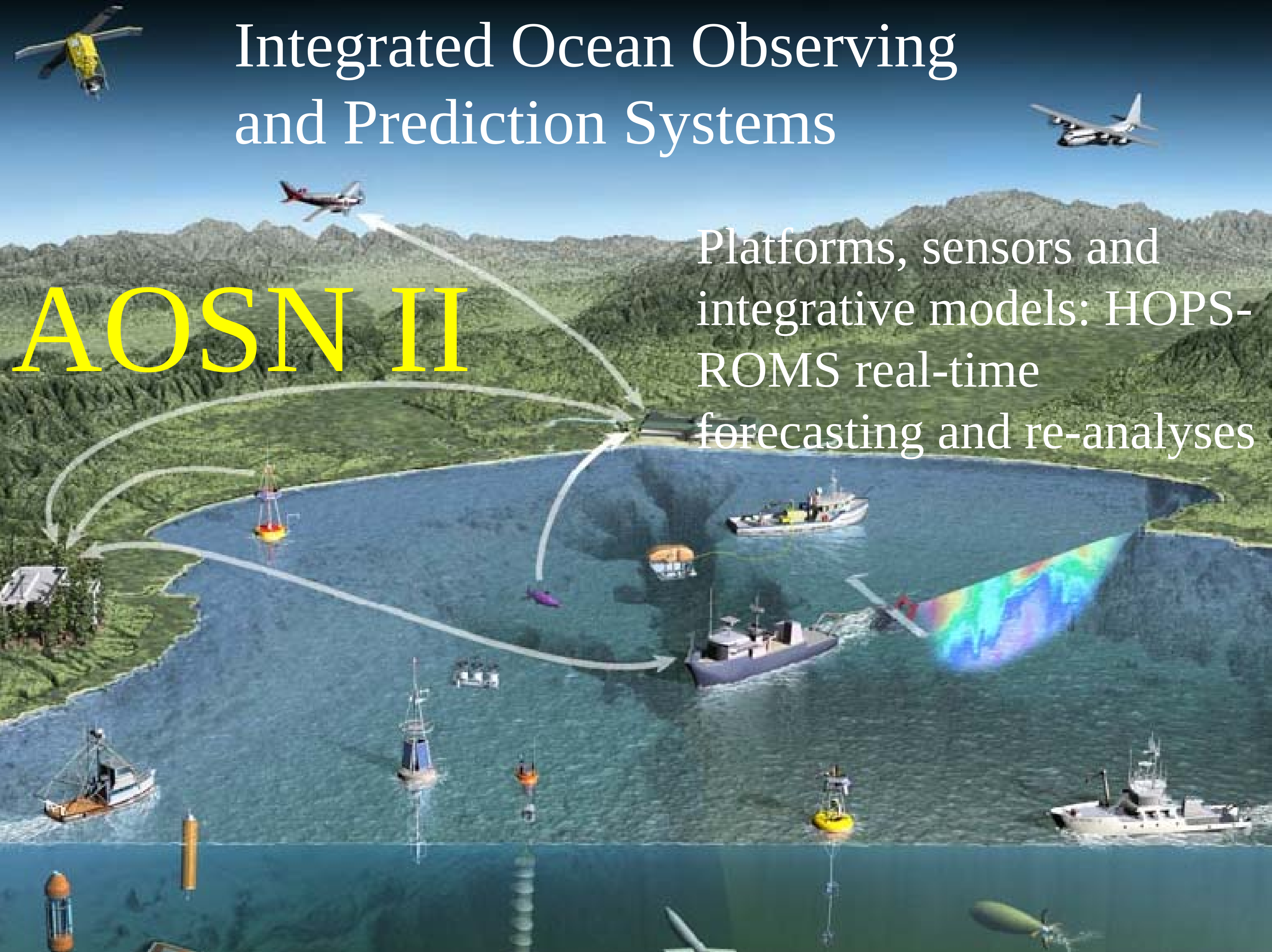
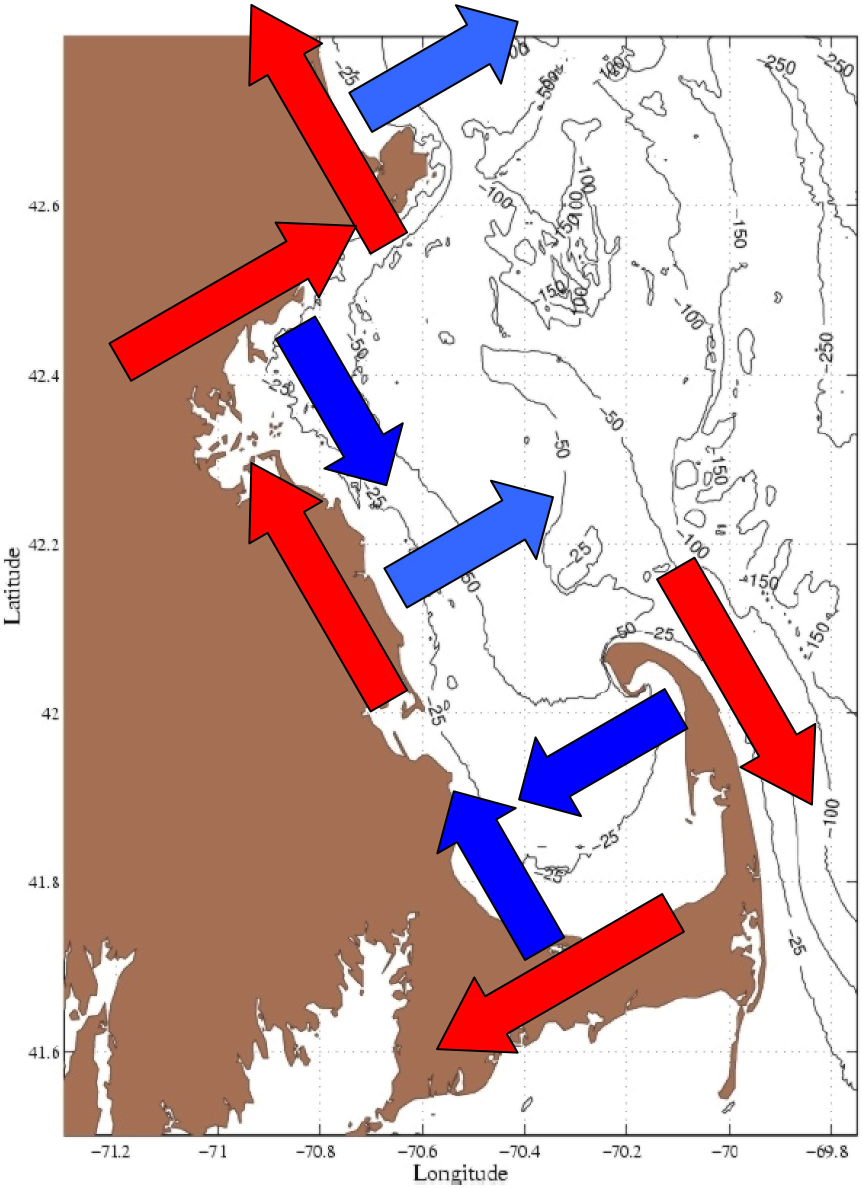
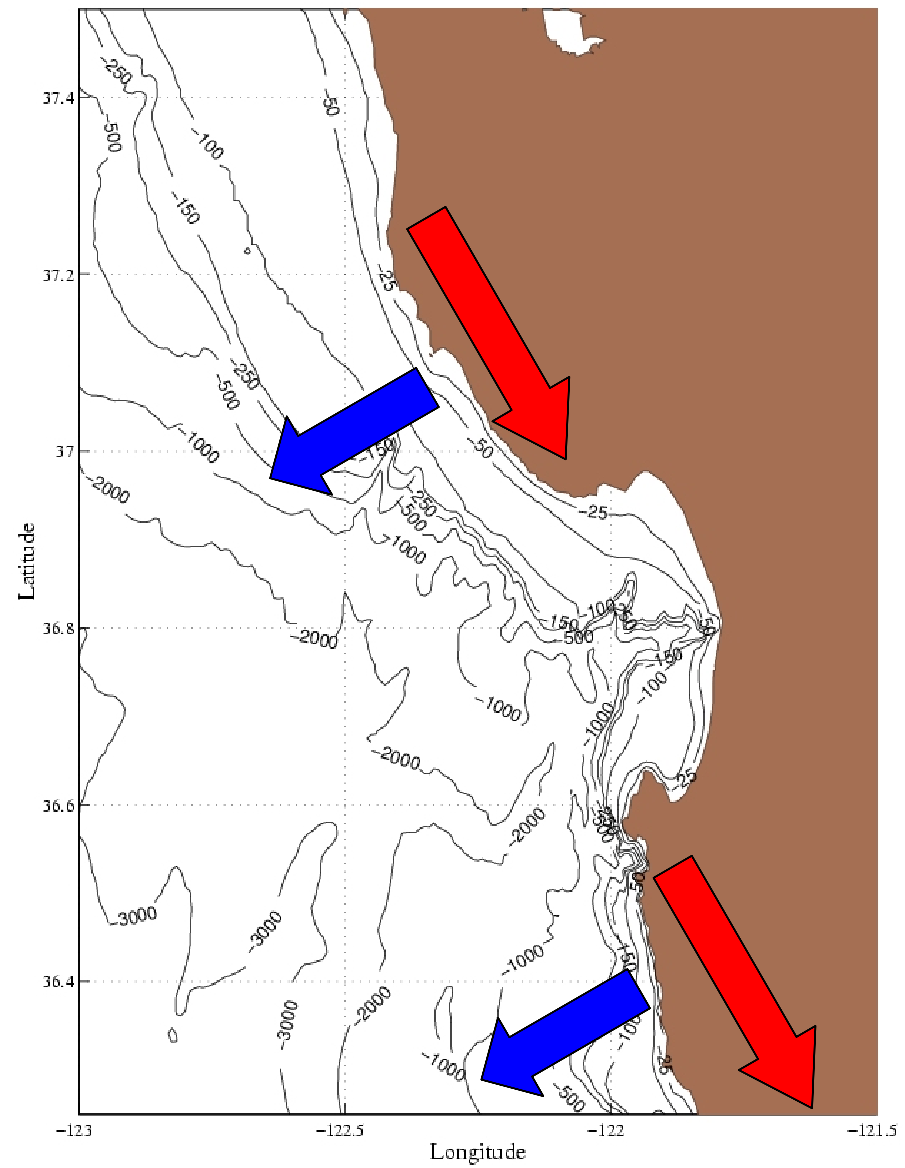

Integrated Ocean Observing
and Prediction Systems
AOSN II
Platforms, sensors and
integrative models: HOPS-
ROMS real-time
forecasting and re-analyses

Wind-Induced Upwelling

Massachusetts Bay
Episodic upwelling



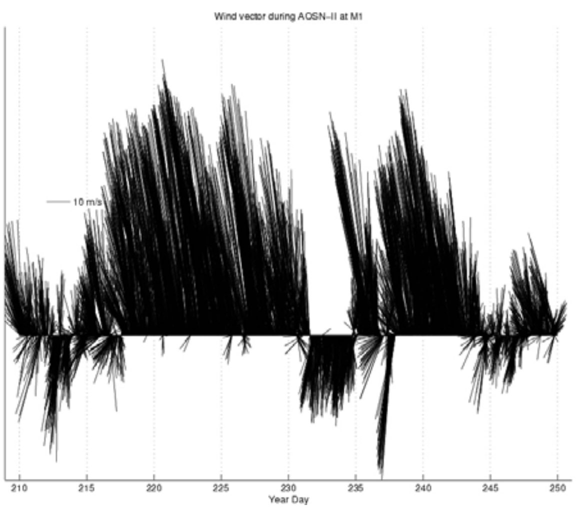
Monterey Bay
Sustained Upwelling



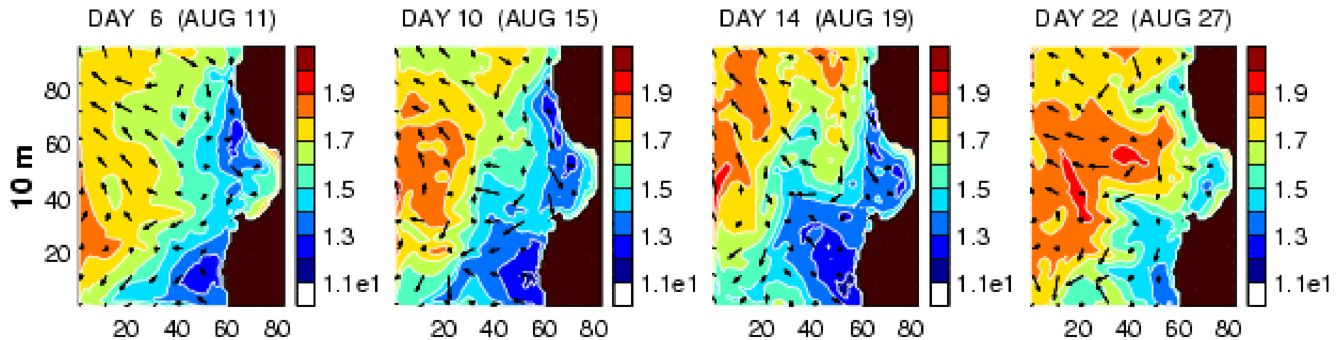
Red = Wind, Blue = Upwelling

Coastal upwelling system: sustained upwelling – relaxation – re-establishment

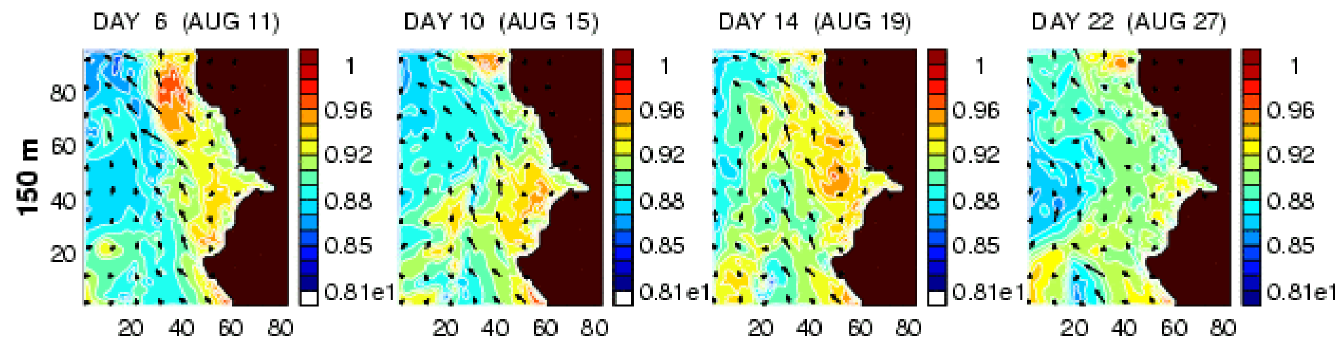
Monterey Bay and California Current System August 2003



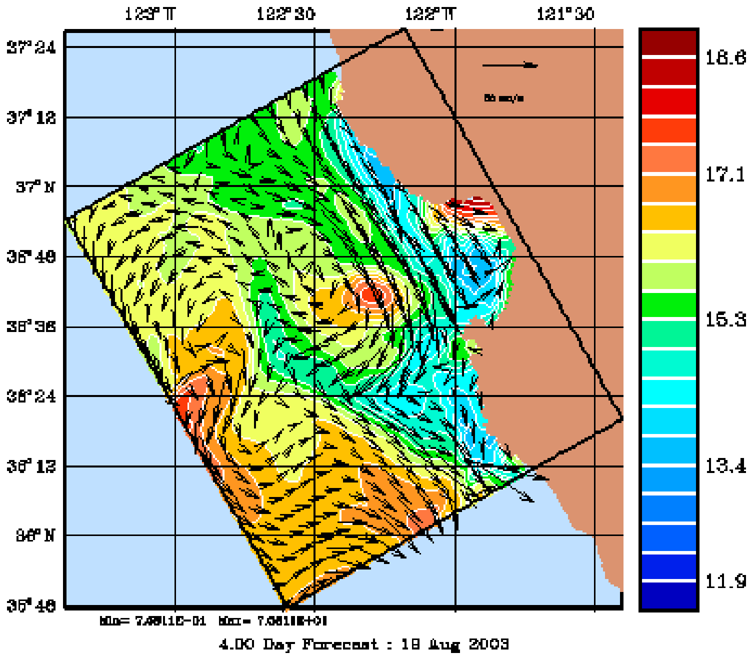
M1 Winds

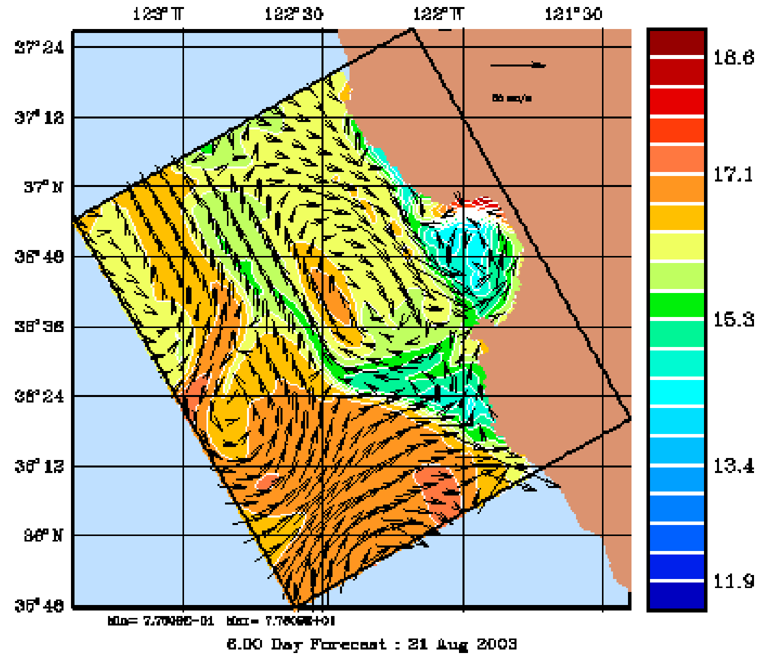


Temperature at 10m



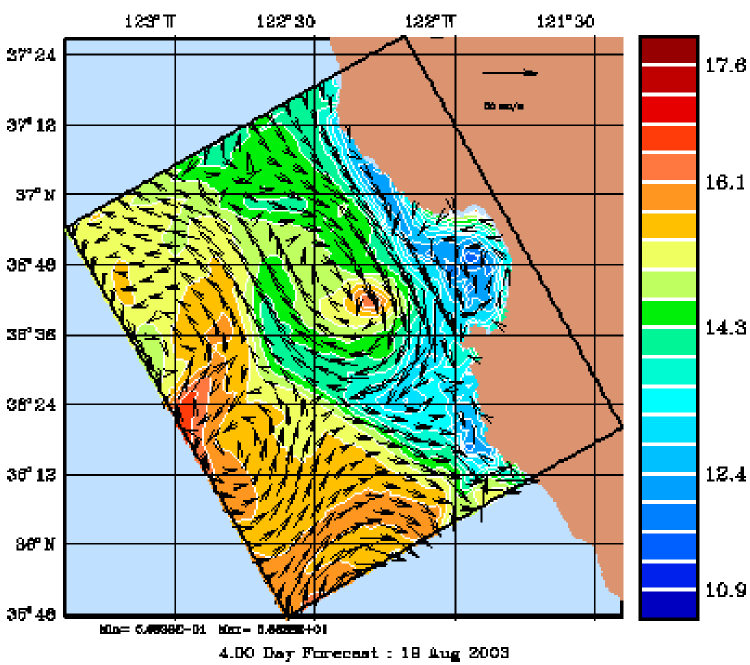
Temperature at 150m

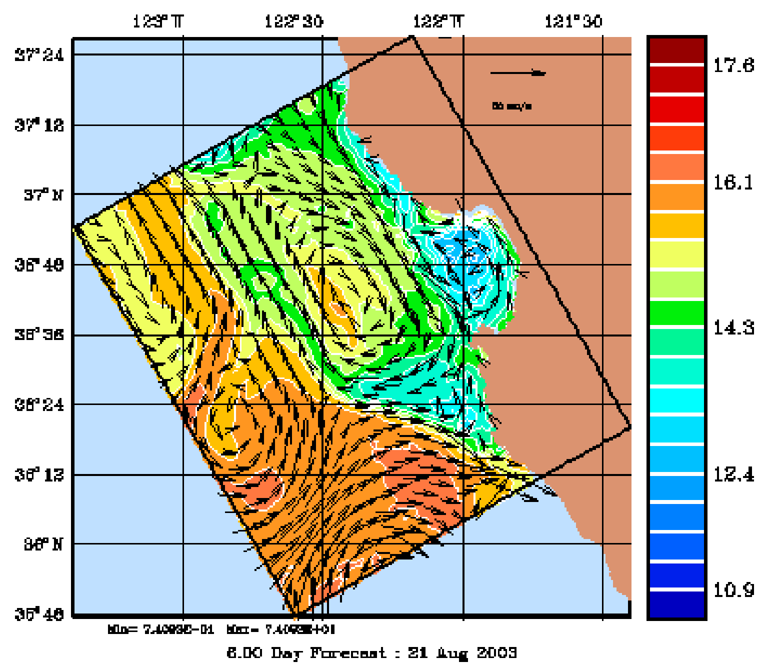




Surface (top) and 10m (bottom) Temperature: 19 Aug and 21 Aug

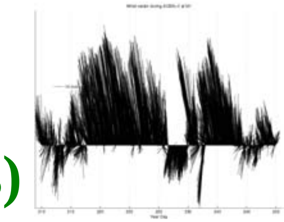
Example real-time forecast issued 19 August 2003



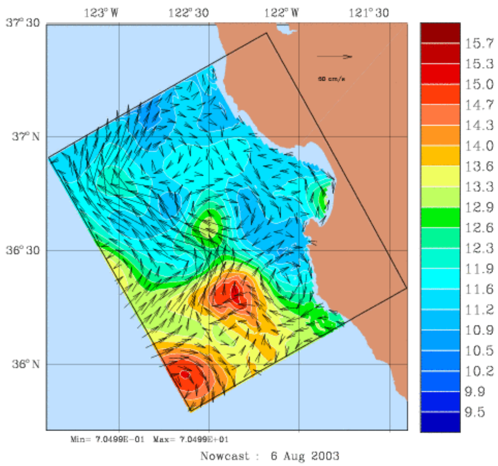


Forecast warms the ocean and reduces the upwelling signature in response to less favorable forecast winds

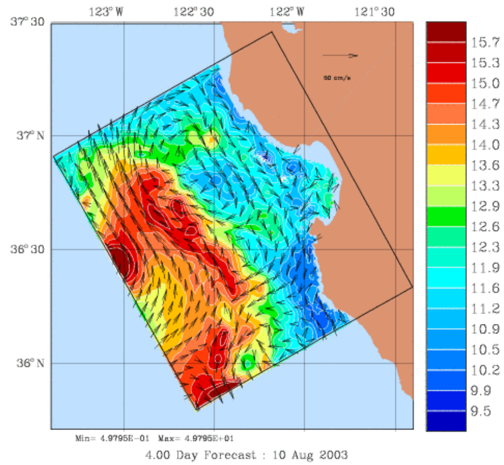
HOPS AOSN-II Re-Analysis



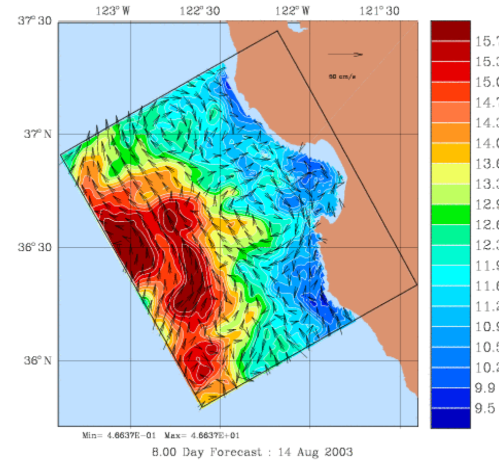
30m Temperature: 6 August – 3 September (4 day intervals)



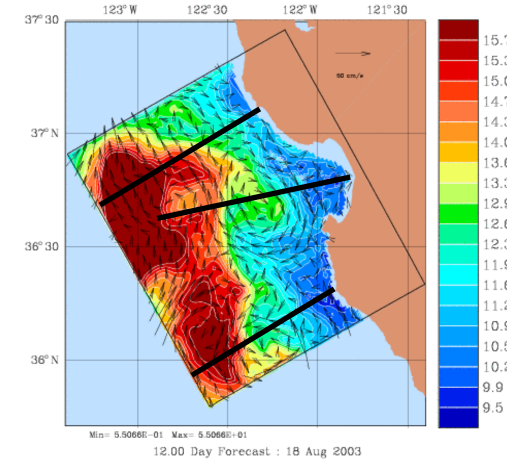
6 Aug



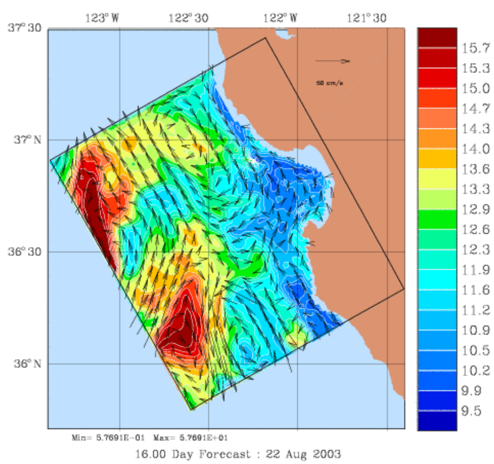
10 Aug



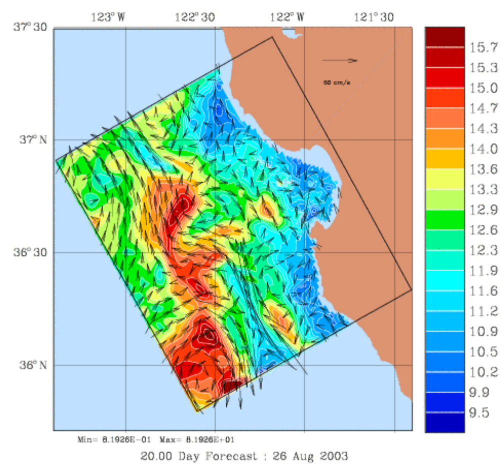
14 Aug



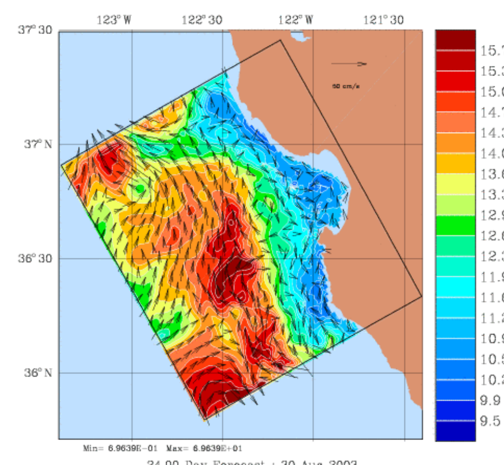
18 Aug



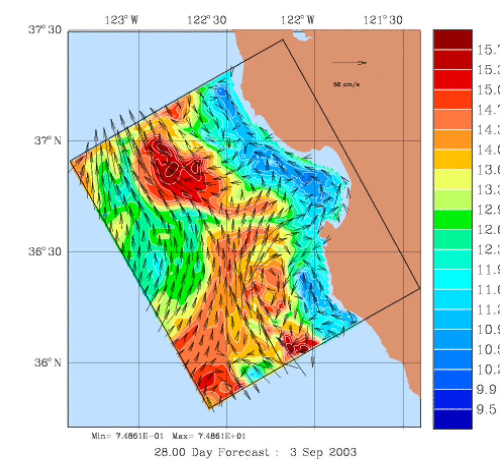
22 Aug



26 Aug



30 Aug



3 Sep

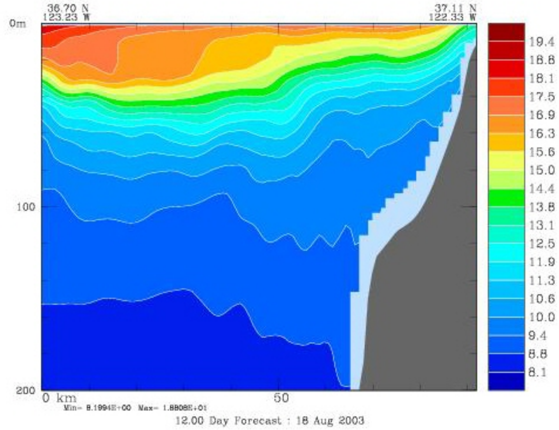
Descriptive oceanography of re-analysis fields and and real-time error fields initiated at the mesoscale.

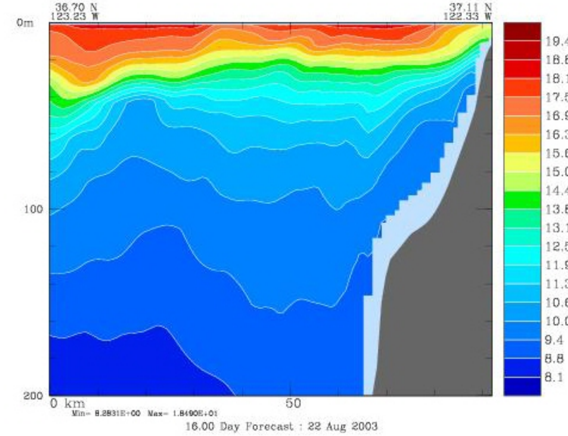
Description includes: Upwelling and relaxation stages and transitions, Cyclonic circulation in Monterey Bay, Diurnal scales, Topography-induced small scales, etc.

HOPS AOSN-II Re-Analysis

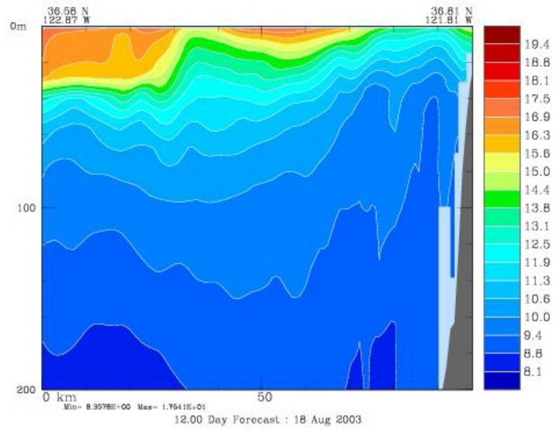
18 August | **22 August**

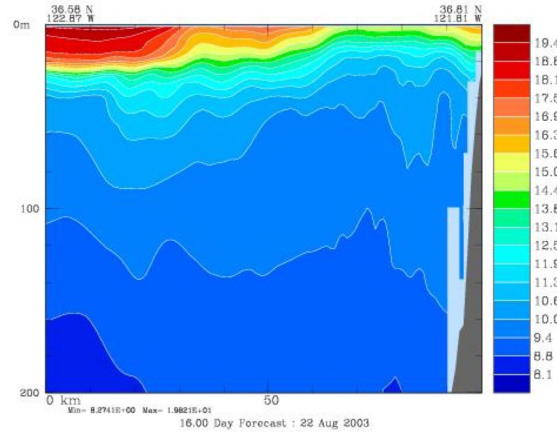
Ano Nuevo



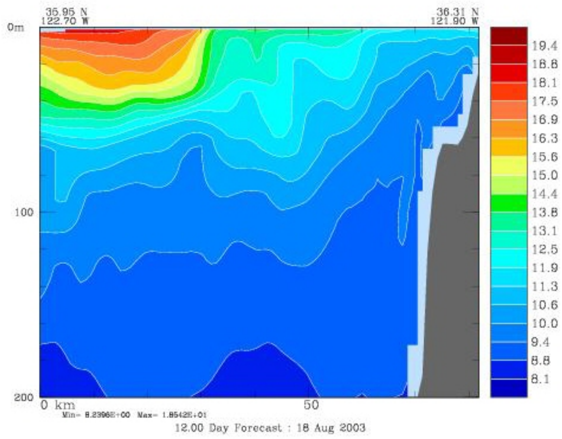


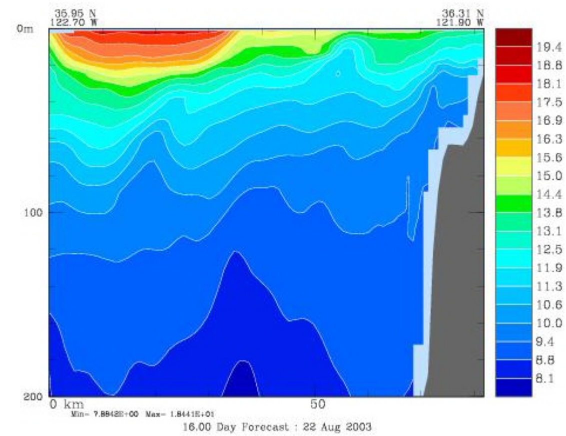
Monterey Bay



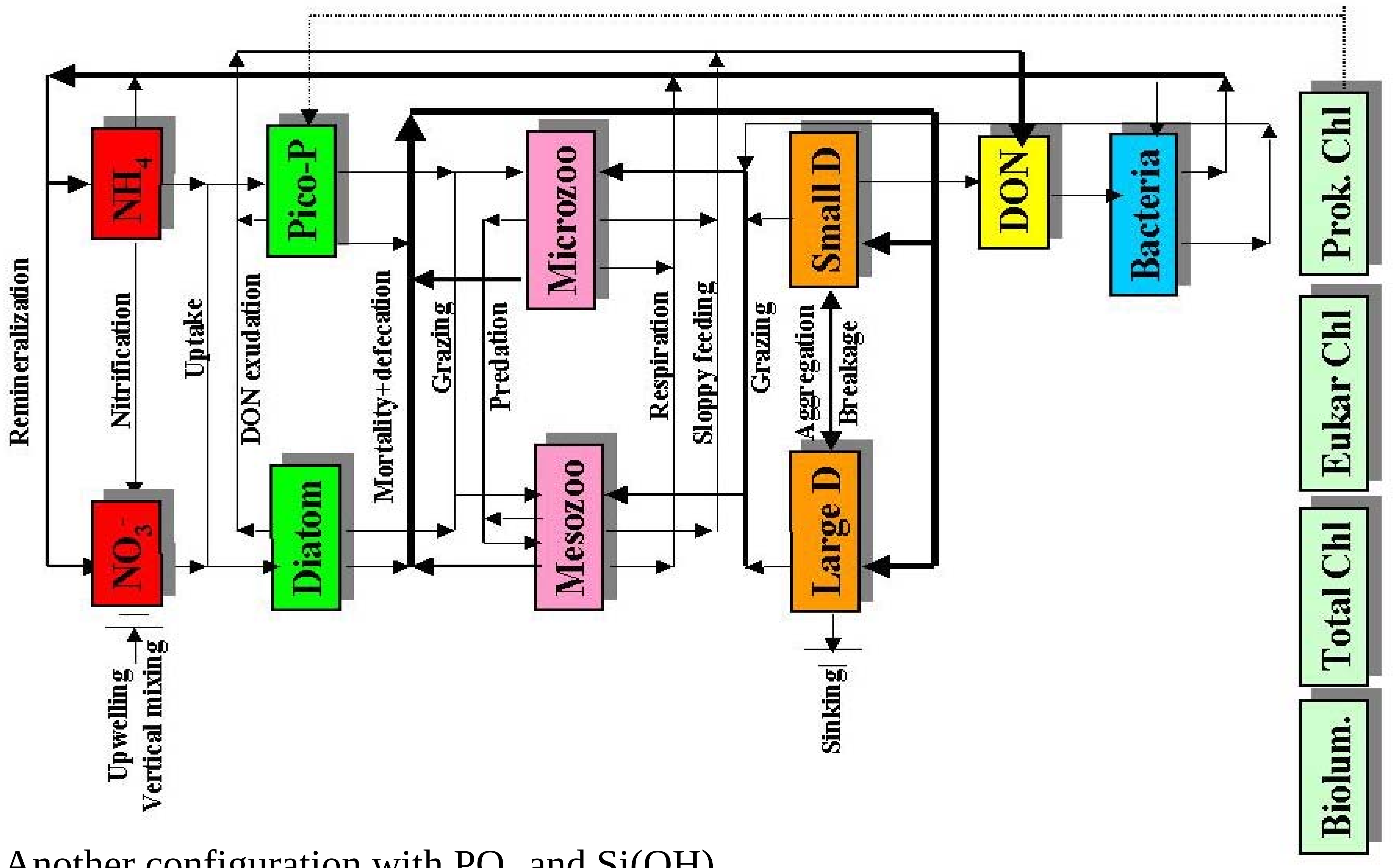


Point Sur





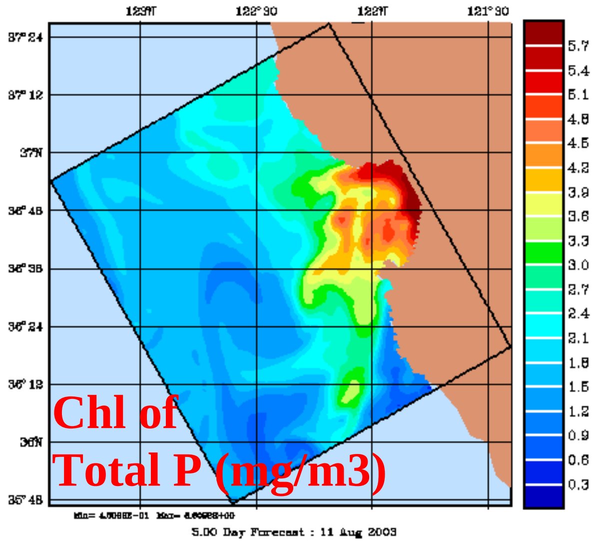
A Priori Biological Model for Monterey Bay

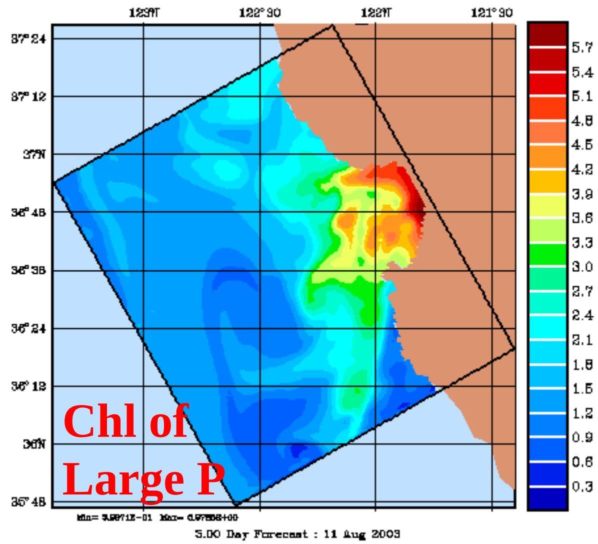


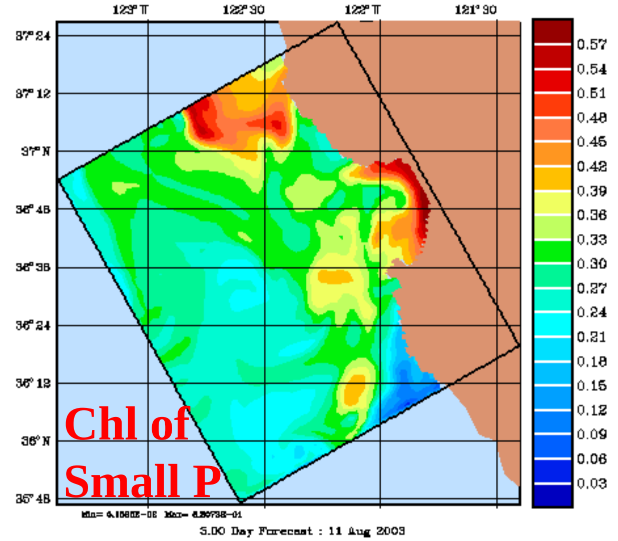
Another configuration with PO_4 and $Si(OH)_4$

Towards automated quantitative model aggregation and simplification

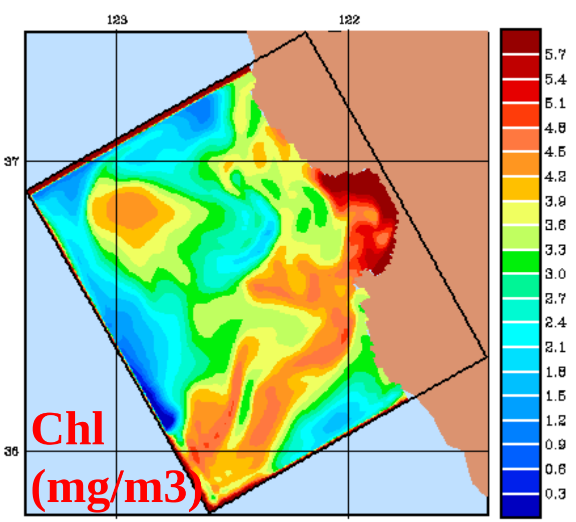
A priori configuration of generalized model on Aug 11 during an upwelling event

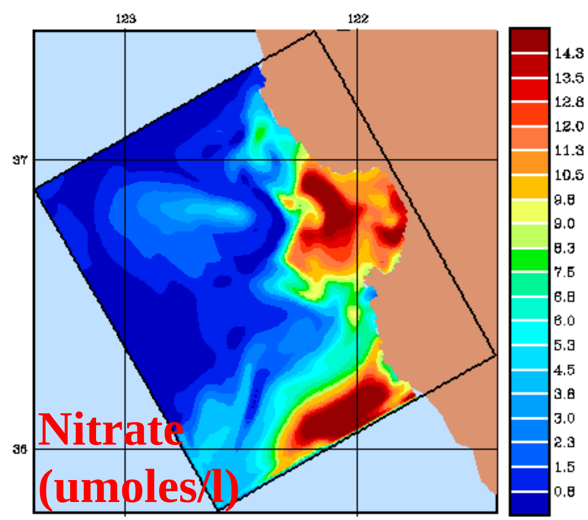


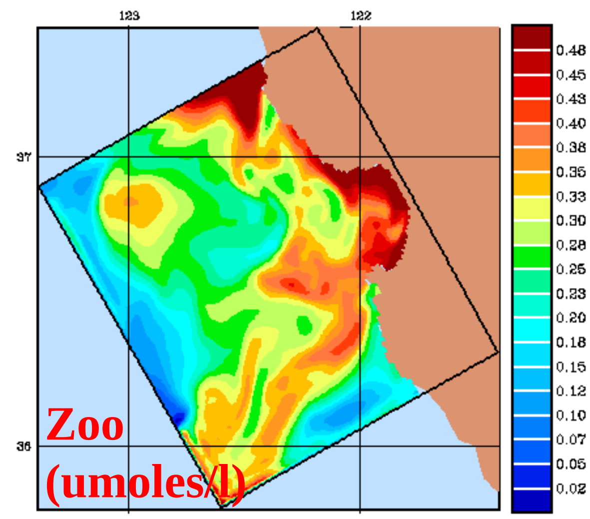




Simple NPZ configuration of generalized model on Aug 11 during same upwelling event

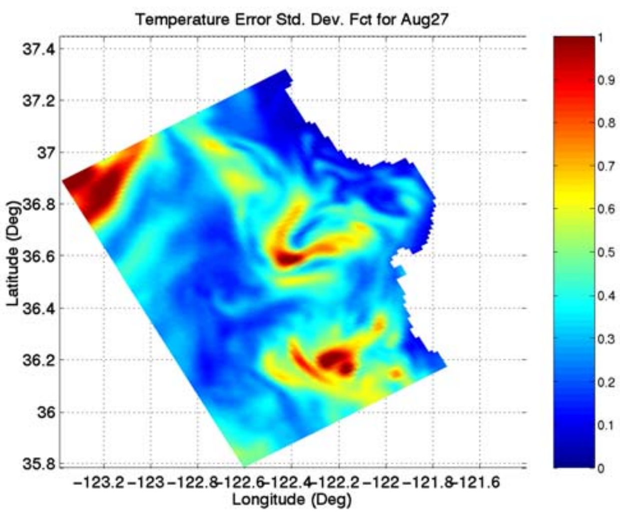




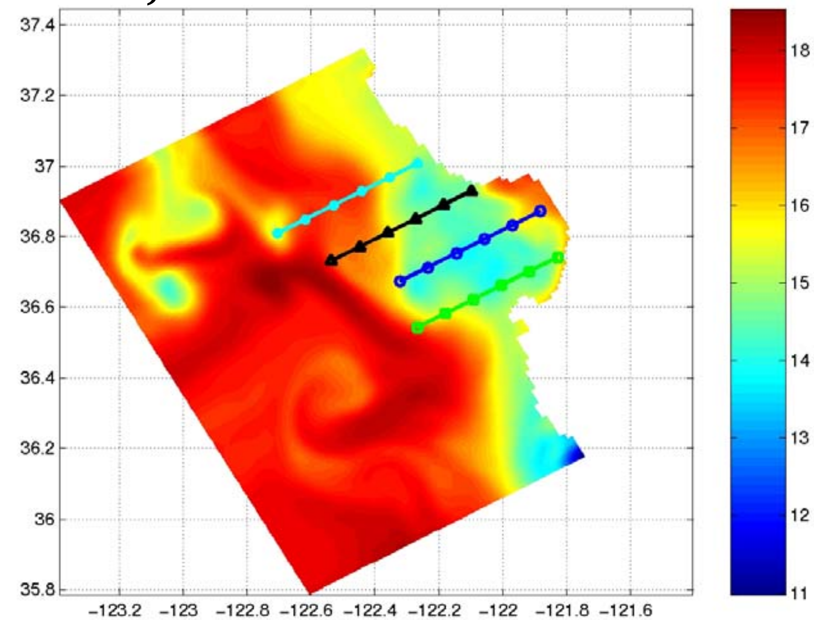


Dr. Rucheng Tian

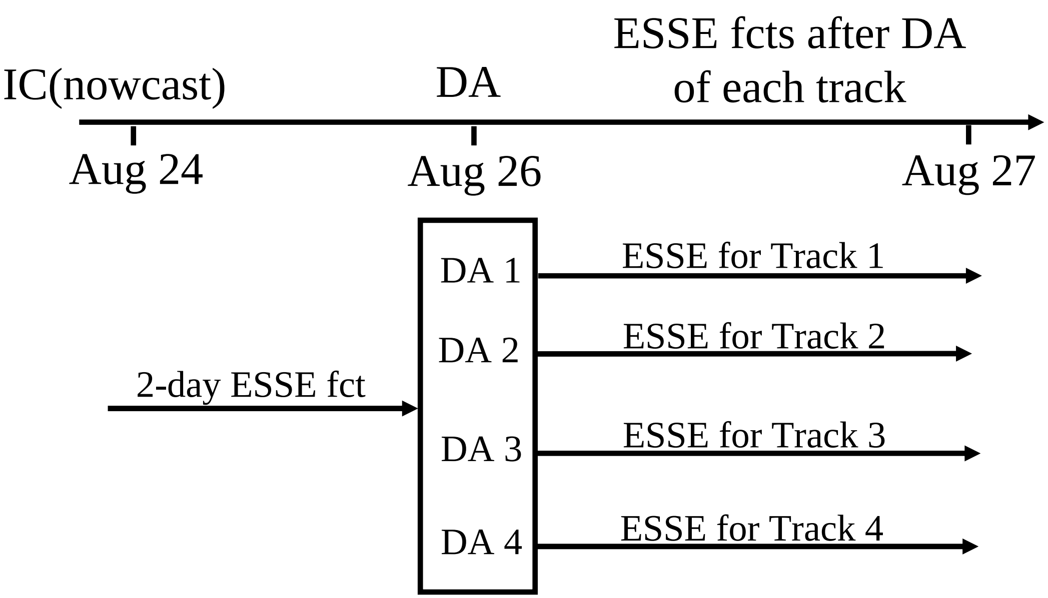
Which sampling on Aug 26 optimally reduces uncertainties on Aug 27?



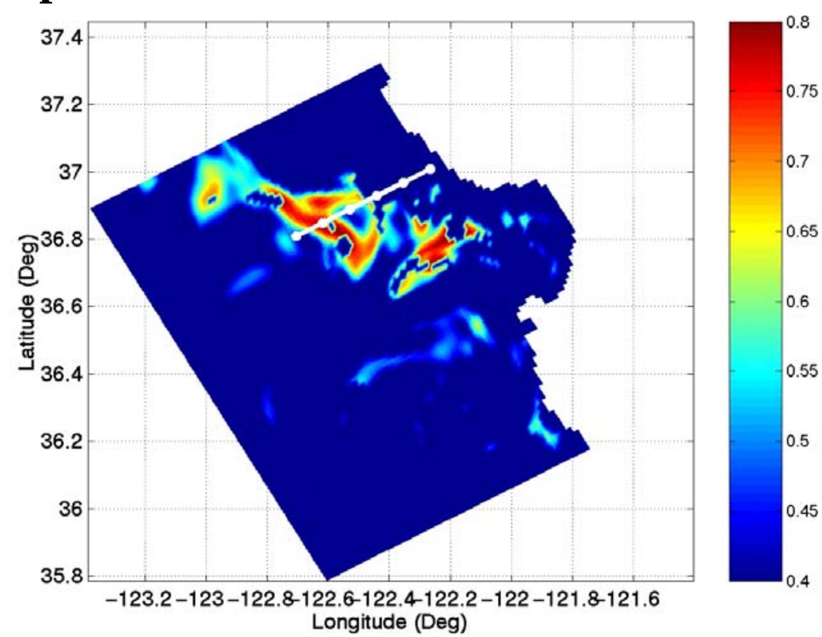
4 candidate tracks, overlaid on surface T fct for Aug 26



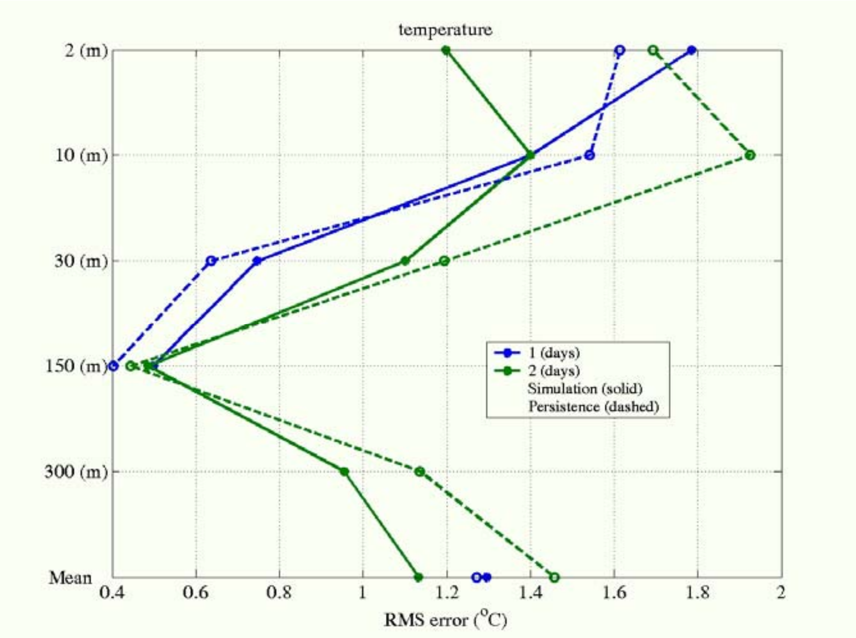
- Based on nonlinear error covariance evolution
- For every choice of adaptive strategy, an ensemble is computed

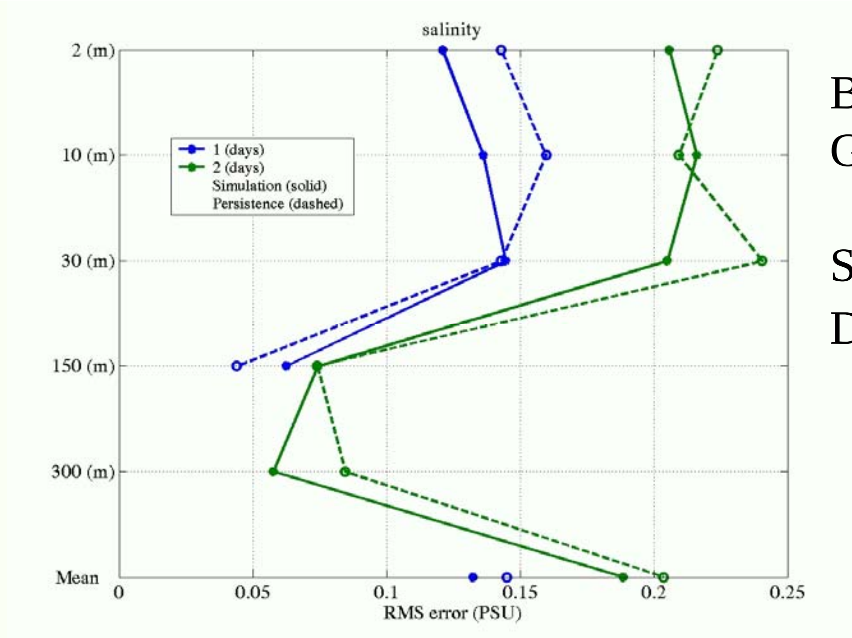


Best predicted relative error reduction: track 1



Forecast RMS Error Estimate– Temperature (left), Salinity (right)



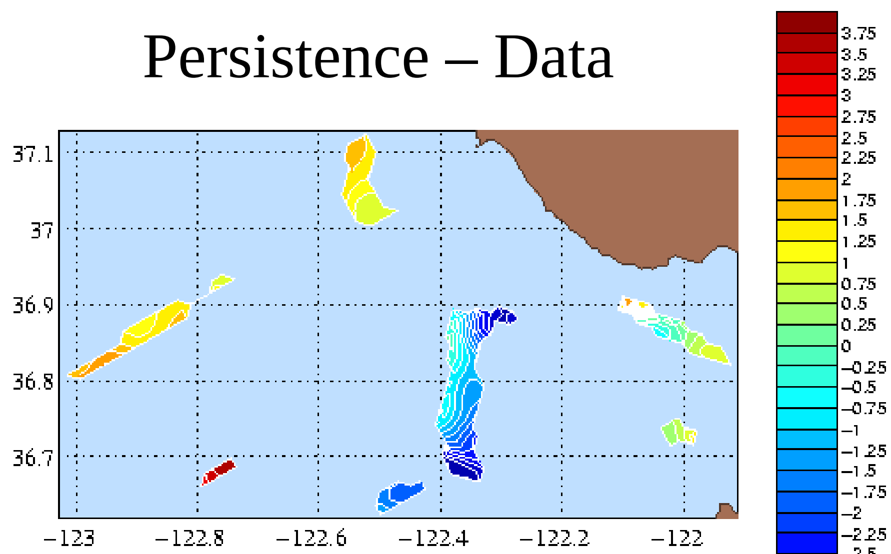


Blue – 12 Aug
Green – 13 Aug

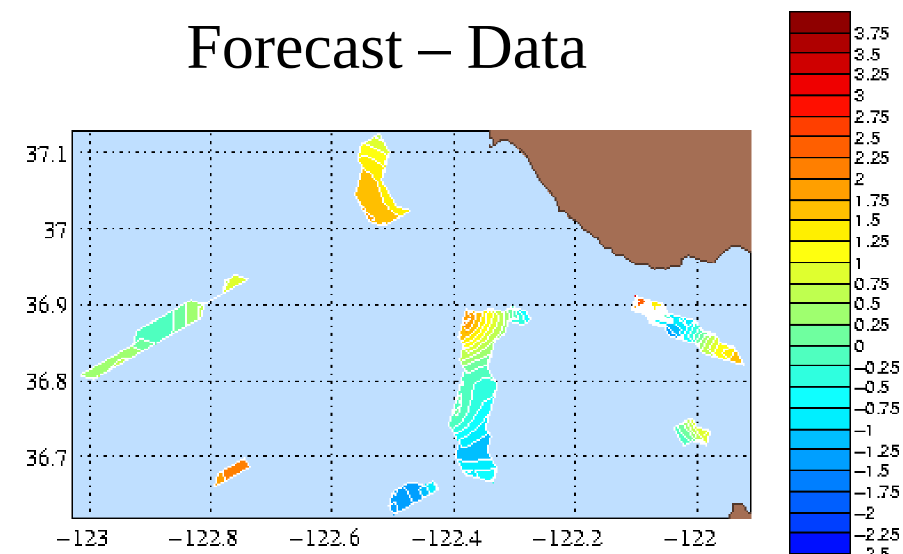
Solid – Forecast
Dash – Persistence

T Difference (at 2m) for 13 August

Persistence – Data

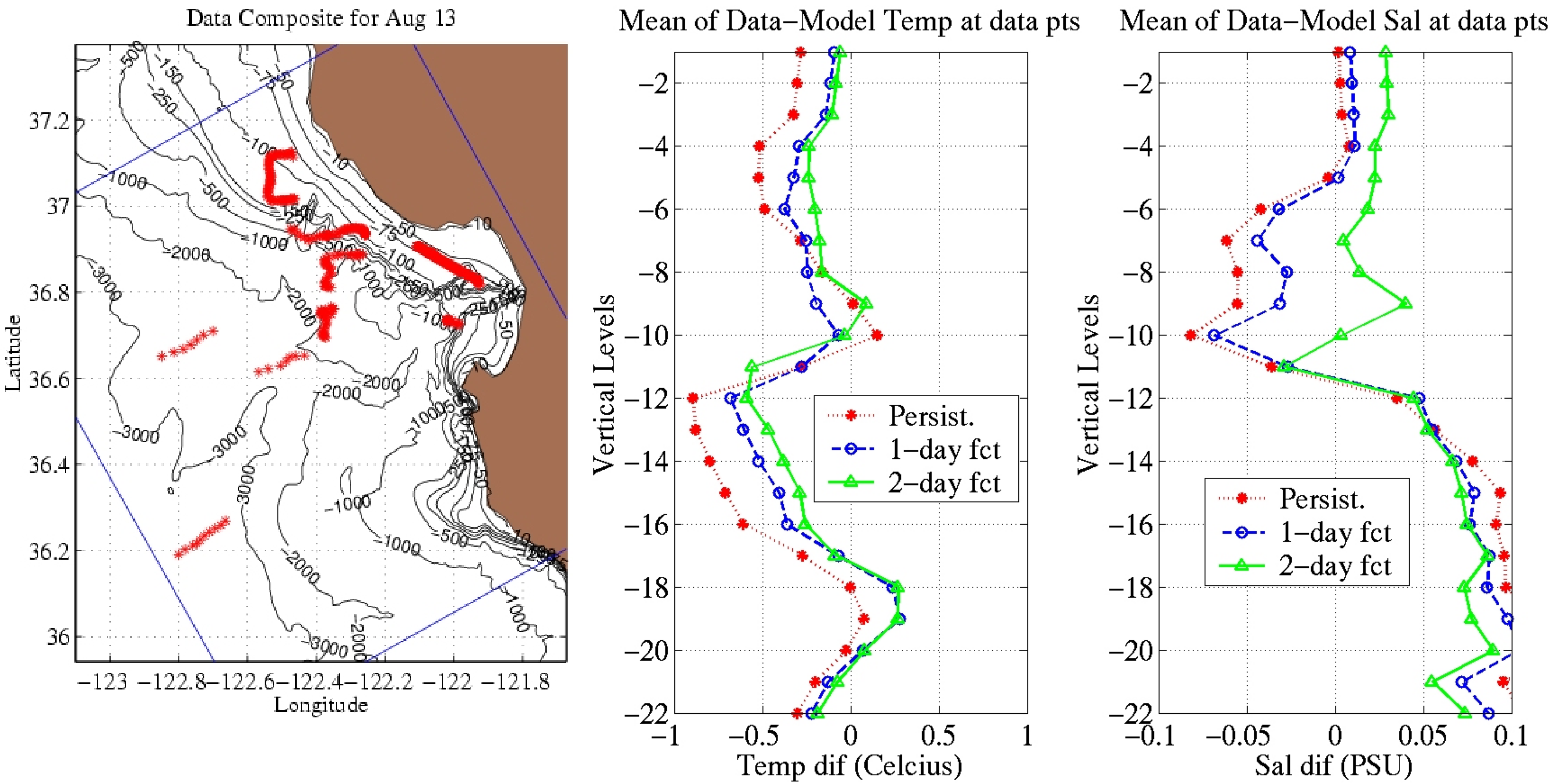


Forecast – Data



Bias Estimate

Horizontally-averaged data-model differences

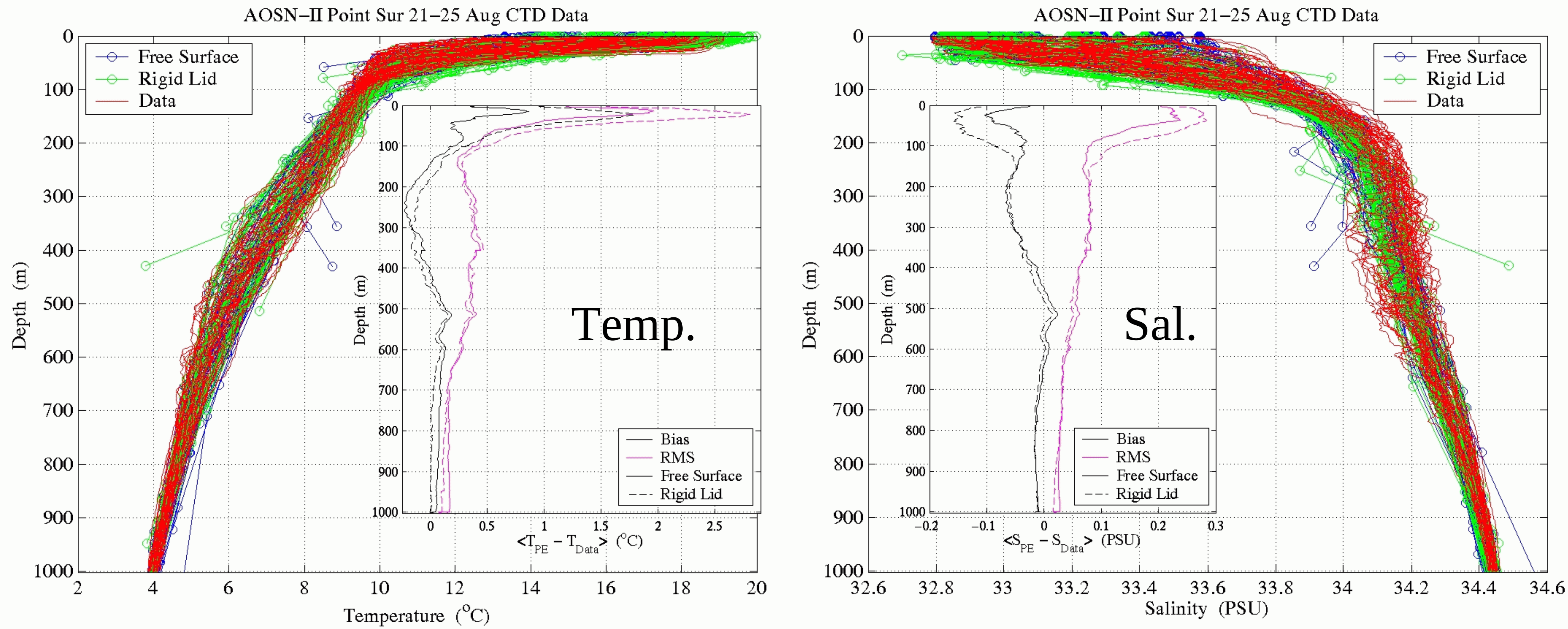


Verification data time: Aug 13

Nowcast (Persistence forecast): Aug 11 **1-day/2-day forecasts: Aug 12/Aug 13**

Implementation of Free Surface in HOPS

AOSN-II Validation

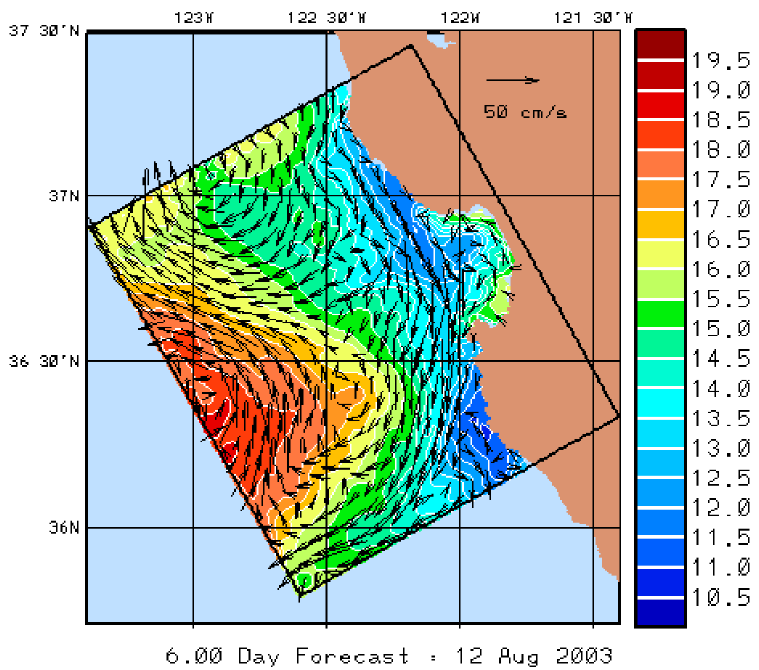


20 day simulation spanning Aug 6-26, 2003
Assimilate CTDs, gliders and aircraft SST from Aug 7-20, 2003
Compare to Pt Sur CTDs from Aug 21-25, 2003

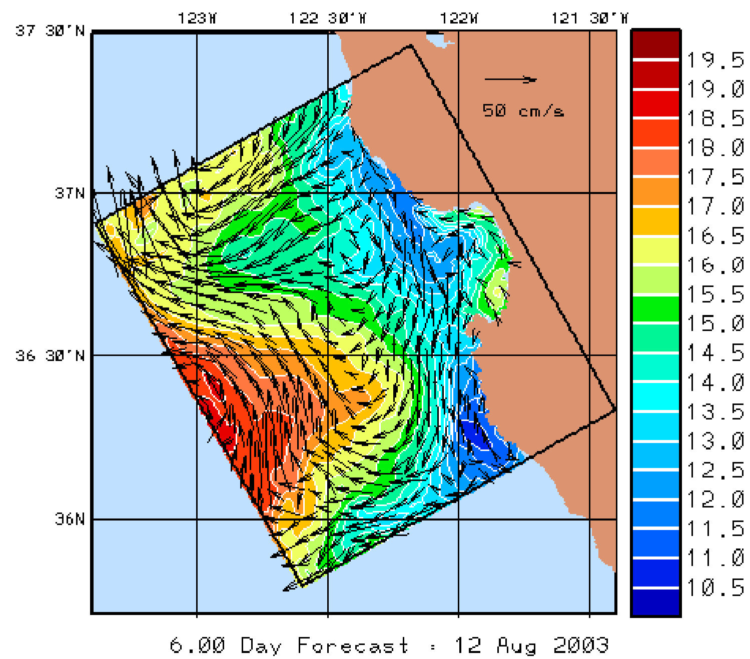
- **Overall comparable skill**
- **Significant improvement in main thermocline**

Implementation of tides in HOPS

- Generate linear barotropic tidal velocities and surface elevation with OTIS using TOPEX BCs.
- Superimpose on HOPS geostrophic initial conditions from AOSN-II hydrography.
- Force HOPS free surface PE with tidal surface elevations.



1.5km HOPS 10m T,V - No Tides

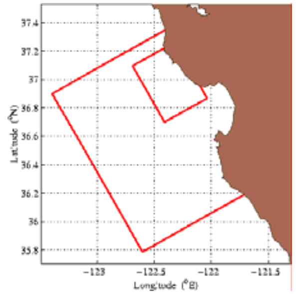


1.5km HOPS 10m T,V - Tides

Work in progress:

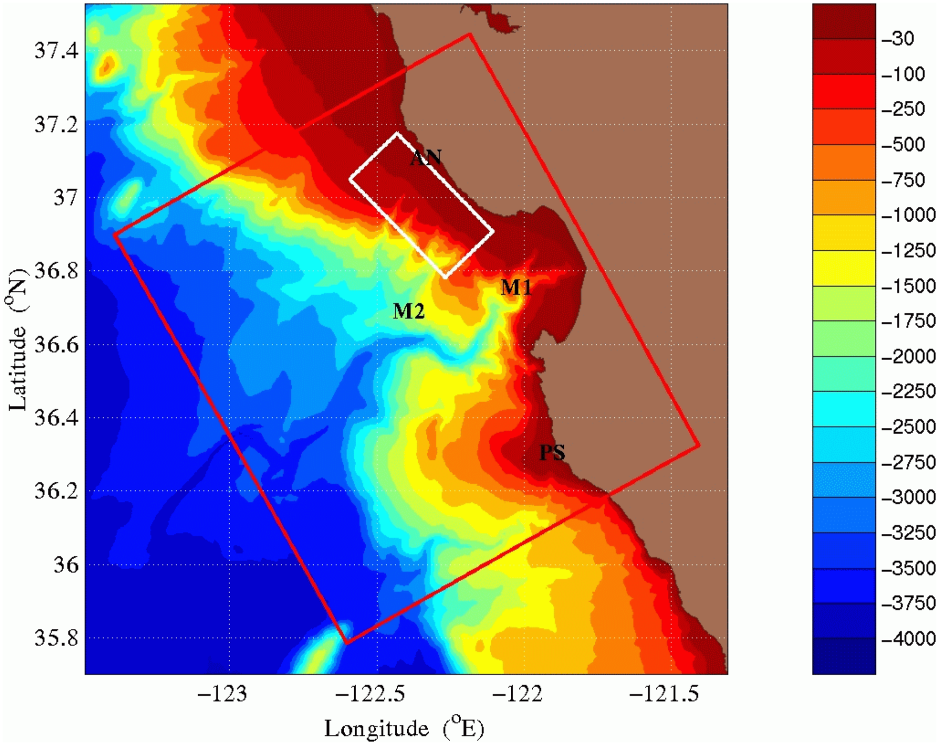
Assimilate tide gauge data in OTIS

2-way nest with 0.5km HOPS PE

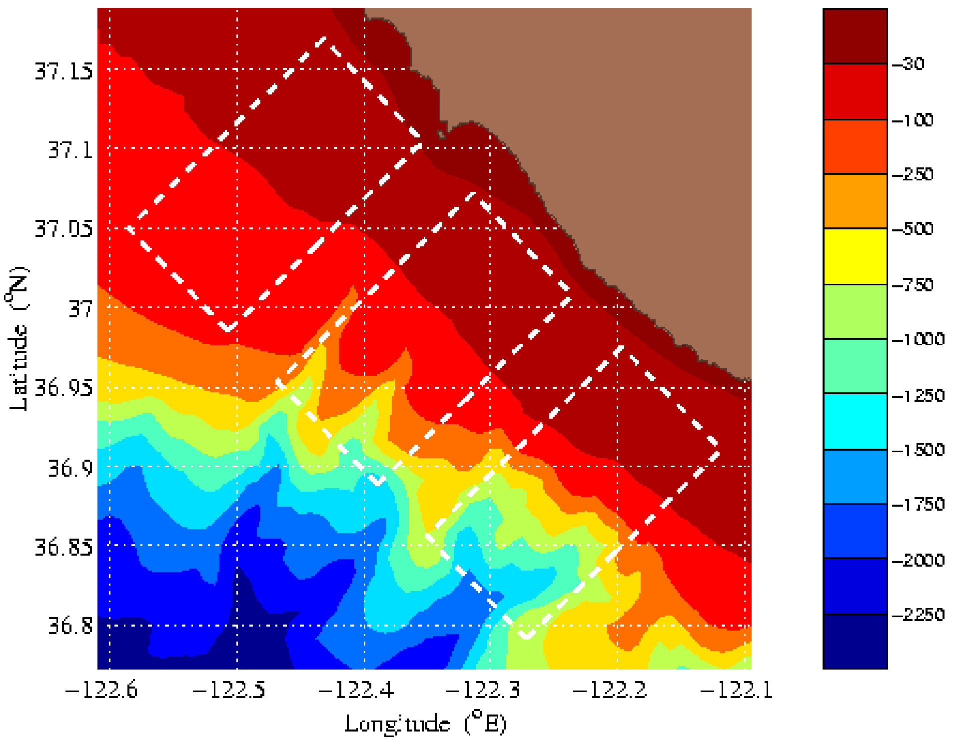


ASAP OSSE #1 – *N Gliders per Track*

OSSE Domains



AOSN2 and ASAP Domains



ASAP "Race-Tracks"

Utilizes HOPS re-analysis with free surface model (no tides)

http://oceans.deas.harvard.edu/AOSN2/OSSE2005/Exp0001/

ASAP OSSE #1 – *N Gliders per Track*

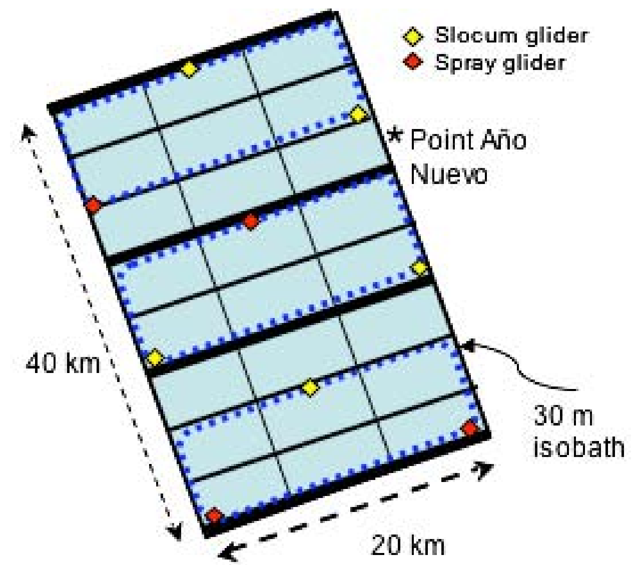
OSSE #1 being guided by "ASAP Team Adaptive Sampling Plan for Gliders in 2006 Field Experiment" – 27 July 2005

ASAP Goals and Objectives

1. Demonstrate ability to provide adaptive sampling and evaluate benefits of adaptive sampling. Includes responding to:
   a) changes in ocean dynamics
   b) model uncertainty/sensitivity
   c) changes in operations (e.g., a glider comes out of water)
   d) unanticipated challenges to sampling as desired (e.g., very strong currents)

2. Coordinate multiple assets to optimize sampling at the physical scales of interest.

3. Understand dynamics of 3D upwelling centers
   - Focus on transitions, e.g., onset of upwelling, relaxation.
   - Close the heat budget for a control volume with an eye on understanding the mixed layer dynamics in the upwelling center.
   - Locate the temperature and salinity fronts and predict acoustic propagation.



Robinson, Haley, Lermusiaux, Leslie

ASAP OSSE #1 – *N Gliders per Track*

OSSE Definition

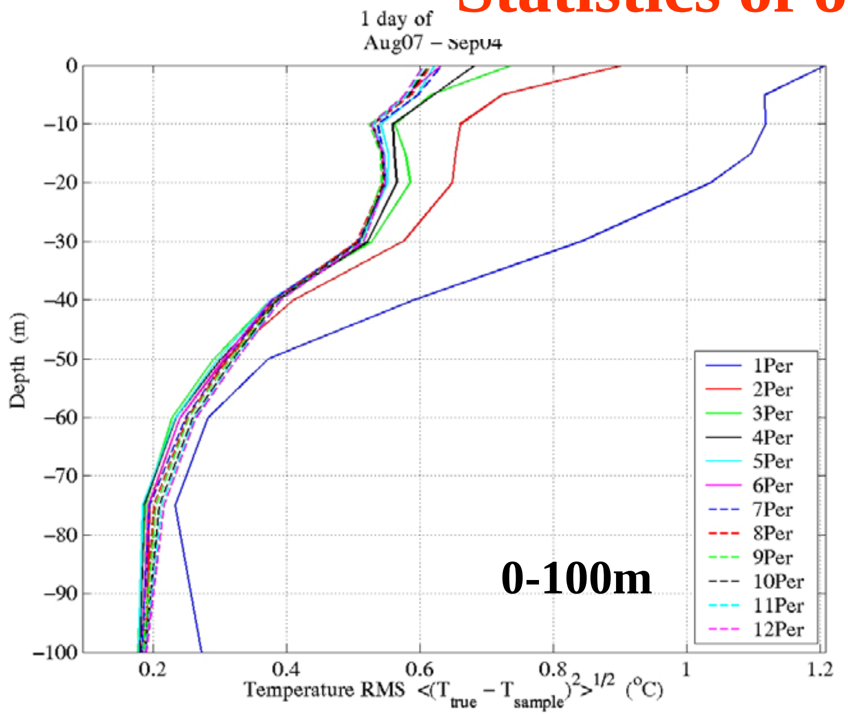
- Ability of N gliders to quantitatively represent a simulated "true" ocean with and without melding with dynamics

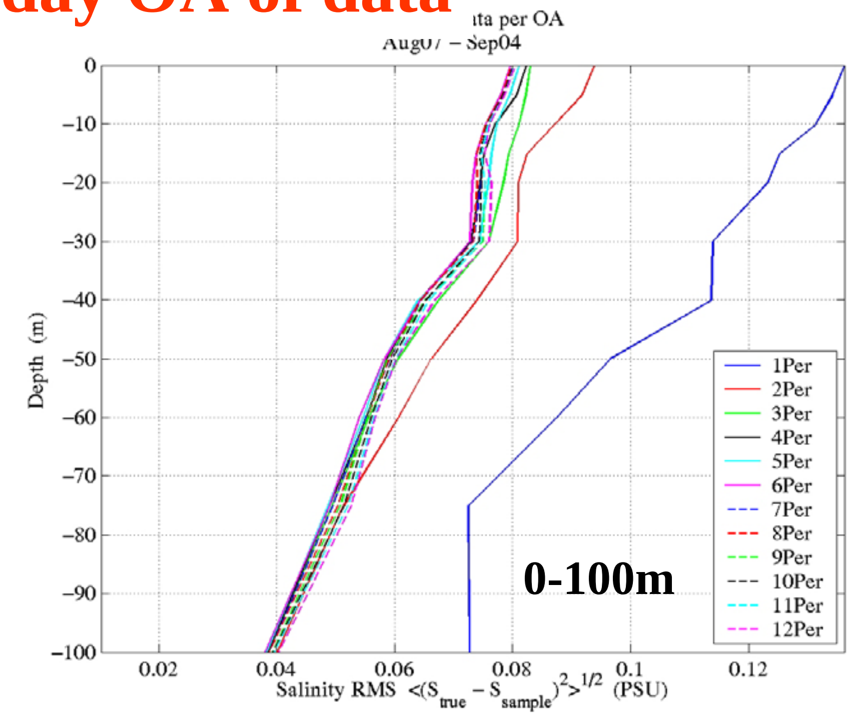
- Without dynamics: objectively analyze
  i. Once per day (more realistic) **(one day OA)**

- With dynamics: assimilate data once per day and compare
  i. *A priori* estimate
  ii. *A posteriori* estimate

  Compare these estimates with once a day OA's above

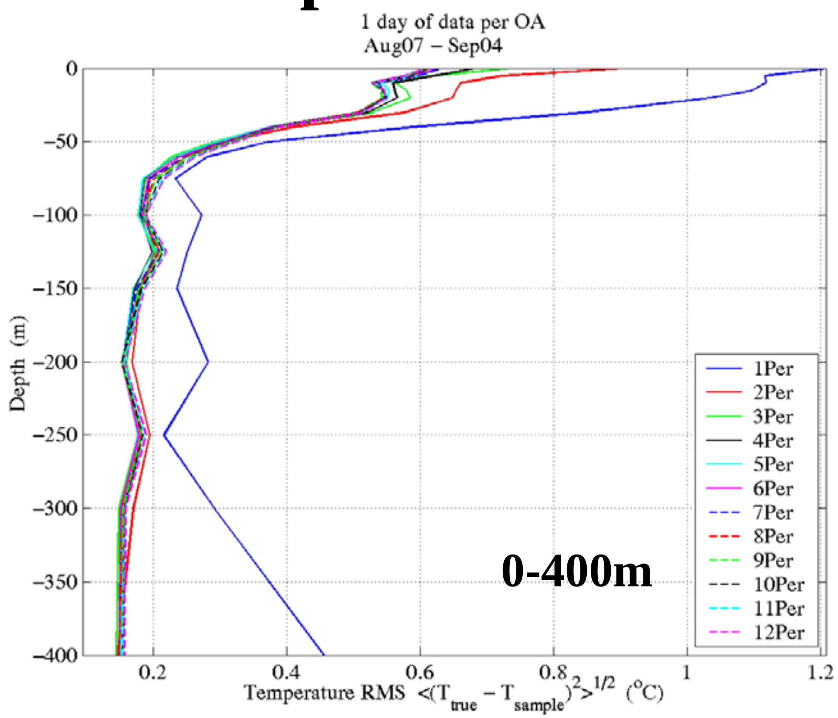
Statistics of once/day OA of data

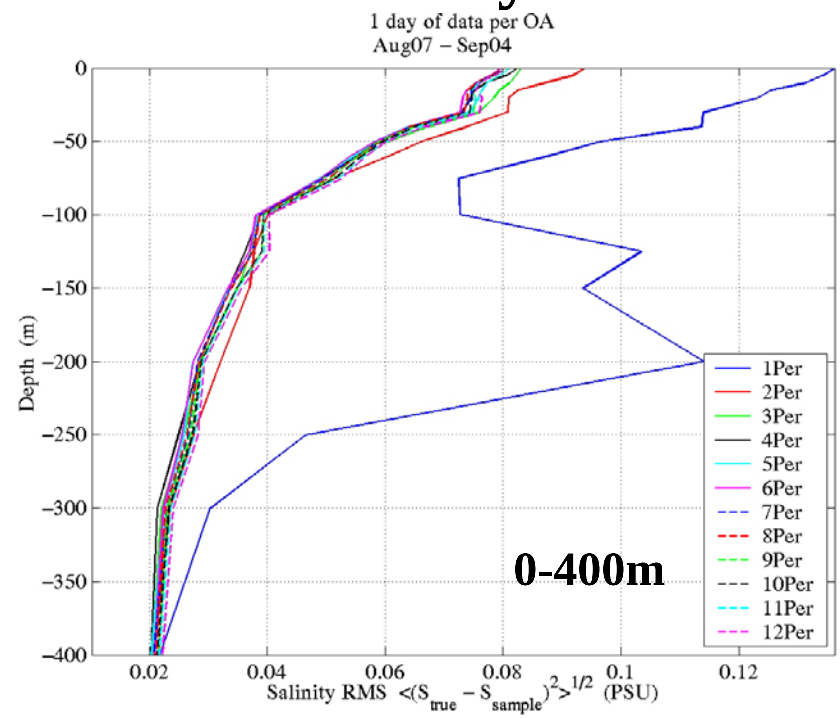




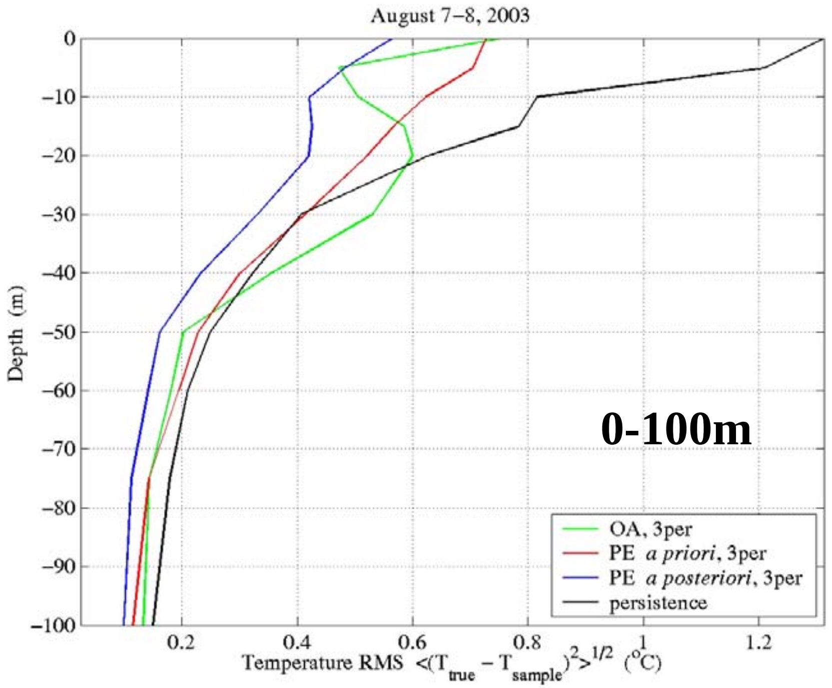
Temperature RMS

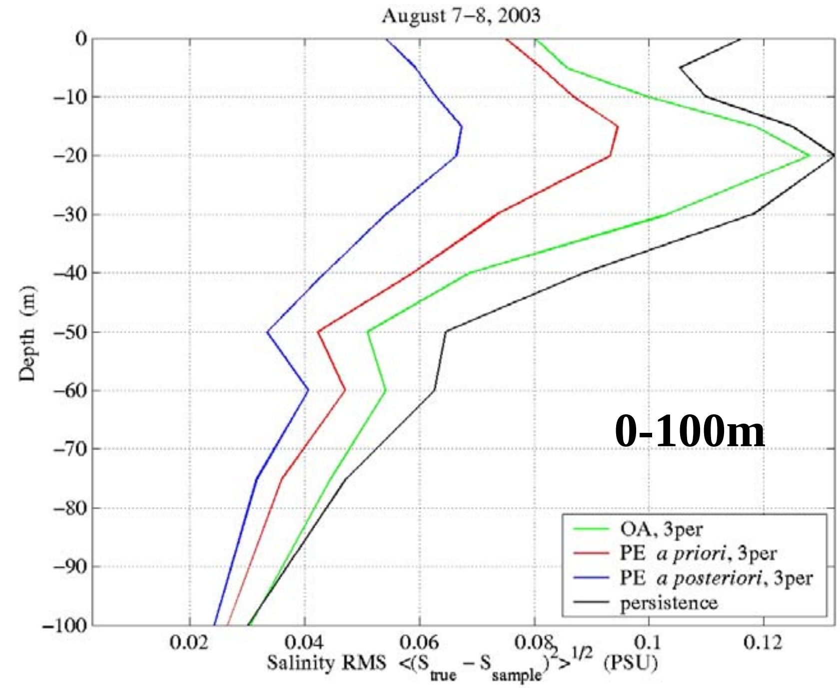
Salinity RMS





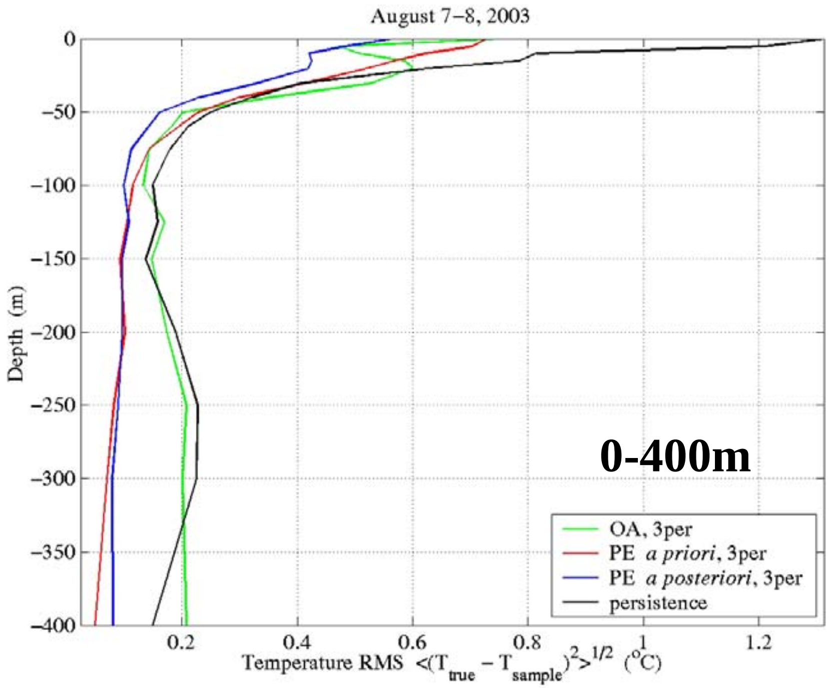
Effect of Dynamics

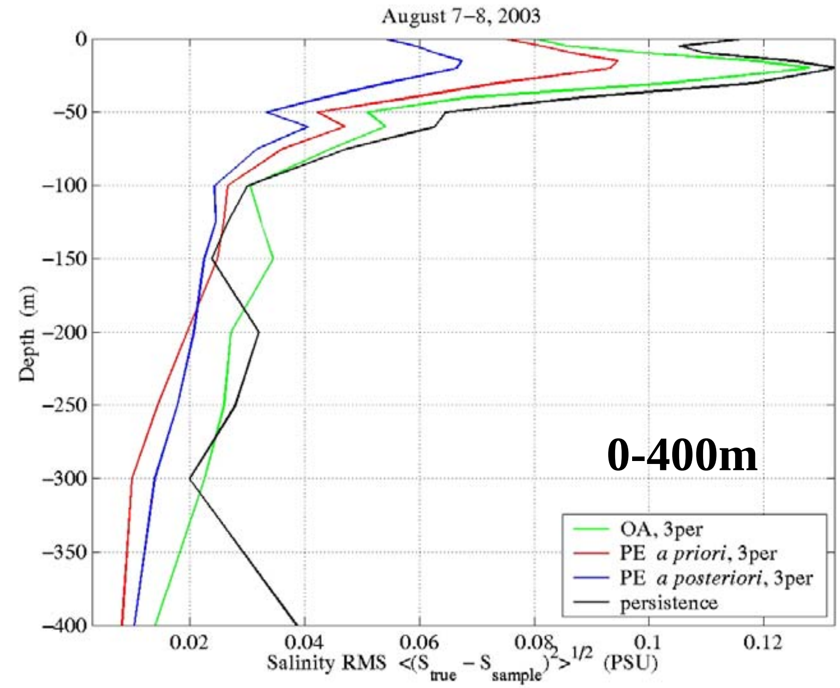




Temperature RMS

Salinity RMS





Error Analyses and Optimal (Multi) Model Estimates

Strategies For Multi-Model Adaptive Forecasting

- Error Analyses: *Learn individual model forecast errors in an on-line fashion through developed formalism of multi-model error parameter estimation*
- Model Fusion: *Combine models via Maximum-Likelihood based on the current estimates of their forecast errors*

3-steps strategy, using model-data misfits and error parameter estimation

1. Select forecast error covariance $\mathbf{B}$ and bias $\boldsymbol{\mu}$ parameterization $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$

$$\mathrm{B} \approx \tilde{\mathrm{B}}(\boldsymbol{\alpha}); \qquad \boldsymbol{\mu} \approx \tilde{\boldsymbol{\mu}}(\boldsymbol{\beta}); \qquad \boldsymbol{\Theta} = \{\boldsymbol{\alpha}, \boldsymbol{\beta}\}$$

2. Adaptively determine forecast error parameters from **model-data misfits** based on the Maximum-Likelihood principle:

$\boldsymbol{\Theta}^* = \arg\max_{\boldsymbol{\Theta}} p(\boldsymbol{\mathcal{Y}}|\boldsymbol{\Theta})$ Where $\boldsymbol{\mathcal{Y}} = \{\mathbf{y}_1^o, \mathbf{y}_2^o, \ldots, \mathbf{y}_T^o\}$ is the observational data

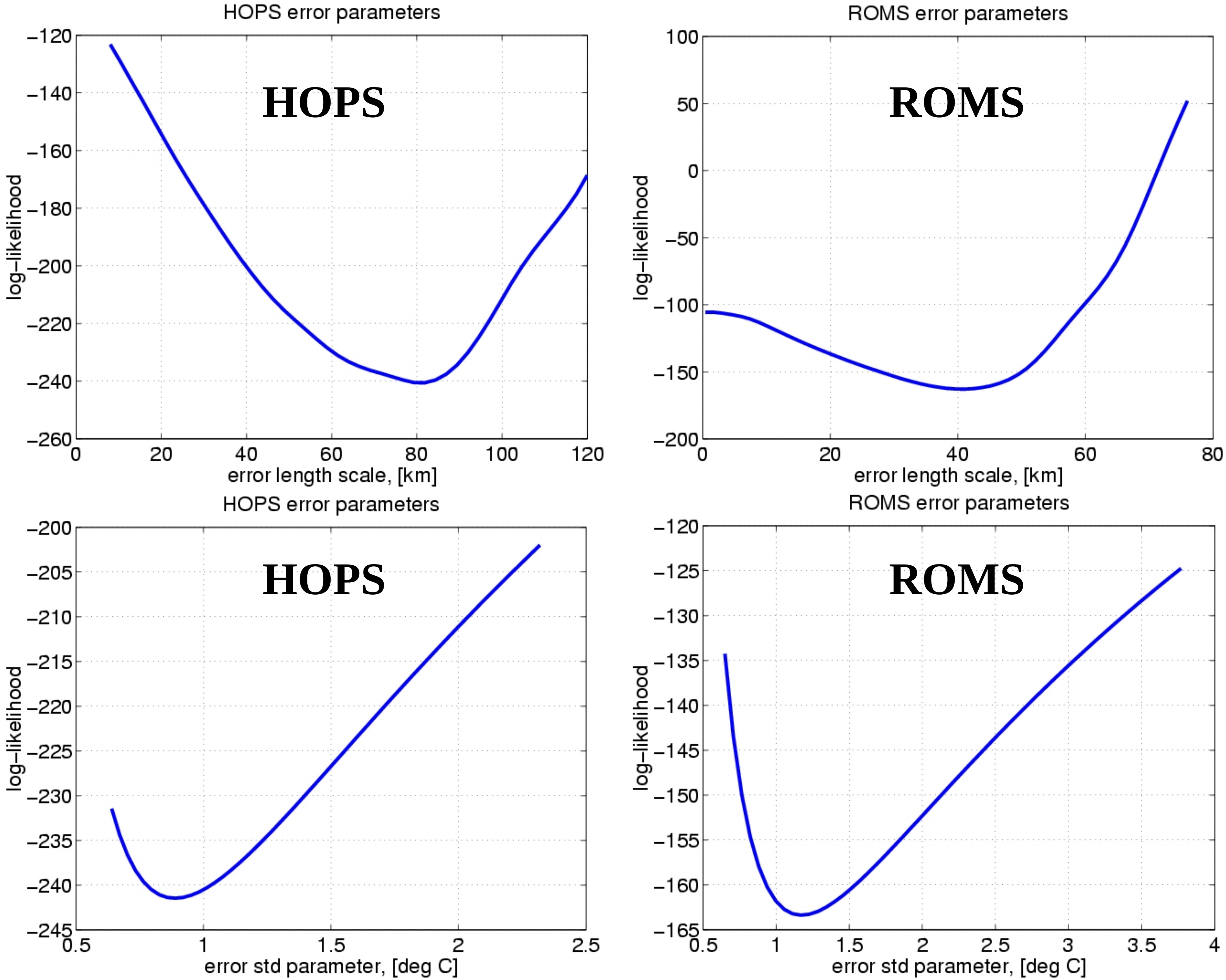
3. Combine model forecasts $\mathbf{x}_i$ via Maximum-Likelihood based on the current estimates of error parameters (Bayesian Model Fusion)

O. Logoutov

$$\mathbf{x}^* = \arg\min_{\mathbf{x}} \sum_{m=1}^{M} (\mathbf{x} - \mathbf{H}_m \mathbf{x}_m)^T \mathcal{B}^{-1}_{(\boldsymbol{\Theta}_m)} (\mathbf{x} - \mathbf{H}_m \mathbf{x}_m)$$

Error Analyses and Optimal (Multi) Model Estimates

An Example of Log-Likelihood functions for error parameters



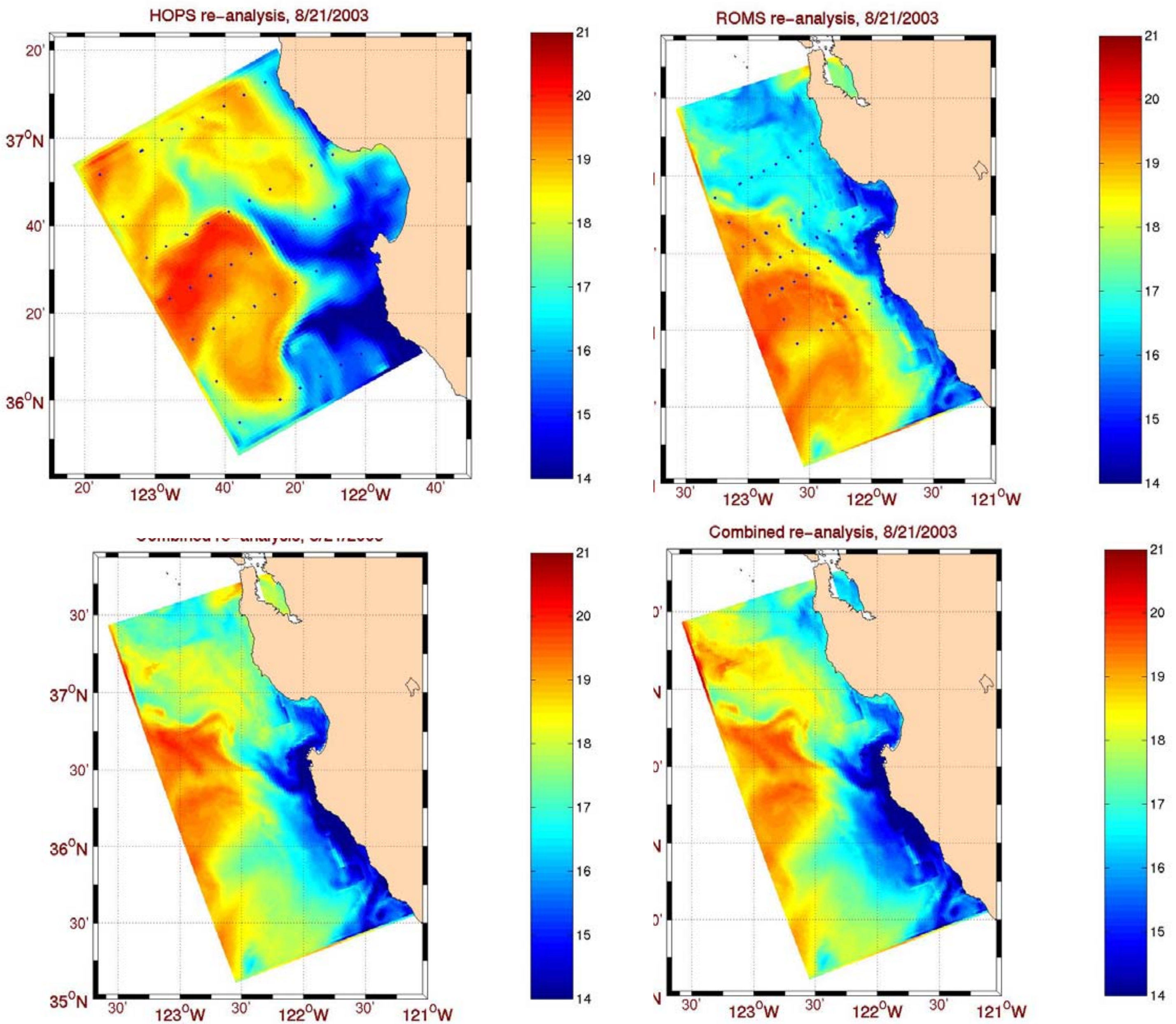
Length Scale

Variance

Error Analyses and Optimal (Multi) Model Estimates

Two-Model Forecasting Example

combine based on relative model uncertainties



HOPS and ROMS SST forecast

Left – HOPS (re-analysis)

Right – ROMS (re-analysis)

Combined SST forecast

Left – with *a priori* error parameters

Right – with Maximum-Likelihood error parameters

Model Fusion

Adaptive Multi-Model Forecasting: Thoughts and Perspectives

- Multi-model systems have a considerable potential:
  - Boost the predictive skill by reducing random errors as $\epsilon \sim 1/\sqrt{m}$ where ***m*** number of models (assuming errors in models are independent)
  - Sample forecast uncertainty with ***Model error included*** (the only alternative is developing a stochastic ocean model which is costly and involves parameterizations that need to be validated and tuned)

Multi-Model Forecasting belongs in the mainstream of many real-world applications, particularly in the area of regional ocean forecasting, ... however, it's not there yet

- Use of Multi-Models is hampered by the fact that the time scale for changes to a forecasting system is typically shorter than the time it takes to collect a significant sample of past validating events
  - For example, in our practice with HOPS, as soon as several validating events become available a change to a forecasting system is typically made to correct for deficiencies exemplified in validating data. As a result, in most cases only a few batches of spatially distributed measurements are available as training data for the purposes of model combination.
  - It is imperative that a forecast combination methodology was adaptive and capable to operate with a small sample of past validating events
  - We must address and resolve this difficulty to be able to have a successful multi-model ocean forecasting system

Bayesian Adaptive Multi-Model Forecasting

Goal: a forecast combination methodology that is ADAPTIVE and capable to operate with a SMALL SAMPLE of past validating events.

- Corresponds to maximizing of the posterior probability

$$\hat{\mathbf{x}}^t = \arg\max_{\mathbf{x}} \left\{ p\left(\mathbf{x} \middle| \mathbf{x}_1^t, \mathbf{x}_2^t, \ldots, \mathbf{x}_m^t, \mathcal{D}\right) \right\}$$

  where $\mathcal{D} = \left\{\mathbf{x}_1^k, \mathbf{x}_2^k, \ldots, \mathbf{x}_m^k, \mathbf{y}^k\right\}_{k=1}^K$ denotes all past validating data within the time window K.

- Implemented in two steps:

  – Adaptive error parameter tuning via Maximum-Likelihood:

$$\hat{\mathbf{\Theta}}^* = \arg\max_{\mathbf{\Theta}} \mathcal{L}(\mathbf{\Theta}|\mathcal{D})$$

  where $\mathbf{\Theta} \equiv \{\boldsymbol{\alpha}_i\}_{i=1}^m$ are error covariance parameters, and $\mathcal{L}$ is

$$\log \mathcal{L}(\boldsymbol{\alpha}|\mathcal{D}) \propto \left(\boldsymbol{\alpha}-\boldsymbol{\alpha}_0\right)^T \mathbf{\Sigma}^{-1}\left(\boldsymbol{\alpha}-\boldsymbol{\alpha}_0\right) + K \log\det \mathbf{Q}(\boldsymbol{\alpha}) + \sum_{k=1}^K \mathbf{d}_k^T \mathbf{Q}^{-1}(\boldsymbol{\alpha})\mathbf{d}_k$$

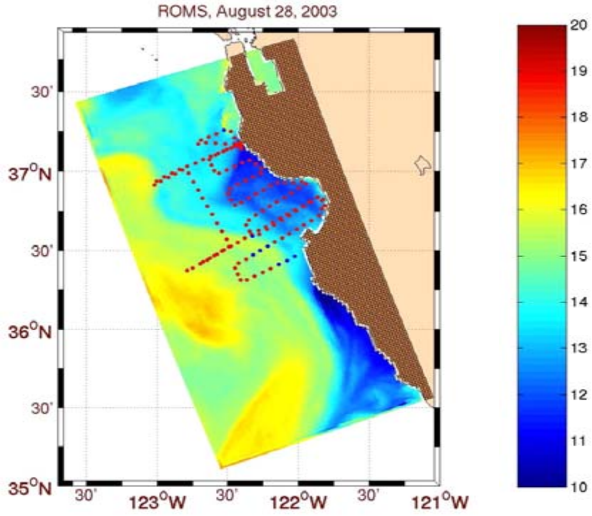
  where $\mathbf{d}_k = \mathbf{y}^k - \mathbf{H}\mathbf{x}_i^k$ are model-data misfits.

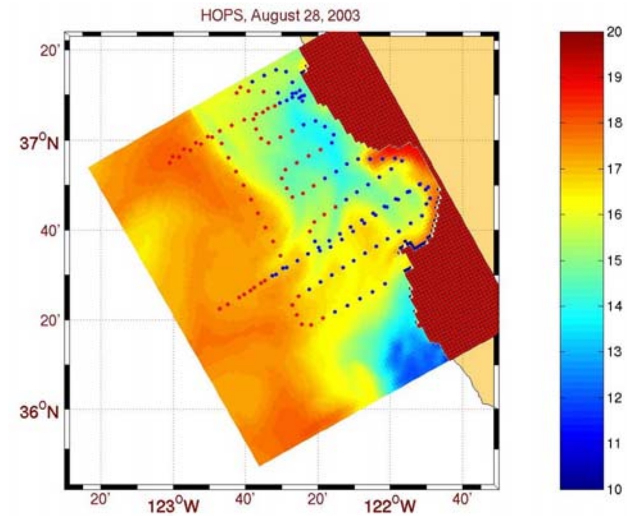
  – Model fusion based on error parameters:

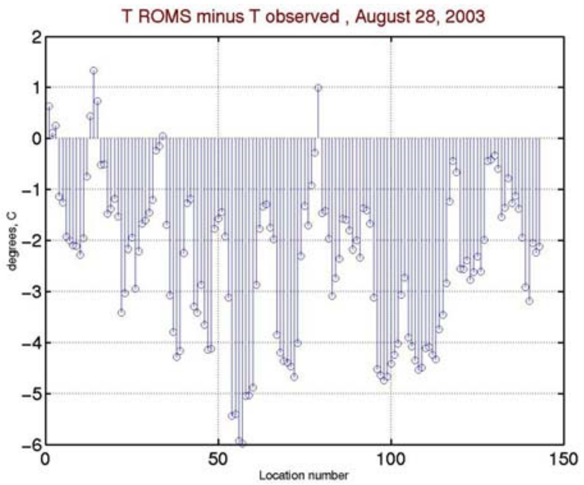
$$\mathbf{x}_c^t = \arg\min_{\boldsymbol{x}} \sum_{i=1}^m \left(\mathbf{x} - \mathbf{H}_i^c \mathbf{x}_i^t\right)^T \mathbf{B}_i^{-1}(\hat{\boldsymbol{\alpha}}_i)\left(\mathbf{x} - \mathbf{H}_i^c \mathbf{x}_i^t\right)$$

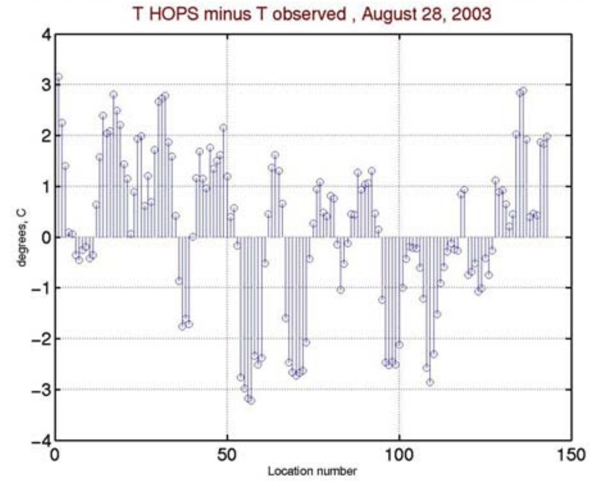
Bayesian Adaptive Multi-Model Forecasting

ROMS and HOPS SST forecasts for August 28, 2003 with track of validating NPS aircraft SST data taken on August 29, 2003







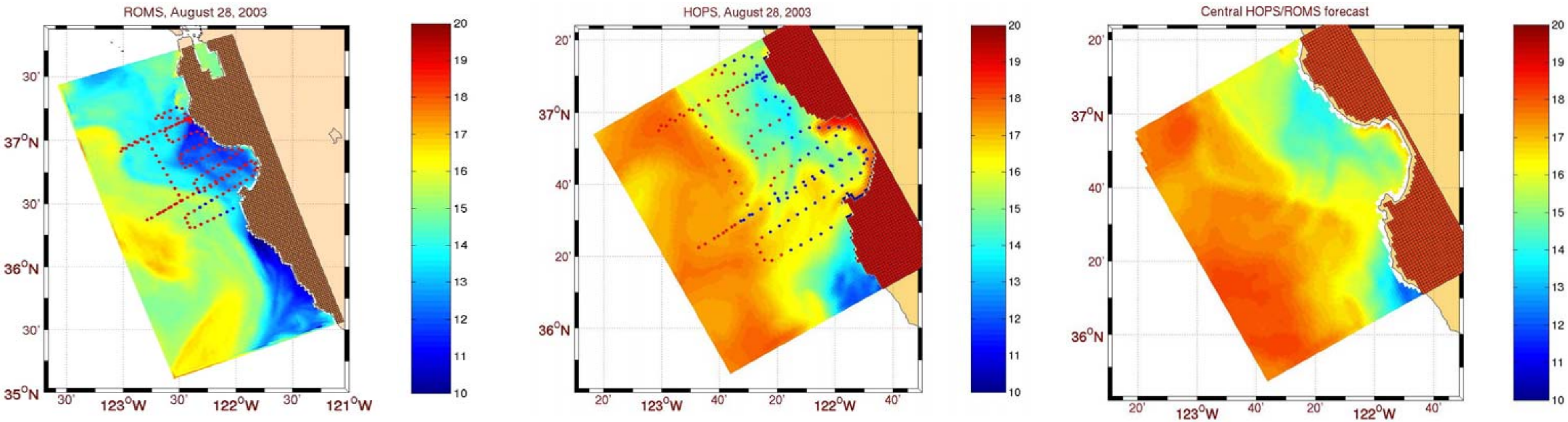


Model-data misfits is the source of information that is utilized to estimate the uncertainty parameters in models via Maximum-Likelihood. The models are then combined based on the uncertainty parameters, $\hat{\boldsymbol{\alpha}}_i$ as

$$\mathbf{x}_c^t = \arg \min_{\boldsymbol{x}} \sum_{i=1}^{m} \left(\mathbf{x} - \mathbf{H}_i^c \mathbf{x}_i^t\right)^T \mathbf{B}_i^{-1}(\hat{\boldsymbol{\alpha}}_i)\left(\mathbf{x} - \mathbf{H}_i^c \mathbf{x}_i^t\right)$$

Bayesian Adaptive Multi-Model Forecasting

ROMS and HOPS individual SST forecasts and the NPS aircraft SST data are combined based on their estimated uncertainties to form the central forecast



- A new batch of model-data misfits and priors on uncertainty parameters determine via the Bayesian principle uncertainty parameter values that are employed to combine the forecasts.

- The Bayesian model fusion technique that we advocate treats forecast errors from different models as uncorrelated in order to gain its capability to work with a small sample of past validating events, however, accounts for spatial structure in forecast error covariances.

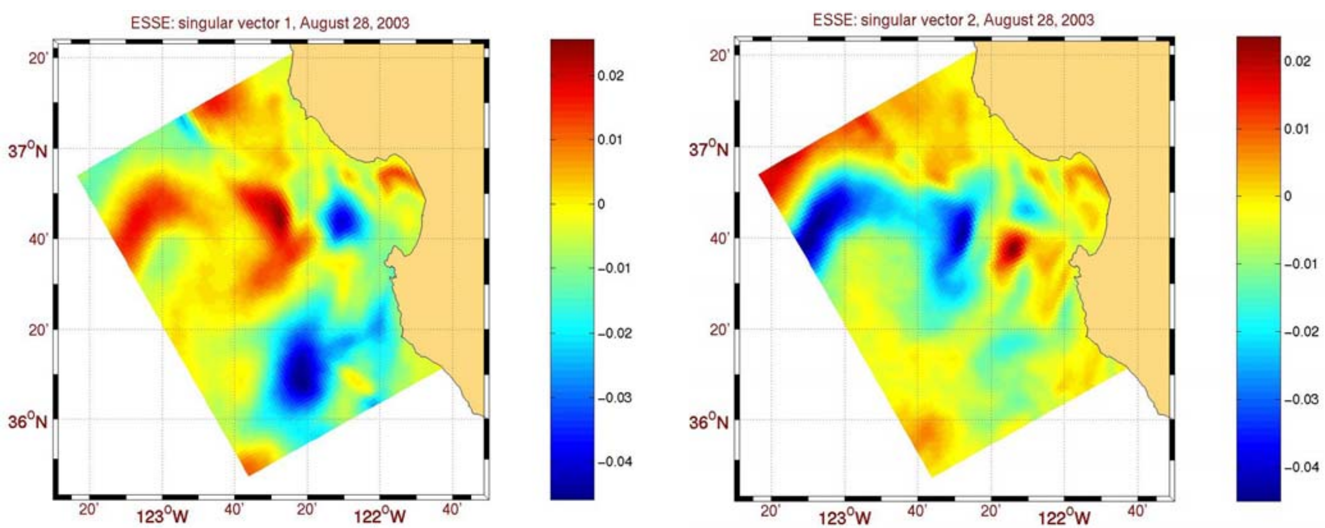
Maximum-Likelihood Parameter Estimation Within ESSE

- ESSE 1st and 2nd dominant error subspaces on August 28, 2003 (AOSN2)

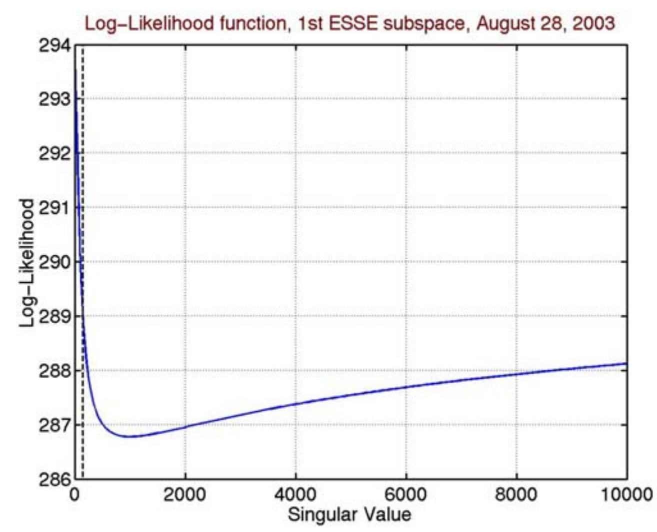
  ESSE seeks a low-rank error covariance representation: $\mathbf{B}(\hat{\boldsymbol{\alpha}}) = \mathbf{U}\mathbf{S}(\hat{\boldsymbol{\alpha}})\mathbf{U}^T$

  New Approach: use error subspace singular values as tunable parameters. The likelihood function for ESSE singular values:

  $$\log \mathcal{L}(\boldsymbol{\alpha}|\mathcal{D}) \propto \left(\boldsymbol{\alpha}-\boldsymbol{\alpha}_0\right)^T \boldsymbol{\Sigma}^{-1} \left(\boldsymbol{\alpha}-\boldsymbol{\alpha}_0\right) + \log \prod \operatorname{diag} \mathbf{S}(\hat{\boldsymbol{\alpha}}) + \mathbf{d}^T \left(\mathbf{B}(\boldsymbol{\alpha}) + \mathbf{R}\right)^{-1} \mathbf{d}$$



First (left) and second (right) dominant error subspaces (First and second columns of **U**)



Log-likelihood function of the 1st ESSE subspace singular value

Multi-Scale Energy and Vorticity Analysis

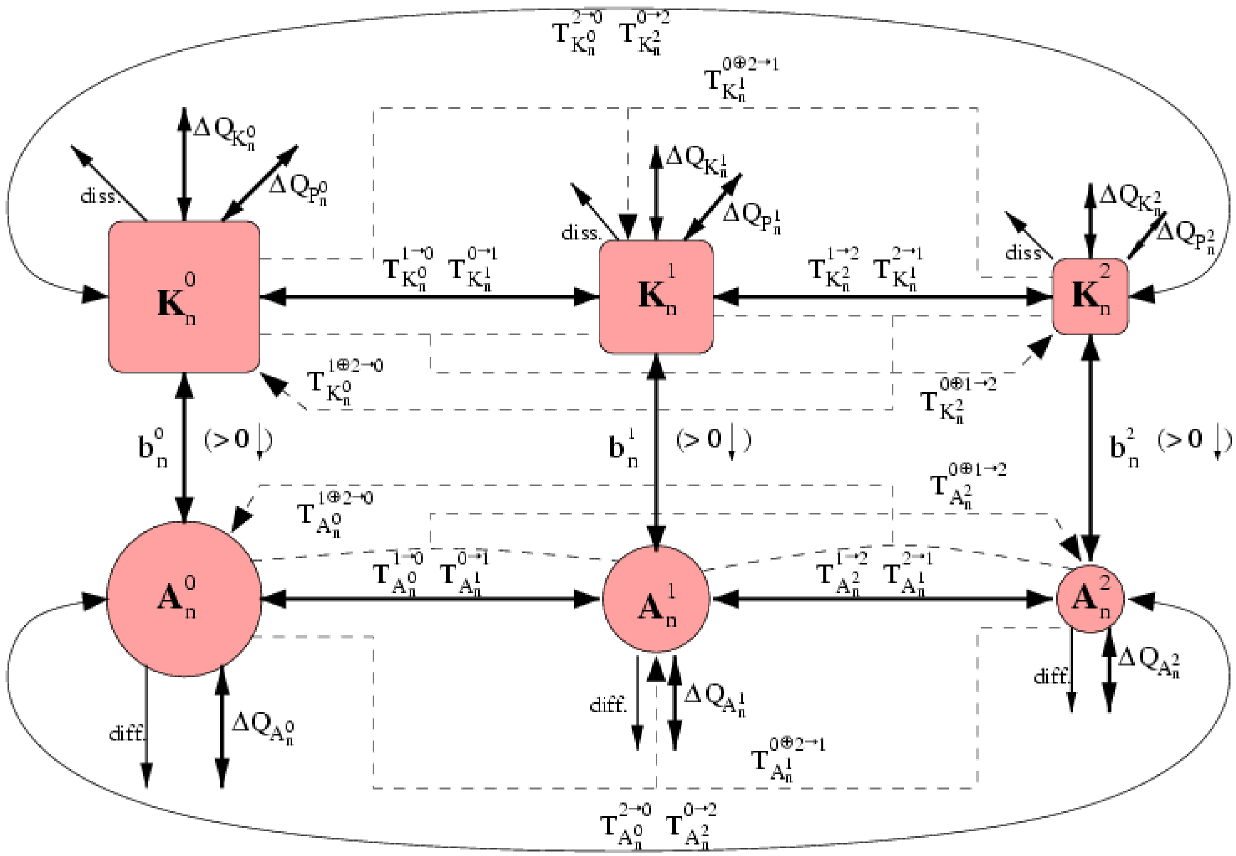
Symbols for multiscale energetics (time step n, scale window ϖ).

Kinetic energy (KE)		Available potential energy (APE)	
$\dot{K}_n^{\varpi}$	Time rate of change of KE	$\dot{A}_n^{\varpi}$	Time rate of change of APE
$\Delta Q_{K_n^{\varpi}}$	KE advective working rate	$\Delta Q_{A_n^{\varpi}}$	APE advective working rate
$T_{K_n^{\varpi}}$	Total KE transfer	$T_{A_n^{\varpi}}$	Total APE transfer
$\Delta Q_{P_n^{\varpi}}$	Pressure working rate	b_n^{ϖ}	Rate of buoyancy conversion
$F_{K_n^{\varpi},z}$	Rate of vertical dissipation	$F_{A_n^{\varpi},z}$	Rate of vertical diffusion

Multi-Scale Energy and Vorticity Analysis

MS-EVA is a new methodology utilizing multiple scale window decomposition in space and time for the investigation of processes which are:

- multi-scale interactive
- nonlinear
- intermittent in space
- episodic in time



Through exploring:

- pattern generation and
- energy and enstrophy
  - transfers
  - transports, and
  - conversions

MS-EVA helps unravel the intricate relationships between events on different scales and locations in phase and physical space.

Dr. X. San Liang

Multi-Scale Energy and Vorticity Analysis

Window-Window Interactions:
MS-EVA-based Localized Instability Theory

Perfect transfer:

A process that exchanges energy among distinct scale windows which does not create nor destroy energy as a whole.

In the MS-EVA framework, the perfect transfers are represented as field-like variables. They are of particular use for real ocean processes which in nature are non-linear and intermittent in space and time.

Localized instability theory:

BC: Total perfect transfer of APE from large-scale window to meso-scale window.

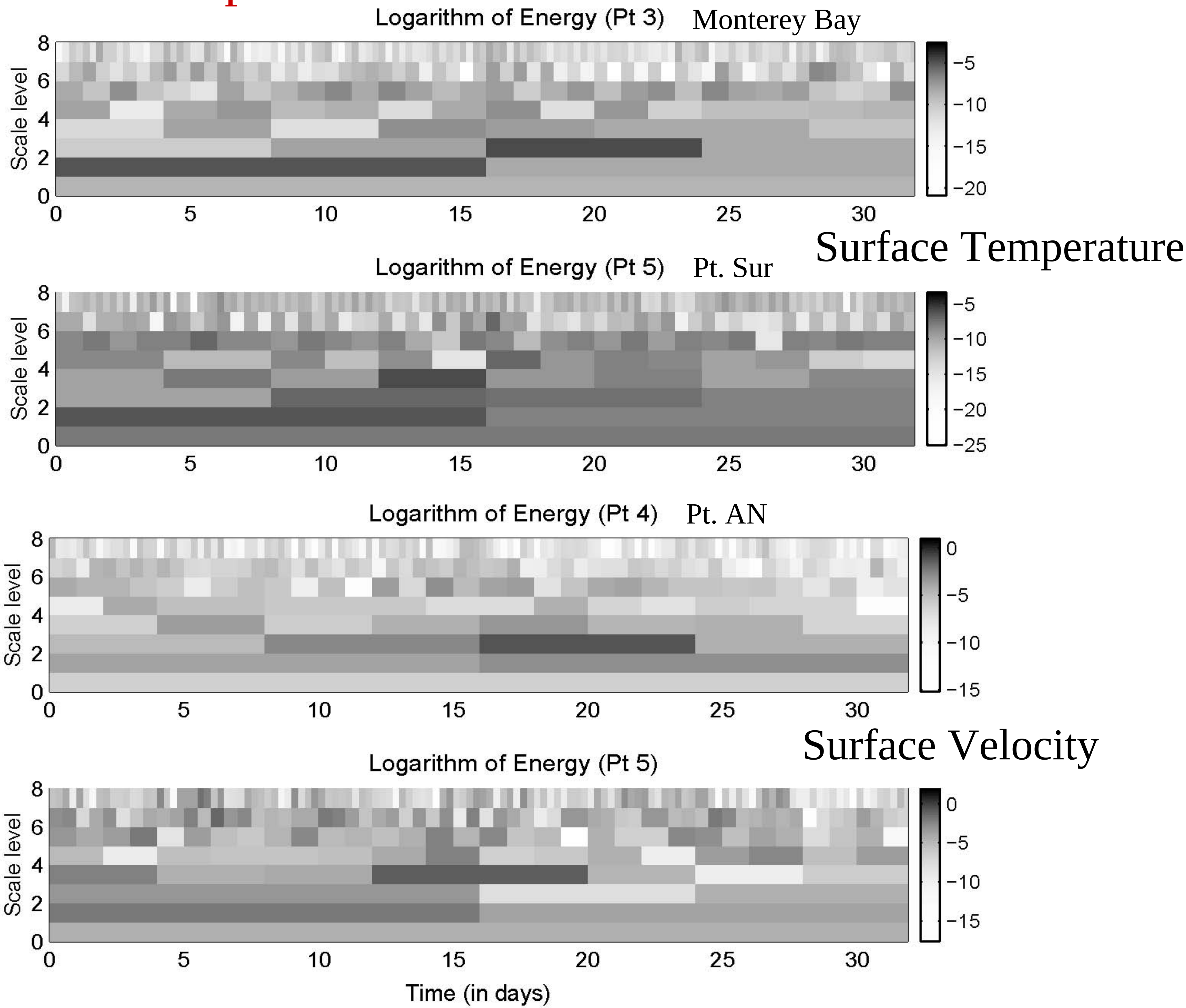
BT: Total perfect transfer of KE from large-scale window to meso-scale window.

$BT + BC > 0$ => system locally unstable; otherwise stable

If $BT + BC > 0$, and

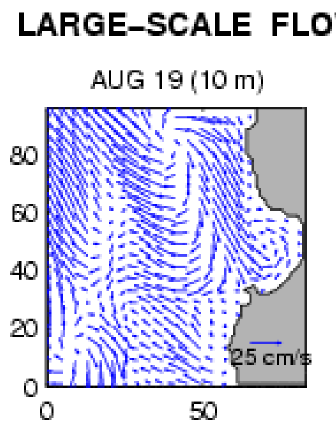
- $BC \leq 0$ => barotropic instability;
- $BT \leq 0$ => baroclinic instability;
- $BT > 0$ and $BC > 0$ => mixed instability

Wavelet Spectra



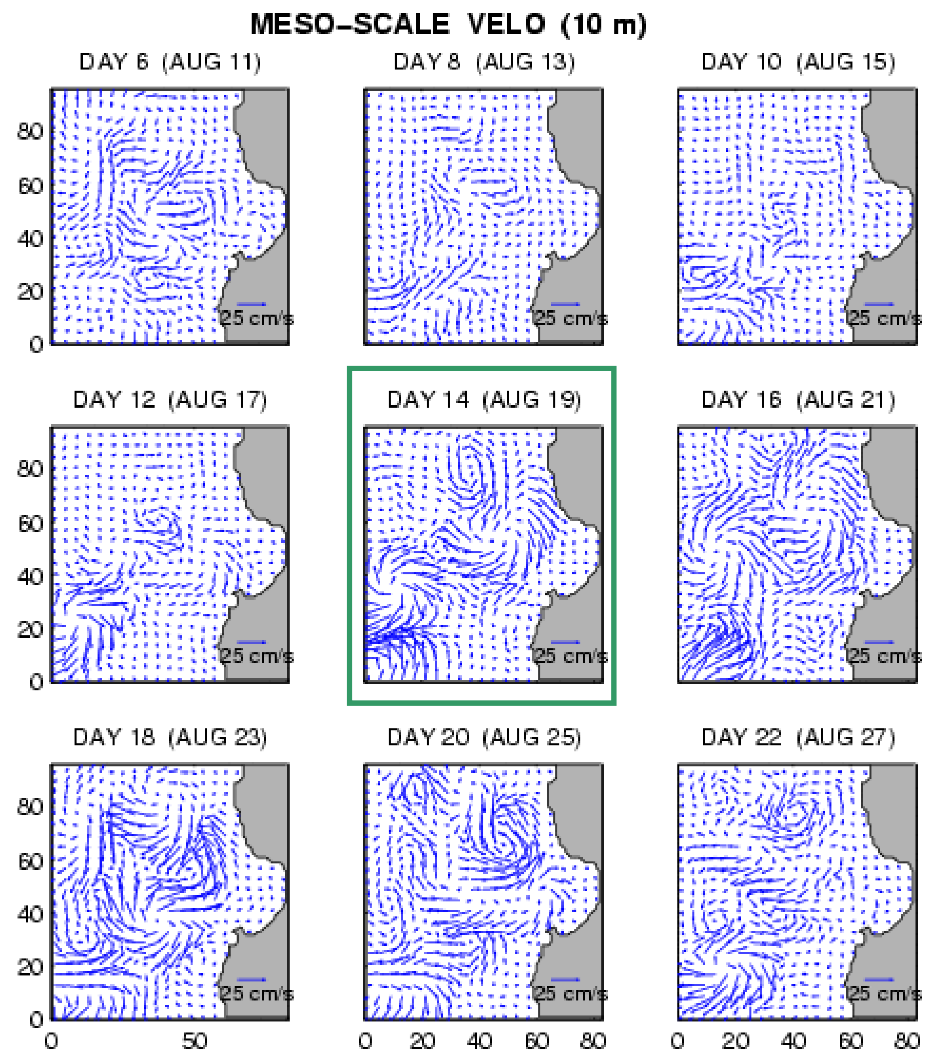
Multi-Scale Energy and Vorticity Analysis

Multi-Scale Window Decomposition in AOSN-II Reanalysis



The reconstructed large-scale and meso-scale fields are filtered in the horizontal with features < 5km removed.

Time windows
Large scale: > 8 days
Meso-scale: 0.5-8 days
Sub-mesoscale: < 0.5 day

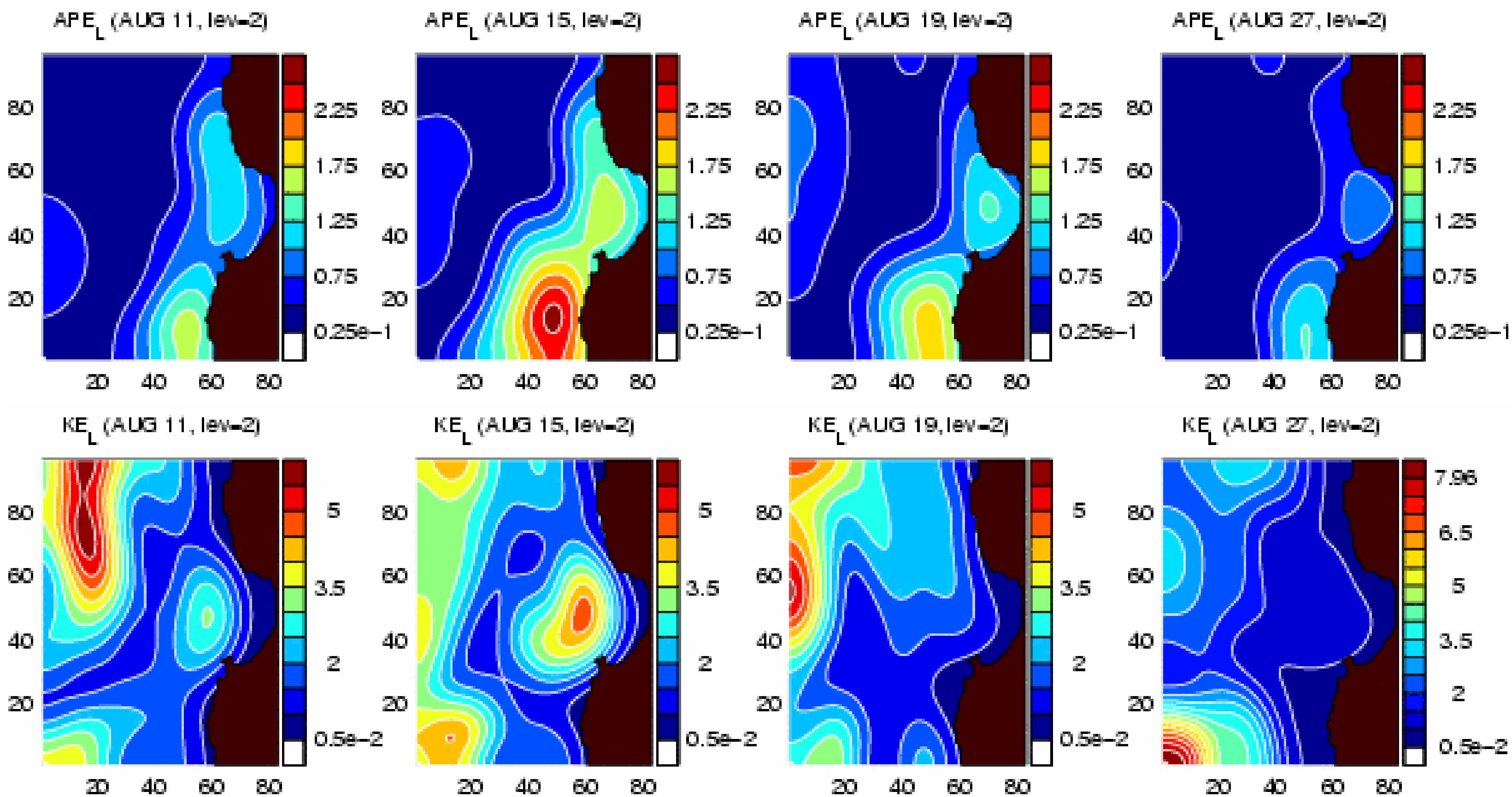


Question: How does the large-scale flow lose stability to generate the meso-scale structures?

Multi-Scale Energy and Vorticity Analysis

- Decomposition in space and time (wavelet-based) of energy/vorticity eqns.

Large-scale Available Potential Energy (APE)



Large-scale Kinetic Energy (KE)

- Both APE and KE decrease during the relaxation period
- Transfer from large-scale window to mesoscale window occurs to account for decrease in large-scale energies (as confirmed by transfer and mesoscale terms)

Windows: Large-scale (>= 8days; > 30km), mesoscale (0.5-8 days), and sub-mesoscale (< 0.5 days)

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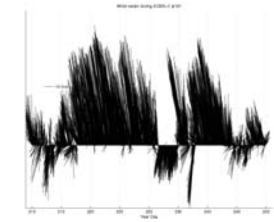
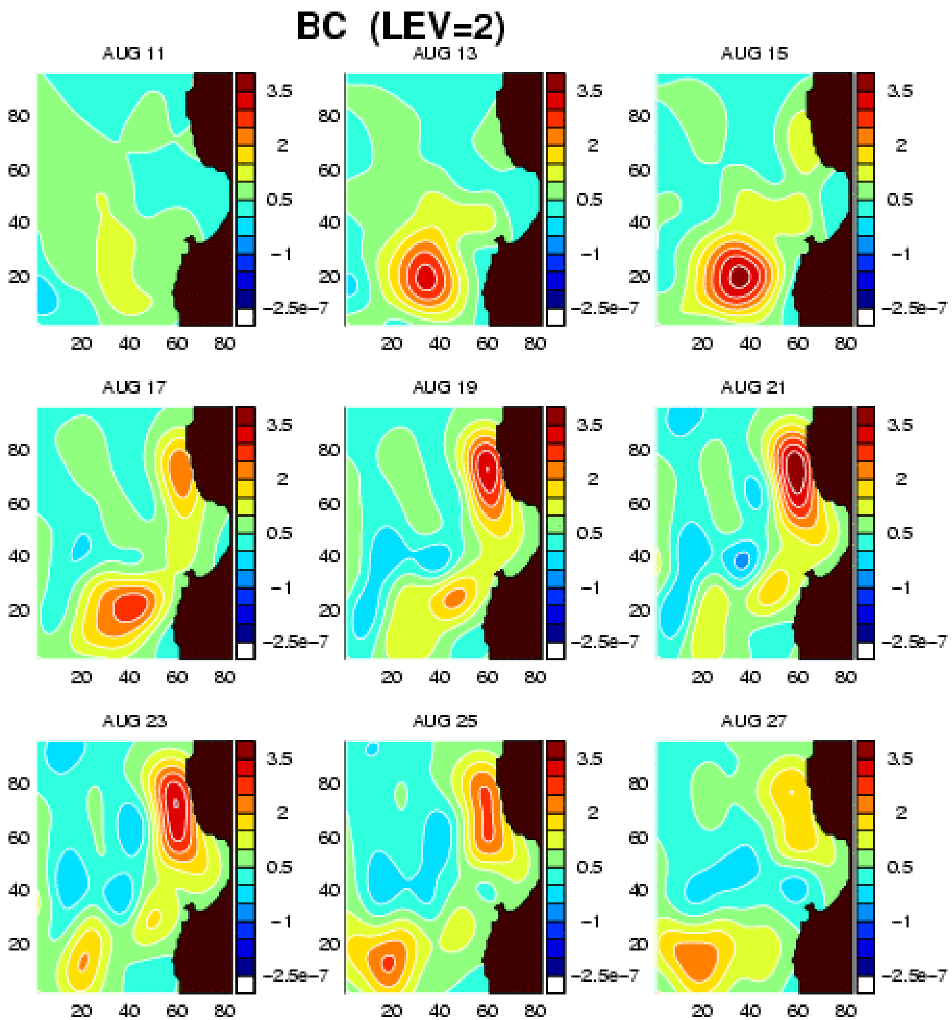
Multi-Scale Energy and Vorticity Analysis

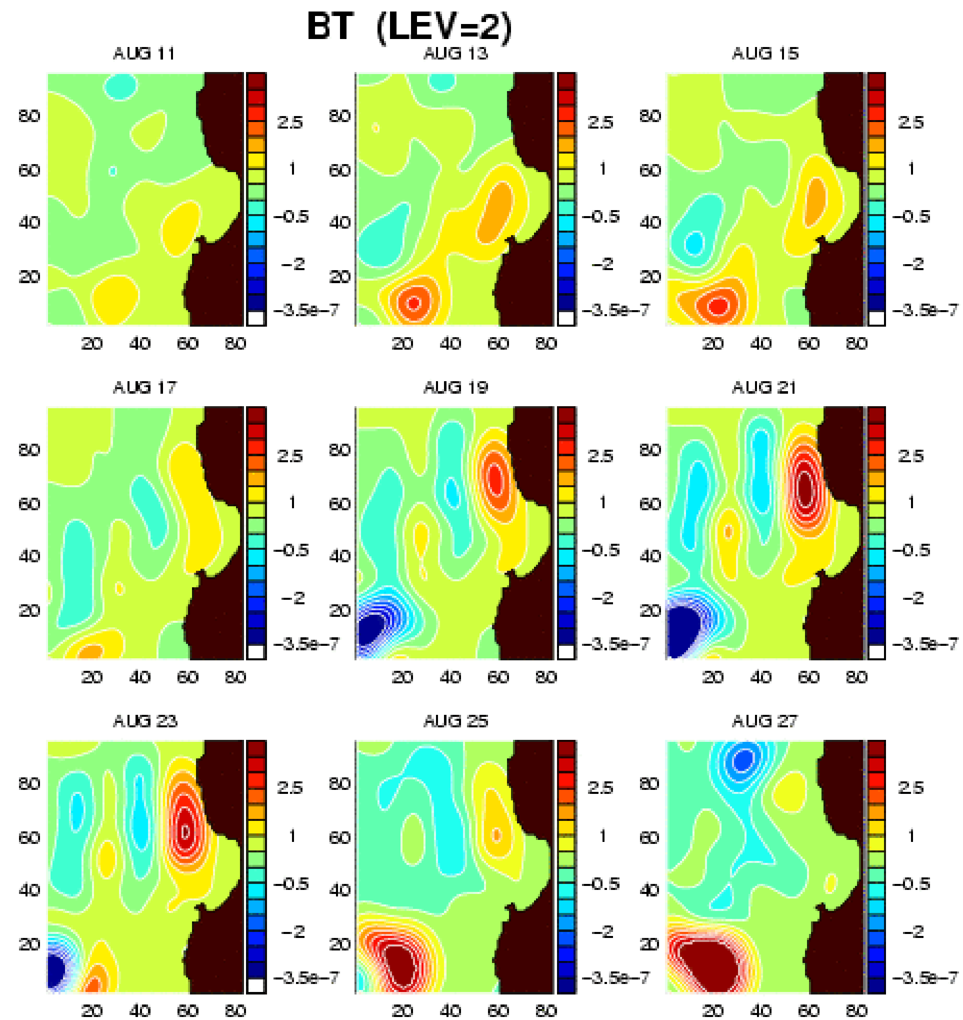
MS-EVA Analysis: 11-27 August 2003



Transfer of APE from
large-scale to meso-scale

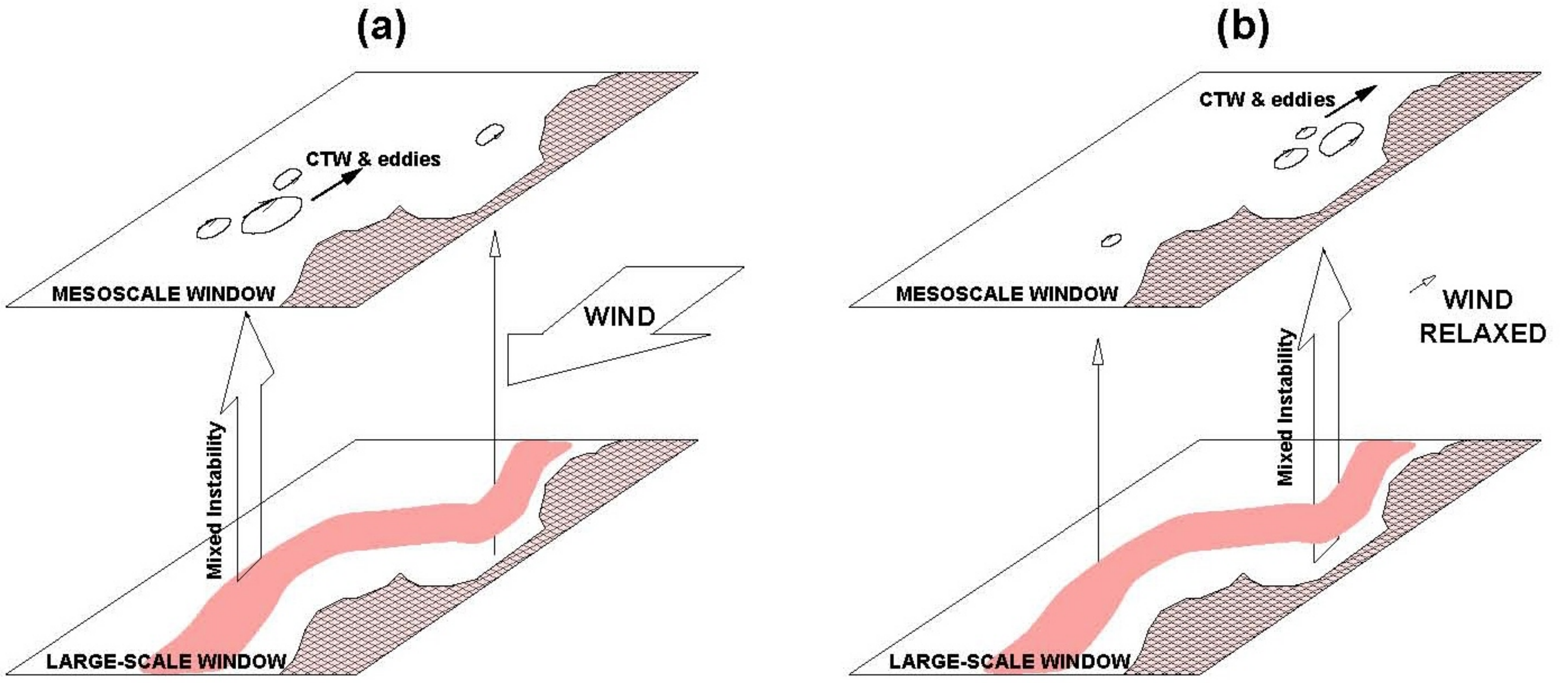


Transfer of KE from
large-scale to meso-scale



Multi-Scale Energy and Vorticity Analysis

Process Schematic

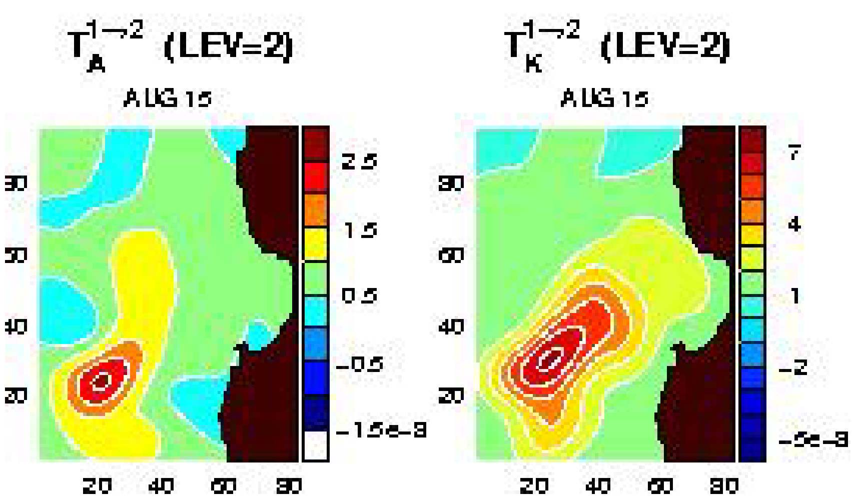


Multi-Scale Energy and Vorticity Analysis

Multi-Scale Dynamics

- Two distinct centers of instability: both of mixed type but different in cause.
- Center west of Pt. Sur: winds destabilize the ocean directly during upwelling.
- Center near the Bay: winds enter the balance on the large-scale window and release energy to the mesoscale window during relaxation.
- Monterey Bay is source region of perturbation and when the wind is relaxed, the generated mesoscale structures propagate northward along the coastline in a surface-intensified free mode of coastal trapped waves.

- Sub-mesoscale processes and their role in the overall large, mesoscale, sub-mesoscale dynamics are under study.



Energy transfer from meso-scale window to sub-mesoscale window.