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

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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

\[ \tilde{y}_k = z_k - H_k \hat{x}_{k|k-1} \]
\[ S_k = H_k P_{k|k-1} H_k^T + R_k \]
\[ K_k = P_{k|k-1} H_k^T S_k^{-1} \]
\[ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \tilde{y}_k \]
\[ P_{k|k} = (I - K_k H_k) P_{k|k-1} \]

Linear/Gaussian assumption
Misspecified error characteristics

OBSERVATIONS

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

Sparse

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

Typical resolution is from $\frac{1}{4}$ to 1 degree (25 to 100 km)*

Size of the state $\sim$ 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
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- Systematic biases
- Unresolved processes

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**OBSERVATIONS**
- Sparse
- Inhomogeneous
- Changing in time

**A SUBOPTIMAL DA METHOD**

**AN IMPERFECT OCEAN MODEL**

**OBSERVATIONS**
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

Number of observations varies wildly with time/depth/location
In-situ hydrographic observations

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

TEMP-1700m 1980’s/1990’s

TEMP-1700 m present

TEMP-3000 m 1980’s/1990’s

TEMP-3000 m present
A fundamental challenge:

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

\[
\begin{align*}
    u &= -\frac{1}{f\rho} \frac{\partial}{\partial y} \int_{-z}^{0} \rho(z)dz - \frac{g}{f} \frac{\partial \eta}{\partial y} \\
    v &= \frac{1}{f\rho} \frac{\partial}{\partial x} \int_{-z}^{0} \rho(z)dz + \frac{g}{f} \frac{\partial \eta}{\partial x}
\end{align*}
\]

Density of Seawater

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

Thermal wind

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.

\[ \frac{\partial \eta}{\partial t} = \frac{\partial_t (p_b - p_a)}{g \rho(\eta)} - \frac{1}{\rho(\eta)} \int_{-H}^{\eta} \frac{\partial \rho}{\partial t} \, dz \]

mass contribution  \quad 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.
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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

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

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

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.

From Balmaseda et al 2007

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?

+ 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?

From Balmaseda et al 2013

The CESM model drifting over 1400 years

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

Argo?
What happens when you use a biased model for forecasting?

An example of “drift” in the NCAR CESM model

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)
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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
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

std of temperature errors at 100m

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)

<table>
<thead>
<tr>
<th>GROUP</th>
<th>METHOD</th>
<th>INSITU T/S</th>
<th>ALT</th>
<th>SST</th>
<th>NoAssim Control run?</th>
<th>Atm forcing</th>
<th>DP INIT?</th>
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<tbody>
<tr>
<td>GECCO2 (U. Hamburg)</td>
<td>4DVAR</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>[NCEP]*</td>
<td>YES</td>
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<tr>
<td>ORAS4 (ECMWF)</td>
<td>NEMOVAR 3DVar</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>ERA-40/ERA-I</td>
<td>YES</td>
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<tr>
<td>MOVE-CORE (MRI)</td>
<td>3DVar</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
<td>CORE II IAF</td>
<td>[NO]</td>
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<tr>
<td>SODA (U.Maryln/TAMU)</td>
<td>OI</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
<td>20-CR</td>
<td>YES</td>
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<tr>
<td>DePreSys (UKMET)</td>
<td>Coupled nudging to OI product</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
<td>N/A</td>
<td>YES</td>
</tr>
<tr>
<td>ECDA3.2 (GFDL)</td>
<td>coupled EaKF</td>
<td>YES</td>
<td>INDIRECTLY</td>
<td>YES</td>
<td>NO</td>
<td>[NCEP]*</td>
<td>YES</td>
</tr>
</tbody>
</table>
AMOC time mean (1961-2007)

AMOC variance [std] (1961-2007)
Annual-mean AMOC variability @ 1000m

Reanalyses @ 45N

No Assimilation @ 45N

Reanalyses @ 26.5N

No Assimilation @ 26.5N

RAPID
GECCO2
ORAS4
MOVE-CORE
SODA
DEPRESYS
ECDA

RAPID-REF
ORAS4-CNTRL
MRI-CORE
SODA-NOASSIM
Hydrographic similarities*

*measured by average model-model correlation
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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 \( \rightarrow \) 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