Ocean Dynamics and Prediction

Allard, Barron, Bartels, Berg, Blain, Broome, Buijsman, Campbell, Carrier, Carroll, Chu, Coelho, Condon, Crout, Cummings, Dastugue, Douglas, Dykes, Edwards, Fan, Fanguy, Flampouris, Franklin, Gravois, Gremes-Cordero, Hawkins, Hebert, Helber, Holmberg, Hogan, Hurlburt, Jacobs, Jensen, Keen, Ko, Maloy, Lind, Linzell, Martin, May, McKay, McKinney, Metzger, Moore, Muscarella, Ngodock, Odom, Orzech, Peggion, Phelps, Piacsek, Posey, Rainey, Richman, Riedlinger, Rogers, Rowley, Sitton, Shriver, Smedstad, Smith, Smith, Spence, Summers, Thoppil, Townsend, Vandevoorde, Veeramony, WarnVarnas, Wallcraft, Wei, Yaremchuk, Zamudio, Ziegeler

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GULF OF MEXICO RESEARCH INITIATIVE

Background

Classes of environmental processes

1. Predictable
   - Generating force is accurately known, and predictions may be made far in advance
   - Uncertainty in physics and geometry (bathymetry) may lead to prediction errors
   - Tides
2. Deterministic
   - Generating force contains errors
   - Uncertainty in physics and geometry lead to prediction errors
   - Waves, wind-generated sea level changes and currents
3. Nondeterministic
   - Regardless of accuracy in forcing, physics or geometry, any small error grows in time leading to unpredictability without continuous observations
   - Eddies, deep ocean currents
4. Conditionally deterministic
   - Deterministic if something else is already predicted
   - Frontogenesis

What is predictable, what is not, under what conditions?

Eddy Kinetic Energy

1/25 Model (Free Run)

1/12 Model (Data Assimilation)

1/12 Model (Free Run)

Drifter

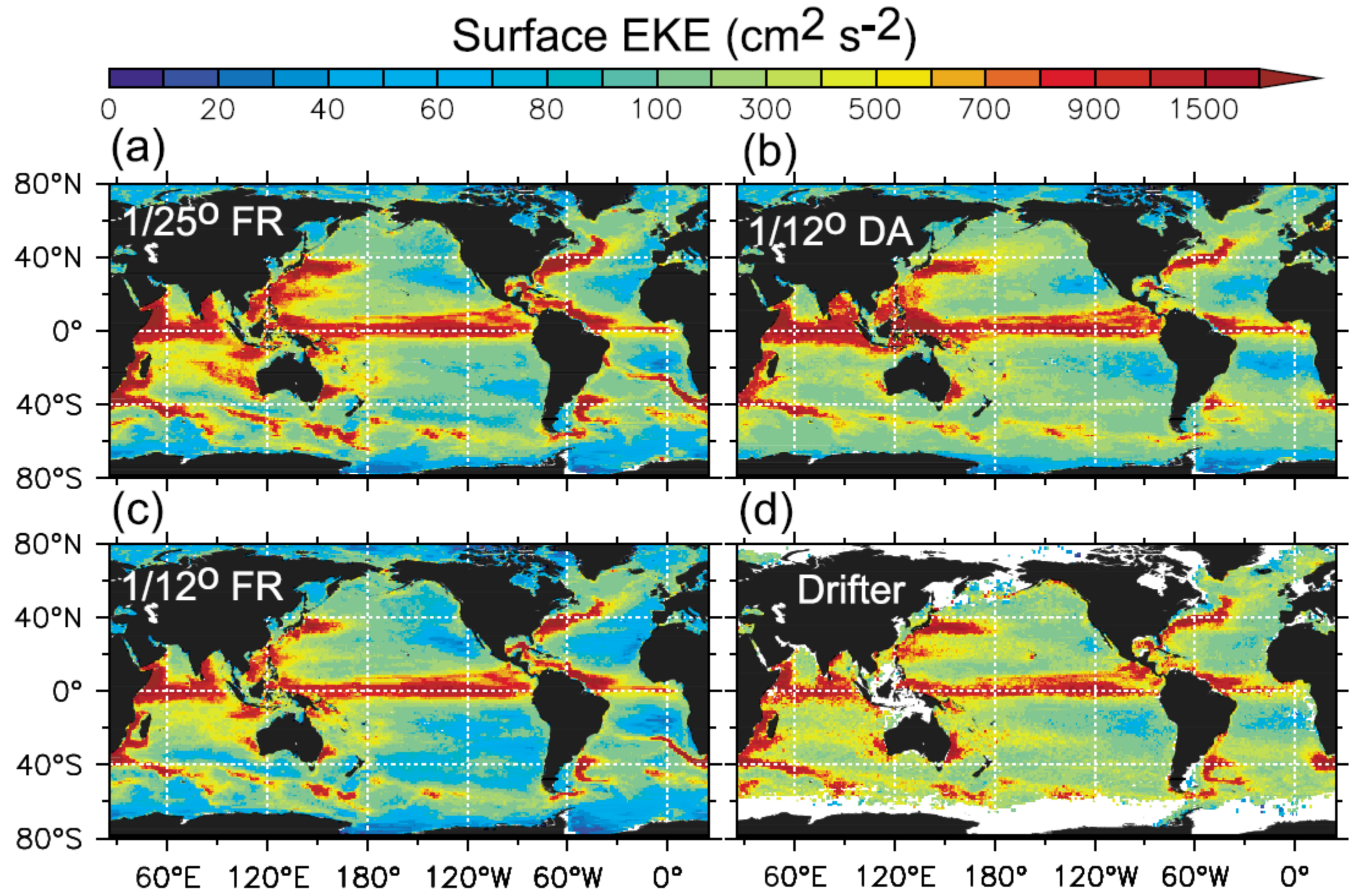


Figure 1. Surface eddy kinetic energy (EKE in cm^2 s^{-2}) from the three numerical experiments (a) 1/25° FR (2005–2009), (b) 1/12.5° DA (2008–2009), and (c) 1/12.5° FR (2005–2009) and (d) drifter observations encompassing the period 1983–2009. The surface drift observations are binned into 1° × 1° grids using daily values and those grid points with at least 100 observations are considered. The EKE is computed from the daily velocity fields using the equation $(\langle u'^2\rangle + \langle v'^2\rangle)/2$, where brackets indicate time means and primes denote deviations from the time-mean velocities, $(u', v') = (u, v) - (\langle u\rangle, \langle v\rangle)$.

Statistics may be predictable but synoptic state is limited

Thoppil et al., GRL 2011

How is prediction done?

Based on Newton

- Conservation of momentum
- Conservation of mass (water and salt)
- Conservation of energy (heat)

These provide the Navier-Stokes and continuity equations

$$\frac{\partial u}{\partial t} = Momentum\_Forcing$$

$$\frac{\partial T}{\partial t} = Temperature\_Forcing$$

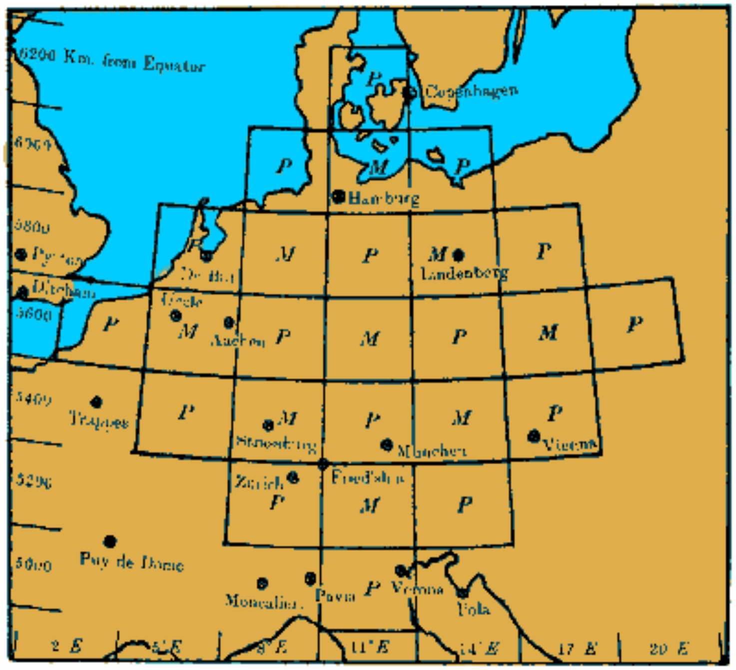
$$\frac{\partial S}{\partial t} = Salinity\_Forcing$$

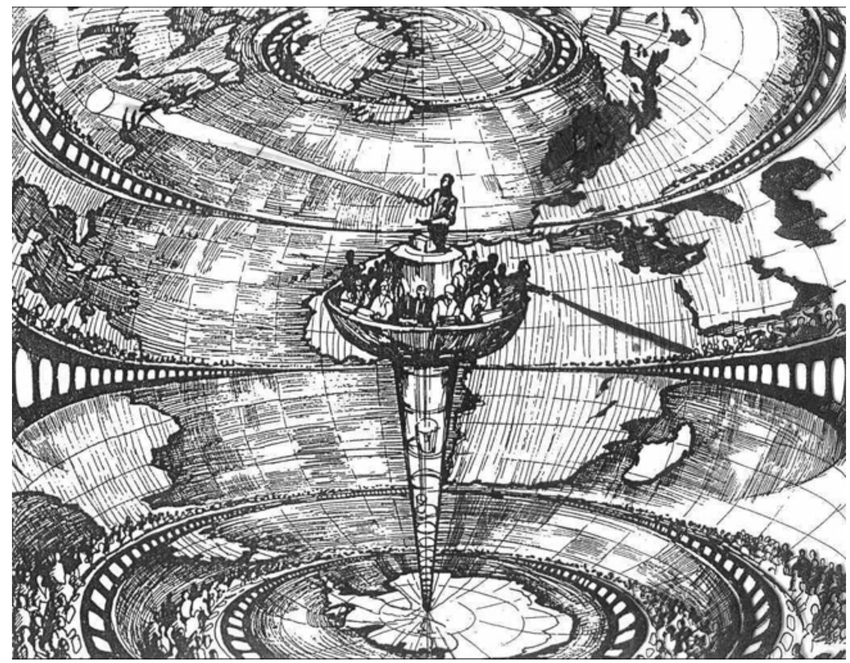
$$\frac{\partial \eta}{\partial t} = Sea\_Surface\_Height\_Forcing$$

Equations of evolution are integrated through time

Where did this begin?

Richardson’s first atmospheric forecast, 1910



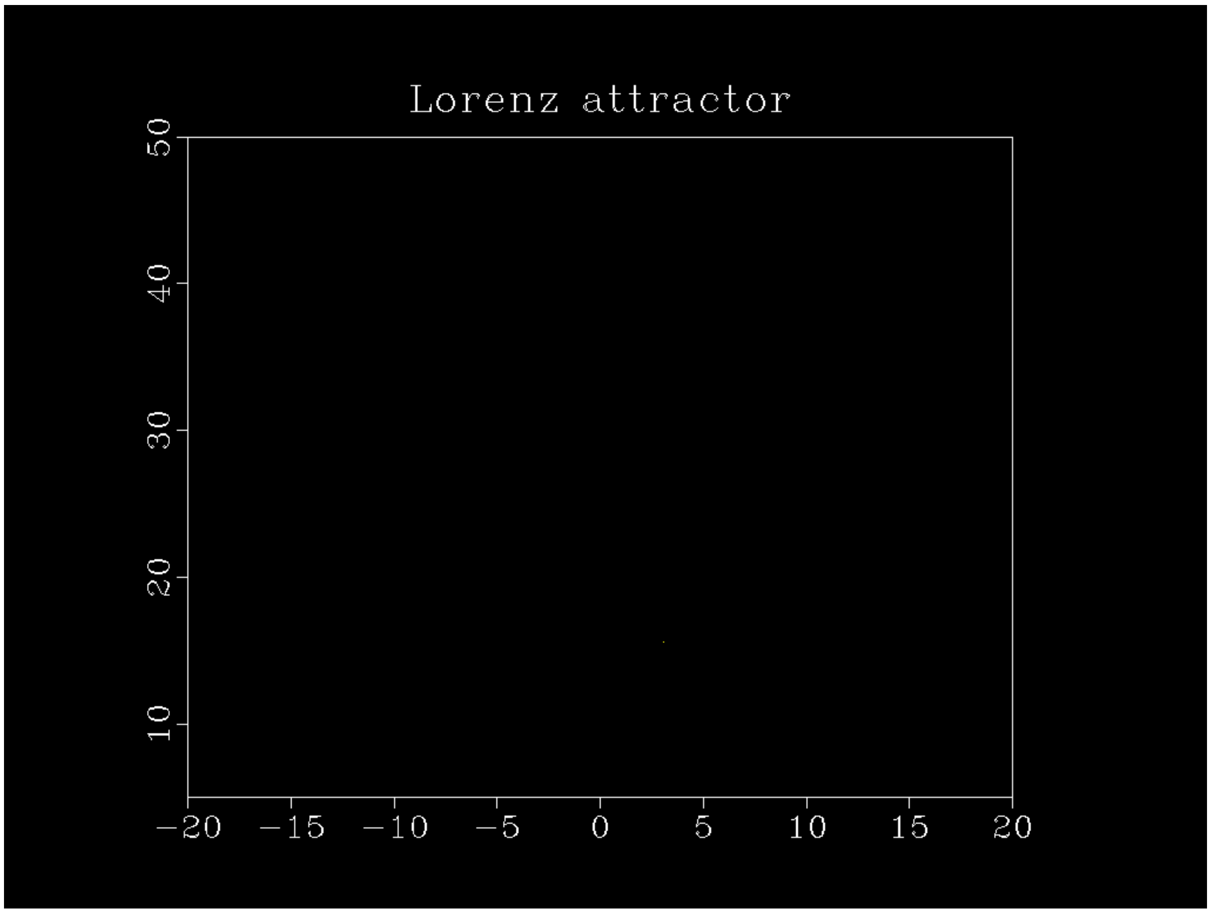


Failed due to Courant–Friedrichs–Lewy time step criteria (1928) for numerical stability in finite difference formulas representing derivatives

A fantastic failure, but brilliantly insightful

What are the limits of predictability?

At some point, predictability ends
Tide predictions are limited as we do not know where the continents will be in 50M years



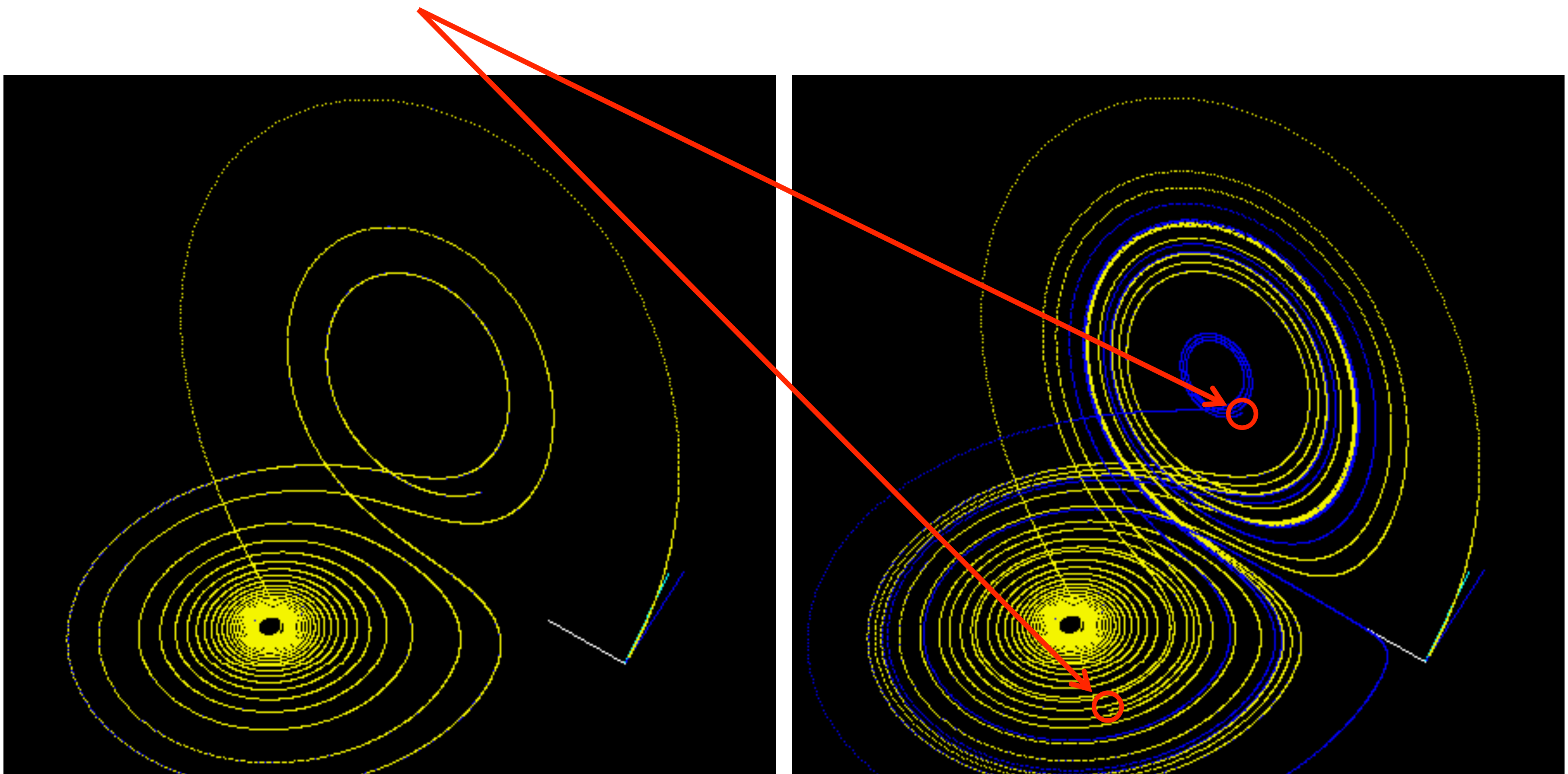
Lorenz Equations

$$\frac{dx}{dt} = \sigma(y - x)$$
$$\frac{dy}{dt} = x(\rho - z) - y$$
$$\frac{dz}{dt} = xy - \beta z$$

All predictions are eventually limited by system input or internal instability

What are the limits of predictability?

Start with 2 x,y,z very close to each other
Initially the x,y,z solutions are similar
Eventually the x,y,z solutions diverge
Nondeterministic vs Deterministic



All predictions are eventually limited by system input or internal instability

Assimilation

What is a common canonical characteristic calculation?

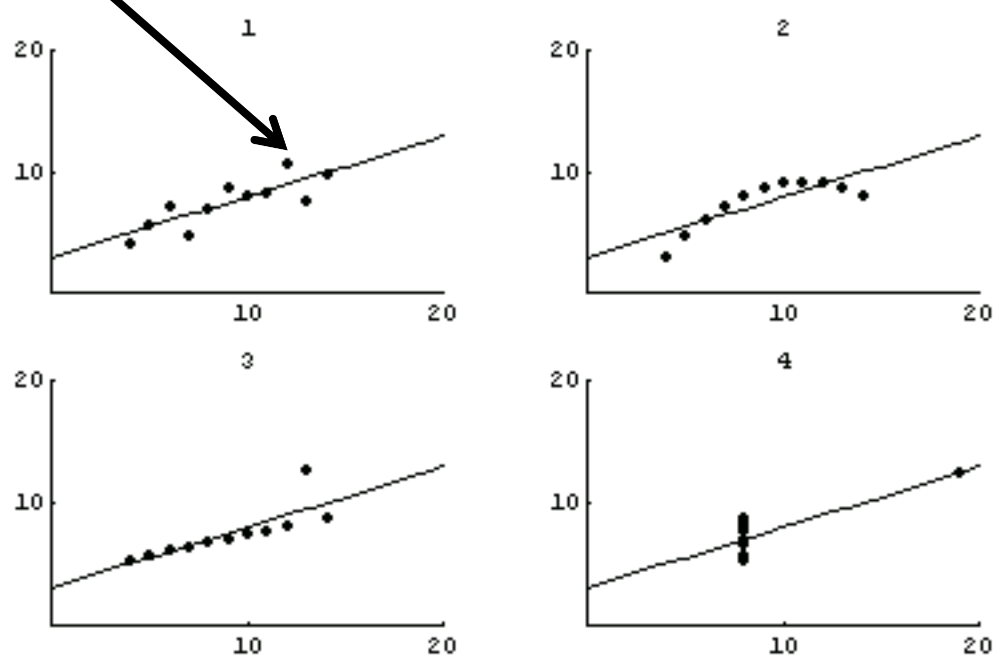
Areas of active research in many aspects of assimilation

- Physics of the model
- Assimilation of data

$y=at+b$

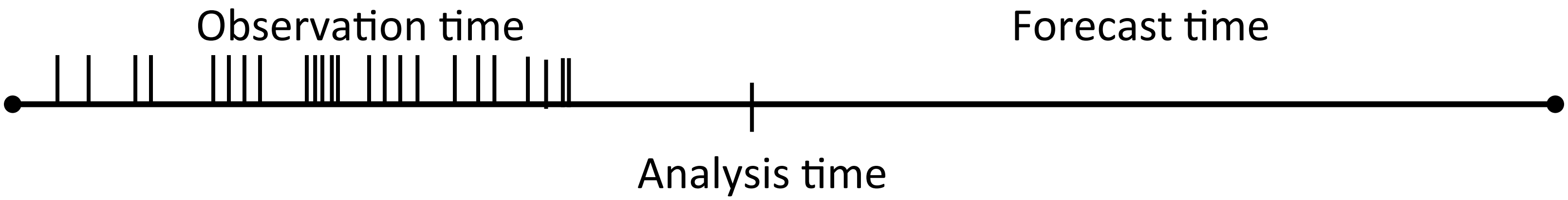
Objective:
estimate the state

x=[■*a*@*b*]



It's Gaussian least squares fitting

What should be optimized to estimate the state **x**?



x contains all variables at all spatial points over all observation and forecast time

Define the quantity to minimize (cost function):

J(x) = weighted squared error to our knowledge

Knowledge:

- Parameters, initial & boundary conditions
- Dynamics
- Measurements

$$\mathbf{A}_B\mathbf{x} = \mathbf{b}_B$$
$$\mathbf{A}_D\mathbf{x} = \mathbf{b}_D$$
$$\mathbf{A}_M\mathbf{x} = \mathbf{b}_M$$

Therefore, minimize:

$$\begin{bmatrix}\mathbf{A}_D\\ \mathbf{A}_B\\ \mathbf{A}_M\end{bmatrix}^{\mathrm{T}} \mathbf{W} \begin{bmatrix}\mathbf{A}_D\\ \mathbf{A}_B\\ \mathbf{A}_M\end{bmatrix} \mathbf{x} = \begin{bmatrix}\mathbf{b}_D\\ \mathbf{b}_B\\ \mathbf{b}_M\end{bmatrix}$$ or $\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\mathbf{x} = \mathbf{b}$ and the solution is: $\mathbf{x} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$

Find a state trajectory x that minimizes the errors to our knowledge

Problem 1: Unknown error covariances

How is the error in turbulent momentum flux at one point and time related to the error in surface radiation forcing?

What is W?

$$\begin{bmatrix} \mathbf{A}_D \\ \mathbf{A}_B \\ \mathbf{A}_M \end{bmatrix}^{\mathrm{T}} \mathbf{W} \begin{bmatrix} \mathbf{A}_D \\ \mathbf{A}_B \\ \mathbf{A}_M \end{bmatrix} \mathbf{x} = \begin{bmatrix} \mathbf{b}_D \\ \mathbf{b}_B \\ \mathbf{b}_M \end{bmatrix}$$ or $$\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\mathbf{x} = \mathbf{b}$$ and the solution is: $$\mathbf{x} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$$

Relations between errors in evolution equations are unmeasurable and unknown

Problem 2: It's a big problem

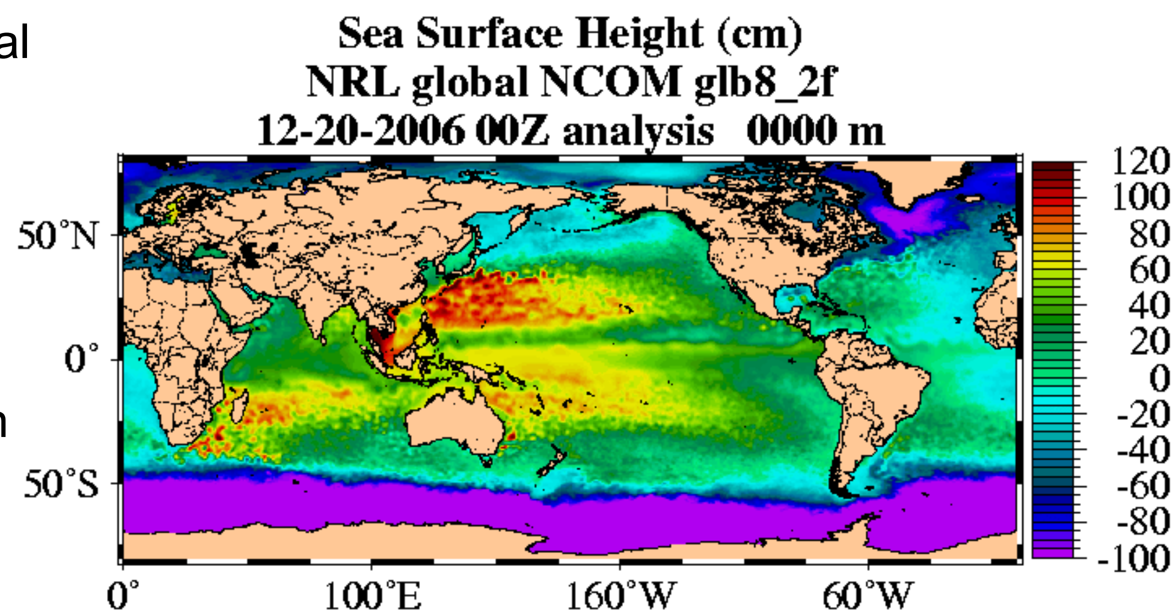
- Previous generation operational global model

- Medium horizontal resolution (1/8°)

- Medium vertical representation (41 sigma/Z layers)

- Each layer contains U, V, T, S

- Includes Sea Surface Height



At one time there are about 360*180*8*8*(41*4+1) = 684,288,000 variables

With a time step of 10 minutes, 1 week would be 689,762,304,000 ~ 10^{12} variables

The dimensionality is at the limit of what a supercomputer can output

What is the inverse problem size?

x contains all variables at all spatial points over all analysis and forecast time

Define the quantity to minimize (cost function):

J(x) = weighted squared error to our knowledge

Knowledge:

- Parameters, initial & boundary conditions $\mathbf{A}_B\mathbf{x} = \mathbf{b}_B$
- Dynamics $\mathbf{A}_D\mathbf{x} = \mathbf{b}_D$
- Measurements $\mathbf{A}_M\mathbf{x} = \mathbf{b}_M$

Therefore, minimize:

10^{12}x10^{12}=10^{24} variables

$$\begin{bmatrix}\mathbf{A}_D\\ \mathbf{A}_B\\ \mathbf{A}_M\end{bmatrix}^{\mathrm{T}} \mathbf{W} \begin{bmatrix}\mathbf{A}_D\\ \mathbf{A}_B\\ \mathbf{A}_M\end{bmatrix} \mathbf{x} = \begin{bmatrix}\mathbf{b}_D\\ \mathbf{b}_B\\ \mathbf{b}_M\end{bmatrix}$$ or $\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\mathbf{x} = \mathbf{b}$ and the solution is: $\mathbf{x} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$

The inversion problem is size N^2

What does Moore's law imply?

Assume present Terrabyte computer capability

Time for 10^{12} increase: 80 years assuming a doubling every 2 years

Computers will not hold the covariance matrix in our lifetimes

What are our options to an intractable problem? $\mathbf{x} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$

Two options:

1. ~~Go Home~~
2. Simplify the problem, be creative
    - Set vast areas of the covariance and dynamical operator to 0 or 1
    - 4DVar inverts $\mathbf{A}^{\mathrm{T}}$ then **W** then **A** (assumptions in W are still hazardous)
    - Kalman filtering is a simplification by reducing time correlation (but does provide a methodology for propagating W, fraught with hazards)
    - Simplified Ensemble Kalman filtering assumes W is fixed over time and reduces to 3DVar
    - 3DVar is simplification by setting vast areas of W to 0
    - OI assumes A is an identity matrix with no errors

There is only one option, simplify the problem

What are our options to an intractable problem? $\mathbf{x} = \left(\mathbf{A}^{\mathbf{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$

4DVar: Few assumptions, though costly (compute and implement)

- 4DVar must invert $\mathbf{A}^{\mathbf{T}}$ (the adjoint) then **W** (covariance convolution) then **A** (forward model)
- Often done through the representer method
  - Every observation has a representer function
  - Solution is a linear combination of representer functions
  - Amplitude coefficients are computed through a conjugate gradient
  - Process involves iterative solutions of applying dynamical portion of $\mathbf{A}^{\mathbf{T}}$ to a set of weights at the observation points, apply **W** then **A**
- Great assumptions in W are made
- Control variables can be any initial condition, boundary condition, input parameter, error to dynamical equation (e.g. turbulent mixing)
- Strong constraints can be applied to any control variable (e.g. conservation of mass equation in **A**)
- Observation errors are often assumed uncorrelated though need not be

4DVar assumes the least, though still has unknown **W**

How does inclusion of dynamics change the problem?

$$\mathbf{x} = \left(\mathbf{A}^{T}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$$

Observation time

Forecast time

1 Invert $\mathbf{A}^{\mathbf{T}}$ (the adjoint)

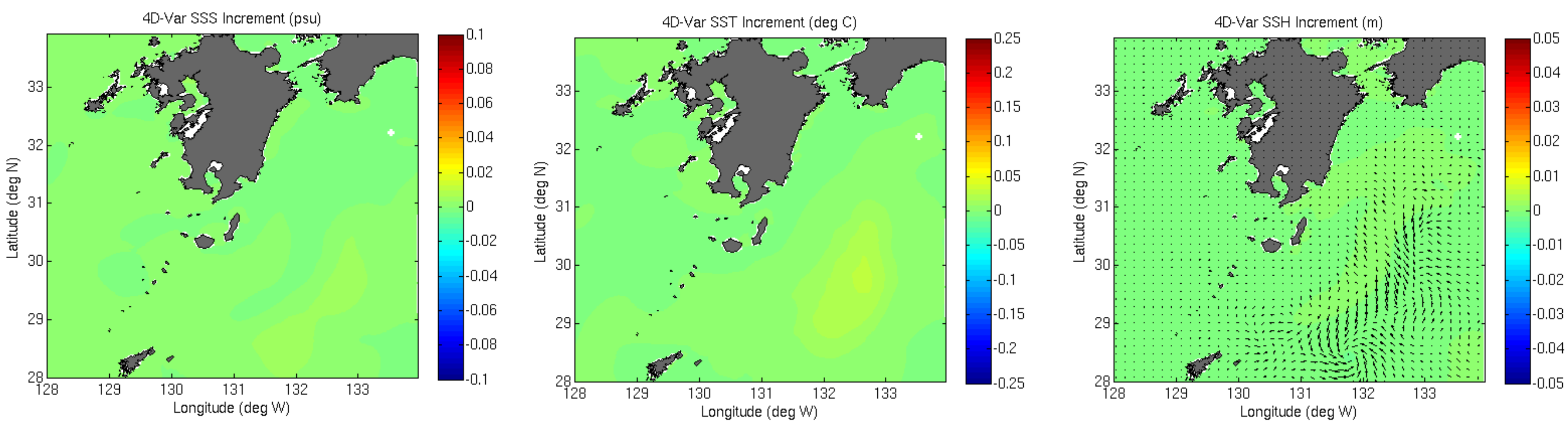
2 Invert **W** (space / time error covariance convolution)

3 Invert **A** (forward model)

4DVar increments from 1K SST innovation

A representer function for one observation

SSS increments **SST increments** **SSH & velocity increments**



Dynamics result in solution matching observations and equations of motion

Ngodock

What are our options to an intractable problem? $\mathbf{x} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$

Kalman filter / smoother: Formalism for **W**, though intractable

- **W** is propagated forward with the state through linearized dynamics
- Small state problems are feasible analytically
- Ocean problem is too large
- Avoids the need for an adjoint
- Can provide all the sensitivity information an adjoint provides

Kalman approach provides everything 4DVar and can propagate **W**

What are our options to an intractable problem? $\mathbf{x} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$

Simplified Ensemble Kalman filter: Brute force **W**

- **W** is propagated by ensembles
- **W** is represented by an ensemble with its own challenges
- Avoids the need for an adjoint
- Can provide all the sensitivity information an adjoint provides given a sufficiently large ensemble set (how large, no one knows)
- **W** is sometimes assumed to be time-fixed during the analysis time, which can collapse the analysis into a 3DVar

Kalman approach provides everything 4DVar and can propagate **W**

What are our options to an intractable problem? $\mathbf{x} = \left(\mathbf{A}^{\mathbf{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$

3DVar: Computationally cheaper though includes assumptions

- Errors exist only in initial condition (control variable is correction to the background initial condition)
- Observations occur at initial time (observation operator in **A** is incorrect, dynamics do not connect observations to control variable)
- No errors to dynamical equations in **A** (strong constraint)
- Observation errors are uncorrelated
- Often formulated as a minimization of $J=\varphi^T B\varphi+(H\varphi-y)^T R(H\varphi-y)$, with φ being the subset of the full state trajectory x only at the initial time and H is the observation function portion of **A**
- **W** contains B and R, and representation of these is challenging just as in 4DVar
- **W** is assumed to be a delta function at analysis time (errors during observation time are uncorrelated to errors at analysis time)

3DVar makes several simplifying assumptions making the problem smaller

How does inclusion of dynamics change the problem?

$$\mathbf{x} = \left(\mathbf{A}^T\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$$

Observation time | Forecast time

Move observation to analysis time

1 Invert $\mathbf{A}^T$ (the adjoint)

W is a delta(t) at analysis time
Result is values only at analysis time

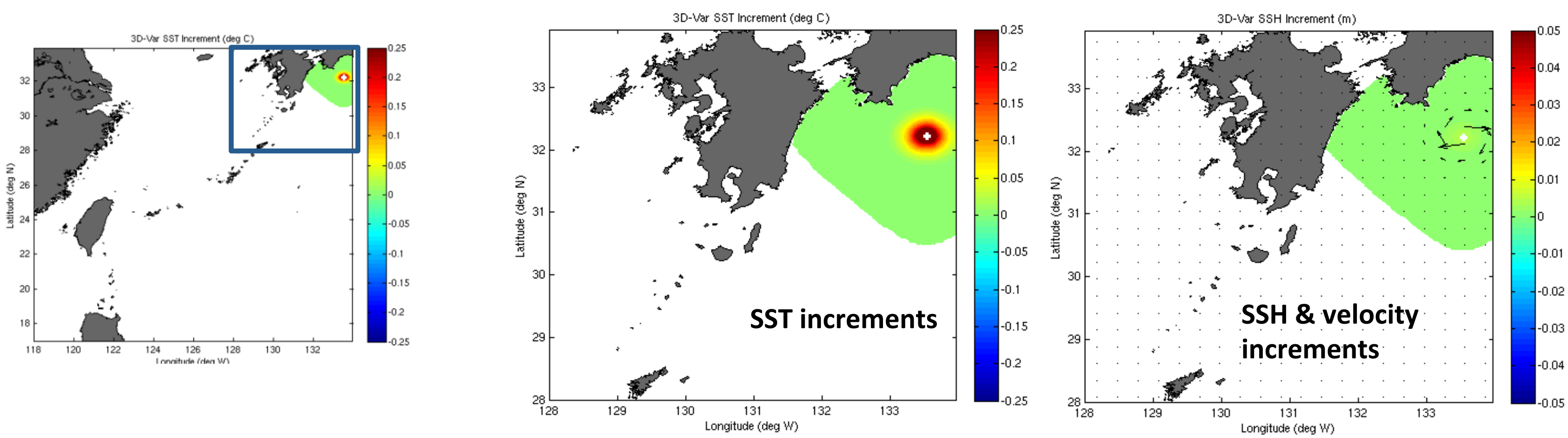
2 Invert **W** (space / time error covariance convolution)

Forward model carries analysis time information forward

3 Invert **A** (forward model)

3DVar increments from 1K SST innovation

A representer function for one observation



Dynamics result in solution matching observations and equations of motion

Ngodock

What are our options to an intractable problem? $\mathbf{x} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$

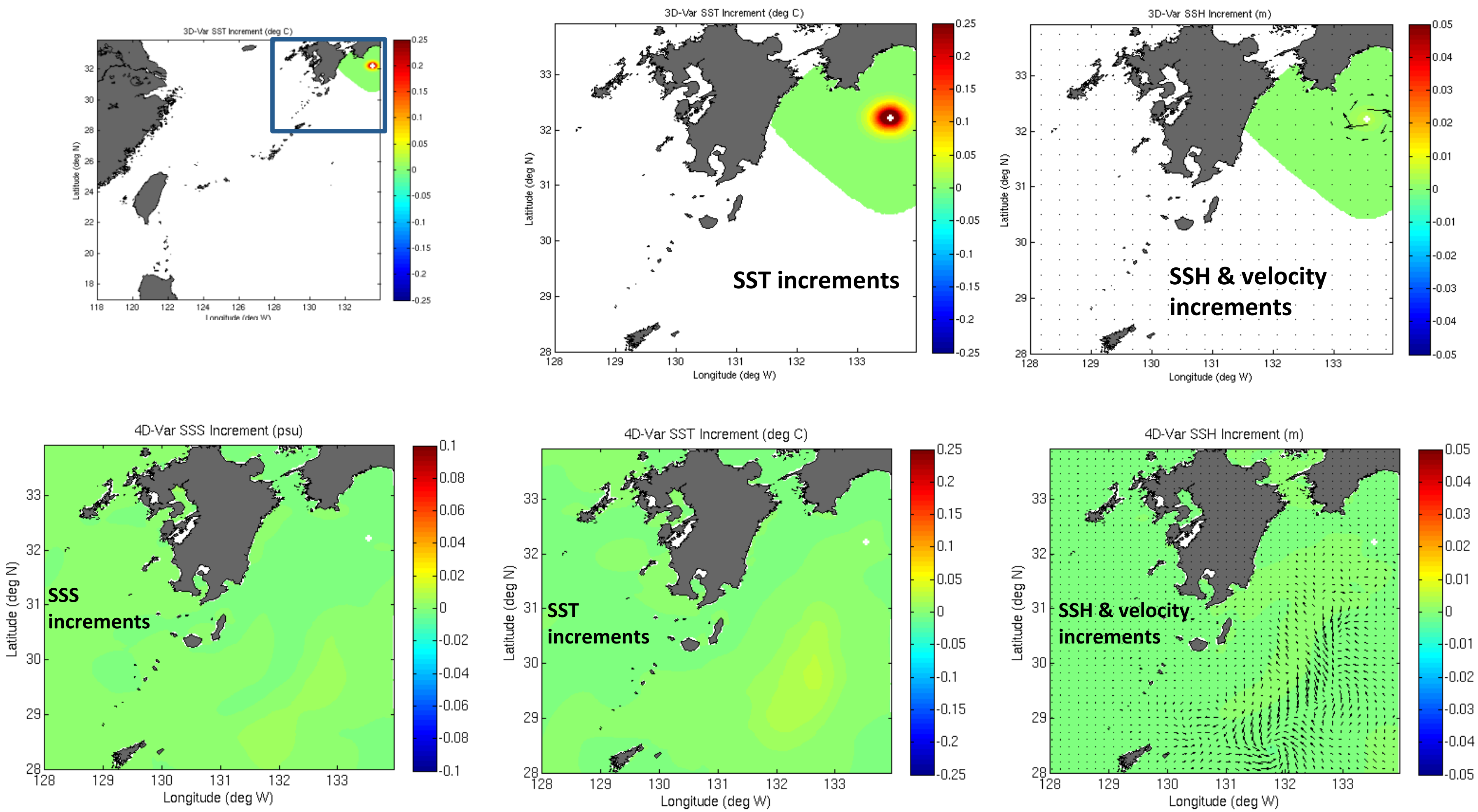
OI: Computationally very cheap though includes worse assumptions

- Initial condition is the unknown
- Observations occur at initial time (observation operator in **A** is incorrect, dynamics do not connect observations to control variable)
- No errors to dynamical equations in **A** (strong constraint)
- Observation errors are uncorrelated
- No prior background
- Often formulated as a minimization of $J=(H\varphi-y)\uparrow T\ R(H\varphi-y)$, with φ being the subset of the full state trajectory x only at the initial time and H is the observation function portion of **A**
- **W** contains only R
- **W** is assumed to be a delta function at analysis time (errors during observation time are uncorrelated to errors at analysis time)

OI has no background information

How does inclusion of dynamics change the problem?

Increments from 3dvar and 4dvar 1K SST innovation



Dynamics result in solution matching observations and equations of motion

Ngodock

How can the problem be solved by simplifying?

4DVar is feasible in small areas, and the challenges are

- Determine **W**

4DVar can extend observations far beyond the initial system

$$\begin{bmatrix} \mathbf{A}_D \\ \mathbf{A}_B \\ \mathbf{A}_M \end{bmatrix}^{\mathrm{T}} \mathbf{W} \begin{bmatrix} \mathbf{A}_D \\ \mathbf{A}_B \\ \mathbf{A}_M \end{bmatrix} \mathbf{x} = \begin{bmatrix} \mathbf{b}_D \\ \mathbf{b}_B \\ \mathbf{b}_M \end{bmatrix}$$ or $\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\mathbf{x} = \mathbf{b}$ and the solution is: $\mathbf{x} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$

Reduce order of the dynamics, reduce areas of W to 0, simplify form of W

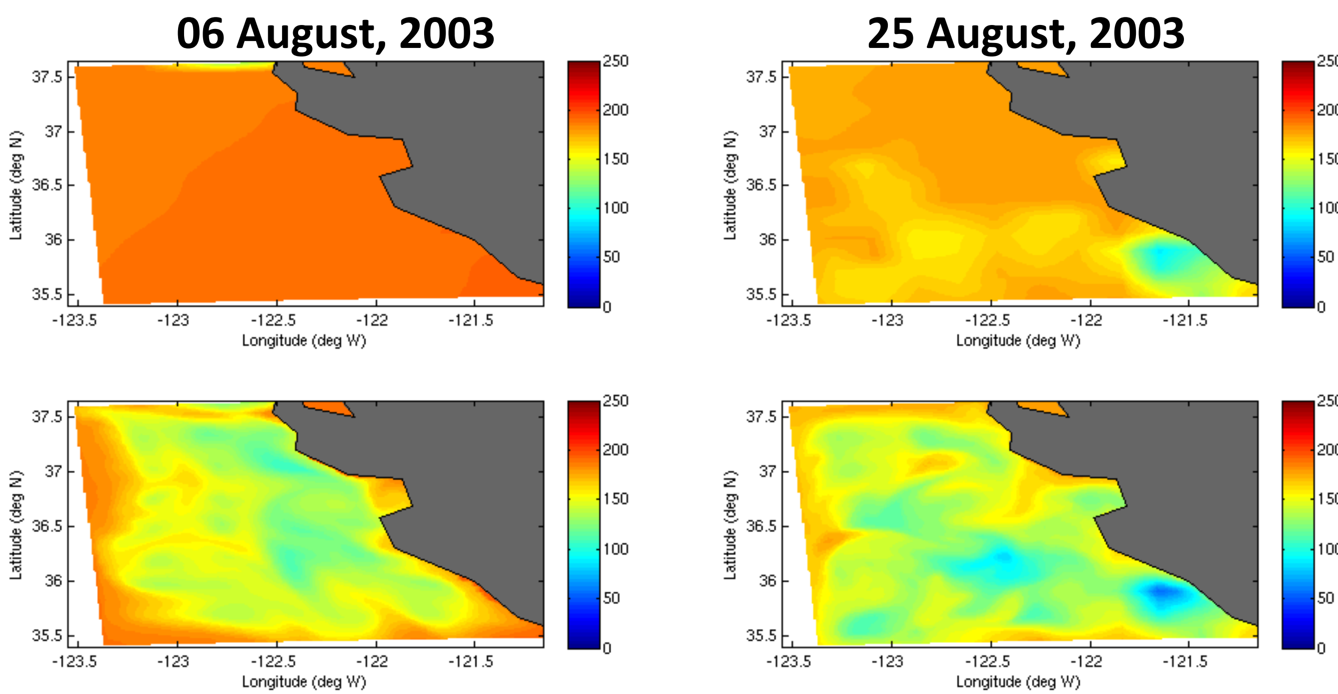
How far can corrections be traced, where is the error?

3 model runs:
#1 Nature run sampled
#2 Provided 'bad' heat fluxes (30% error)
#3 Provided 'bad' heat fluxes and profile observations of #1 to attempt to correct heat fluxes

Absolute difference between the nature run solar heat flux

#2, Provided bad heat fluxes

#3, Provided bad heat fluxes and profile observations to correct heat fluxes



Observations can be connected to any source, it's up to us to attribute errors

How far can corrections be traced, where is the error?

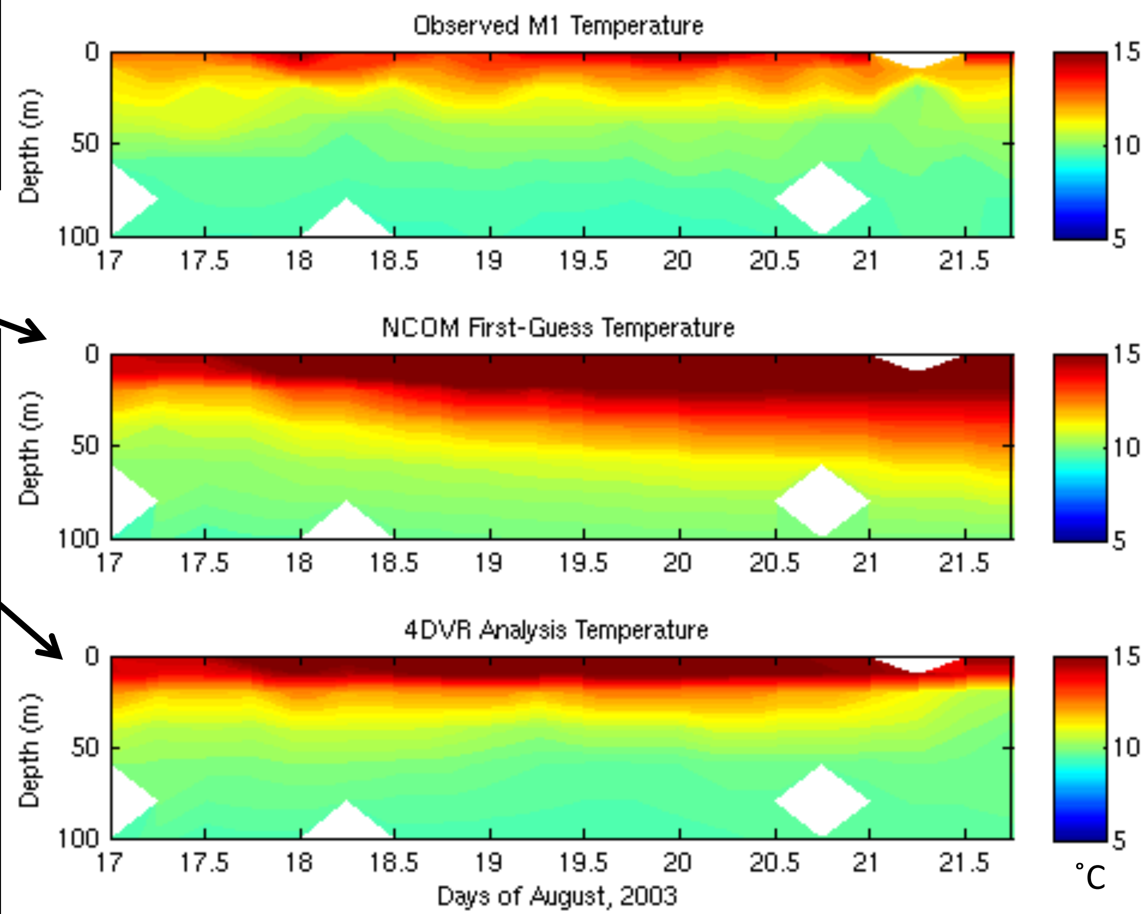
Example from AOSN in Monterey Bay

The non-assimilative forecast predicts excessive warming and over deepening of the mixed layer.

4DVar corrects the fluxes by extending observation influence over time and into the future

The 4DVAR analysis extends forecast skill from the analysis time over the 5-day window.

S&T Challenge: partition error among flux and ocean sources.



Observations can be connected to any source, it's up to us to attribute errors

How can the problem be solved by simplifying?

3DVar must be applied globally, and the challenges are

- Force 3DVar gain the positive characteristics of 4DVar
- Determine **W**

Initially, consider 3DVar with **W** provided by a separable function:

f(x) * g(y) * h(z) * i(t)

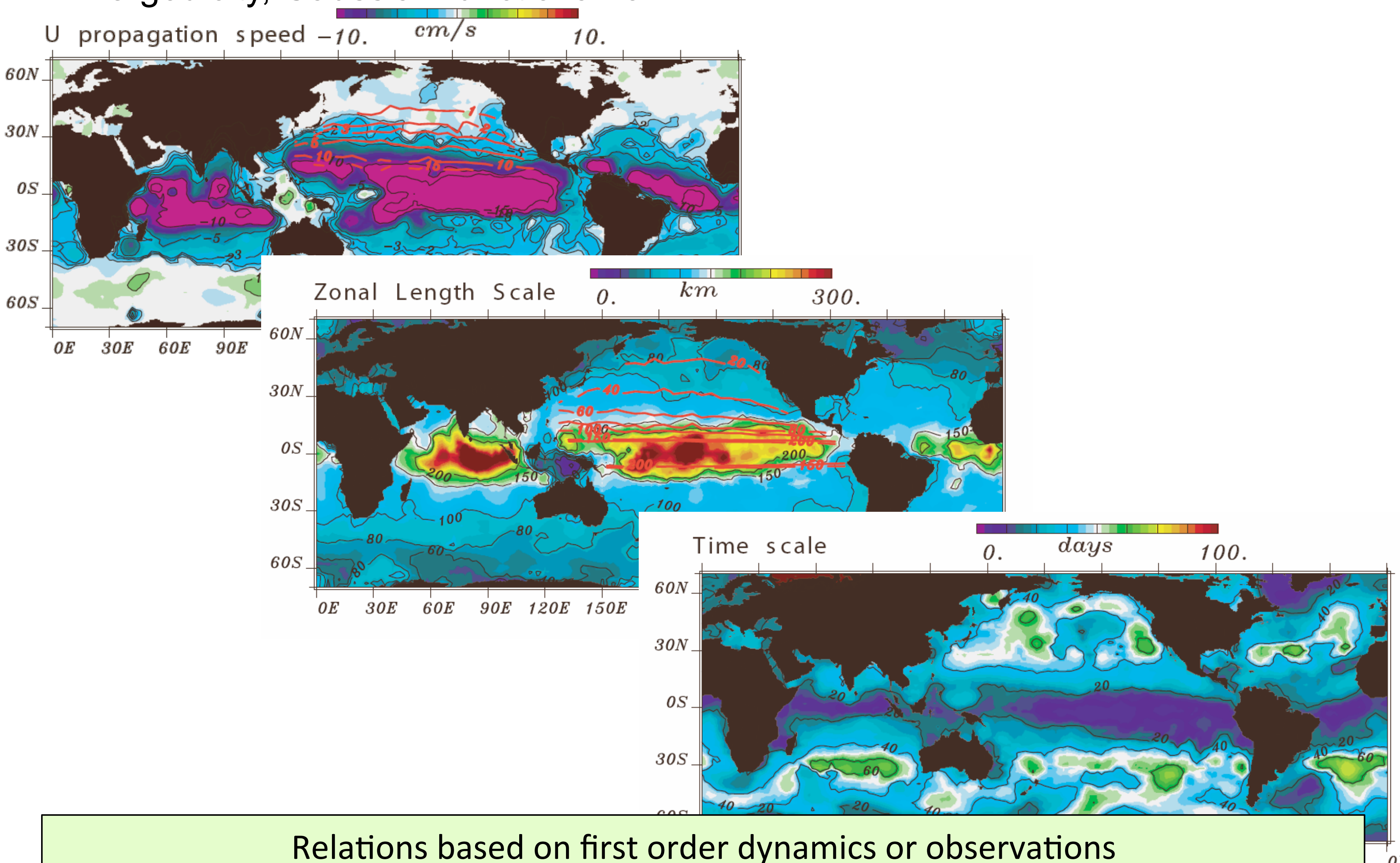
This is valuable relative to 4DVar because assumptions and structure in **W** relate as well

$$\begin{bmatrix} \mathbf{A}_D \\ \mathbf{A}_B \\ \mathbf{A}_M \end{bmatrix}^{\mathrm{T}} \mathbf{W} \begin{bmatrix} \mathbf{A}_D \\ \mathbf{A}_B \\ \mathbf{A}_M \end{bmatrix} \mathbf{x} = \begin{bmatrix} \mathbf{b}_D \\ \mathbf{b}_B \\ \mathbf{b}_M \end{bmatrix}$$ or $$\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\mathbf{x} = \mathbf{b}$$ and the solution is: $$\mathbf{x} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{W}\mathbf{A}\right)^{-1}\mathbf{b}$$

Reduce order of the dynamics, reduce areas of W to 0, simplify form of W

How are horizontal covariances specified?

- Fraction of a Rossby radius of deformation
- Very simplified based on historical data, assumptions of stationarity ergodicity, Gaussian functional form



Relations based on first order dynamics or observations

What additional information can be considered?

Ensemble-based covariances
Either from historical run or synoptic ensembles
Provides relations that account for local physics

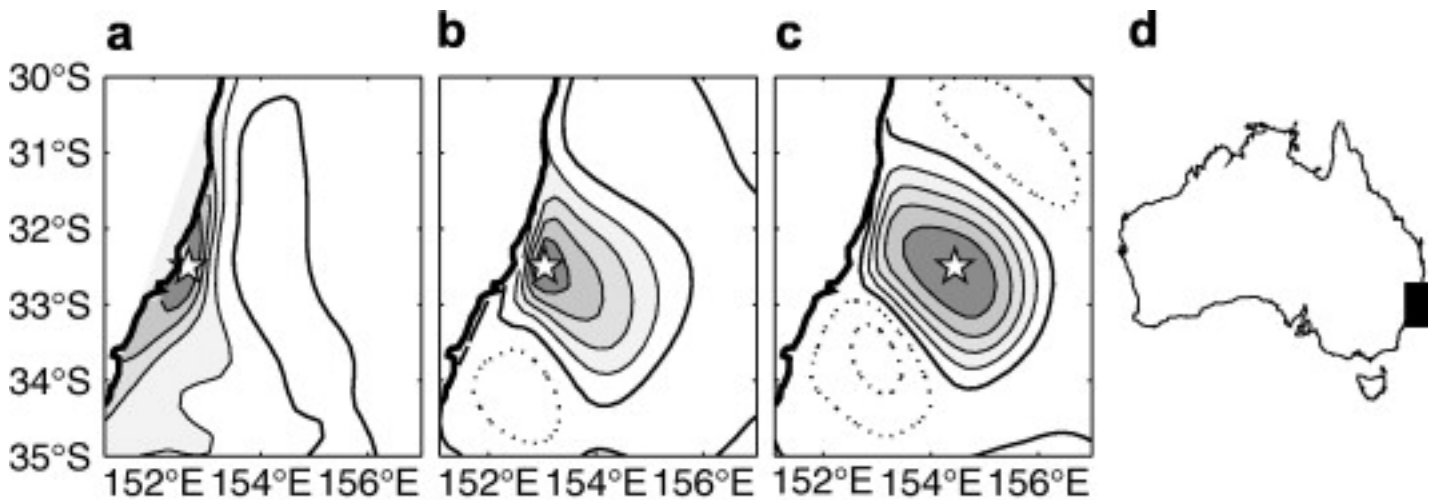


Fig. 4 Examples of the ensemble-based cross-correlations between sea-level at a reference location, denoted by the star, and sea-level in the surrounding region for a reference location (a) on the continental shelf, (b) over the continental slope and (c) o...

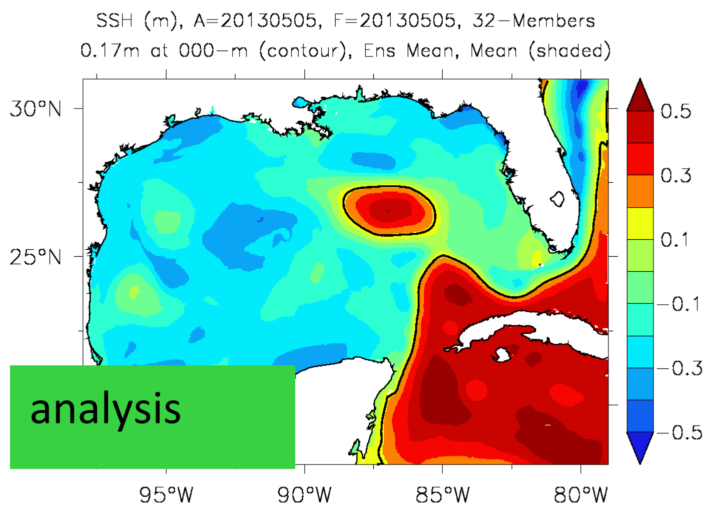
Extending horizontal covariance form

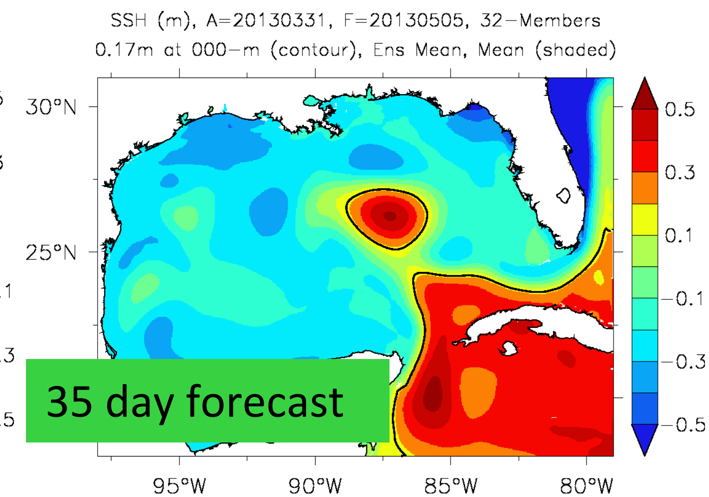
Oke et al., Ocean Modeling 2008

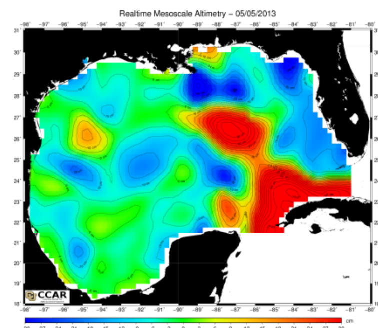
How are temporal covariances specified?

- Analysis is at one time
- Implication is that time decorellation is 0
- Time scales are much longer in the ocean
- To estimate a state trajectory requires information over a longer time

Example
- NCOM using a 7 days window for analysis
- 60 day forecast







SSH-CCAR
Altimetry Analysis

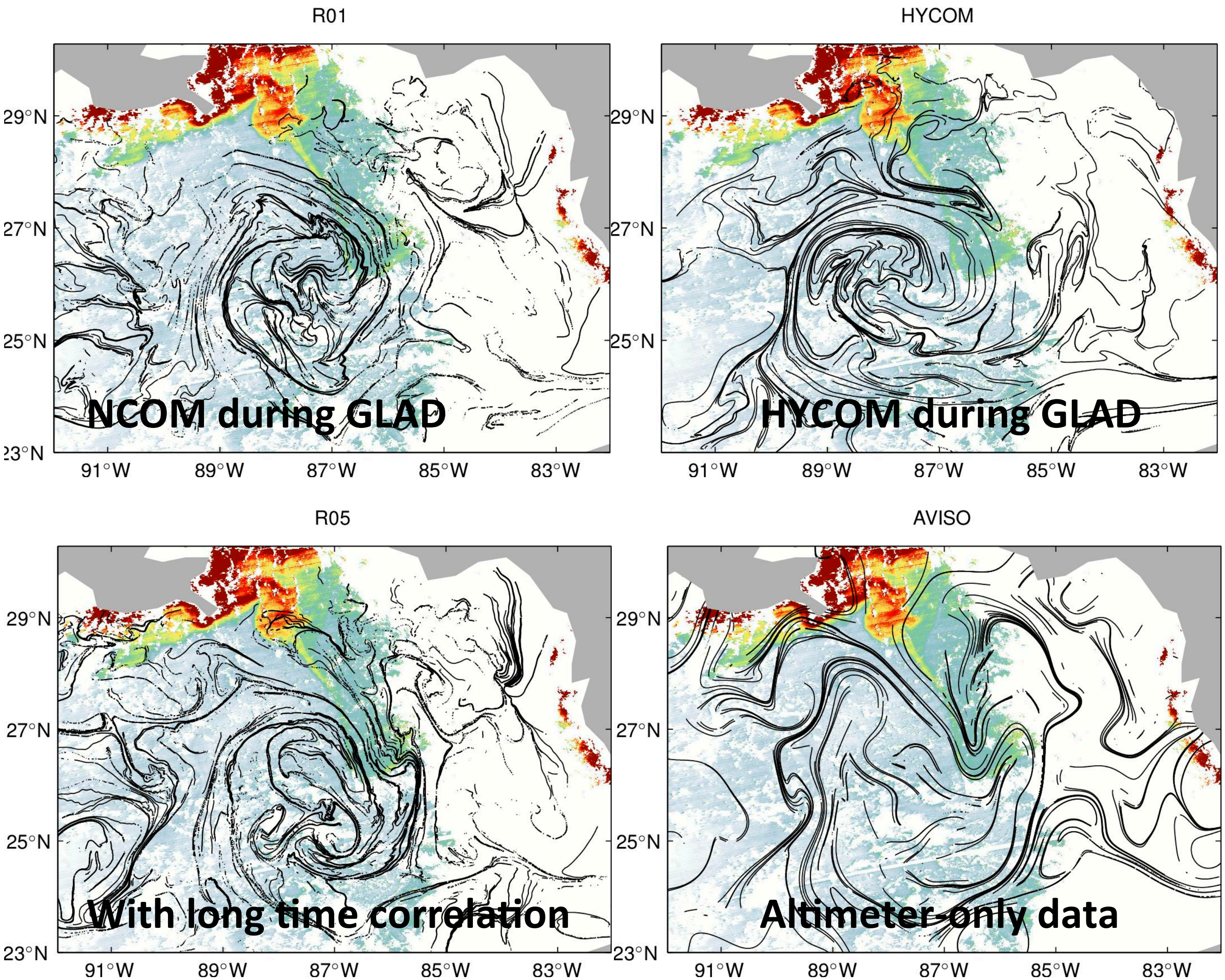
May, 5 2013

Note:
- Cornuelle et al. use a 2 month hindcast for a sequential 4DVAR analysis for the GoM
- Oke uses 11 days (BlueLink)

Time is as important as space

Coelho

How does this affect CARTHE?



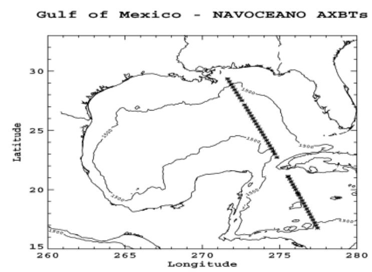
Time covariances result in advancements in predictability.

How do synthetic profiles relate?

Local correlation information is used to relate satellite observations to subsurface T&S

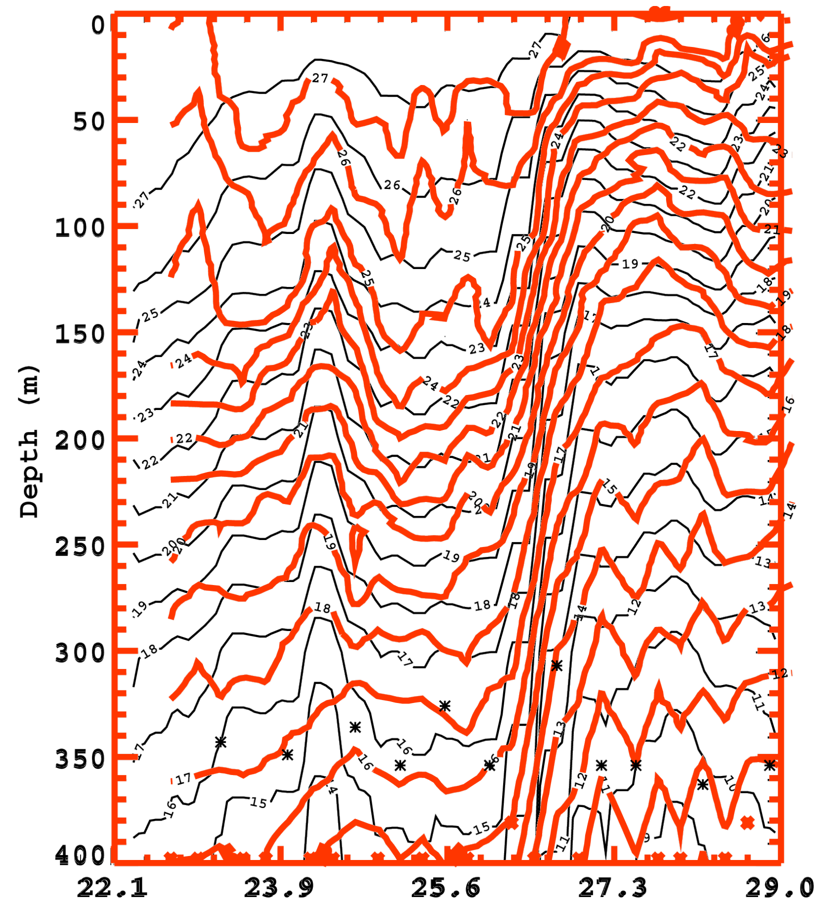
What are the assumptions?

- Apart from ignoring dynamical constraints
- Stationary statistics
- Ignores correlated errors between depths



AXBT survey during May 1999

AXBT vs. MODAS/ GFO



Synthetic profiles imply simplifications to the least squares problem

What do data-based vertical covariances provide?

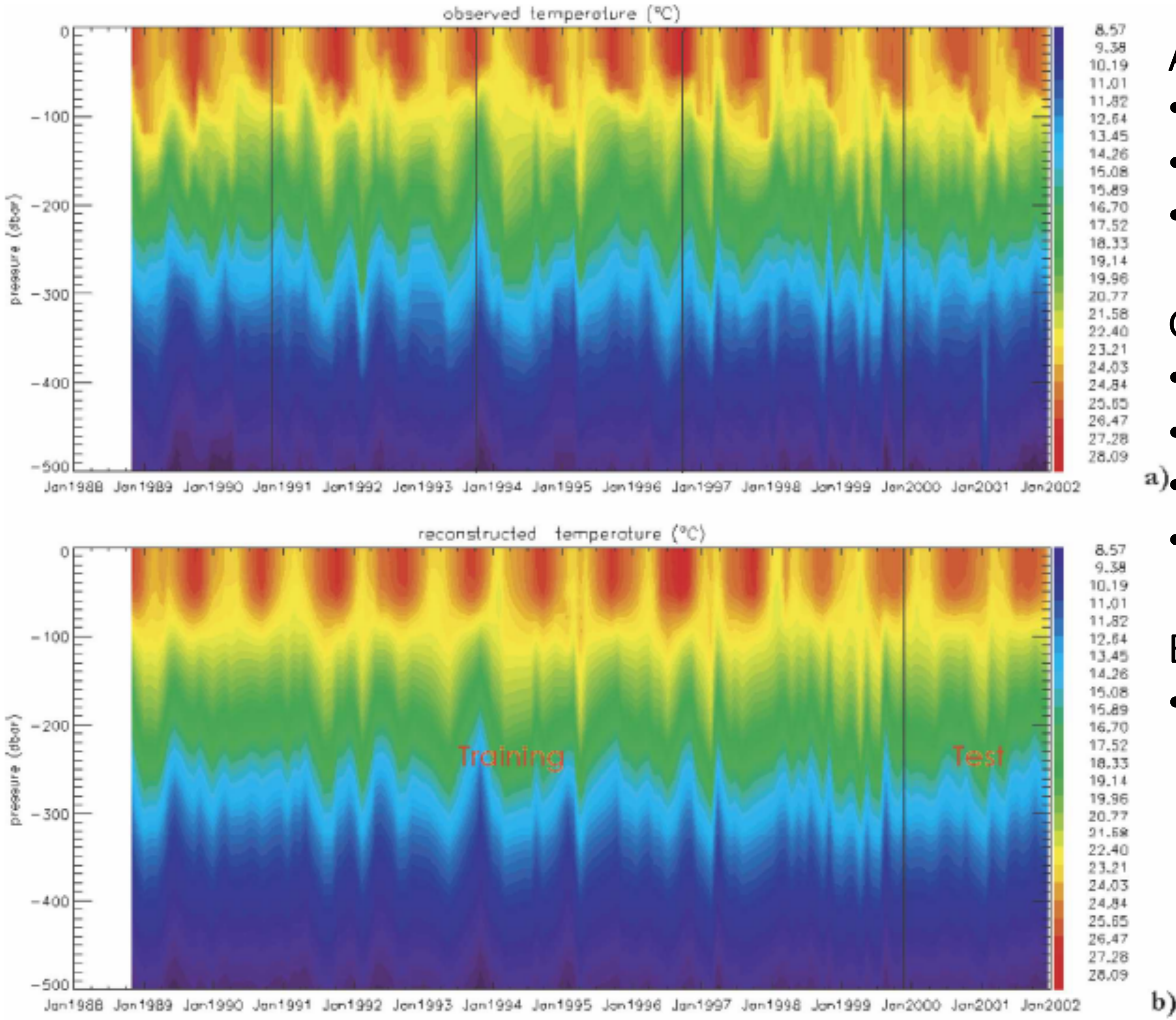


FIG. 11. Time series of (a) observed, (b) reconstructed from the 11-yr learning period starting in 1988, and (c) corresponding climatological temperature (°C) profiles at the HOT ALOHA site. The climatological time series has been obtained by taking the climatological profile instead of the observed one, at the same instant. A bold vertical line separates the training and test periods.

A range of methods

- Gravest Empirical Mode (GEM)
- Single-EOF
- Multivariable-EOF

Good

- Real data
- Real modes of variability
- No model bias
- No missing physics

Bad

- Never sufficient data

Allows localized high-content information

Buongiorno et al., JAOT 2005

What alternatives exist?

Good
- Sufficient data to achieve statistics
- Dynamically consistent
- Just a matter of determining reduction methods

Bad
- Model bias
- Model dynamics insufficient

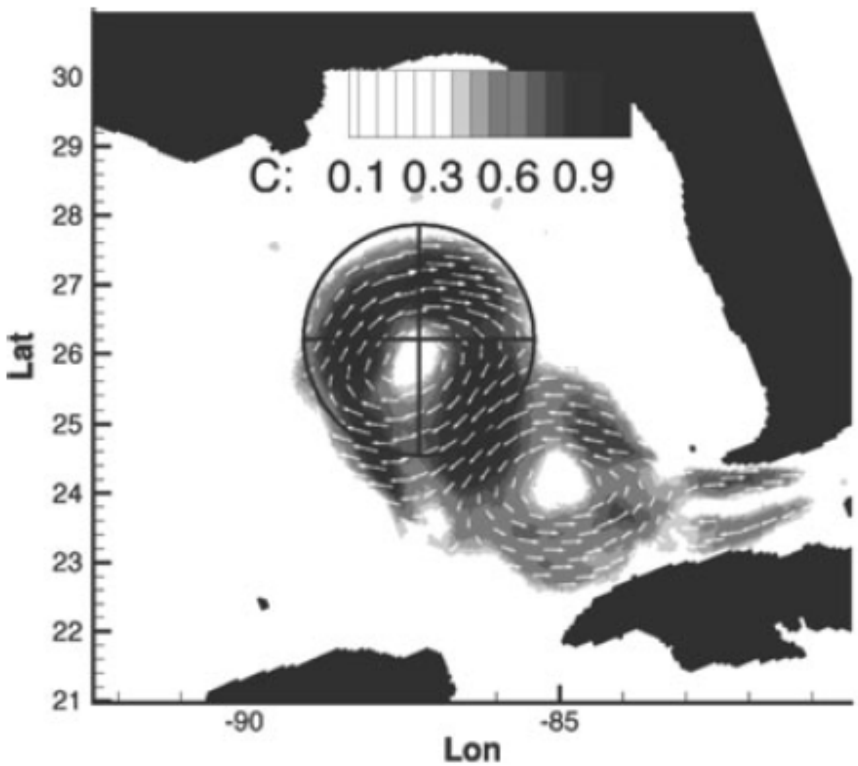
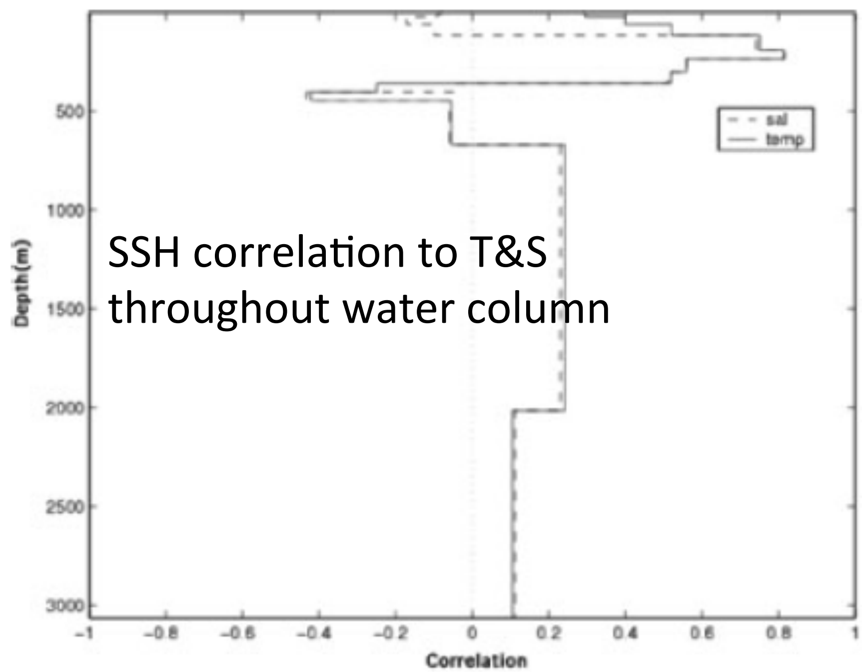


Fig. 2. Ensemble correlation plots between the SSH point marked by a cross and the surface currents in all model gridpoints in the Gulf of Mexico. The white arrows represent the correlation with total eastward and northward velocities. The background colour highlights regions where the correlations with the total eastward and northward velocities



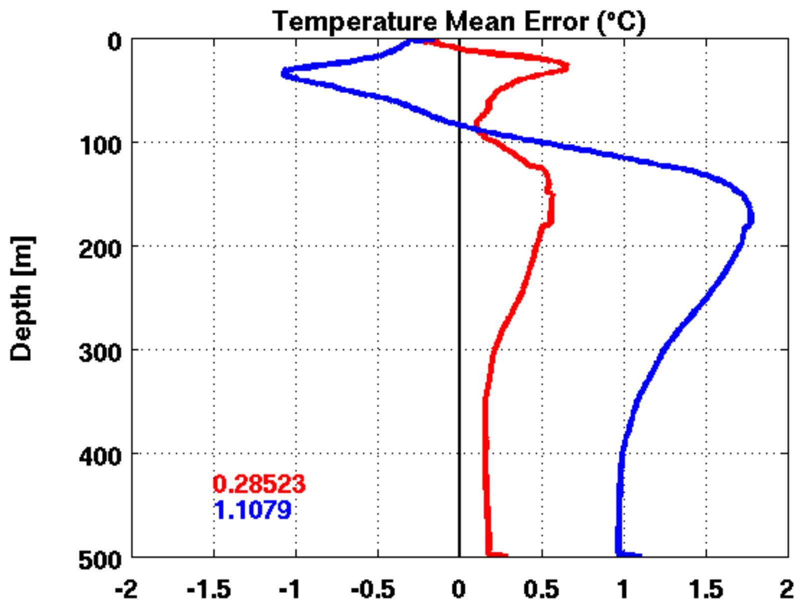
Ensembles / data-based covariances have trade-offs

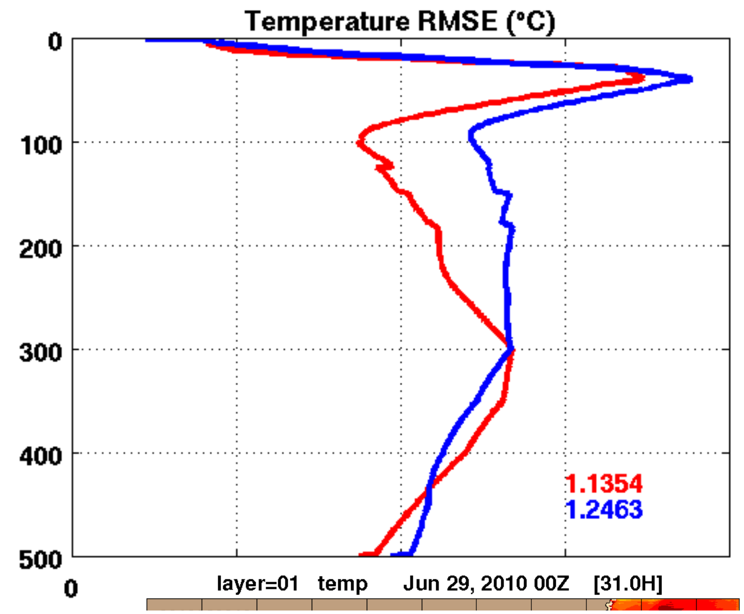
Counillon and Bertino, Tellus 2009

How much do data-based covariances vary?

HYCOM - Gulf of Mexico

ISOP 1.0/NCODA vs. MODAS/NCODA

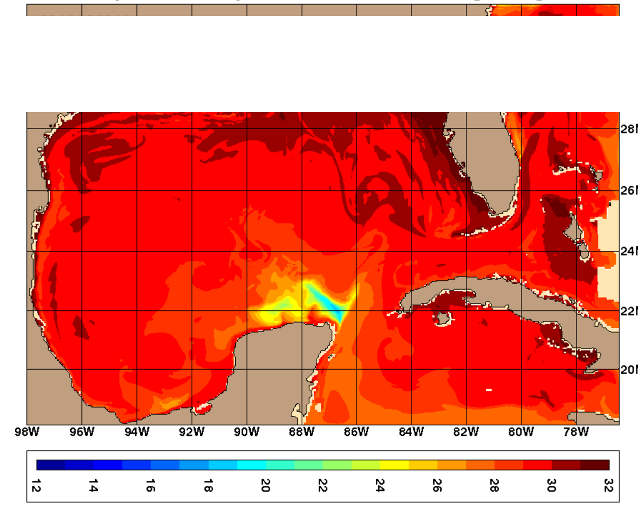




Gulf of Mexico HYCOM on a 1/25° (~4 km) grid using NCODA 3DVAR with ISOP 1.0 or MODAS synthetics.

Comparison relative to 3331 independent profiles

Using ISOP 1.0 leads to significantly smaller bias and smaller RMS error

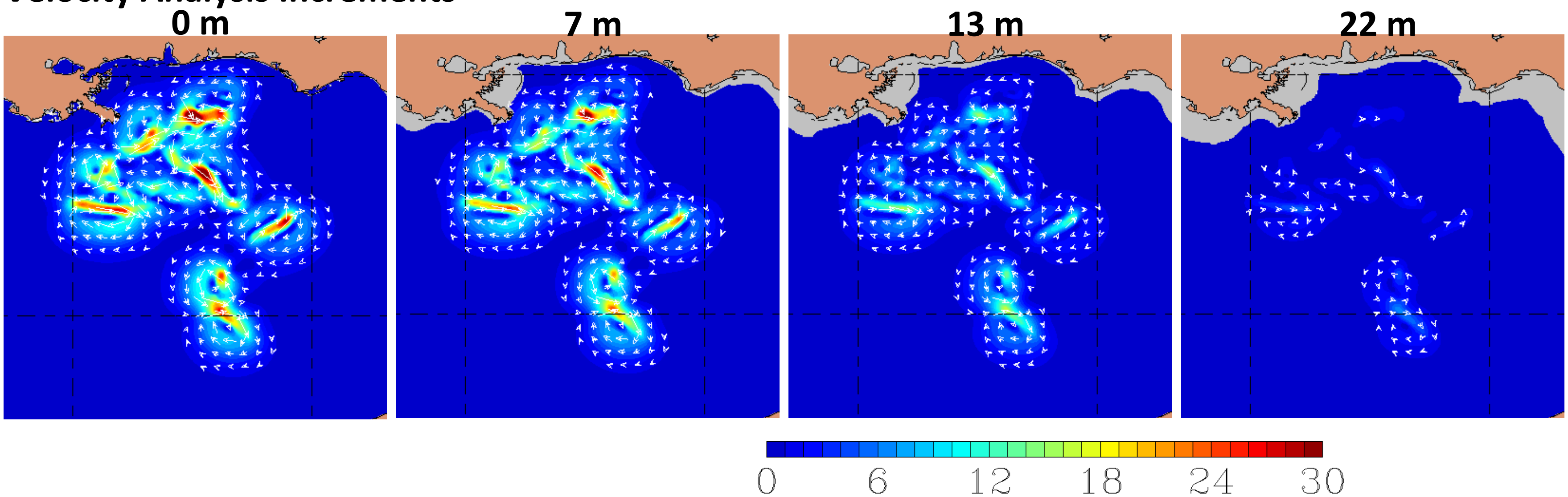


Data-based covariances are not all equal

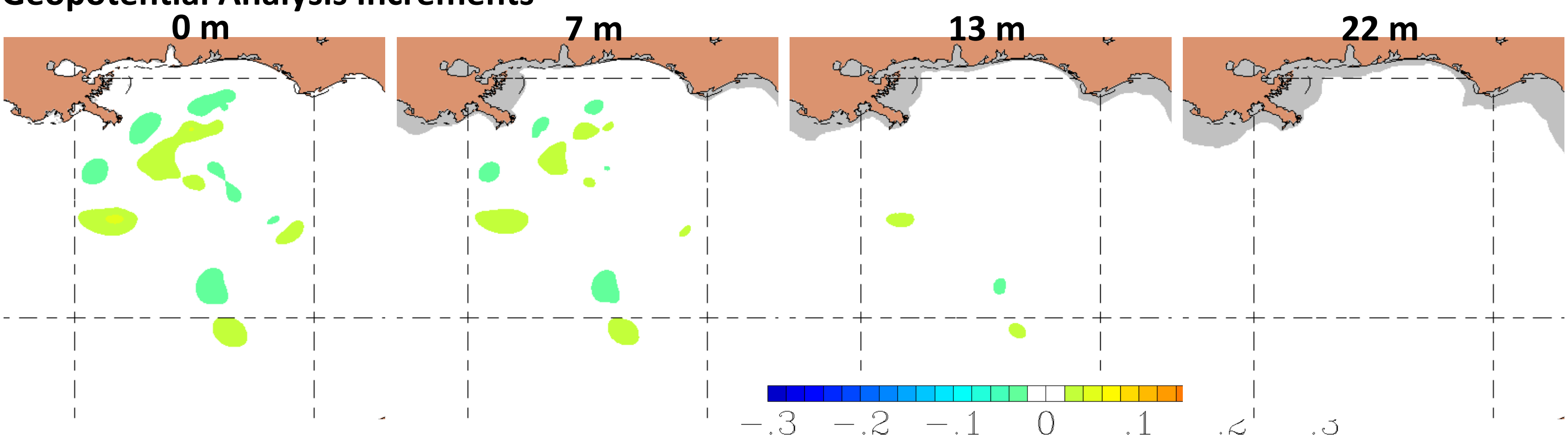
How do covariances impact CARTHE?

Example from CARTHE drifter analysis

Velocity Analysis Increments



Geopotential Analysis Increments

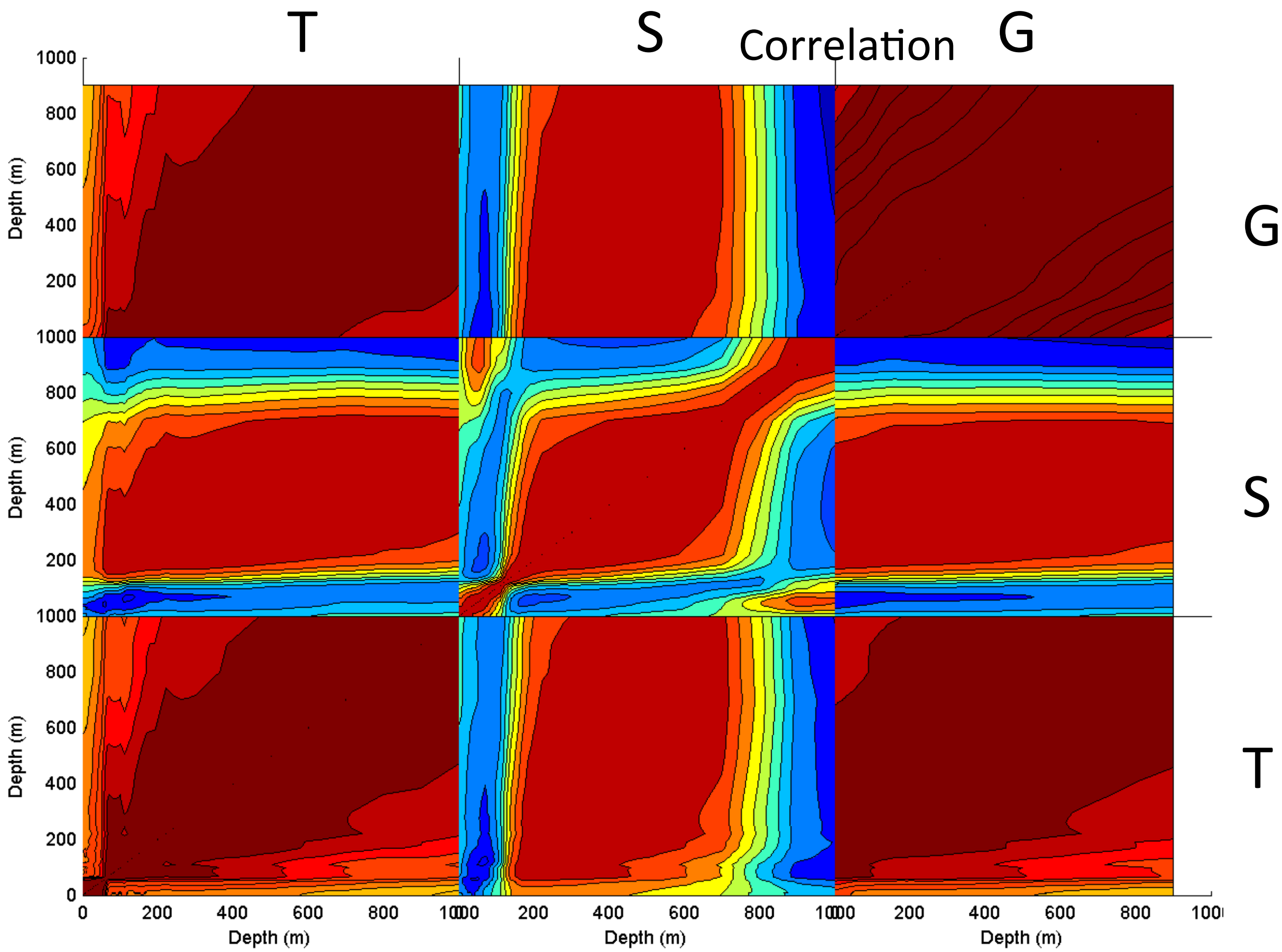


Horizontal, vertical and temporal correlations determine influence

How is velocity related to T&S vertically and horizontally?

Horizontally, velocity is related to geopotential through geostrophy
Vertically, T&S are related to geopotential

B=⟨Y Y ↑T ⟩=[■X X ↑T &X X ↑T δ↑T G↑T @G↑T δ↑T X ↑T X &δGX X ↑T G↑T ∂



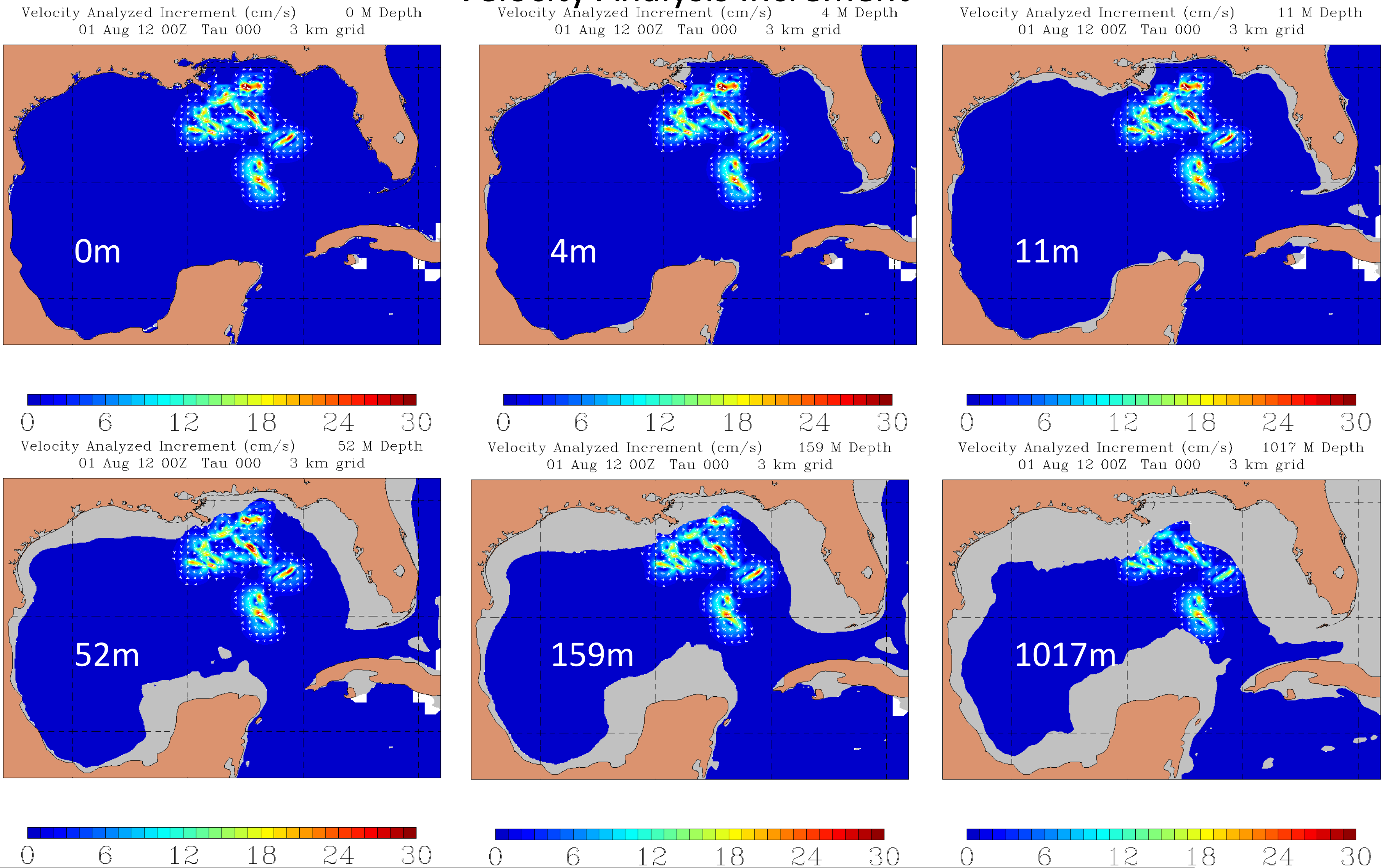
Cross Correlation February, 275°E, 24°N, Gulf of Mexico in Loop Current just off Cuba

Vertical T&S relations extended to geopotential

How does geopotential relation to T&S impact results?

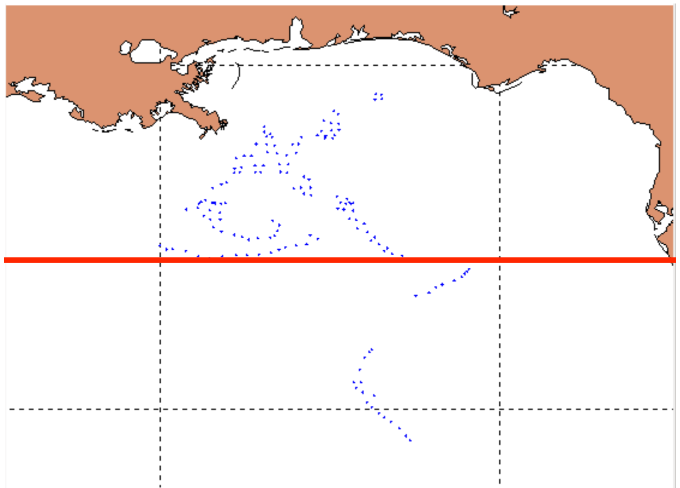
Including observed historical correlation information results in more realistic result

Velocity Analysis Increment



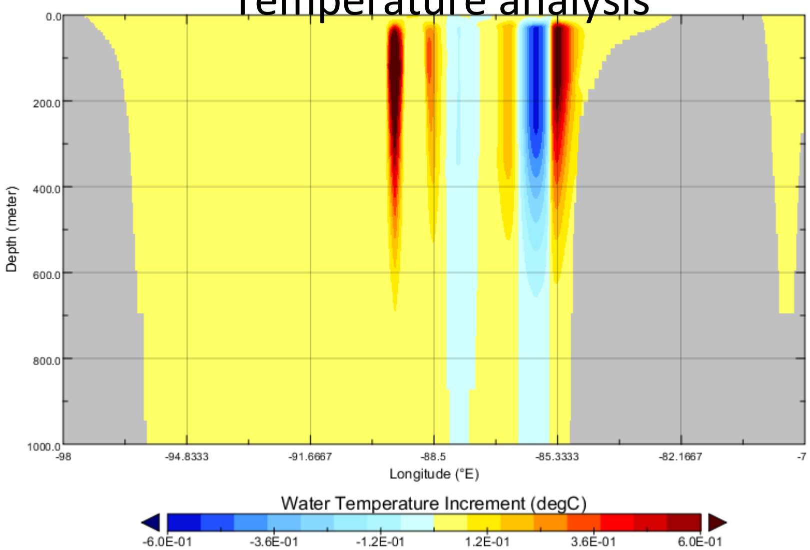
Horizontal, vertical and temporal correlations determine influence

How does geopotential to T&S structure relation impact results?



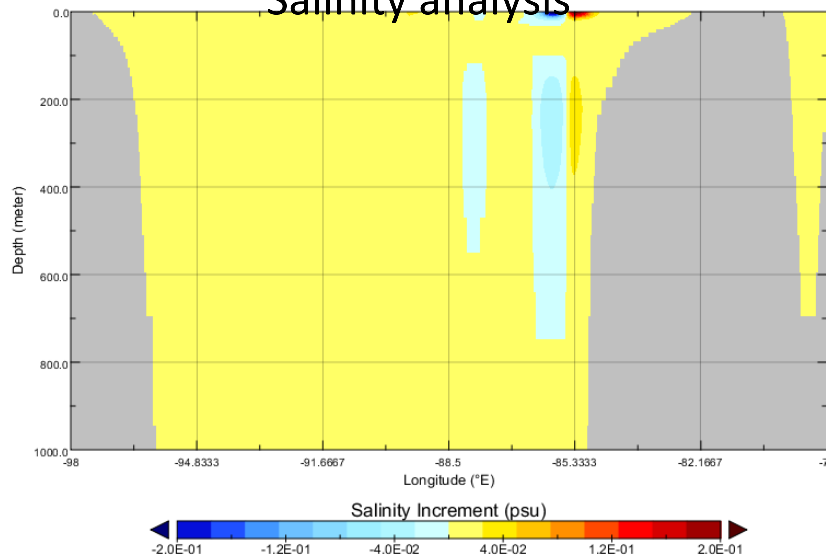
Experiment during Aug 1-20 2012
Parallel to regular daily cycling
EXP2: Assimilating only velocity observations

Temperature analysis



-0.6°C 0.6°C

Salinity analysis



-0.2 psu 0.2 psu

Including vertical relations G/T/S extends observation impact

Smith

What can be learned from assimilation?

Errors can be estimated in

- State
- initial condition
- boundary condition
- Parameters
- Dynamics
- Anything connected to the system…

Errors in barotropic tide solutions are the result of dynamics converting energy to baroclinic tides

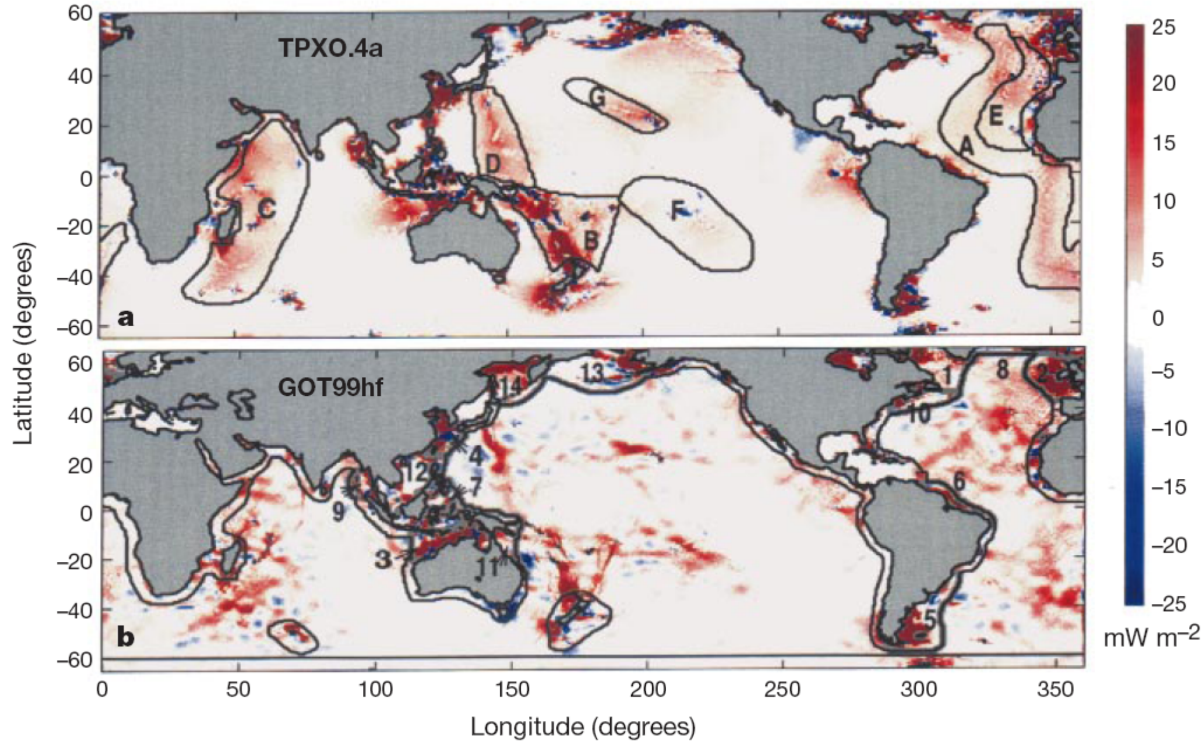


Figure 1 Estimates of M_2 tidal energy dissipation. These estimates of *D* are computed for two recent Topex/Poseidon (T/P) M_2 tidal solutions. **a**, TPXO.4a elevations and transports, estimated using a variational data assimilation method[25]. **b**, GOT99hf with transports obtained by least-squares fitting[27] of equations (1) and (2) to gridded elevations estimated from the altimetry data[26]. Deep and shallow ocean areas discussed in the text and in Fig. 2 are outlined and labelled in **a** (deep) and **b** (shallow). The thin line in **b** is the boundary between deep ocean and shallow seas.

Correction estimates imply dynamics

Egbert and Ray, Nature 2000

Conditionally Predictable

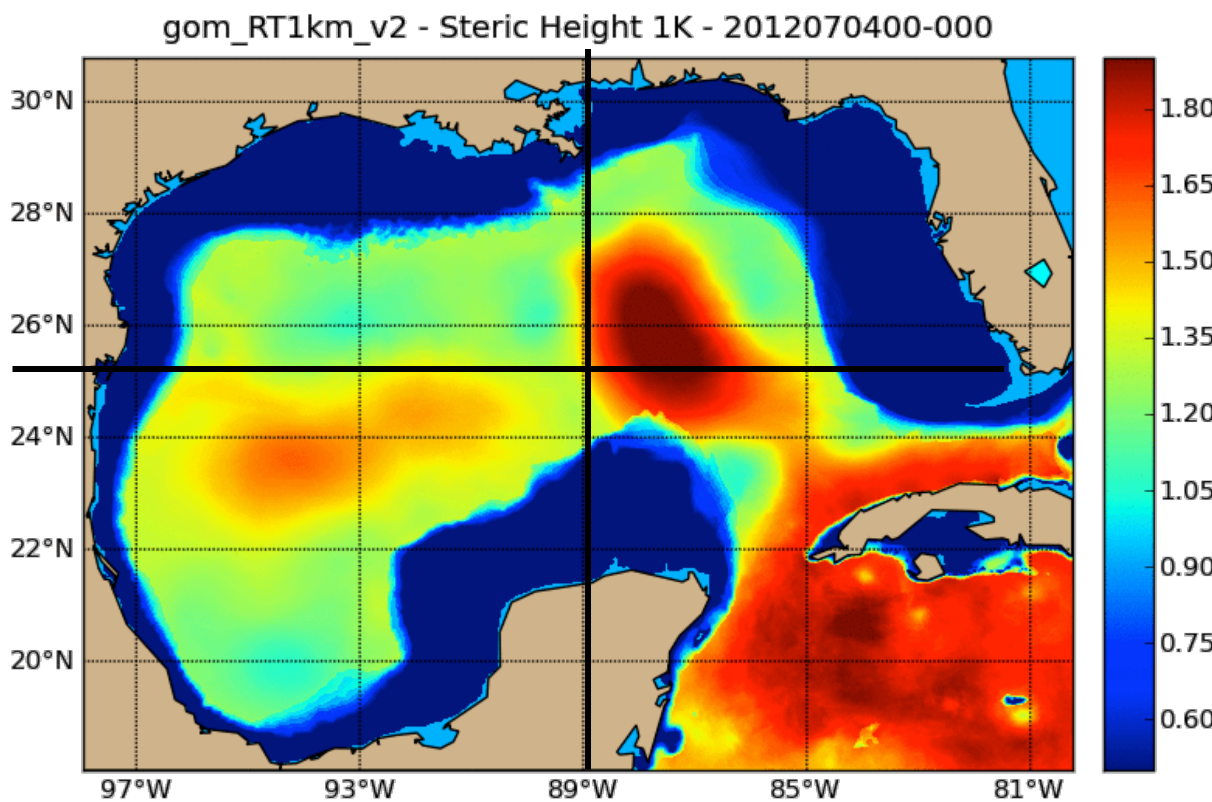
What processes affect dispersion?

- Mesoscale geostrophically driven flow
- Associated Lagrangian Coherent Structures
- Submesoscale added on top

- Ocean assimilation targets the geostrophically driven mesoscale flow
    - Length and time scales are on the order of mesoscale
    - Primary observations do not detect or resolve submesoscale

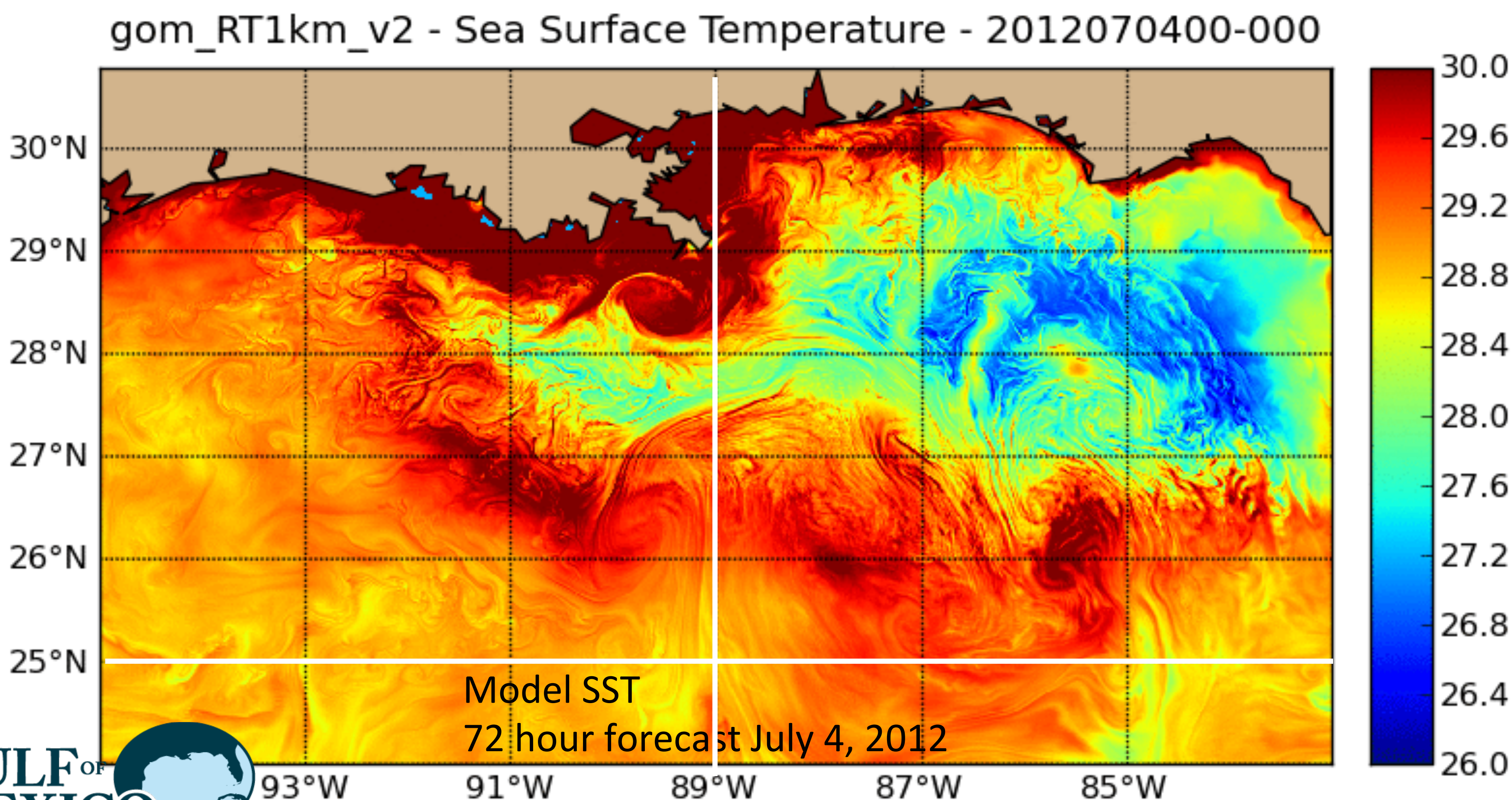
- 1km horizontal resolution model
- Assimilating satellite SSHA (Jason-2, Jason-1G, CryoSat2), SST and in situ
- Reproduces the large scale dynamic height

Model Steric Height, 72 hour forecast July 4, 2012



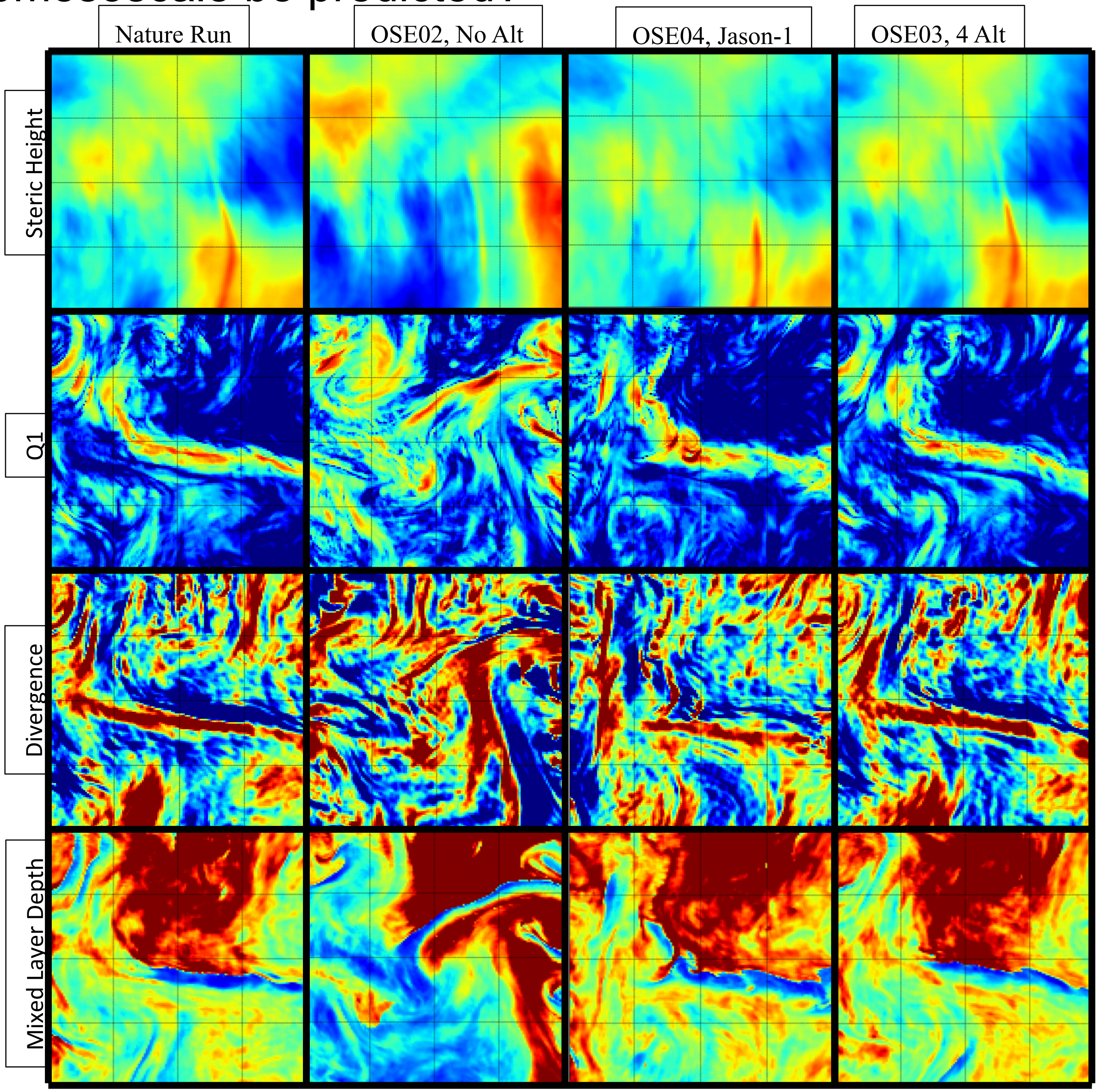
Can submesoscale be predicted?

- Mesoscale density field is pulled and strained by the velocity field
- Vertical secondary circulations develop
- Cooler waters are transported to the surface along fronts
- Impacts chemistry, biology, fisheries, HABS, recreational, commercial, coastal management



GULF OF MEXICO RESEARCH INITIATIVE

Can submesoscale be predicted?



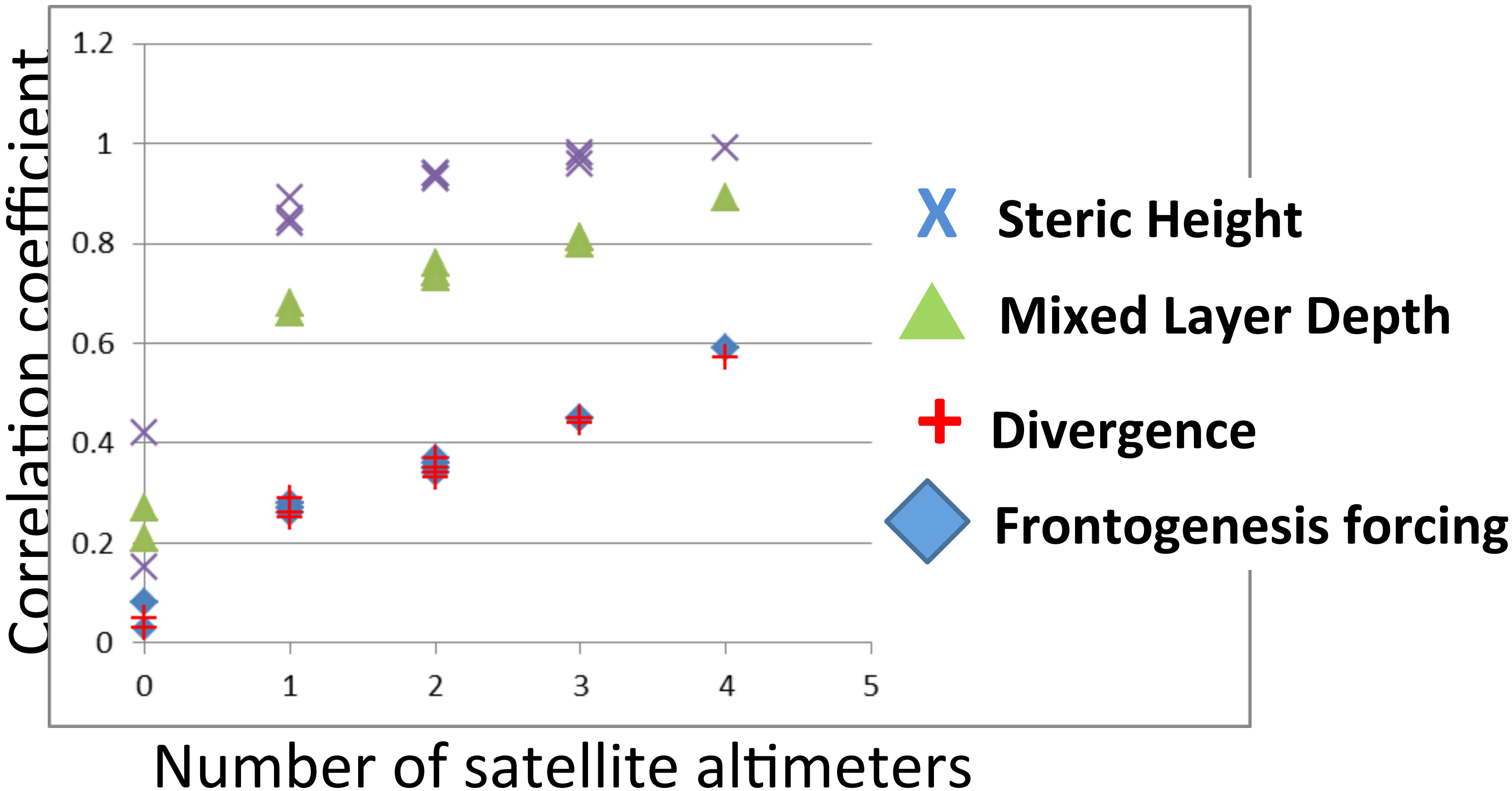
Observation System Experiments indicate prediction in frontogenesis

Can submesoscale be predicted?

Frontogenesis is forced by buoyancy confluence increasing horizontal buoyancy gradients

Ageostrophic flow is induced that decreases horizontal gradients

If the mesoscale circulation is accurately predicted, the generated frontogenesis is predicted

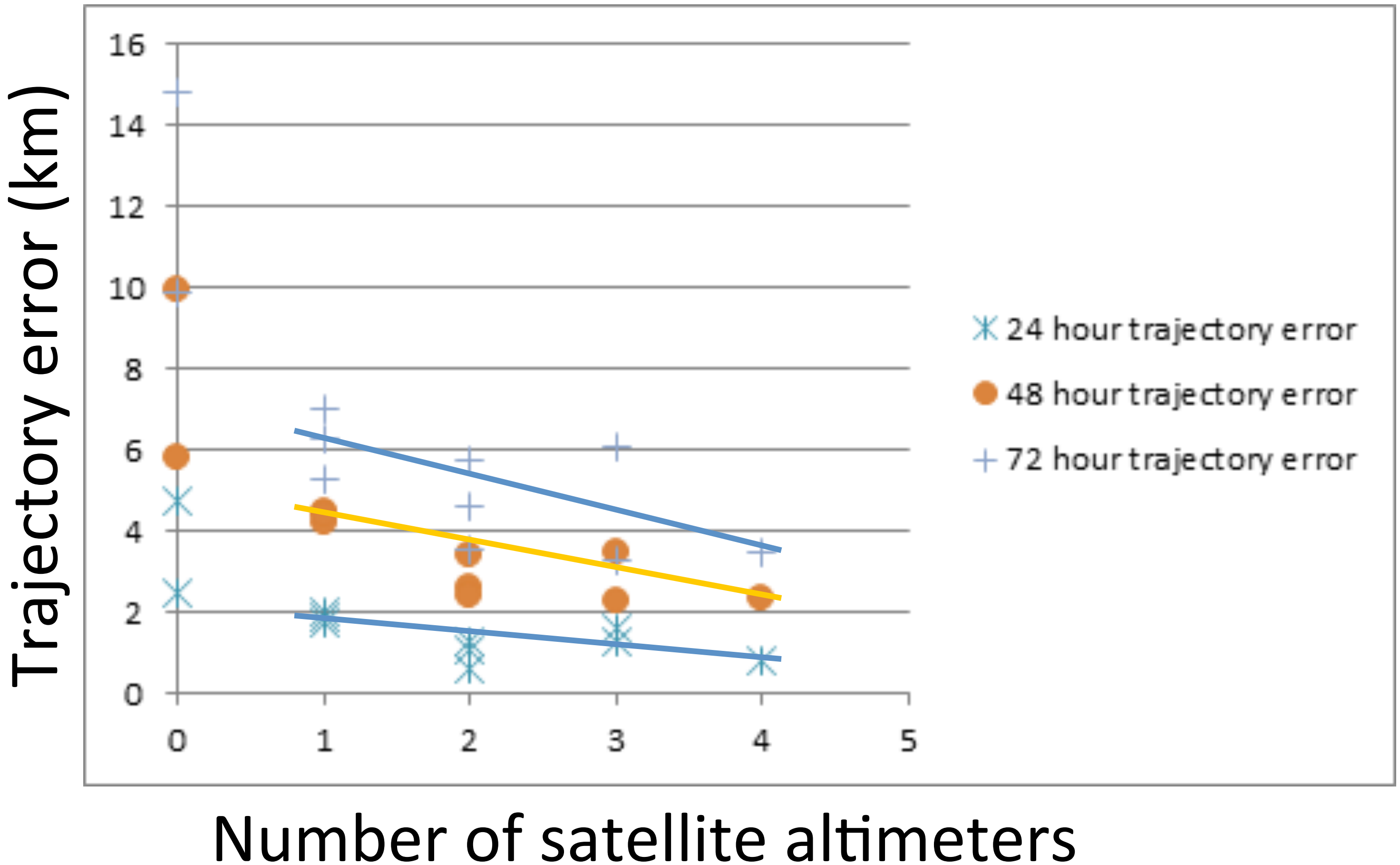


Frontogenesis has conditional predictability, conditioned on predicting the mesoscale

Does it impact trajectory forecasts for CARTHE?

Steric height improvement with more data is minor from 2 to 3 to 4 data sets

Continual improvement of trajectory errors with data indicates submesoscale forecast accuracy is a factor



Trajectory forecasts improve with added data, more than expected by mesoscale

What is predictable, what is not, under what conditions?

Eddy Kinetic Energy

1/25 Model (Free Run)

1/12 Model (Data Assimilation)

1/12 Model (Free Run)

Drifter

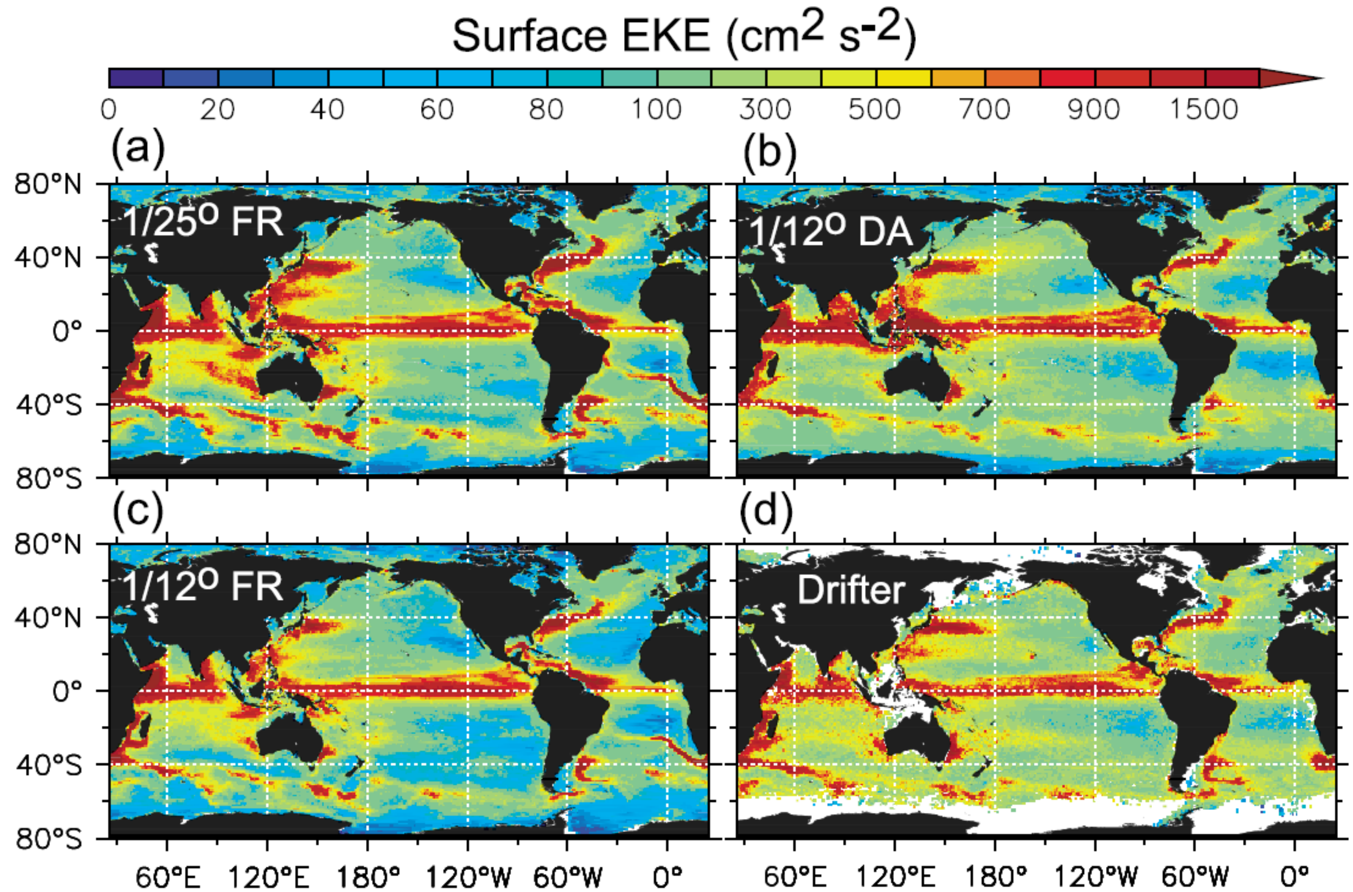


Figure 1. Surface eddy kinetic energy (EKE in cm^2 s^{-2}) from the three numerical experiments (a) 1/25° FR (2005–2009), (b) 1/12.5° DA (2008–2009), and (c) 1/12.5° FR (2005–2009) and (d) drifter observations encompassing the period 1983–2009. The surface drift observations are binned into 1° × 1° grids using daily values and those grid points with at least 100 observations are considered. The EKE is computed from the daily velocity fields using the equation $(\langle u'^2\rangle + \langle v'^2\rangle)/2$, where brackets indicate time means and primes denote deviations from the time-mean velocities, $(u', v') = (u, v) - (\langle u\rangle, \langle v\rangle)$.

At some point, only statistics are predictable

Thoppil et al., GRL 2011

There is a length scale at which deterministic and stochastic forecasting appear in any model (L_{ds})

We want to correct scales that are observed and leave stochastic scales to develop on their own

If the model resolution supports features smaller than L_{ds}, then L_{ds} depends on the observing systems

Observation Impact & Targeted Observations

What is the expected effect of an observation?

Addressed from the perspective of the in situ data

$$Y=\begin{bmatrix} T_1 \\ \vdots \\ T_N \\ S_1 \\ \vdots \\ S_N \\ \varphi_1 \\ \vdots \\ \varphi_N \end{bmatrix}$$

$$B=\langle Y Y^T \rangle=\begin{bmatrix} X X^T & X X^T \delta^T G^T \\ G^T \delta^T X^T X & \delta \end{bmatrix}$$

$$P^A=(I-KH)B$$

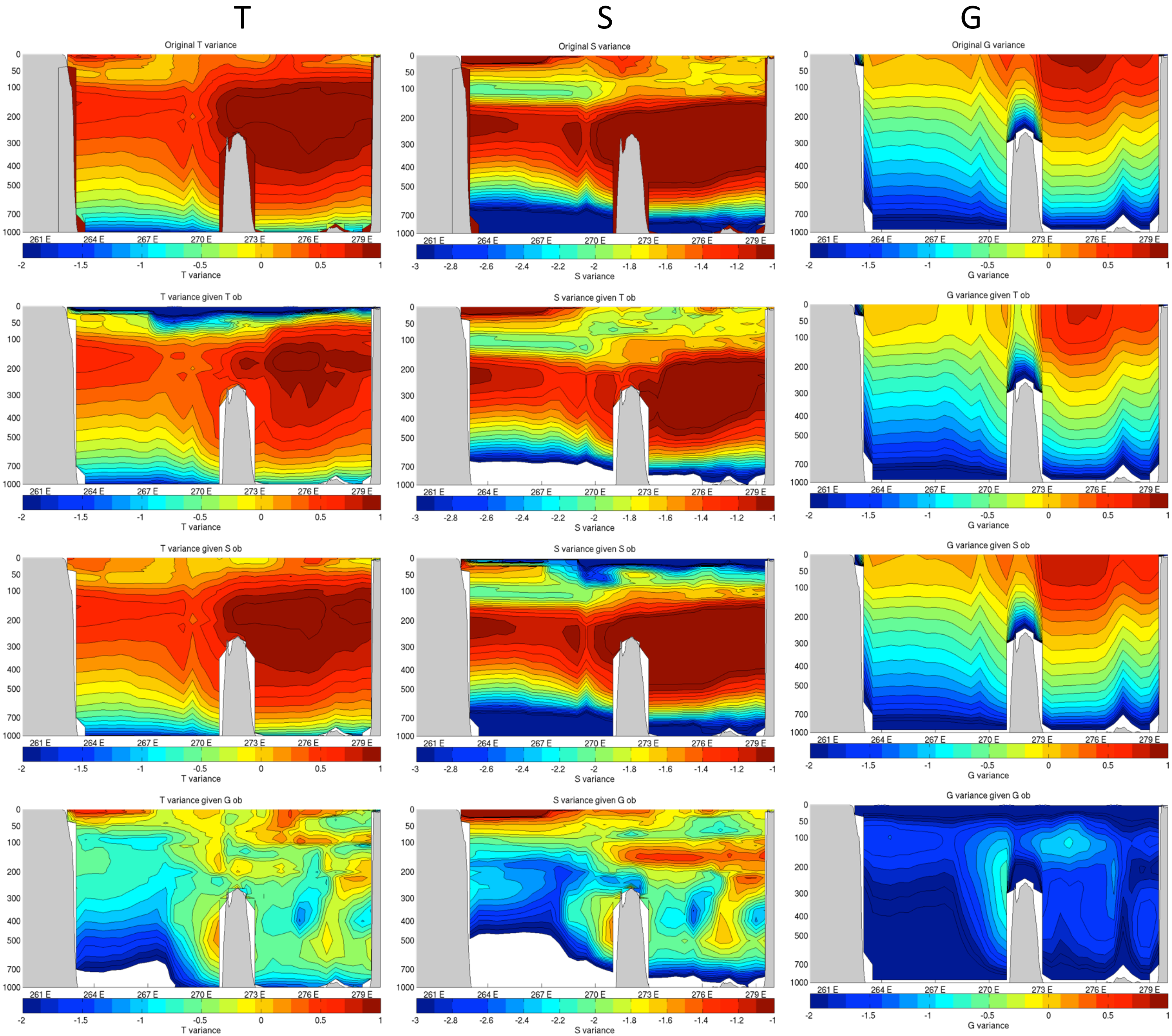
$$K=BH^T(HBH^T+R)^{-1}$$

Posterior variance is a function of
- Background variance B
- Observation operator H
- Observation error R (let's assume observation has errors smaller than the variance, so R is small)

Because we now have B,
We can compute the impact of a satellite observation of T,S or G

The effect depends on the observation distribution H and background error B

24°N Feb



Original Variance

Variance given SST

Variance given SSS

Variance given SSH

How is the problem be turned around?

Suppose we want to optimize some estimate of a metric
Is it possible to determine what observations should be taken where?

If the correlation of forecast variance of the metric can be computed to all variables over all space over all prior time, then yes.

Marchuk, G.I., 1994. Adjoint equations and analysis of complex systems. Kluwer Academic Publishers, Boston.

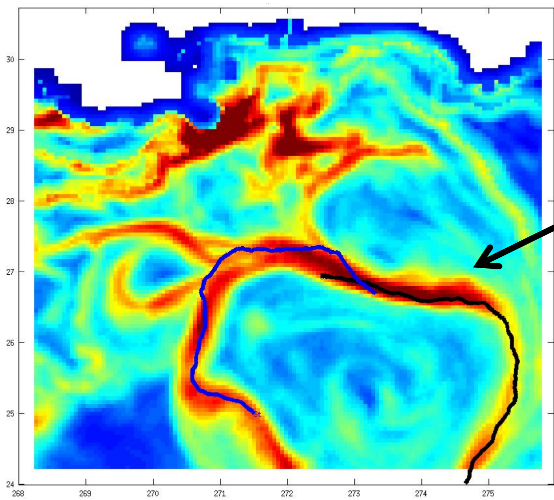
$dJ/dx = A\uparrow T$

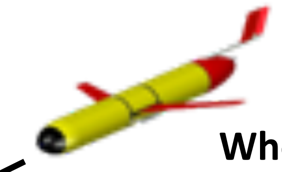
The information can be provide by

- Adjoints
- Ensembles

Given a desired effect, we can compute what observation is required

What does this enable?





Where should this asset be deployed and directed to best support mission objectives?

Glider Observation STrategies (GOST)

Additional restrictions (speed limitations, restricted areas, …)

Instructions from glider pilot

Glider observations over dive sequence

Sampling strategy, automated waypoints

Adaptive sampling, prioritizing areas for observations

Present management needs

Sensor QC, Data QC

Data assimilation

Numerical prediction

Management relevant environment

A feedback loop to directed observation platforms

An example from an adjoint?

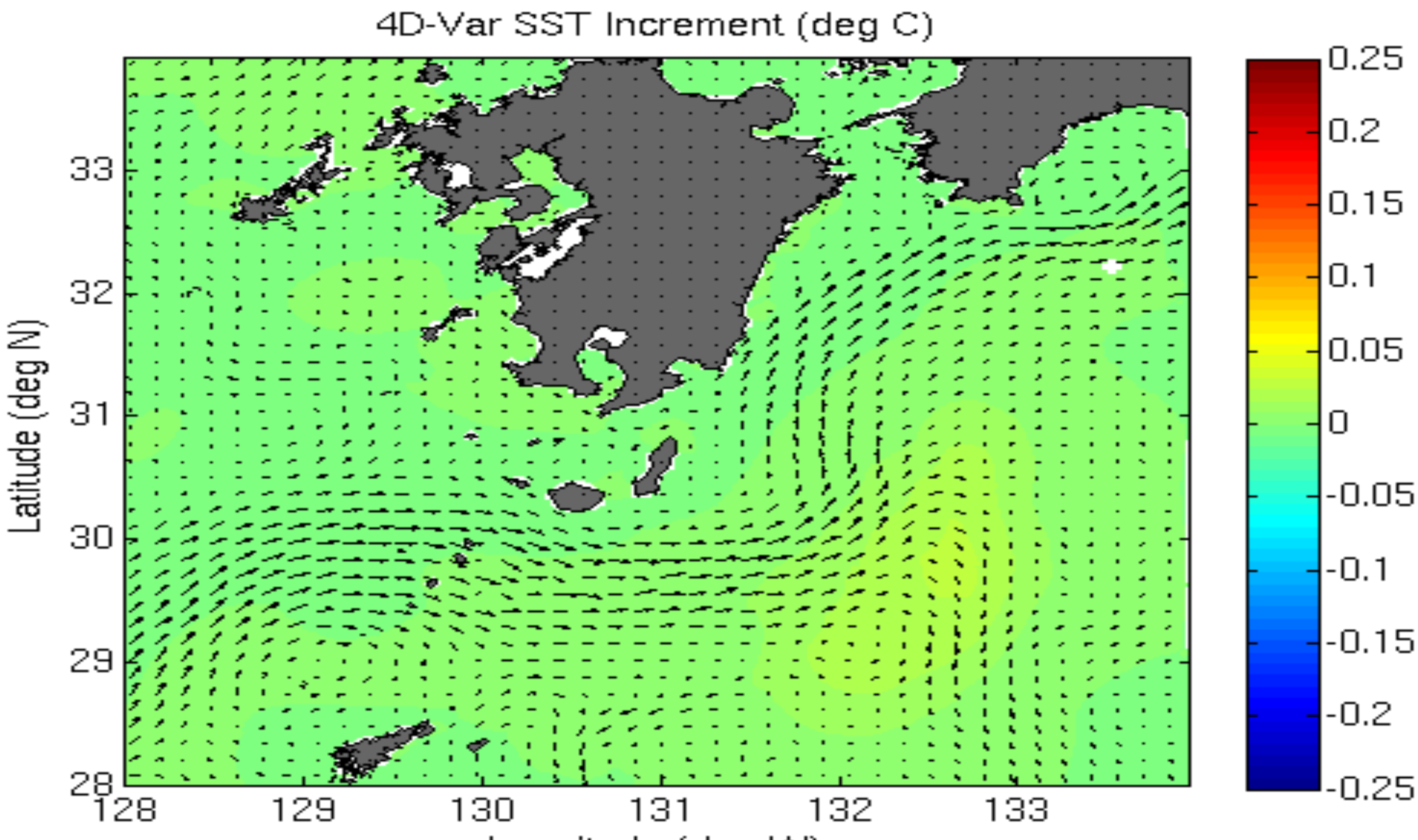
This is a representer function = $AWA\hat{\ }T\ H$

The error reduction of a single observation is proportional to the representer function

There is a reciprocity principle in representer functions

The error reduction of an observation some where at the designated point is equal to the representer at that point

Thus, this is a map of sensitivity of forecast error to observations over space and time



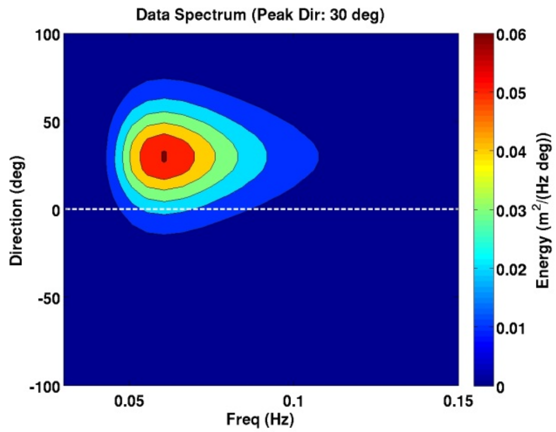
One adjoint run provides entire sensitivity

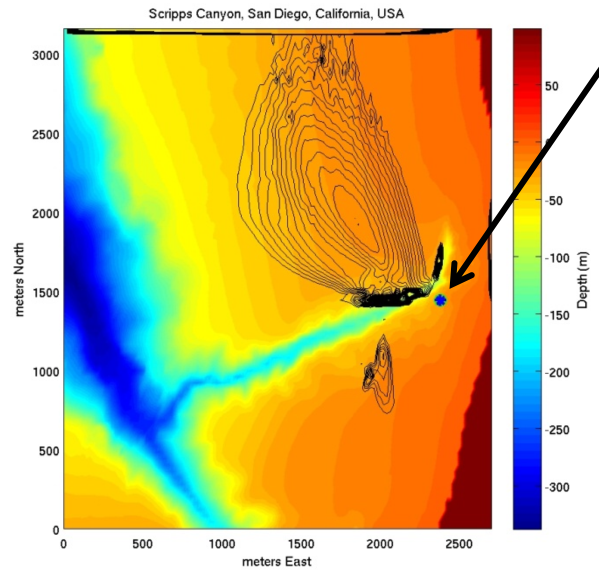
Ngodock, Carrier

How does it translate to other dynamical systems?

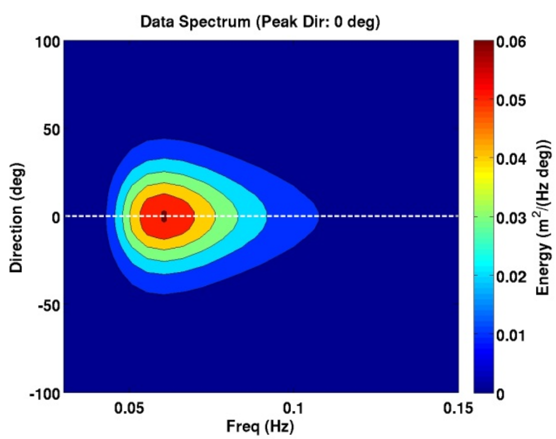
Where should a wave buoy be placed to better predict waves off Scripps?

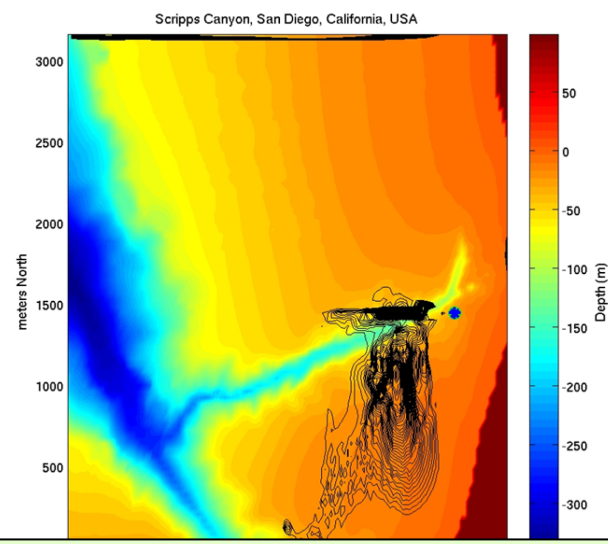
Waves from NW (300°)





Waves from West (270°)





Adjoint of wave model SWAN

Results depend on background state (flow-dependent covariances)

The canyon refracts wave energy depending on incoming direction

Different areas of sensitivity result

One adjoint run provides entire sensitivity

Orzech, Veeramony

Why ensembles vs. adjoints?

Adjoints are hard to construct, maintain and verify are truly the adjoint of the forward model code (we have NCOM, SWAN, NSPE and are working towards coupled NCOM/SWAN and NCOM/NSPE)
Dynamics must be linearized around background state
Tangent linear models have finite accuracy time interval
Nonlinearities are sometimes insurmountable

Doing it by ensembles is trivial
Correlation information is immediate
Nonlinearities are surmountable

Of course, infinite ensembles are required, or at least many more than the dimensionality of the problem

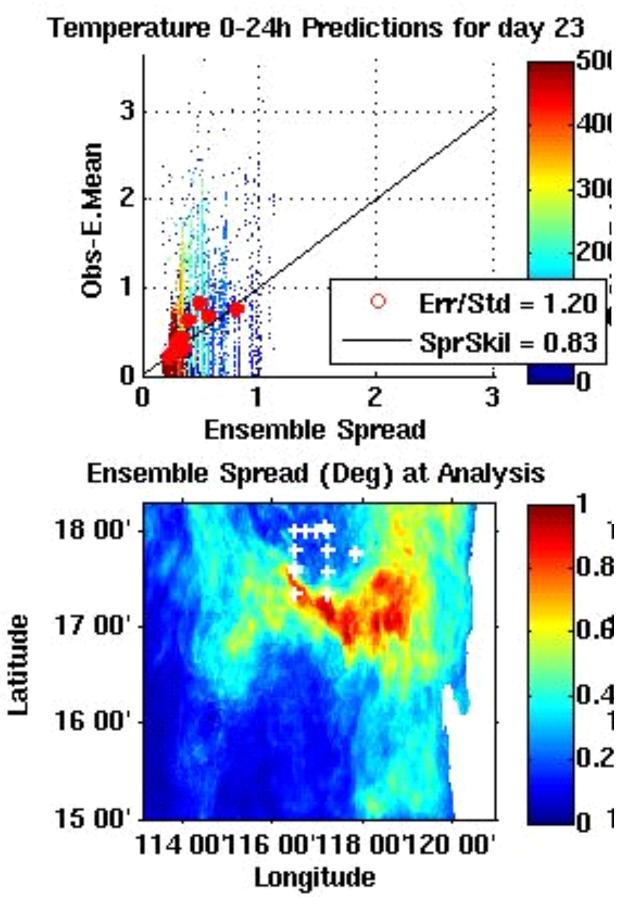
Regardless of the targeted observation problem, we need forecasts of error distributions
Ensembles are needed to achieve this with large complex systems

Each approach extends certain applications

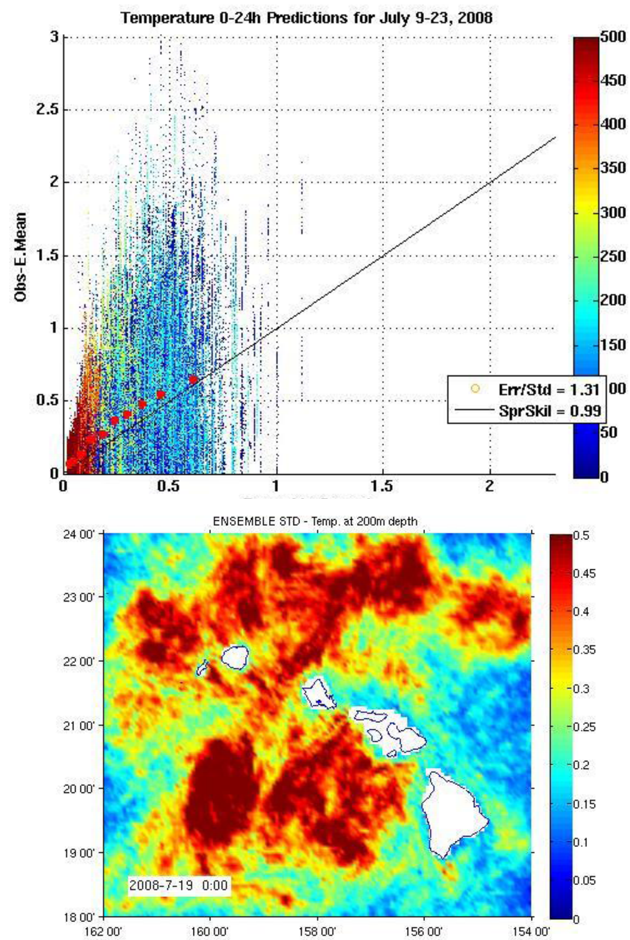
What is required of ensembles?

Adjoints are hard to construct, maintain and verify are truly the adjoint of the forward model code (we have NCOM, SWAN, NSPE and are working towards coupled NCOM/ SWAN)

South China Seas, 2009



Hawaii 2008



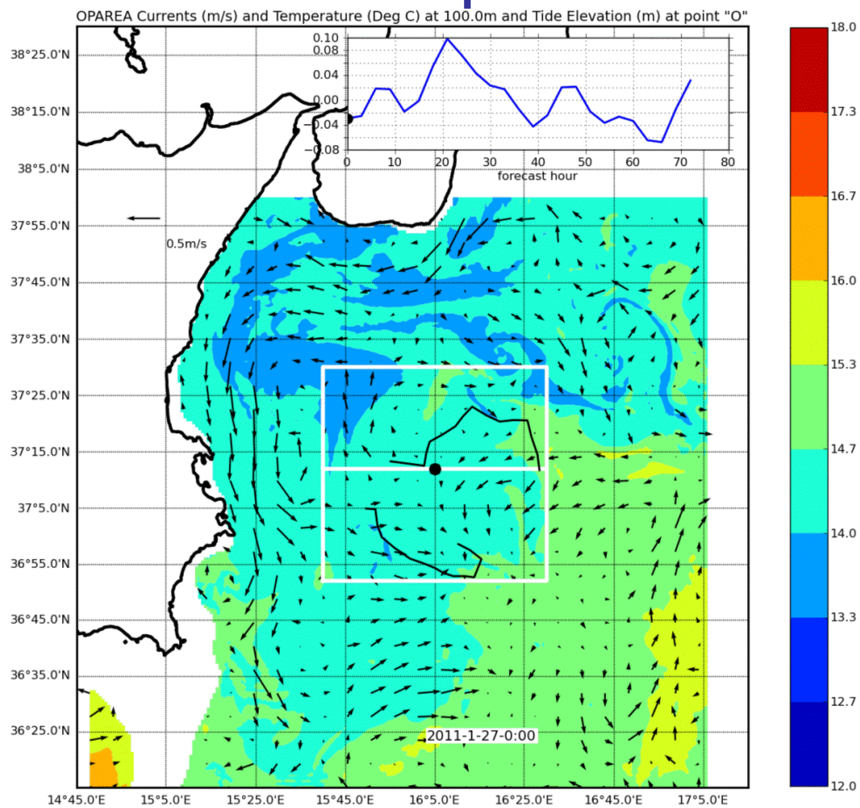
Skill-Spread relation
Does the observed forecast error (obs – forecast) match the ensemble standard deviation?

Example temperature standard deviation

Ensembles must forecast the errors

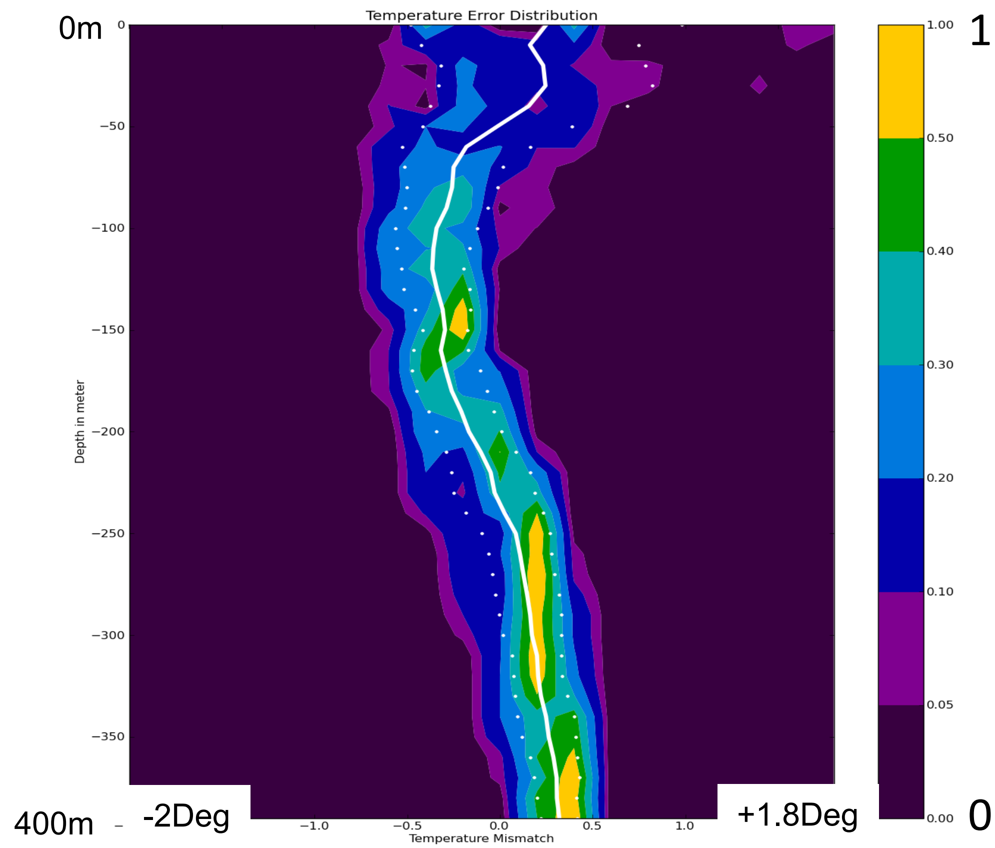
What is required of ensembles?

Temperature 100m depth



Temperature Forecast Error

Probability Distribution Functions

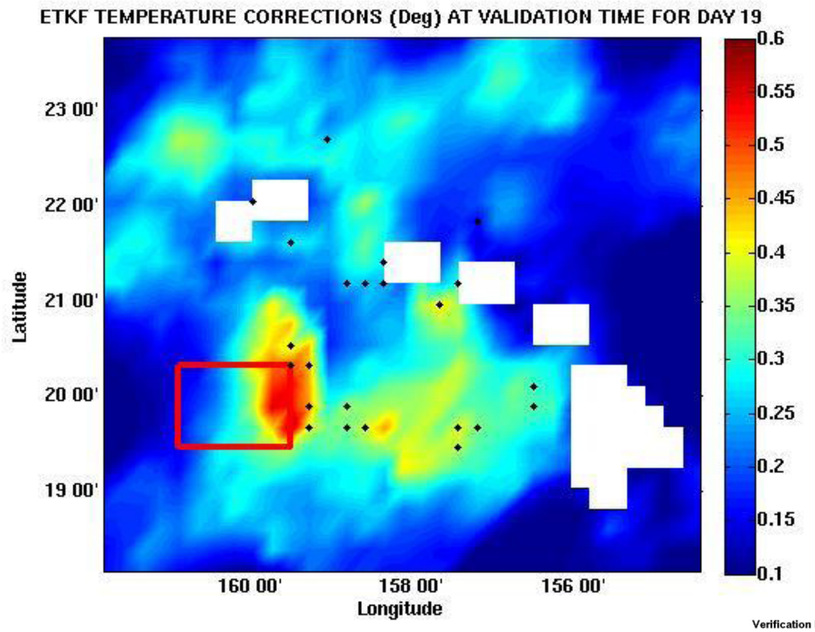


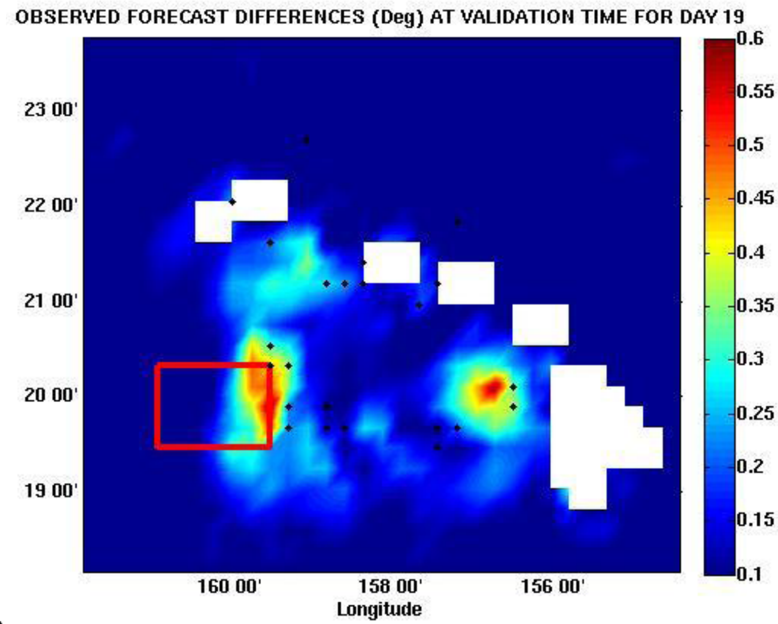
Ensembles spread must contain observations

Can targeted observations be validated?

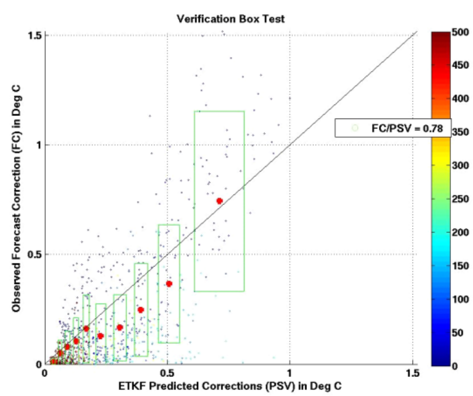
Forecasted errors for 00Z July 21 from 48 hour forecast done at 00Z July 19 prior to assimilation

Change in forecast at 00Z July 21 from 24 hour forecast done at 00Z July 20 after assimilation





Forecasted impact of observations

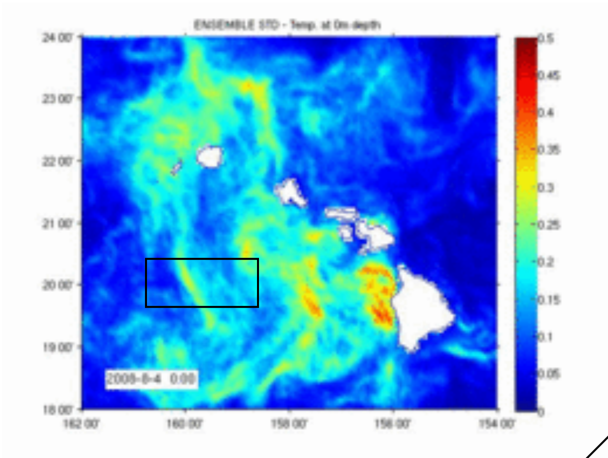


Observed impact of observations

Correlation of forecast and observed reduction in error within target box

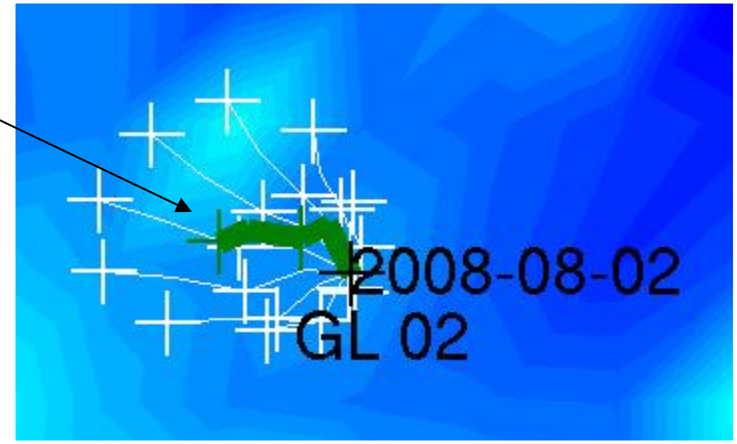
Observation impact has been validated

How does this enable automated systems?



Ensemble spread at sfc from 08/04 to 08/06

Proposed Optimal Track for the next 24h



Note impact of NWestward currents

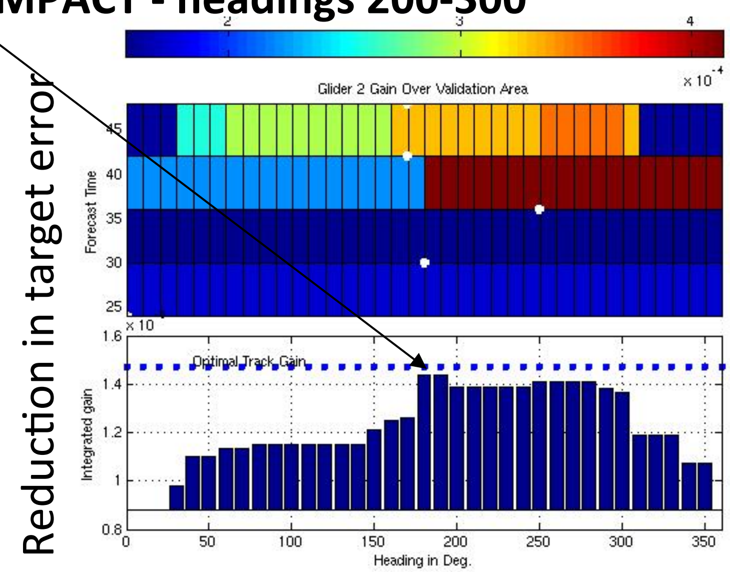
Detailed Guidance

Way Points

Lat / long /date /GL number /recommended heading / estimated gain

20.305000 -157.684006 2008 8 4 0.000000 2 0.00 24.520775
20.383238 -157.726009 2008 8 4 3.000000 2 180.00 21.777078
20.361463 -157.772982 2008 8 4 6.000000 2 250.00 63.718407
20.373428 -157.871954 2008 8 4 9.000000 2 170.00 53.282980
20.353877 -157.922425 2008 8 4 12.000000 2 170.00 58.416319

HIGH IMPACT - headings 200-300



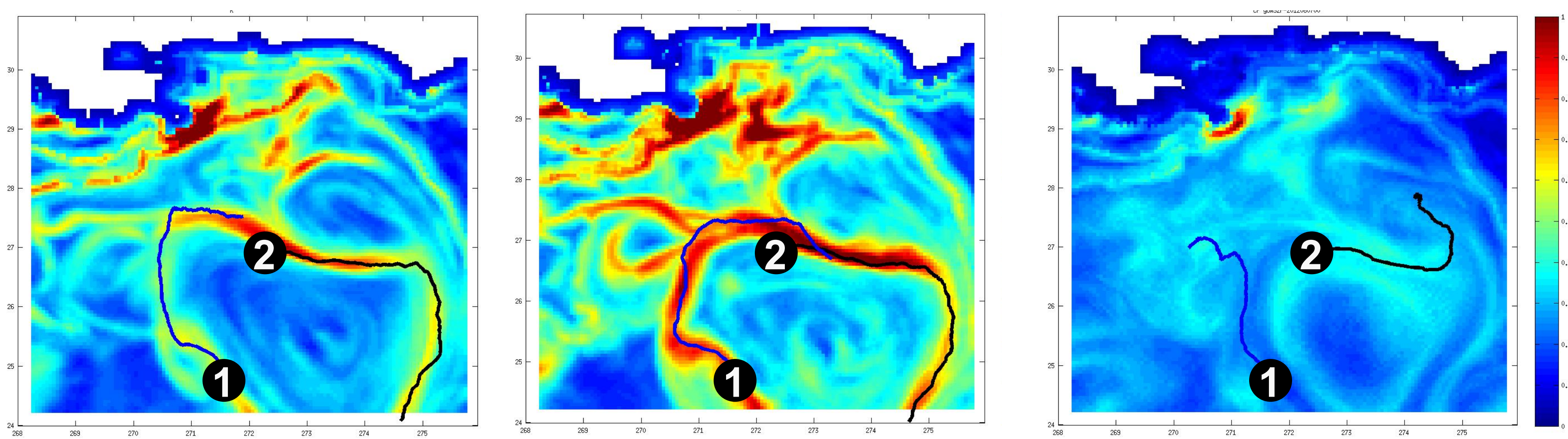
Possible headings

An optimized and automated system for ocean forecasting is enabled

What missions can be defined?

- Optimize targeted forecast error
- Maintain coverage
- Minimize forecast error
- Define features
- Return / recover

Feature definition mission cost functions from different real-time model forecasts in the northern central Gulf of Mexico on 7 June 2012. We have superimposed the 7-day paths for two gliders as determined by maximizing the daily cost function. Red areas indicate regions of higher cost function value (in this case, higher variability).

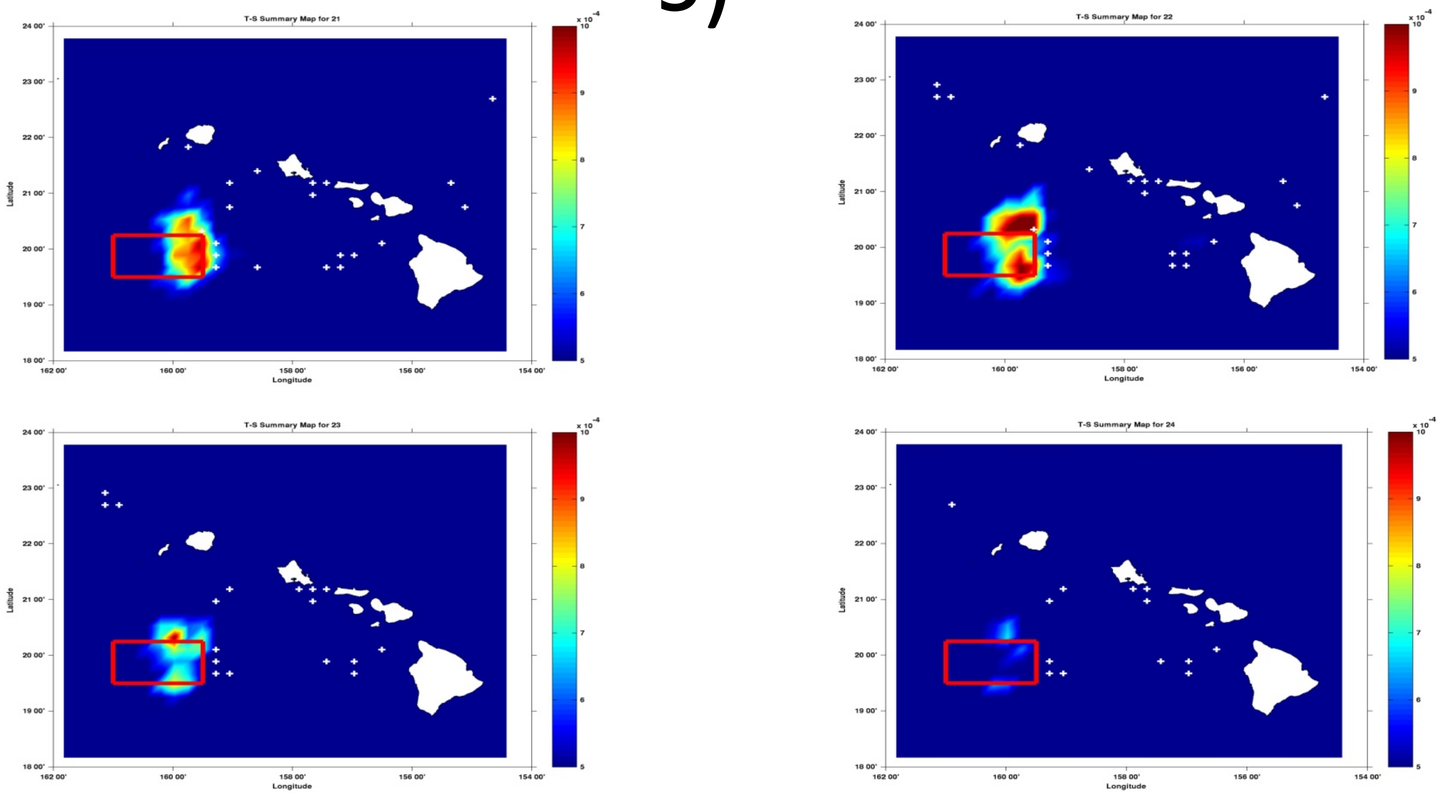


GoM 3km **GoM 1km** **GoM 3km ensemble**

Different assets can be assigned different missions or combinations

Barron, Coelho

Impact of Observations (T-S)



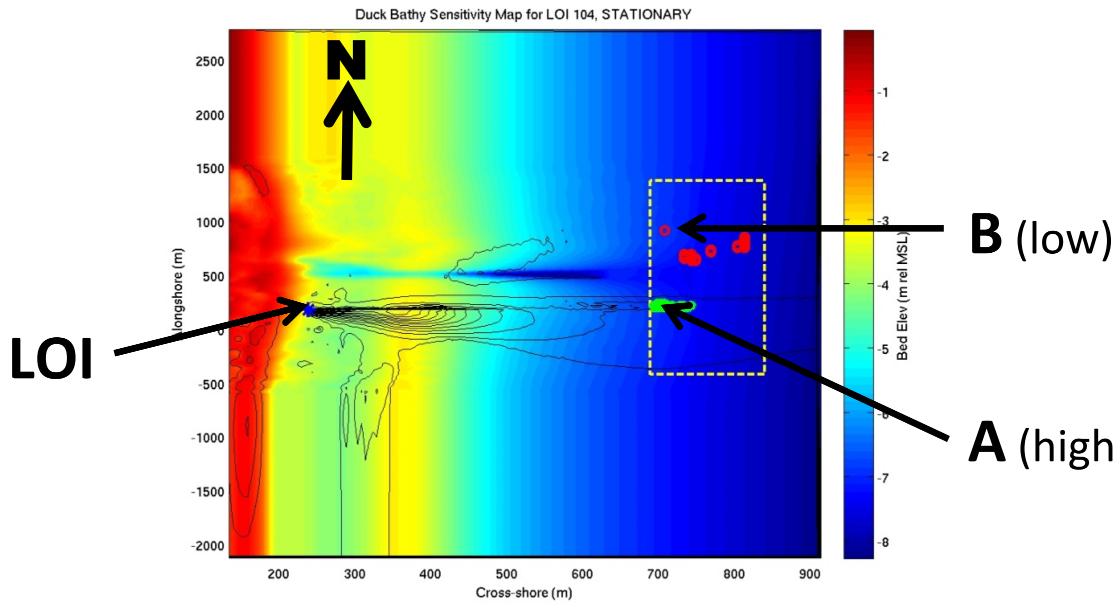
- Summary maps for T-S profile error reduction: this maps show the relative impact of T-S observations during a 24-48 hours observations window in reducing the T-S errors in the target box (red box) for the next analysis at hour 48.

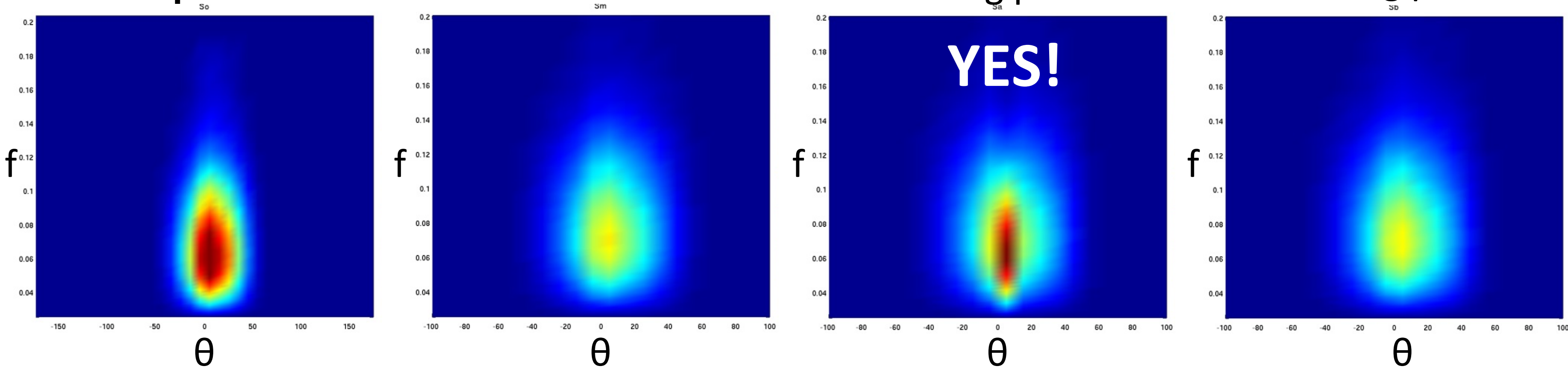
Nearshore Sensitivity Maps: Application

<u>Qualitative Test</u>:

1. Assimilate spectrum from **A**.
2. Assimilate spectrum from **B**.

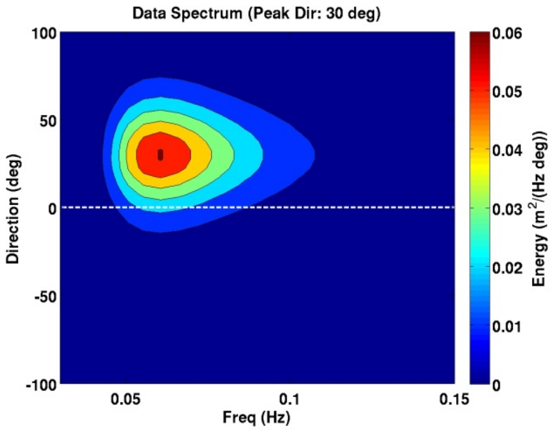
Does assimilation from high sensitivity location **A** give a better result at LOI?

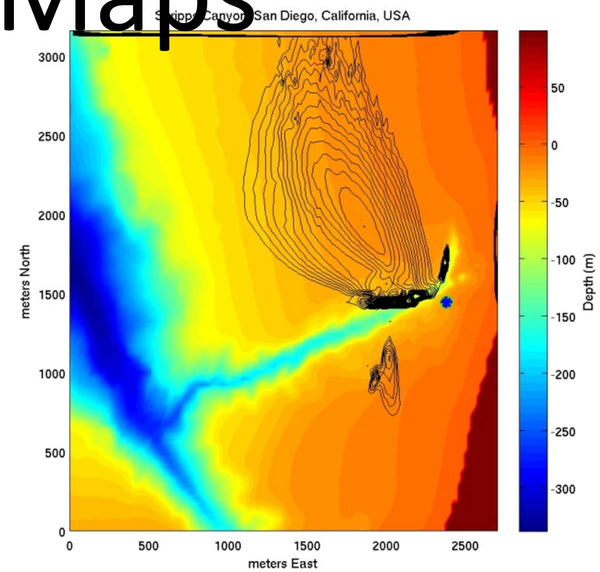




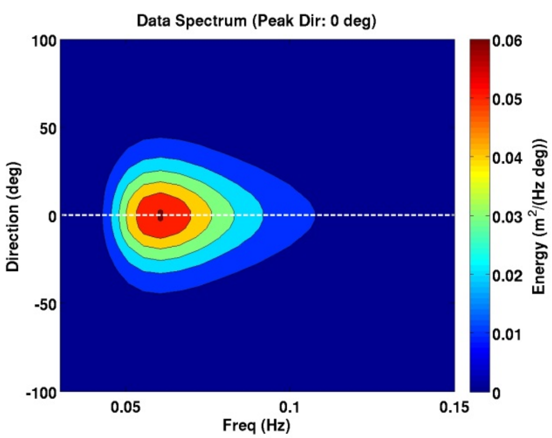
Sensitivity Maps

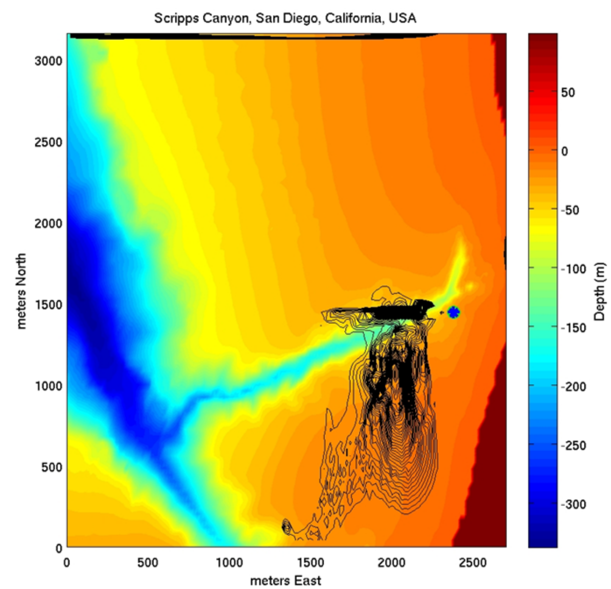
Waves from NW (300°)





Waves from West (270°)





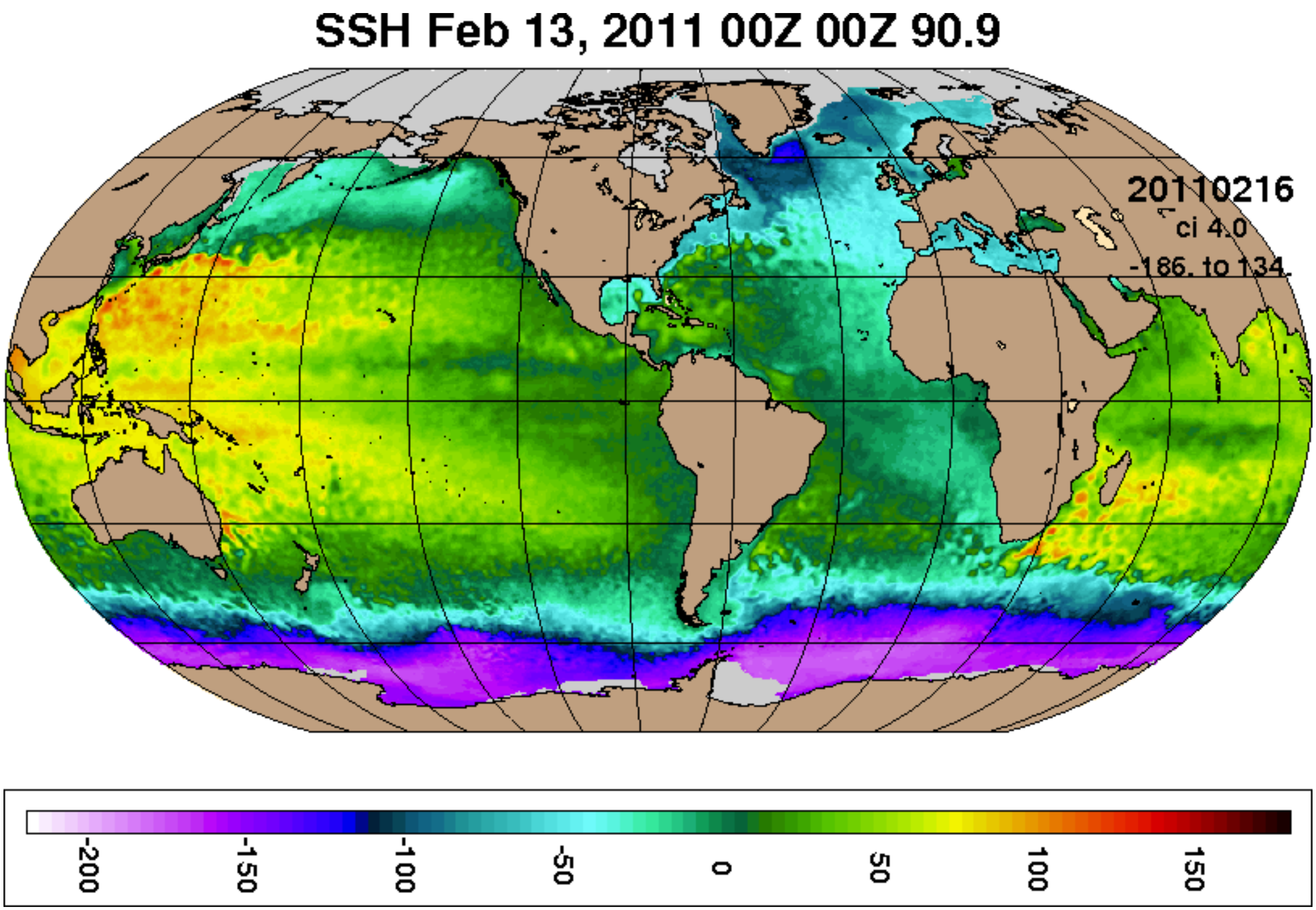
Global to nearshore modeling

Ocean prediction

Extending physics

Hybrid Coordinate Ocean Model (HYCOM)
Run daily at Naval Oceanographic Office

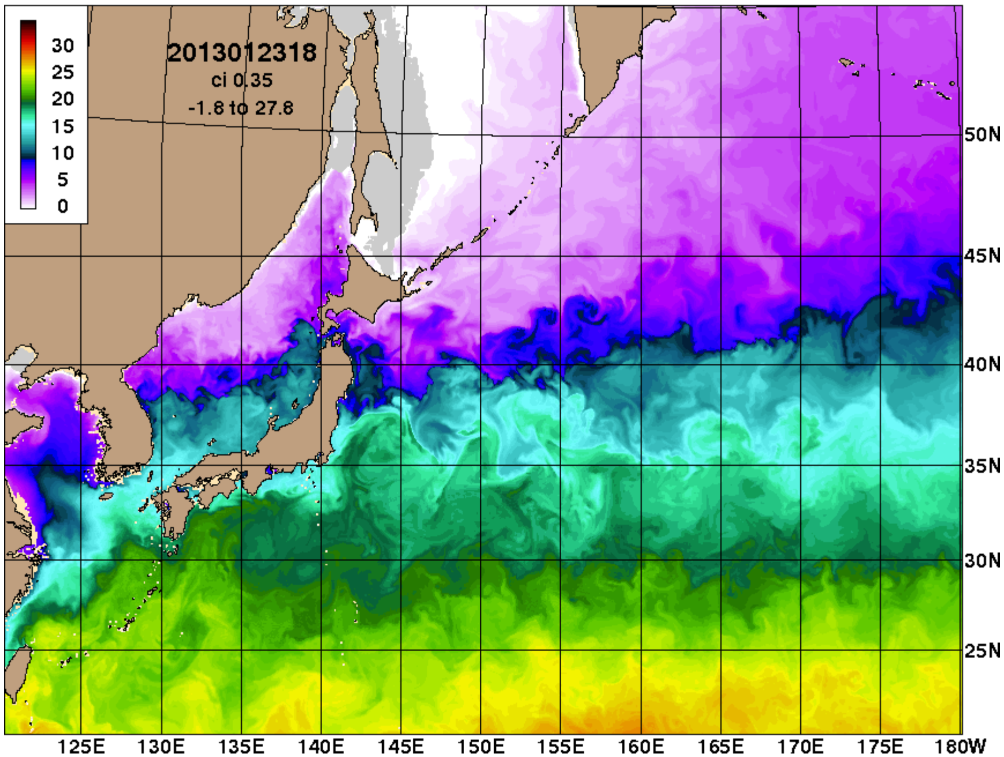
1/12° (~7km) horizontal resolution
800 CPUs, 17 hours for a 3 day forecast
1.1x10^9 variables every time step



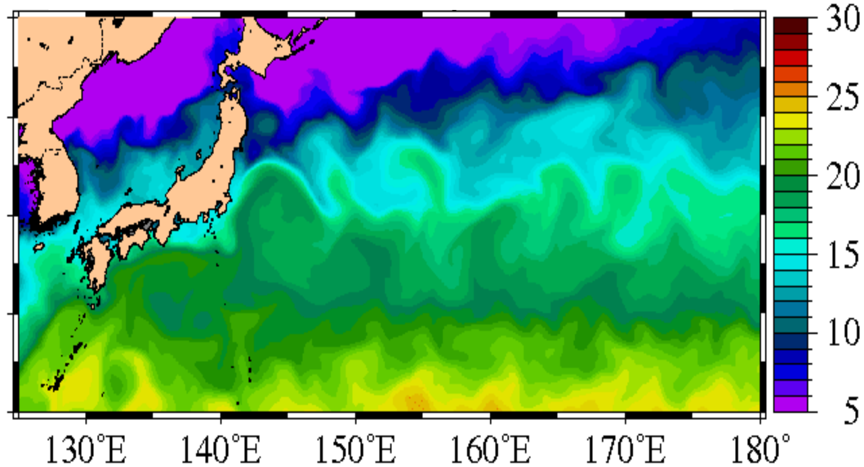
GOFS 3.01: New Operational Prediction System at NAVOCEANO

30-day SST (°C) animation of the Kuroshio Extension Region

GOFS 3.01



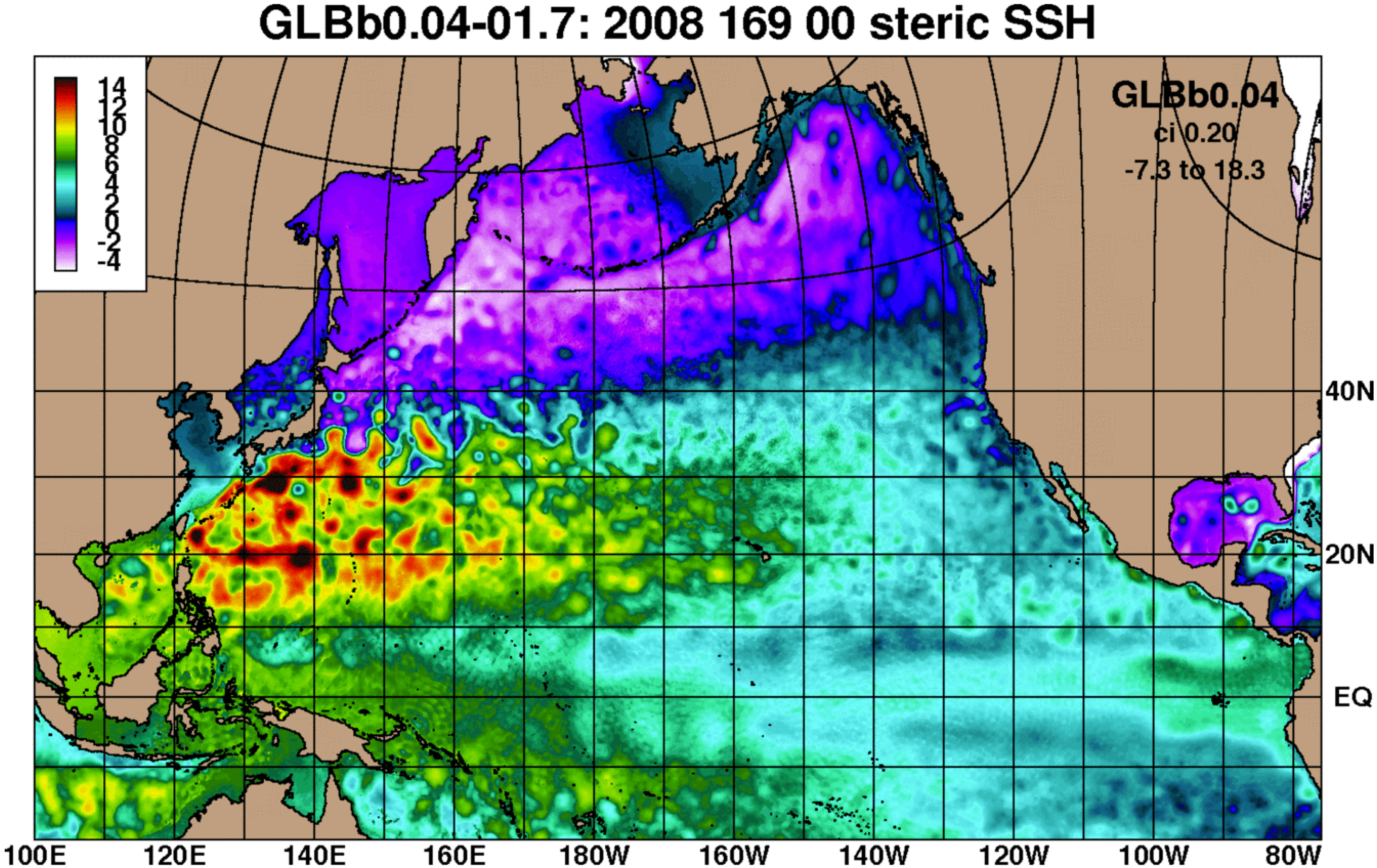
GOFS 2.6



GOFS 3.01 under NAVOCEANO control
Operational as of 28 Feb 2013

ESPC Integration from Prior and Present Oceanography 6.2-6.4

1/25° HYCOM with tides, 5 day animation of hourly steric SSH

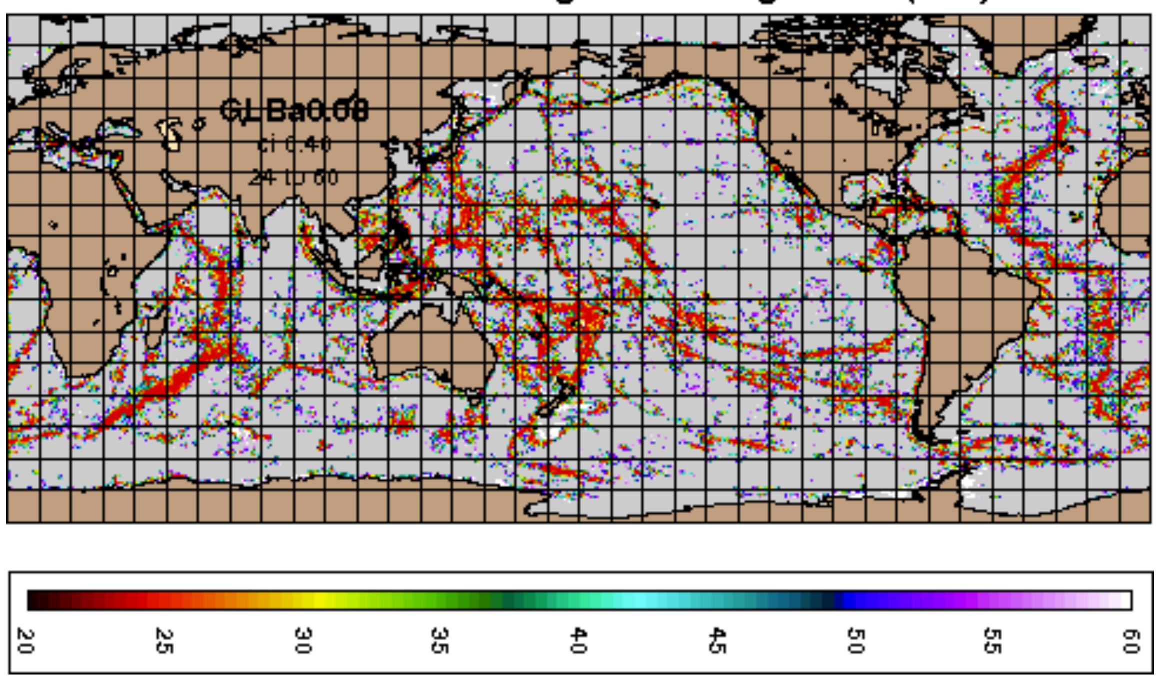


Long period modulation of internal tides from mesoscale over 30 to 60 days

Tides in Global HYCOM

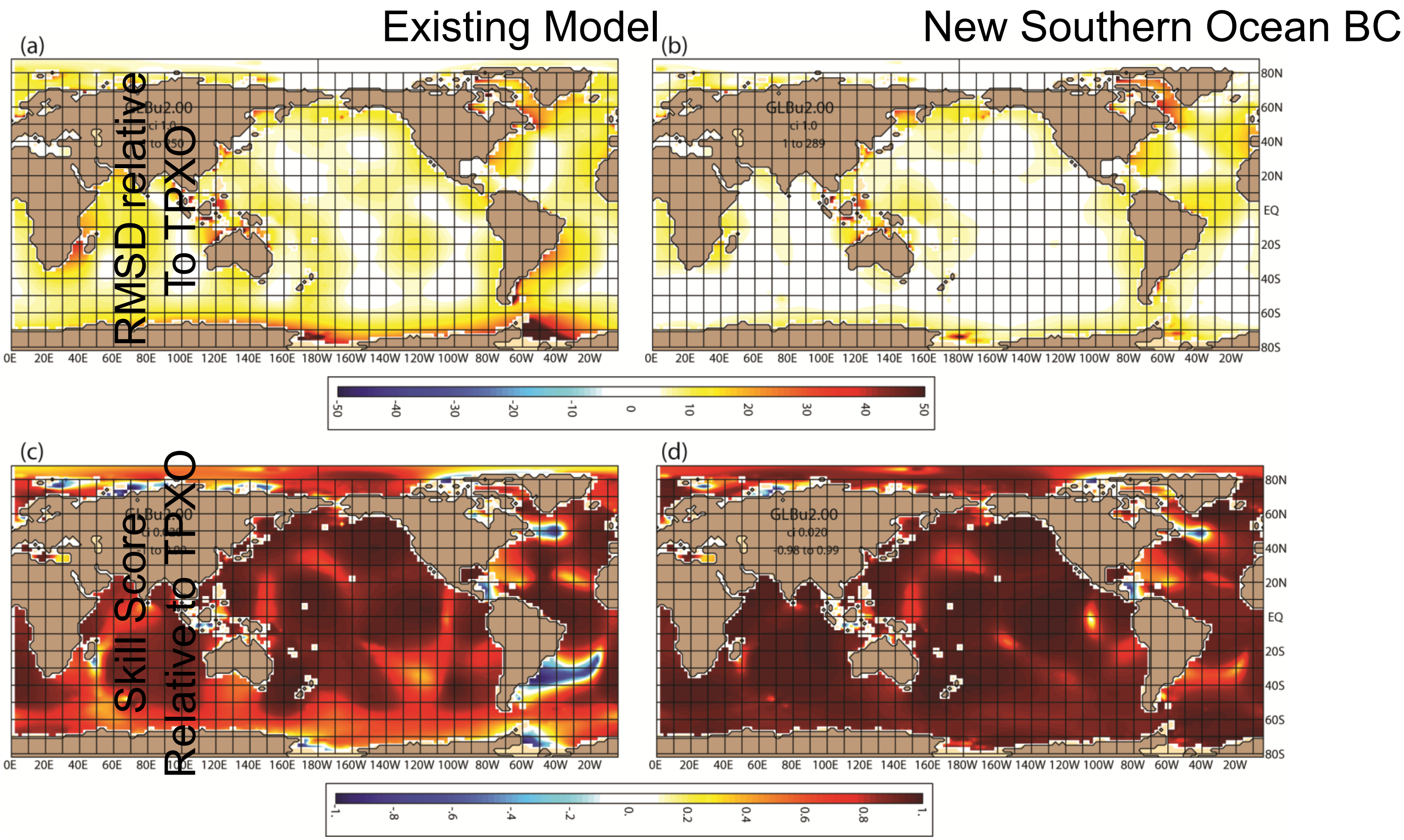
- Tripole grid from 78.6°S to 90°N, at 1/12° and 1/25°
- Tidal body forcing with 8 constituents
  - Semidiurnal M_2, S_2, N_2 and K_2
  - Diurnal O_1, P_1, Q_1 and N_1
- Scalar self-attraction and loading
- Topographic wave drag applied only to the tides

18.5 Tidal Wave Drag E-Folding Time (hrs)



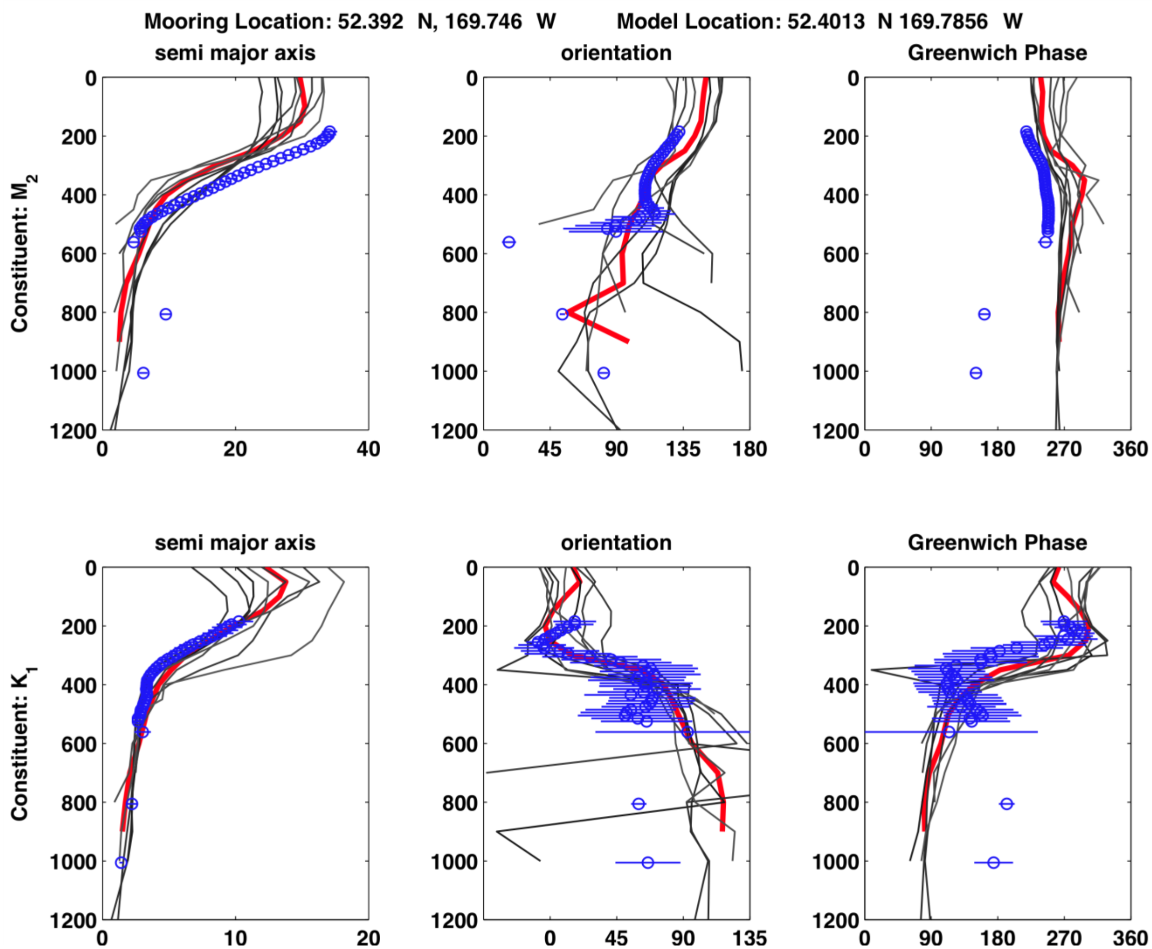
No drag (grey) over 75% of the world’s oceans

Effects of Floating Ice Shelves on Tides



- A large difference between the data-assimilative TPXO model and HYCOM is the treatment of the floating ice shelves around Antarctica. TPXO extends further south to include water under the shelves, HYCOM treats them as land.
- Using the TPXO tides as a boundary condition at the floating ice shelves reduces the RMS difference (top) and improves the skill (bottom) over much of the globe, not just the Southern Ocean.

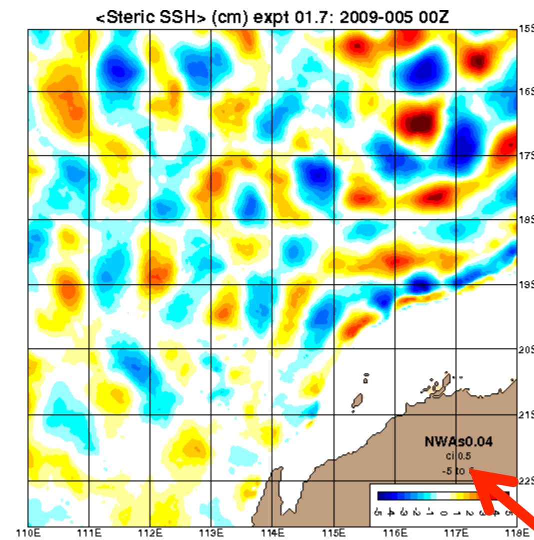
Tidal Currents in HYCOM: comparison in North Pacific

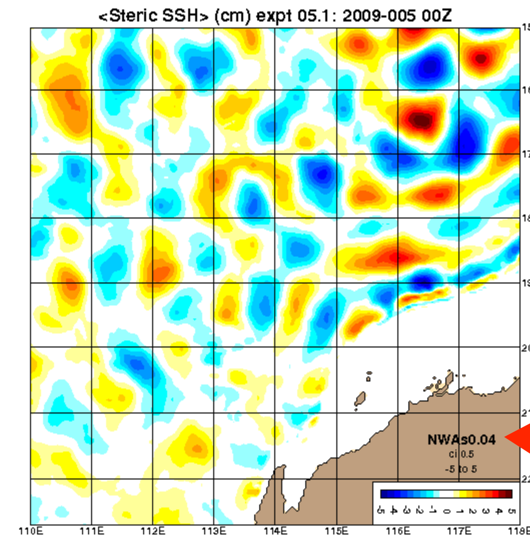


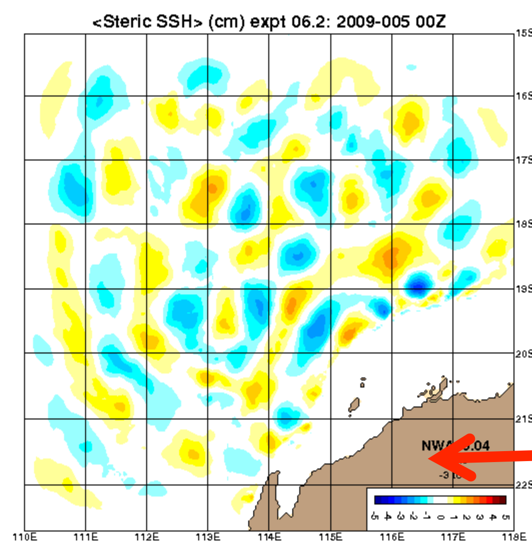
Blue: ADCP data Red: nearest model point Black: 8 surrounding model points

(Timko, et al., in revision)

Internal Tides from Global to Regional Domains







Filtered steric SSH near Australia

Global 32-layer 1/25° HYCOM with tides

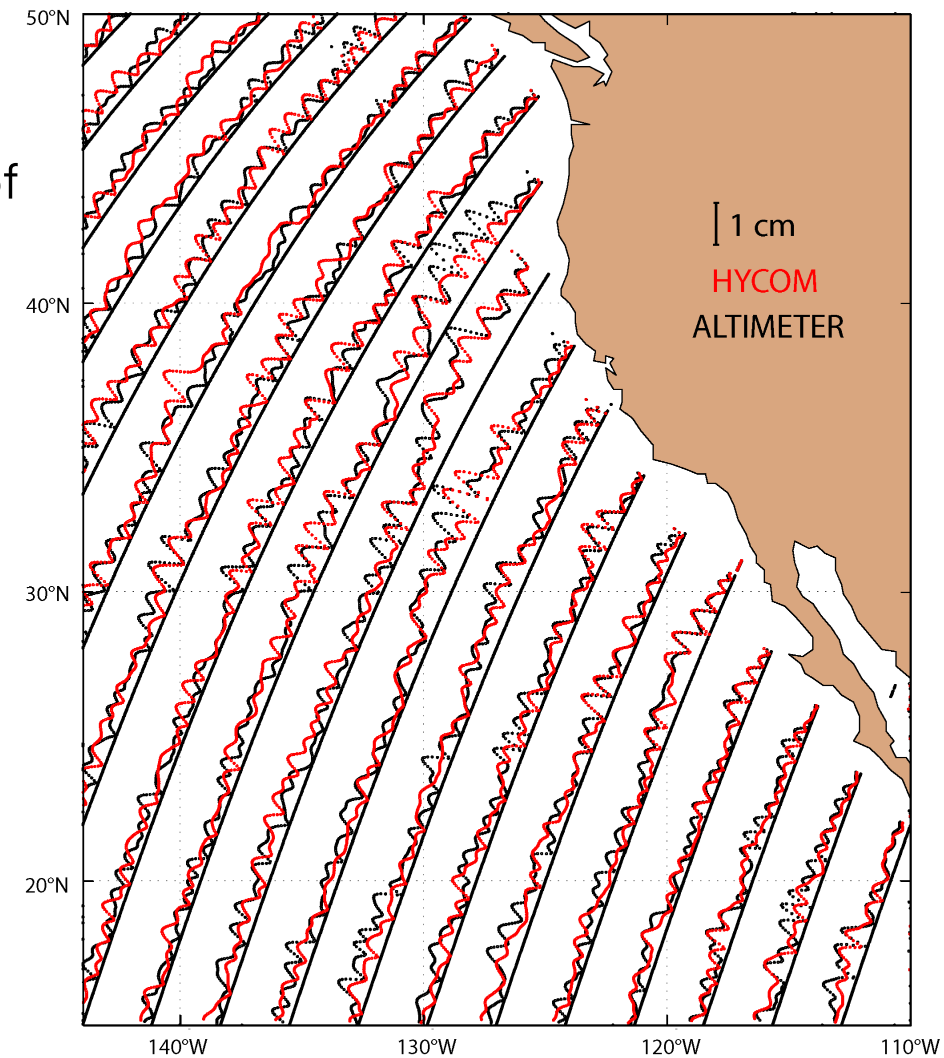
Regional 41-layer 1/25° HYCOM, hourly barotropic boundary conditions

With hourly 3-D boundary conditions

With daily mean 3-D boundary conditions

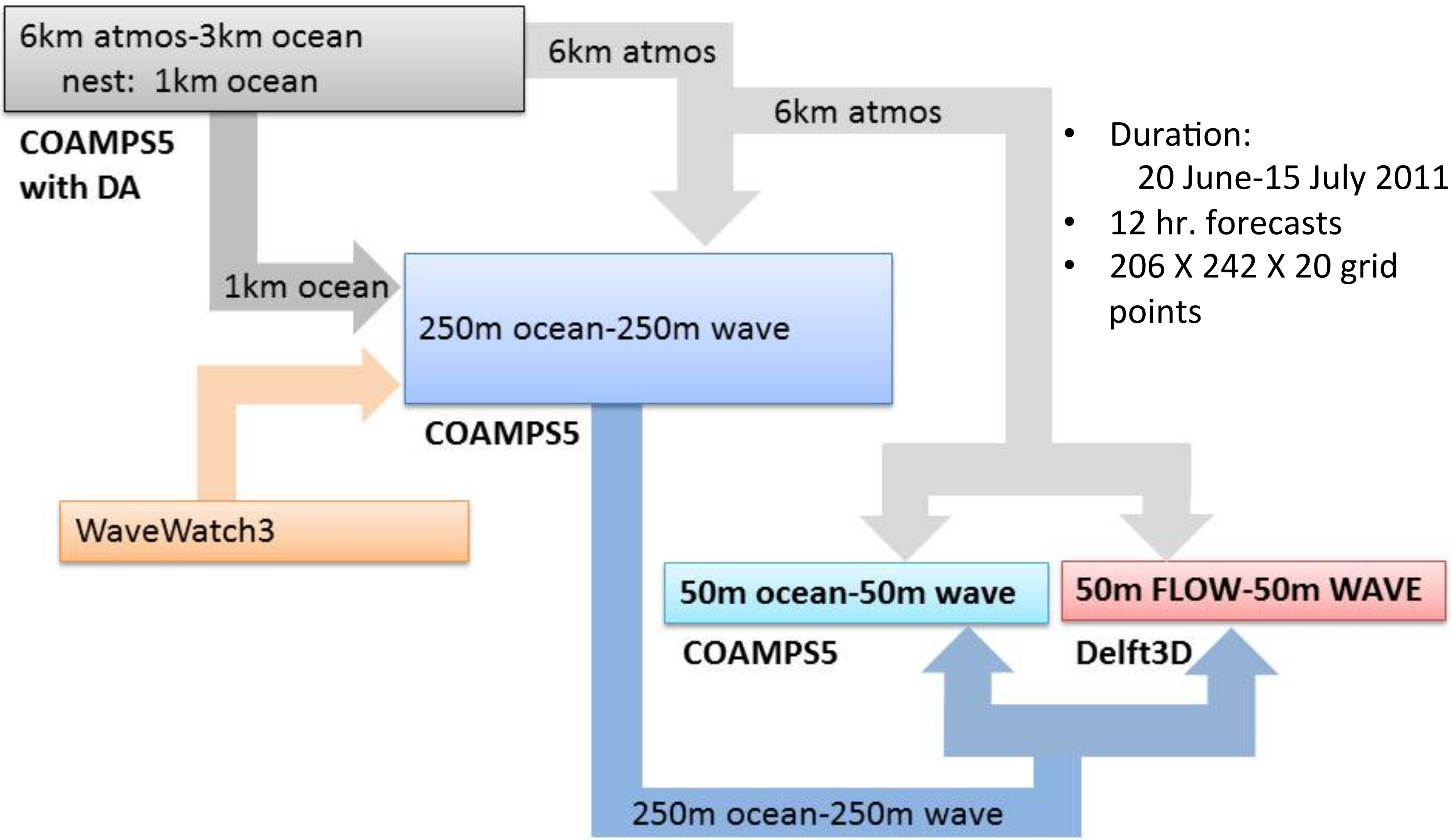
M_2 internal tides at the surface
(Shriver et al. 2012)

The hourly output of the model can be sampled by virtual altimeters



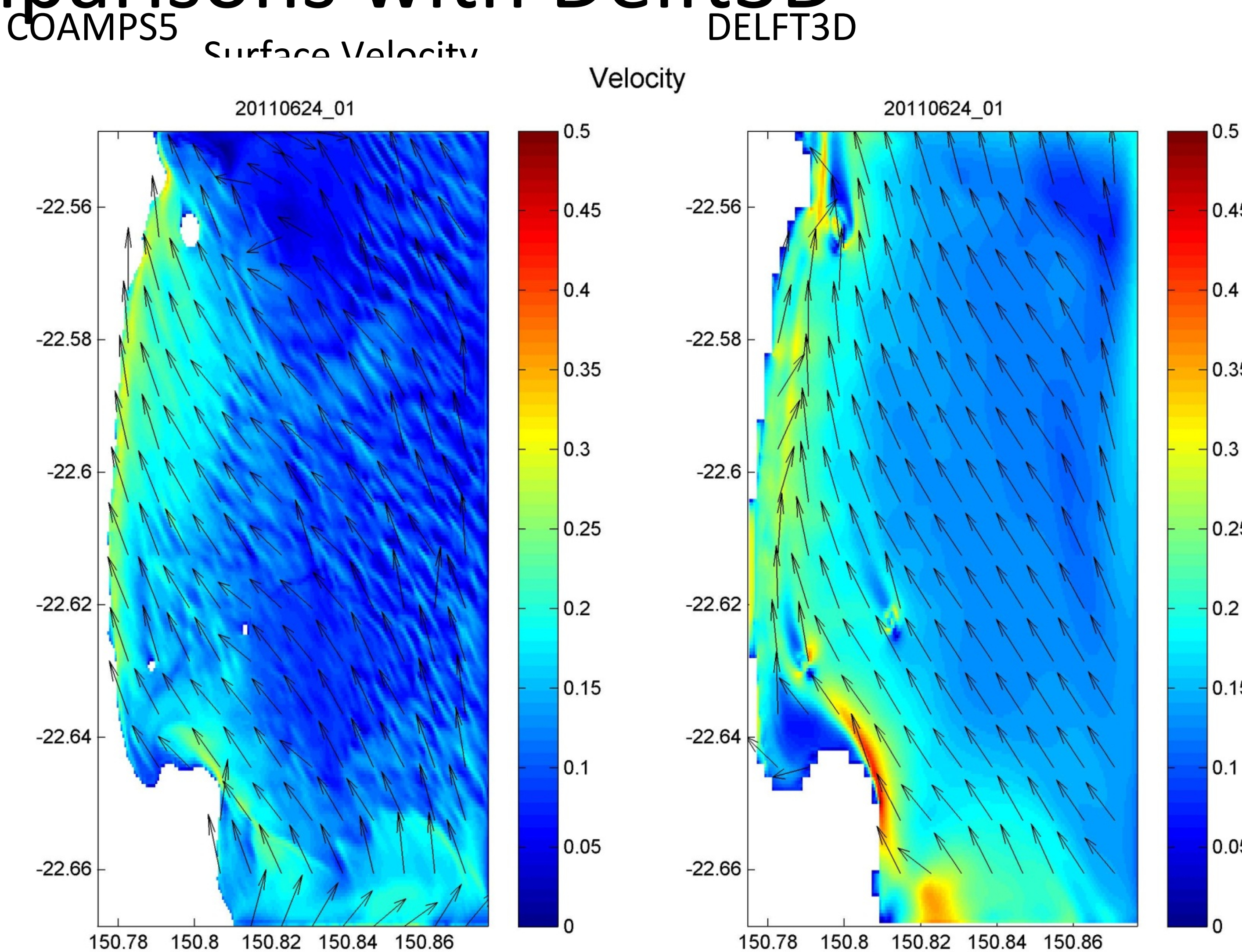
Tidal amplitudes along tracks from model and aliased altimeter data

COAMPS5 Nearshore Demonstration:



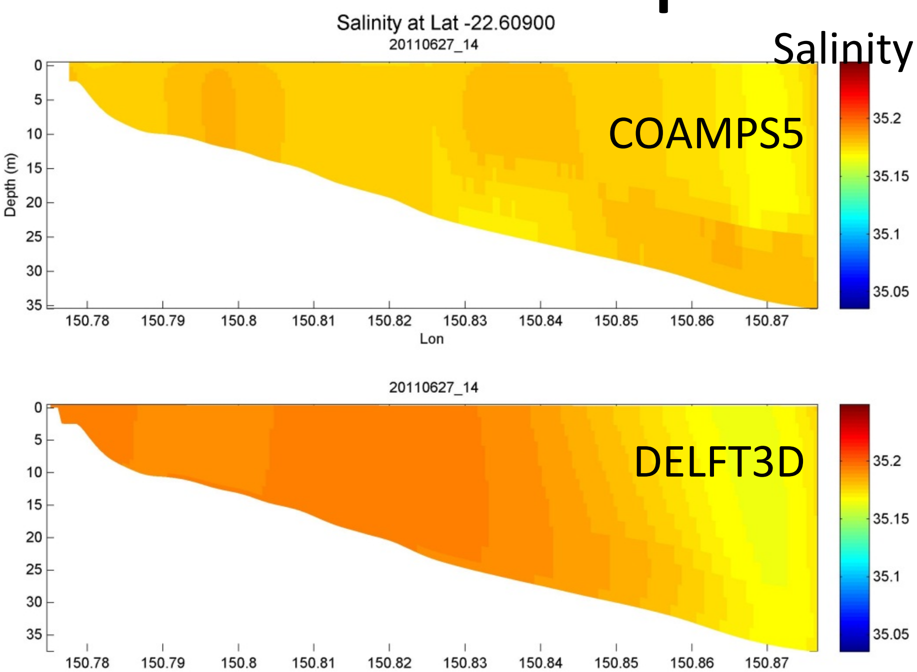
- Duration:
  20 June-15 July 2011
- 12 hr. forecasts
- 206 X 242 X 20 grid points

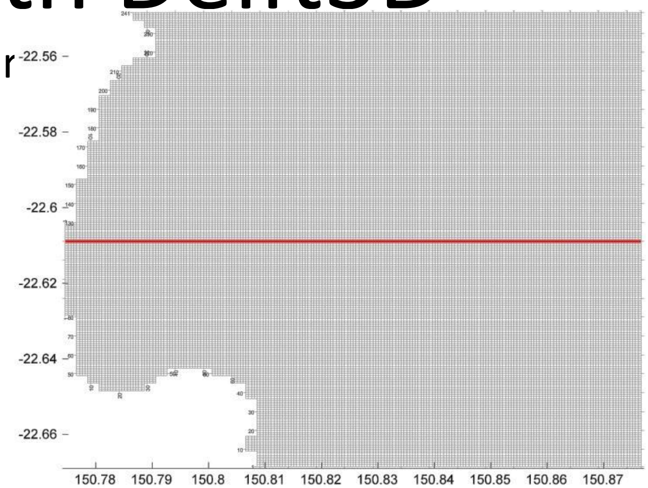
COAMPS5 Nearshore Demonstration: Comparisons with Delft3D

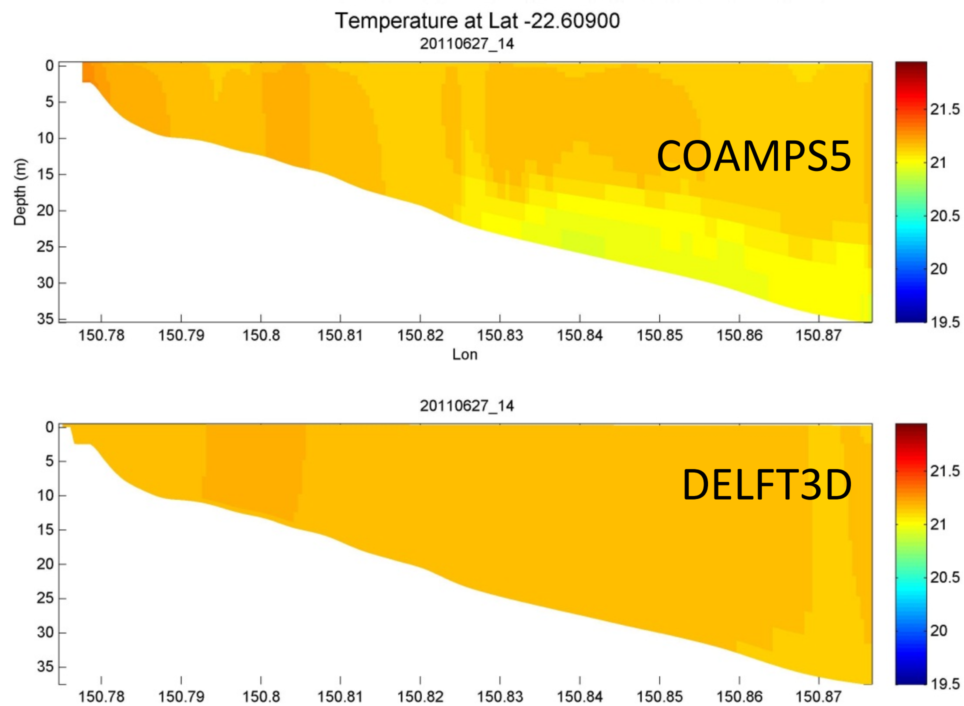


COAMPS5 Nearshore Demonstration: Comparisons with Delft3D

Salinity and Temper

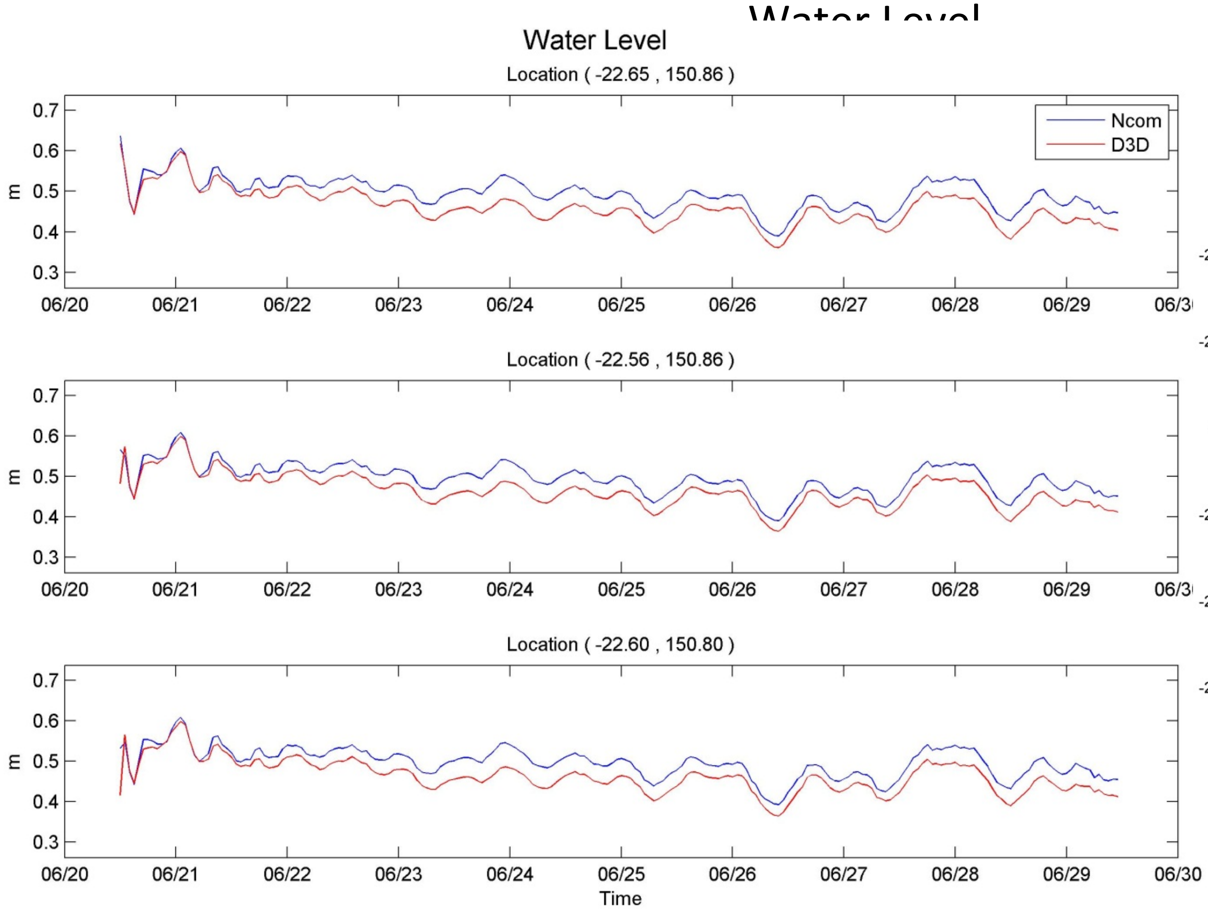


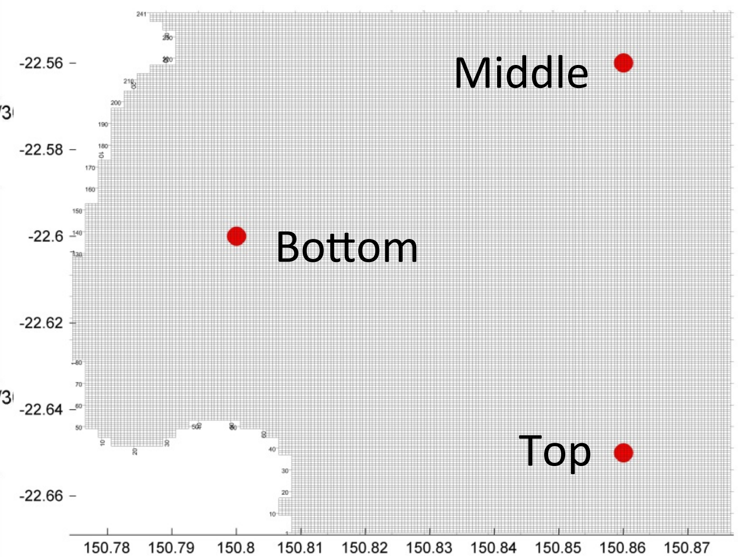




- Overall, well-mixed
  - < 0.05 diff in Salinity
  - < 0.5 degree diff in temperature
- More vertical structure in COAMPS5 than in Delft3D

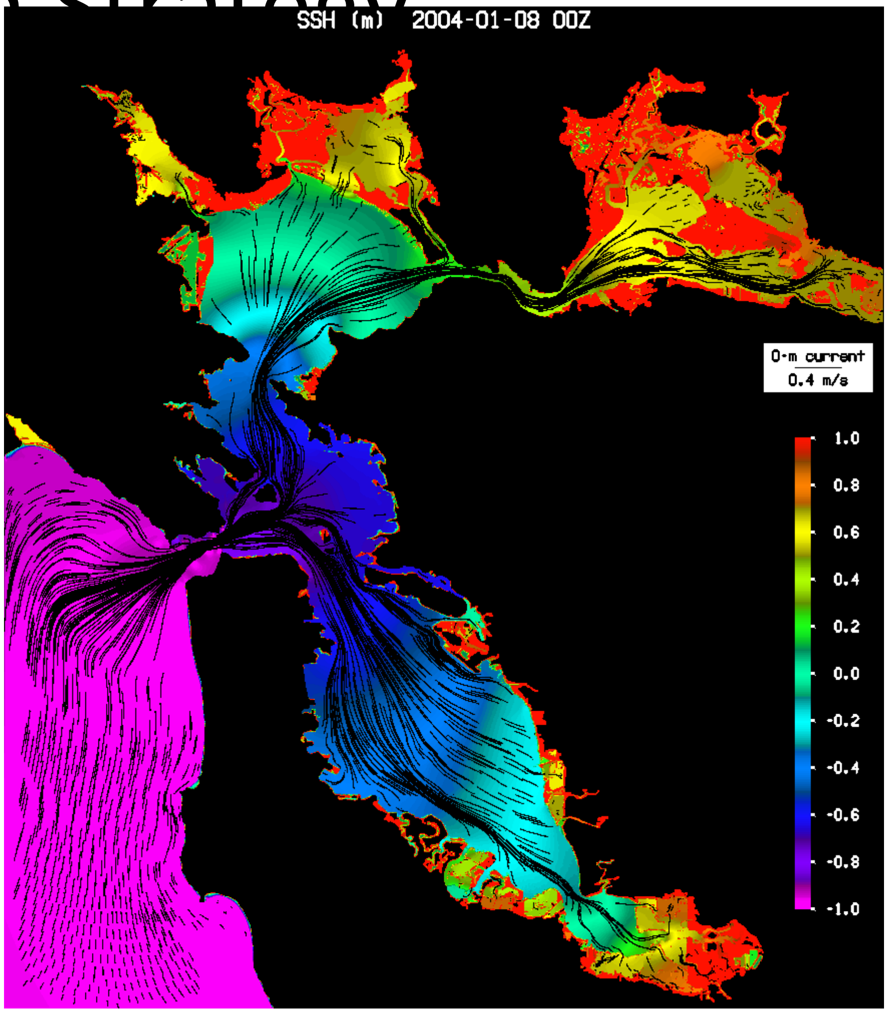
COAMPS5 Nearshore Demonstration: Comparisons with Delft3D



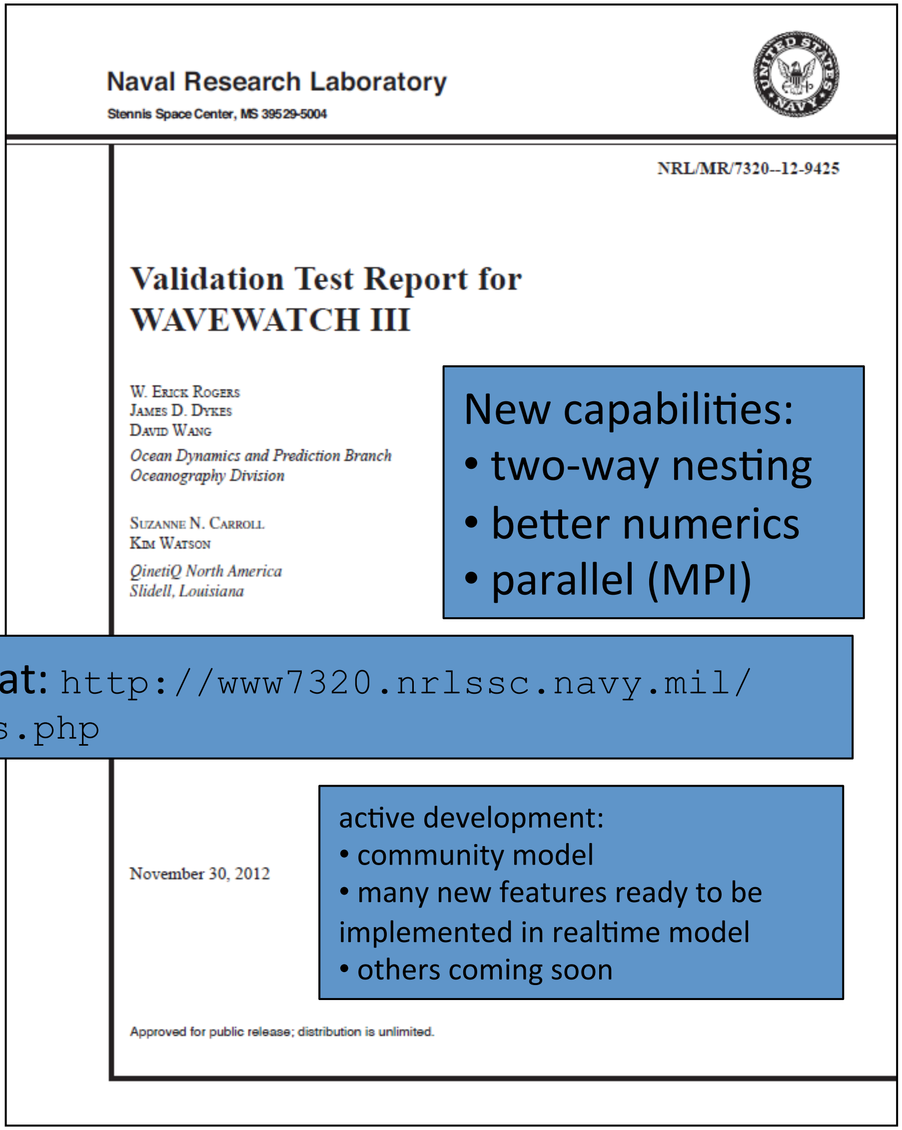


Wetting/Drying (WAD) in NCOM: Implementation Strategy

- ✓ Tested well in TIDES5
- ✓ Implement barotropic scheme in NCOM
  - ✓ Test on single and multiple processors
  - ✓ Test in San Francisco Bay at 500, 200, and 100 m resolutions.
- Develop multi-layer aspects of scheme for constant density flow
  - Use POM implementation as a guide
  - Test on single and multiple processors
  - Test in San Francisco Bay, CA and Cook Inlet, AK
- Develop multi-layer aspects of scheme for variable density flow
  - Test on single and multiple processors
  - Test in San Francisco Bay, CA and Cook Inlet, AK



FY12: VTR submitted and VTP approved


Naval Research Laboratory
Stennis Space Center, MS 39529-5004

NRL/MR/7320--12-9425

Validation Test Report for WAVEWATCH III

W. Erick Rogers
James D. Dykes
David Wang
Ocean Dynamics and Prediction Branch
Oceanography Division

Suzanne N. Carroll
Kim Watson
QinetiQ North America
Slidell, Louisiana

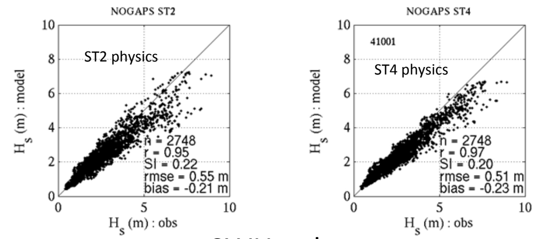
November 30, 2012

Approved for public release; distribution is unlimited.

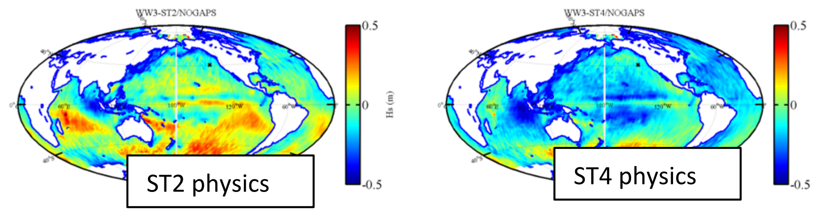
New capabilities:
- two-way nesting
- better numerics
- parallel (MPI)

pdf at: `http://www7320.nrlssc.navy.mil/pubs.php`

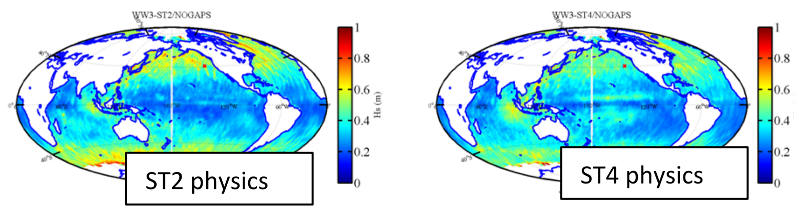
active development:
- community model
- many new features ready to be implemented in realtime model
- others coming soon



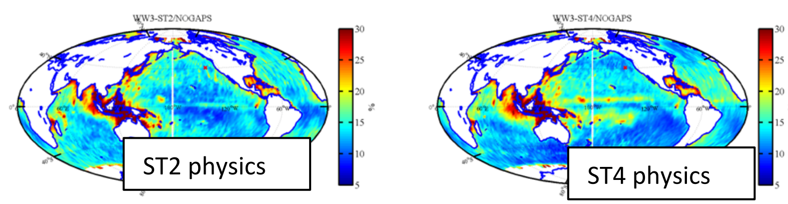
SWH at buoy



SWH bias vs. altimetry (m)



SWH RMSE vs. altimetry (m)



SWH normalized RMSE vs. altimetry

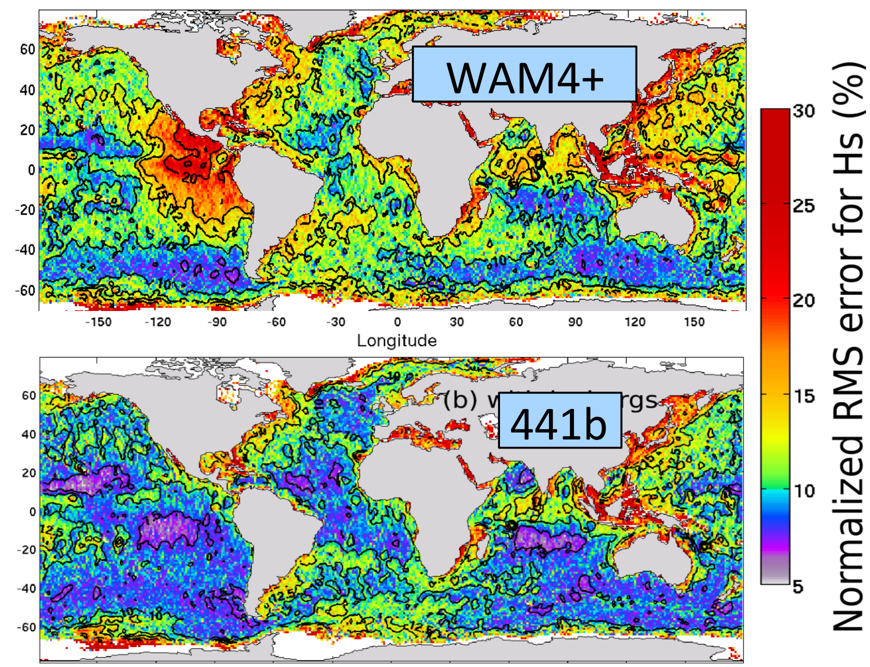
Important WAVEWATCH III collaborations: physics

Improving Wind-Wave Predictions: Global to Regional Scales

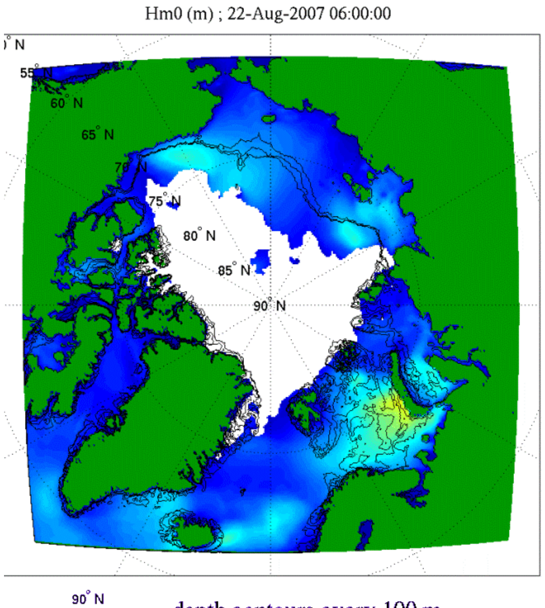
NATIONAL OCEANOGRAPHIC PARTNERSHIP PROGRAM

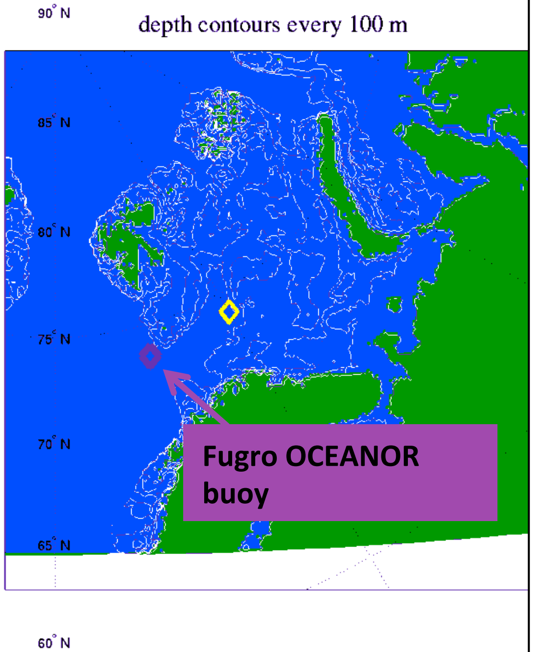
- ONR
- NOAA/NCEP/EMC
- MMS/BOEM
- Bedford Institute of Oceanography (Canada)
- San Francisco State University
- IFREMER (France)
- Georgia Tech
- Swinburne University (Australia)
- ERDC, Army Corps of Engineers
- Naval Research Laboratory
- Texas A&M University
- University of Florida
- University of New South Wales (Australia)
- Delft University of Technology (Netherlands)
- University of Arizona
- Shell (Netherlands)

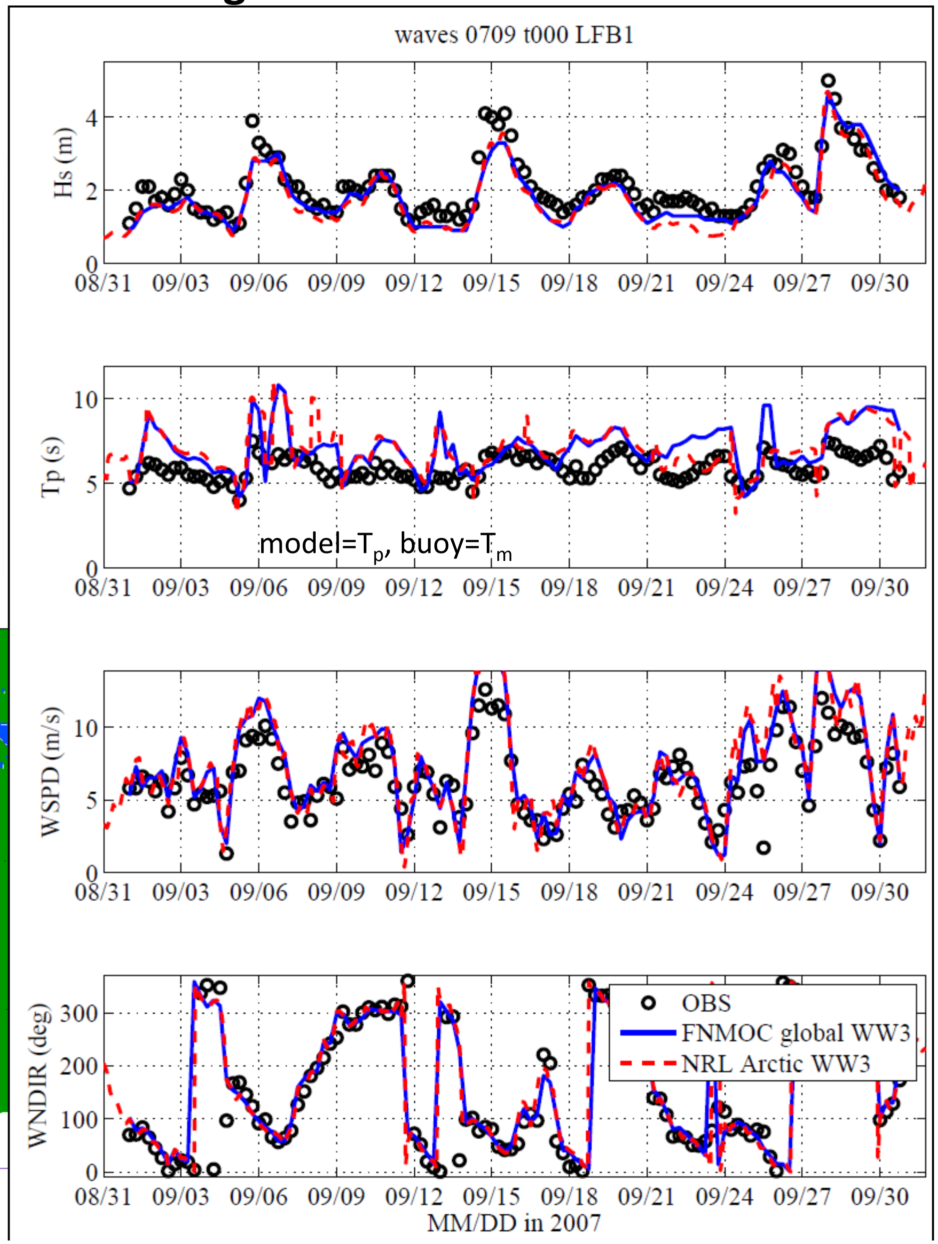
Specific focus on physics of waves models (WW3, SWAN)



1498 Small Scale Ocean Modeling: Regional Wave Modeling with WAVEWATCH III
Progress Demonstration

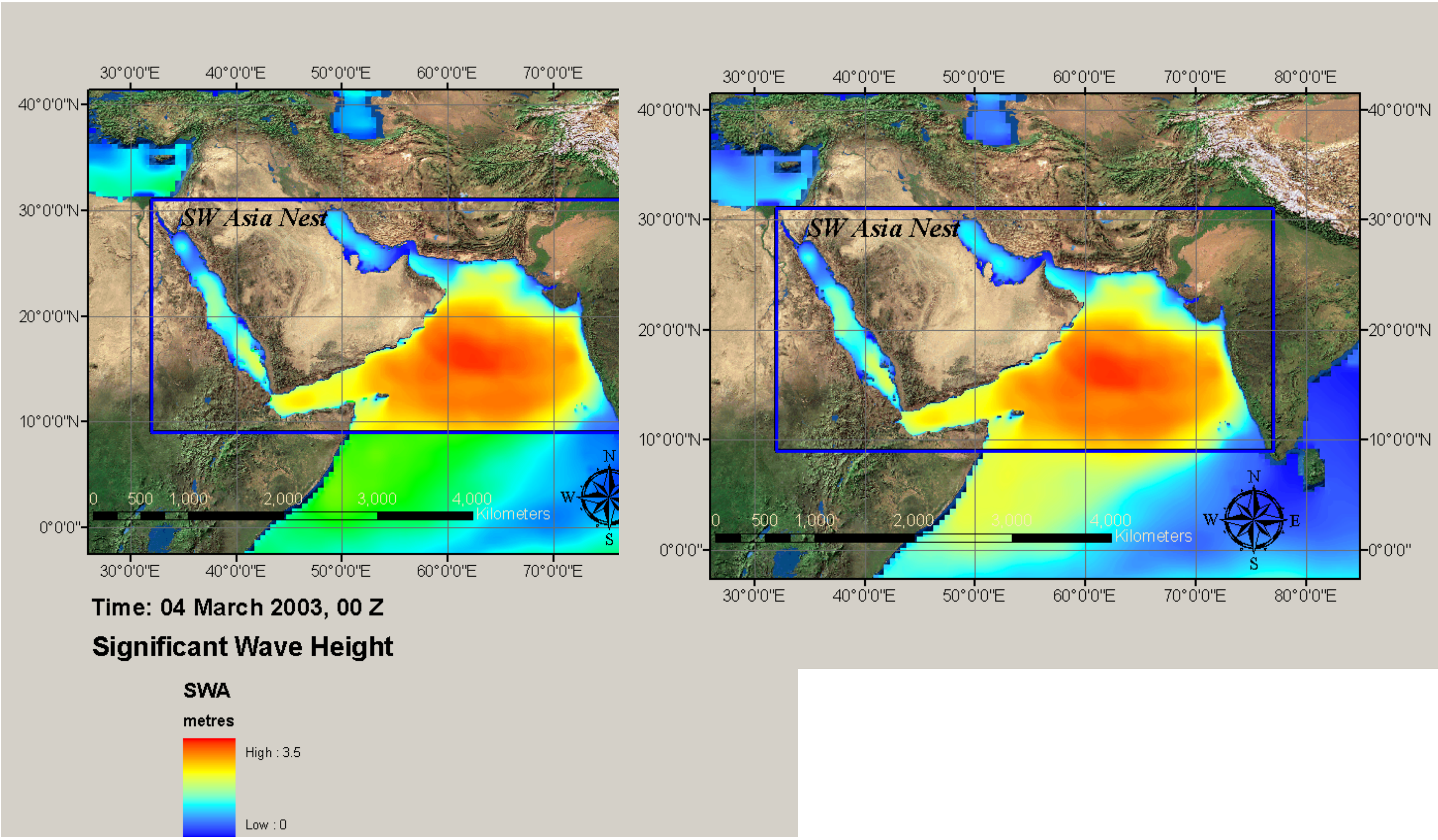






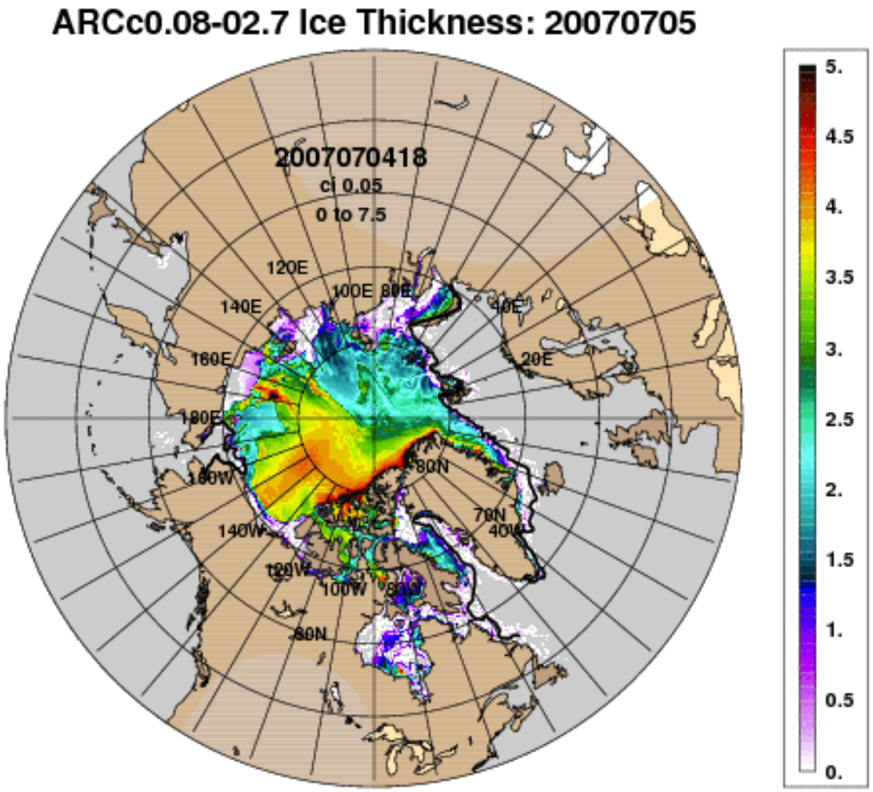
Shown: NRL model with wind speeds from NOGAPS and ice concentrations from PIPS vs. FNMOC global WW3 vs. buoy observations (Barents Sea)

1498 Small Scale Ocean Modeling: Regional Wave Modeling with WAVEWATCH III
Progress Demonstration, Slide 2 of 5



ESPC Integration from Prior and Present Oceanography 6.2-6.4

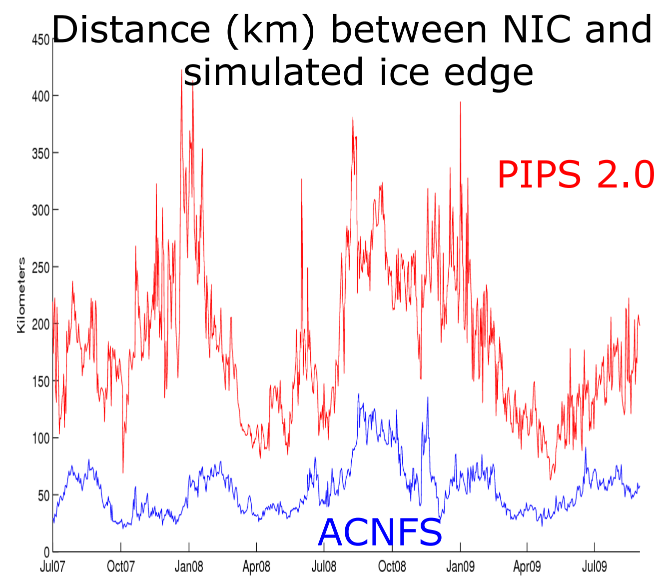
Arctic Cap, 1/12° HYCOM with CICE



Black line denotes independent ice edge analysis from the National Ice Center

- Heat loss changes not presently feeding back
- New implementation will advance feedback

Local feedback between ice and ocean
Not a global feedback

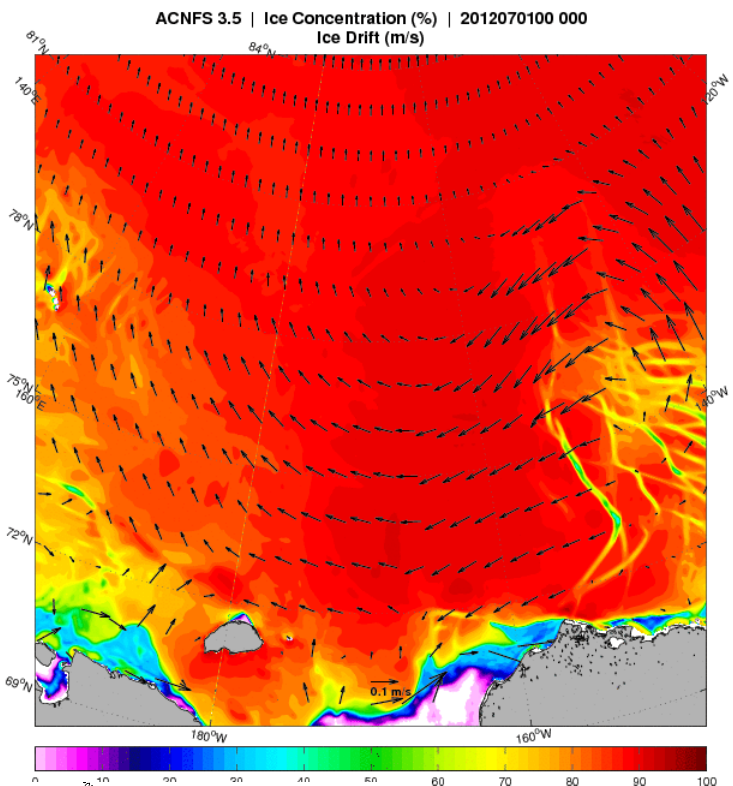


Mean ice edge error

PIPS 2.0	183 km
ACNFS	55 km

Long period modulation of internal tides from mesoscale over 30 to 60 days

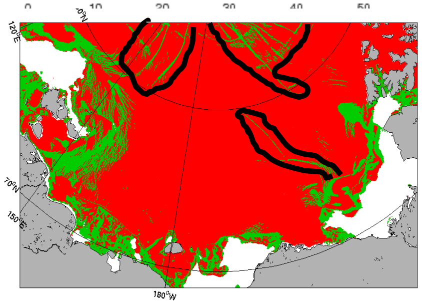
Ice Modeling Assimilation from Satellites



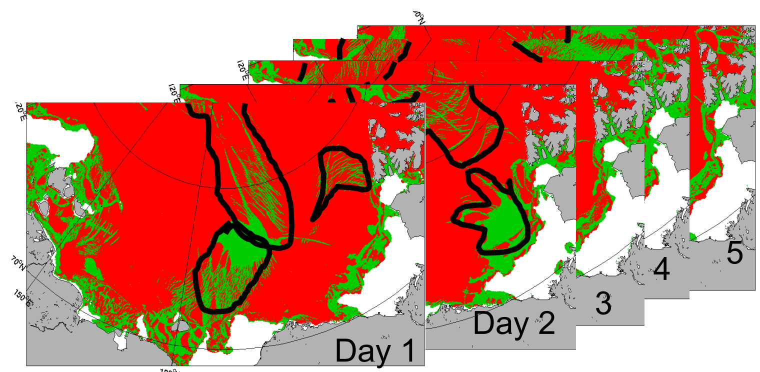
Develop an automated FLAP-like ACNFS product (nowcast/forecast) using ACNFS fields (divergence and openings).

Evaluate the ability to identify the same FLAP regions

- Establish thresholds
- Uncertainties
- Evaluate success in identifying orientations of FLAPs



Green = areas of possible leads

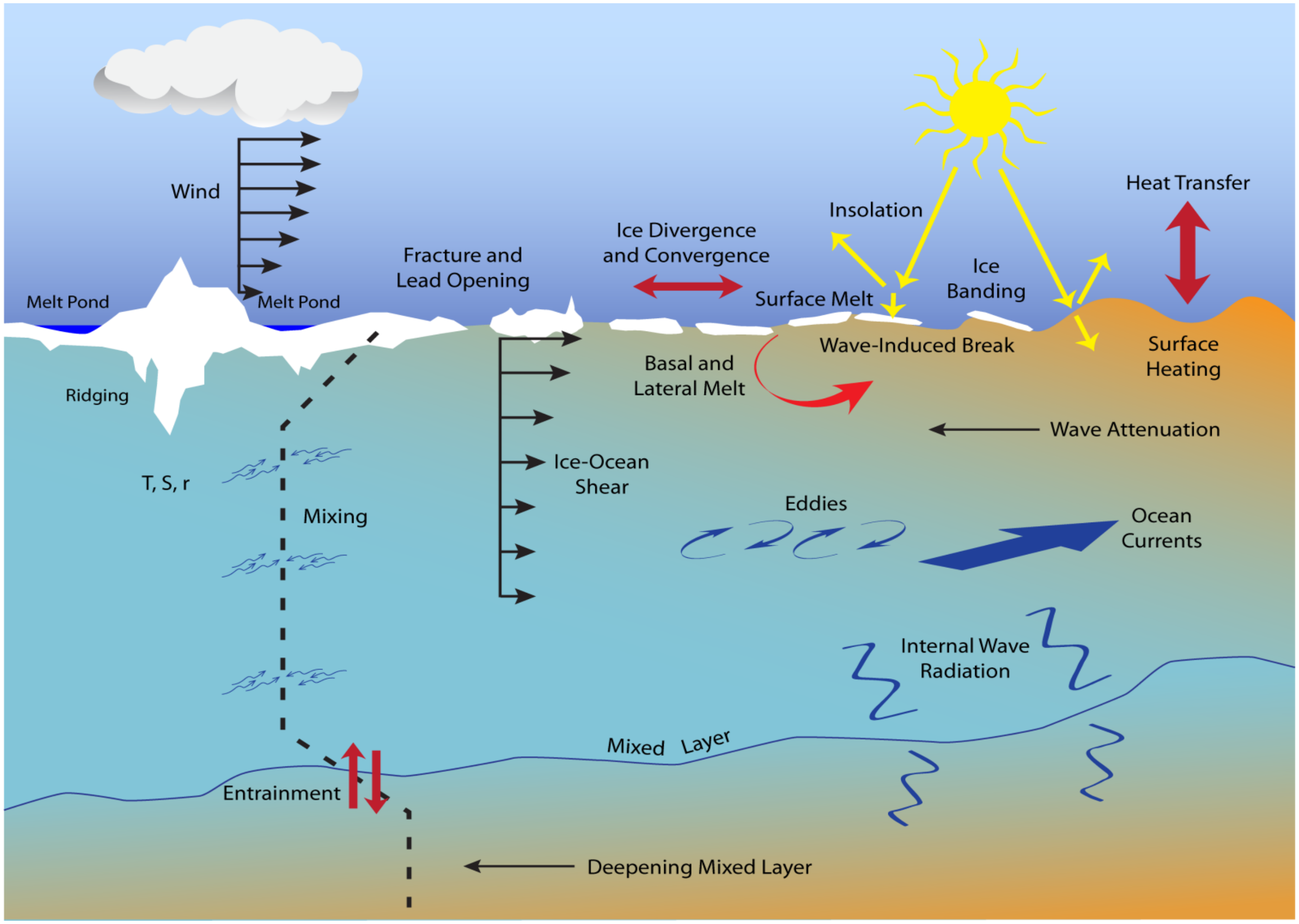


delayed Current Conditions

5-Day Forecasts

Coupled modeling

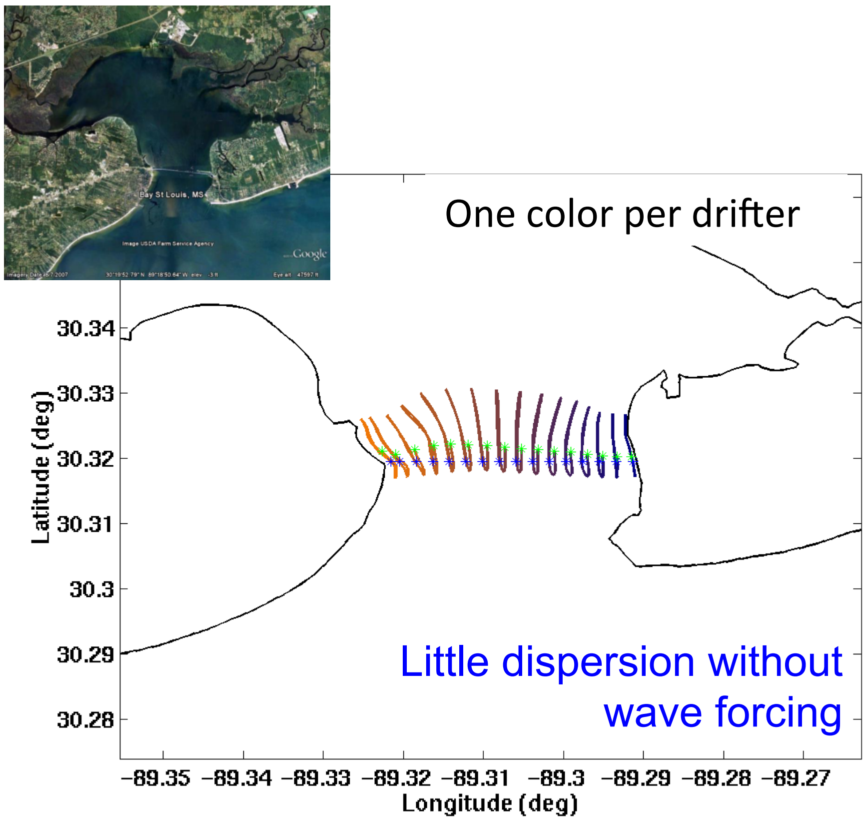
Coupled Physical Processes



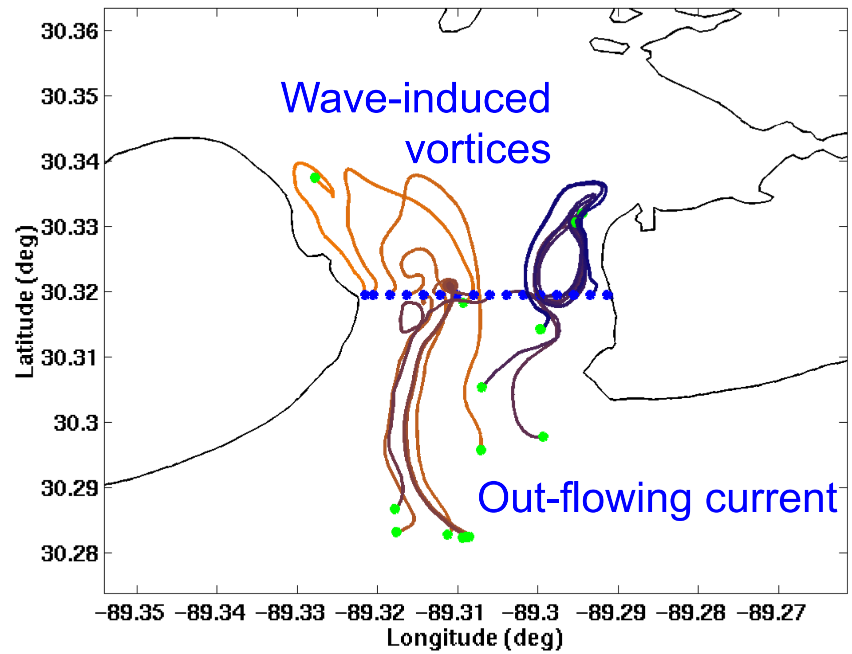
ONR MIZ Slide

Why is ocean-wave coupling so important?

Coupled Wave-Tide Circulation in Bay St. Louis, MS

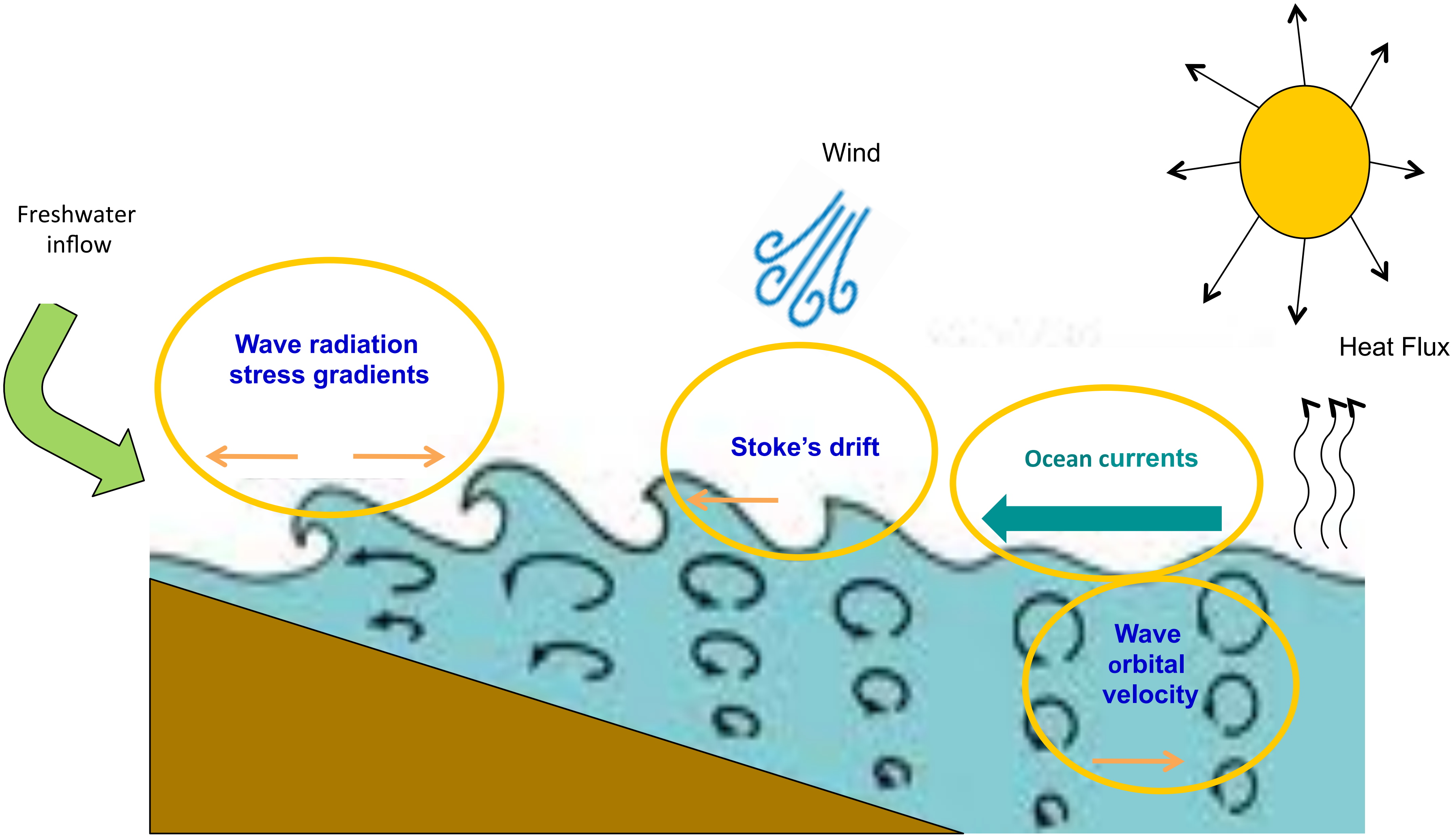


Tidal Forcing Only



Wave-Current Interaction

Coupled coastal ocean-wave dynamics



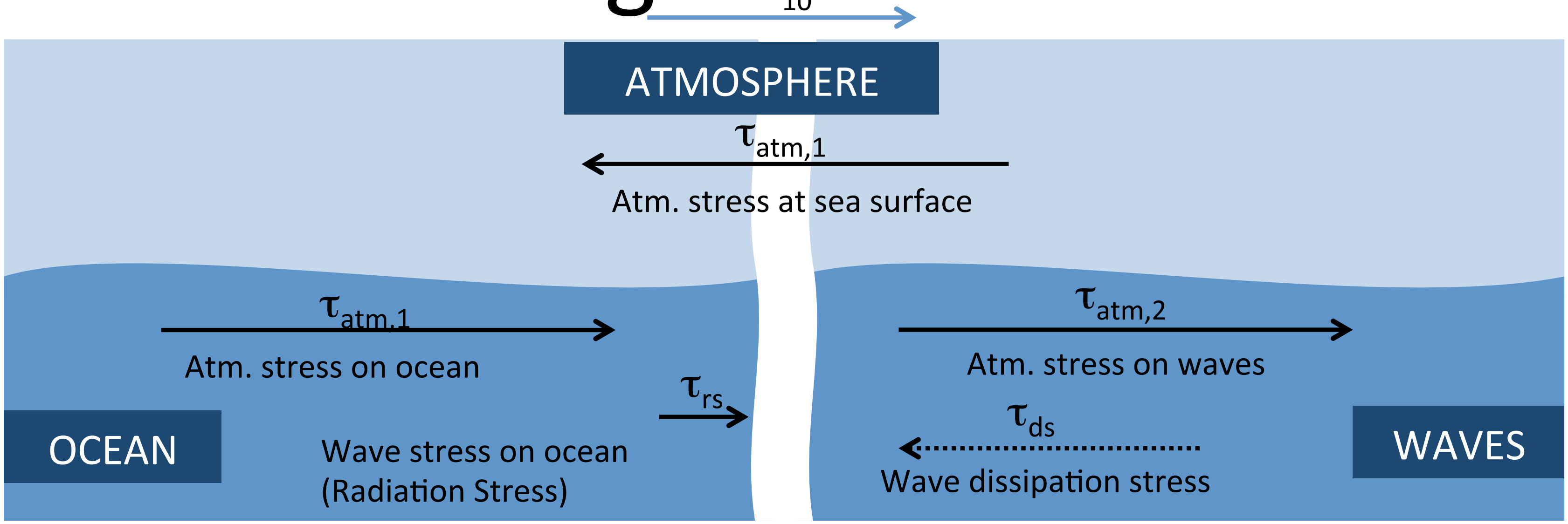
Momentum transfer in the ocean: Waves → Ocean

What happens in the real ocean:

- Growing seas: $\tau_{in} > \tau_{ds}$
  - Waves take some of the stress and advect it away (this is not available to the ocean currents locally)
- Fully-developed seas: $\tau_{in} = \tau_{ds}$
  - Currents get all of stress, though indirectly
- Swell (non-local waves): $\tau_{in} = \tau_{ds} = 0$
  - All about advection
- Surf breaking: $\tau_{in} < \tau_{ds}$
  - Waves release the stored momentum

τ_{in} = wave -supported normal wind stress (from wave model S_{in})
τ_{ds} = momentum flux via wave breaking (from wave model S_{ds})

Existing n U_{10} thod



Atmospheric model:

$D(\rho u_a)/Dt \approx -\nabla p + \partial \tau_{atm,1}/\partial z + \Phi_a$

Ocean Model:

$D(\rho u_w)/Dt \approx -\nabla p + \partial \tau_{atm,1}/\partial z + \nabla \tau_{rs} + \Phi_w$

Wave Model:

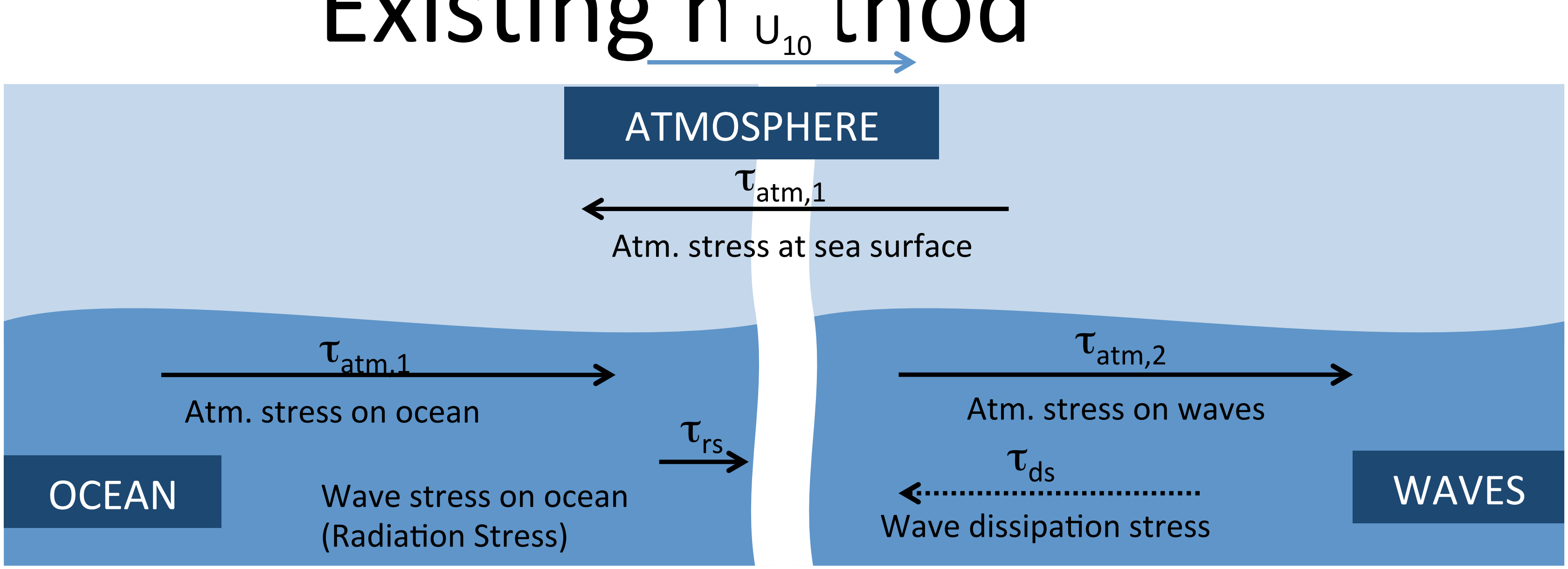
$\partial E/\partial t + (c_g + u_w)\nabla E \approx S_{in} + S_{ds}$

$\tau_{rs} \propto \nabla E$

$S_{in} \propto \tau_{atm,2}$

Coupling Terms

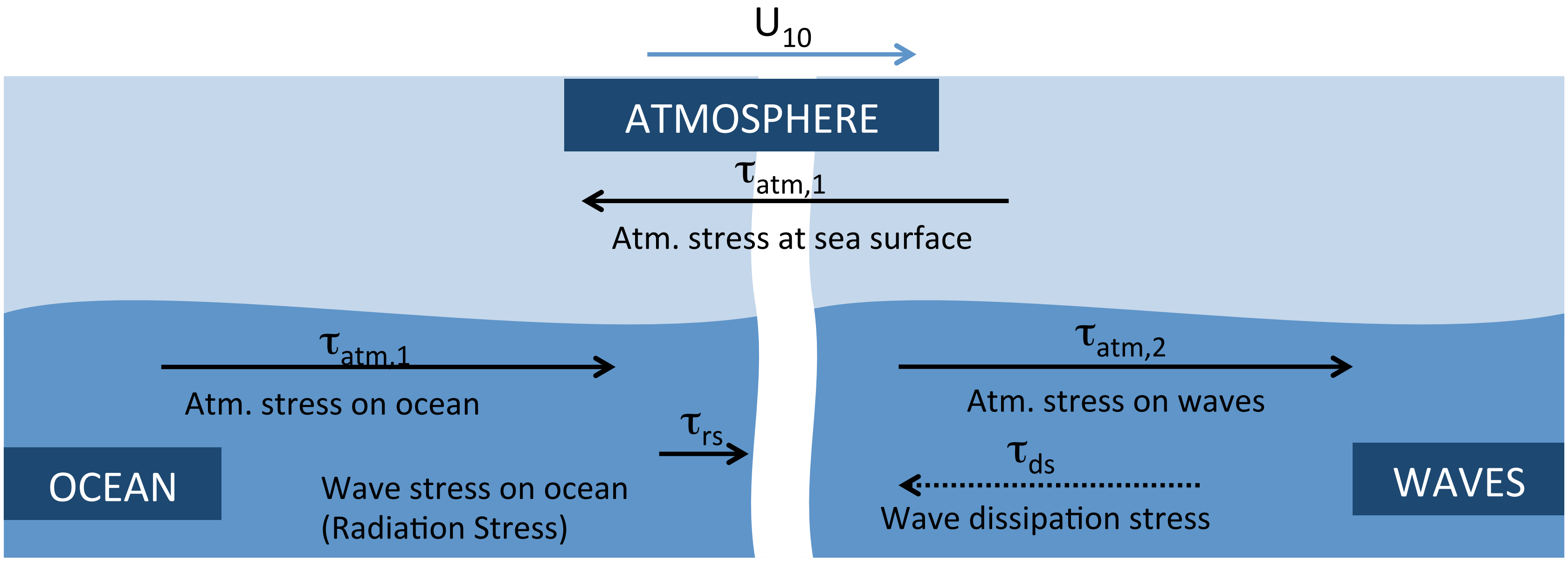
Existing n thod



Issues:

1. Atmospheric stress (wind drag parameterization) calculated in the wave model is different from the ocean or atmospheric model (
2. Total stress does not add up to zero
3. All of the momentum lost by waves due to breaking does not go to the ocean
4. Effect of waves on atmosphere uses only bulk (integrated) parameters

Issue #1: Unify wind stress parameterization



Total stress: $\tau_{atm} = \rho U_*^2$

U_* - friction velocity

U_{10} – 10m wind speed

<u>Atmospheric & Ocean model</u>:

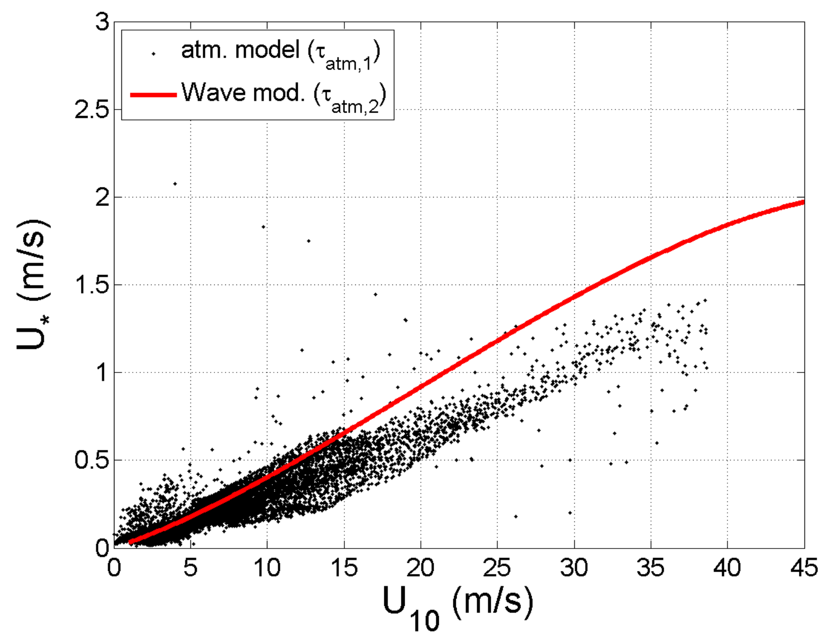
$U_* = f(U_{10}, \textit{roughness len., stability par.})$

(based on similarity theory)

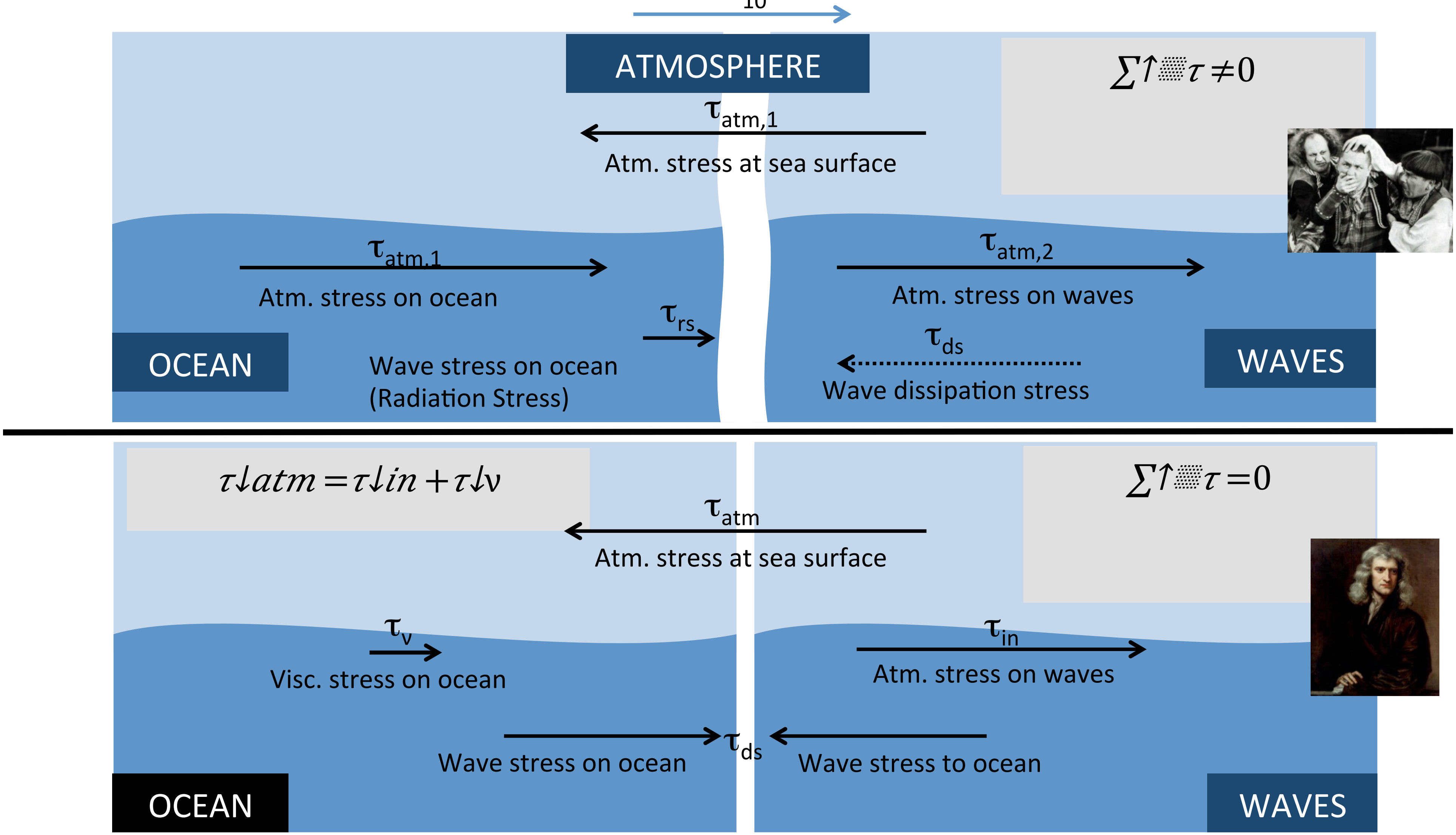
<u>Wave model</u>:

$U_* = f(U_{10})$

(empirical equation based on field data)

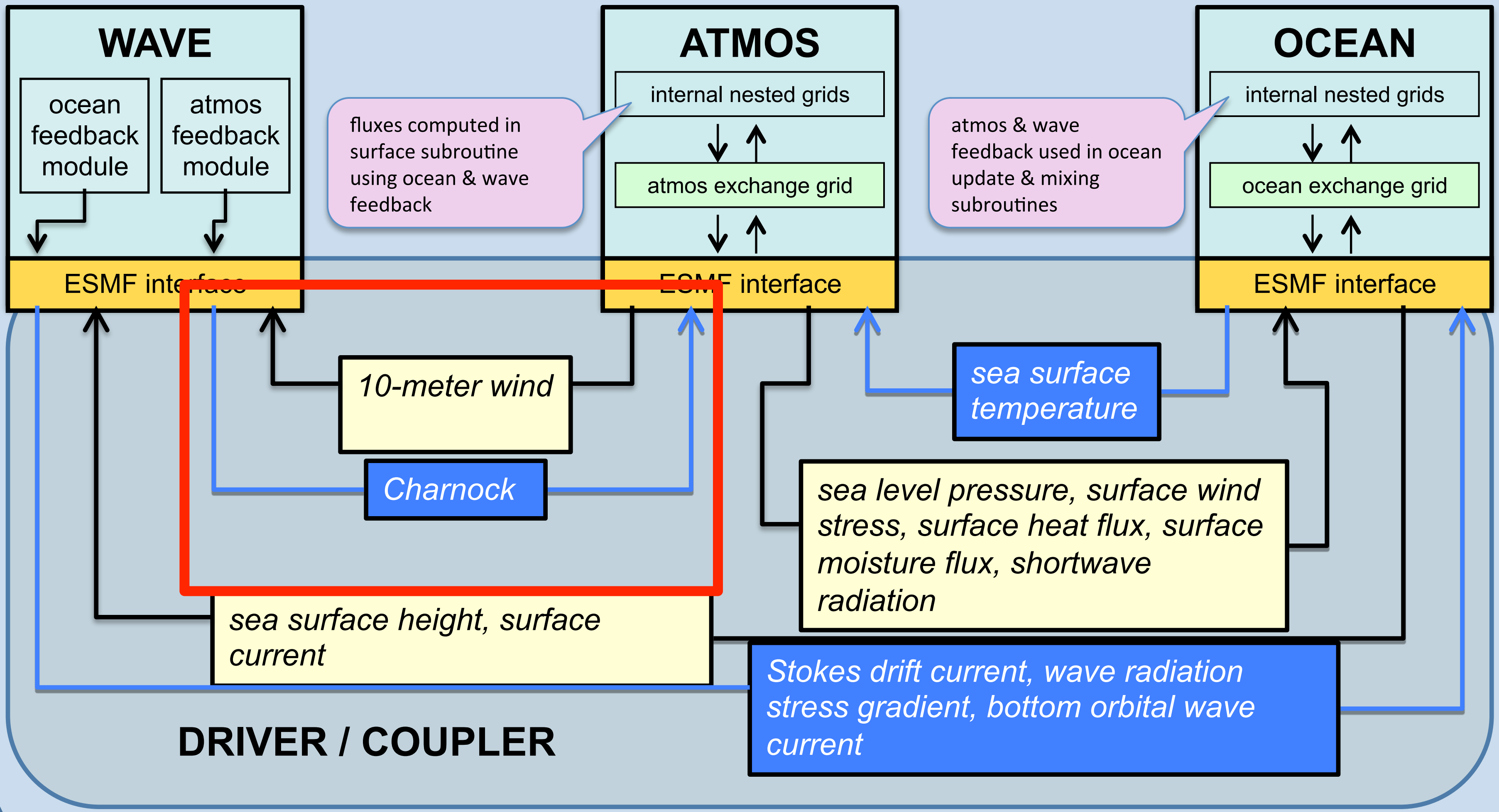


Issue #2: Balance [illegible]ess transfers



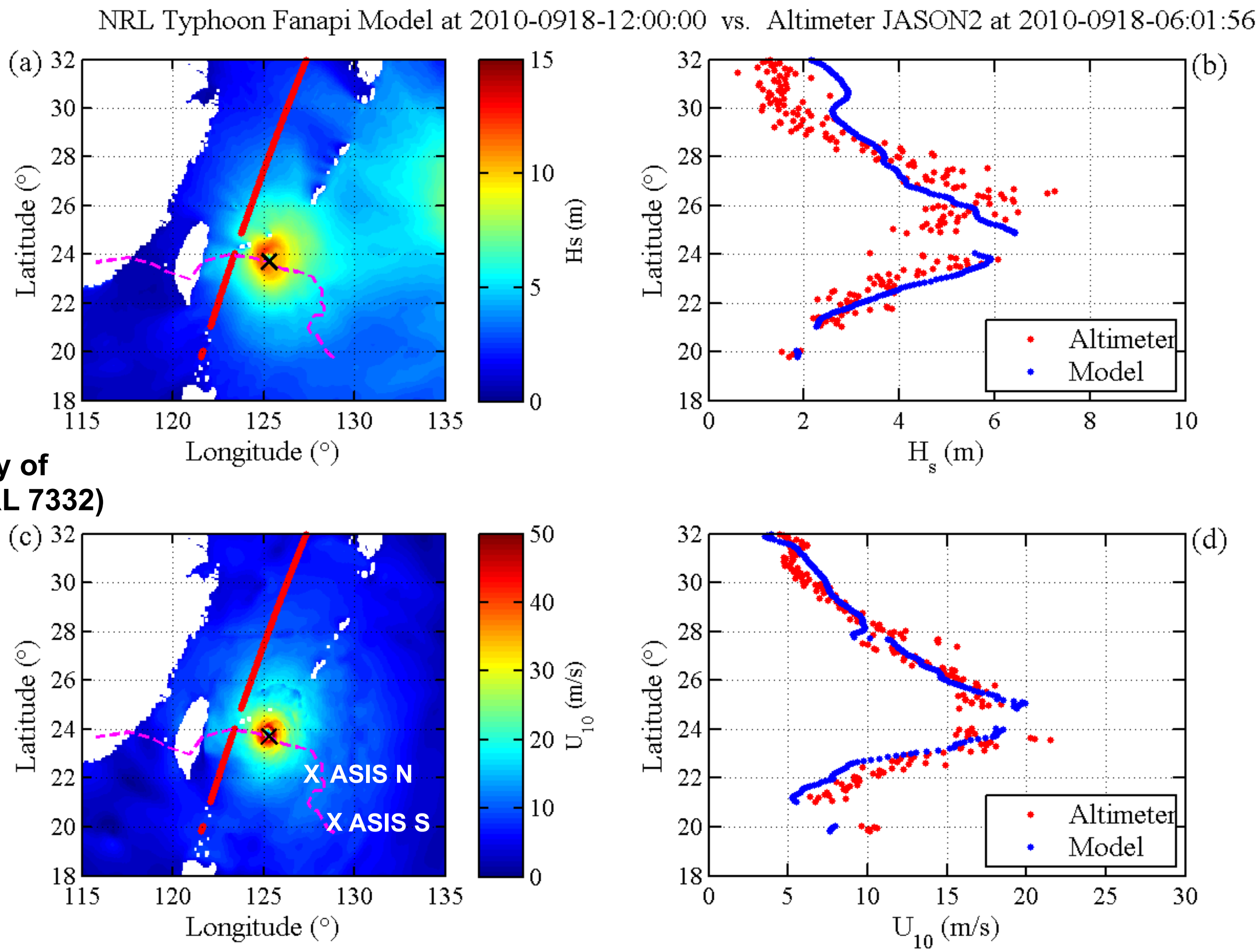
QUESTION: When/where do waves release momentum to ocean?

COAMPS Coupling Interface



Chen *et al.* 2011 (NRL Review)

Test Case 2: Fanapi Altimeter Wave/Wind Comparisons (model adjusted +6 hours)

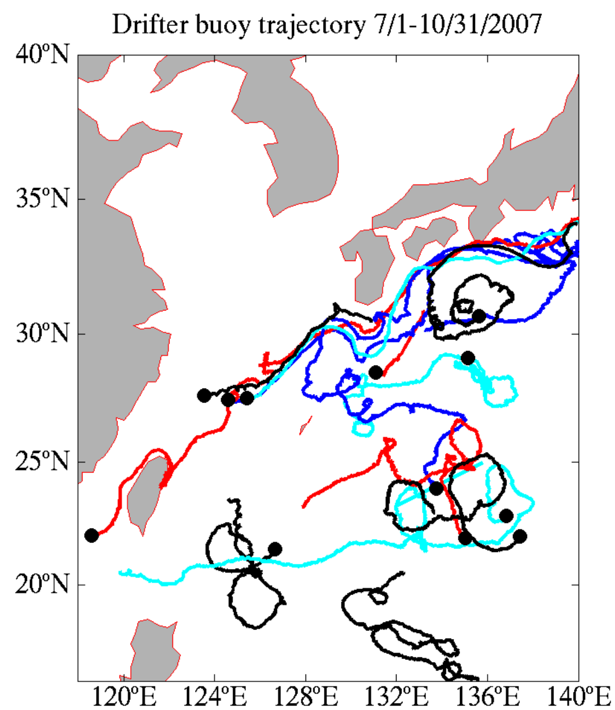


Figures courtesy of David Wang (NRL 7332)

- **COAMPS sig. wave height and wind forecast compare well with altimeter**
- **Max of 6 m significant wave height west of Fanapi**

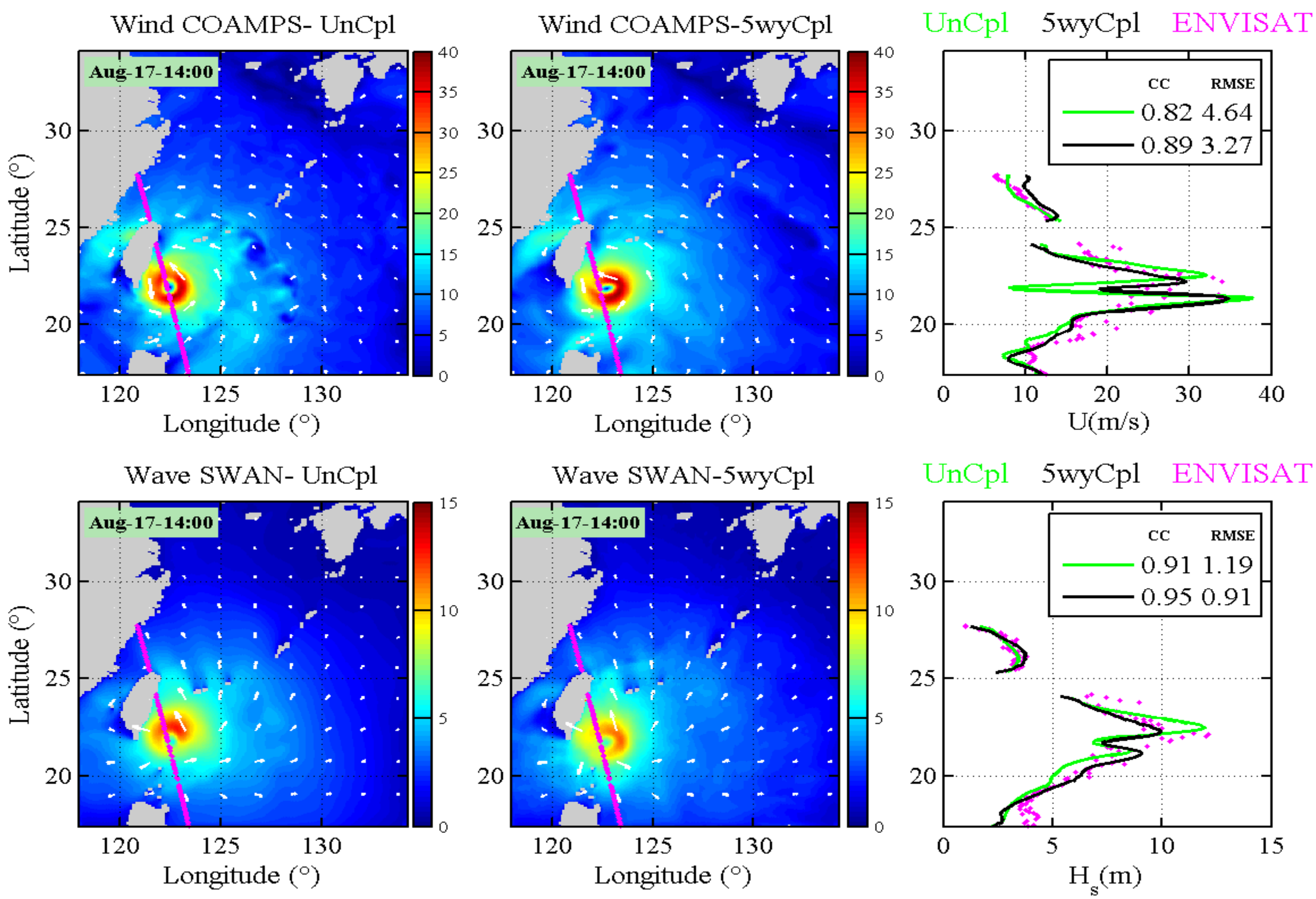
Drifter Analysis

- Model currents validated against Argo satellite-tracking Lagrangian drifters
- 6-hr kriged surface currents from NOAA/AOML/DAC database

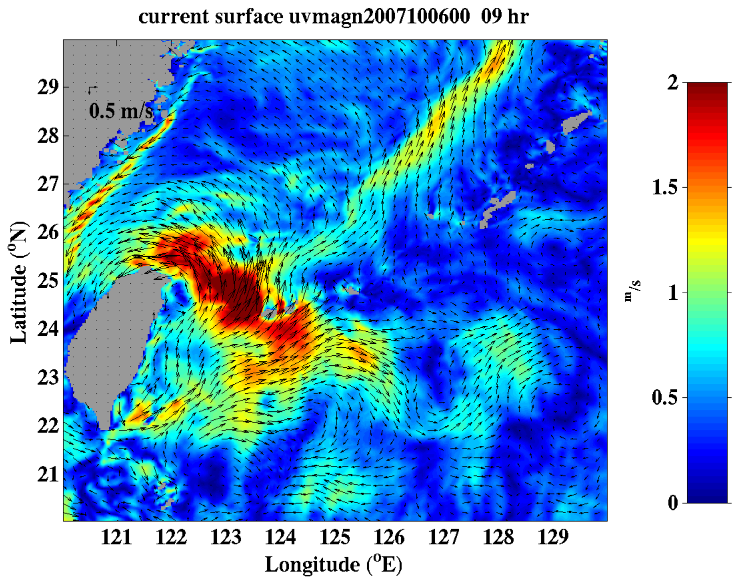


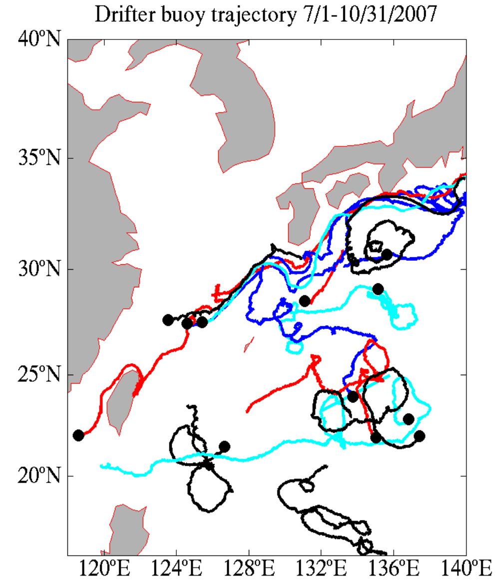
	Uncoupled	Coupled case
Mean separation (km)	13.16	13.13
Standard deviation	9.36	9.70

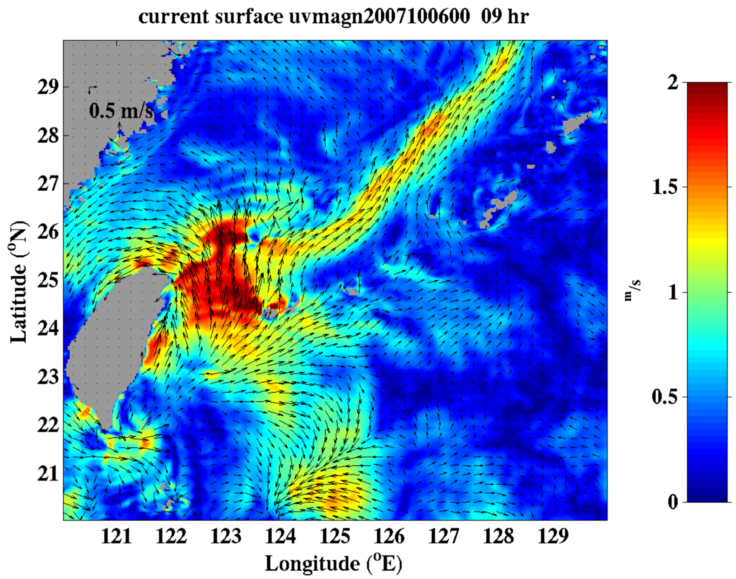
Wind and Wave Validation



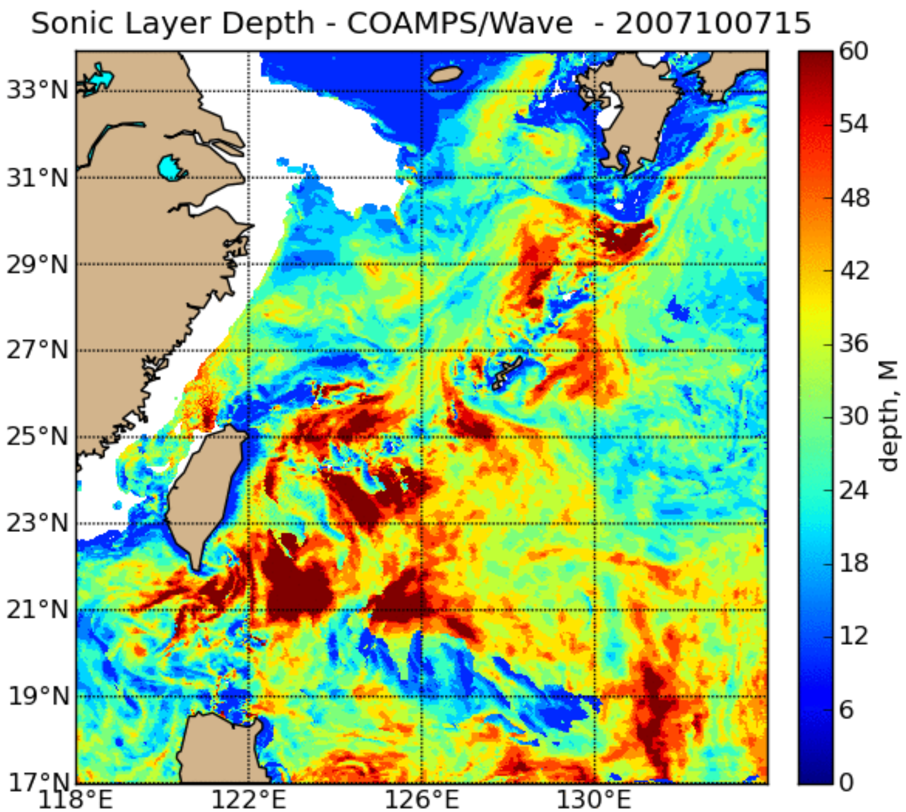
Current Velocity Comparison

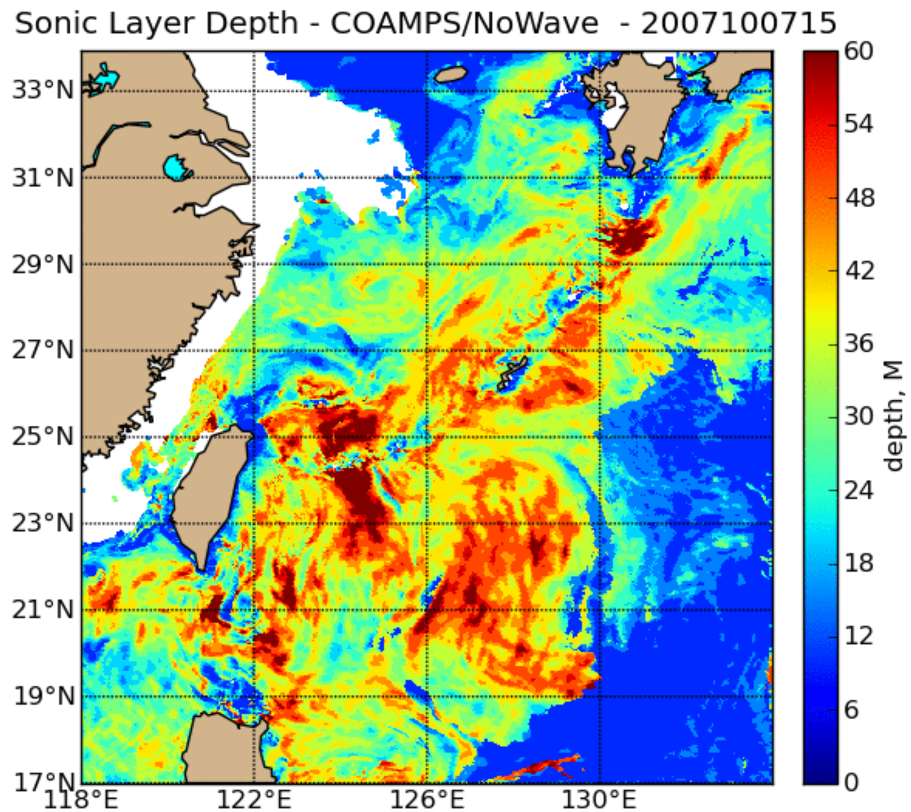




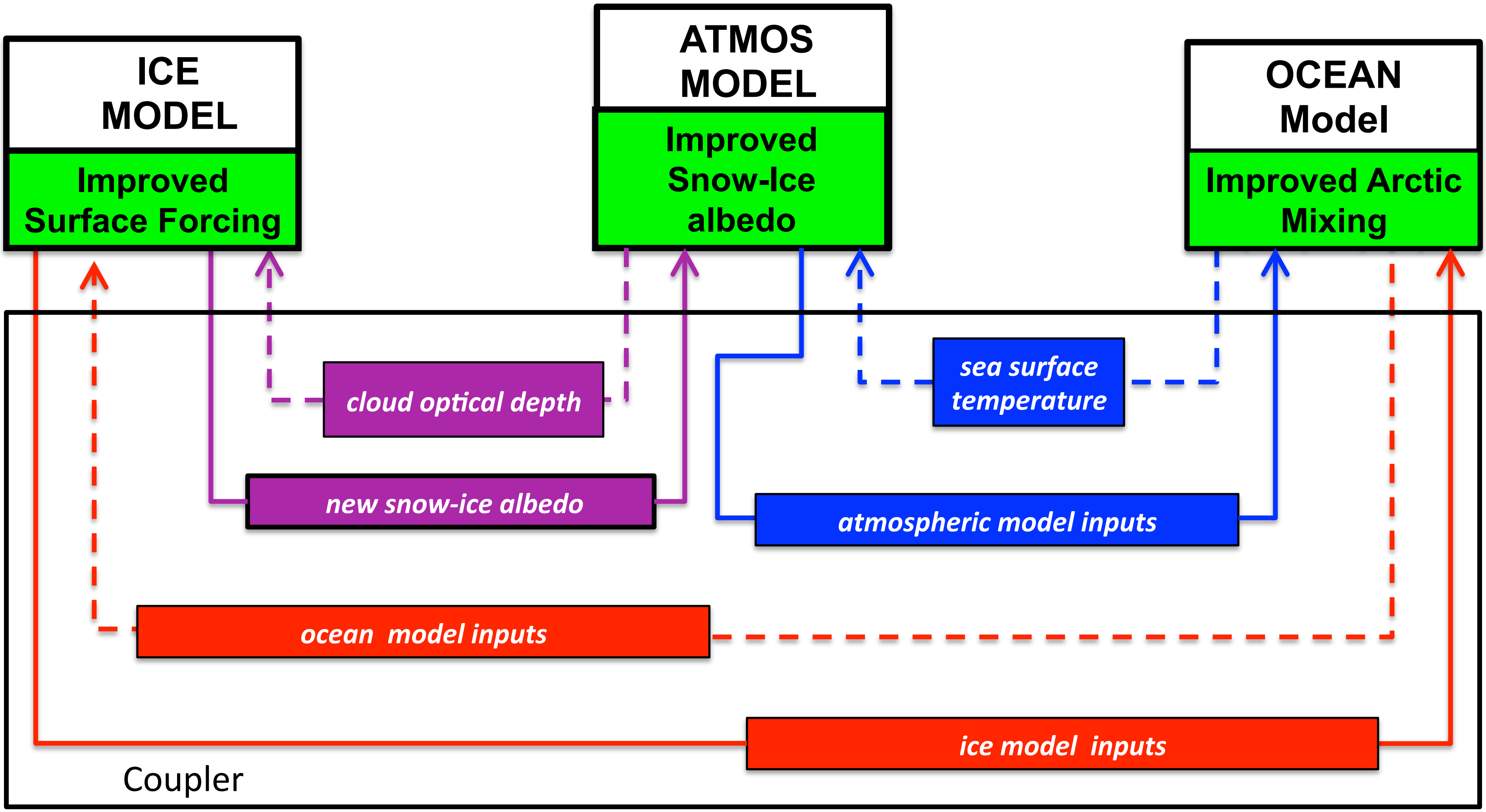


SLD deepening due to wave coupling

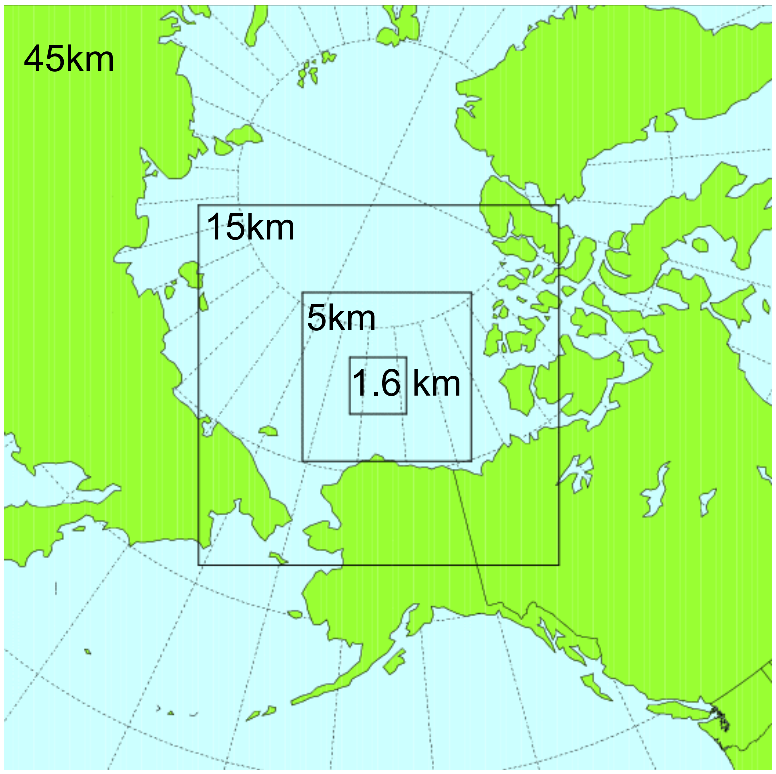




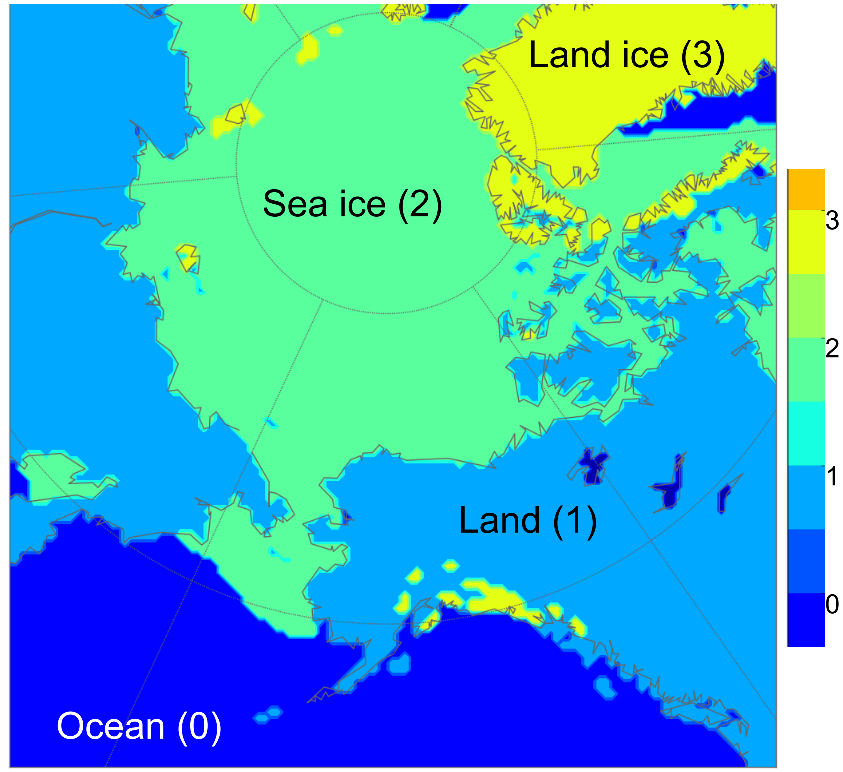
Proposed Ice-Ocean-Air Coupling



Preliminary Experiments



Model Domain



COAMPS Land-sea Mask Index

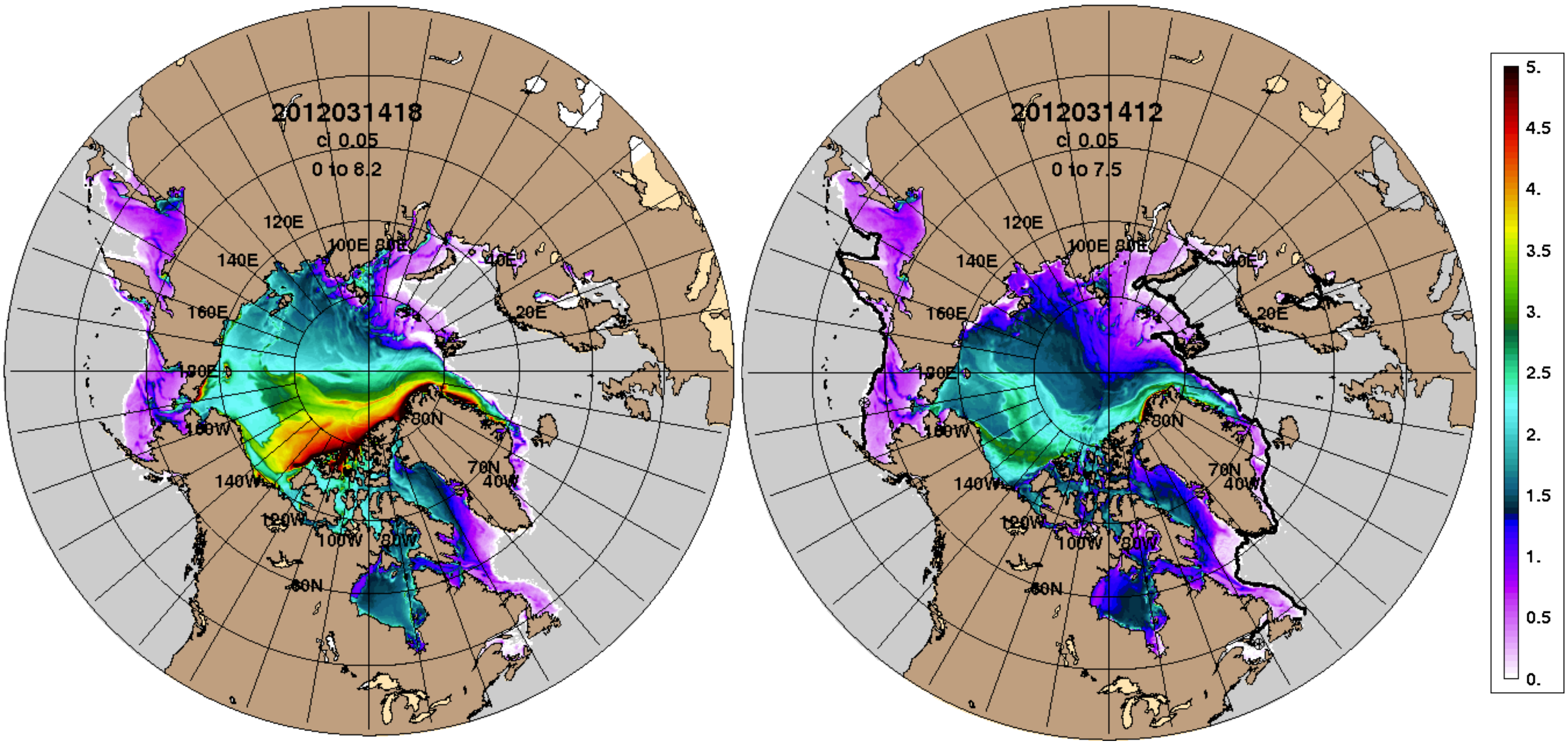
- The model domain setup is flexible; it is intended for future input from the relocatable regional sea ice model.
- The land-sea mask index is dynamic because sea ice fields constantly change in an air-sea ice coupled system.

HYCOM/CICE Improvements

Ice thickness (m) – 15 Mar 2012

Pre-operational ACNFS

New GOFS 3.05 hindcast



Black line is the independent NIC ice edge analysis

Overall improvement in Arctic ice thicknesses

Ice Modeling Assimilation fr Satellites

Arctic Cap Nowcast/Forecast System (ACNFS)

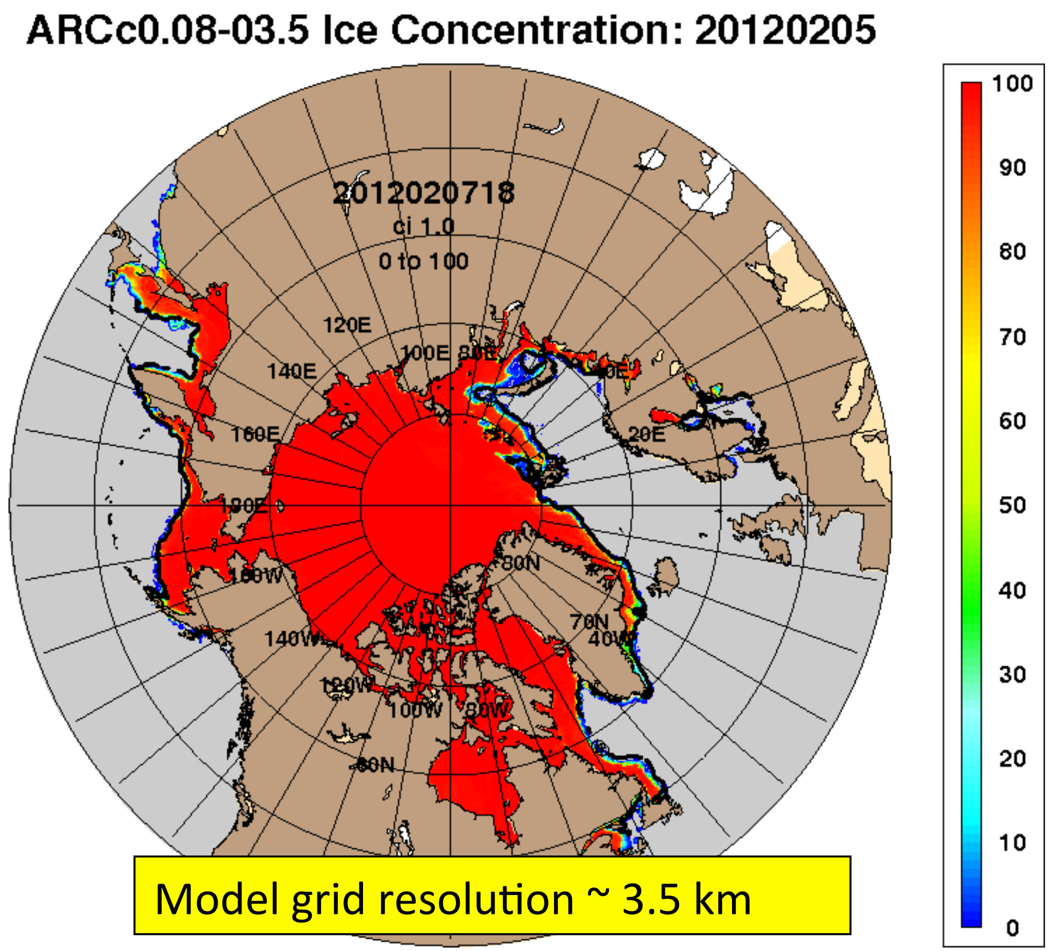
- ACNFS consists of 3 state-of-the-art components:

  Ice Model: Community Ice CodE (CICE)

  Ocean Model: HYbrid Coordinate Ocean Model (HYCOM)

  Data assimilation: Navy Coupled Ocean Data Assimilation (NCODA)

- OPTEST Final Report completed by NIC – Aug 2012
- Presently only DMSP SSMIS ice concentration (25 km resolution) is assimilated into CICE
- Mis-match in resolution between observations and model grid (25 vs 3.5 km resolution)



Black line is the independent ice edge location (NIC)

ESPC

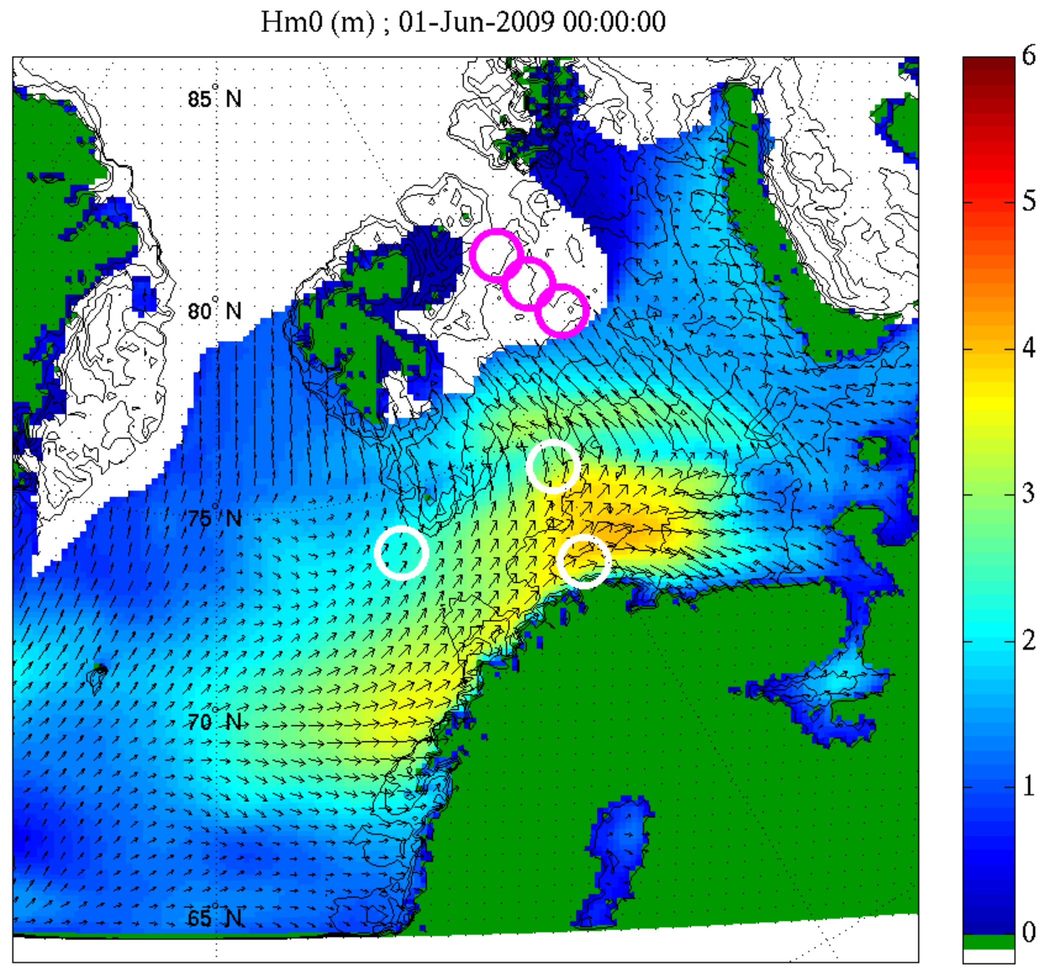
WAVEWATCH III curvilinear Arctic grid, implemented on FNMOC "beta" queue (Wittmann)

Completed in FY10

Inputs:

- PIPS
  - ice concentration
  - irregular grid
  - ~30 km
- NOGAPS
  - 10 m wind vectors
  - regular grid
  - 0.5°

Arctic grid resolution ~ 16 km



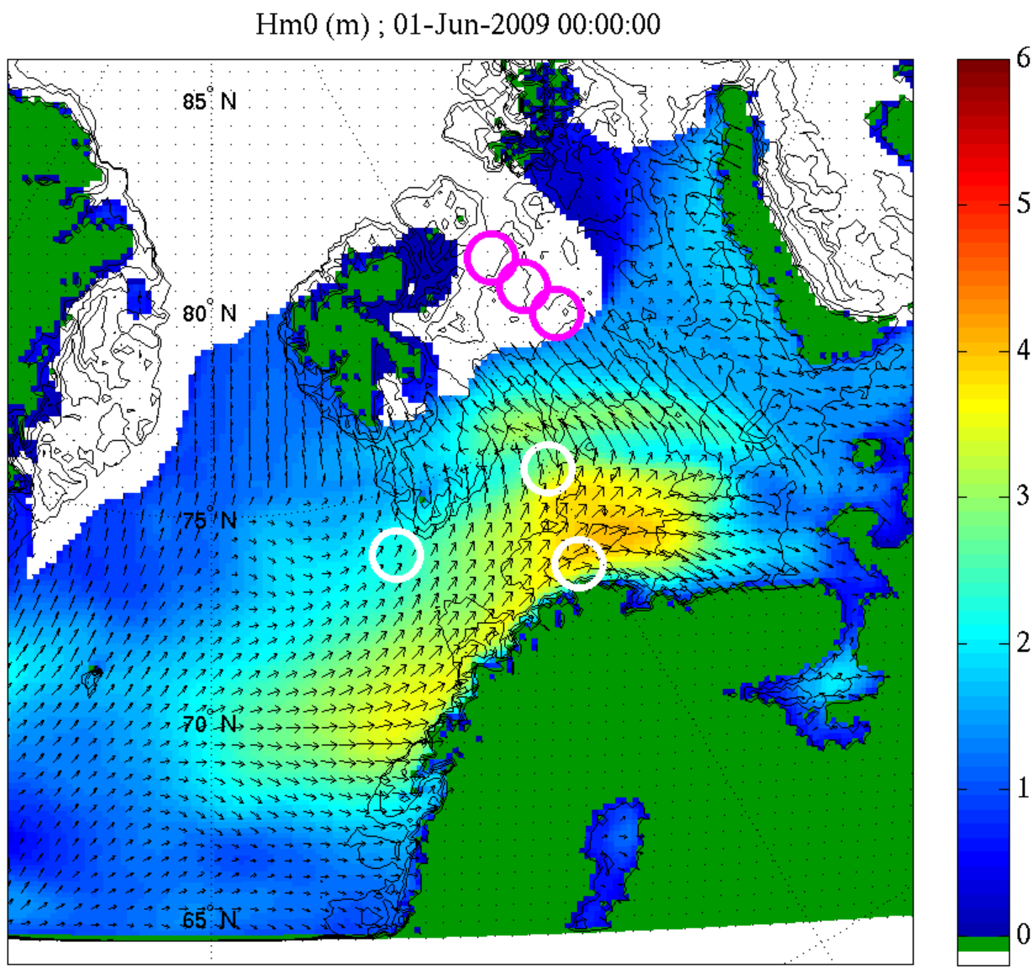
Rogers and Campbell (2009 report)

Animation: WW3 propagation and source term test on COAMPS Arctic grid (zoom on Nordic Seas). Waveheight in meters.

ESPC Integration from Prior and Present Oceanography 6.2-6.4

PIPS ice concentration affects nested wave model

Affect on waves does not feed back to circulation



Rogers and Campbell (2009 report)

Partial connects still lead to inconsistencies

Earth System Prediction Capability (ESPC)

Daniel P. Eleuterio, Ph.D.
Jessie C. Carman, Ph.D.

ESPC Overview

Introduction

- ESPC is an **interagency collaboration** (DoD, NOAA, DoE, NASA, NSF) to coordinate R2O for an extended range earth system analysis and prediction capability at the **weather to climate interface**.
- Common **prediction requirements and forecast model standards** enable agencies to improve leverage and collaboration.
- Cooperative five-year **demonstration projects** inform S&T and R&D efforts.
- Integrate of atmosphere-ocean-land-ice and space predictions into a **fully coupled global prediction** capability.

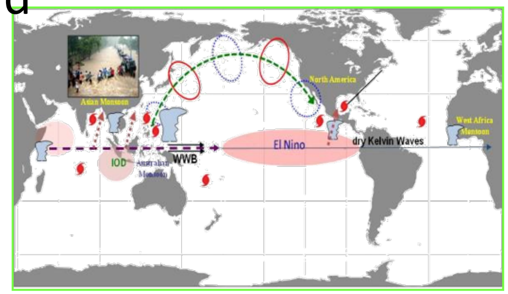
Sources of Predictability:

- Improve Model Physics through:
  - Coupled global modeling
  - Improved resolution & parameterization
- Improve Initial Value Problem through
  - Joint observational retrievals
  - New hybrid DA approaches
- Increase Forecast Information through
  - Stochastic prediction and post-model processing
  - National Multi-model ensembles
  - Seamless prediction
- Increase System Resolution affordably through
  - Efficient Computational Architectures
  - Efficient Numerics/Discretization

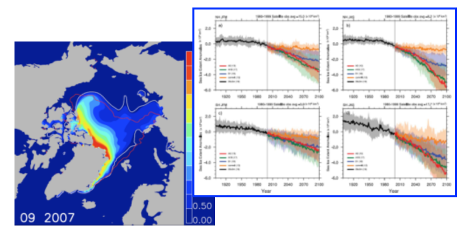
ESPC Demonstrations

(10 days to 1-2 years)

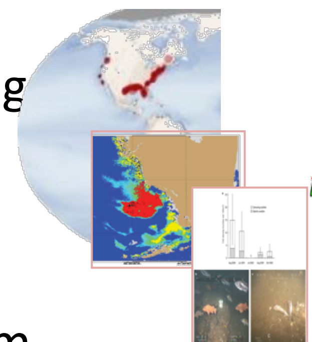
• Extreme Weather Events: Predictability of Blocking Events and Related High Impact Weather at Leads of 1-6 Weeks (Stan Benjamin, ESRL)



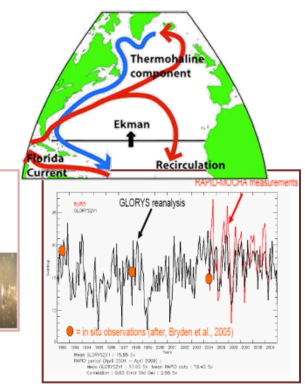
• Seasonal Tropical Cyclone Threat: Predictability of Tropical Cyclone Likelihood, Mean Track, and Intensity from Weekly to Seasonal Timescales (Melinda Peng, NRL MRY)



• Arctic Sea Ice Extent and Seasonal Ice Free Dates: Predictability from Weekly to Seasonal Timescales (Phil Jones, LANL)



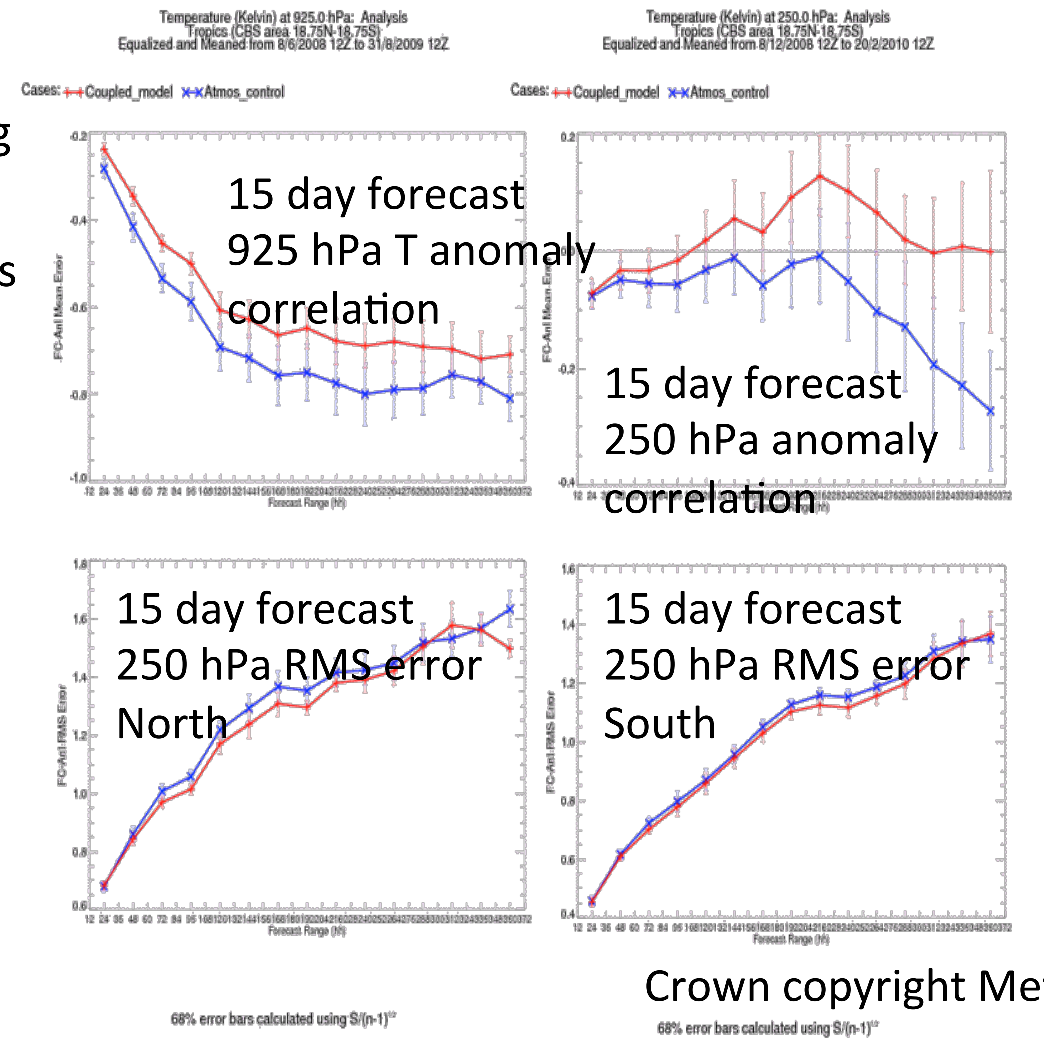
• Coastal Seas: Predictability of Circulation, Hypoxia, and Harmful Algal Blooms at Lead Times of 1-3 months (Greg Jacobs, NRL SSC)



• Open Ocean: Predictability of the Atlantic Meridional Overturning Circulation (AMOC) from Monthly to Decadal Timescales for Improved Weather and Climate Forecasts (Jim Richman, NRL SSC)

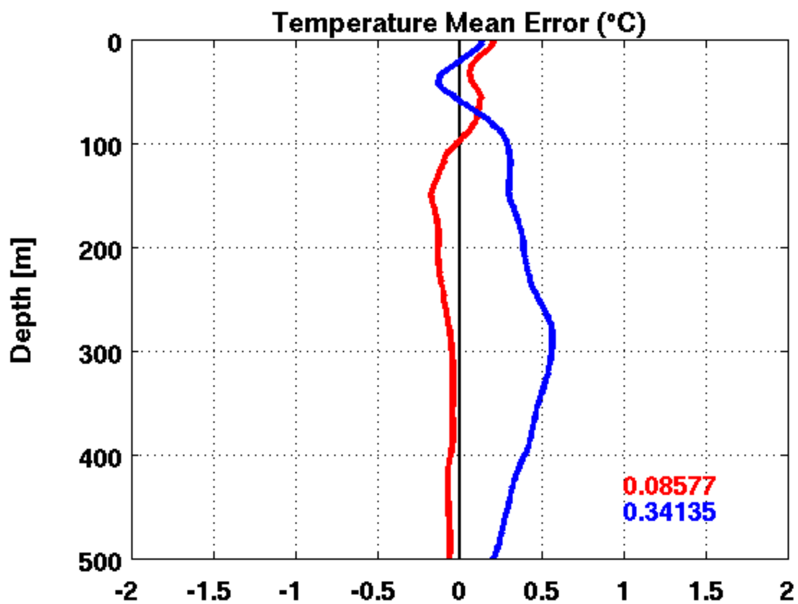
Global Coupled Models (ocn/atm/wav/ice/land)

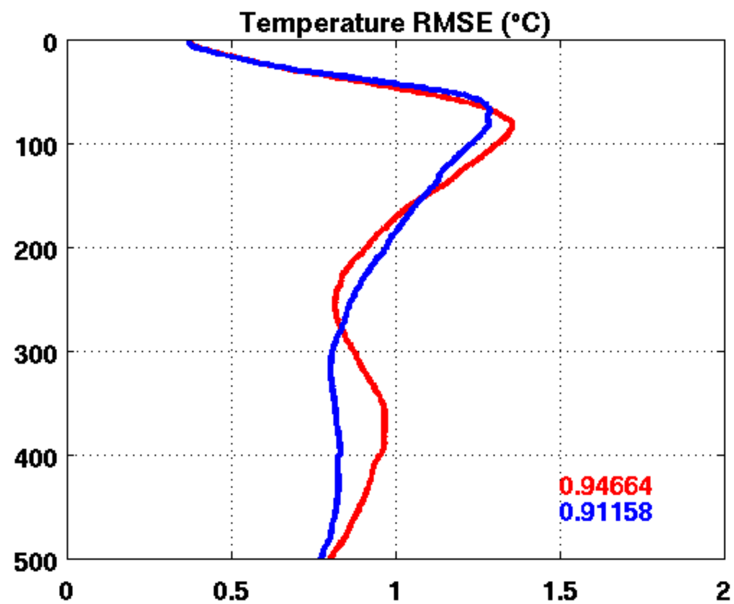
- Global air-sea coupled models were first implemented for climate applications but are increasingly being used at subseasonal to ISI timescales.
- Benefit is seen especially in the tropics in both atmospheric and oceanic verification with largely comparable skill in extra-tropics and some benefit still seen at higher latitudes from coupling in the Southern Hemisphere.
- At week two and beyond, coupling produces skill improvements comparable to doubling resolution in some research cases.



Assimilation

NCOM – Okinawa Trough
ISOP 1.0/NCODA vs. MODAS/NCODA

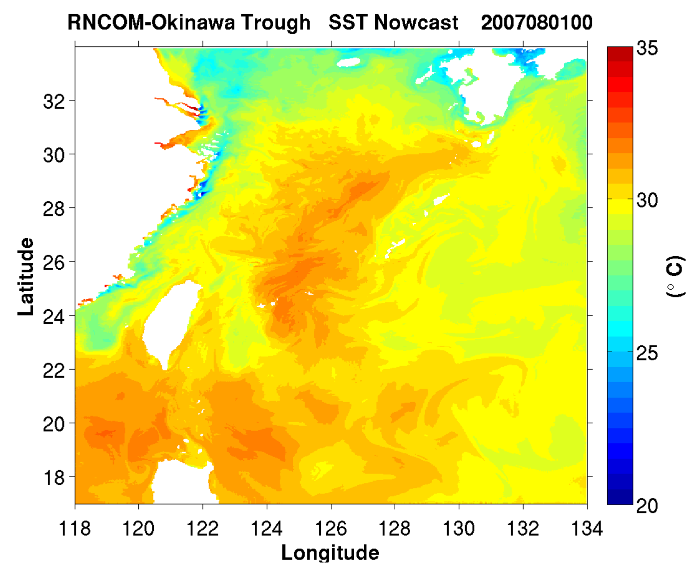




Okinawa Trough RELO NCOM on a 3 km grid using NCODA 3DVAR with ISOP 1.0 or MODAS synthetics.

Aug – Oct 2007; Comparison relative to 3586 independent profiles

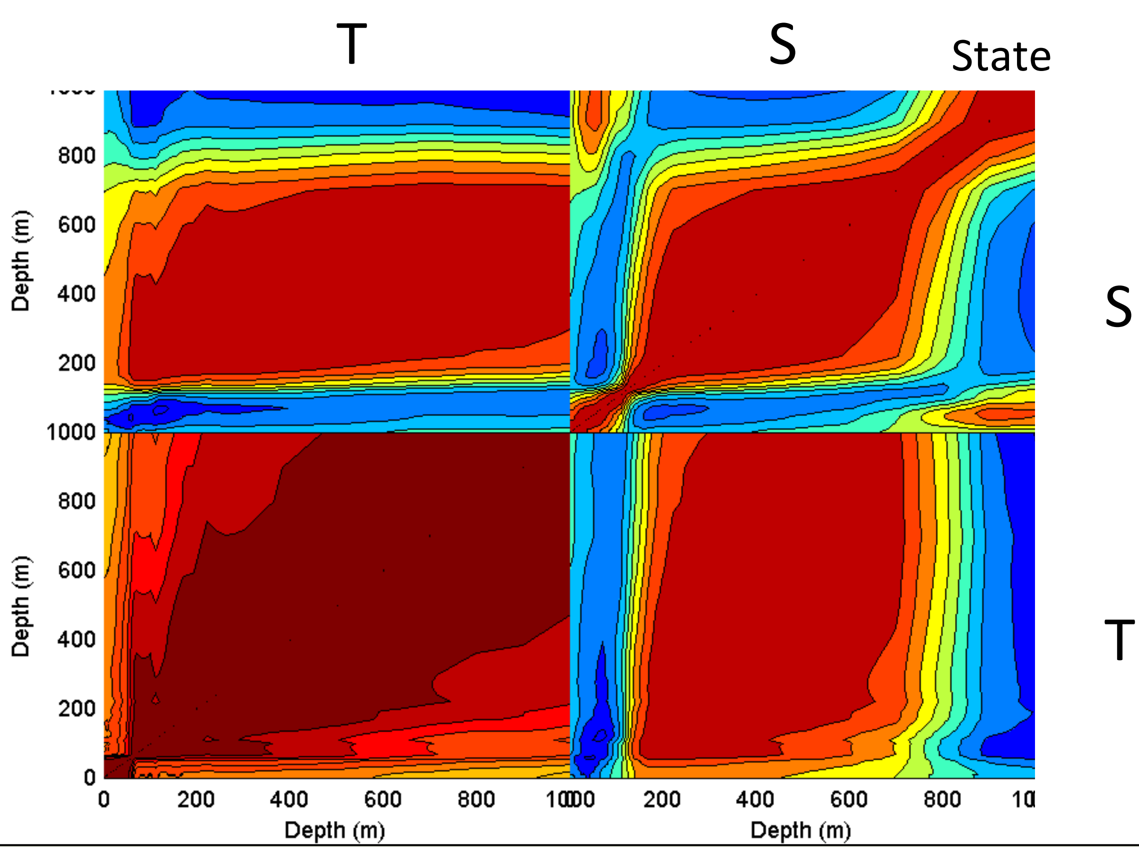
Using ISOP 1.0 leads to significantly smaller bias; similar RMS error



Velocity Assimilation

X=[■■T↓1 @: ⋯ S↓1 @: ⋯]

$\langle X X^T \rangle$ Cross covariance



Average Anomaly

Cross Correlation at one point (275°E, 24°N, February, Gulf of Mexico in Loop Current just off Cuba)

ISOP used as starting point for vertical relation of T&S to velocity

Velocity Assimilation

Variations in T&S result in displacements of geopotential (surfaces of constant pressure)

δ is a linearization of specific volume anomaly (linearized around mean state)

G is an integral over pressure of specific volume anomaly

$$Y = [\blacksquare\blacksquare\blacksquare T\downarrow 1 \quad @\vdots \ @\blacksquare T\downarrow N \quad @S\downarrow 1 \quad @$$

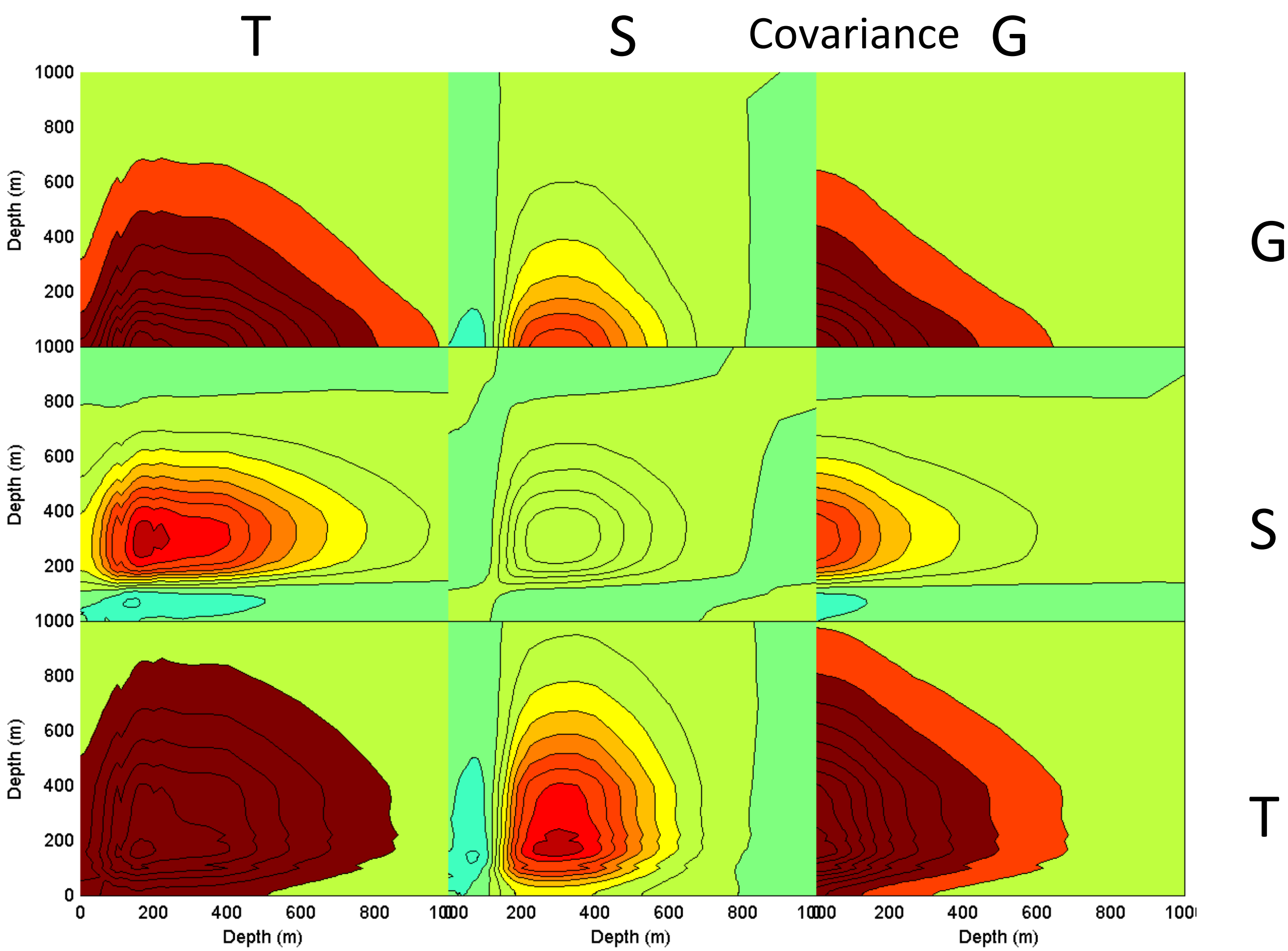
$$\varphi = G\delta[\blacksquare\blacksquare T\downarrow 1 \quad @\vdots \ @\blacksquare T\downarrow N \quad @S\downarrow 1 \quad @\blacksquare\vdots @S\downarrow N \quad]$$

Extend the T,S anomaly vector to include geopotential anomaly

$$B = \langle Y\, Y\uparrow T \rangle = [\blacksquare X\, X\uparrow T \ \& X\, X\uparrow T\, \delta\uparrow T\, G\uparrow T \ @G\uparrow T\, \delta\uparrow T\, X\uparrow T\, X \ \& \delta G X\, X\uparrow T\, G\uparrow T\, \delta\uparrow T \quad]$$

ISOP extended to include correlation to geopotential

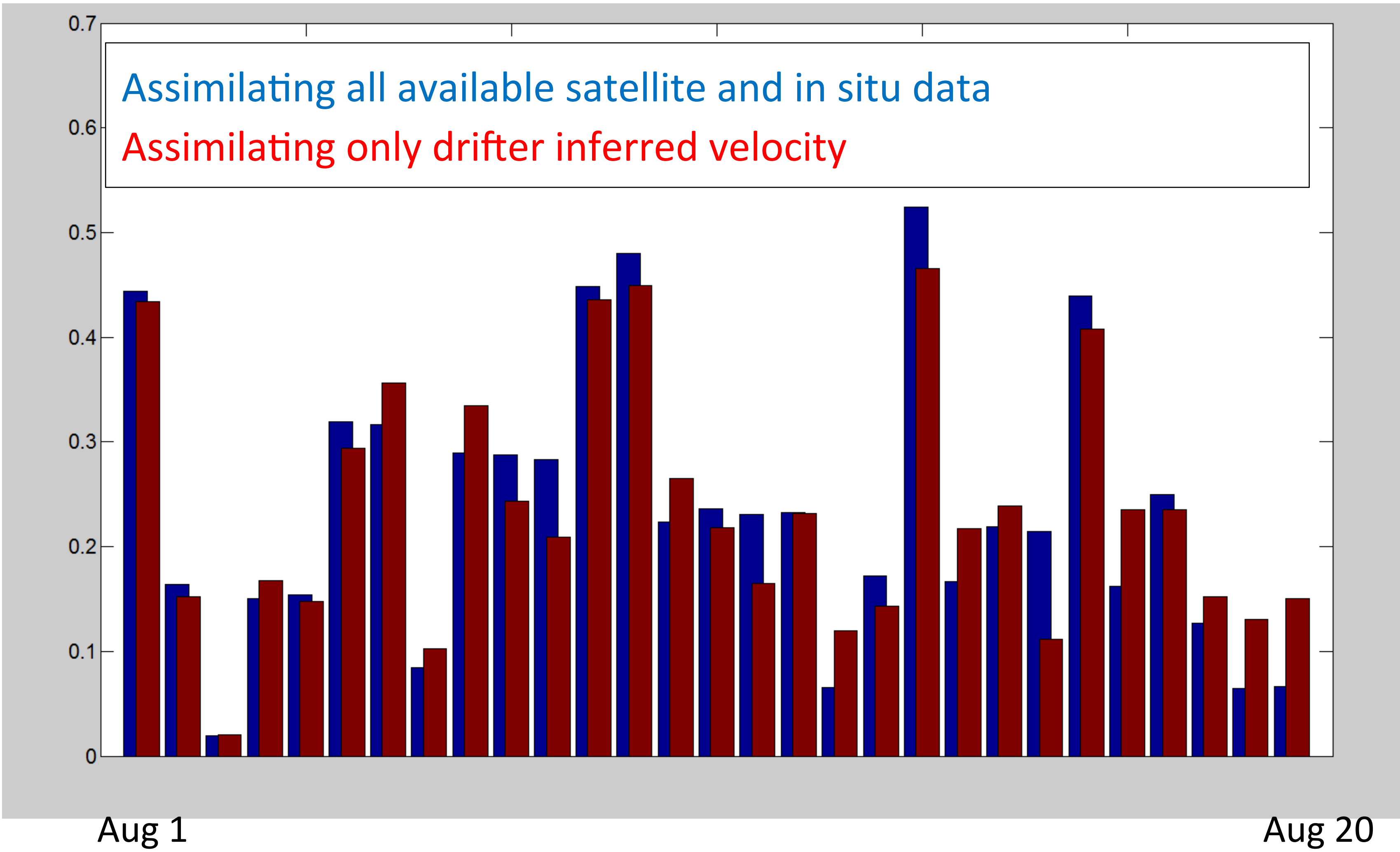
Velocity Assimilation



Cross Correlation February, 275°E, 24°N, Gulf of Mexico in Loop Current just off Cuba

Correlation is high throughout water column, covariance decreases with depth

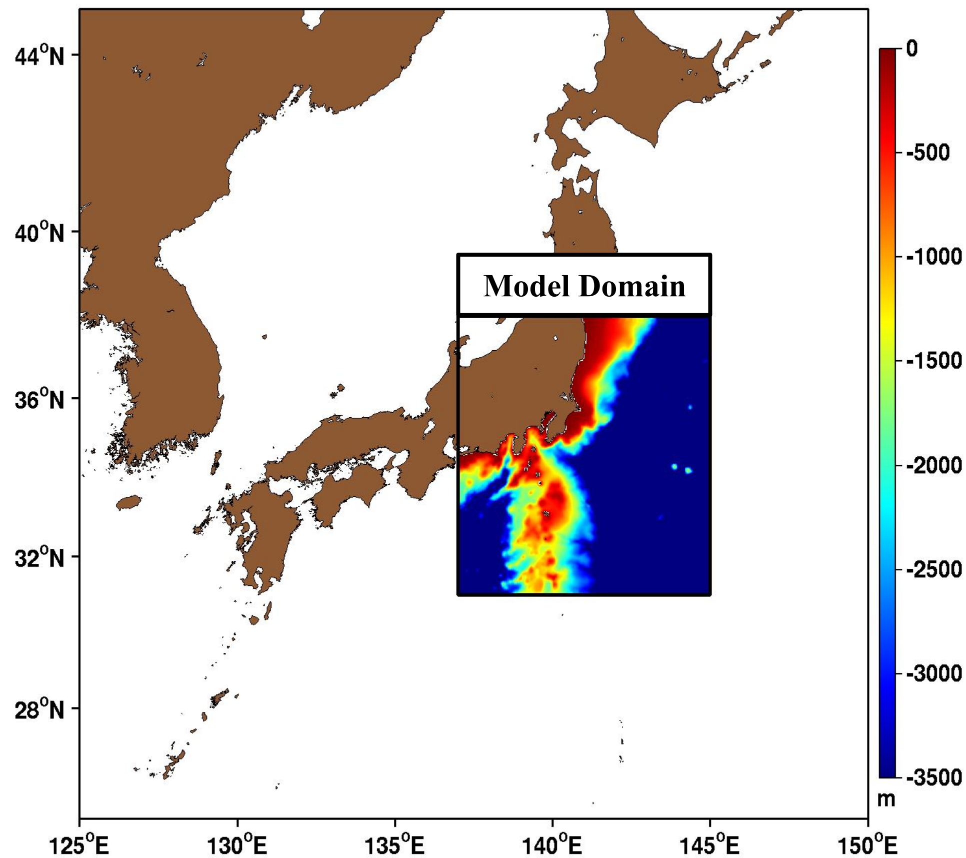
Velocity Assimilation



Velocity-only experiment out-performs traditional experiment

Multiscale 3DVAR
Simulated observations (3km)

- Navy Coastal Ocean Model (NCOM)
- 3km horizontal resolution
- 50 vertical levels
- Kuroshio Extension western boundary current
- MS-3DVAR assimilation system



Color plot: Bathymetry

Multiscale 3DVAR Formulation

Traditional 3DVAR Cost Function

$$J(\delta x) = \frac{1}{2}\delta x^T B^{-1}\delta x + \frac{1}{2}(H\delta x - d)^T R^{-1}(H\delta x - d)$$

$$d = y - Hx$$

First partition increment into large and small spatial scales :

$$\delta x = \delta x_L + \delta x_S$$

Large

$$J_L(\delta x_L) = \frac{1}{2}\delta x_L^T B_L{}^{-1}\delta x_L + \frac{1}{2}(H\delta x_L - d)^T (R + HB_s H^T)^{-1}(H\delta x_L - d)$$

Small

$$J_S(\delta x_S) = \frac{1}{2}\delta x_S^T B_S{}^{-1}\delta x_S + \frac{1}{2}(H\delta x_S - d)^T (R + HB_L H^T)^{-1}(H\delta x_S - d)$$

Li, Z., Chao, Y., McWilliams, J.C., Ide, K., and Farrara, J.D. 2013. A Multi-Scale Three-Dimensional Variational Data Assimilation Scheme and Its Application to the Coastal Oceans. *Submitted to Quart. J. Roy. Meteorol. Soc.*

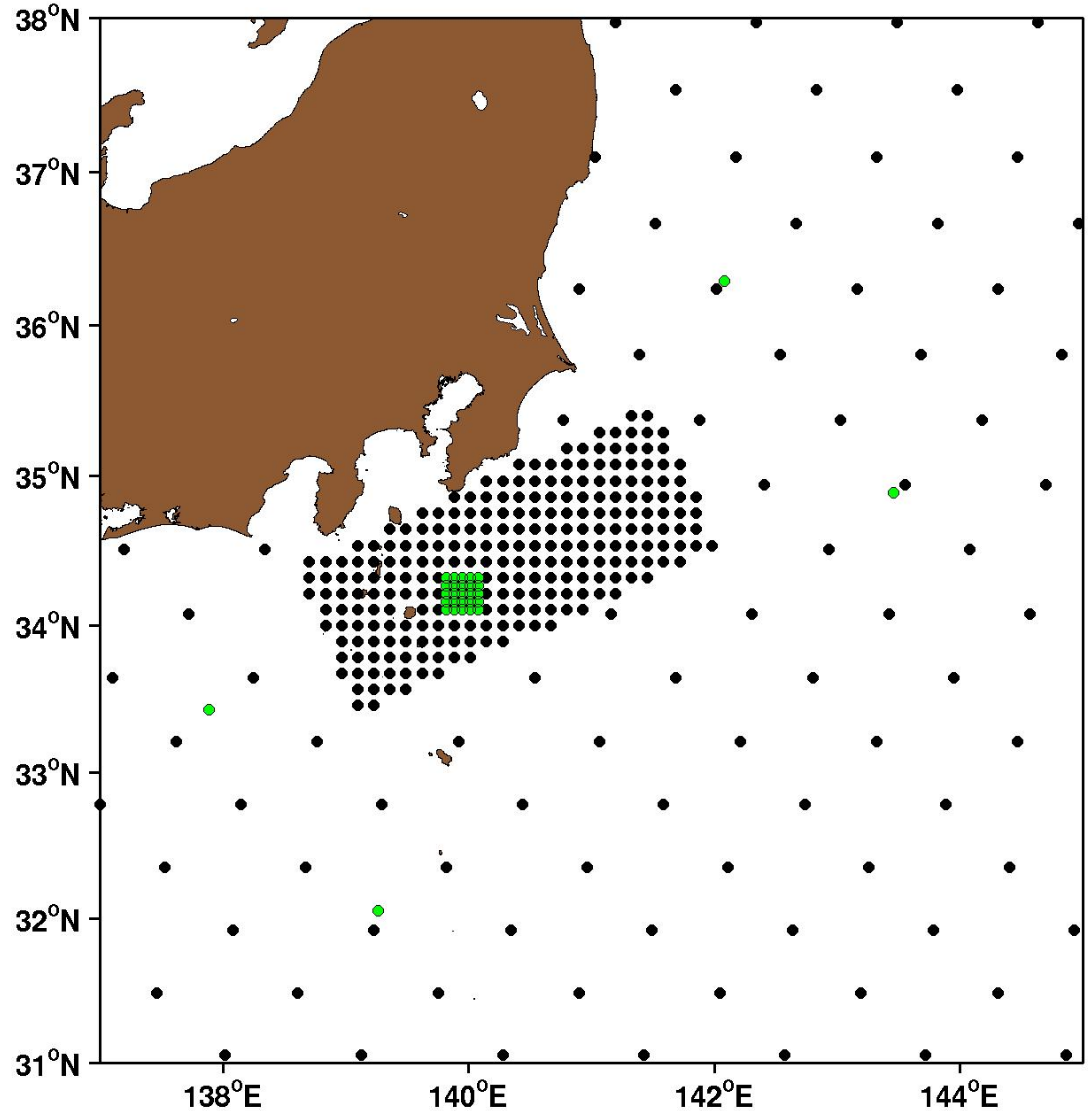
Multiscale 3DVAR
Twin data Experiment

Simulated observations of temperature and salinity taken from a free model run. (i.e. nature run)

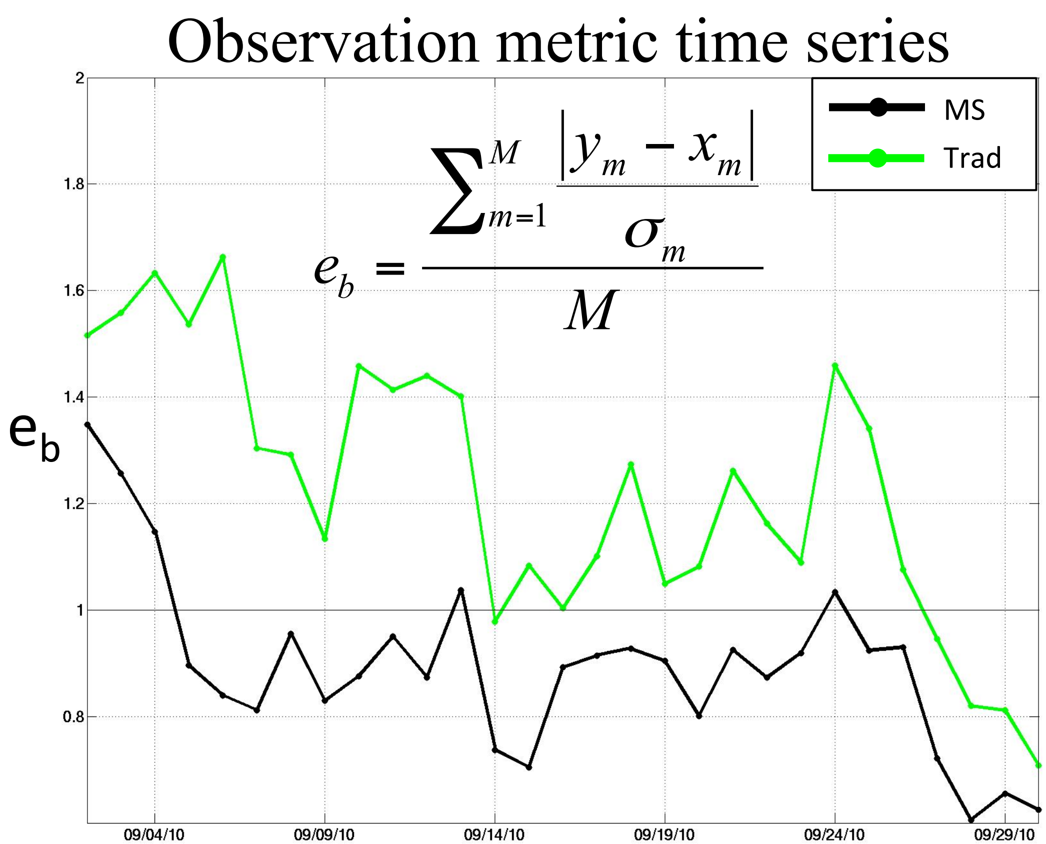
Initial condition of the assimilative run delayed from the observations by 13 days

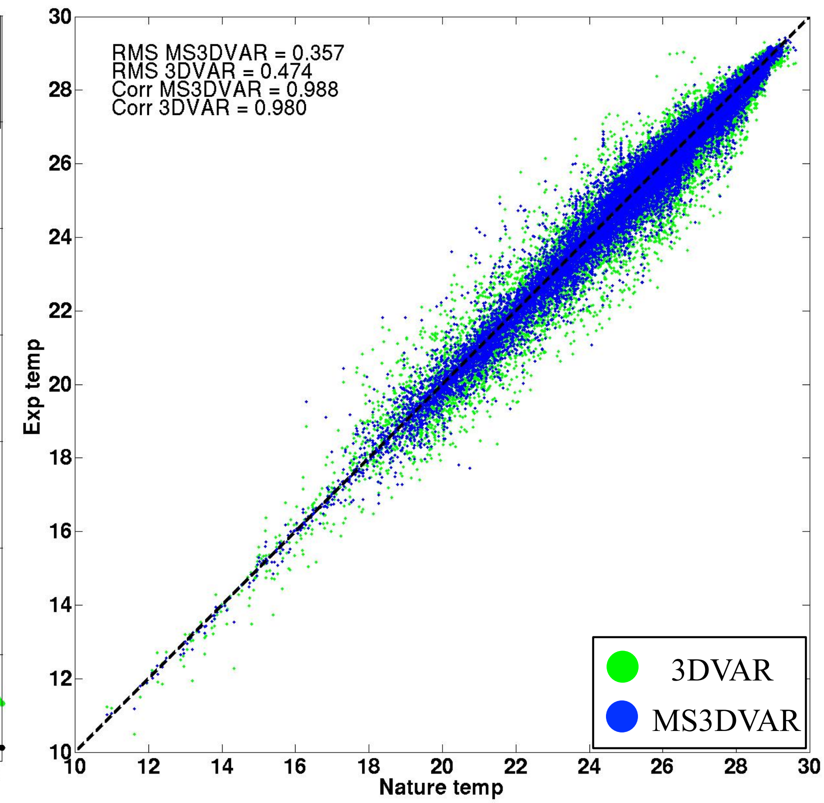
Profile observations

Surface observations



Multiscale 3DVAR
Twin data analysis



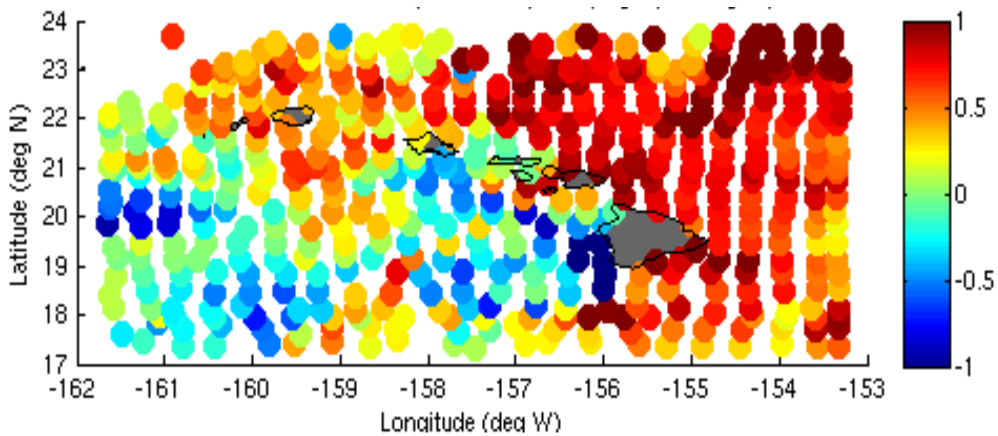


NCOM-4DVAR

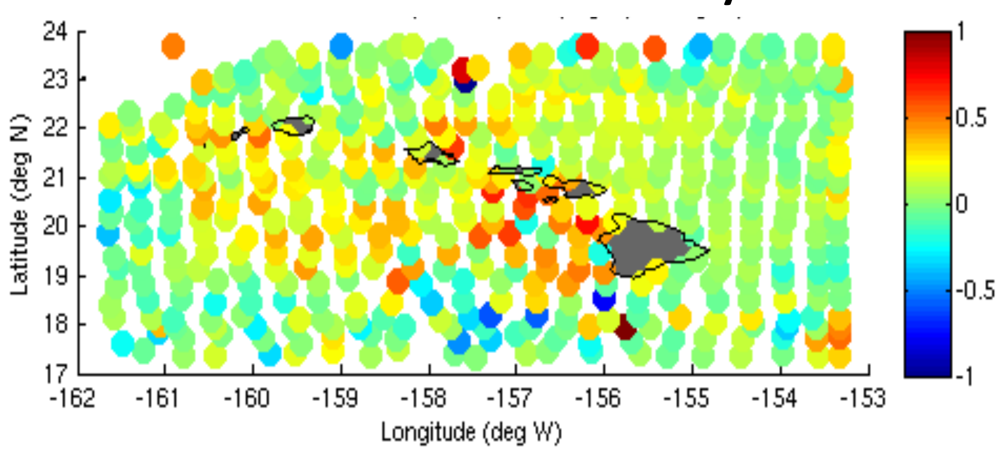
RIMPAC 08: Satellite & in situ data, August 2008

8/6/2008

SST Data minus first guess

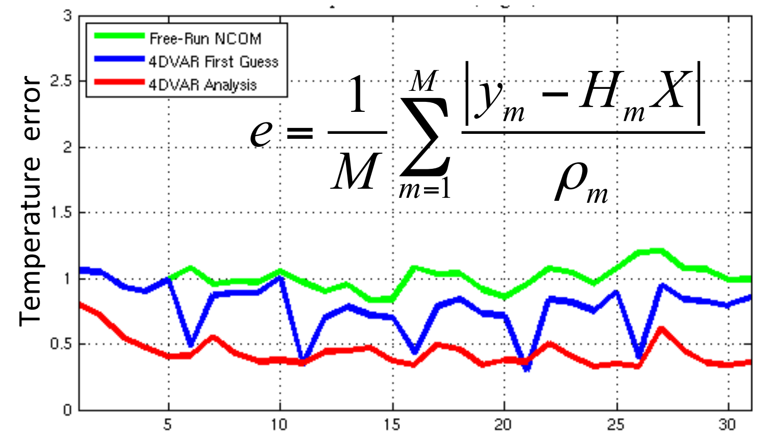


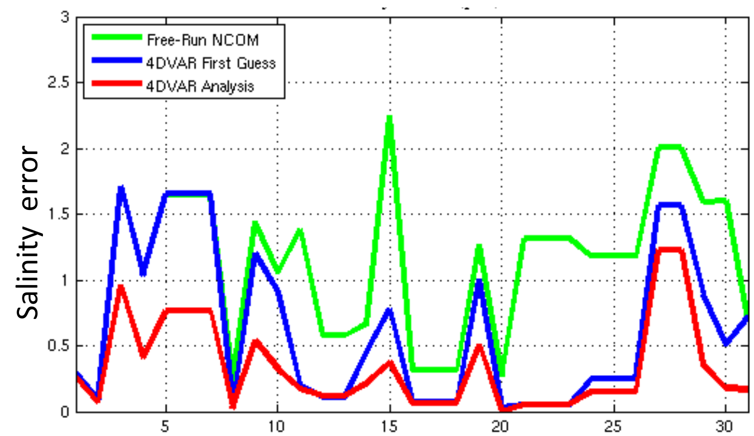
SST Data minus 4DVAR analysis



Fit to the observations metric

$$e = \frac{1}{M}\sum_{m=1}^{M}\frac{\left|y_m - H_m X\right|}{\rho_m}$$





Days of August 2008

System Evaluation

Test Setup

- Twin experiment, initialize adjoint at 5 locns.
- Planar beach, 1:500, from 12m to 1m depth.
- Background and "observations" from NL SWAN.
  - Range of boundary spectra types:
    - f_{mean} : Wind waves, Swell
    - Θ_{mean} : Shore normal, Oblique
    - H_s: 0.67m, 1.64m, 2.3m

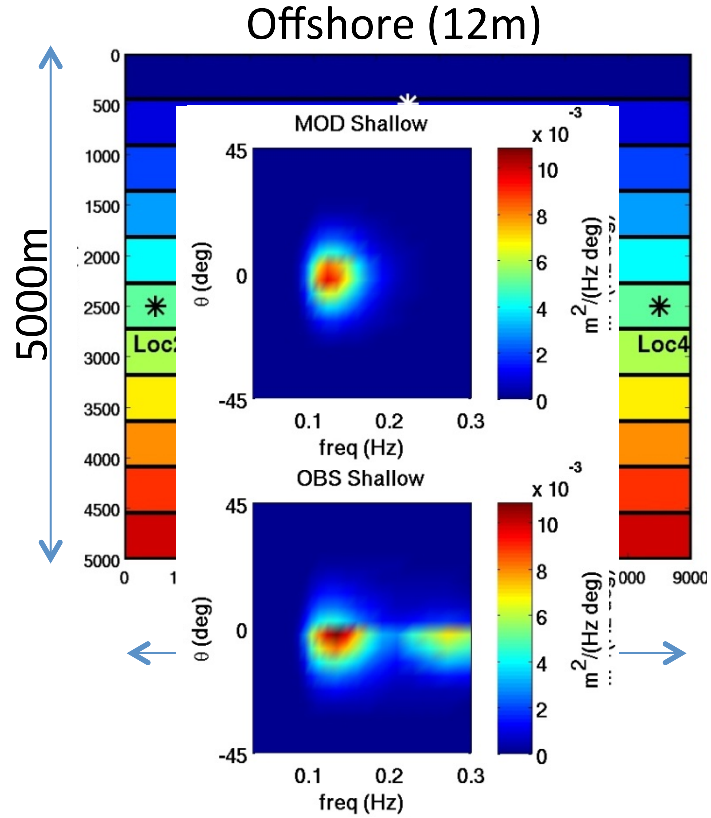
Performance Metrics

- Model Statistics (H_s, T_m, θ_m, *Dir Sprd*)

- ***RMS Skill Score***

$$\boxed{skill = 1 - \frac{\sqrt{\sum_{i,j}\left(E_{\mathrm{mod}}(f_i,\theta_j) - E_{obs}(f_i,\theta_j)\right)^2}}{\sqrt{\sum_{i,j}\left(E_{obs}(f_i,\theta_j)\right)^2}}}$$

5 "Observation" Locations



Loc 3:

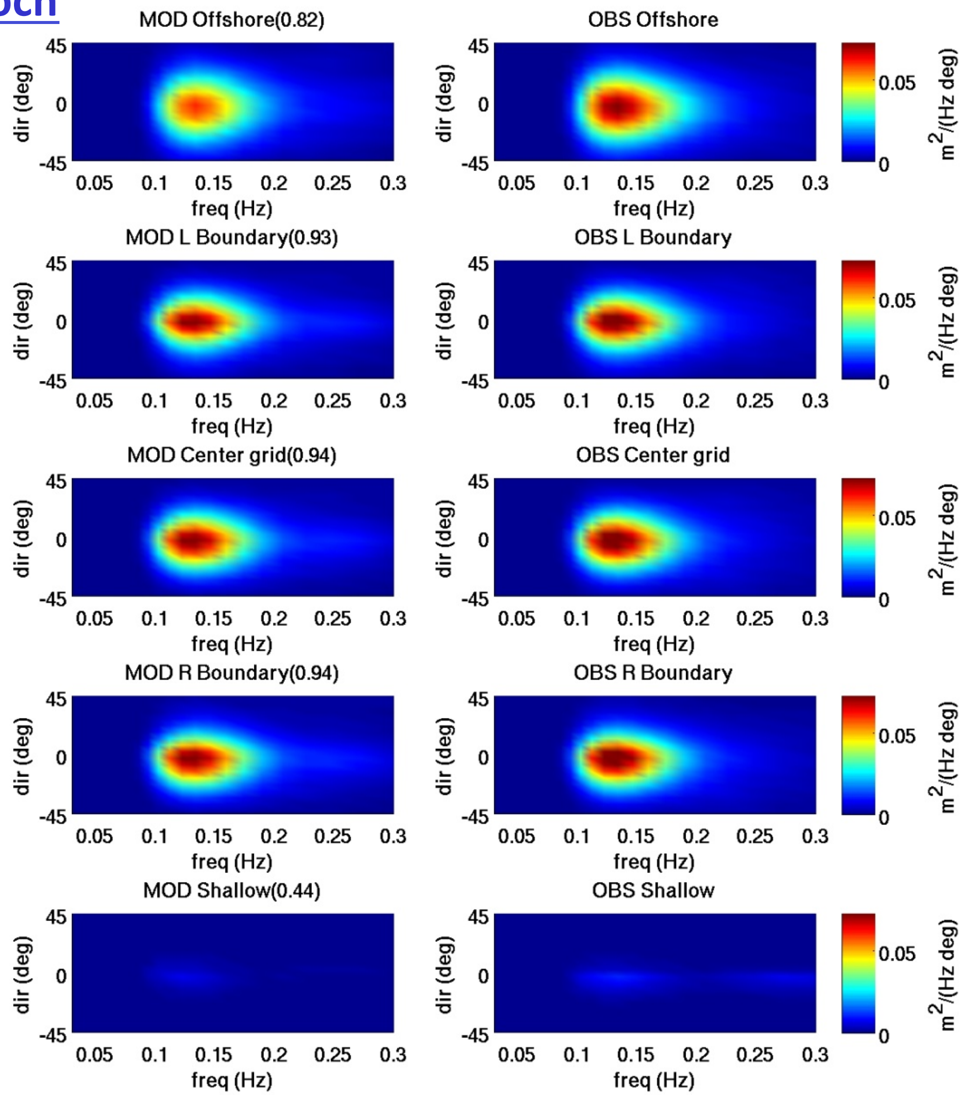
skill = 0.98

Assimilation in Shallow Water (#5) and at a Deeper Location (#3)

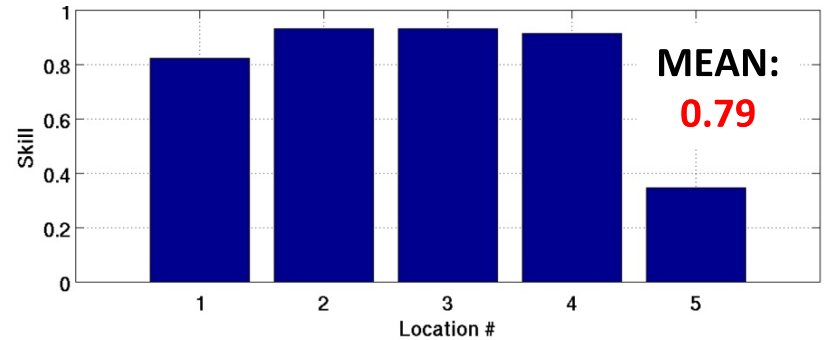
Locn

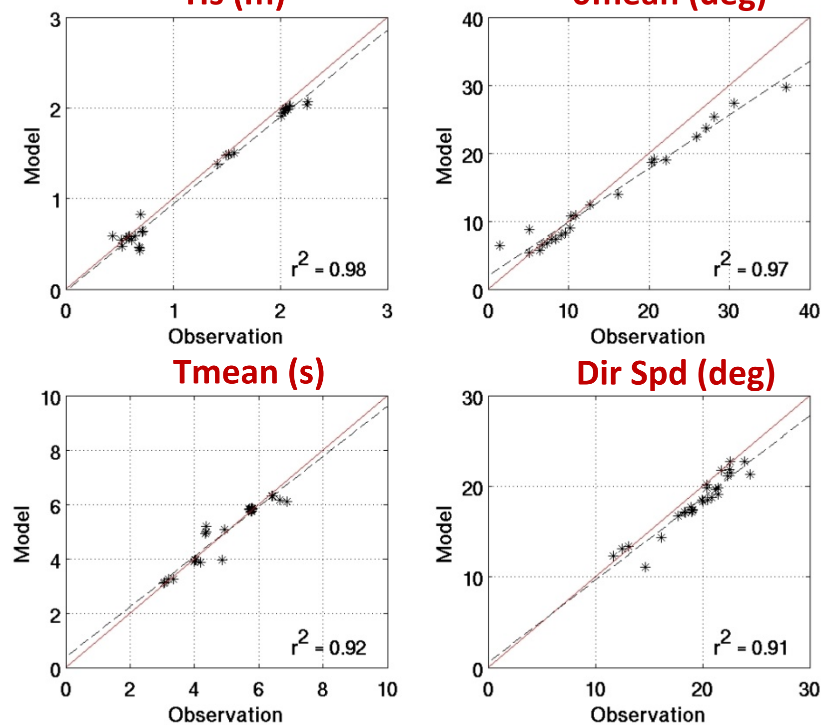
Sample Spectra

1
2
3
4
5



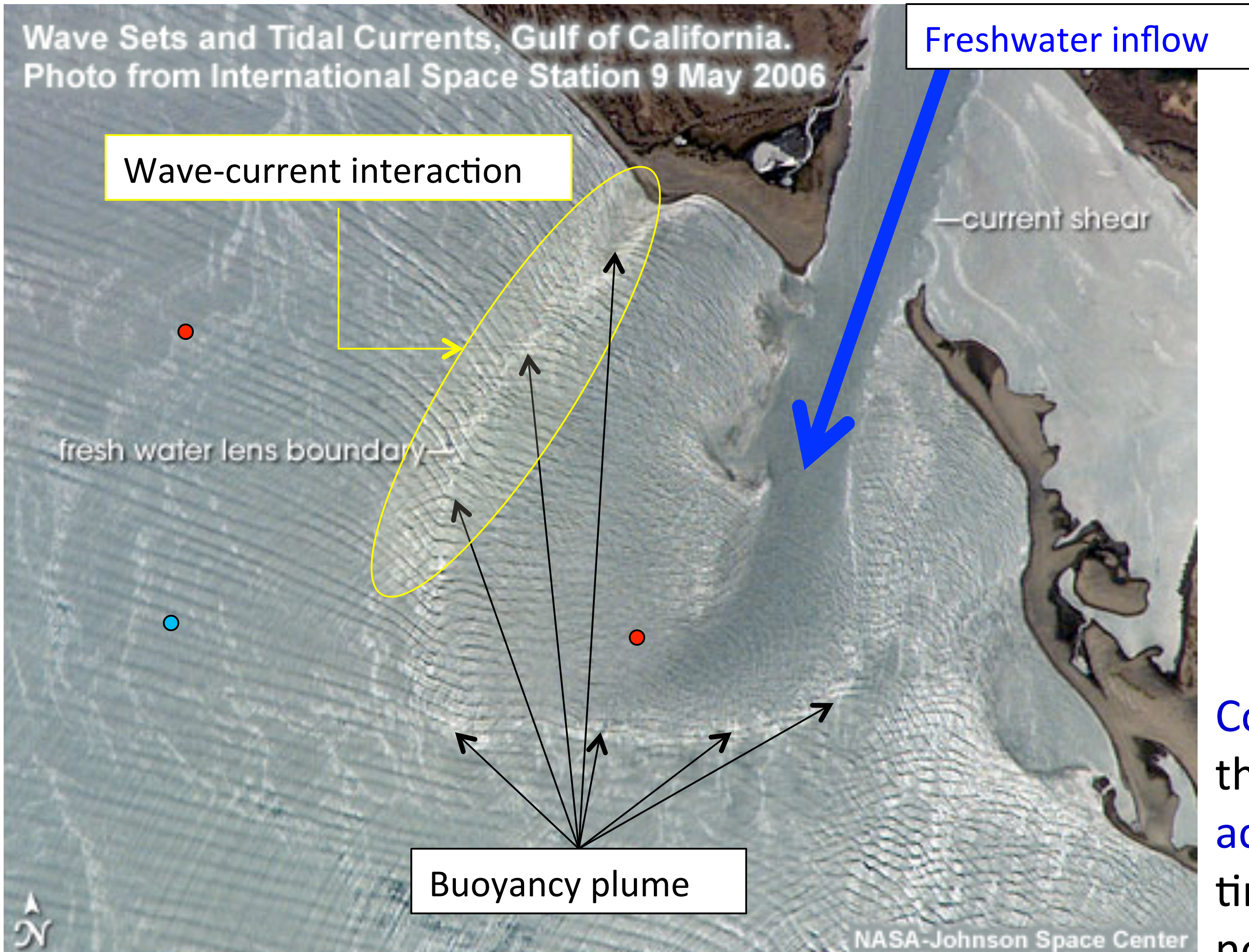
RMS Skill





Need data from outside surf zone

Why is coupled data assimilation essential?



Wave-current interactions in the Gulf of California

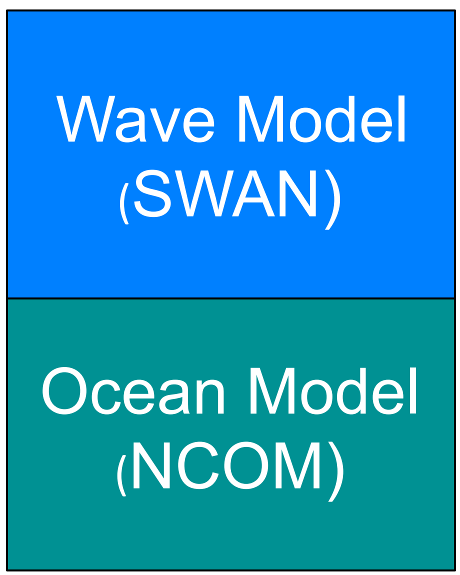
Coastal processes are diverse and highly nonlinear

Observations of one process (waves) affects the forecast of another process (currents)

Coupled assimilation is the proper way to account for these time-evolving, nonlinear relationships

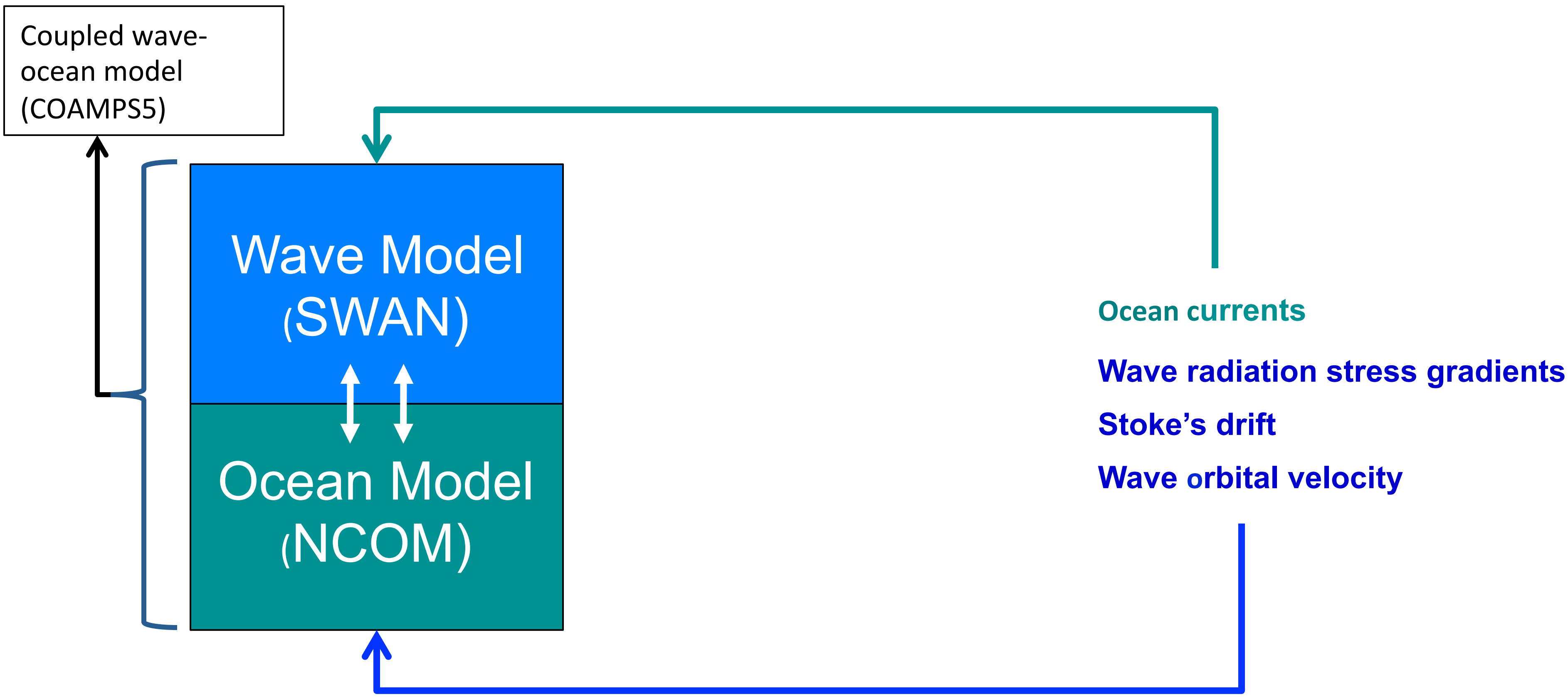
Approach

Build on developed coupled model and advanced data assimilation capabilities



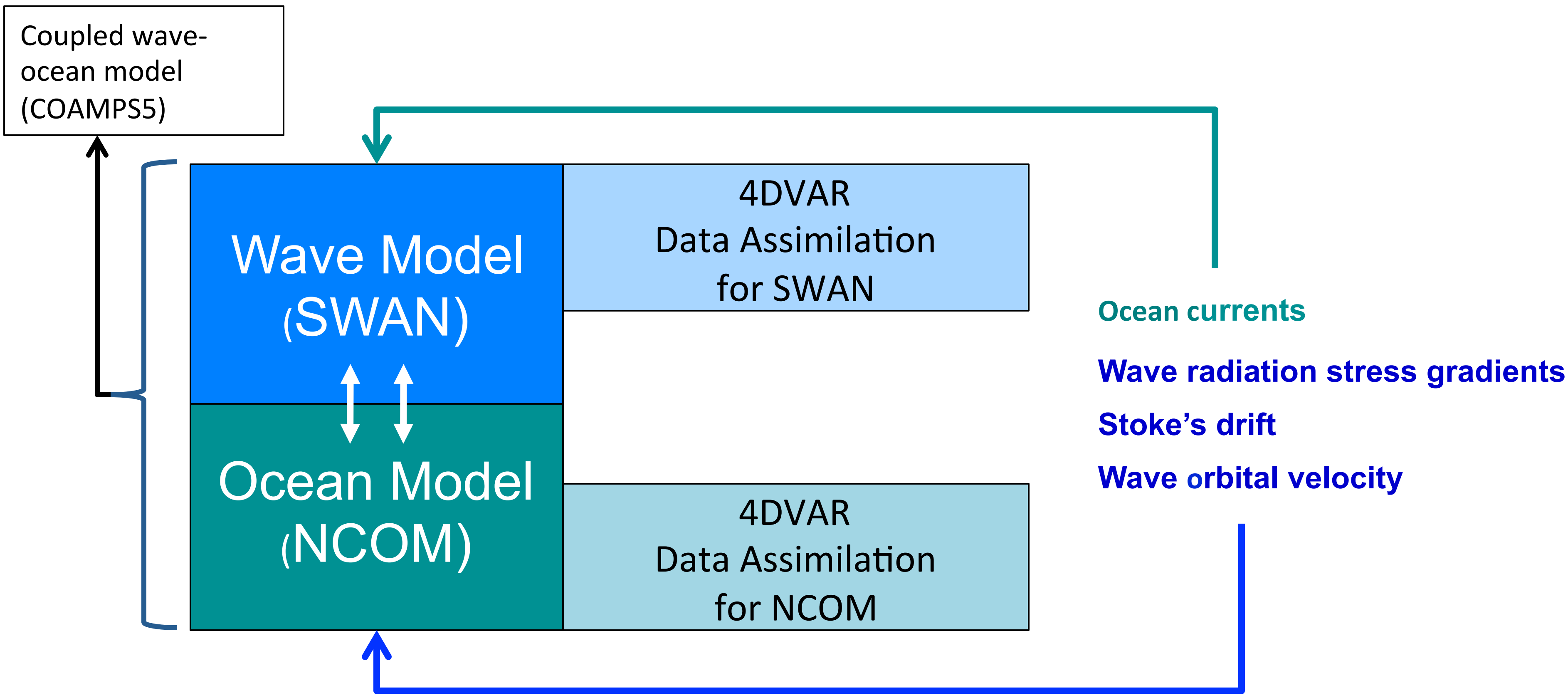
Approach

Build on developed coupled model and advanced data assimilation capabilities



Approach

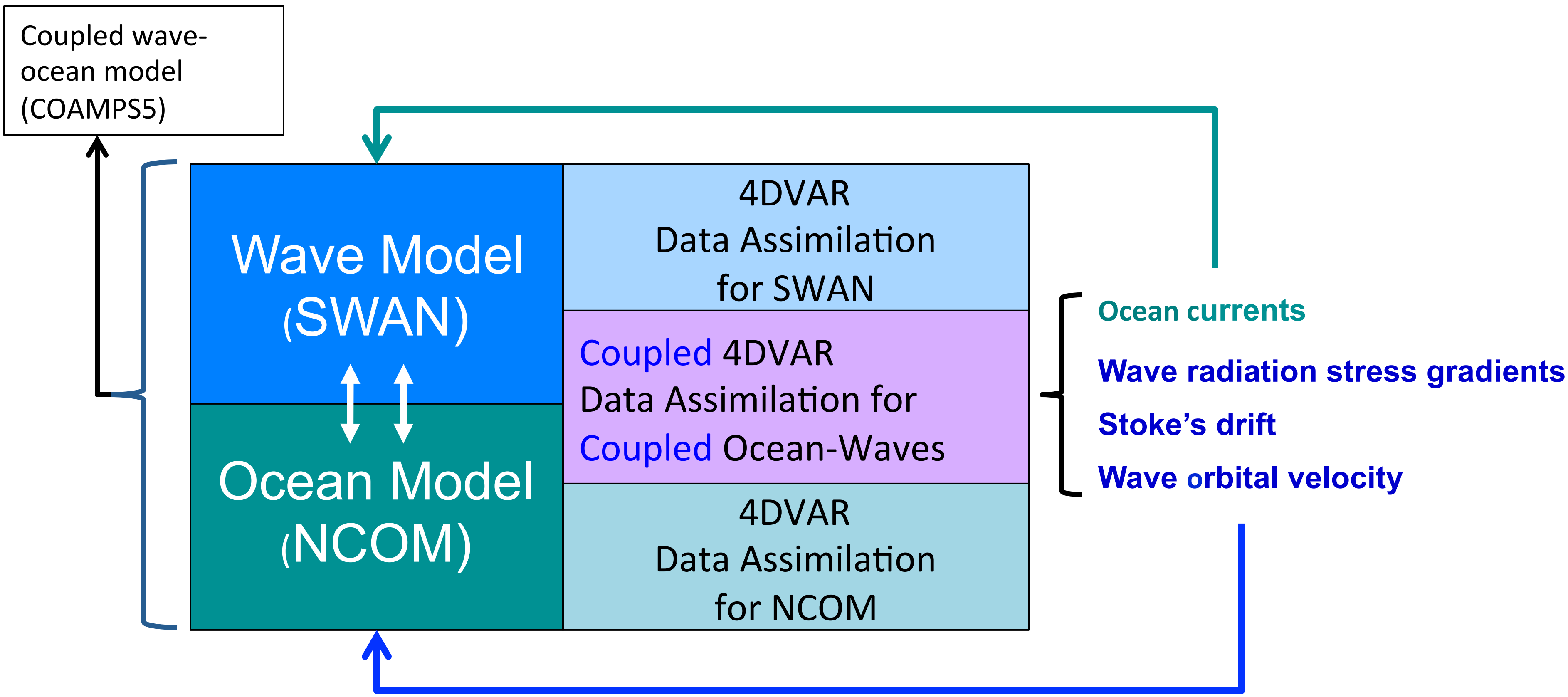
Build on developed coupled model and advanced data assimilation capabilities



Approach

Build on developed coupled model and advanced data assimilation capabilities

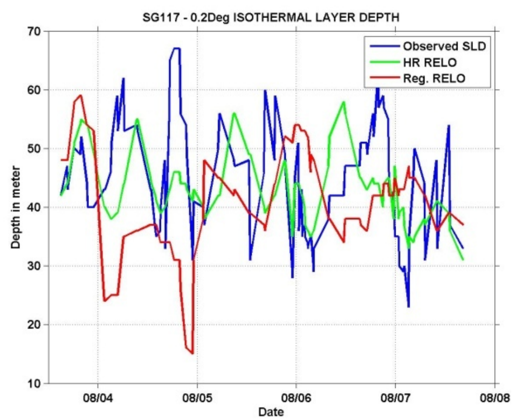
Develop adjoints for each of the coupling terms to complete the coupled 4DVAR data assimilation

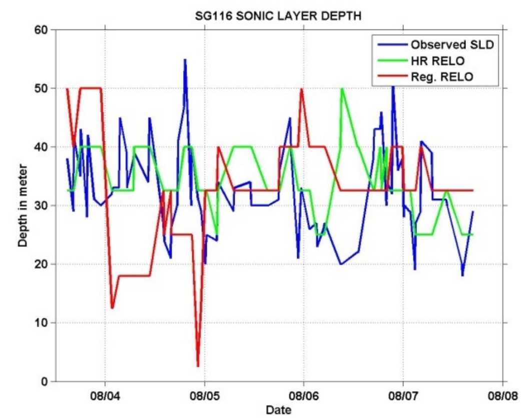


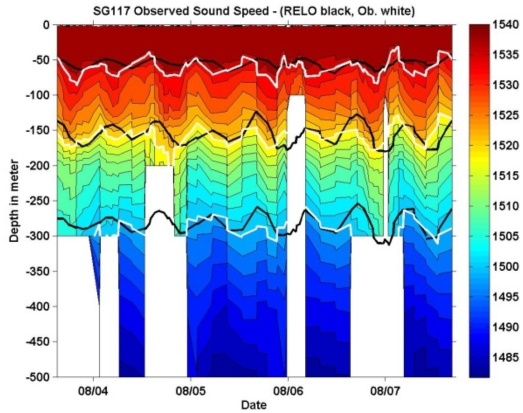
Forecasting distribution

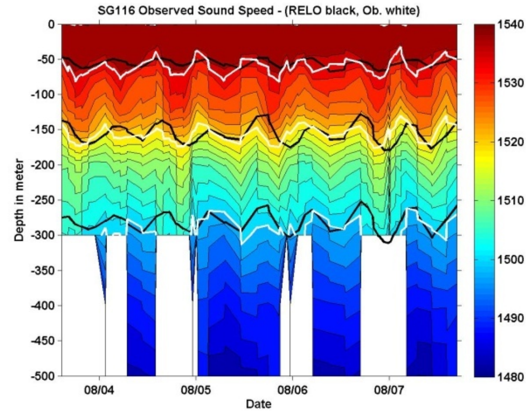
TESTING AND VALIDATION
ONR PLUS Kauai 09

Reg RELO – 3km resolution (all Hawaii region full assimilation)
HR RELO – 1km resolution (local ~100-100km free run)

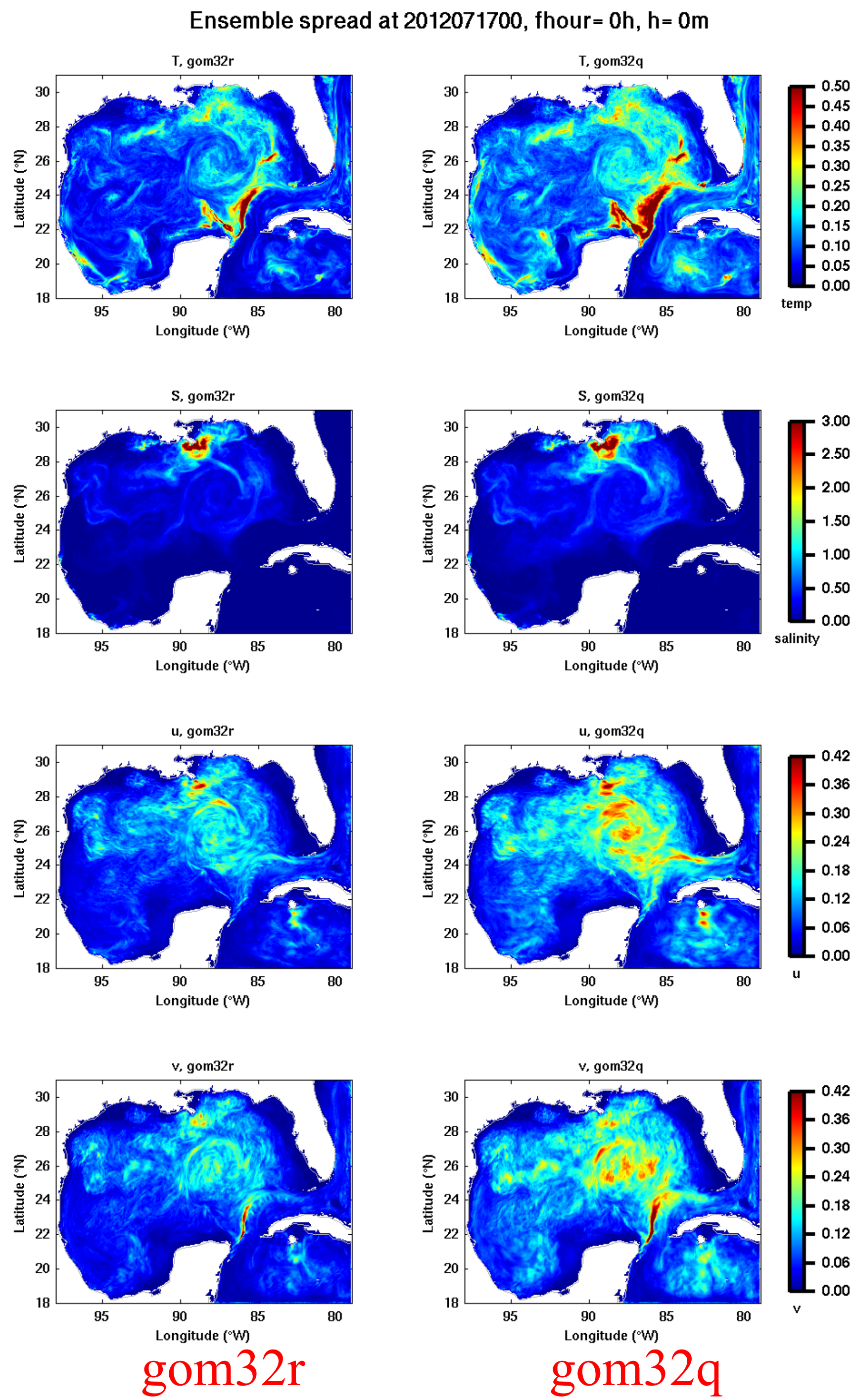


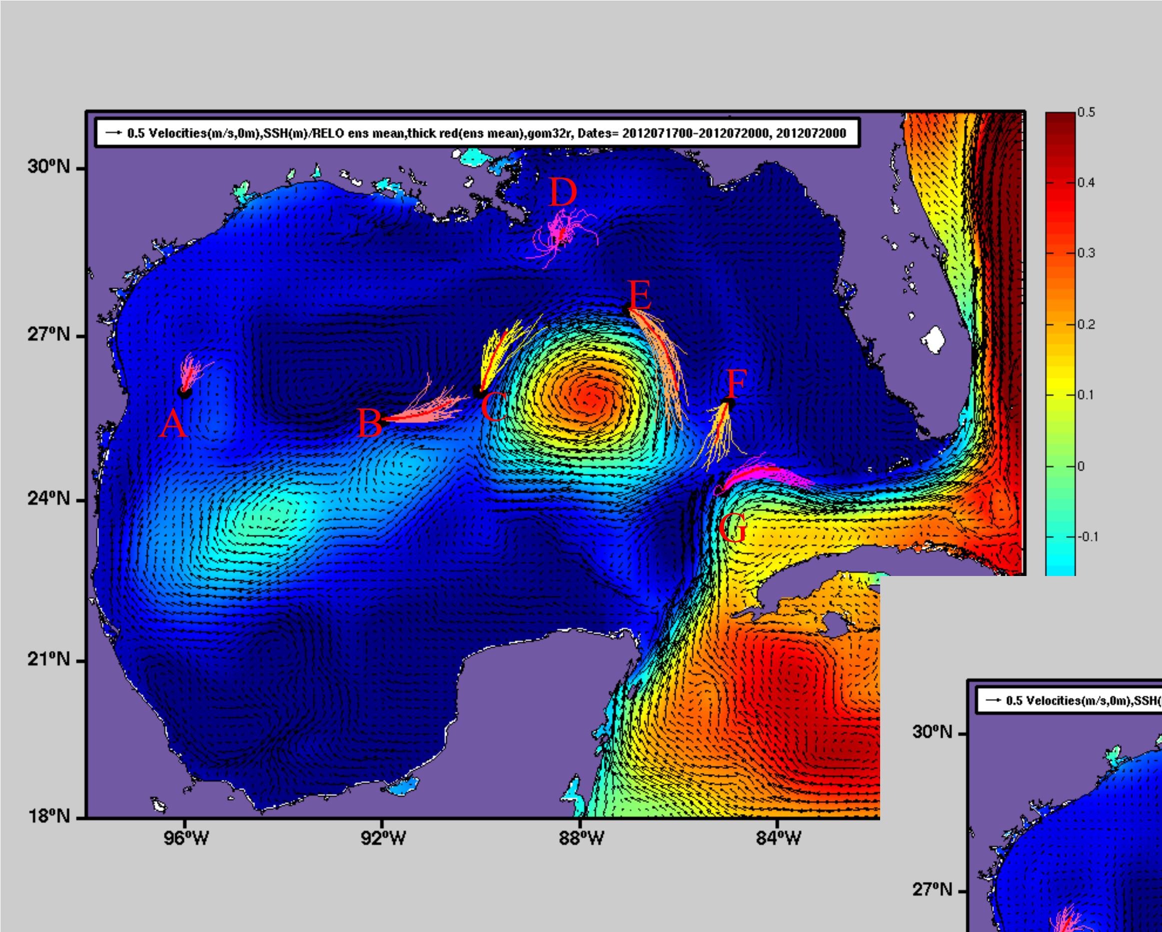




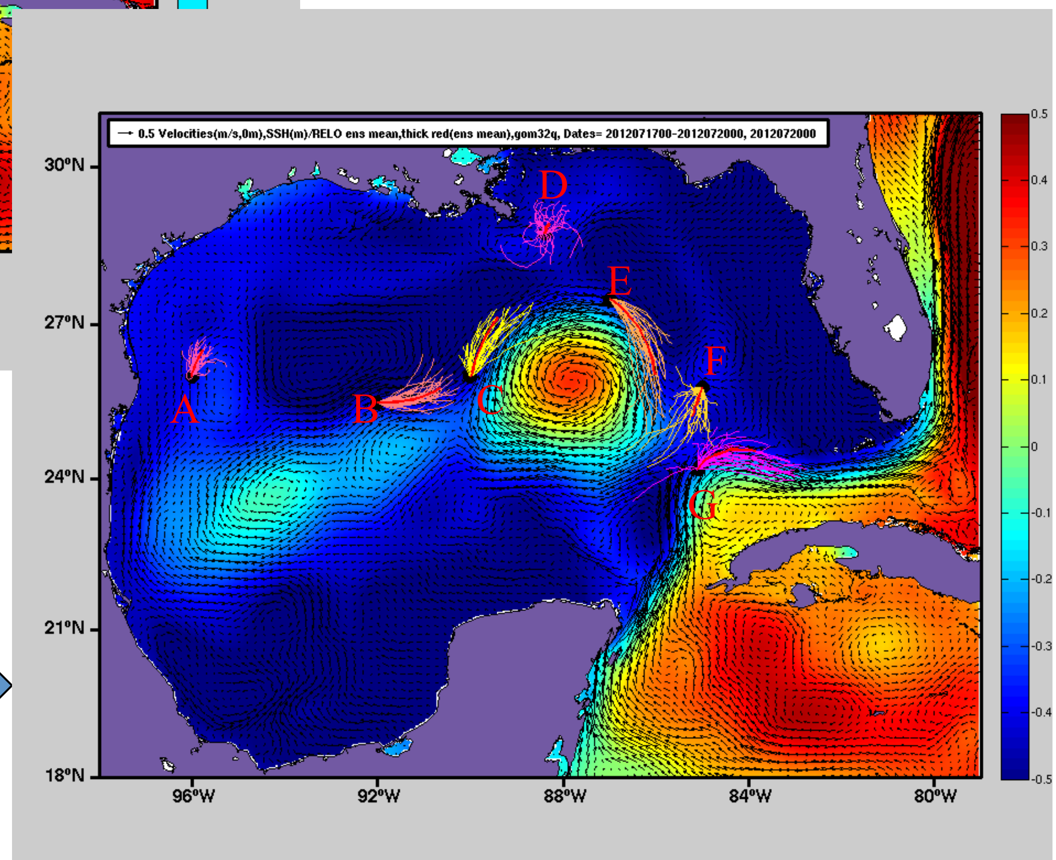


Ensemble Spread Comparison at 2012071700 0hour, 0m





Lagrangian Trajectories
2012071700 – 2012072000
Ens mean: solid red
SSH: color contour
Surface current: arrows
D: BP/DWH accident

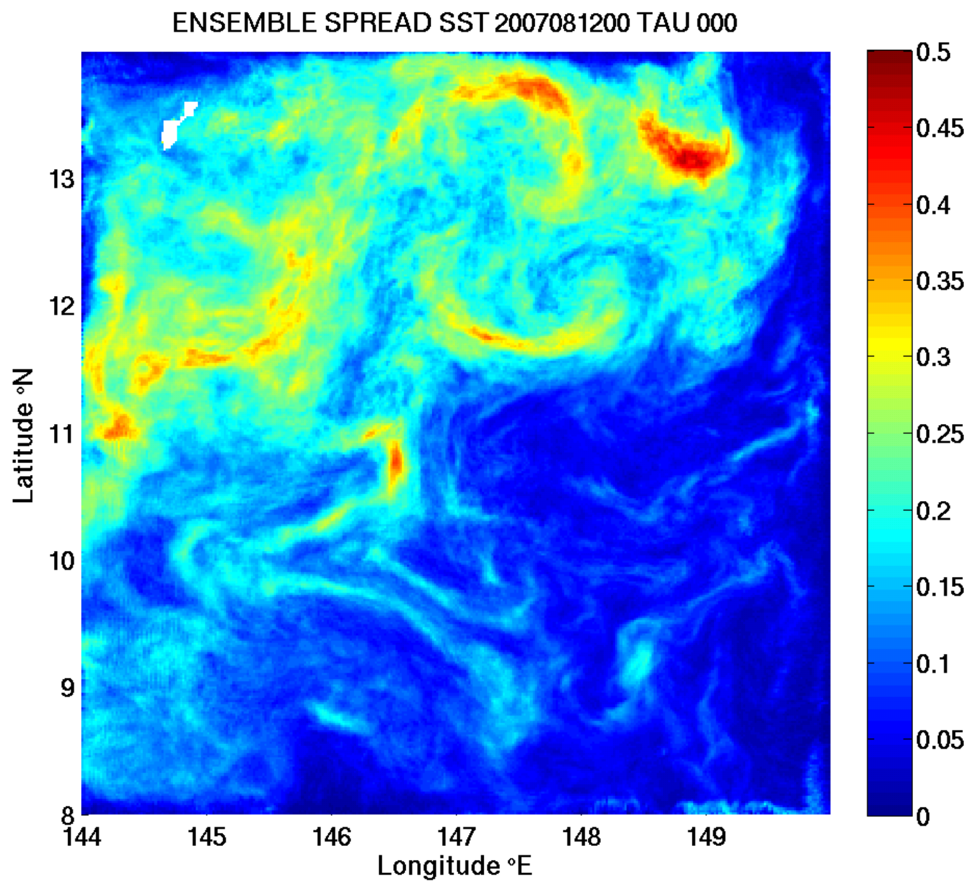


Ensemble gom32r

Ensemble gom32q

ESPC Integration from Prior and Present Oceanography 6.2-6.4

Ensemble forecast provides uncertainty due to surface forcing and initial conditions

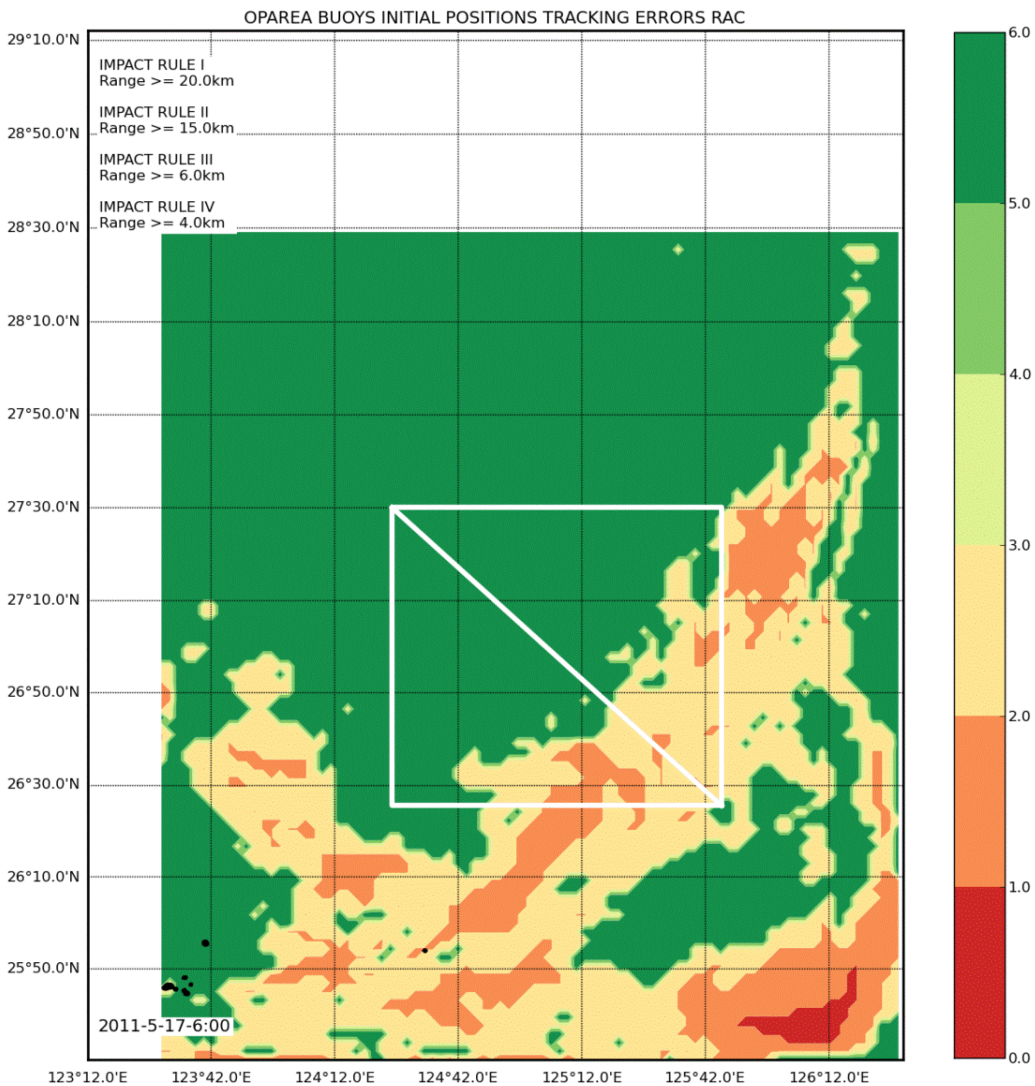


Animation of ensemble sea surface temperature spread (standard deviation, °C) from a Guam area implementation using 40 members.

Forecast variance gains further importance

UCUP – Common Uncertainty Picture
Operational Risk Management (ORM)

Risk of SONOBUOY Tracking Errors after 6 hours
(i.e. errors in predicting sonobuoy position if using model velocity forecasts)



From ensemble pdf's

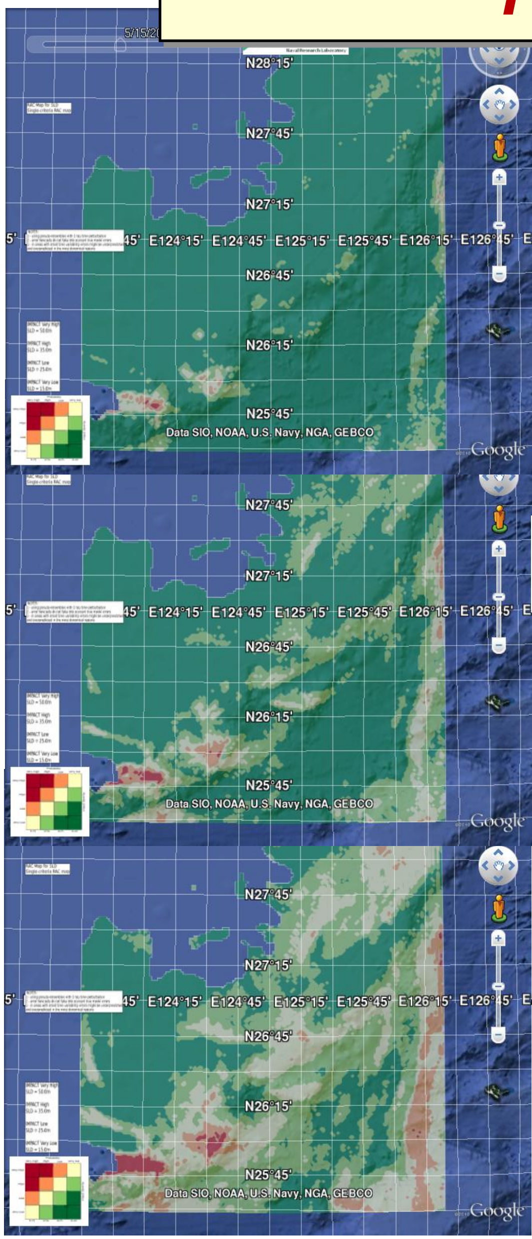
From operators

Risk Management RAC Codes		Probability			
		A >0.75	0.75>B>0.5	0.5>C>0.25	0.25>D>0.1
Severity	Level I – Very High	1	1	2	3
	Level II – High	1	2	3	4
	Level III - Medium	2	3	4	5
	Level IV - Minimal	3	4	5	5

1 – Critical 2 – Serious 3 – Moderate 4 – Minor 5 – Negligible

Risk Assessment Codes (RAC) used to define surfaces weighting ***Severity*** and ***Probability*** of impacts based on pre-defined awareness/impact thresholds (Level I to IV)

Awareness Thresholds and Forecast Quality Analysis



6h Updates
Prob. error

12h Updates
Prob. error

24h Updates
Prob. error

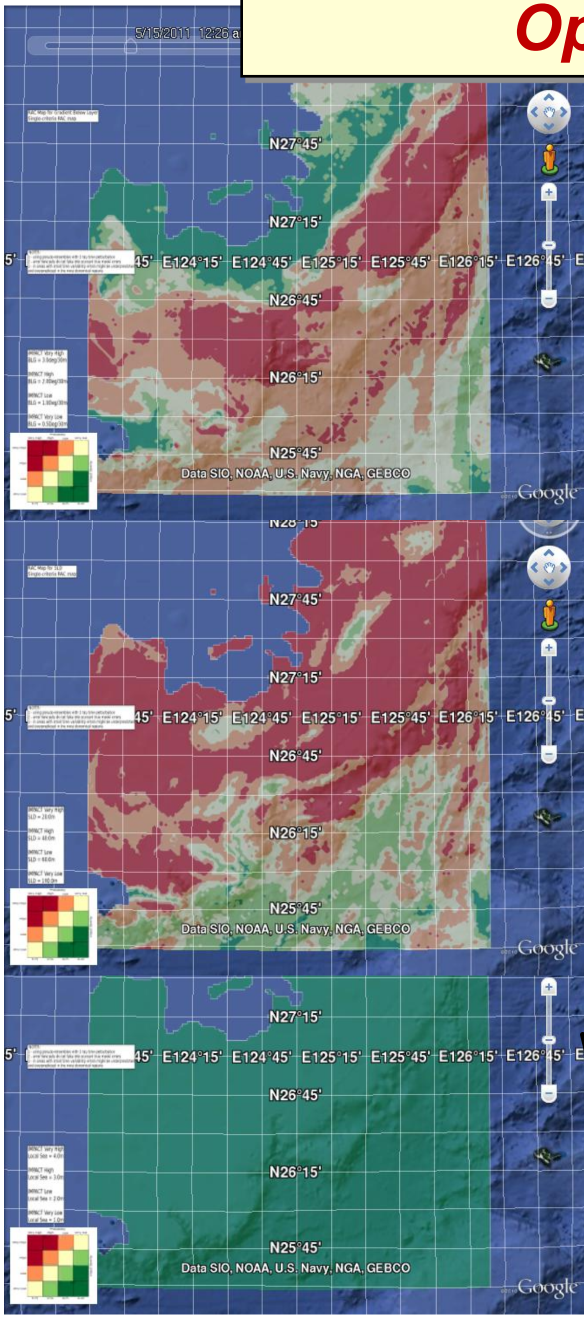
refreshing rates guidance

Probability that **Sonic layer Depth** changes

- •50m for very high impact prediction error
- •35m for high impact error
- •25m for low impact and
- •15m for very low impact

over a 6, 12 and 24 hours update period

Awareness Thresholds and Operational Risk Management

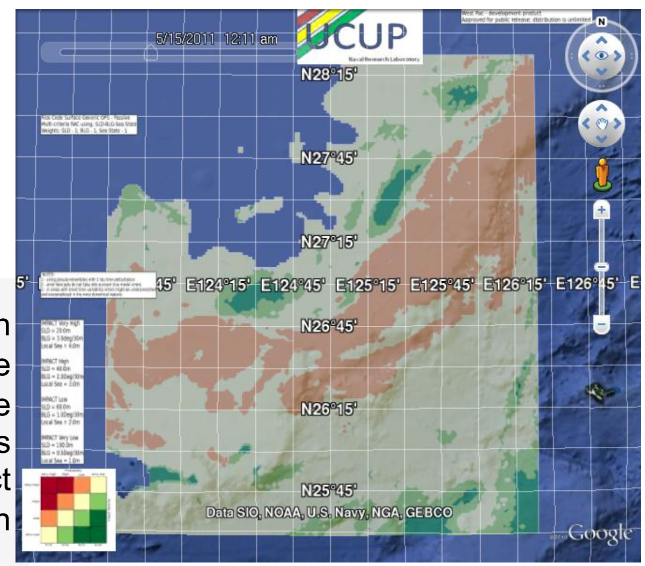


Generic Surface Operations Rule

• Sonic layer depth (if too shallow surface ducting is less likely):
  very high impact if below 20m; high impact if smaller than 40m and above 20m; moderate impact if smaller than 60m and above 40m; low impact if smaller than 100m but above 60m.

•Gradient below layer (if too high favors downward reflection):
  very high impact if above 3 degrees/30m, high impact if above 2 degrees/30m and below 3 degrees/30m; moderate impact if above 1 degrees/30m and below 2 degrees/30m; low impact if above 0.5 degrees/30m and below 1 degrees/30m;

•Sea State (high sea state generates higher noise and damping at surface reflections):
  very high impact if above 4m; high impact if above 3m and below 4m; moderate impact if above 2m and below 3m; low impact if above 1m but below 2m.



Note: the fact there is less high impact (full red) areas in the integration map on the right than in the SLD and BLG maps on the left is because is less likely for high impact SLD and BLG to occur together than independently.

TRACK THE ERROR SOURCES IN MODELS

$$\varepsilon_{forecast} = \varepsilon_{forcing} + \varepsilon_{IC} + \varepsilon_{grid} + \boxed{\varepsilon_{physics} + \varepsilon_{BC}}$$

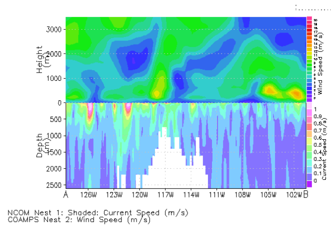
Not in present capabilities

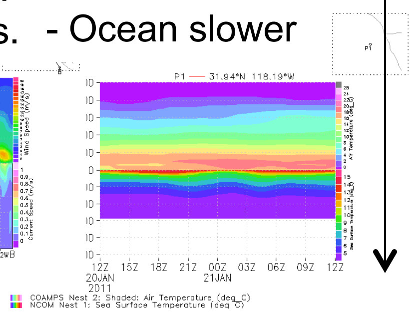
Grid set-up

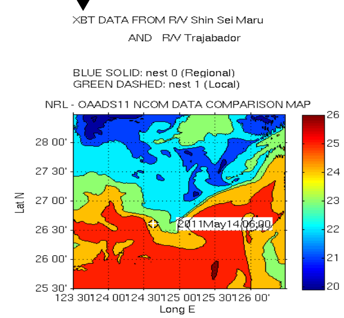
Coupling

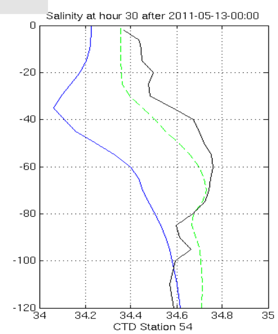
CROSS SECTION
- Ocean higher res.

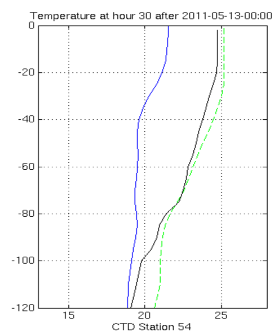
TIME SERIES
- Ocean slower

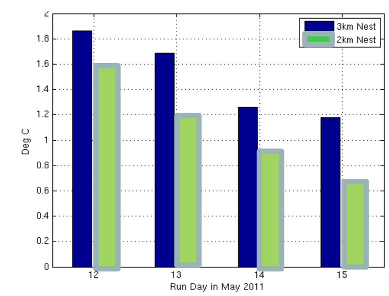












Data Assimilation + (Ensemble Initialization

$$X'^{a} = X'^{0}\,T$$

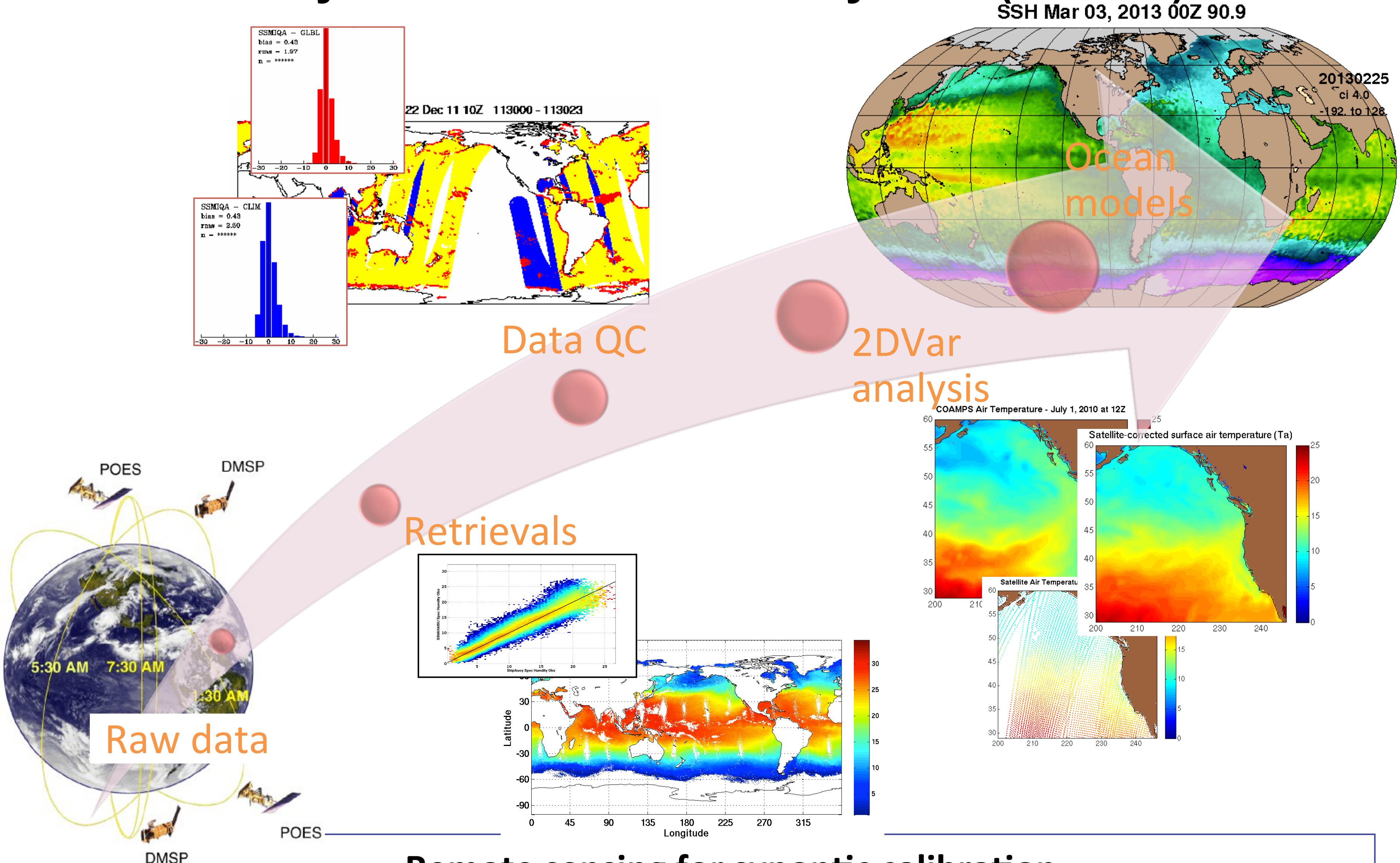
$$\mathbf{T} = \mathbf{B}\Lambda^{-1/2}\mathbf{B}^{T}$$

where $\mathbf{B} = [\mathbf{b}_1, \mathbf{b}_2, ..., \mathbf{b}_K]$ is a *KxK* orthogonal matrix containing the eigenvectors of the symmetric matrix $\left(\mathbf{X}^{oT}\mathbf{P}_g^{a-1}\mathbf{X}^{0}/N\right)$

Bishop and Toth (1999, JAS)

Data

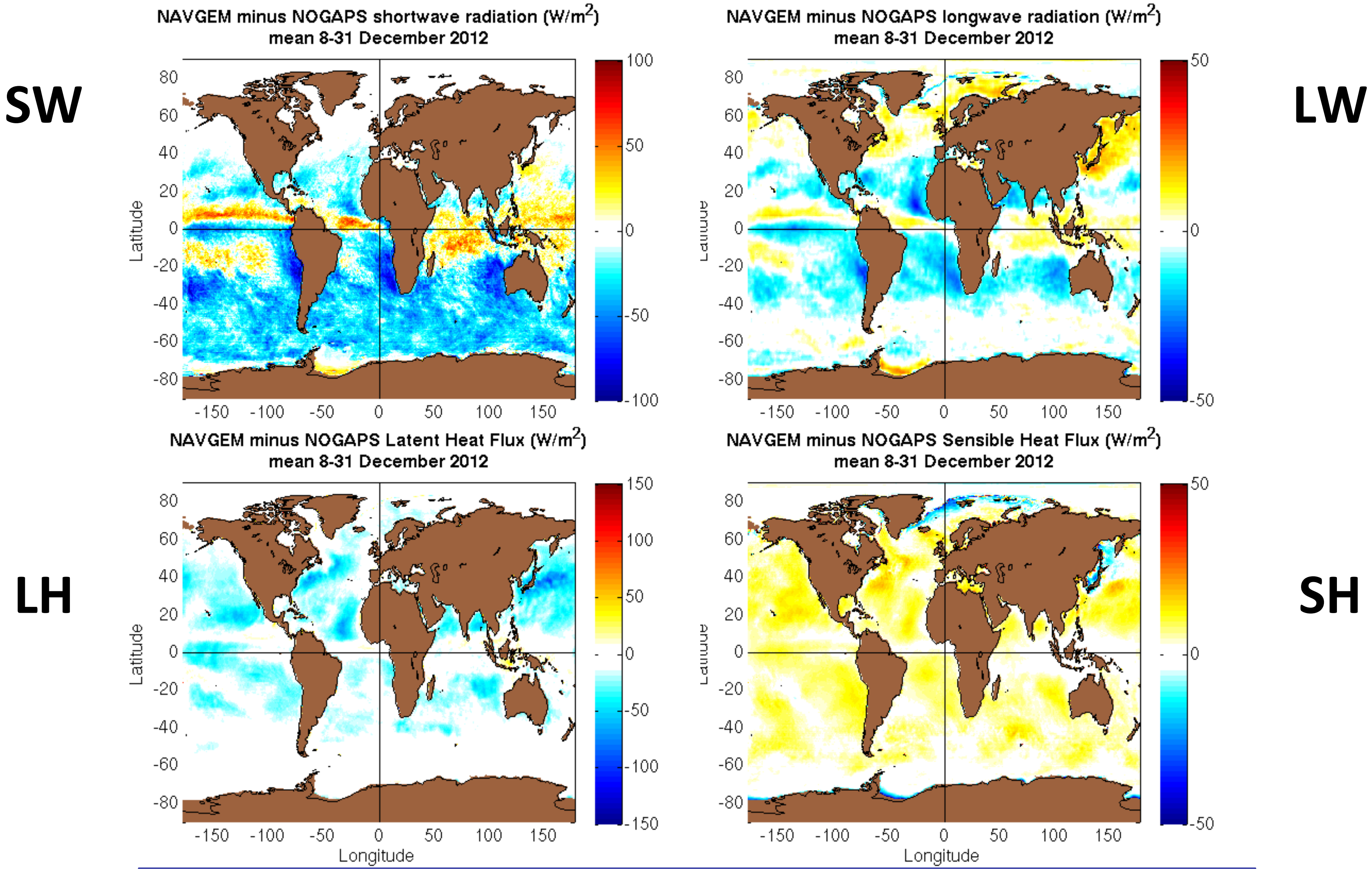
Ocean Surface Fluxes from Satellite
Navy Ocean Surface Flux System (NFLUX)



Remote sensing for synoptic calibration

Ocean Surface Fluxes from Satellite

NAVGEM minus NOGAPS 8-31 DEC

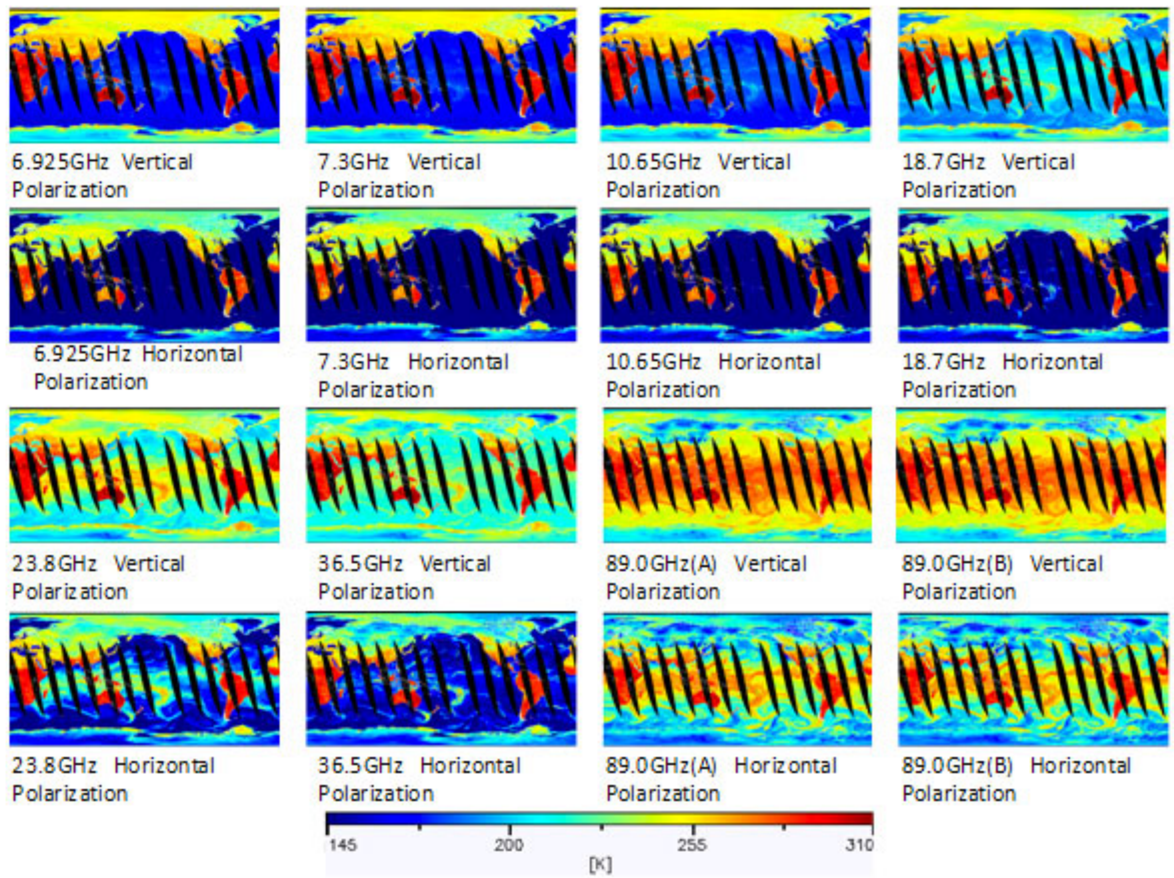


New calibration information is needed

AMSR2 on GCOM-W1

cloud-penetrating microwave sensor

- NAVO has SDR data from NOAA
- Initial work beginning with RSS to provide NAVO capability to derive SST



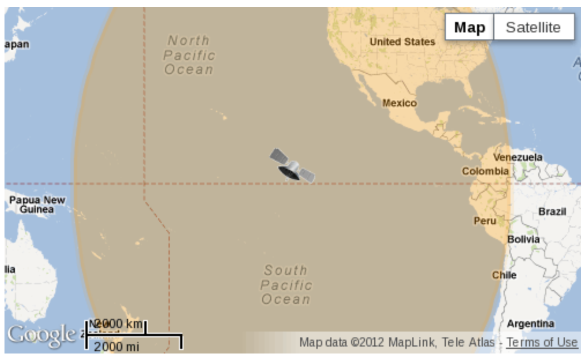
JAXA (Japan Aerospace Exploration Agency) began releasing brightness temperature products on 25 Jan 2013.

NAVO will use RSS algorithms to derive AMSR2 SST.

FY14+ plans new sensors: Geostationary SST coverage

INSAT 82°E

COMS-1 128°E



GOES WEST 135°W

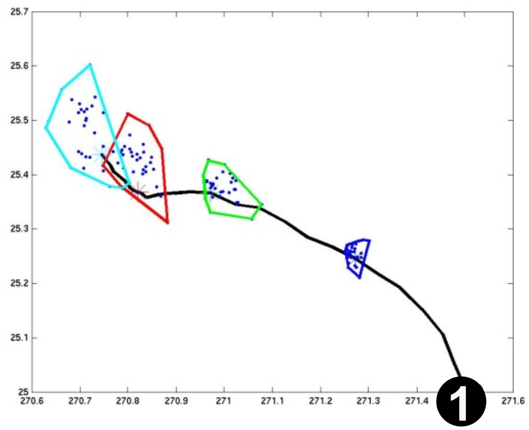
METEOSAT 0°E

GOES EAST 75°W

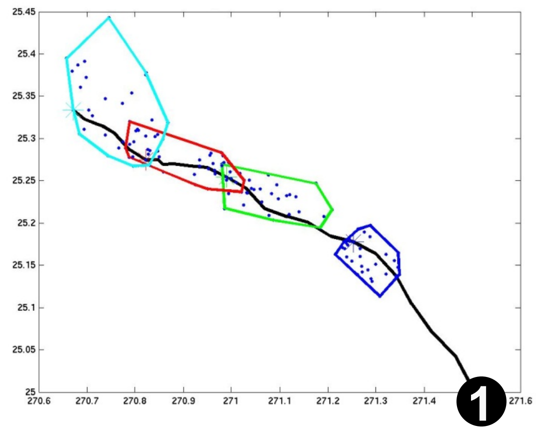
Targeted observations / system control

Automation of glider pilot guidance path tolerance

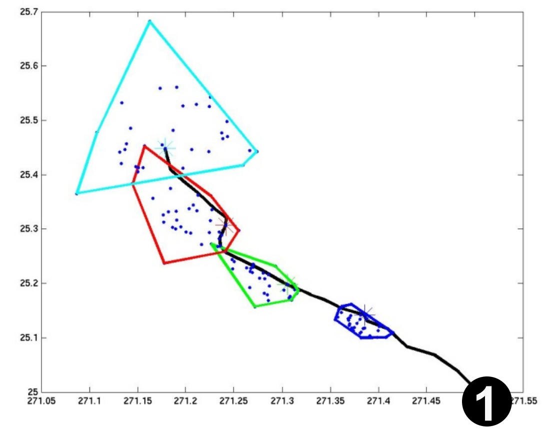
Glider 1 path for July 7 based on the different model forecast inputs for mission type 2. The spread every 6 hours shows waypoints from the top 20% of paths as evaluated by the genetic algorithm.



GoM 3km



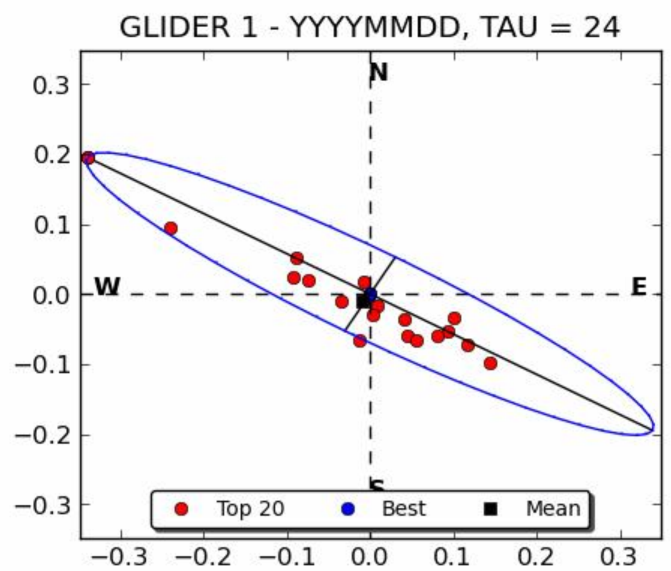
GoM 1km

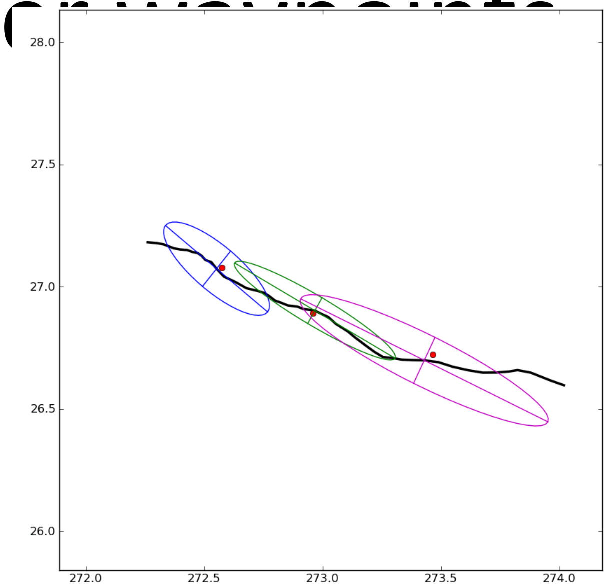


GoM 3km ensemble

This product gives the glider pilots as estimate of the tolerance and uncertainty in achieving optimum glider trajectories.

Work in progress
quantify tolerances in glider waypoints

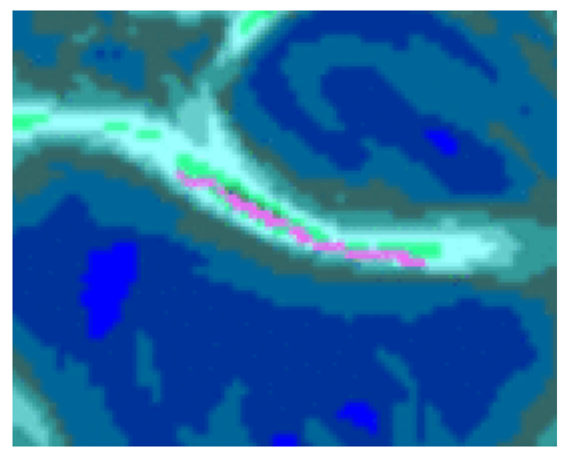




Best:
87.033 W, 26.902 N

Mean:
87.043 W, 26.893 N

Angle of max spread:
119.91



Nearshore Sensitivity Maps: Application

Denied areas: Alternate sensor locations for data assimilation (Duck, NC)