-covariance may improve effectiveness of ocean data assimilation.

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Data Assimilation and Dynamical Time Scales

- Predictability comes from large scales.
- Ocean dynamics of large scales is slow.
  - Topography at 0.1^o *is not used* in 1^o ocean model.
  - Parameterizations used in 0.1^o resolution runs *are not used* in 1^o simulations.
  - Suggests *filtering* of observations commensurate with resolution of simulation.

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First Step: Try to Estimate Mean Ocean State

- There are simple dynamical objects underlying chaotic dynamical behavior.
  - Time averages of chaotic trajectories are related to underlying unstable fixed points.
- Rather than hit ocean model with obs. frequently, repeatedly use averaged/filtered obs to convey information about average state rather than instantaneous state.
- Consistently average forcing as well.

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Data Assimilation and Uncertainty

- DA is a statistical procedure of blending 2 data streams—background and observations—depending on their respective uncertainities.
- Quality of DA determined by the accuracy of the estimate of background covariance (P^b).
- One of the data streams comes from a dynamical model.
- Ensemble DA considers an ensemble of model forecasts to estimate P^b.
- Phase space dimension enormous, but can afford only a few ensemble members. So assume forecast errors lie in a local and low dimensional subspace. (i.e., rank of P^b is small)
  - This is the justification for localization.

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Instability and Error Covariance

Can a knowledge of dynamical instabilities help in DA?

- Adaptive Inflation in DART is statistics-based.
- Reduce dimension of subspace further by considering dominant unstable directions (dynamical information).
- Better following instabilities may be a recipe for better estimating background covariance.
- Instabilites bring coherence to otherwise Monte Carlo nature of ensemble simulations.
- Add info. about unstable directions in DART using Bred Vector and ETKF-based schemes

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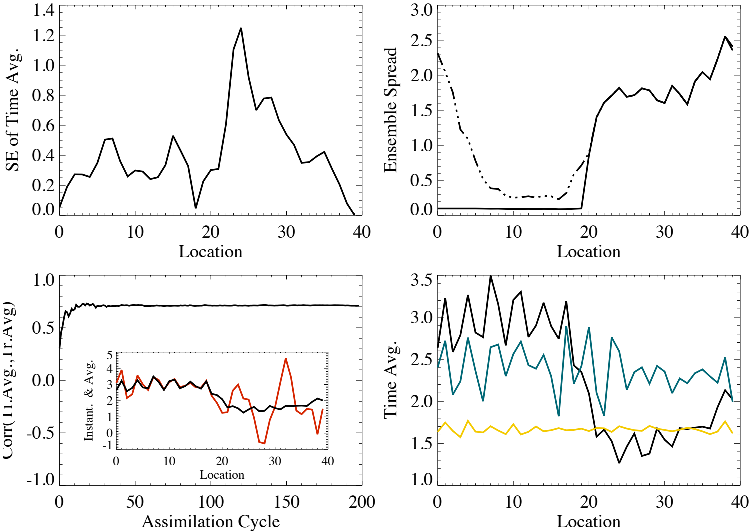
Lorenz '96 Model Setup

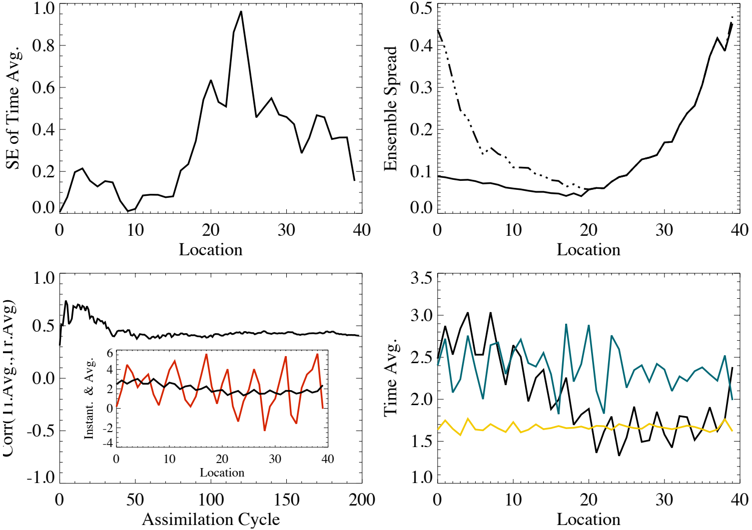
- $$\frac{dx_j}{dt} = (x_{j+1} - x_{j-2})x_{j-1} - x_j + F; \quad j = 1, \ldots, 40$$
- Well-observed and poorly-observed regions
- An assimilation every 10 timesteps if not specified otherwise.
- Model error through different forcing for observations (F=8; more chaotic) and assimilation runs (F=5; sluggish)
  - Larger F $\Rightarrow$ larger mean and variability
  - Diff. F for obs. and model run $\Rightarrow$ bias

Highly Localized (c=0.02); Std. adaptive inflation



Inst. field nudged to time avg. obs!

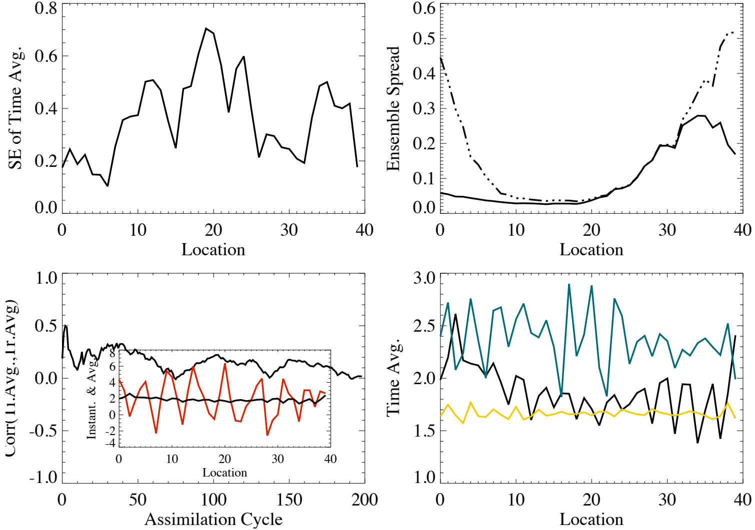
Highly Localized (c=0.02); ETKF-based scheme



Inst. field not nudged to time avg. obs

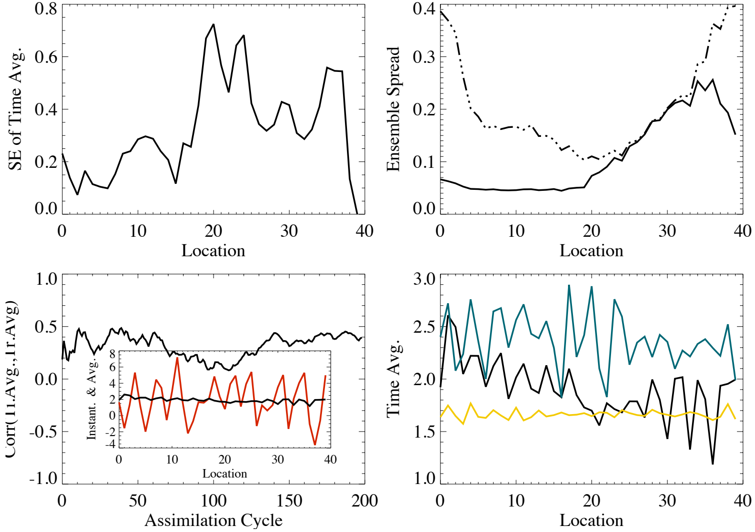
smaller errors; lower uncertainity

Reduced Localization (c=0.2); Std. adaptive inflation



Bias not being corrected even where there is data
large error; low correlation

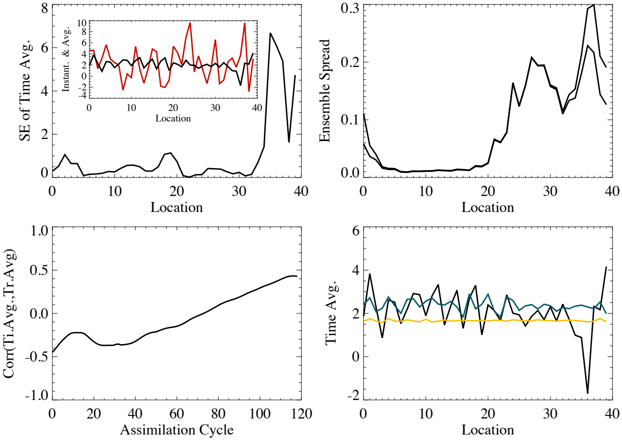
Reduced Localization (c=0.2); ETKF-based scheme



Better bias correction where there is data; reduced error better correlation; but no bias correction where there is no data

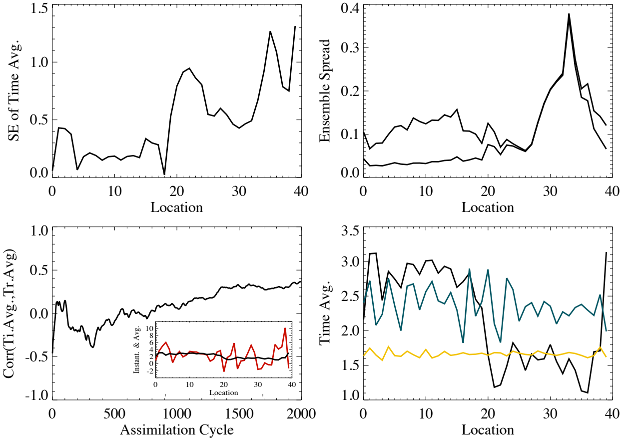
Reduced Localization (c=0.2)
Blowup with std. adaptive inflation at 142 cycles

Assimilation every timestep. Considering averages before blowup



Reduced Localization (c=0.2)
Stabilized with ETKF-based scheme

Assimilation every timestep.



Effect of reduced localization is seen in terms of trying to infer state of the system in poorly observed region

Summary

- After some missteps and false starts, we have gotten around to getting POP and DART work with our scripts. But we still have problems with some of the setups that we like to run.
- Even with short runs, collapse of ensemble spread is a serious problem.
- We propose to use a dynamics-based alternative to statistics based inflation.
- By repeatedly assimilating averaged obs, we propose to obtain the mean state of the ocean as a first step; later follow up with seasonally and interannually varying state estimation.

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