Ocean Prediction Systems: Advanced Concepts and Research Issues

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- **System Concepts**
- **Research Issue Examples**
- **Demonstration of Concept Multi-Institutional Experiment off California Coast (AOSN-II)**

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Interdisciplinary Ocean Science Today

- **Research underway on coupled physical, biological, chemical, sedimentological, acoustical, optical processes**

- **Ocean prediction for science and operational applications has now been initiated on basin and regional scales**

- **Interdisciplinary processes are now known to occur on multiple interactive scales in space and time with bi-directional feedbacks**

System Concept

- **The concept of Ocean Observing and Prediction Systems for field and parameter estimations has recently crystallized with three major components**
  * **An observational network: a suite of platforms and sensors for specific tasks**
  * **A suite of interdisciplinary dynamical models**
  * **Data assimilation schemes**

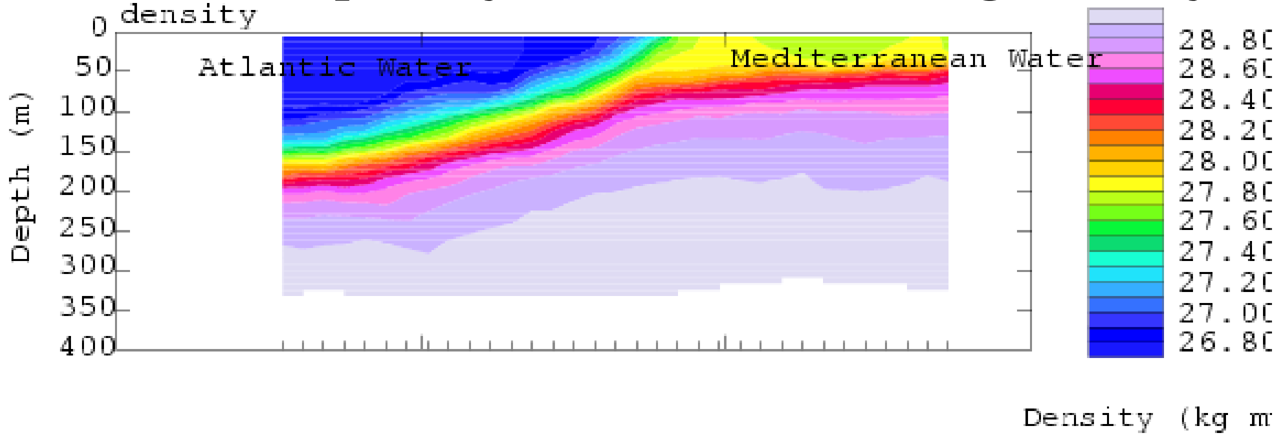
- **Systems are modular, based on distributed information providing shareable, scalable, flexible and efficient workflow and management**

Interdisciplinary Data Assimilation

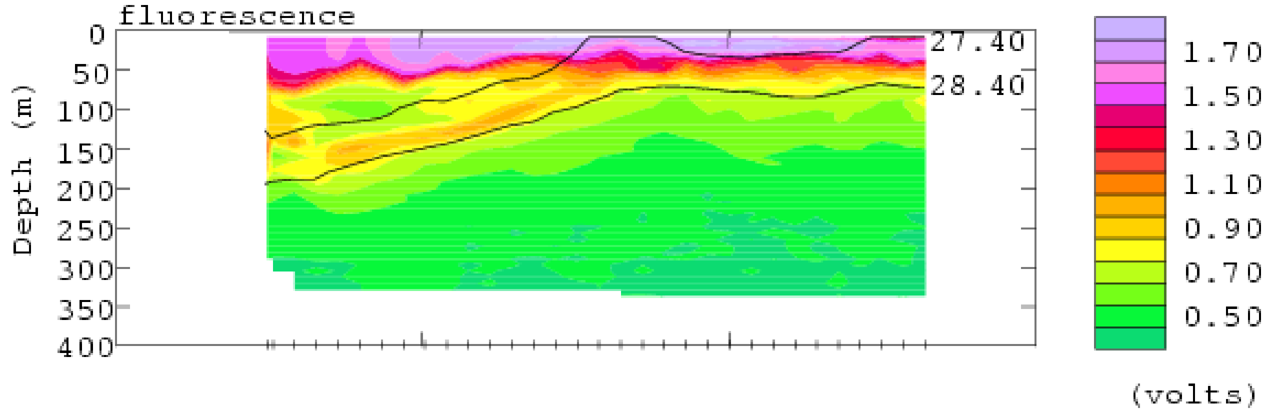
- **Data assimilation can contribute powerfully to understanding and modeling physical-acoustical-biological processes and is essential for ocean field prediction and parameter estimation**

- **Model-model, data-data and data-model compatibilities are essential and dedicated interdisciplinary research is needed**

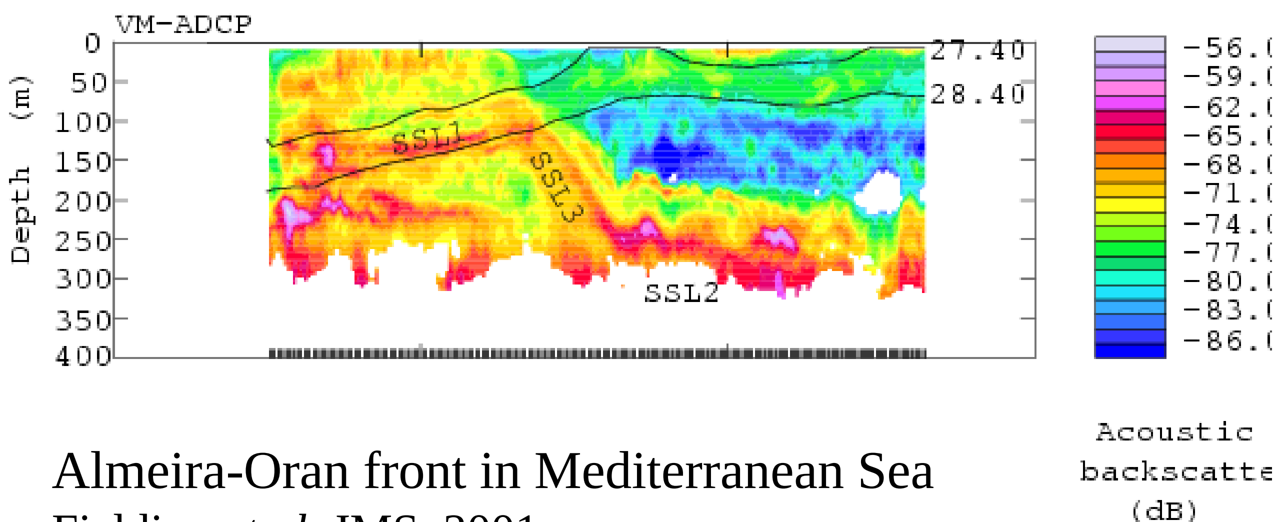
Interdisciplinary Processes - Biological-Physical-Acoustical Interactions



Physics - Density



Biology – Fluorescence (Phytoplankton)



Acoustics – Backscatter (Zooplankton)

Almeira-Oran front in Mediterranean Sea
Fielding *et al*, JMS, 2001

Griffiths *et al*,
Vol 12, THE SEA

Biological-Physical-Acoustical Interactions

- **Distribution of zooplankton is influenced by both animal behavior (diel vertical migration) and the physical environment.**
- **Fluorescence coincident with subducted surface waters indicates that phytoplankton were drawn down and along isopycnals, by cross-front ageostrophic motion, to depths of 200 m.**
- **Sound-scattering layers (SSL) show a layer of zooplankton coincident with the drawn-down phytoplankton. Layer persists during and despite diel vertical migration.**
- **Periodic vertical velocities of ~20 m/day, associated with the propagation of wave-like meanders along the front, have a significant effect on the vertical distribution of zooplankton across the front despite their ability to migrate at greater speeds.**

Coupled Interdisciplinary Data Assimilation

$\boldsymbol{x} = [\boldsymbol{x}_A \;\; \boldsymbol{x}_O \;\; \boldsymbol{x}_B]$ **Unified interdisciplinary state vector**

Physics: $\boldsymbol{x}_O = [T, S, U, V, W]$

Biology: $\boldsymbol{x}_B = [N_i, P_i, Z_i, B_i, D_i, C_i]$

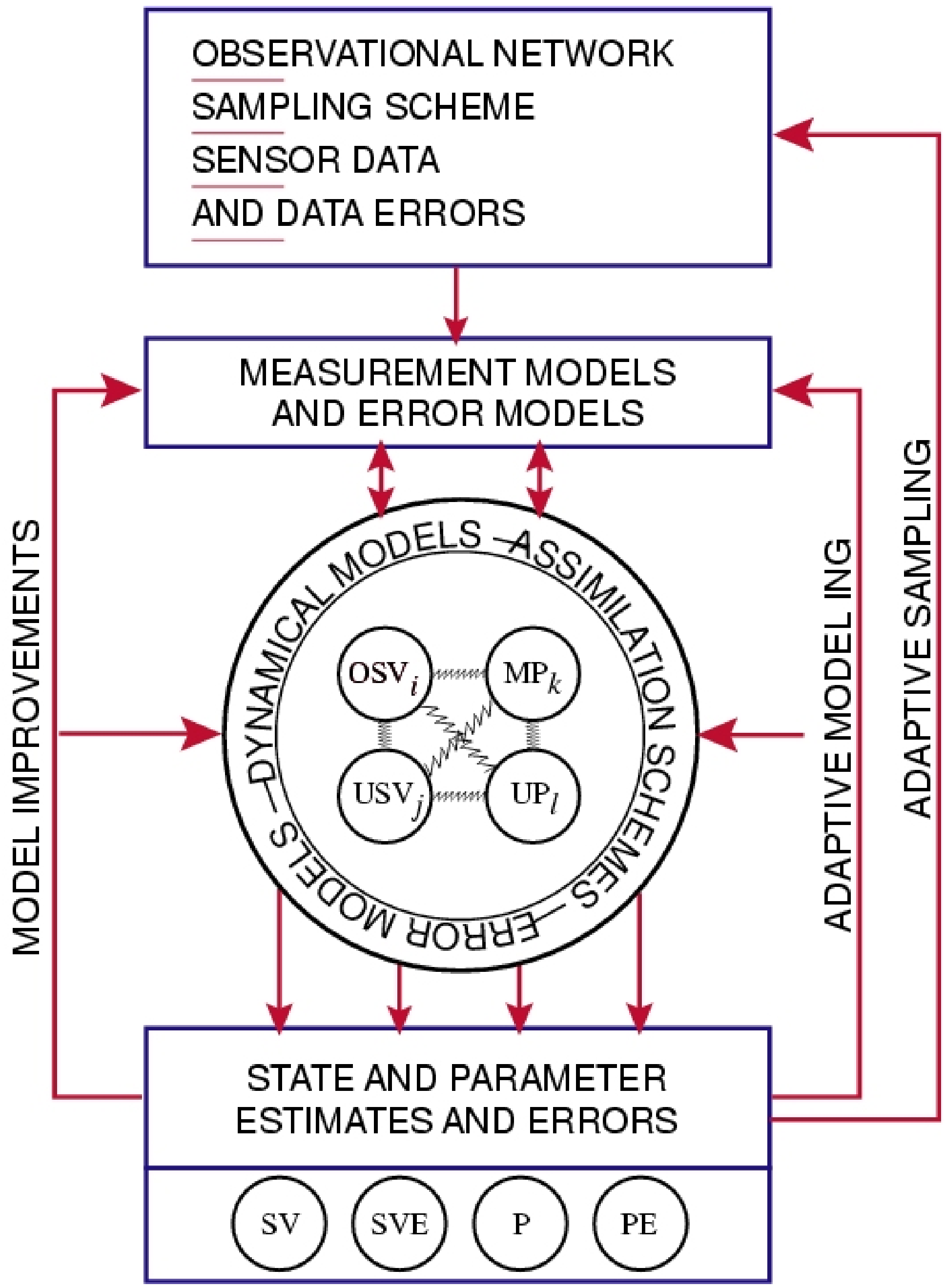
Acoustics: $\boldsymbol{x}_A = [\text{Pressure } (p), \text{ Phase } (\varphi)]$

$$\boldsymbol{P} = \varepsilon \left\{ (\hat{\boldsymbol{x}} - \boldsymbol{x}^t)(\hat{\boldsymbol{x}} - \boldsymbol{x}^t)^T \right\}$$

Coupled error covariance with off-diagonal terms

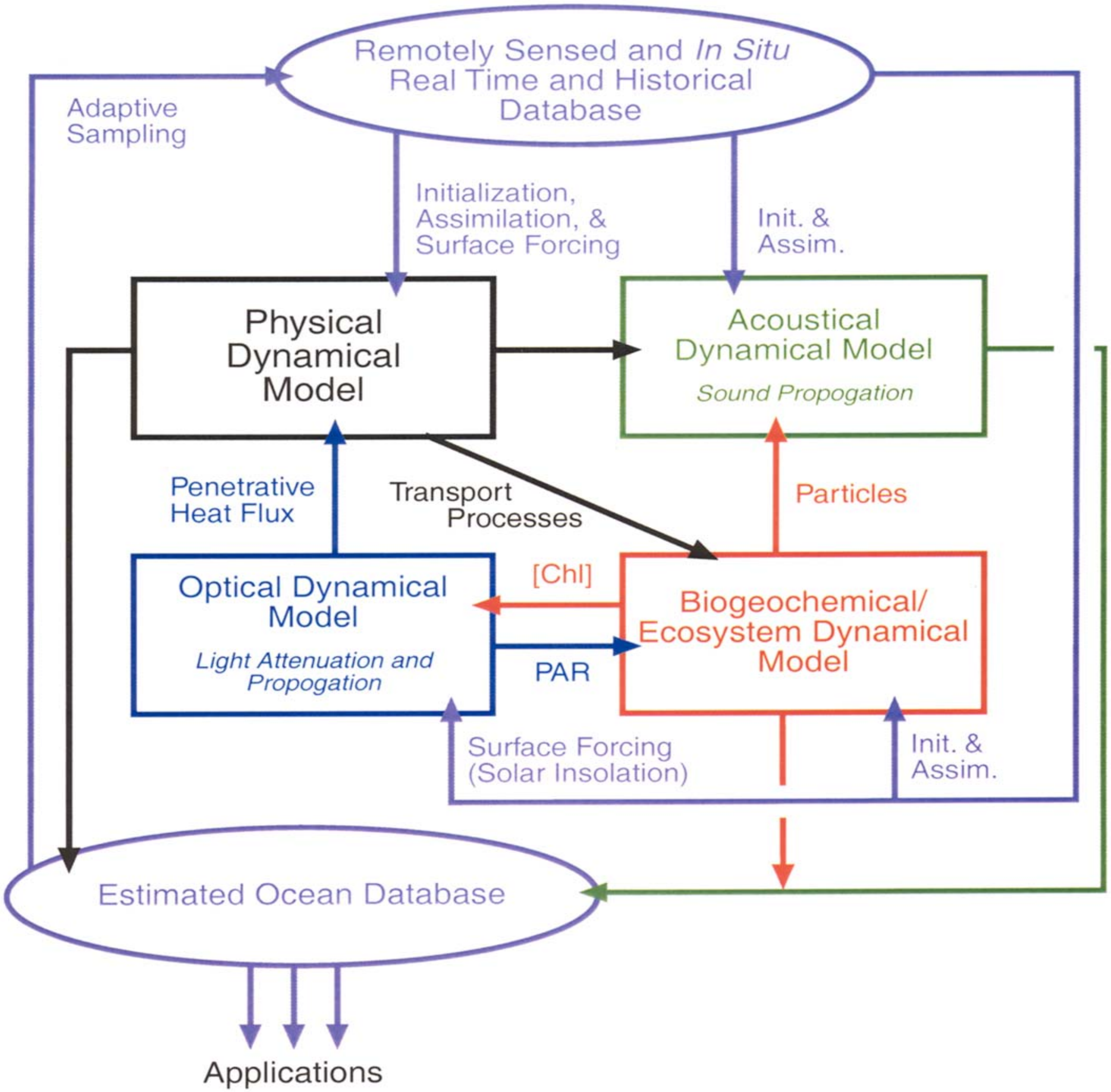
$$\boldsymbol{P} = \begin{pmatrix} P_{AA} & P_{AO} & P_{AB} \\ P_{OA} & P_{OO} & P_{OB} \\ P_{BA} & P_{BO} & P_{BB} \end{pmatrix}$$

Data Assimilation in Advanced Ocean Prediction Systems



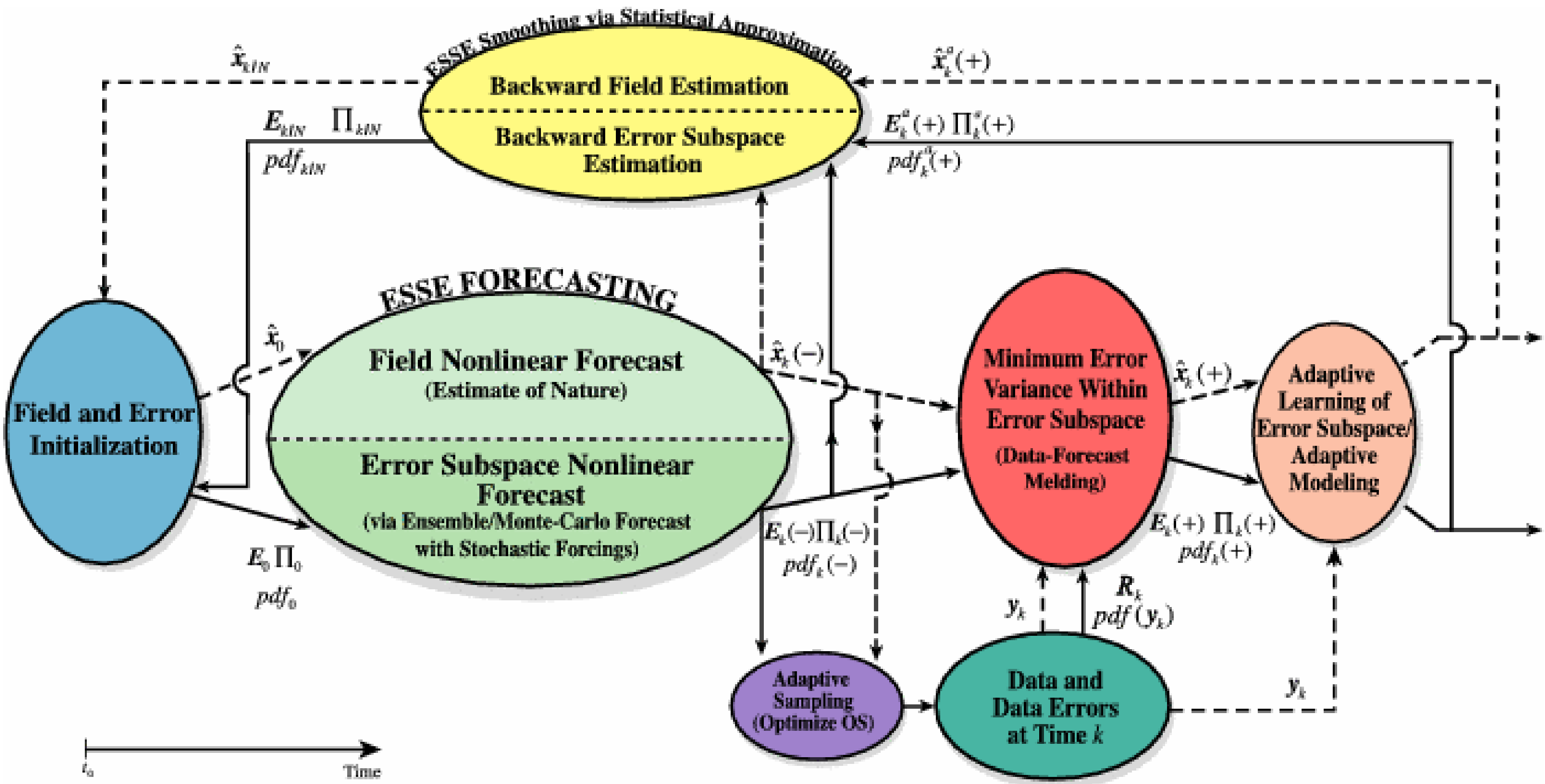
SV: STATE VARIABLE
P: PARAMETER
O: OBSERVED
M: MEASURED
U: UNOBSERVED OR UNMEASURED
E: ERROR
: DYNAMICAL LINKAGES

HOPS/ESSE System
Harvard Ocean Prediction System - HOPS



HOPS/ESSE System

Error Subspace Statistical Estimation - ESSE



- Uncertainty forecasts (with dynamic error subspace, error learning)
- Ensemble-based (with nonlinear and stochastic primitive eq. model (HOPS)
- Multivariate, non-homogeneous and non-isotropic Data Assimilation (DA)
- Consistent DA and adaptive sampling schemes

HOPS/ESSE Long-Term Research Goal

To develop, validate, and demonstrate an advanced relocatable regional ocean prediction system for the real-time ensemble forecasting and simulation of interdisciplinary multiscale oceanic fields and their associated errors and uncertainties, which incorporates both autonomous adaptive modeling and autonomous adaptive optimal sampling

Approach

To achieve regional field estimates as realistic and valid as possible, an effort is made to acquire and assimilate both remotely sensed and *in situ* synoptic multiscale data from a variety of sensors and platforms in real time or for the simulation period, and a combination of historical synoptic data and feature models are used for system initialization.

Ongoing Research Objectives

To extend the HOPS-ESSE assimilation, real-time forecast and simulation capabilities to a single interdisciplinary state vector of ocean physical-acoustical-biological fields.

To continue to develop and to demonstrate the capability of multiscale simulations and forecasts for shorter space and time scales via multiple space-time nests (Mini-HOPS), and for longer scales via the nesting of HOPS into other basin scale models.

To achieve a multi-model ensemble forecast capability.

Examples Illustrating Research Issues

Gulf Stream

Coupled physical-biological dynamics studied via compatible physical-biological data assimilation

Combined feature model and *in situ* data assimilation in western boundary current

Ligurian Sea and Portuguese Coast

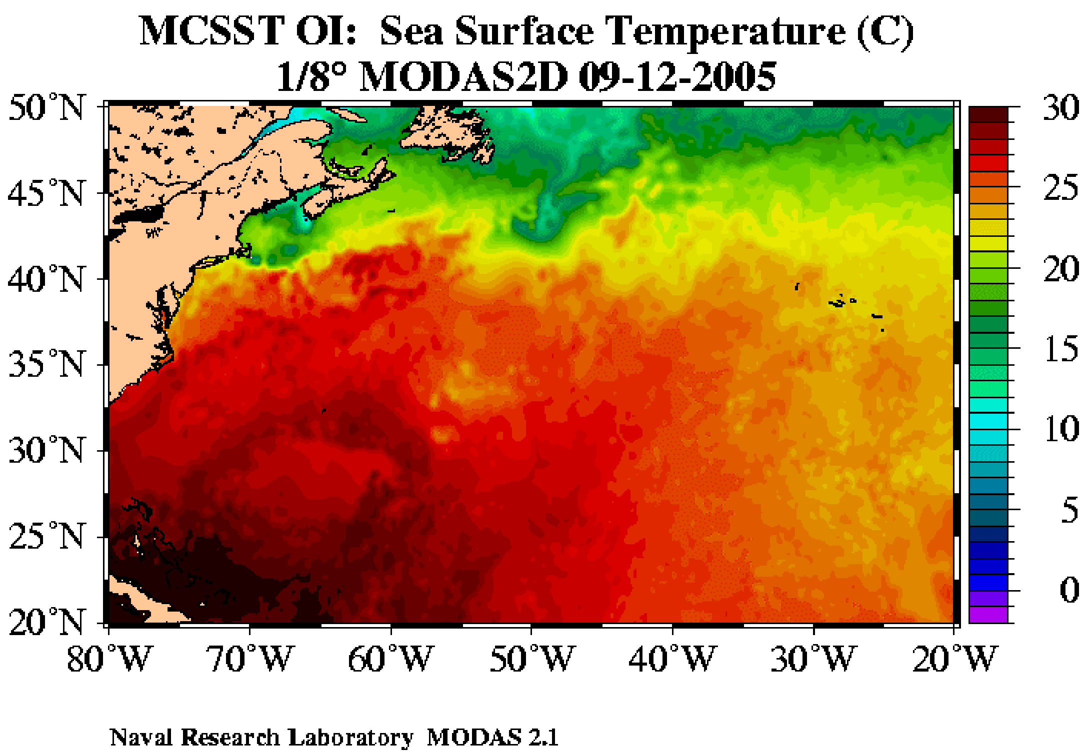
Multi-scale real-time forecasting in two-way nested domains – Mini-HOPS: faster time scales, shorter space scales, sub-mesoscale synopticity

New England Shelfbreak Front

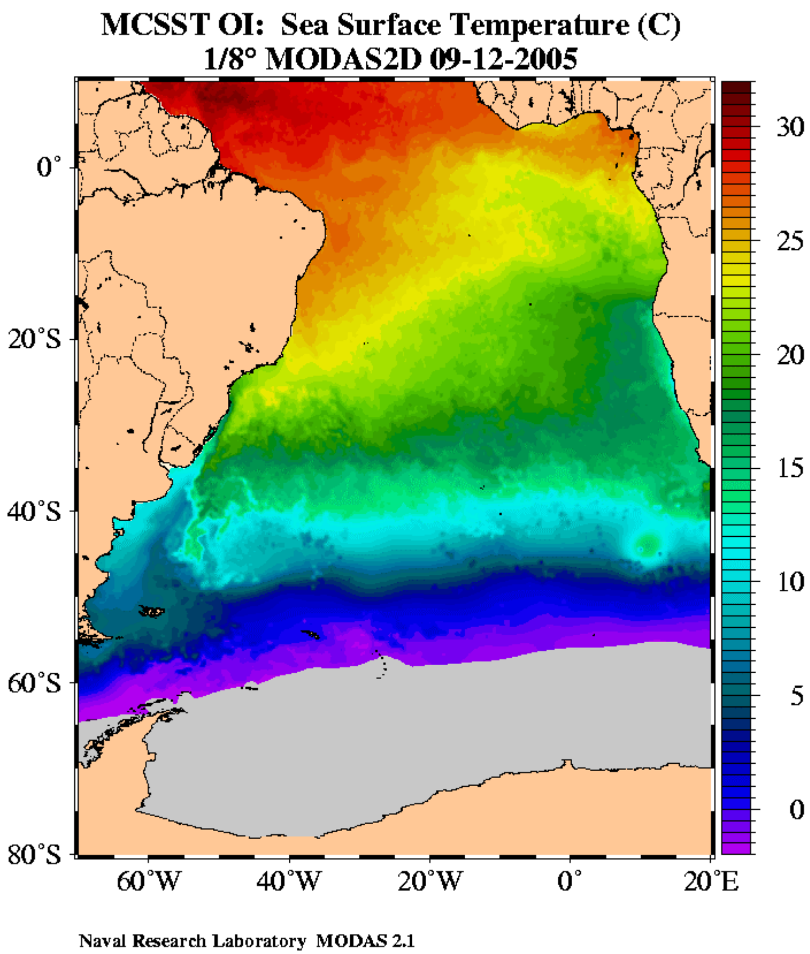
End-to-End system concept with uncertainties, e.g. sonar system

Coupled physical-acoustical data assimilation with coupled error covariances

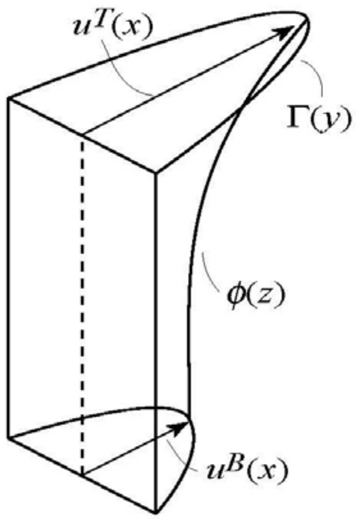
Gulf Stream



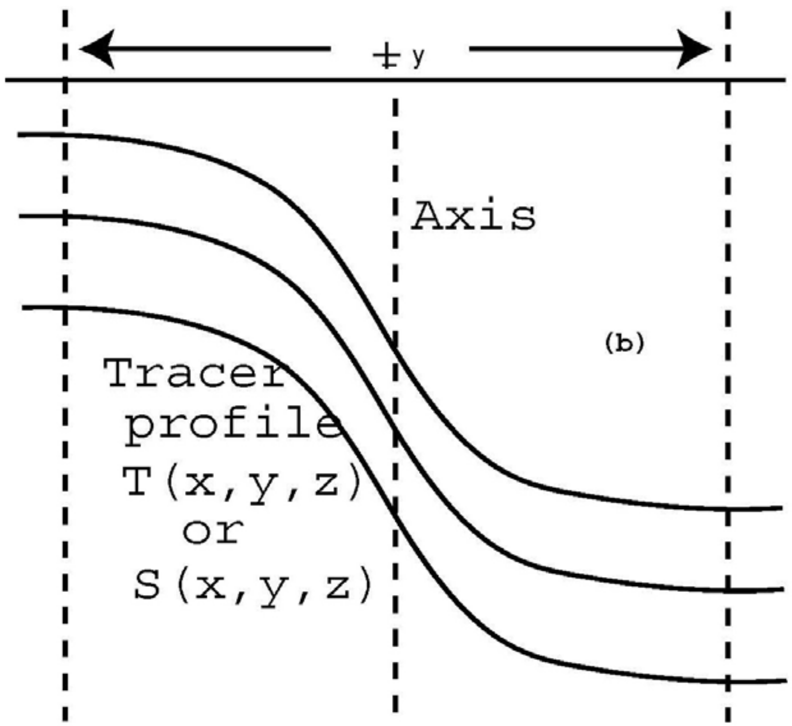
Brazil Current

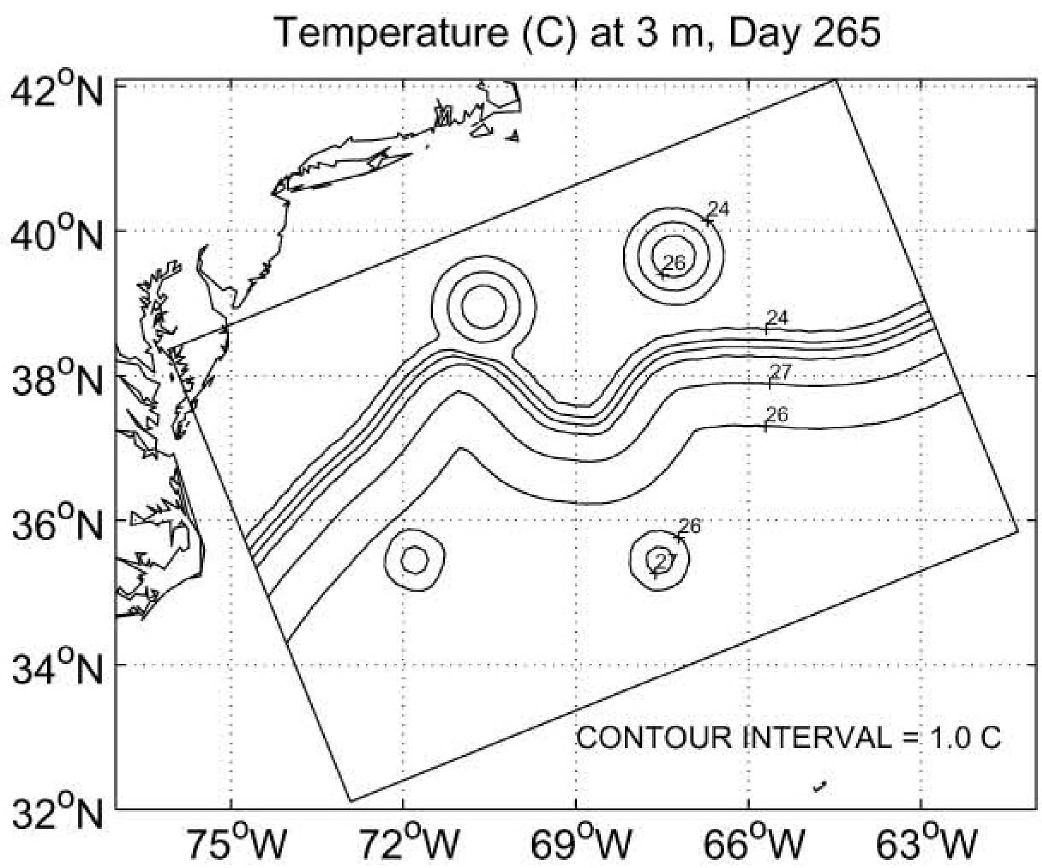


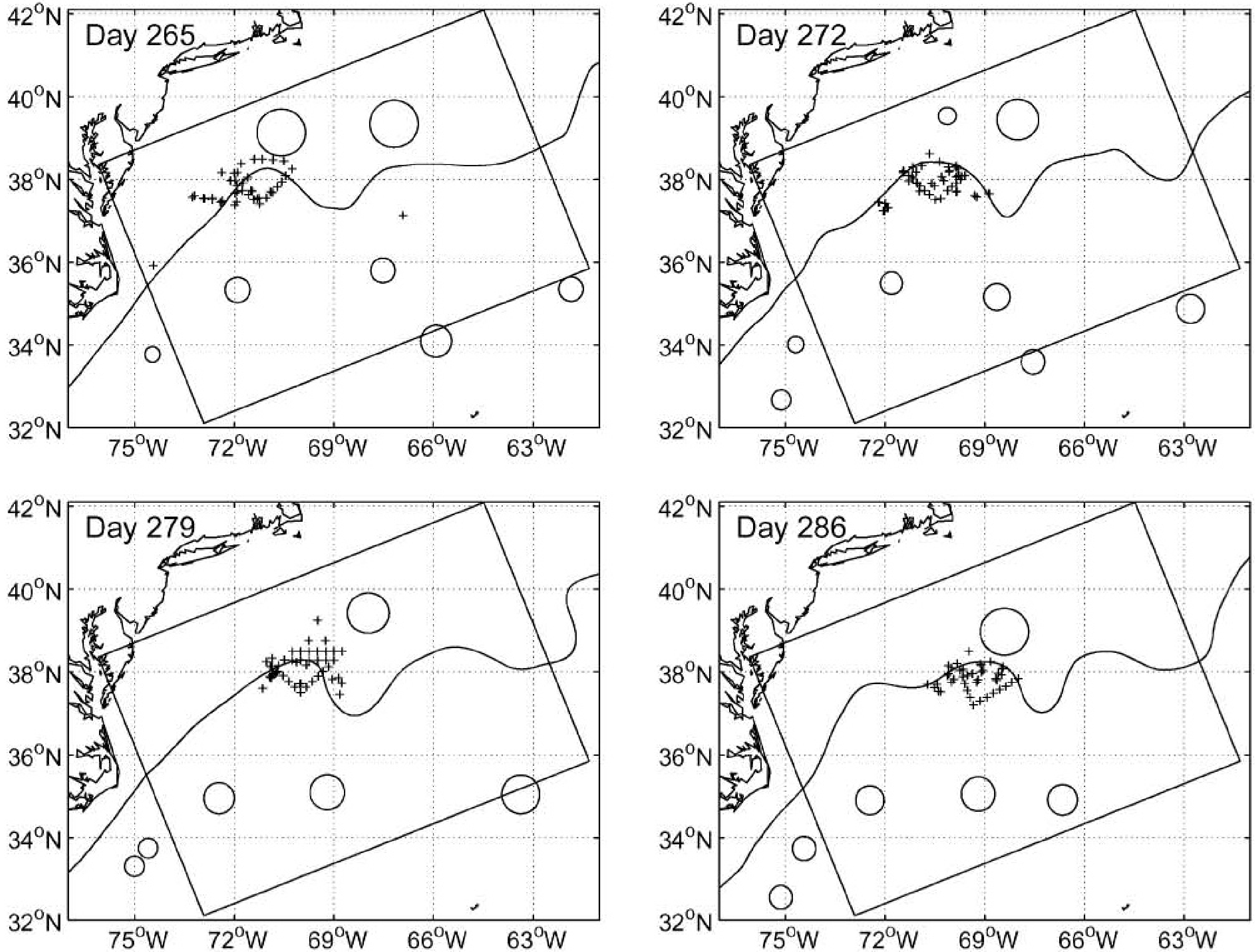
Feature Model

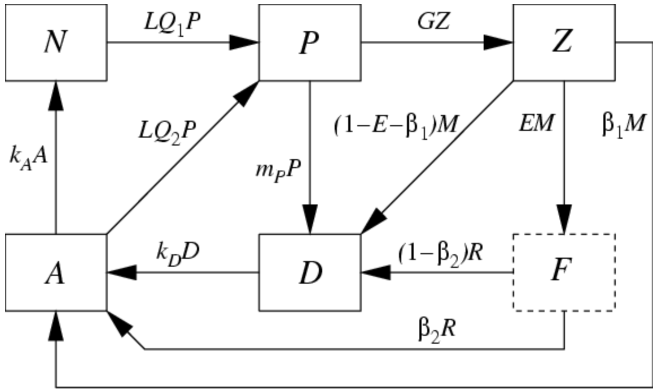


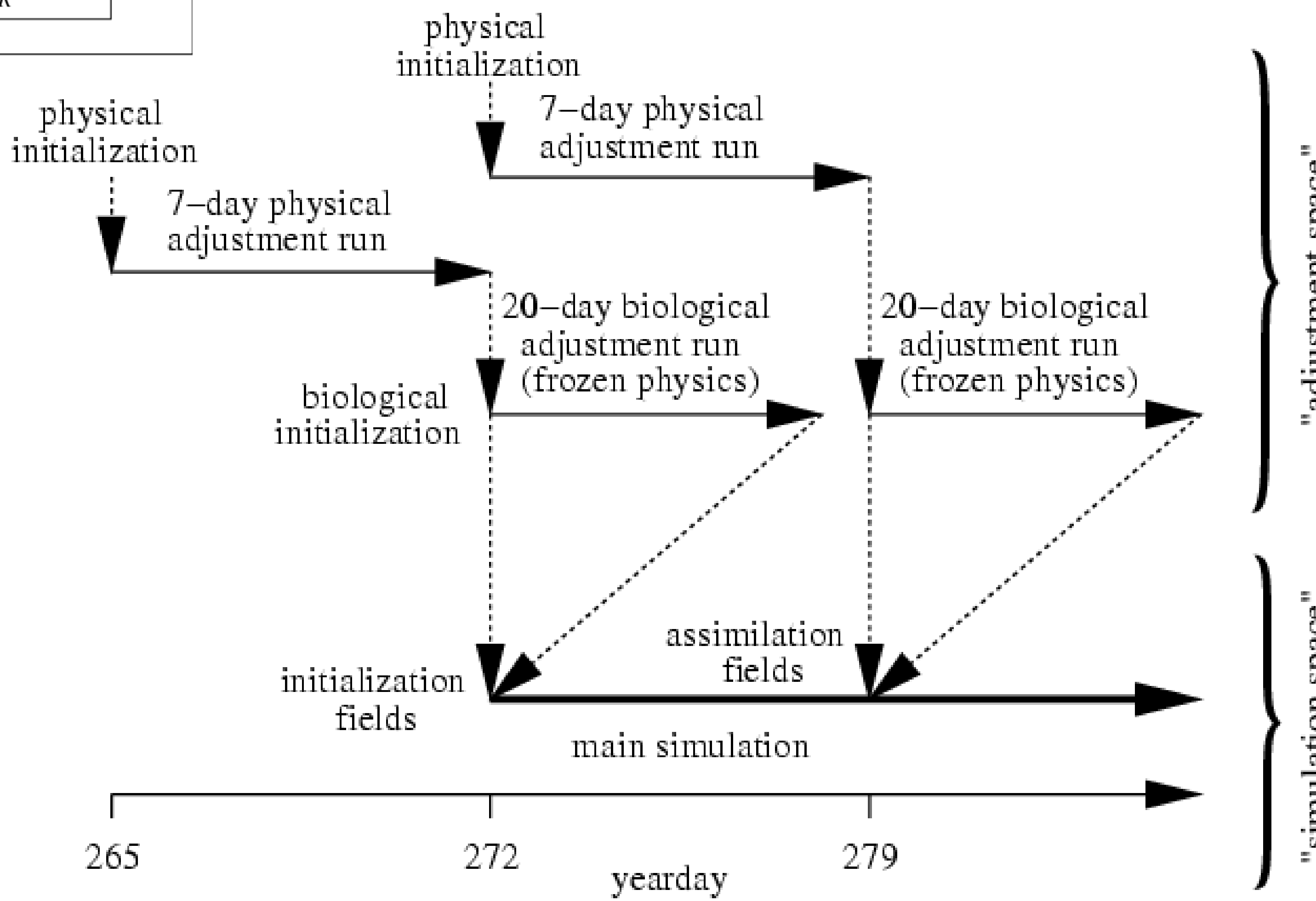
(a)






Day 265
Day 272
Day 279
Day 286
42°N
40°N
38°N
36°N
34°N
32°N
75°W
72°W
69°W
66°W
63°W


N
P
Z
A
D
F
LQ_1P
GZ
LQ_2P
k_AA
m_PP
$(1-E-\beta_1)M$
EM
β_1M
k_DD
$(1-\beta_2)R$
β_2R

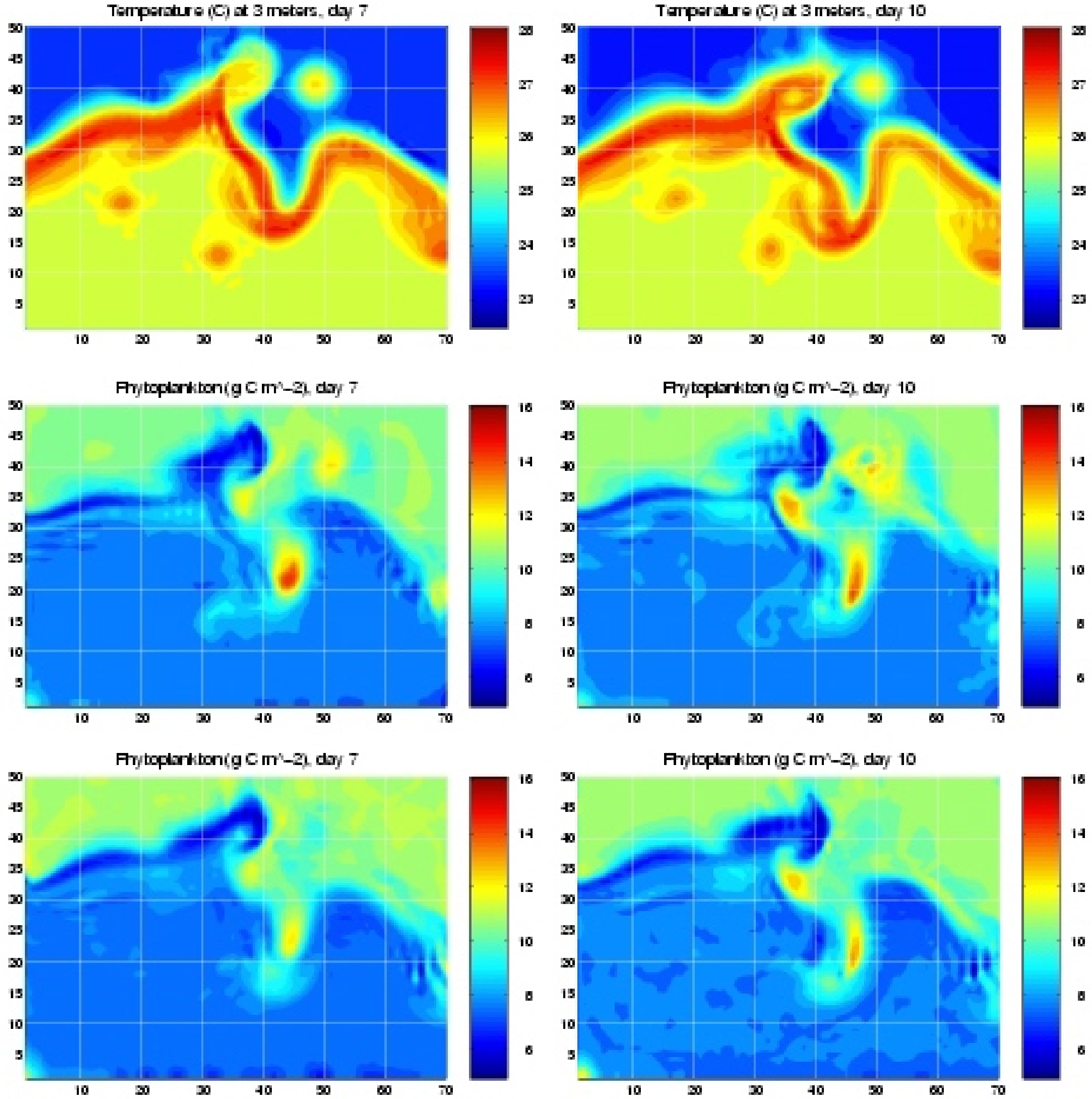

physical initialization
7−day physical adjustment run
physical initialization
7−day physical adjustment run
20−day biological adjustment run (frozen physics)
20−day biological adjustment run (frozen physics)
biological initialization
assimilation fields
initialization fields
main simulation
265
272
279
yearday
"adjustment space"
"simulation space"

Day 7 **Day 10**

Temperature

Phytoplankton
Physical Assim.

Phytoplankton
Coupled Assim.



Conclusions – Compatible Physical/Biological Assimilation

- **Physical data assimilation only – adjustment of the physical fields leads to misalignment between physical and biological fronts, causing spurious cross-frontal fluxes and consequently spurious biological responses (e.g. enhanced productivity).**

- **Biological data assimilation only – little or no feedback to the physics. Physical and biological fronts become misaligned, causing spurious cross-frontal fluxes and consequently spurious biological responses (e.g. enhanced productivity).**

- **Six-step method:**
  a) initial estimation of synoptic physical features
  b) melding physical data into these fields to obtain the best real-time estimates
  c) physical dynamical adjustment to generate vertical velocities
  d) initial estimation of mesoscale biological fields based on Physical-biological correlations
  e) melding biological data into these fields, and
  f) biological dynamical adjustment with frozen physical fields to balance the biological fields with each other, the model parameters, and the 3-D physical transports.

- **The generation of these fields is done in "adjustment space", outside of the simulation of interest ("simulation space").**

Conclusions – Coupled Dynamical Processes

- **Vertical velocities associated with Gulf Stream meanders enhance new production at the front. Meandering not the primary cause of phytoplankton maxima.**

- **Ring-stream interactions cause high vertical velocities, which combine with horizontal velocities to laterally detrain water from the Gulf Stream. Surface phytoplankton patches in meander trough recirculation gyres due to detrainment of nutrients and plankton from the Gulf Stream by Ring-stream interactions.**

- **Winds affect biological tracers in two ways:**
  - **a) influence on mixed-layer depth and the vertical entrainment/detrainment of nutrients and plankton**
  - **b) driving of surface convergence or divergence and therefore vertical advection**

- **Wind events generally short-lived and do not override vertical velocities due to meandering. Simulations show no significant biological enhancement at the Gulf Stream front due to winds.**

- **Realistic high-resolution 4-D dynamical field estimates, brought into close correlation with observations by data assimilation, are generally necessary to identify the essential physical-biological interactions that explain the data.**

Mini-HOPS

- Designed to locally solve the problem of accurate representation of sub-mesoscale synopticity
- Involves rapid real-time assimilation of high-resolution data in a high-resolution model domain nested in a regional model
- Produces locally more accurate oceanographic field estimates and short-term forecasts and improves the impact of local field high-resolution data assimilation
- Dynamically interpolated and extrapolated high-resolution fields are assimilated through 2-way nesting into large domain models

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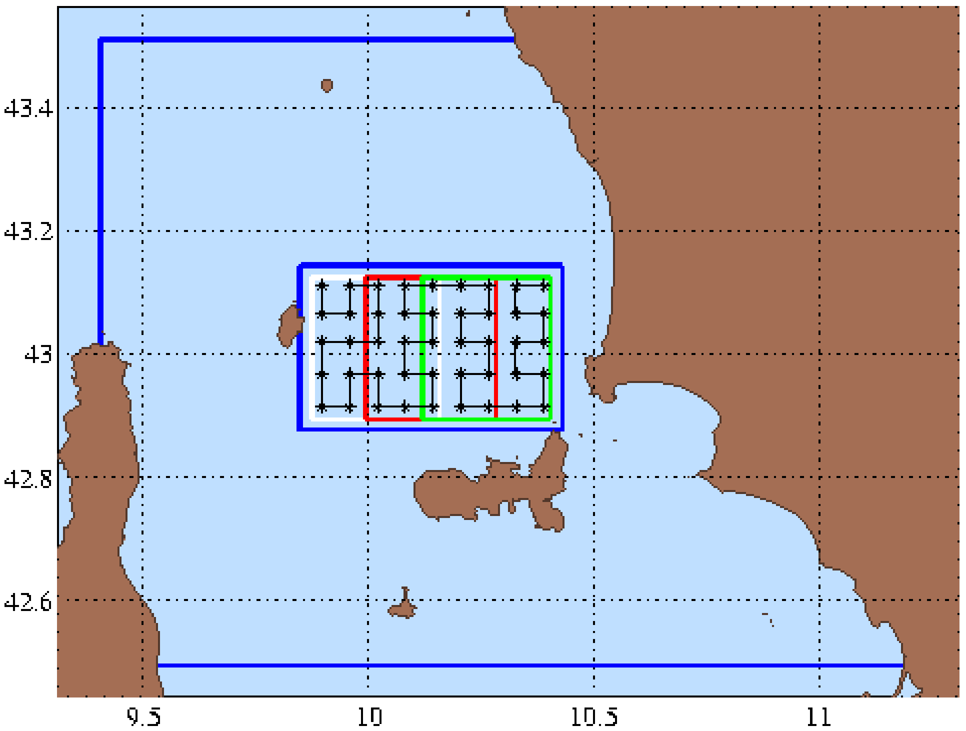
In collaboration with Dr. Emanuel Coelho (NATO Undersea Research Centre)

MREA-03 Mini-HOPS Protocol

- Regional Domain (1km) run at Harvard in a 2-way nested configuration with a super-mini domain.
  - Super mini has the same resolution (1/3 km) as the mini-HOPS domains and is collocated with them
- From the super-mini domain, initial and boundary conditions were extracted for all 3 mini-HOPS domains for the following day and transmitted to the NRV Alliance.
- Aboard the NRV Alliance, the mini-HOPS domains were run the following day, with updated atmospheric forcing and assimilating new data.

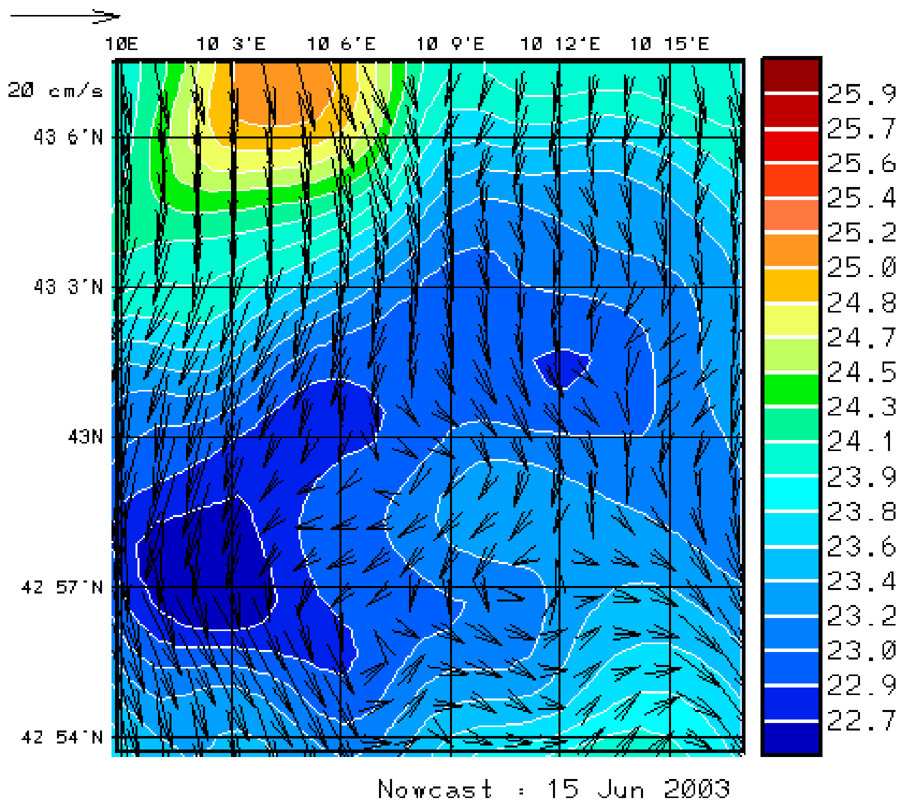
MREA-03 Domains



Mini-HOPS for MREA-03

Prior to experiment, several configurations were tested leading to selection of 2-way nesting with super-mini at Harvard

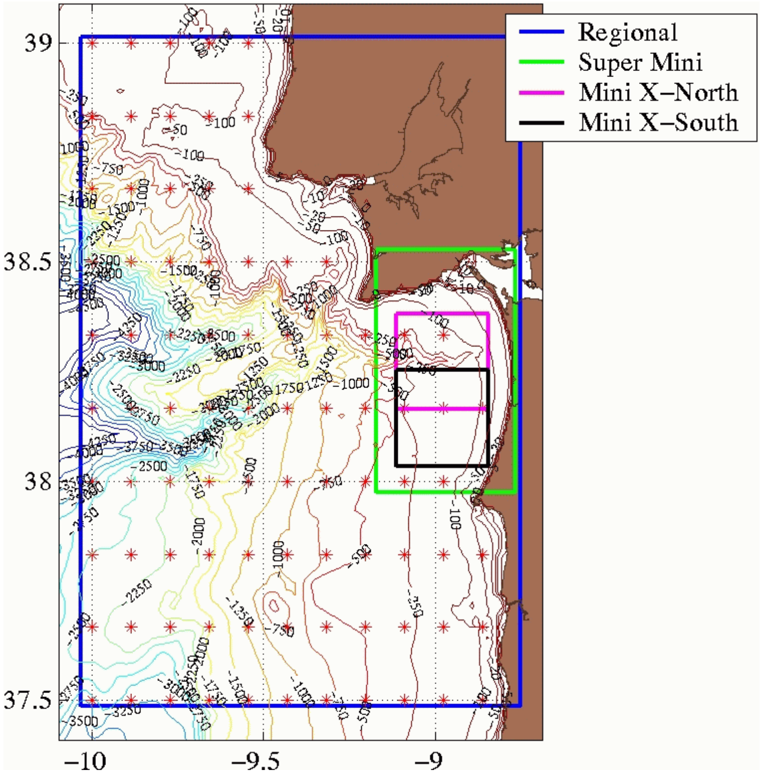
- During experiment:
  - Daily runs of regional and super mini at Harvard
  - Daily transmission of updated IC/BC fields for mini-HOPS domains
  - Mini-HOPS successfully run aboard NRV Alliance

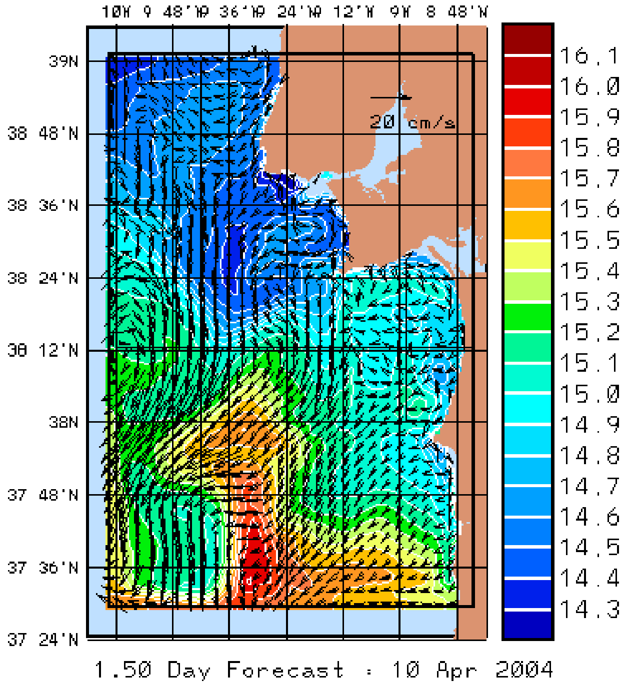


Mini-HOPS simulation run aboard NRV Alliance in Central mini-HOPS domain (surface temperature and velocity)

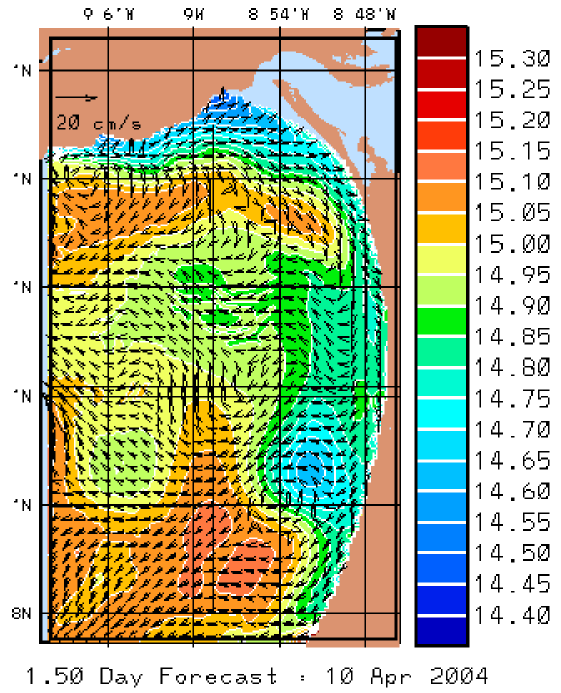
Mini-HOPS for MREA-04

- Portuguese Hydrographic Office utilizing regional HOPS
- Daily runs of regional and super mini at Harvard
- Daily transmission of updated IC/BC fields for mini-HOPS domains to NURC scientists for mini-HOPS runs aboard NRV Alliance





Regional Domain
1km resolution



Super Mini Domain
1/3 km resolution

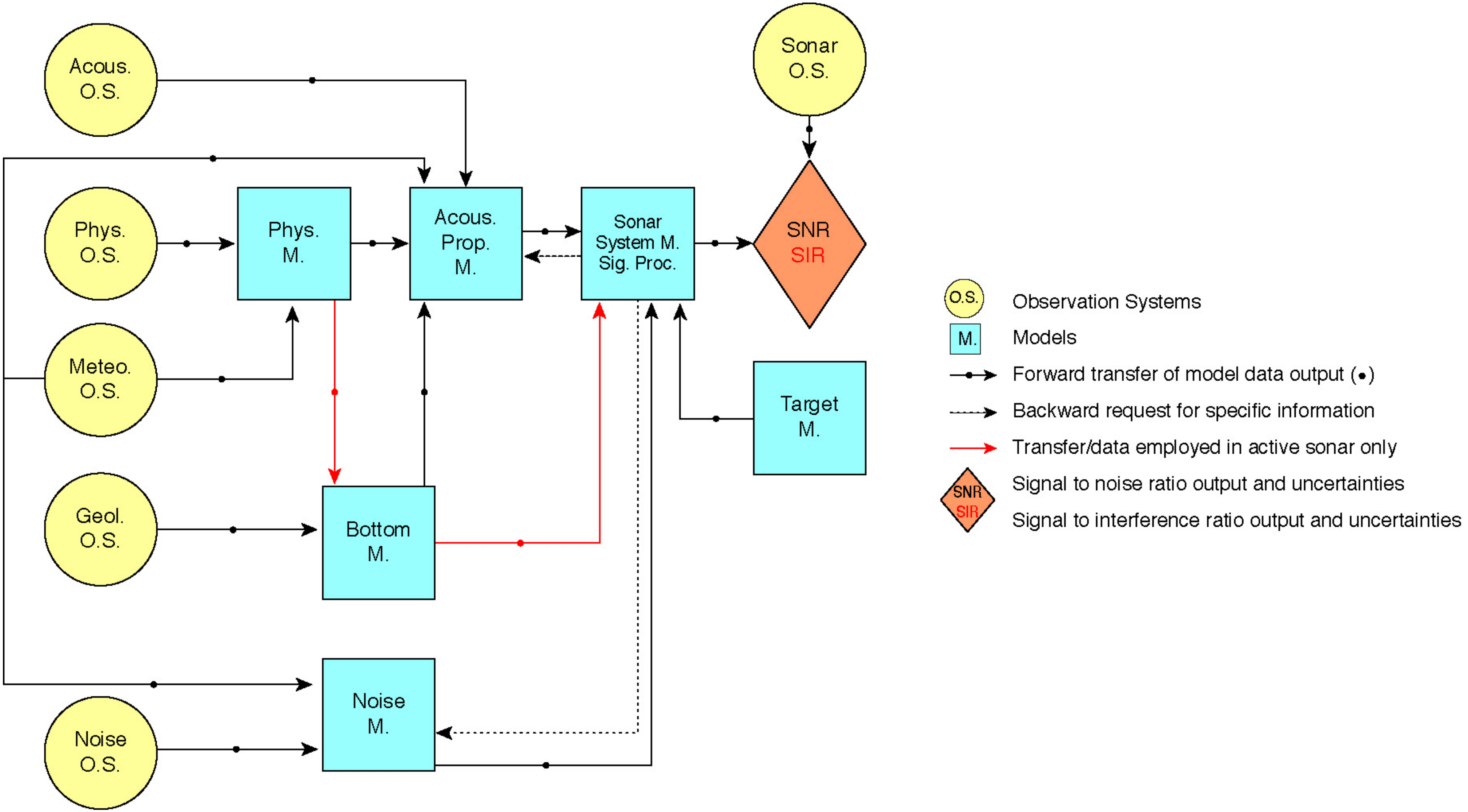
End-to-End System Concept

- Sonar performance prediction requires end-to-end scientific systems: ocean physics, bottom geophysics, geo-acoustics, underwater acoustics, sonar systems and signal processing

- Uncertainties inherent in measurements, models, transfer of uncertainties among linked components

- Resultant uncertainty in sonar performance prediction itself

- Specific applications require the consideration of a variety of specific end-to-end systems


Acous. O.S.
Sonar O.S.
Phys. O.S.
Phys. M.
Acous. Prop. M.
Sonar System M. Sig. Proc.
SNR
SIR
Meteo. O.S.
Target M.
Geol. O.S.
Bottom M.
Noise M.
Noise O.S.
O.S.
Observation Systems
M.
Models
Forward transfer of model data output (•)
Backward request for specific information
Transfer/data employed in active sonar only
Signal to noise ratio output and uncertainties
Signal to interference ratio output and uncertainties

Coupled discrete state vector $\boldsymbol{x}$ (from continuous ϕ_i)

$\boldsymbol{x} = [\boldsymbol{x}_A \;\; \boldsymbol{x}_O]$

Physics: $\boldsymbol{x}_O = [T, S, U, V, W]$

Acoustics: $\boldsymbol{x}_A = [\text{Pressure } (p), \text{Phase } (\varphi)]$

$\boldsymbol{c}_O$

Coupled error covariance

$$\boldsymbol{P} = \varepsilon \left\{ (\hat{\boldsymbol{x}} - \boldsymbol{x}^t)(\hat{\boldsymbol{x}} - \boldsymbol{x}^t)^T \right\} \qquad \boldsymbol{P} = \begin{pmatrix} P_{AA} & P_{AO} \\ P_{OA} & P_{OO} \end{pmatrix}$$

Coupled assimilation

$$\boldsymbol{x}_+ = \boldsymbol{x}_- + \mathbf{PH}^T [\mathbf{HPH}^T + \mathbf{R}]^{-1} (\mathbf{y} - \mathbf{H}\boldsymbol{x}_-);$$

x_- = *A priori* estimate (for forecast)
x_+ = *A posteriori* estimate (after assimilation)

Real-Time Initialization of the Dominant Error Covariance Decomposition

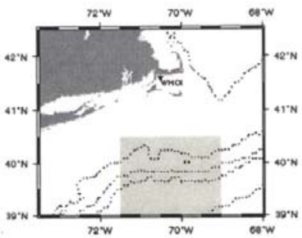
- **Real-time Assumptions**
  - **Dominant uncertainties are missing or uncertain variability in initial state, e.g., smaller mesoscale variability**

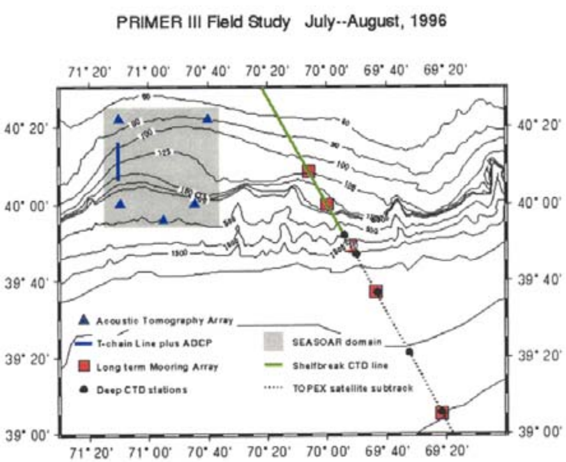
- **Issues**
  - **Some state variables are not observed**
  - **Uncertain variability is multiscale**

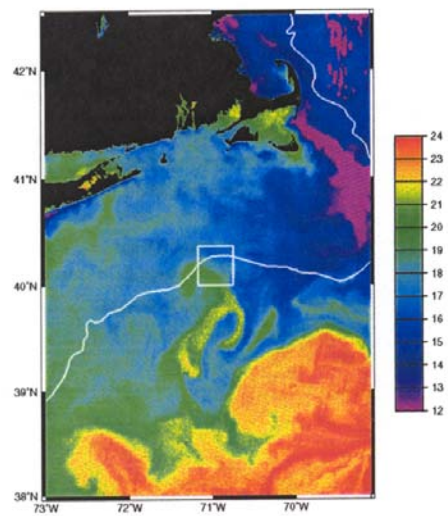
- **Approach: Multi-variate, 3D, Multi-scale**
  - **“Observed” portions**
    - **Directly specified and eigendecomposed from differences between the intial state and data, and/or from a statistical model fit to these differences**

  - **“Non-observed” portions**
    - **Keep “observed” portions fixed and compute “non-observed”portions from ensemble of numerical (stochastic) dynamical simulations**

PRIMER End-to-End Problem
Initial Focus on Passive Sonar Problem







Location: Shelfbreak PRIMER Region

Season: July-August 1996

***Sonar System** (Receiver):* Passive Towed Array

Target: Simulated UUV (with variable source level)

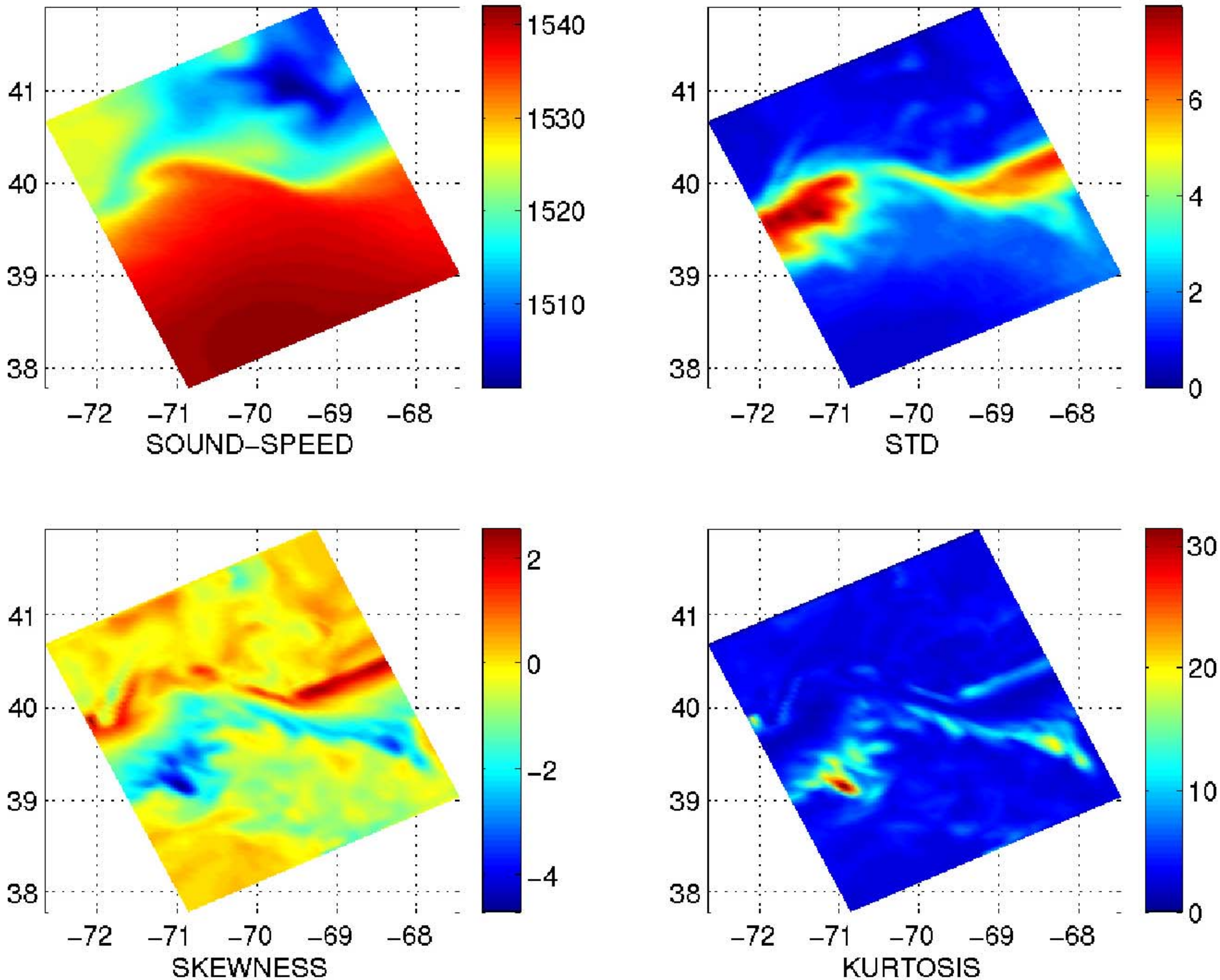
Frequency Range: 100 to 500 Hz

Geometries: Receiver operating on the shelf shallow water;
target operating on the shelf slope (deeper water than receiver)

Environmental-Acoustical Uncertainty Estimation and Transfers, Coupled Acoustical-Physical DA and End-to-End Systems in a Shelfbreak Environment

Note the front

Variability at the front



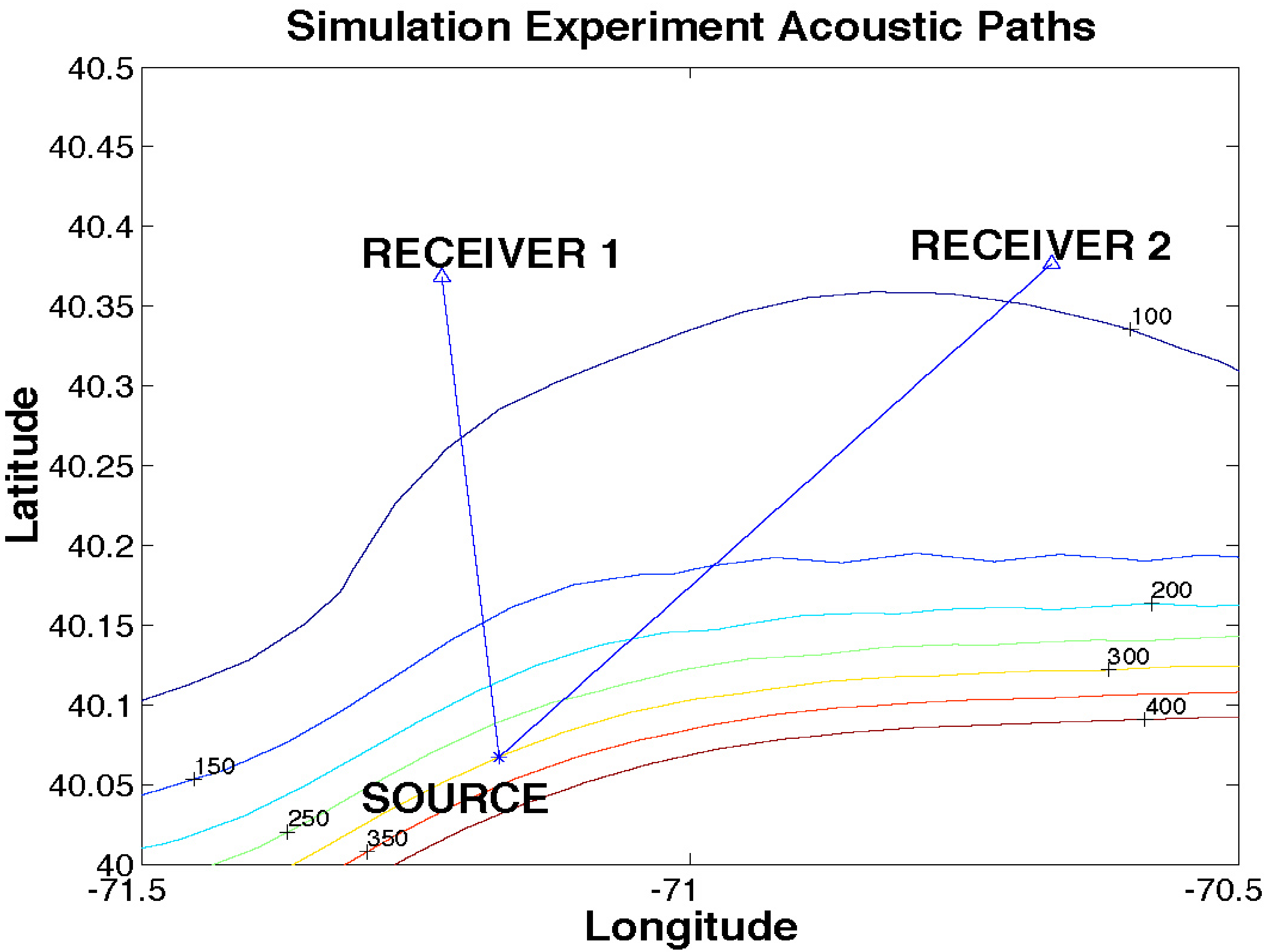
Warm/cold events on each side

Extreme events

Starting with physical environmental data, compute the Predictive Probability Of Detection (PPD) from first principals via broadband Transmission Loss (TL)

- Novel approach: coupled physical-acoustical data assimilation method is used in TL estimation

- Methodology:
  - HOPS generates ocean physics predictions
  - NPS model generates ocean acoustics predictions
  - 100 member ESSE ensemble generates coupled covariances
  - Coupled ESSE assimilation of CTD and TL measurements



Shelfbreak-PRIMER Acoustic paths considered, overlaid on bathymetry.

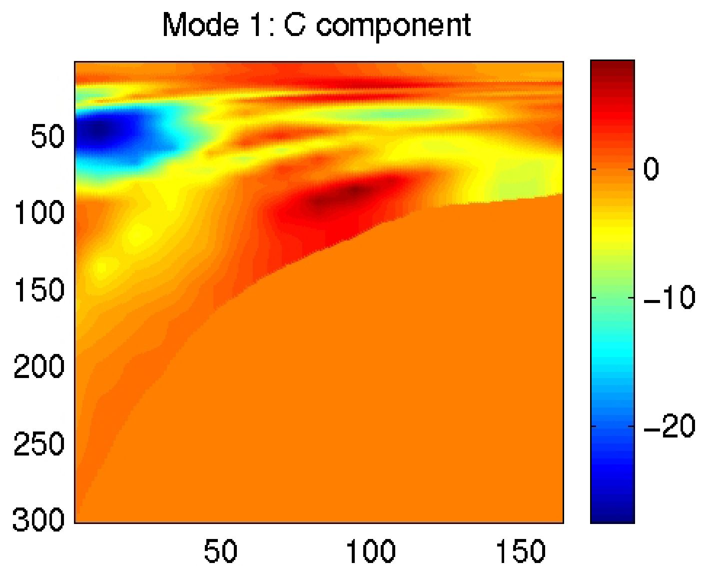
Path 1:

- **Source: at 300m, 400 Hz**
- **Receiver: VLA at about 40 km range, from 0-80m depths**

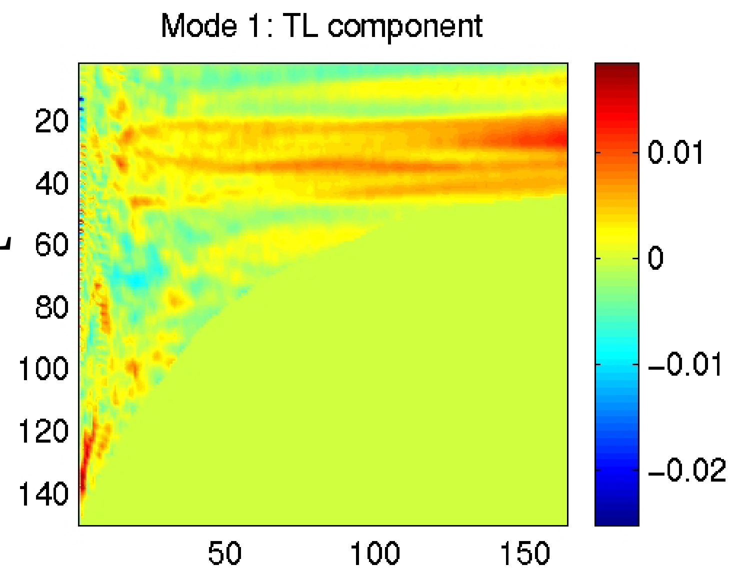
Coupled Physical-Acoustical Data Assimilation of real TL-CTD data:

First Eigenmode of coupled normalized error covariance on Jul 26

Sound-speed Component



Broadband TL Component



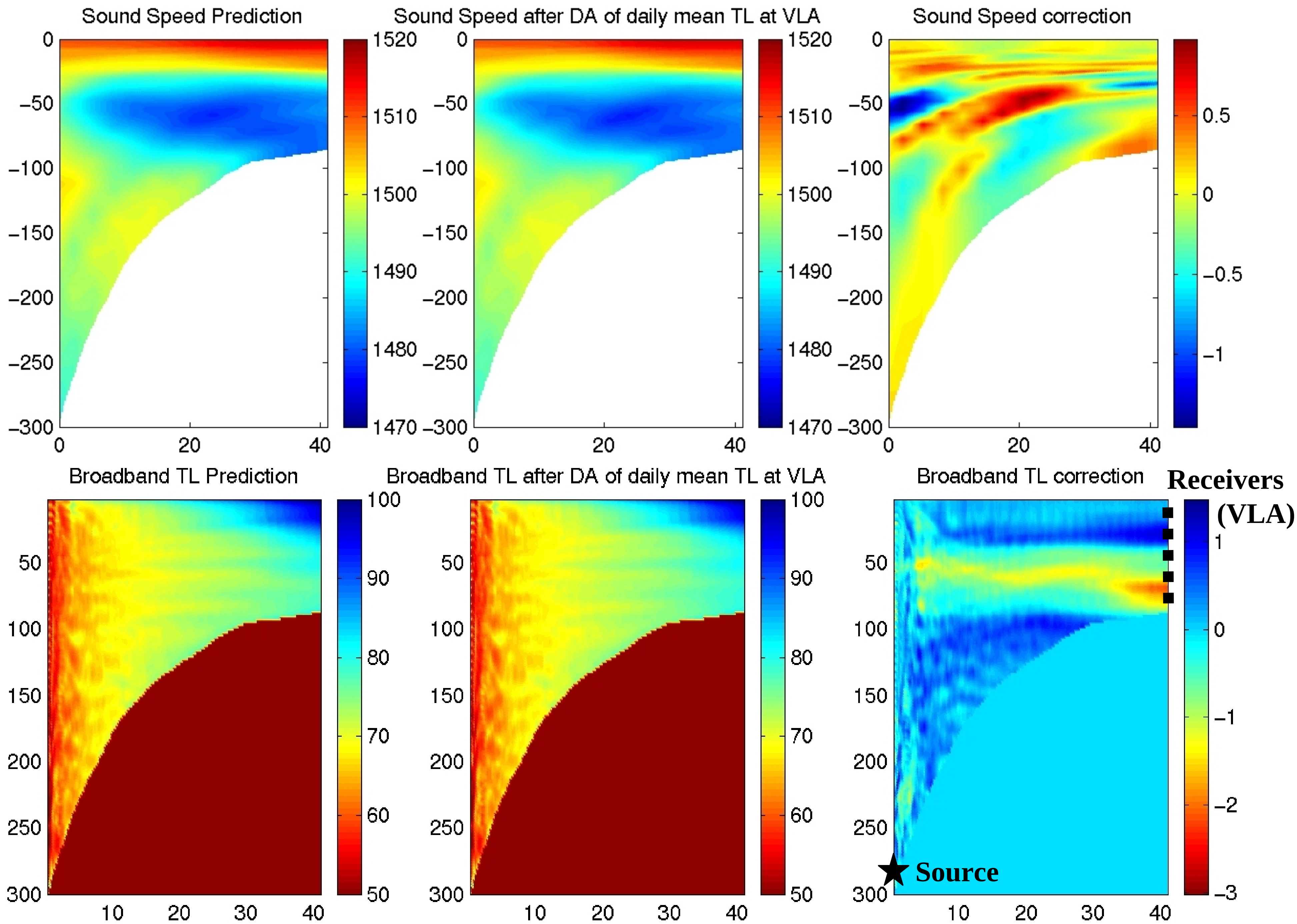
Shift in frontal shape (e.g. meander)

and

its acoustic TL counterpart above the source and in the cold channel on the shelf

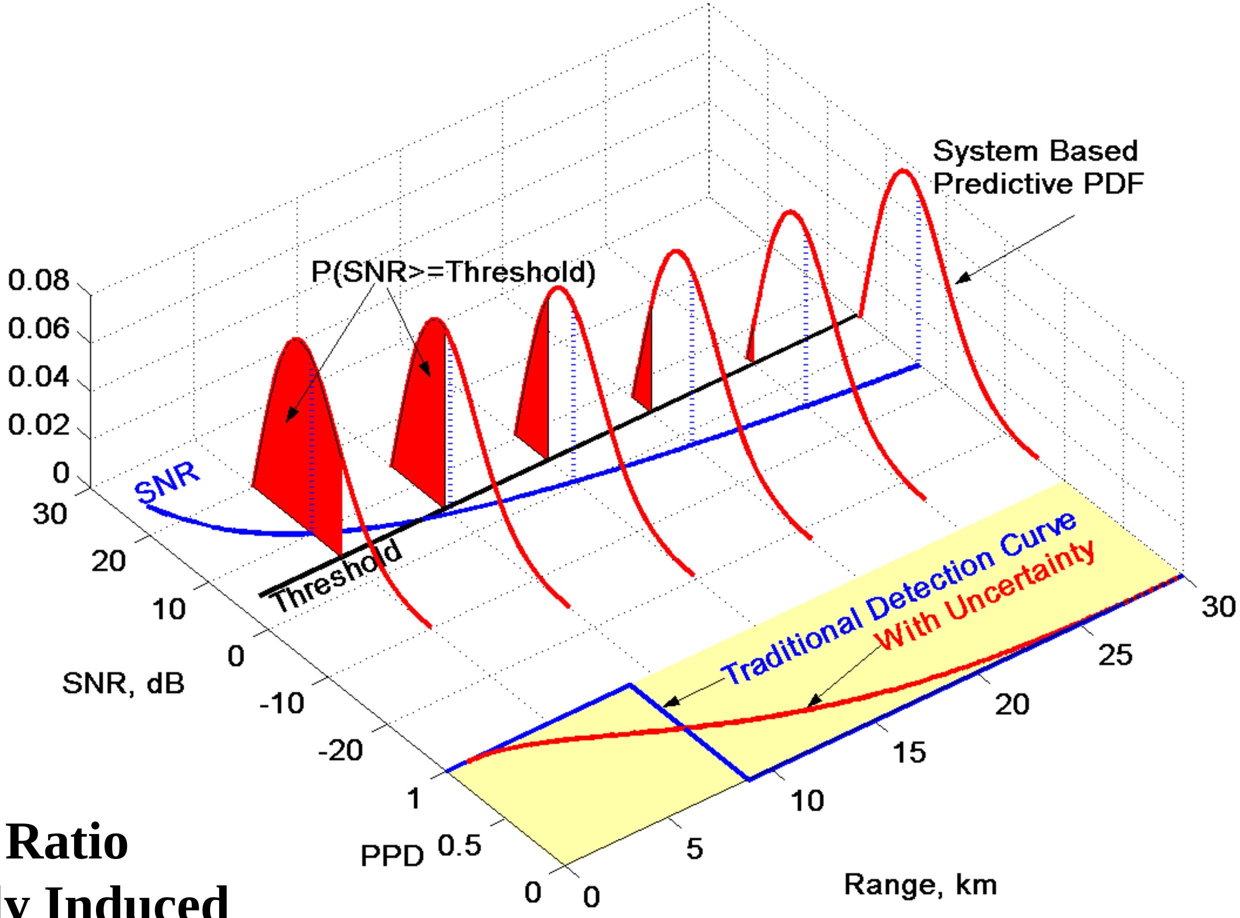
Coupled Physical-Acoustical Data Assimilation of real TL-CTD data:

TL measurements affect TL and C everywhere.



Determination of PPD (Predictive Probability Of Detection) using SNRE-PDF

Systems - based PDF (incorporates environmental and system uncertainty)

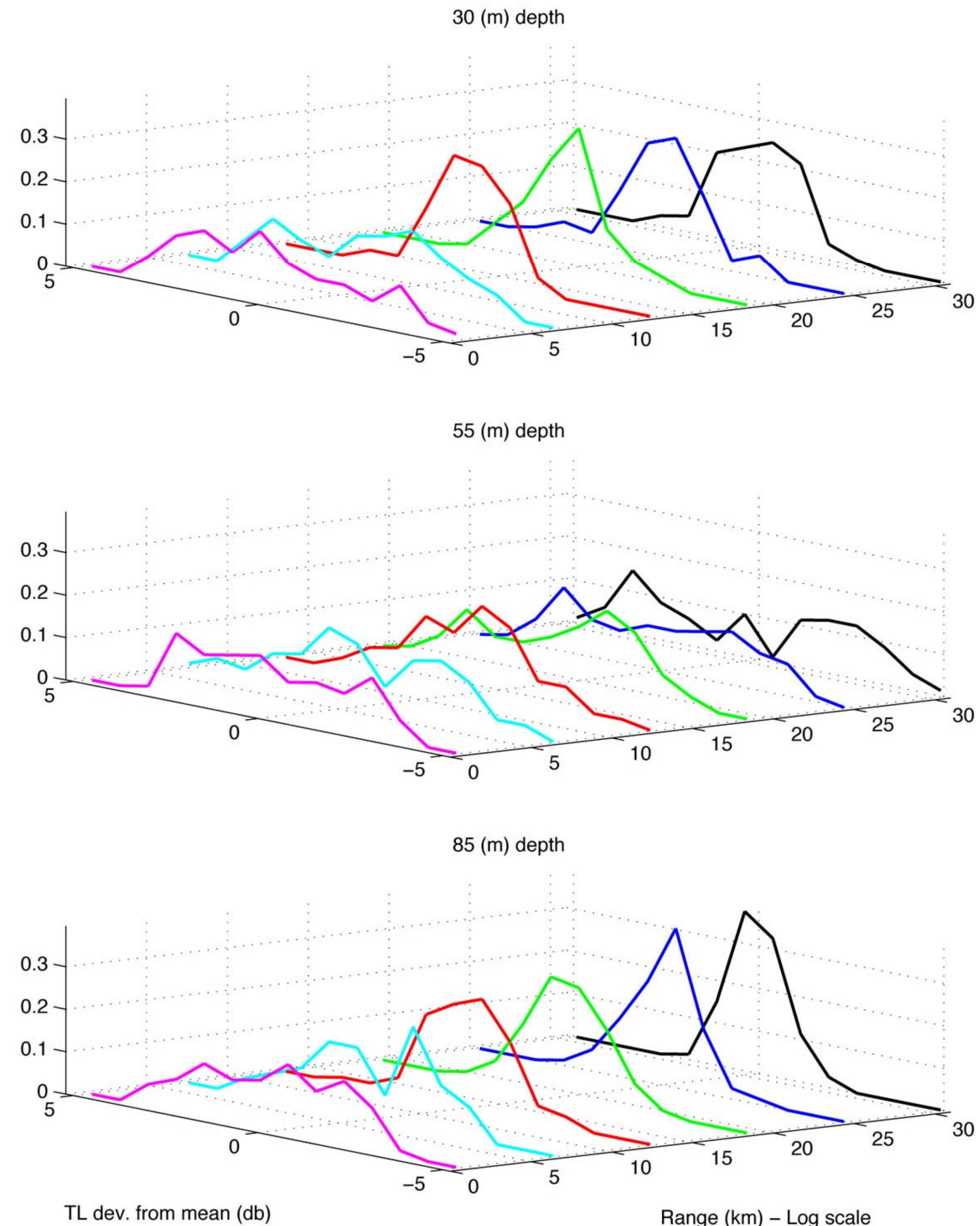


SNRE =
Signal-to-Noise Ratio
Environmentally Induced

Used by UNITES to characterize and transfer uncertainty from environment through end-to-end problems

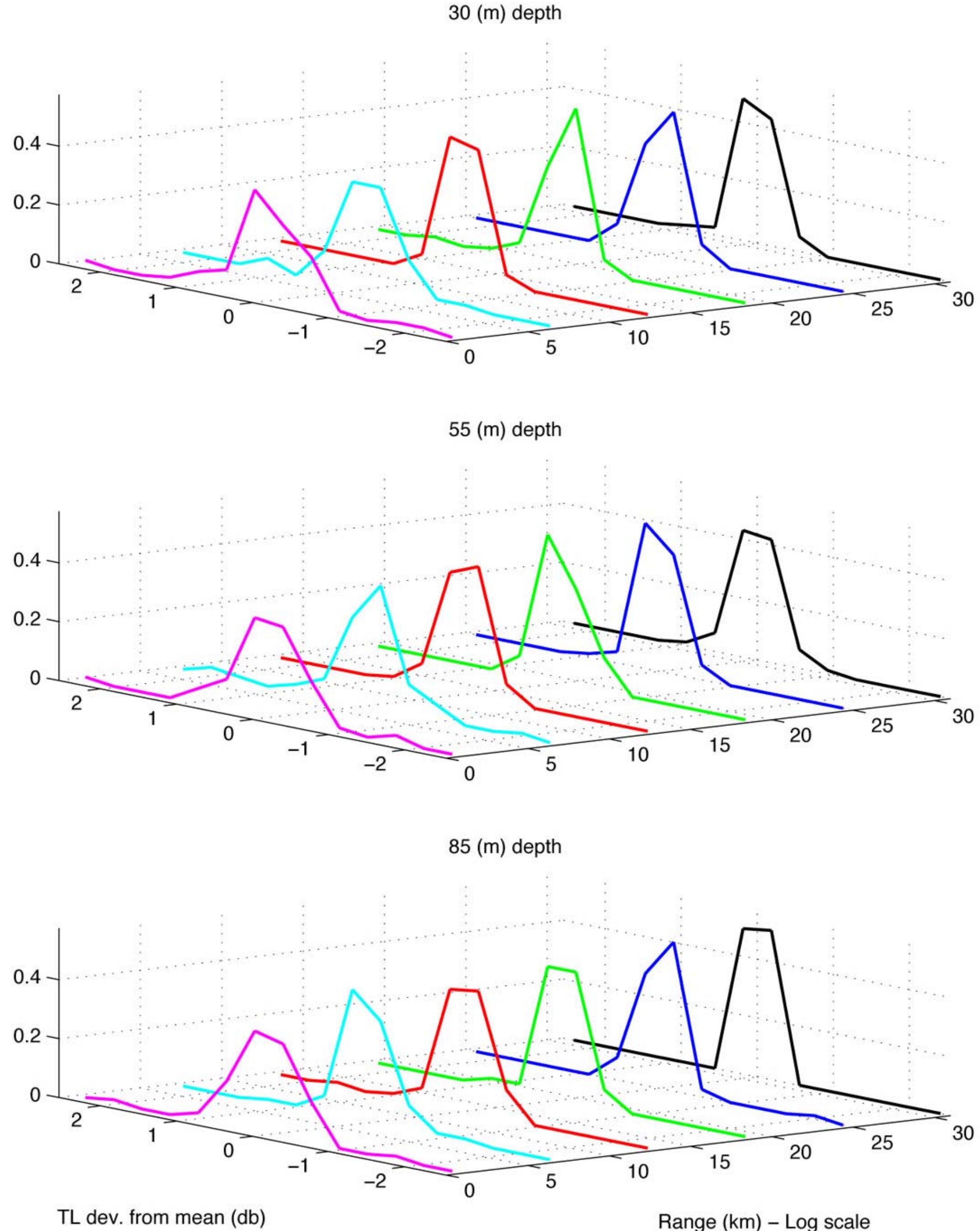
Prior (FCST) uncertainty of variable−width (224Hz/32Hz) running−range avg. TL

Predicted PDF of broadband TL



After Assimilation PDF of broadband TL

Posterior (after DA) uncertainty of variable–width (224Hz/32Hz) running–range avg. TL



Coupled HOPS/ESSE/NPS Physics/Acoustics Assimilation

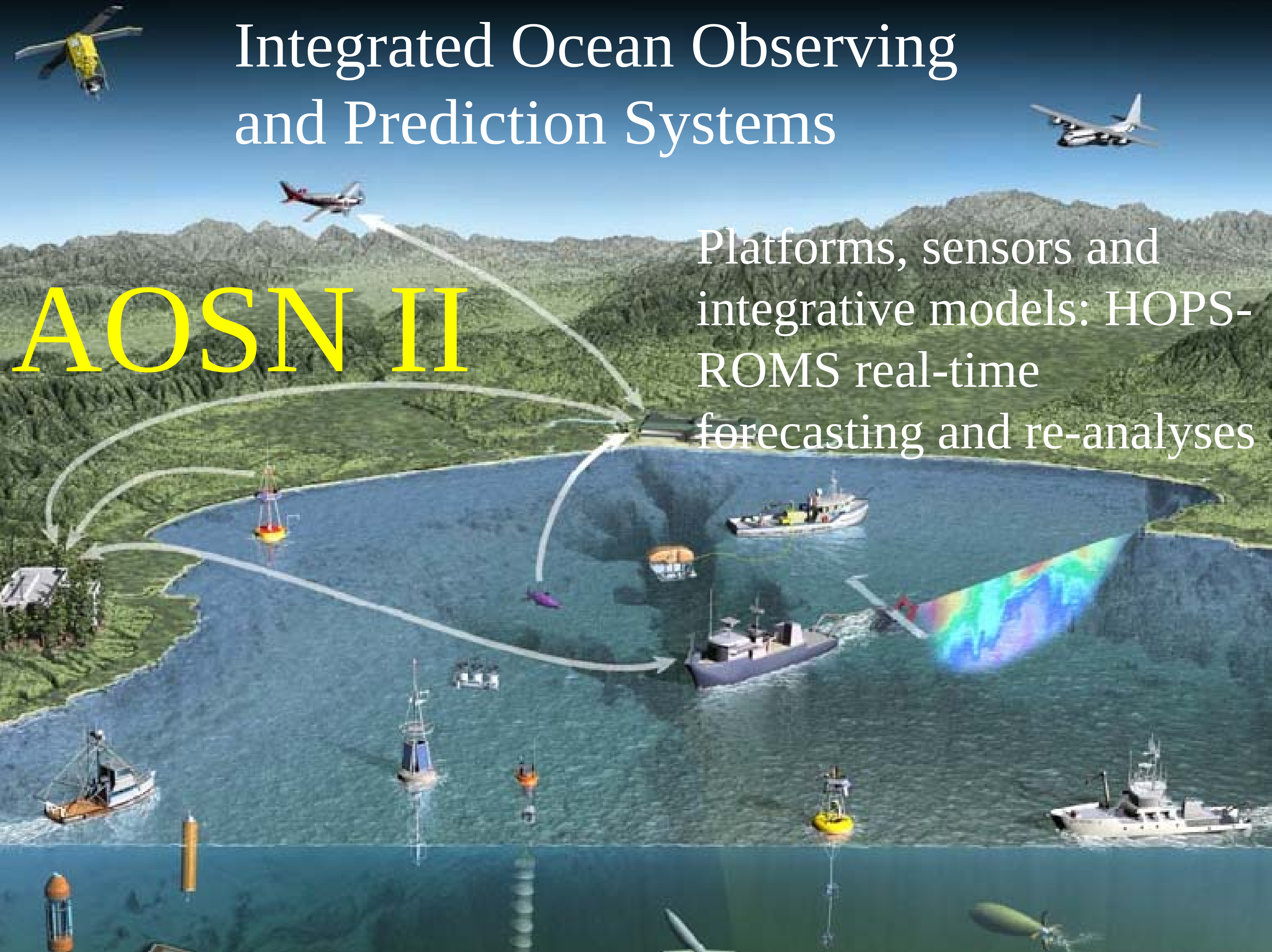
- Oceans physics/acoustics data assimilation: carried-out as a single multi-scale joint estimation for the first time

- ESSE nonlinear coupled assimilation recovers fine-scale TL structures and mesoscale ocean physics from real daily TL data and CTD data

- Shifts in the frontal shape (meander, etc.) leads to more/less in acoustic waveguide (cold pool on the shelf)

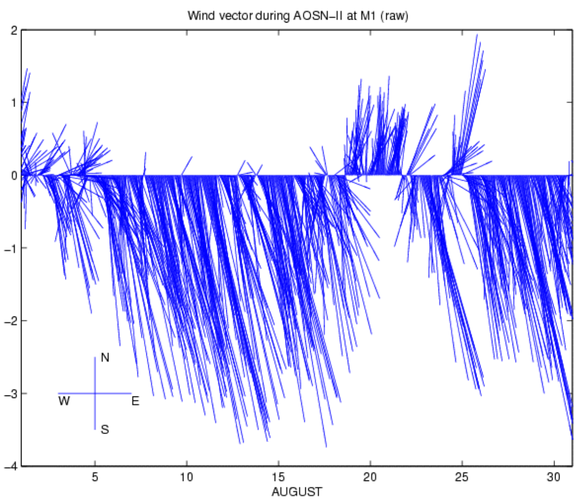
- Broadband TL uncertainties predicted to be range and depth dependent

- Coupled DA sharpens and homogenizes broadband PDFs

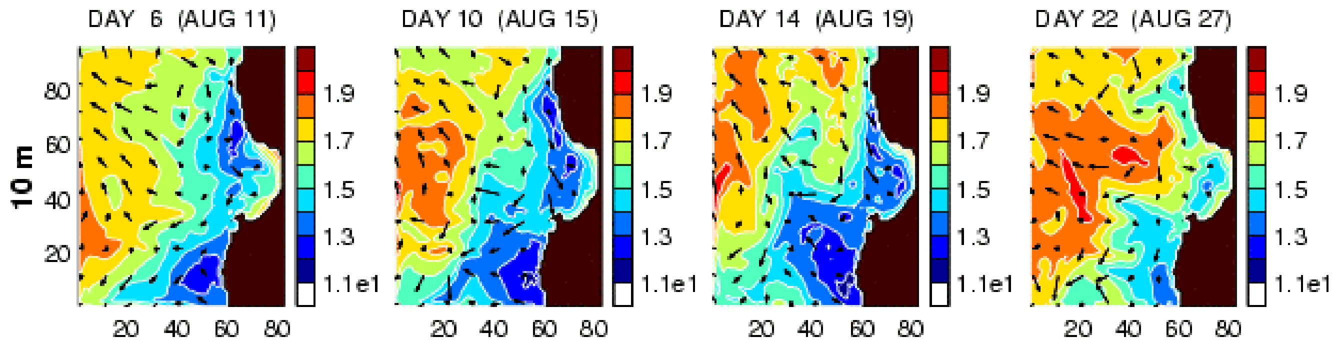

Integrated Ocean Observing
and Prediction Systems
AOSN II
Platforms, sensors and integrative models: HOPS-ROMS real-time forecasting and re-analyses

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

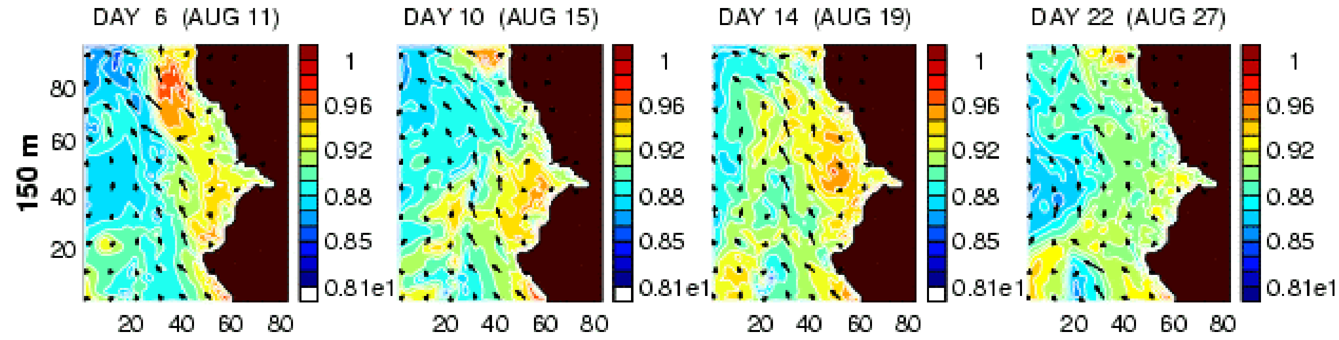
Monterey Bay and California Current System August 2003



M1 Winds

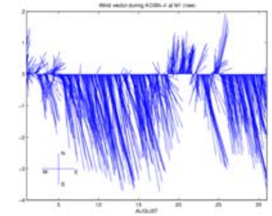


Temperature at 10m

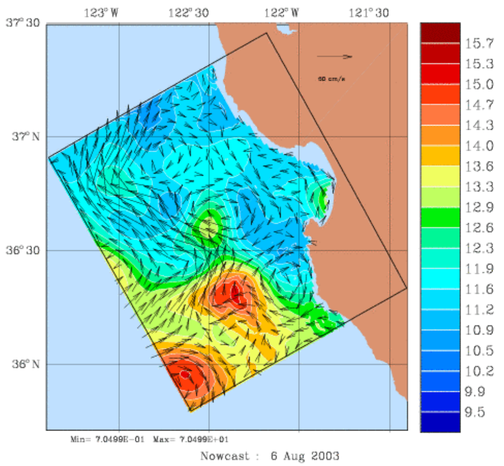


Temperature at 150m

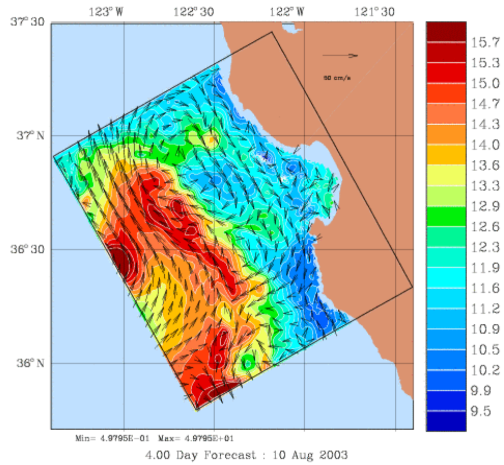
HOPS AOSN-II Re-Analysis



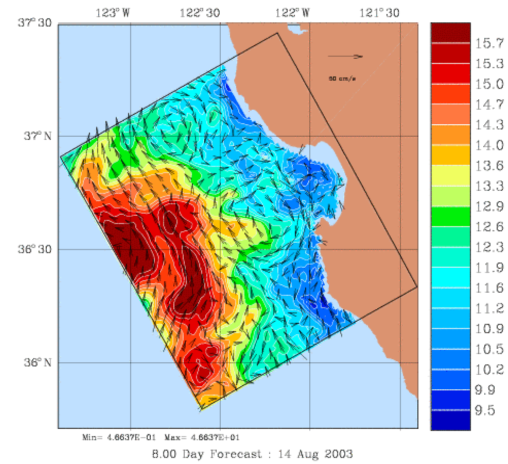
30m Temperature: 6 August – 3 September (4 day intervals)



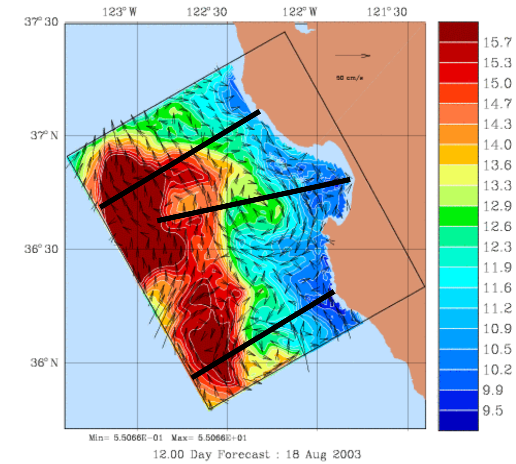
6 Aug



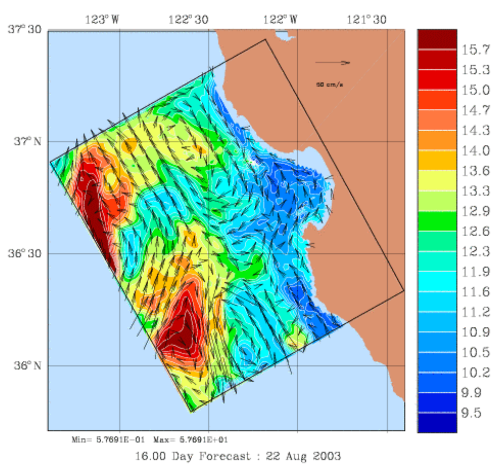
10 Aug



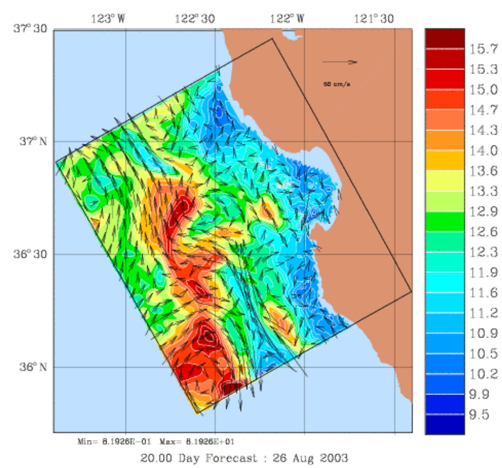
14 Aug



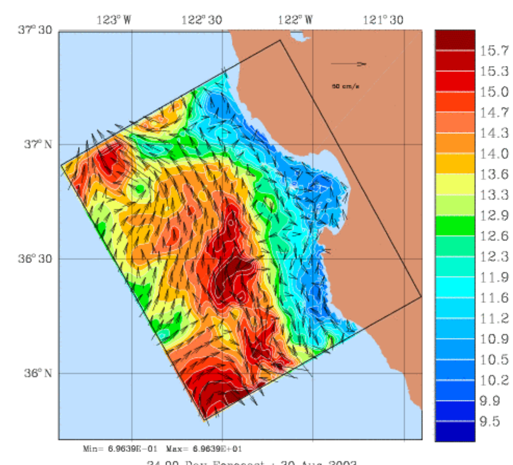
18 Aug



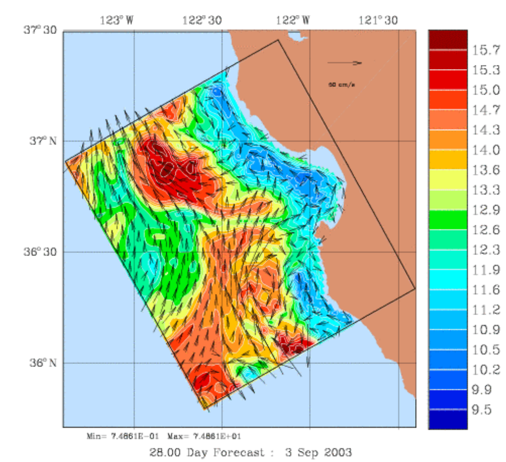
22 Aug



26 Aug



30 Aug

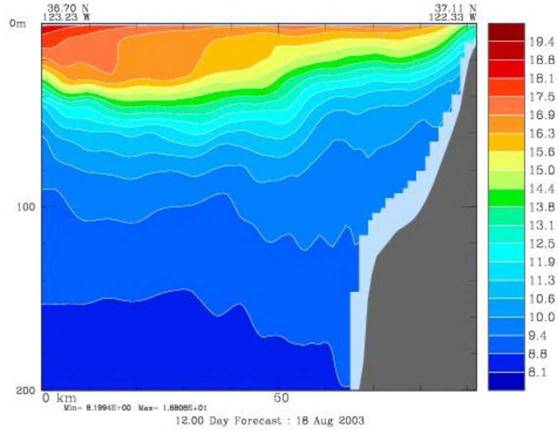
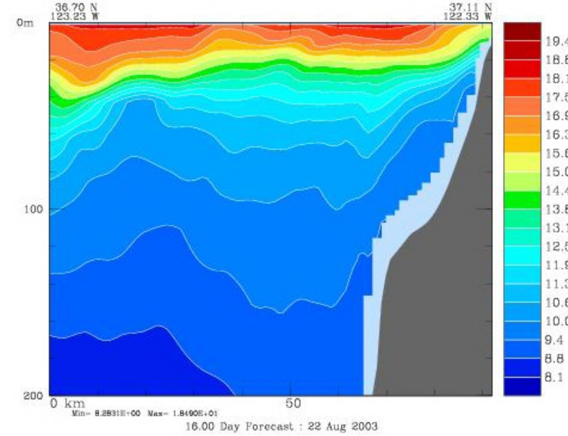
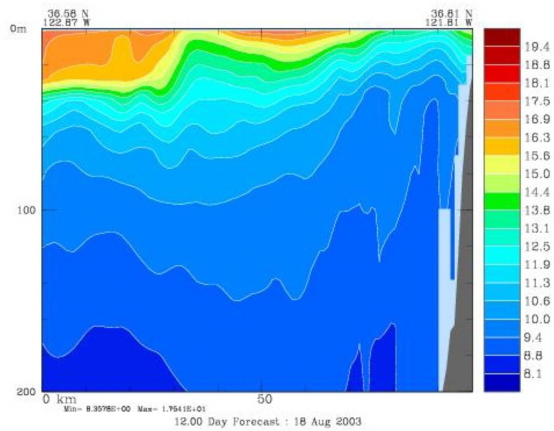
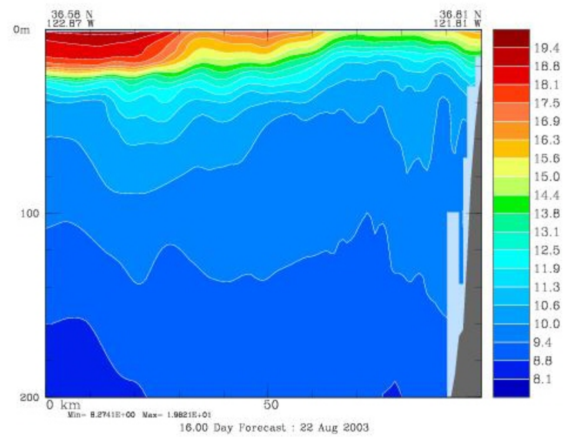
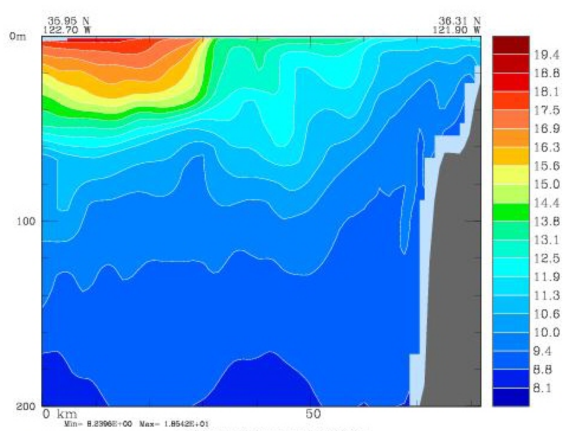
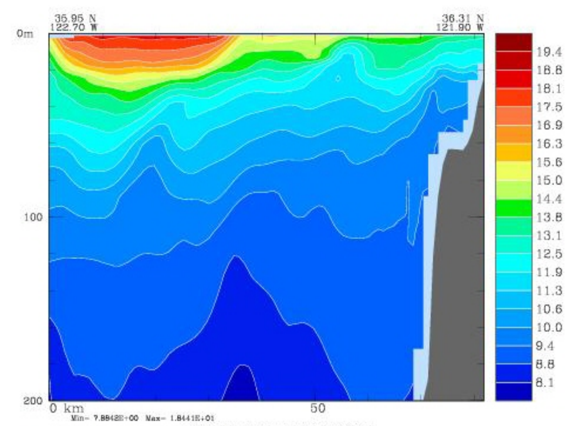


3 Sep

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		

Adaptive sampling via ESSE

- Objective: Minimize predicted trace of full error covariance (T,S,U,V error std Dev).
- Scales: Strategic/Experiment (not tactical yet). Day to week.
- Assumptions: Small number of pre-selected tracks/regions (based on quick look on error forecast and constrained by operation)
- Problem solved: e.g. Compute today, the tracks/regions to sample tomorrow, that will most reduce uncertainties the day after tomorrow.

- Predicted objective field changes during computation and is affected by data to-be-collected

- Model errors ***Q*** can account for coverage term

Dynamics:	$dx = M(x)dt + d\eta$	$\eta \sim N(0, Q)$
Measurement:	$y = H(x) + \varepsilon$	$\varepsilon \sim N(0, R)$

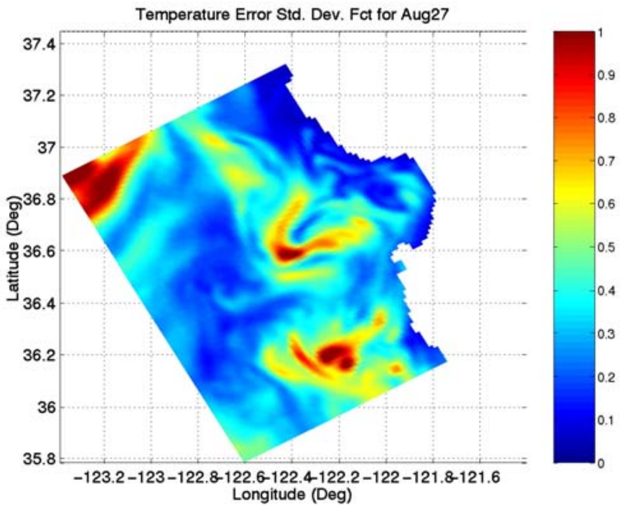
Non-lin. Err. Cov.:

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

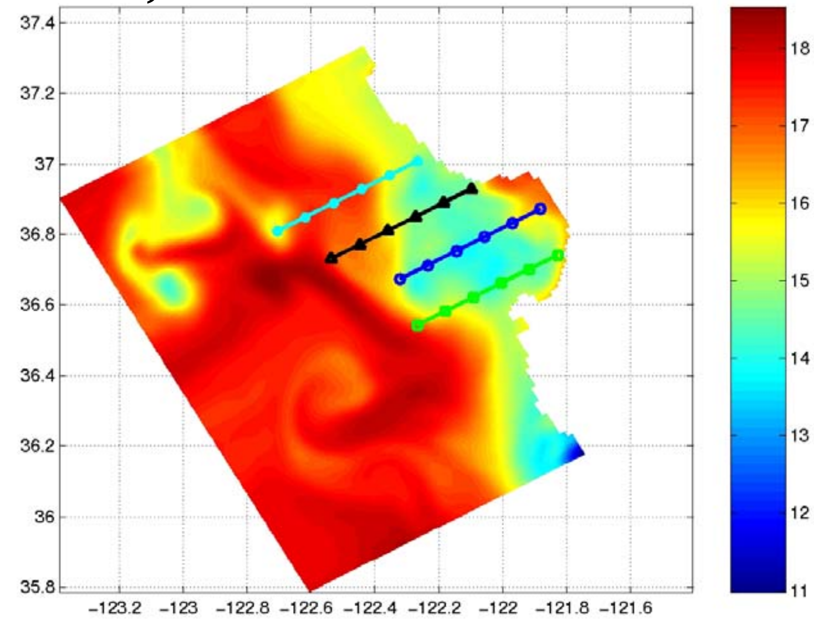
Metric or Cost function: e.g. Find future H_i and R_i such that

$$\underset{Hi,Ri}{Min} \quad tr(P(t_f)) \qquad or \qquad \underset{Hi,Ri}{Min} \int_{t_0}^{t_f} tr(P(t))\ dt$$

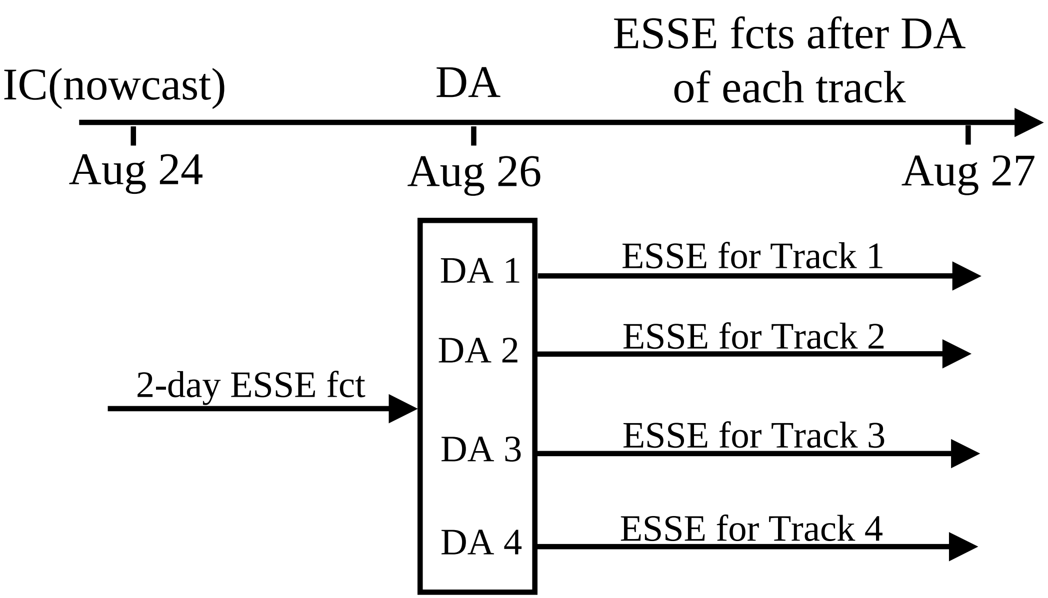
Which sampling on Aug 26 optimally reduces uncertainties on Aug 27?



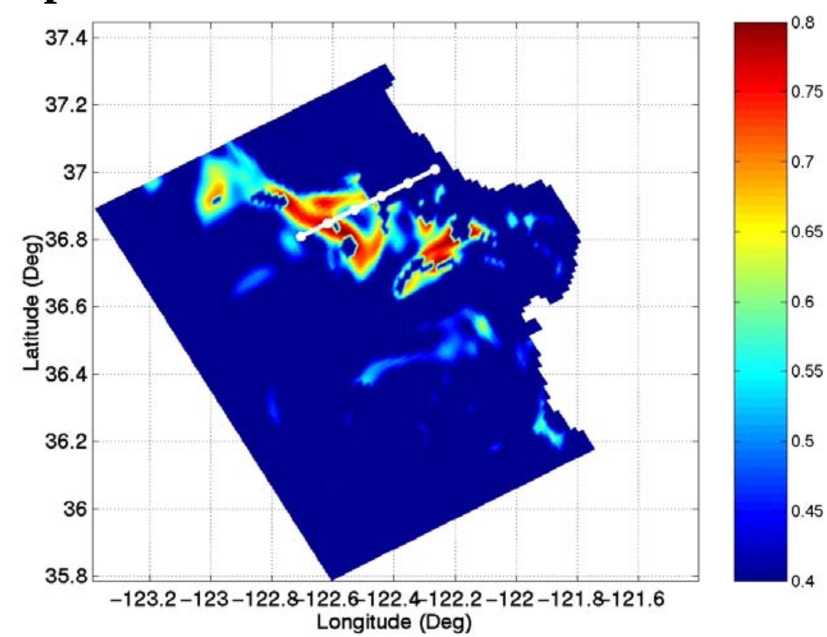
4 candidate tracks, overlaid on surface T fct for Aug 26



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



Best predicted relative error reduction: track 1



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

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

Error Analyses and Optimal (Multi) Model Estimates

Forecast Error Parameterization

Limited validation data motivates use of few free parameters

- Approximate forecast error covariances and biases as some parametric family, e.g. isotropic covariance model:

$$\mathbf{B}_m(i,j) = \sigma(\mathbf{x}_i)\sigma(\mathbf{x}_j)\rho\left(||\mathbf{x}_i - \mathbf{x}_j||\right) ; \quad \rho(r) = \exp\left(\frac{-r^2}{2L^2}\right)$$

  – Choice of covariance and bias models $\tilde{\mathbf{B}}$ and $\tilde{\boldsymbol{\mu}}$ should be sensible and efficient in terms of $\tilde{\mathbf{B}}\mathbf{v}, \tilde{\mathbf{B}}^{-1}\mathbf{v}$ and storage
    - * functional forms (positive semi-definite), e.g. isotropic
      - facilitates use of Recursive Filters and Toeplitz inversion
    - * feature model based
      - sensible with few parameters. Needs more research.
    - * based on dominant error subspaces
      - needs ensemble suite, complex implementation-wise

Error Analyses and Optimal (Multi) Model Estimates

Error Parameter Tuning

Learn error parameters in an on-line fashion from model-data misfits based on Maximum-Likelihood

- We estimate error parameters via Maximum-Likelihood by solving the problem:

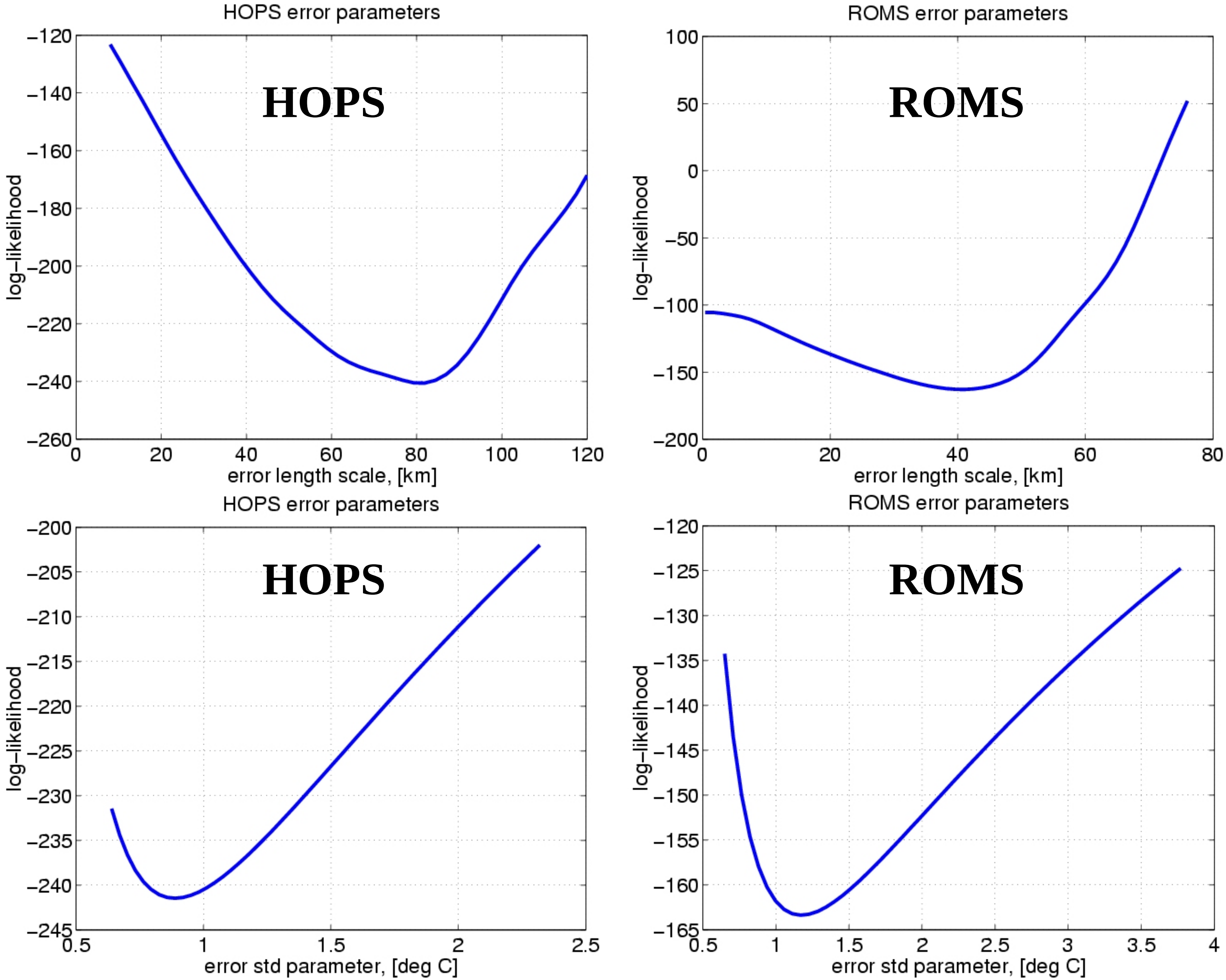
$$\mathbf{\Theta}^* = \arg\max_{\mathbf{\Theta}} p(\mathcal{Y}|\mathbf{\Theta}) \tag{1}$$

Where $\mathcal{Y} = \{\mathbf{y}_1^o, \mathbf{y}_2^o, \ldots, \mathbf{y}_T^o\}$ is the observational data, $\mathbf{\Theta} = \{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, \ldots, \boldsymbol{\theta}_M\}$ the forecast error covariance parameters of the M models

- (1) implies finding parameter values that maximize the probability of observing the data that was, in fact, observed
- By employing the Expectation-Maximization methodology, we solve (1) relatively efficiently

Error Analyses and Optimal (Multi) Model Estimates

An Example of Log-Likelihood functions for error parameters



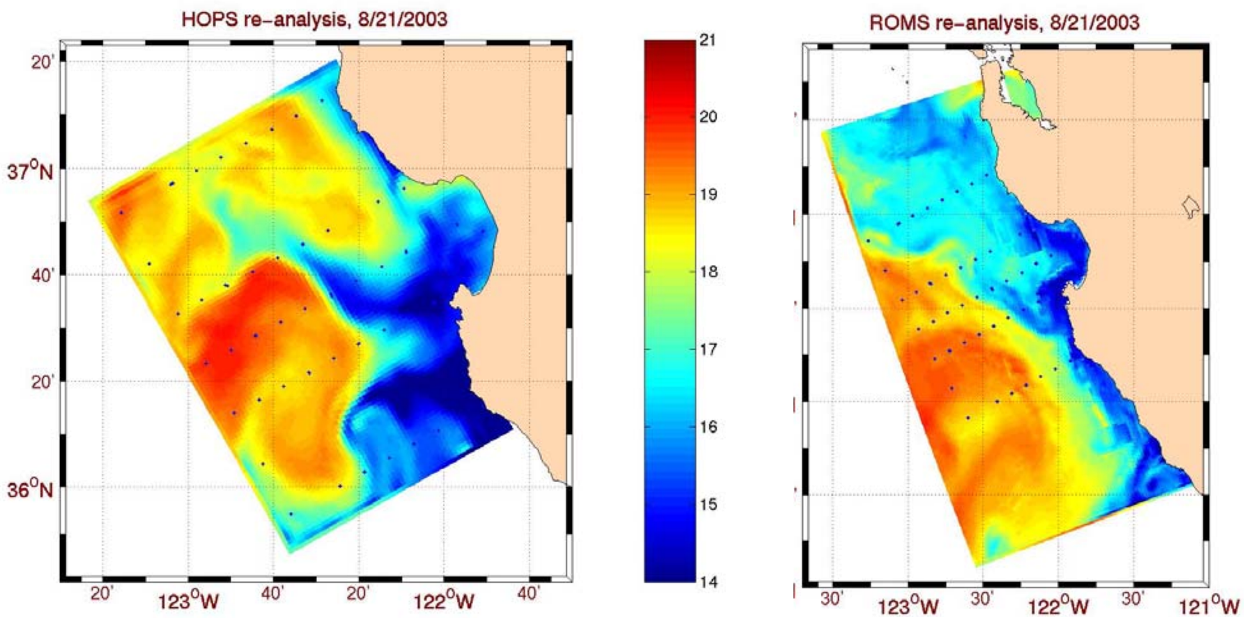
Length Scale

Variance

Error Analyses and Optimal (Multi) Model Estimates

Two-Model Forecasting Example

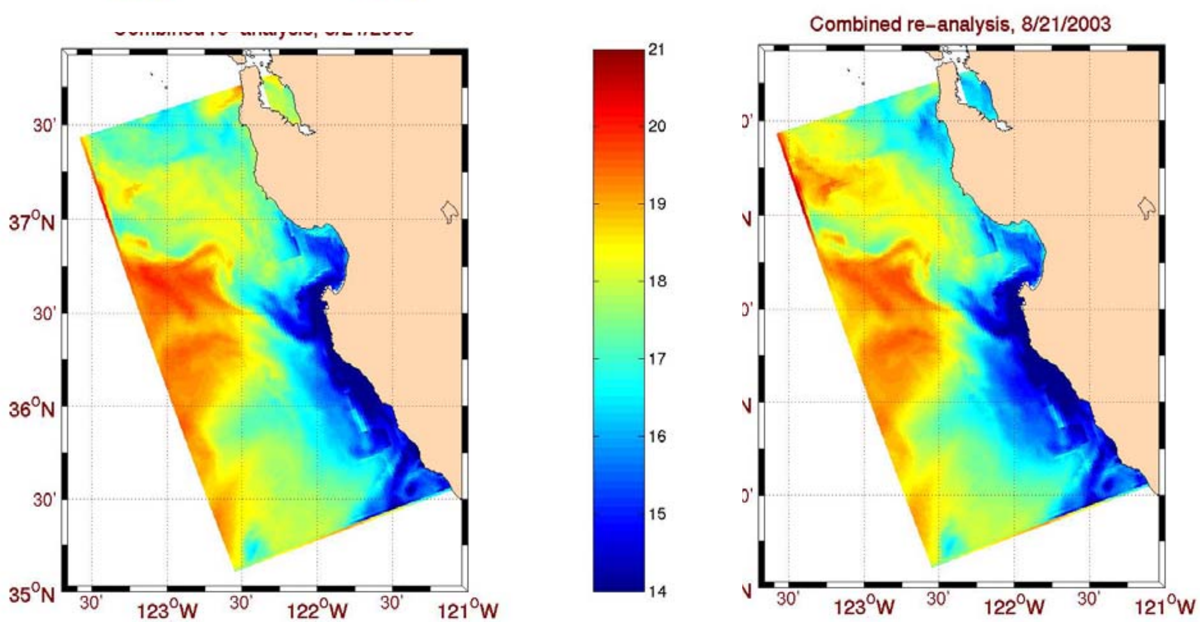
combine based on relative model uncertainties



HOPS and ROMS SST forecast

Left – HOPS (re-analysis)

Right – ROMS (re-analysis)



Model Fusion

Combined SST forecast

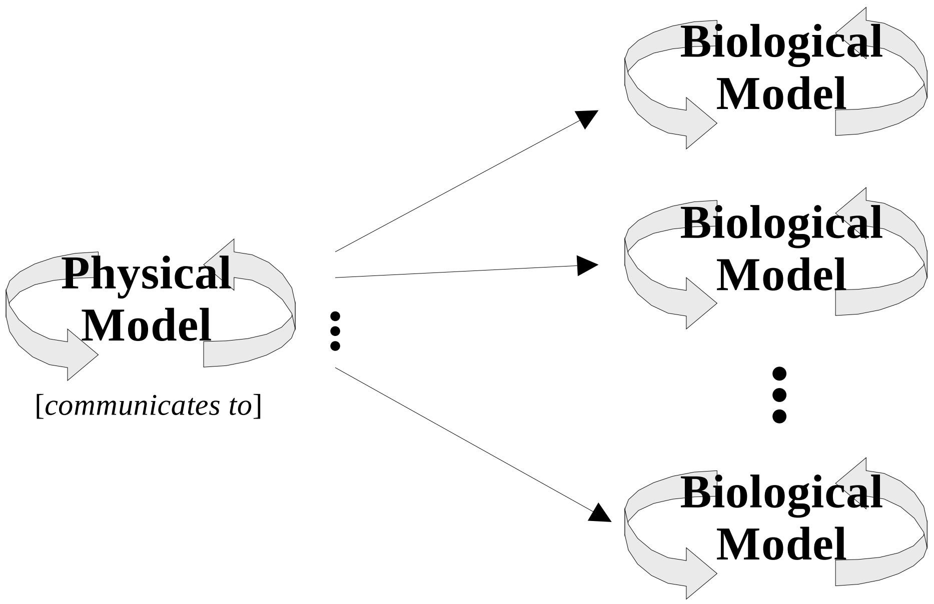
Left – with *a priori* error parameters

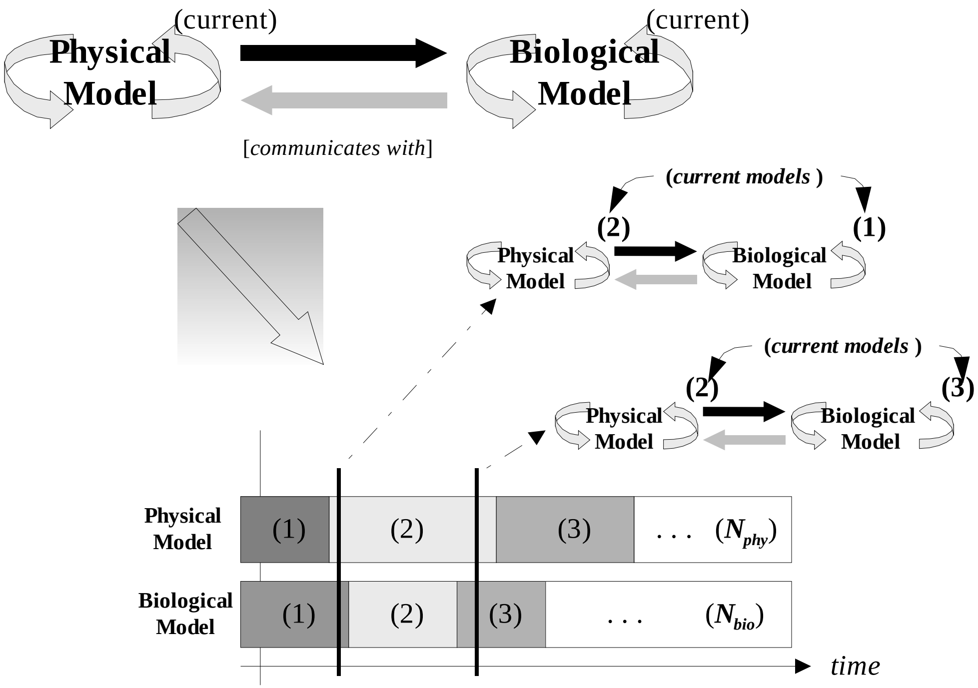
Right – with Maximum-Likelihood error parameters

Towards Real-time Adaptive Physical and Coupled Models

- Different Types of Adaptation:
  - Physical model with multiple parameterizations in parallel (hypothesis testing)
  - Physical model with a single adaptive parameterization (adaptive physical evolution)

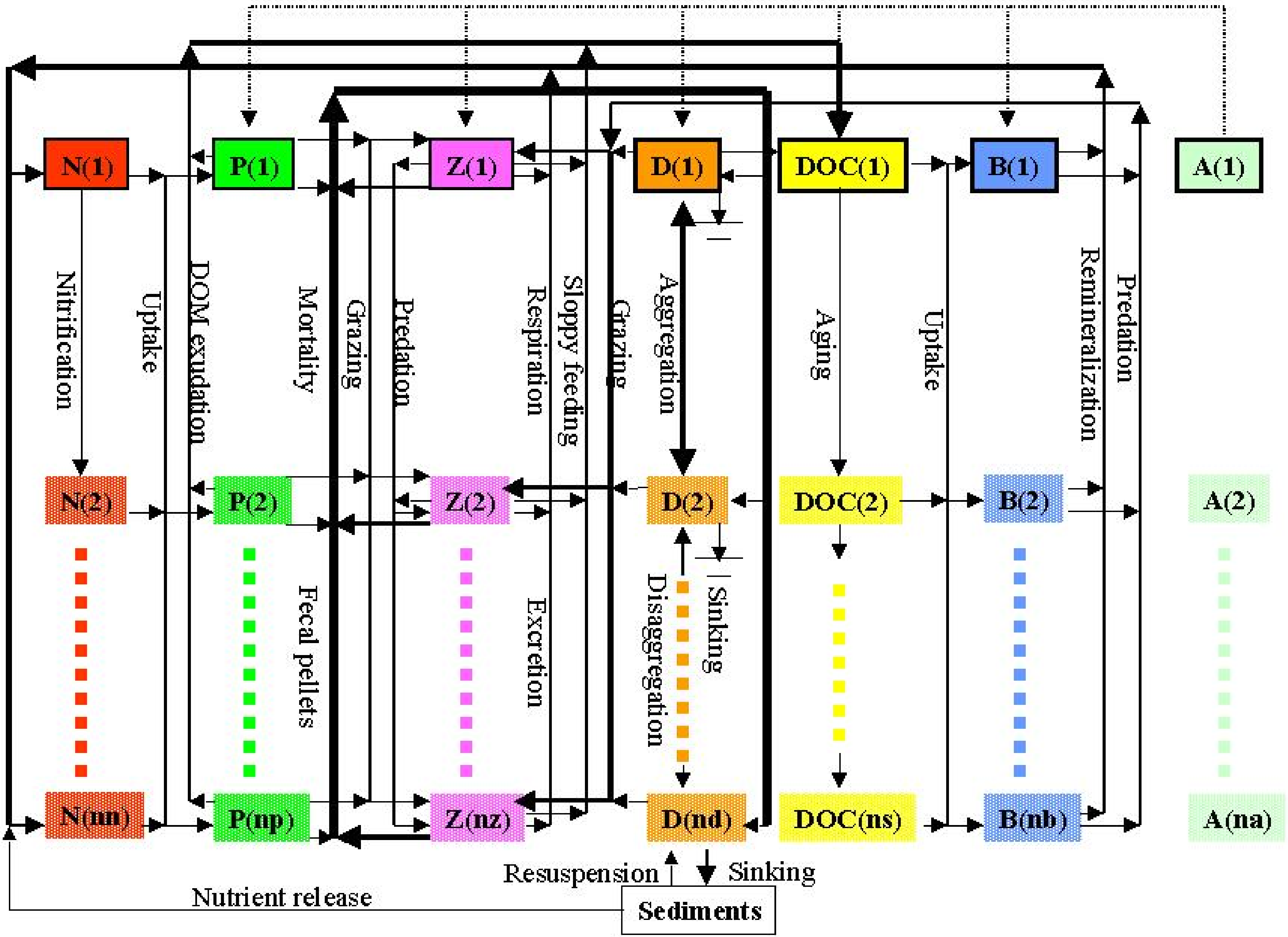
  - Adaptive physical model drives multiple biological models (biology hypothesis testing)
  - Adaptive physical model and adaptive biological model proceed in parallel





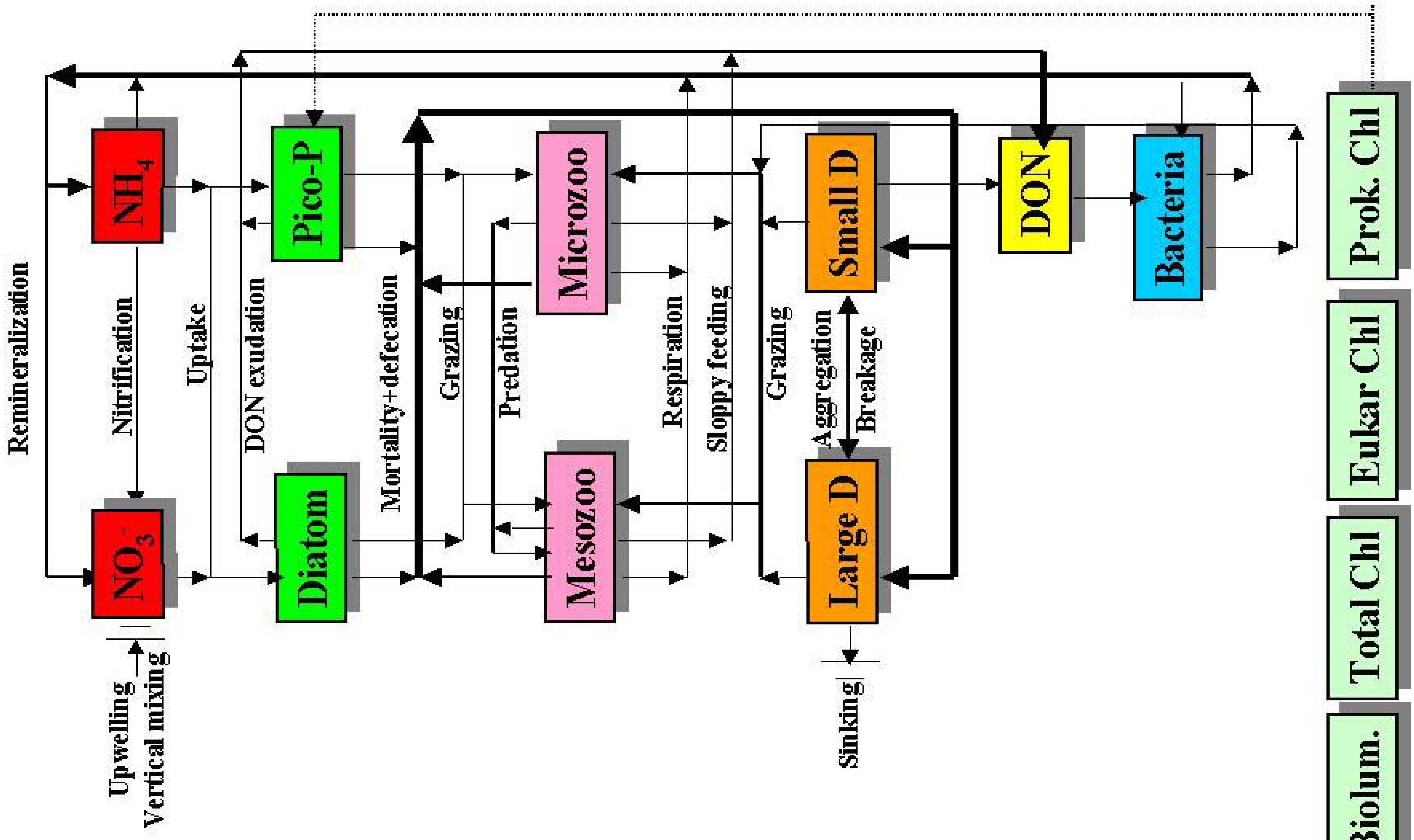
- Model selection based on quantitative dynamical/statistical study of data-model misfits
- Mixed language programming (C function pointers and wrappers for functional choices) to be used for numerical implementation

Harvard Generalized Adaptable Biological Model



(R.C. Tian, P.F.J. Lermusiaux, J.J. McCarthy and A.R. Robinson, HU, 2004)

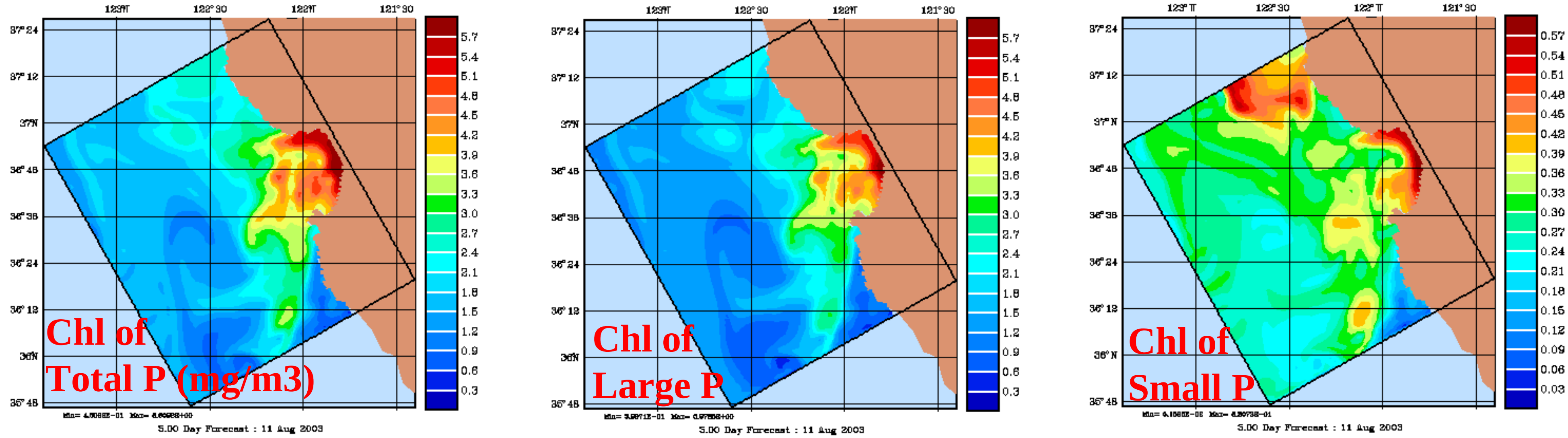
A Priori Biological Model for Monterey Bay



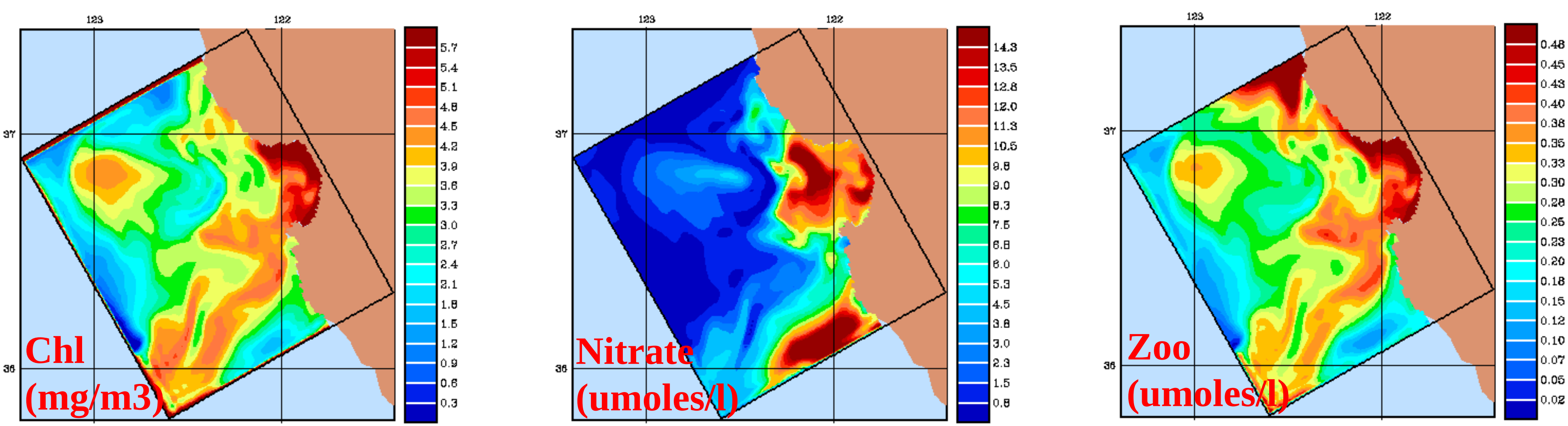
Another configuration with PO_4 and $Si(OH)_4$

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

Multi-Scale Energy and Vorticity Analysis

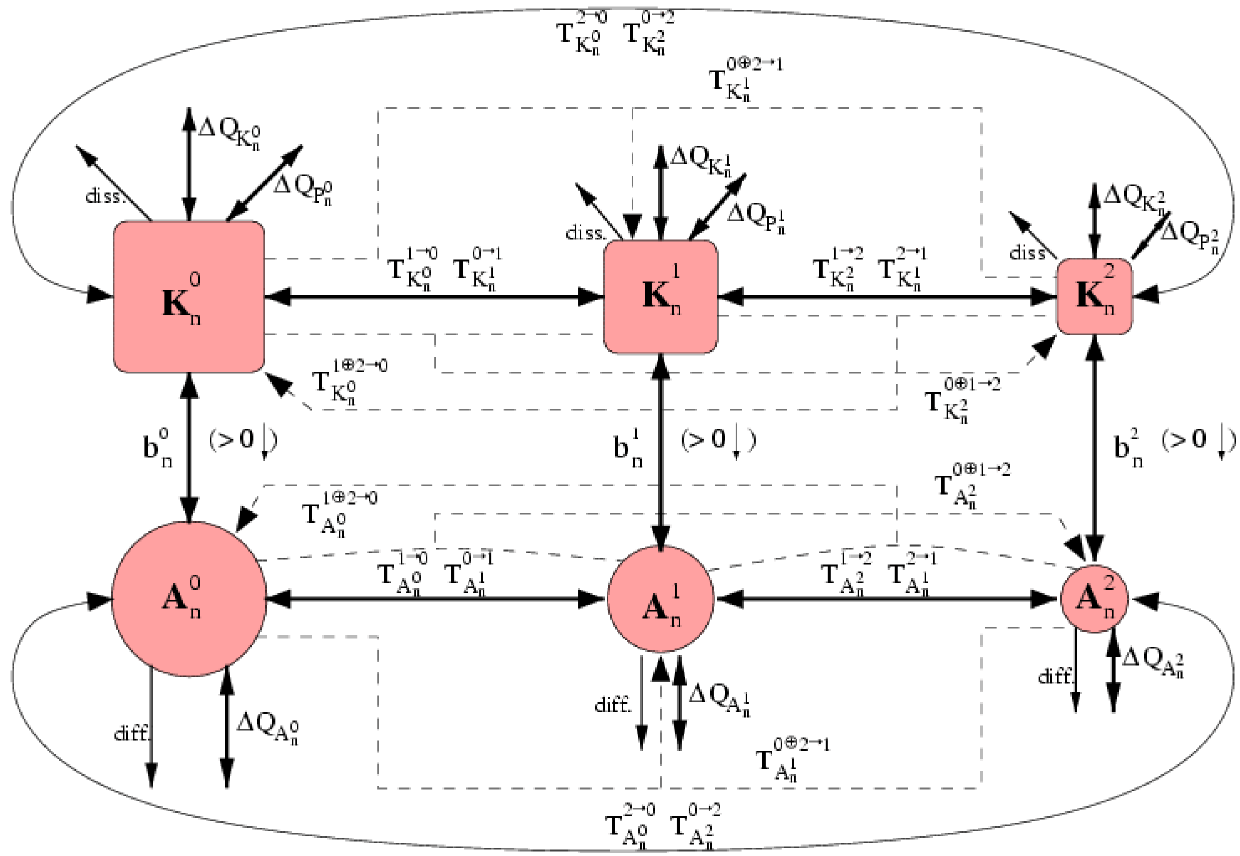
Symbols for multiscale energetics (time step n, scale window ϖ).

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.

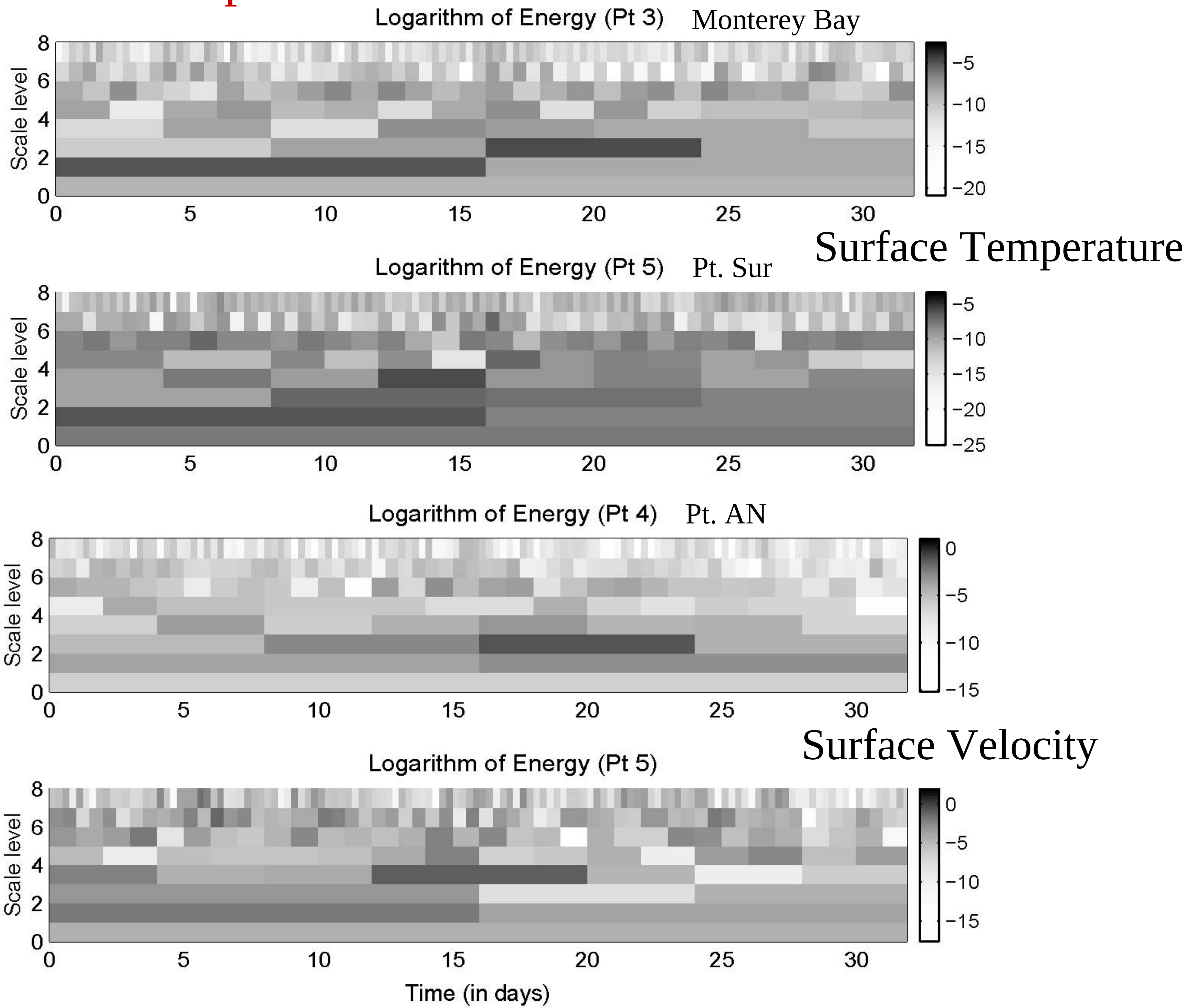
BT: Total perfect transfer of KE from large-scale window to meso-scale window.

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

If $BT + BC > 0$, and

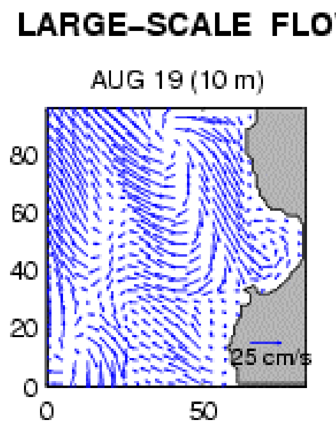
- $BC \leq 0$ => barotropic instability;
- $BT \leq 0$ => baroclinic instability;
- $BT > 0$ and $BC > 0$ => mixed instability

Wavelet Spectra

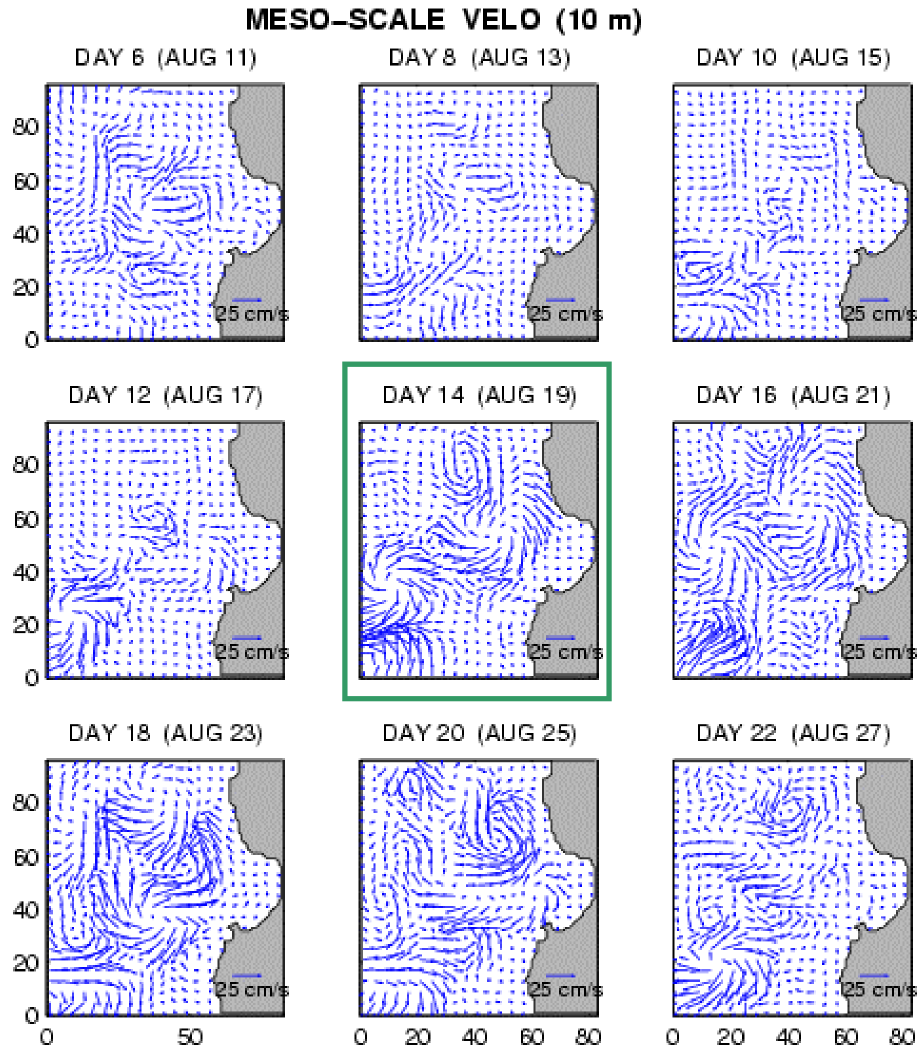


Multi-Scale Energy and Vorticity Analysis

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.



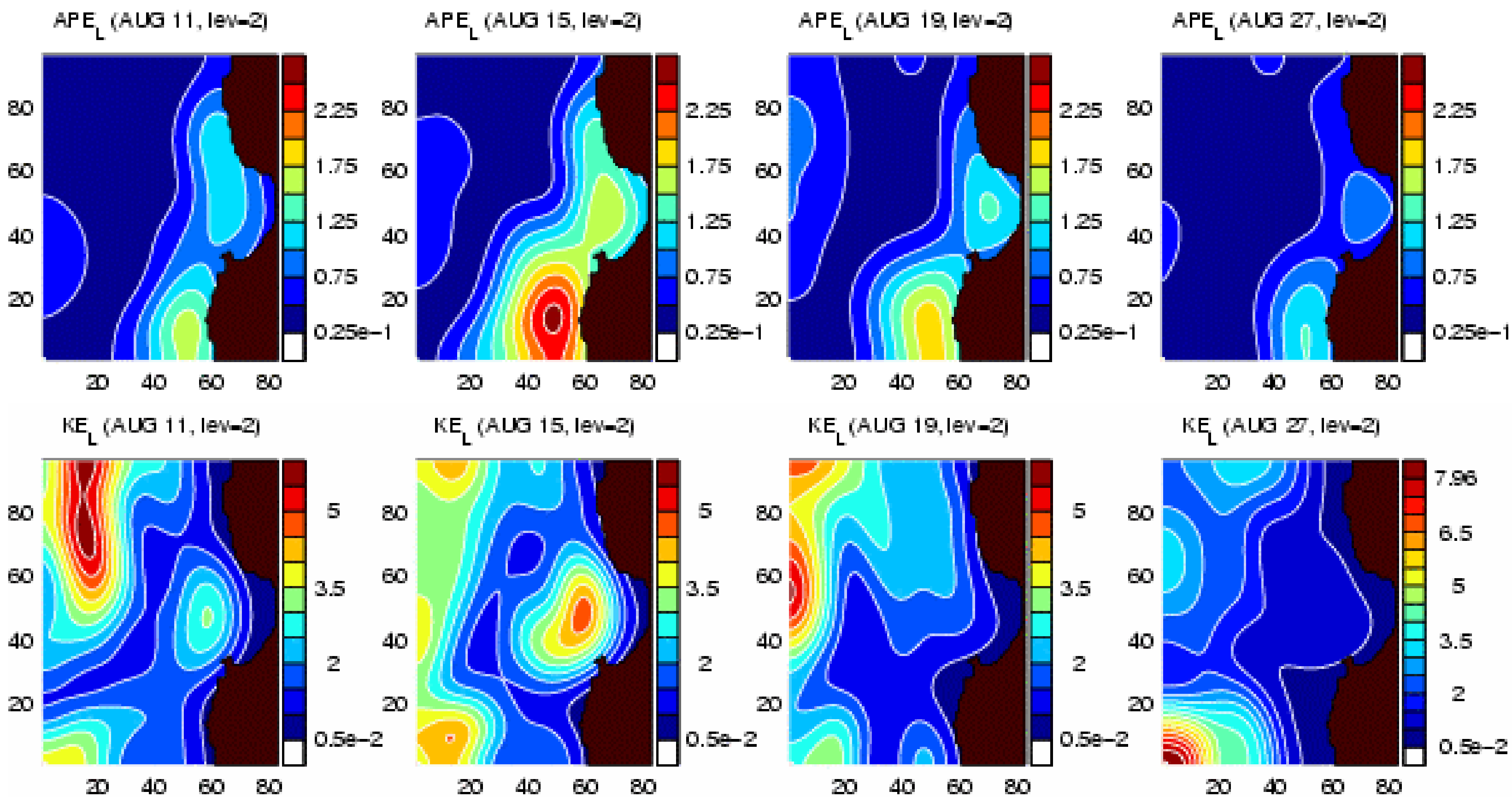
Time windows
Large scale: > 8 days
Meso-scale: 0.5-8 days
Sub-mesoscale: < 0.5 day

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)

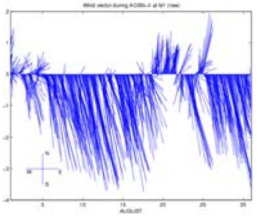
- Both APE and KE decrease during the relaxation period
- Transfer from large-scale window to mesoscale window occurs to account for decrease in large-scale energies (as confirmed by transfer and mesoscale terms)

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

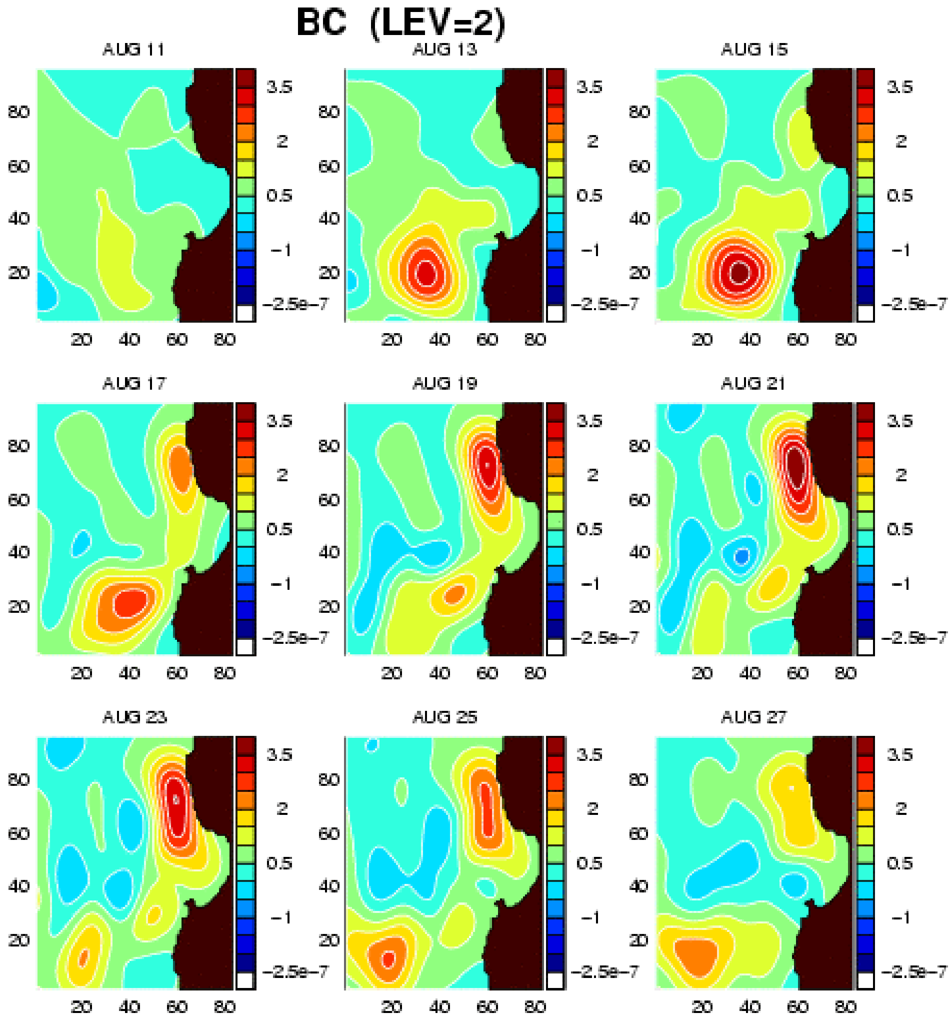
Dr. X. San Liang

Multi-Scale Energy and Vorticity Analysis

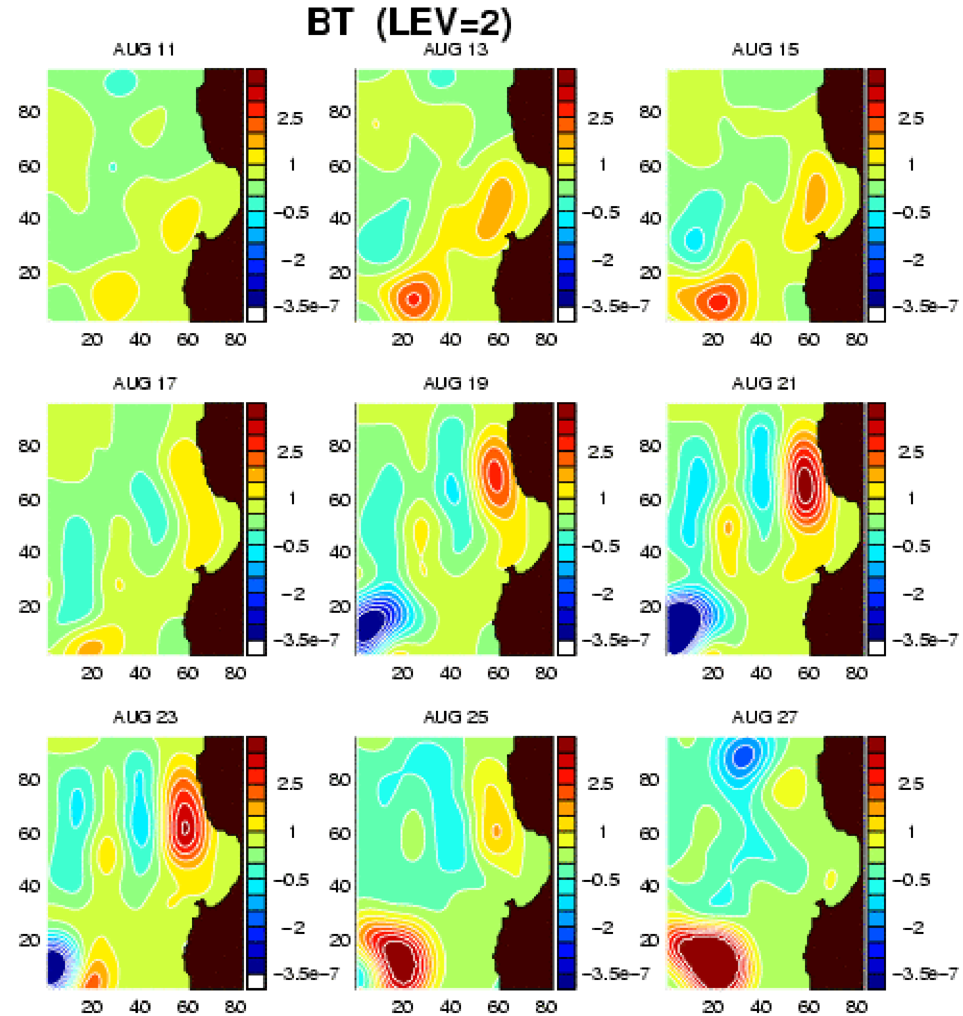
MS-EVA Analysis: 11-27 August 2003



Transfer of APE from large-scale to meso-scale

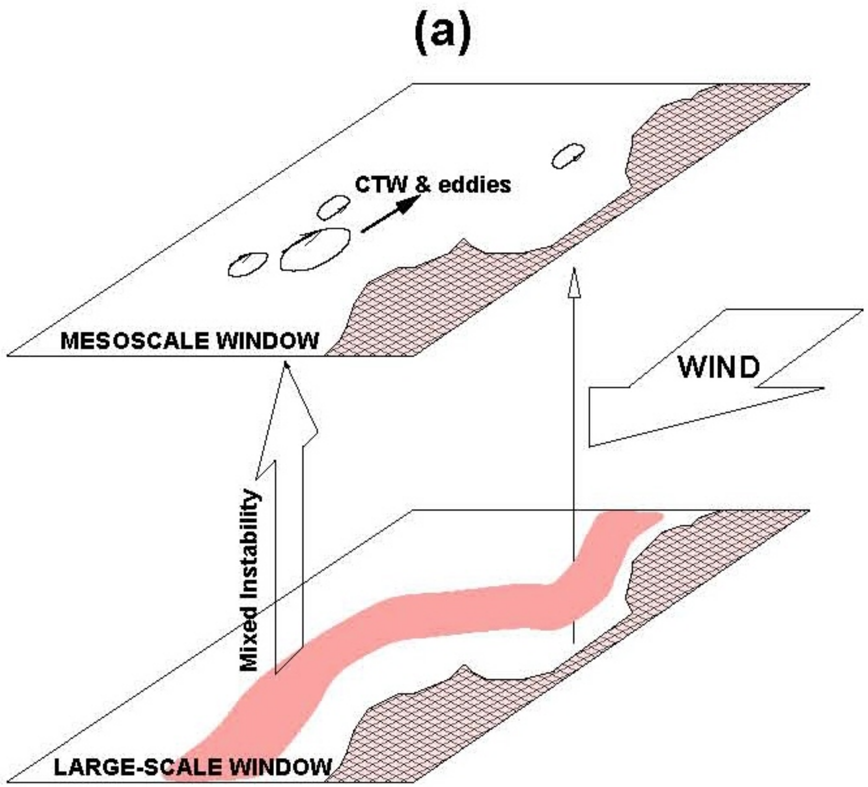


Transfer of KE from large-scale to meso-scale



Multi-Scale Energy and Vorticity Analysis

Process Schematic

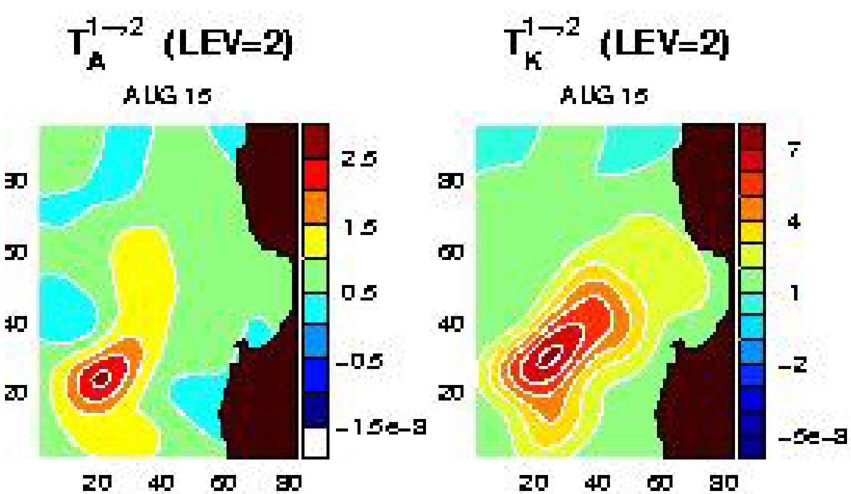


Multi-Scale Energy and Vorticity Analysis

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.

CONCLUSIONS

- Entering a new era of fully interdisciplinary ocean science: physical-biological-acoustical-biogeochemical

- Advanced ocean prediction systems for science, operations and management: interdisciplinary, multi-scale, multi-model ensembles

- Interdisciplinary estimation of state variables and error fields via multivariate physical-biological-acoustical data assimilation

http://www.deas.harvard.edu/~robinson