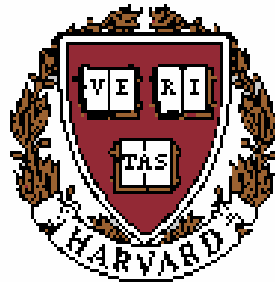


# **AOSN-II in Monterey Bay: Real-Time Error Predictions, Data Assimilation, Adaptive Sampling and Dynamics**

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Applied Sciences



Department of Earth and  
Planetary Sciences

**<http://www.deas.harvard.edu/~pierrel>**

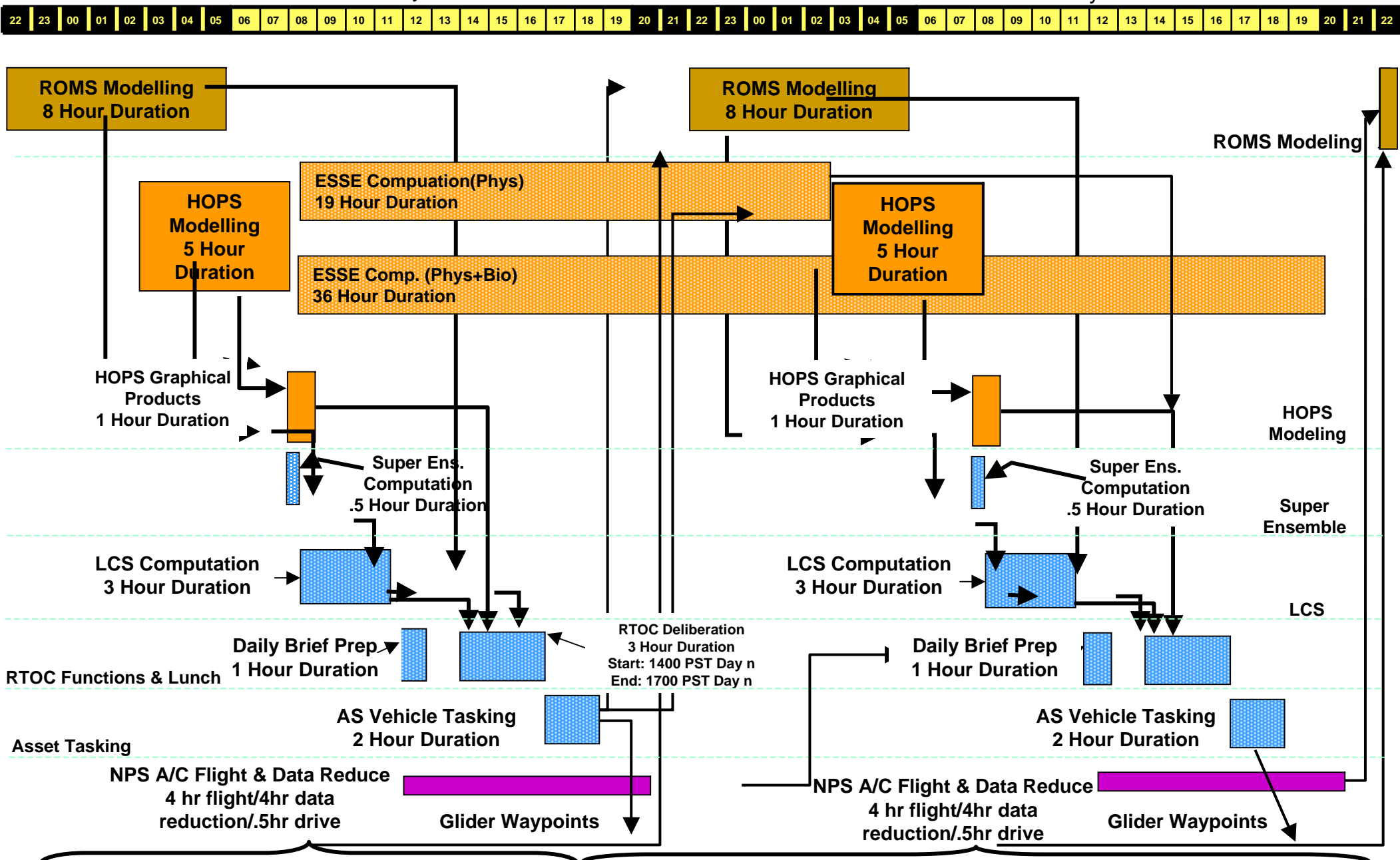
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## **Table of Contents**

1. AOSN-II: August 2003 experiment and Error Subspace Statistical Estimation
2. Real-time ESSE results and physical dynamics
3. Quantitative Autonomous Adaptive Sampling
4. Tidal effects and Coupled Biology
5. Multi-Scale Energy and Vorticity Analysis
6. Multi-Model Adaptive Combination

Day N

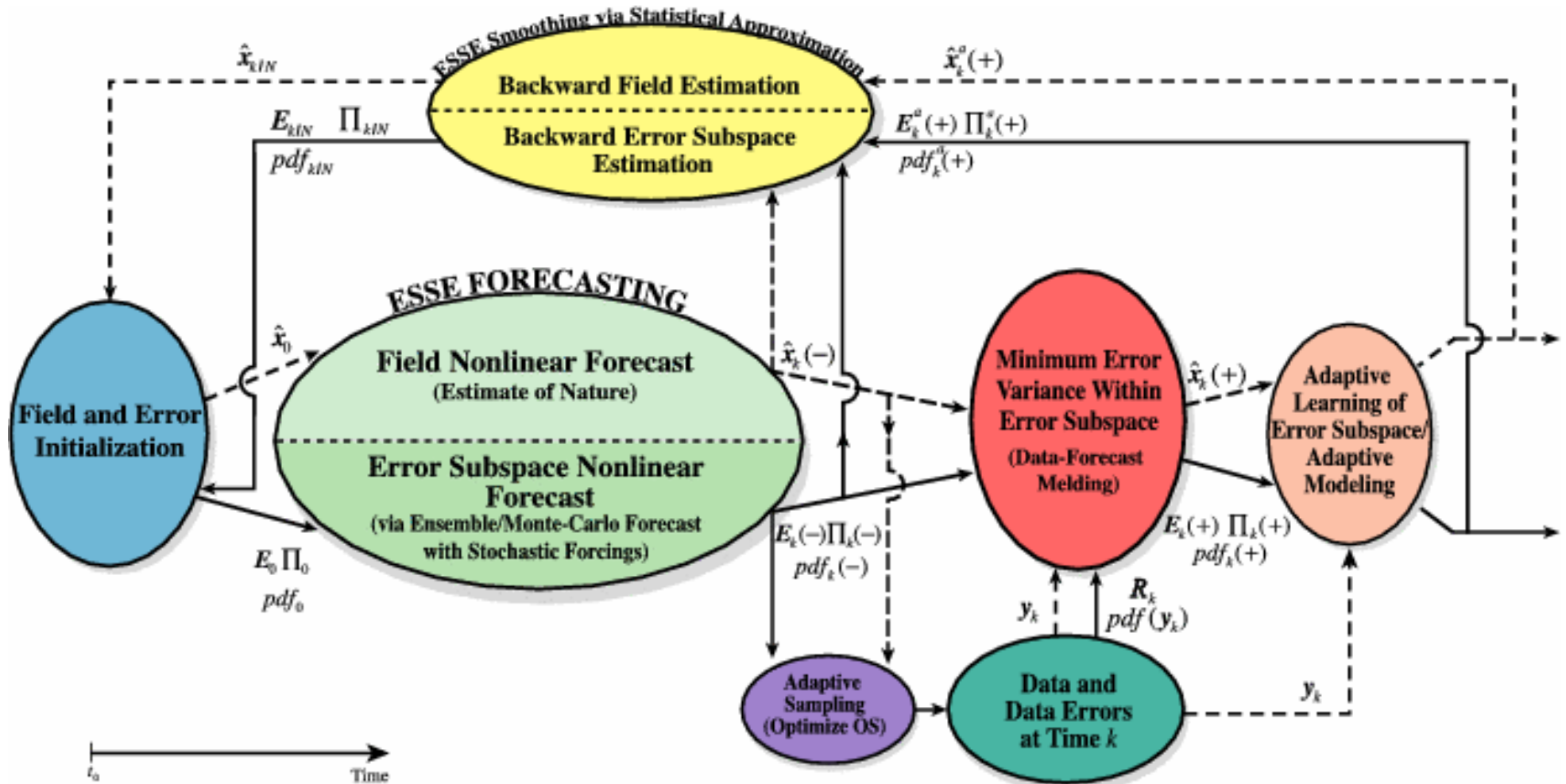
Day N+1



## Two-scale Adaptive Sampling:

- Daily identification of features and errors from model forecasts
- Two-hourly data feedback for glider coordination

# Error Subspace Statistical Estimation (ESSE)



- Uncertainty forecasts (dynamic error subspace and adaptive error learning)
- Ensemble-based (with nonlinear and stochastic model)
- Multivariate, non-homogeneous and non-isotropic DA
- Consistent DA and adaptive sampling schemes
- Software: not tied to any model, but specifics currently tailored to HOPS

# **Ocean Regions and Experiments/Operations for which ESSE has been utilized in real-time**

- Strait of Sicily (AIS96-RR96), Summer 1996
- Ionian Sea (RR97), Fall 1997
- Gulf of Cadiz (RR98), Spring 1998
- Massachusetts Bay (LOOPS), Fall 1998
- Georges Bank (AFMIS), Spring 2000
- Massachusetts Bay (ASCOT-01), Spring 2001
- Monterey Bay (AOSN-2), Summer 2003

# Real-time ESSE : AOSN-II Accomplishments

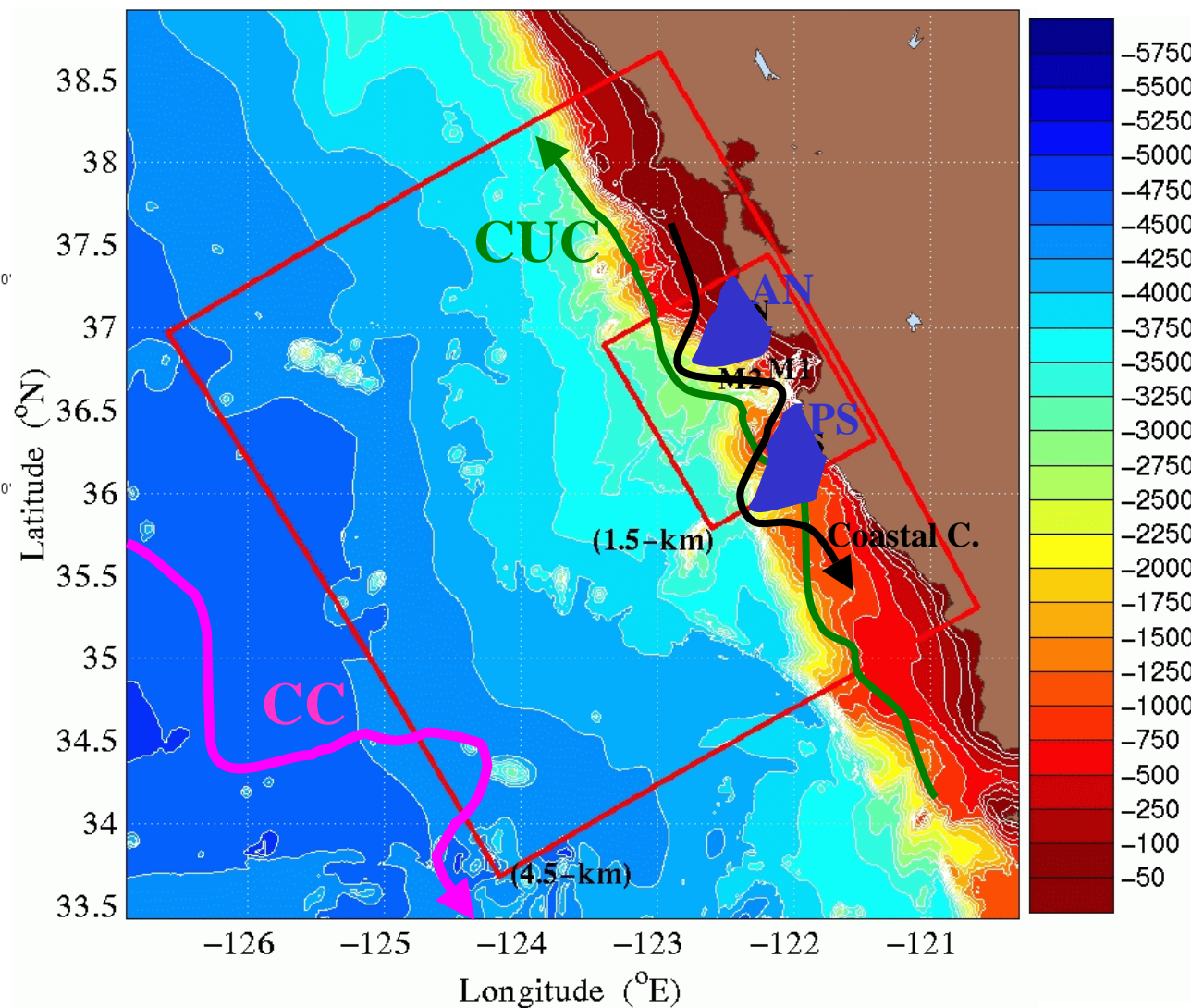
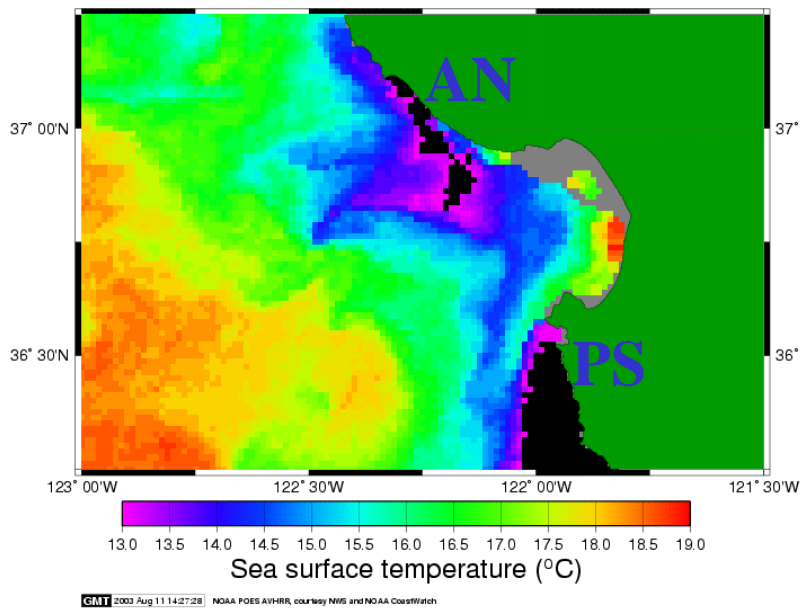
- 10 sets of ESSE nowcasts and forecasts of temperature, salinity and velocity, and their uncertainties, issued from 4 Aug. to 3 Sep.
  - Total of 4323 ensemble members: 270 – 500 members per day ( $7 \times 10^5$  state var.)
  - ESSE fields included: central forecasts, ensemble means, *a priori* (forecast) errors, *a posteriori* errors, dominant singular vectors and covariance fields
  - $10^4$  data points quality controlled and assimilated per day: ship (Pt. Sur, Martin, Pt. Lobos), glider (WHOI and Scripps) and aircraft SST data
- Ensemble of stochastic PE model predictions (HOPS)
  - Deterministic atmospheric forcing: 3km and hourly COAMPS flux predictions
  - Stochastic oceanic/atmos. forcings: for sub-mesoscale eddies, BCs and atmos. fluxes
- ESSE fields formed the basis for daily adaptive sampling recommendations
- Adaptive ocean modeling: BCs and model parameters for transfer of atmos. fluxes calibrated and modified in real-time to adapt to evolving conditions
- ESSE dynamical results described and posted on the Web daily
- Real-time research: stochastic error models, coupled physics-biology, tides



# REGIONAL FEATURES of Monterey Bay and California Current System and Real-time Modeling Domains (4 Aug. – 3 Sep., 2003)

## SST on August 11, 2003

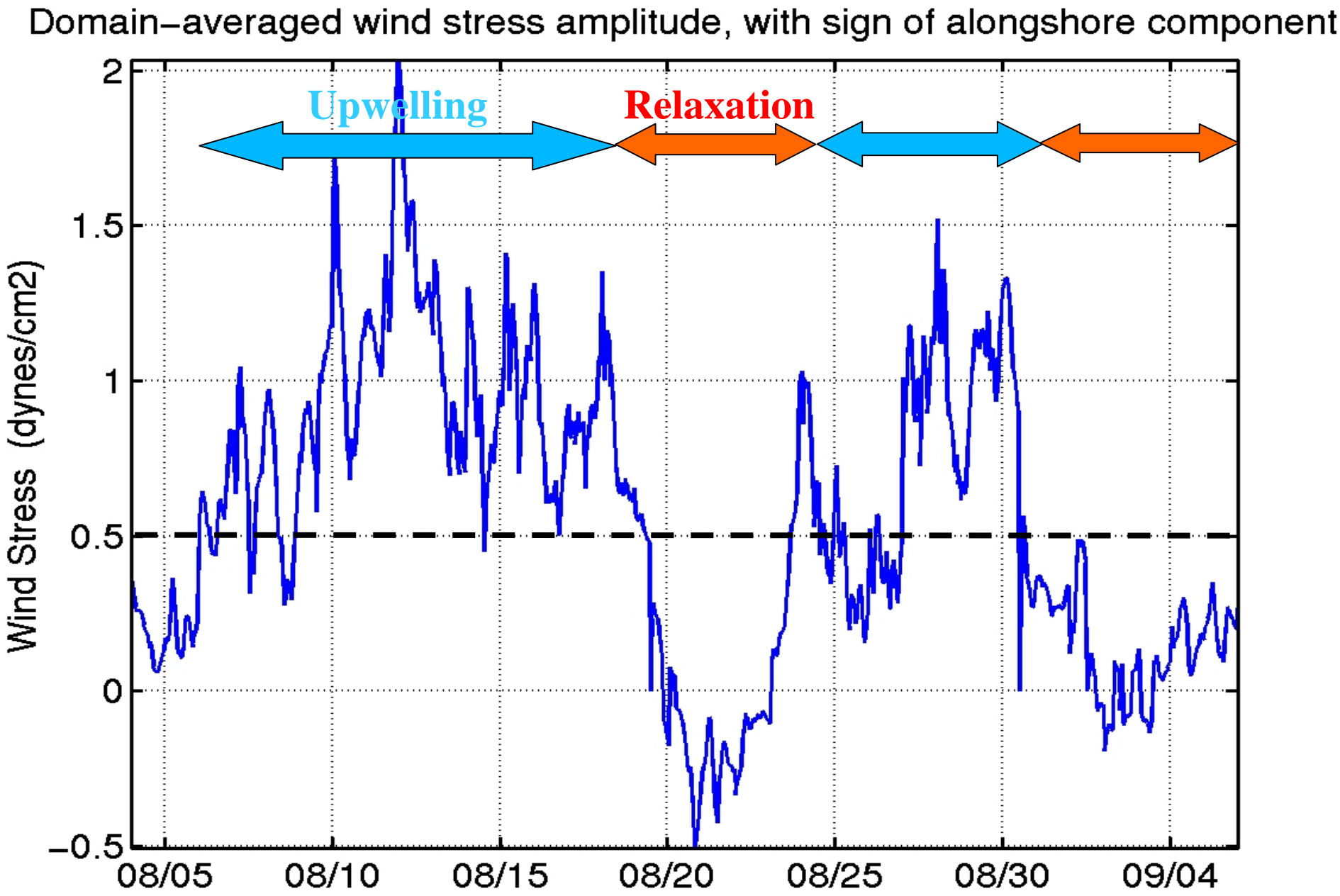
Experimental AVHRR HRPT SST August 11, 2003 1850 h UTC



## REGIONAL FEATURES

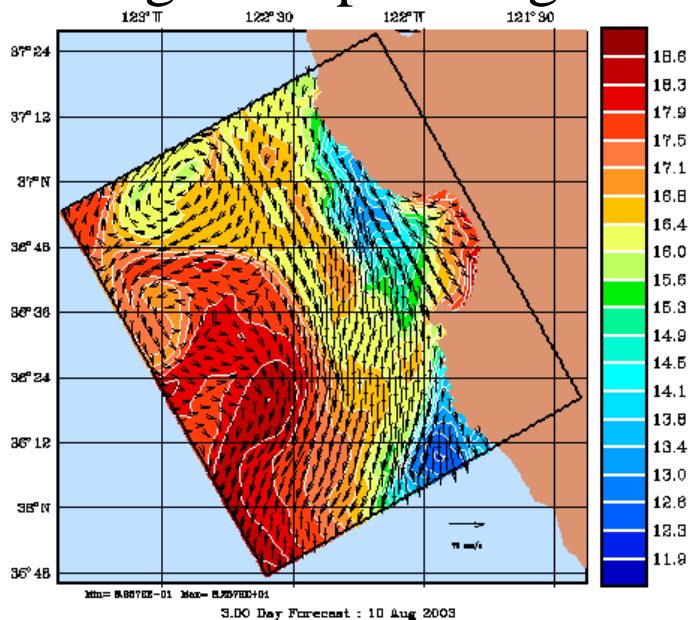
- **Upwelling centers at Pt AN/ Pt Sur:**.....Upwelled water advected equatorward and seaward
- **Coastal current, eddies, squirts, filam., etc:**....Upwelling-induced jets and high (sub)-mesoscale var. in CTZ
- **California Undercurrent (CUC):**.....Poleward flow/jet, 10-100km offshore, 50-300m depth
- **California Current (CC):**.....Broad southward flow, 100-1350km offshore, 0-500m depth

# Oceanic responses and atmospheric forcings during August 2003

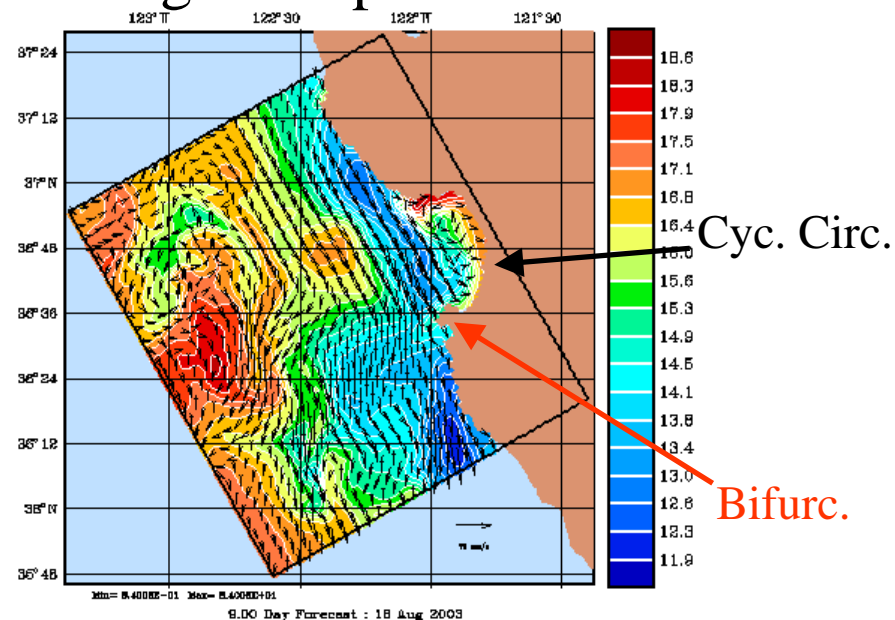


# Oceanic responses and atmospheric forcings during August 2003

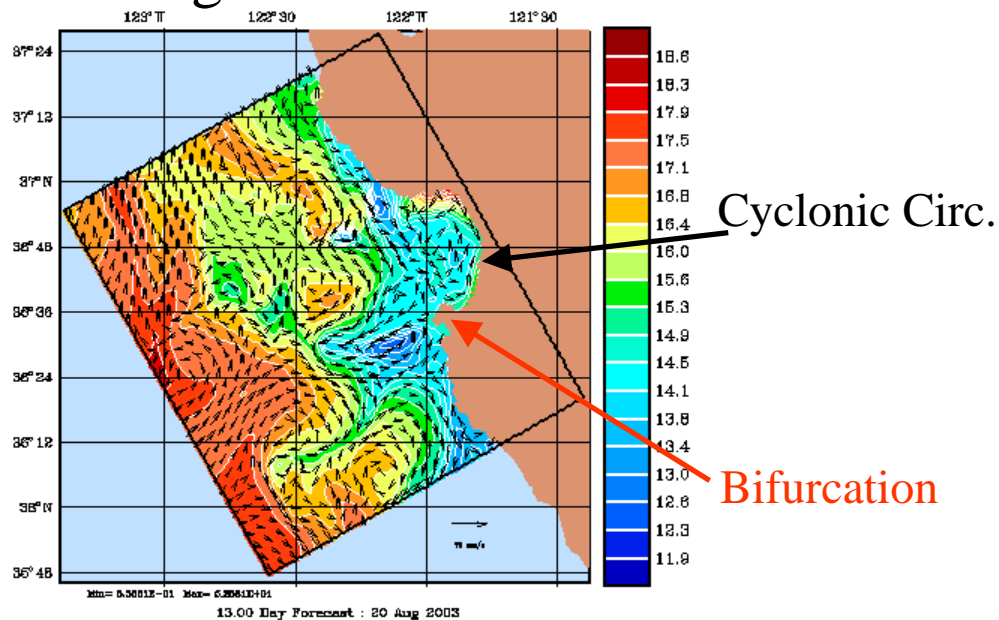
## Aug 10: Upwelling



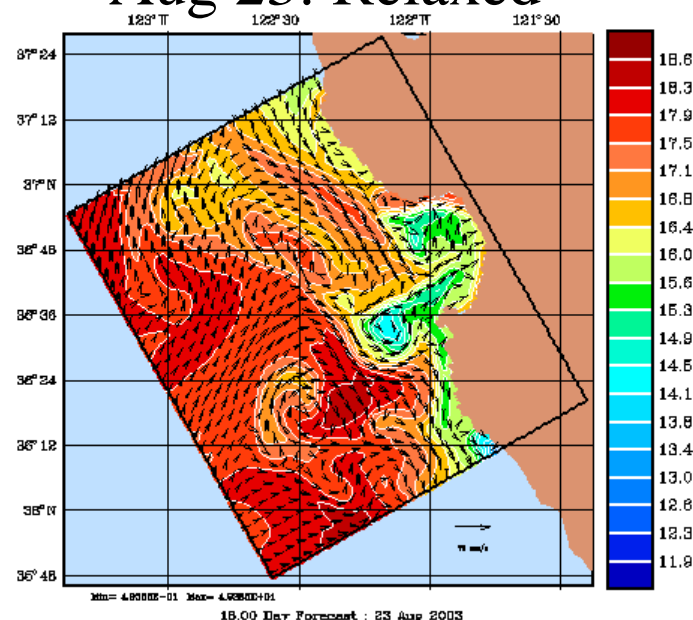
## Aug 16: Upwelled



## Aug 20: Relaxation

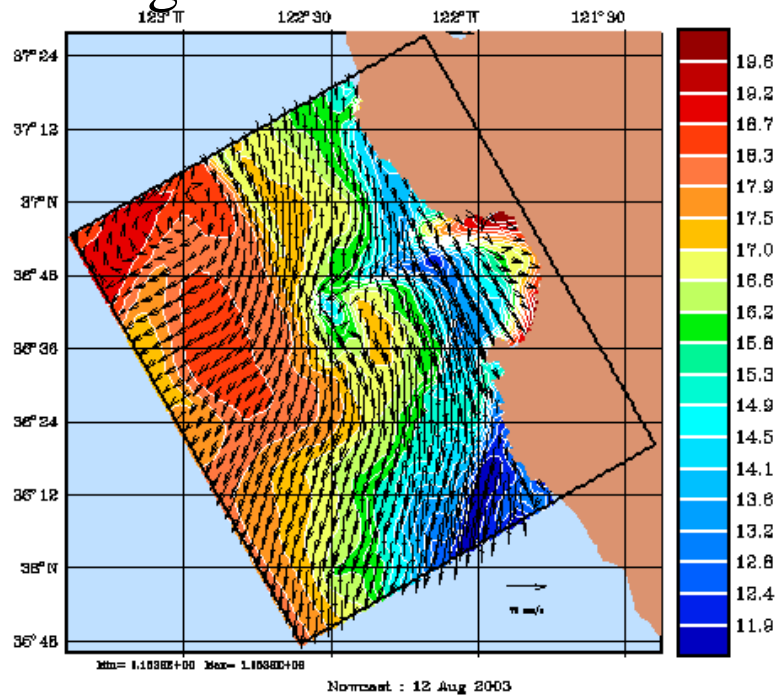


## Aug 23: Relaxed

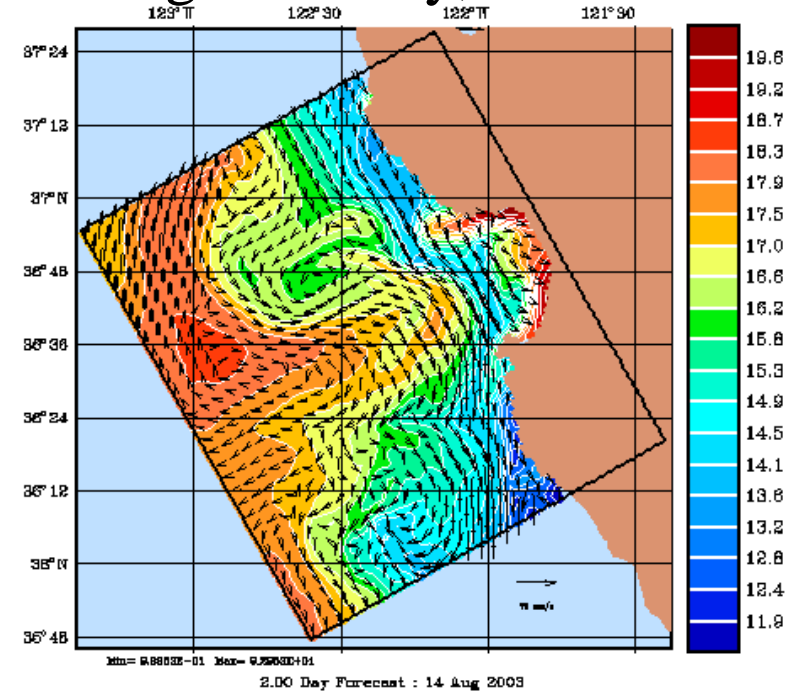




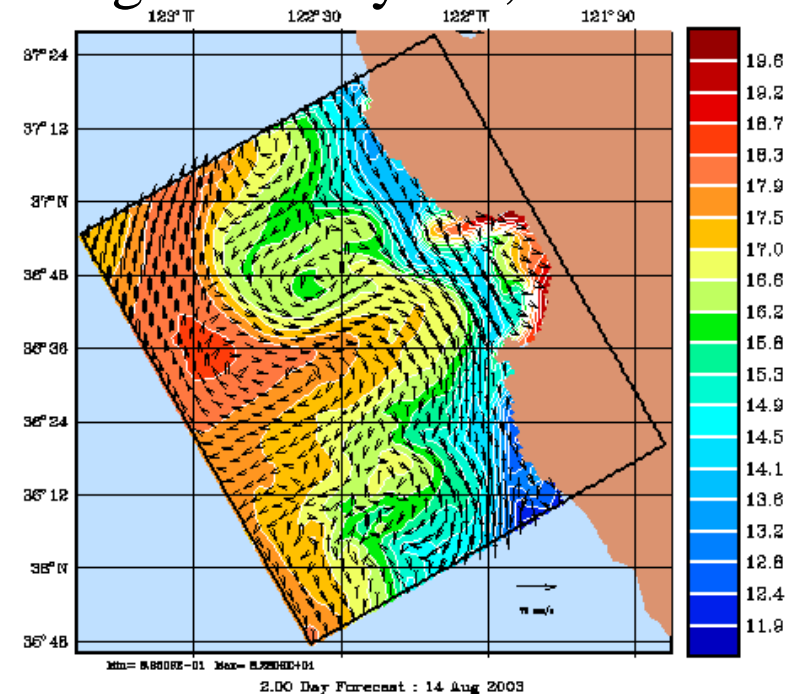
# Aug 12: Initial Conditions



# Aug 14: 2-day, central fct.



# Aug 14: 2-day fct., ens mean

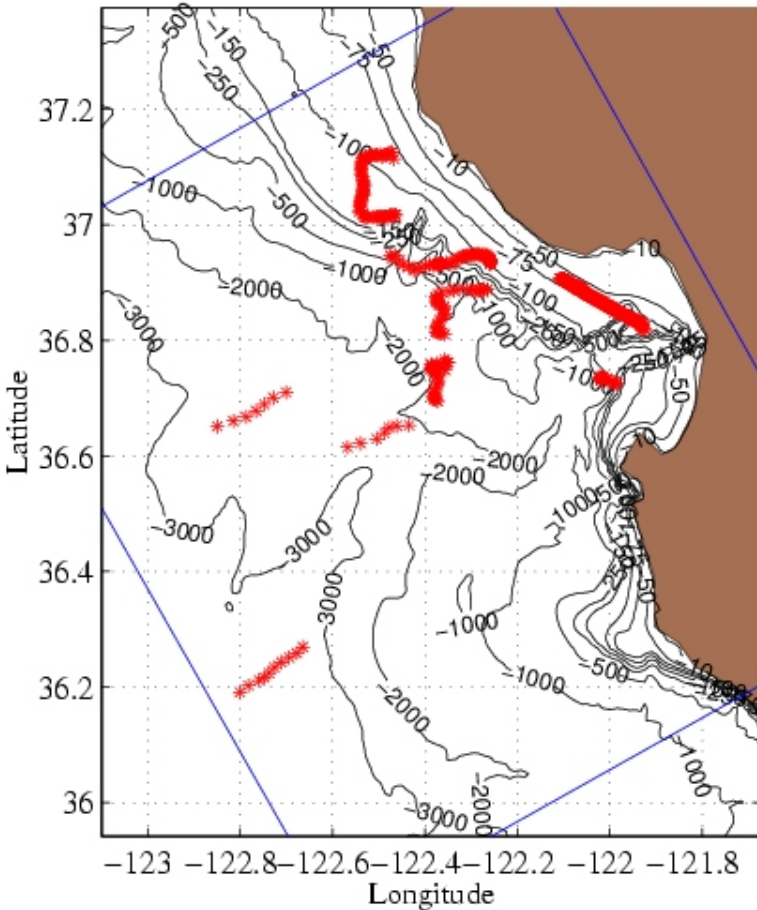


**Sample real-time ESSE Products:  
Ensemble Mean and Central Forecast  
Issued in real-time**

# RMSE Estimate

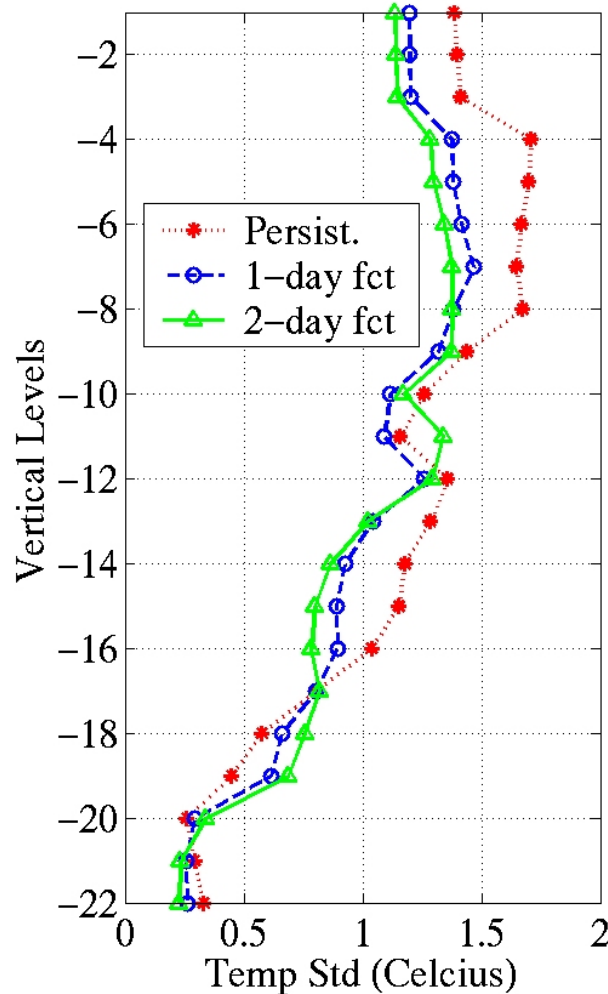
## Standard deviations of horizontally-averaged data-model differences

Data Composite for Aug 13

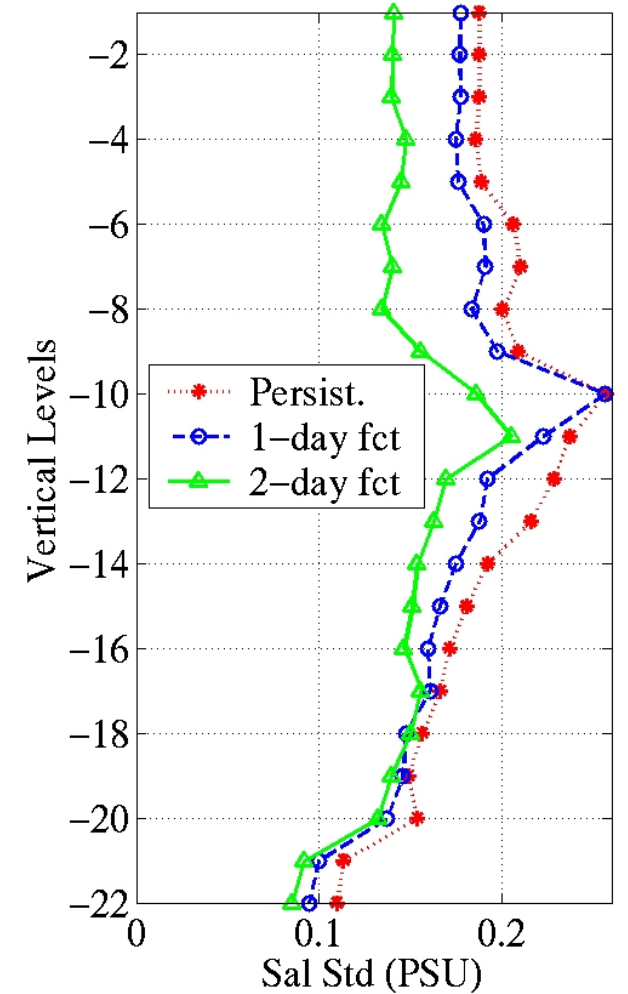


**Verification data time: Aug 13**  
**All forecasts are compared to this Aug 13 data**

Std of Data–Model Temp at data pts



Std of Data–Model Sal at data pts

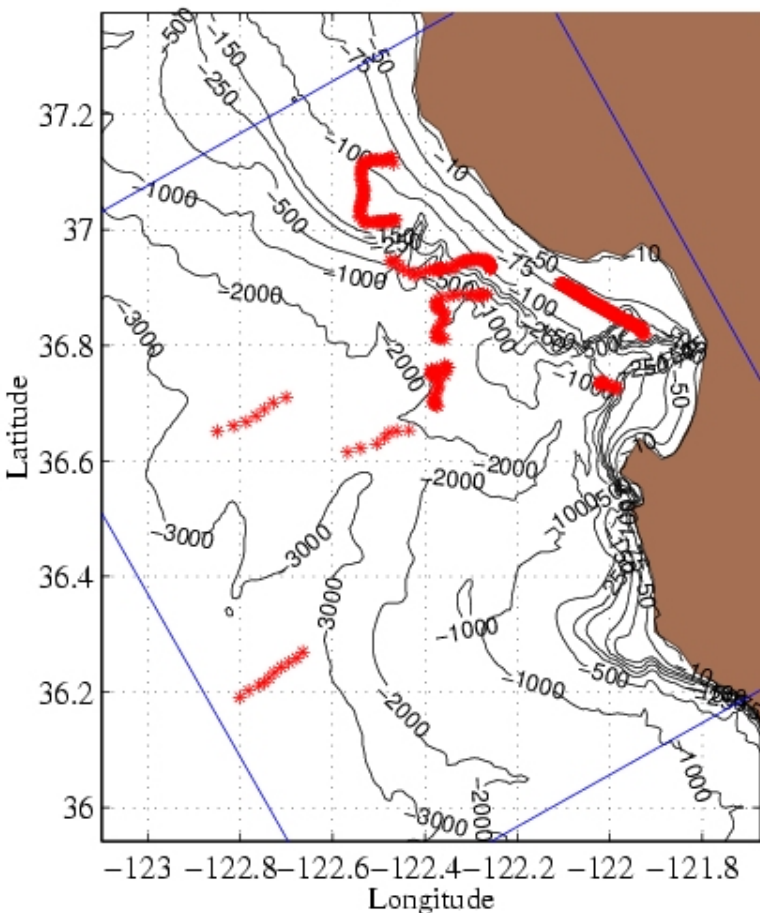


- **Nowcast: Aug 11** (persistence forecast, red)
- **2-day forecast for Aug 13** (green)
- **1-day forecast for Aug 12** (blue, to check phase error)

# Bias Estimate

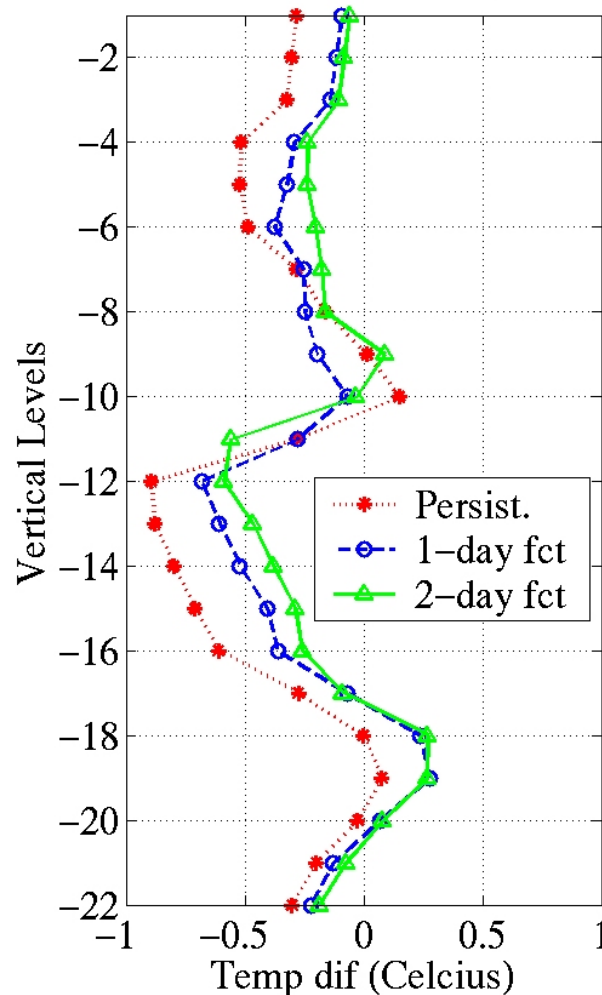
## Horizontally-averaged data-model differences

Data Composite for Aug 13

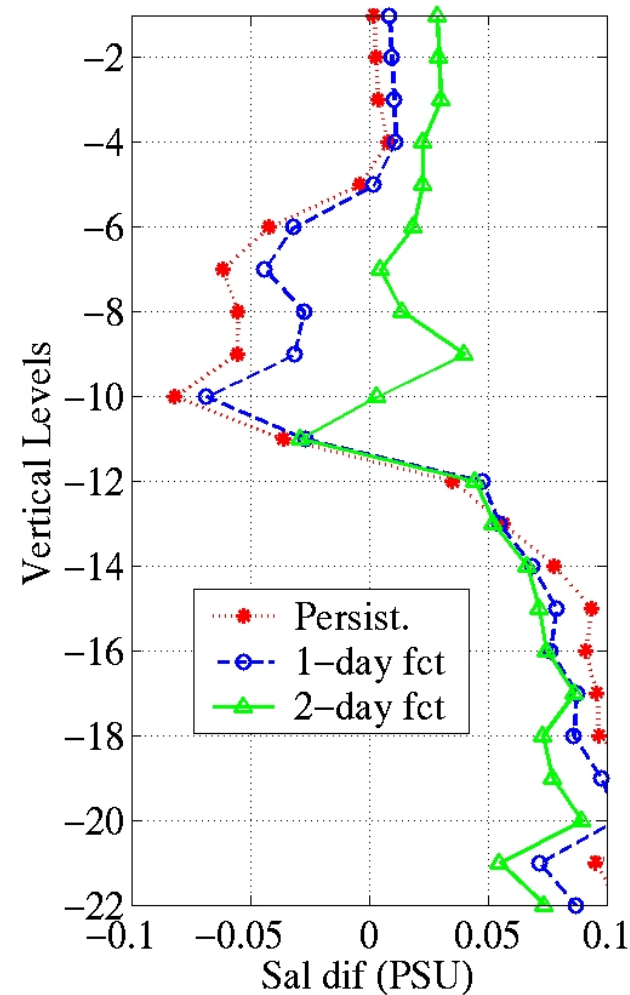


**Verification data time: Aug 13**  
**All forecasts are compared to this Aug 13 data**

Mean of Data-Model Temp at data pts

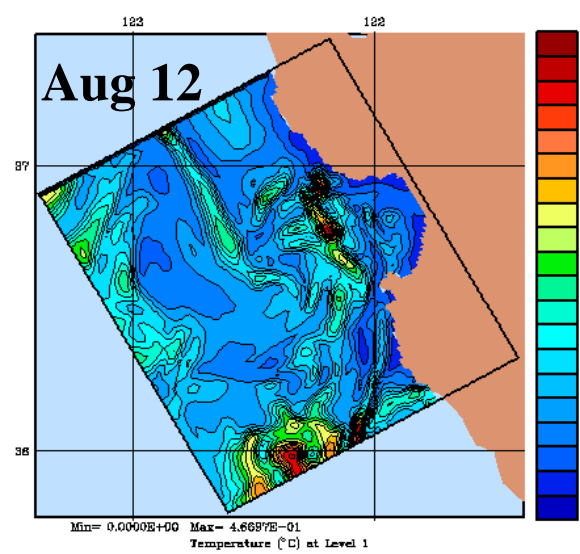


Mean of Data-Model Sal at data pts

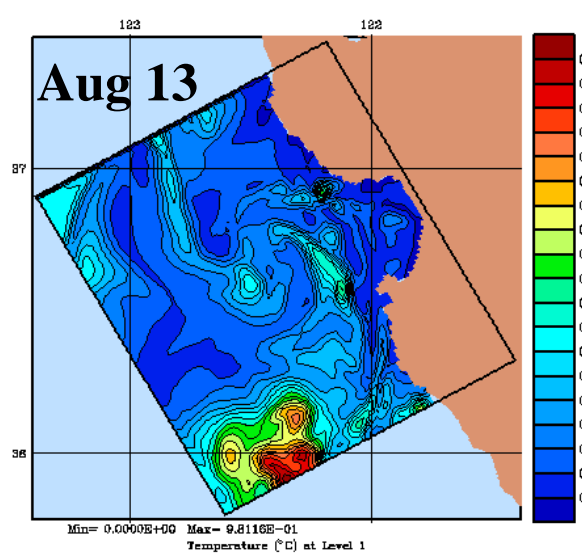


- **Nowcast: Aug 11** (persistence forecast, red)
- **2-day forecast for Aug 13** (green)
- **1-day forecast for Aug 12** (blue, to check phase error)

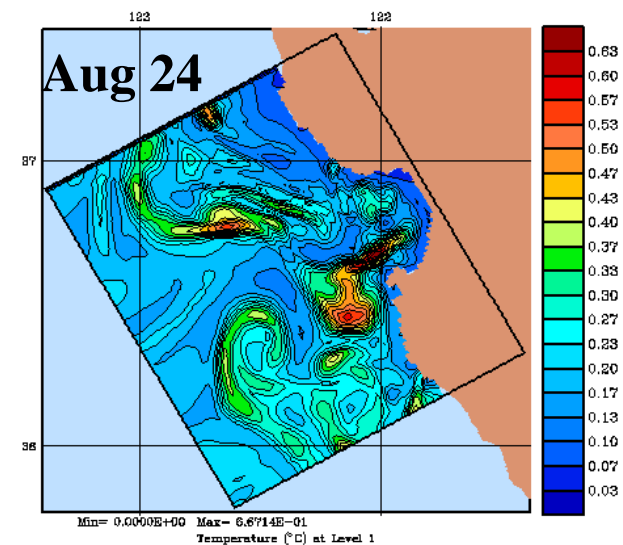
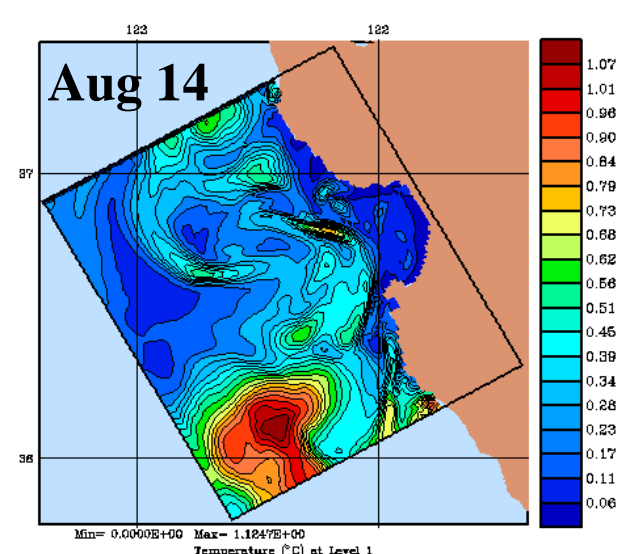
# ESSE Surface Temperature Error Standard Deviation Forecasts



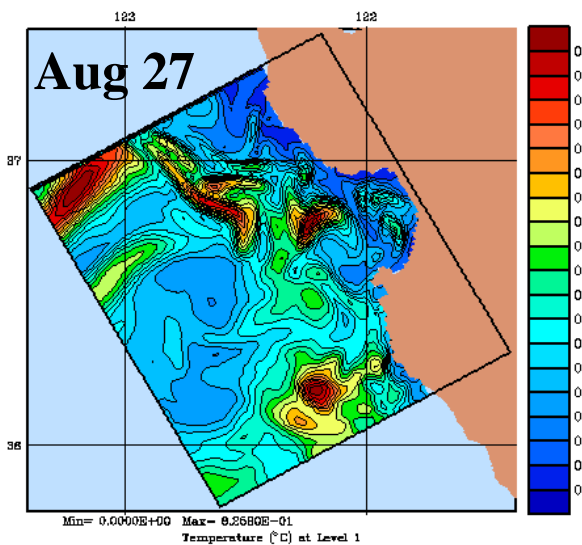
Start of Upwelling



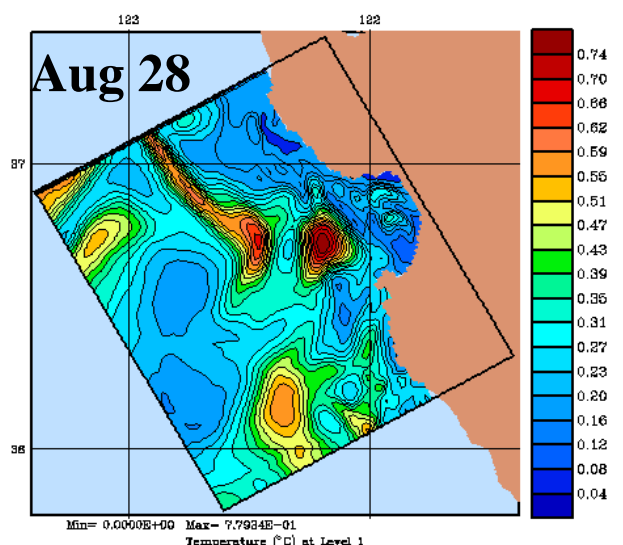
First Upwelling period



End of Relaxation

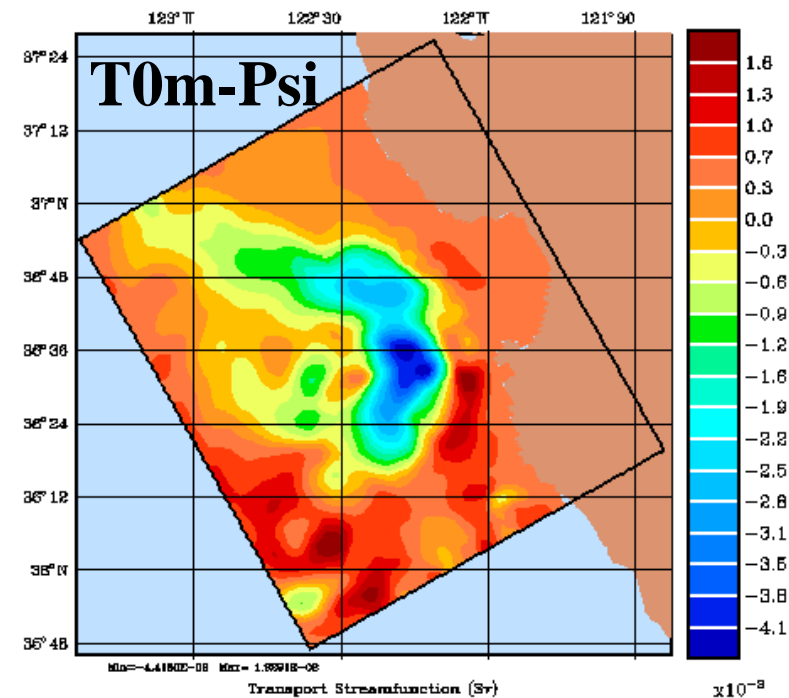
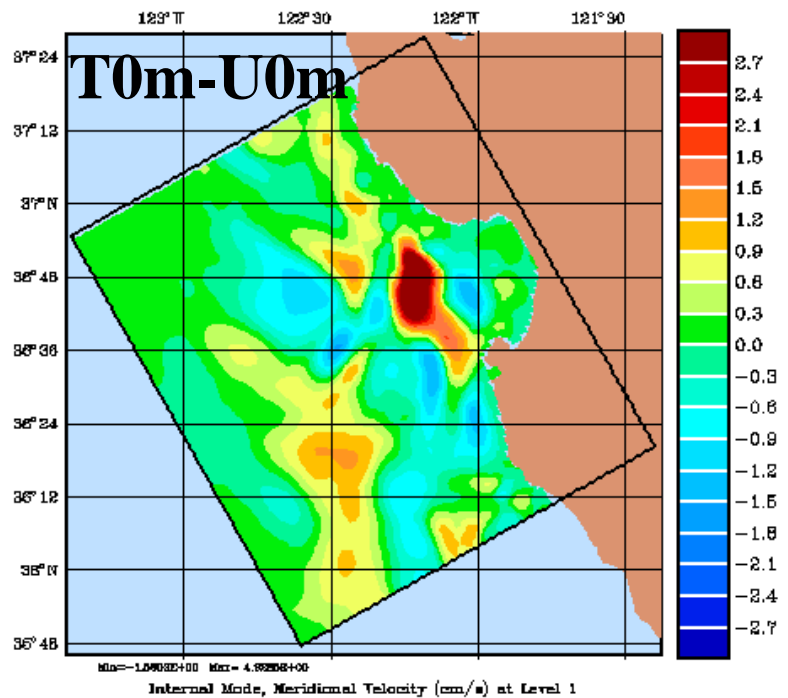
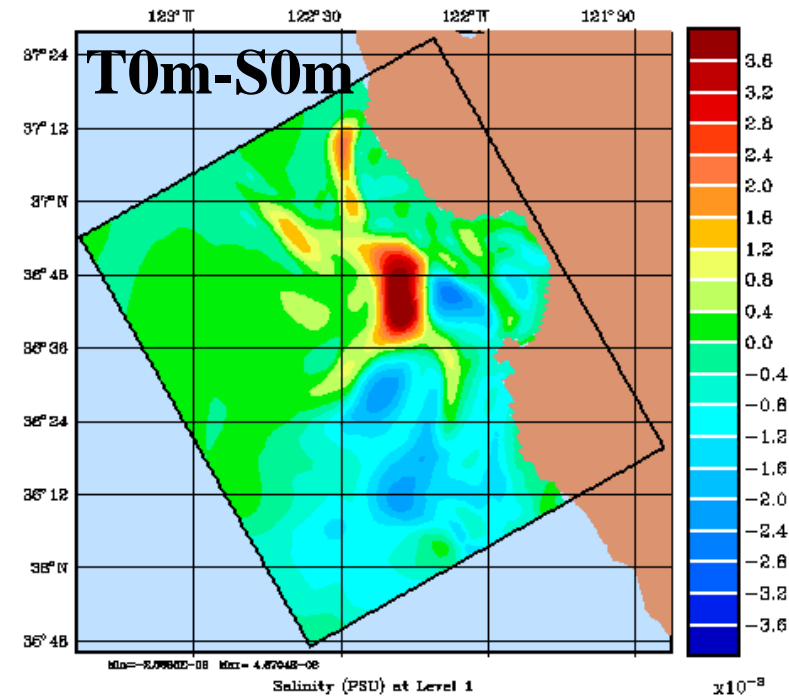
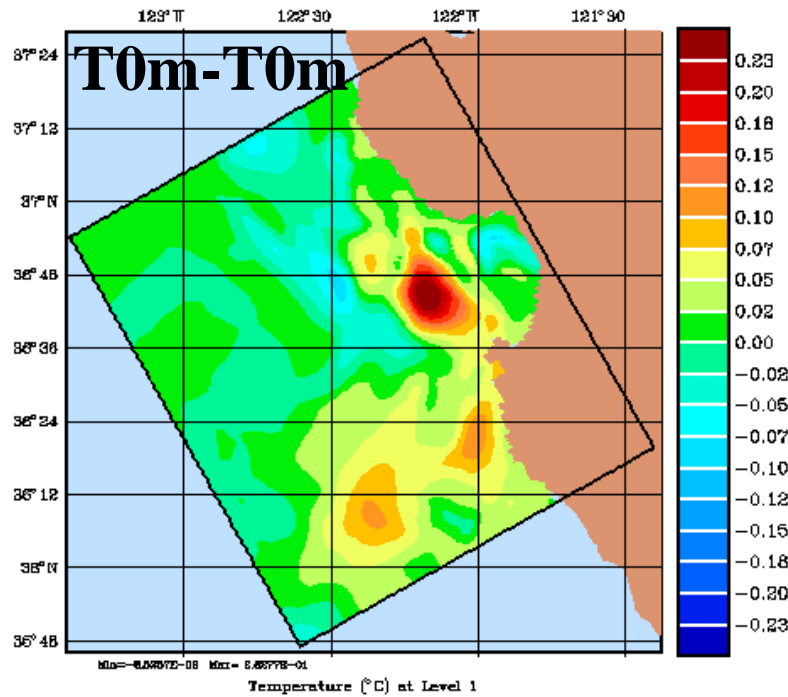


Second Upwelling period





# ESSE DA properties: Error covariance function predicted for 28 August





# Adaptive sampling schemes via ESSE

Adaptive Sampling: Use forecasts and their uncertainties to predict the most useful observation system in space (locations/paths) and time (frequencies)

$$\begin{array}{lll} \text{Dynamics:} & dx = M(x)dt + d\eta & \eta \sim N(0, Q) \\ \text{Measurement:} & y = H(x) + \varepsilon & \varepsilon \sim N(0, R) \end{array}$$

Non-lin. Err. Cov.:

$$dP/dt = \langle (x - \hat{x})(M(x) - M(\hat{x}))^T \rangle + \langle (M(x) - M(\hat{x}))(x - \hat{x})^T \rangle + Q$$

**Adaptive Sampling Metric or Cost function:**

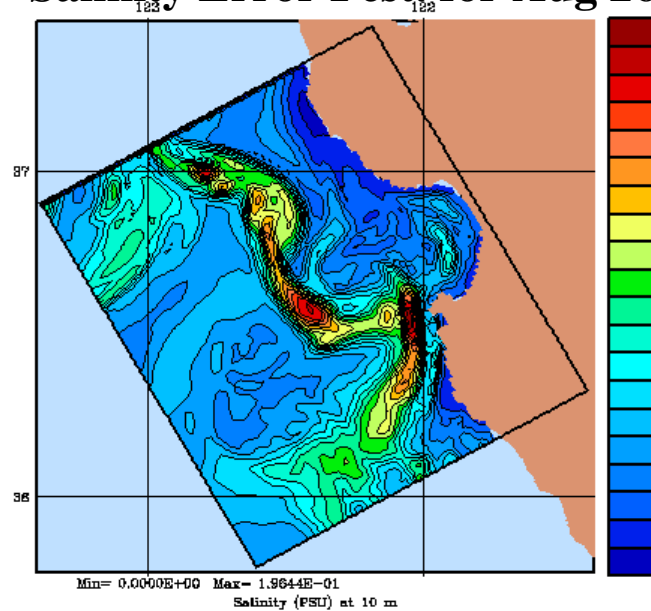
e.g. Find  $H_i$  and  $R_i$  such that

$$\underset{H_i, R_i}{\text{Min}} \quad \text{tr}(P(t_f)) \quad \text{or} \quad \underset{H_i, R_i}{\text{Min}} \quad \int_{t_0}^{t_f} \text{tr}(P(t)) \, dt$$

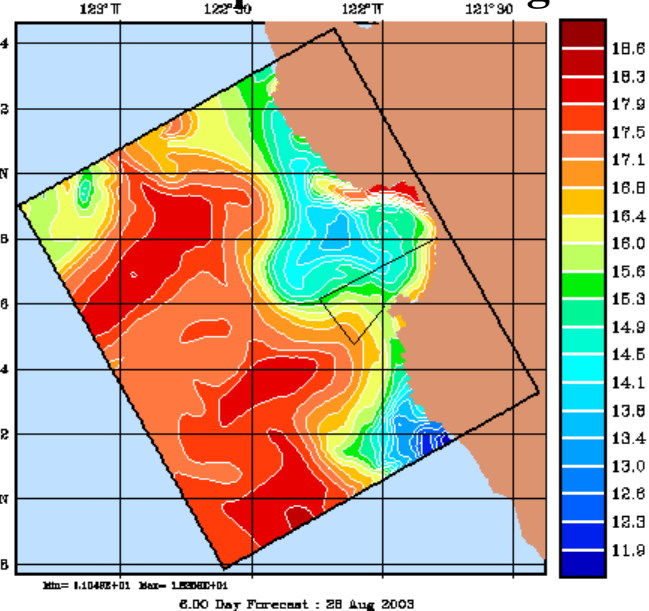
# Real-time Adaptive Sampling – R/V Pt. Lobos

- 25 Aug forecast: Large uncertainty for 26 Aug. related to predicted meander of the coastal current which advects warm and fresh waters towards Monterey Bay Peninsula.
- Position and strength of meander were very uncertain (e.g. T and S error St. Dev., based on 450 2-day fcsts.).
- Different ensemble members showed that the meander could be very weak (almost not present) or further north than in the central forecast
- Sampling plan designed to investigate position and strength of meander and region of high forecast uncertainty.

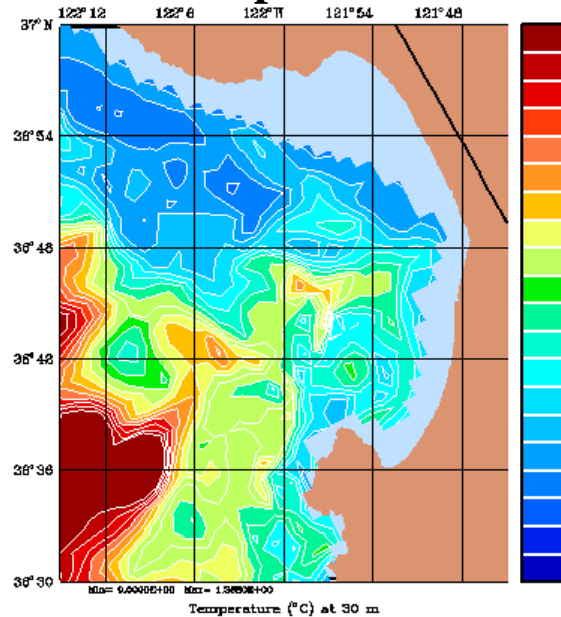
**Salinity Error Fcst. for Aug 26**



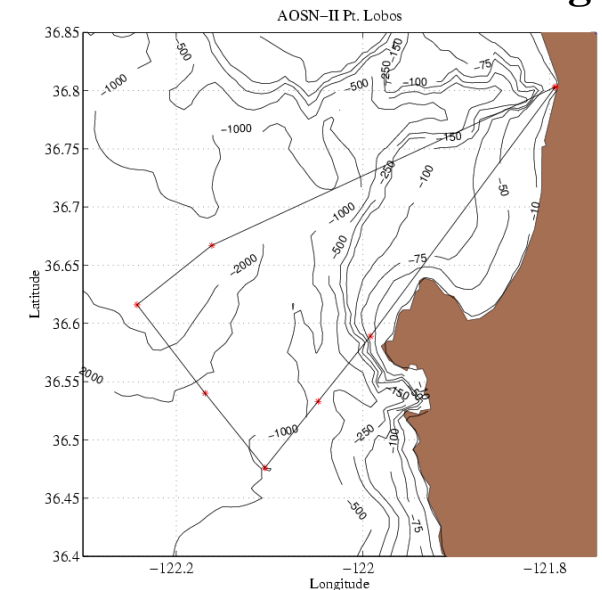
**Surf. Temp. Fcst. for Aug 26**



**MB Temp. Error Fcst.**



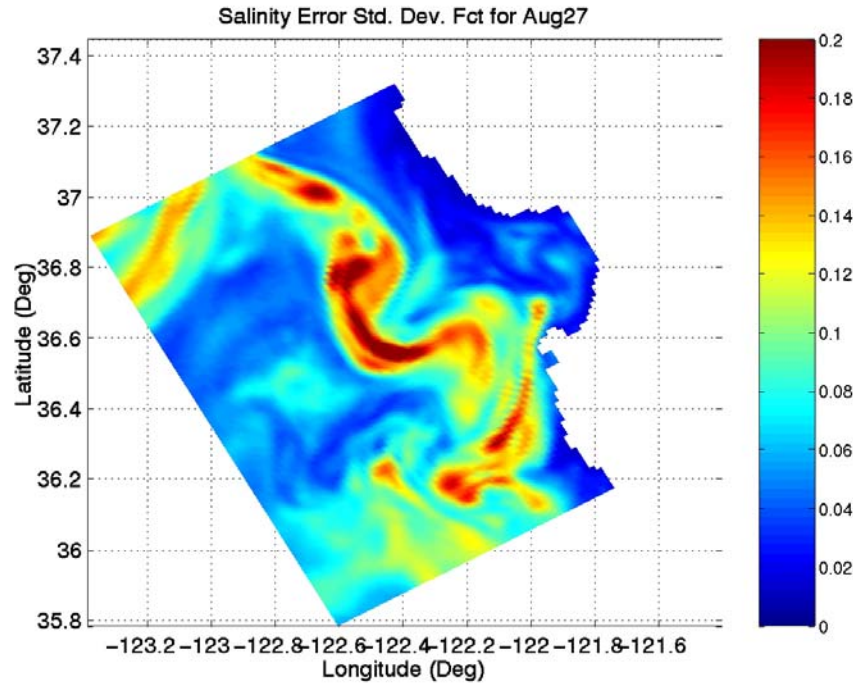
**R/V Pt Lobos track for Aug 26**



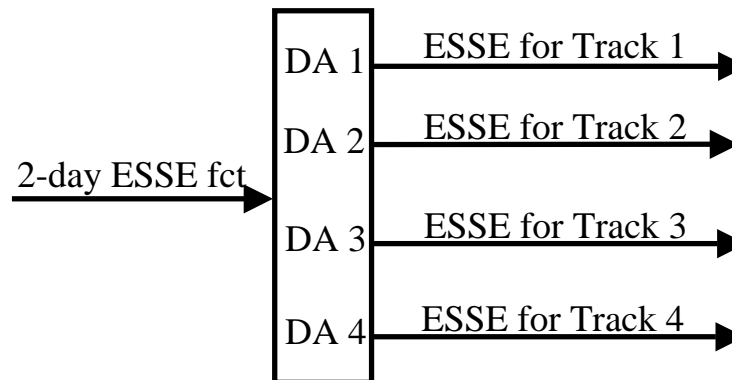
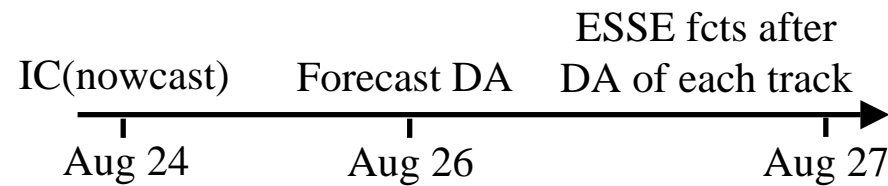
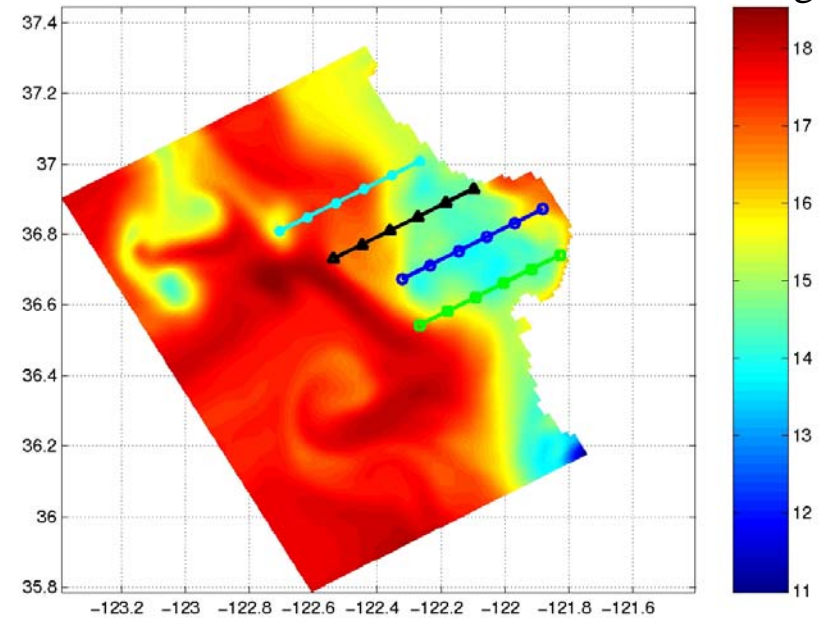
# Quantitative Adaptive Sampling via ESSE

- Use exact nonlinear error covariance evolution
  - For every choice of adaptive strategy, an ensemble is computed
1. Select sets of candidate sampling paths/regions and variables that satisfy operational constraints
  2. Forecast reduction of errors for each set based on a tree structure of small ensembles and data assimilation
  3. Optimization of sampling plan: select sequence of paths/regions and sensor variables which maximize the predicted nonlinear error reduction in the spatial domain of interest, either at  $t_f$  (trace of ``information matrix'' at final time) or over  $[t_0, t_f]$
- Outputs:
    - Maps of predicted error reduction for each sampling paths/regions
    - Information (summary) maps: assigns to the location of each sampling region/path the average error reduction over domain of interest
    - Ideal sequence of paths/regions and variables to sample

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

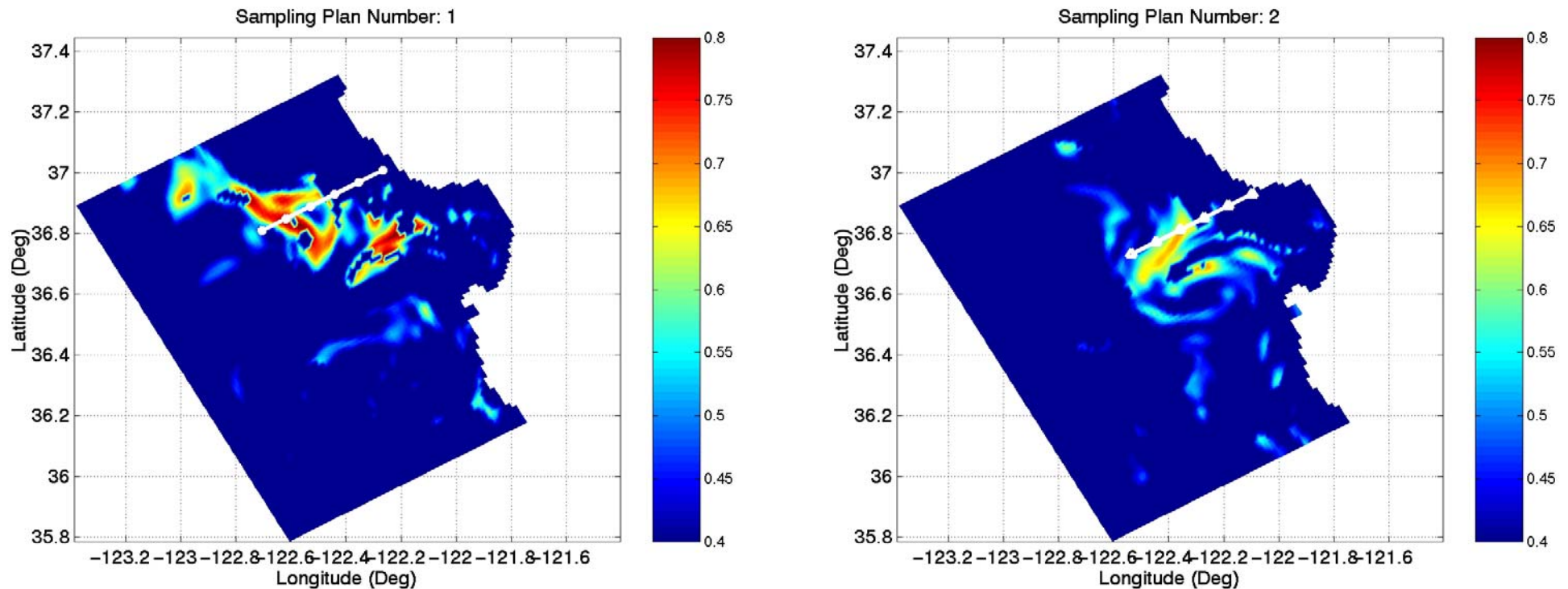


4 candidate tracks, overlaid on surface T fct for Aug 26



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

1. Define relative error reduction as:
$$\begin{aligned} &(\sigma_{27} - \sigma_{27}^{\text{track } i}) / \sigma_{27} \dots \text{for } \sigma_{27} > \sigma_{\text{noise}} \\ &0 \dots \dots \dots \text{for } \sigma_{27} \leq \sigma_{\text{noise}} \end{aligned}$$
2. Create relative error reduction maps for each sampling tracks, e.g.:

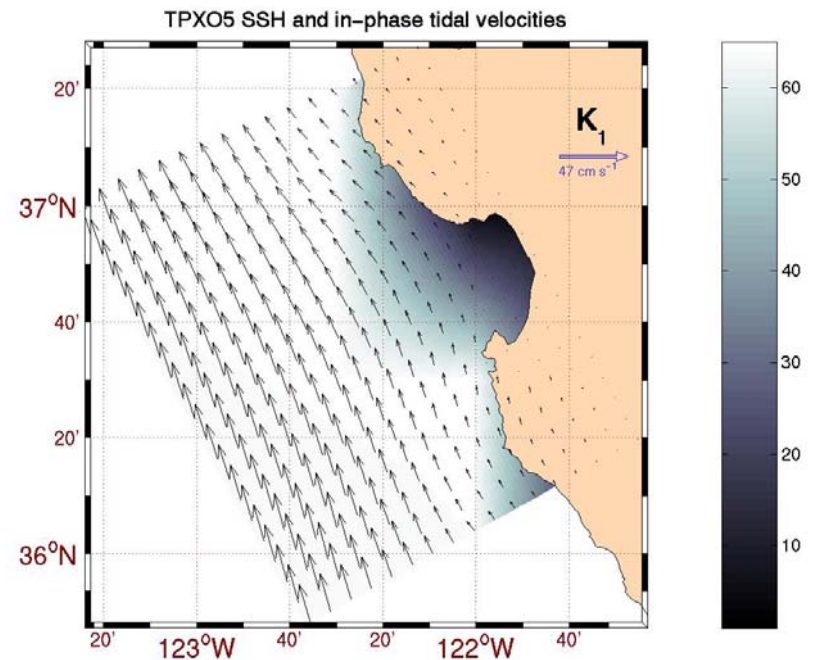
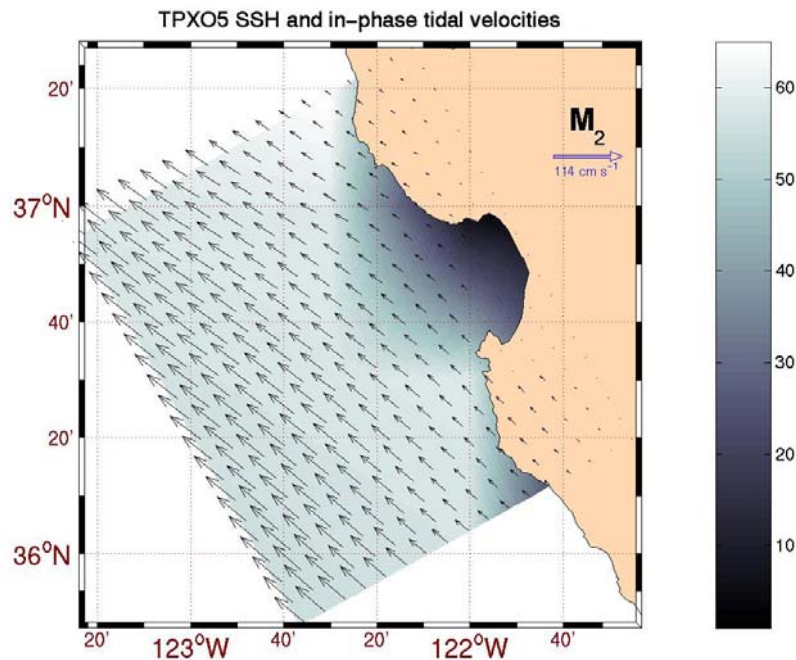


3. Compute average over domain of interest for each variable, e.g. for full domain:  
Best to worst error reduction: Track 1 (18%), Pt Lobos (17%), ..., Track 3 (6%)
4. Create “Aug 26 information map”: indicates where to sample on Aug 26 for optimal error reduction on Aug 27



# Modeling of tidal effects in HOPS

- Obtain first estimate of principal tidal constituents via a shallow water model
  1. Global TPXO5 fields (Egbert, Bennett et al.)
  2. Nested regional OTIS inversion using tidal-gauges and TPX05 at open-boundary

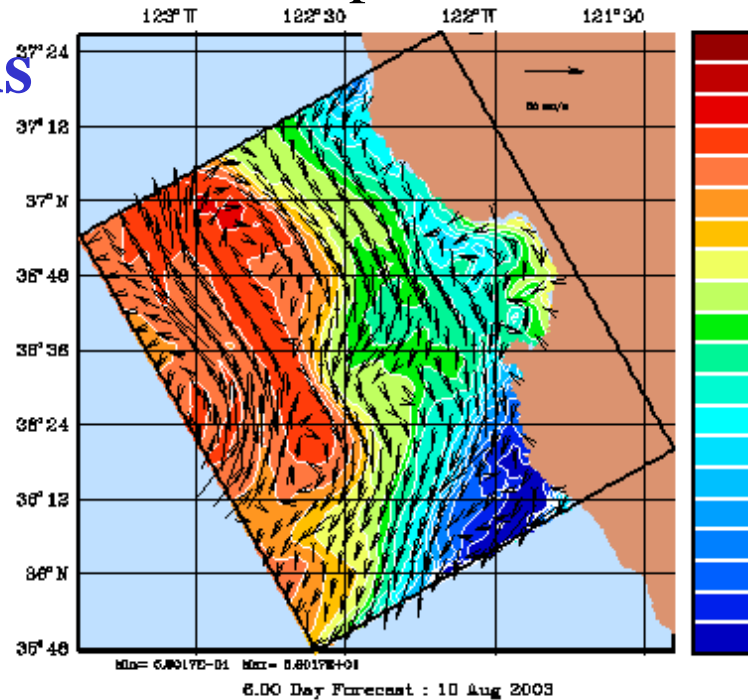


- Used to estimate hierarchy of tidal parameterizations :
  - Vertical tidal Reynolds stresses (diff., visc.)**  $K_T = \alpha ||\mathbf{u}_T||^2$  and  $K = \max(K_S, K_T)$
  - Modification of bottom stress**  $\tau = C_D ||\mathbf{u}_{S+} \mathbf{u}_T|| \mathbf{u}_S$
  - Horiz. momentum tidal Reyn. stresses**  $\Sigma_\omega$  (Reyn. stresses averaged over own  $T_\omega$ )
  - Horiz. tidal advection of tracers  $\frac{1}{2}$  free surface
  - Forcing for free-surface HOPS full free surface

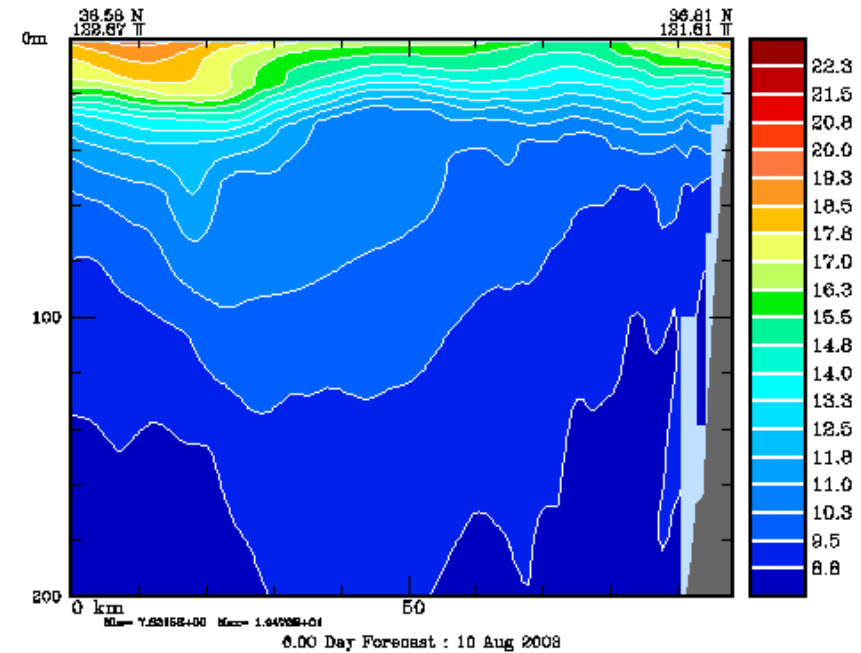
# Two 6-day model runs

No-tides

Temp. at 10 m



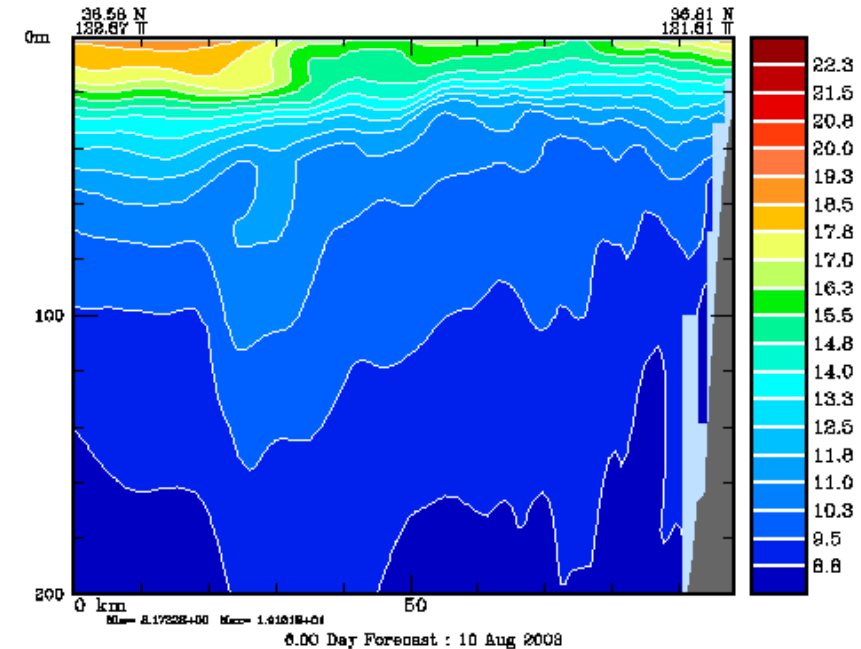
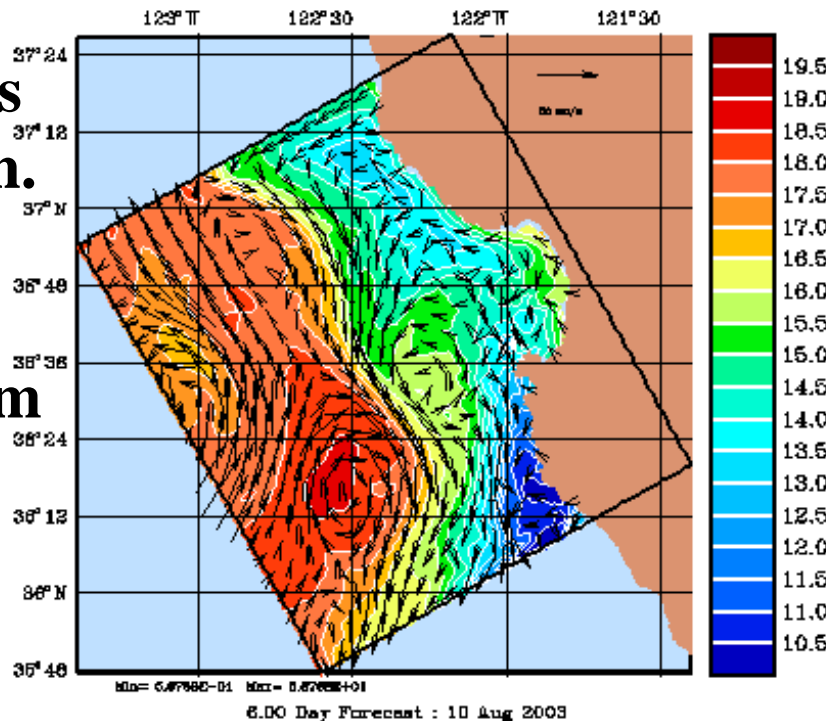
T section across Monterey-Bay



Tidal effects

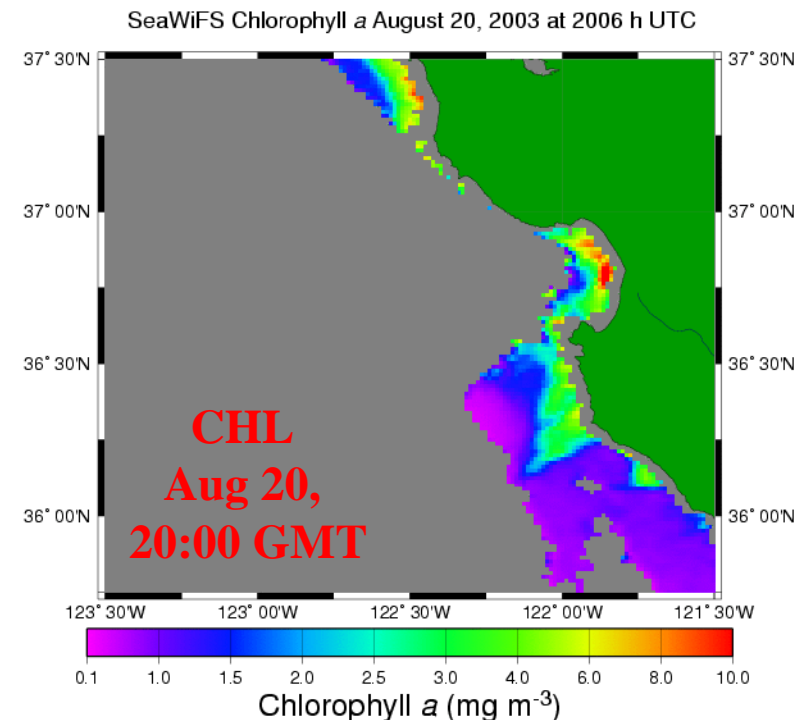
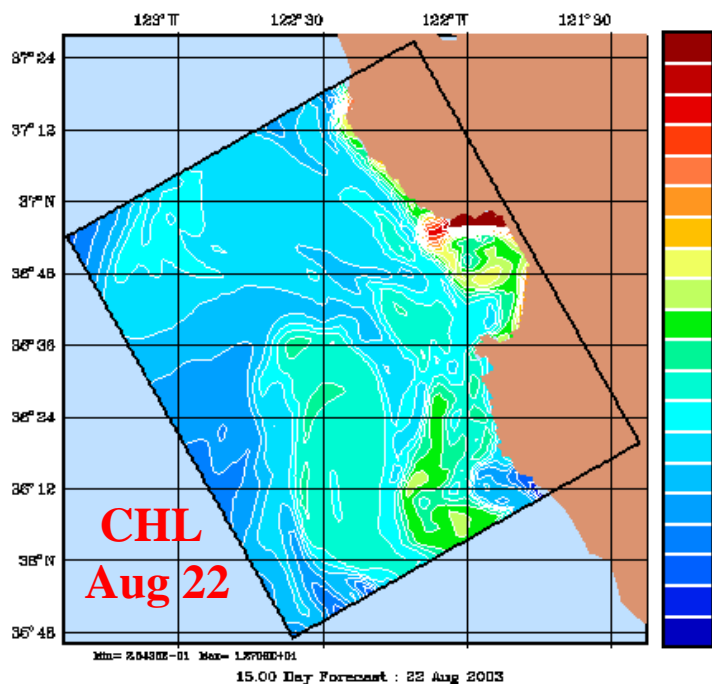
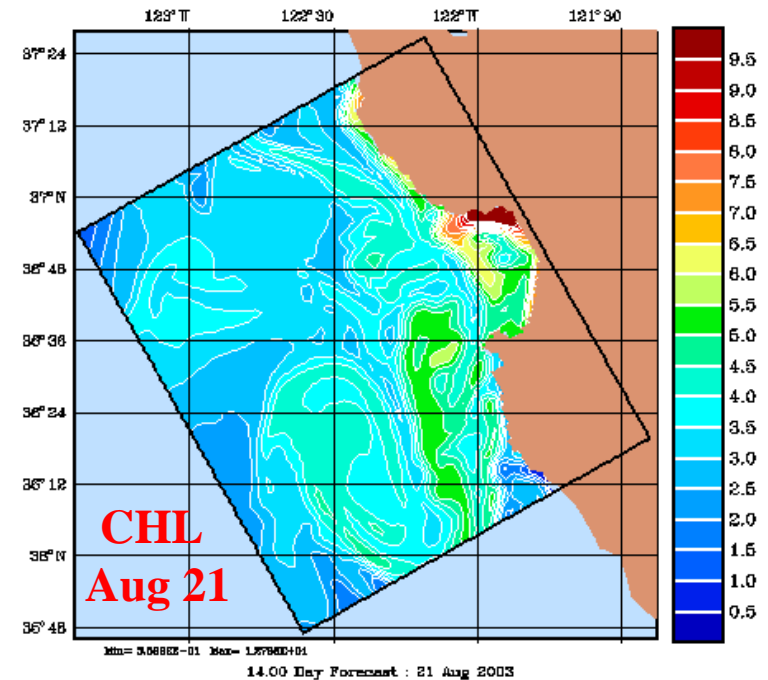
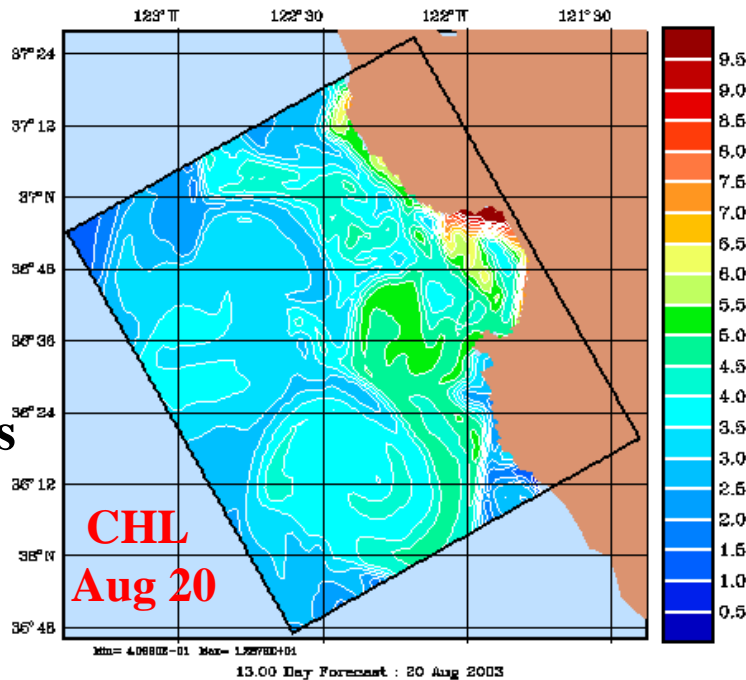
- Vert. Reyn.
- Horiz.

Stress  
Momentum  
Stress



# Post-Cruise Surface CHL forecast (Hindcast)

- Starts from zeroth-order dynamically balanced IC on Aug 4
- Then, 13 days of physical DA
- Forecast of 3-5 days afterwards

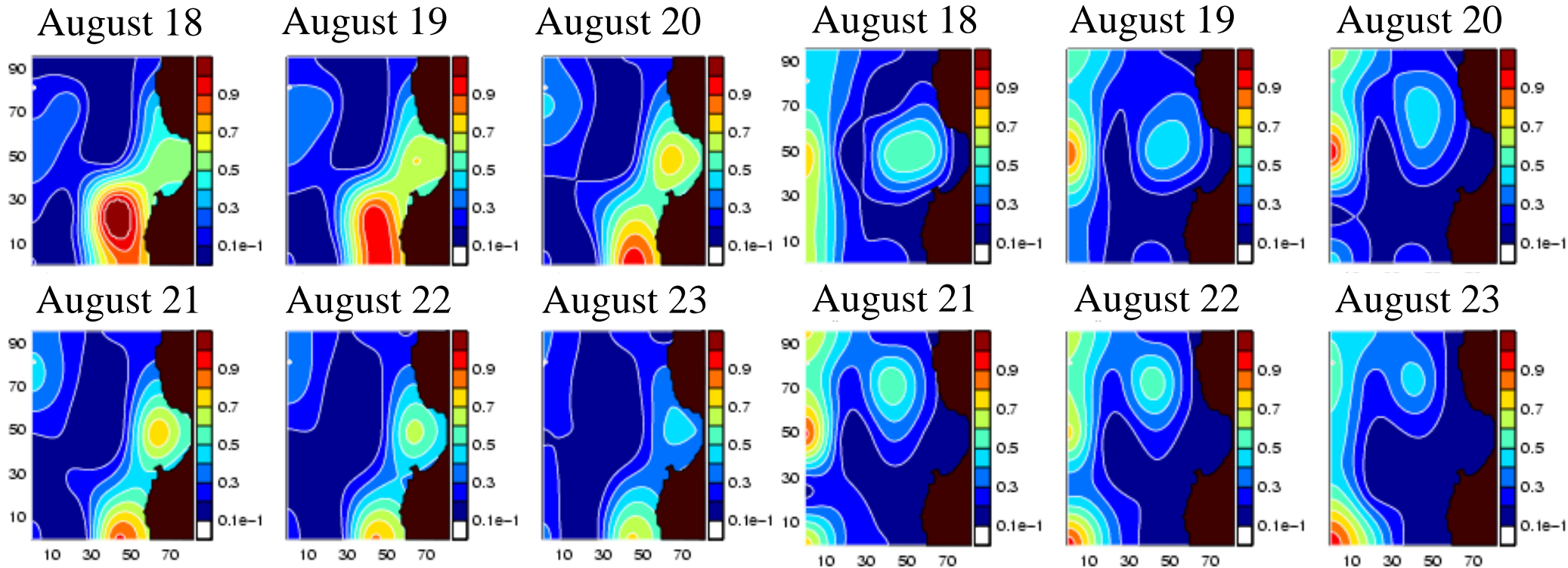


# Multi-Scale Energy and Vorticity Analysis

- Multiscale window decomposition in space and time (wavelet-based) of energy/vorticity eqns.
- For example, consider Energetics During Relaxation Period:

## 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 takes place to account for the decrease in energy (as confirmed by transfer and mesoscale terms)

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



# Approaches to Multi-Model Adaptive Forecasting

Combine ROMS/HOPS re-analysis temperatures  
to fit the M2-buoy temperature at 10 m

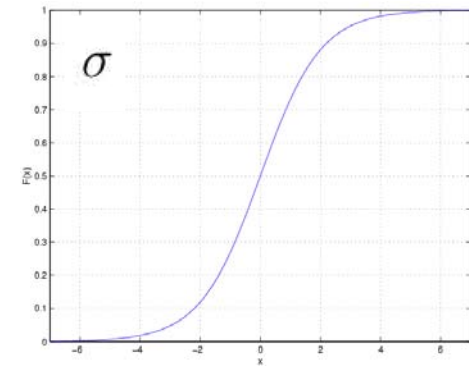
By combining the models  $x_1$  and  $x_2$  we attempt to:

1. eliminate and learn systematic errors
2. reduce random errors

- Approach utilized here: neural networks
- A neural network is a non-linear operator which can be adapted (trained) to approximate a target arbitrary non-linear function measuring model-data misfits:

$$I(\mathbf{w}) = \frac{1}{2T} \int_0^T (\mathcal{F}\{\mathbf{x}(t)\} - d(t))^2 dt$$

## Sigmoidal Transfer Function

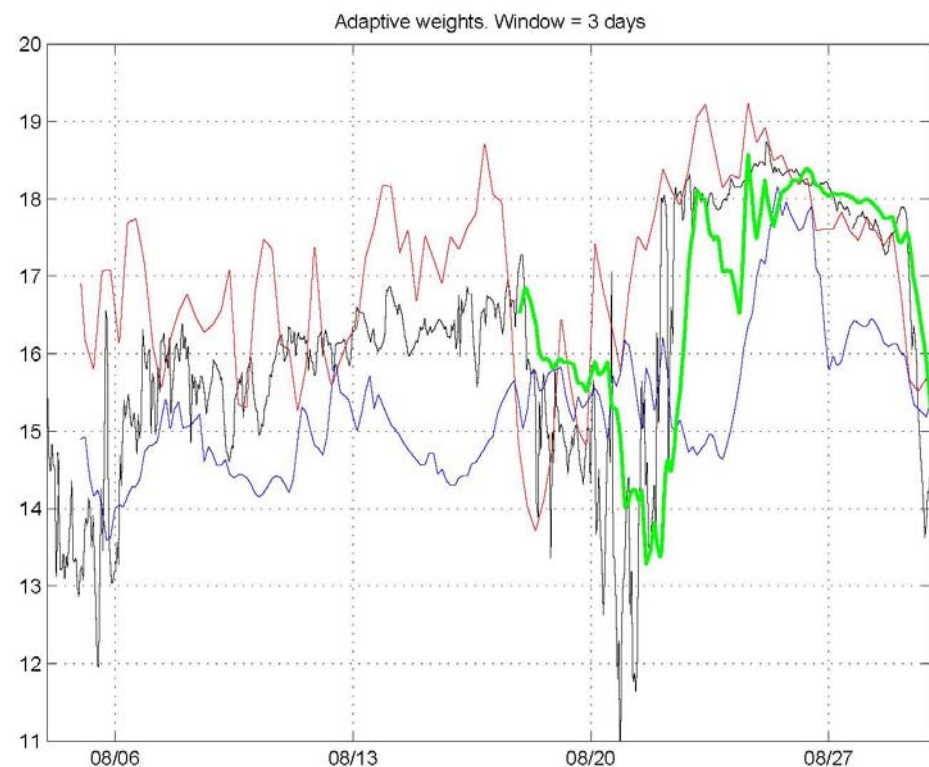
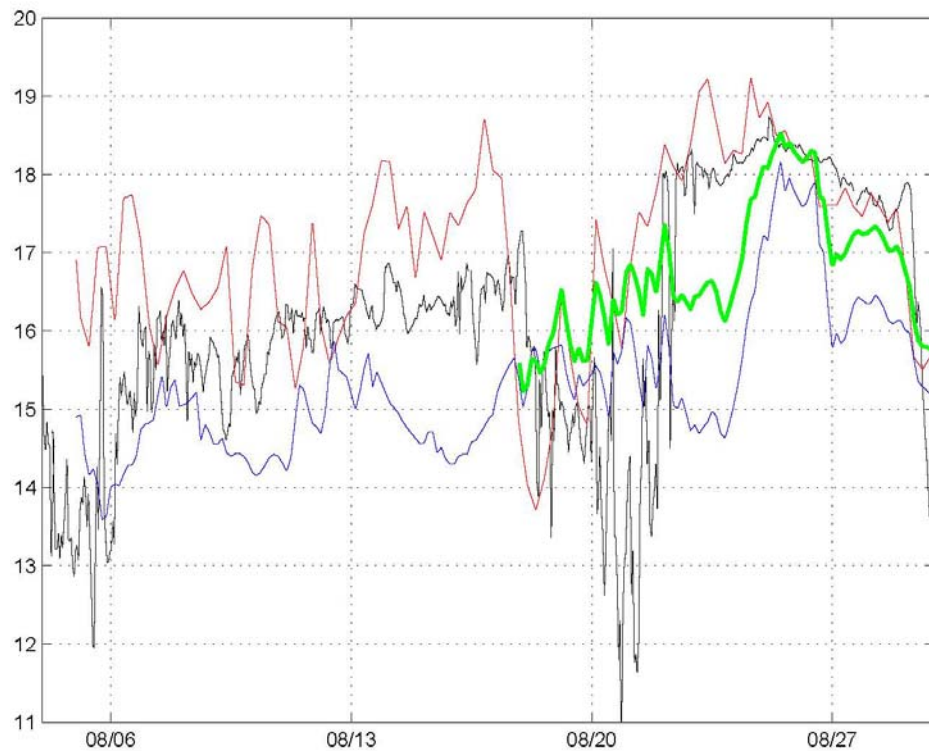


Linear least-squares fit:  $\mathcal{F}\{\mathbf{x}(t)\} = \mathcal{L}\{\mathbf{x}(t)\} = w_0 + \sum_{k=1}^2 w_k x_k(x, y, t)$

Single Sigmoidal layer:

$$\mathcal{F}\{\mathbf{x}(t)\} = \mathcal{L}_2 \Sigma_1 \mathcal{L}_1\{\mathbf{x}\} = w_{20} + w_{21} \sigma(w_{10} + w_{11}x_1(t) + w_{12}x_2(t))$$





- Observed (black) temp at the M2mooring
- Modeled temp at the M2mooring:  
**ROMS re-analysis**, **HOPS re-analysis**

Top: **Green** – HOPS/ROMS reanalysis combined via neural network trained on the first subset of data (before Aug 17).

Bottom: **Green** – HOPS/ROMS reanalysis combined via **adaptive** neural network also trained on the first subset of data (before Aug 17), but over moving-window of 3 days decorrelation

### Neural Network Least Squares Fit

Training data	$w_{20}$	$w_{21}$	$w_{10}$	$w_H$	$w_R$	$rms_{1st}$	$rms_{2nd}$
First half	9.472	11.015	-6.175	0.301	0.121	0.72	1.34
Second half	13.197	10.862	-10.764	0.222	0.372	0.80	1.27

### Linear Least Squares Fit

Training data	$w_0$	$w_H$	$w_R$	$rms_{1st}$	$rms_{2nd}$
First half	-3.118	0.965	0.277	0.733	1.576
Second half	-2.842	0.478	0.690	0.85	1.35

### Equal Weights

	$w_1$	$w_2$	$rms_1$	$rms_2$
	0.5	0.5	0.79	1.39

Model	$rms_{1st}$	$rms_{2nd}$
HOPS	1.28	1.82
ROMS	1.45	1.54

Individual Models

# **AOSN-II Conclusions**

- **Monterey-California Current System August 2003 Real-time:**
  - **Fully nonlinear ESSE carried-out consistent: ensemble forecast of fields and errors of 2-3 days duration, Data assimilation, Adaptive sampling and Dynamical analyses**
  - **Onset and sustained upwelling and relaxation phenomena were successfully captured, together with their dynamic mesoscale variabilities and their impacts on uncertainties**
  - **Preliminary evaluations of real-time forecasts indicate generally good RMS/Bias values that beat persistence**
- **Quantitative adaptive sampling through forecasts optimal error reduction**
- **Field and error evolutions, and multi-scale dynamical analyses indicate that during relaxation, energies are transferred from large-scale to mesoscales**
- **Combined HOPS-ROMS model estimates trained via neural networks yields an estimate with less error than each**
- **Tidal effects introduce smaller scales and alter mesoscale features**
- **Ongoing research includes:**
  - **Re-analysis fields, descriptive dynamics, methods for skill determination and error models, Coupled physical-biological estimation, Predictability studies**