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

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with Brodie Pearson, Samantha Bova, Tim Herbert, Seonmin Ahn, Chip Lawrence (Brown), Arin Nelson & Jeff Weiss (CU-ATOC), Royce Zia (Va. Tech.), Samantha Stevenson (UCSB)

USC Dornsife Earth Sciences Dept. Seminar Series
Los Angeles, 4/2/18

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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.

# News from Brown

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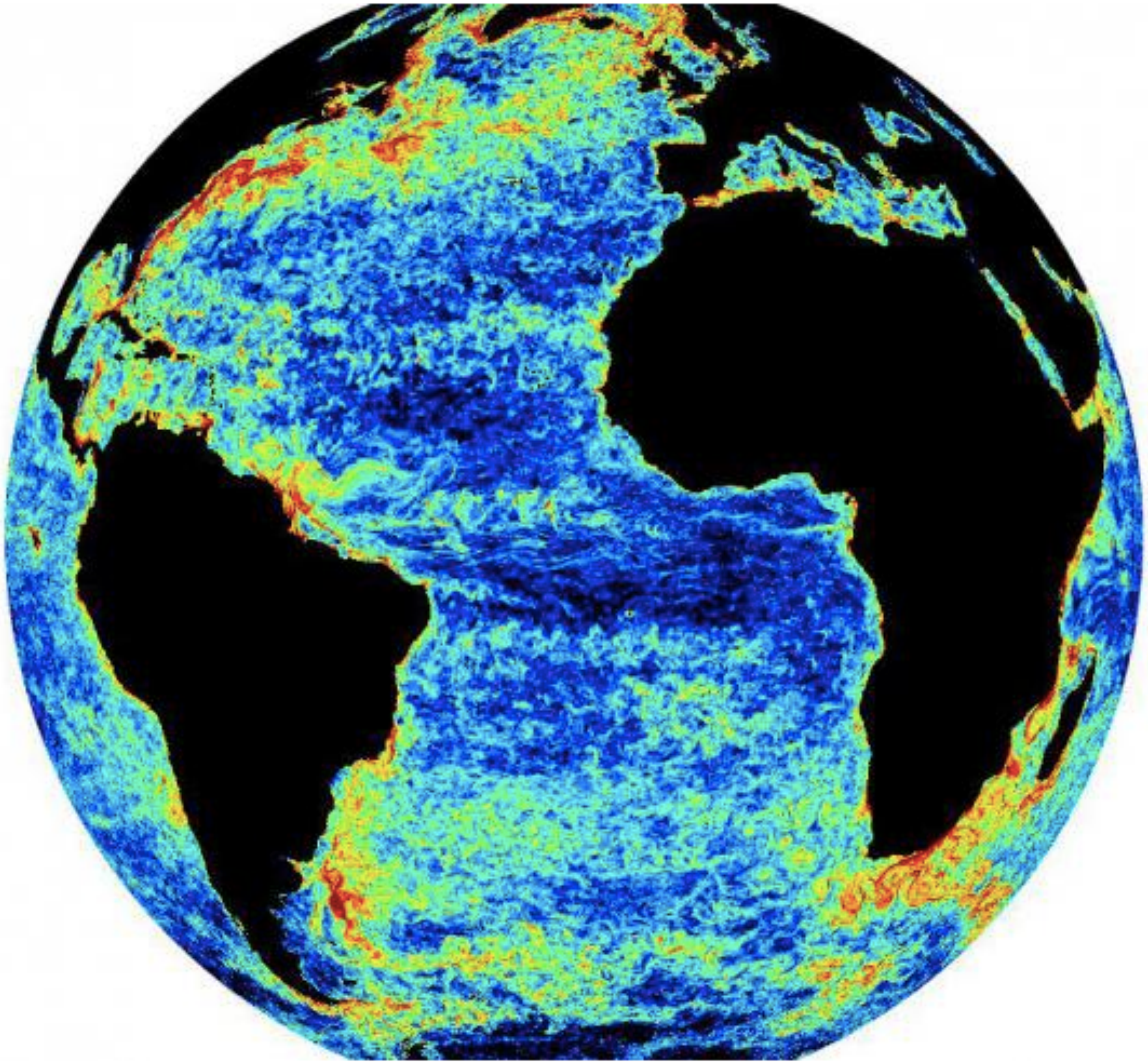


Hotspots
Brown University researchers have made a new

## New understanding of ocean turbulence could improve climate models

February 26, 2018 Media contact: Kevin Stacey
401-863-3766

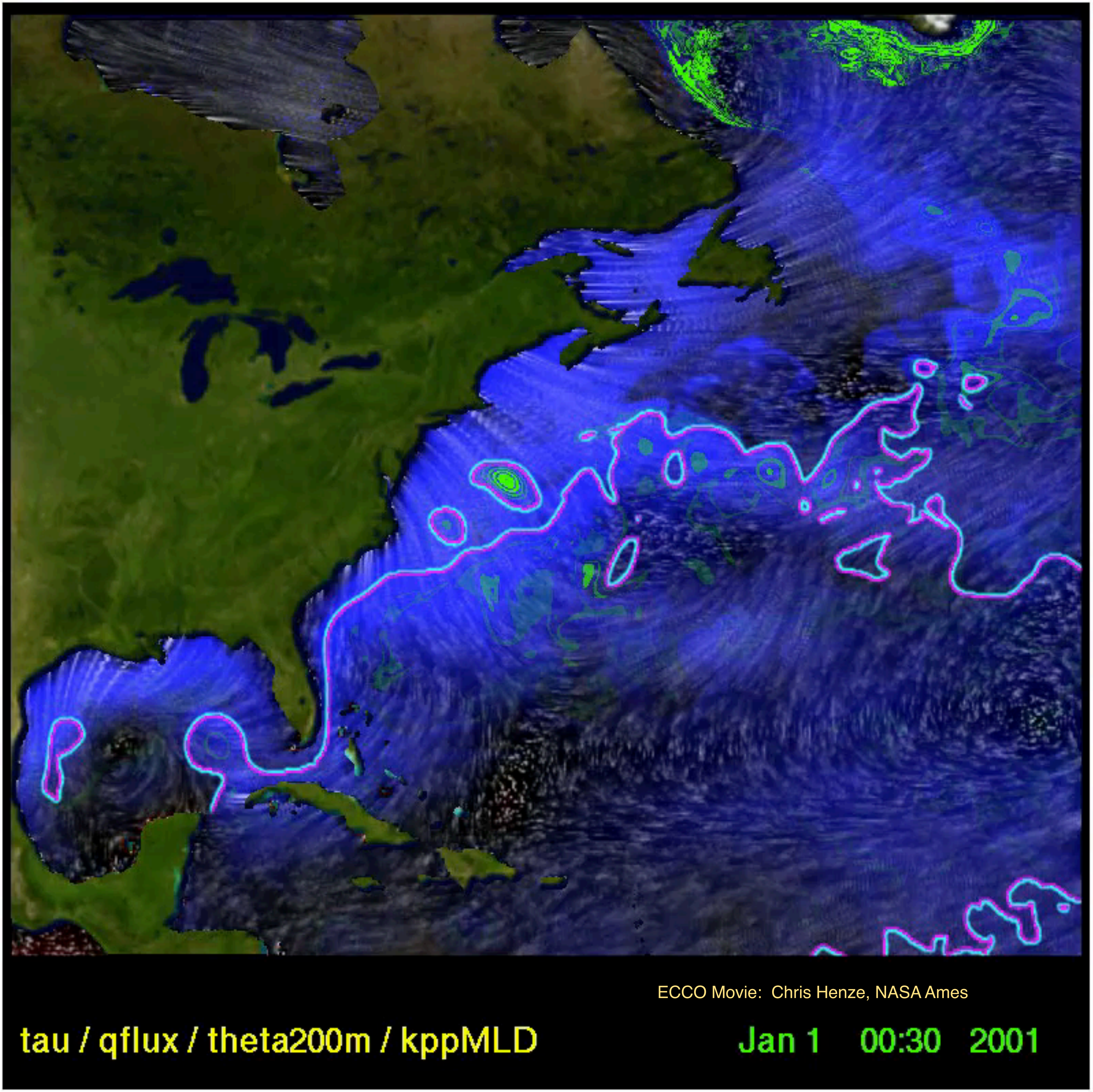
Researchers have developed a new statistical understanding of how turbulent flows called mesoscale eddies dissipate their energy, which could be helpful in creating better ocean and climate models.

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.

B. Pearson and BFK. Log-normal turbulence dissipation in global ocean models. Physical Review Letters, 120(9):094501, March 2018.

# What?

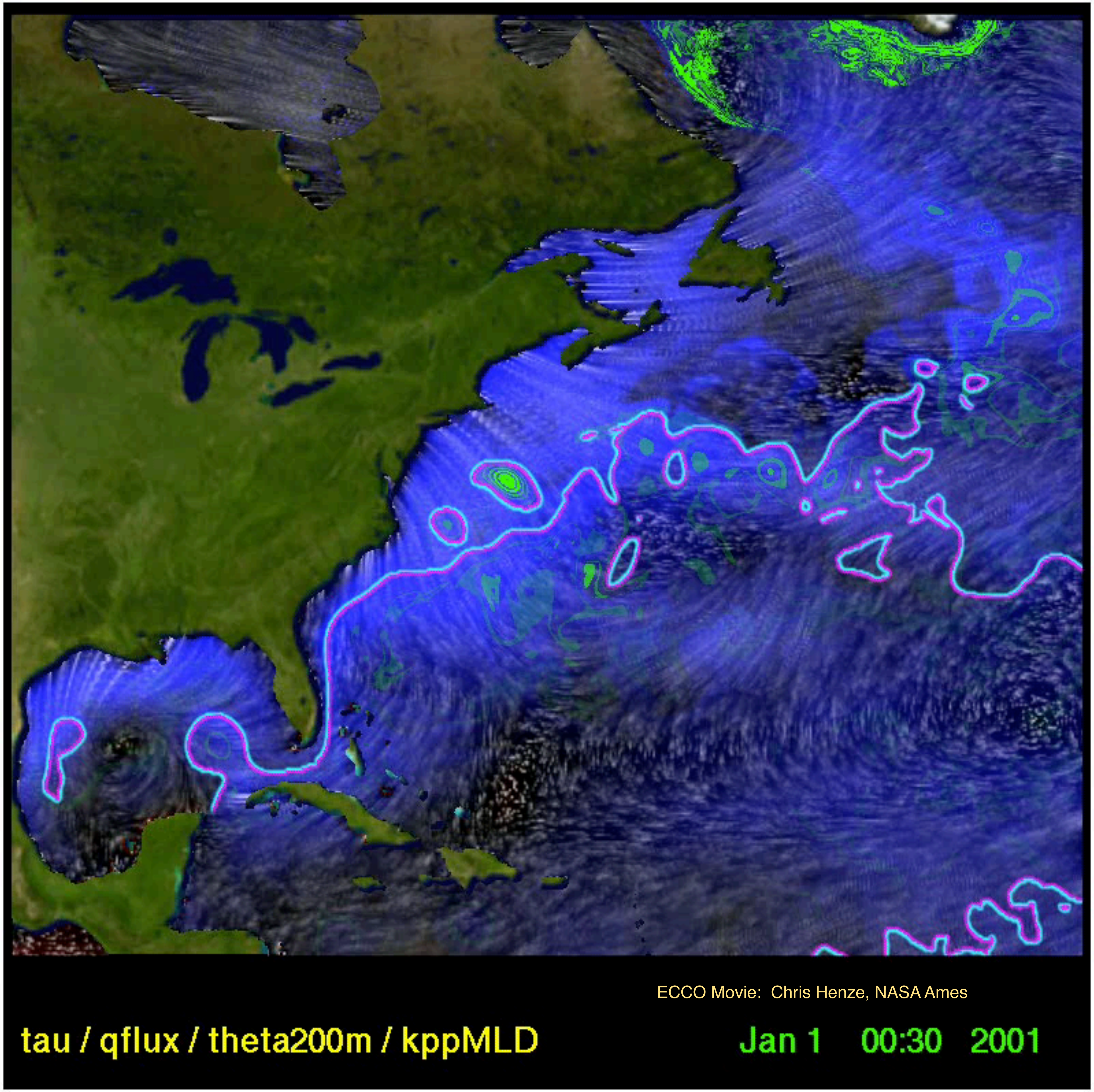
- I am going to explain a bit of this process, and show interesting cases where statistics comes into play.
- First, we need to understand a bit about ocean variability and model resolution.




Weather,
Atmosphere
Fast

Ocean,
Climate
Slow

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



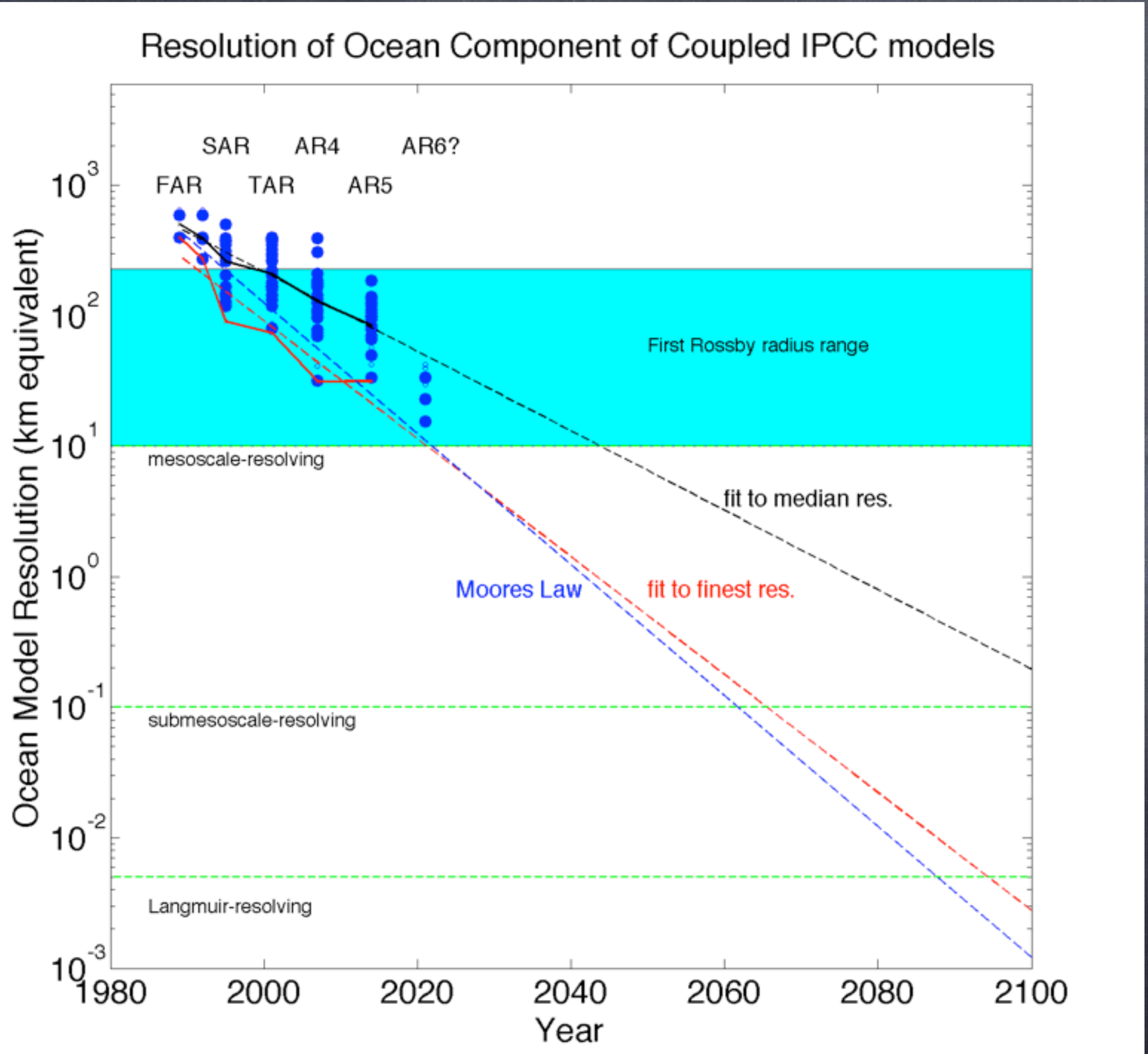

Weather,
Atmosphere
Fast

Ocean, Climate
Slow

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

# We are modeling important processes in climate models, right?

## Don't we have big enough computers?




Here are the collection of IPCC models...

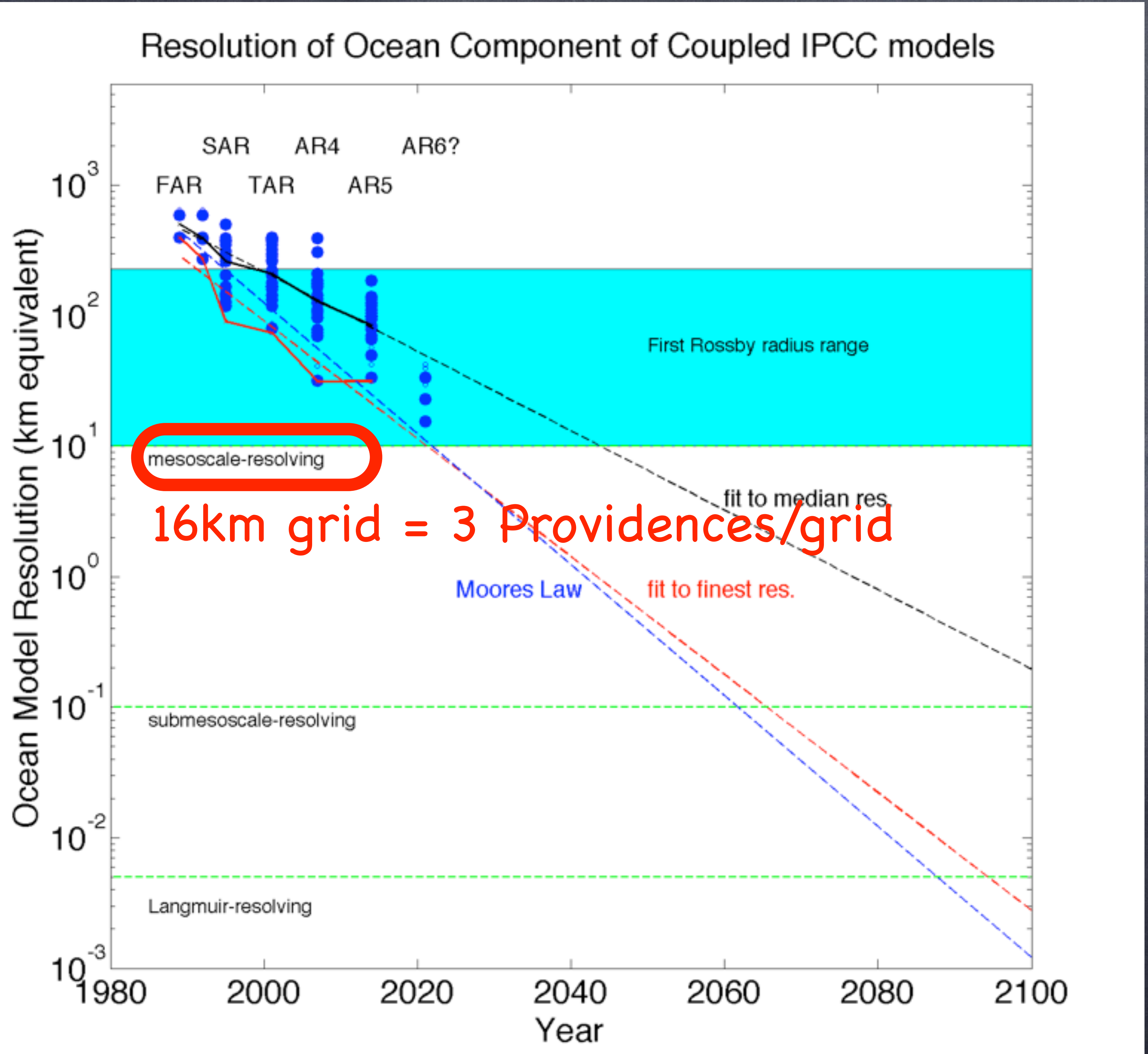
If we can't resolve a process, we need to develop a parameterization or subgrid model of its effect

# ECCO2 Model

Viscosity Scheme: BFK and D. Menemenlis. Can large eddy simulation techniques improve mesoscale-rich ocean models? In M. Hecht and H. Hasumi, editors, Ocean Modeling in an Eddying Regime, volume 177, pages 319-338. AGU Geophysical Monograph Series, 2008.

# 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...

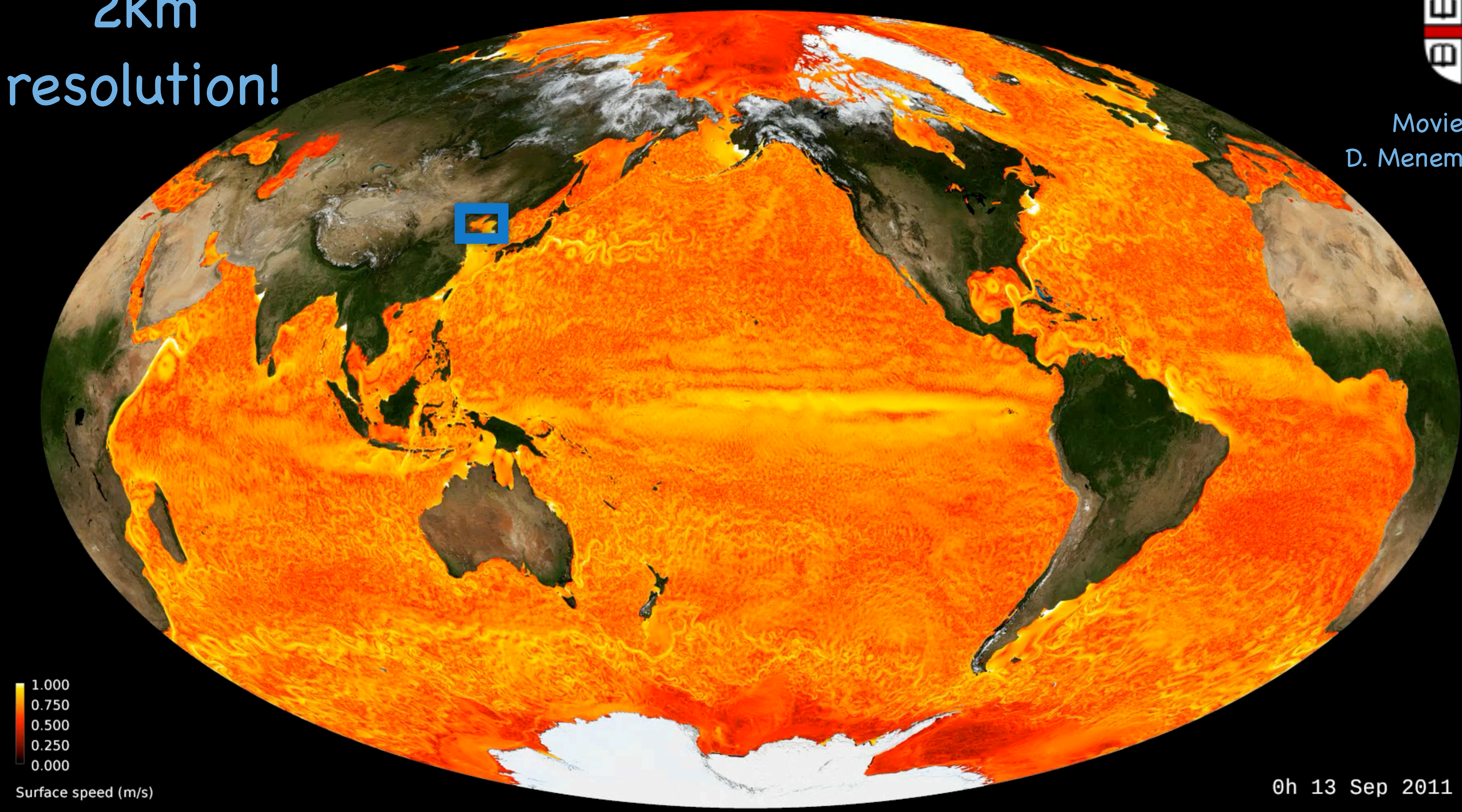
If we can't resolve a process, we need to develop a parameterization or subgrid model of its effect

Estimating the Circulation & Climate of the Ocean

# LLC4320 Model

2km resolution!

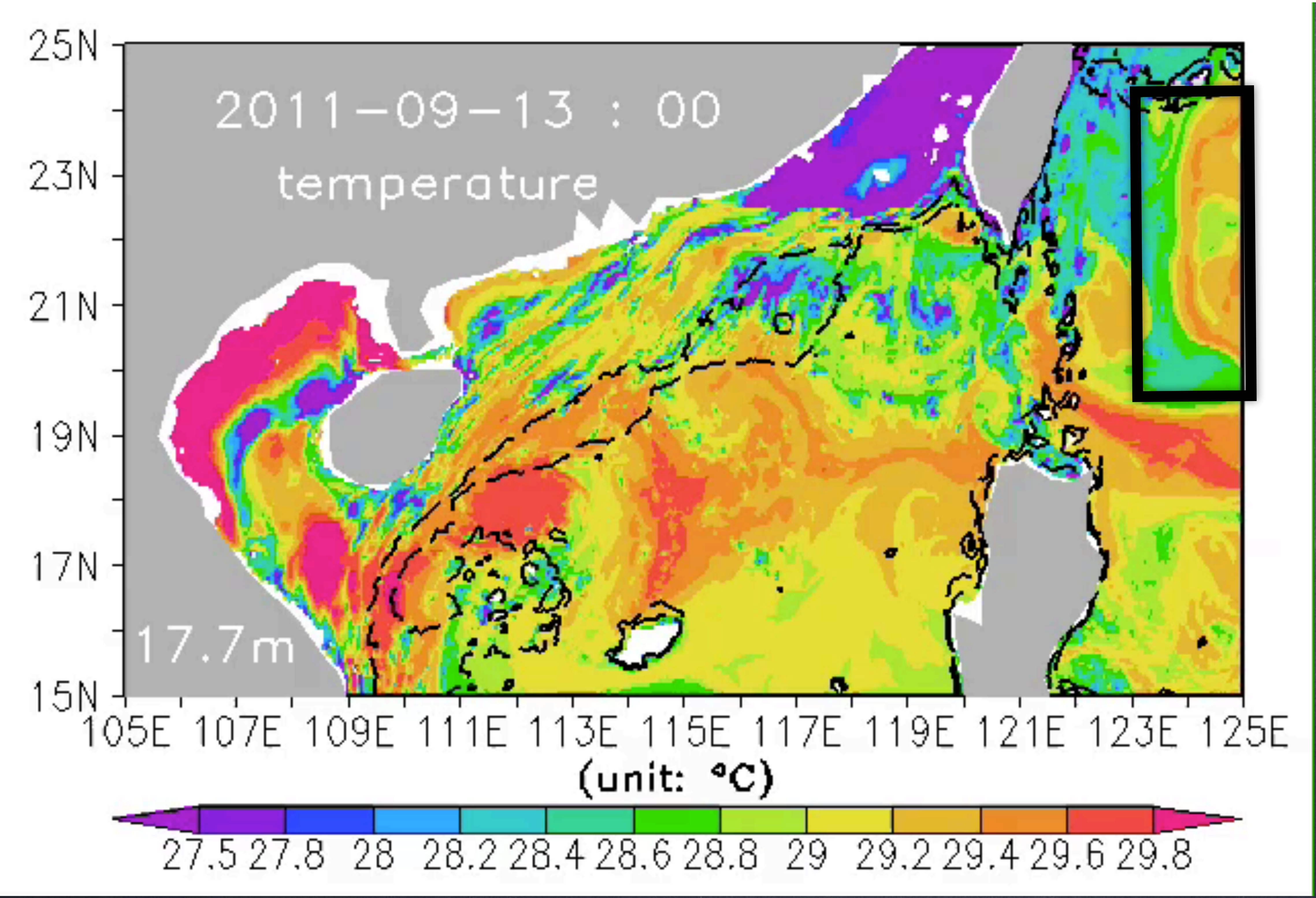
Movie: D. Menemenlis




B. Fox-Kemper, S. Bachman, B. Pearson, and S. Reckinger. Principles and advances in subgrid modeling for eddy-rich simulations. CLIVAR Exchanges, 19(2):42-46, July 2014.

Estimating the Circulation & Climate of the Ocean

# LLC4320 Model

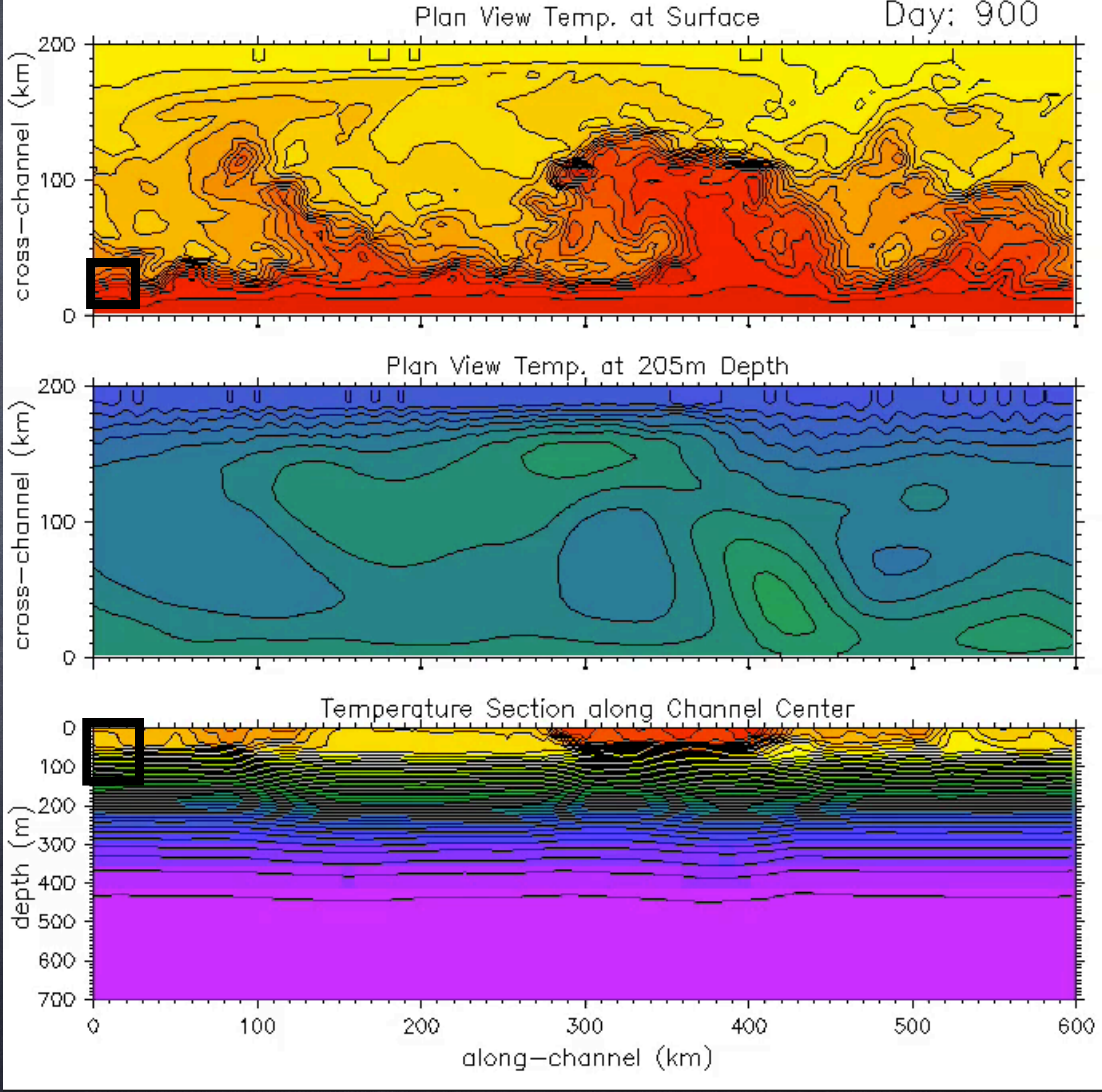



Movie:
Z. Jing

Local Analysis: Z. Jing, Y. Qi, B. Fox-Kemper, Y. Du, and S. Lian. Seasonal thermal fronts and their associations with monsoon forcing on the continental shelf of northern South China Sea: Satellite measurements and three repeated field surveys in winter, spring and summer. Journal of Geophysical Research-Oceans, 121:1914-1930, April 2016.

200km x 600km x 700m domain

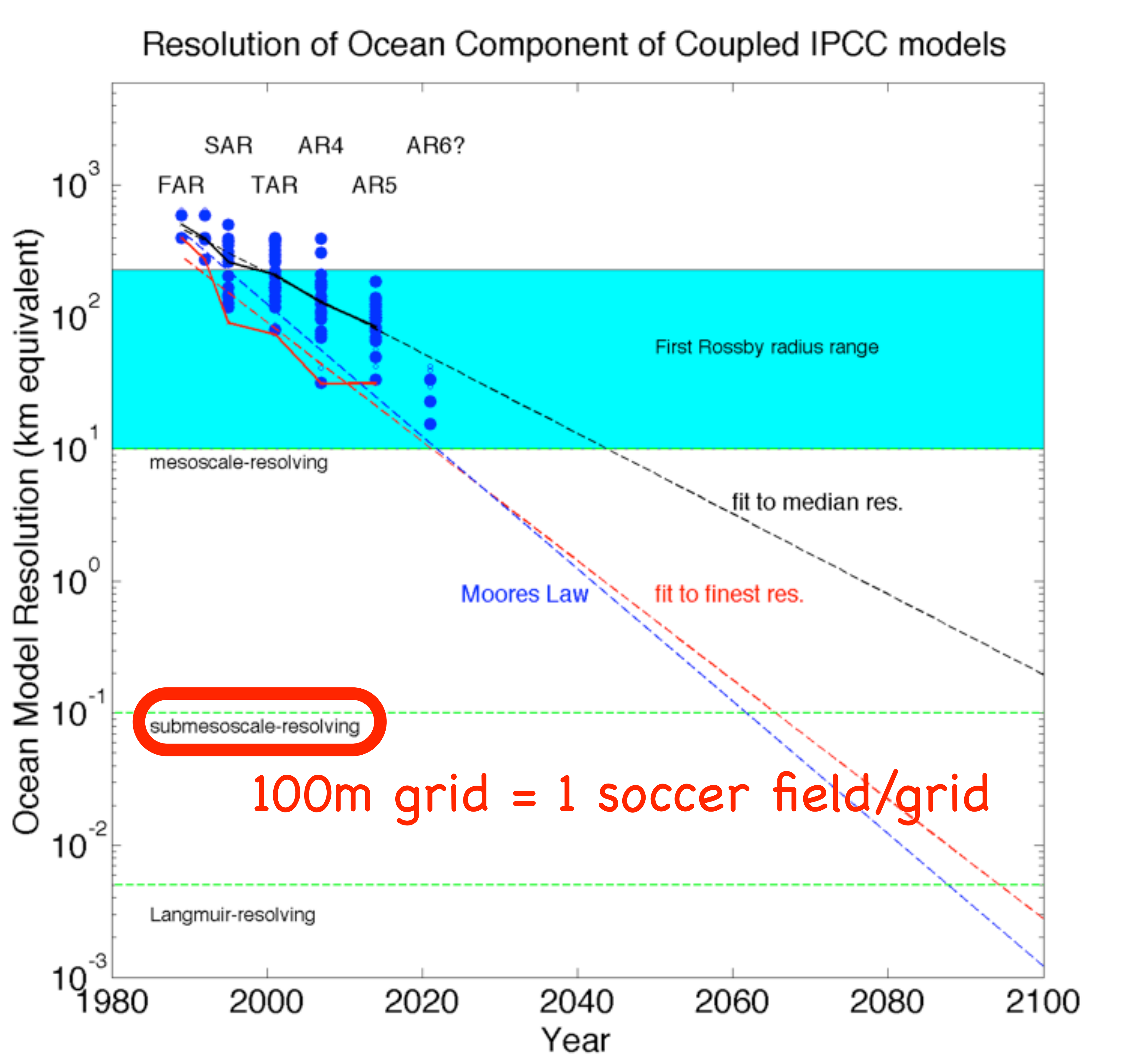
1000 Day Simulation




G. Boccaletti, R. Ferrari, and BFK. Mixed layer instabilities and restratification. Journal of Physical Oceanography, 37(9):2228-2250, 2007.

# What about modeling important processes in climate models?

## Don't we have big enough computers? or won't we soon?

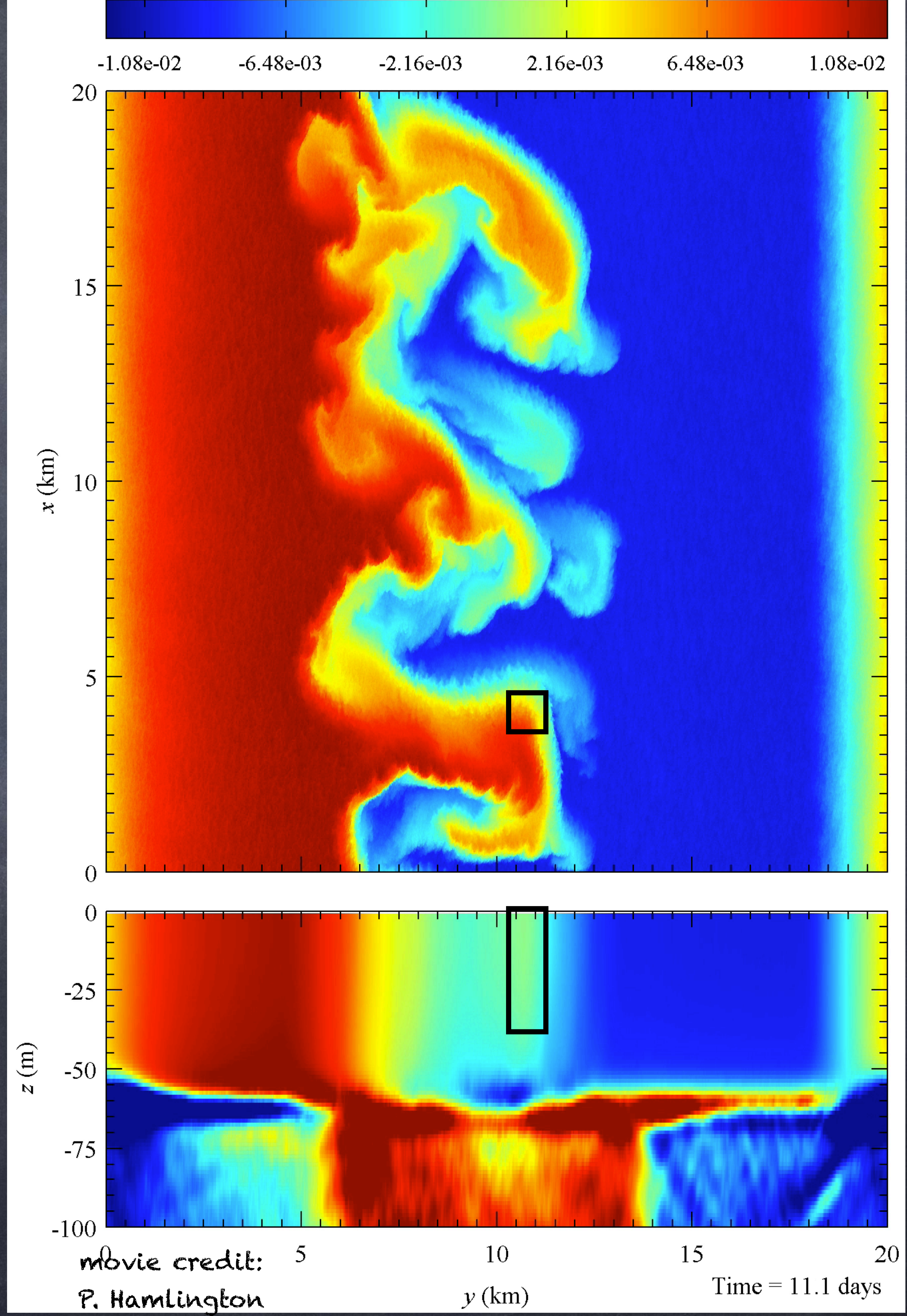



Here are the collection of IPCC models...

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

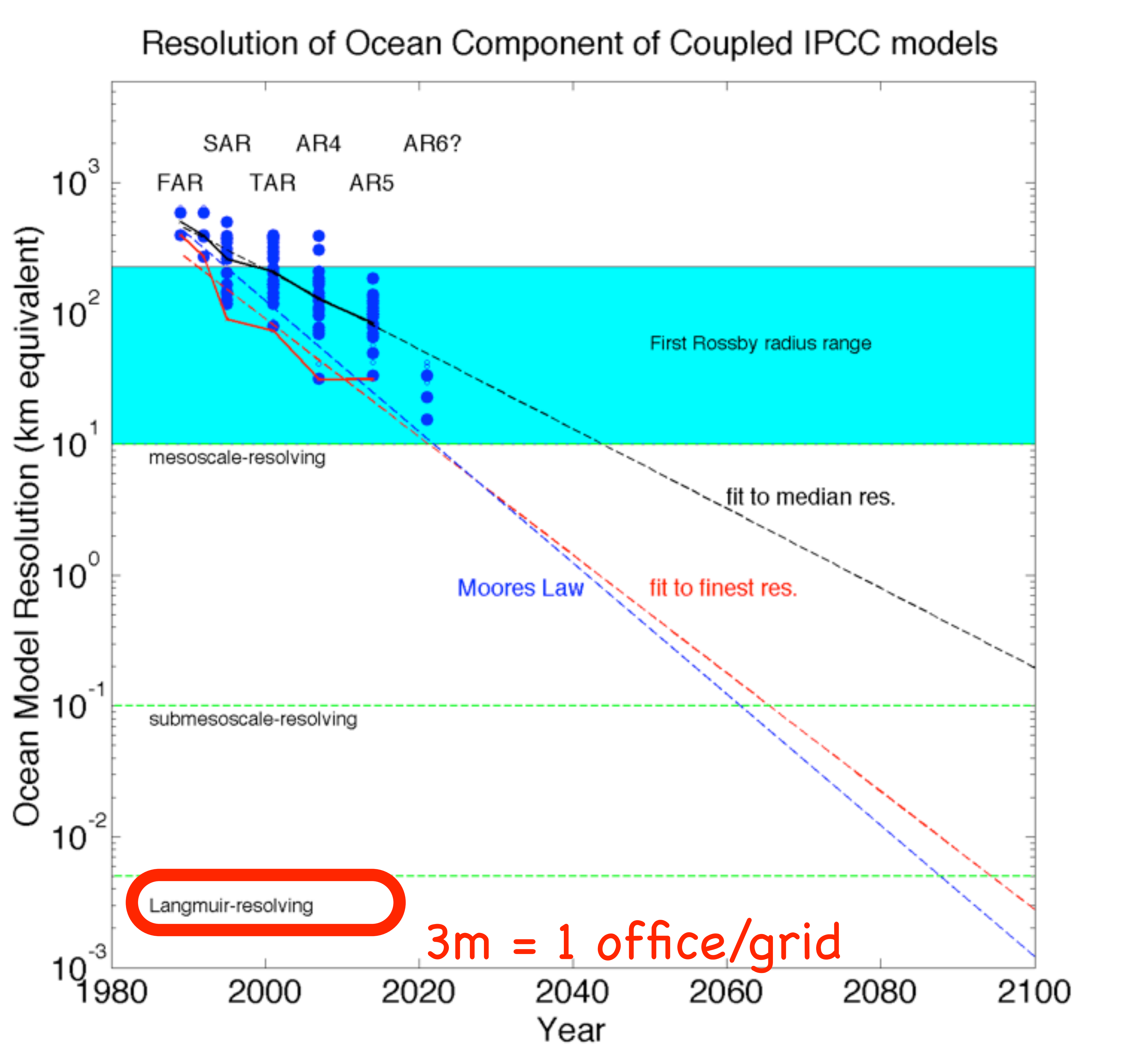
# 10 Day Simulation




movie credit: P. Hamlington

P. E. Hamlington, L. P. Van Roekel, BFK, K. Julien, and G. P. Chini. Langmuir-submesoscale interactions: Descriptive analysis of multiscale frontal spin-down simulations. Journal of Physical Oceanography, 44(9):2249-2272, September 2014.

# Climate Model Resolution: an issue for centuries to come!

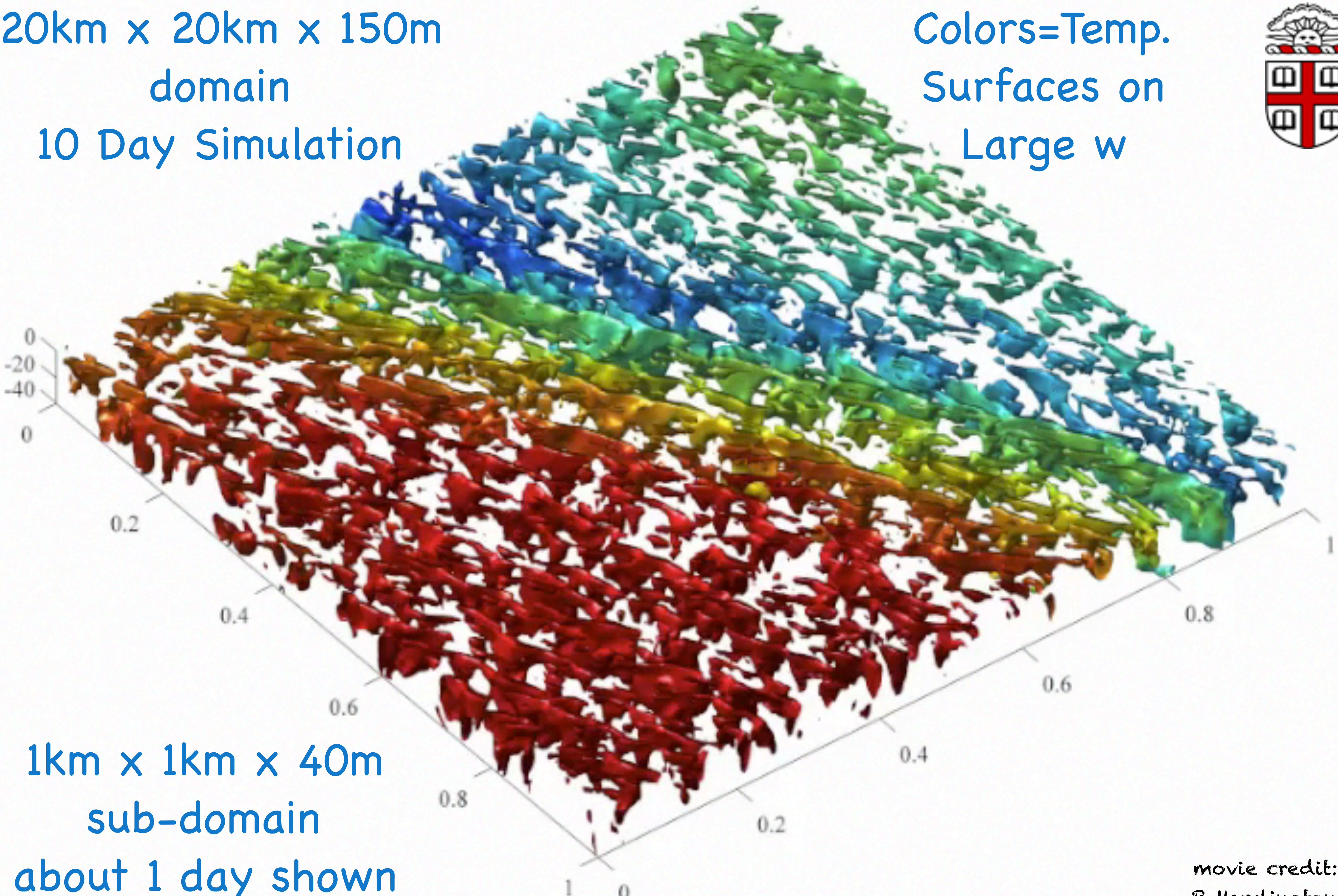



Here are the collection of IPCC models...

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

Colors=Temp.
Surfaces on
Large w




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

movie credit:
P. Hamlington

P. E. Hamlington, L. P. Van Roekel, BFK, K. Julien, and G. P. Chini. Langmuir-submesoscale interactions: Descriptive analysis of multiscale frontal spin-down simulations. Journal of Physical Oceanography, 44(9):2249-2272, September 2014.

# 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!

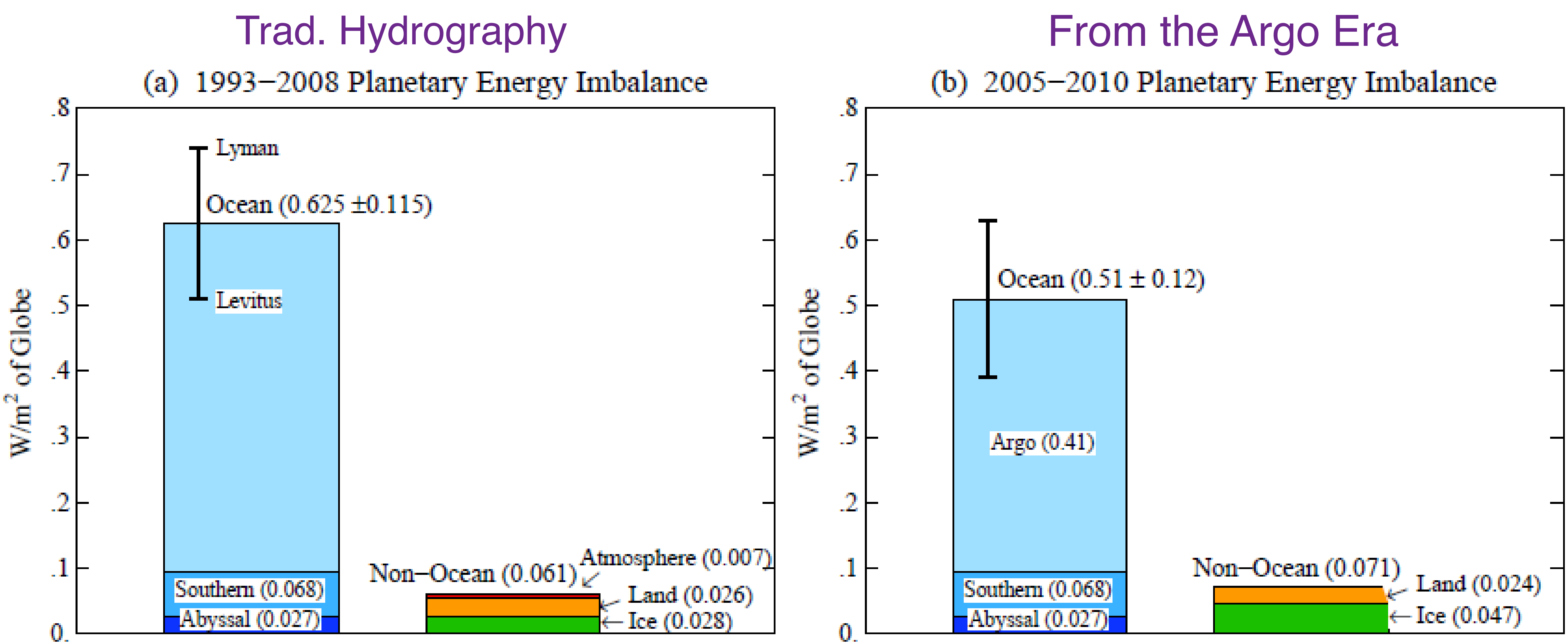
# Observable: What do hydrographic observations show?

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.

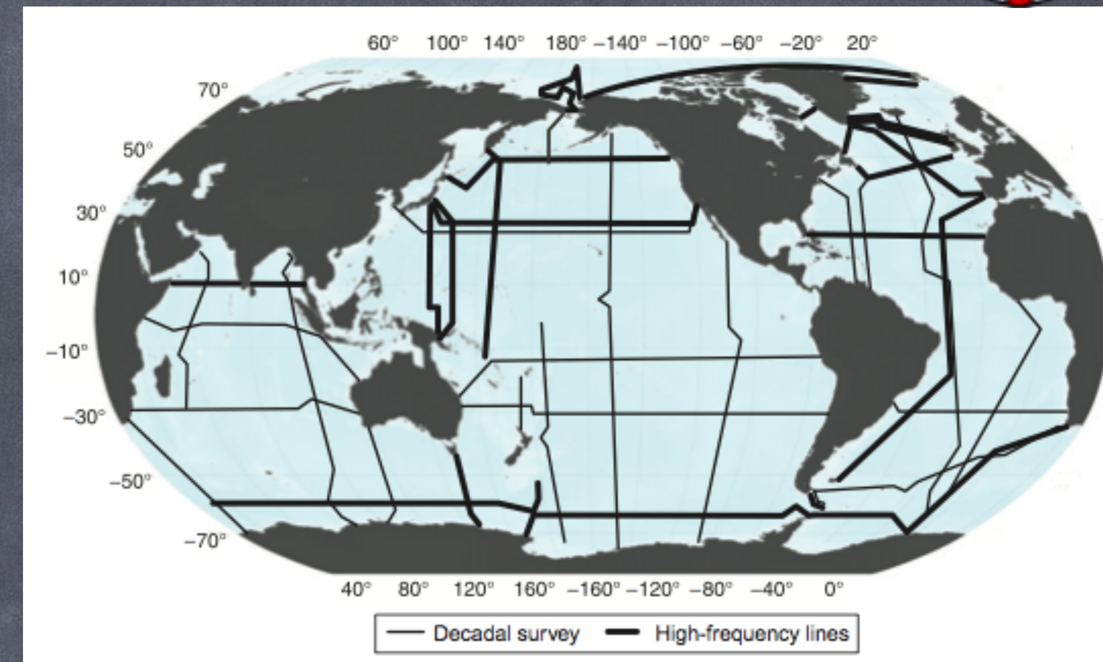
0.7 W/m² to atmosphere only is about 1.5K/yr




Hansen et al. (2011)

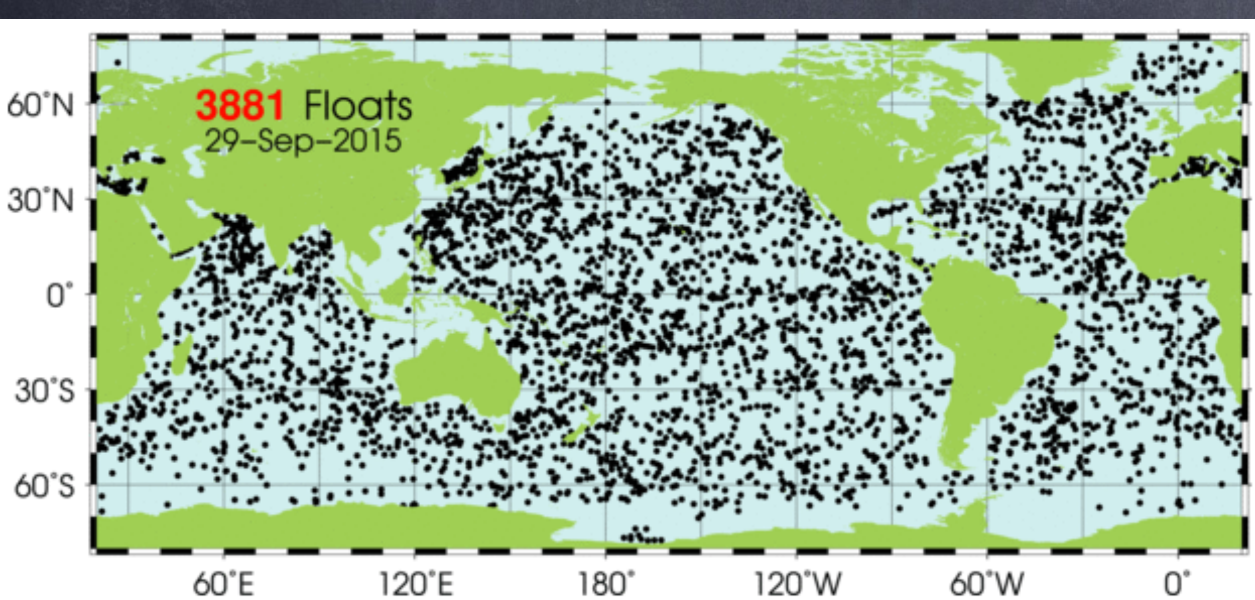
# How do we know OHC?

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



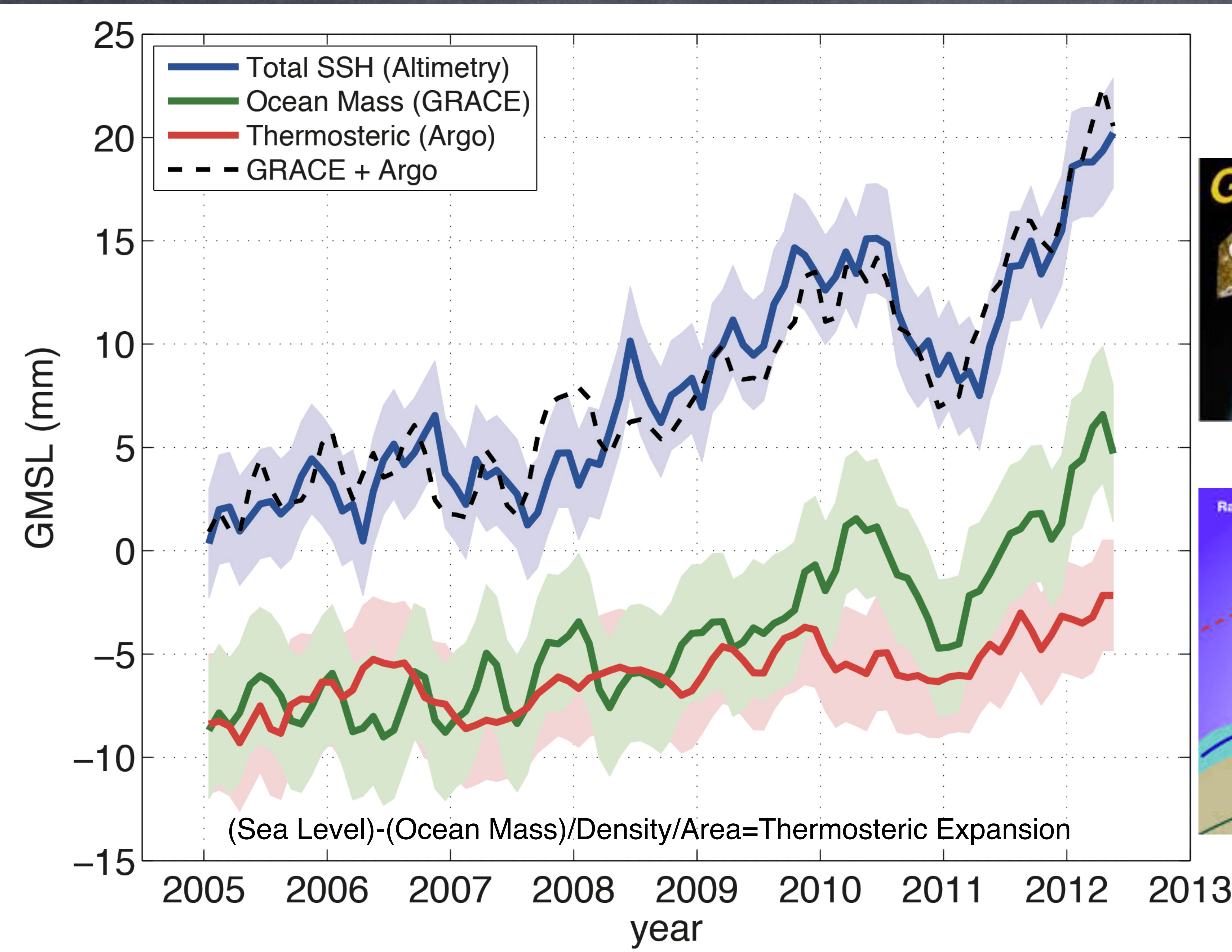

GO-SHIP repeat sections: Siedler et al. 2013

Autonomous: e.g., Argo and Satellites.
http://www.argo.ucsd.edu/



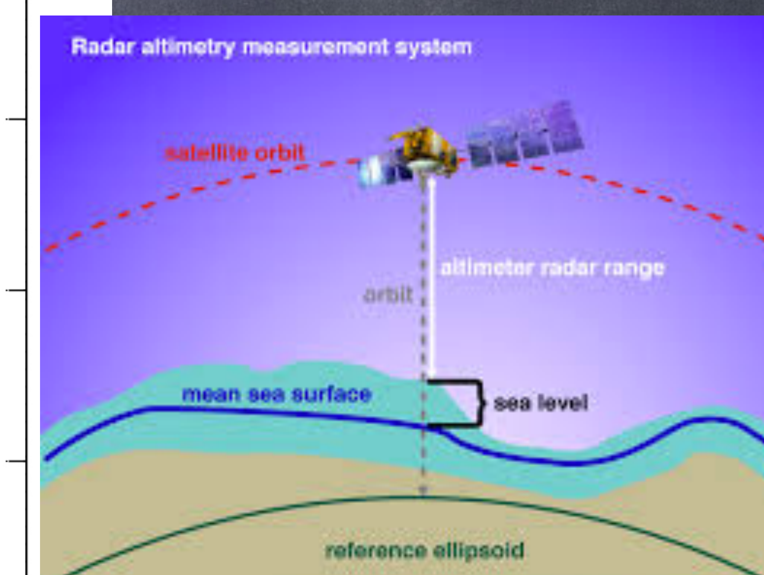

Argo floats presently active

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





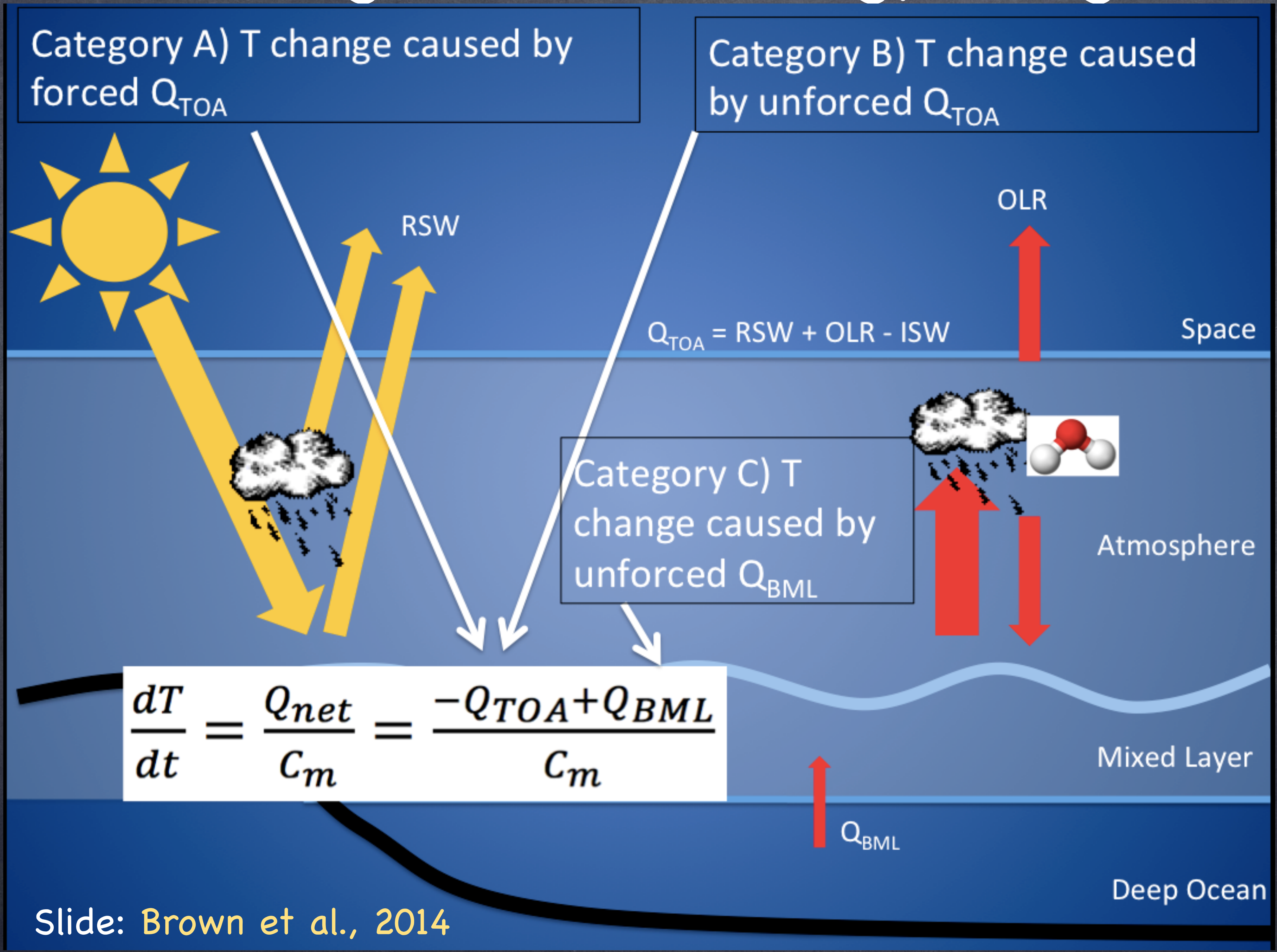
podaac.jpl.nasa.gov




nesdis.noaa.gov

IPCC AR5, 2013

# Modeling: Surface Energy Budget




- O(2W/m²) change to $Q_{BML}$ as important as GHG
- Slight oversimplification—sensitivity + budget

# Surface, Mixed Layer, Seasons? Temporal Sampling

0.7 W/m²

=

Atmosphere:

1.5K/yr

=

3.4m Ocean:

1.5K/yr

=

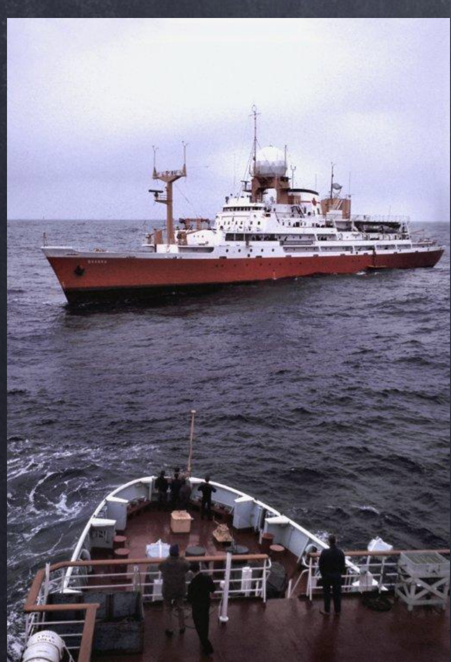
34m Ocean:

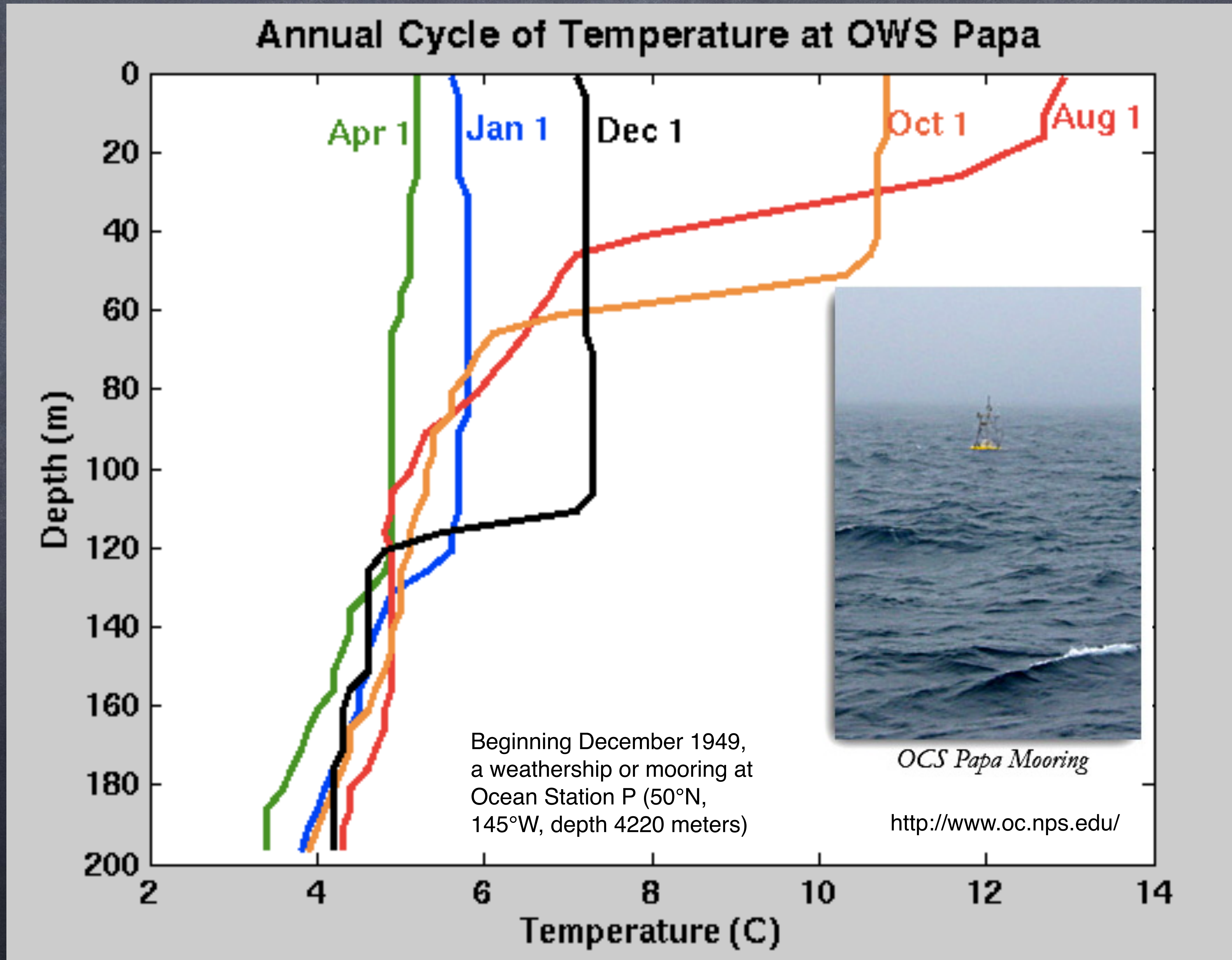
0.15K/yr

=1% of

mixed layer

seasonality

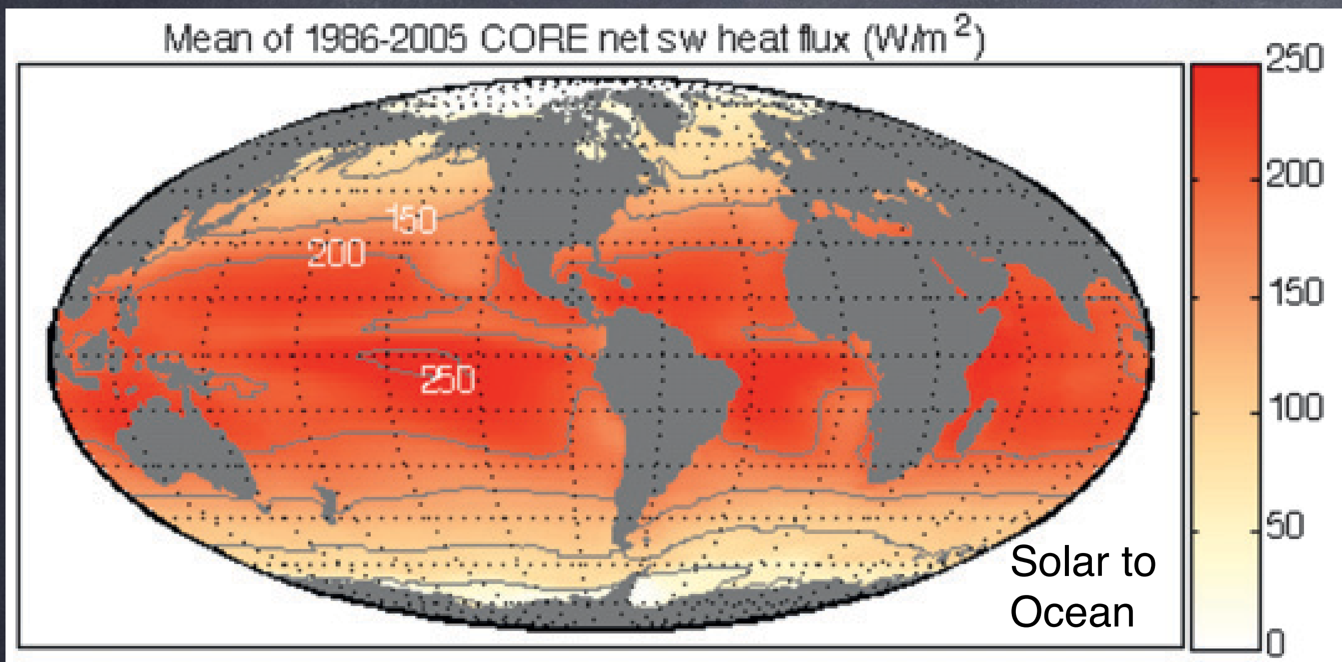


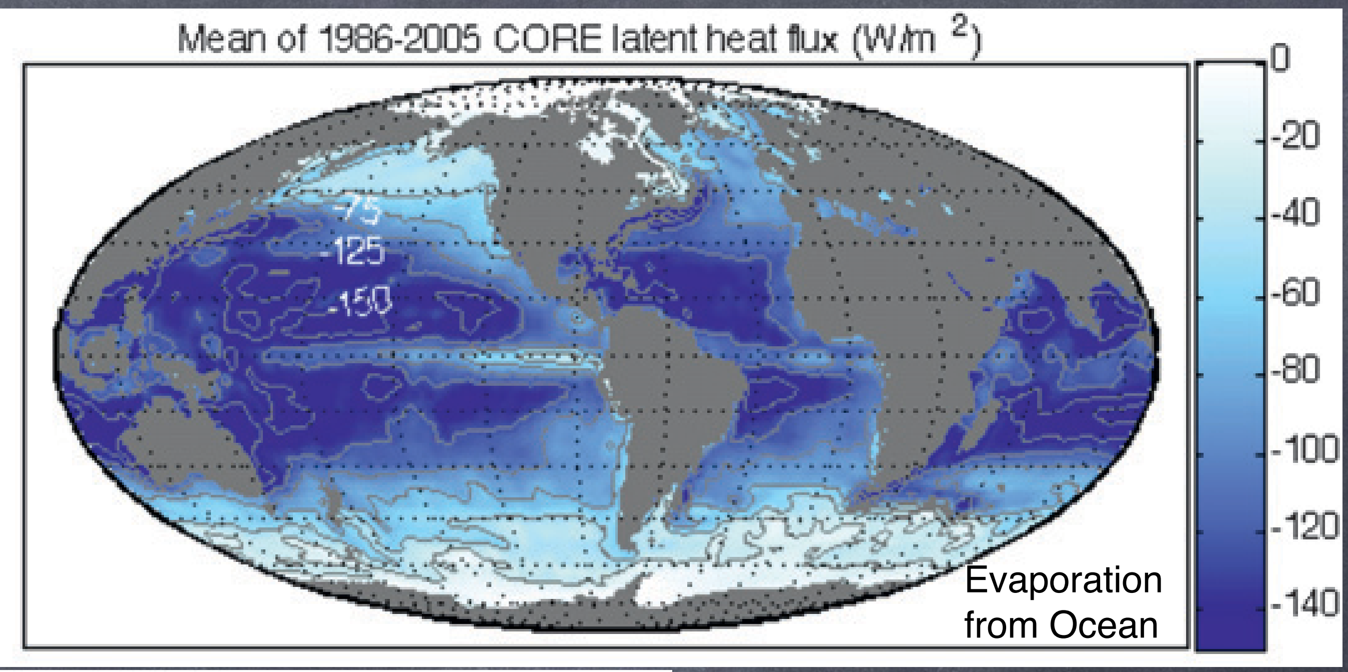


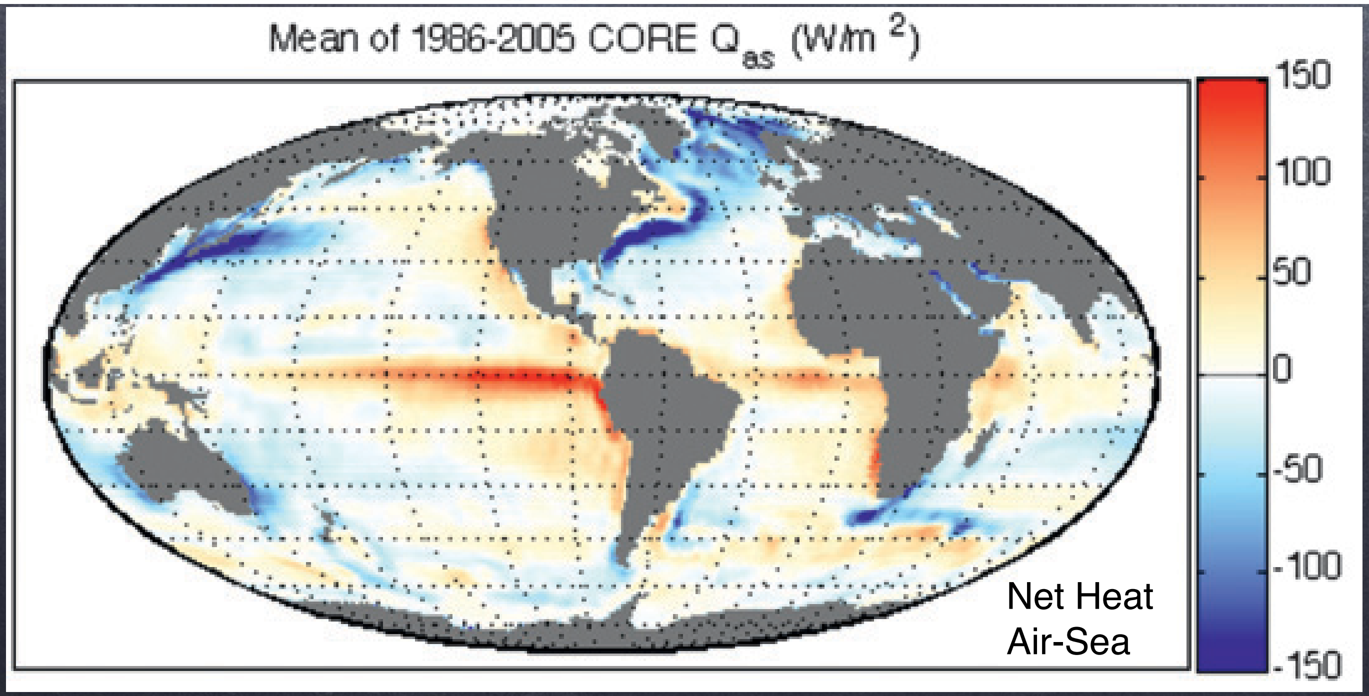
# The net $Q_{BML}$ is about 1% of different flux components and 1% of net spatial values: spatial & process sampling


CU, now NCAR

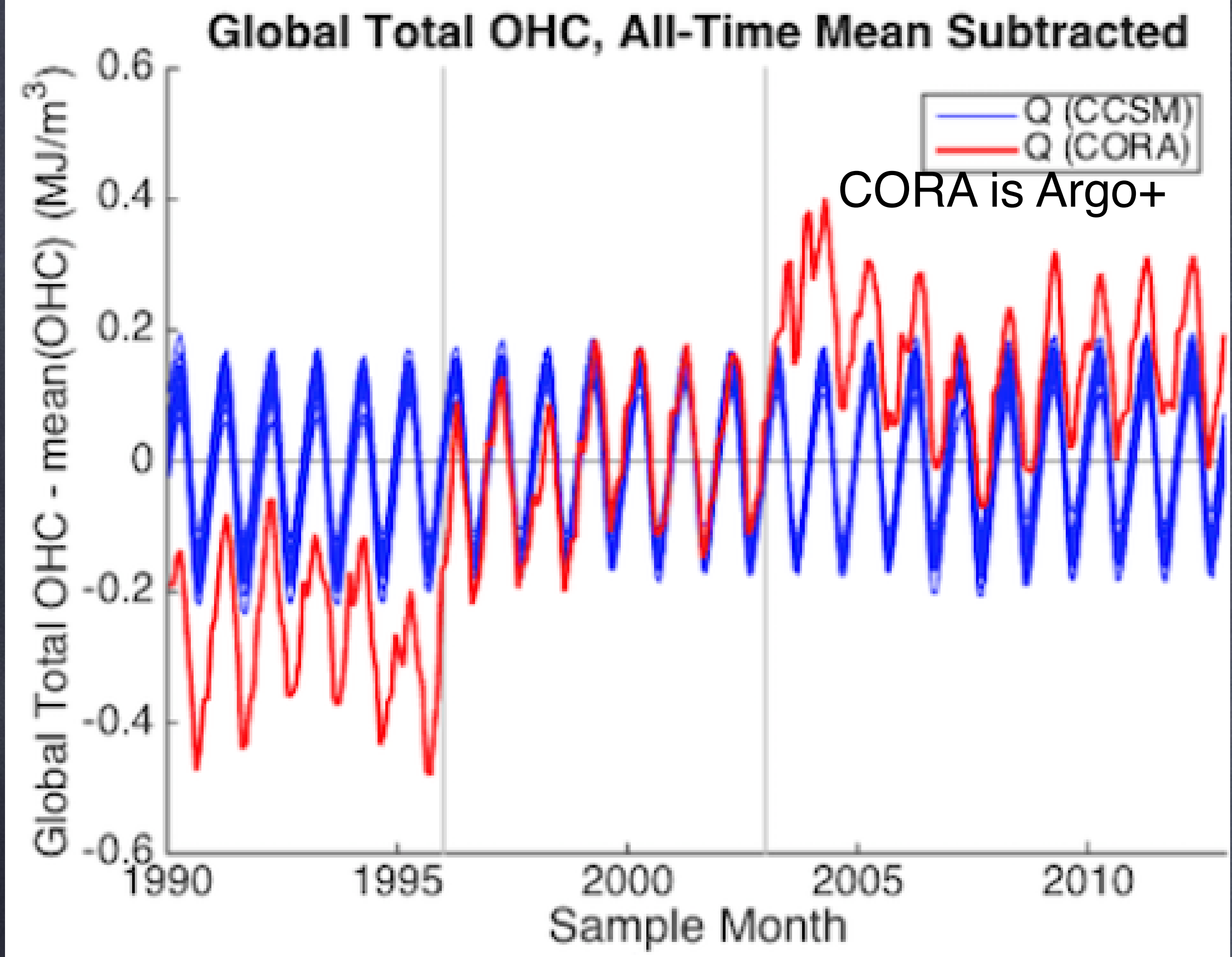

CU, now NCAR

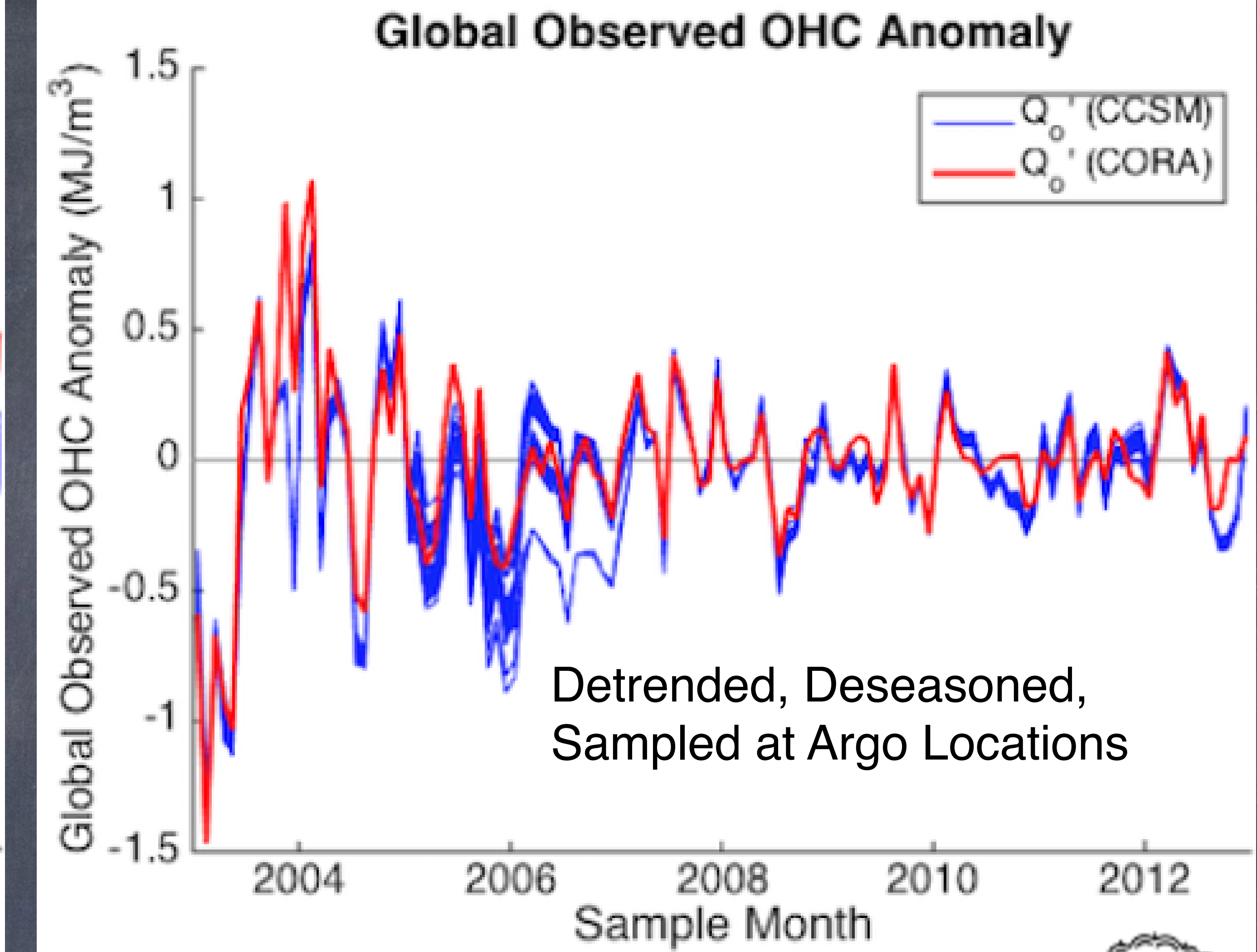


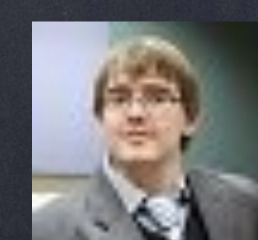

S. C. Bates, BFK, S. R. Jayne, W. G. Large, S. Stevenson, and S. G. Yeager. Mean biases, variability, and trends in air-sea fluxes and SST in the CCSM4. Journal of Climate, 25(22):7781-7801, November 2012.



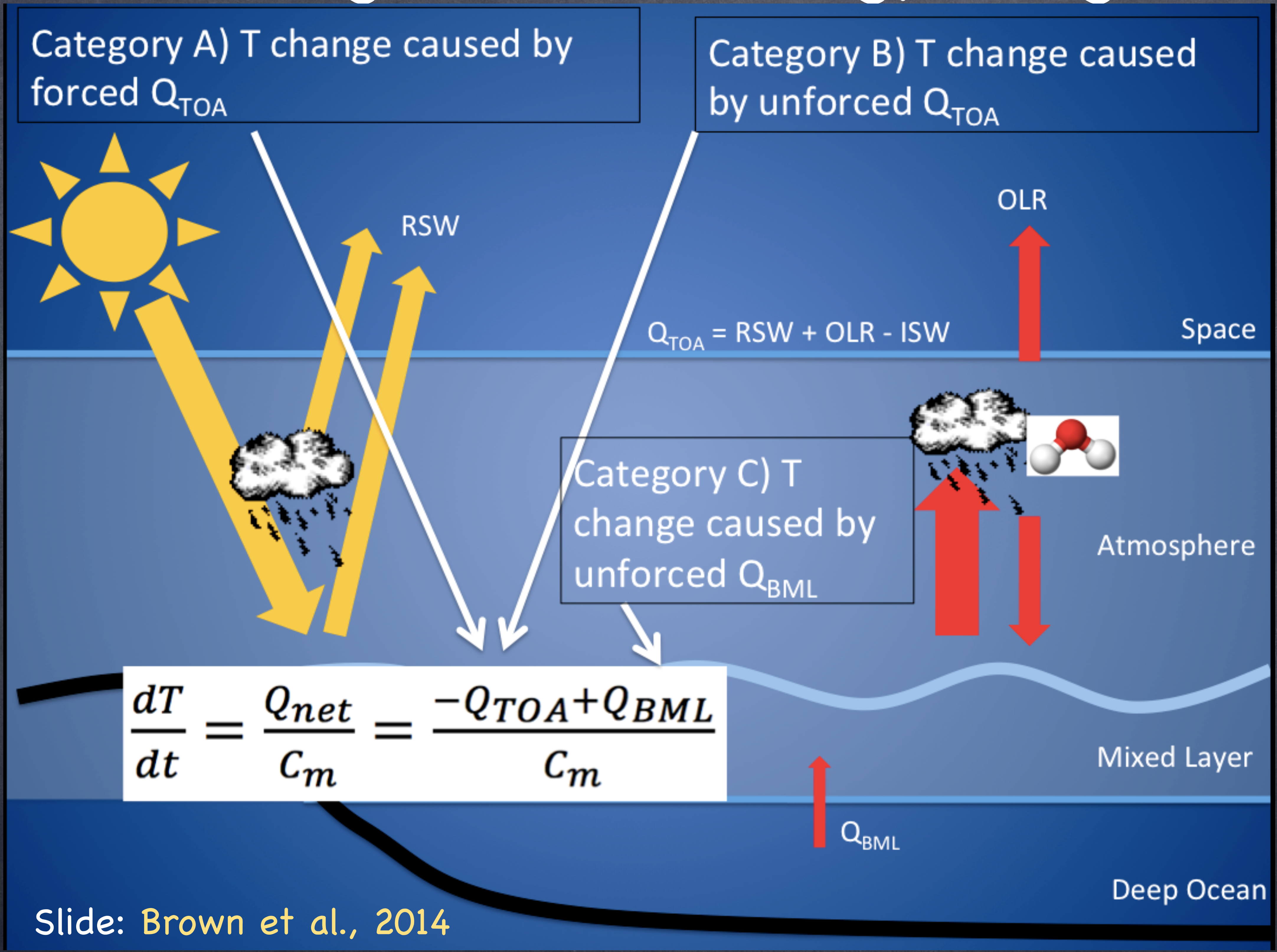

Sophisticated analysis to overcome Ship & Argo sampling problems—inherent uncertainty, O(0.2W/m$^2$), on interannual to decadal timescales in global average.

O(10W/m$^2$) without analysis.



Nelson, A. D., Weiss, J., BFK, B., Zia, R. K. P., and Gaillard, F.: An Ensemble Observing System Simulation Experiment of Global Ocean Heat Content Variability, Ocean Sci. Discuss., http://sci-hub.tw/10.5194/os-2016-105, in review, 2017.

# Modeling: Surface Energy Budget

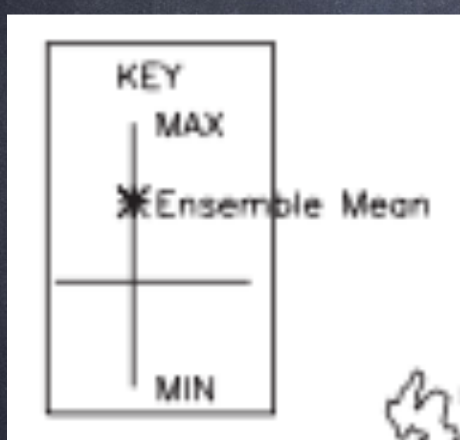


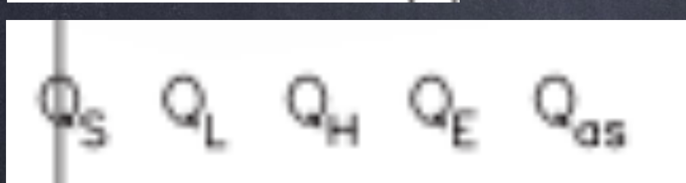

- O(2W/m²) change to $Q_{BML}$ as important as GHG
- Slight oversimplification—sensitivity + budget

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




S. C. Bates, BFK, S. R. Jayne, W. G. Large, S. Stevenson, and S. G. Yeager. Mean biases, variability, and trends in air-sea fluxes and SST in the CCSM4. Journal of Climate, 25(22):7781-7801, November 2012.

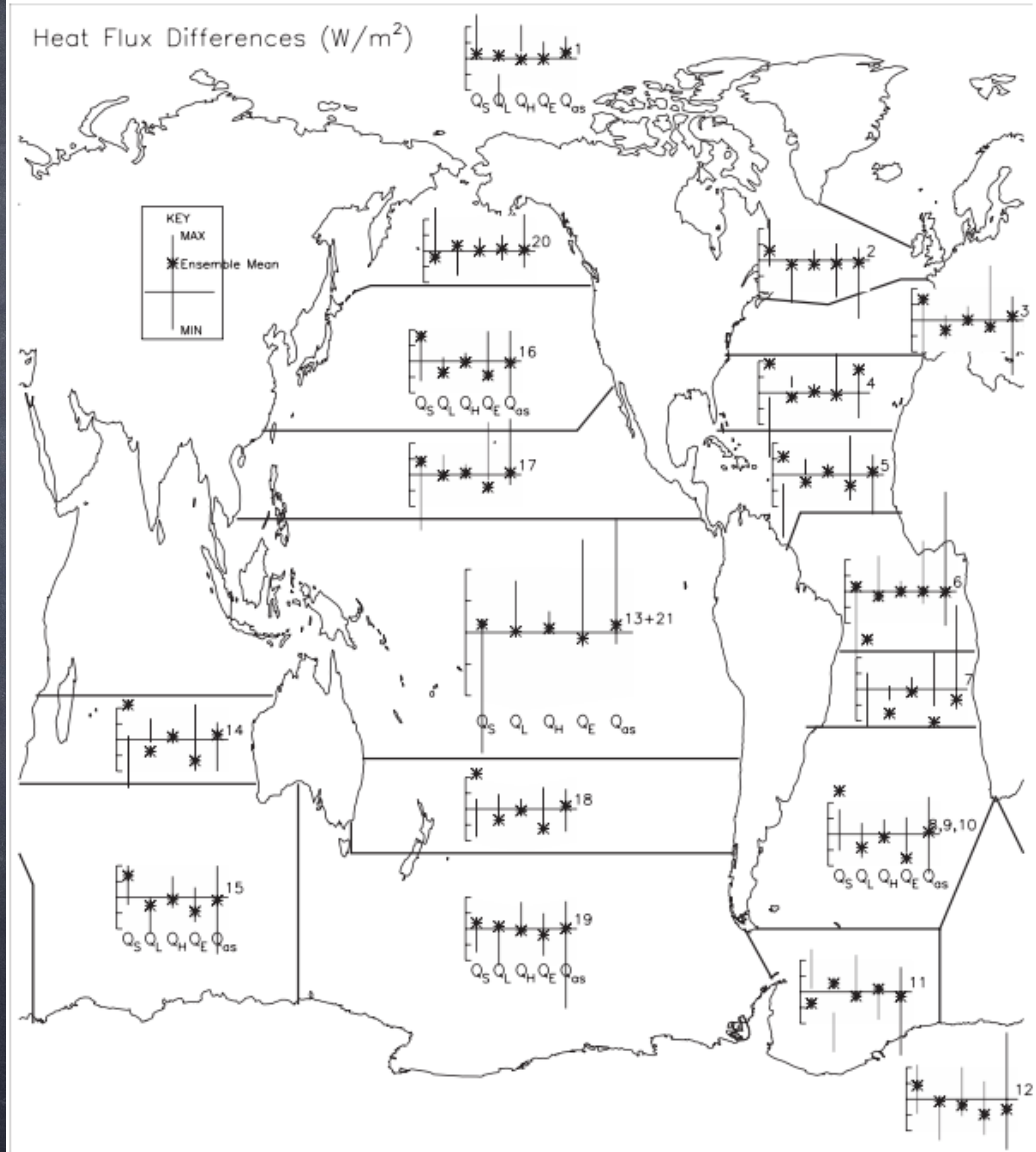



FIG. 4. Regional averages of the CCSM4 20C ensemble mean heat flux components differenced with the CORE

# Sampling & accuracy are issues: now what?

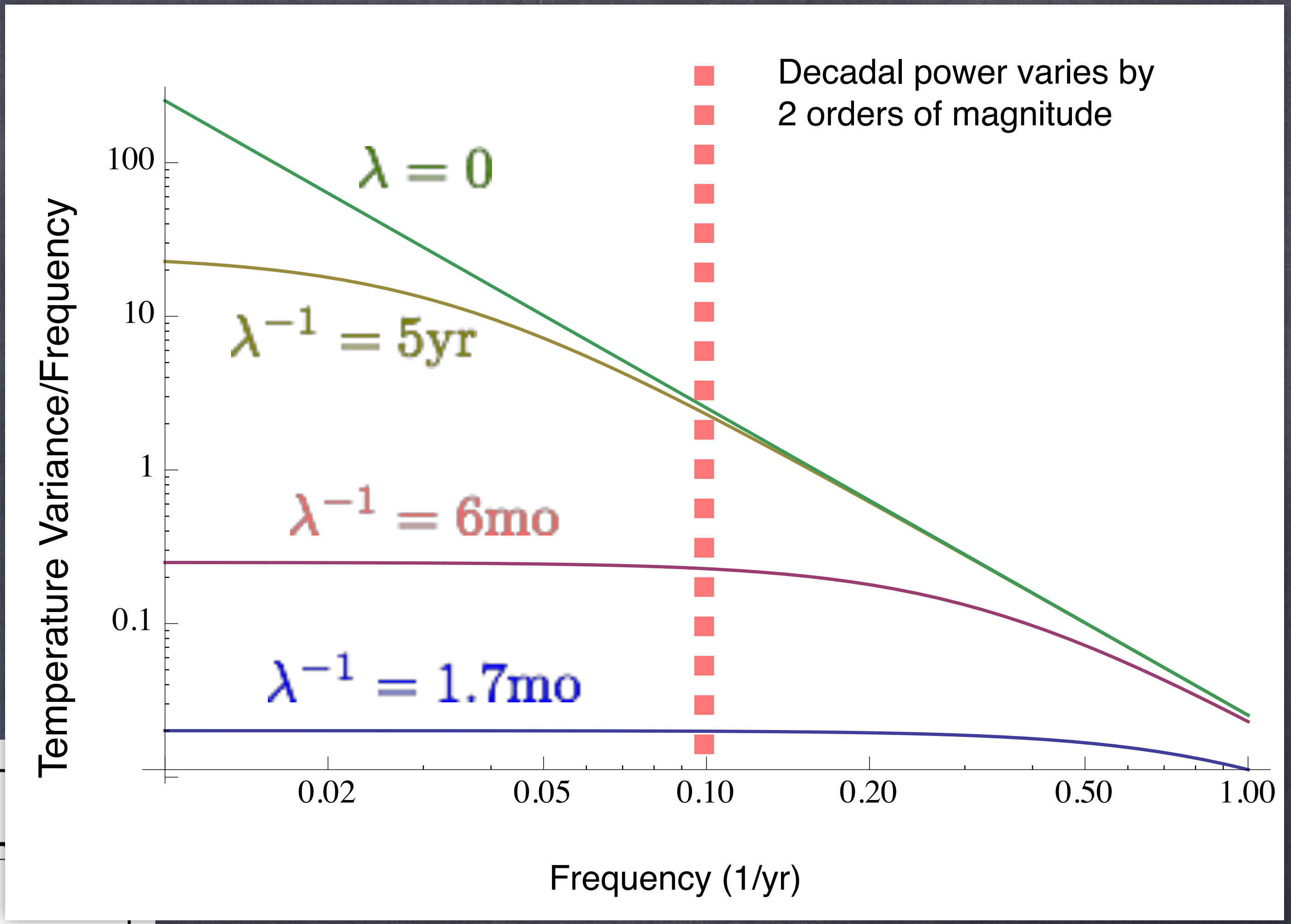
- We expect that observations will be understood as sampling from distributions of possible values.
- Models also produce distributions.
- We compare the distributions to see when the model succeeds or fails.
- But, different processes have different stats!
  - 2 Examples: Ocean Heat Content & El Nino

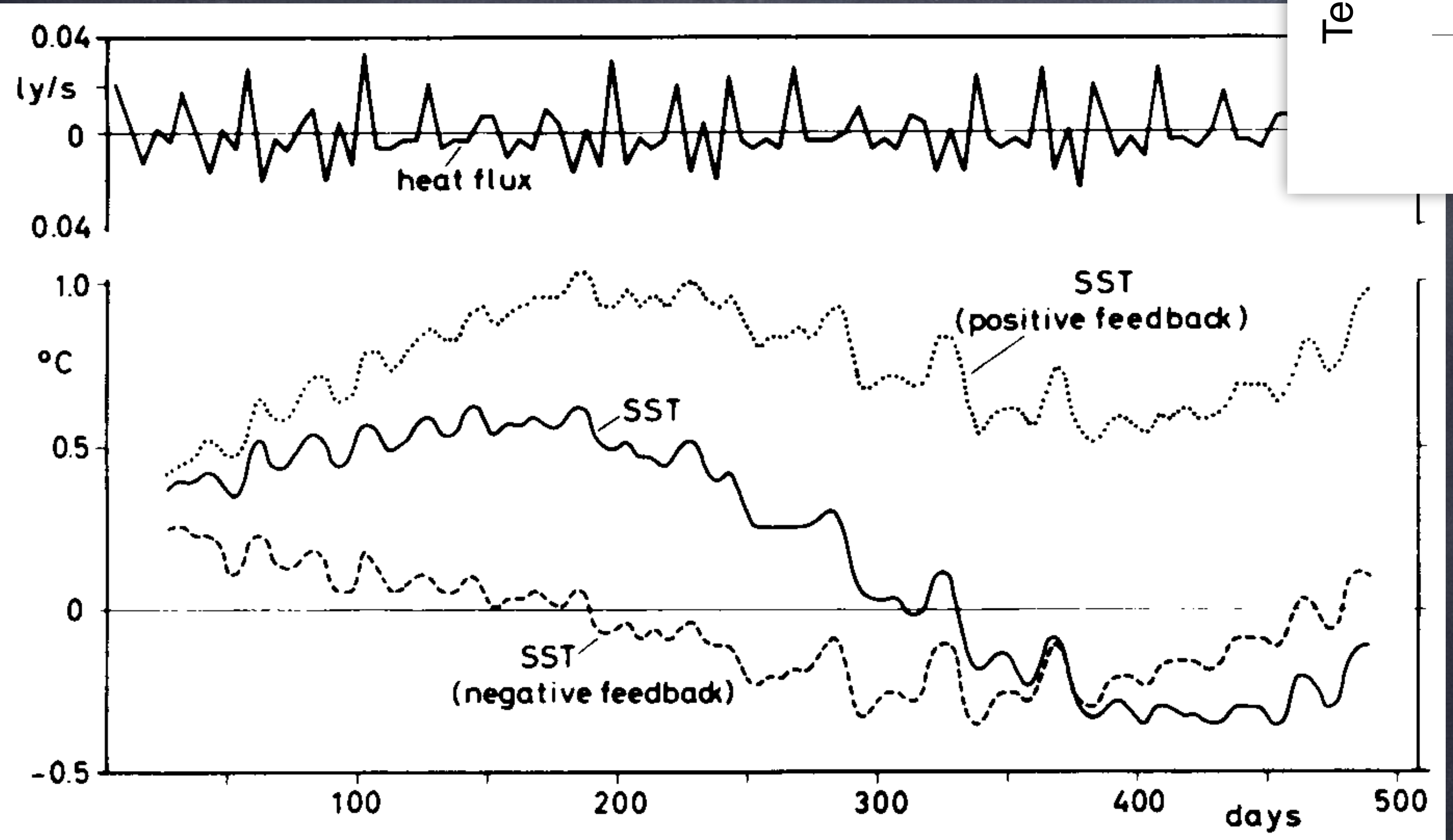
# Modeling Ocean Heat Content

## A stochastic, predictable persistence model: Frankignoul & Hasselmann (77)

Temp Change, Random Atmosphere, Restoring, Mixed Layer

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

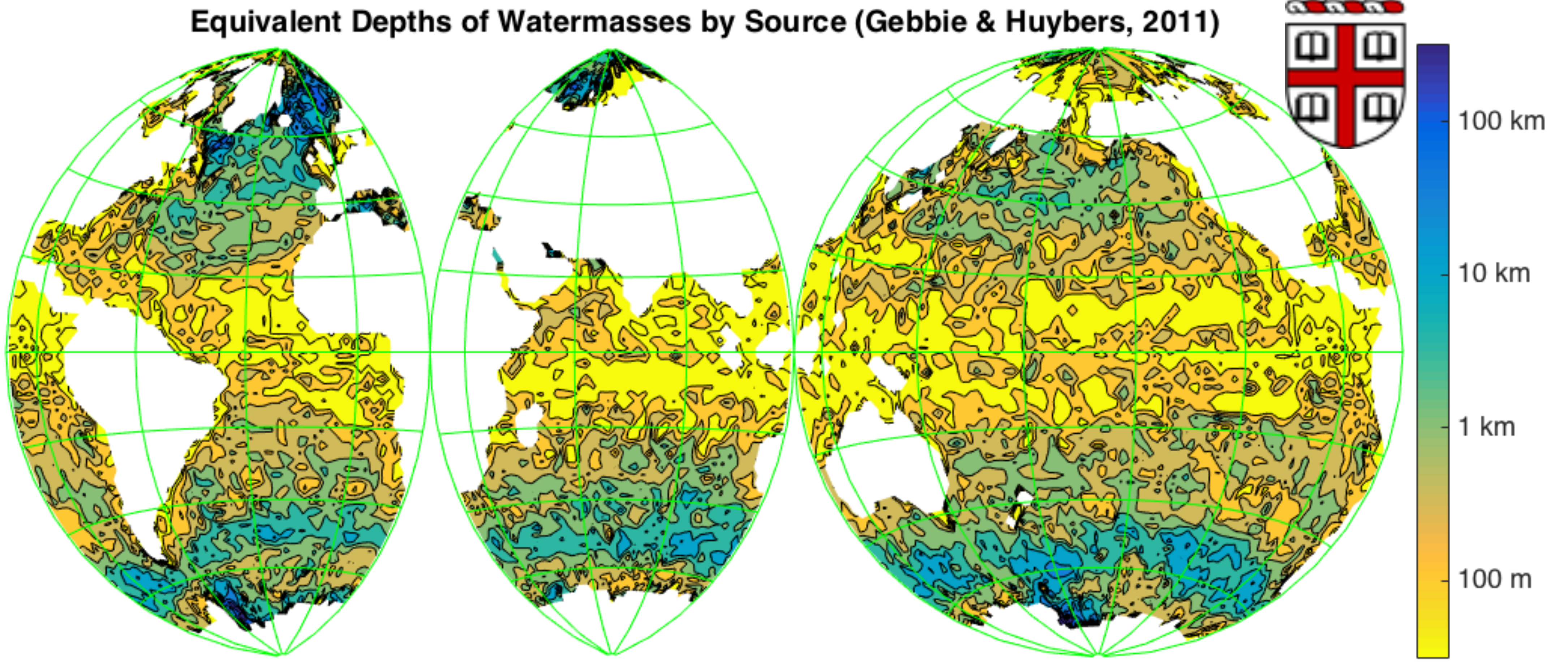


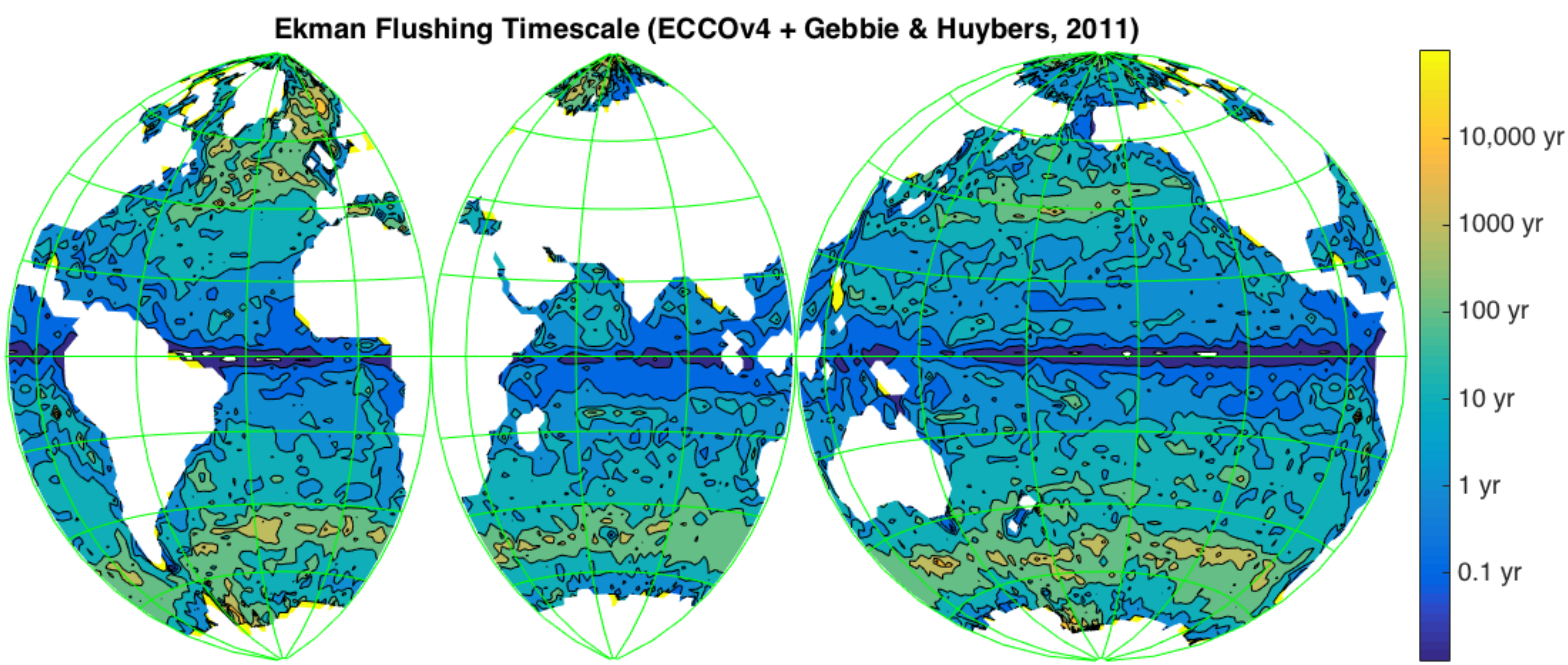

$$\lambda = \rho^a C_p^a (\rho^w C_p^w)^{-1} C_H (1 + B) \langle |U| \rangle h^{-1}$$

$$= (1.7 \text{ month})^{-1}$$

Consider lots of 1D Oceans: one per watermass

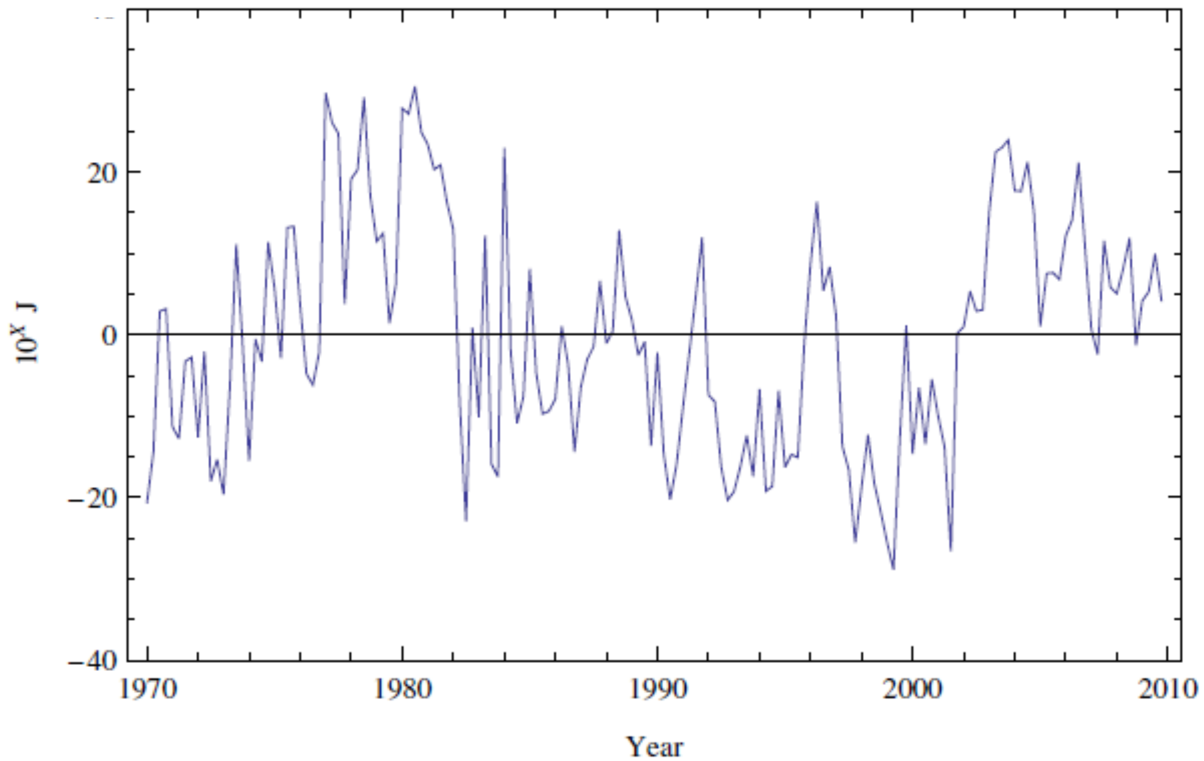



Wind (Ekman) flushing gives upper limit to $\lambda^{-1}$ timescale

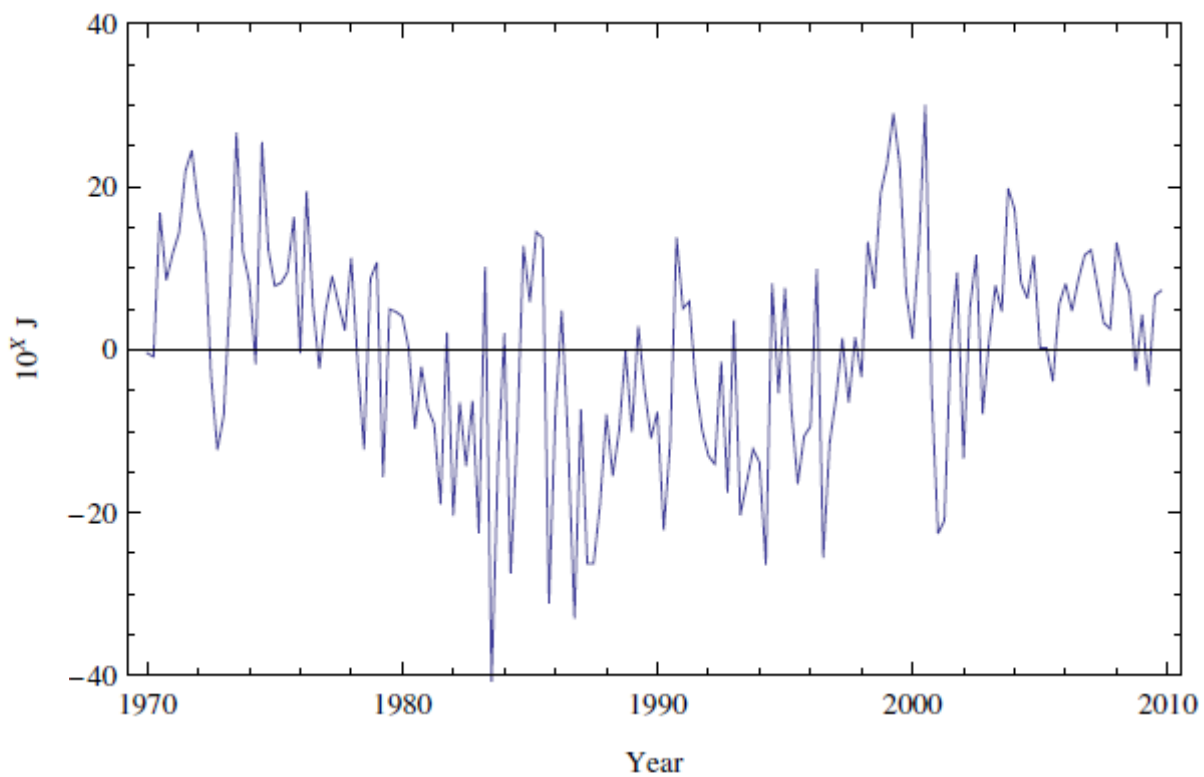


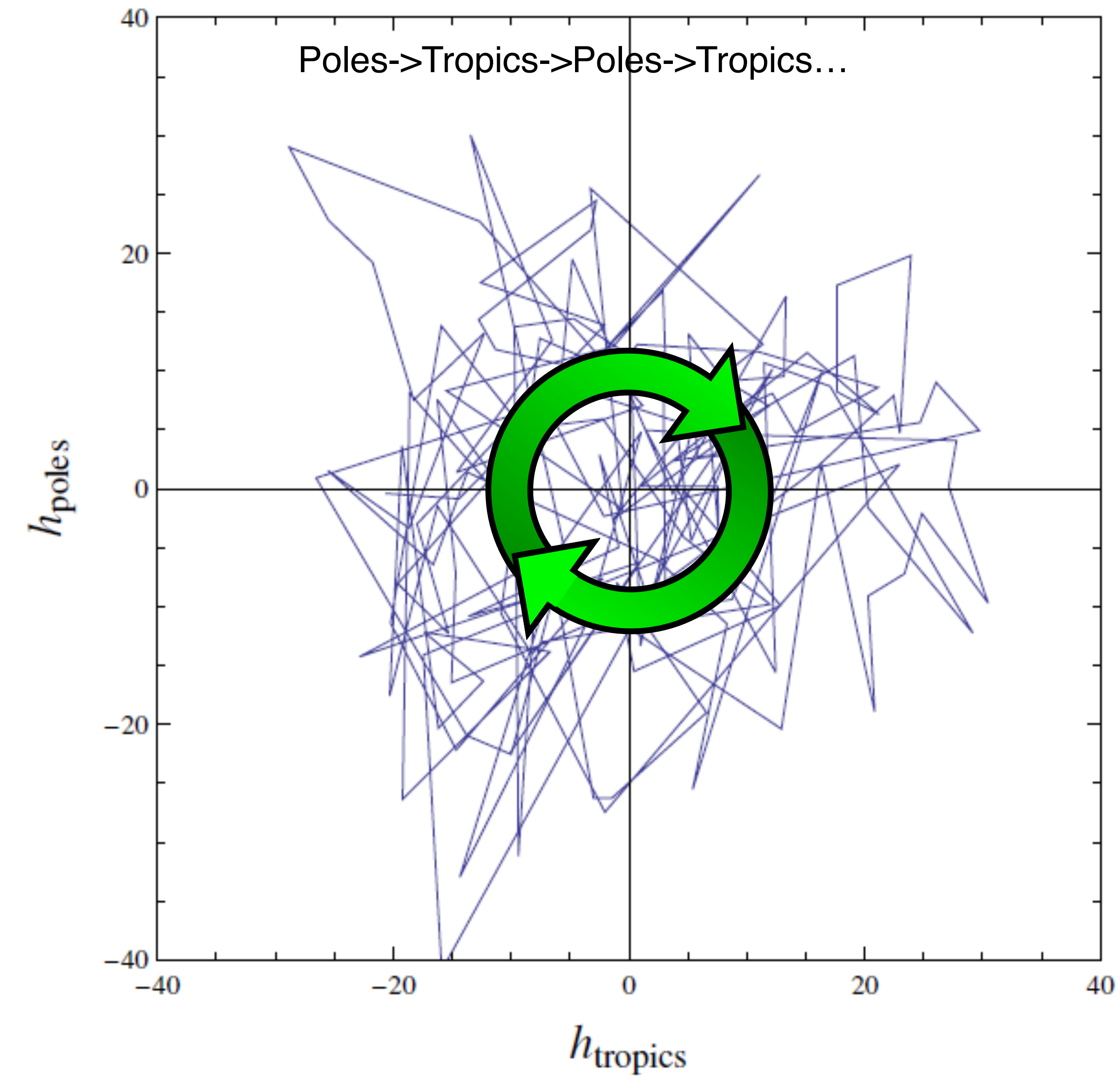
# If Connections Occur Between Regions— Predictability Can Arise, Even in Stochastic Systems.

Tropical Ocean Heat Content $h_{\text{tropics}}$




Polar Ocean Heat Content $h_{\text{poles}}$



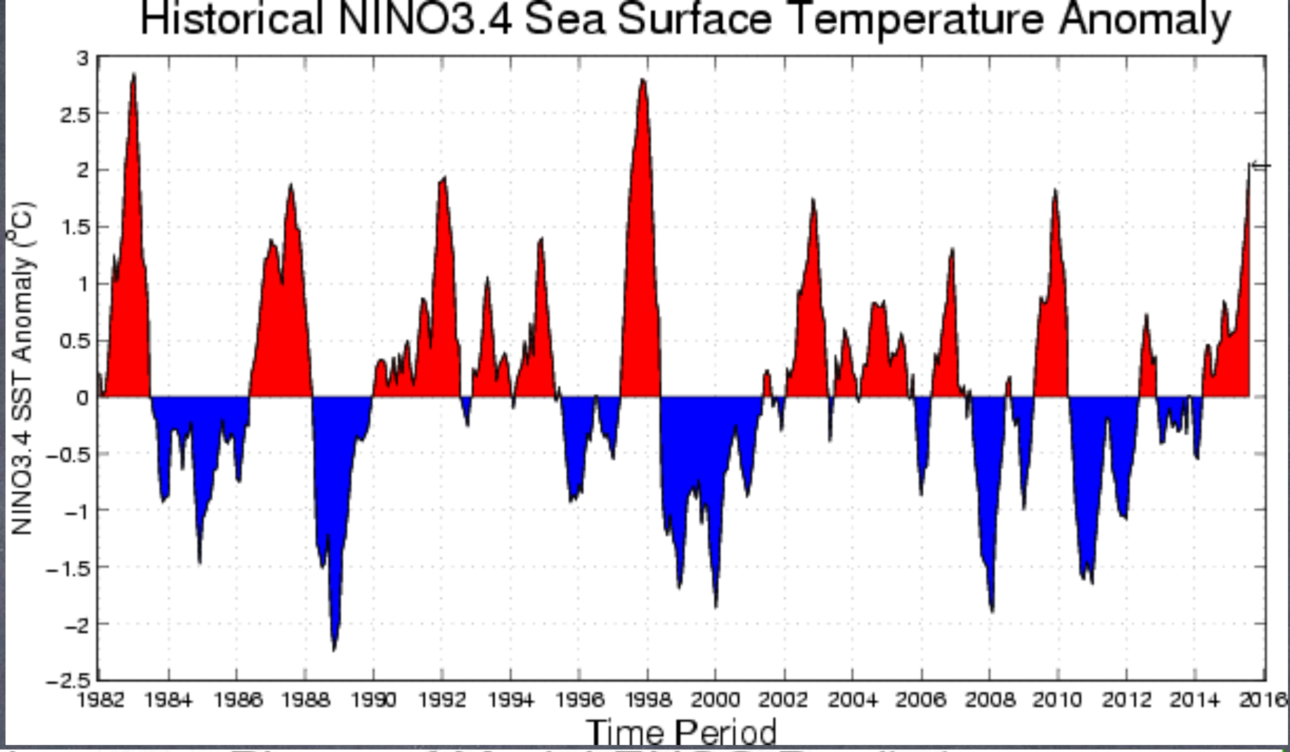

This is the root of most stochastic model predictability beyond persistence

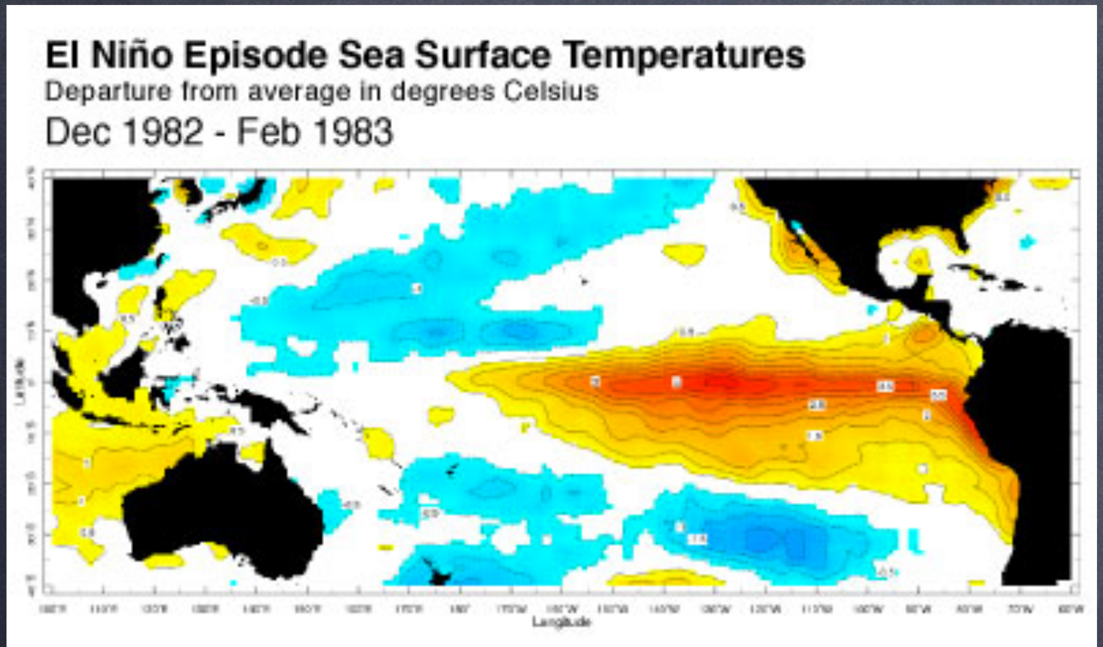

R. Zia, J. B. Weiss, D. Mandal, and B. Fox-Kemper. Manifest and subtle cyclic behavior in nonequilibrium steady states. In Journal of Physics: Conference Series, volume 750, page 012003. IOP Publishing, 2016.

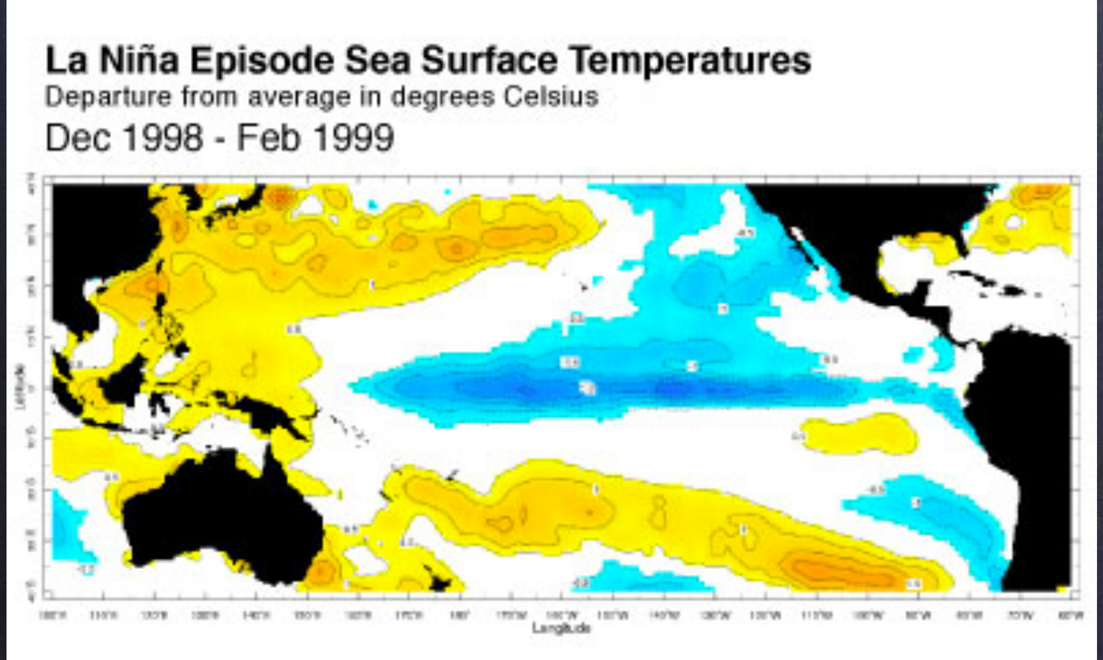
# El NINO!

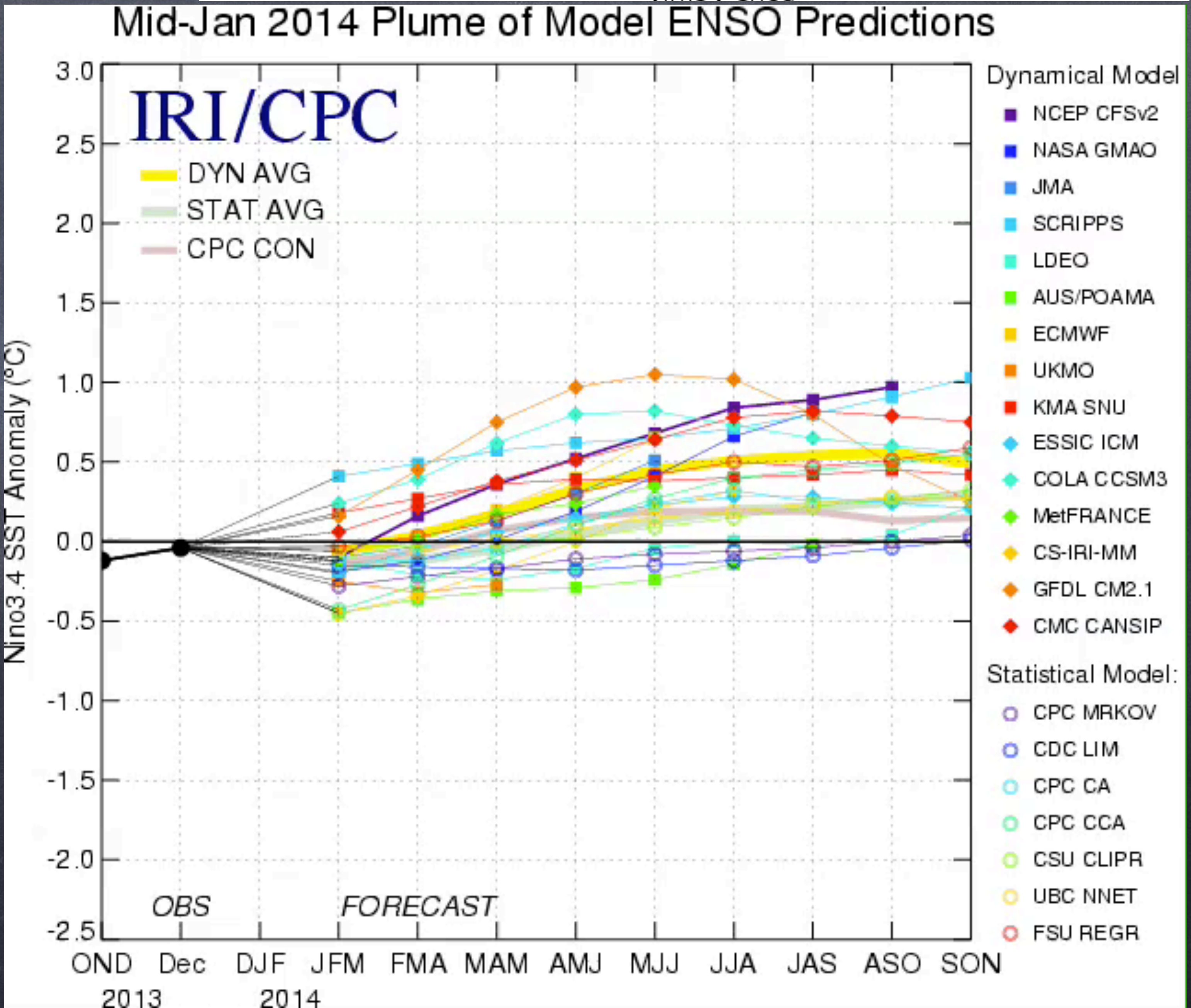
Predictability of ENSO events limited to < 1yr

ENSO statistics more predictable?

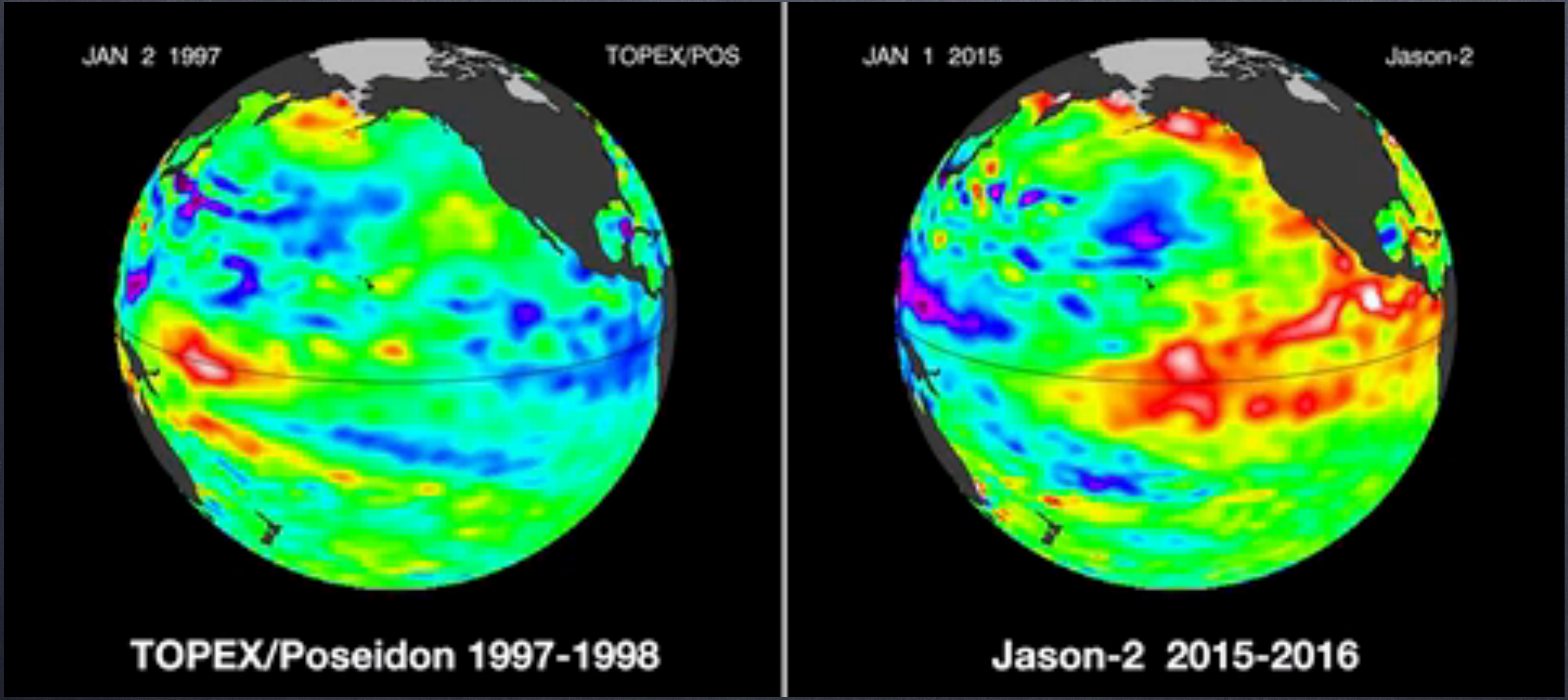


# El Nino: 1998 vs 2015




- SSH Movie Credit: NASA JPL

Are ENSO statistics predictable?

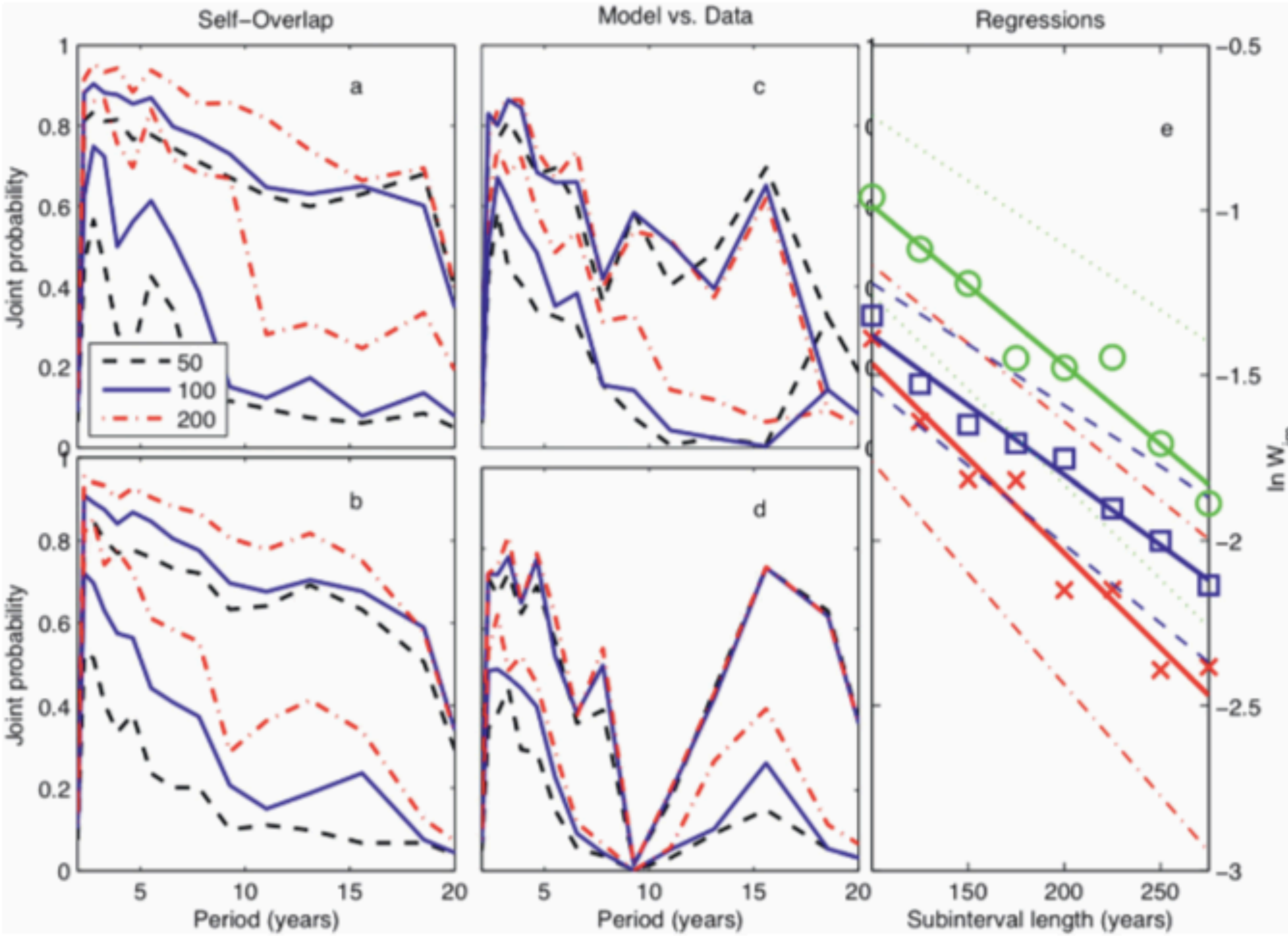
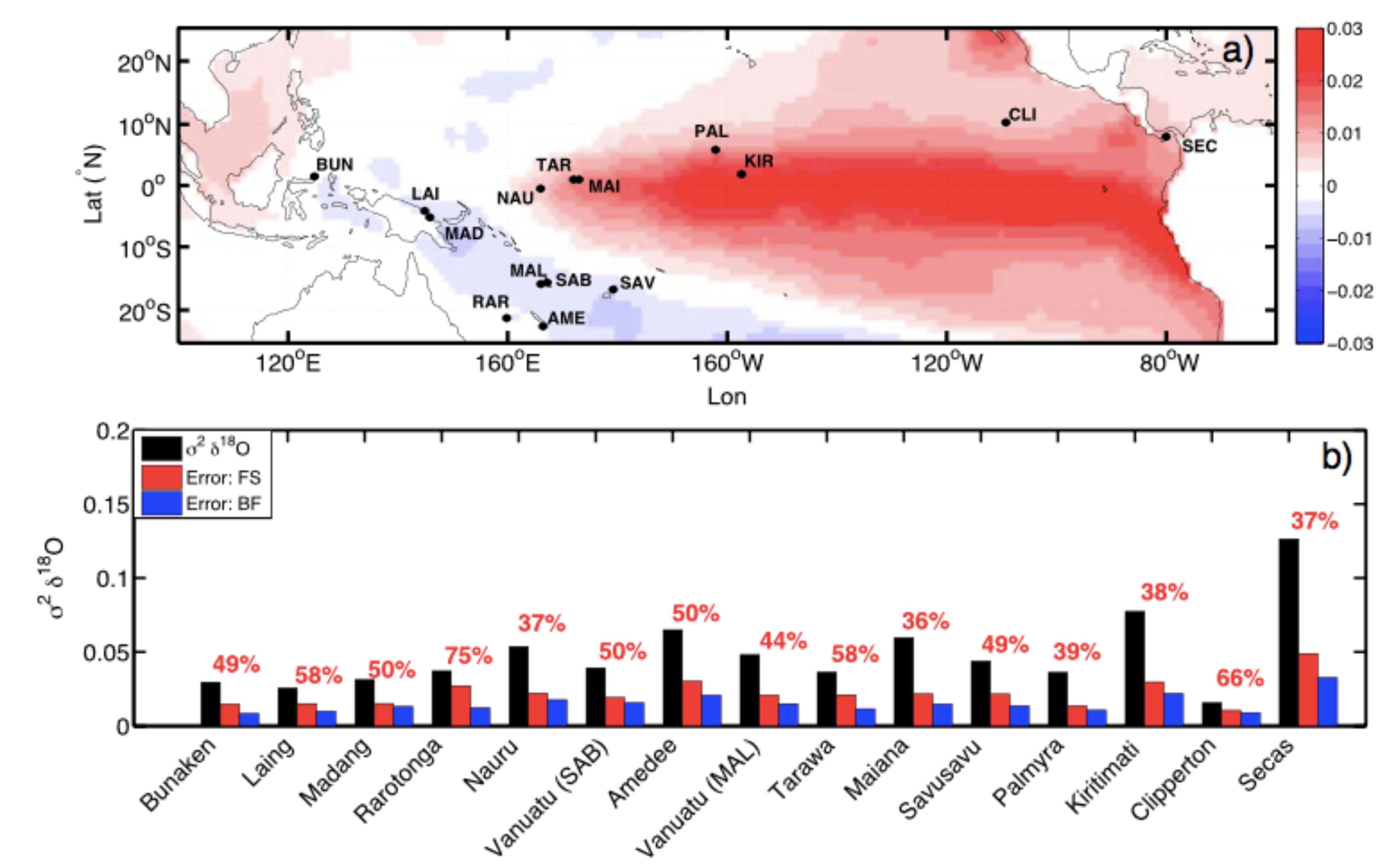
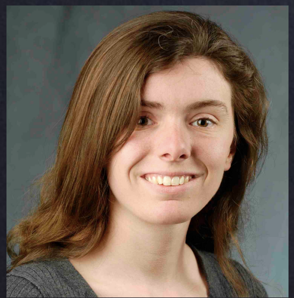



FIG. 2. (a),(b) The 90% confidence interval on WPI distributions for self-overlap calculations (CCSMcontrol and CM2.1, respectively). (c),(d) As in (a),(b), but for model–data WPI distributions. (a)–(d) Higher values of WPI indicate better agreement, ranging from 0 to 1. (e) The regression of 90% confidence interval widths against subinterval length, for self-overlap calculations. CCSMcontrol (NCAR CCSM3.5) data appear as red ×'s, GFDL CM2.1 as blue squares, and IPSL CM4 as green circles.

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

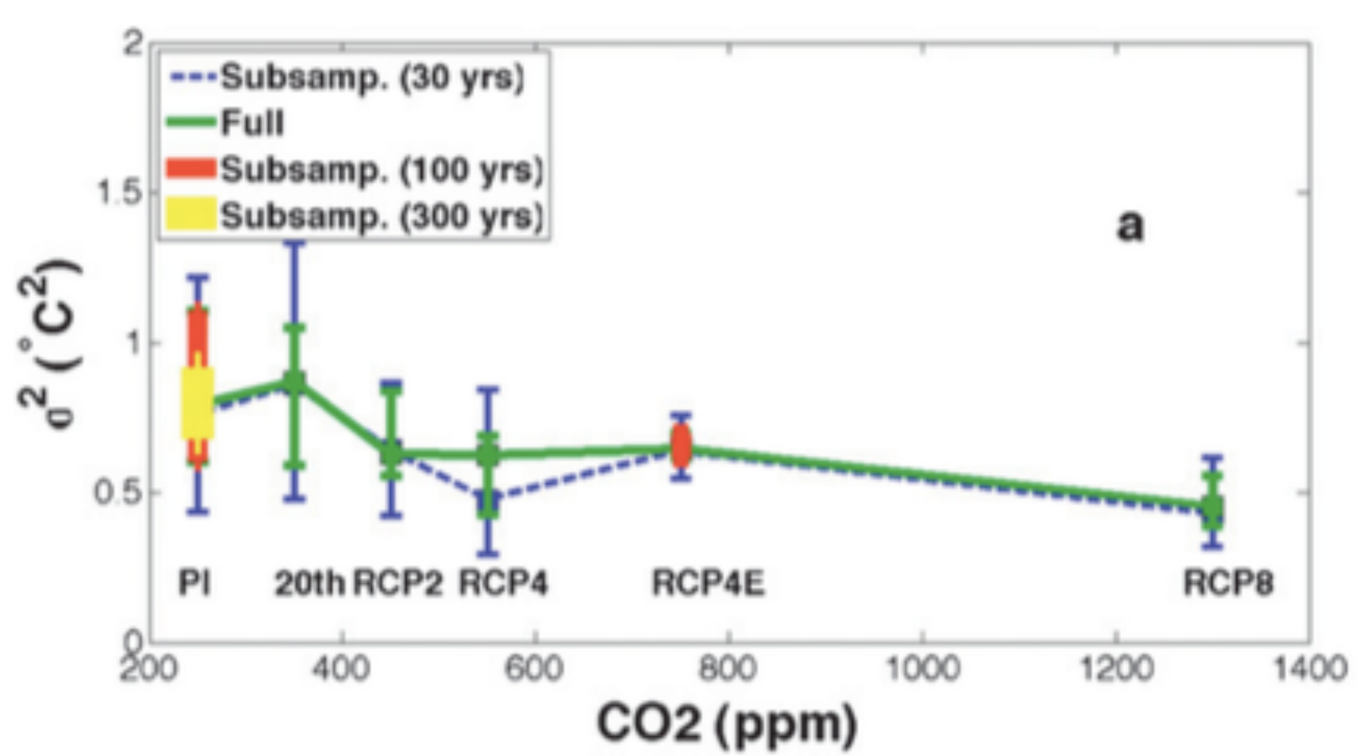
S. Stevenson, BFK, M. Jochum, B. Rajagopalan, and S. G. Yeager. ENSO model validation using wavelet probability analysis. Journal of Climate, 23:5540-5547, 2010.



Stevenson, UCSB

S. Stevenson, H. V. McGregor, S. J. Phipps, and B. Fox-Kemper. Quantifying errors in coral-based ENSO estimates: Towards improved forward modeling of δ18O. Paleoceanography, 28(4):633-649, December 2013.




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

CU, now NCAR

## But Big GHG Change to ENSO impacts!

## INDIRECT Proxy Reconstructions won't work!!!

S. Stevenson, BFK, M. Jochum, R. Neale, C. Deser, and G. Meehl. Will there be a significant change to El Nino in the 21st century? Journal of Climate, 25(6):2129-2145, March 2012.

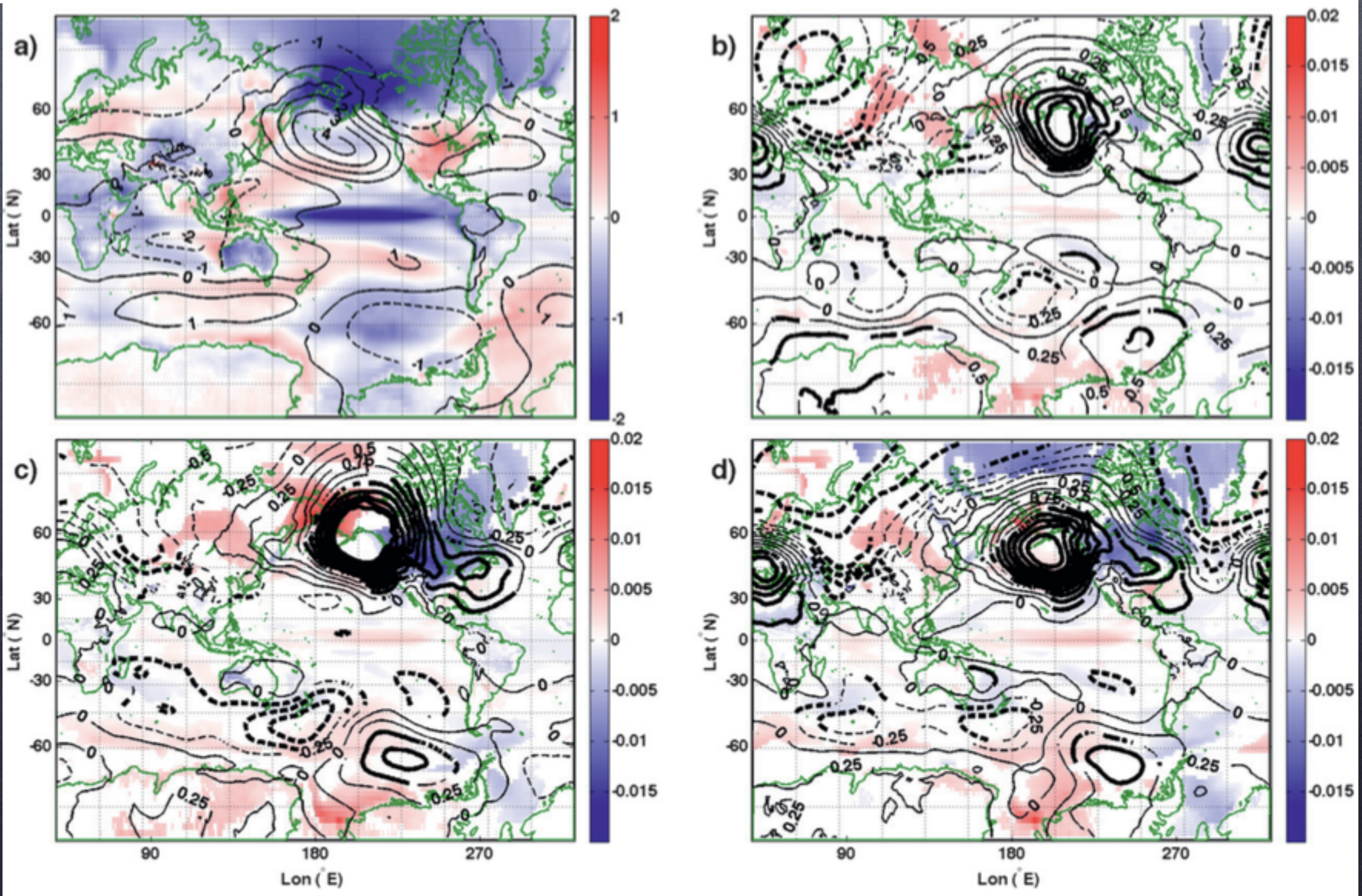
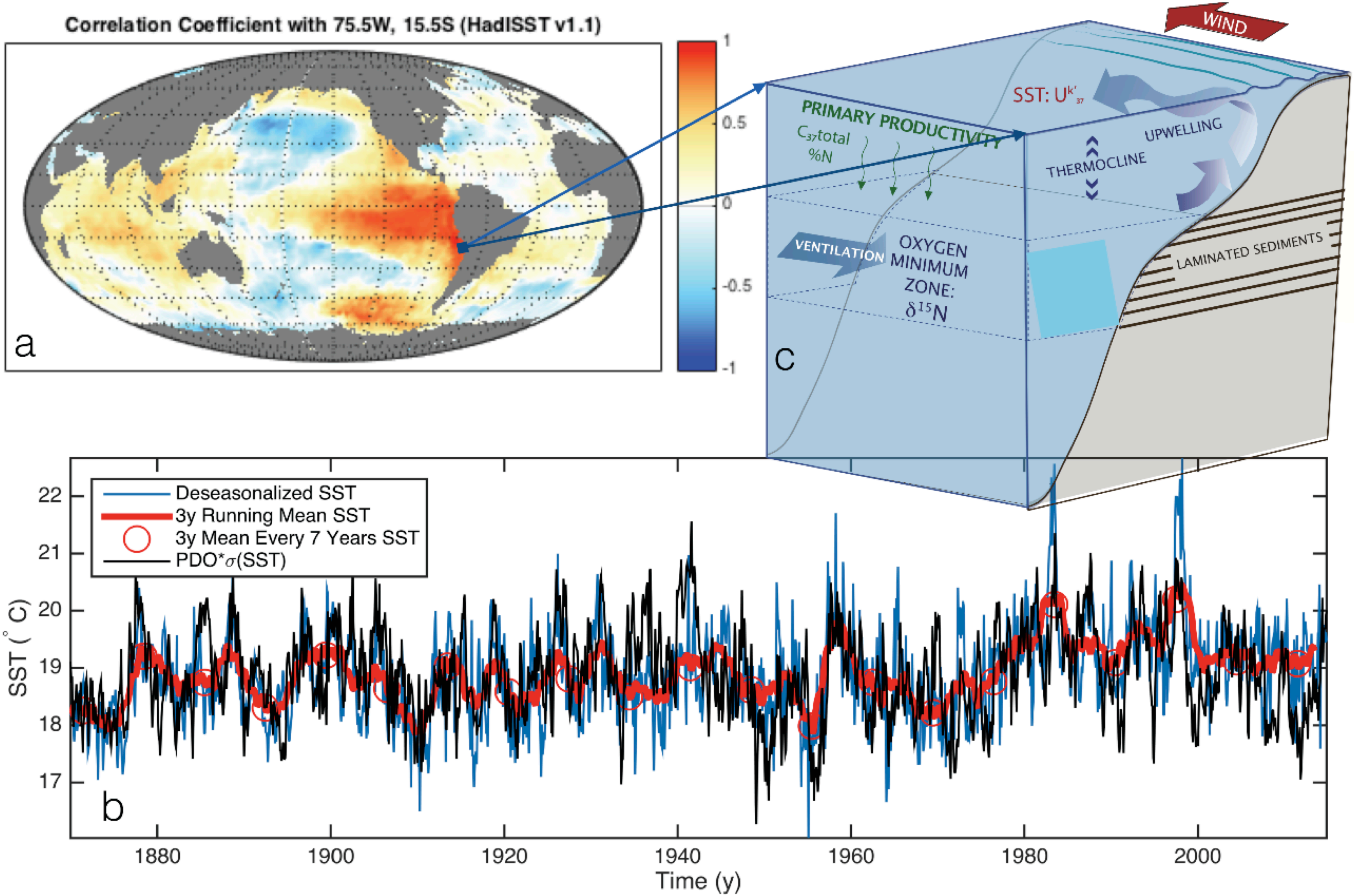



FIG. 6. As in Fig. 5, but for La Niña DJF.

# 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.

S. Ahn, BFK, T. Herbert, and C. Lawrence. Autoregressive statistical modeling of a peru margin multi-proxy holocene record shows correlation not cause, flickering regimes and persistence. Climate of the Past, January 2018. In discussion review.




S. Ahn, BFK, T. Herbert, and C. Lawrence. Autoregressive statistical modeling of a peru margin multi-proxy holocene record shows correlation not cause, flickering regimes and persistence. Climate of the Past, January 2018. In discussion review.

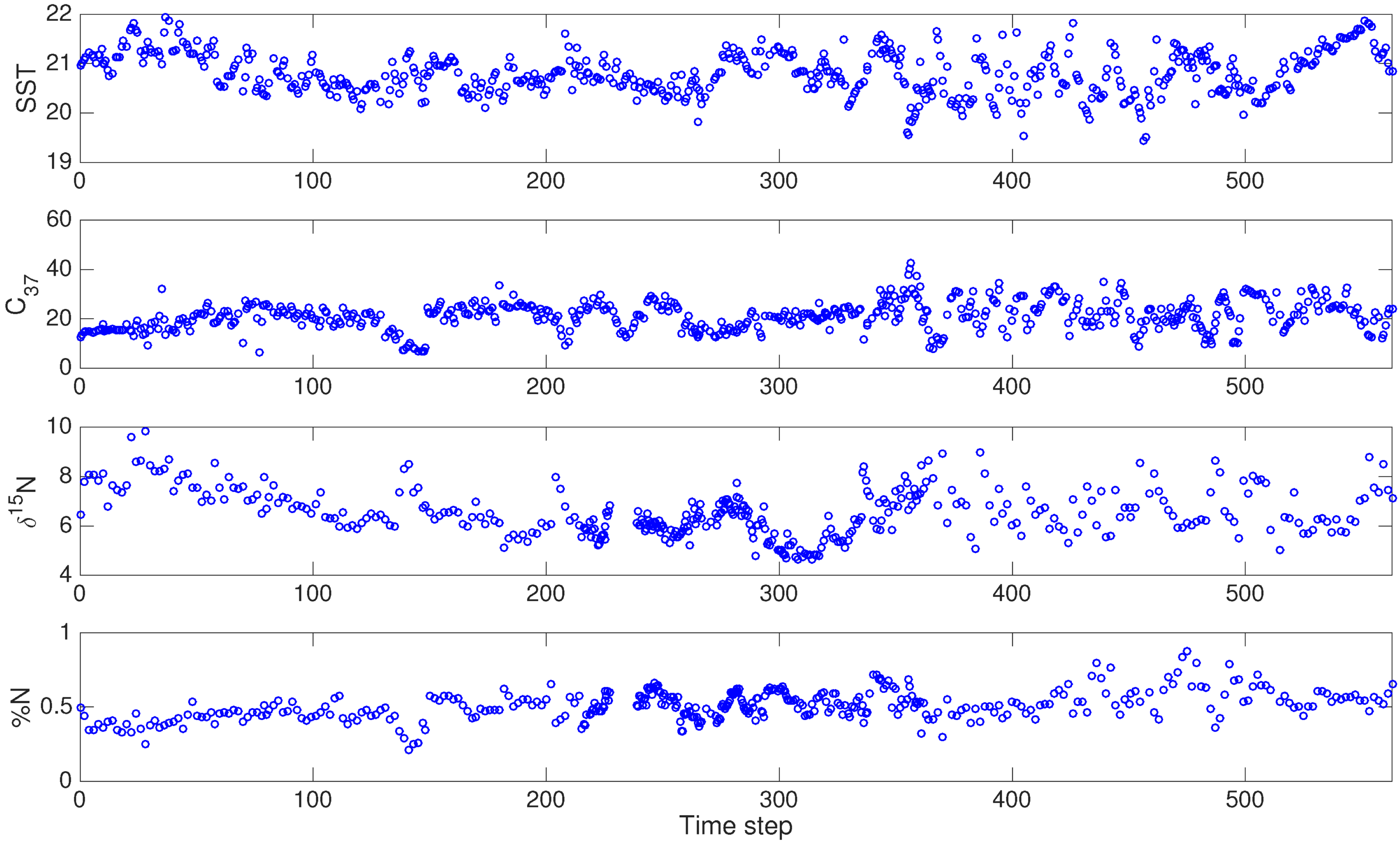



Figure 2 Observed data for time steps 0 to 563 (0.60 to 9.44 kA B.P.), with being the most recent point (time increasing to the right). 47% *SST* and $C_{37}$ are missing, and 65% of $\partial^{15}N$ and *%N* are missing.

S. Ahn, BFK, T. Herbert, and C. Lawrence. Autoregressive statistical modeling of a peru margin multi-proxy holocene record shows correlation not cause, flickering regimes and persistence. Climate of the Past, January 2018. In discussion review.

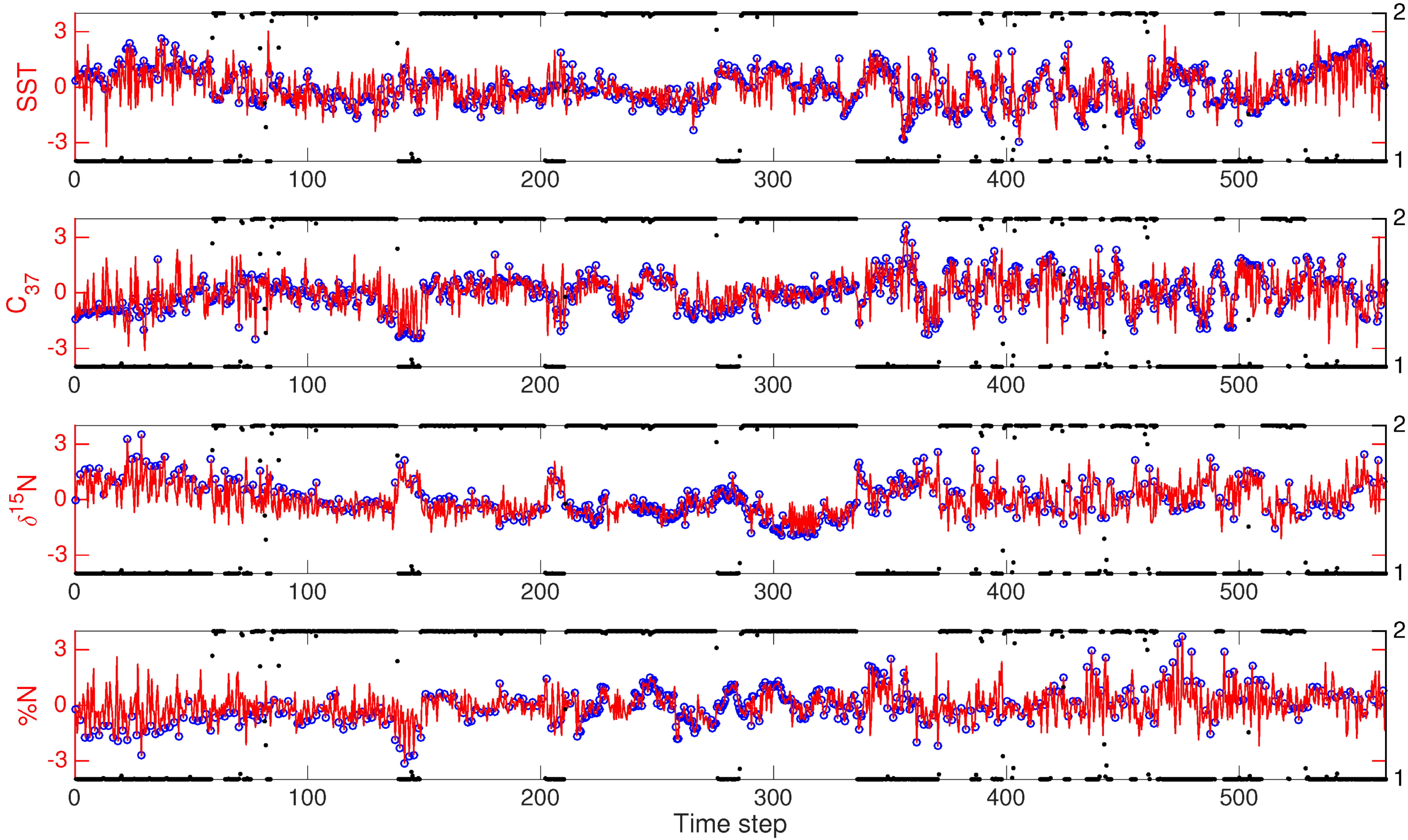



Figure 3 [HMM] State assignments by the HMM (black dots). State 1 is indicated by a black dot near the

# Hidden Markov Model infills & predicts regimes

S. Ahn, BFK, T. Herbert, and C. Lawrence. Autoregressive statistical modeling of a peru margin multi-proxy holocene record shows correlation not cause, flickering regimes and persistence. Climate of the Past, January 2018. In discussion review.

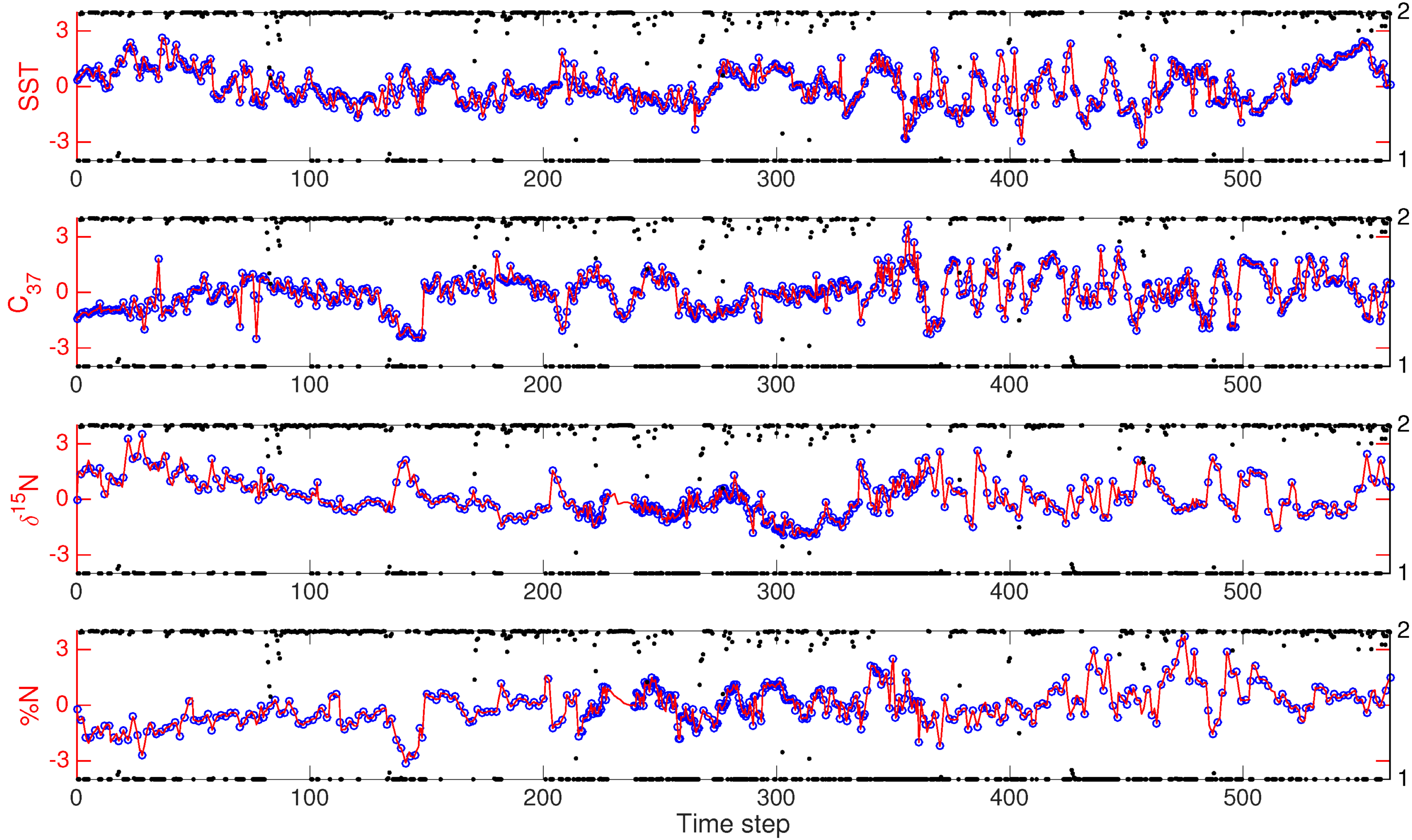


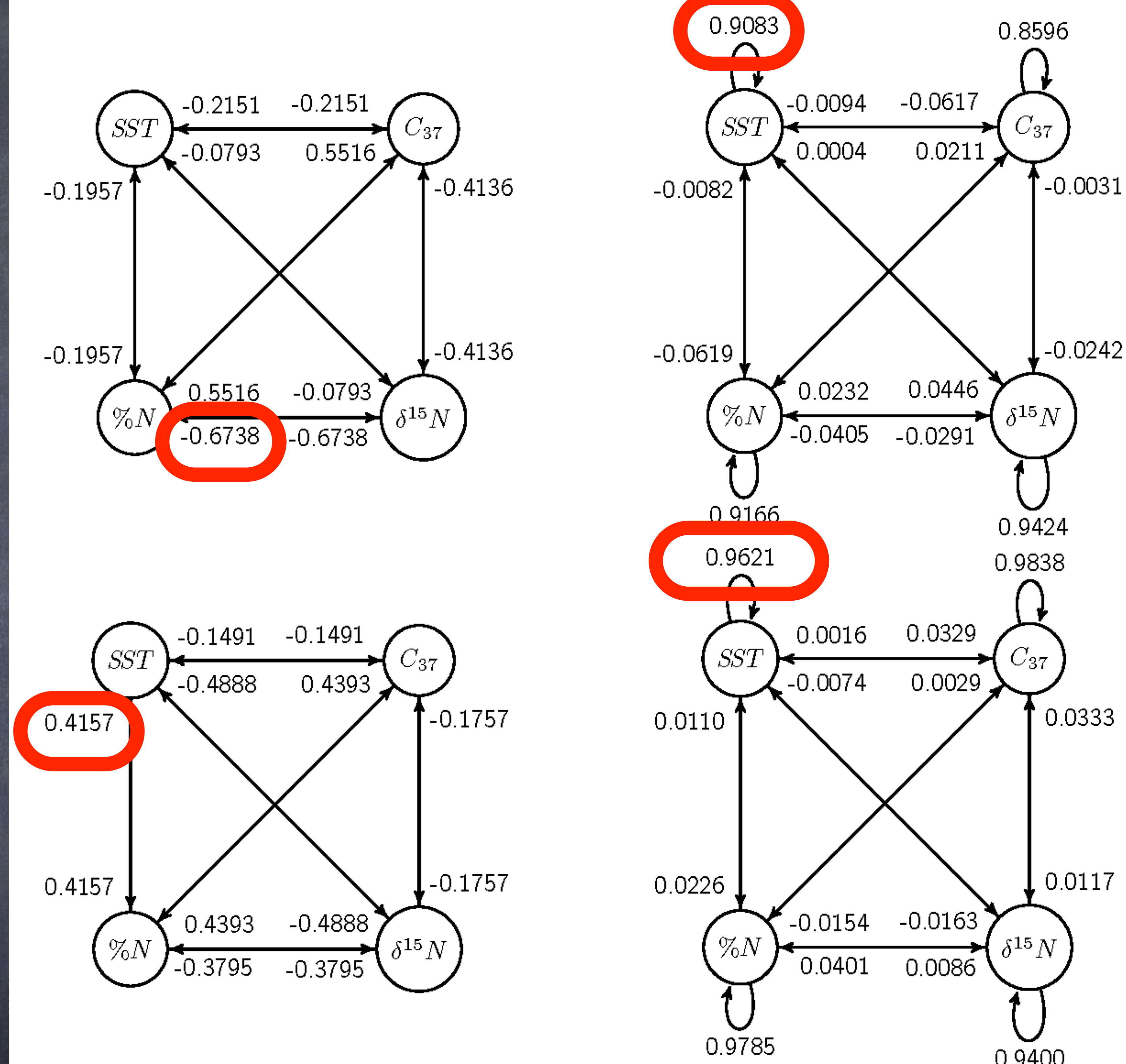

Figure 4 [AR-HMM] State assignments by the HMM (black dots). State 1 is indicated by a black dot near

# Auto-Regressive Hidden Markov Model infills & predicts regimes

S. Ahn, BFK, T. Herbert, and C. Lawrence. Autoregressive statistical modeling of a peru margin multi-proxy holocene record shows correlation not cause, flickering regimes and persistence. Climate of the Past, January 2018. In discussion review.

Calm Regime

Noisy Regime




Hidden Markov

Auto-Regressive Hidden Markov

Granger Causality: What is causing what ?

Correlation is not Causation

S. Ahn, BFK, T. Herbert, and C. Lawrence. Autoregressive statistical modeling of a peru margin multi-proxy holocene record shows correlation not cause, flickering regimes and persistence. Climate of the Past, January 2018. In discussion review.

# Deep Variability is the HARDEST!

## Intermittency?

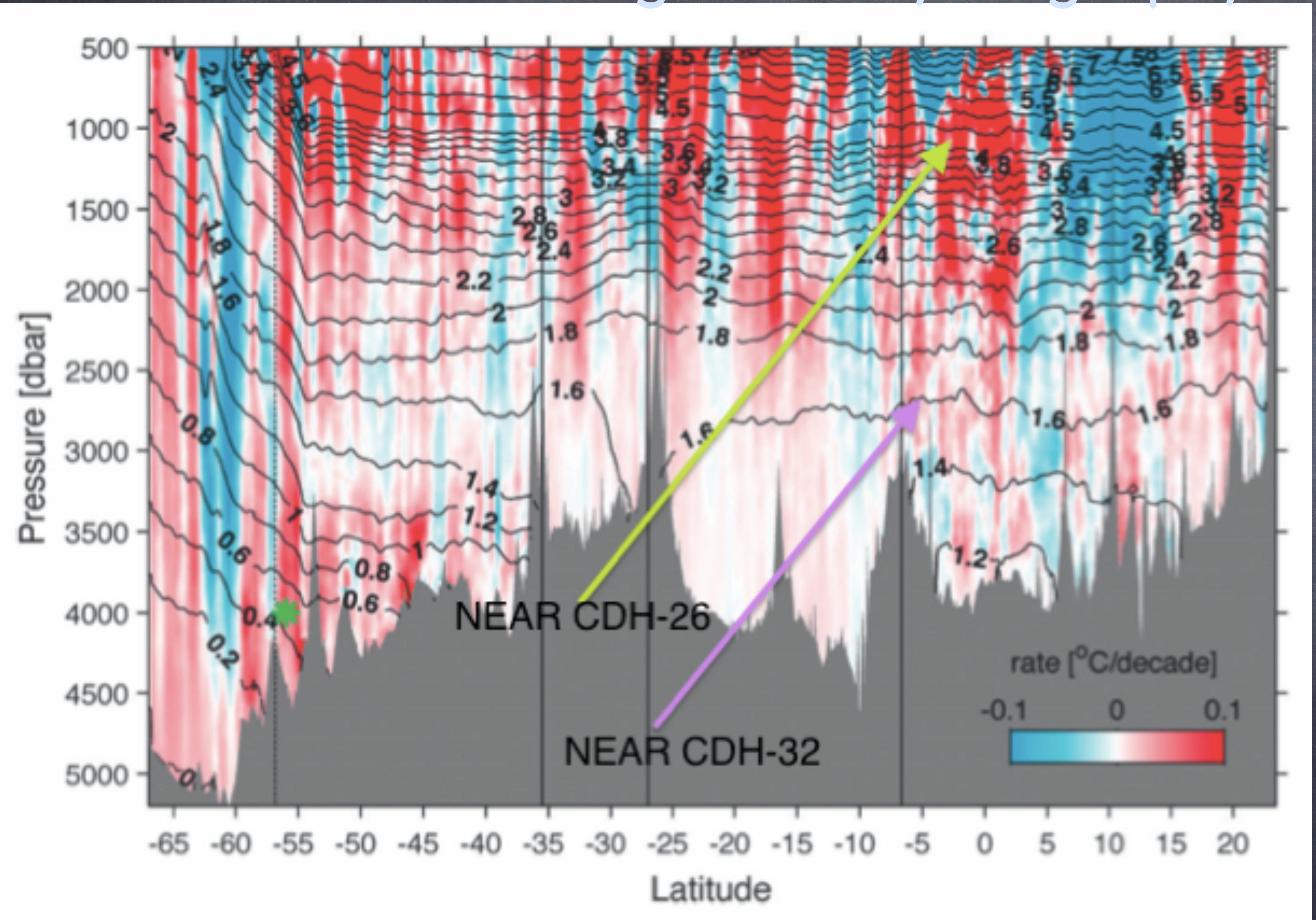
- Stochastic damping very slow!
  - huge heat capacity (biggest watermasses on Earth)!
- Timescales may be very long!
  - Watermasses O(1500yr) old by radiocarbon
- Lengthscales may be very short!
  - (weak stratification implies a Rossby radius of O(2km) for modes trapped in AABW only)
- Water "formed"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

- Difficult to observe, IMPOSSIBLE TO MODEL = FUN!

# Understanding of past variability

Even with Argo, it will be a while until we have long timescale variability. What to do?

## Pattern of Warming from Hydrography



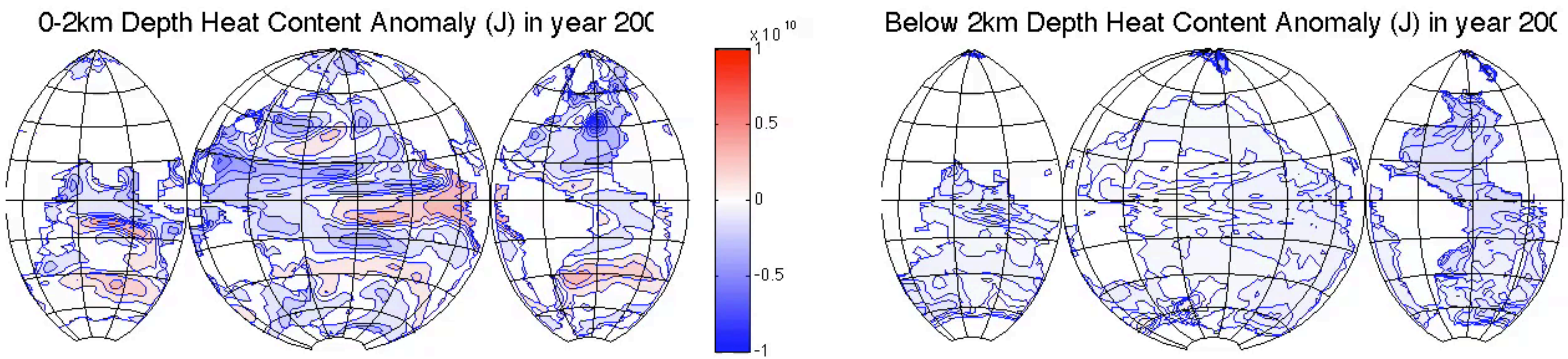

Purkey & Johnson, 2010

Examine CDH-26 sediment core from the Holocene indicated

now Rutgers

# What does a climate model—WITHOUT WARMING—look like in Ocean Heat Content Variability?

## Doesn't even include mesoscale eddies




Contours = 4 units

Contours = 1 unit

From the >1000yr steady forcing CCSM3.5

S. Stevenson, BFK, and M. Jochum, 2012: Understanding the ENSO-CO2 link using stabilized climate simulations. Journal of Climate, 25(22):7917–7936.

CU, now NCAR

# Understanding of past variability

# Assessing variability using individual benthic foraminifera

$$\delta^{18}O = \left( \frac{\left(\frac{^{18}O}{^{16}O}\right)_{sample}}{\left(\frac{^{18}O}{^{16}O}\right)_{standard}} - 1 \right) * 1000 \ ‰$$

- Benthic foraminiferal $\delta^{18}O$ values record temperature and salinity properties of ambient seawater

  T (°C) = 21.6 - 5.50 × ($\delta^{18}O_c$-$\delta^{18}O_{sw}$)
  
  Bemis et al. 2002

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

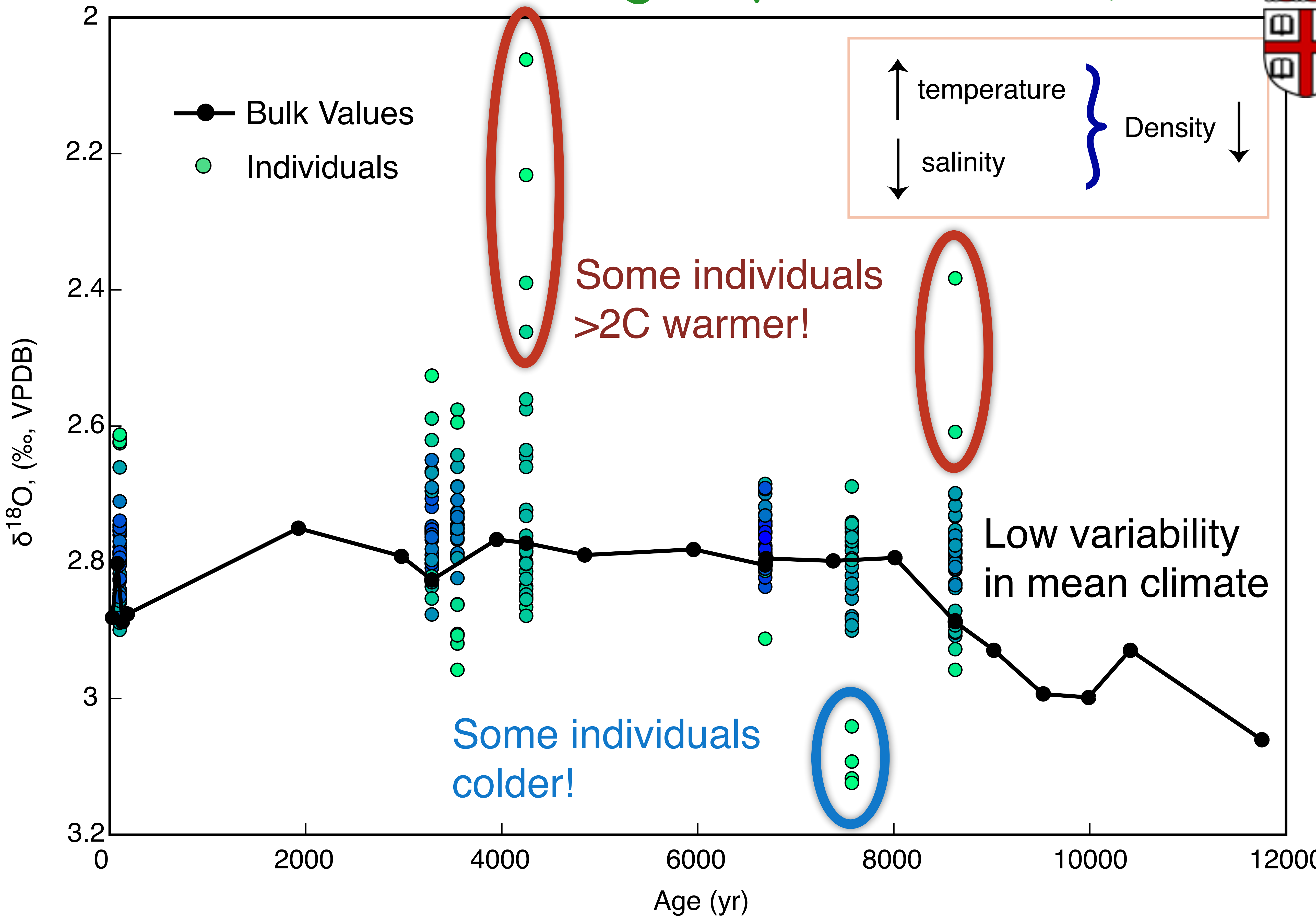
- Individual foraminifera provide 2-3 week snapshots of seawater properties

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


*Uvigerina* spp.

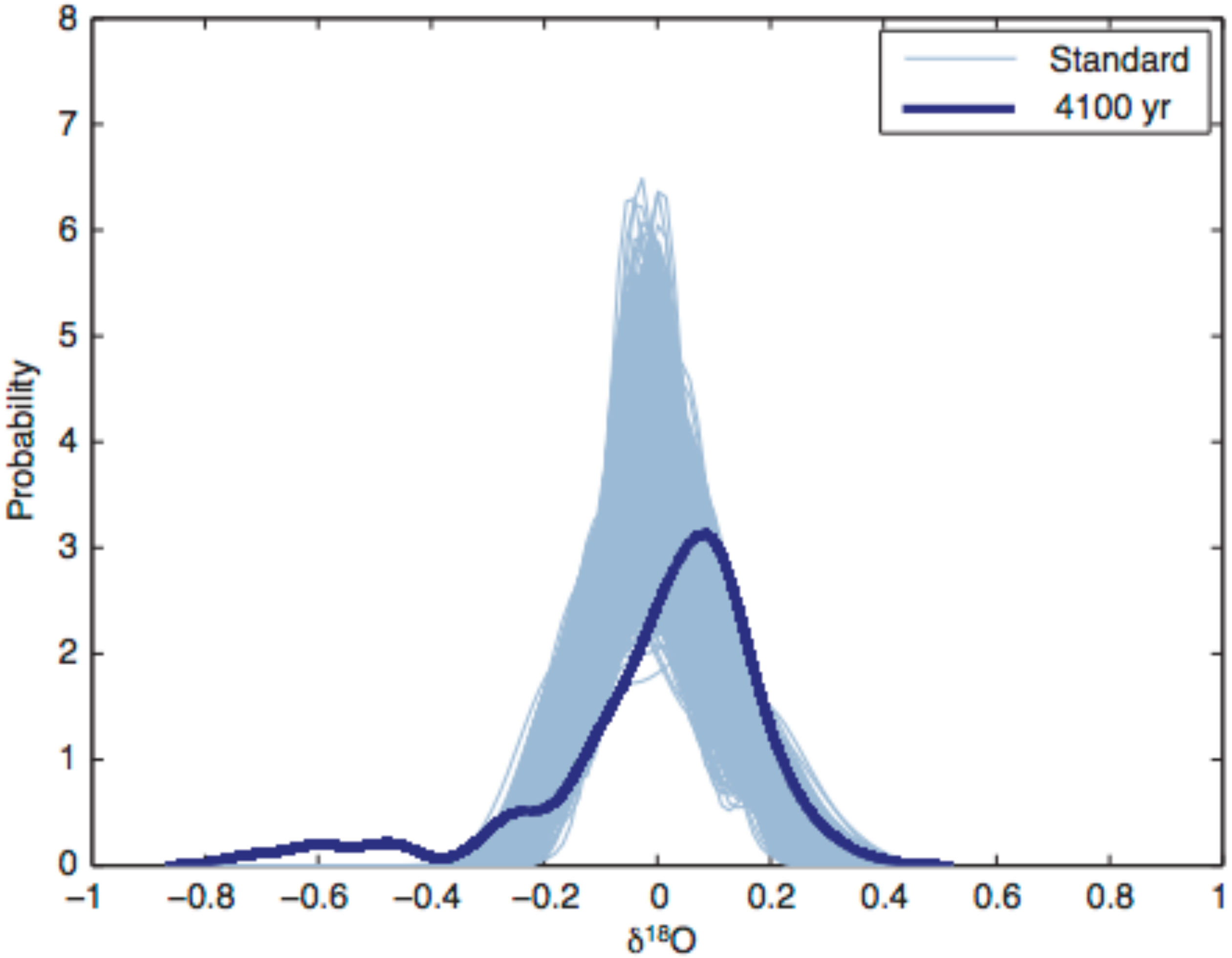
S. Bova, T. D. Herbert, and BFK. Rapid variations in deep ocean temperature detected in the holocene. Geophysical Research Letters, 43, December 2016.

# Understanding of past variability

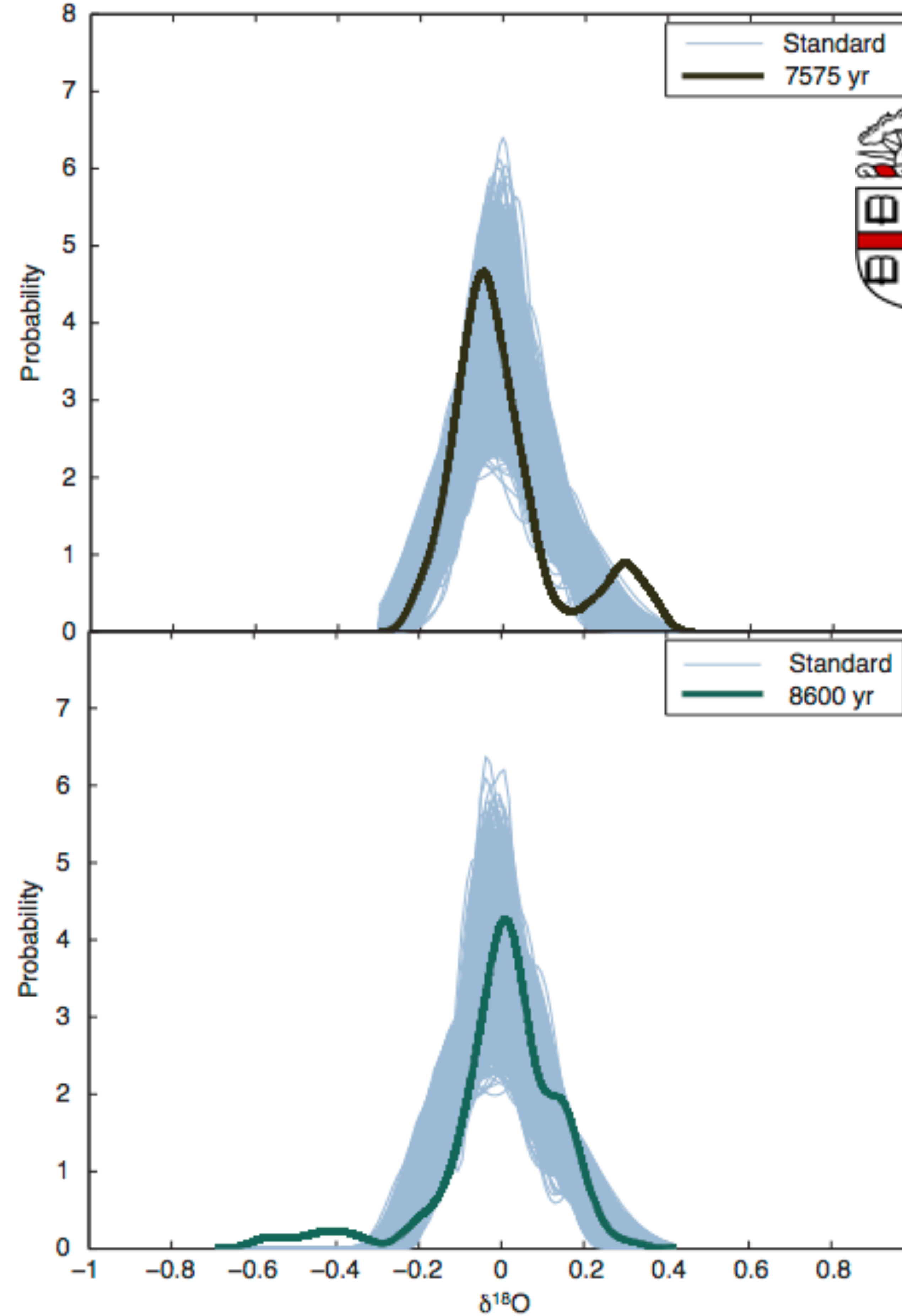



S. Bova, T. D. Herbert, and BFK. Rapid variations in deep ocean temperature detected in the holocene. Geophysical Research Letters, 43, December 2016.

p<0.01




p<0.10



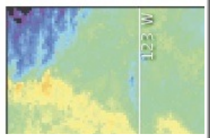

At these three time intervals, the spread of individual values exceeds a size-matched spread of instrumental standards.

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

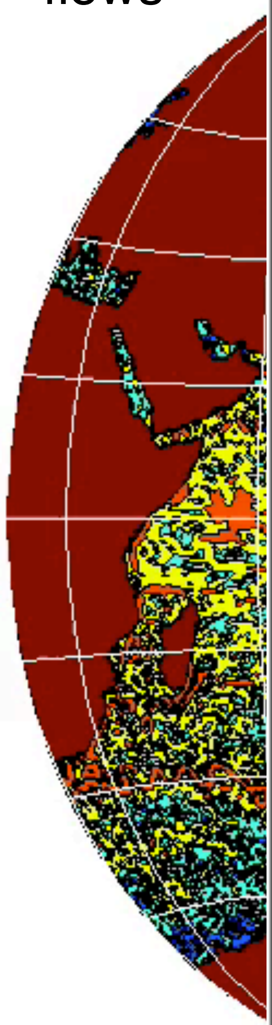
According to these forams—deep water variability is **unexpectedly important, intermittently** through the past!

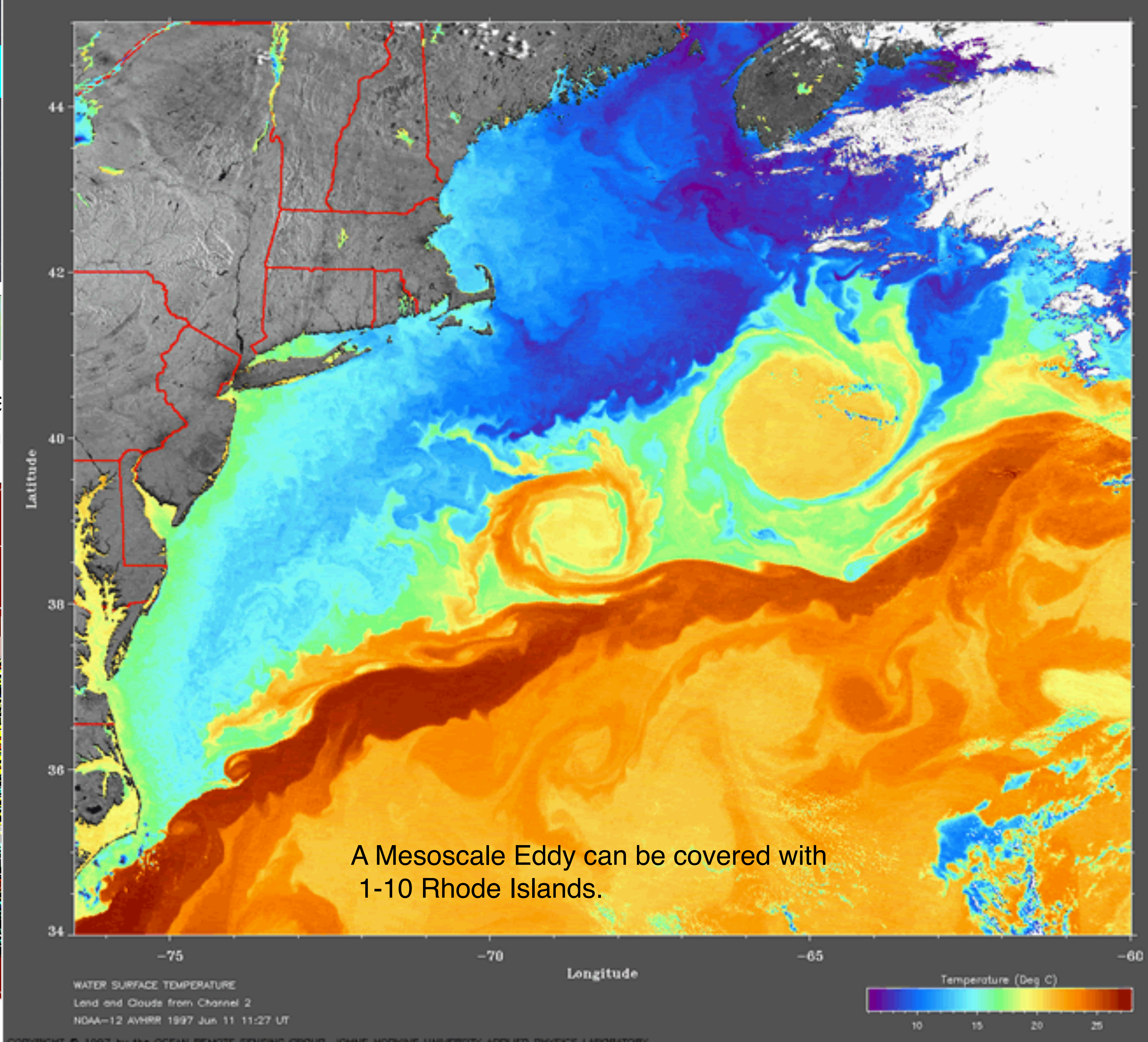
# Tl

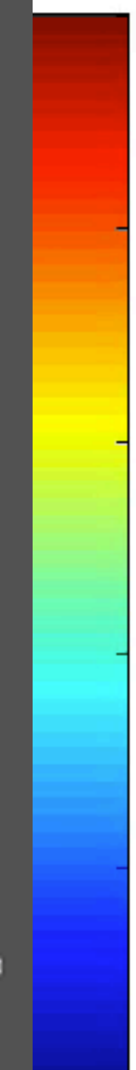
(Cap



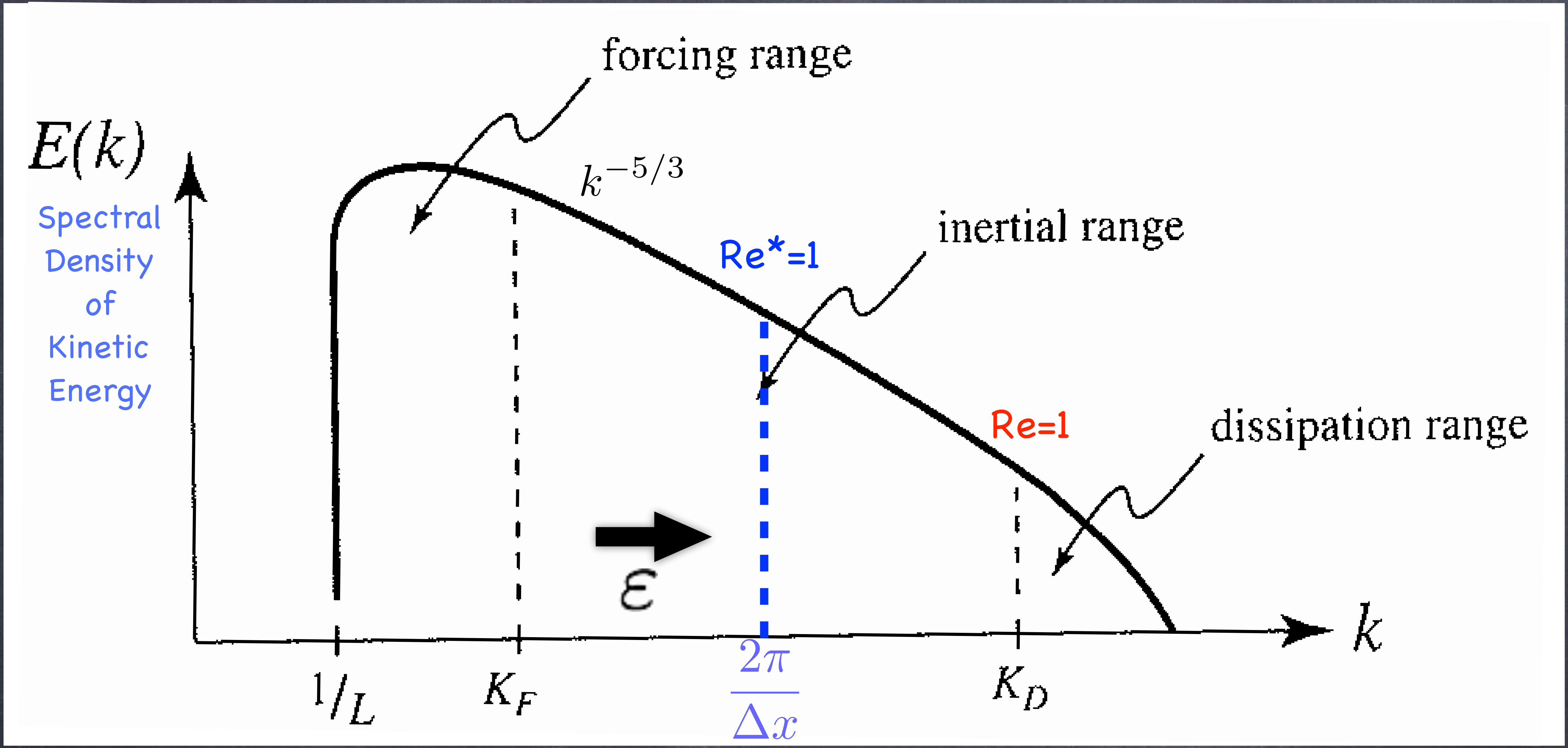
Satellite a
view of m
flows





# 3D Turbulence Cascade



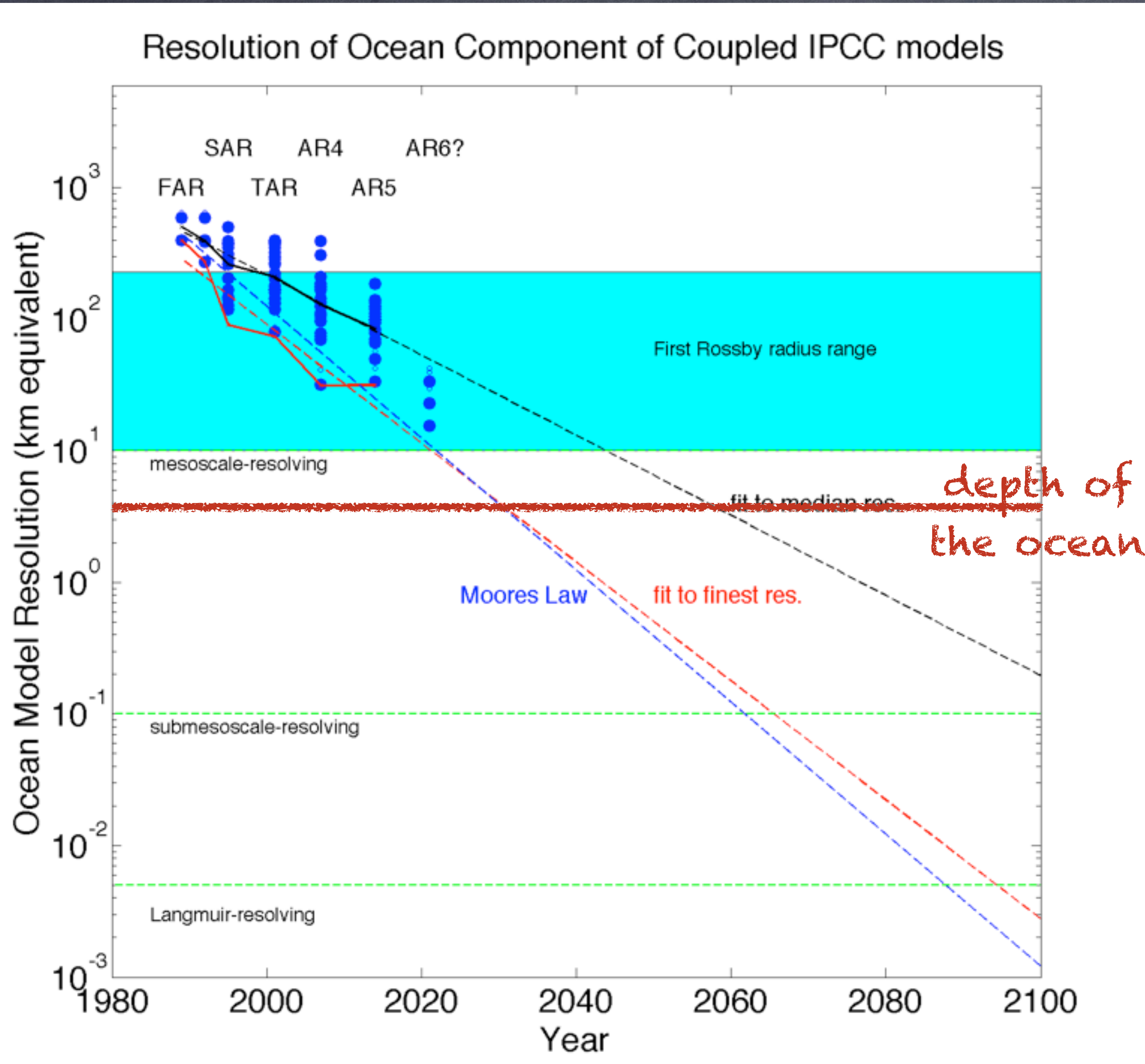

1963: Smagorinsky Scale & Flow Aware Viscosity Scaling,

So the Energy Cascade is Preserved,

but order-1 gridscale Reynolds #: $Re^* = UL/\nu_*$

$$\nu_{*h} = \left(\frac{\Upsilon_h \Delta x}{\pi}\right)^2 \sqrt{\left(\frac{\partial u_*}{\partial x} - \frac{\partial v_*}{\partial y}\right)^2 + \left(\frac{\partial u_*}{\partial y} + \frac{\partial v_*}{\partial x}\right)^2}$$

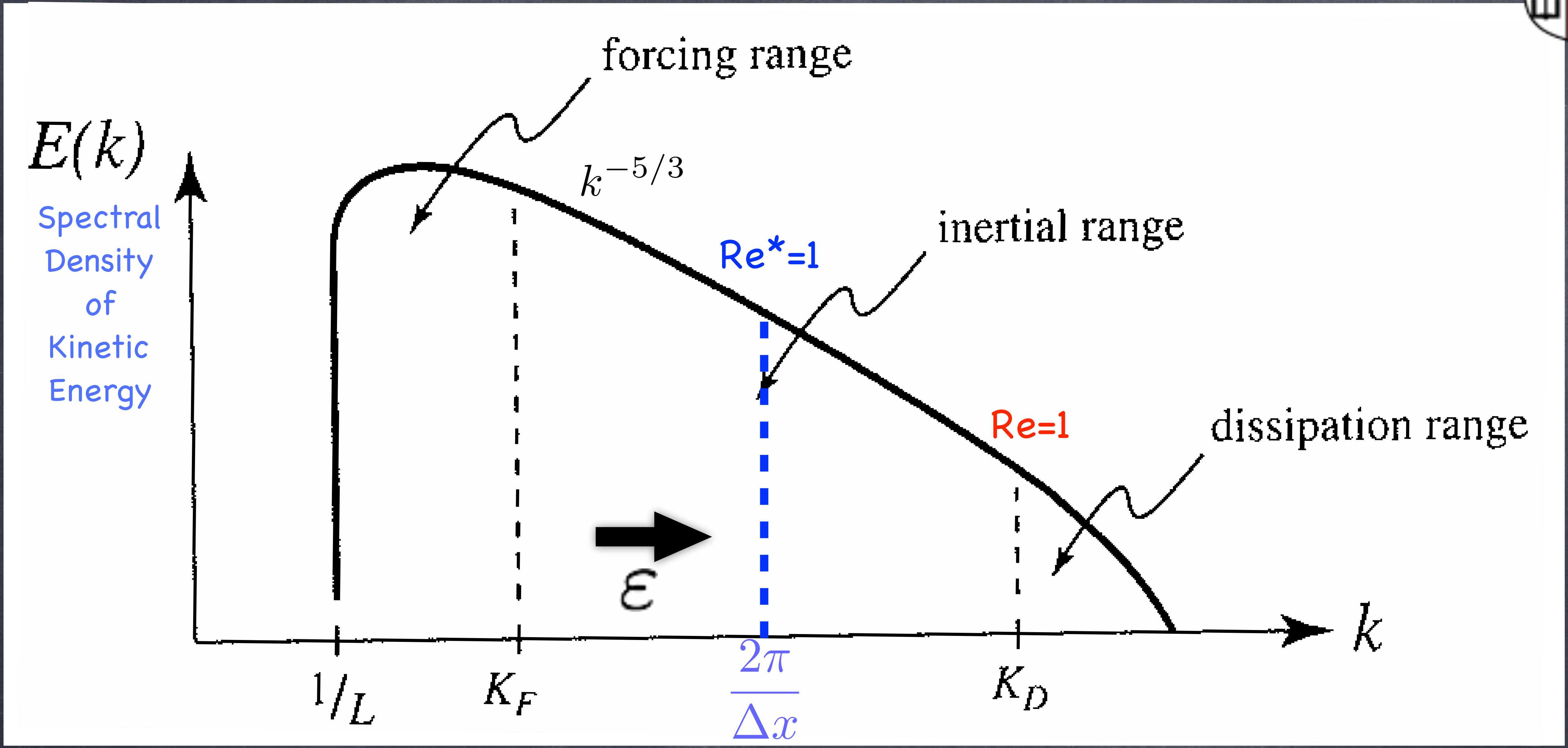
# Climate Model Resolution: an issue for centuries to come!




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

# 3D Turbulence Cascade




1963: Smagorinsky Scale & Flow Aware Viscosity Scaling,
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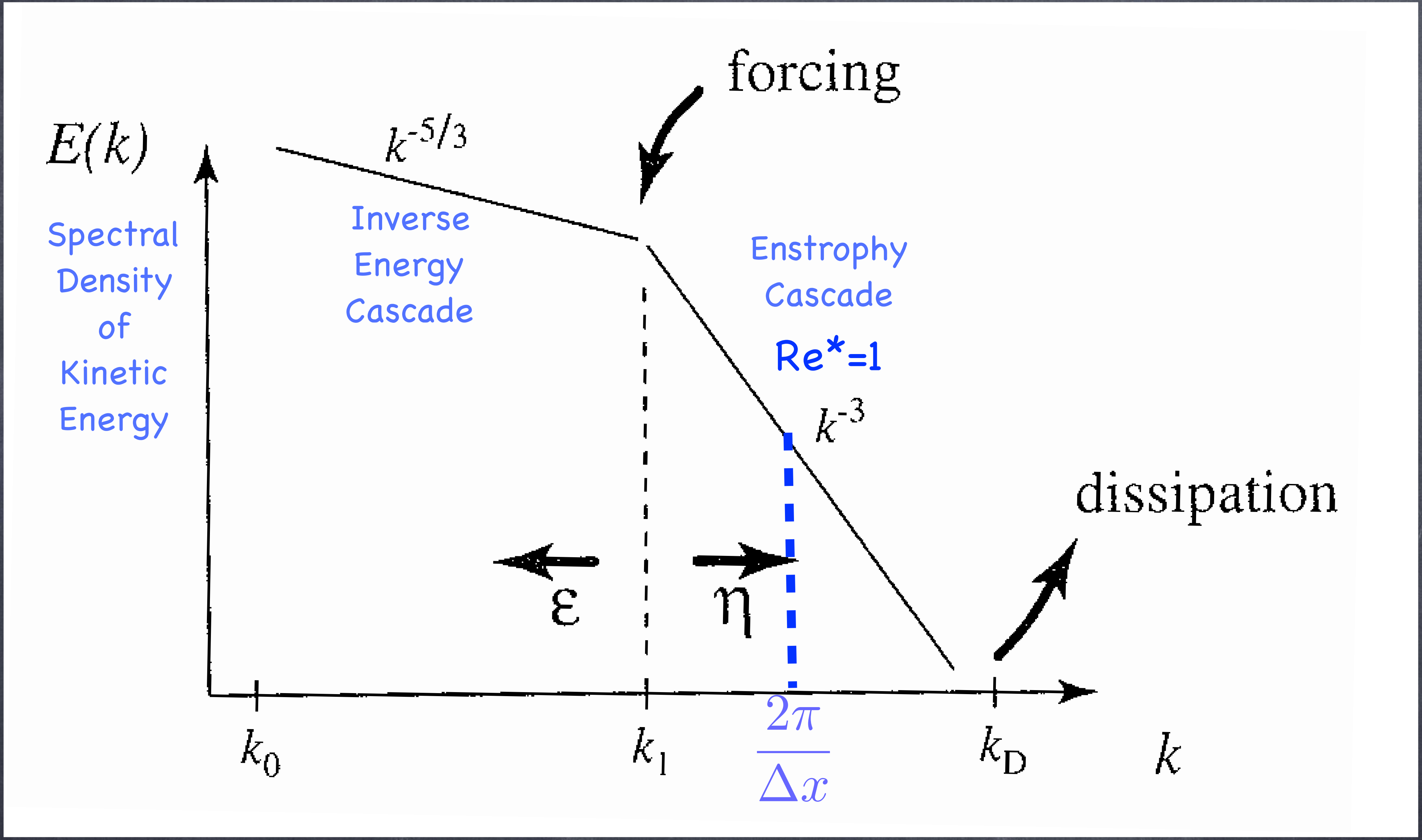
but order-1 gridscale Reynolds #: $Re^* = UL/\nu_*$

$$\nu_{*h} = \left(\frac{\Upsilon_h \Delta x}{\pi}\right)^2 \sqrt{\left(\frac{\partial u_*}{\partial x} - \frac{\partial v_*}{\partial y}\right)^2 + \left(\frac{\partial u_*}{\partial y} + \frac{\partial v_*}{\partial x}\right)^2}$$

# 2D Turbulence Differs




R. Kraichnan, 1967 JFM

1996: Leith Devises Viscosity Scaling,
So that the Enstrophy (vorticity²) Cascade is Preserved

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

Barotropic or
stacked layers

# ECCO2 Model

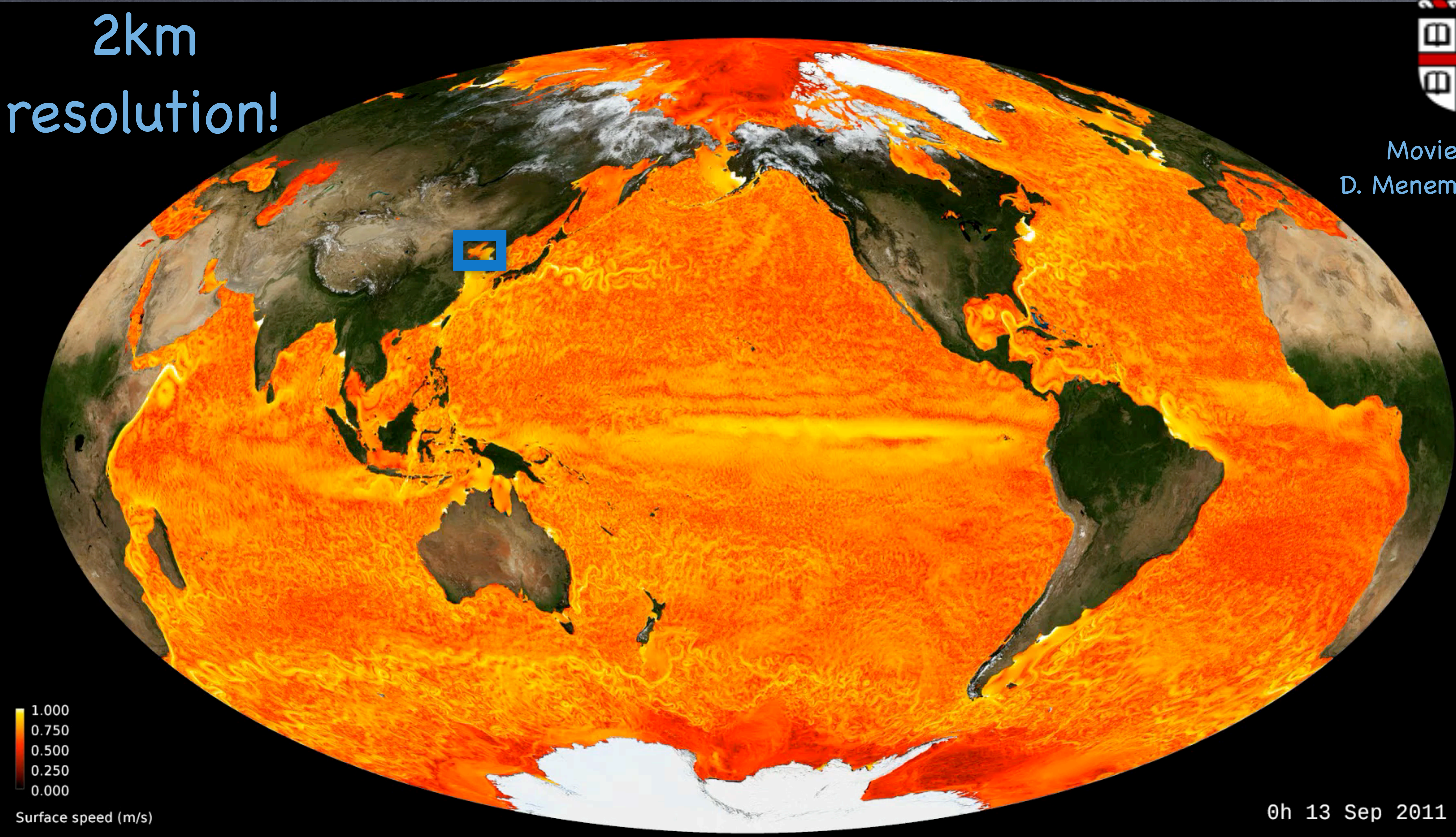
Viscosity Scheme: BFK and D. Menemenlis. Can large eddy simulation techniques improve mesoscale-rich ocean models? In M. Hecht and H. Hasumi, editors, Ocean Modeling in an Eddying Regime, volume 177, pages 319-338. AGU Geophysical Monograph Series, 2008.

18km resolution

# LLC4320 Model

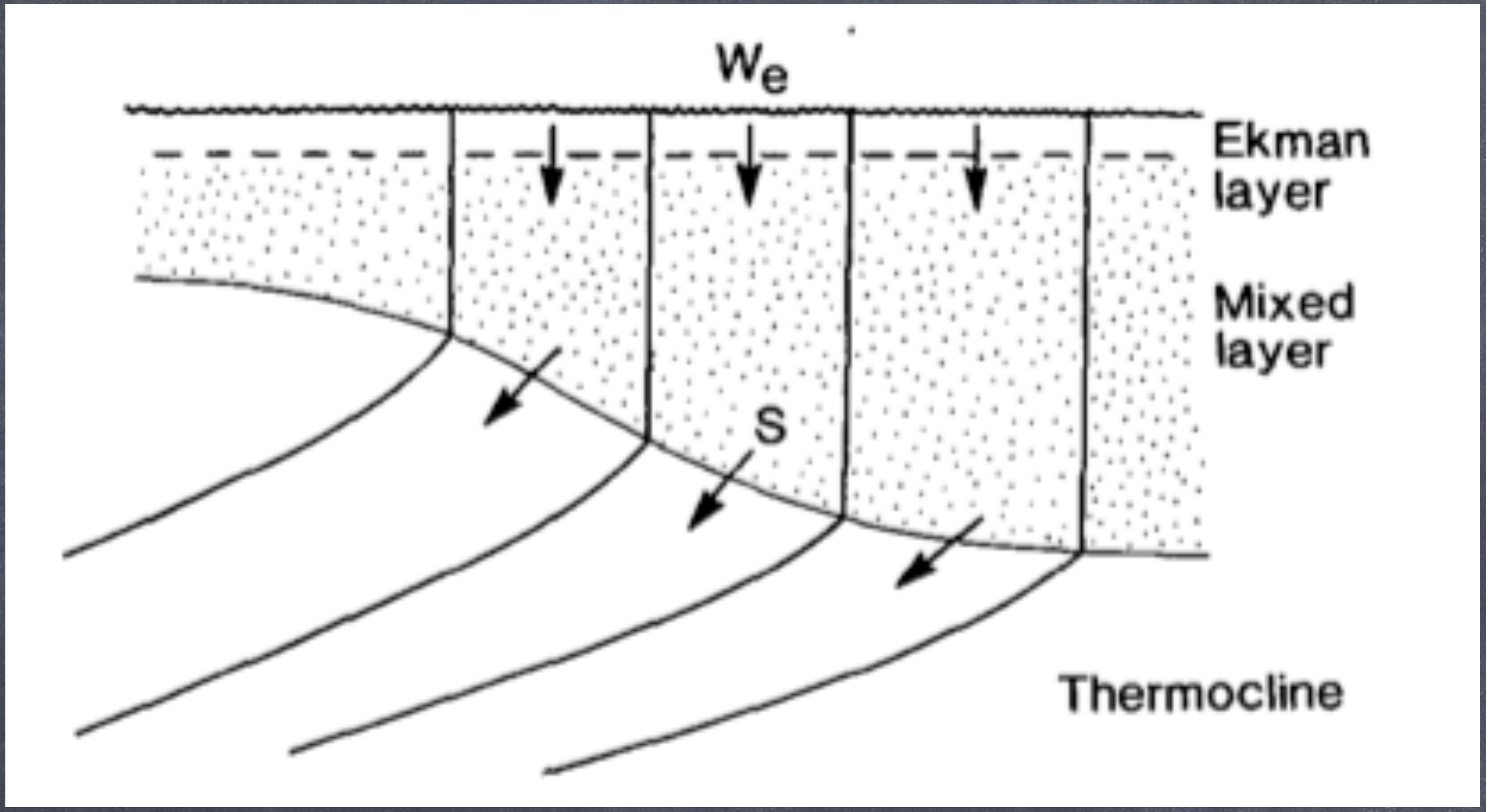
2km resolution!

Movie: D. Menemenlis




Viscosity Scheme: BFK and D. Menemenlis. Can large eddy simulation techniques improve mesoscale-rich ocean models? In M. Hecht and H. Hasumi, editors, Ocean Modeling in an Eddying Regime, volume 177, pages 319-338. AGU Geophysical Monograph Series, 2008.

# Is 2D Turbulence a good proxy for stratified flow?




Nurser & Marshall, 1991 JPO

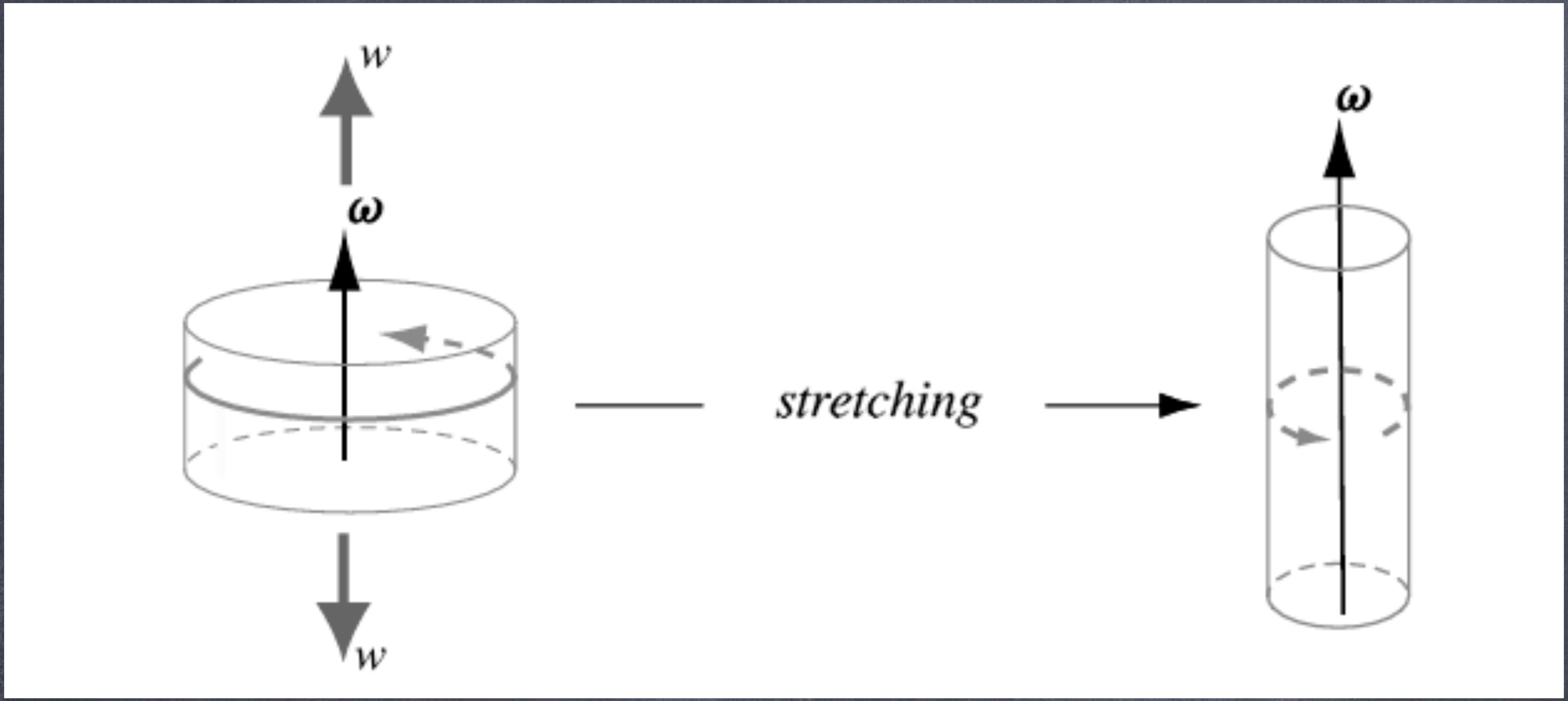
Yes:

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

No:

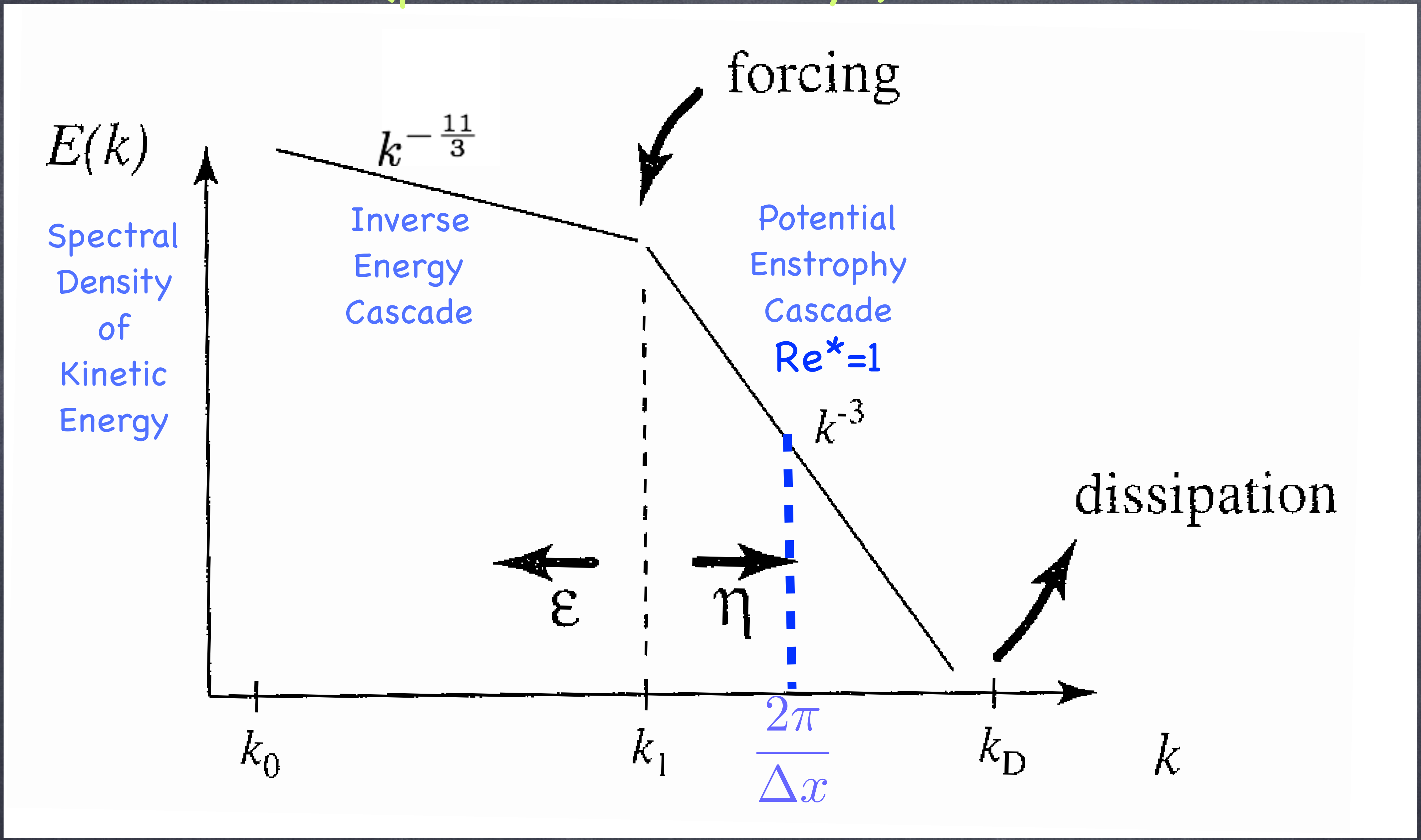
- Eddy Fluxes--Divergent 2d flow & advective fluxes
- Sloped, not horiz.
- Surface Effects?

# Stretching & Squashing




Potential Vorticity: $$\frac{\hat{k}\cdot\omega}{h} = \frac{\hat{k}\cdot\nabla\times\mathbf{v}}{h}$$

# QG Turbulence: Pot'l Enstrophy cascade (potential vorticity²)

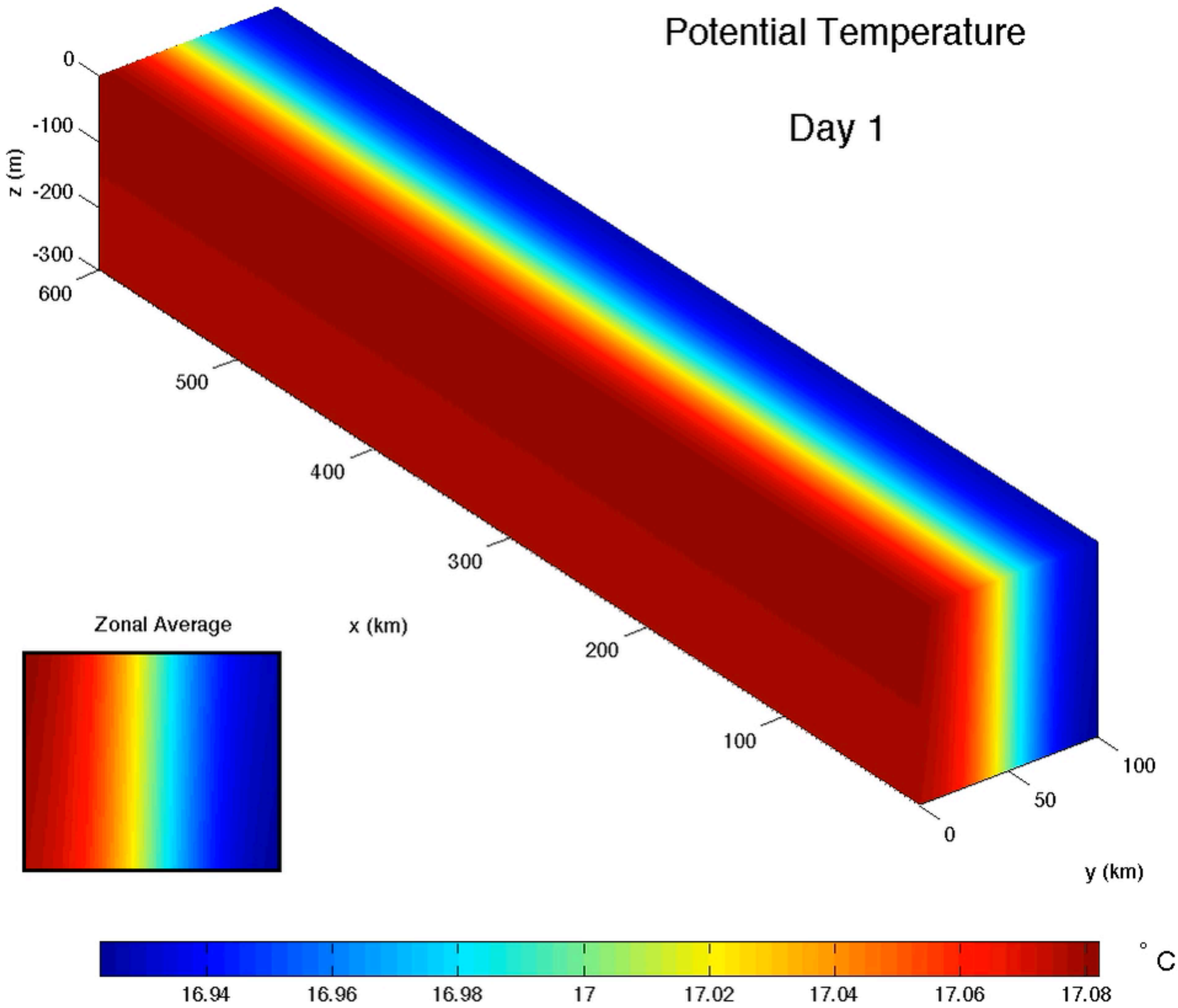



J. Charney, 1971 JAS

## (quasi-geostrophic), or QG Leith

S. D. Bachman, B. Fox-Kemper, and B. Pearson. A scale-aware subgrid model for quasigeostrophic turbulence.Journal of Geophysical Research-Oceans, 122:1529-1554, March 2017.

# Movie: S. Bachman

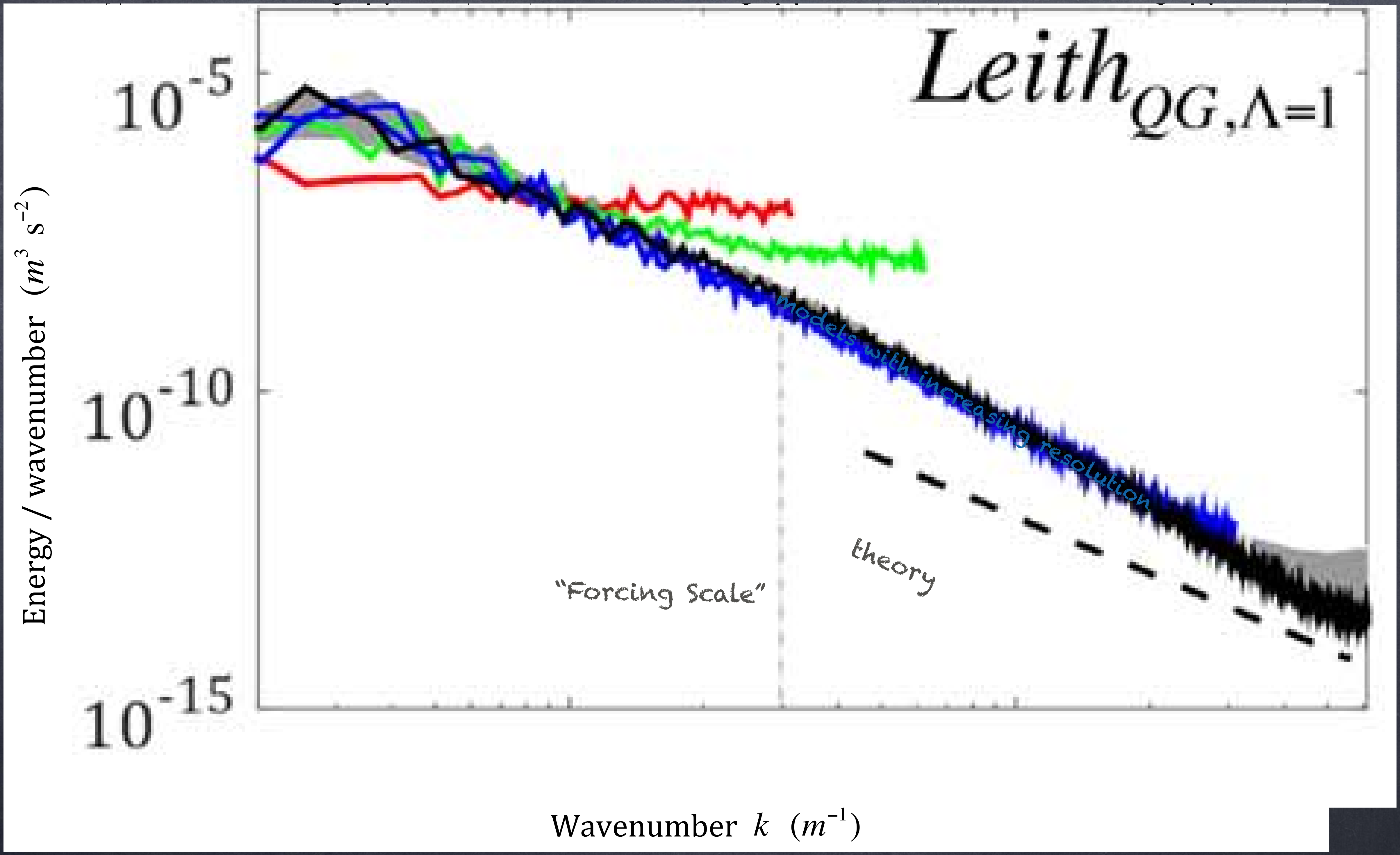



S. Bachman and B. Fox-Kemper. Eddy parameterization challenge suite. I: Eady spindown. Ocean Modelling, 64:12-28, 2013.

S. D. Bachman, BFK, and B. Pearson. A scale-aware subgrid model for quasigeostrophic turbulence. Journal of Geophysical Research-Oceans, February 2017. In press.

# Where does ocean energy go?

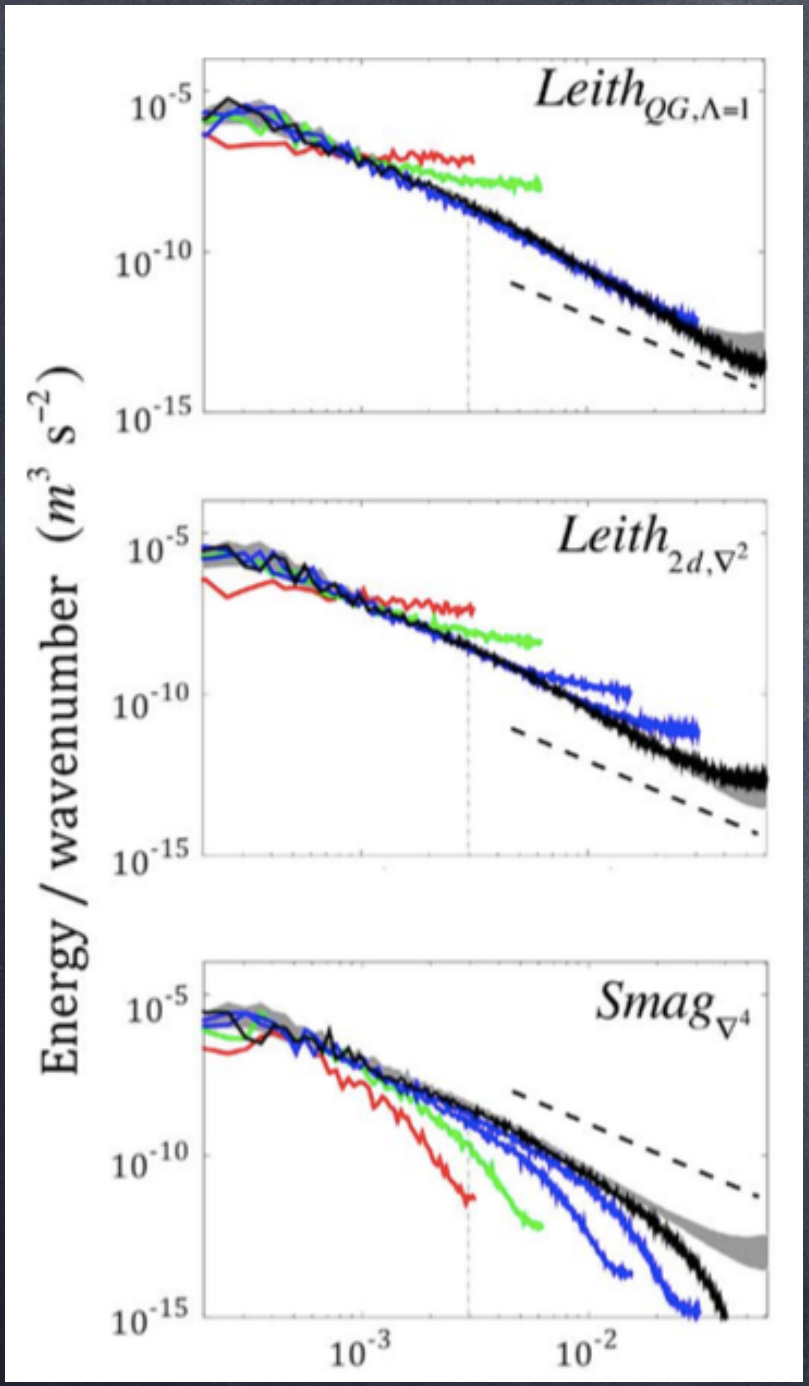
Spectrally speaking




S. D. Bachman, B. Fox-Kemper, and B. Pearson, 2017: A scale-aware subgrid model for quasi- geostrophic turbulence. Journal of Geophysical Research–Oceans, 122:1529–1554. URL http: //dx.doi.org/10.1002/2016JC012265.

# Where does ocean energy go?

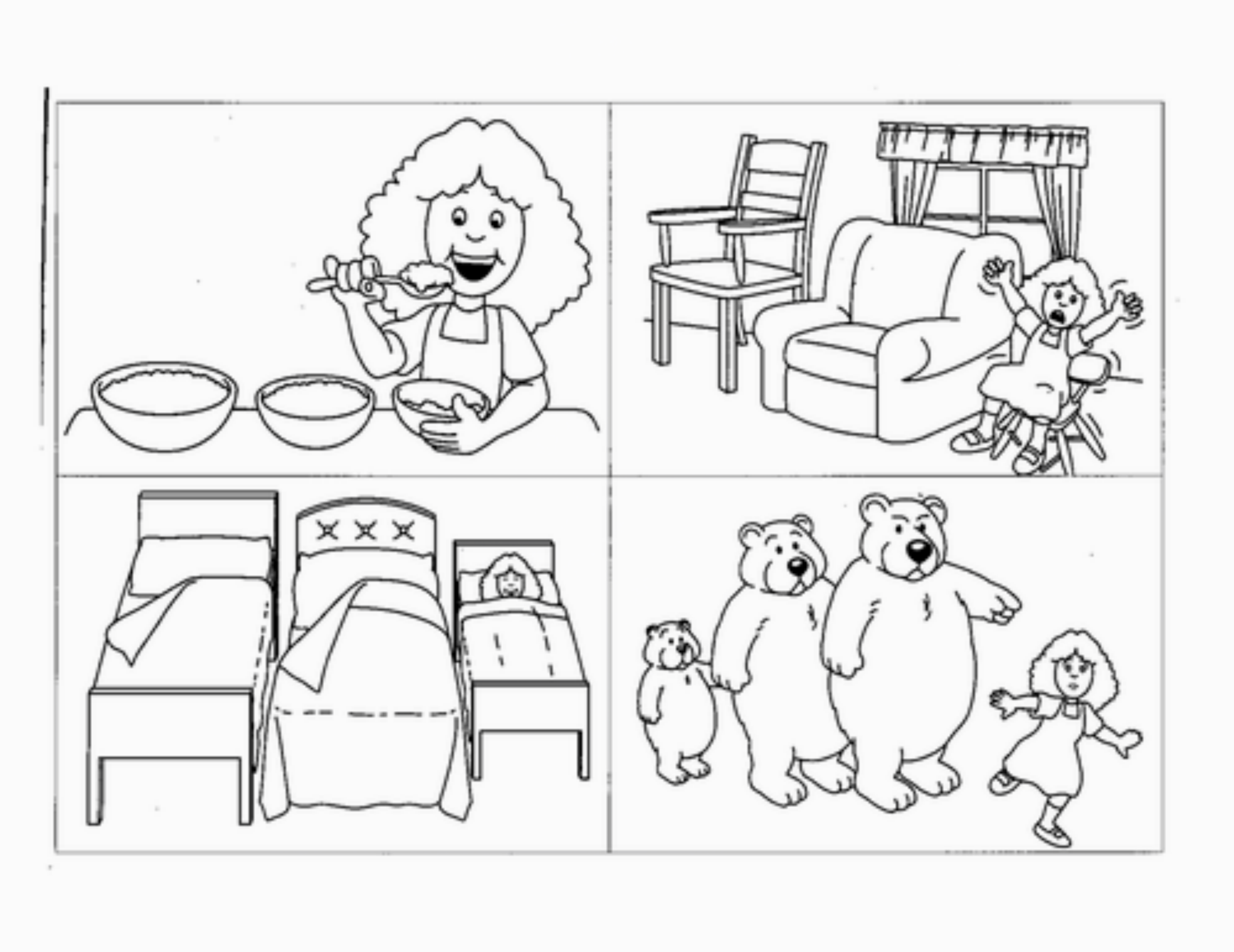
Spectrally speaking




QGLeith: Just Right!

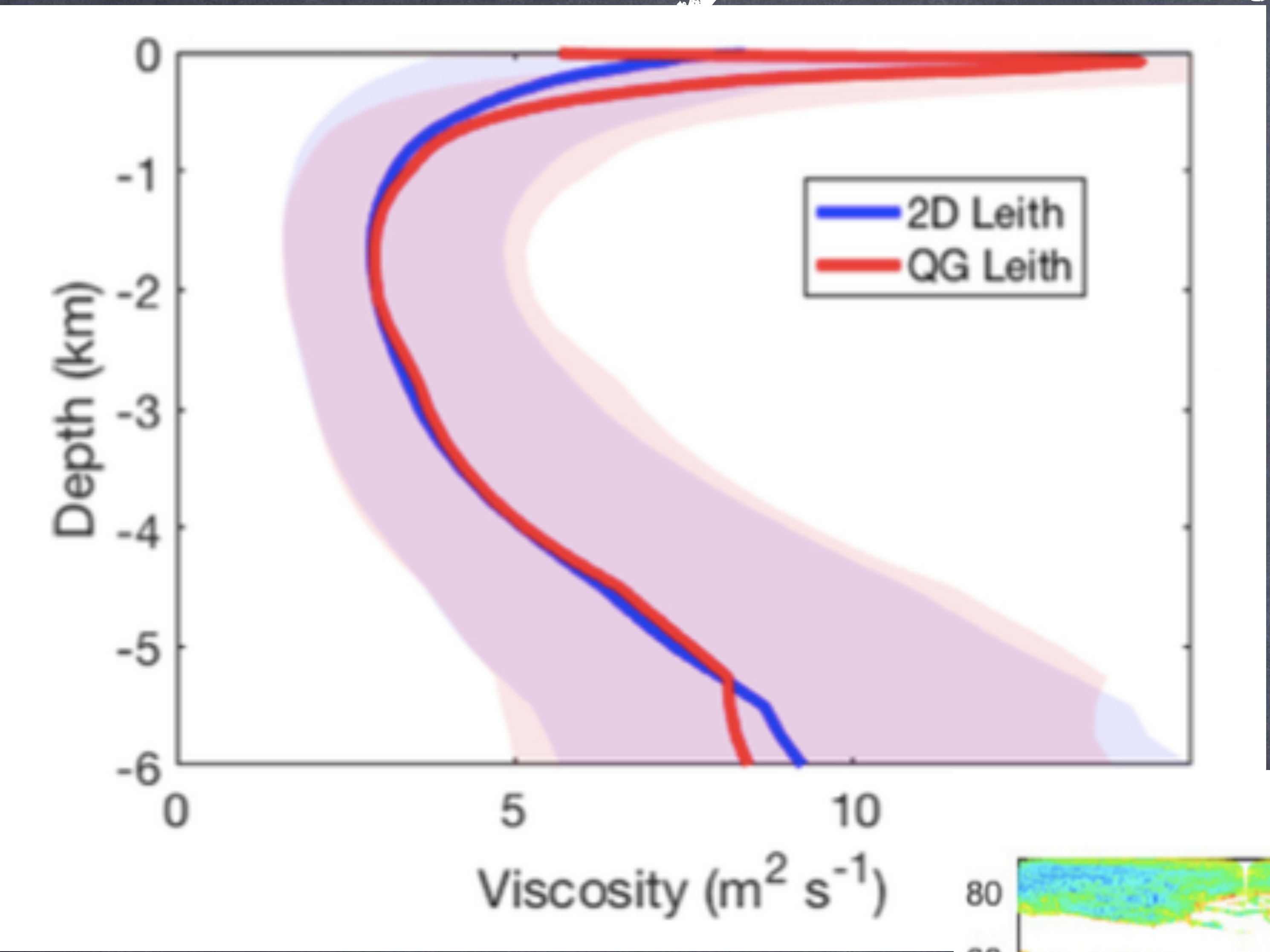
2DLeith: Too Noisy

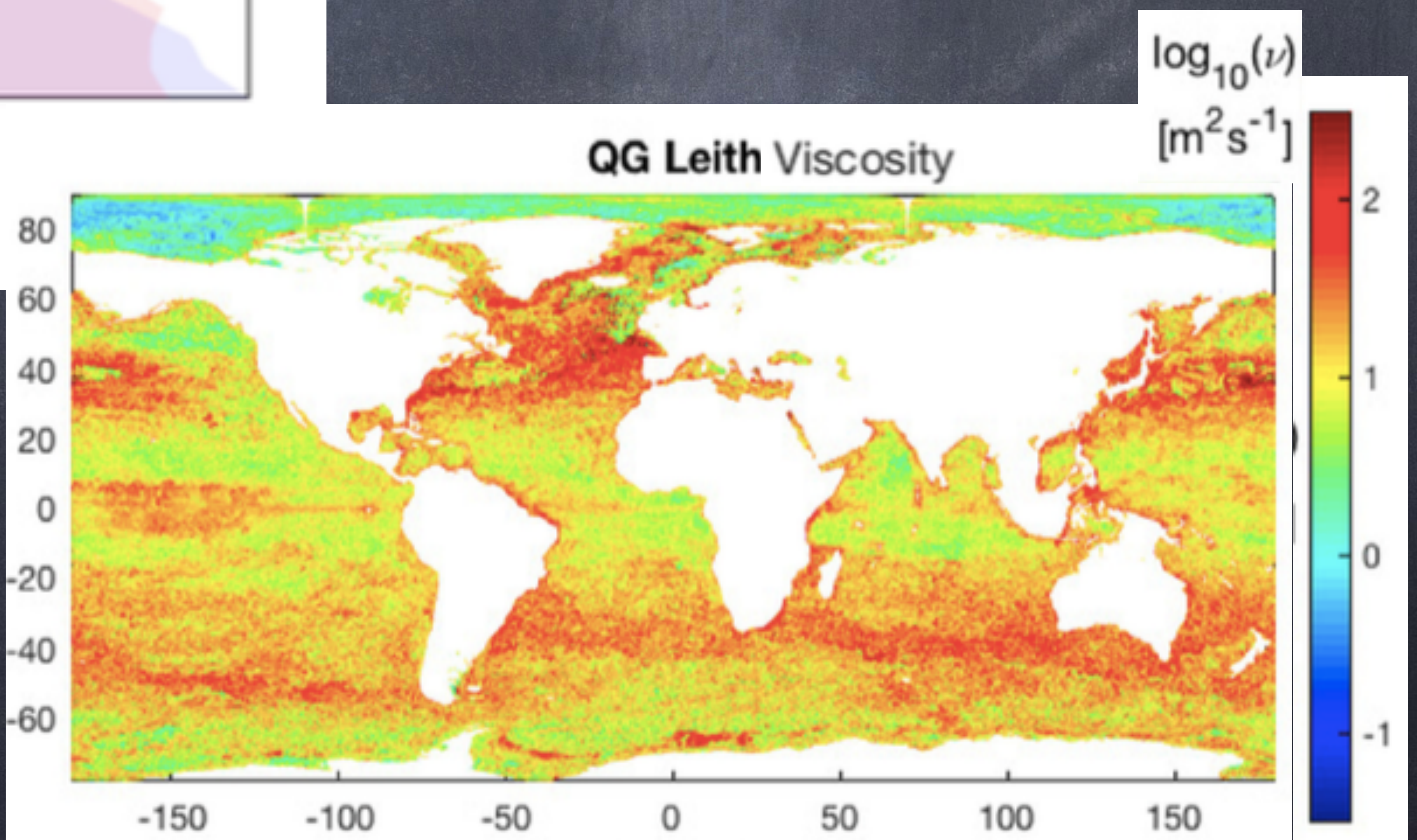
Smagorinsky: Too Smooth



S. D. Bachman, B. Fox-Kemper, and B. Pearson, 2017: A scale-aware subgrid model for quasi- geostrophic turbulence. Journal of Geophysical Research–Oceans, 122:1529–1554. URL http: //dx.doi.org/10.1002/2016JC012265.

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

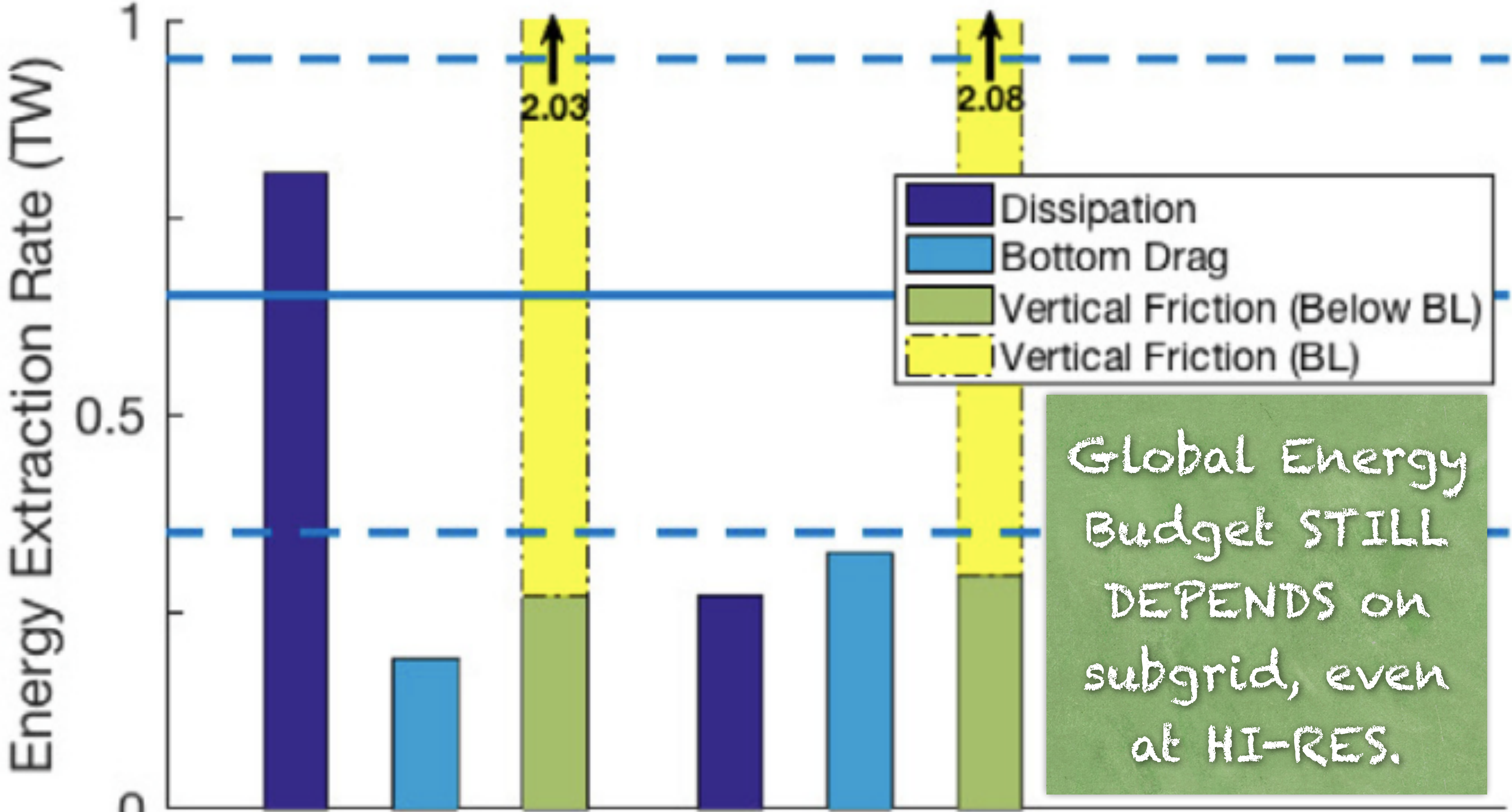




S. D. Bachman, BFK, and B. Pearson, 2017: A scale-aware subgrid model for quasi-geostrophic turbulence. Journal of Geophysical Research–Oceans, 122:1529–1554.

B. Pearson, BFK, S. D. Bachman, and F. O. Bryan, 2017: Evaluation of scale-aware subgrid mesoscale eddy models in a global eddy-rich model. Ocean Modelling, 115:42–58.

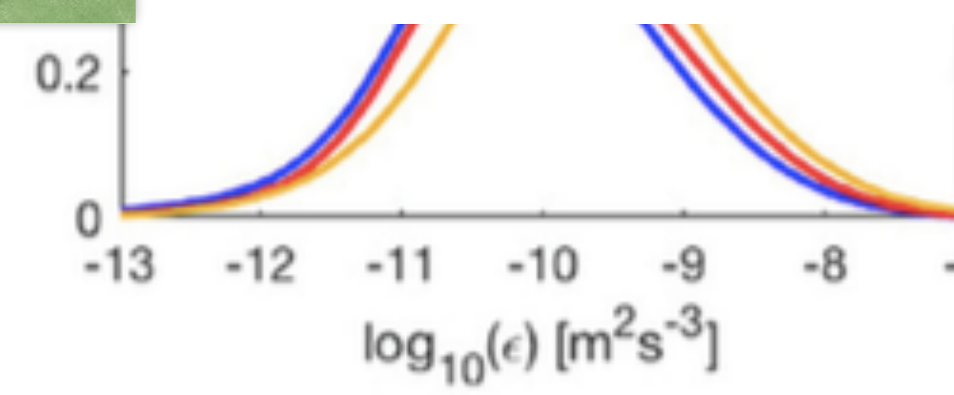



Global Energy Budget STILL DEPENDS on subgrid, even at HI-RES.

Traditional

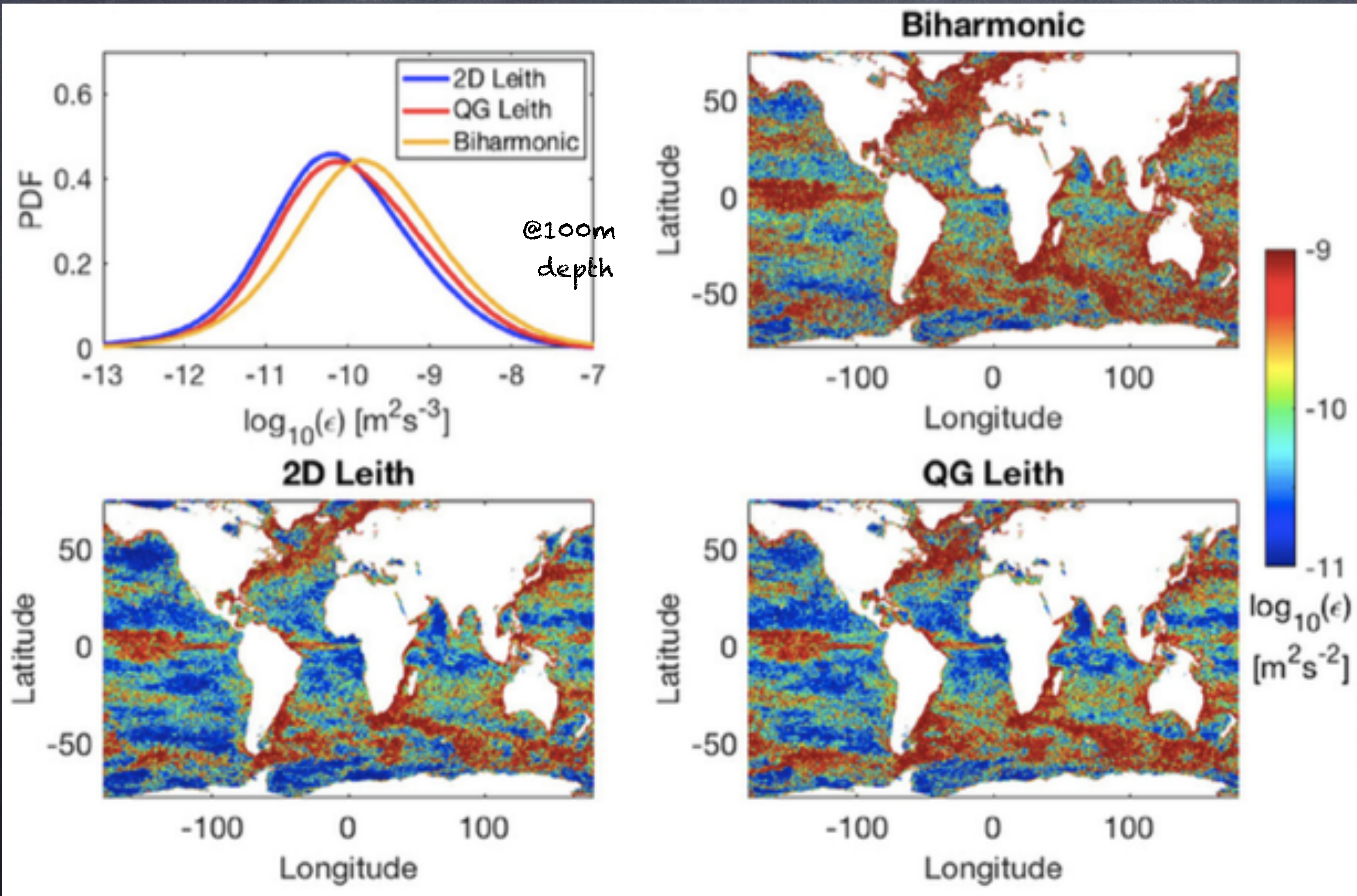
QG Leith

(most in upper 200m)

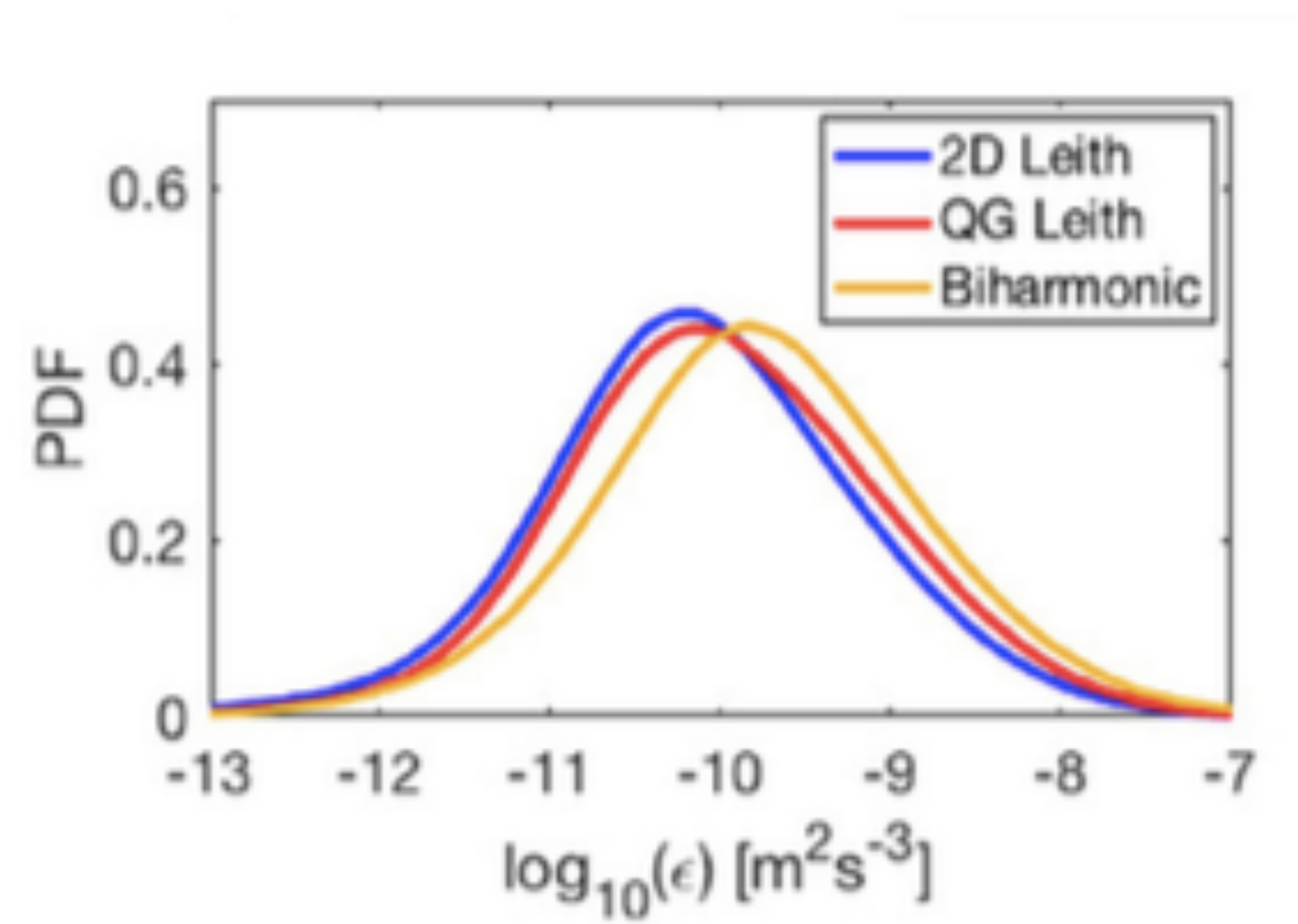



B. Pearson, BFK, S. D. Bachman, and F. O. Bryan, 2017: Evaluation of scale-aware subgrid mesoscale eddy models in a global eddy-rich model. Ocean Modelling, 115:42–58.

# Lognormally distributed–AND knows where the Gulf Stream is!



# Wait—log-normal…

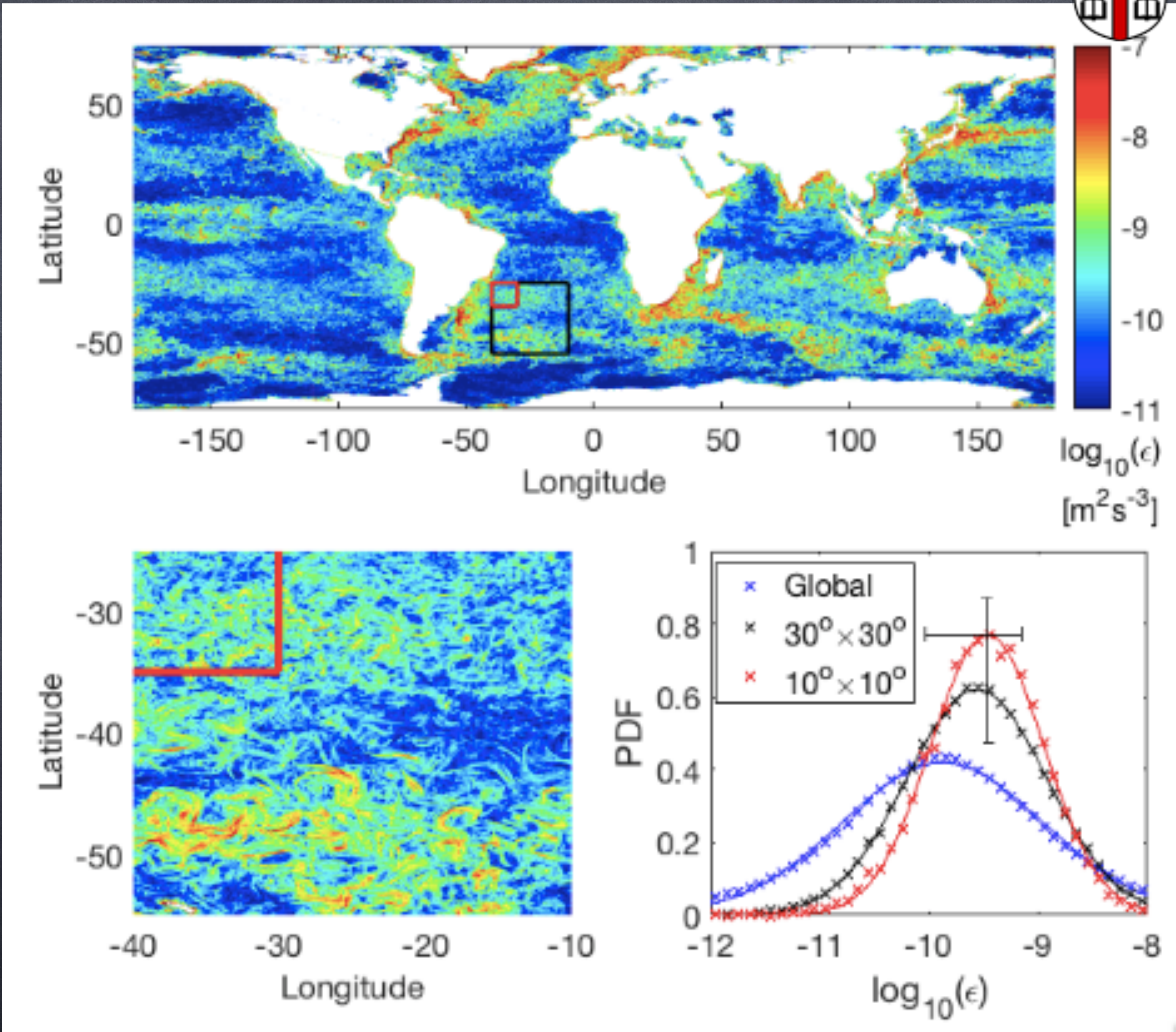


# MOLES: Log-Normal Dissipation Intermittency

A (weak) dissipation of energy with pot'l enstrophy cascade ... that's lognormally distributed (super-Yaglom '66)

90% of KE dissipation in 10% of ocean

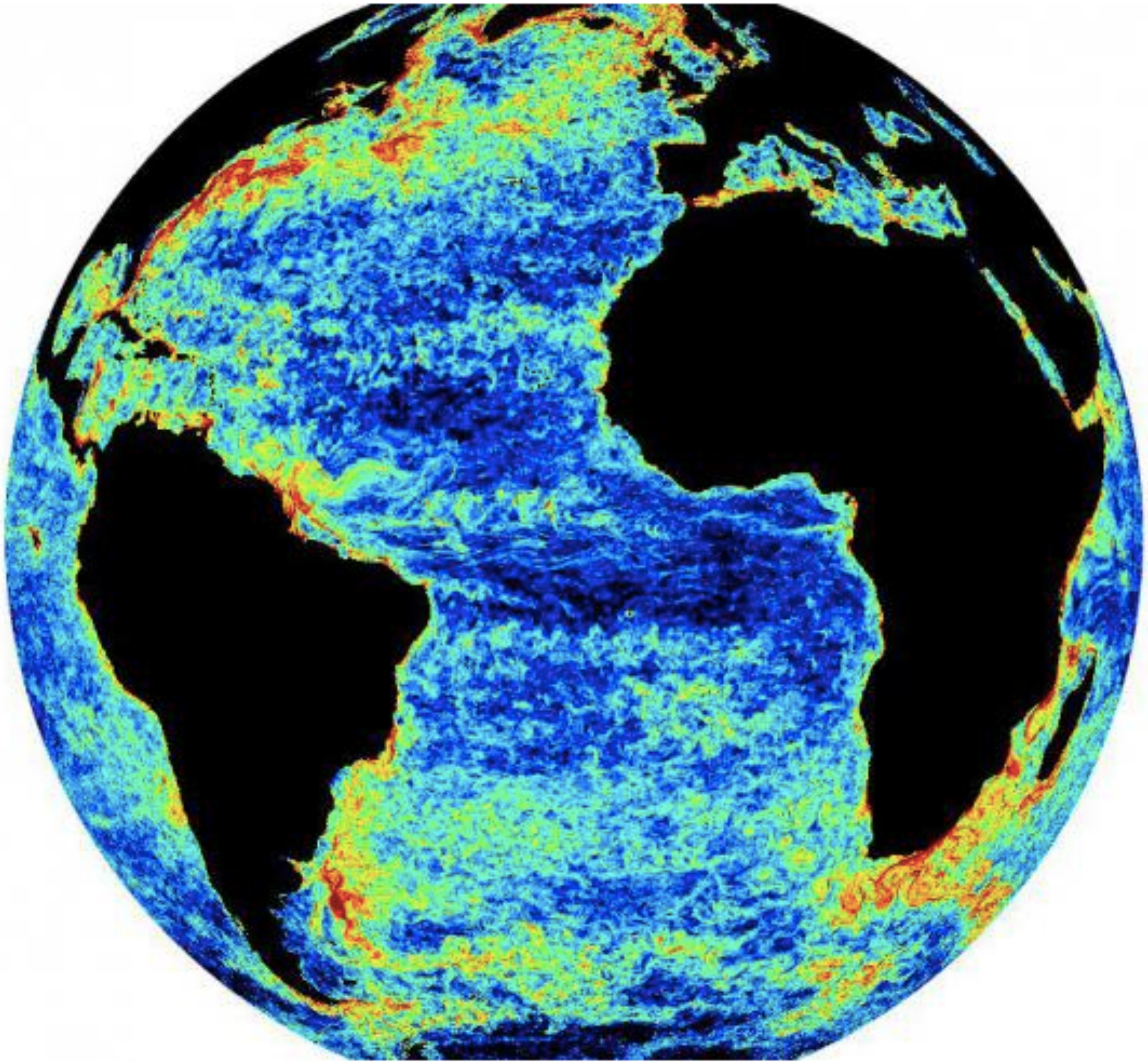
B. Pearson and BFK. Log-normal turbulence dissipation in global ocean models. Physical Review Letters, 120(9): 094501, March 2018.



# News from Brown

News | For Journalists | Featured Events

Search Brown News



Hotspots
Brown University researchers have made a new

## New understanding of ocean turbulence could improve climate models

February 26, 2018   Media contact: Kevin Stacey
401-863-3766

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.

B. Pearson and BFK. Log-normal turbulence dissipation in global ocean models. Physical Review Letters, 120(9):094501, March 2018.

# 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