

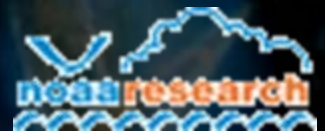
Climate models and fisheries: Challenges and opportunities

OR

Can climate models tell us anything about
bottom-up control?

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Climate Change Effects on Fish and Fisheries

April 28, 2010

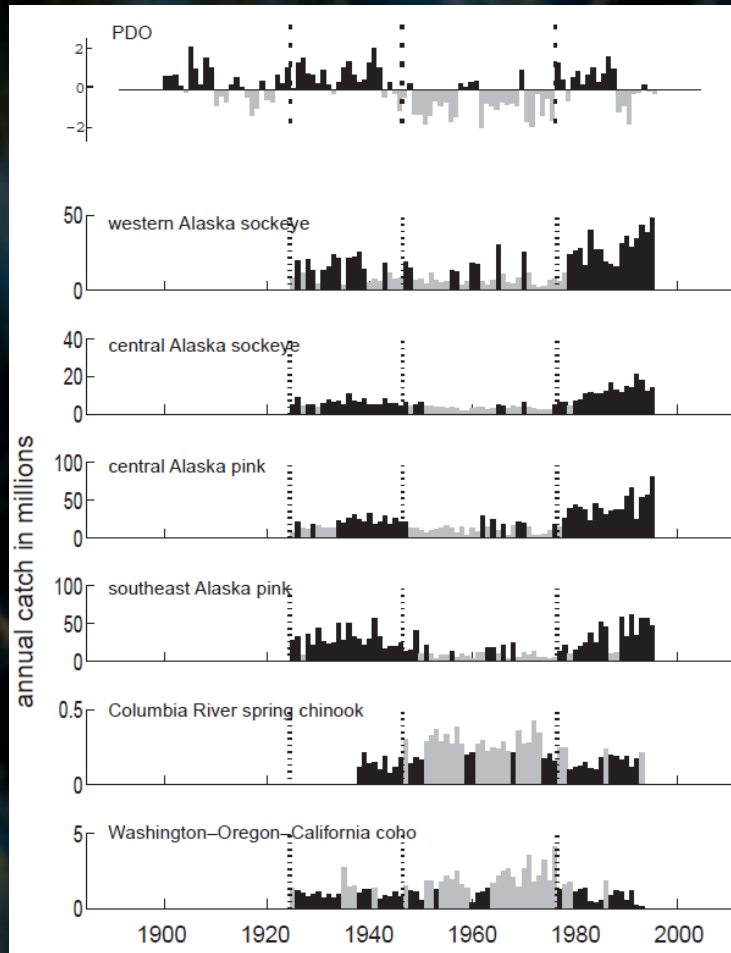


Why focus on bottom-up control

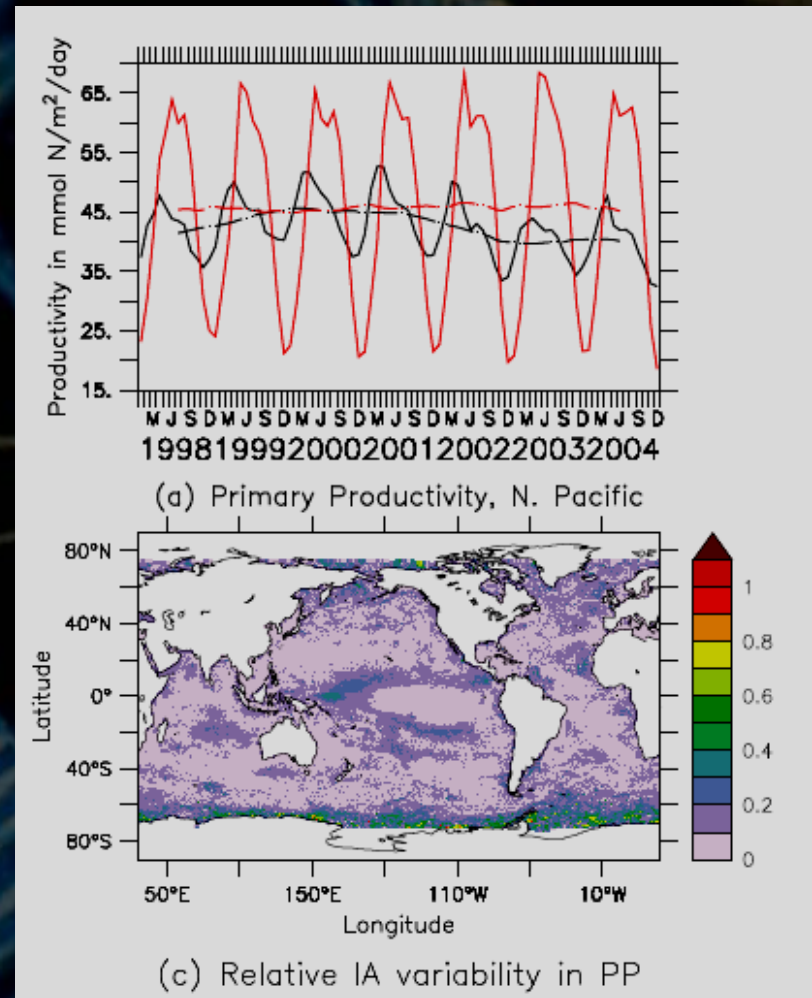
- Strength of ocean biogeochemical-circulation models is their ability to get transport.
- So IF we get the nutrient fields right and the transport right, we can say something intelligent about productivity.
- ... and its links to climate modes.

Challenge 1: Is there bottom up control?

While large changes are seen in fisheries...



(Mantua et al., 1997)



Changes in PP are much smaller!

One response- food supply doesn't matter

- Range/habitat changes (Nye-winter flounder)
- Temperature/oxygen control of growth rates
- Larval transport
- Extreme events (Hare-N. Atl. croaker)
- Insert your favorite mechanism here...

Or are there amplifiers that we might be missing?

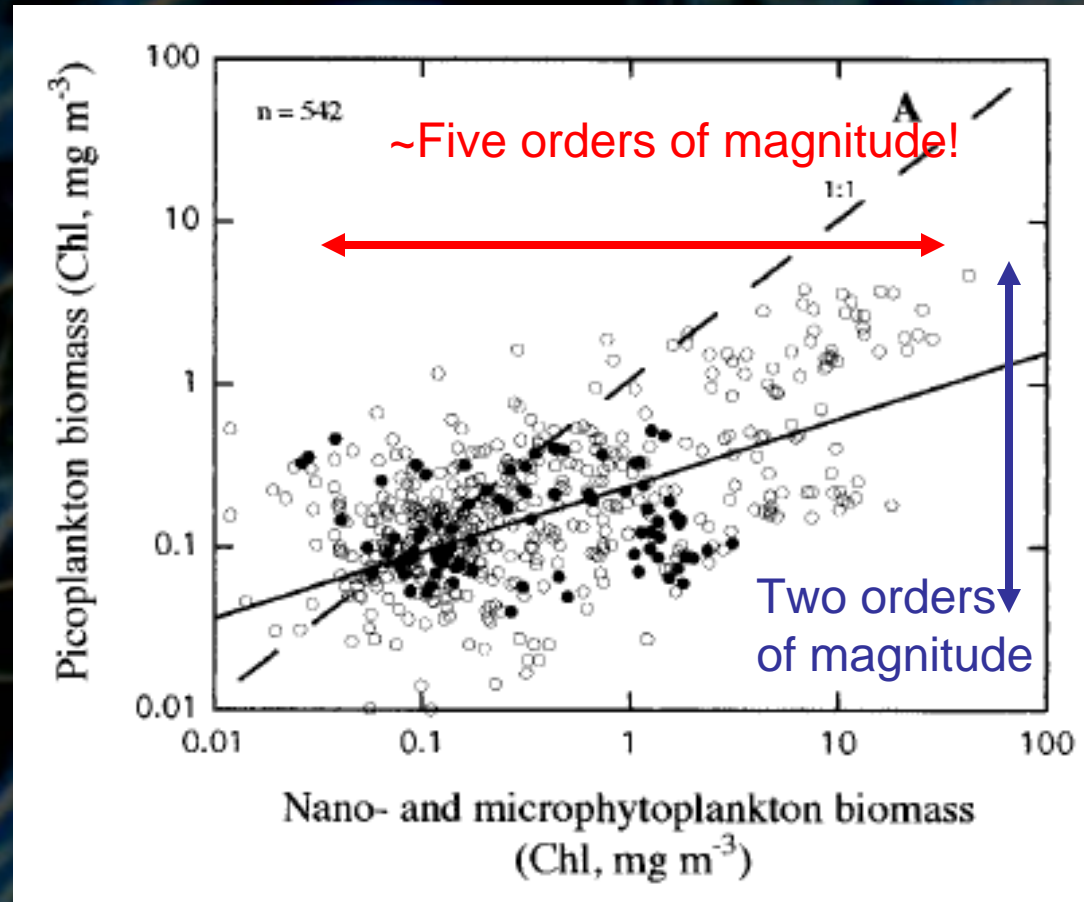
Opportunities: Evaluating/quantifying ideas

- Size structure (“All fish is diatoms”)
- Seasonality (“match-mismatch”)
- Salinity (important in high latitudes)
- Surroundings (not core regions of high production)

Models can *quantify* the potential impacts as these ideas work their way through the system.

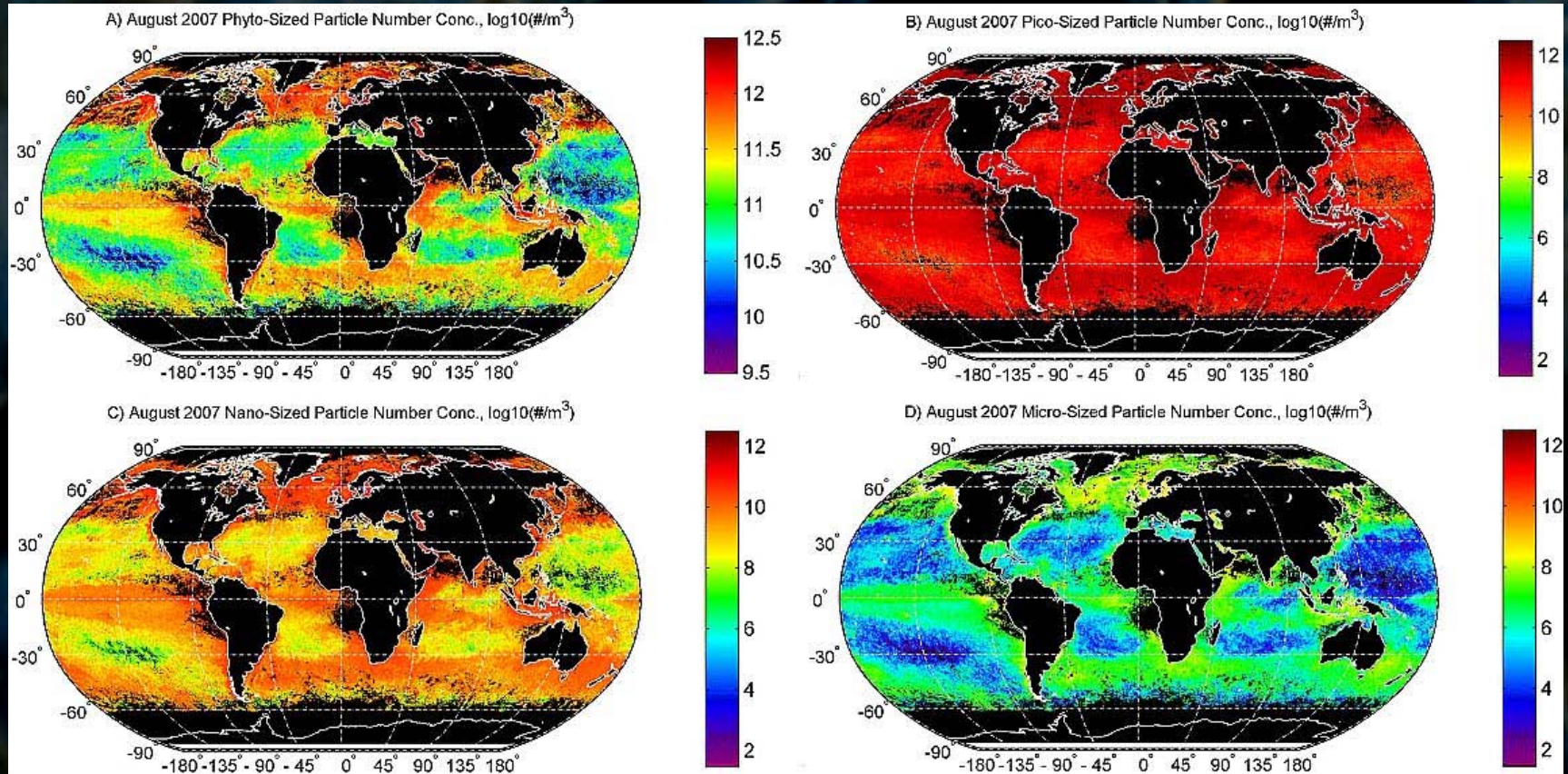
Key idea 1: Size structure

- When phytoplankton productivity is low, large plankton are rare.
- When phytoplankton productivity is high, large plankton are more common.



Agawin, Duarte and Agustí, LO, 2000

Other evidence for this



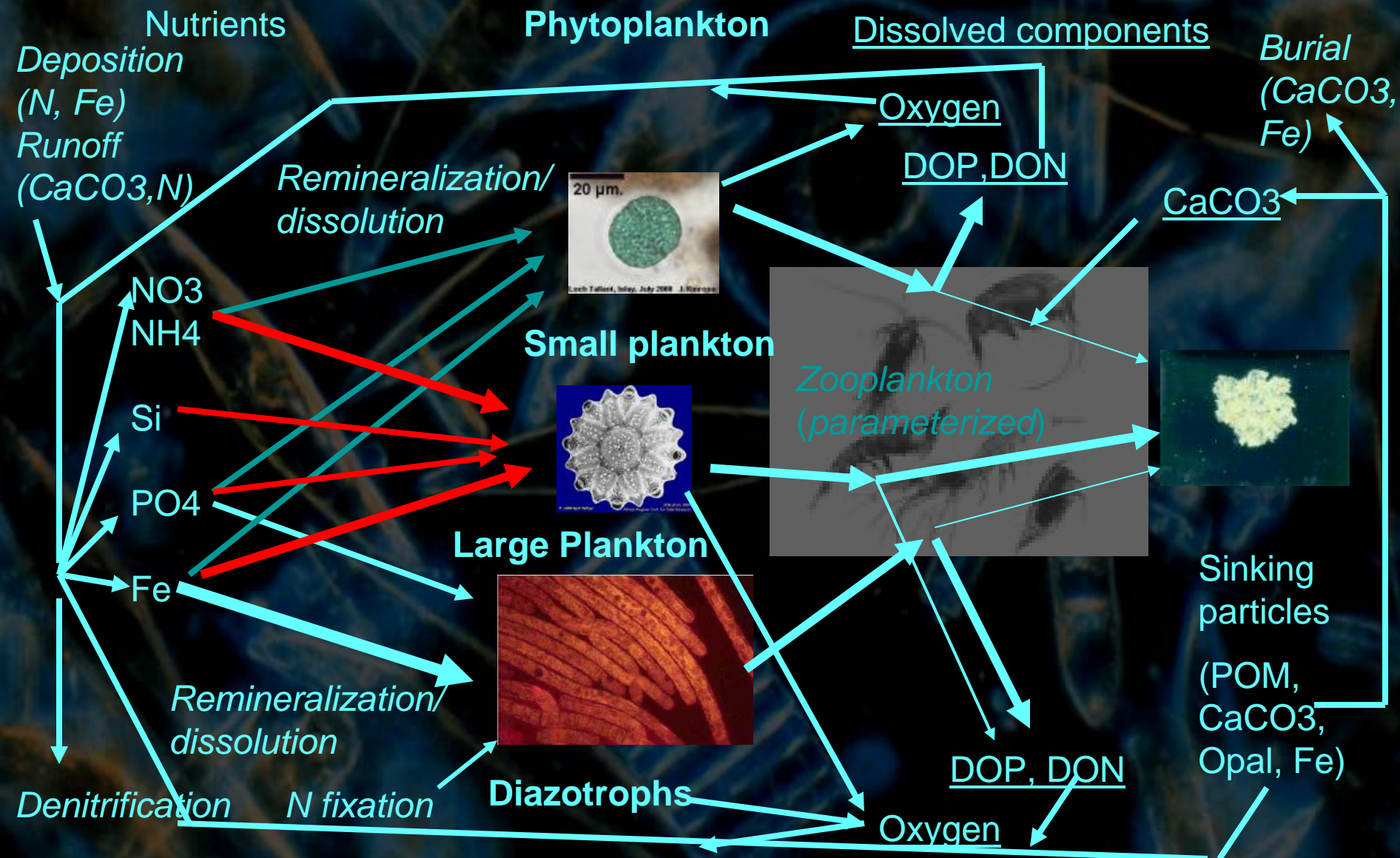
Kostadinov et al., JGR, 2009

Smallest particles (plankton?) range over 2 orders of magnitude.

Largest particles (plankton?) range over 6 orders of magnitude

Can we use these relationships to put constraints on biological cycling?

GFDL's new Ocean BGC model (TOPAZ)



Implementation: Allometric grazing

Dunne, Armstrong, Gnanadesikan and Sarmiento, GBC, 2005

$$\frac{\partial S}{\partial t} = \mu S - \lambda \left(\frac{S}{P_*} \right) S$$

Logistic growth for small plankton.

$$\frac{\partial L}{\partial t} = \mu L - \lambda \left(\frac{L}{P_*} \right)^{1/3} L$$

Different power law for large plankton.

Result: Approximate steady state

Dunne, Armstrong, Gnanadesikan and Sarmiento, GBC, 2005

$$0 = \mu S - \lambda \left(\frac{S}{P_*} \right) S \rightarrow S = \frac{\mu}{\lambda} P_*$$

$$0 = \mu L - \lambda \left(\frac{L}{P_*} \right)^{1/3} L \rightarrow L = \left(\frac{\mu}{\lambda} \right)^3 P_*$$

Same range of growth rates gives much larger range in large plankton

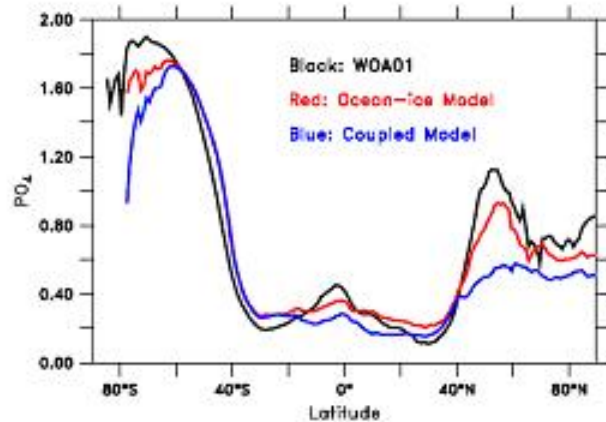
Embedded in physical model

- Start with temperature and salinity.
- Find density
- Find pressure
- Compute velocities given pressure, surface winds (*Coordinate system*)
- Compute transport of mass, T, salt given surface fluxes. (*Eddies, mixing*)
- Redo.

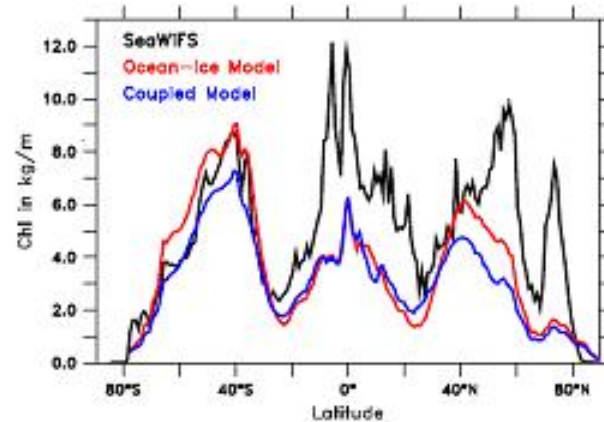
Code: GFDL Modular Ocean model (model also being run in isopycnal model)

Forcing: Reanalysis (CORE) and Coupled Model (ESM2.1)

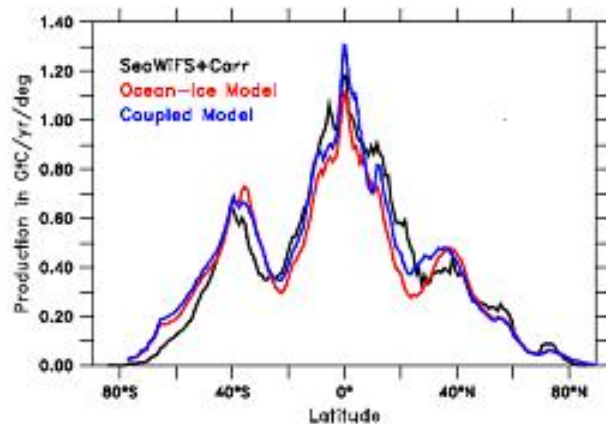
Evaluation of model fidelity



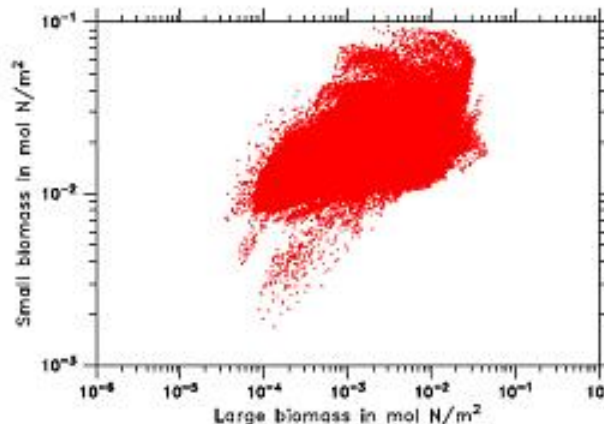
(a) Mean Macronutrient: Ocean Model



(b) Zonally Integrated Chl

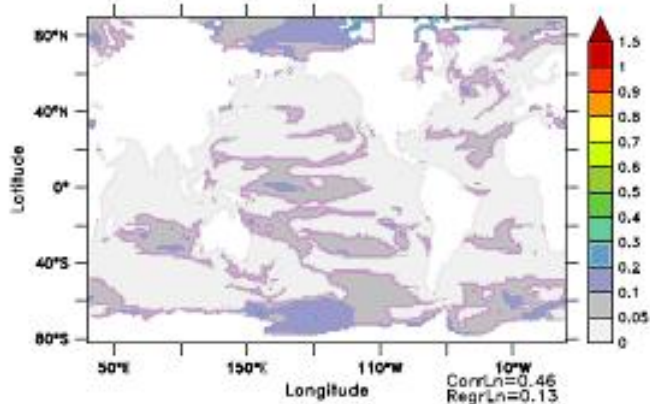


(c) Primary Productivity

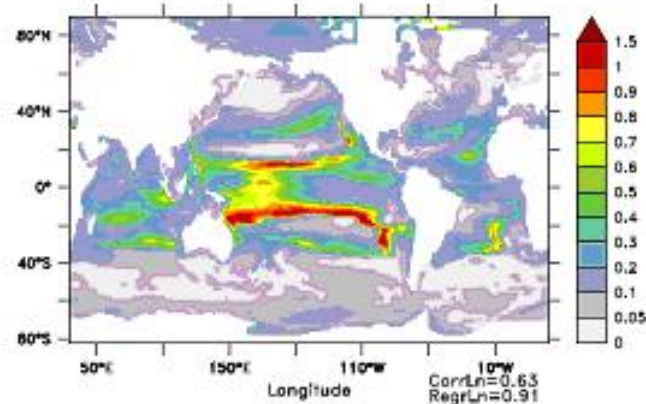


(d) Large vs. Small Biomass

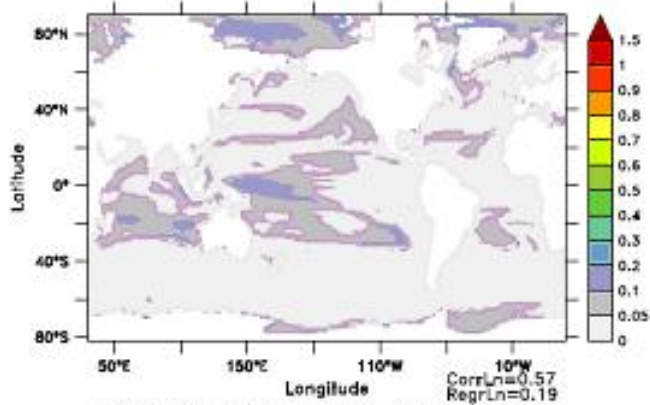
Relative interannual variability



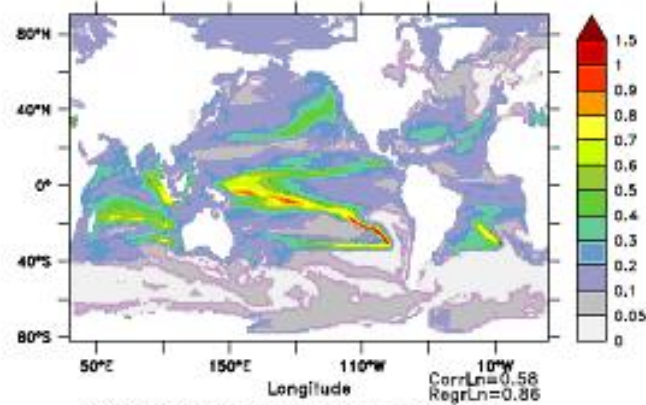
(a) Relative Variability, Small Biomass, CORE



(b) Relative Variability, Large Biomass, CORE



(c) Relative Variability, Small Biomass, ESM2.1



(d) Relative Variability, Large Biomass, ESM2.1

Ocean-only

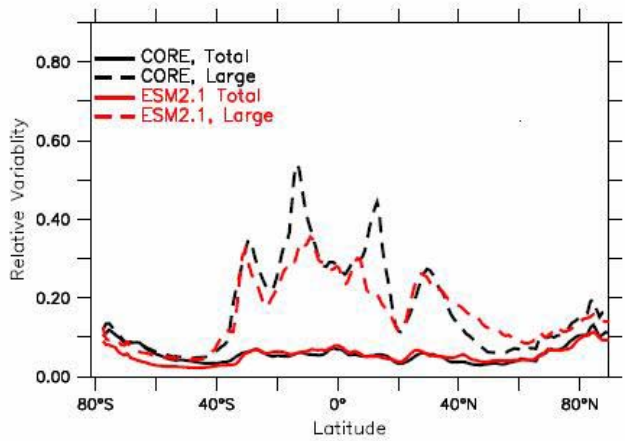
Fully coupled

Small biomass

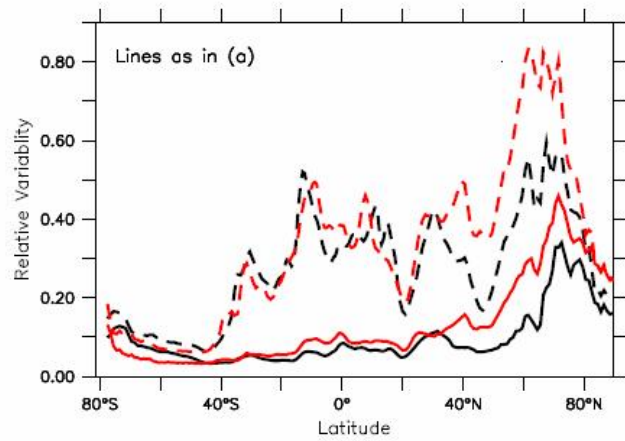
Large biomass

Large plankton vary much more than small!

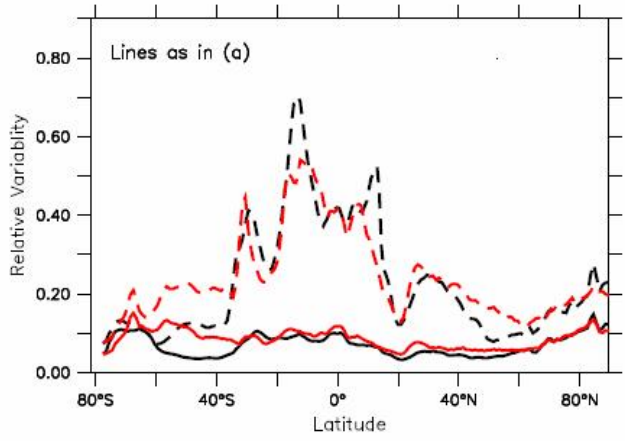
Average relative IA variability



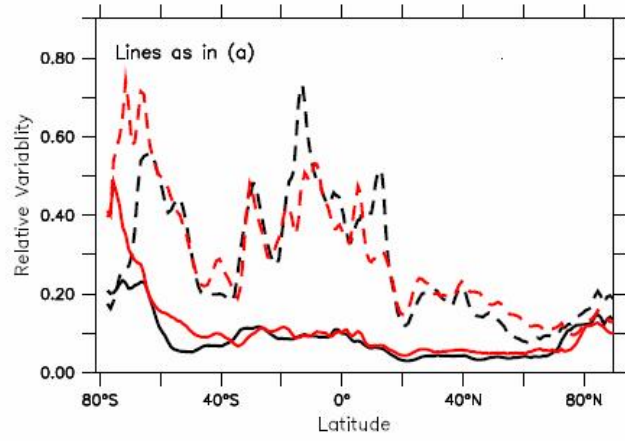
(a) Relative IA Var. - Yearly



(b) Relative IA Var. - April



(c) Relative IA Var. - July



(d) Relative IA Var. - October

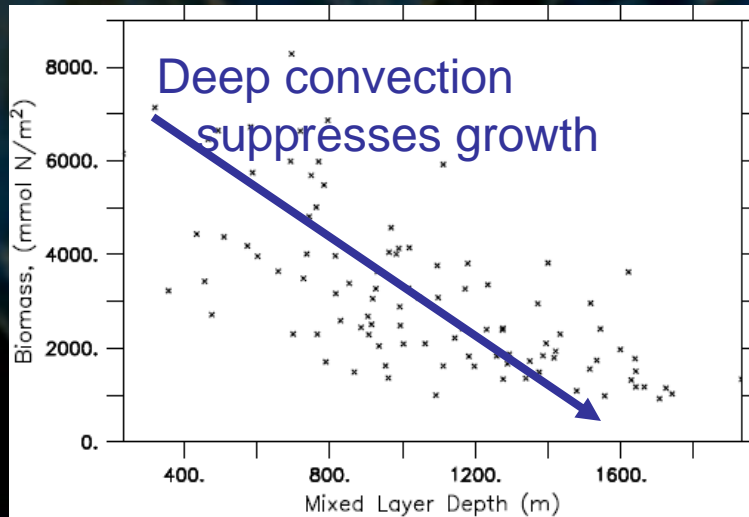
Large varies more than small in tropics

Interannual variability similar in coupled, ocean-only models

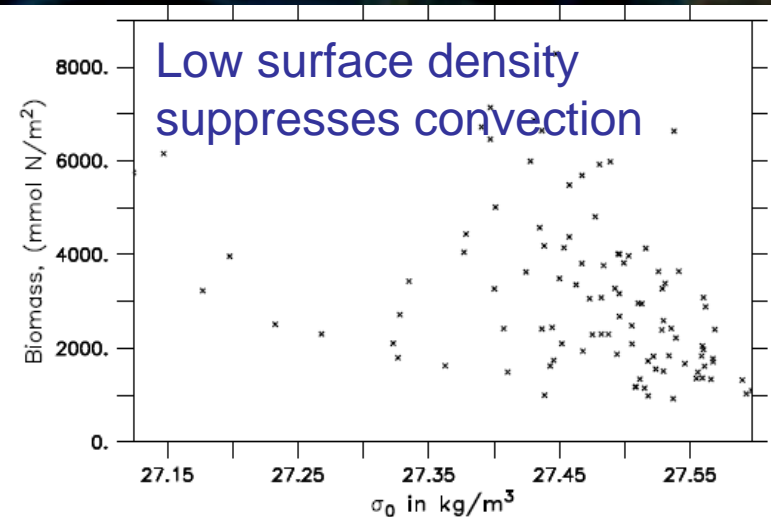
Seasonal shifts in spring important!

Coupling increases seasonal shifts!

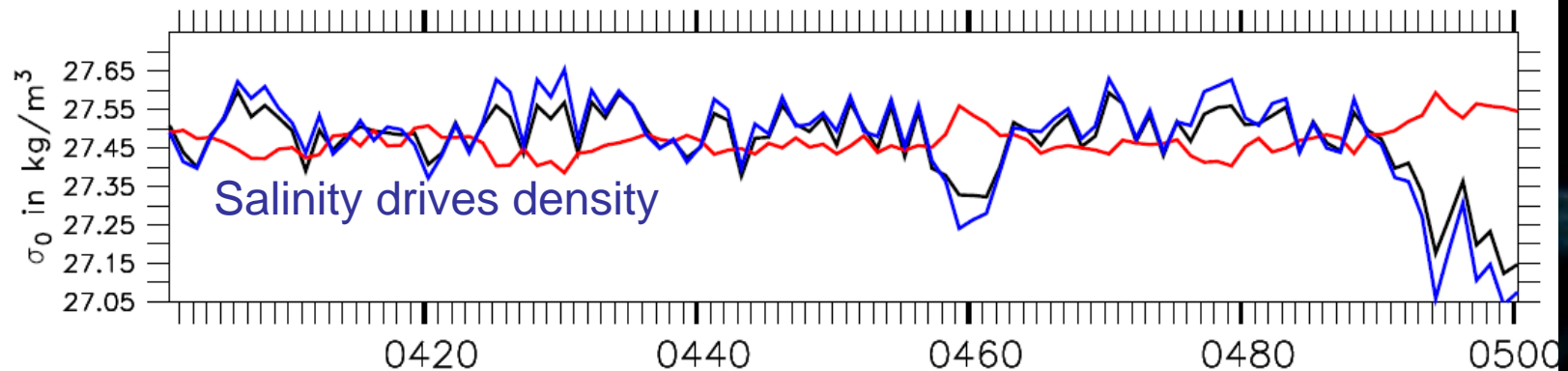
High latitude variability- the central Labrador Sea



(a) April MLD, Lg. Biomass



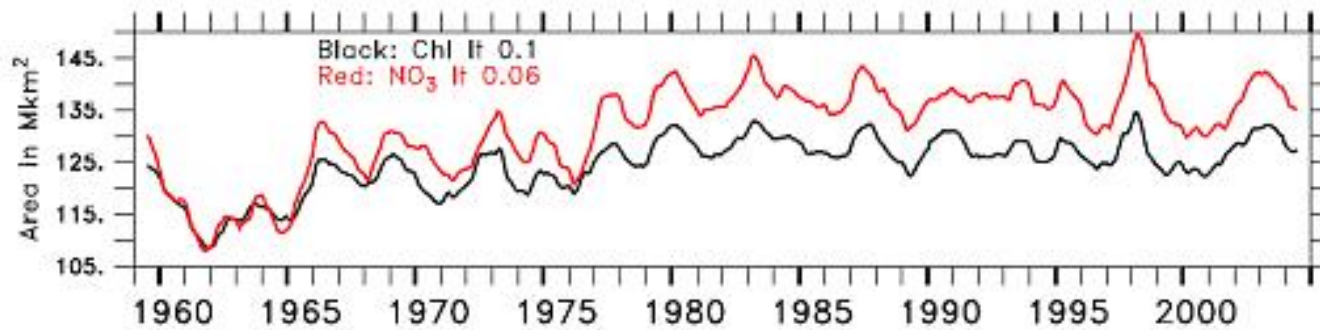
(b) April Surface density, Lg. Biomass



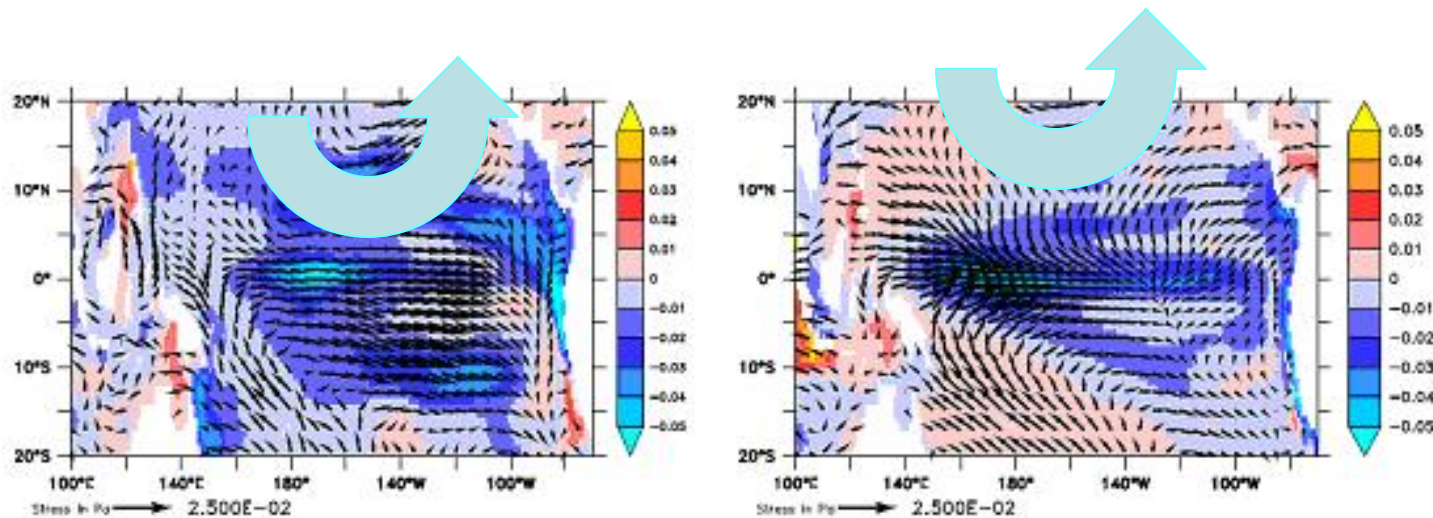
(c) April Surface Density, (Total, Temp Only, Salt Only)

Challenge: How do we get this kind of variability in reanalyses?

Tropical variability driven by winds



(a) Pacific Gyre area, CORE Run

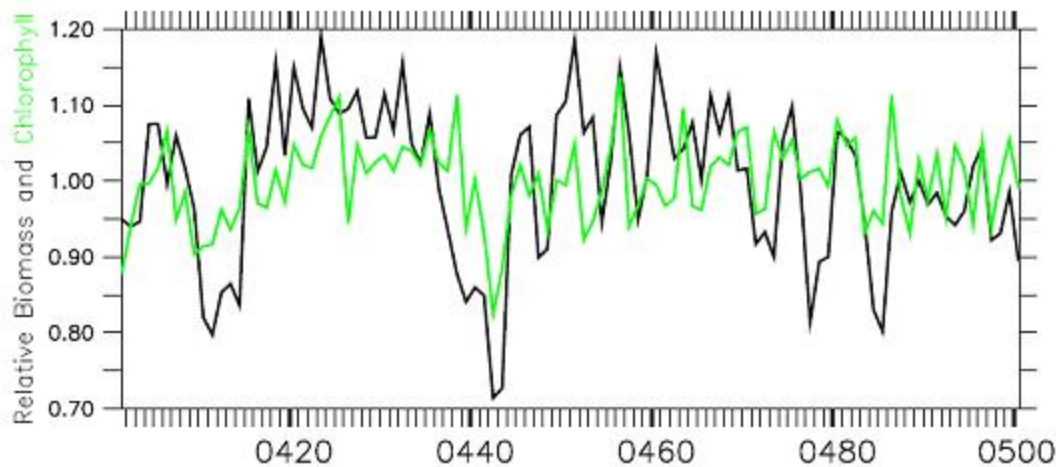


(b) Chl and Stress vs. Gyre Area, CORE

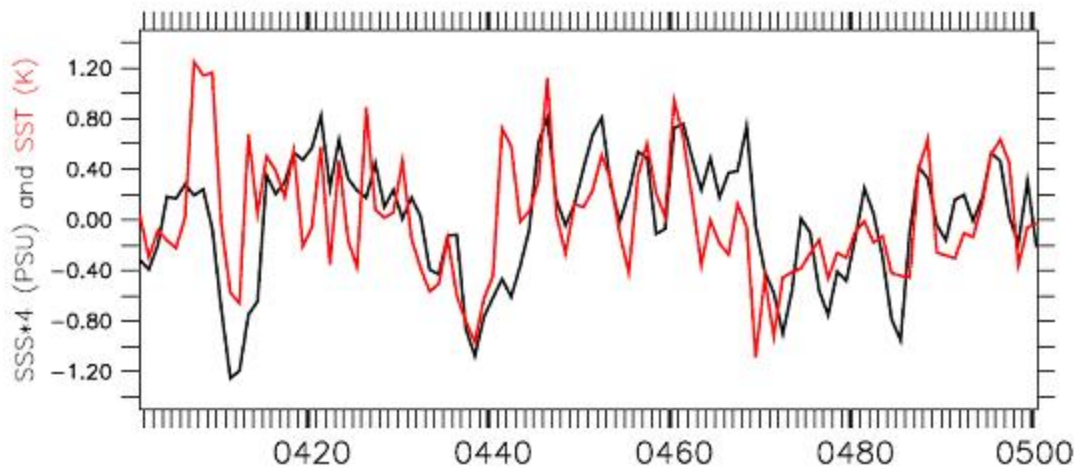
(c) Chl and Stress vs. Gyre Area, ESM2.1

Challenge: Small details in ENSO physics can matter!

A cautionary example



(a) Large Plankton Biomass and Chlorophyll



(b) Salinity and Temperature Anomaly

- Chlorophyll can vary less than large biomass.
- Variations not necessarily correlated.
- Salinity can be driver instead of temperature

Need to move beyond...

- Focus on chlorophyll, start to verify particle size as remotely sensed tool.
- Forced models (coupled reanalysis?) to get *salinity-forced* **seasonal** variations in high latitudes.
- *Focus on highly productive regions- are surrounding areas more important for recruitment (and for which species)?*

Arigato!

Dunne, Armstrong, Gnanadesikan and Sarmiento, 2005, Empirical and mechanistic models for the particle export ratio. *Global Biogeochemical Cycles*, 19, GB4026, doi:10.1029/2004GB002390.

Gnanadesikan and 27 coauthors, 2006: GFDL's CM2 Global Coupled Climate Models. Part I: Formulation and Simulation Characteristics. *Journal of Climate*, 19(5), doi:10.1175/JCLI3629.1.

Galbraith, Gnanadesikan, Dunne, and Hiscock, 2010: Regional impacts of iron-light colimitation in a global biogeochemical model. *Biogeosciences*, 7(3), 1043-1064.

<http://www.gfdl.noaa.gov/anand-gnanadesikan-home-page>