Prediction Systems With Data Assimilation For Coupled Ocean Science And Ocean Acoustics

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- Introduction
- An End-to-End System: Physical-Geological-Acoustical-Signal Processing-Sonar System
- Interdisciplinary Data Assimilation
- An End-to-End Example – Shelfbreak PRIMER
- Concluding Remarks

Collaborators: Phillip Abbot (OASIS, Inc.), Ching-Sang Chiu (NPS, Monterey), Wayne Leslie and Pat Haley (Harvard)

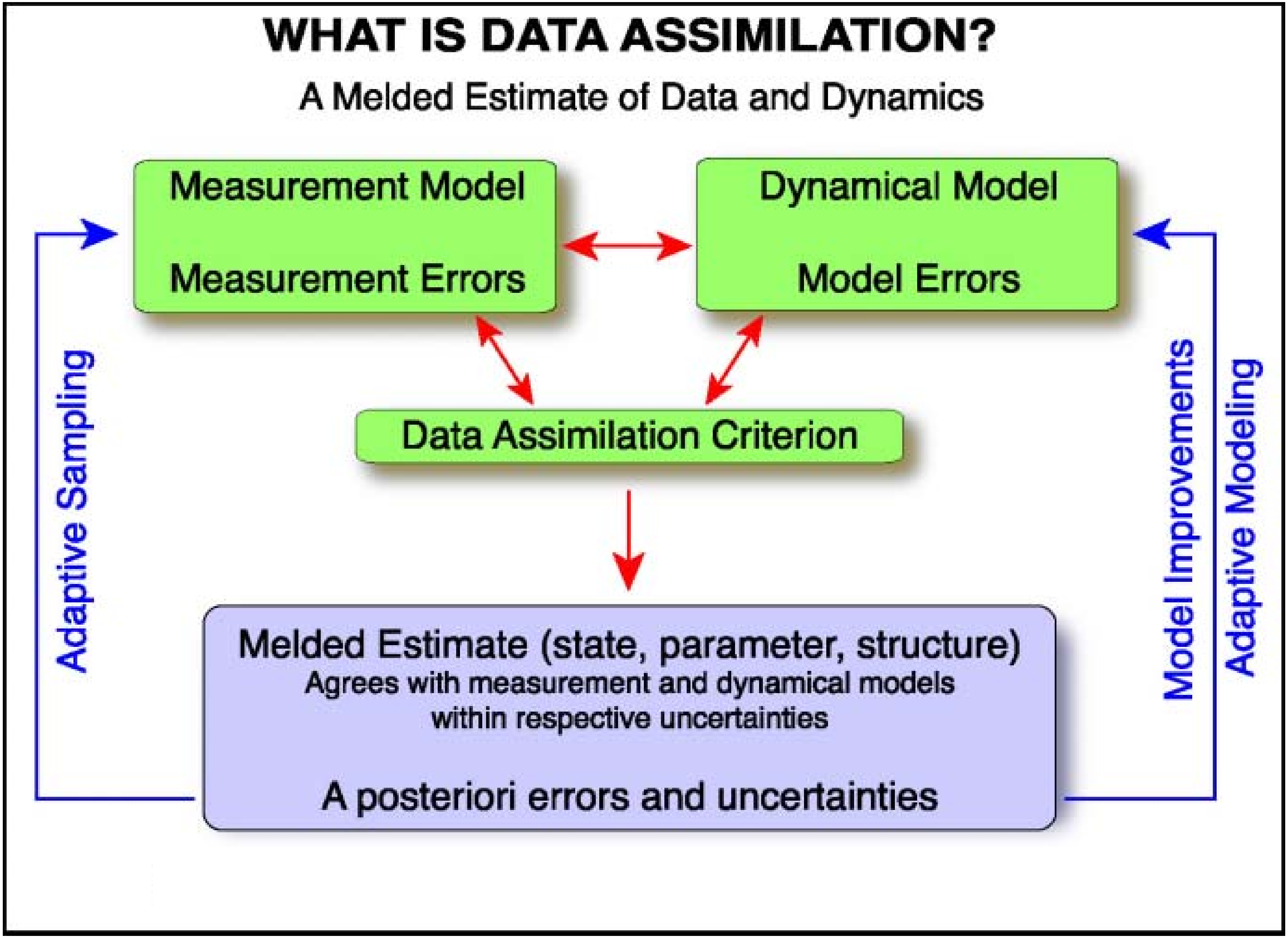
Interdisciplinary Ocean Science Today

- **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**

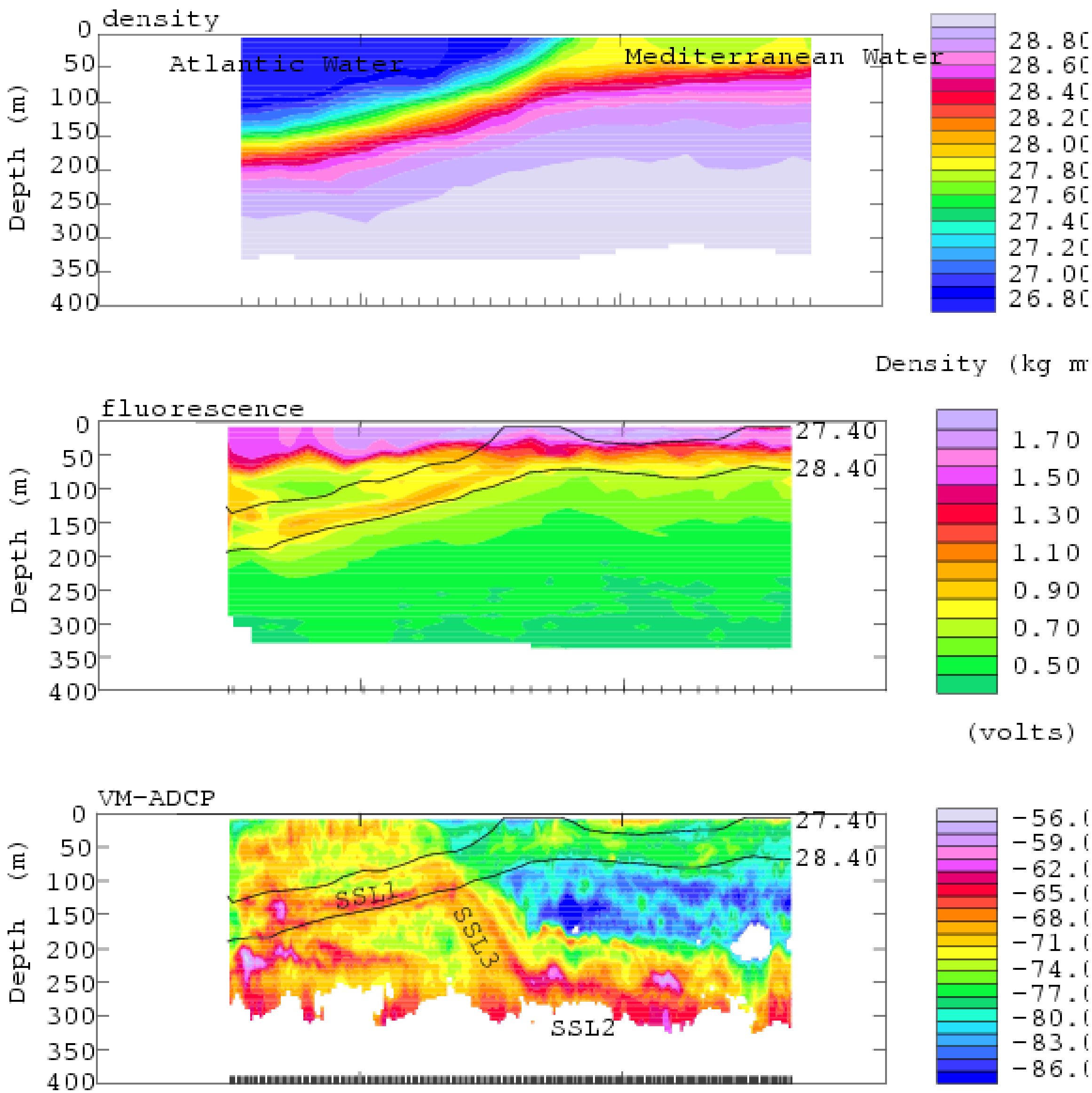
- **Systems are modular, based on distributed information providing shareable, scalable, flexible and efficient workflow and management**


WHAT IS DATA ASSIMILATION?
A Melded Estimate of Data and Dynamics
Measurement Model
Measurement Errors
Dynamical Model
Model Errors
Data Assimilation Criterion
Melded Estimate (state, parameter, structure)
Agrees with measurement and dynamical models
within respective uncertainties
A posteriori errors and uncertainties
Adaptive Sampling
Model Improvements
Adaptive Modeling

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**



Acoustic backscatte (dB)

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

Coupled Interdisciplinary Error Covariances

$\boldsymbol{x} = [\boldsymbol{x}_{\mathrm{A}} \;\; \boldsymbol{x}_{\mathrm{O}} \;\; \boldsymbol{x}_{\mathrm{B}}]$

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

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

Acoustics: $\boldsymbol{x}_{\mathrm{A}}$ = [Pressure (p), Phase (φ)]

$\boldsymbol{x}_{\mathrm{O}}$ (Physics + Biology)

$\boldsymbol{c}_{\mathrm{O}}$ (Physics + Biology + Acoustics)

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

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

End-to-End System Concept

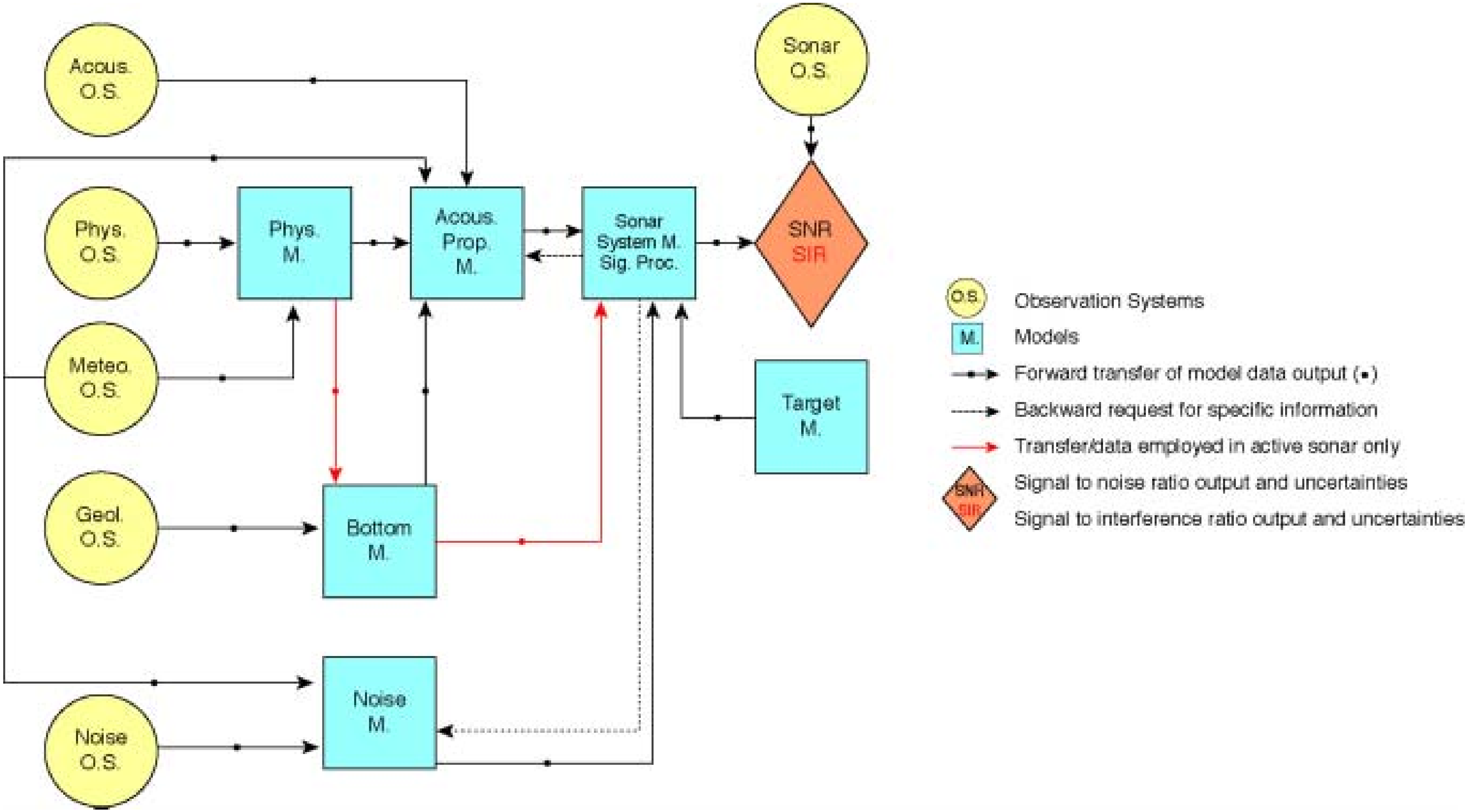
- Sonar performance prediction requires end-to-end scientific systems: ocean physics, bottom geophysics, geo-acoustics, underwater acoustics, sonar systems and signal processing

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

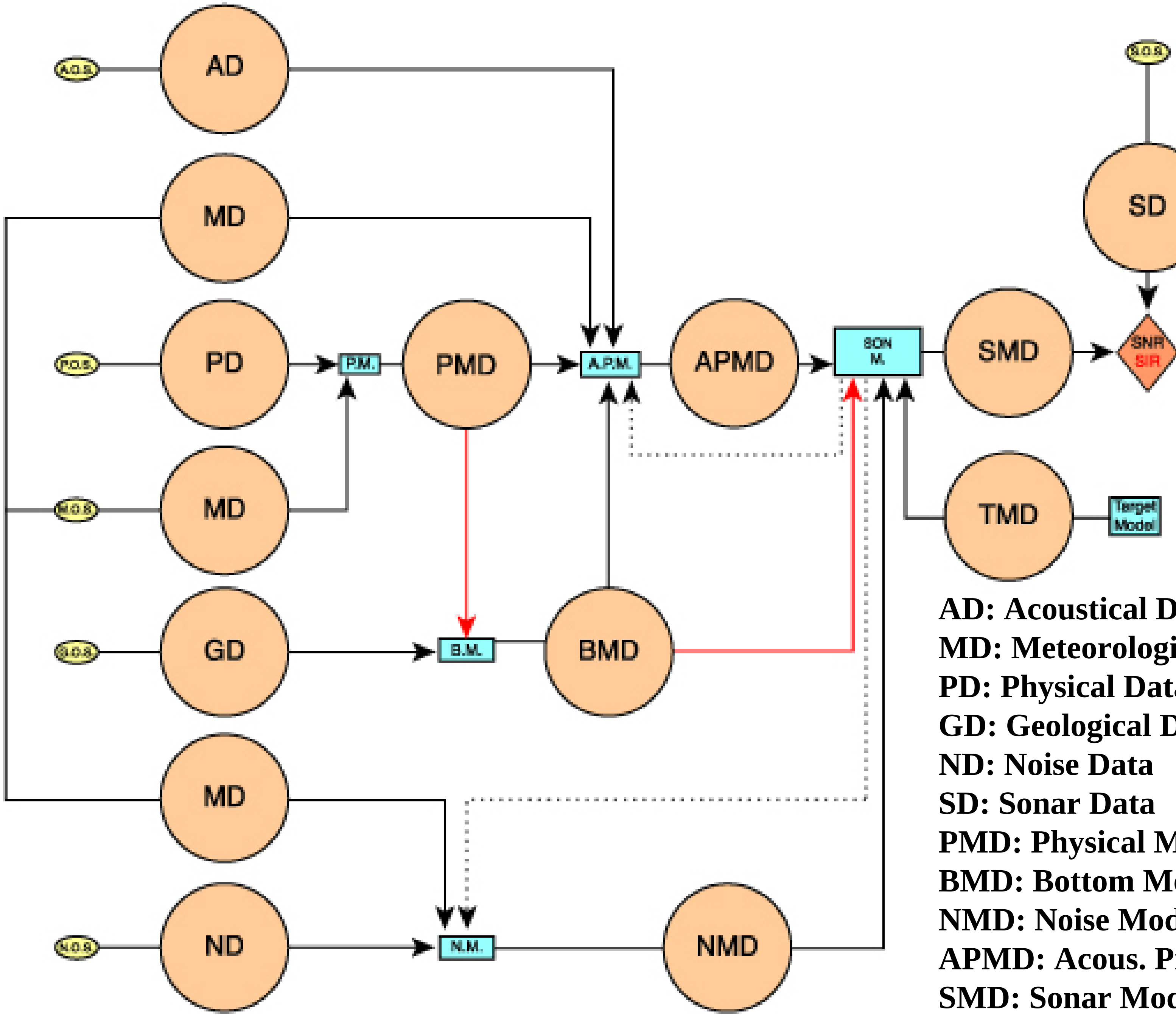
- Resultant uncertainty in sonar performance prediction itself

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

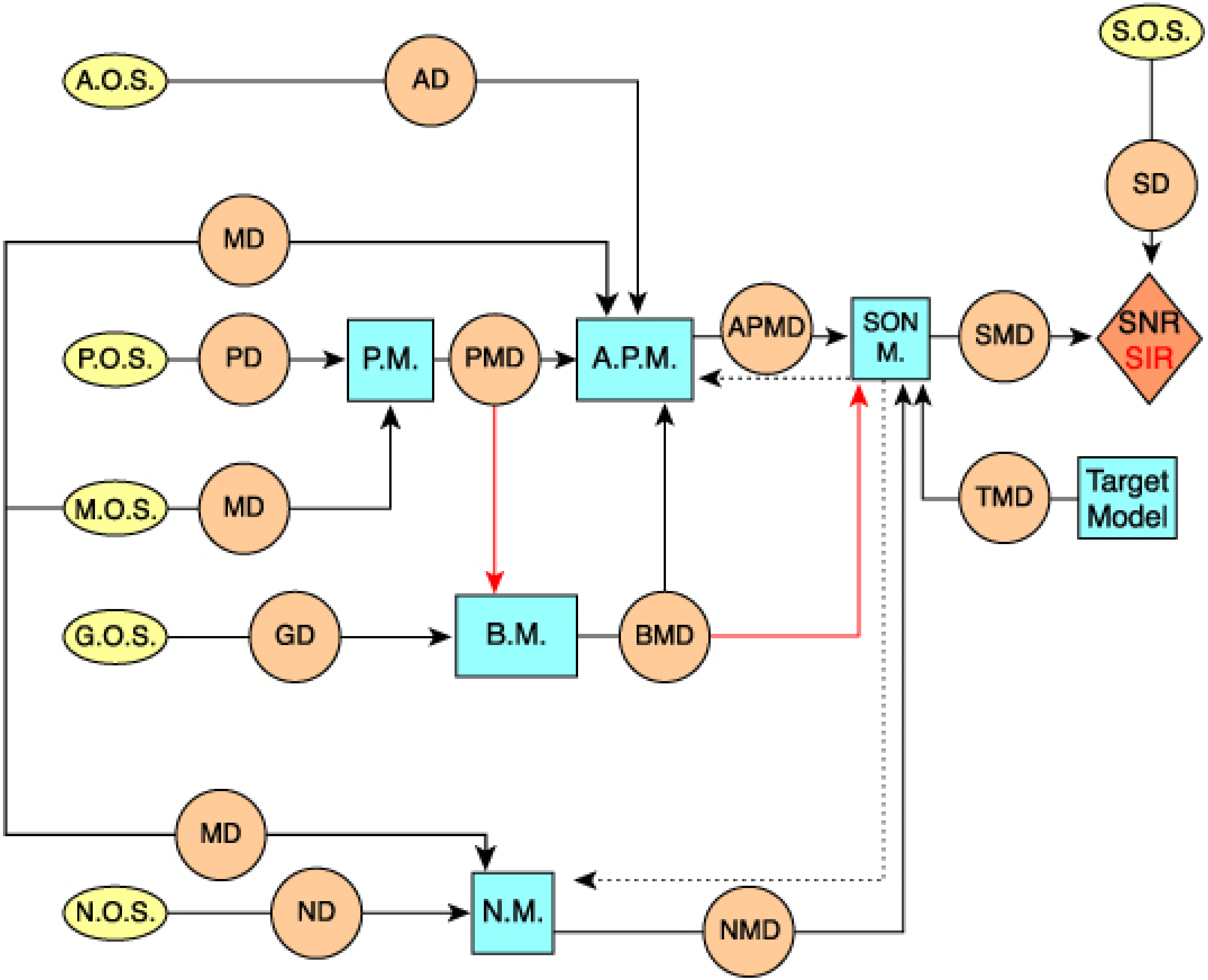
End-to-End System



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
SNR
SIR
Signal to noise ratio output and uncertainties
Signal to interference ratio output and uncertainties



AD: Acoustical Data
MD: Meteorological Data
PD: Physical Data
GD: Geological Data
ND: Noise Data
SD: Sonar Data
PMD: Physical Model Data
BMD: Bottom Model Data
NMD: Noise Model Data
APMD: Acous. Prop. Model Data
SMD: Sonar Model Data
TMD: Target Model Data



S.O.S.
A.O.S.
AD
SD
MD
APMD
SON M.
SMD
SNR
SIR
P.O.S.
PD
P.M.
PMD
A.P.M.
M.O.S.
MD
TMD
Target Model
G.O.S.
GD
B.M.
BMD
MD
N.O.S.
ND
N.M.
NMD

Coupled (Dynamical) Models and Outputs

PHYSICAL MODELS
•Non-hydrostatic models (PDE, *x,y,z,t)*
•Primitive-Eqn. models (PDE, *x,y,z,t*)
•Quasi-geostrophic models, shallow-water
•Objective maps, balance eqn. (thermal-wind)
•Feature models

OUTPUTS
•*T*, *S* , velocity fields and parameters, *C* field
•Dynamical balances

ACOUS. PROP. MODELS
•Parabolic-Eqn. models (*x,y,z,t/f*)
•(Coupled)-Normal-Mode parabolic-eqn. (*x,z,f*)
•Wave number eqn. models (*x,z,f*: OASIS)
•Ray-tracing models (CASS)

OUTPUTS
•Full-field TL (pressure *p*, phase φ)
•Modal decomposition of *p* field
•Processed series: arrival strut., travel times, etc.
•CW / Broadband TL

REVERBERATION MODELS (active)
•Surface, volume and bottom scattering models

OUTPUTS: scattering strengths

BOTTOM MODELS
•Hamilton model, Sediment flux models (G&G), etc
•Statistical/stochastic models fit-to-data

OUTPUTS
•Wave-speed, density and attenuation coefficients

NOISE MODELS
•Wenz diagram, empirical models/rule of thumbs

OUTPUTS
•*f*-dependent ambient noise (*f,x,y,z,t*): due to sea-surface, shipping, biologics

SONAR SYS. MODELS AND SIGNAL PROCES.
•Sonar equations (*f,t*)
•Detection, localization, classification and tracking models and their inversions

OUTPUTS
•SNR, SIR, SE, FOM
•Beamforming, spectral analyses outputs (time/frequency domains)

TARGET MODELS
•Measured/Empirical

OUTPUTS: SL, TS for active

DEFINITION AND REPRESENTATION OF UNCERTAINTY

- $\boldsymbol{x}$ = estimate of some quantity (measured, predicted, calculated)

- $\boldsymbol{x}^t$ = actual value (unknown true nature)

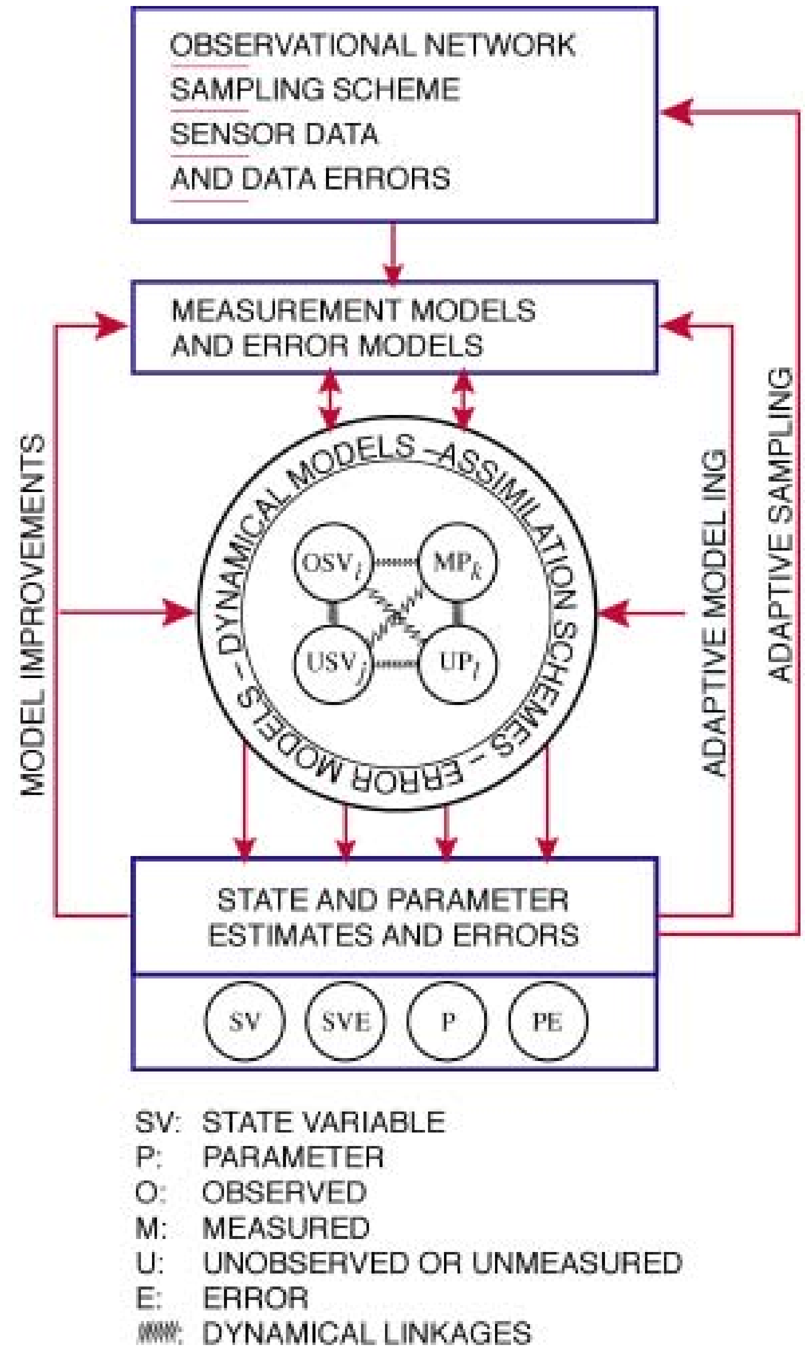
- $\boldsymbol{e} = \boldsymbol{x} - \boldsymbol{x}^t$ (unknown error)

Uncertainty in $\boldsymbol{x}$ is a representation of the error estimate $\boldsymbol{e}$

e.g. probability distribution function of $\boldsymbol{e}$

- Variability in $\boldsymbol{x}$ vs. Uncertainty in $\boldsymbol{x}$
- Uncertainties in general have structures, in time and in space

Data Assimilation



OBSERVATIONAL NETWORK
SAMPLING SCHEME
SENSOR DATA
AND DATA ERRORS
MEASUREMENT MODELS
AND ERROR MODELS
– DYNAMICAL MODELS – ASSIMILATION SCHEMES – ERROR MODELS
OSV_i
MP_k
USV_j
UP_l
MODEL IMPROVEMENTS
ADAPTIVE MODEL ING
ADAPTIVE SAMPLING
STATE AND PARAMETER
ESTIMATES AND ERRORS
SV
SVE
P
PE
SV: STATE VARIABLE
P: PARAMETER
O: OBSERVED
M: MEASURED
U: UNOBSERVED OR UNMEASURED
E: ERROR
DYNAMICAL LINKAGES

GENERIC DATA ASSIMILATION PROBLEM

Dynamical models:

$$d\phi_i + \mathbf{u} \cdot \nabla \phi_i dt - \nabla(K_i \nabla \phi_i) dt = B_i(\phi_1, \ldots, \phi_i, \ldots, \phi_n) dt + d\eta_i \qquad (i = 1, \cdots, n)$$

e.g. i= u, v, T, $\cdots$, *ZOO*, $\cdots$, p

Parameter equations:

$$dP_\ell = C_\ell(\phi_1, \ldots, \phi_i, \ldots, \phi_n) dt + d\zeta_\ell \qquad (\ell = 1, \cdots, p)$$

e.g. $P_\ell = \{ K_i, R_i, \cdots \}$

Measurement models:

$$y_j = \mathcal{H}_j(\phi_1, \cdots, \phi_i, \cdots, \phi_n) + \epsilon_j \qquad (j = 1, \cdots, m)$$

e.g. $y_j = \{ XBT_j, Fluo_j, SSH_j, CODAR_j \}$

Assimilation criterion:

$$\min_{\phi_i, P_\ell} \quad J(d\eta_i\, ,\, d\zeta_\ell\, ,\, \epsilon_j\, ,\, q_\eta\, ,\, q_\zeta\, ,\, q_\epsilon)$$

CLASSES OF DATA ASSIMILATION SCHEMES

- **Estimation Theory (Filtering and Smoothing)**

1. Direct Insertion, Blending, Nudging	- Lin
2. Optimal interpolation	- Lin., LS
3. Kalman filter/smoother	- Linear, LS
4. Bayesian estimation (Fokker-Plank equations)	- Non-linear, Non-LS
5. Ensemble/Monte-Carlo methods	- Non-linear, LS/Non-LS
6. Error-subspace/Reduced-order methods: Square-root filters, e.g. SEEK	- (Non)-Linear, LS
7. Error Subspace Statistical Estimation (ESSE): 5 and 6	-Non-linear, LS/Non-LS

- **Control Theory/Calculus of Variations (Smoothing)**

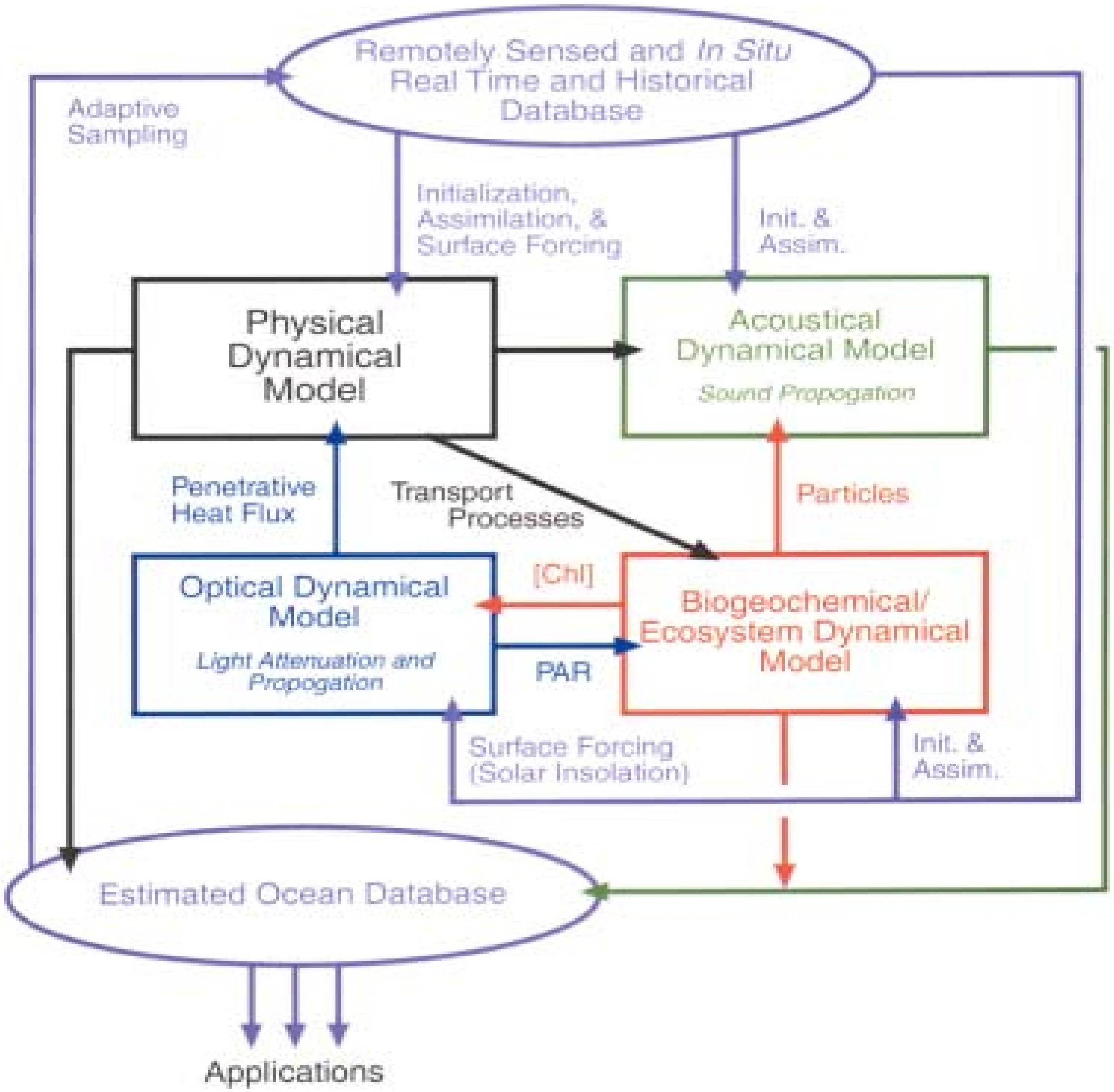
1. "Adjoint methods" (+ descent)	- Lin, LS
2. Generalized inverse (e.g. Representer method + descent)	- Lin, LS

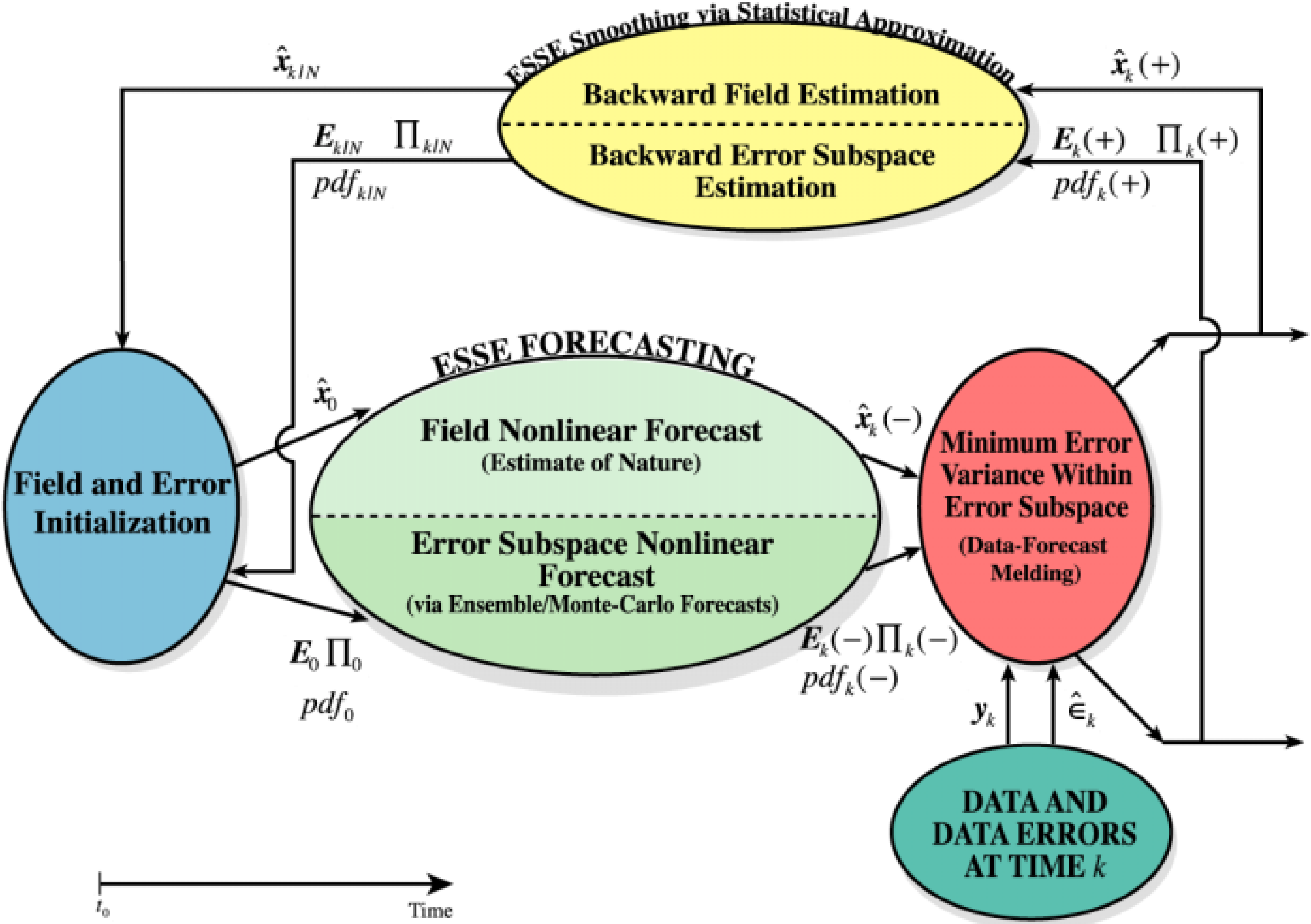
- **Optimization Theory (Direct local/global smoothing)**

1. Descent methods (Conjugate gradient, Quasi-Newton, etc)	- Lin, LS/Non-LS
2. Simulated annealing, Genetic algorithms	- Non-linear, LS/Non-LS

- **Hybrid Schemes**
  - Combinations of the above

Harvard Ocean Prediction System - HOPS





ESSE Smoothing via Statistical Approximation
Backward Field Estimation
Backward Error Subspace Estimation
$\hat{x}_{k|N}$
$E_{k|N}$ $\Pi_{k|N}$
$pdf_{k|N}$
$\hat{x}_k(+)$
$E_k(+)$ $\Pi_k(+)$
$pdf_k(+)$
Field and Error Initialization
ESSE FORECASTING
Field Nonlinear Forecast
(Estimate of Nature)
Error Subspace Nonlinear Forecast
(via Ensemble/Monte-Carlo Forecasts)
$\hat{x}_0$
E_0 Π_0
pdf_0
$\hat{x}_k(-)$
$E_k(-)$ $\Pi_k(-)$
$pdf_k(-)$
Minimum Error Variance Within Error Subspace
(Data-Forecast Melding)
y_k
$\hat{\epsilon}_k$
DATA AND DATA ERRORS AT TIME k
t_0
Time

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

$\boldsymbol{c}_O$

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**

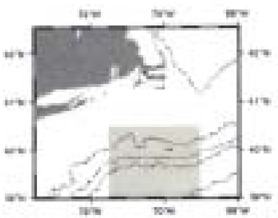
- **Issues**
  - **Some state variables are not observed**
  - **Uncertain variability is multiscale**

- **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**

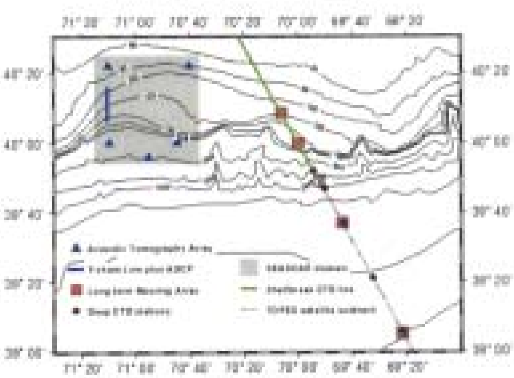
  - **“Non-observed” portions**
    - **Keep “observed” portions fixed and compute “non-observed”portions from ensemble of numerical (stochastic) dynamical simulations**

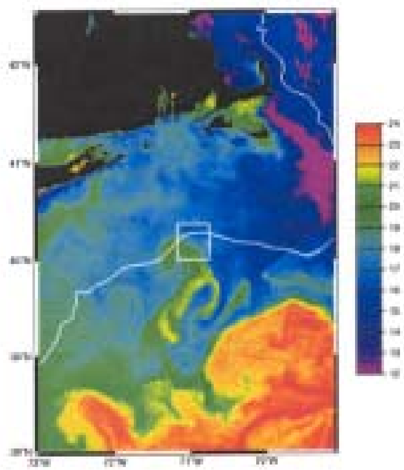
PRIMER

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



PRIMER III Field Study July--August, 1996





Location*:* Shelfbreak PRIMER Region

Season*:* July-August 1996

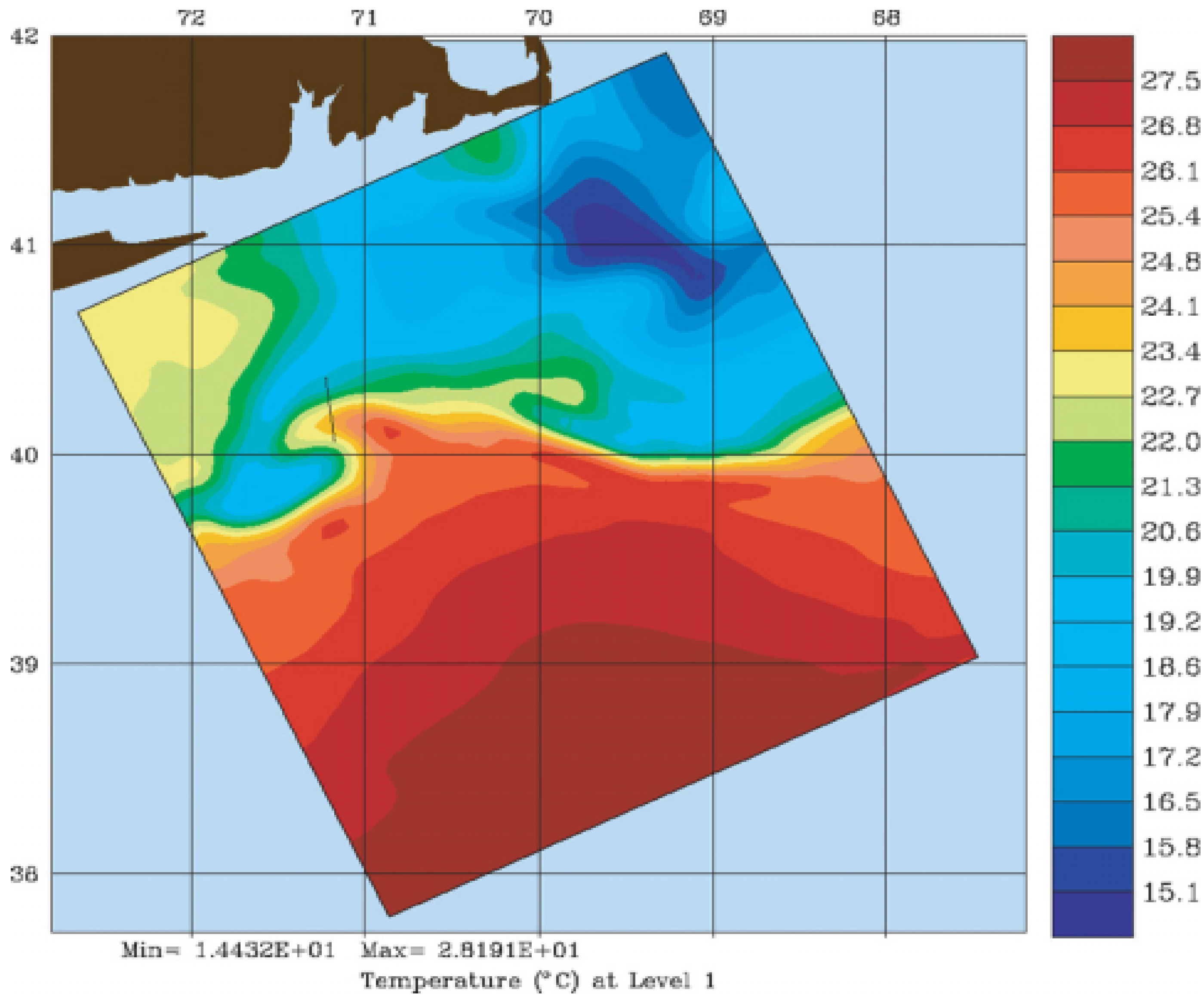
Sonar System *(Receiver):* Passive Towed Array

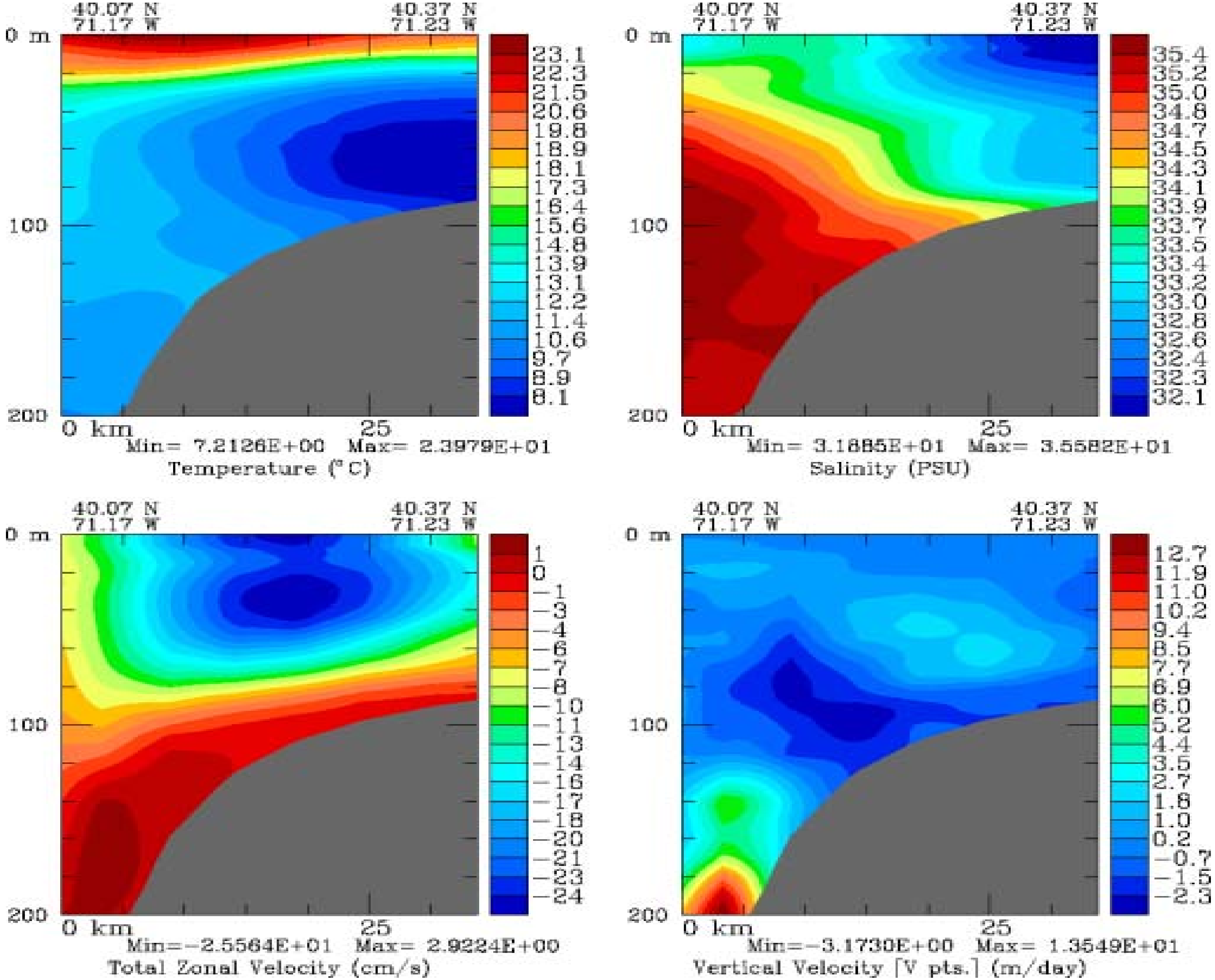
Target*:* Simulated UUV (with variable source level)

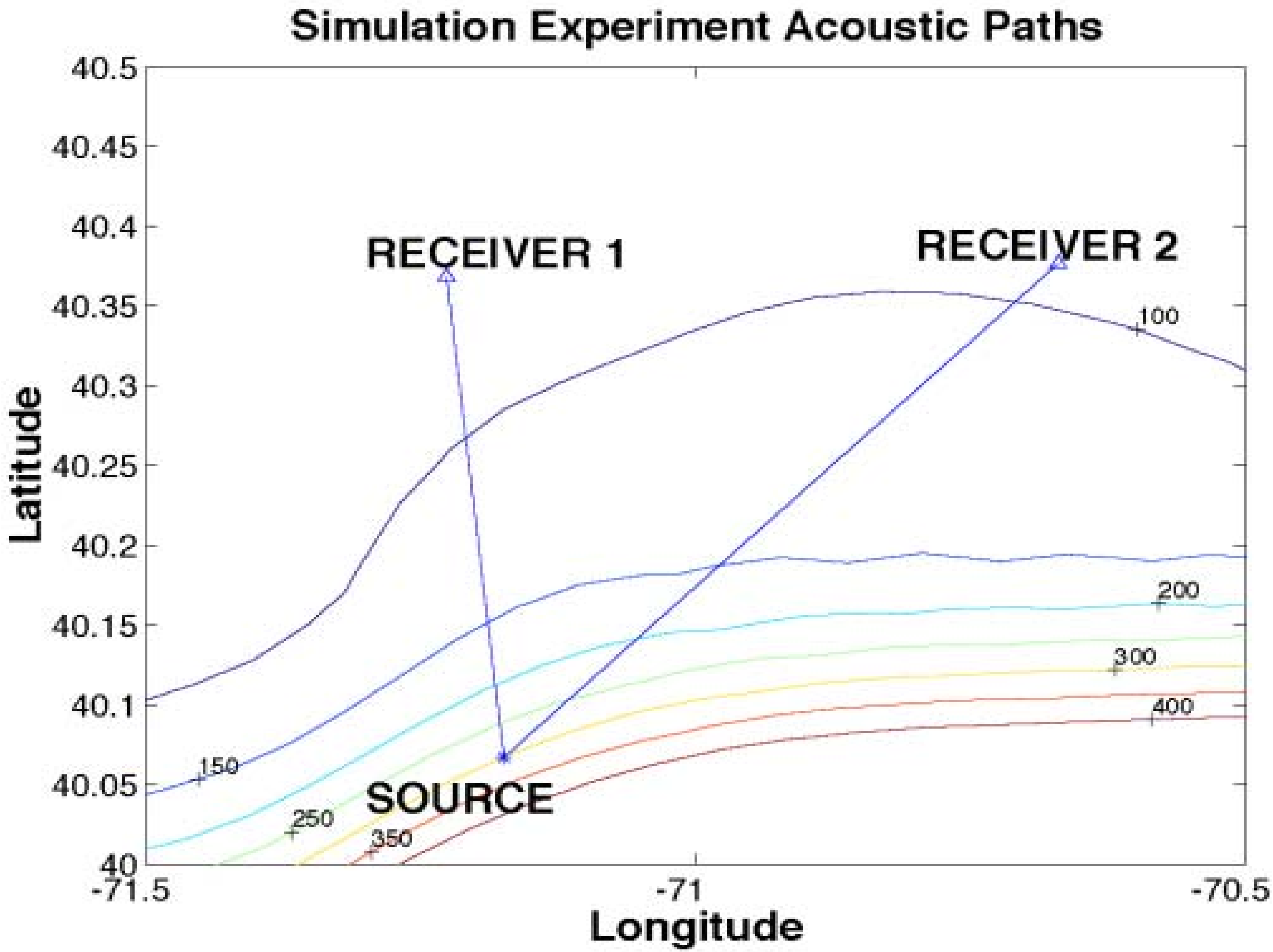
Frequency Range*:* 100 to 500 Hz

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

PHYSICAL-ACOUSTICAL FILTERING IN A SHELFBREAK ENVIRONMENT

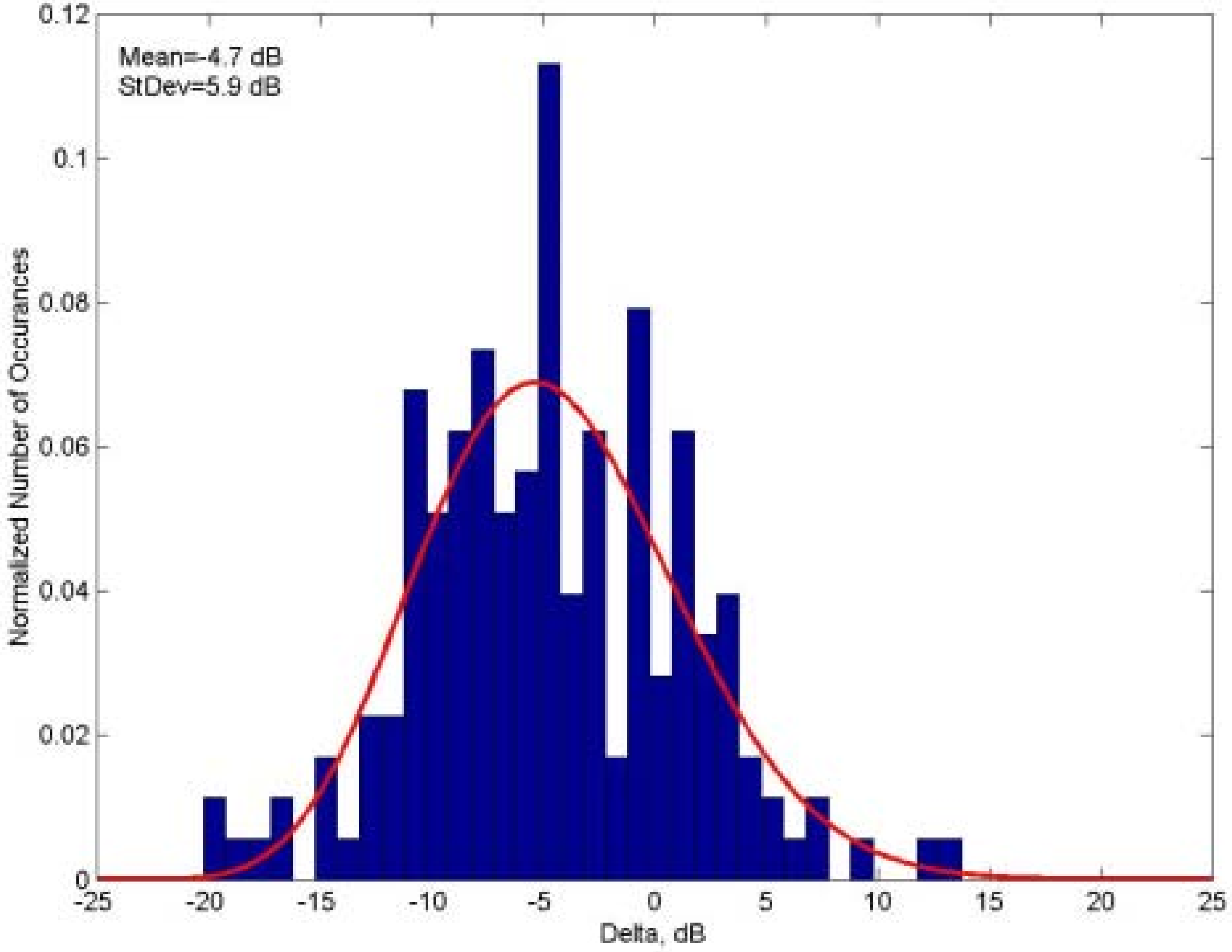



40.07 N
71.17 W
40.37 N
71.23 W
0 m
100
200
0 km
25
23.1
22.3
21.5
20.6
19.8
18.9
18.1
17.3
16.4
15.6
14.8
13.9
13.1
12.2
11.4
10.6
9.7
8.9
8.1
Min= 7.2126E+00 Max= 2.3979E+01
Temperature (°C)
35.4
35.2
35.0
34.8
34.7
34.5
34.3
34.1
33.9
33.7
33.5
33.4
33.2
33.0
32.8
32.6
32.4
32.3
32.1
Min= 3.1885E+01 Max= 3.5582E+01
Salinity (PSU)
1
0
−1
−3
−4
−6
−7
−8
−10
−11
−13
−14
−16
−17
−18
−20
−21
−23
−24
Min=−2.5564E+01 Max= 2.9224E+00
Total Zonal Velocity (cm/s)
12.7
11.9
11.0
10.2
9.4
8.5
7.7
6.9
6.0
5.2
4.4
3.5
2.7
1.8
1.0
0.2
−0.7
−1.5
−2.3
Min=−3.1730E+00 Max= 1.3549E+01
Vertical Velocity [V pts.] (m/day)



Acoustic paths considered (as in Shelfbreak-PRIMER), overlaid on bathymetry.

Histogram of Difference Between Model and Measured SIR, SIRE-PDF

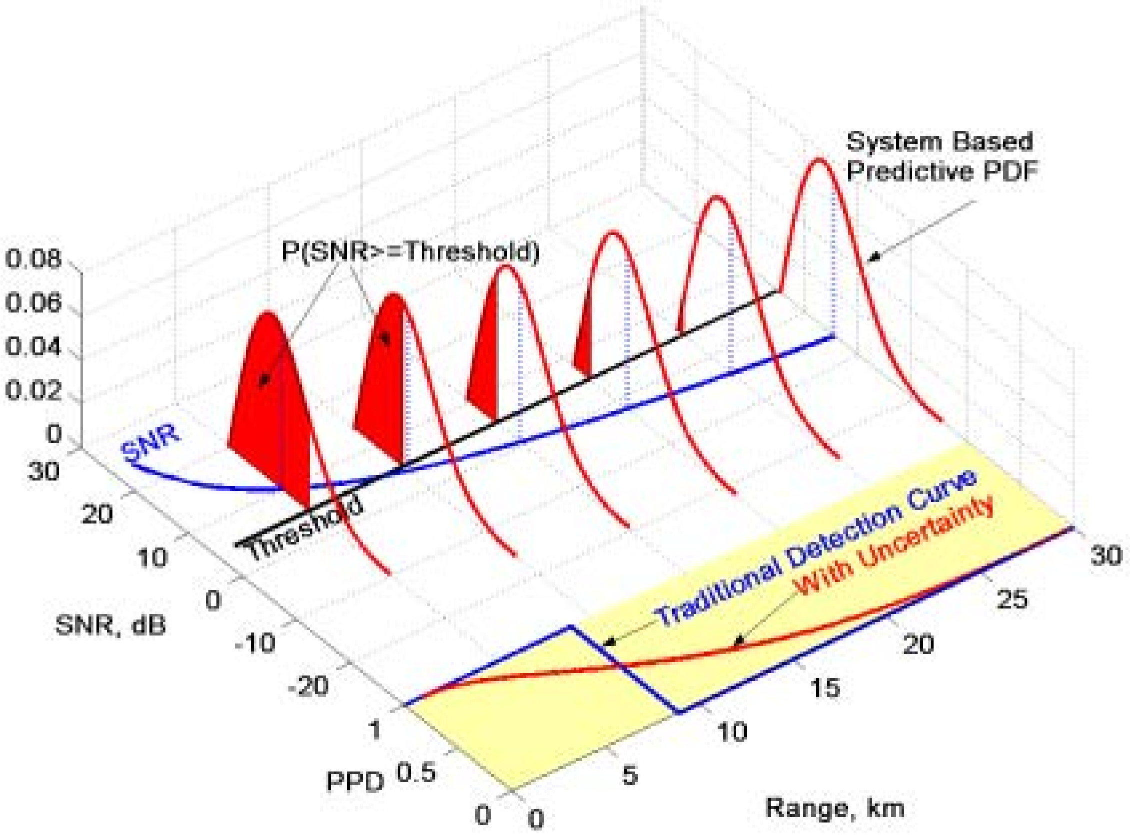


Difference Between Model and Measurement, dB

- Represents uncertainty in our ability to model actual performance of system
- Accounts for inherent variability of environment not known by current model

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

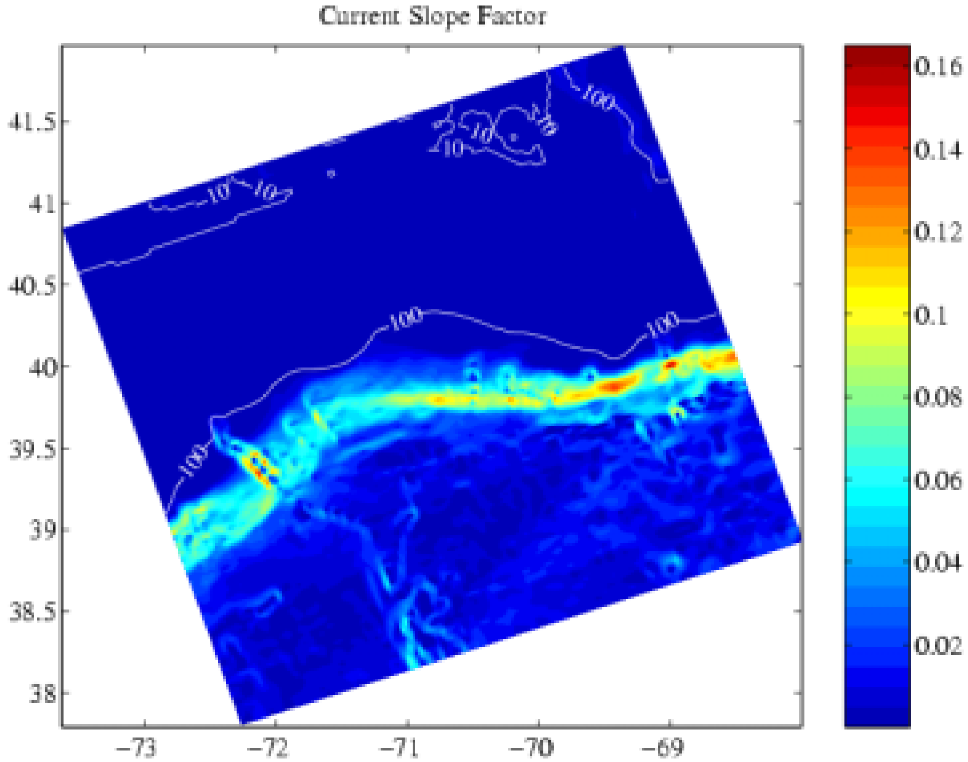
Systems-based PDF (incorporates environmental and system uncertainty)



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

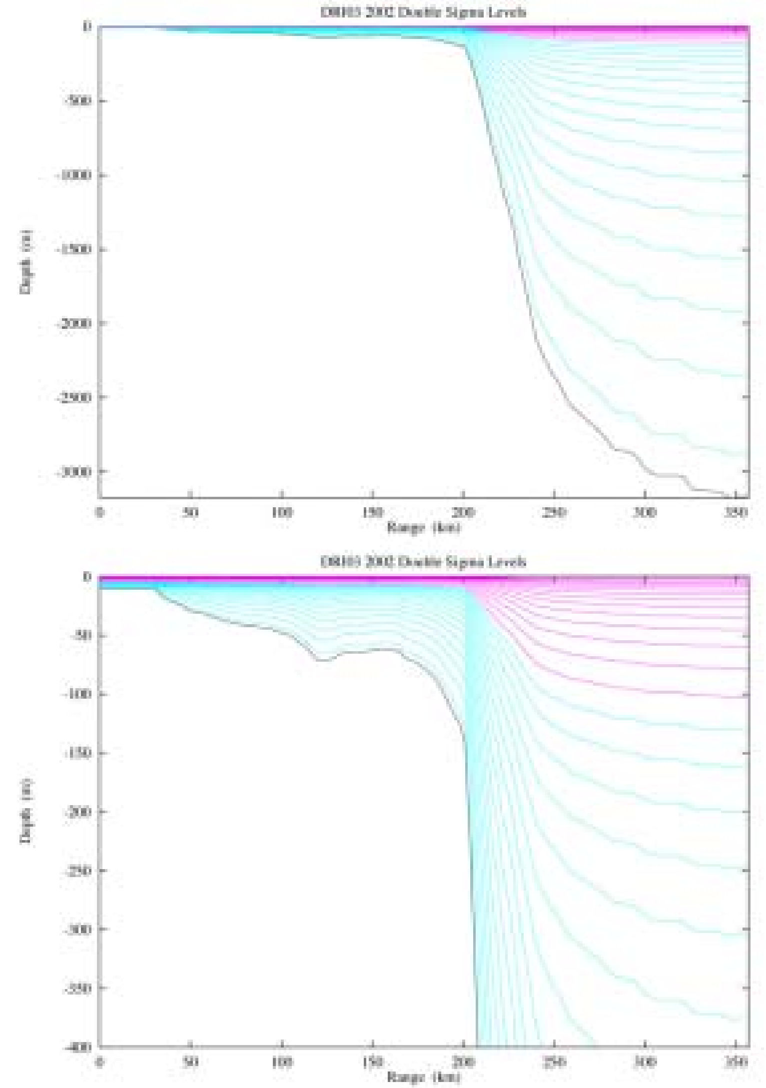
Starting with physical environmental data, compute the PPD from first principals via broadband TL

- Novel approach: coupled physical-acoustical data assimilation method is used in TL estimation
- Methodology: coupled physical-acoustical identical-twin experiment
  - ESSE based
  - Model generates “true” ocean
  - 79 member ensemble for *a priori* estimate
  - Coarsely sampled CTD and TL measurements are assimilated for *a posteriori* estimate



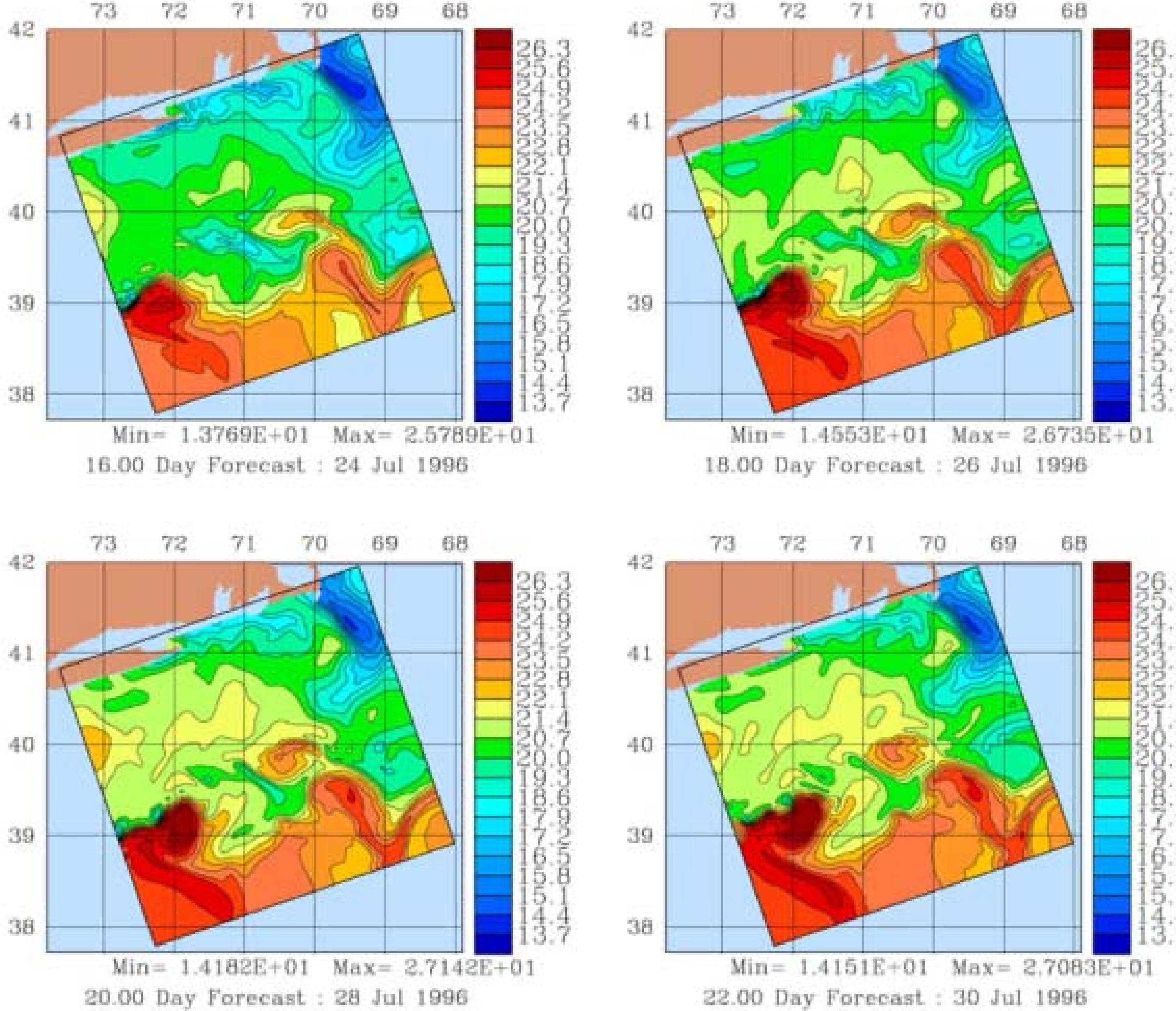
Case 13 (Conditioned): C=4.7, α = 0.04

-73.4818 40.8695 **-72.1200 37.8340**

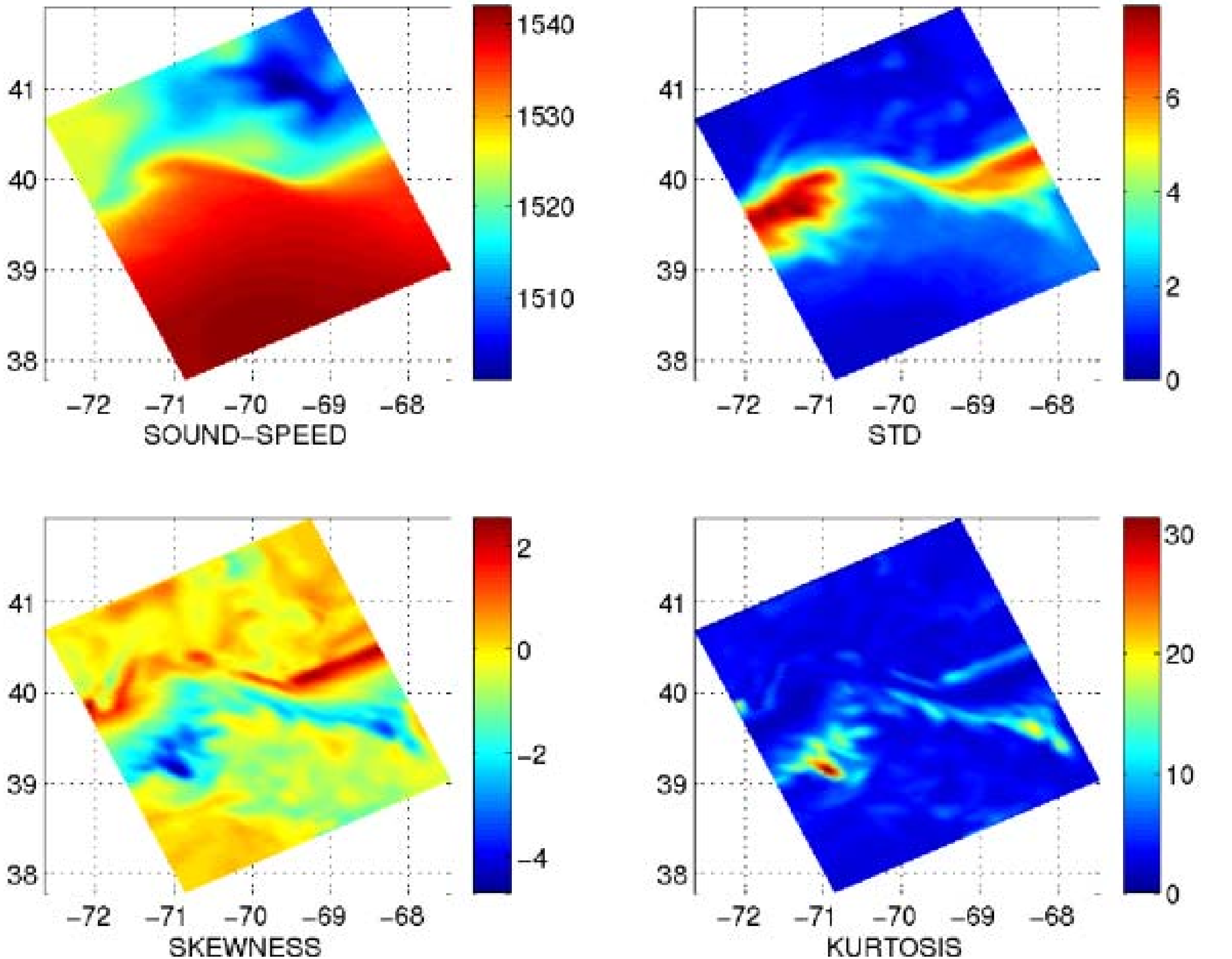


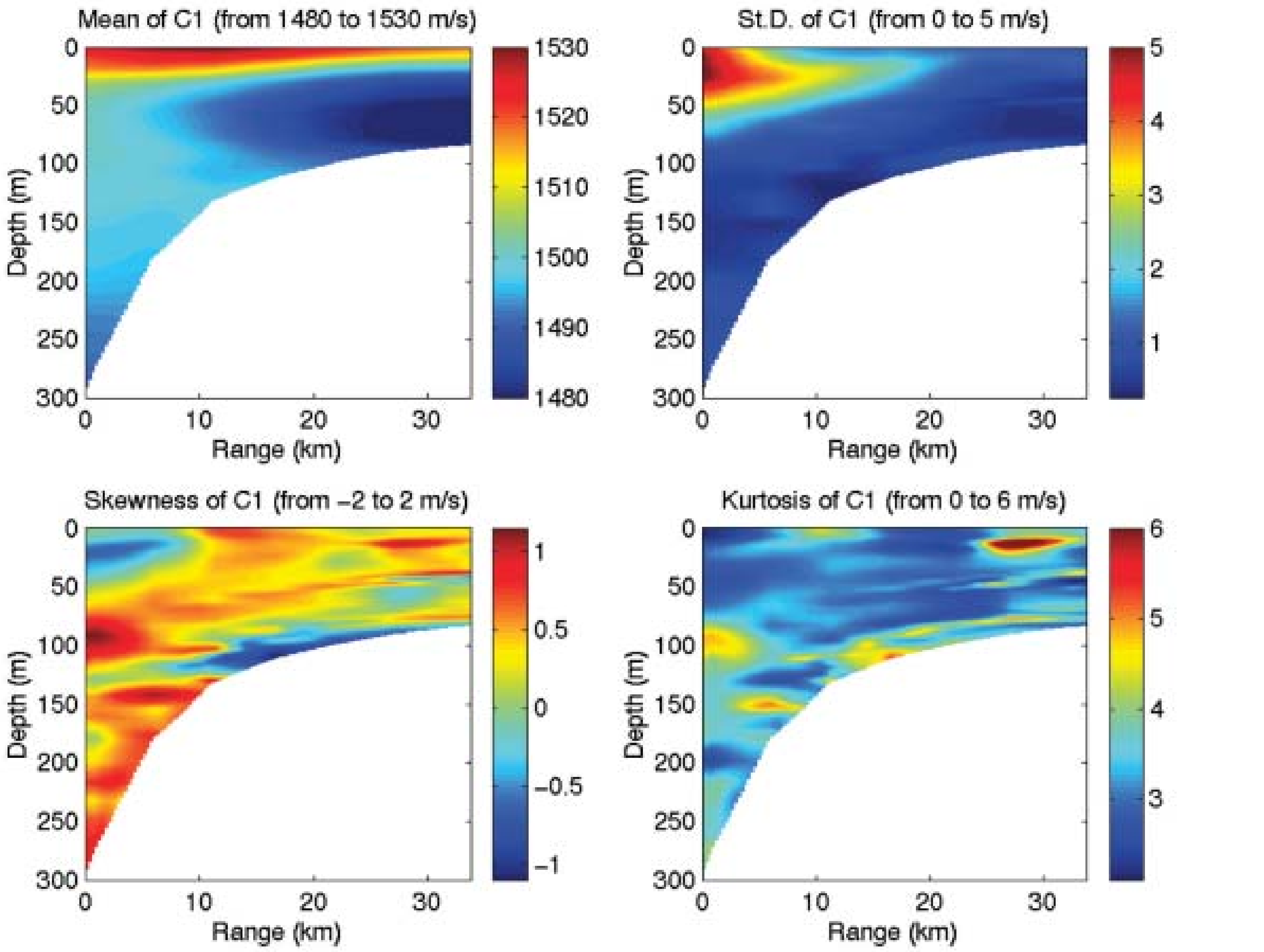
Physical fields: SST

July–August 1996



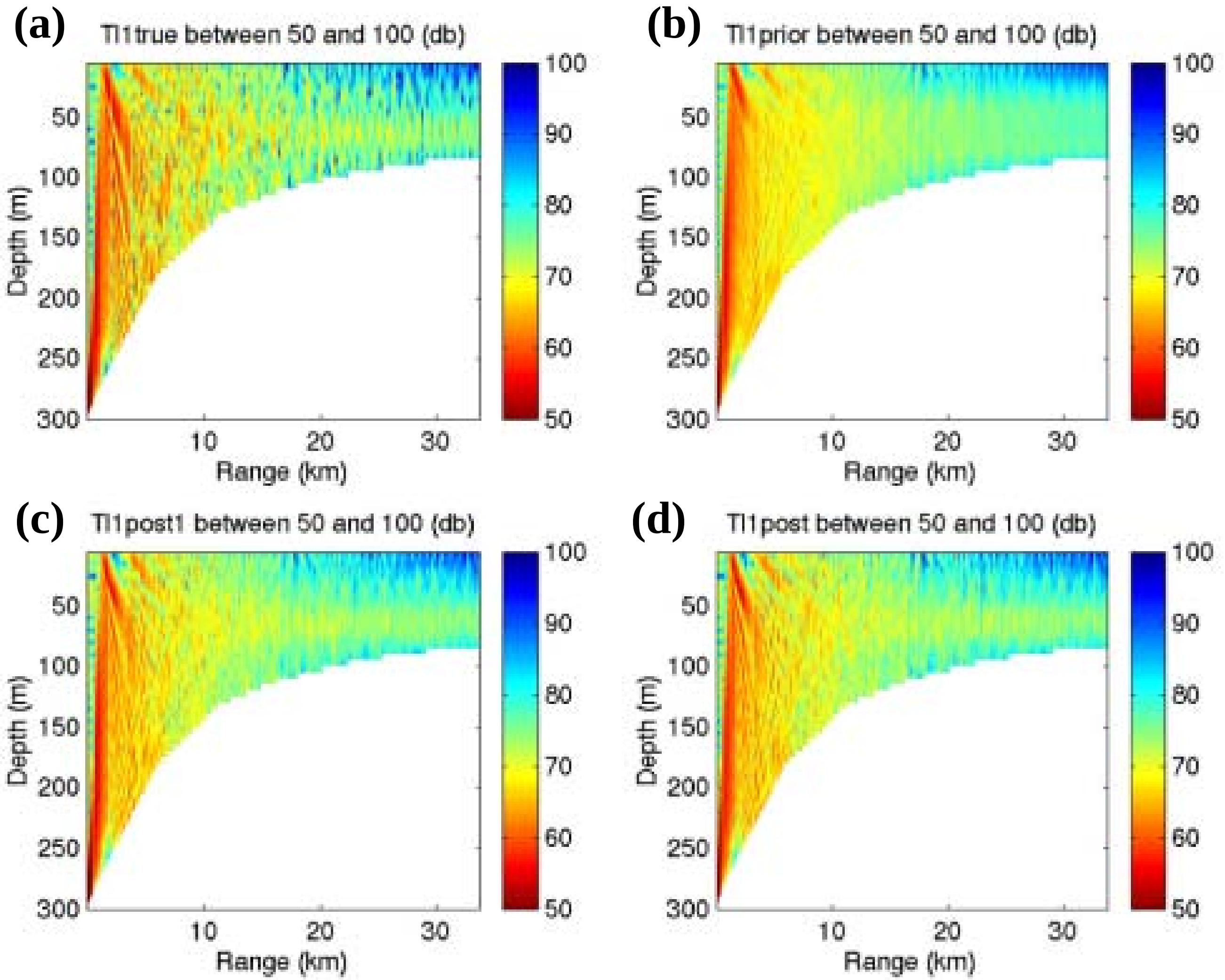
Monte Carlo simulation example: transfer of ocean physical forecast Uncertainty to acoustic prediction uncertainty in a shelfbreak environment.





Mean of C1 and statistics of error estimate for C1

Coupled ESSE data assimilation of sound-speed and TL data for a joint estimate of sound-speed and TL fields



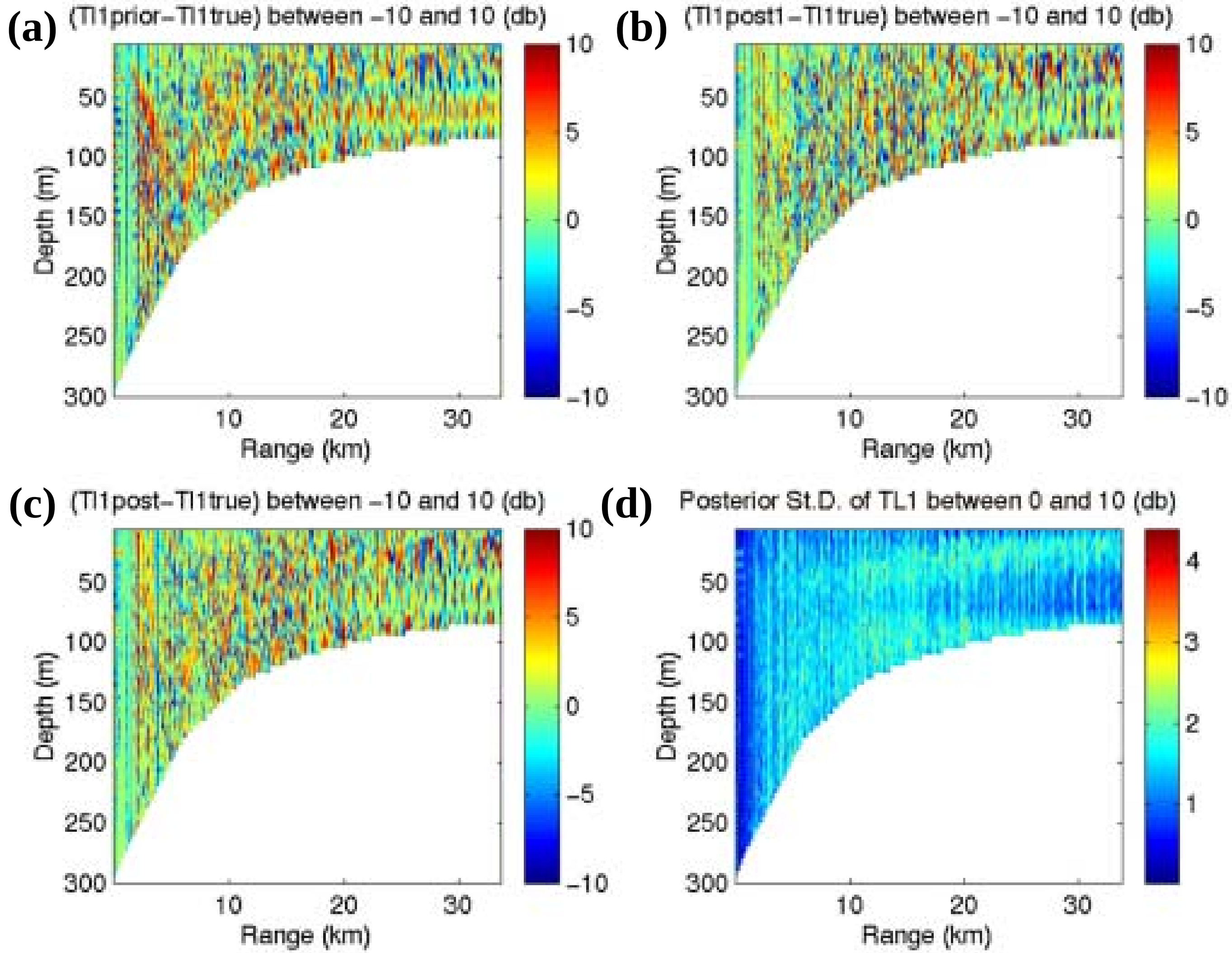
ESSE assimilation results (Twin Experiment)

(a): "True" TL (truth provides towed-rec. TL + 3 C prof.),

(b): *A priori* TL (ensemble mean forecast),

(c): *A posteriori* TL (after assimilation of TL data), and,

(d): *A posteriori* TL (after assimilation of TL and C data)



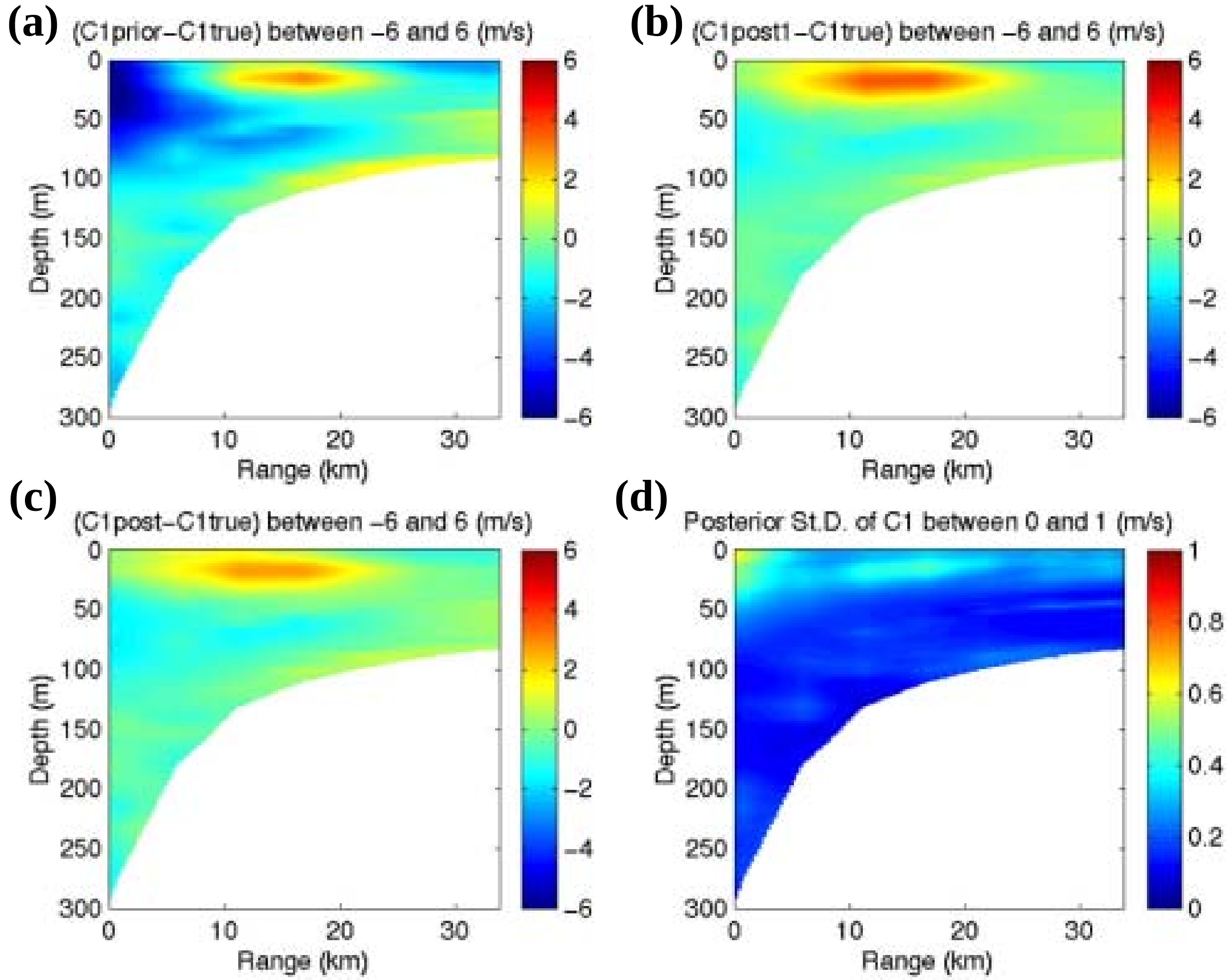
(a): *A priori* **(before assimilation) TL residuals,**

(b): TL residuals after TL data assimilation,

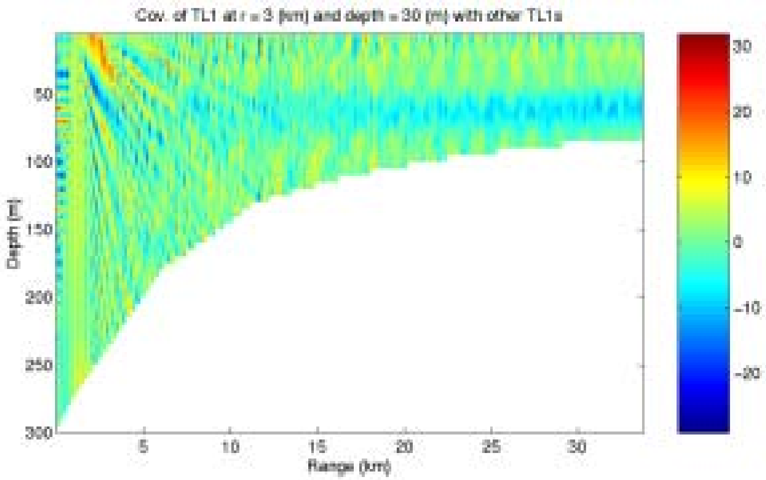
(c): TL residuals after TL and C data assimilation, and,

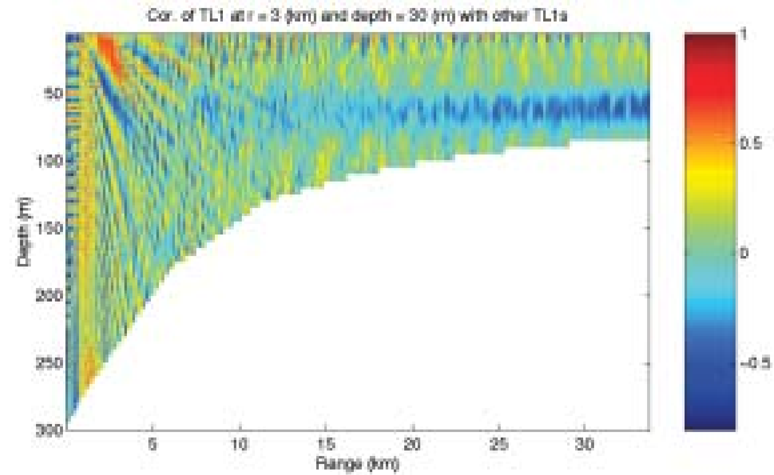
(d): *A posteriori* **error Std. dev. for TL,**

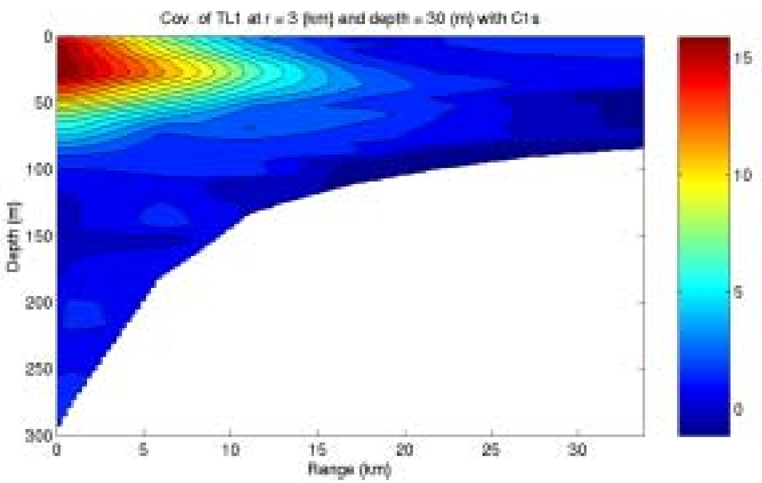
(all along cross-section of path 1).

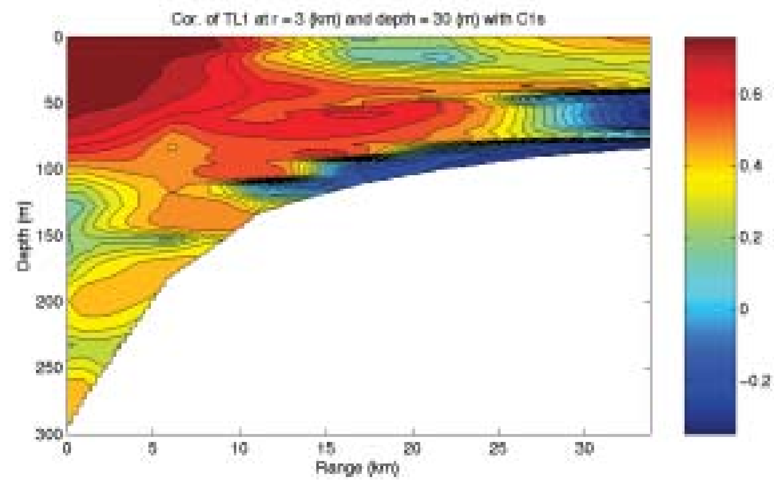


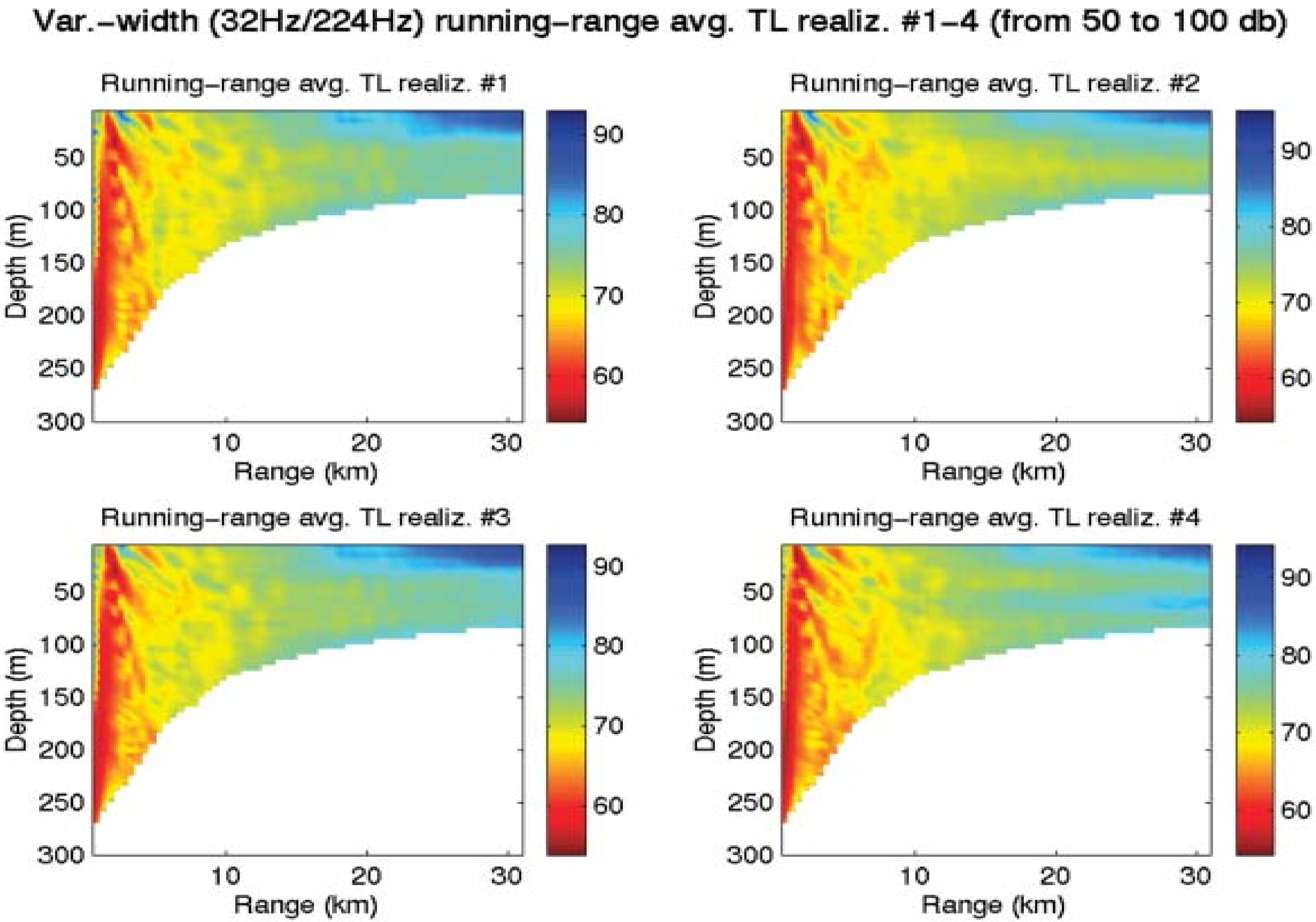
(a): *A priori* (before assimilation) sound-speed (C) residuals,
(b): C residuals after TL data assimilation,
(c): C residuals after TL and C data assimilation, and,
(d): *A posteriori* error Std. dev. for C.
(all along cross-section of path 1).


Cov. of TL1 at r = 3 (km) and depth = 30 (m) with other TL1s
Depth (m)
Range (km)

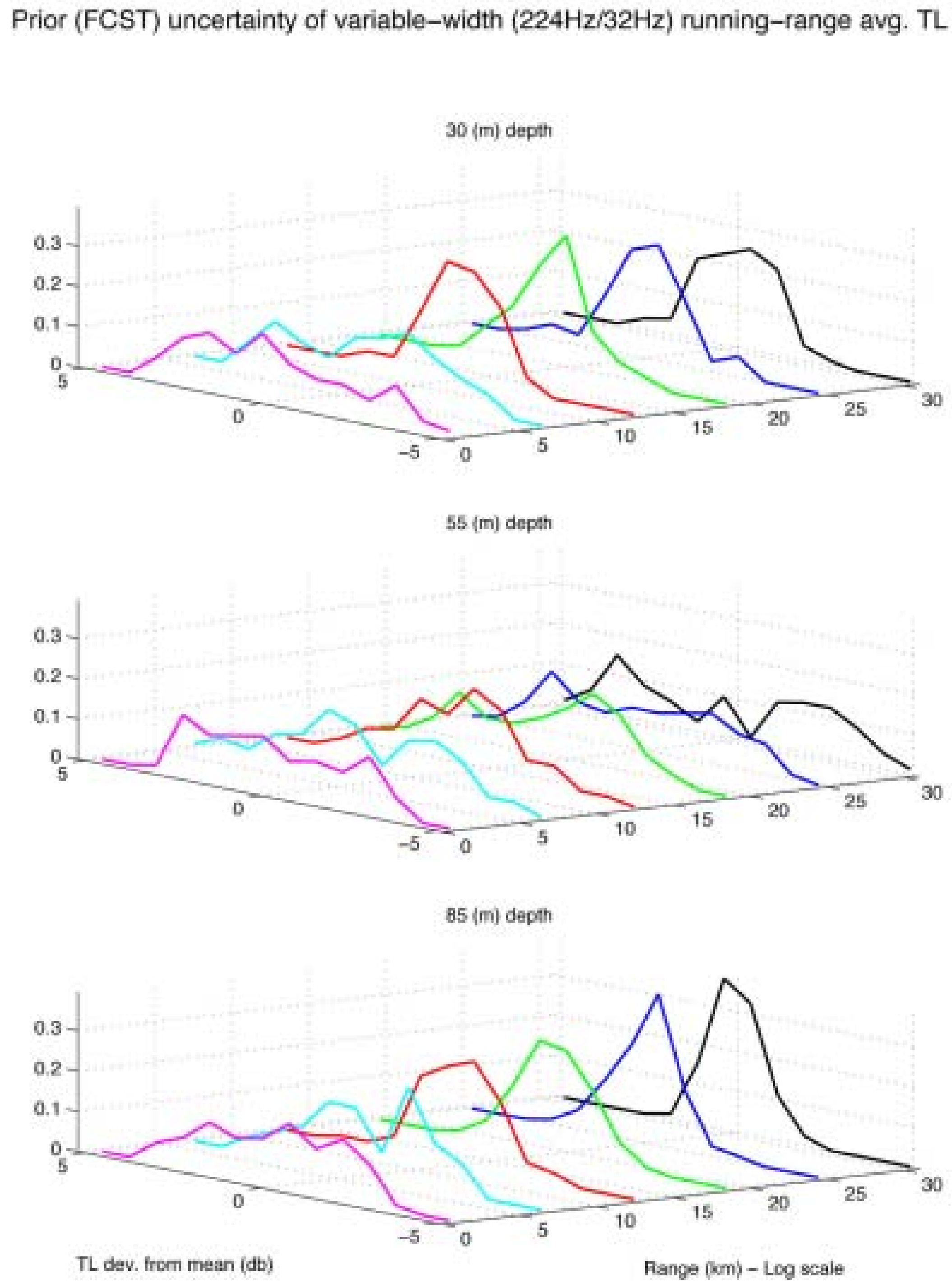

Cor. of TL1 at r = 3 (km) and depth = 30 (m) with other TL1s
Depth (m)
Range (km)


Cov. of TL1 at r = 3 (km) and depth = 30 (m) with C1s
Depth (m)
Range (km)

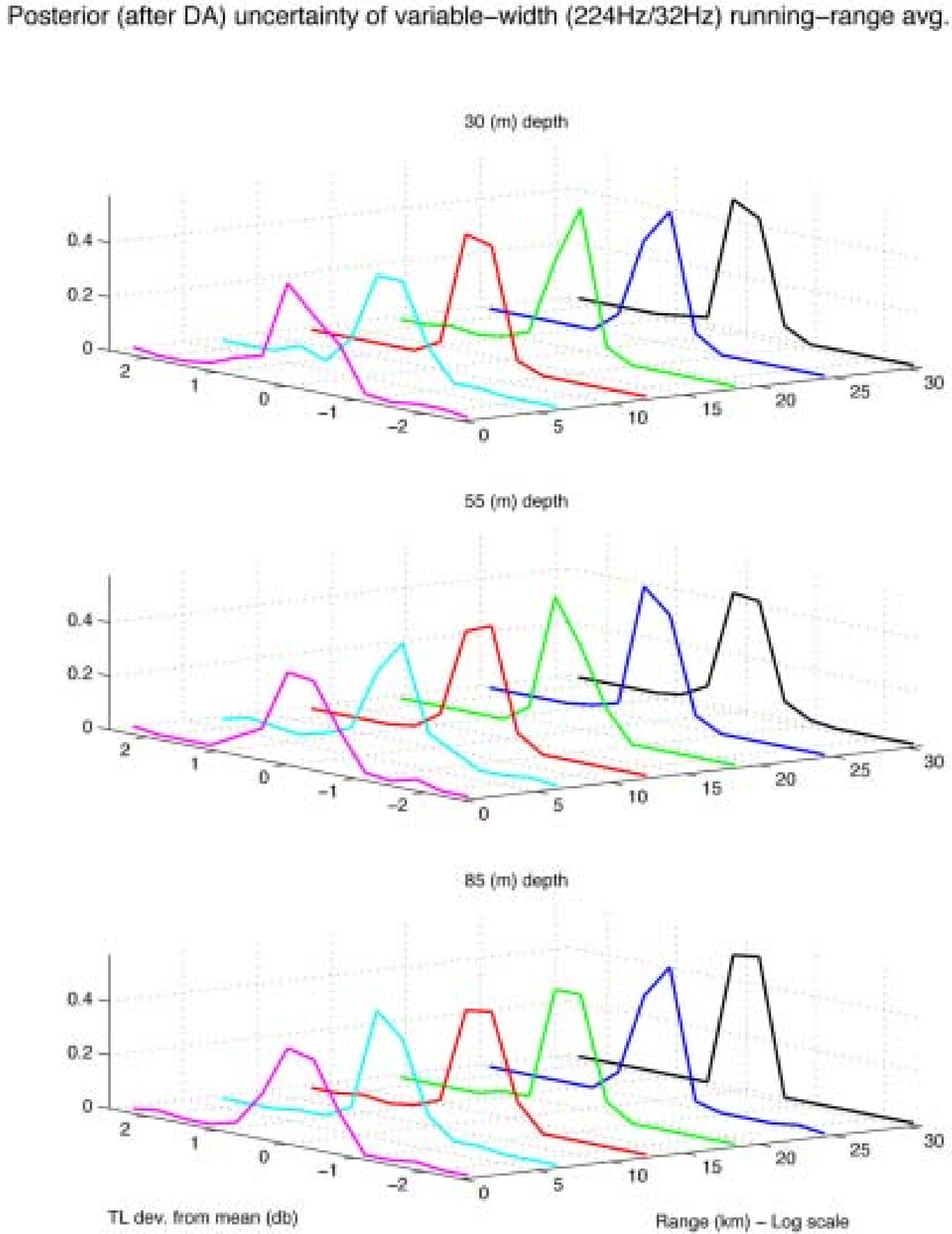

Cor. of TL1 at r = 3 (km) and depth = 30 (m) with C1s
Depth (m)
Range (km)


Var.-width (32Hz/224Hz) running-range avg. TL realiz. #1-4 (from 50 to 100 db)
Running-range avg. TL realiz. #1
Running-range avg. TL realiz. #2
Running-range avg. TL realiz. #3
Running-range avg. TL realiz. #4
Depth (m)
Range (km)
50
100
150
200
250
300
10
20
30
60
70
80
90

Predicted PDF of broadband TL



PDF of broadband TL after assimilation



CONCLUSIONS: Coupled ESSE Identical-Twin Experiments

- Oceans physics/acoustics data assimilation: carried-out as a single multi-scale joint estimation for the first time, using higher-moments to characterize uncertainties
- ESSE nonlinear coupled assimilation recovers fine-scale TL structures (10-100m) and mesoscale ocean physics (10km) from coarse TL data (towed-receiver at 70m depth, one data every 500m) and/or coarse C data (2-3 profiles over 40km)
- Two notable coupled processes:
  - Shoreward meander of upper-front leads to less loss in acoustic waveguide (cold pool) on shelf
  - Corresponding thickening of thermocline at the front induces phase shifts in ray patterns on the shelf
- Broadband TL uncertainties predicted to be range and depth dependent
- Coupled DA sharpens and homogenizes broadband PDFs

Summary

CONCLUSIONS

- Entering a new era of fully interdisciplinary ocean science and ocean acoustics
- Ocean prediction systems for science, operations and management
- Interdisciplinary estimation of state variables and error fields via multivariate physical-biological-acoustical data assimilation
- Novel and challenging opportunities for theoretical and computational acoustics