

Coupled acoustical-physical uncertainty predictions, data assimilation and adaptive sampling for MREA

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Applied Sciences



Department of Earth and
Planetary Sciences

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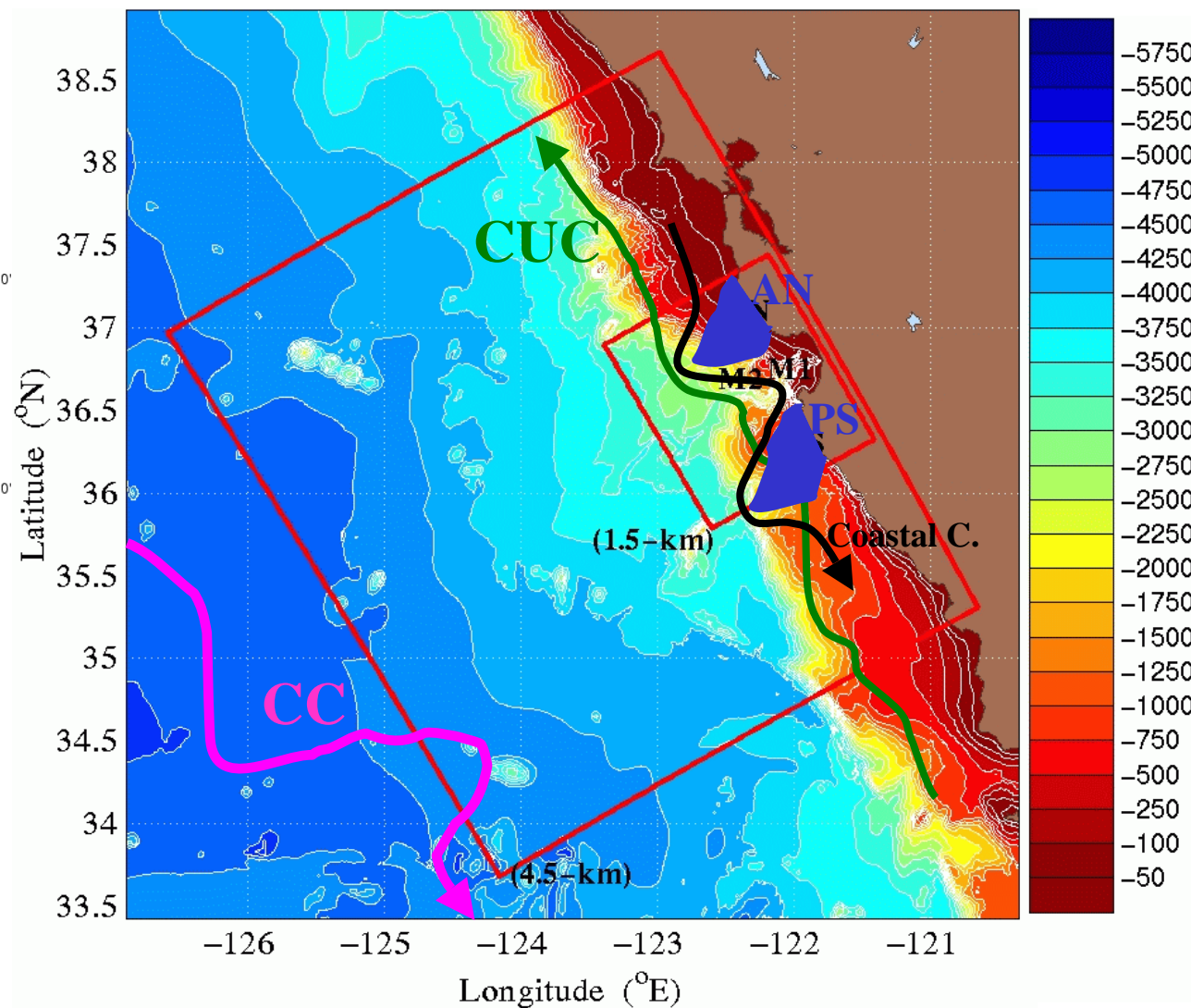
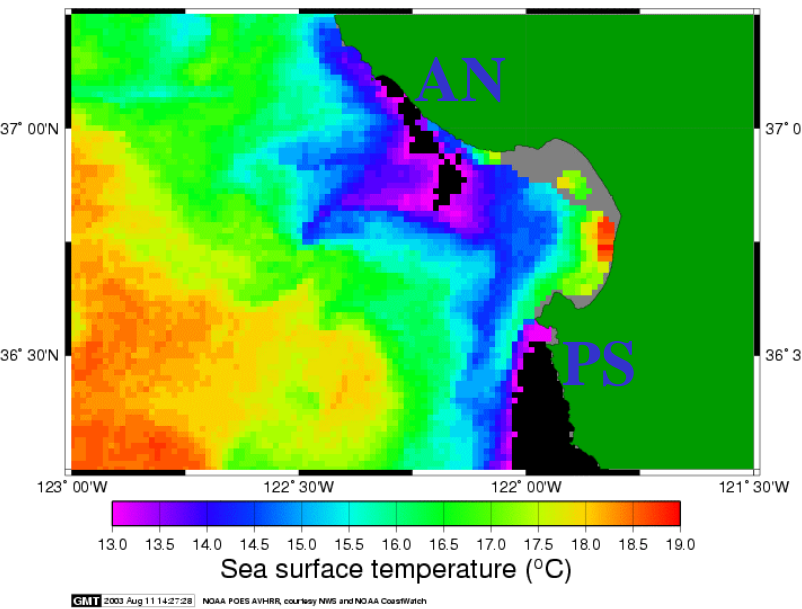
1. **AOSN-II**: Error Forecasting, Data Assimilation and Quantitative Adaptive Sampling in Monterey Bay via Error Subspace Statistical Estimation (*ESSE*)
2. **PRIMER**: Environmental-Acoustical Uncertainty Estimation and Transfers, Acoustical-Physical DA and End-to-End (physical-geological-acoustical-sonar-noise) system for advanced sonar performance prediction via *ESSE*
3. **PLUSNet**: Persistent Littoral Undersea Surveillance Network
4. **Conclusions** for upcoming *MREA-NURC* exercises



REGIONAL FEATURES of Monterey Bay and California Current System and Real-time Modeling Domains (AOSN2, 4 Aug. – 3 Sep., 2003)

SST on August 11, 2003

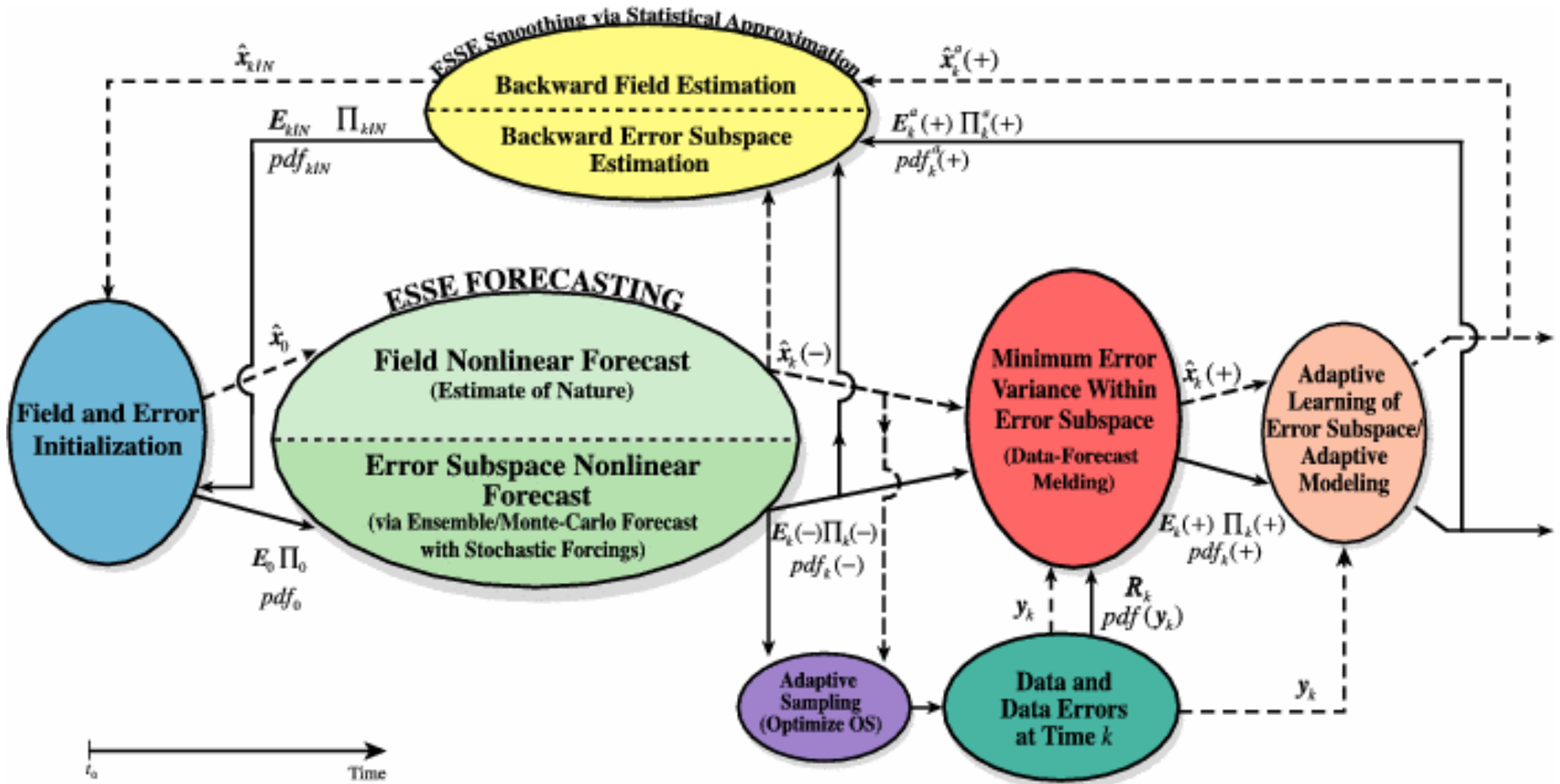
Experimental AVHRR HRPT SST August 11, 2003 1850 h UTC



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

Error Subspace Statistical Estimation (ESSE)

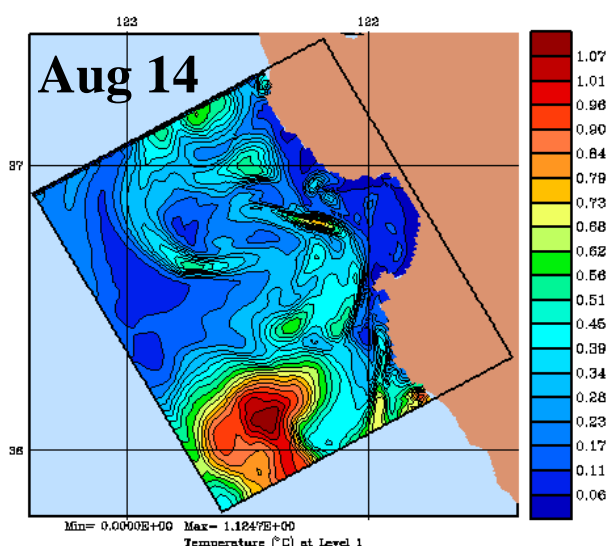
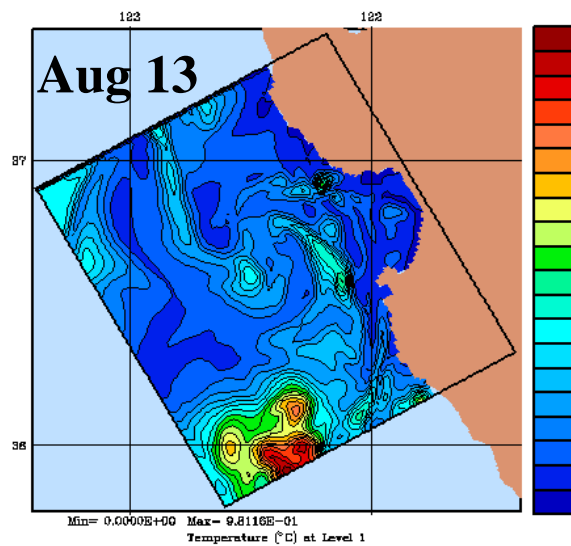
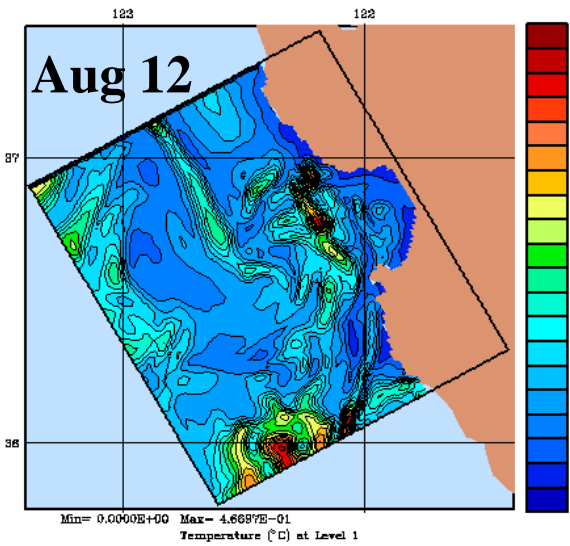


- Uncertainty forecasts (with dynamic error subspace, error learning)
- Ensemble-based (with nonlinear and stochastic primitive eq. model (HOPS))
- Multivariate, non-homogeneous and non-isotropic Data Assimilation (DA)
- Consistent DA and adaptive sampling schemes
- Software: not tied to any model, but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

Real-time ESSE : AOSN-II Accomplishments

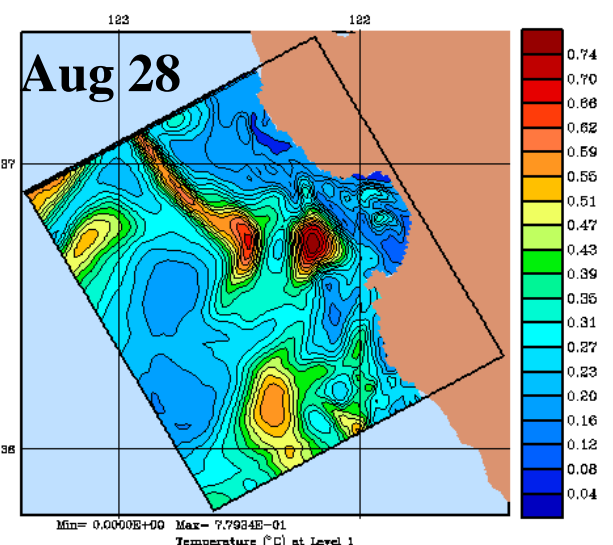
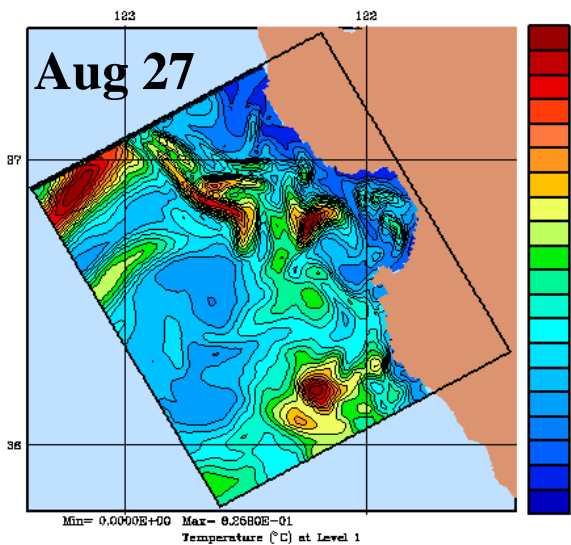
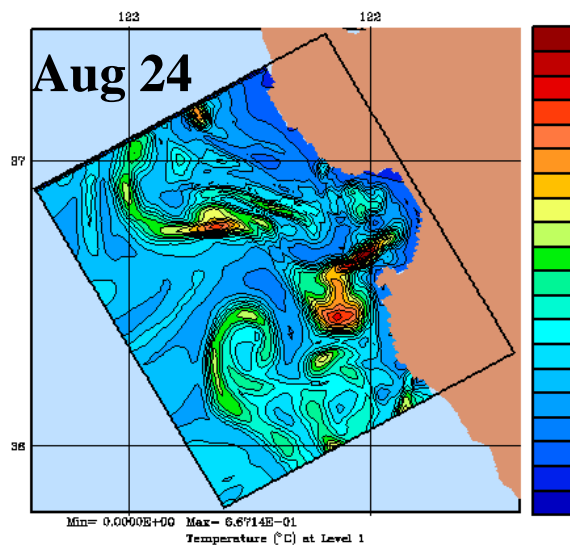
- 10 sets of ESSE nowcasts and forecasts of temperature, salinity and velocity, and their uncertainties, issued from 4 Aug. to 3 Sep.
 - Total of 4323 ensemble members: 270 – 500 members per day (7×10^5 state var.)
 - ESSE fields included: central forecasts, ensemble means, *a priori* (forecast) errors, *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 results described and posted on the Web daily
- Real-time research: stochastic error models, coupled physics-biology, tides

ESSE Surface Temperature Error Standard Deviation Forecasts



Start of Upwelling

First Upwelling period



End of Relaxation

Second Upwelling period

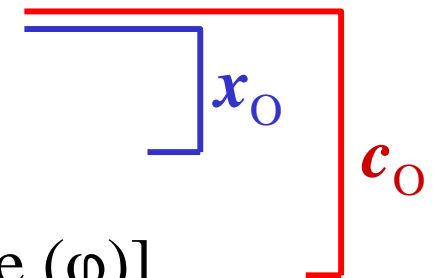
Coupled Interdisciplinary Error Covariances

$$\mathbf{x} = [\mathbf{x}_A \ \mathbf{x}_O \ \mathbf{x}_B]$$

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

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

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

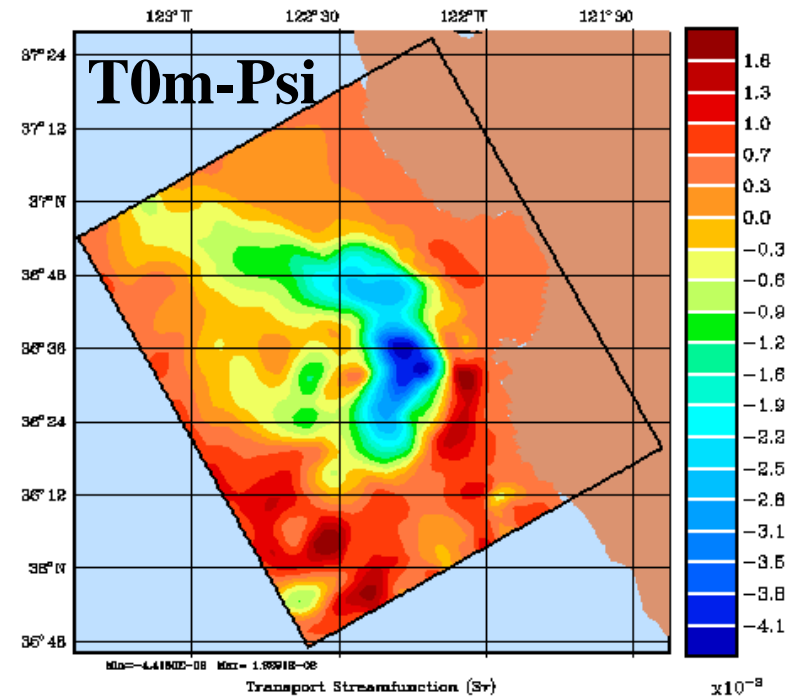
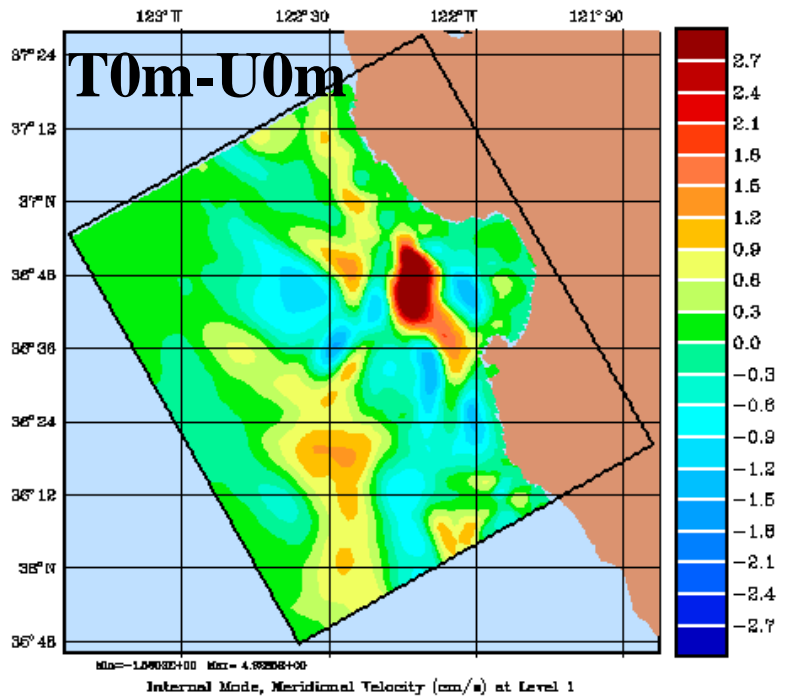
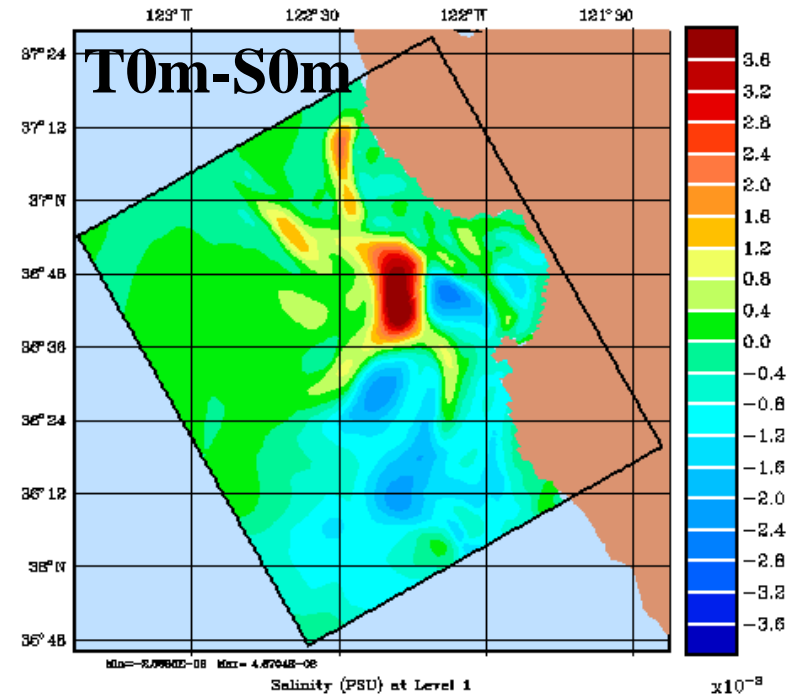
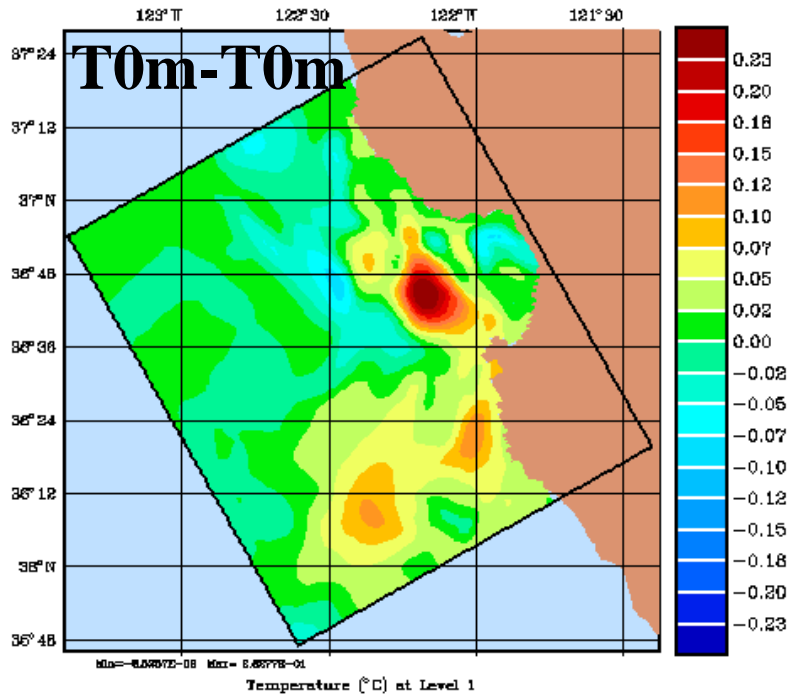


$$\mathbf{P} = \varepsilon \left\{ (\hat{\mathbf{x}} - \mathbf{x}^t) (\hat{\mathbf{x}} - \mathbf{x}^t)^T \right\}$$

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

The matrix \mathbf{P} is shown with a blue bracket under the P_{OO} element and a red bracket under the P_{AO} and P_{OA} elements.

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)

$$\text{Dynamics:} \quad dx = M(x)dt + d\eta \quad \eta \sim N(0, Q)$$

$$\text{Measurement:} \quad y = H(x) + \varepsilon \quad \varepsilon \sim N(0, R)$$

Non-lin. Err. Cov.:

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

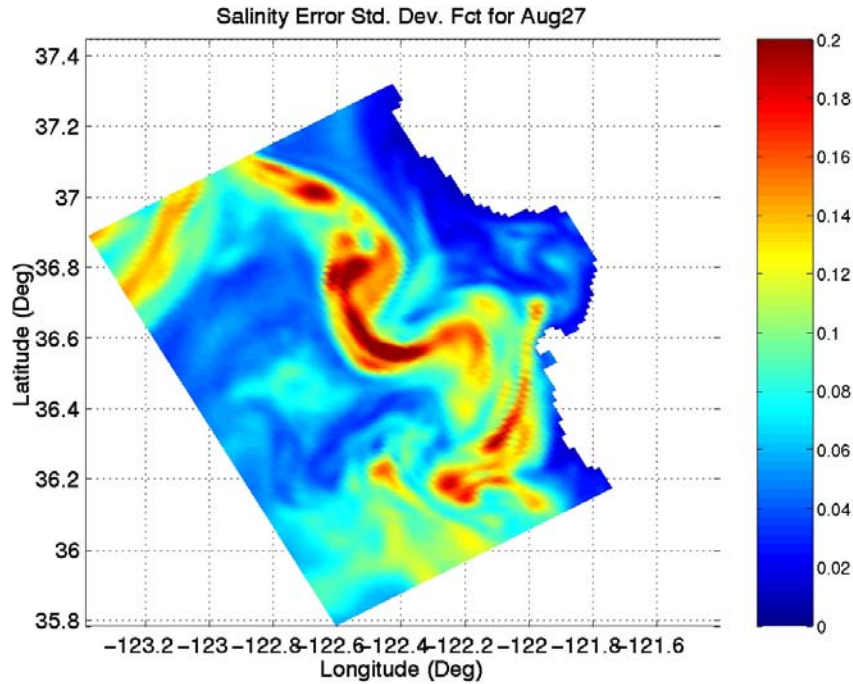
Metric or Cost function: e.g. Find H_i and R_i such that

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

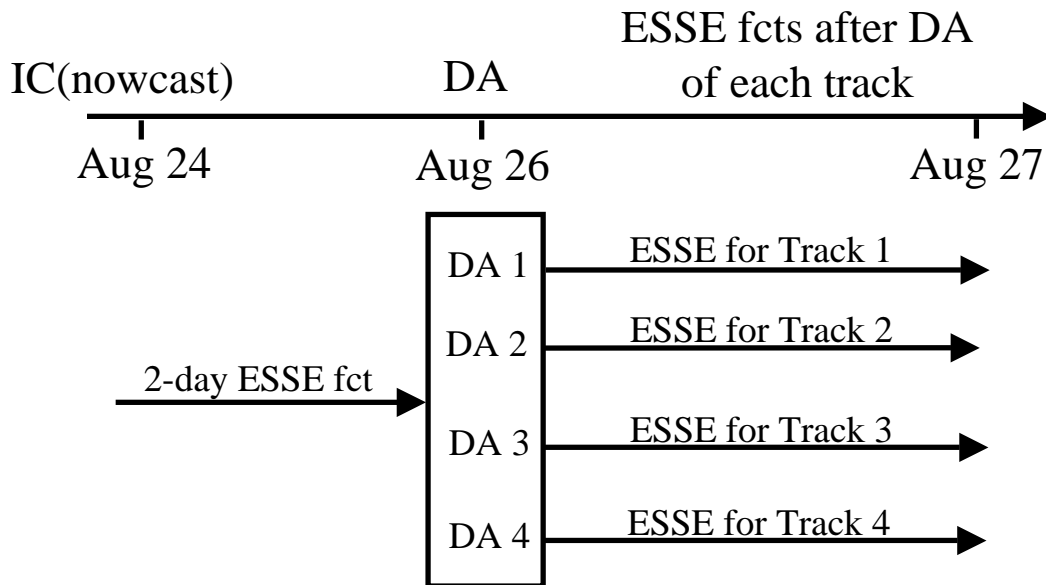
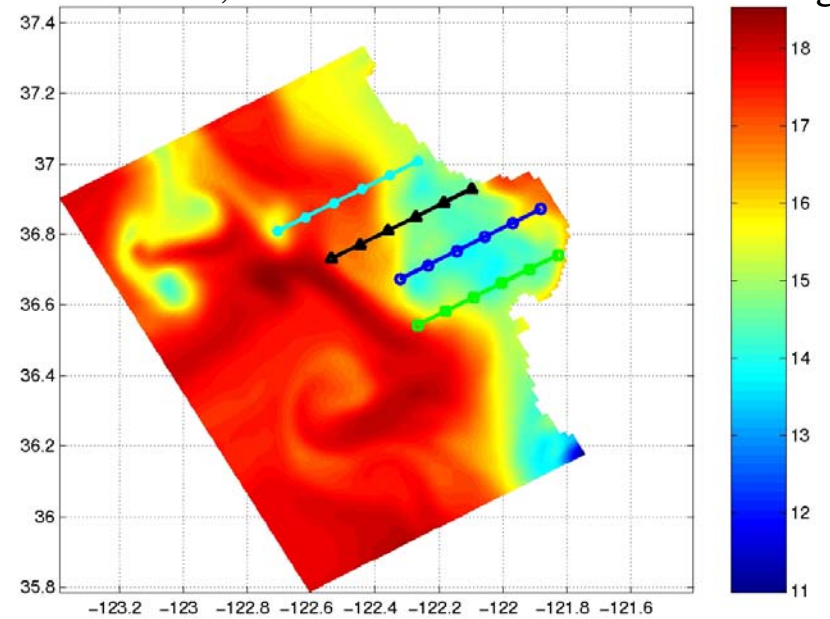
Quantitative Adaptive Sampling via ESSE

- 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

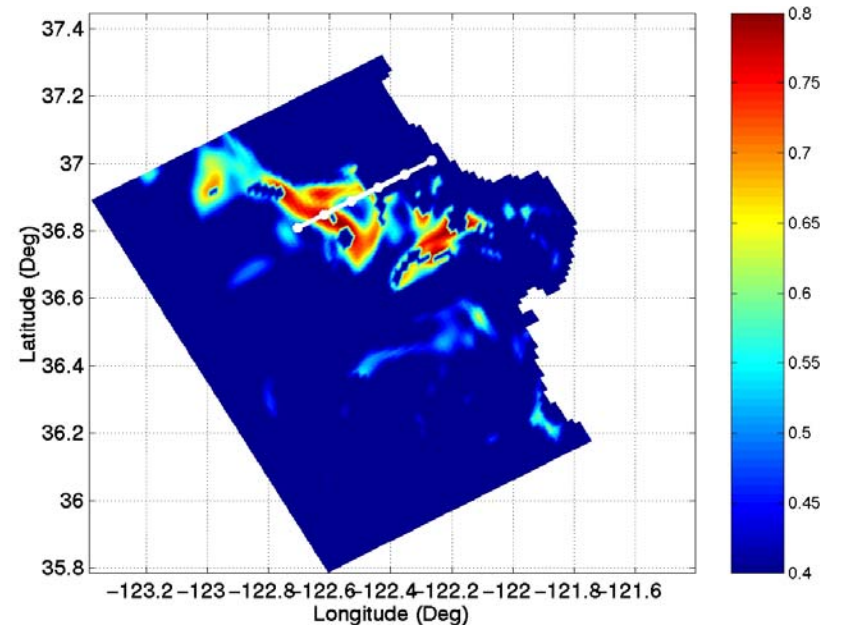
Which sampling on Aug 26 optimally reduces uncertainties on Aug 27?



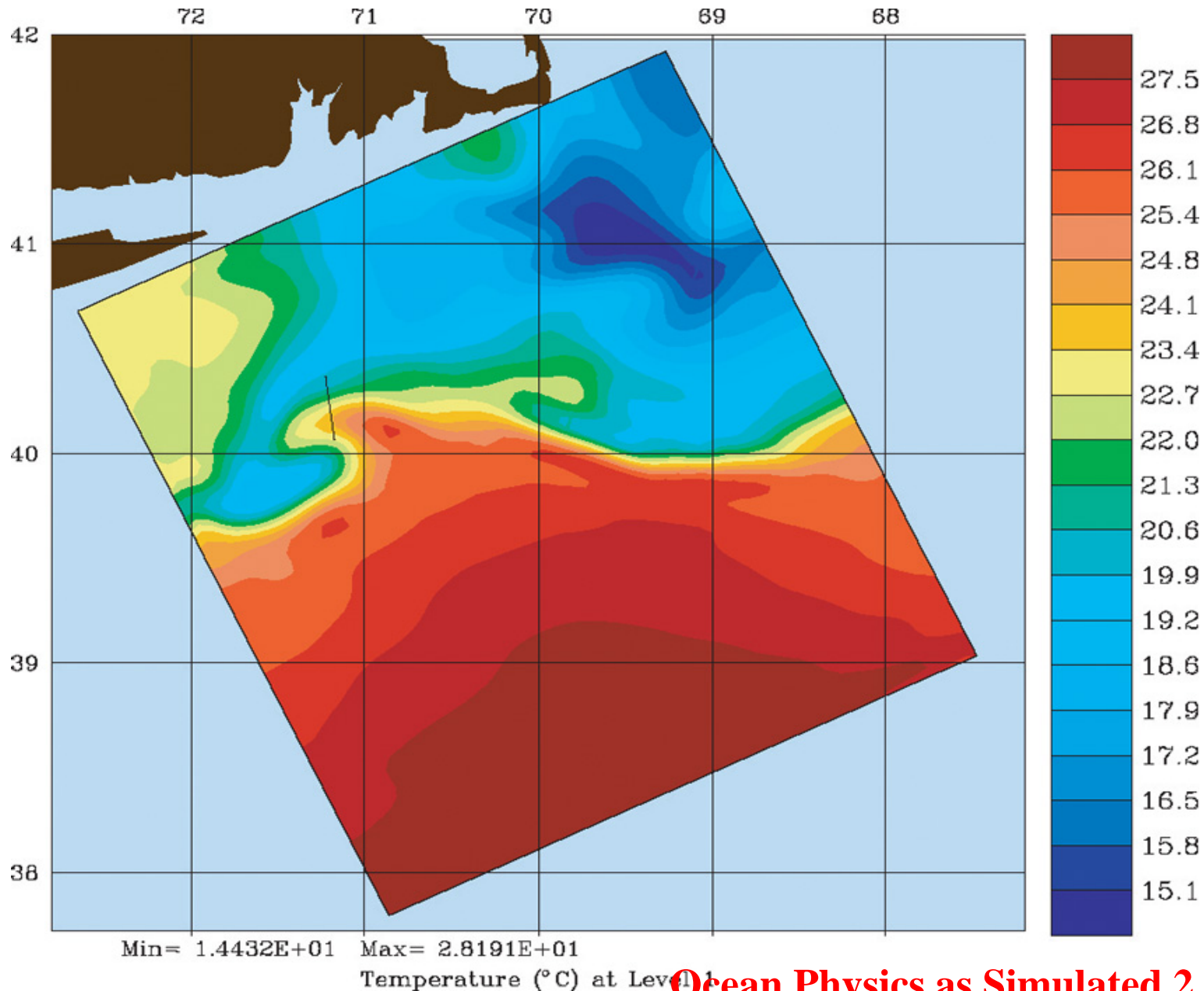
4 candidate tracks, overlaid on surface T fct for Aug 26



Best predicted relative error reduction: track 1



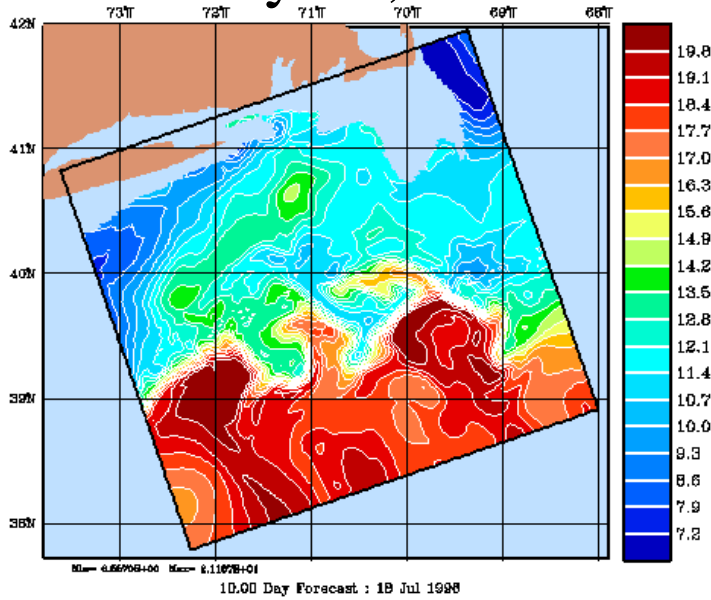
Environmental-Acoustical Uncertainty Estimation and Transfers, Coupled Acoustical-Physical DA and End-to-End Systems in a Shelfbreak Environment



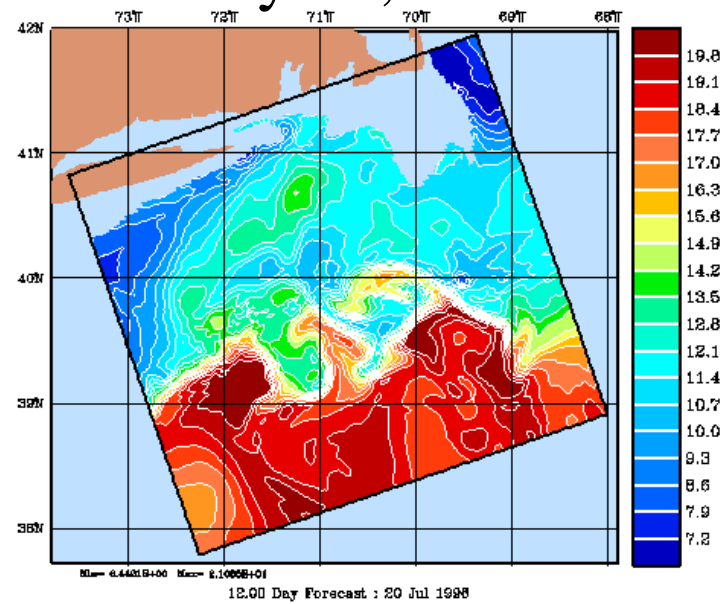
Ocean Physics as Simulated 2 Years Ago

30m Temperature as Simulated in June 04

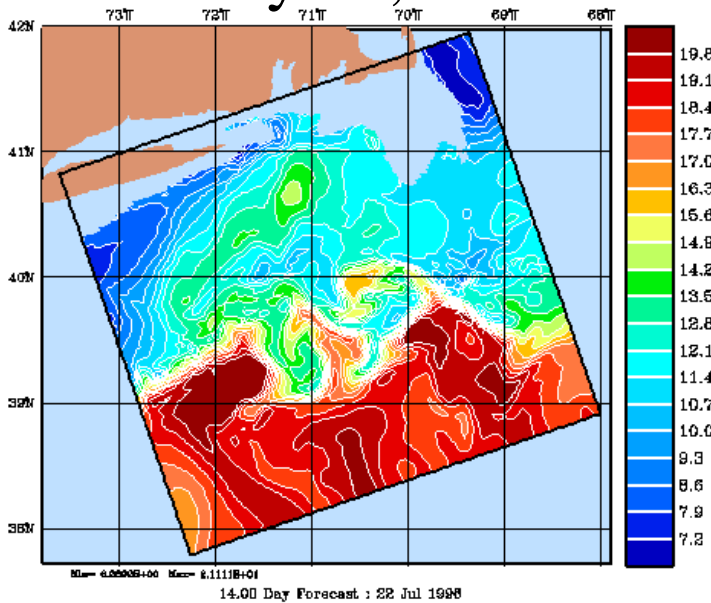
July 18, 1996



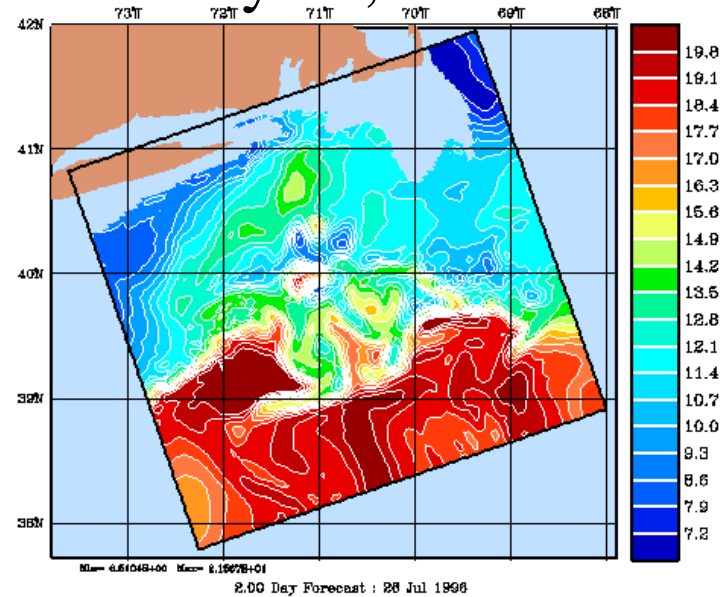
July 20, 1996



July 22, 1996

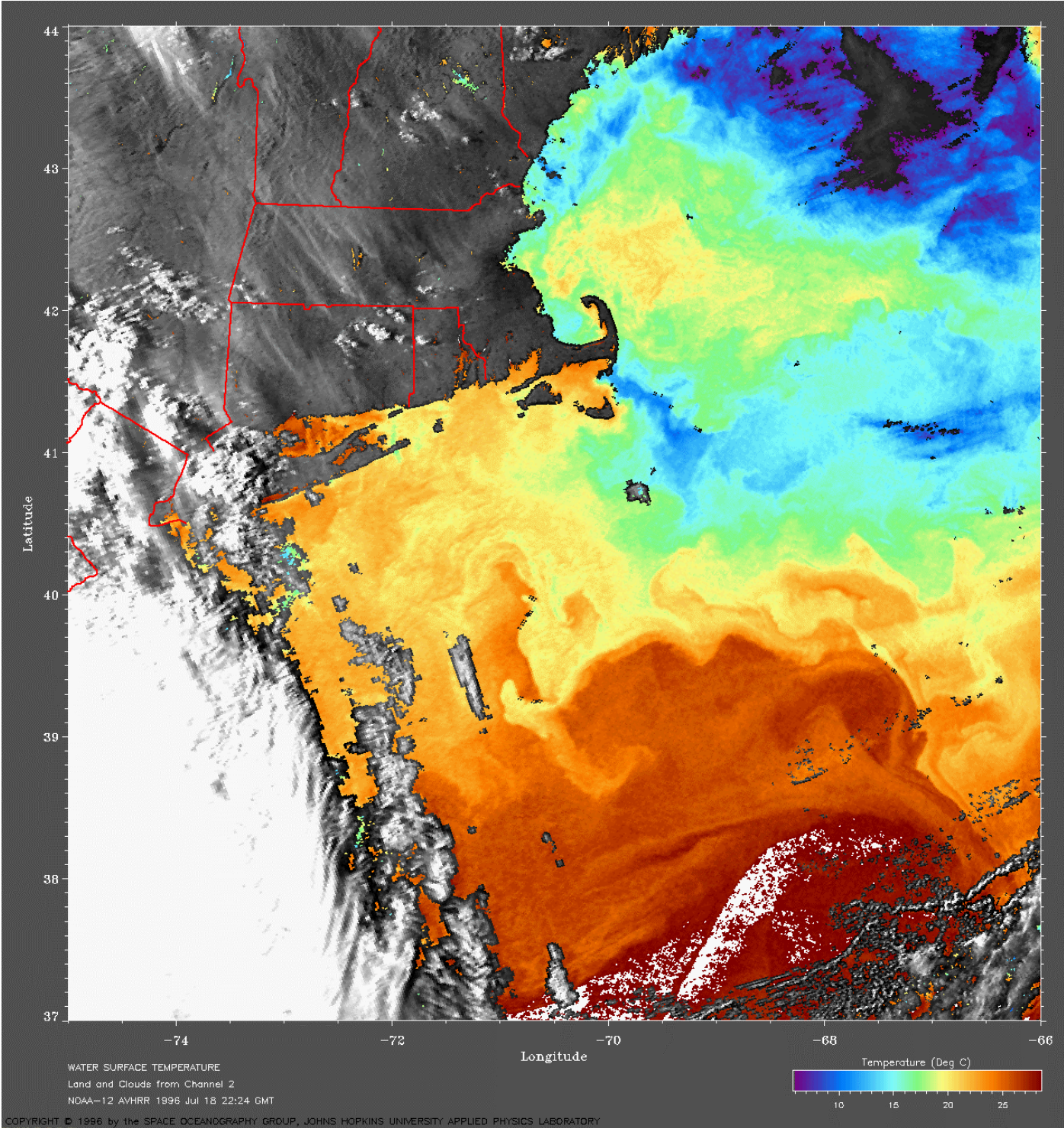


July 26, 1996



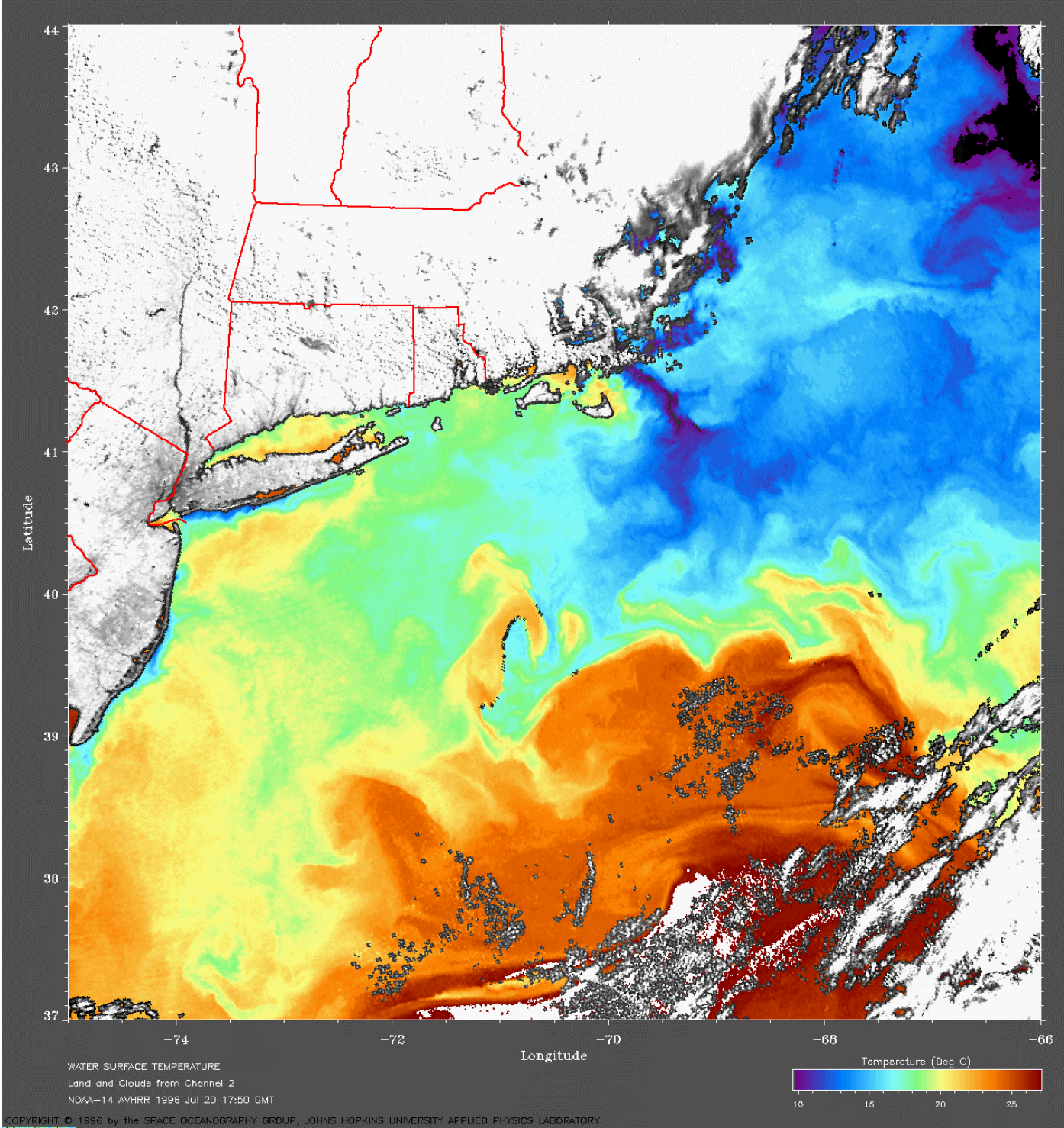
Evaluation
based on
SST

July 18



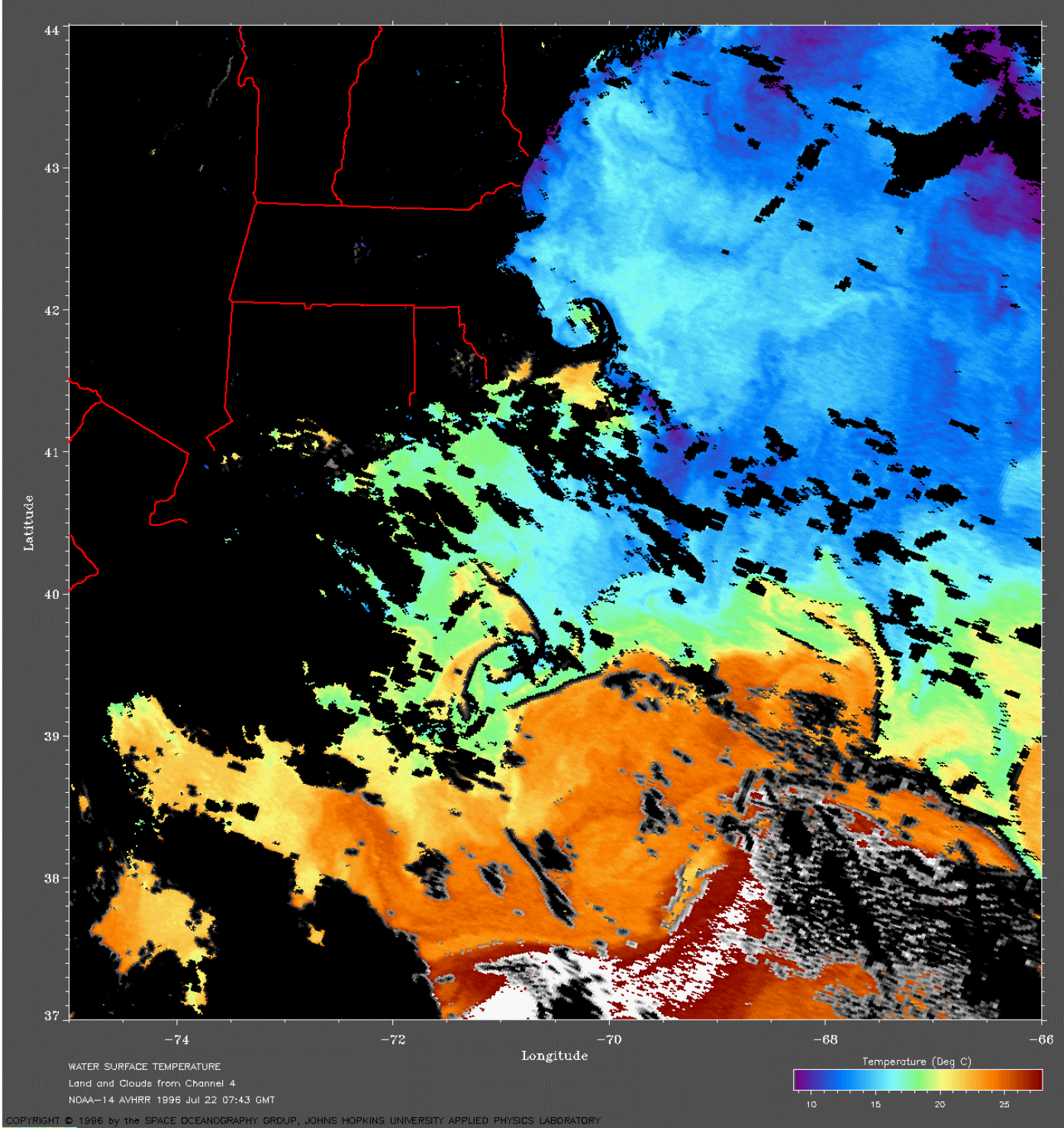
Evaluation
based on
SST

July 20



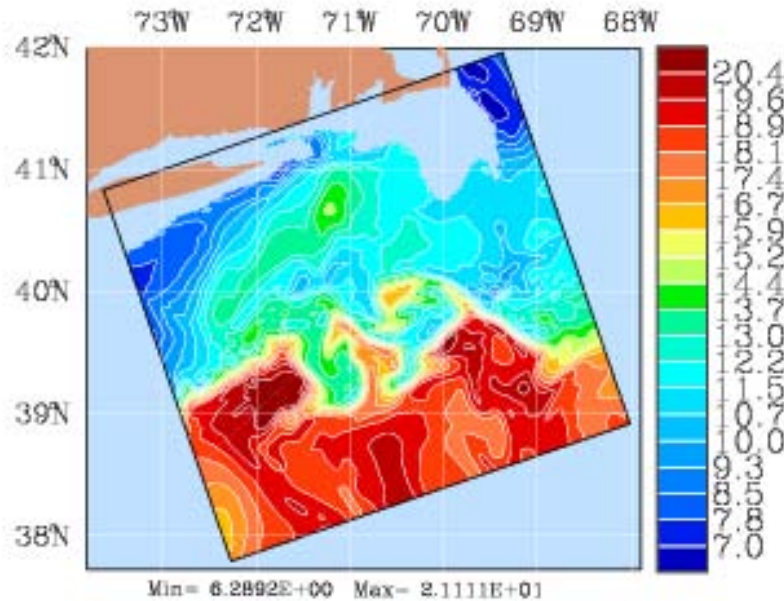
Evaluation based on SST

July 22

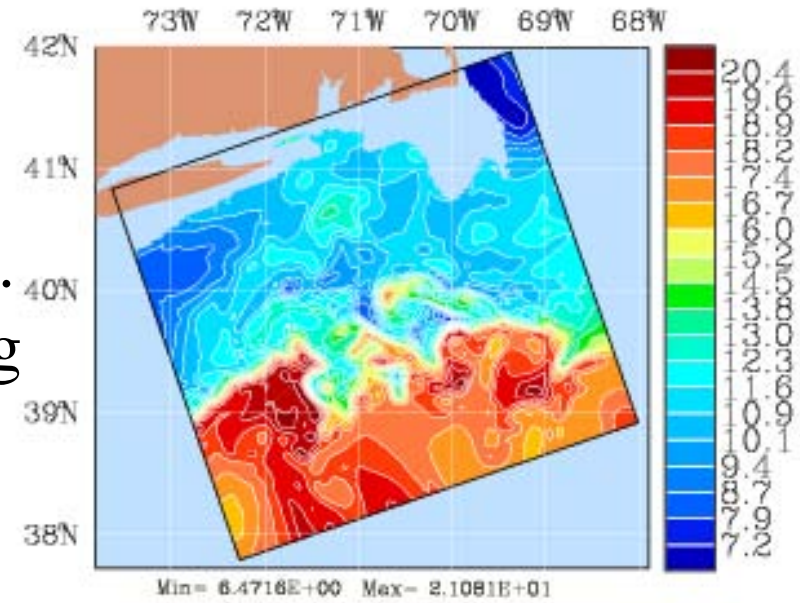


Importance and Effects of Atmospheric Forcings and Uncertainties

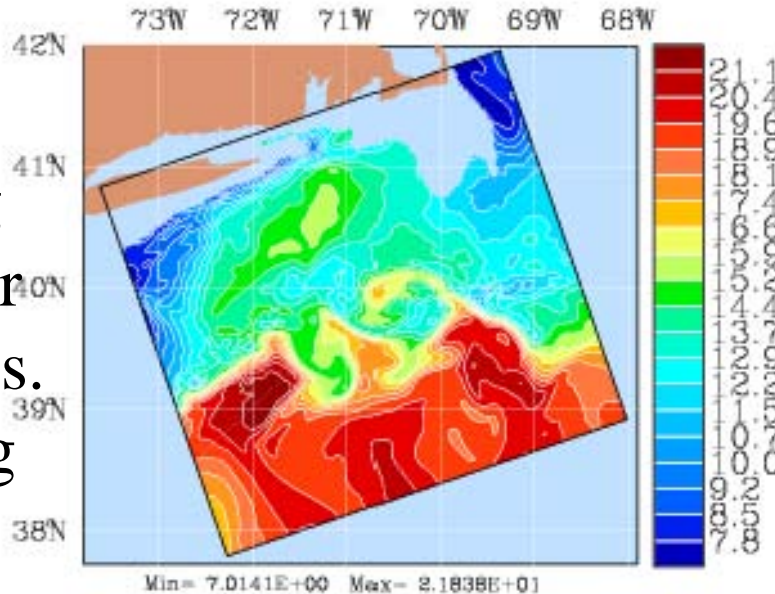
Best
Run



No
Atmos.
Forcing



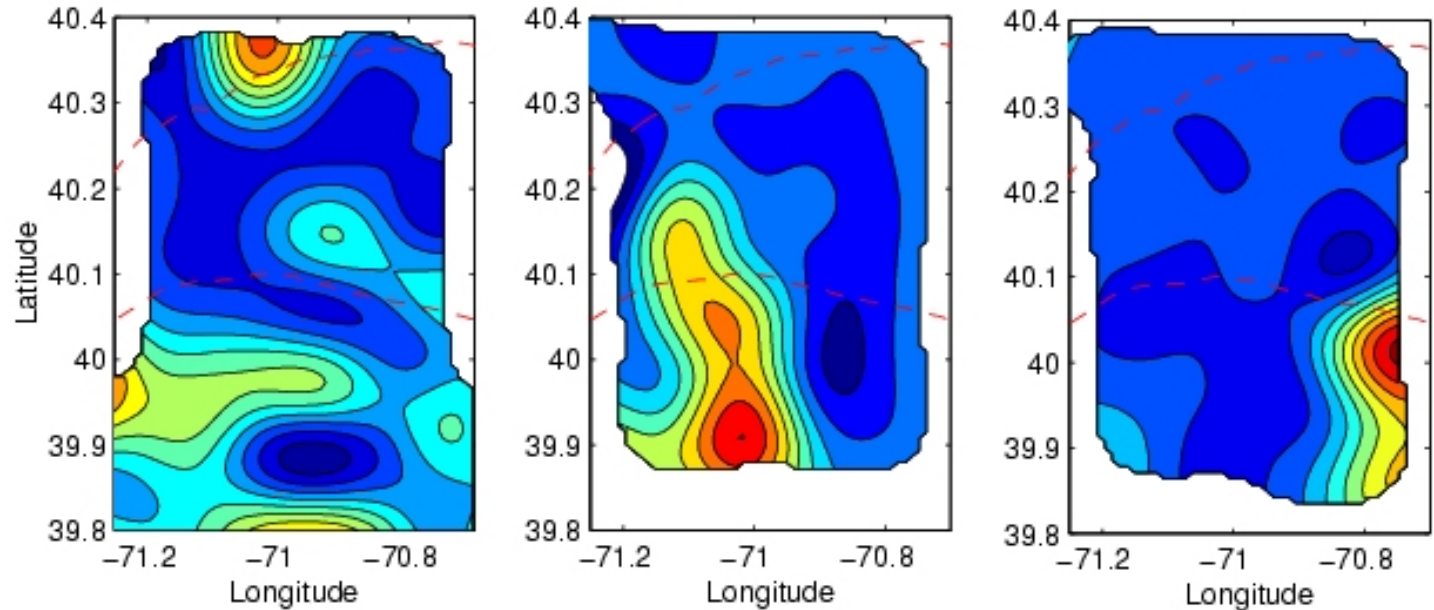
Too
strong
transfer
of atmos.
forcing



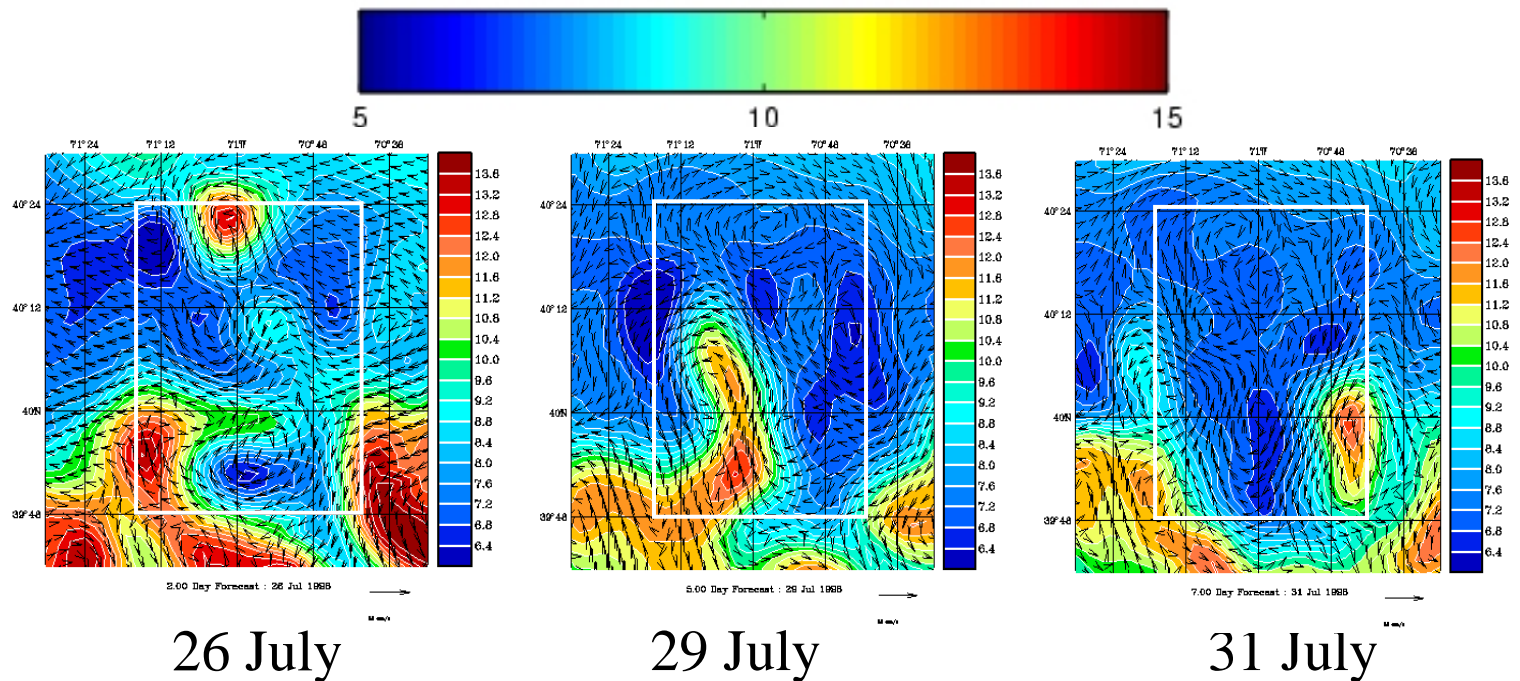
- Oceanic frontal instabilities occur from sub-mesoscales to mesoscales
- Atmospheric forcing impose certain scales on multi-scale oceanic frontal instability
- Deeper surface boundary layer and increased SBL mixing deepens large frontal meander but does not lead to much stronger surface signal

Quick-Look evaluations of 50m Temperature: July 26, 1996

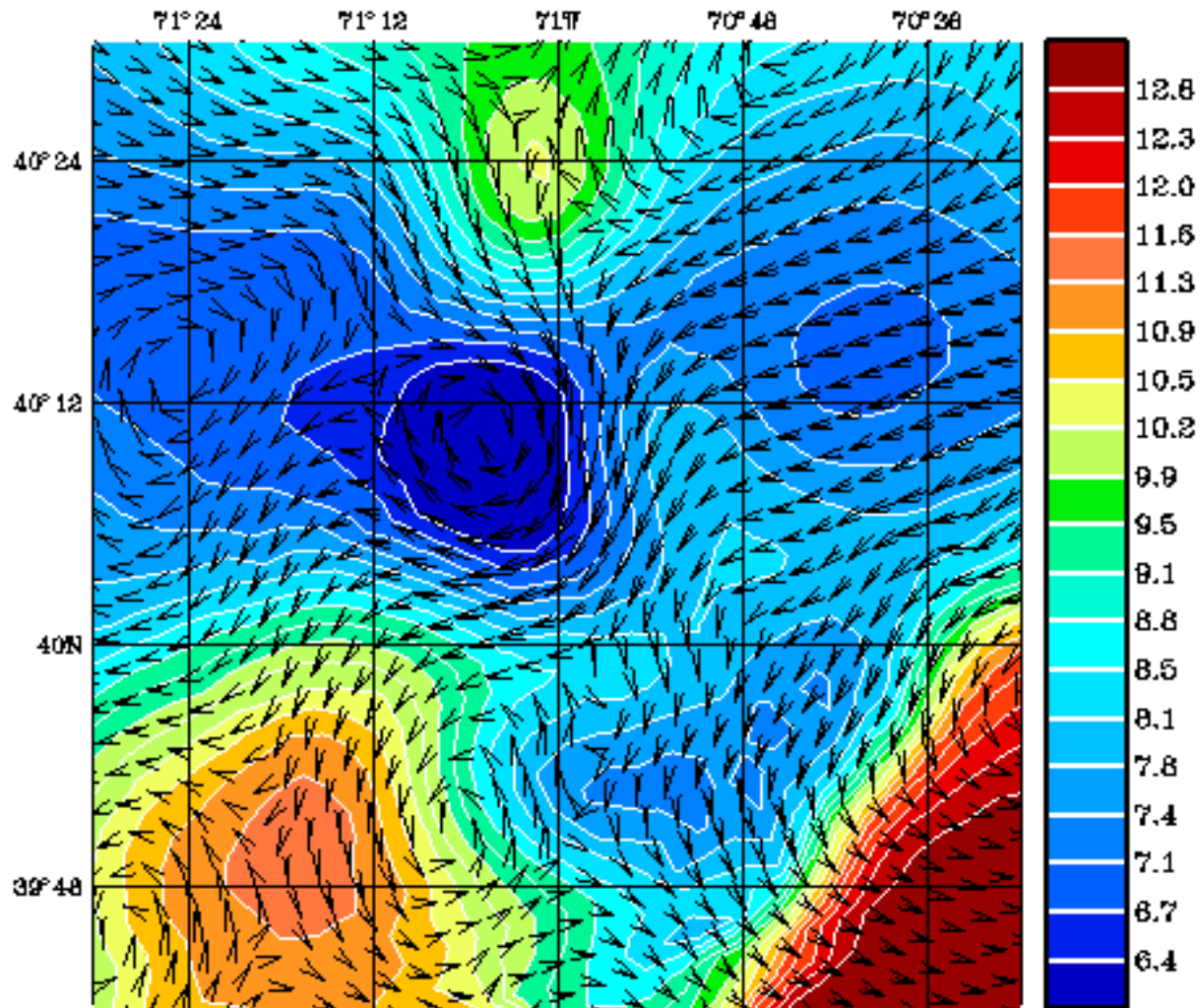
Gawarkiewicz, et al.
50m potential
temperature for 26
July, 29 July and 31
July, objectively
analyzed from
Seasoar data



50m temperature
in HOPS
simulation with
data assimilation
for the same dates



50m Temperature: 8 July – 7 August 1996



Normalized : 8 Jul 1996

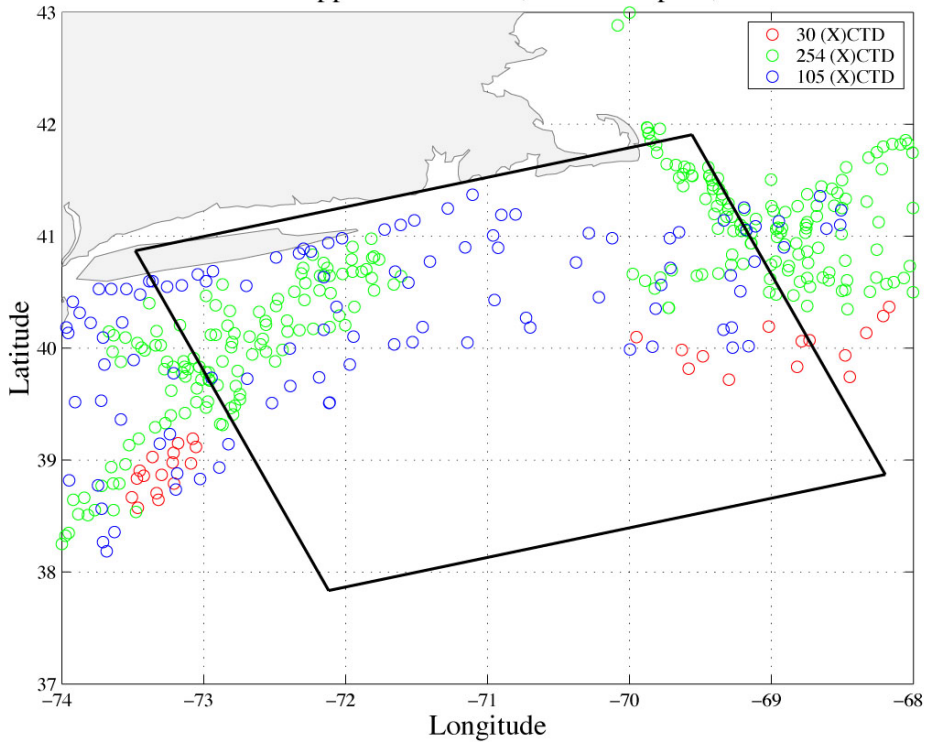


10 m/s

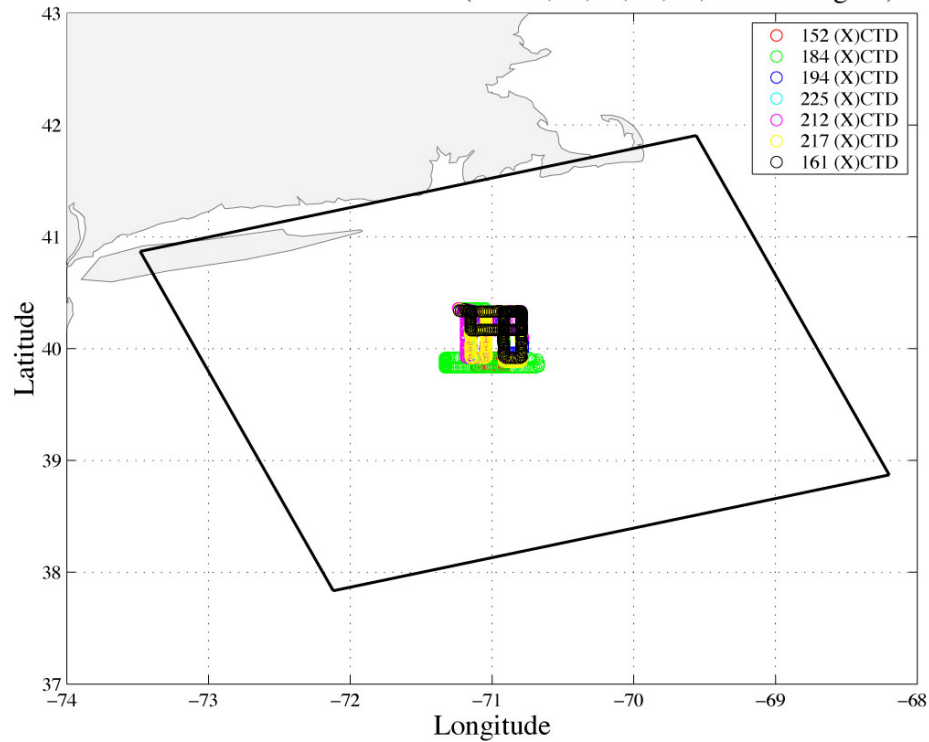
Sources of Uncertainty in Simulations of Ocean Physics

- Bathymetry
- Boundary conditions
 - Surface atmospheric forcing
 - Coastal-estuary and open-boundary fluxes
- Initial conditions
- Ocean physics data
- Model parameters and parameterized processes: sub-grid-scales, turbulence closures, un-resolved processes
 - e.g. tides and internal tides, internal waves and solitons, microstructure and turbulence
- Numerical errors: steep topographies/pressure gradient, non-convergence

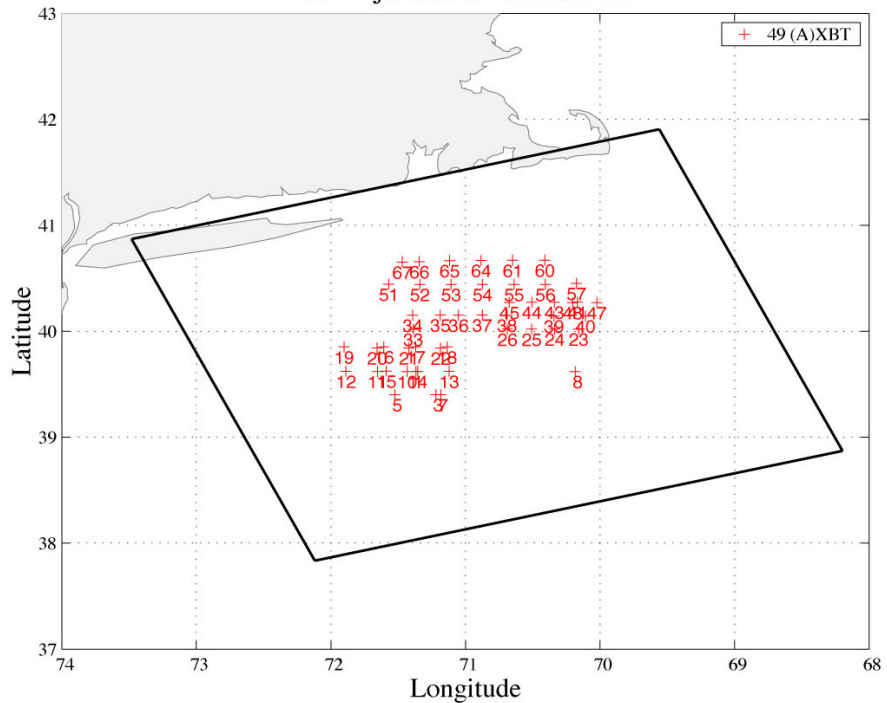
NMFS-supplied CTD data, Jul 1 – Sep 30, 1996



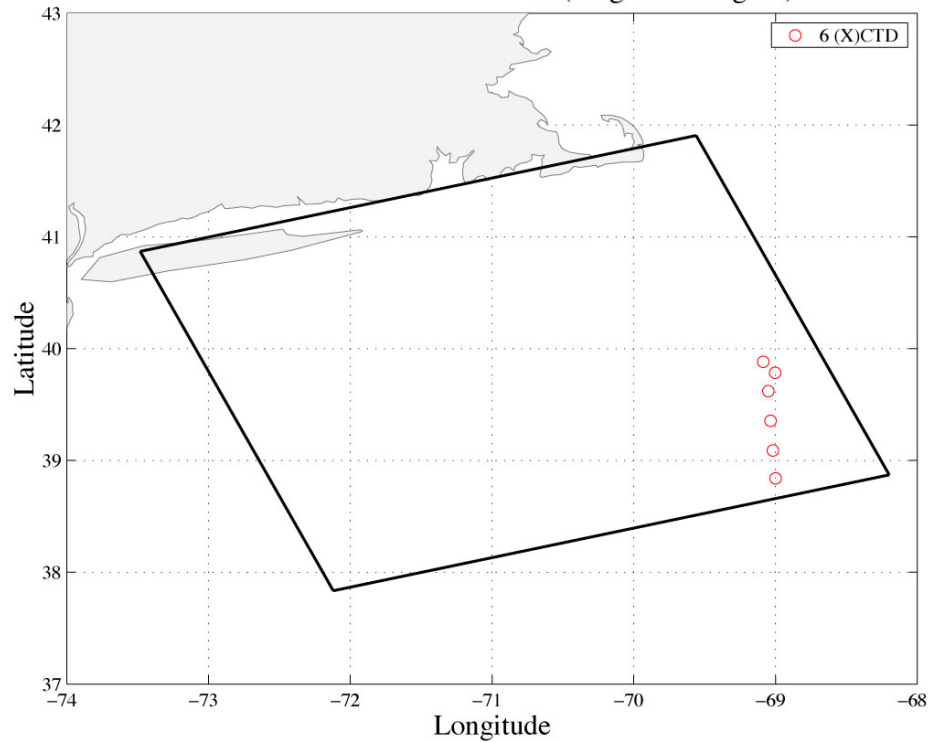
WHOI PRIMER Seasonar data (Jul 26,27,28,29,30,31 and Aug 01)



axbt jul28.1m nodbl.mods

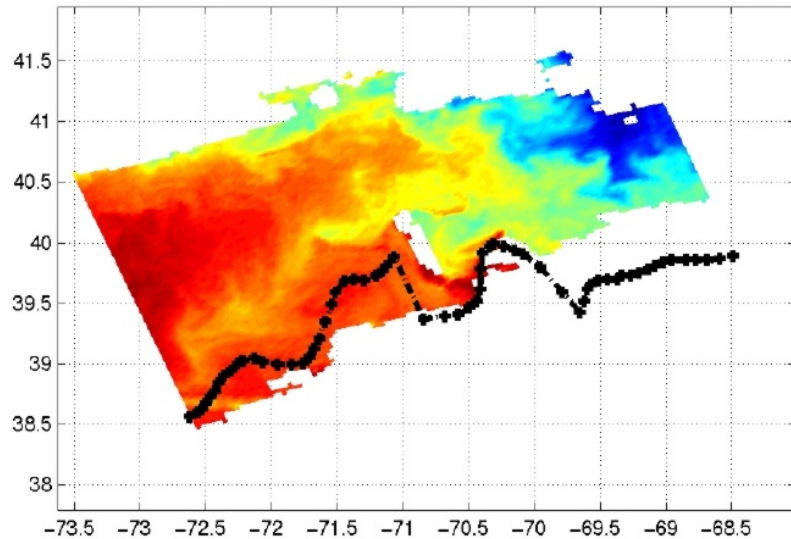


WHOI Cross-shelf CTD data (Aug 05 – Aug 06)

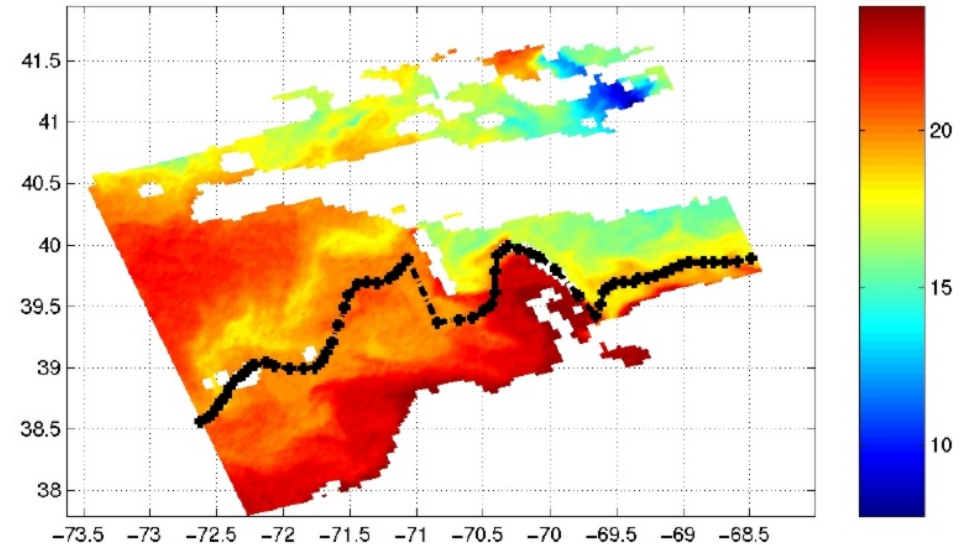


Initial condition uncertainties: Positions and shapes of the tilted shelfbreak front

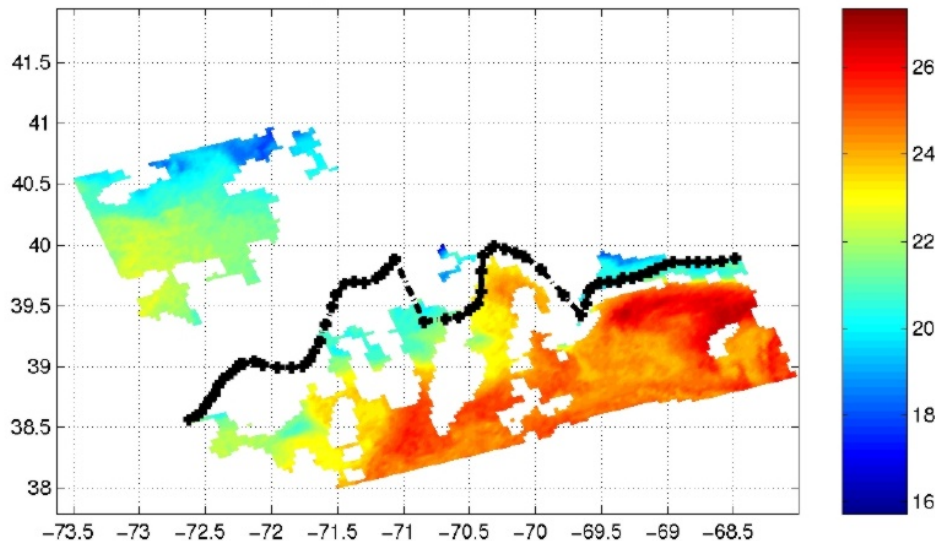
SST snapshot for Jul 6, 18:41 GMT



SST snapshot for Jul 07, 11:41 GMT



SST snapshot for Jul 08, 06:54 GMT

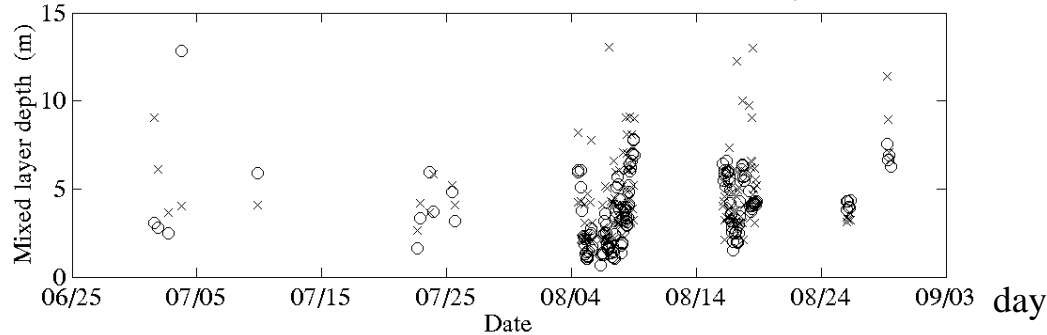


Outcropping of surface front

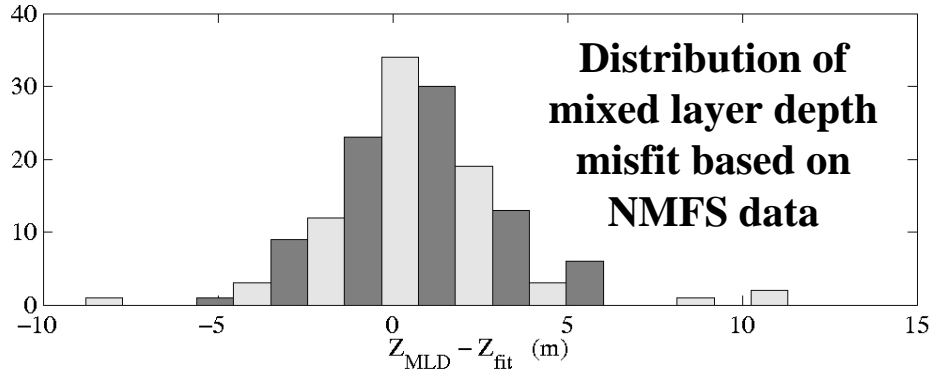
- Upstream positions relatively certain, with sharp ring-front interactions
- Downstream positions very uncertain:
 - Notice surface signature of advected shelf waters
 - SBF meandering and “old” weak warm core rings
 - Squirts of slope and shelf waters

Uncertainties in Multiple Model Parameters: Example of mixing layer depth (Ekman factor E_k)

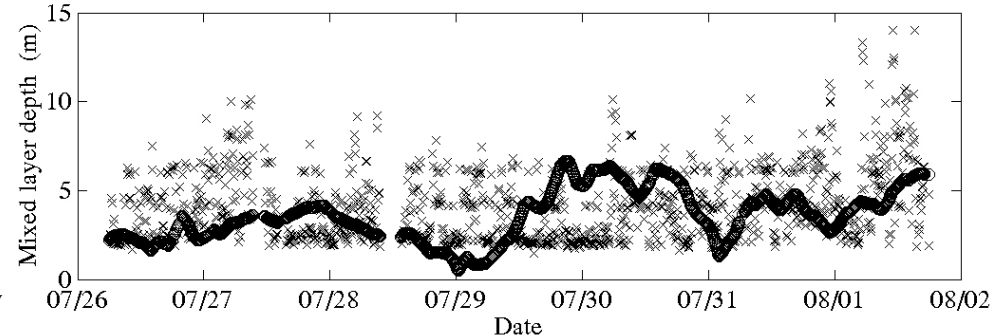
NMFS data + Adjusted Eta 29 fluxes
Fitted Eckman Factor: 0.0977338154 $E_k=0.1$



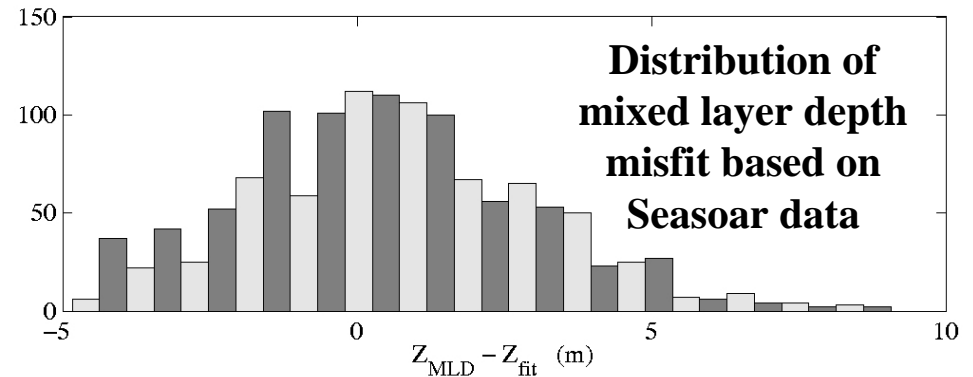
Fitted Eckman Factor: 0.0977338154



Primer3 seasoar data + Adjusted Eta 29 fluxes
Fitted Eckman Factor: 0.0586487083 $E_k=0.06$

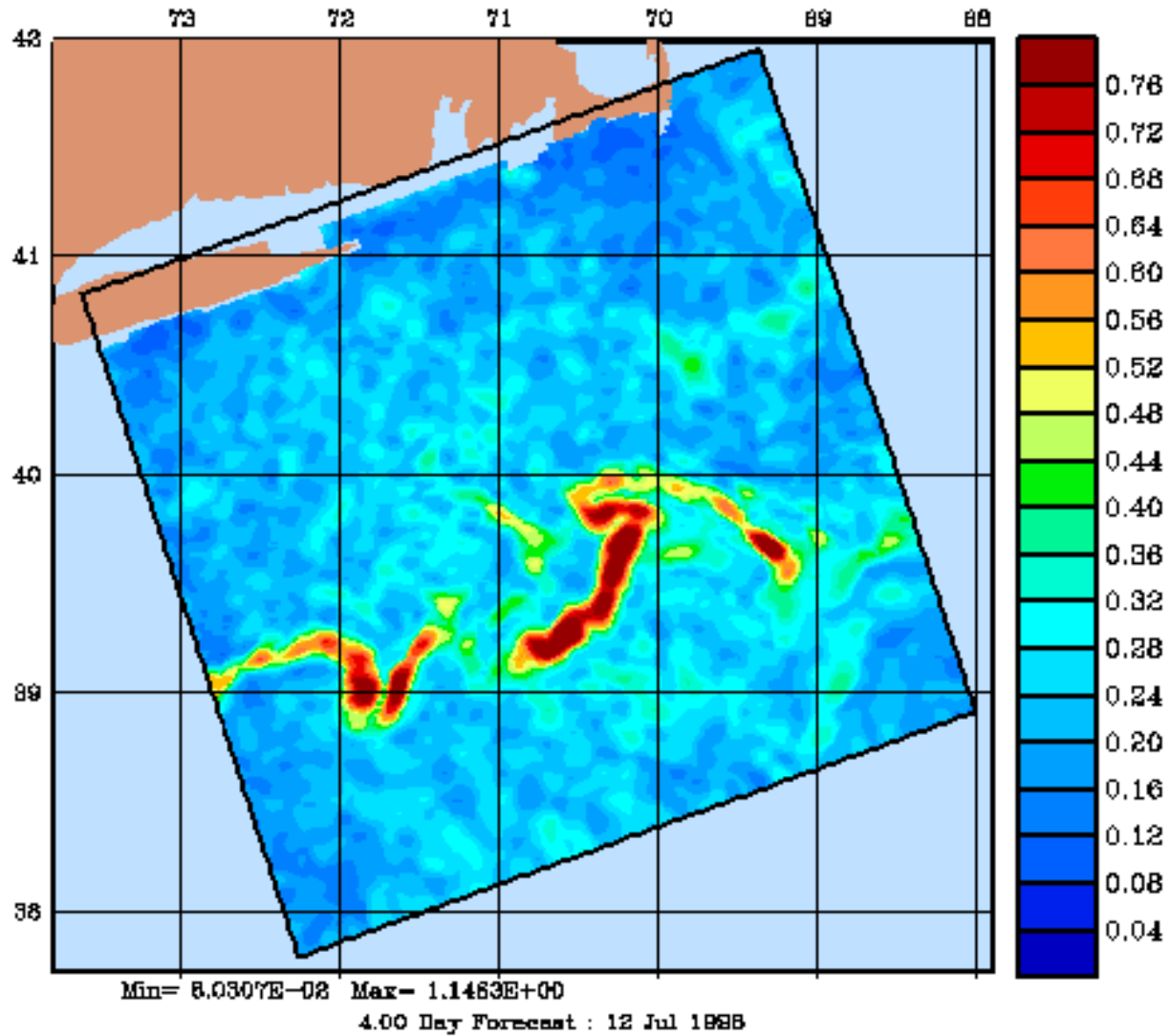


Fitted Eckman Factor: 0.0586487083

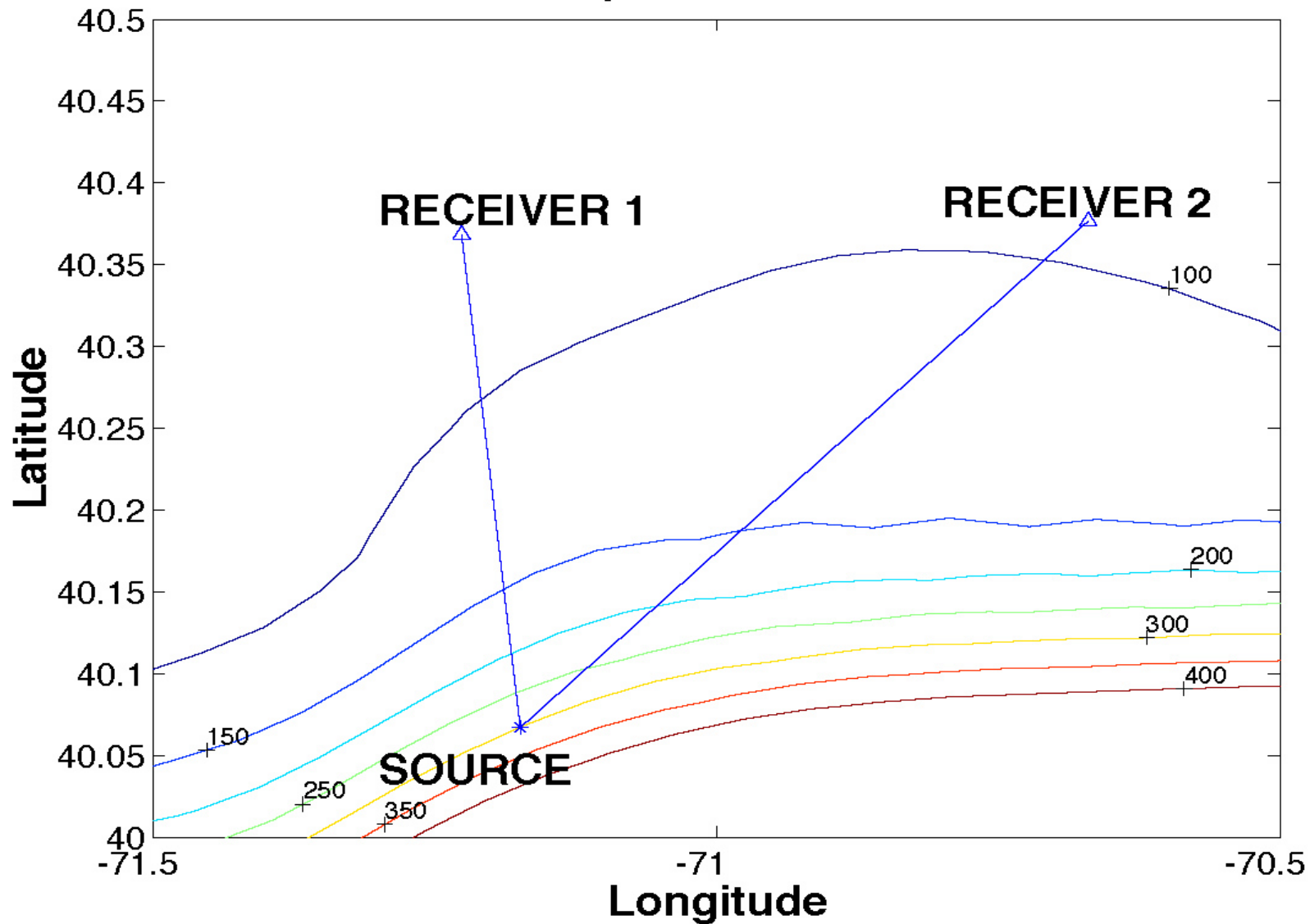


- Similar uncertainties and fit for a few other parameters
- Need for adaptive modeling (e.g. parameter values that evolve in time as a function of data)
- One reason: (sub)-mesoscale coastal variabilities and atmosphere-ocean interactions are not stationary at scales of days to a month

Evolution of Uncertainties: Predicted Standard Deviation of Temperature Error at 10m



Simulation Experiment Acoustic Paths



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 DYNAMICAL MODELS

- Physical model: Primitive-Equation (PDE, x, y, z, t : HOPS)

Horiz. Mom. $\frac{D\mathbf{u}_h}{Dt} + f \mathbf{e}_3 \wedge \mathbf{u}_h = -\frac{1}{\rho_0} \nabla_h p_w + \nabla_h \cdot (A_h \nabla_h \mathbf{u}_h) + \frac{\partial A_v}{\partial z} \frac{\partial \mathbf{u}_h}{\partial z}$ (1-2)

Vert. Mom. $\rho g + \frac{\partial p_w}{\partial z} = 0$ (3)

Thermal en. $\frac{DT}{Dt} = \nabla_h \cdot (K_h \nabla_h T) + \frac{\partial K_v}{\partial z} \frac{\partial T}{\partial z}$ (4)

Cons. of salt $\frac{DS}{Dt} = \nabla_h \cdot (K_h \nabla_h S) + \frac{\partial K_v}{\partial z} \frac{\partial S}{\partial z}$ (5)

Cons. of mass $\nabla \cdot \mathbf{u} = 0$ (6)

Eqn. of state $\rho(\mathbf{r}, z, t) = \rho(T, S, p_w)$ (7)

Sound speed eqn. $c(\mathbf{r}, z, t) = C(T, S, p_w)$ (8)

- Acoustical model: Coupled Normal-Mode model (PDE, f, r, z, t : NPS)

Wave eqn. $\rho c^2(\mathbf{r}, z, t) \nabla \cdot \left(\frac{1}{\rho} \nabla p_s(\mathbf{r}, z, t) \right) = \frac{\partial^2 p_s(\mathbf{r}, z, t)}{\partial t^2}$

Pres. transfer fct. $\nabla^2 P_s - \frac{1}{\rho} \nabla \rho \cdot \nabla P_s + k^2 P_s = -2 \frac{r_0}{r} \delta(r-r_0)(z-z_0)$

where $k \doteq 2\pi f/c(\mathbf{r}, z, t)$ (9)

Coupled With $P_s(r, z; f) \doteq \sum_n \frac{r_0}{\sqrt{r}} P_n(r; f) Z_n(z; r, f)$ (10)

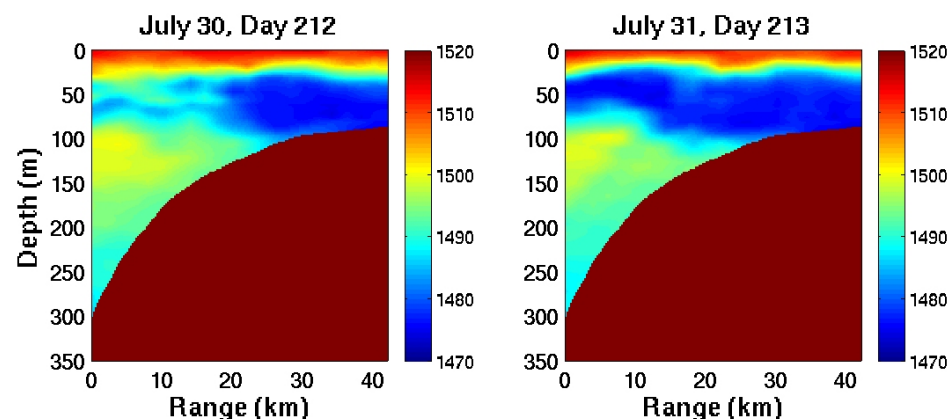
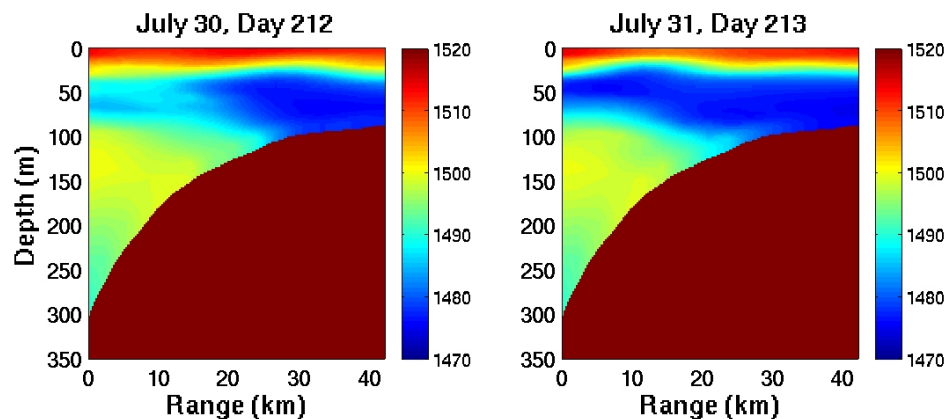
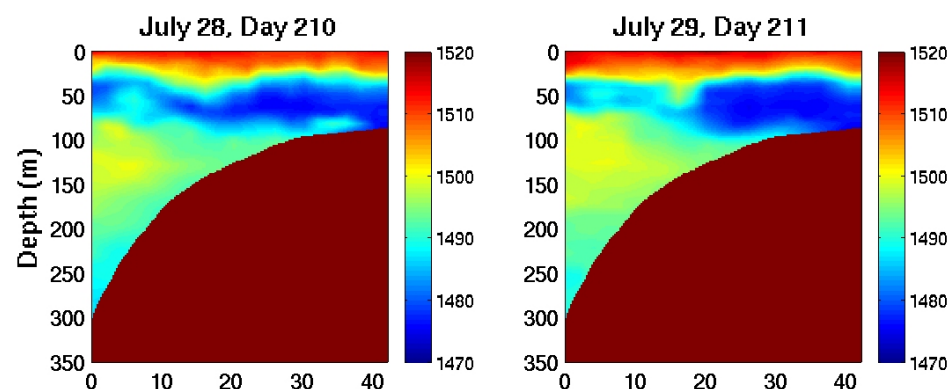
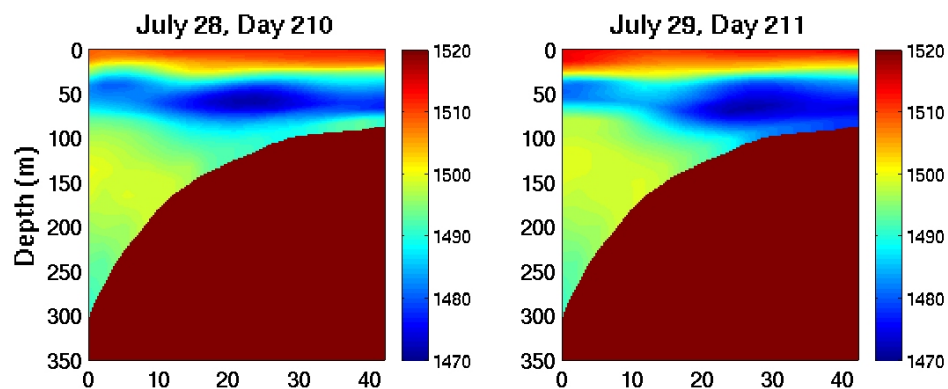
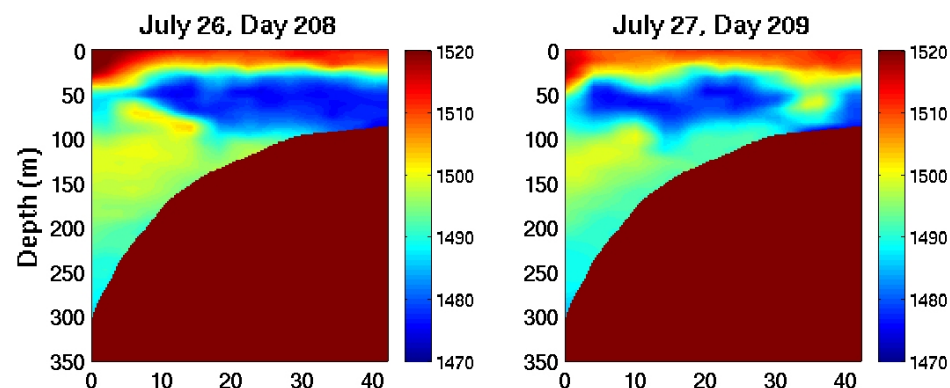
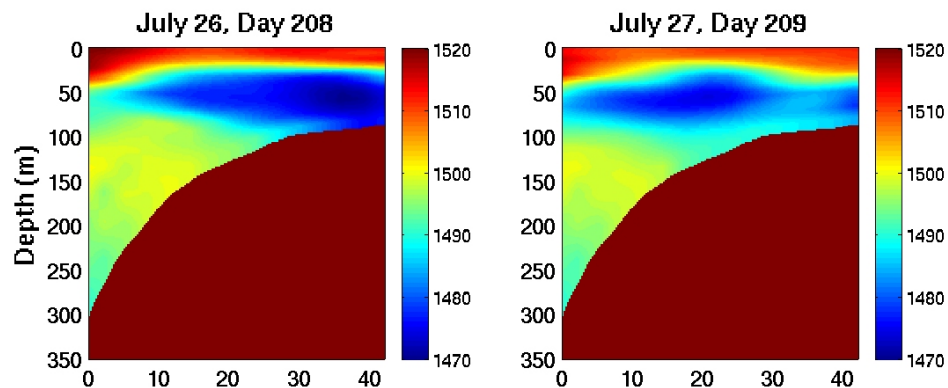
Normal-modes $\left\{ \frac{\partial^2}{\partial z^2} - \frac{1}{\rho(r, z)} \frac{\partial \rho(r, z)}{\partial z} \frac{\partial}{\partial z} + (k(r, z)^2 - k_n(r; f)^2) \right\} \times Z_n(z; r, f) = 0$ (11)

Modal amplit. $\left(\frac{d^2}{dr^2} + k_n^2 \right) P_n = - \sum_m (\gamma_{mn} \frac{d}{dr} + C_{mn}) P_m$ (12)

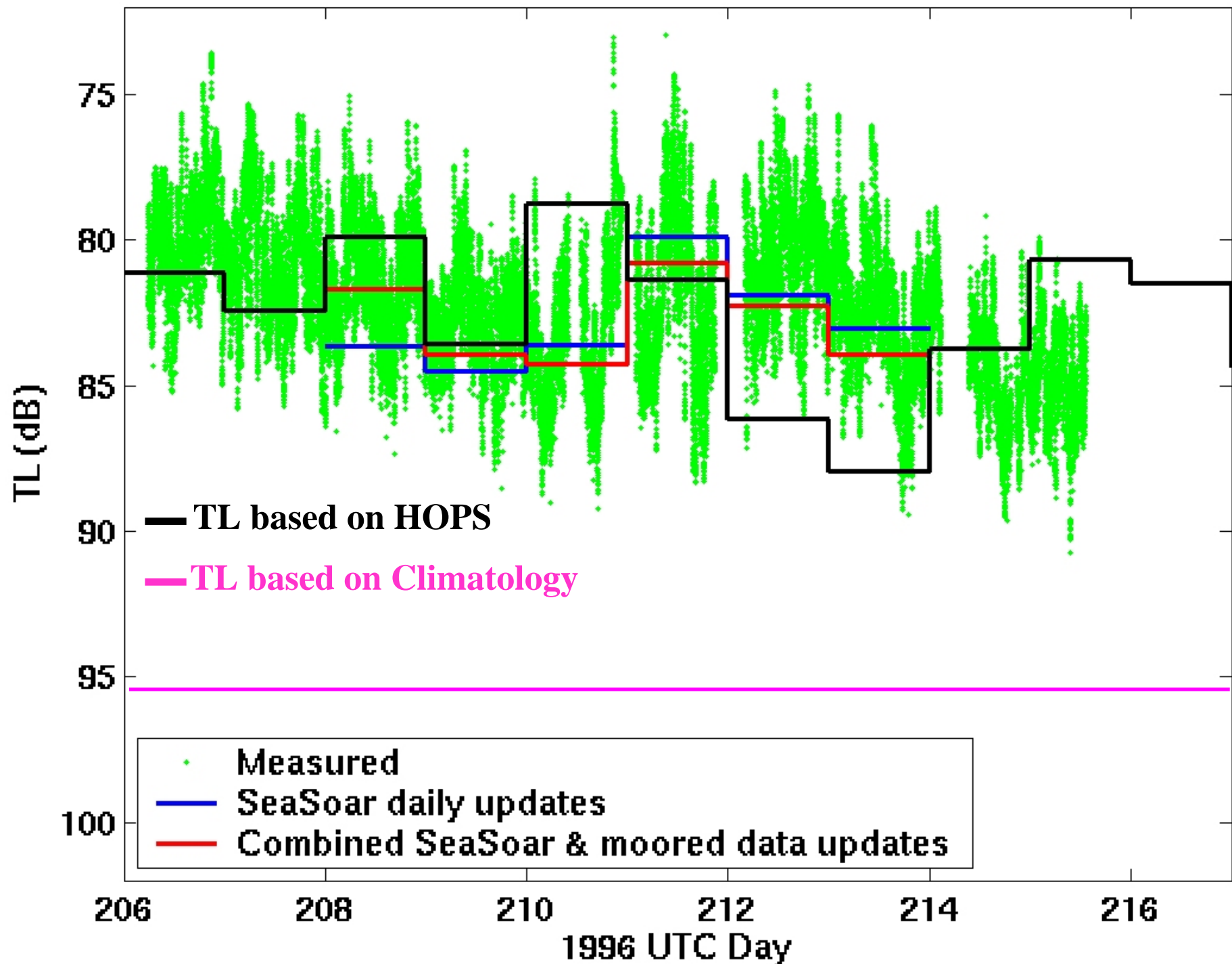
Acoustic Propagation Parameter: HOPS sound-sections at noon time

HOPS sections: 3 km grid (6-10 km scale)

Seasoar + moored data (4 km cor. scale)

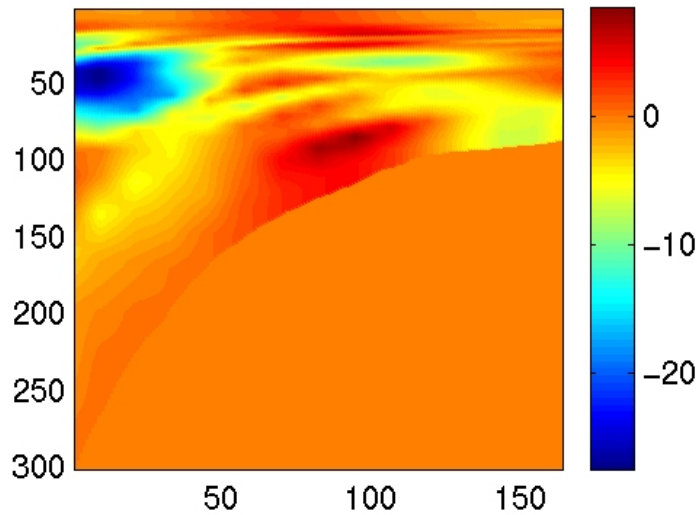


Average of Hydrophones 1 2 3 4

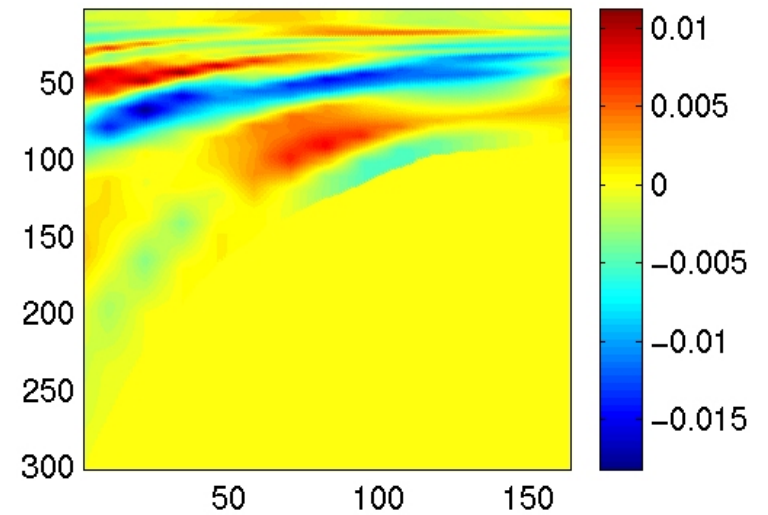


Coupled Physical-Acoustical Data Assimilation of real TL data: Eigenmodes of coupled normalized error covariance on Jul 26

Mode 1: C component

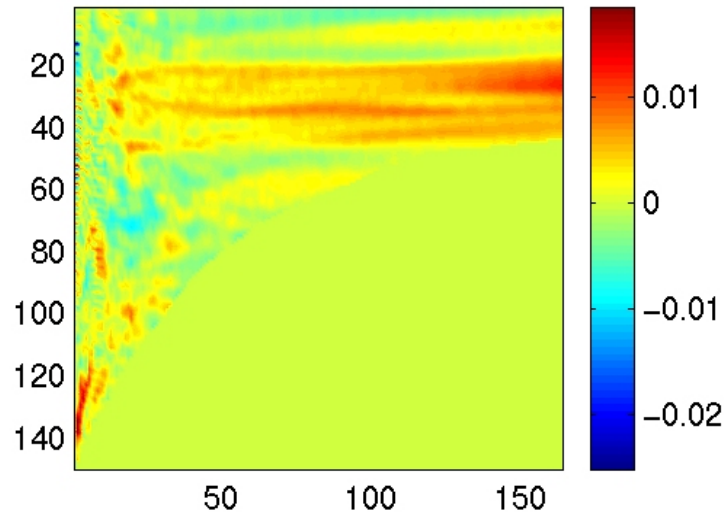


Mode 2: C component



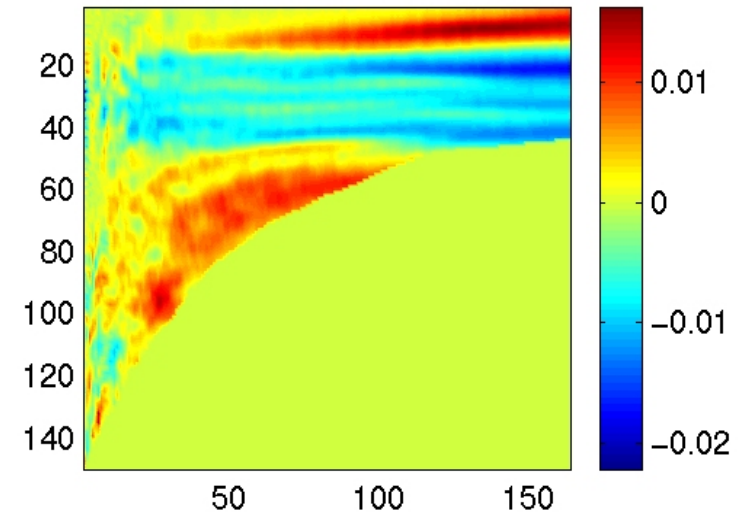
Sound-speed
Component

Mode 1: TL component



Broadband TL
Component

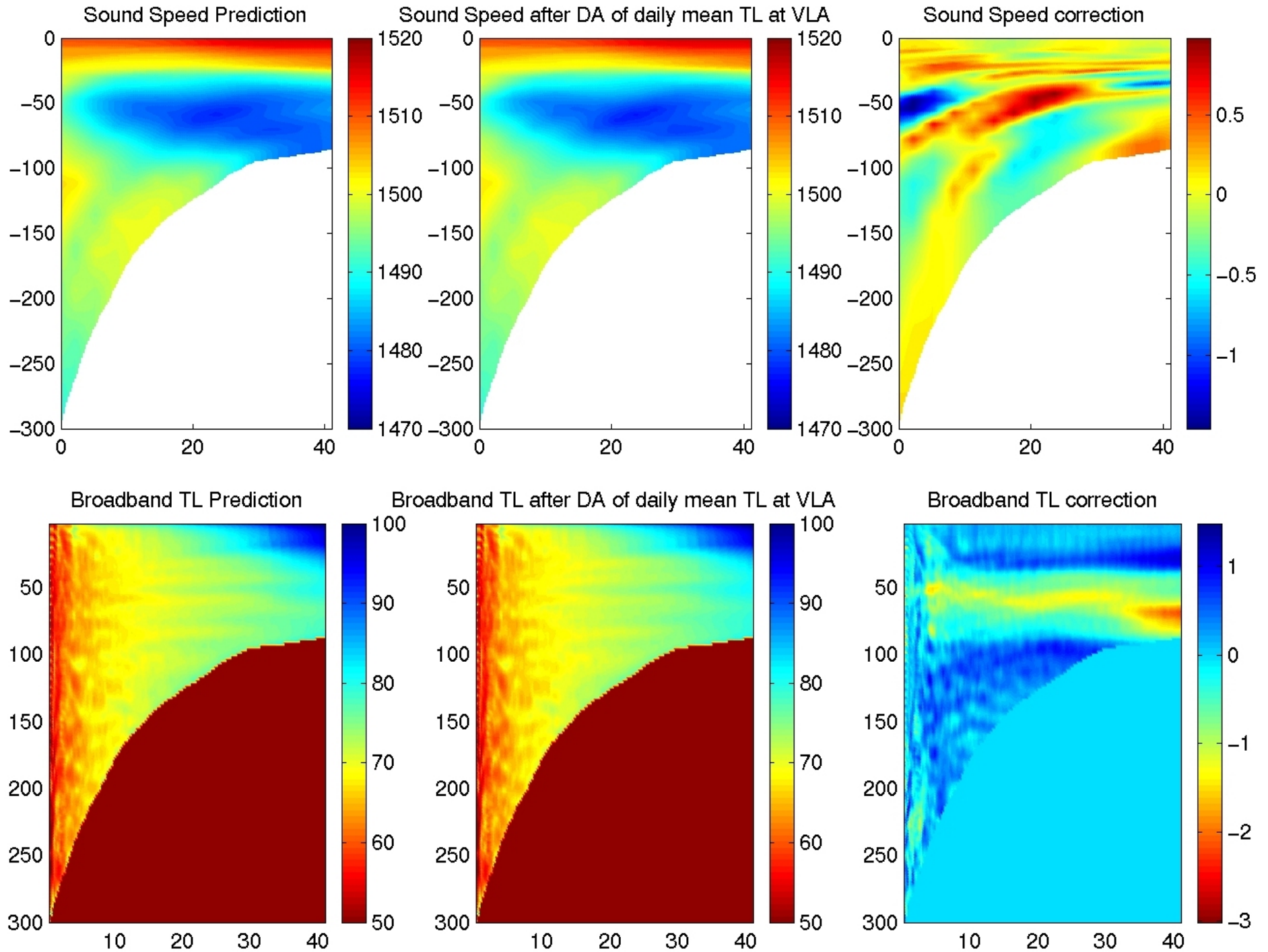
Mode 2: TL component



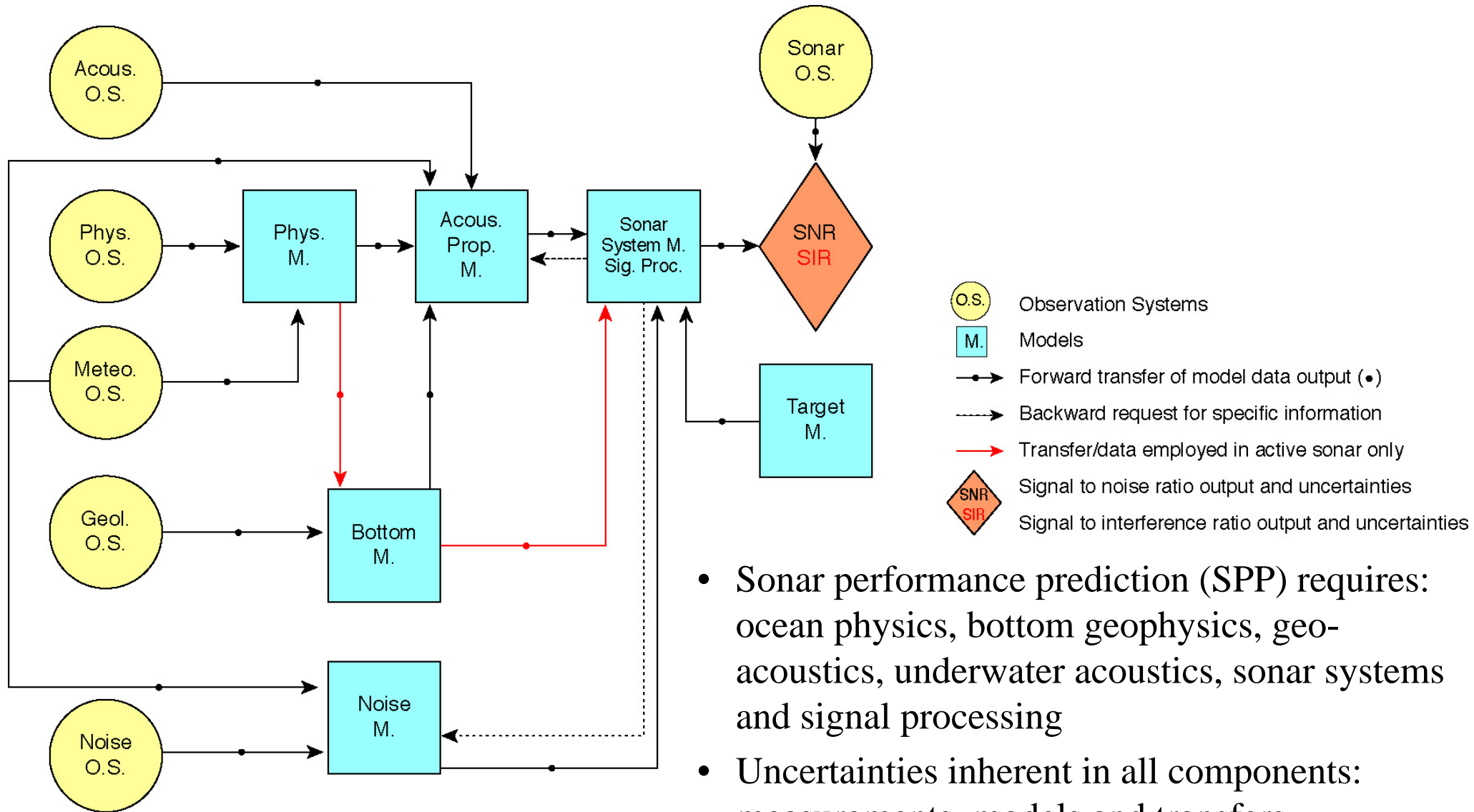
**Shift in frontal shape (meander)
and its acoustic TL counterpart
above source and in cold channel**

**Opposition to mode 1 + surface
thermocline tilt, leading to less (more) loss
in cold channel (surface and bottom duct)**

Coupled Physical-Acoustical Data Assimilation of real TL data



Data-Driven Dynamical End-to-End Systems for Sonar Performance Prediction

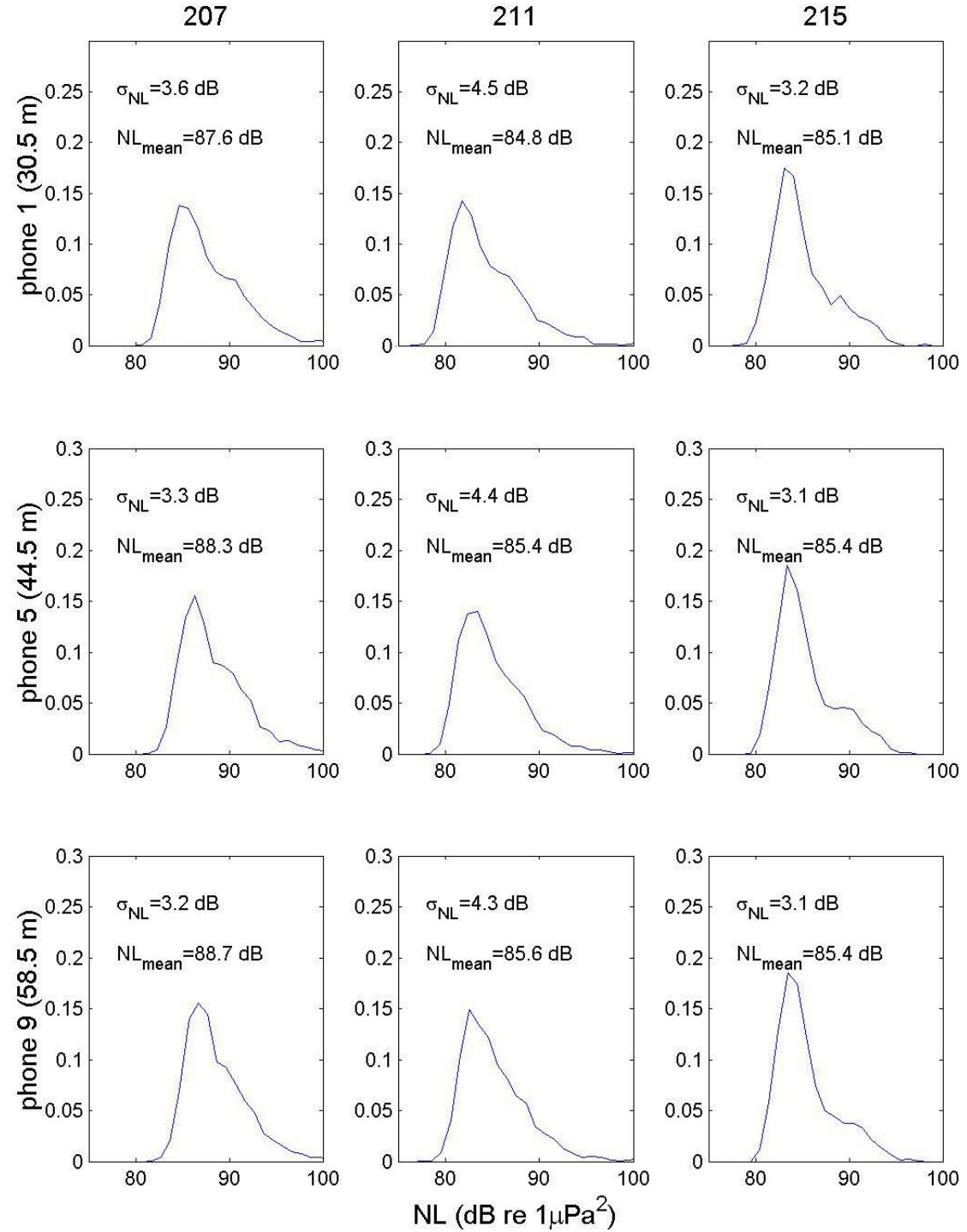


- Sonar performance prediction (SPP) requires: ocean physics, bottom geophysics, geo-acoustics, underwater acoustics, sonar systems and signal processing
- Uncertainties inherent in all components: measurements, models and transfers
- All of them result in uncertainties in SPP itself
- Here, all couplings and transfers accounted for from first principles

Illustration: Simple Passive End-to-End System (physical-geological-acoustical-sonar-noise) for Advanced Uncertainty Sonar Performance Prediction

- Estimated: Broadband TL and its uncertainties (pdf), from source to VLA, with acoustical-physical data assimilation
- Specific passive system:
 - Apply reciprocal principle and assume receiving array at 300m on the slope and estimate performance prediction probability for target on the shelf
 - $SNR = L^T_S - TL^A - L^N_n + AG - 10 \log b - DT$
- Add simple effects of bottom attenuation uncertainty (re-compute TL)
 - Uniform Gaussian: $N(0.5, 0.15)$ dB/m
- Add effects of noise level (pdfs convolution)
 - PRIMER measured ambient noise histograms
- Assume perfectly known (zero uncertainty):
 - Receiver System (array gain, bandwidth and detection threshold)
 - Target Level

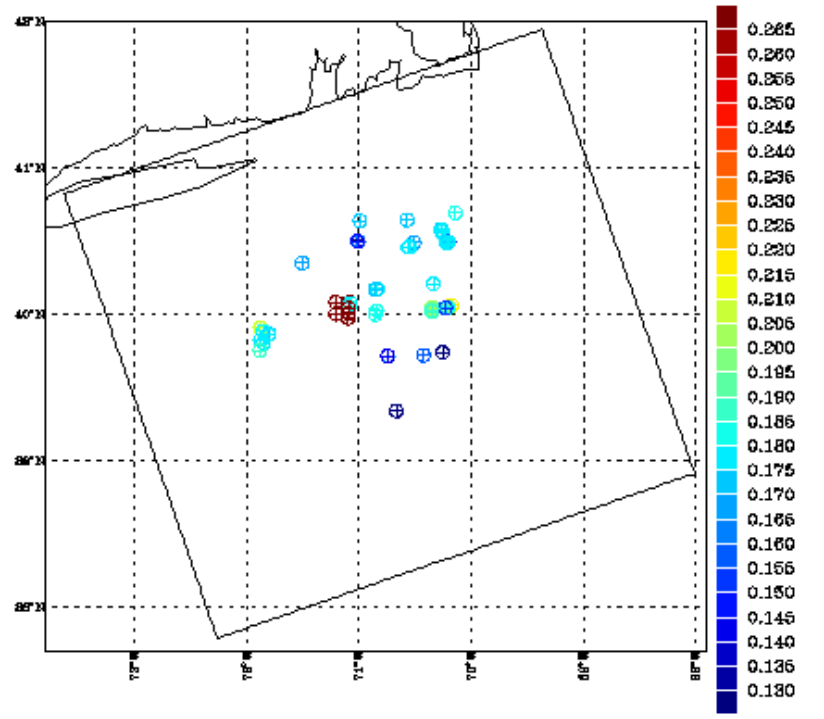
Daily Noise Uncertainty Histograms in the 350-450 Hz band



Sea-Bottom Surface: Attenuation data

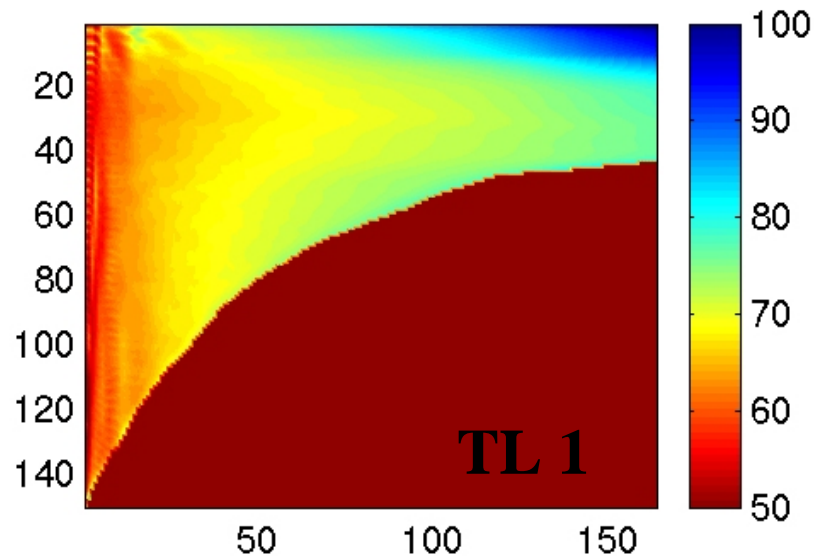


DUKE Data
Bottom attenuation (db/m@1kHz) at 0.0m

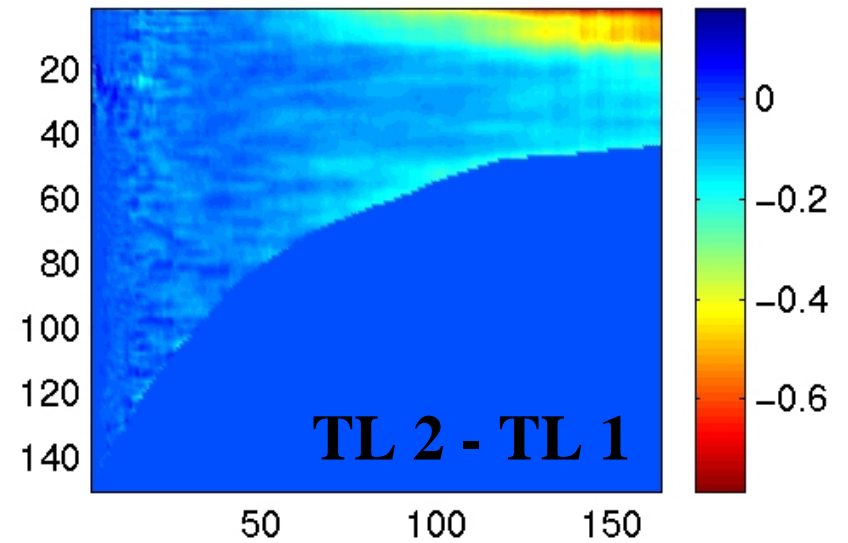


Mean TL (dB), for different seabed atten. coef.

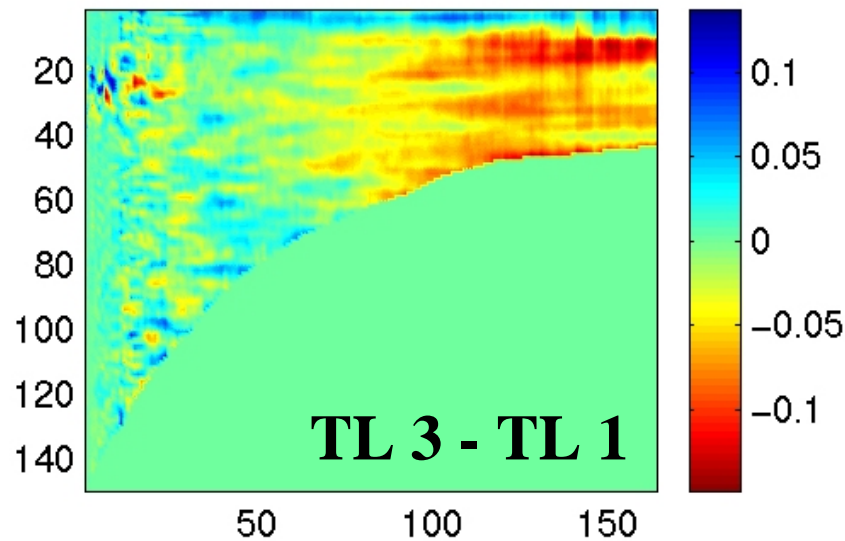
TL 1: fixed bot atten=0.5 dB/m



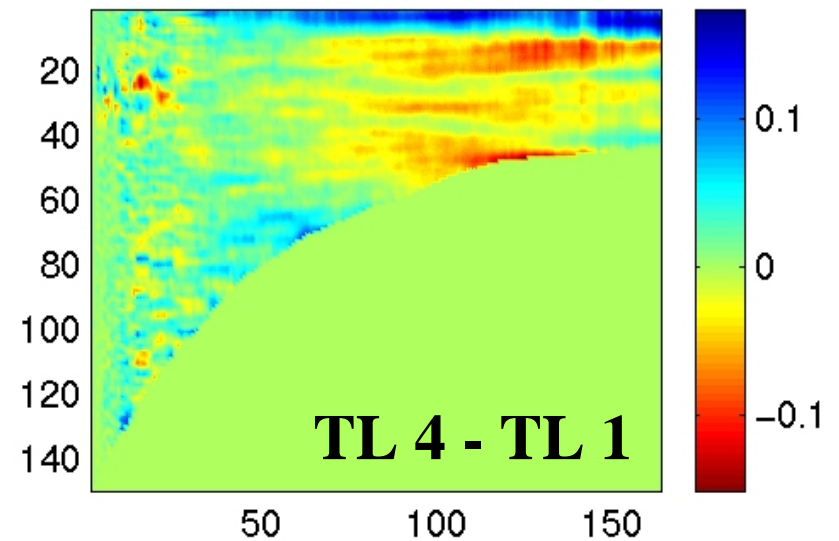
TL 2: with rnd bot. atten., $N(0.5, \sigma=0.15)$ dB/m



TL 3: as 2, but new set of rnd bot. atten. pert.

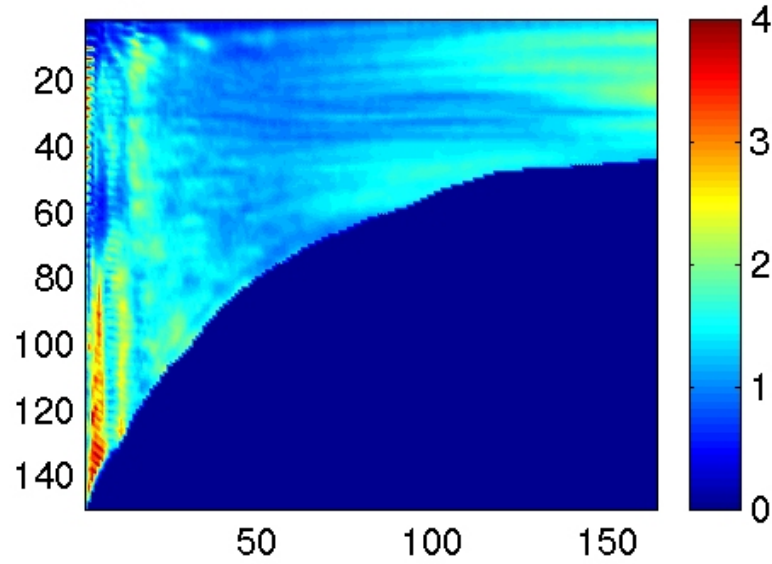


TL 4: as 2, but reversing sign of bot. atten. pert.

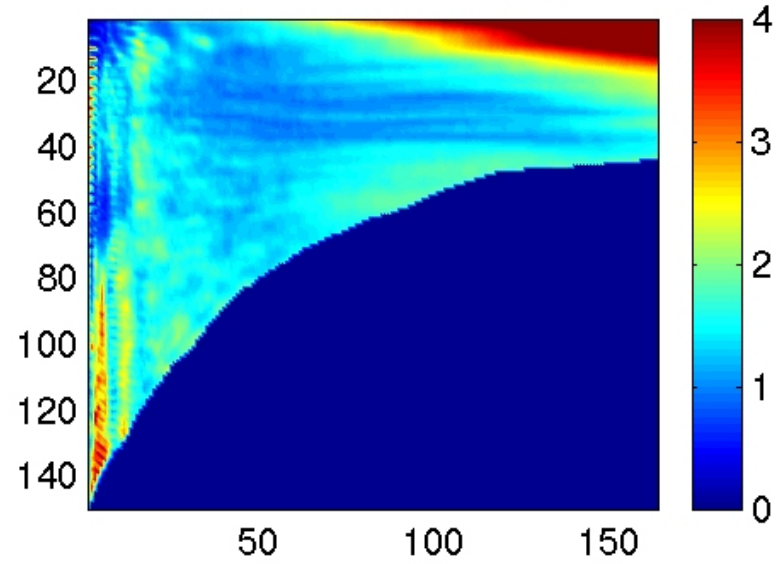


Error Stand. Dev. of TL (dB), for different seabed atten. coef.

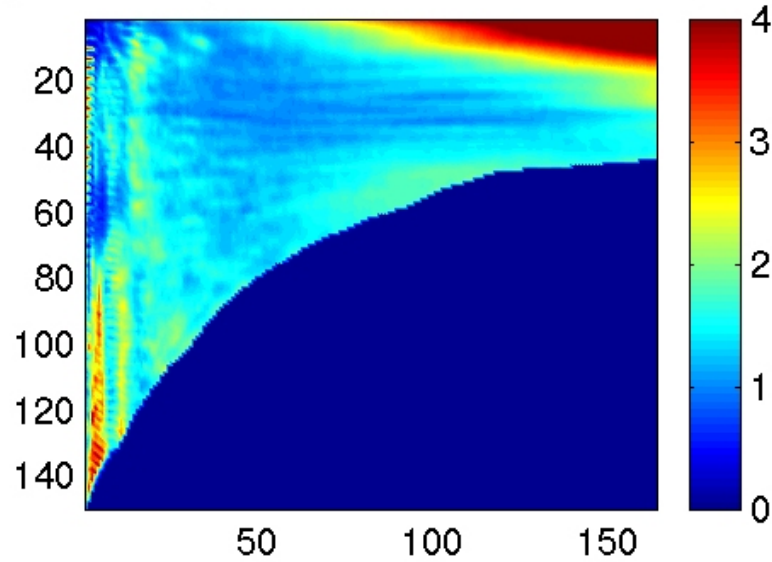
Sig. TL 1: fixed bot atten=0.5 dB/m



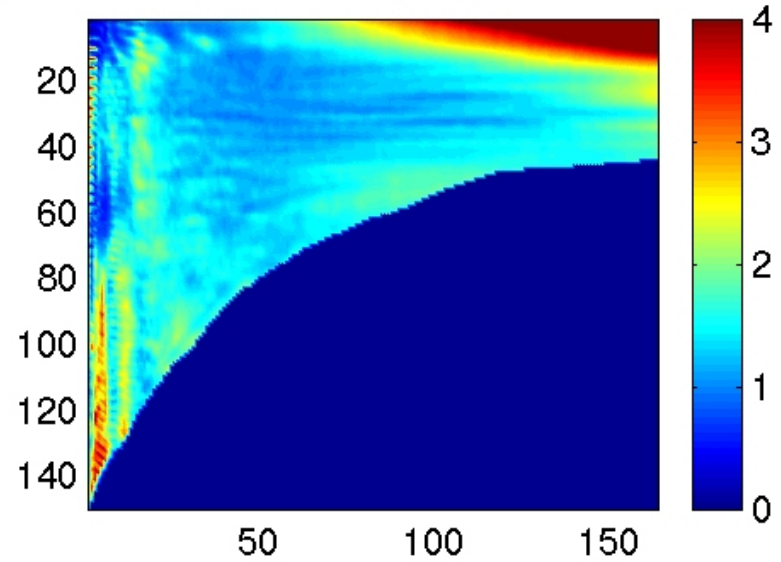
Sig. TL 2: with rnd bot. atten., $N(0.5, \sigma=0.15)$ dB/m



Sig. TL 3: as 2, but new set of rnd bot. atten. pert.

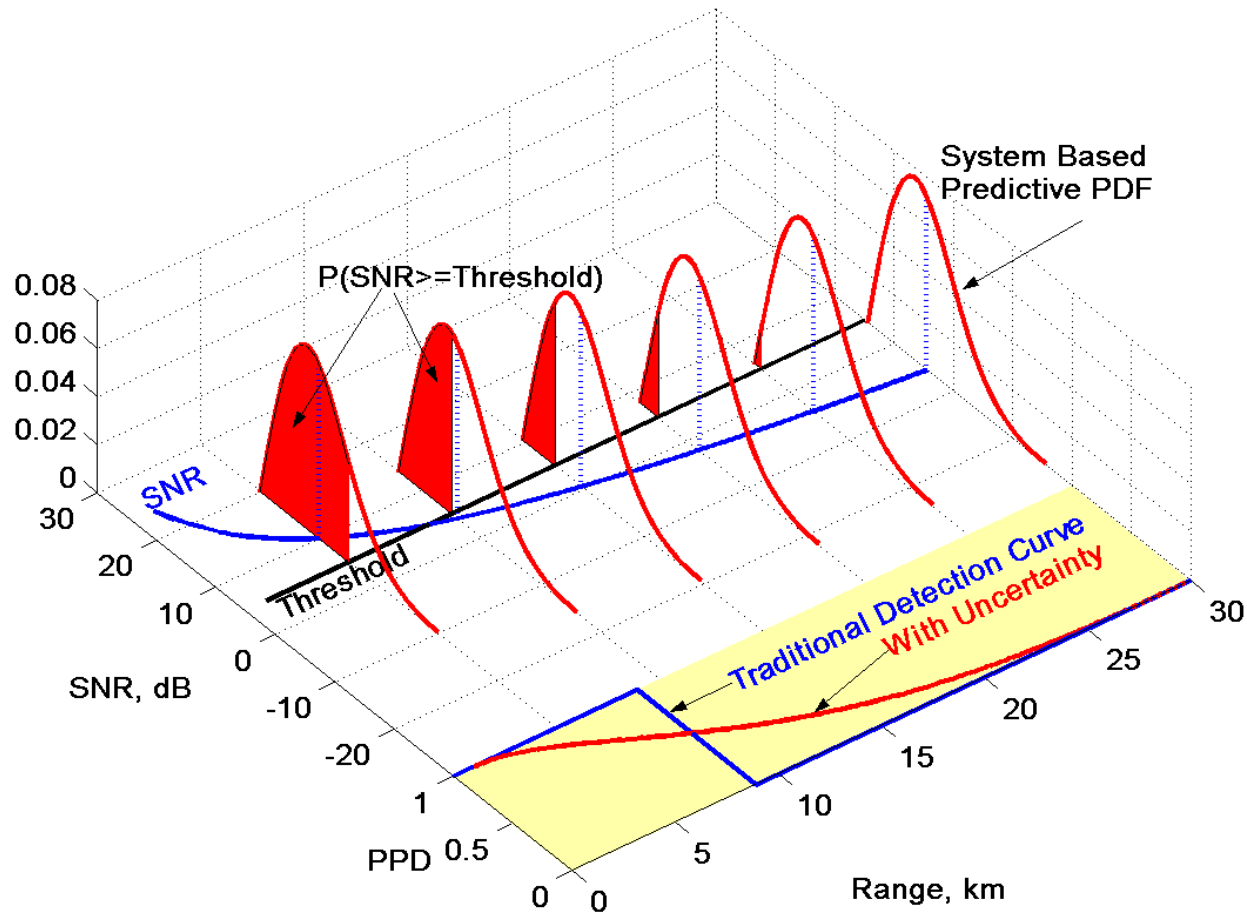


Sig. TL 4: as 2, but reversing sign of bot. atten. pert.



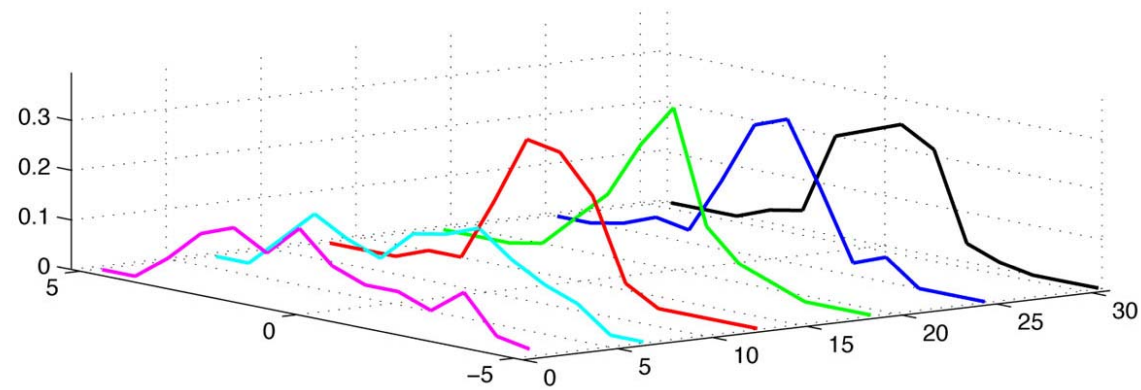
Determination of PPD (Predictive Probability Of Detection) using SIRE-PDF

Systems-based PDF (incorporates environmental and system uncertainty)

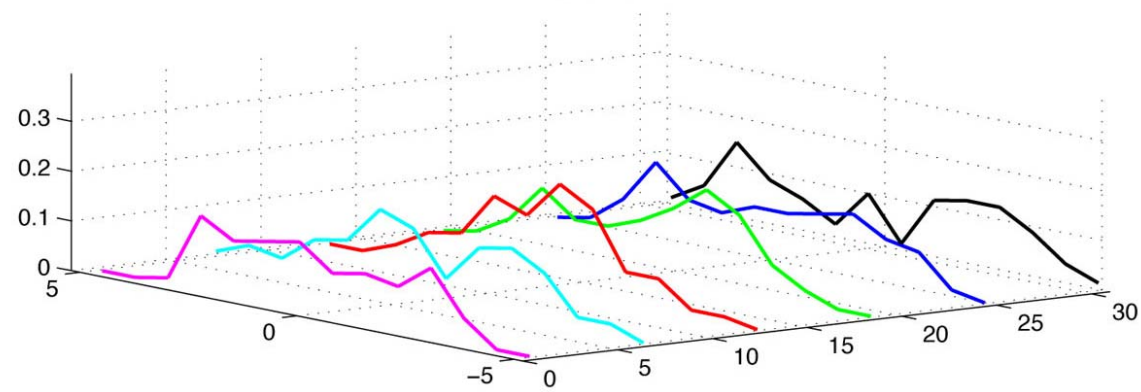


Used by UNITES to characterize and transfer uncertainty from environment through end-to-end problems

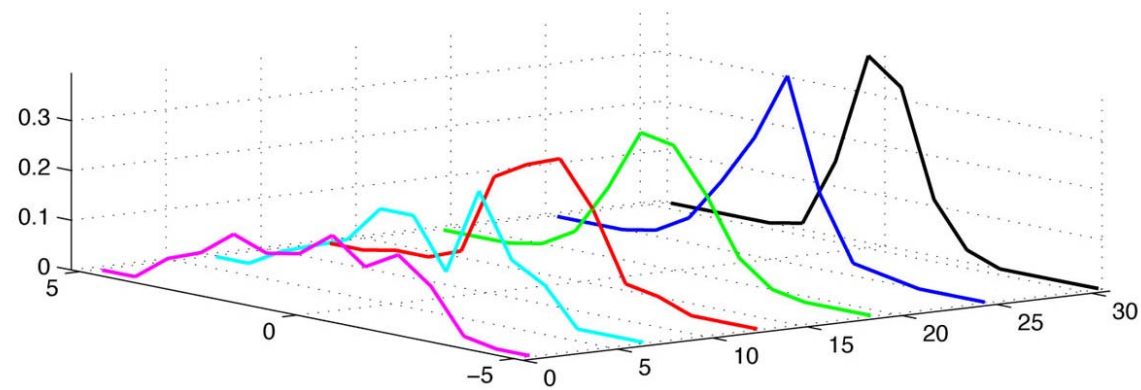
30 (m) depth



55 (m) depth



85 (m) depth

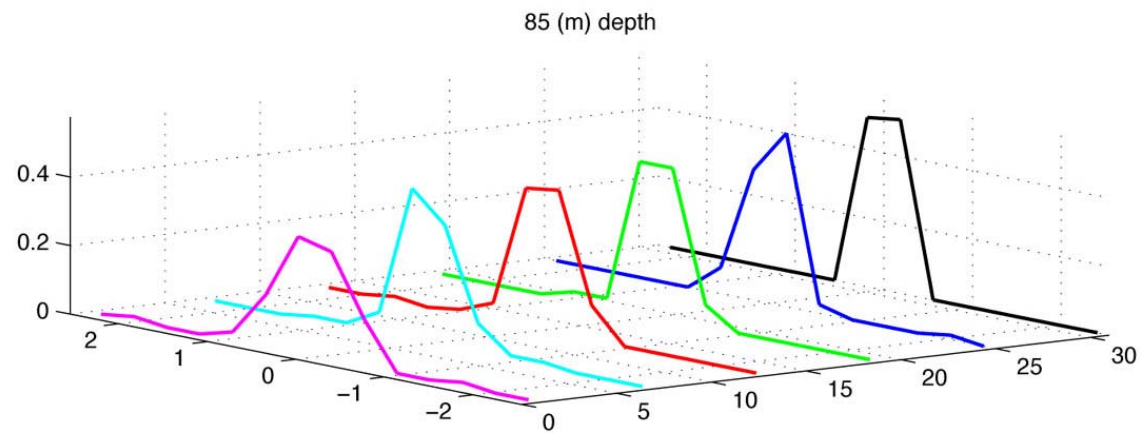
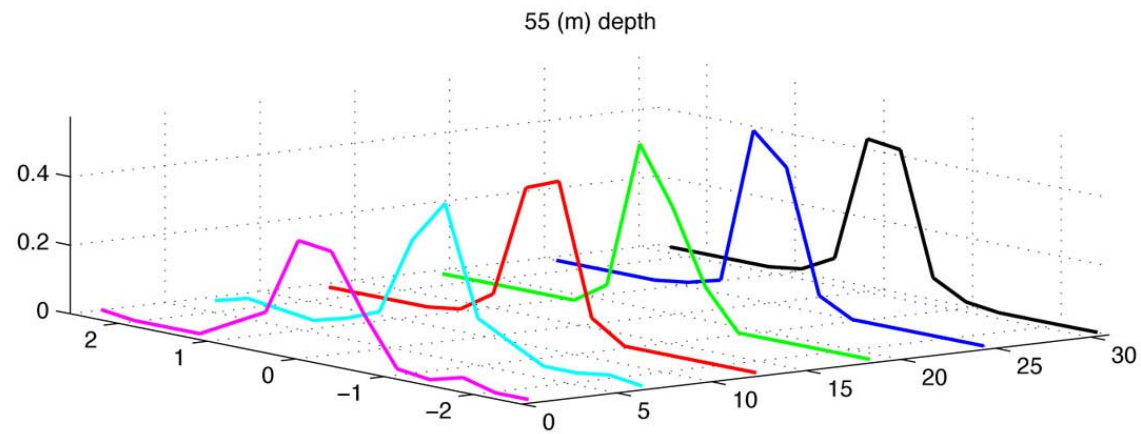
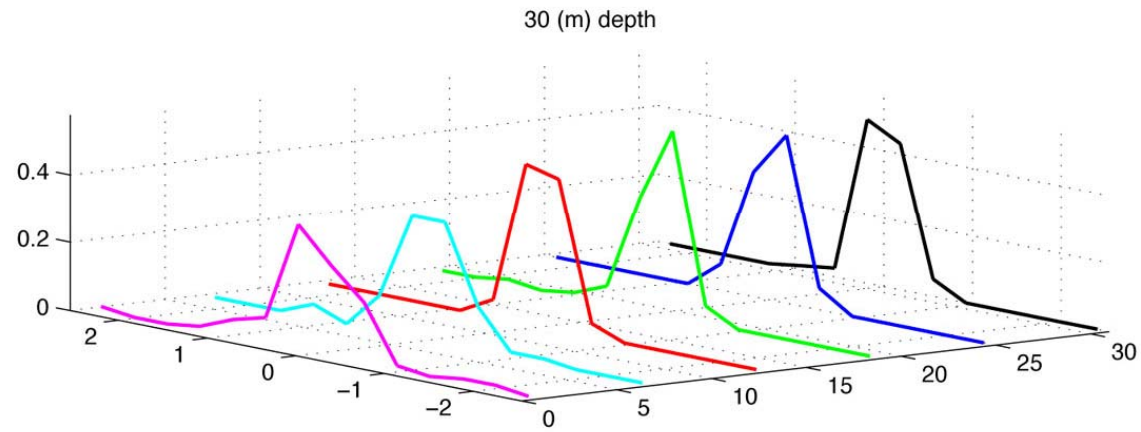


Predicted PDF of broadband TL

TL dev. from mean (db)

Range (km) - Log scale

After Assimilation PDF of broadband TL



TL dev. from mean (db)

Range (km) - Log scale



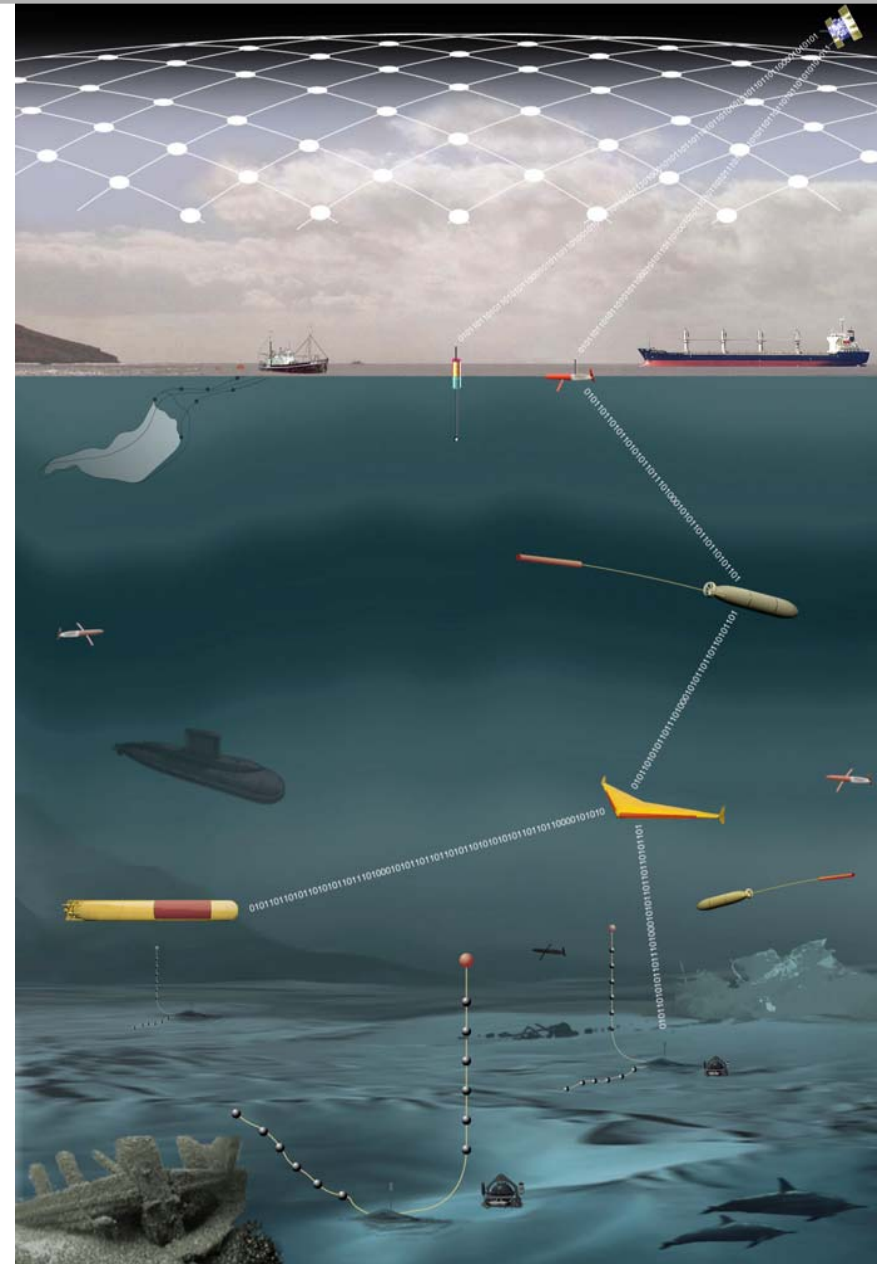
PENNSTATE



Persistent Littoral Undersea Surveillance Network (PLUSNet)

Lead: Kuperman, Schmidt et al.

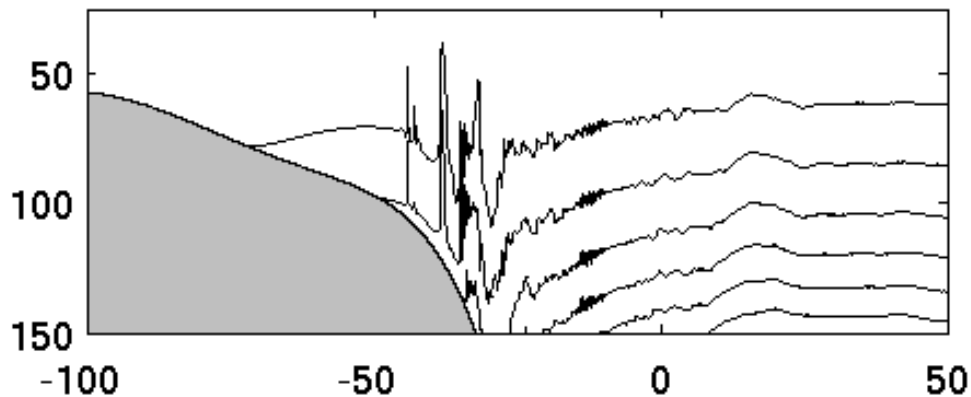
- Distributed network of fixed and mobile sensors
- Coordination via network control architecture and covert communications
- Real time sensing of the tactical and oceanographic environments allows reconfiguring the distributed network of sensors for improved DCL
- Existing and emerging technologies available within the PLUSNet Team enables a system level concept demonstration in three years



PLUSNet: HOPS and ESSE innovations

1. Non-Hydrostatic and Multi-Scale Nested Ocean Modeling

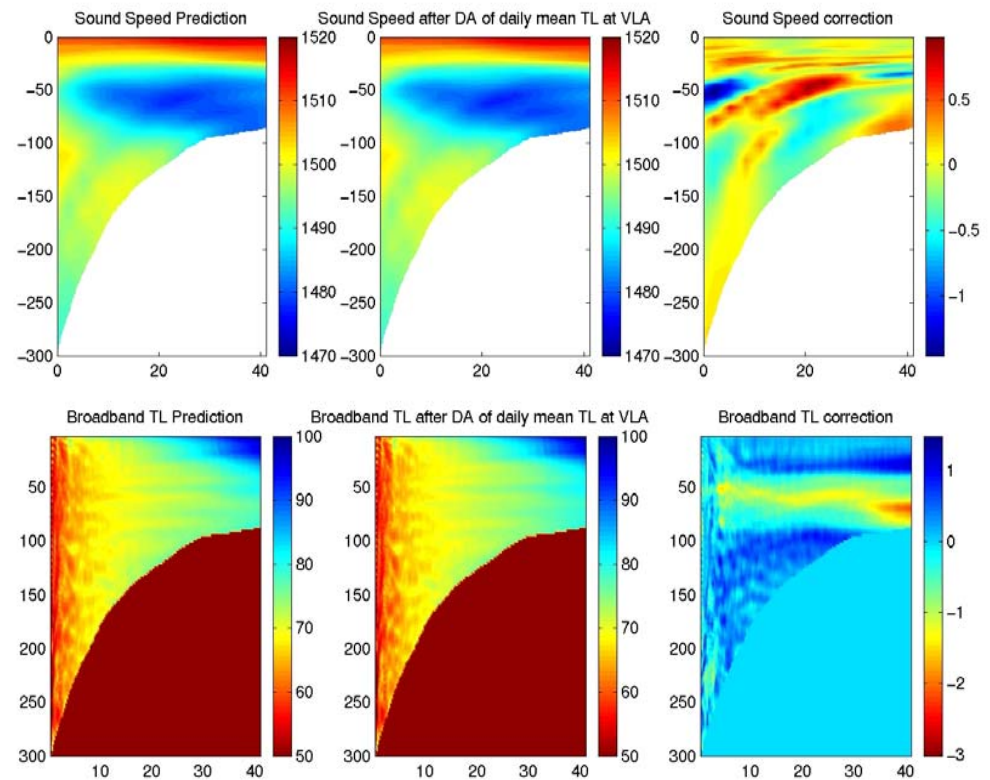
- Develop relocatable sub-mesoscale nested modeling capability:
 - Higher-resolution hydrostatic model (Mini-HOPS)
 - HOPS coupled with non-hydrostatic models (2D to 3D, e.g. Lamb, Smolarkiewicz or MIT-GCM)
- Compare parameterisations of sub-mesoscales and boundary layers, and evaluate with HOPS and ROMS (run at HU)
- Couple mini-HOPS and ESSE with sonar performance prediction



Density cross-section with internal waves and solitons using 2.5D non-hydrostatic Lamb model (HU collaborating with A. Warn-Varnas)

2. Coupled Physical-Acoustical Data Assimilation in real-time

- Integrate and optimise physical-acoustical DA software with Mini-HOPS and AREA
- Initiate coupled physical-acoustical-seabed DA

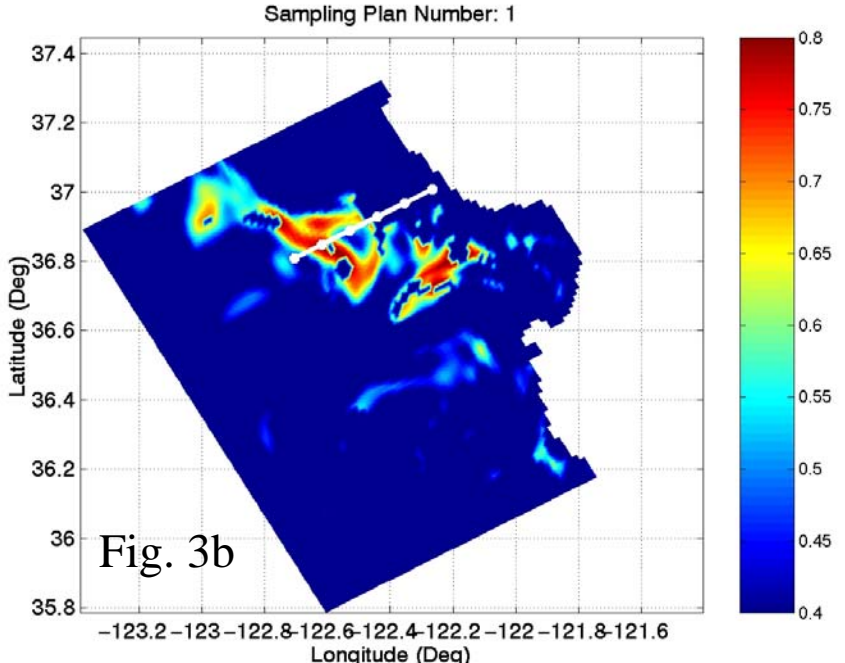
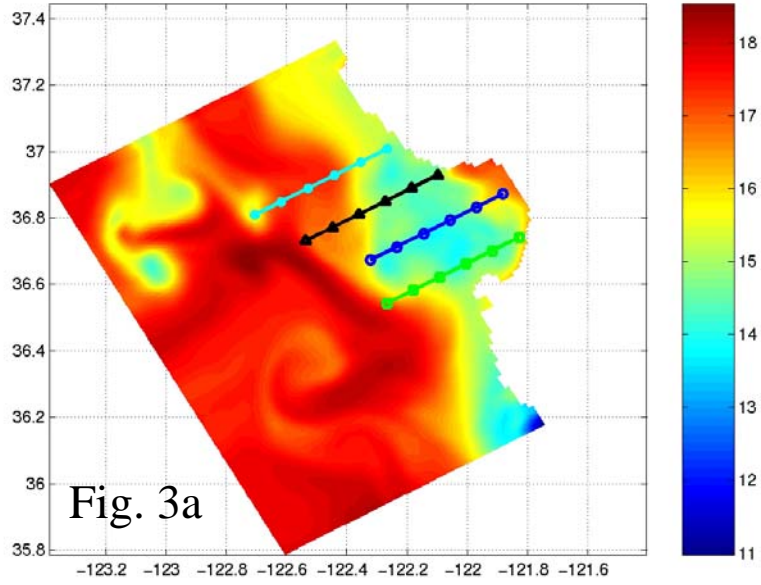
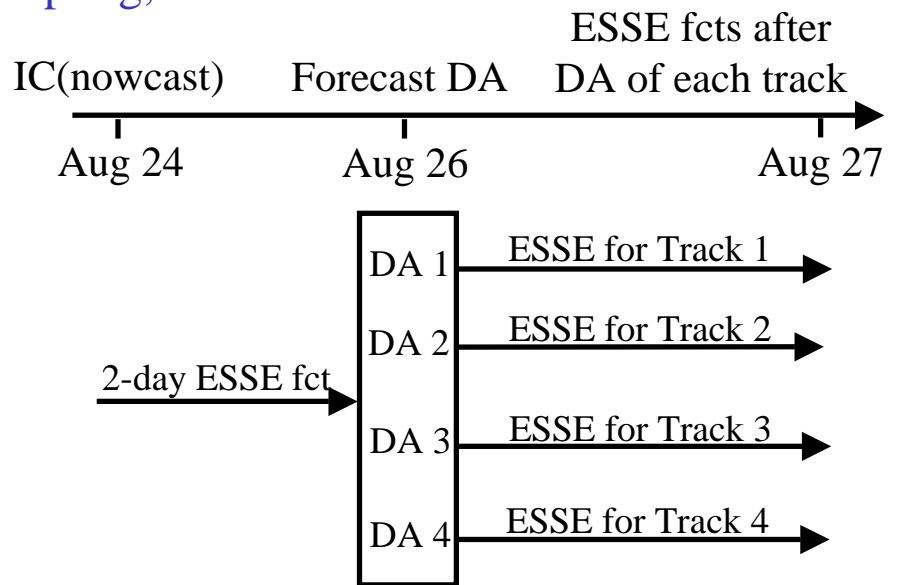


C and TL, before and after coupled DA of real data

3. Acoustical-Physical Nonlinear Adaptive Sampling with ESSE and AREA

- Implement and progressively demonstrate in FY05-06-07 experiments an automated adaptive environmental sampling, integrating mini-HOPS/ESSE with AREA

Example: Which of the 4 sampling tracks for tomorrow (see Fig. 3a below) will optimally reduce uncertainties the day after tomorrow?

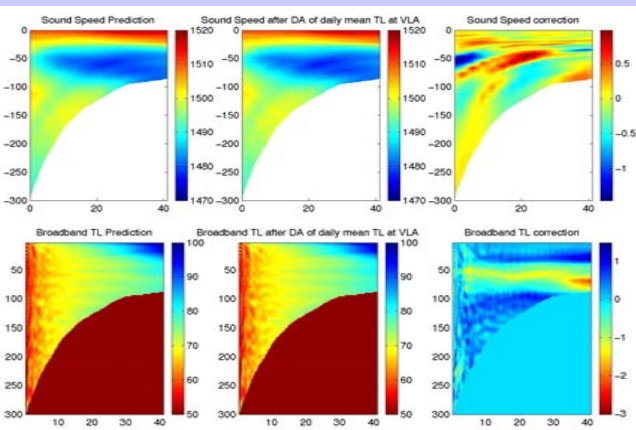
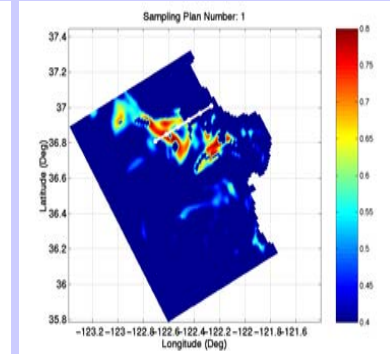
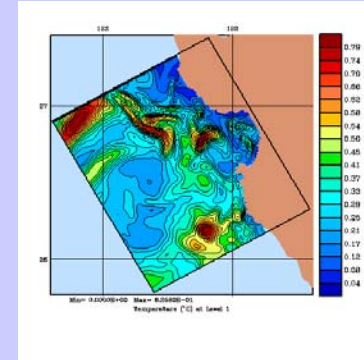


Use HOPS/ESSE and compute average error reduction over domain of interest. For full domain, best error reduction here (see Fig 3b on the right) is with Track 1

CONCLUSIONS for upcoming MREA-NURC exercises

- ESSE powerful nonlinear scheme for interdisciplinary estimation of state variables and error fields via multivariate environmental-acoustical DA

- AOSN-II: Real-time Consistent Error Forecasting, Data Assimilation and Quantitative Adaptive Sampling in Monterey Bay via ESSE for 1 month



- PRIMER: Environmental-acoustical uncertainty estimated and transferred, Acoustical-physical DA and End-to-end (physical-geological-acoustical-sonar-noise) system for advanced sonar performance prediction via ESSE

- Entering a new era of fully interdisciplinary oceanic dynamical system science, with novel and challenging opportunities for
 - PLUSNet, MREA-NURC exercises
 - Acoustical-physical-geological-noise-sonar multi-scale dynamical systems
 - Quantitative assimilation feedbacks, e.g. via Adaptive (Bayesian) estimation/learning

