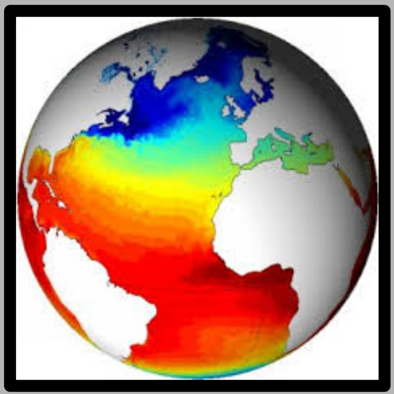
Practical challenges in global ocean data assimilation: moving beyond the theory

Alicia R. Karspeck

NCAR/IMAGe Theme of the Year
Frontiers in Ensemble Data Assimilation for Geoscience Applications

The ingredients for a challenging problem:

AN IMPERFECT OCEAN MODEL



A SUBOPTIMAL DA METHOD

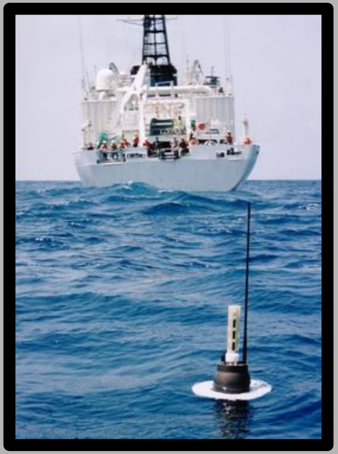
$$
\begin{aligned}
\tilde{\mathbf{y}}_k &= \mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_{k|k-1} \\
\mathbf{S}_k &= \mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k^T + \mathbf{R}_k \\
\mathbf{K}_k &= \mathbf{P}_{k|k-1}\mathbf{H}_k^T\mathbf{S}_k^{-1} \\
\hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k\tilde{\mathbf{y}}_k \\
\mathbf{P}_{k|k} &= (I - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_{k|k-1}
\end{aligned}
$$

Linear/Gaussian assumption

Misspecified error

(adjoint imperfect,
costly iterations)

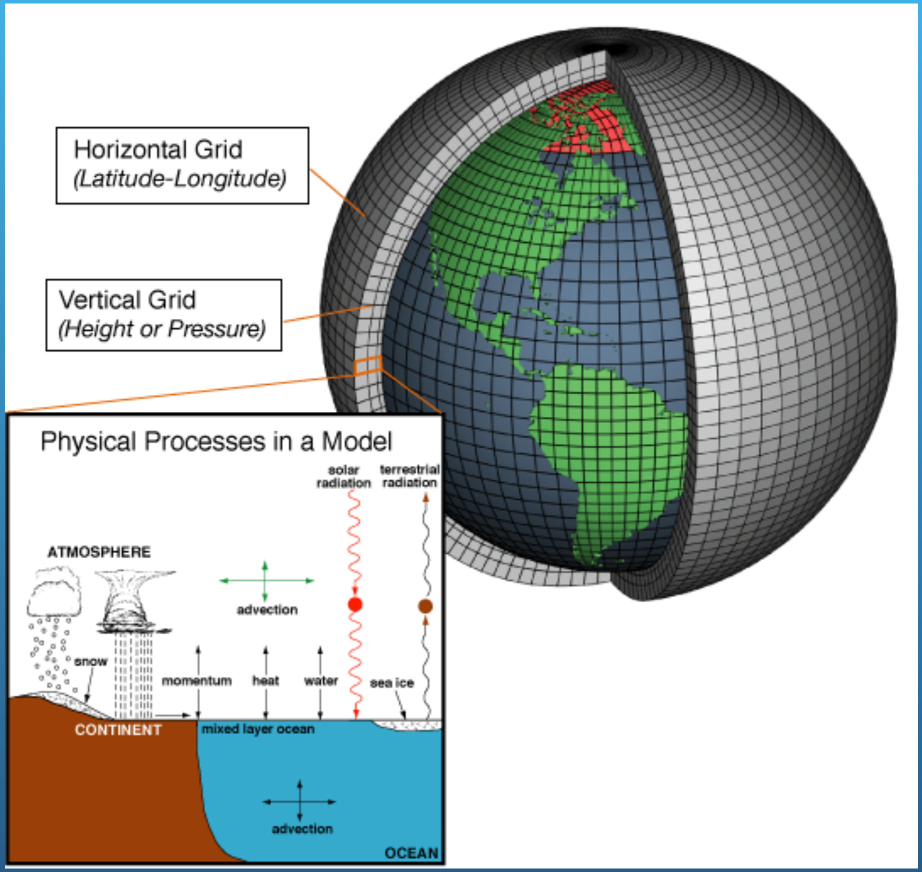
OBSERVATIONS



Sparse

The ocean has A LONG MEMORY over which to convolve these problems!

What do *most* global ocean assimilation systems look like?

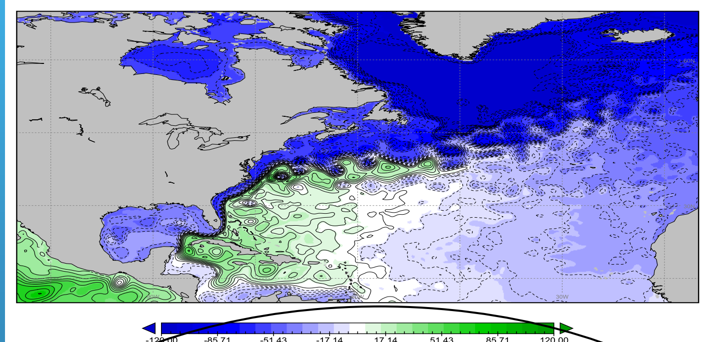


Global (horizontal and vertical) discretization of equations describing the time evolution of the ocean "state:"
* temp (x,y,z,t),
* salinity(x,y,z,t)
* currents(x,y,z,t)
* SSH(x,y,t)
(+ other tracers)

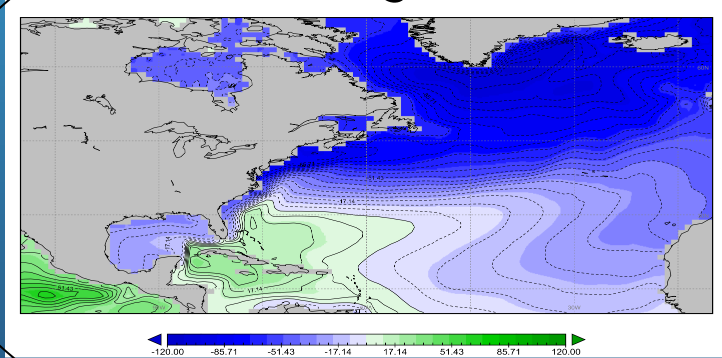
Prescribed atmospheric boundary conditions
("forced ocean model")

What do *most* global ocean assimilation systems look like?

~1/10 degree



~1 degree



Typical resolution is from ¼ to 1 degree (25 to 100 km)*

Size of the state ~ 1e7

What do we use to constrain our ocean models?

- In-situ* subsurface temperature and salinity
  -sparse in space, time, but relatively long historical record (~1940's forward)

- Sea surface height derived from satellite altimetry
  -dense in time/space, but only available since mid-1990's;
  -An integrated measure of density (no unique mapping from SSH to T/S in the water column)

- Sea surface temperature products
  -From a combination of surface in-situ and satellite observation
  -Long records, but they are typically analyzed products and (by definition) represent only the temperature at the interface.

- Atmospheric forcing product (not assimilated, but implicitly providing a strong constraint on the system)

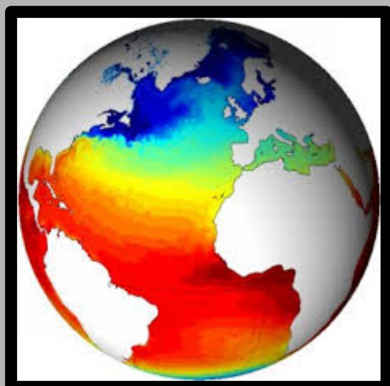
* Literally "in position"

Why do we do global ocean data assimilation?

- Climate analysis (60+ years in length)
  - Want to generate a historical record of the ocean
    - e.g.: “Has the ocean warmed in the last 50 years?”
  - Want to understand physical processes
- Climate forecasting
  - Seasonal, interannual and decadal prediction are thought to be initial value problems that depend on the state of the ocean
- Model improvement
  - Using DA increments to diagnose and understand(?) the biases in our ocean models
- Assessment of the global observing system

The ingredients for a challenging problem:

AN IMPERFECT OCEAN MODEL



Systematic biases

Unresolved processes

A SUBOPTIMAL DA METHOD

$$\tilde{\mathbf{y}}_k = \mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_{k|k-1}$$
$$\mathbf{S}_k = \mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k^T + \mathbf{R}_k$$
$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}_k^T\mathbf{S}_k^{-1}$$
$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k\tilde{\mathbf{y}}_k$$
$$\mathbf{P}_{k|k} = (I - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_{k|k-1}$$

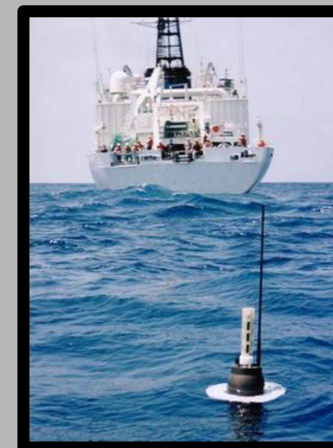
Linear/Gaussian assumption violated

Misspecified error characteristics

Undersampling (small number of samples, for large state-space)

4DVar – cannot perfectly find the minimum (adjoint imperfect, costly iterations)

OBSERVATIONS

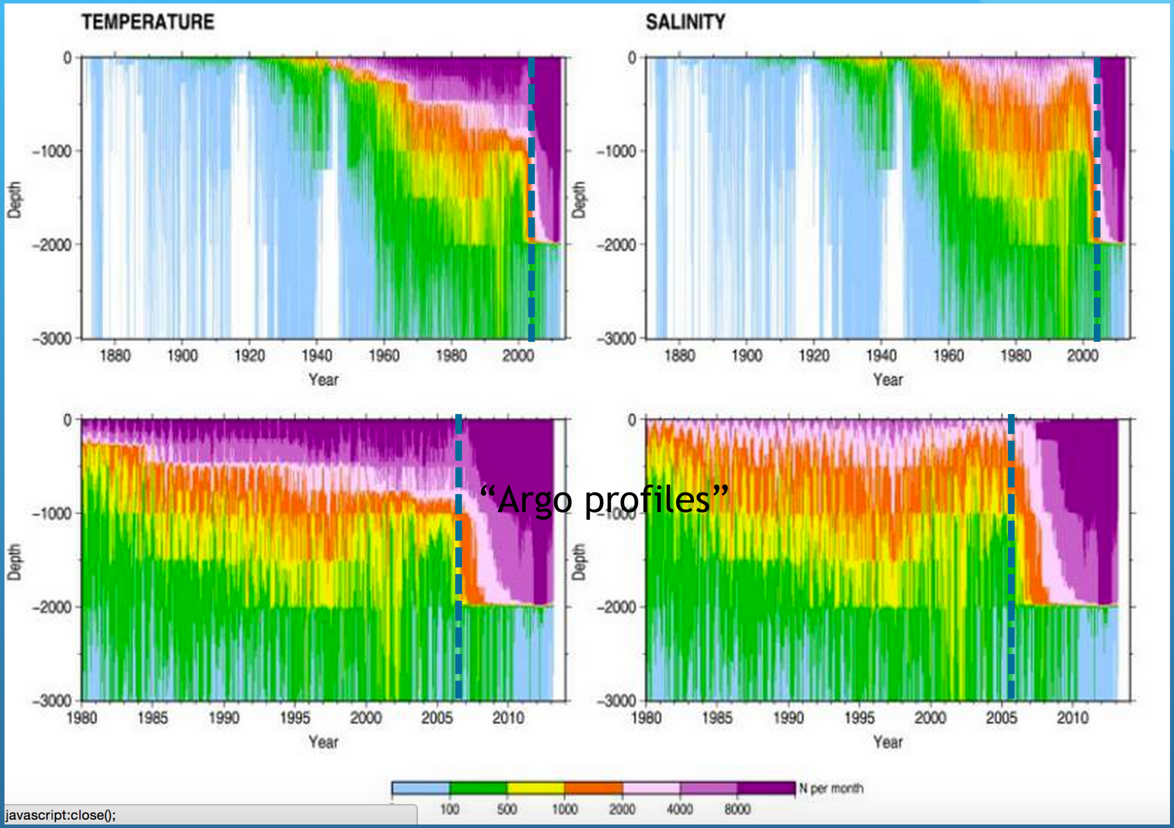


Sparse

Inhomogeneous

Changing in time

Number of in-situ hydrographic observations: temperature and salinity

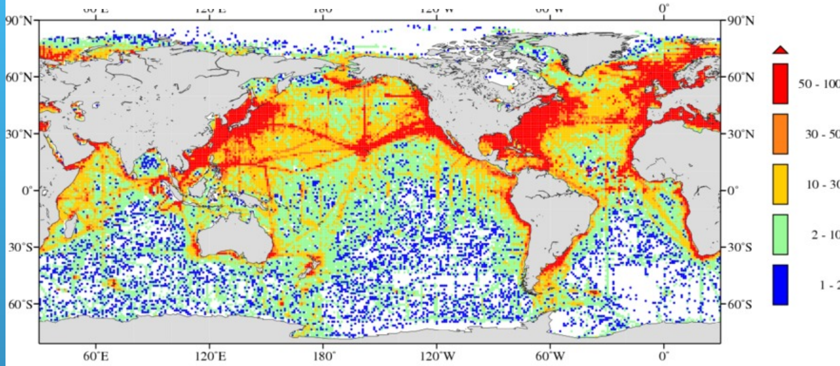


-Number of observations varies dramatically with time/depth/location

-The deep ocean is by and large unconstrained in the past, in the present, and for the foreseeable future.

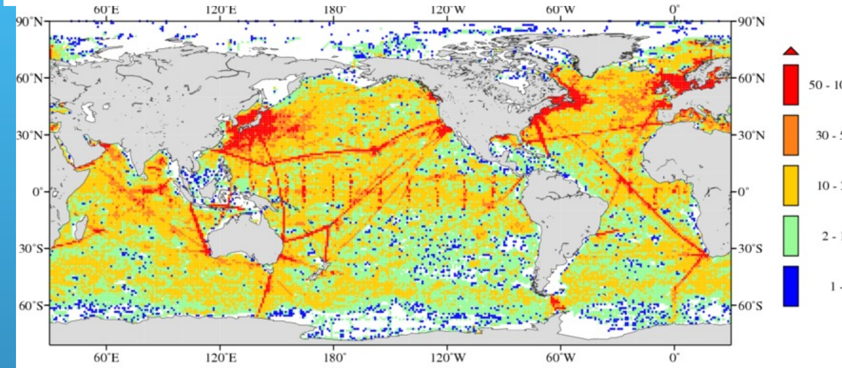
In-situ hydrographic observations

TEMP-SURFACE 1960’s



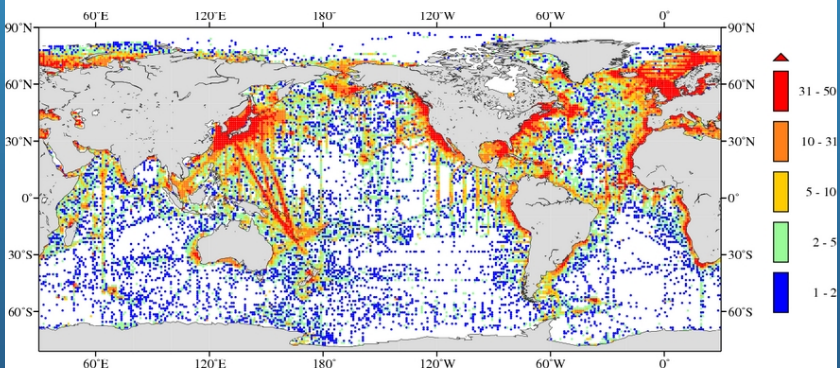
Annual temperature observations at the surface (one-degree grid)

TEMP-SURFACE present



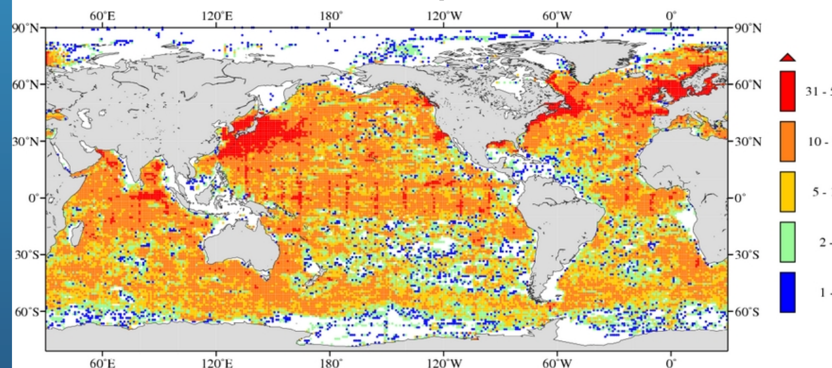
Annual temperature observations at the surface (one-degree grid)

SALINITY-SURFACE 1960’s



Annual salinity observations at the surface (one-degree grid)

SALINITY-SURFACE present

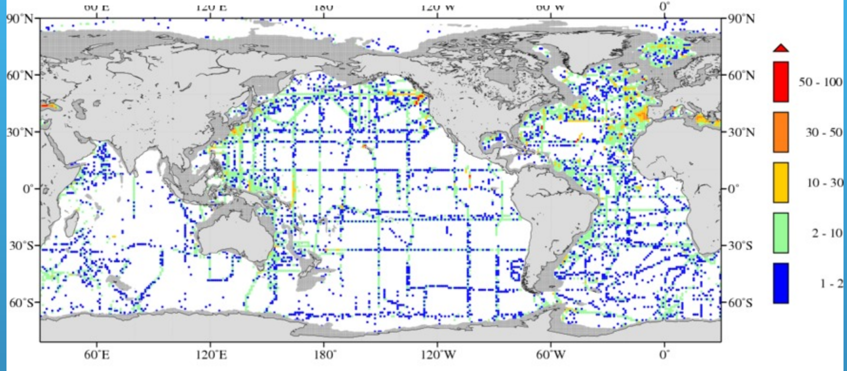


Annual salinity observations at the surface (one-degree grid)

Number of observations varies wildly with time/depth/location

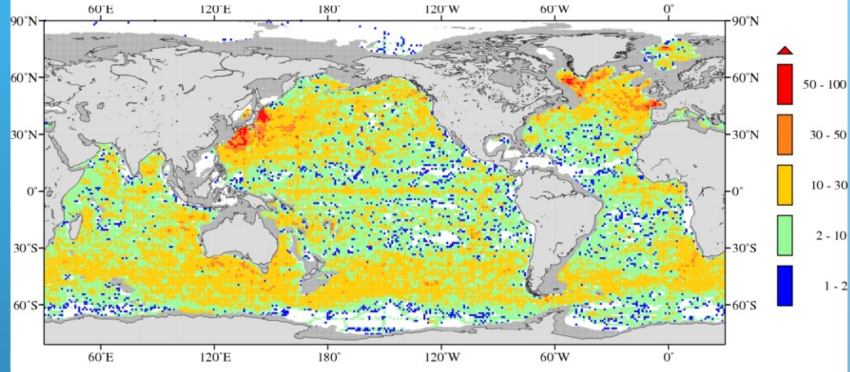
In-situ hydrographic observations

TEMP-1700m 1980's/1990's



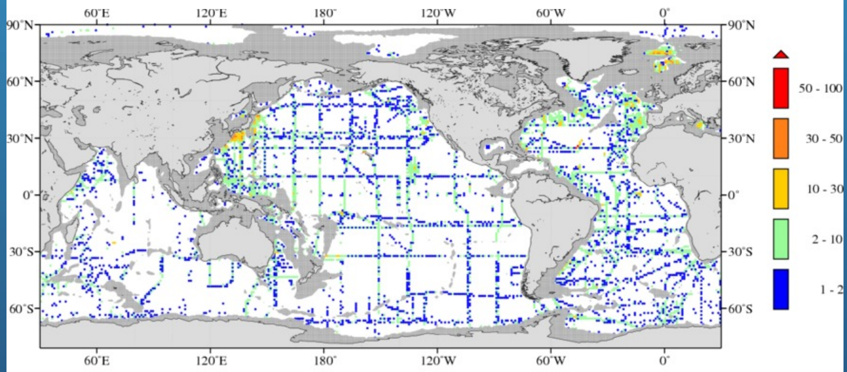
Annual temperature observations at 1700 m. depth (one-degree grid)

TEMP-1700 m present



Annual temperature observations at 1700 m. depth (one-degree grid)

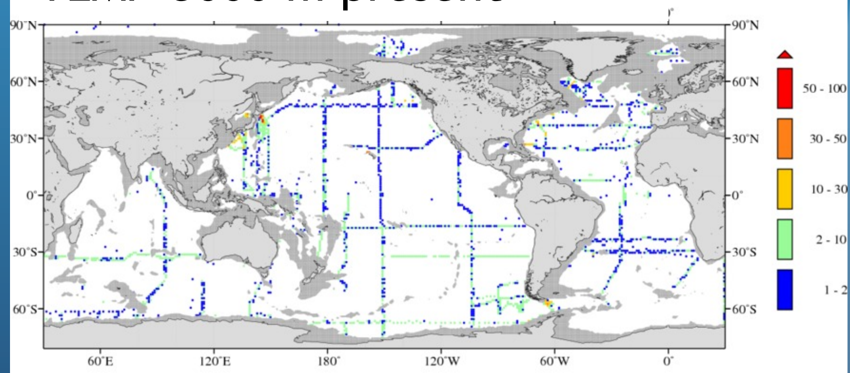
TEMP-3000 m 1980's/1990's



Annual temperature observations at 3000 m. depth (one-degree grid)

World Ocean Atlas Climatology

TEMP-3000 m present



Annual temperature observations at 3000 m. depth (one-degree grid)

Big changes from the 1990s to the present at mid-depths due in large part to Argo

A fundamental challenge:

The dynamics of the ocean depend on the density distribution.
Density is a (non-linear) function of temperature and salinity:

$$u = -\frac{1}{f\rho}\frac{\partial}{\partial y}\int_{-z}^{0}\rho(z)dz - \frac{g}{f}\frac{\partial \eta}{\partial y}$$

$$v = \underbrace{\frac{1}{f\rho}\frac{\partial}{\partial x}\int_{-z}^{0}\rho(z)dz}_{V_{baroclinic}} + \underbrace{\frac{g}{f}\frac{\partial \eta}{\partial x}}_{V_{barotropic}}$$

Thermal wind

Density of Seawater

Equation of State: $\rho = \rho(T, S, p)$

Hydrographic measurements of T,S are not always co-located →

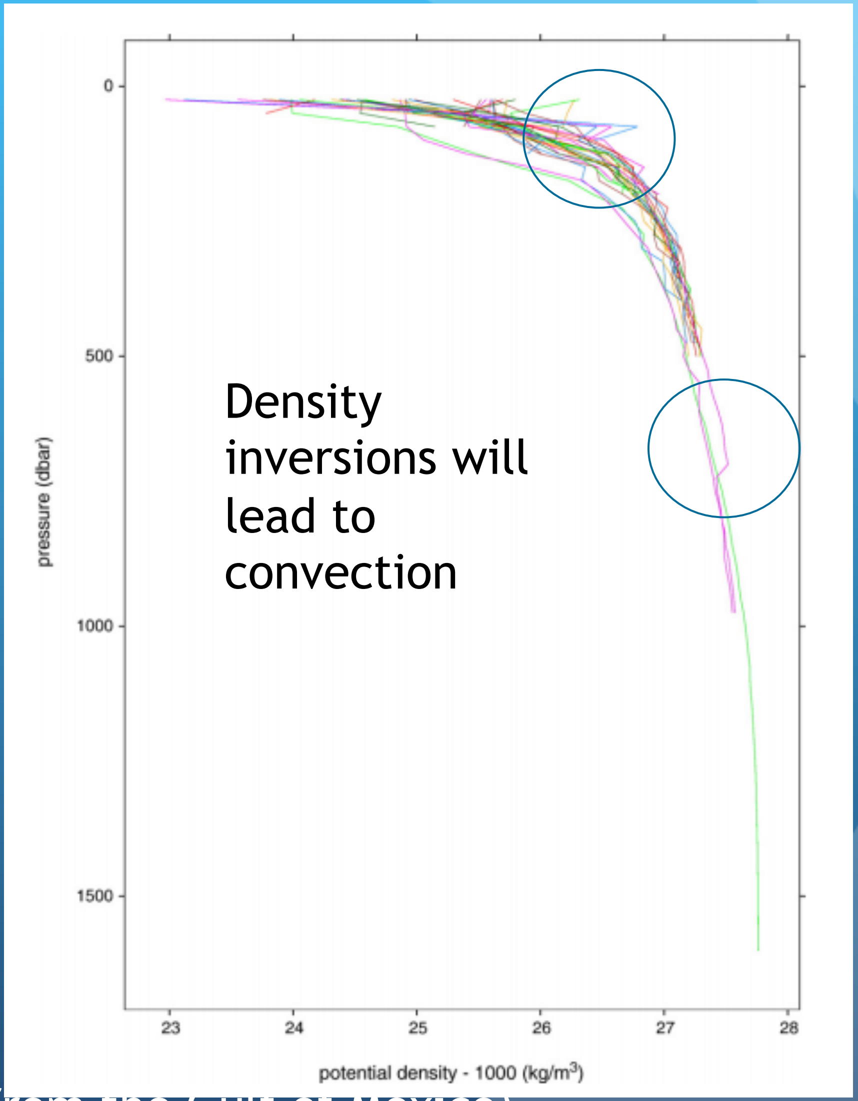
<u>The dynamics of the model are extremely sensitive to the prescribed or modeled prior covariance between T and S</u>

At best, misspecification can lead to spurious currents…

A fundamental challenge:

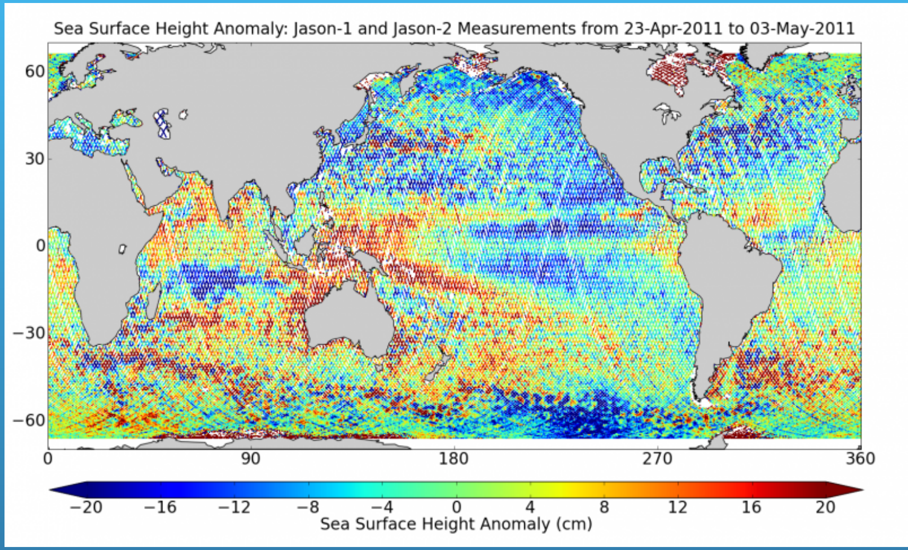
Worse, density inversions, spurious convection and numerical failure of the model ("blow up")

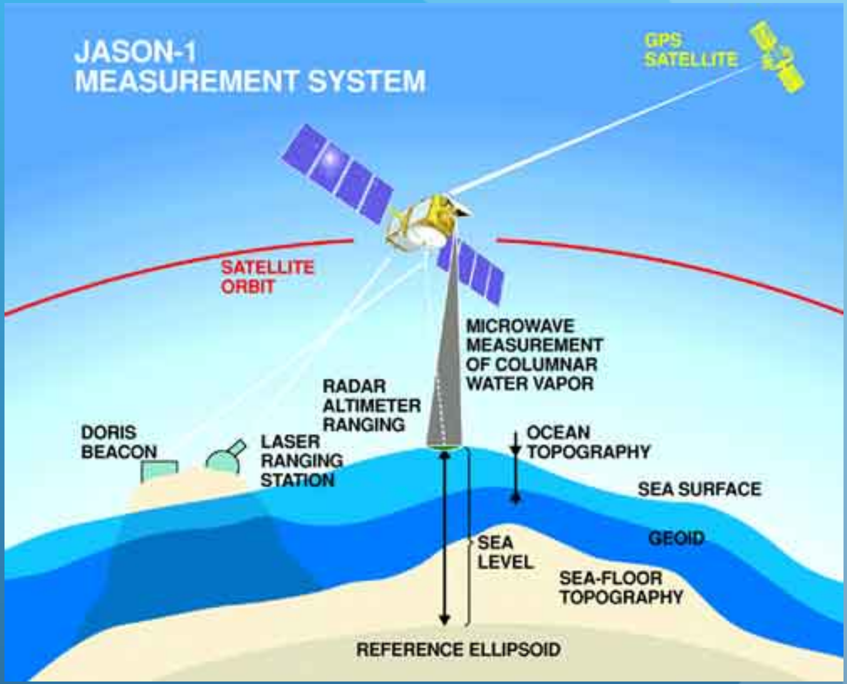
[… a vivid reminder that the ocean is non-linear/ non-Gaussian]



From Thacker et al 2007 (example from the Gulf of Mexico)

SSH from altimetry





Pro: Very dense, high-resolution data source

**Geoid: The equipotential surface of the earth's gravity field, i.e. "the surface of the ocean under the influence of gravity alone"*

Con: contains the geoid*, which models do not have and which is poorly known.

Another fundamental challenge:

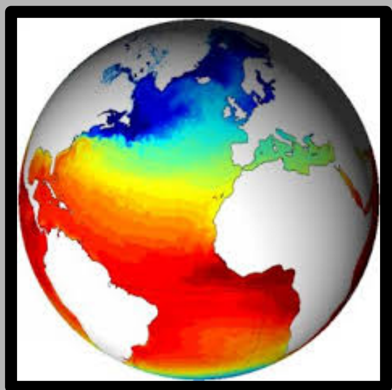
There is no unique distribution of T/S over the water column for an observation of sea level.

$$\frac{\partial \eta}{\partial t} = \underbrace{\frac{\partial_t \left(p_{\mathrm{b}} - p_{\mathrm{a}}\right)}{g\,\rho(\eta)}}_{\text{mass contribution}} \underbrace{- \frac{1}{\rho(\eta)} \int_{-H}^{\eta} \frac{\partial \rho}{\partial t}\, \mathrm{d}z}_{\text{local steric contribution}}$$

Thus, the incremental adjustment in T/S due to altimetry information is sensitive to the modeled or prescribed relationship between SSH, T, S.

The ingredients for a challenging problem:

AN IMPERFECT OCEAN MODEL



Systematic biases

Unresolved processes

A SUBOPTIMAL DA METHOD

$$\begin{aligned}
\tilde{\mathbf{y}}_k &= \mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_{k|k-1} \\
\mathbf{S}_k &= \mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k^T + \mathbf{R}_k \\
\mathbf{K}_k &= \mathbf{P}_{k|k-1}\mathbf{H}_k^T\mathbf{S}_k^{-1} \\
\hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k\tilde{\mathbf{y}}_k \\
\mathbf{P}_{k|k} &= (I - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_{k|k-1}
\end{aligned}$$

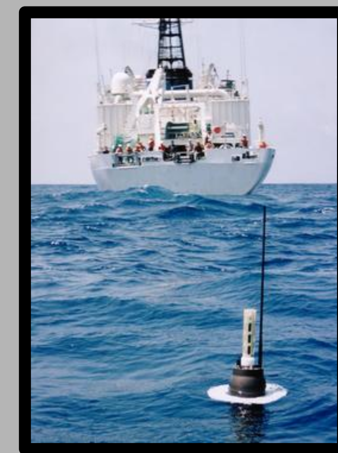
Linear/Gaussian assumption violated

Misspecified error characteristics

Undersampling (small number of samples, for large state-space)

4DVar – cannot perfectly find the minimum (adjoint imperfect, costly iterations)

OBSERVATIONS



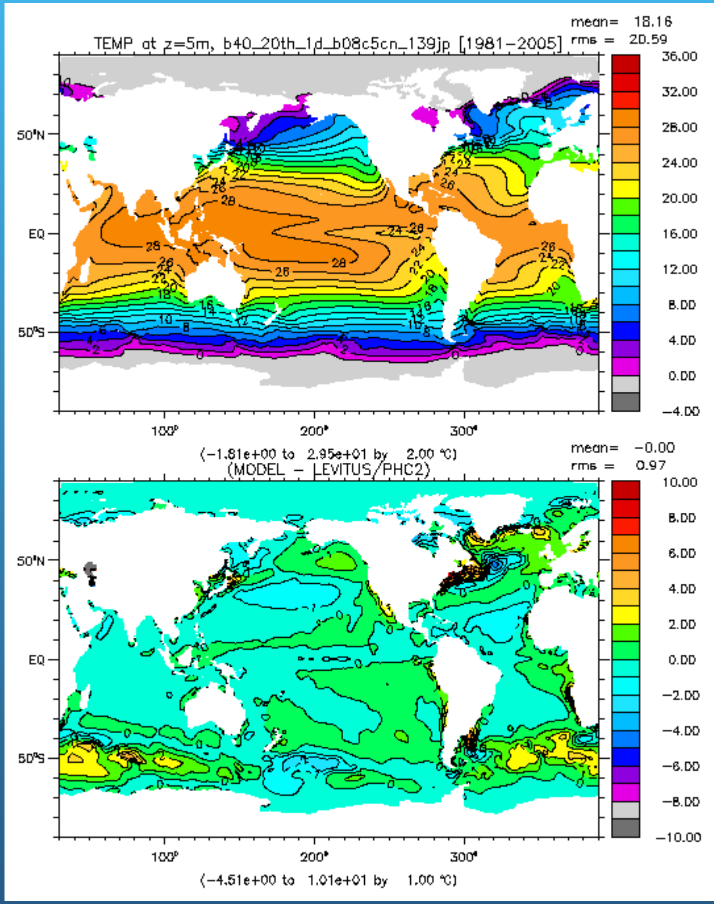
Sparse

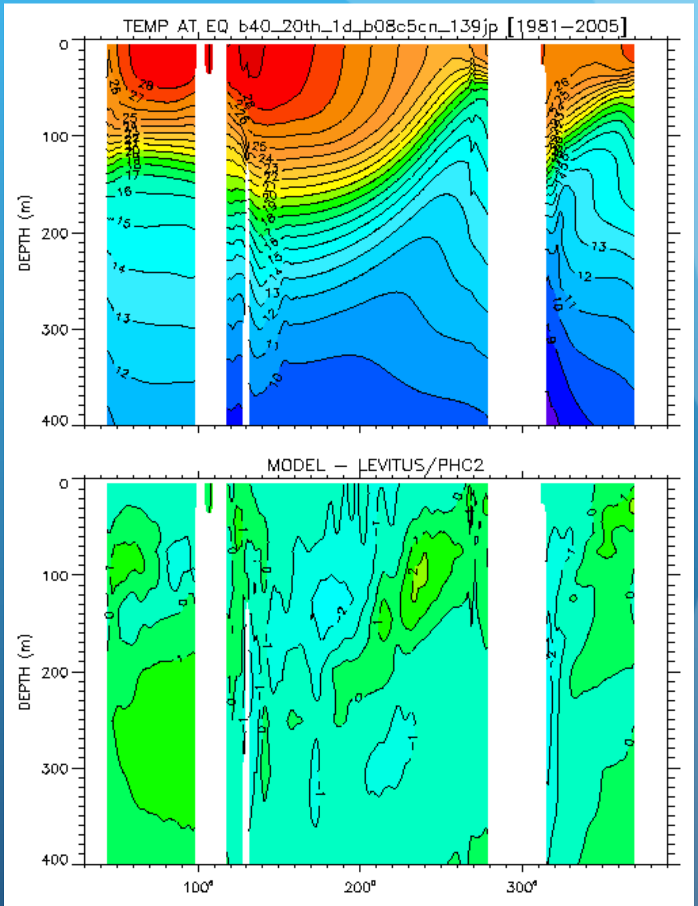
Inhomogeneous

Changing in time

Imperfect models – systematic bias

"… all models are wrong, but some are useful"
George Box, Statistician

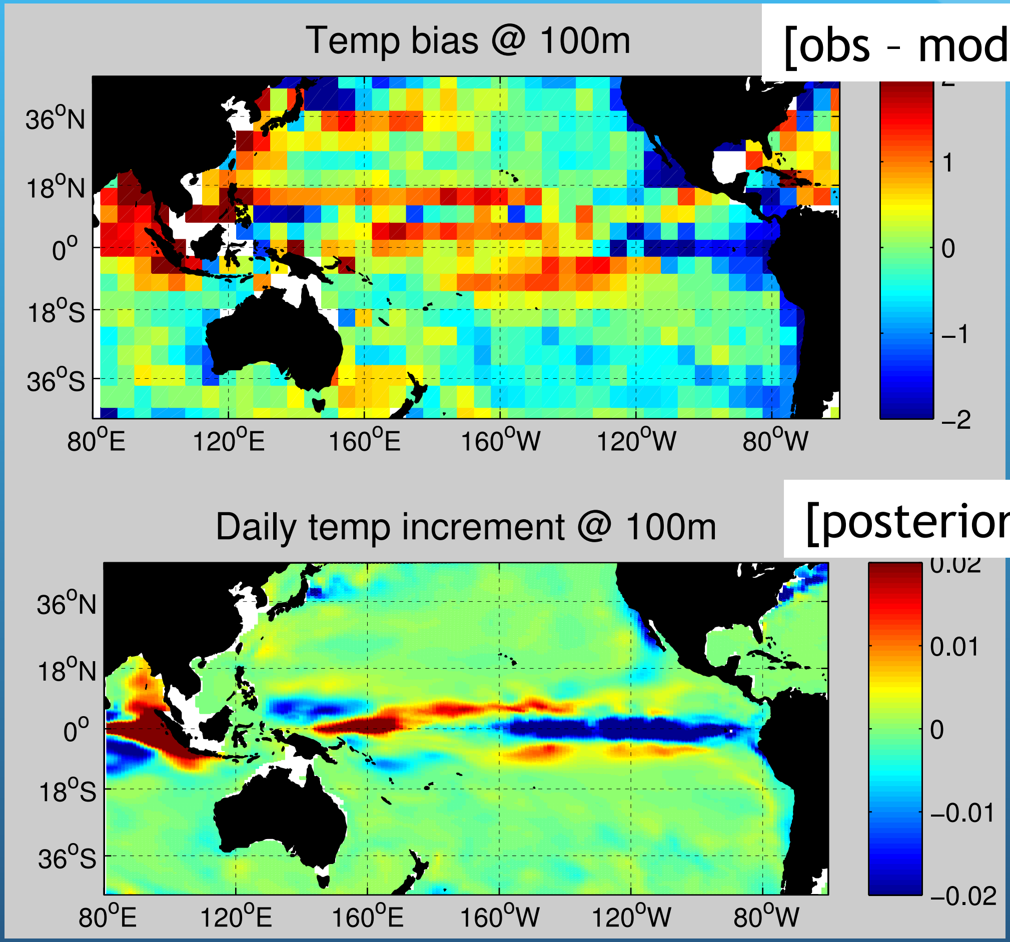




Ocean models have very strong systematic biases

systematic bias -> systematic increments in the DA scheme

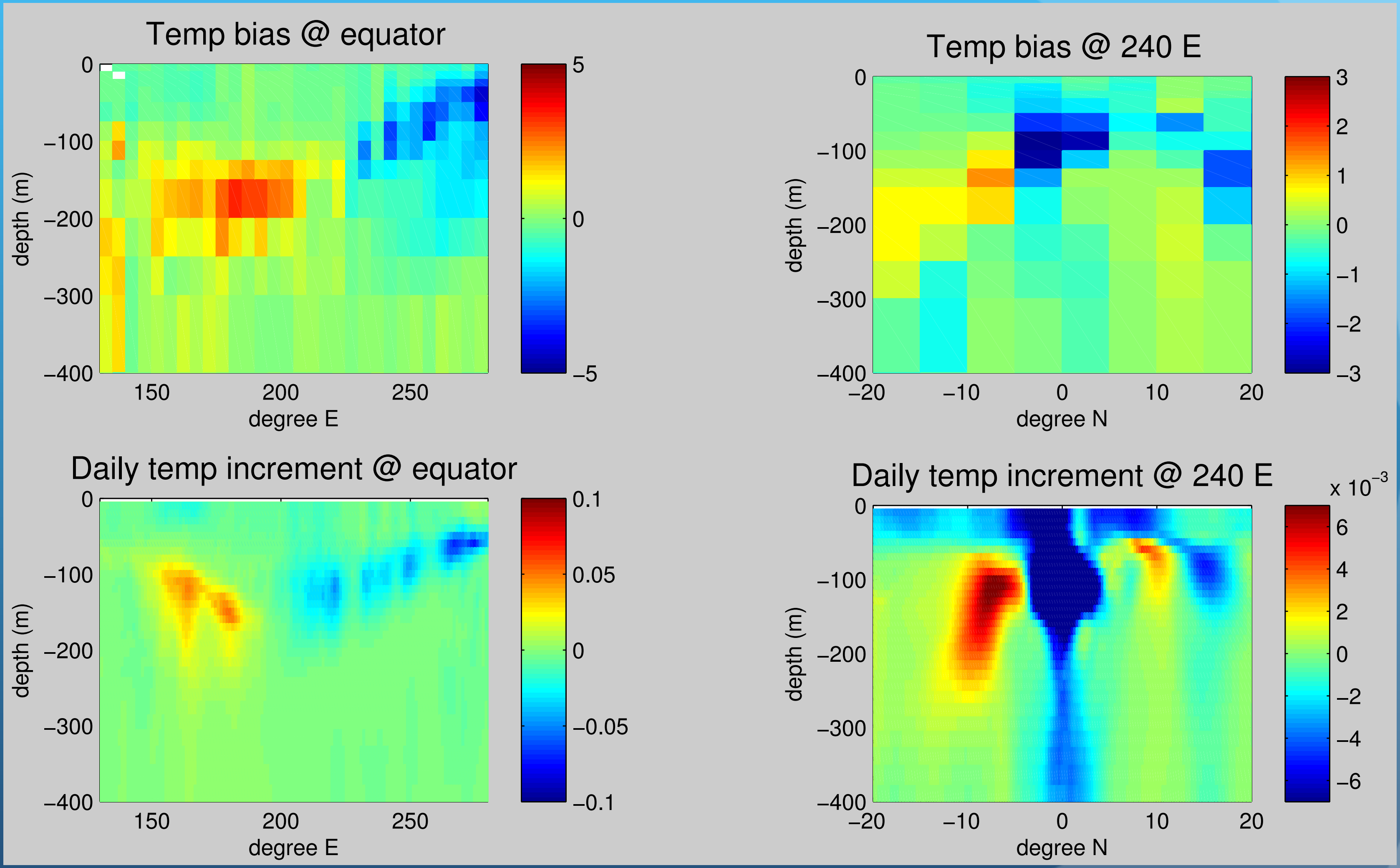
[obs – model, no assimilation]



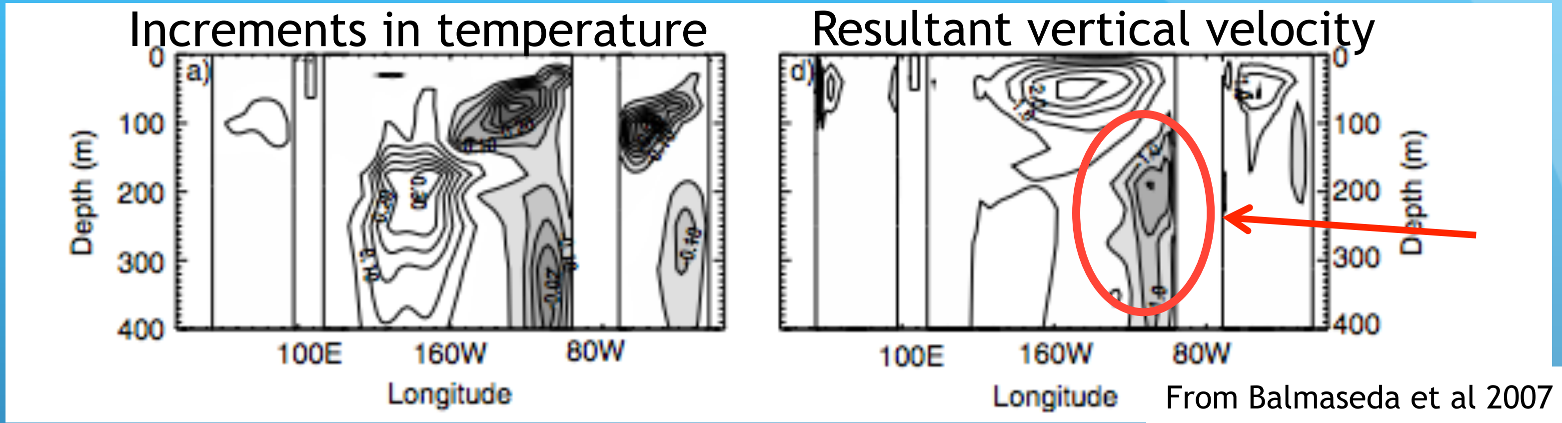
[posterior-prior, 1 day forecast]

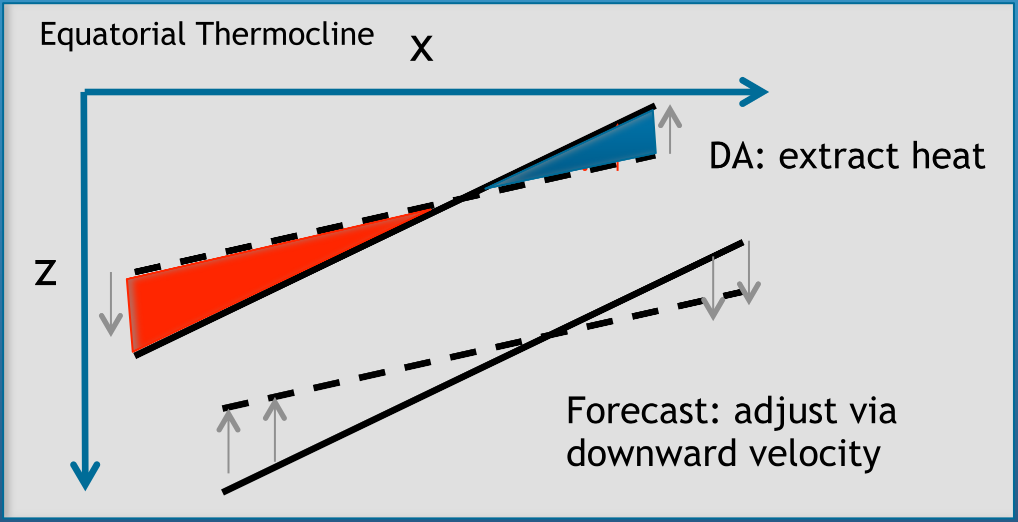
Example from the POP1x1 global ocean model with EaKF assimilation

systematic bias -> systematic increments in the DA scheme



Consequences of systematic increments in the DA scheme





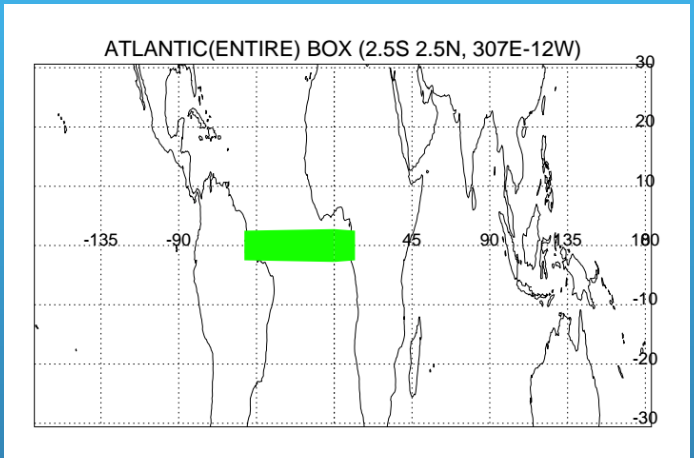
DA increment the density so as to sharpen and steepen the slope of the thermocline

Development of spurious vertical velocity during forecast as the thermocline slumps back to its preferred position.

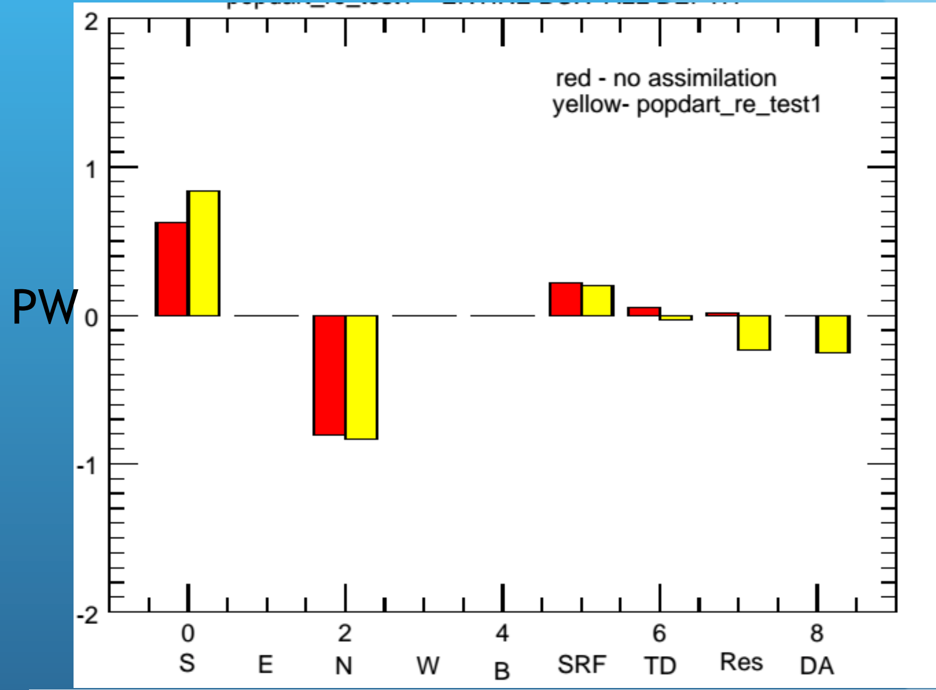
Why? The systematic bias (due to incorrect wind strength, poor mixing, etc) re-emerges rapidly. DA only fixes the symptom.

This idea was first considered by Burgers et al 2002, Bell et al 2002,2004.

Consequences of systematic increments in the DA scheme



Heat budget in the equatorial Atlantic

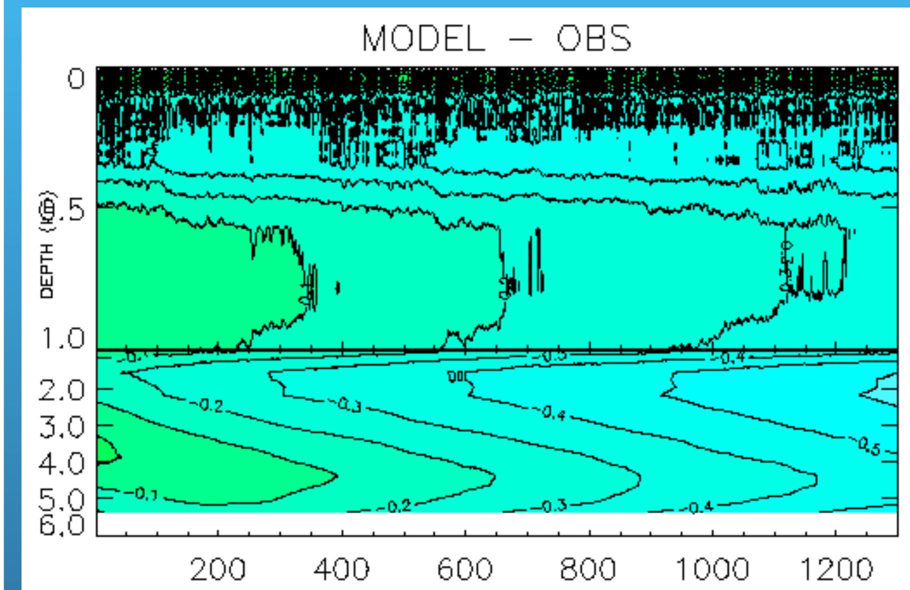


Heat budget will not close without accounting for the heat sources or sinks

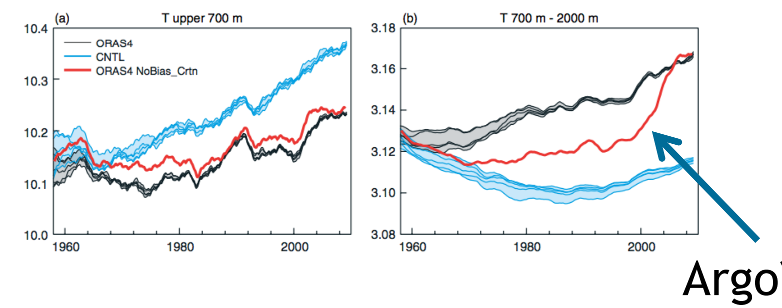
In this example, the systematic extraction of heat by the DA system changes the heat budget, increasing the net import of heat across the southern boundary

Plots from S. Karol

What happens when you mix a biased model with a changing observing system?



The CESM model drifting over 1400 years



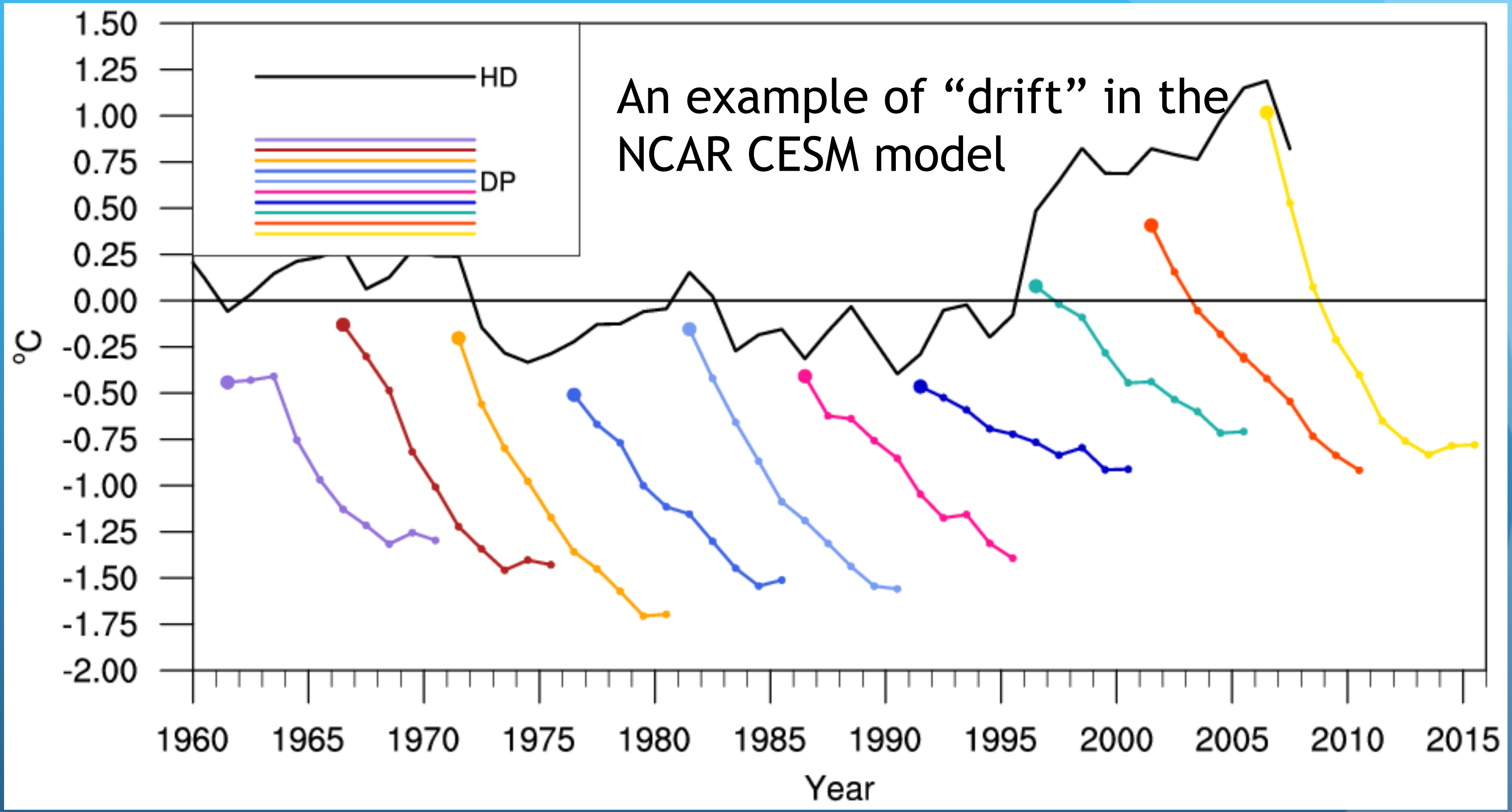
Blue: forced ocean model
Red: DA but no bias correction
Black: DA and bias correction

Figure 4. Time series of the globally averaged temperature (°C) for (a) 0–700 m, (b) 700–2000 m, and (c) below 2000 m, showing the five ensemble members of ORAS4, the five ensemble members of CNTL, and the sensitivity experiment ORAS4 NoBias_Crtn, which is equivalent to the unperturbed member of ORAS4 but without bias correction. The bias correction has a noticeable impact in the mean and variability.

From Balmaseda et al 2013

+ When a model is biased, it will drift away from observations
+ The amount of drift (in time and space)will be impacted by the changing observing system.
+ The climate is also changing, how to disentangle the imprint of the observing system and real change in the climate system?

What happens when you use a biased model for forecasting?



Surface temperature in the North Atlantic systematically cooling during the decade of prediction

Why does model bias matter?

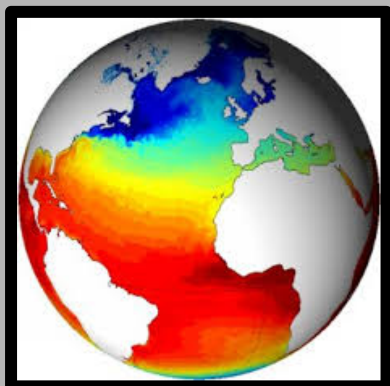
- Violates the basic assumptions of most DA methods
  … how to address this is an area of active research
- Can result in systematic increments to the model state if the bias emerge faster than the frequency of assimilation. (impact on budgets, circulation)
- Can interact with observing system to produce a non-stationary climate and drifting model forecasts.

What is done about it?

- Sometimes nothing!
- Extend the state vector to include a bias term (Dee and da Silva 1998, Bell et al 2000) Estimate it!
- Try to correct it by altering the model dynamics (see Balmaseda et al 2013). e.g. pressure correction.
- Heuristic "nudge/relaxation" to a observed climatology (+ more)

The ingredients for a challenging problem:

AN IMPERFECT OCEAN MODEL



Systematic biases

Unresolved processes

A SUBOPTIMAL DA METHOD

$$
\begin{aligned}
\tilde{\mathbf{y}}_k &= \mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_{k|k-1} \\
\mathbf{S}_k &= \mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k^T + \mathbf{R}_k \\
\mathbf{K}_k &= \mathbf{P}_{k|k-1}\mathbf{H}_k^T\mathbf{S}_k^{-1} \\
\hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k\tilde{\mathbf{y}}_k \\
\mathbf{P}_{k|k} &= (I - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_{k|k-1}
\end{aligned}
$$

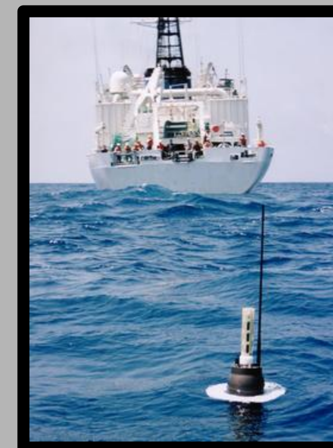
Linear/Gaussian assumption violated

Misspecified error characteristics

Undersampling (small number of samples, for large state-space)

4DVar – cannot perfectly find the minimum (adjoint imperfect, costly iterations)

OBSERVATIONS



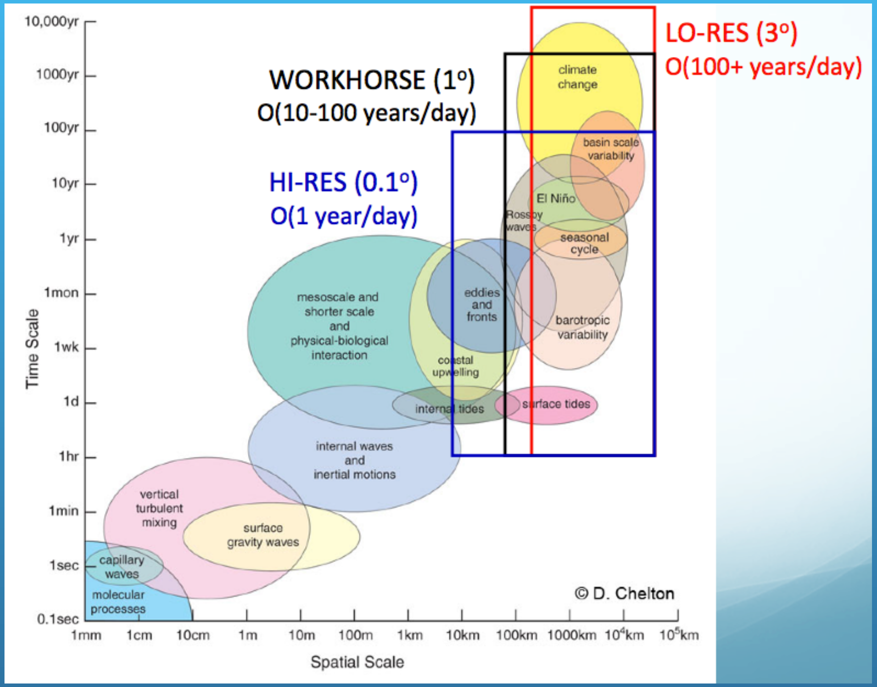
Sparse

Inhomogeneous

Changing in time

Imperfect models – unresolved processes

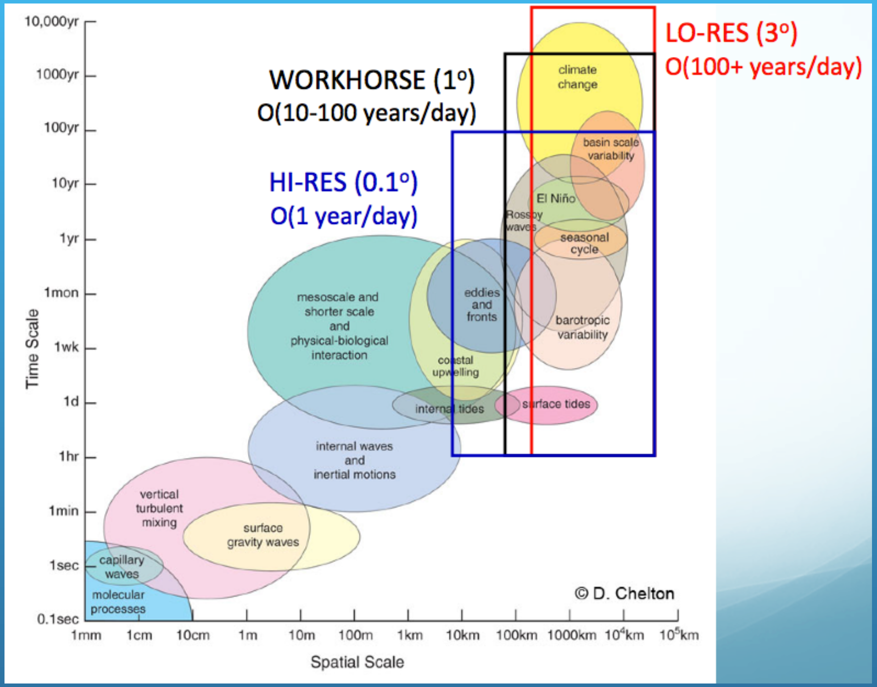
"… all models are wrong, but some are useful"
George Box, Statistician



Representativeness error accounts for processes that are detectable through observation, but not resolvable by the model

- It is model dependent
- It is geographically variable (spatially inhomogeneous)
- In a 1° ocean model rep-error can be an order of magnitude larger than instrumental error in some regions

Imperfect models – unresolved processes

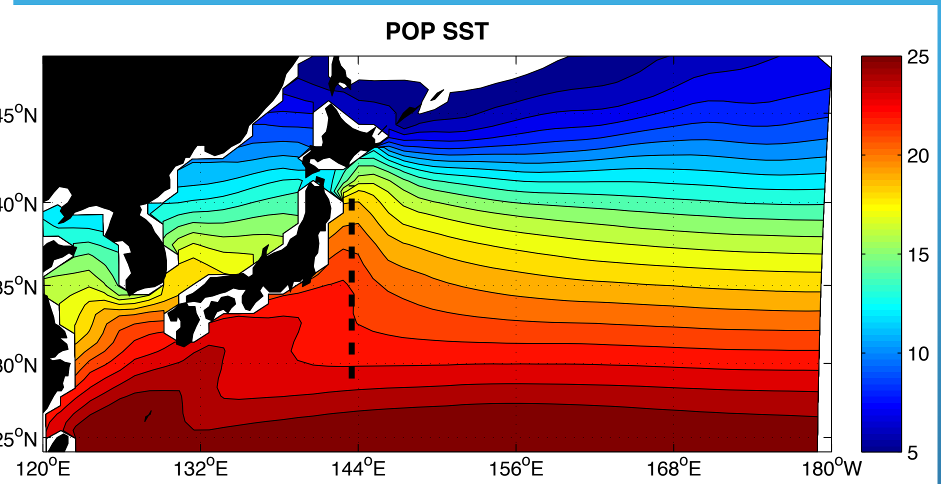


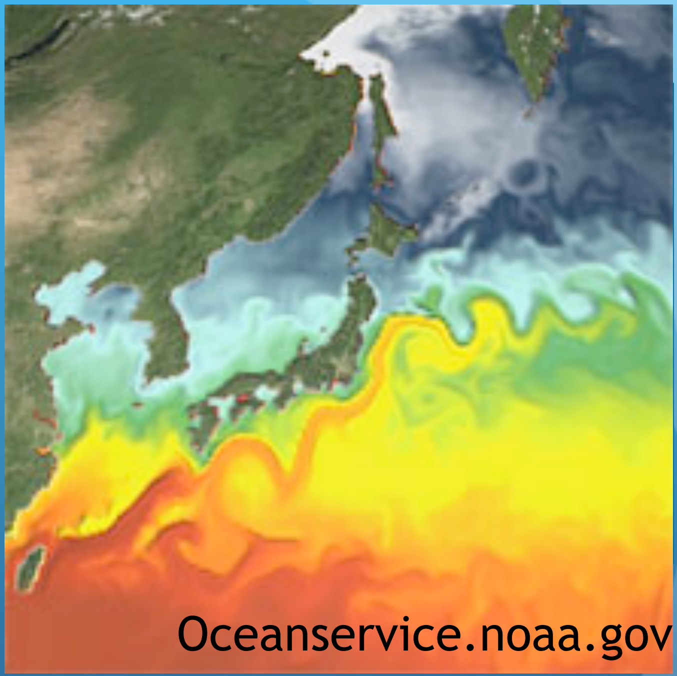
Representativeness error is typically treated as observational error (i.e. it is included in R)*

Kalman gain: $K = B\,H^T\,(HBH^T + R)^{-1}$

Sometimes it is included in B! Which indicates a desire to estimate the unresolved processes

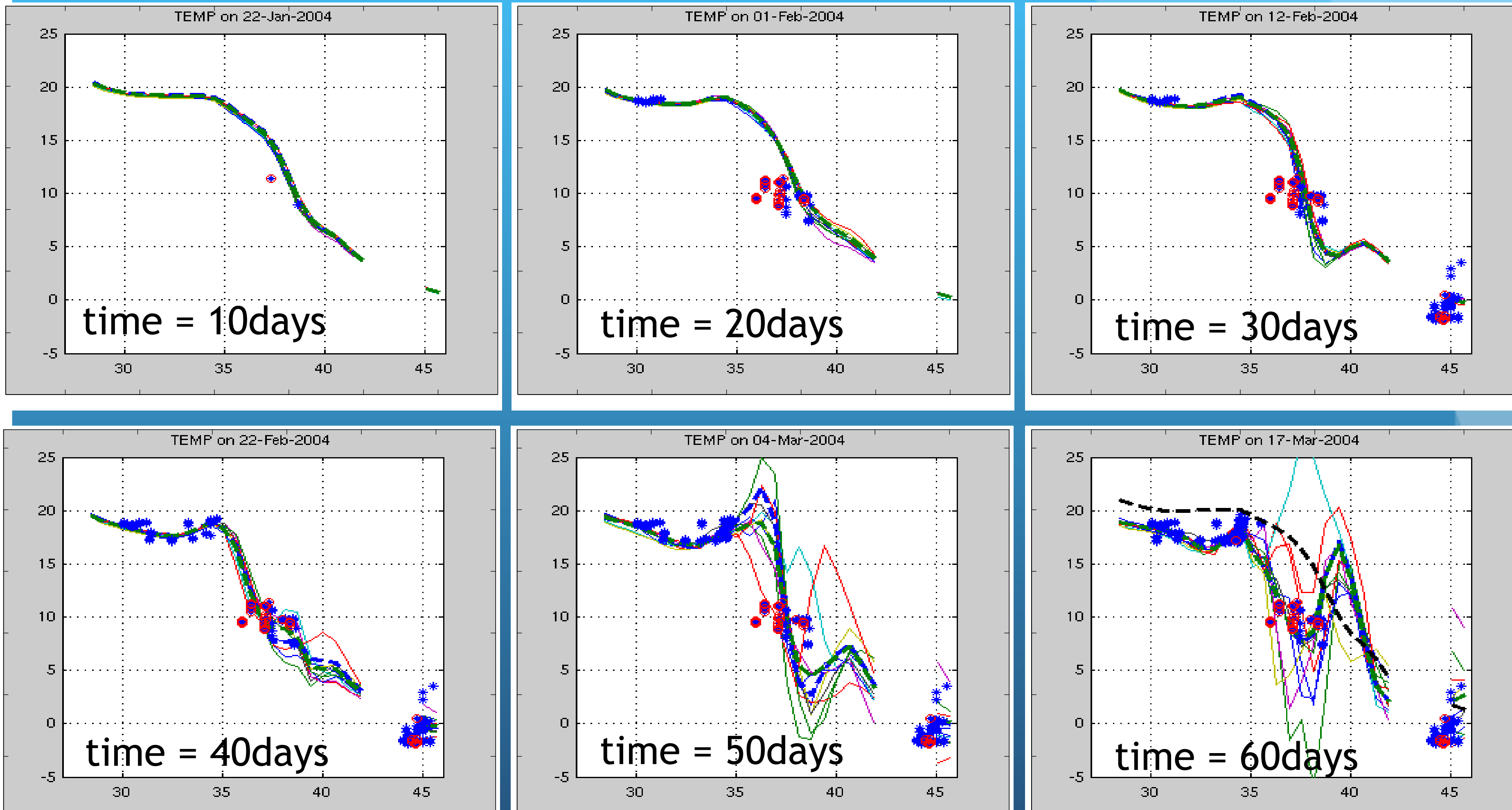
Example of representativeness error in the POP1x1 model



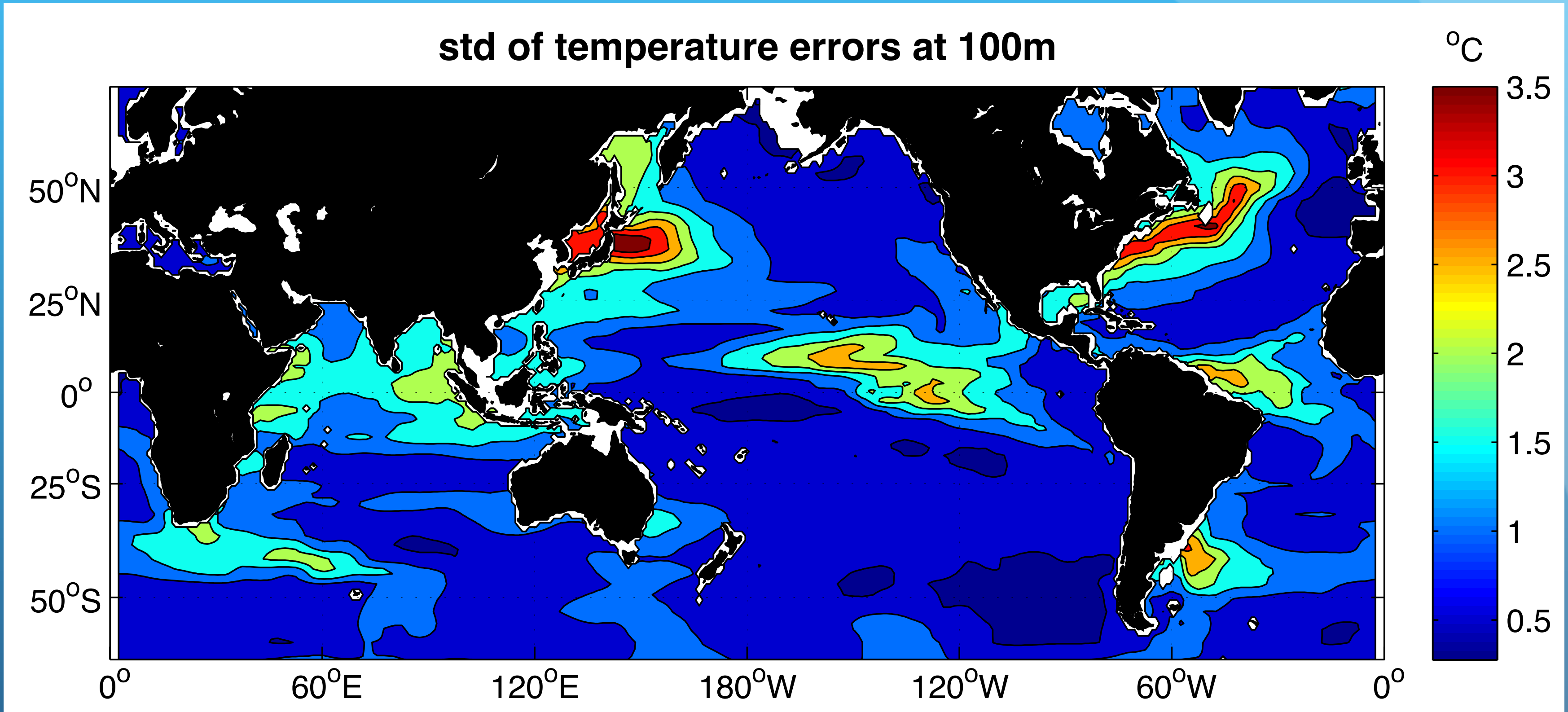


Assimilation will try to shift Kuroshio to the south… and assimilate eddies

Consequence of naively assimilating without treating representativeness error in a 1 degree ocean model

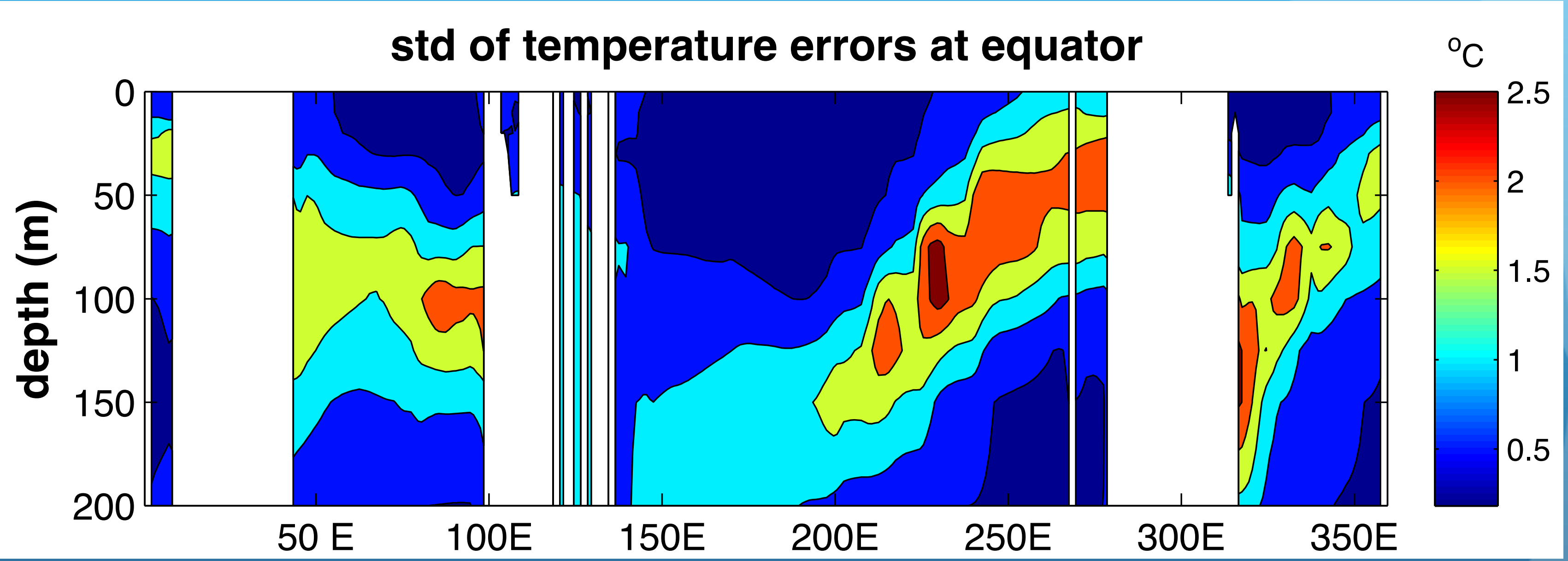


Estimates of representativeness error for POP1x1



Karspeck 2015 (in review MWR)

Estimates of representativeness error for POP1x1



Karspeck 2015 (MWR in review)

The fact of model imperfection raises basic question about the goal of data assimilation

Are we seeking to constrain the model within its imperfect, but self-consistent, attractor?

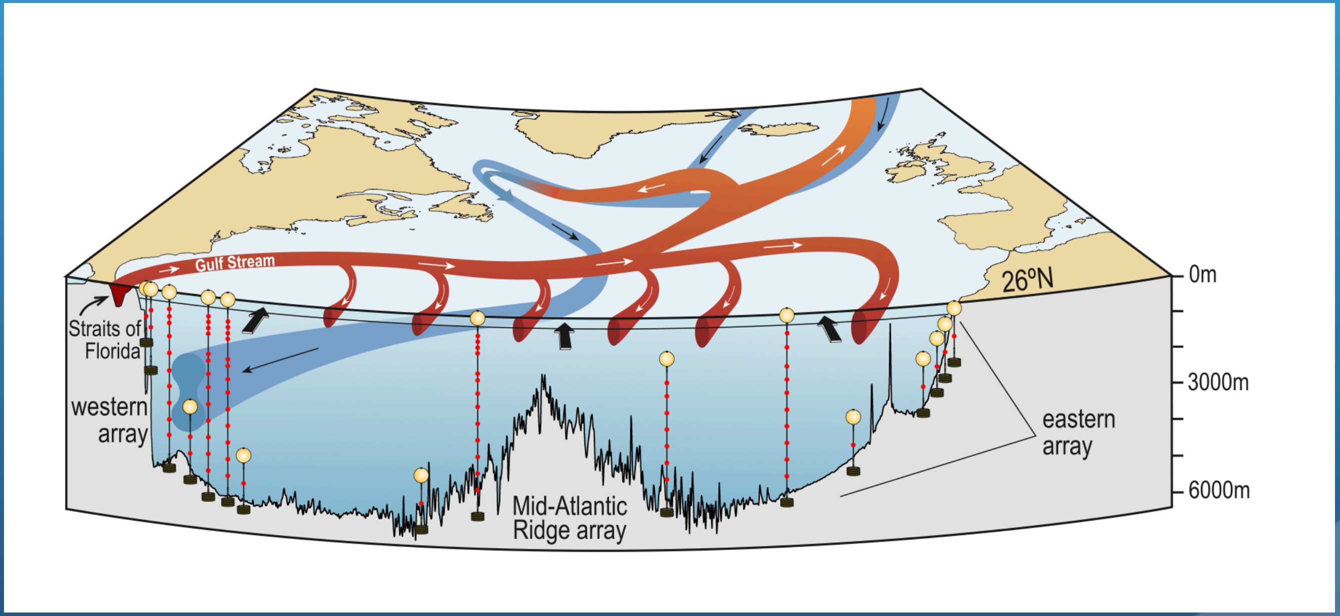
(For forecasting this is sensible)

Are we seeking to draw the model into some alternative phase space that looks more like reality?

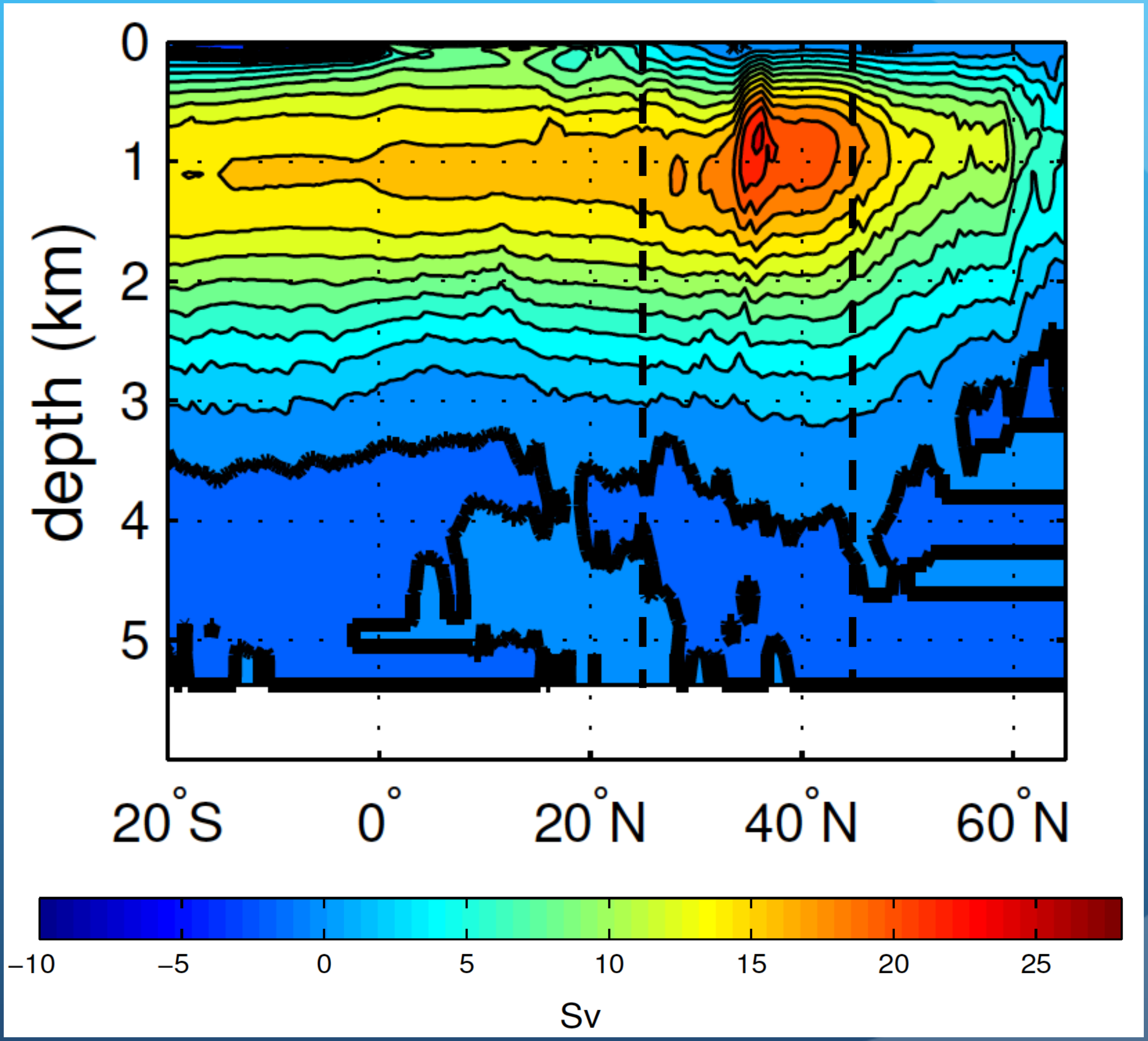
(For state estimation this might be sensible)

For all these reasons (and more) the set of commonly used ocean data assimilation products show inconsistent representations of the ocean over the last fifty years.

Consider the circulation in the Atlantic



Atlantic Meridional Overturning Circulation

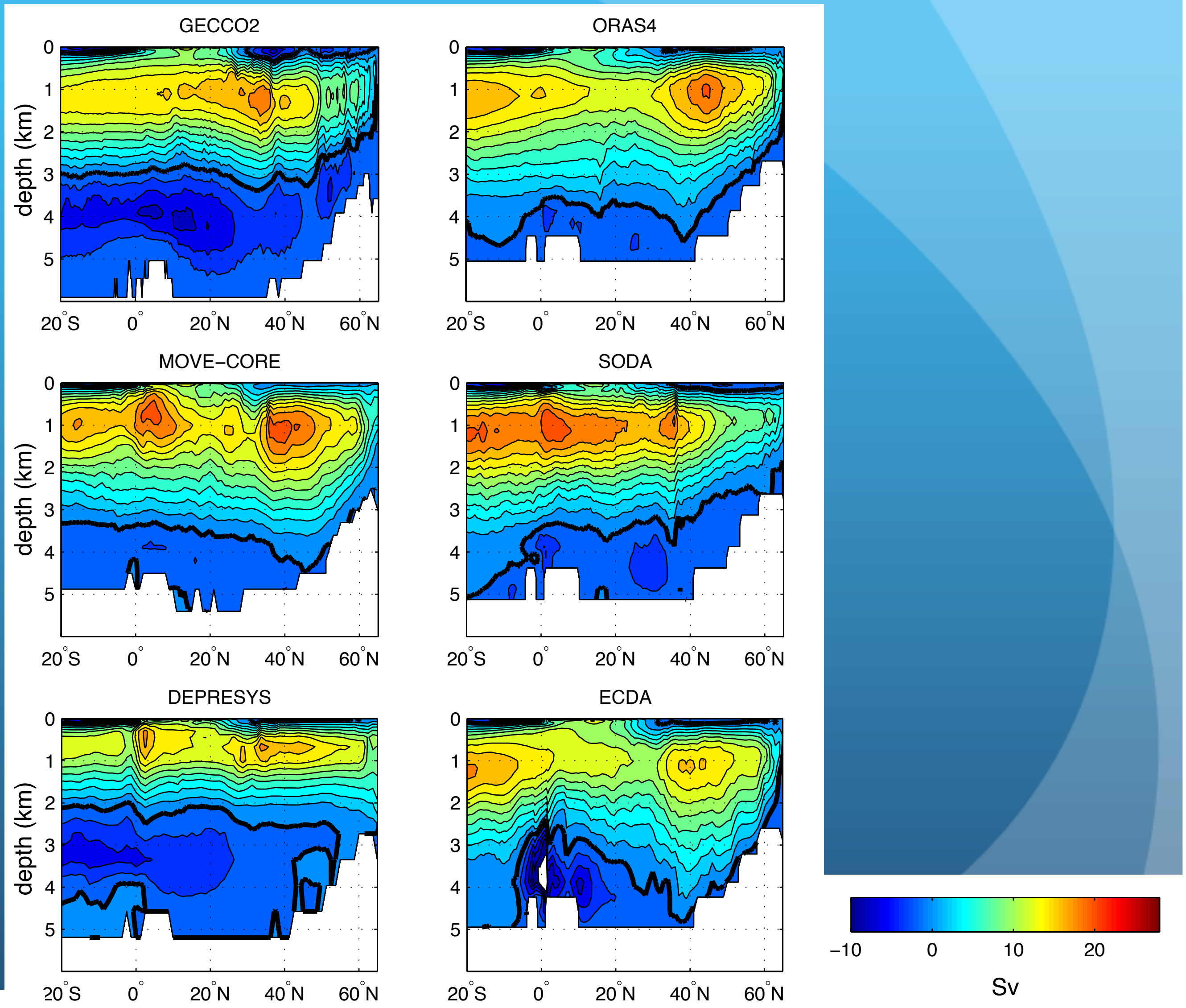


Groups that have contributed AMOC reanalyses

from 1960 – 2007 (or longer)

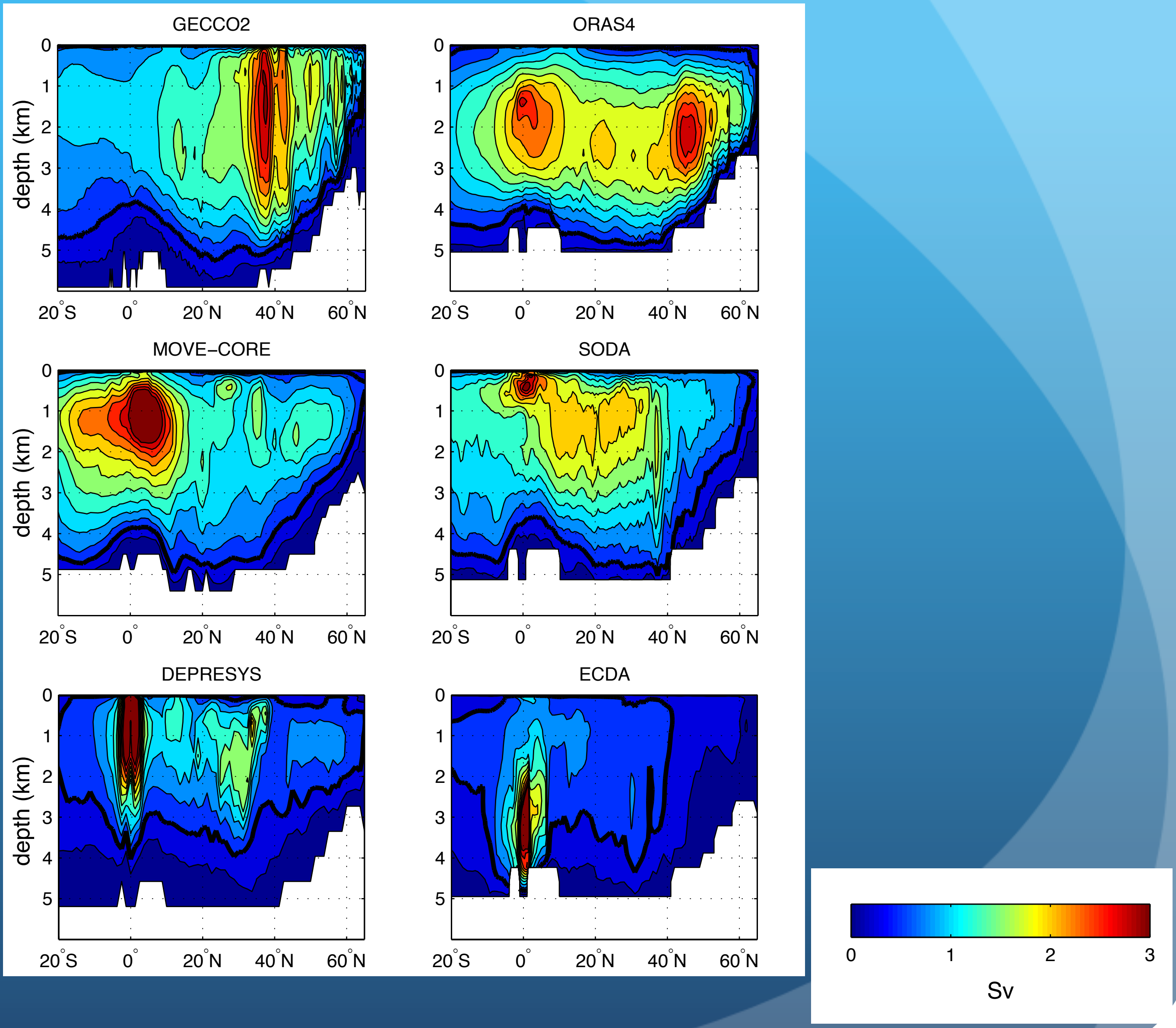
GROUP	METHOD	INSITU T/S	ALT	SST	NoAssim Control run?	Atm forcing	DP INIT?
GECCO2 (U. Hamburg)	4DVAR	YES	YES	YES	YES	[NCEP]*	YES
ORAS4 (ECMWF)	NEMOVAR 3DVar	YES	YES	YES	YES	ERA-40/ ERA-I	YES
MOVE-CORE (MRI)	3DVar	YES	NO	NO	YES	CORE II IAF	[NO]
SODA (U.Marylnd/ TAMU)	OI	YES	NO	YES	YES	20-CR	YES
DePreSys (UKMET)	Coupled nudging to OI product	YES	NO	YES	NO	N/A	YES
ECDA3.2 (GFDL)	coupled EaKF	YES	INDIRECTLY	YES	NO	[NCEP]*	YES

AMOC time mean (1961-2007)



Karspeck et al (2015)

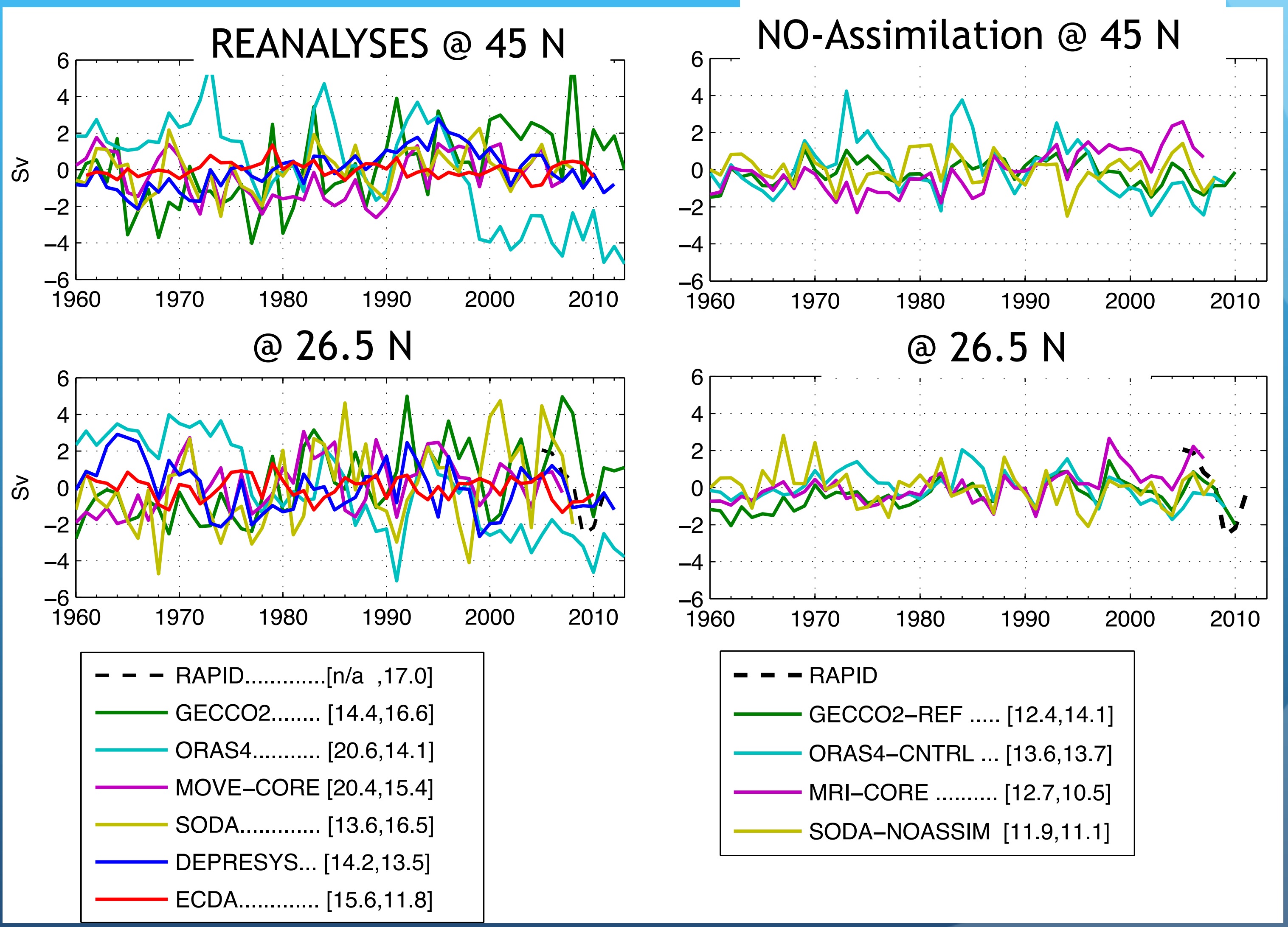
AMOC variance [std] (1961-2007)



Annual-mean AMOC variability @ 1000m

45N

26.5N

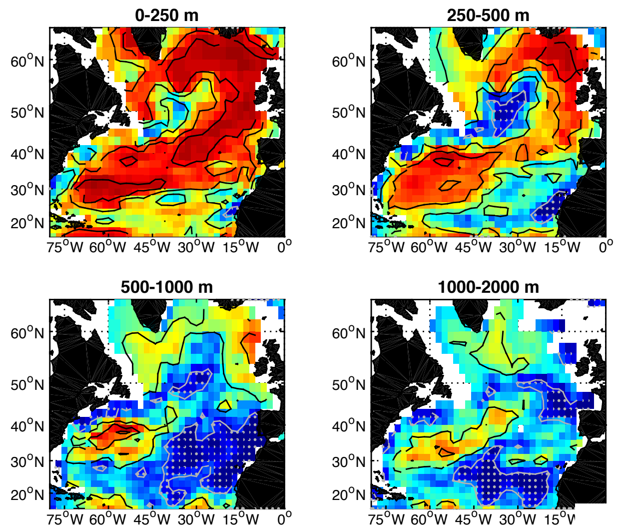


Hydrographic similarities*

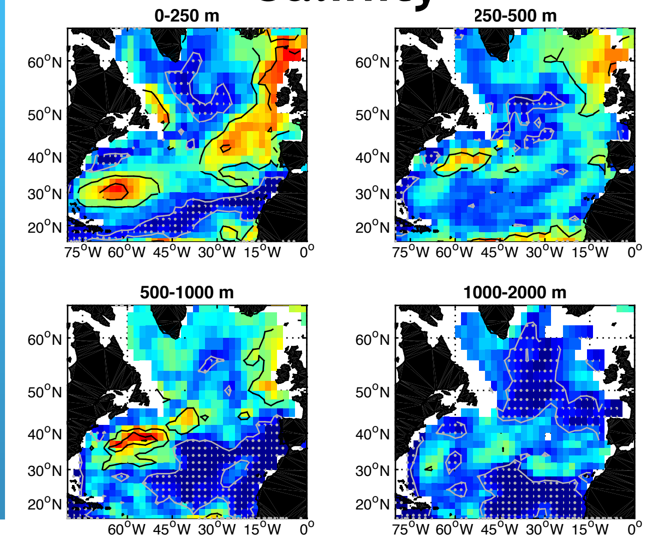
Upper 500 m

500-2000 m

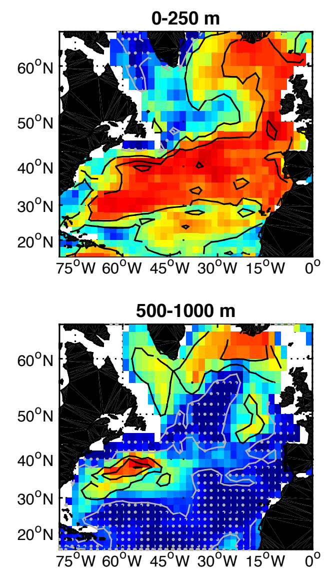
Temp



Salinity



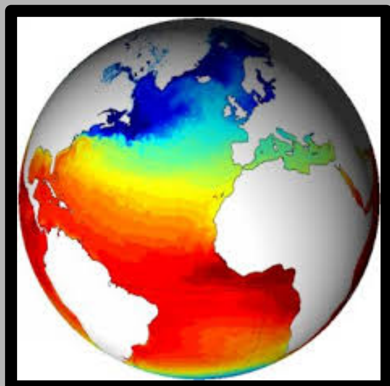
Density



*measured by average model-model correlation

The ingredients for a challenging problem:

AN IMPERFECT OCEAN MODEL



Systematic biases

Unresolved processes

A SUBOPTIMAL DA METHOD

$$
\begin{aligned}
\tilde{\mathbf{y}}_k &= \mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{x}}_{k|k-1} \\
\mathbf{S}_k &= \mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^T + \mathbf{R}_k \\
\mathbf{K}_k &= \mathbf{P}_{k|k-1} \mathbf{H}_k^T \mathbf{S}_k^{-1} \\
\hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \tilde{\mathbf{y}}_k \\
\mathbf{P}_{k|k} &= (I - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_{k|k-1}
\end{aligned}
$$

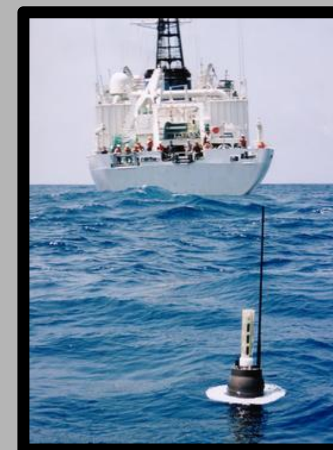
Linear/Gaussian assumption violated

Misspecified error characteristics

Undersampling (small number of samples, for large state-space)

4DVar – cannot perfectly find the minimum (adjoint imperfect, costly iterations)

OBSERVATIONS



Sparse

Inhomogeneous

Changing in time

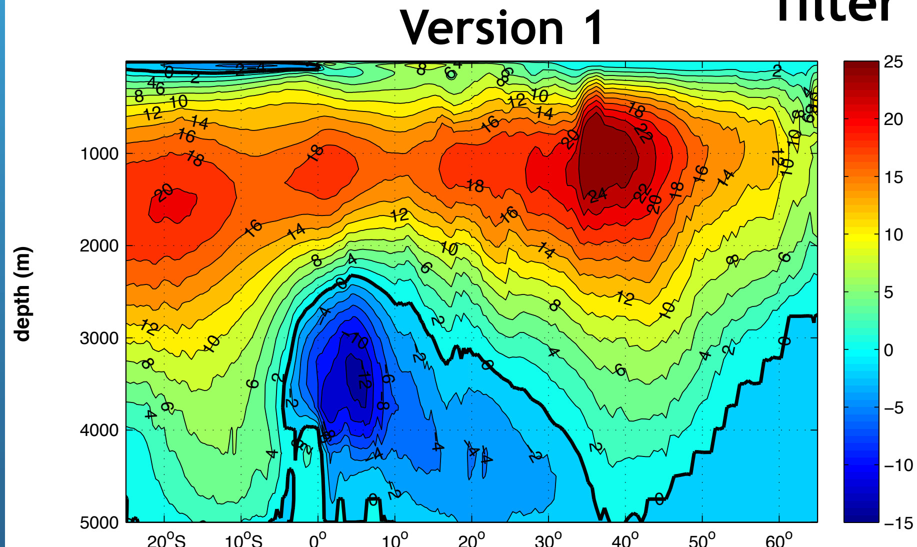
Areas where you can make a difference

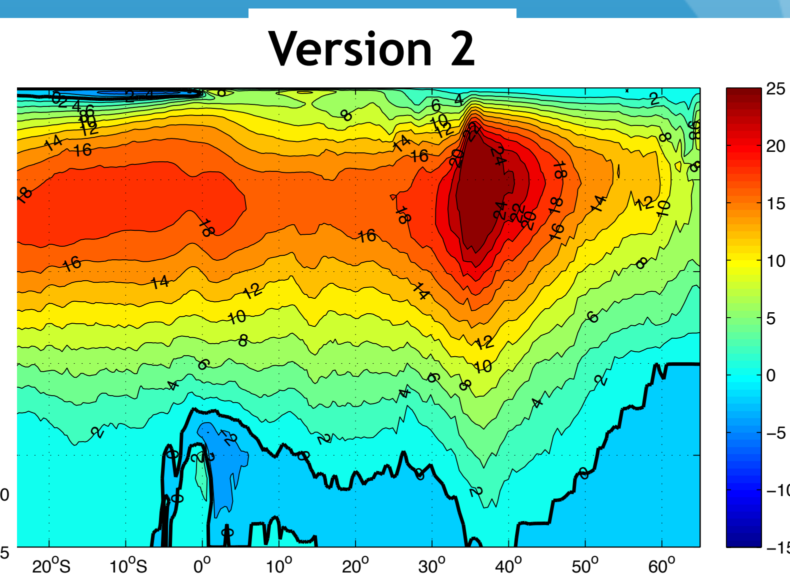
- Improve ocean models!
  - Can the confrontation of models with data (via data assimilation) lead to better models? How do we do this?
- Work on how best to have imperfect models interact with data.
  - Model bias in data assimilation
  - Better characterization of the variance/covariance statistics of the unresolved process
- Joint/multivariate prior distributions (e.g. covariances)
  - How does information from one variable impact others (e.g. SSH → T,S)
- Description and use of “errors of representation” in DA schemes
- “Less approximate” Bayesian methods that can scale to large dimension.

END

New filter initial conditions was successful in reducing the counter-circulation.

Atlantic MOC in the first year after initialization of ensemble filter





old initial conditions **new initial conditions**