Ocean Variability: Models, Observations, Paleoproxies, and Statistics to Glue Them Together

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Who am I?

- Primarily, my group works on process parameterizations for climate models, particularly ocean processes.
- We work out what’s wrong or missing in those models, fix it, and then use the fixed models to quantify what’s going on in the earth system.
New understanding of ocean turbulence could improve climate models

February 26, 2018  Media contact: Kevin Stacey
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Researchers have developed a new statistical understanding of how turbulent flows called mesoscale eddies dissipate their energy, which could be helpful in creating better ocean and climate models.

PROVIDENCE, R.I. [Brown University] — Brown University researchers have made a key insight into how high-resolution ocean models simulate the dissipation of turbulence in the global ocean. Their research, published in Physical Review Letters, could be helpful in developing new climate models that better capture ocean dynamics.

I am going to explain a bit of this process, and show interesting cases where statistics comes into play.

First, we need to understand a bit about ocean variability and model resolution.
Weather, Atmosphere

Fast

Ocean, Climate

Slow

3.4m of ocean water has same heat capacity as the WHOLE atmosphere

ECCO Movie: Chris Henze, NASA Ames
3.4m of ocean water has same heat capacity as the WHOLE atmosphere.

ECCO Movie: Chris Henze, NASA Ames
We are modeling important processes in climate models, right? Don’t we have big enough computers?

Here are the collection of IPCC models...

If we can’t resolve a process, we need to develop a parameterization or subgrid model of its effect.
What about modeling important processes in climate models? Don’t we have big enough computers? or won’t we soon?

Here are the collection of IPCC models...

If we can’t resolve a process, we need to develop a parameterization or subgrid model of its effect.
200km x 600km x 700m domain

1000 Day Simulation

What about modeling important processes in climate models? Don’t we have big enough computers? or won’t we soon?

Here are the collection of IPCC models...

If we can’t resolve a process, we need to develop a parameterization or subgrid model of its effect.
20km x 20km x 150m domain

10 Day Simulation

Climate Model Resolution: an issue for centuries to come!

Resolution of Ocean Component of Coupled IPCC models

Here are the collection of IPCC models...

If we can't resolve a process, we need to develop a parameterization or subgrid model of its effect

3m = 1 office/grid
20km x 20km x 150m domain
10 Day Simulation

1km x 1km x 40m sub-domain
about 1 day shown

Colors=Temp.
Surfaces on Large w

In the face of all of this model ocean & climate variability, how do we know if we’re doing it right?

- **Presence** of observable variability
- **Understanding** of past variability
- **Modeling** of variability
- **Prediction** of variability

All of these vary strongly by scale & process!
Observable: What do hydrographic observations show?

Ocean Heat Content not fixed: $Q_{BML}$ not zero (it even varies)!  
28% of anthropogenic forcing equals the warming in the oceans and about 70% goes back to space.

90% of anomalous warming is in the oceans.

0.7 W/m$^2$ to atmosphere only is about 1.5K/yr

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Trad. Hydrography

![Diagram showing upper ocean heat storage in 1993-2008 and 2005-2010]

From the Argo Era

![Diagram showing upper ocean heat storage in 1993-2008 and 2005-2010]

Hansen et al. (2011)
How do we know OHC?

Traditional Hydrography ([http://www.ukosnap.org/](http://www.ukosnap.org/))

Autonomous: e.g., Argo and Satellites. [http://www.argo.ucsd.edu/](http://www.argo.ucsd.edu/)

GO-SHIP repeat sections: Siedler et al. 2013

Argo floats presently active
Understanding: Another reason to care about ocean warming—and to observe it (by subtraction): Sea Level Rise

\[
\text{Sea Level Rise} \quad \text{(Sea Level)} - \frac{\text{Ocean Mass}}{\text{Density} \times \text{Area}} = \text{Thermosteric Expansion}
\]

IPCC AR5, 2013

nesdis.noaa.gov

podaac.jpl.nasa.gov
Modeling: Surface Energy Budget

Category A) \( T \) change caused by forced \( Q_{TOA} \)

Category B) \( T \) change caused by unforced \( Q_{TOA} \)

Category C) \( T \) change caused by unforced \( Q_{BML} \)

\[
\frac{dT}{dt} = \frac{Q_{net}}{C_m} = \frac{-Q_{TOA} + Q_{BML}}{C_m}
\]

\( O(2W/m^2) \) change to \( Q_{BML} \) as important as GHG

Slight oversimplification—sensitivity + budget

Slide: Brown et al., 2014
Beginning December 1949, a weathership or mooring at Ocean Station P (50°N, 145°W, depth 4220 meters)
The net $Q_{BML}$ is about 1% of different flux components and 1% of net spatial values: spatial & process sampling.

Sophisticated analysis to overcome Ship & Argo sampling problems—inhomogeneous uncertainty, $O(0.2 \text{W/m}^2)$, on interannual to decadal timescales in global average. $O(10 \text{W/m}^2)$ without analysis.

Modeling: Surface Energy Budget

Category A) T change caused by forced $Q_{TOA}$

Category B) T change caused by unforced $Q_{TOA}$

Category C) T change caused by unforced $Q_{BML}$

$dT \over dt = Q_{net} \over C_m = -Q_{TOA} + Q_{BML} \over C_m$

$Q_{TOA} = RSW + OLR - ISW$

Slide: Brown et al., 2014

$O(2W/m^2)$ change to $Q_{BML}$ as important as GHG

Slight oversimplification—sensitivity + budget
Global climate models do pretty well at matching heat fluxes and watermasses.

Statistically significant differences in a few timescales & regions from obs. (Ticks=10 W/m²)

Models get better every generation due to improved resolution and parameterizations.

Sampling & accuracy are issues: now what?

- We expect that observations will be understood as sampling from distributions of possible values.

- Models also produce distributions.

- We compare the distributions to see when the model succeeds or fails.

- But, different processes have different stats!

- 2 Examples: Ocean Heat Content & El Nino
A stochastic, predictable persistence model: Frankignoul & Hasselmann (77)

\[ \frac{dT}{dt} = \frac{f_1'}{h} - \lambda T \]

Where:
- \( f_1' \) is the restoring term
- \( h \) is the mixed layer depth

\[ \lambda = \rho^a C_p^a (\rho^w C_p^w)^{-1} C_H (1 + B) \langle |U| \rangle h^{-1} \]

\[ \approx (1.7 \text{ month})^{-1} \]
Consider lots of 1D Oceans: one per watermass.

Wind (Ekman) flushing gives upper limit to $\lambda^{-1}$ timescale.
If Connections Occur Between Regions—Predictability Can Arise, Even in Stochastic Systems.

Tropical Ocean Heat Content $h_{tropics}$

Polar Ocean Heat Content $h_{poles}$

This is the root of most stochastic model predictability beyond persistence.

Predictability of ENSO events limited to < 1yr

ENSO statistics more predictable?

El Niño Episode Sea Surface Temperatures
Departure from average in degrees Celsius
Dec 1982 - Feb 1983

La Niña Episode Sea Surface Temperatures
Departure from average in degrees Celsius
Dec 1998 - Feb 1999

Historical NINO3.4 Sea Surface Temperature Anomaly

Mid-Jan 2014 Plume of Model ENSO Predictions

IRI/CPC

Dynamical Model:
- NCEP CFSv2
- NASA GMAO
- JMA
- SCRIPPS
- LDEO
- AUS/POAMA
- ECMWF
- UKMO
- KMA/SNU
- ESSIC ICM
- COLA CCSR
- MeFRANCE
- CS/IRI-MM
- GFDL CM2.1
- CMC CNISM

Statistical Model:
- CPC MIRKOV
- CDC LIM
- CPC CA
- CPC CCA
- CSU CLIPR
- UBC NNNT
- FSU REGR

OBS
FORECAST

OND Dec DJF JFM FMA AMJ MJJ JJA ASO OND


NINO3.4 SST Anomaly (°C)

SSH Movie Credit: NASA JPL

Are ENSO statistics predictable?

Takes >200 yrs to know what ENSO stats are!!

Almost no change to Direct ENSO variability with GHG...

But Big GHG Change to ENSO impacts!

INDIRECT Proxy Reconstructions won’t work!!!

Covariances?

The two examples—OHC and ENSO—show that not just variability, but co-variability of different variables is interesting.

In one study, of multiple proxies in a site at 1000m depth off the Peru Margin, the co-variance story is particularly interesting.

Figure 2 Observed data for time steps 0 to 563 (0.60 to 9.44 kA B.P.), with time increasing to the right. 47% SST and $C_{37}$ are missing, and 65% of $\delta^{15}N$ and %N are missing.
Figure 3 [HMM] State assignments by the HMM (black dots). State 1 is indicated by a black dot near the
Figure 4 [AR-HMM] State assignments by the HMM (black dots). State 1 is indicated by a black dot near
Granger Causality: What is causing what?

Correlation is not Causation

Deep Variability is the HARDEST!

Intermittency?

- Stochastic damping very slow!
- Huge heat capacity (biggest watermasses on Earth)!
- Timescales may be very long!
  - Watermasses \( O(1500\text{yr}) \) old by radiocarbon
- Lengthscales may be very short!
  - (weak stratification implies a Rossby radius of \( O(2\text{km}) \) for modes trapped in AABW only)
- Water “formed” in very small areas!
  - Small-scale atmospheric & oceanic phenomena will be disproportionately important on air-sea effects

Difficult to observe, IMPOSSIBLE TO MODEL = FUN!
Even with Argo, it will be a while until we have long timescale variability. What to do?

Pattern of Warming from Hydrography

Examine CDH-26 sediment core from the Holocene indicated by Purkey & Johnson, 2010

now Rutgers
What does a climate model—WITHOUT WARMING—look like in Ocean Heat Content Variability? Doesn’t even include mesoscale eddies

From the >1000yr steady forcing CCSM3.5

Assessing variability using individual benthic foraminifera

- Benthic foraminiferal $\delta^{18}O$ values record temperature and salinity properties of ambient seawater
  
  \[ T (°C) = 21.6 - 5.50 \times (\delta^{18}O_{c}-\delta^{18}O_{sw}) \]
  
  Bemis et al. 2002

  \[ \delta^{18}O_{sw} = -14.38 +0.42* \text{salinity} \]
  
  Conroy et al. 2014

- Individual foraminifera provide 2-3 week snapshots of seawater properties

- We analyze 30-40 individuals within 200 year windows to assess the mean and variance of foraminiferal $\delta^{18}O$ values

At these three time intervals, the spread of individual values exceeds a size-matched spread of instrumental standards.

The statistical significance of this deviation is given by the p-values of a Kolmogorov-Smirnov test comparing the distributions.

According to these forums—deep water variability is unexpectedly important, intermittently through the past!
A Mesoscale Eddy can be covered with 1-10 Rhode Islands.
3D Turbulence Cascade

1963: Smagorinsky Scale & Flow Aware Viscosity Scaling, so the Energy Cascade is Preserved, but order-1 gridscale Reynolds #: \( \text{Re}^* = \frac{UL}{\nu_*} \)

\[
\nu_{*h} = \left( \frac{\gamma_h \Delta x}{\pi} \right)^2 \sqrt{\left( \frac{\partial u_*}{\partial x} - \frac{\partial v_*}{\partial y} \right)^2 + \left( \frac{\partial u_*}{\partial y} + \frac{\partial v_*}{\partial x} \right)^2}
\]
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So the Energy Cascade is Preserved,
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\[
v_{*h} = \left( \frac{\gamma_h \Delta x}{\pi} \right)^2 \sqrt{\left( \frac{\partial u_*}{\partial x} - \frac{\partial v_*}{\partial y} \right)^2 + \left( \frac{\partial u_*}{\partial y} + \frac{\partial v_*}{\partial x} \right)^2}
\]
2D Turbulence Differs

1996: Leith Devises Viscosity Scaling, So that the Enstrophy (vorticity\(^2\)) Cascade is Preserved

\[ \nu_\ast = \left( \frac{\Lambda \Delta x}{\pi} \right)^3 \left| \nabla_h \left( \frac{\partial u_\ast}{\partial y} - \frac{\partial v_\ast}{\partial x} \right) \right| \]

R. Kraichnan, 1967 JFM

Barotropic or stacked layers
Is 2D Turbulence a good proxy for stratified flow?

Yes:
- For a few eddy time-scales QG & 2D AGREE (Bracco et al. '04)
- Barotropic Flow--Obvious 2d analogue

No:
- Eddy Fluxes--Divergent 2d flow & advective fluxes
- Sloped, not horiz.
- Surface Effects?
Potential Vorticity: \[
\frac{\hat{k} \cdot \omega}{h} = \frac{\hat{k} \cdot \nabla \times \mathbf{v}}{h}
\]
Re* = 1

\( \nabla \times \mathbf{u} \)

Turbulence: Pot’l Enstrophy cascade
(potential vorticity\(^2\))


Spectral Density of Kinetic Energy

Inverse Energy Cascade

Potential Enstrophy Cascade

Re* = 1

Forcing

Dissipation

J. Charney, 1971 JAS

(quasi-geostrophic), or QG Leith

Where does ocean energy go?

Spectrally speaking

Energy / wavenumber \((m^3 \, s^{-2})\)

Wavenumber \(k \,(m^{-1})\)

Where does ocean energy go?
Spectrally speaking

QGLeith: Just Right!
2DLeith: Too Noisy
Smagorinsky: Too Smooth

QGLeith: Let's try it in a global model!


Lognormally distributed—AND knows where the Gulf Stream is!
Wait—log-normal...
A (weak) dissipation of energy with potential enstrophy cascade... that's lognormally distributed (super-Yaglom ’66)

90% of KE dissipation in 10% of ocean

News from Brown

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Conclusions

- **Presence of observable variability**
  - Requires accurate obs. & sampling
  - Really only get a distribution to compare to models
  - Many problems require paleothermometry, e.g. ENSO!

- **Understanding of past variability**
  - Correlation is not causation!
  - Variability can be intermittent—even in deep water

- **Modeling of variability**
  - Stochastic models can reveal causation & correlation.
  - Deterministic models: challenges are tuning, params, resolution.

- **Prediction of variability**
  - Possible in some regions, chaos limits the forecast window.
  - Longer predictions can be possible if cross-correlations exist, but sometimes they only seem to exist! (e.g., the multi-proxy record off Peru)
  - Intermittency, e.g., lognormal eddy dissipation, challenges observations and models