ECCO: Estimating the Circulation and Climate of the Ocean

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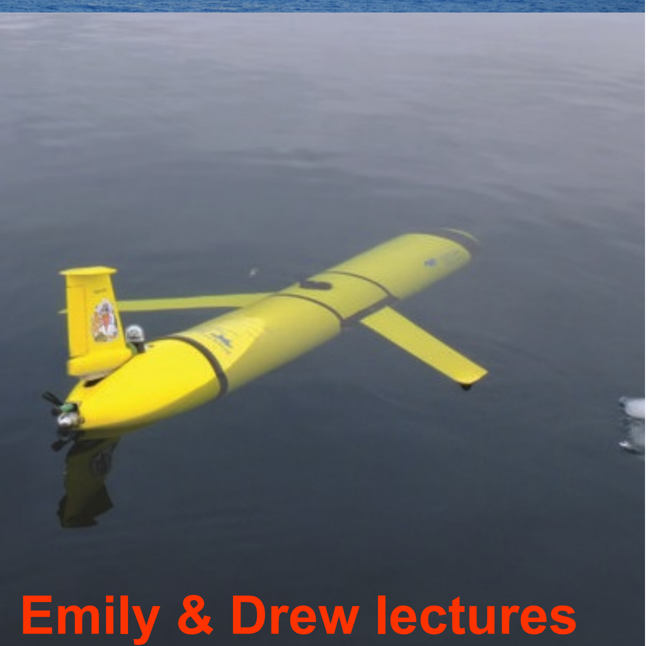
OUTLINE

- **Strengths and limitations of observations**
- **Strengths and limitations of numerical models**
- **Using observations to improve the models**
- **Example applications of ECCO**
  - heat storage and sea level
  - interactions with cryosphere
  - ocean ecology and biogeochemistry
  - mangrove and fisheries studies

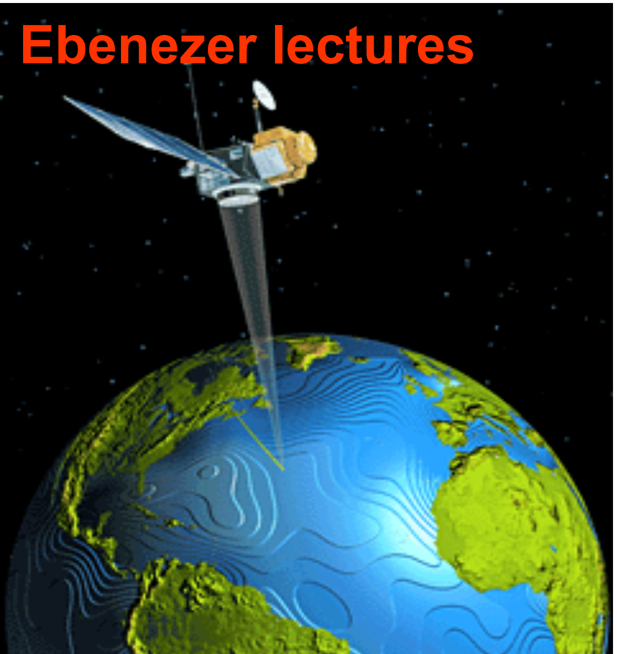
Strengths and limitations of in-situ observations

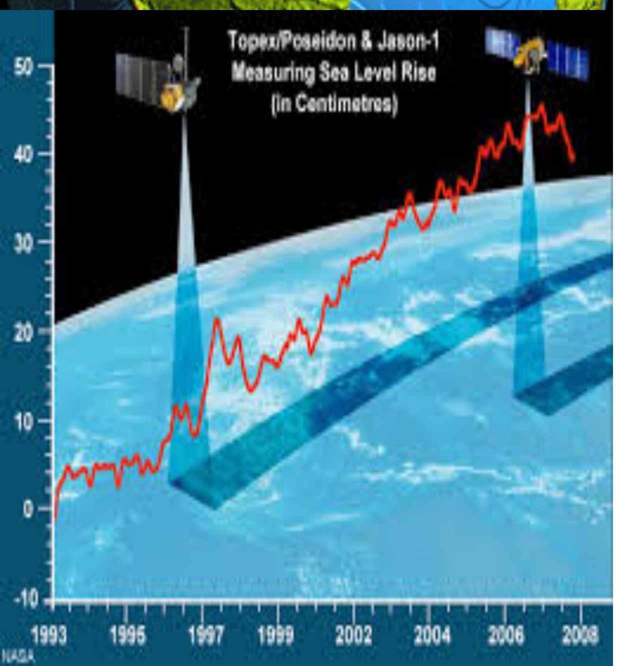


Emily & Drew lectures

- **Closest to ocean truth ☺**
- **… but very limited spatiotemporal coverage ☹**
  - point measurement in time and space is not necessarily representative of large-scale, long-period average
  - contamination by geophysical and instrument noise
  - possibility of aliasing

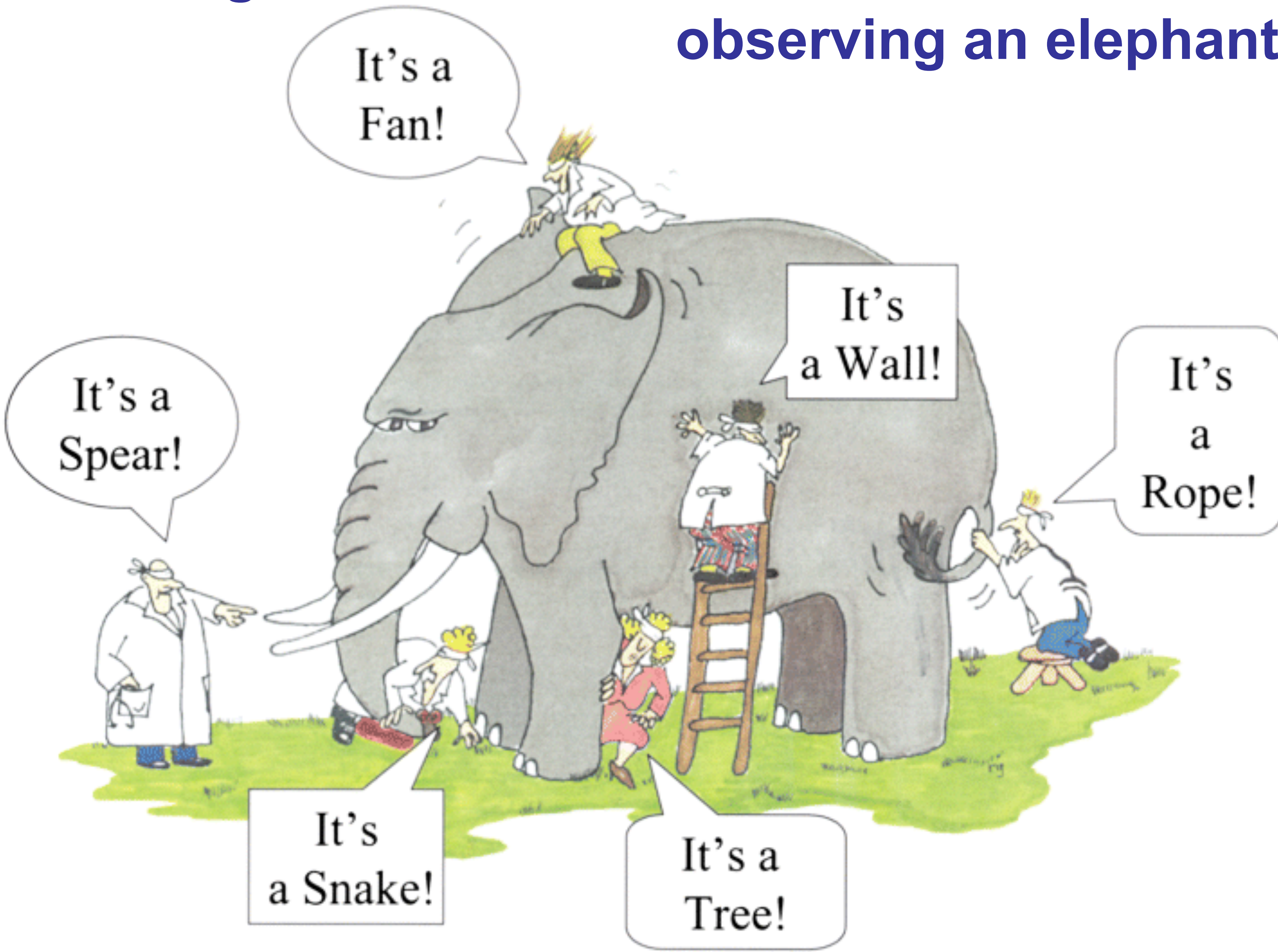
Strengths and limitations of satellite observations



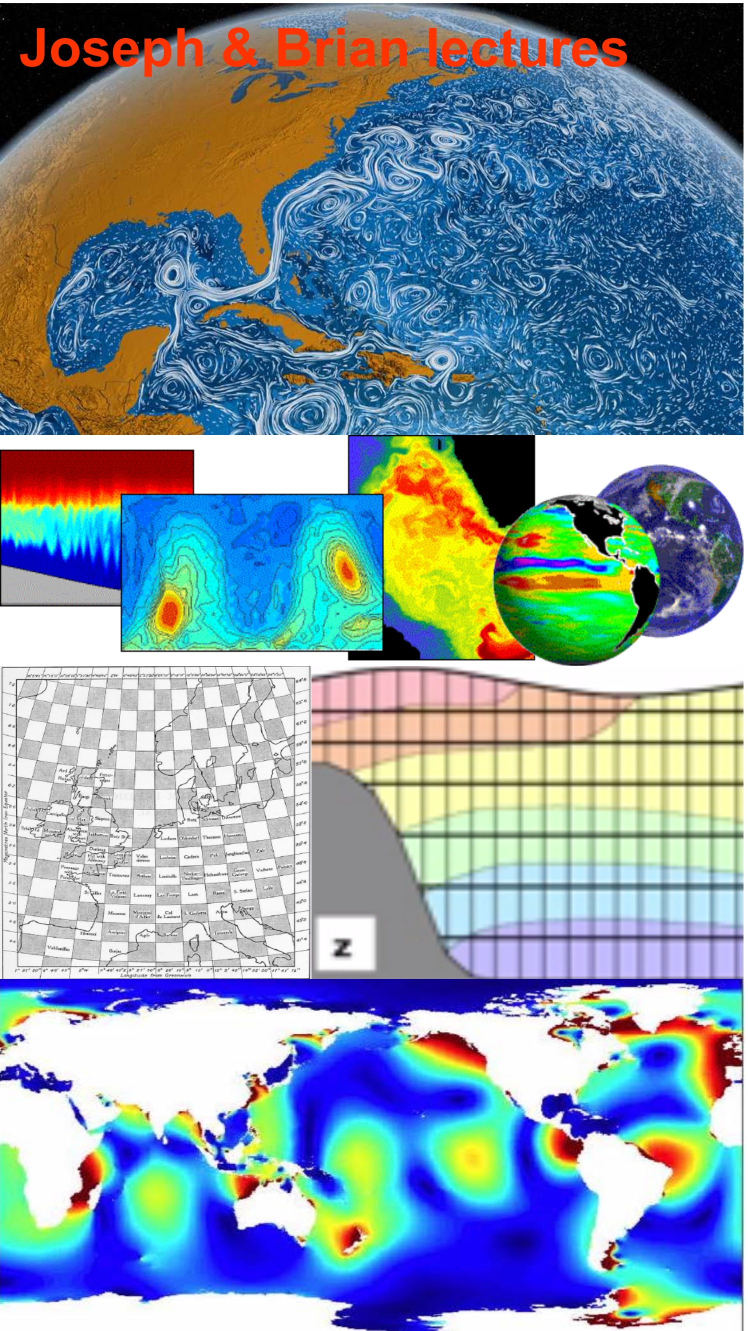


- ❖ **Global coverage ☺**
- ❖ **… but indirect observation of limited oceanographic variables ☹**
  - ➢ limited to near-surface or depth-integrated observables
  - ➢ errors due to, e.g., atmospheric variability and retrieval algorithms
  - ➢ sampling issues due to, e.g., footprint size and episodic sampling

Observing the ocean is like blind men observing an elephant.



Strengths and limitations of numerical models



- Complete space-time description ☺
- … but imperfect representation of truth ☹
  - discretization errors
  - subgrid-scale parameterization errors
  - boundary condition errors

How can we get a description of global ocean circulation that is as complete and as close to truth as possible?

This is the problem that the Estimating the Circulation and Climate of the Ocean (ECCO) project has tried to address during past 20 years.

We use the observations to improve the numerical ocean circulation model and to adjust empirical parameterizations and boundary conditions.

Parallels between ECCO project and the scientific method

1. Observe the physical world.

2. Construct/improve models with descriptive and predictive skill.

3. Use model to make predictions.

4. Acquire new observations and repeat cycle.

In addition to developing an increasingly more realistic ocean model, ECCO's technical objective is a least-squares fit of this model to all available satellite and in situ data.

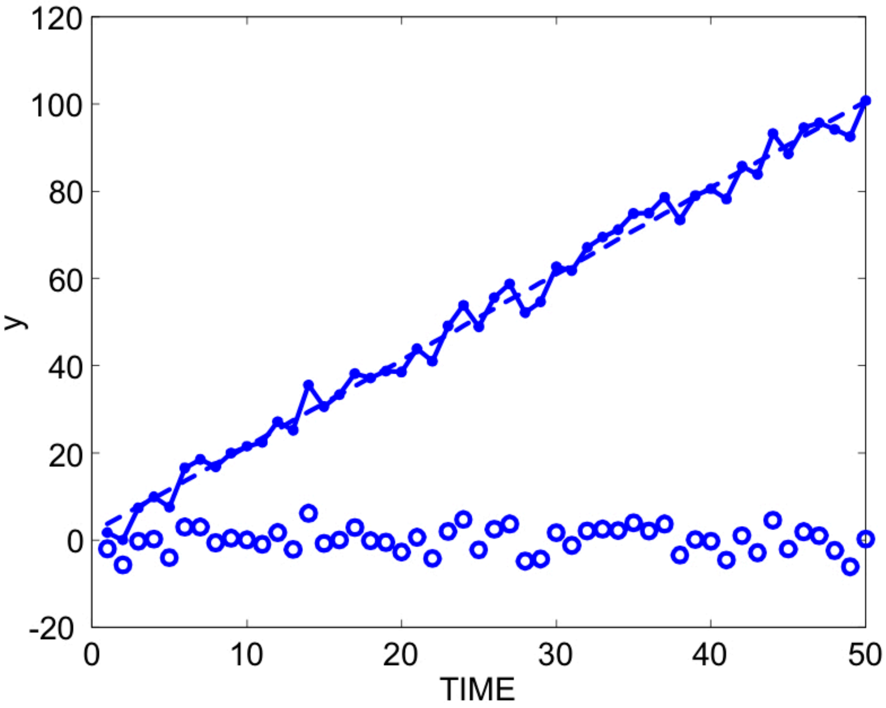
Complications:

There are > 10^8 observational constraints.

The model has > 10^{13} state variables.

The model is non-linear.

Least-squares minimization applied to a large non-linear problem



$$\mathbf{E}\mathbf{x} + \mathbf{n} = \mathbf{y}$$

$$\mathbf{E} = \begin{Bmatrix} 1 & t_1 \\ 1 & t_2 \\ \cdot & \cdot \\ \cdot & \cdot \\ 1 & t_M \end{Bmatrix}, \quad \mathbf{x} = \begin{bmatrix} a \\ b \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} y(t_1) \\ y(t_2) \\ \cdot \\ \cdot \\ y(t_M) \end{bmatrix}, \quad \mathbf{n} = \begin{bmatrix} n(t_1) \\ n(t_2) \\ \cdot \\ \cdot \\ n(t_M) \end{bmatrix}$$

… by restricting discussion to discrete models and finite numbers of measurements (all that ever goes into a digital computer), almost all discrete inverse and state estimation problems can be viewed as a form of ordinary least-squares …

(Wunsch, 2006)

Least squares method based on computation of model Green's functions (i.e., model sensitivity experiments)

GCM: $\mathbf{x}(t_{i+1}) = M(\mathbf{x}(t_i),\eta)$

$\mathbf{x}(t_i)$ is the ocean model state vector at time t_i
M represents the numerical model
η is a set of control parameters

Data: $\mathbf{y}^o = H(\mathbf{x}) + \varepsilon = G(\eta) + \varepsilon$

$\mathbf{y}^o$ is the available observations
H is the measurement model
G is a function of M and H
ε is additive noise

Cost function: $J = \eta^T \mathbf{Q}^{-1} \eta + \varepsilon^T \mathbf{R}^{-1} \varepsilon$

Q and **R** are weight matrices

Linearization: $G(\eta) \approx G(\mathbf{0}) + \mathbf{G}\eta$

G is a kernel matrix whose columns are computed using a GCM sensitivity experiment for each parameter in vector η.

Solution: $\eta^a = \mathbf{P}\mathbf{G}^T\mathbf{R}^{-1}\mathbf{y}^d$

Control parameters that minimize cost function J

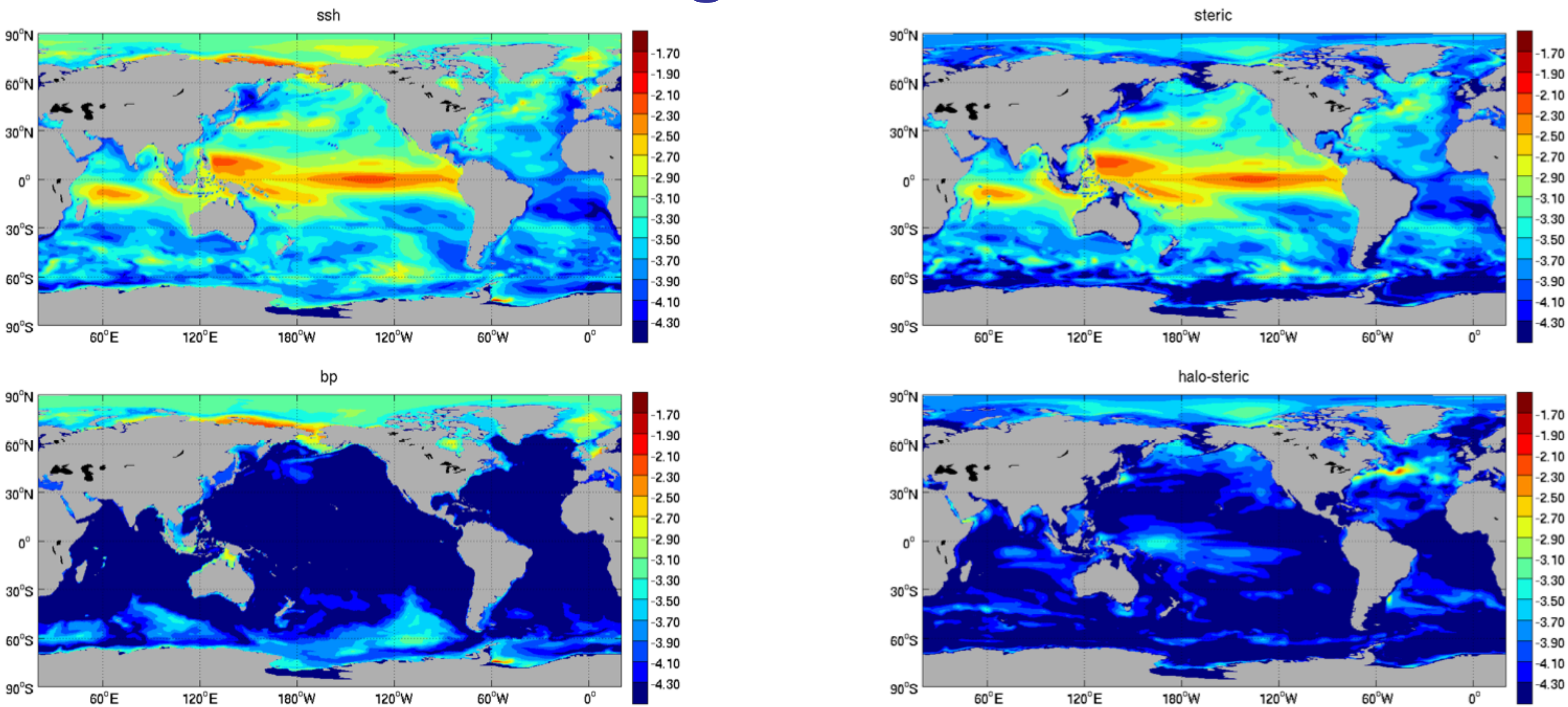
$\mathbf{P} = (\mathbf{Q}^{-1} + \mathbf{G}^T\mathbf{R}^{-1}\mathbf{G})^{-1}$

Posterior uncertainty

Comparison with adjoint method

- The Green's function approach has been called a poor-man's adjoint.
- Advantages relative to the adjoint method are simplicity of implementation, the possibility of offline experimentation with different cost functions, and complete a posteriori error statistics for the parameters being estimated.
- The major drawback of the Green's function approach is that computational cost increases linearly with the number of control parameters. By comparison, the cost of the adjoint method, while substantial, is largely independent from the number of control parameters.

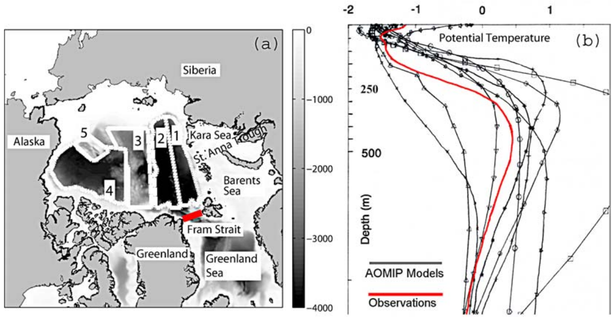
Example application of ECCO: Heat storage and sea level

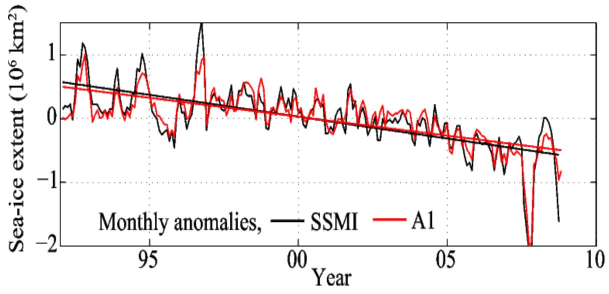


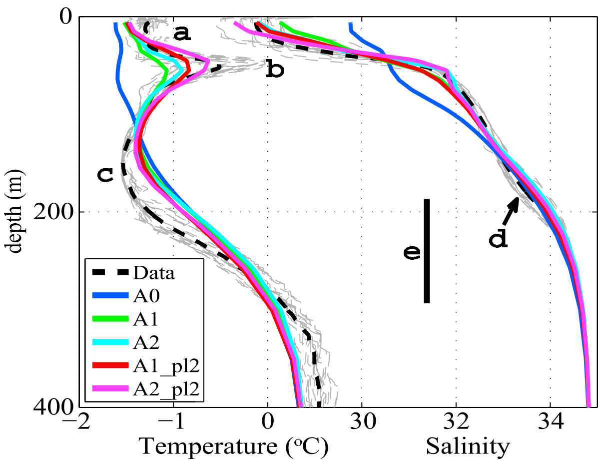
Forget and Ponte (2014)

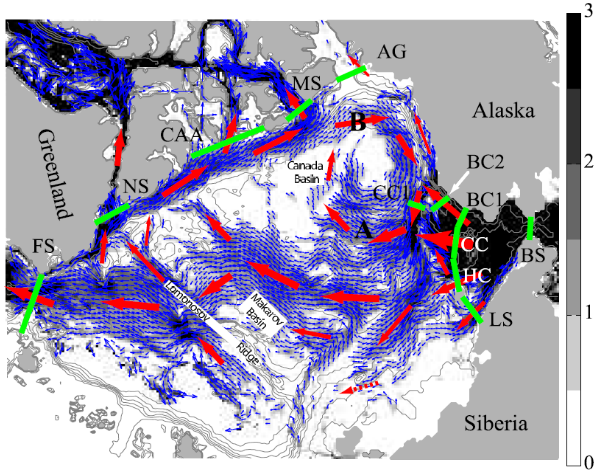
- **Interannual sea level variability is a complicated mixture of thermosteric, halosteric and mass contributions highly dependent on region**
- **Ability to quantitatively determine each contribution, as function of depth and location, is essential to understand causes of sea level change, and relate them to heat and freshwater content**

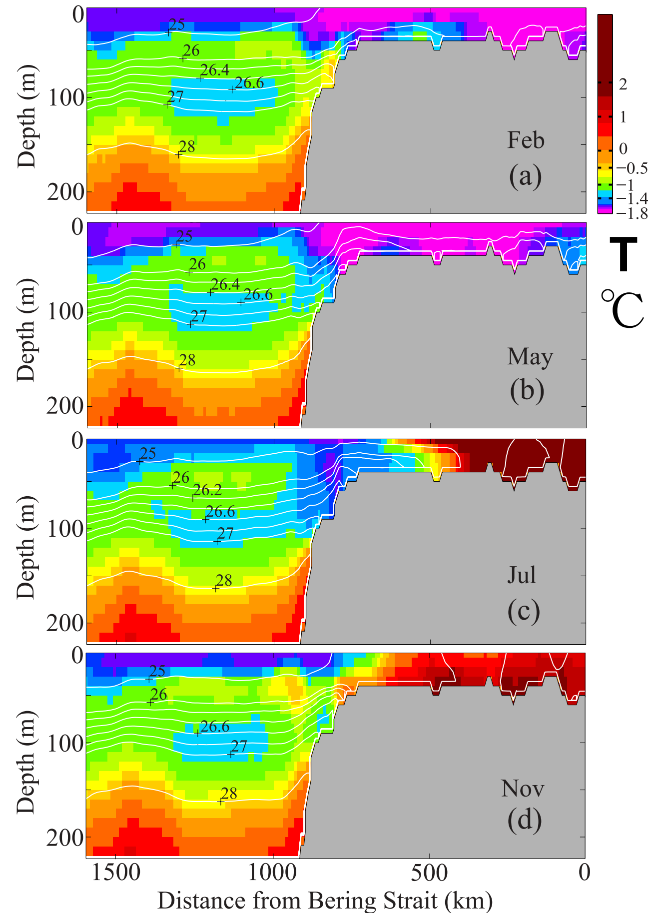
Example ECCO ocean and sea ice science studies









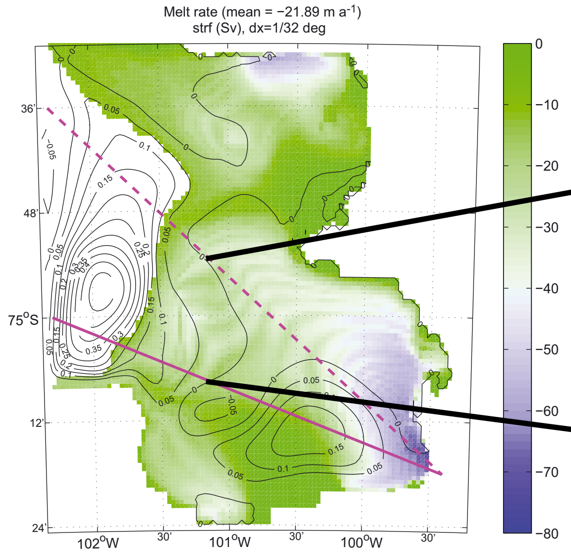


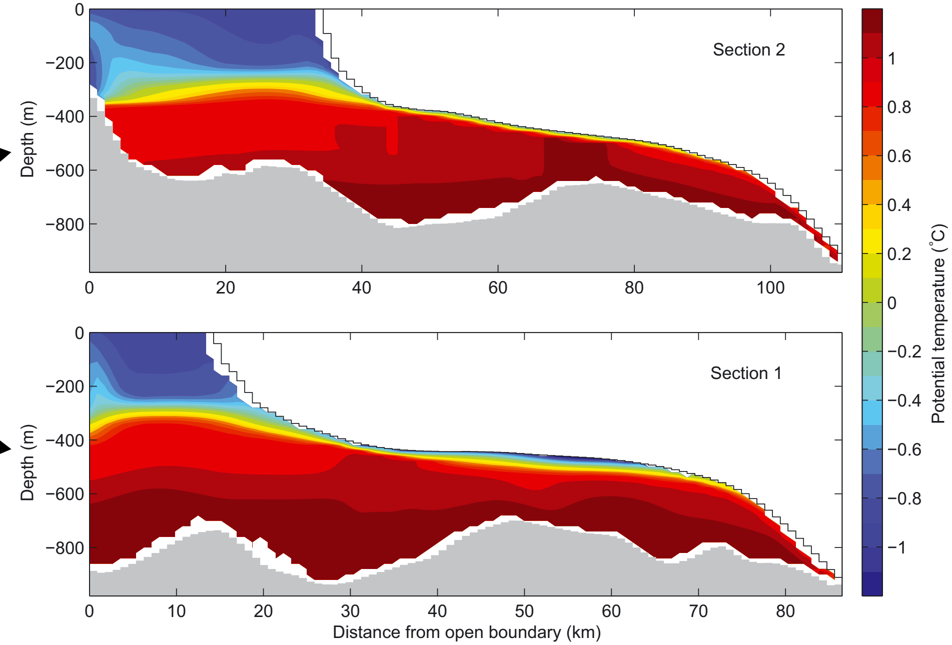
An improved parameterization of salt plumes lead to a more realistic simulation of Arctic halocline (Nguyen et al., 2009)

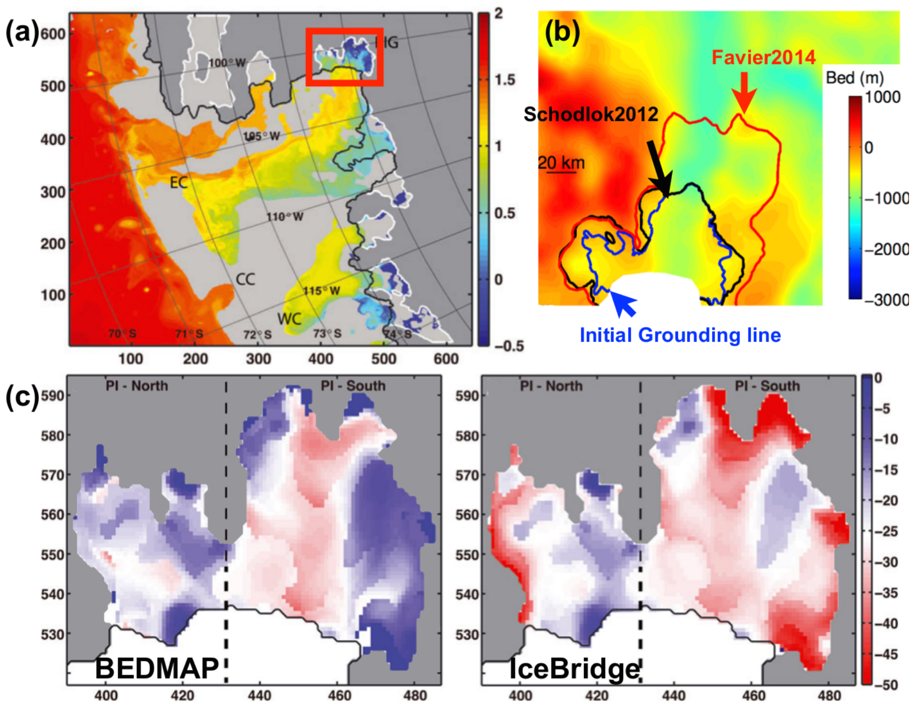
and to an optimized, property-conserving Arctic Ocean simulation (Nguyen et al., 2011)

that was used to study the formation of upper halocline waters (Nguyen et al., 2012).

Ocean circulation and sub-ice-shelf melt rates

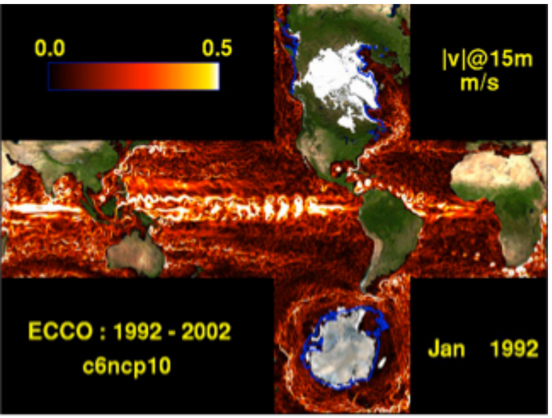




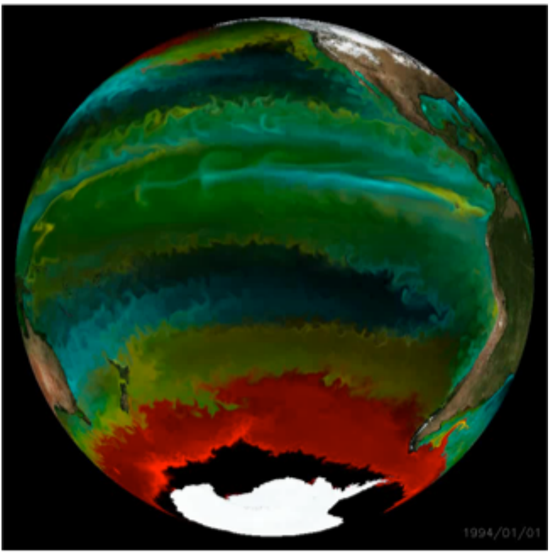


Heimbach and Losch (2012), Schodlok et al. (2012) and Seroussi et al. (2014) studied ocean ice interactions near Pine Island Glacier, West Antarctica, and found high sensitivities of ice shelf basal melt rates to cavity shape and glacier dynamics to basal melt rates, motivating development of a fully-coupled ice-ocean model.

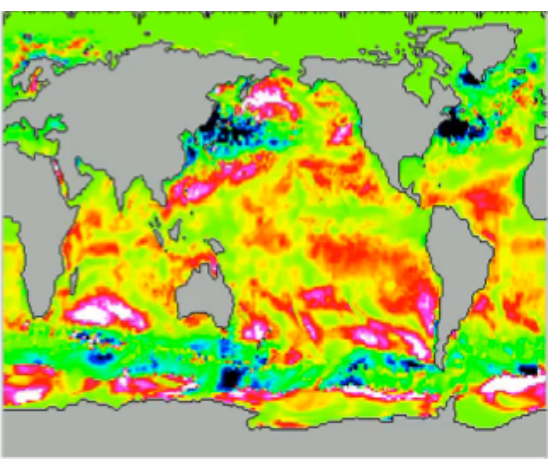
ECCO-Darwin ocean surface carbon flux estimates



ECCO provides an eddying ocean and sea ice data synthesis

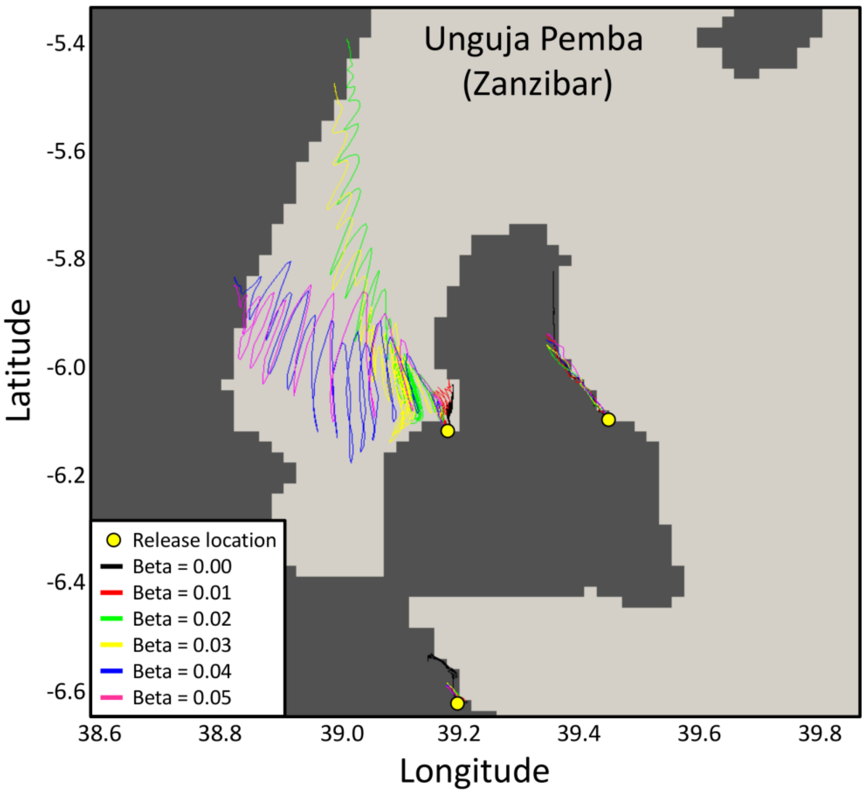


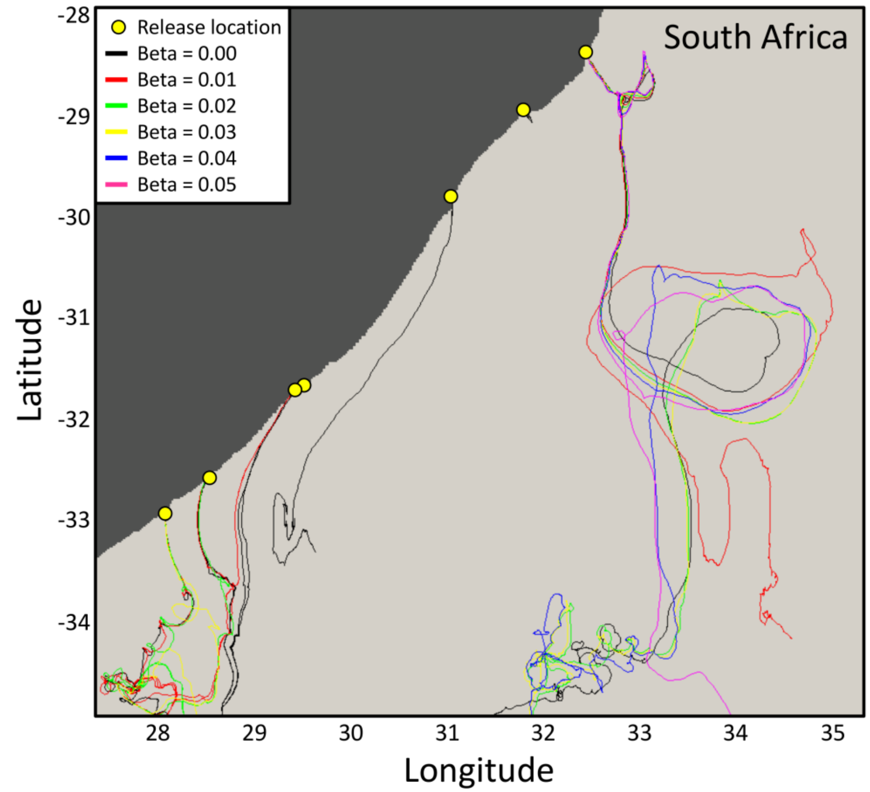
Darwin is a self-organizing marine ecosystem model driven by ECCO circulation estimates



By adding a carbon chemistry model, ECCO-Darwin produces estimates of ocean surface carbon fluxes

Interaction between water and wind as a driver of passive dispersal of mangrove seeds





'Beta' is the weight of wind in the dispersal velocity equation

ECCO Simulations of the Tuna Fishery of the Eastern Tropical Pacific

D A Kiefer, D P Harrison, M G Hinton, E M Armstrong, F J O'Brien

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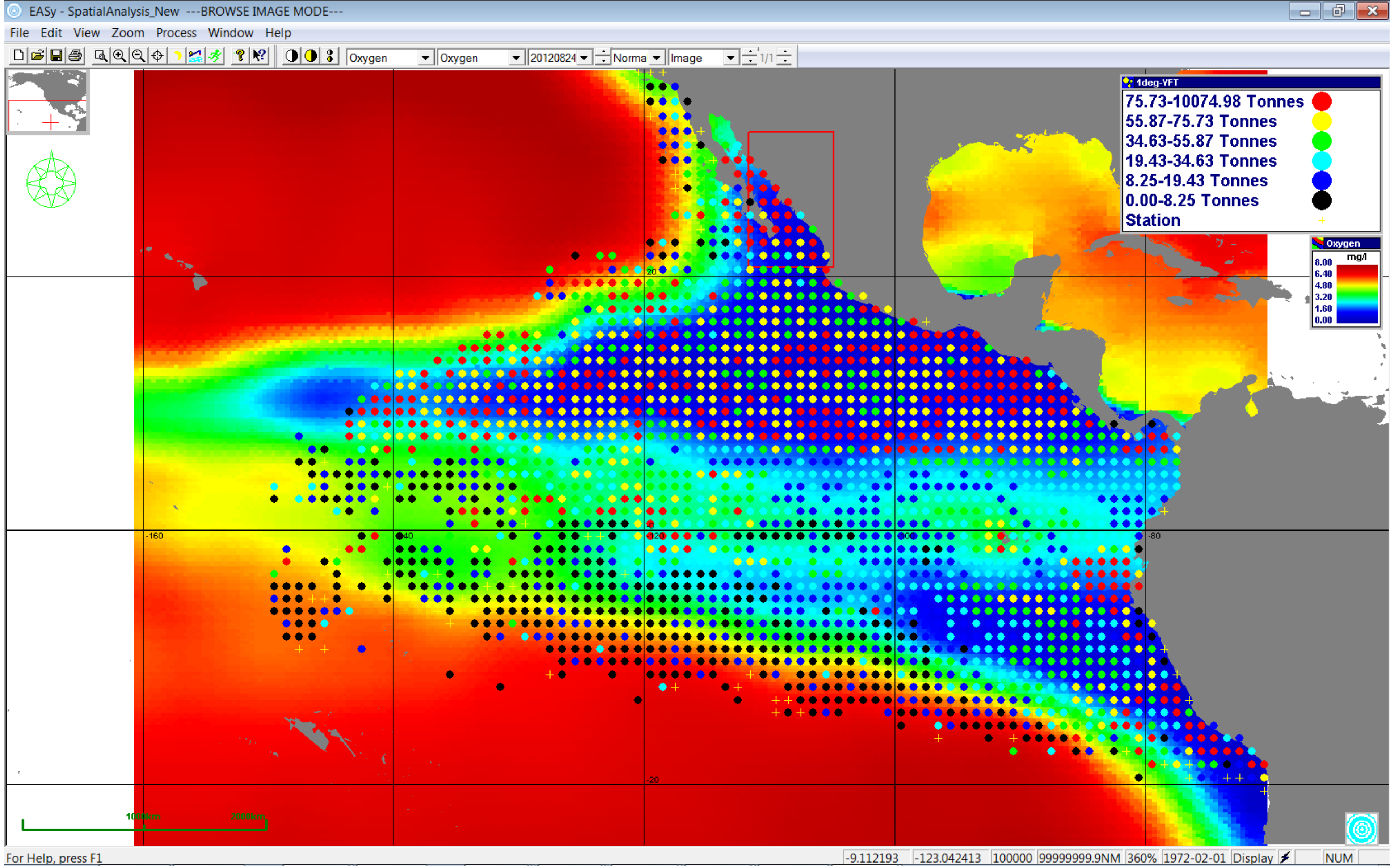

The hypoxic layer also shapes the distribution of the purse seine catch for each of the 3 species. Here we see that average yellowfin catch/month fished is largest in waters where the hypoxic layer is most intense. The dots are color coded catch with warmest colors indicating larger catch. The lowest concentrations of O2 at 150 m is dark blue and the highest are dark red.

SUMMARY

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