Some thoughts about the role of ocean data assimilation in initialized decadal climate prediction

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CLIVAR-ICTP
Workshop on Decadal Climate Variability and Predictability
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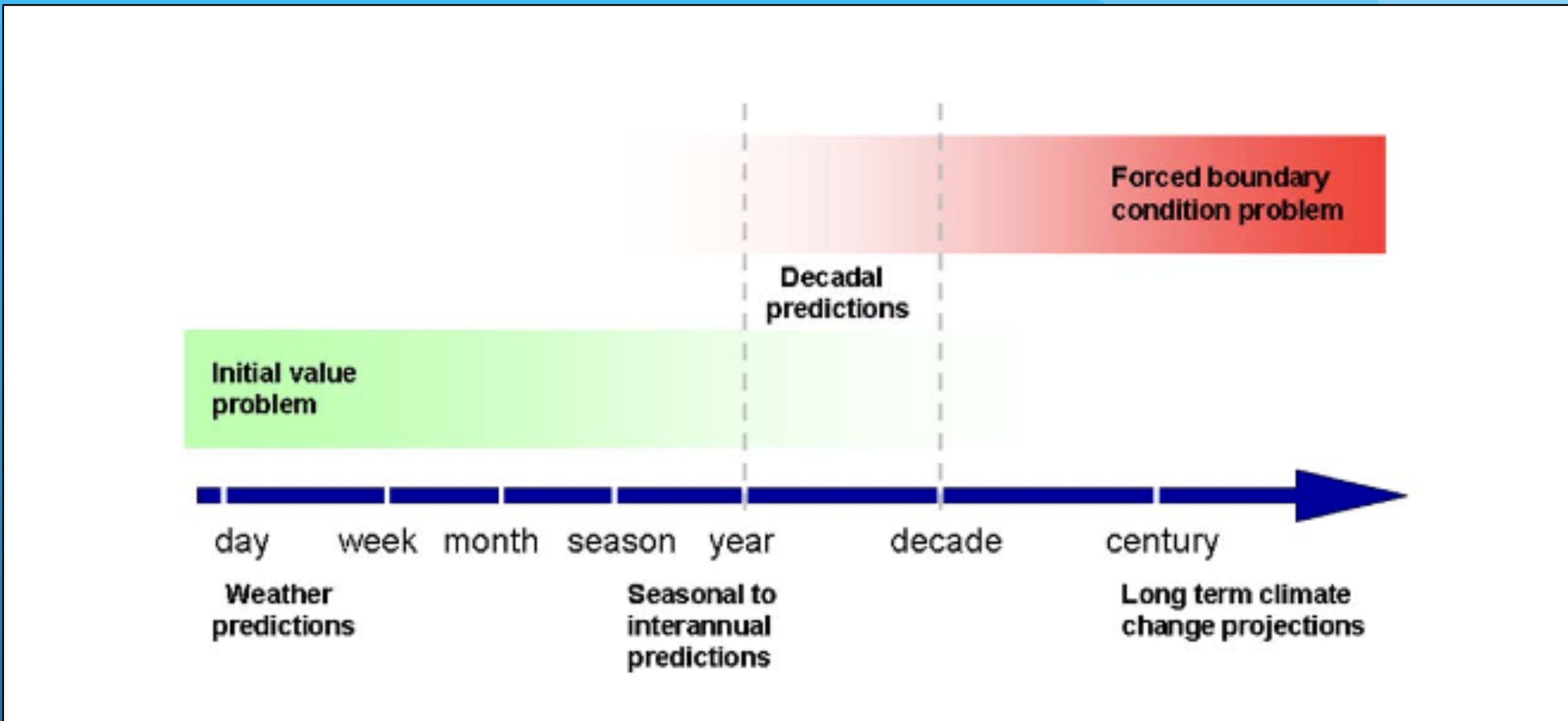
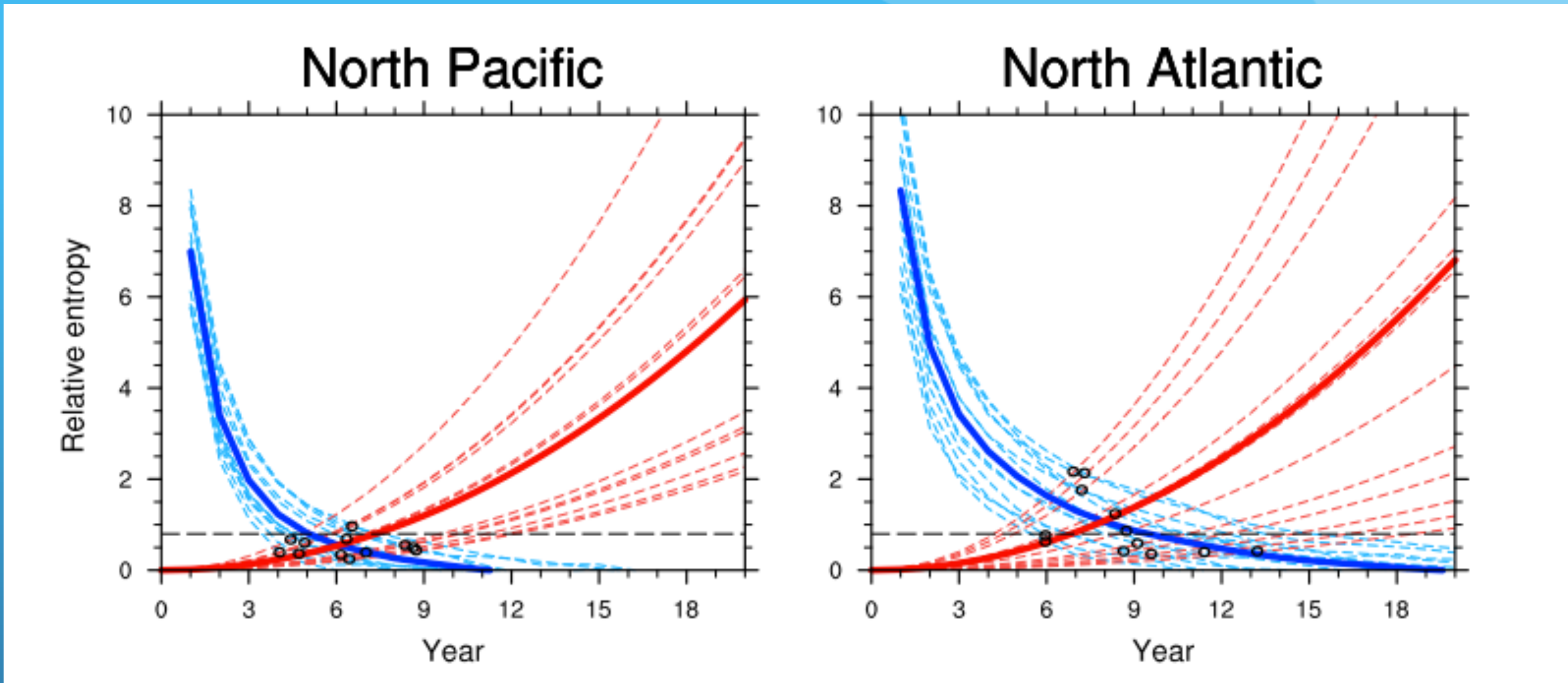
Where did the idea that ocean initialization matters for decadal prediction come from?
(the idealized underpinnings)



Adapted from Meehl et al 2009

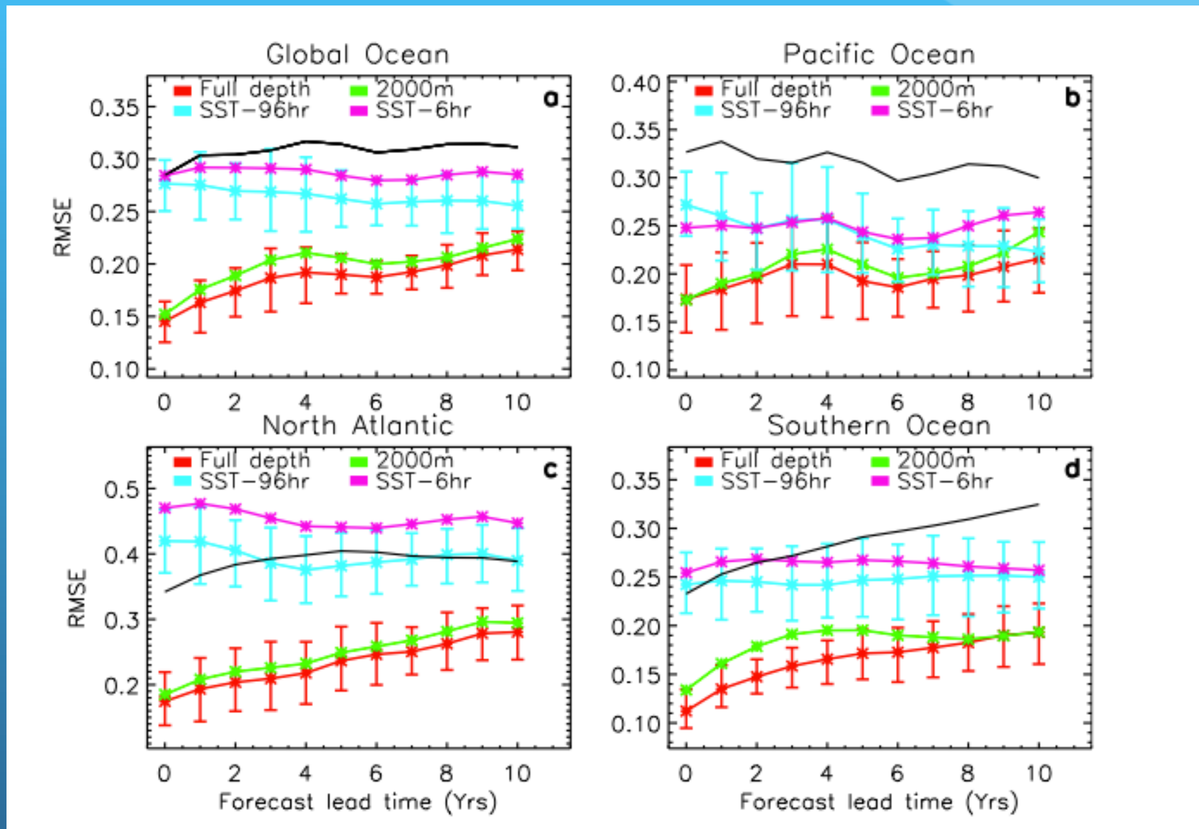


Idealized studies have shown that some amount of near-term predictive skill of ocean surface temperatures comes from ocean initialization.

See also:
Griffies and Bryan 1997 , Hawkins and Sutton 2008
Collins and Sinha 2003
Latif et at 2006, Karspeck et al 2004
Msadek et al 2010, + lots of others

Branstator and Teng, 2012, GRL

In idealized studies, the assimilation of subsurface ocean information is key for enhancing decadal prediction

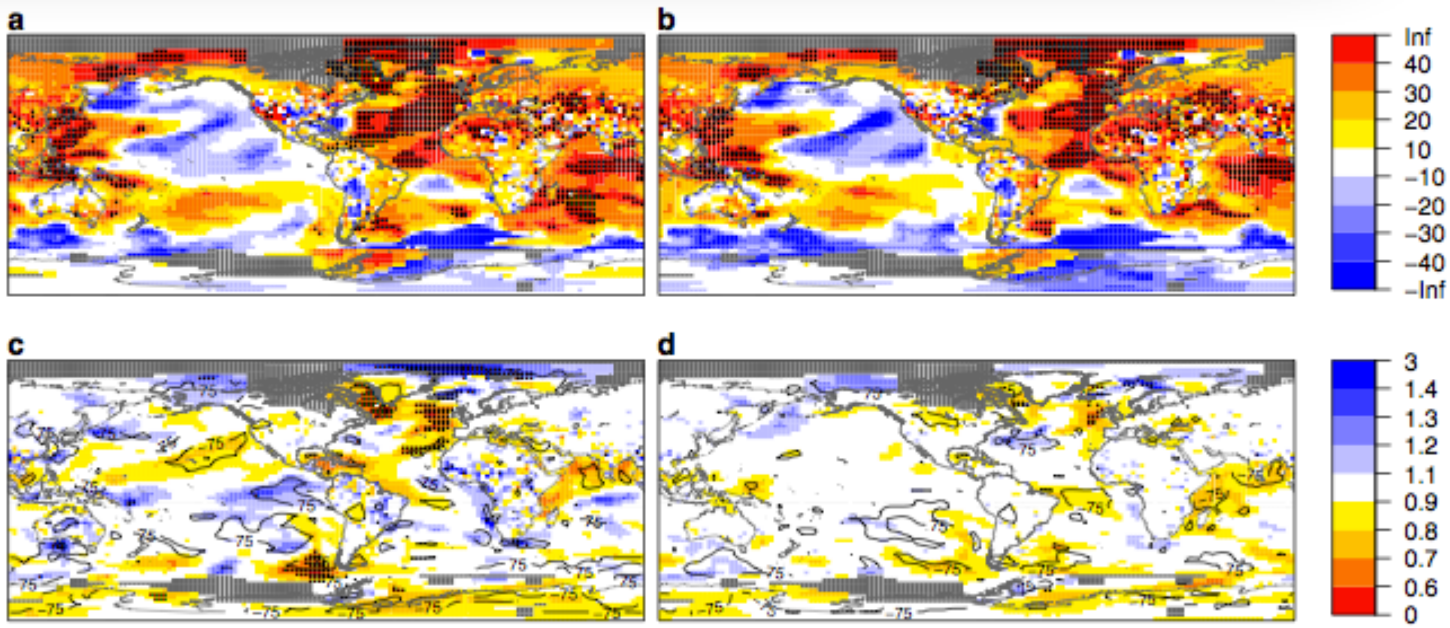


Heat content in the upper ocean is better predicted when temperature and salinity data are used for initialization

Dunstone and Smith 2010, GRL.

But what do we know about the role that ocean initialization plays in determining real prediction skill?

Combined skill* of CMIP5 models in surface air temperature



Total skill

Portion of skill due to ocean initialization

2-5 yr lead

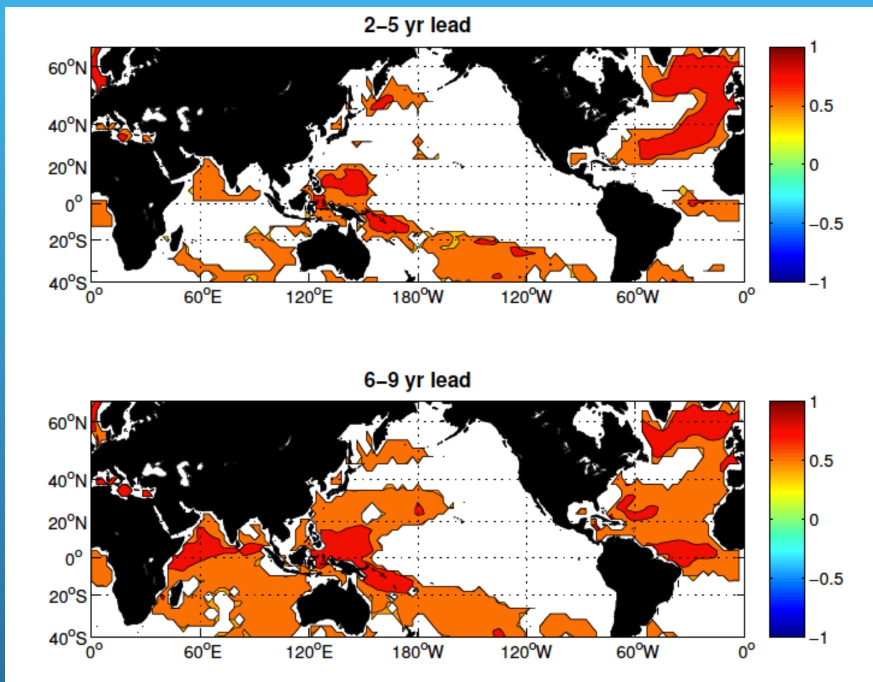
6-9 yr lead

Most skill in the CMIP5 DP archive comes from external forcing

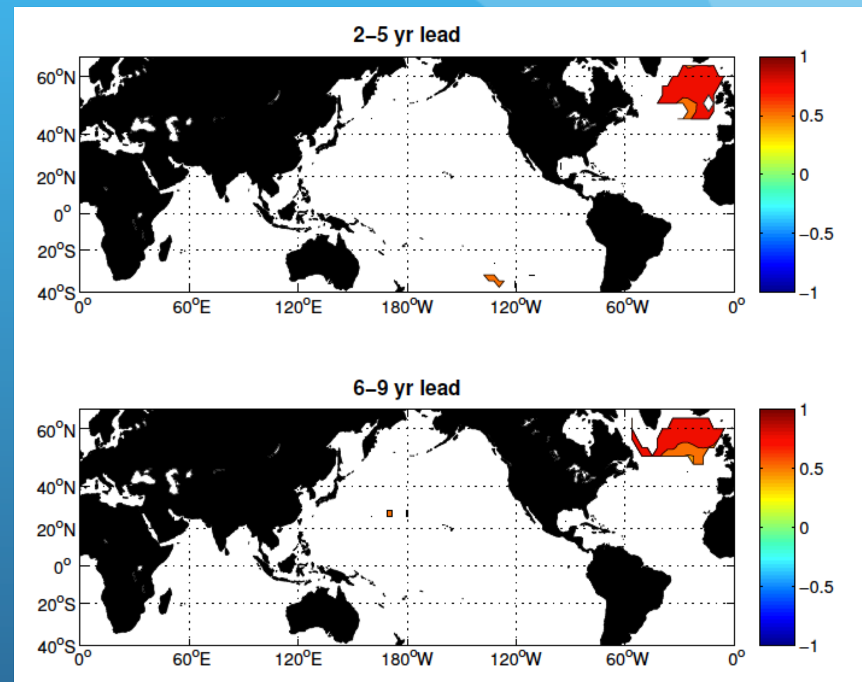
*measured in RMSSSx100

Doblas-Reyes et al 2013 Nature Comm

NCAR-model prediction skill for SST is broadly consistent with multi-model result



Broad regions of high correlation with observations



Only North Atlantic subpolar gyre shows skill that we can attribute to initialization

Karspeck et al 2014 ClimDyn

“The usual challenges”

- Model quality
  - Mean state bias → leads to drift
  - Variability may also be problematic
- Initialization difficulties
  - Best strategies for initializing models are unclear
  - No consensus on the state of the ocean
- Detectability of skill
  - Signal to noise is small
  - Auto-correlation is large
  - Effective sample size is low
  - (we sit in the theoretical predictability minimum)

Initialized Decadal Prediction System

Observations of the climate system

external forcing

Ocean initialization system for the GCM

Coupled General Circulation Model to simulate/predict the climate state

Societally relevant applications

(Note: so many different ways to do this)

- Data assimilation system (dynamic model + ocean hydrography)
- Atm-forced ocean hindcast
- Nudging of an ocean or coupled model to an SST product
- Nudging coupled model to T/S from a product
- Interpolation of a ”foreign” product to you model grid
- Anomaly initialization, full-field, etc etc etc.

What do we know about the best initialization strategies for decadal forecasting?

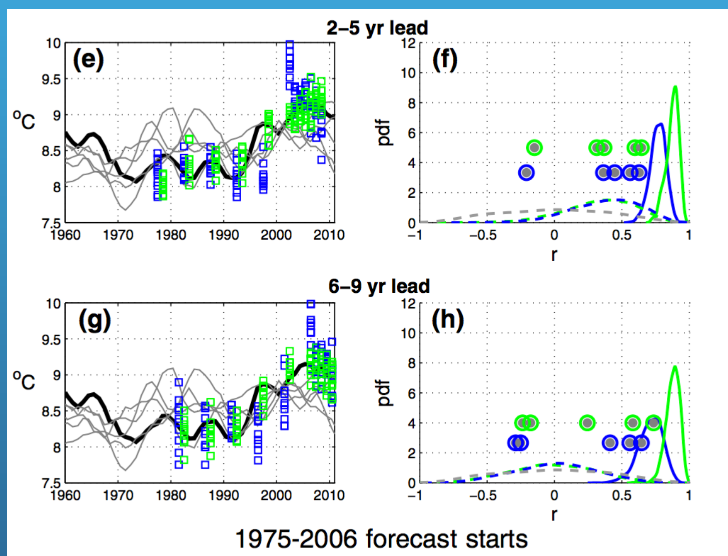
No clear retrospective skill difference between:

- **"anomaly" and "full-field" initialization**
  - Smith et al (2013) "*…differences in hindcast skill for multi—year predictions are generally not significant..*" (MetOffice model)
  - Magnusson et al (2013) "*At decadal time-scales it is difficult to determine whether any of the [initialization] strategies is superior to the others*" (ECMWF coupled model)
  - Polkova et al (2014) (UCLA/MITgcm)

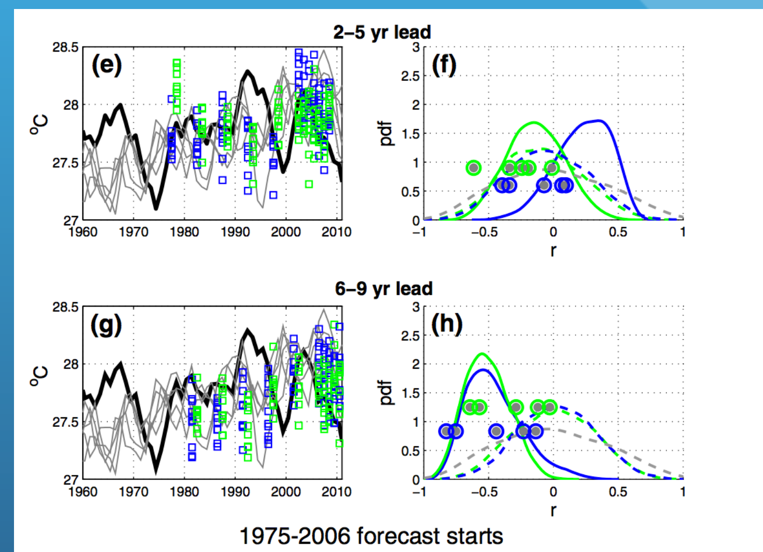
- **initialization from an atm-forced hindcast and the use of data assimilation**
  - Doblas-Reyes et al (2011) "No significant forecast quality benefit was found…"
  - Matei et al (2013): JClim, "At first order, the predictive skill of [DA initialized forecasts and atm-forced hindcasts] is similar"
  - Karspeck et al (2014):

Experience at NCAR with CCSM4: No clear retrospective skill difference between initialization from an atm-forced hindcast and the use of data assimilation

Atlantic subpolar gyre SST



Equatorial Pacific SST



Blue: NCAR/CCSM4 predictions initialized with subsurface data assimilation
Green: initialized with CORE-II forced hindcast

Karspeck et al 2014

"The usual challenges"

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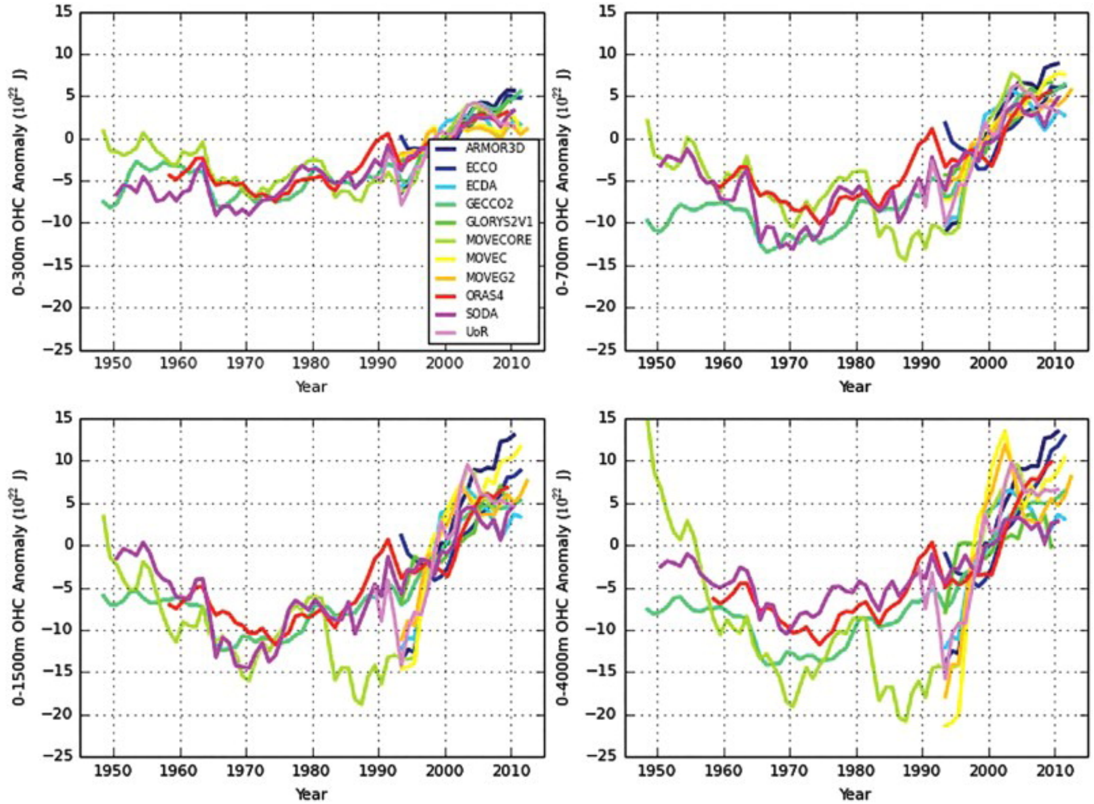
Global Ocean heat content from the ORA-IP

0-300m

0-700m



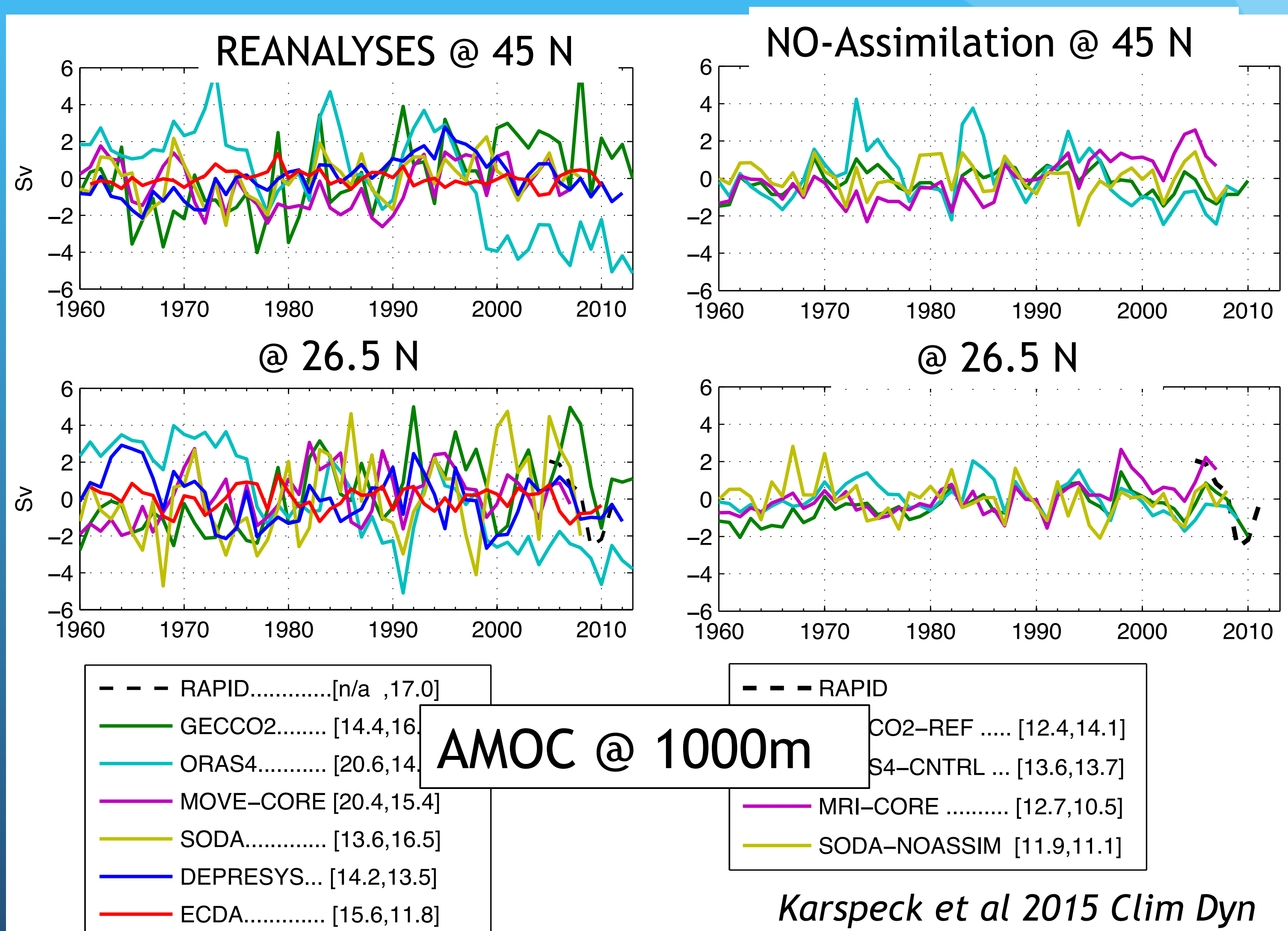
0-1500m

0-4000m

Figure 1. Time series of global ocean heat content anomaly, relative to a baseline period of 1993-2007. Note that SODA only includes grid boxes that span the full column and therefore will tend to underestimate OHC changes as the depth of integration increases. ARMOR3D and EN3 are obs-only analyses and do not include a dynamic model component. [UoR in legend corresponds to the URO25.5 in Table 2].

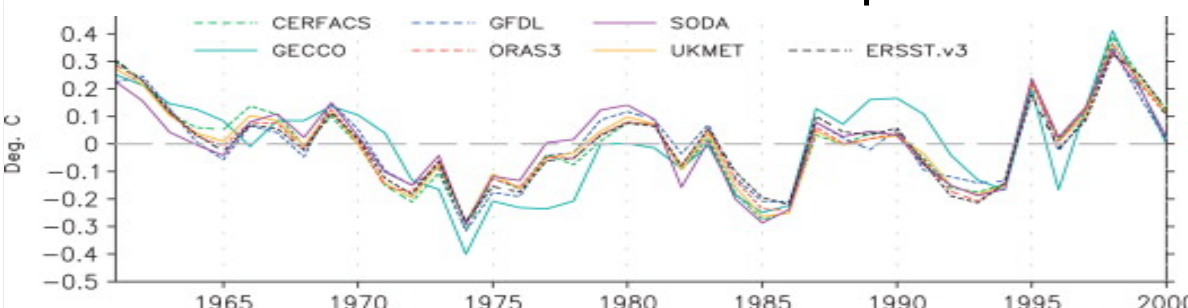
Published in: M.A. Balmaseda; F. Hernandez; A. Storto; M.D. Palmer; O. Alves; L. Shi; G.C. Smith; T. Toyoda; M. Valdivieso; B. Barnier; D. Behringer; T. Boyer; Y-S. Chang; G.A. Chepurin; N. Ferry; G. Forget; Y. Fujii; S. Good; S. Guinehut; K. Haines; Y. Ishikawa; S. Keeley; A. Köhl; T. Lee; M.J. Martin; S. Masina; S. Masuda; B. Meyssignac; K. Mogensen; L. Parent; K.A. Peterson; Y.M. Tang; Y. Yin; G. Vernieres; X. Wang; J. Waters; R. Wedd; O. Wang; Y. Xue; M. Chevallier; J-F. Lemieux; F. Dupont; T. Kuragano; M. Kamachi; T. Awaji; A. Caltabiano; K. Wilmer-Becker; F. Gaillard; *Journal of Operational Oceanography* **2015,** 8, s80-s97.
DOI: 10.1080/1755876X.2015.1022329

Aspects of the ocean state that are thought to be important for decadal prediction are uncertain



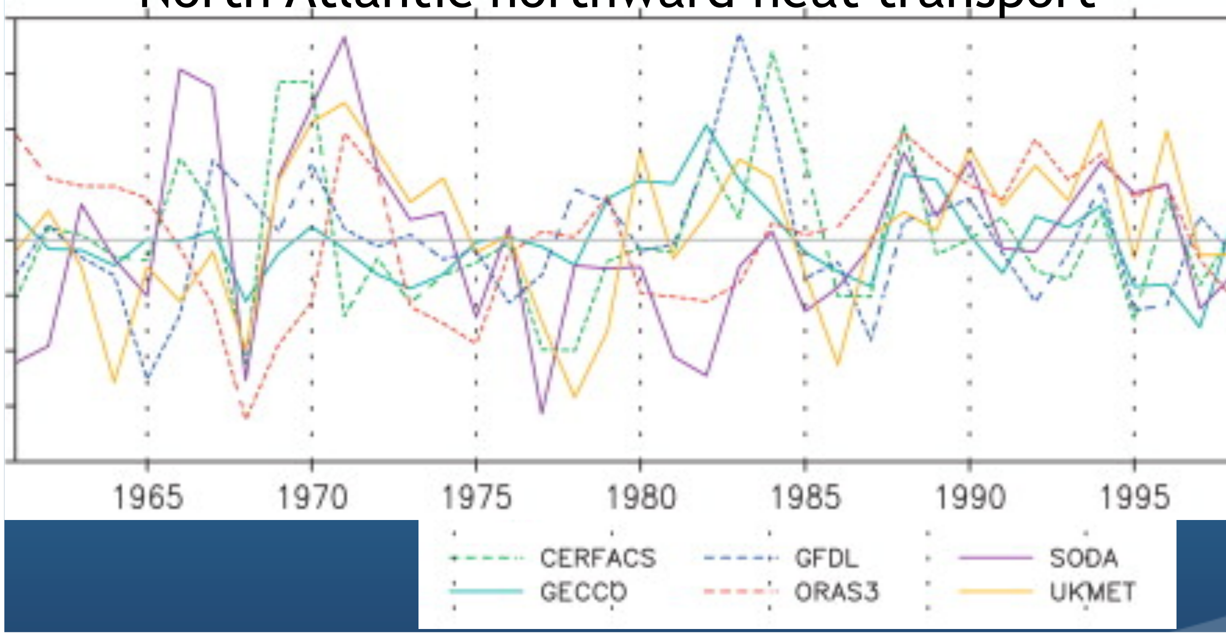
Karspeck et al 2015 Clim Dyn

North Atlantic sea surface temperature



Historical estimates of the ocean agree on some variables (like SST)

North Atlantic northward heat transport



…but are not in agreement for unobserved quantities

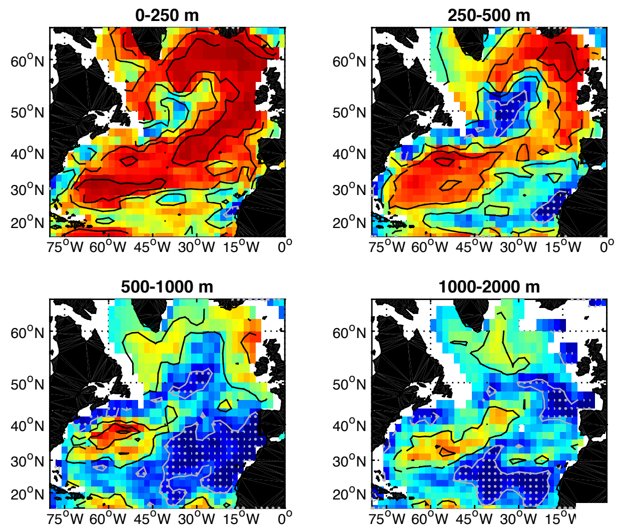
Munoz et al 2011

Hydrographic similarities*

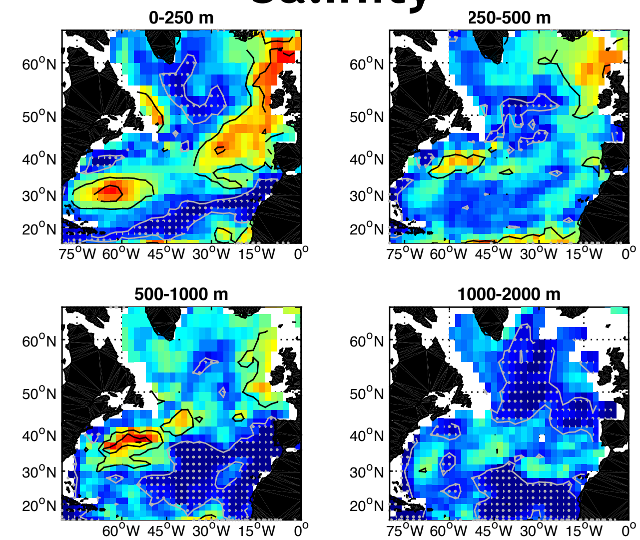
Upper 500 m

500-2000 m

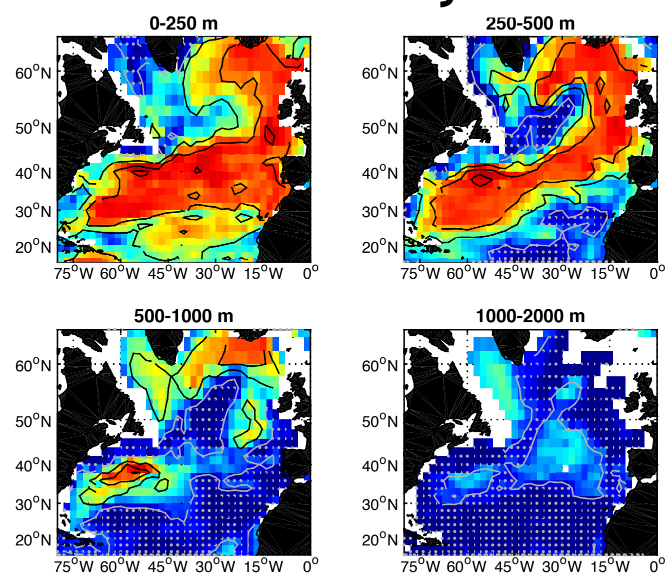
Temp



Salinity



Density

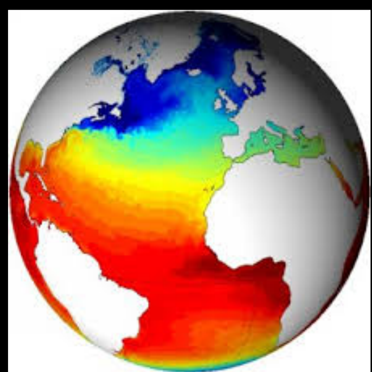


Karspeck et al 2015

*measured by average model-model correlation

The ingredients for a challenging problem:

AN IMPERFECT OCEAN MODEL



A SUBOPTIMAL DA METHOD

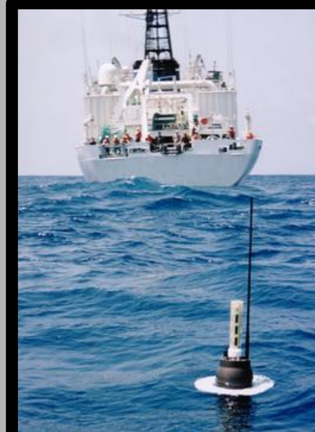
$$
\begin{aligned}
\tilde{\mathbf{y}}_k &= \mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_{k|k-1} \\
\mathbf{S}_k &= \mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k^T + \mathbf{R}_k \\
\mathbf{K}_k &= \mathbf{P}_{k|k-1}\mathbf{H}_k^T\mathbf{S}_k^{-1} \\
\hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k\tilde{\mathbf{y}}_k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

Linear/Gaussian assumption

Misspecified error

(adjoint imperfect,
costly iterations)

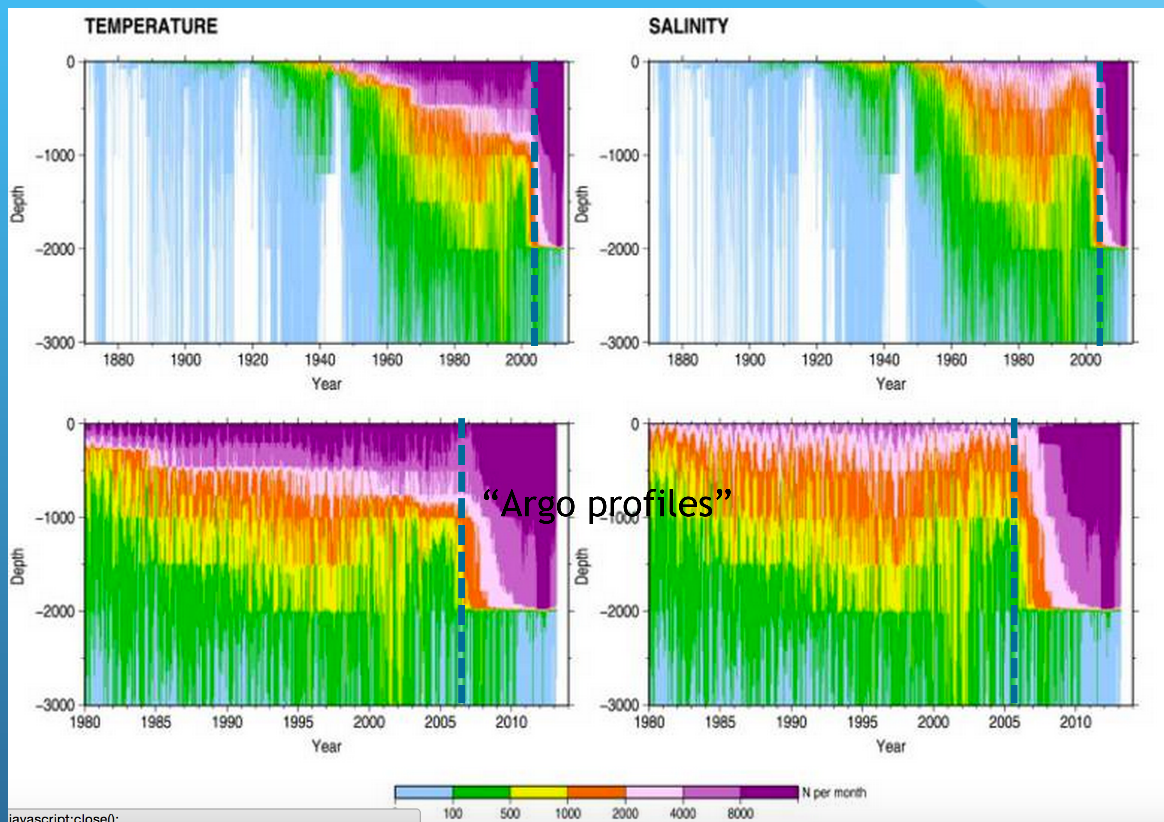
OBSERVATIONS



Sparse

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

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.

Thinking about the path forward

My view on a path forward in the face of Initialization "difficulties"

Re : No consensus on the historical state of the global ocean

My Assertions:

- *There is nothing that can be done about our lack of information in the past (and the near-term future)*
- *There is nothing inherently wrong with diversity of models, diversity of DA methods and the resultant diversity of solutions*
- *Like model development, DA R&D is a long-term endeavor with long-term payoff*

Path forward:

→ **Embrace the Uncertainty**, forming prediction ensembles that use multiple ocean reanalyses for initialization (multi-model archives do this naturally)

→ *Focus on **the observing networks of the future**… from the global ocean DA perspective, **should be "cheap, noisy, ubiquitous and sustainable"***

→ Invest in ocean DA systems with realistic expectations and a long-term view

My view on a path forward in the face of Initialization "difficulties"

Re : Best strategies for initializing models are unclear

My Assertions:

- *It is the nature of the decadal prediction problem that our effective sample size is too low (right now) to detect small modifications in skill*
- *The benefit of of using advanced ocean DA systems will become more evident as samples increase and models improve*
- *Performance of real-time forecasts is the only true measure of progress*

Path forward:

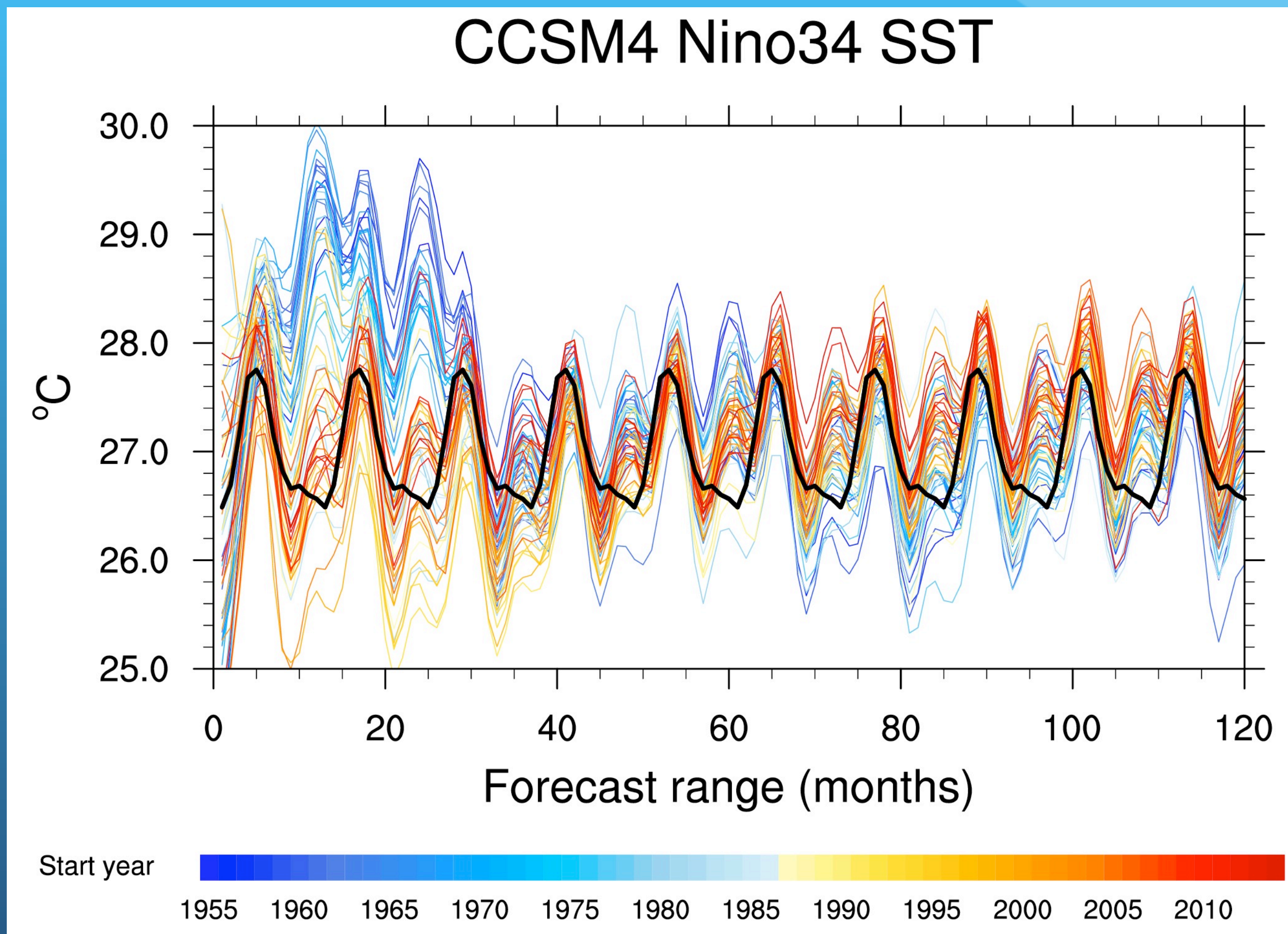
→ Long-term archives of real-time forecasts are essential (e.g. IRI seasonal prediction repository, the NMME, the Decadal Prediction Exchange)

→ Archives should contain initialization states (could involve coordinated archives with the ORAIP)

→ Keep advanced ocean DA in the mix of initialization methods!

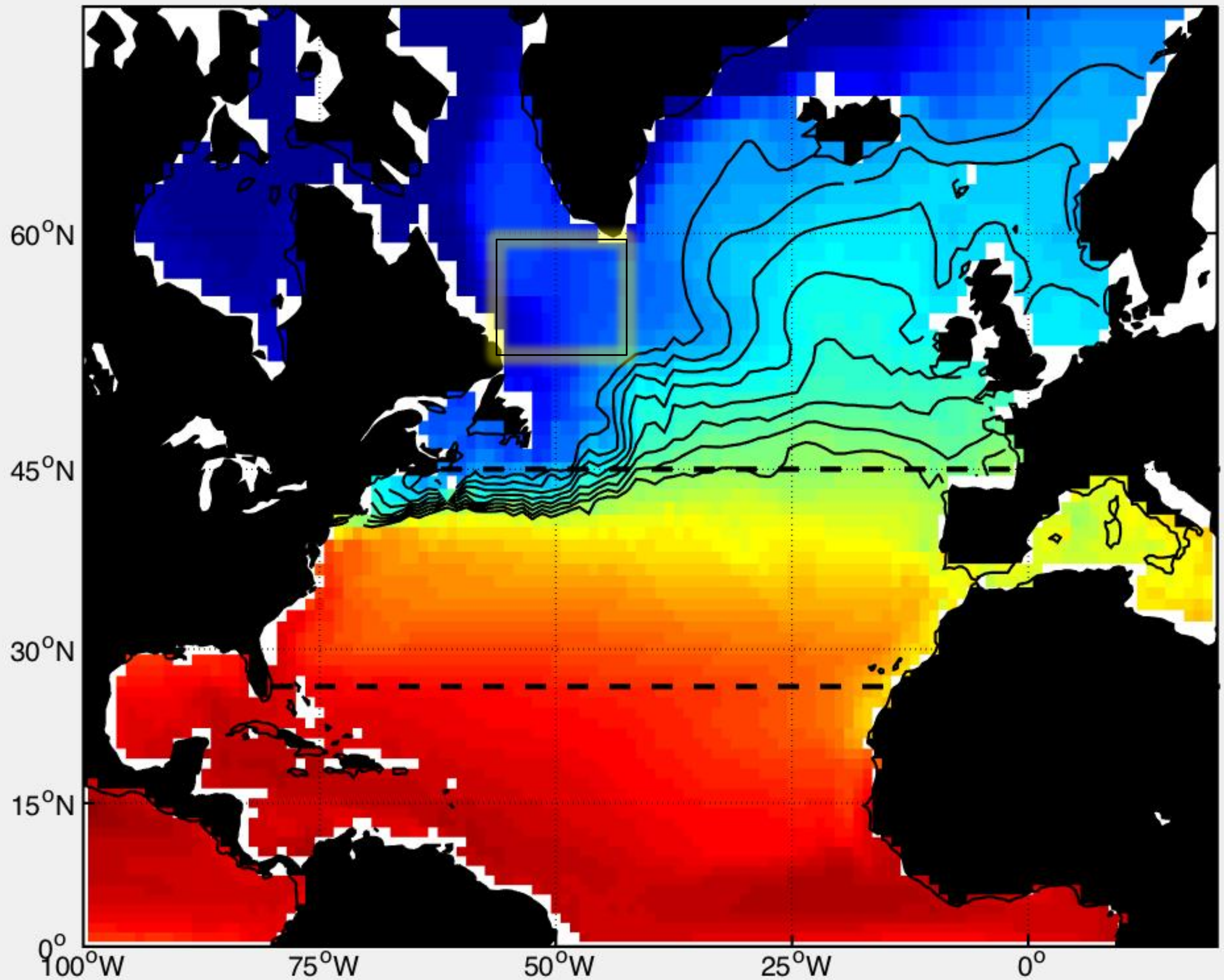
END

Spurious excitation of El Nino events in start dates from mid 1950’s to the mid 1970’s



Plot courtesy of Haiyan Teng

A possible influence: Labrador Sea

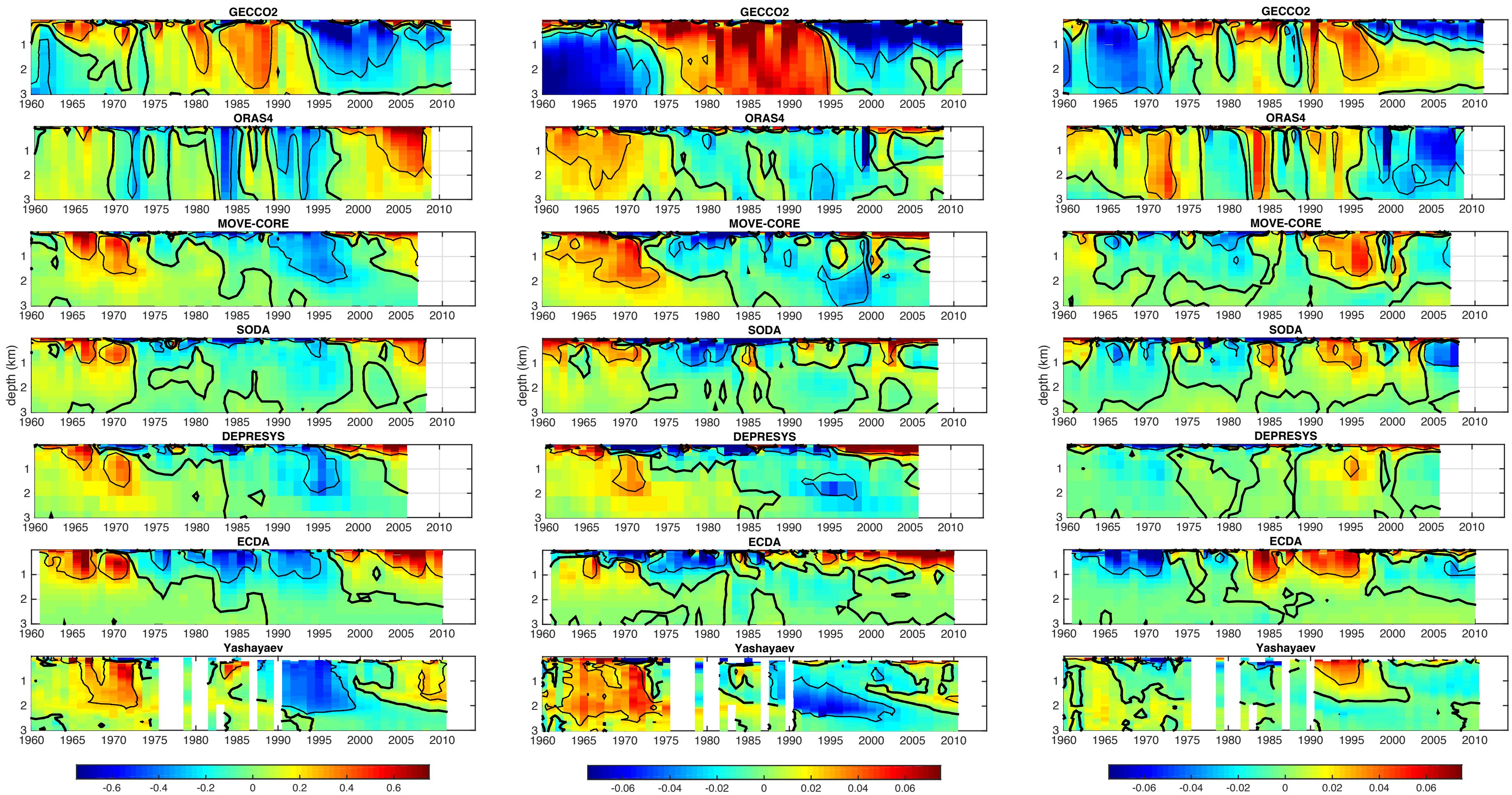


Hydrography in the Labrador Sea

Temp

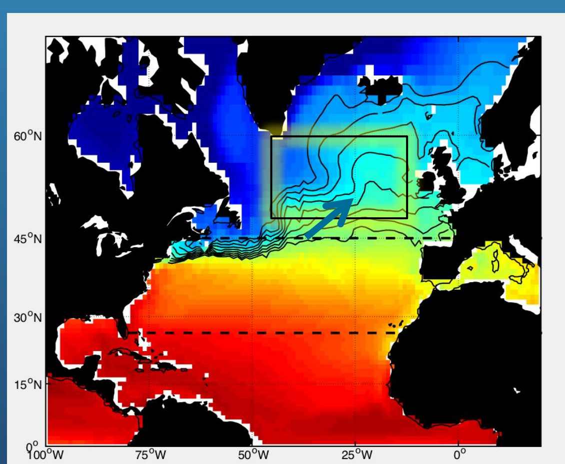
Salinity

Density



AMOC and the initialization of decadal prediction

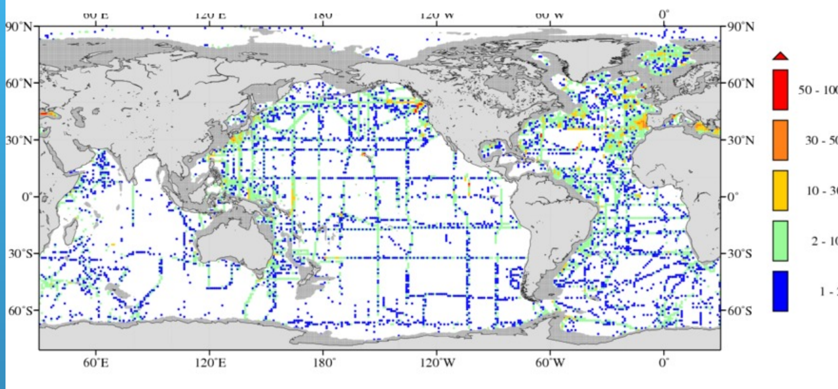
- The AMOC state upon initialization has been cited an important influence on **decadal-scale climate prediction** in the North Atlantic (specifically the subpolar gyre). (Robson et al 2012; Yeager et al 2012, Matei et al 2012; Msadek et al 2014)
- In the context of decadal climate prediction --- An anomalous AMOC is invoked as a reasonable "proxy" for an anomalous net heat transport by the ocean into the subpolar gyre.



$$\mathbf{[vT]'} = \underline{v}T' + \mathbf{v'\underline{T}} + v'T'$$

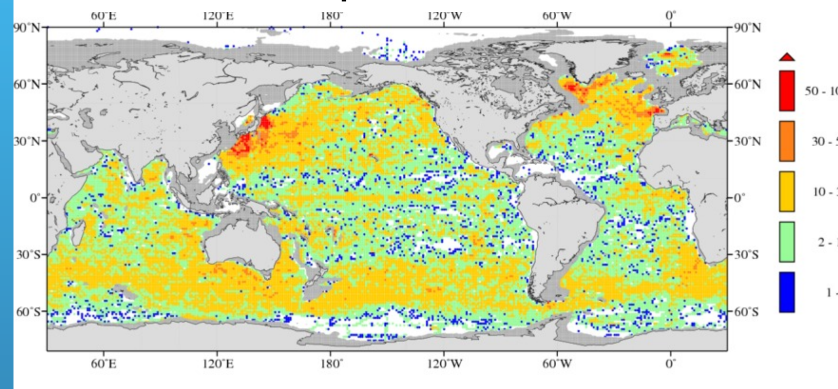
In-situ hydrographic observations

TEMP-1700m 1980's/1990's



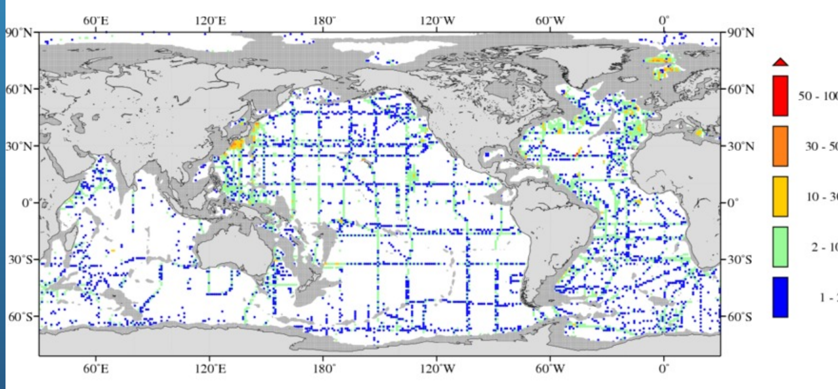
Annual temperature observations at 1700 m. depth (one-degree grid)

TEMP-1700 m present



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

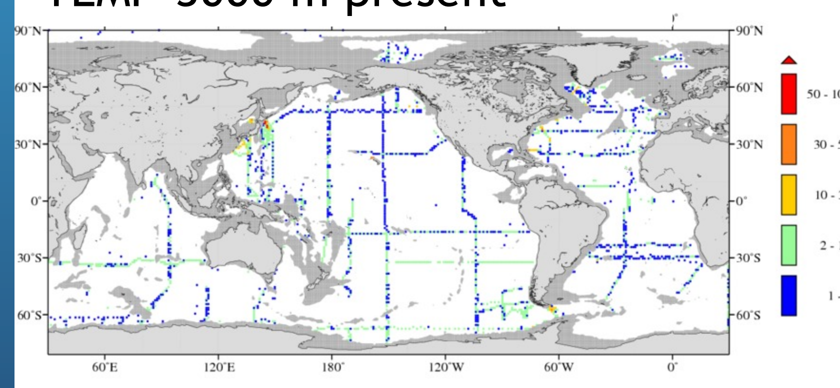
TEMP-3000 m 1980's/1990's



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

World Ocean Atlas Climatology

TEMP-3000 m present

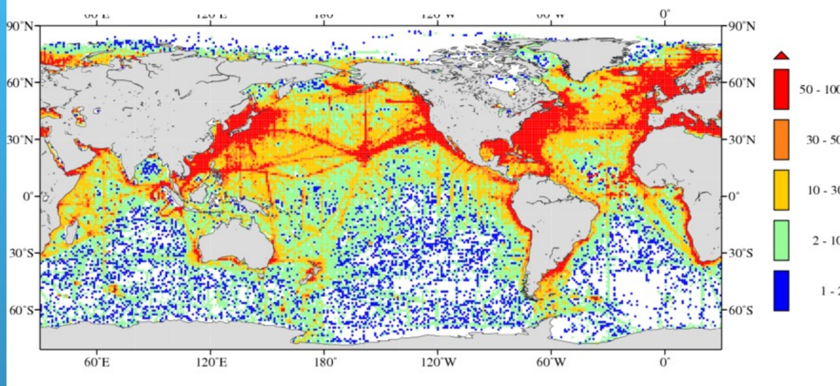


Annual temperature observations at 3000 m. depth (one-degree grid)

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

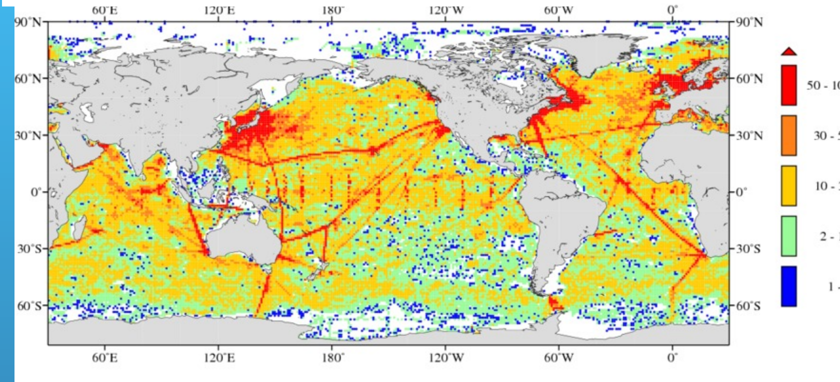
In-situ hydrographic observations

TEMP-SURFACE 1960's



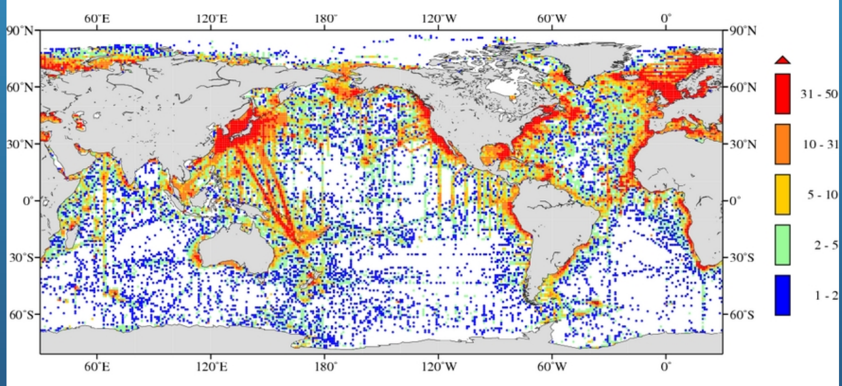
Annual temperature observations at the surface (one-degree grid)

TEMP-SURFACE present



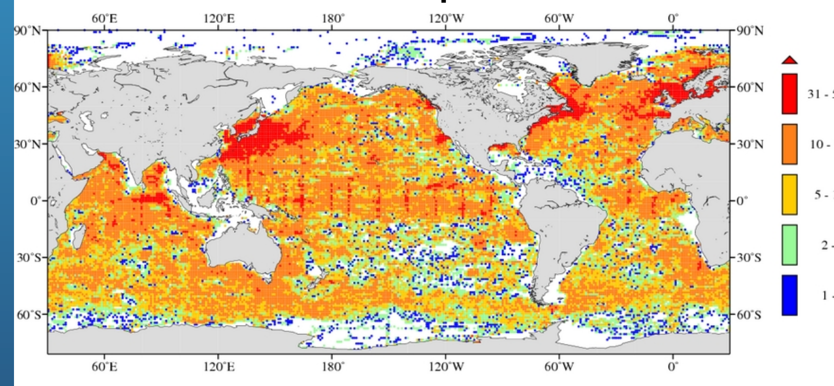
Annual temperature observations at the surface (one-degree grid)

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

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 →

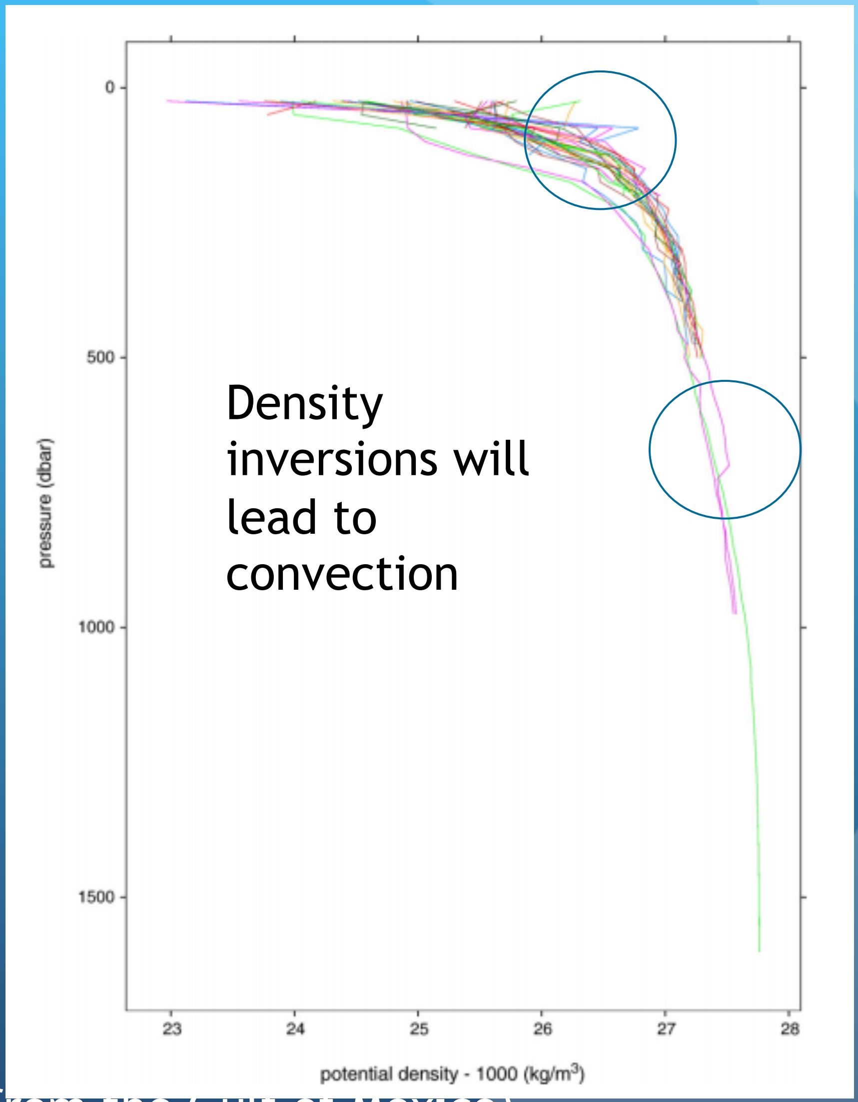
The dynamics of the model are extremely sensitive to the prescribed or modeled prior covariance between T and S

At best, misspecification can lead to spurious currents…

A fundamental challenge:

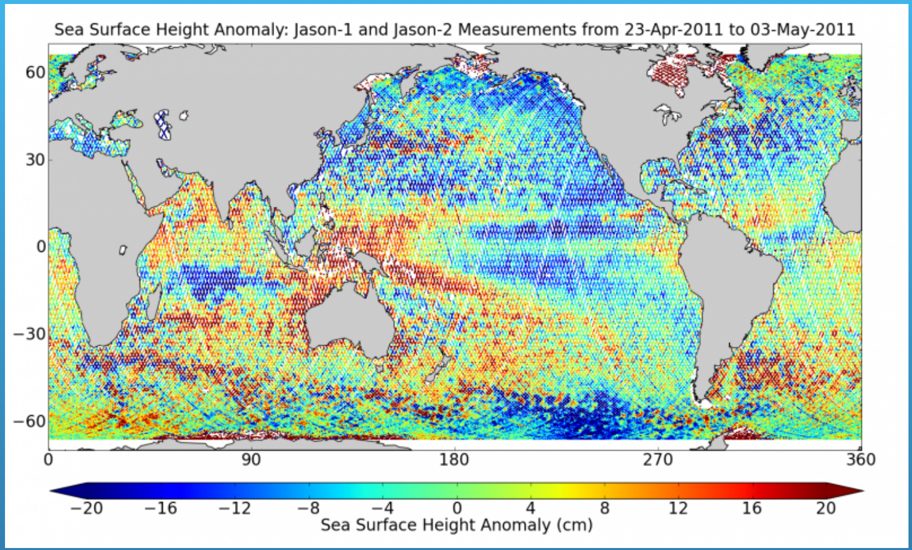
Worse, density inversions, spurious convection and numerical failure of the model (“blow up”)

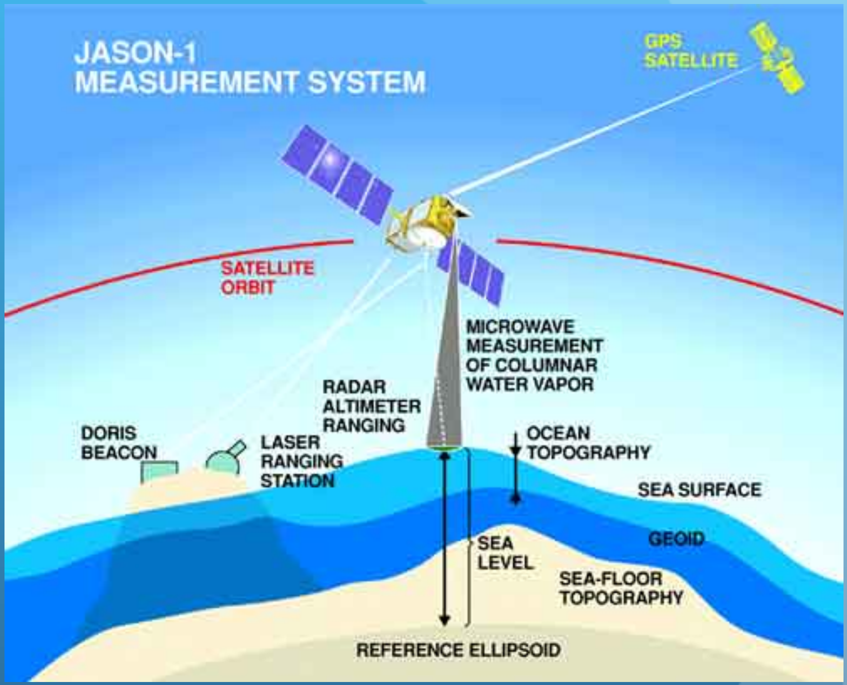
[… a vivid reminder that the ocean is non-linear/ non-Gaussian]



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:

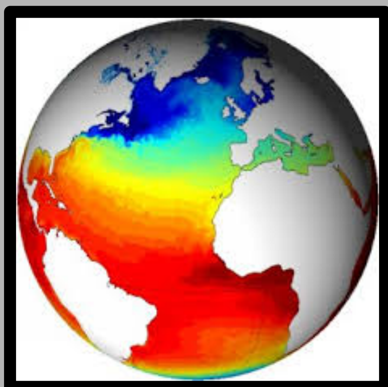
There is no unique distribution of T/S over the water column for an observation of sea level.

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

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

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

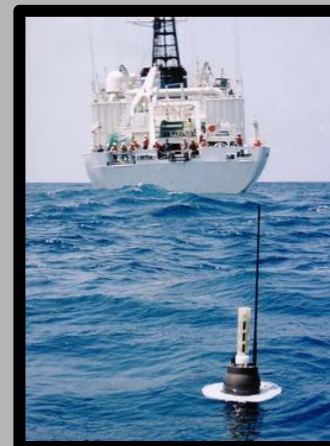
Linear/Gaussian assumption violated

Misspecified error characteristics

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

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

OBSERVATIONS



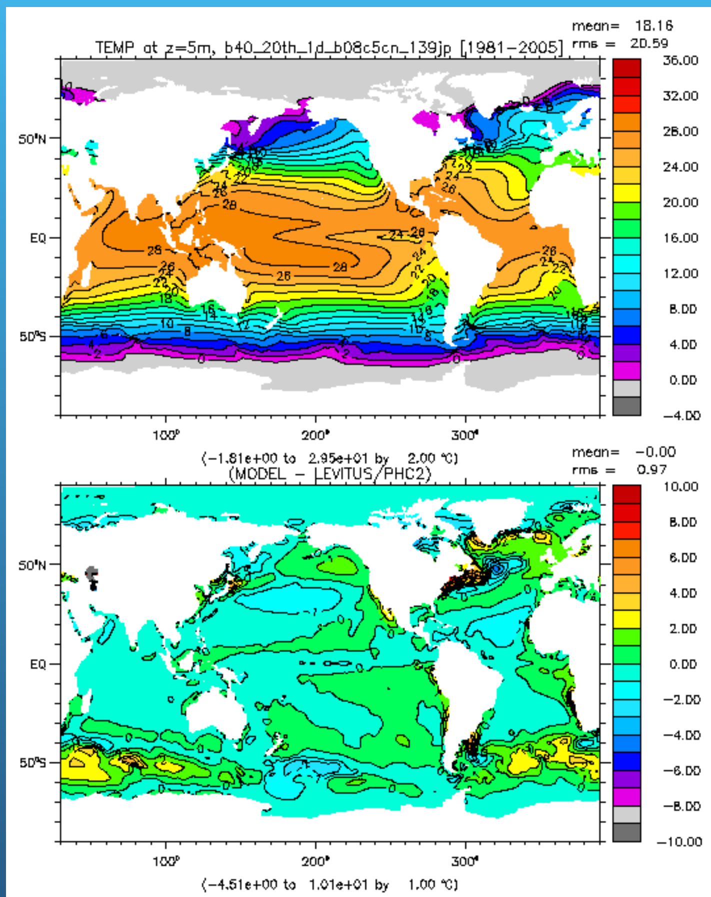
Sparse

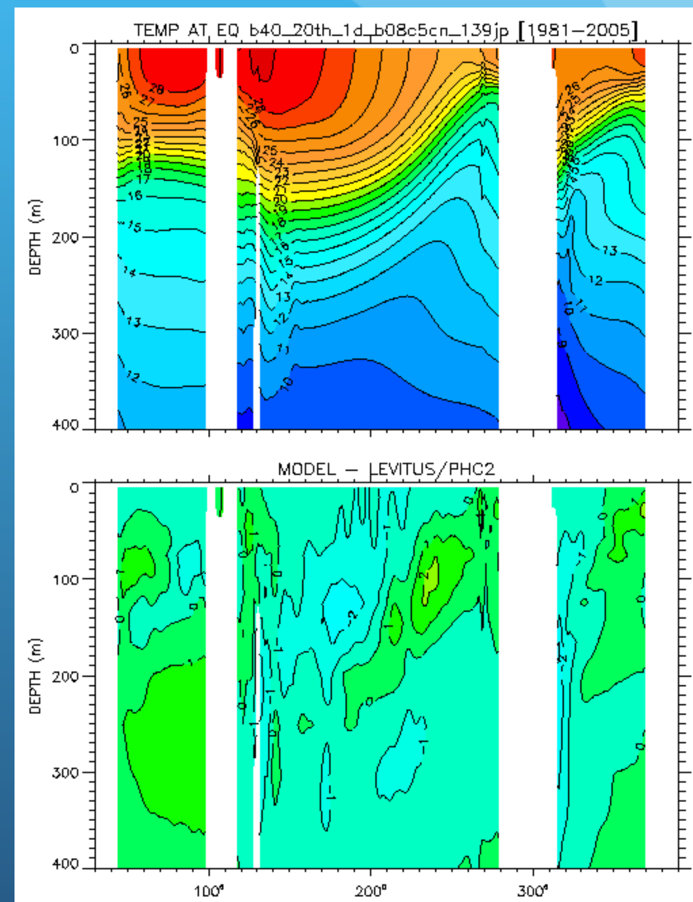
Inhomogeneous

Changing in time

Imperfect models – systematic bias

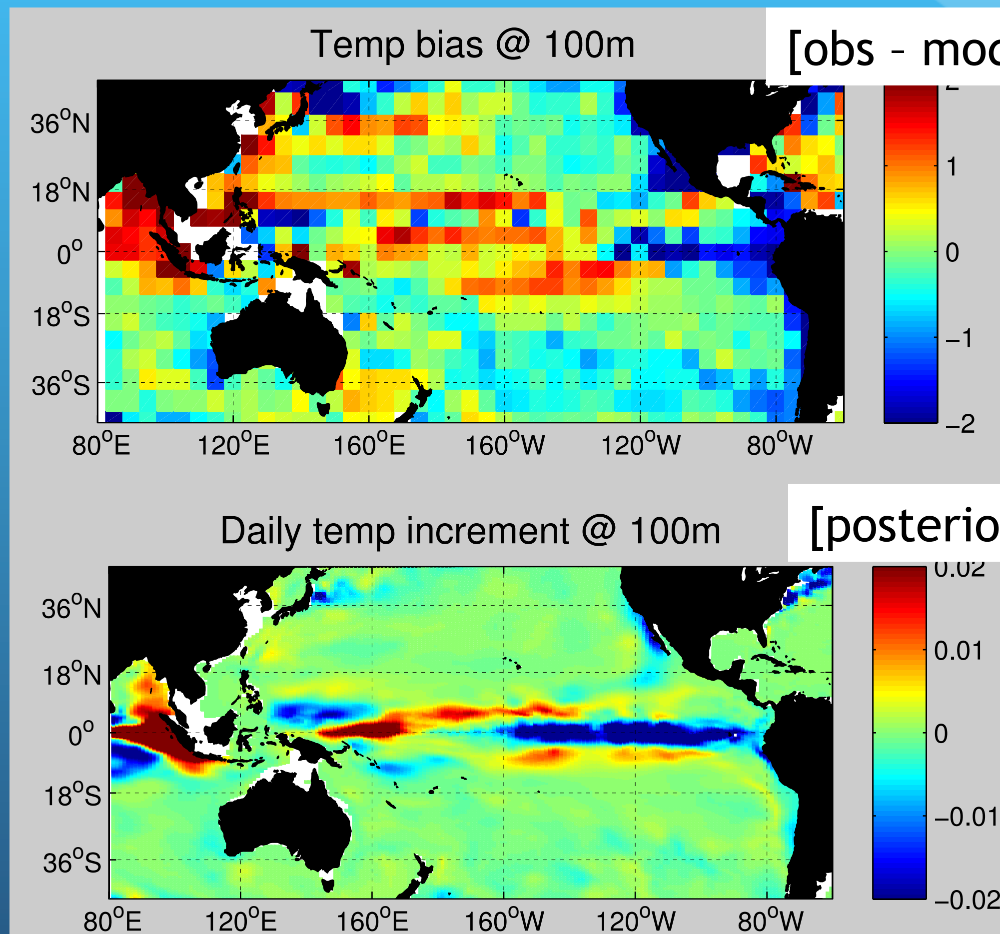
"… all models are wrong, but some are useful"
George Box, Statistician





Ocean models have very strong systematic biases

systematic bias ->
systematic increments in the DA scheme

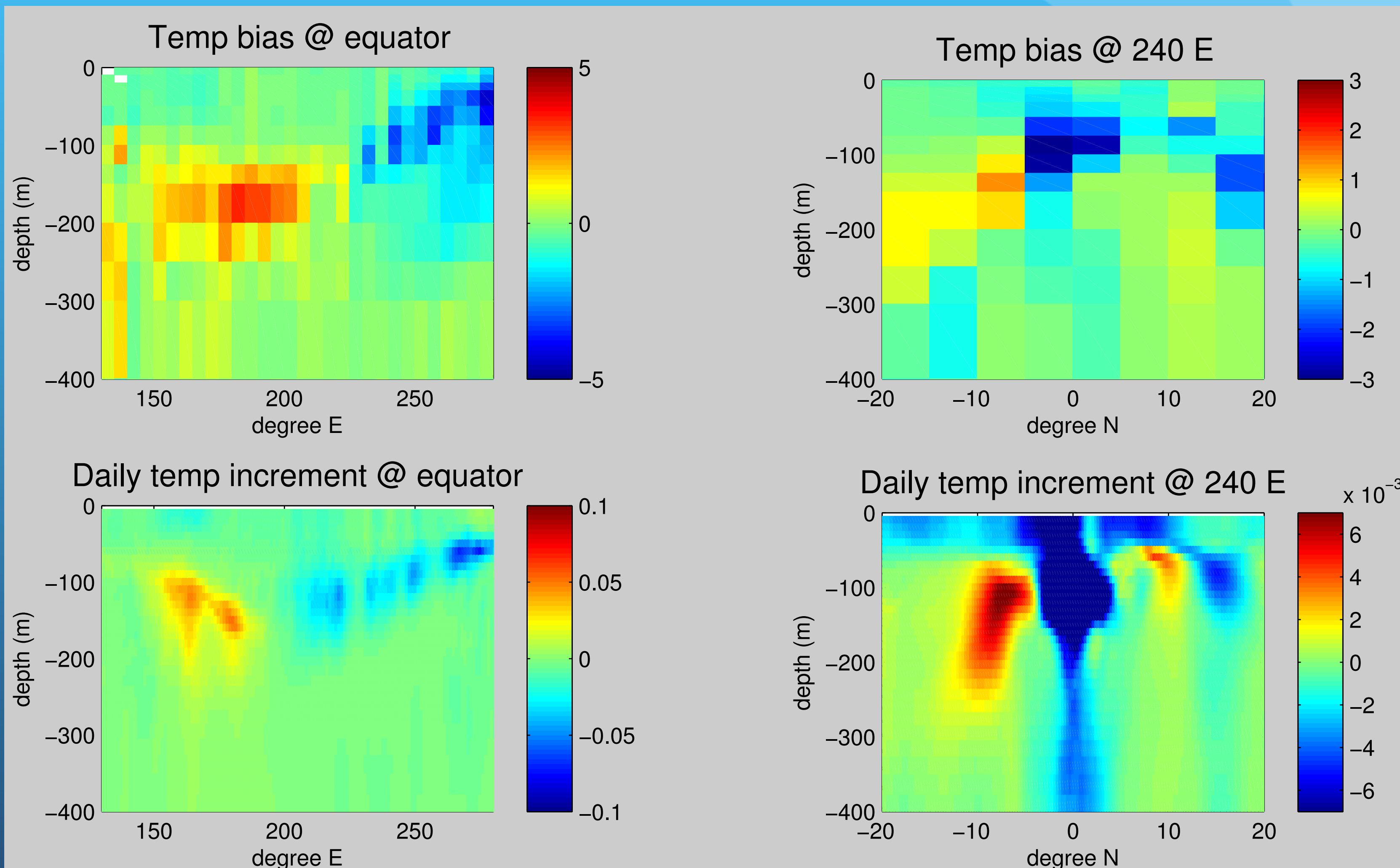


[obs – model, no assimilation]

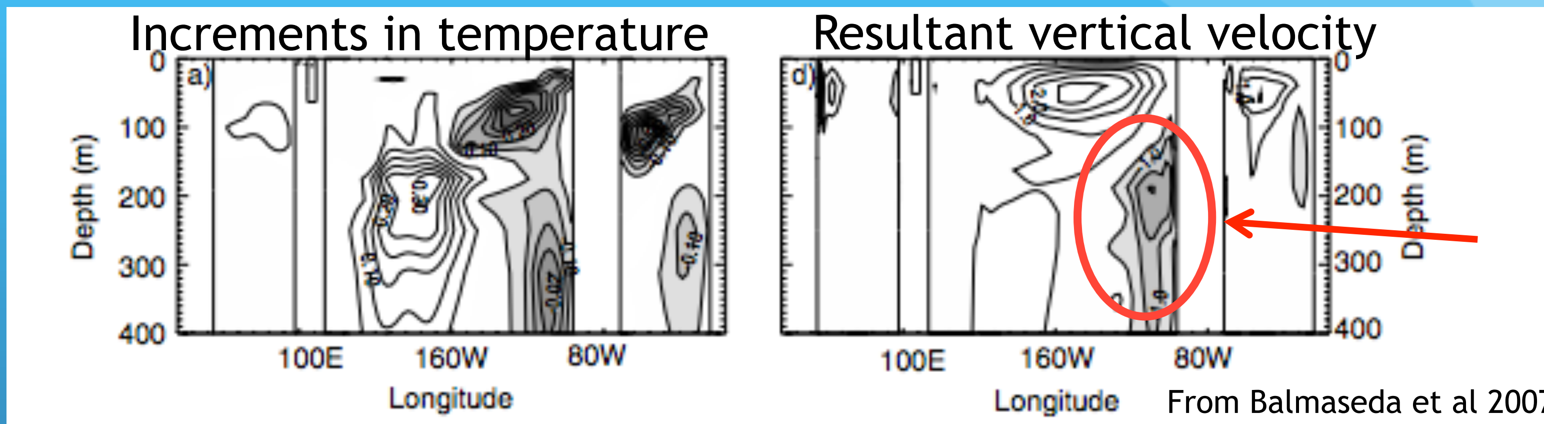
[posterior-prior, 1 day forecast]

Example from the POP1x1 global ocean model with EaKF assimilation

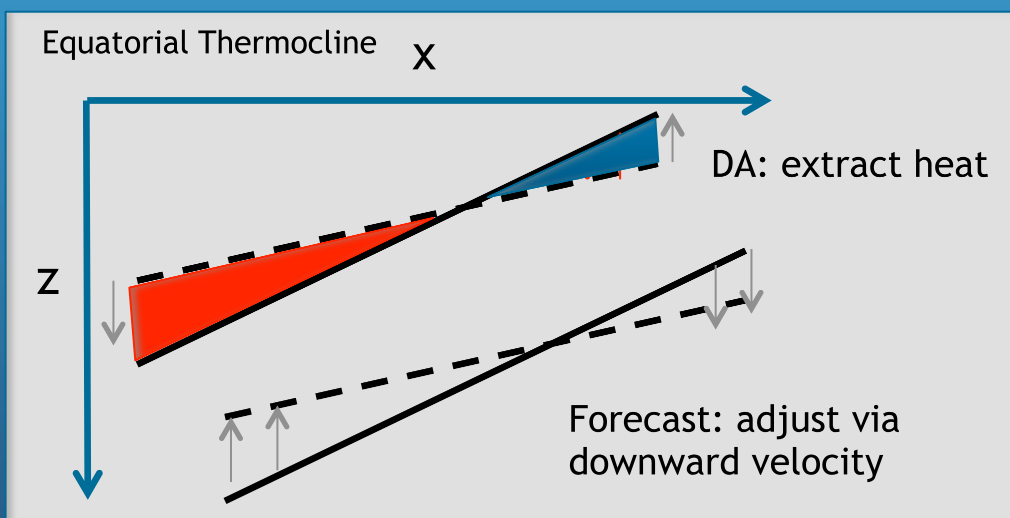
systematic bias ->
systematic increments in the DA scheme



Consequences of systematic increments in the DA scheme



From Balmaseda et al 2007



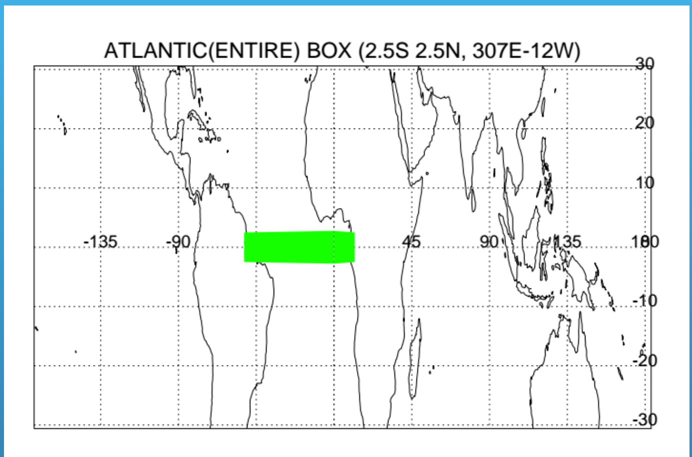
DA increment the density so as to sharpen and steepen the slope of the thermocline

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.

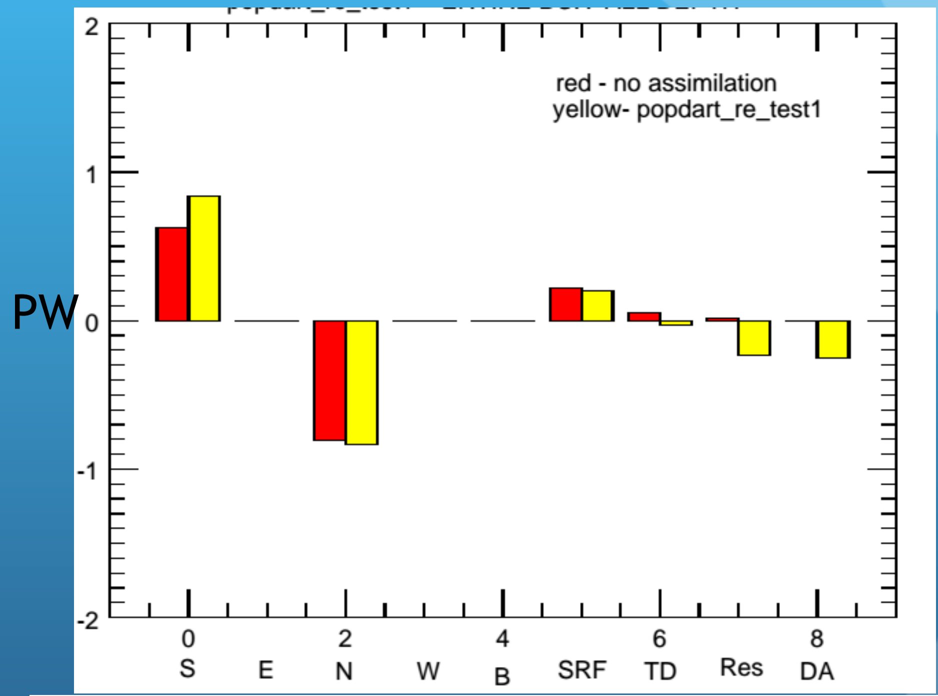
This idea was first considered by Burgers et al 2002, Bell et al 2002,2004.

Consequences of systematic increments in the DA scheme



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

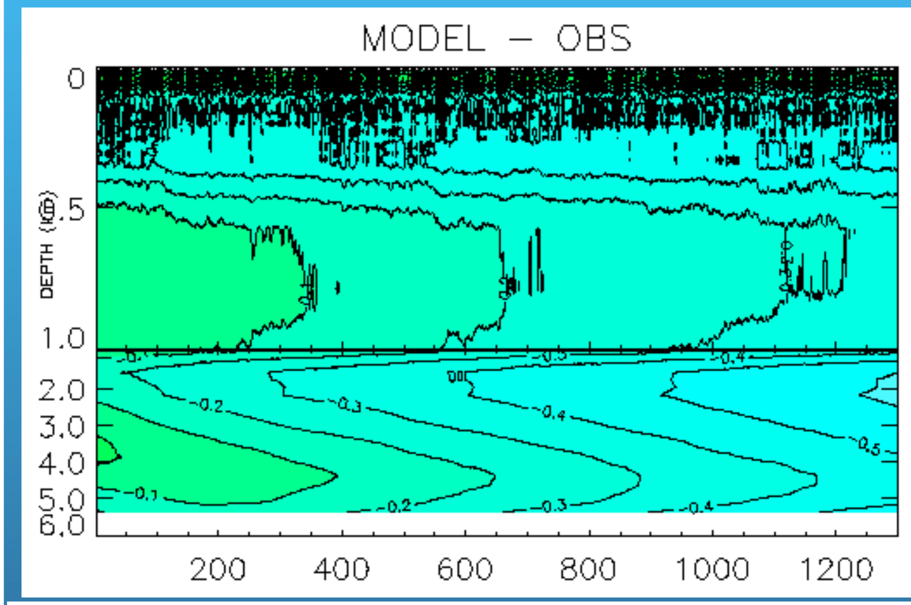
Heat budget in the equatorial Atlantic



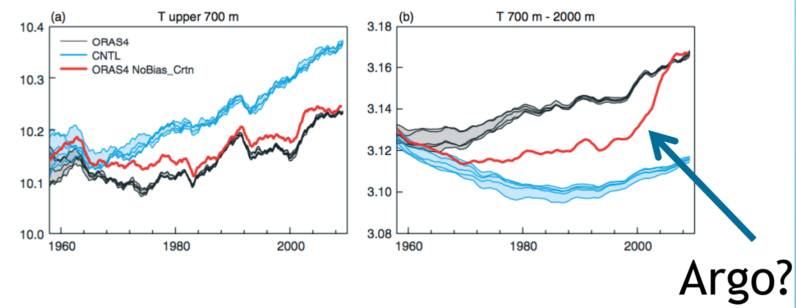
In this example, the systematic extraction of heat by the DA system changes the heat budget, increasing the net import of heat across the southern boundary

Plots from S. Karol

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



The CESM model drifting over 1400 years



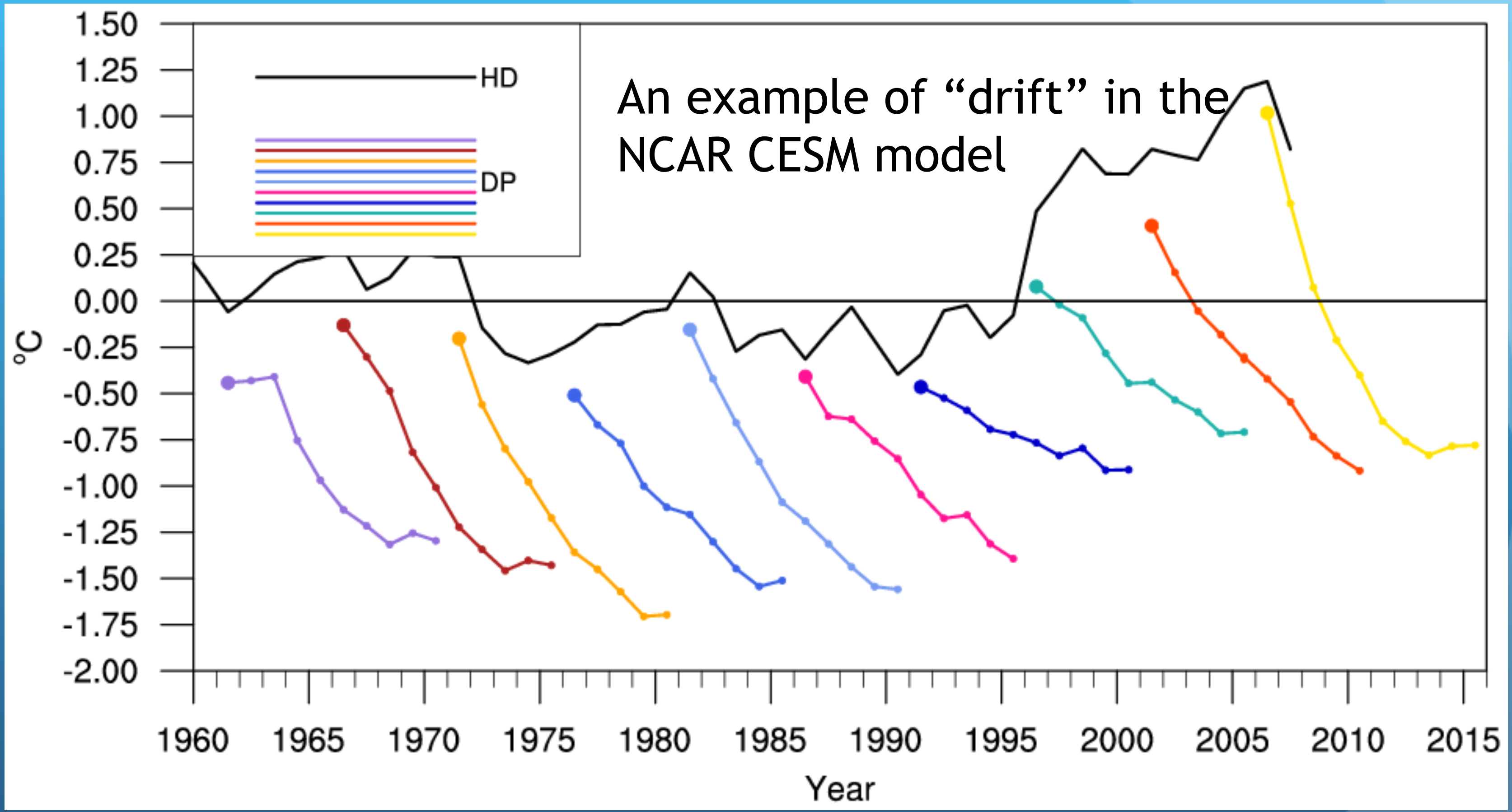
Blue: forced ocean model
Red: DA but no bias correction
Black: DA and bias correction

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?

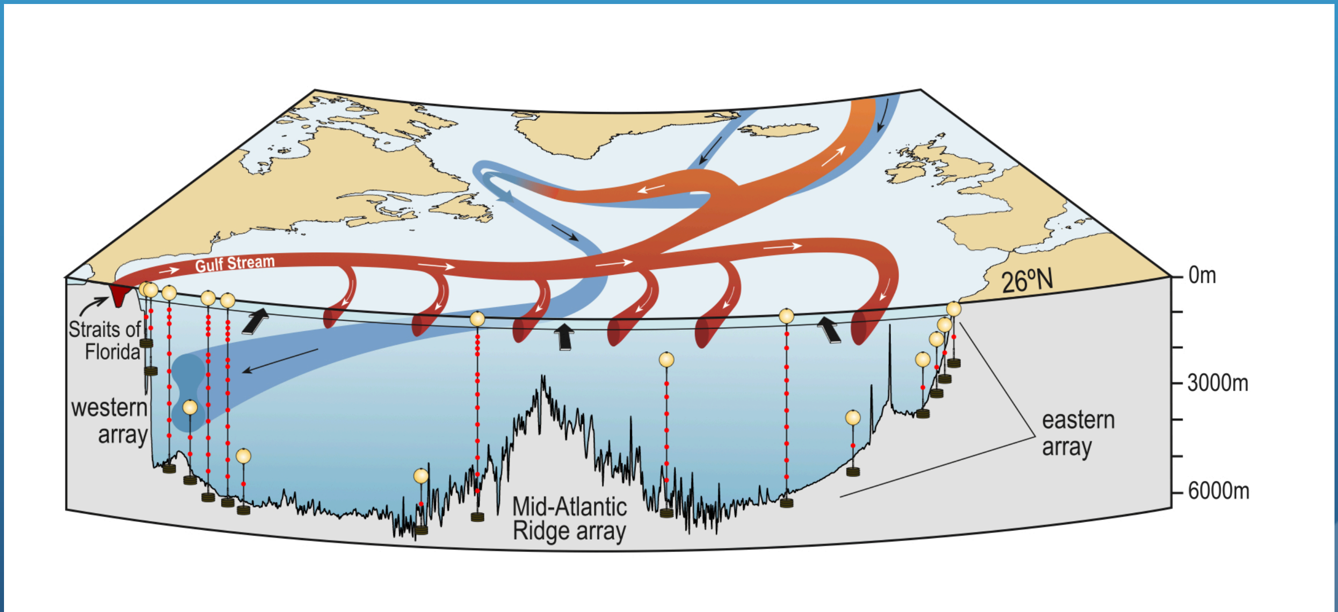
What happens when you use a biased model for forecasting?



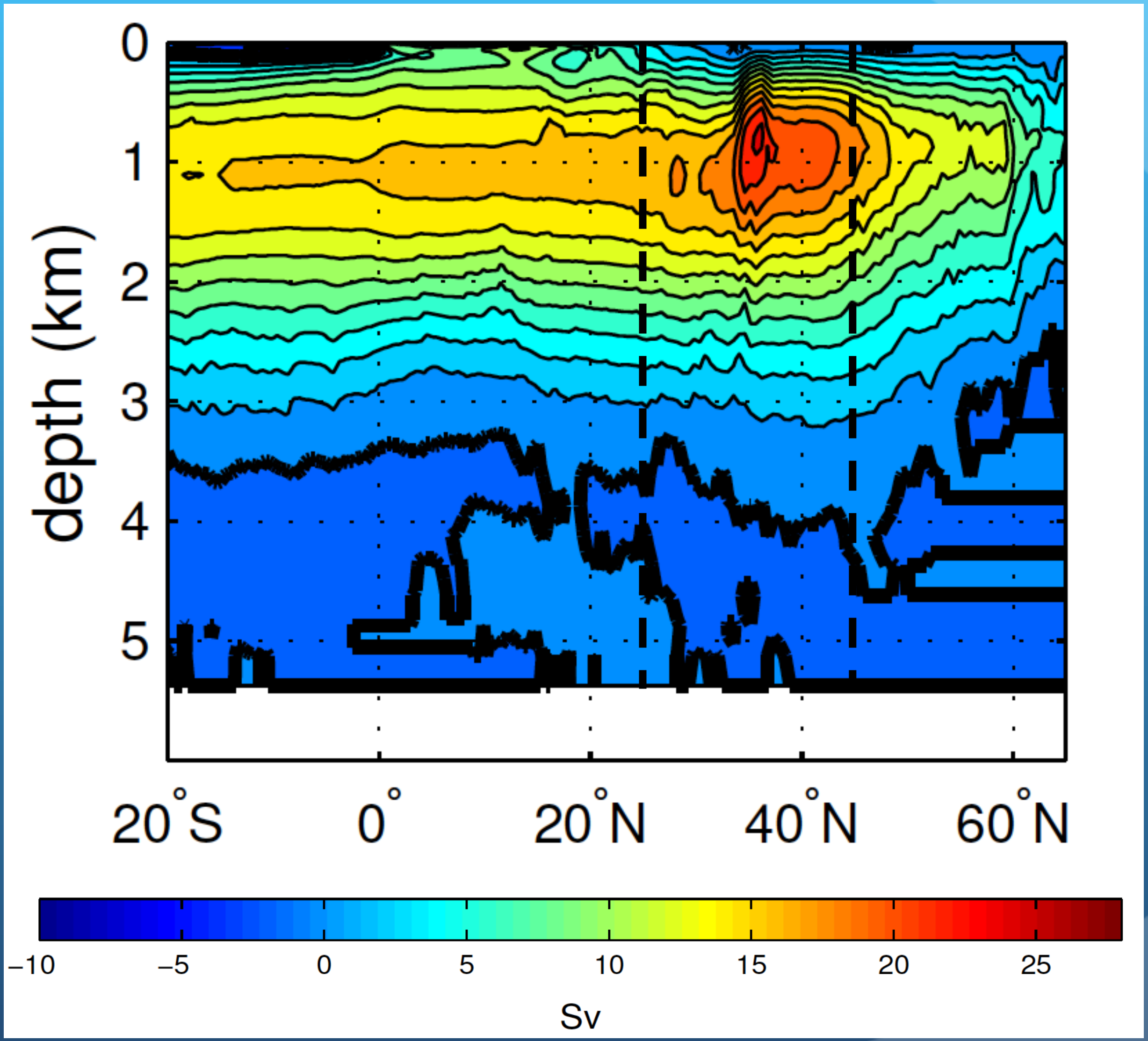
Surface temperature in the North Atlantic systematically cooling during the decade of prediction

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

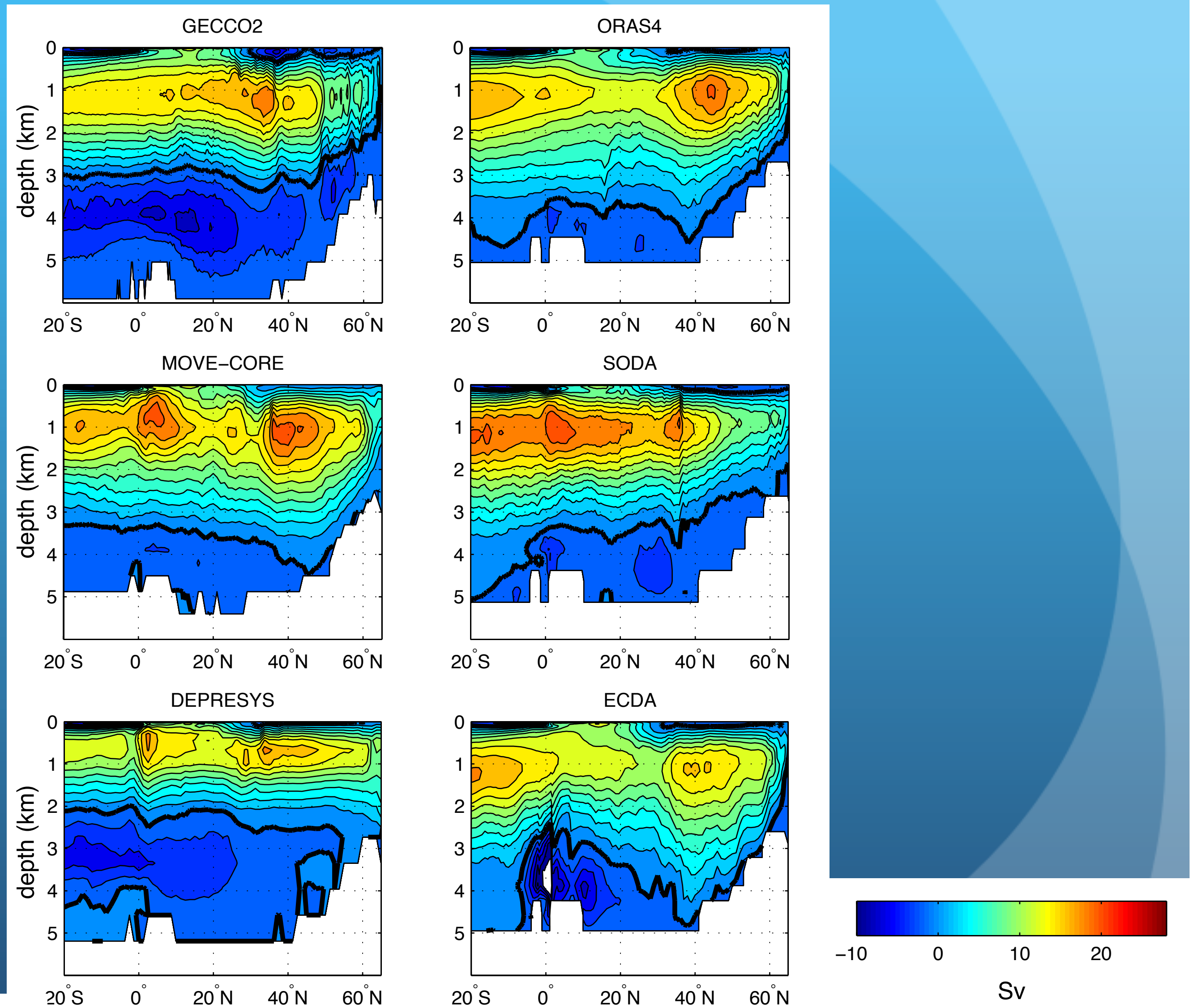


Groups that have contributed AMOC reanalyses

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)