ADVANCED SYSTEMS FOR OPERATIONAL OCEAN FORECASTING OF INTERDISCIPLINARY FIELDS AND UNCERTAINTIES

ALLAN R. ROBINSON AND WAYNE G. LESLIE

Harvard University, 29 Oxford Street, Cambridge MA 02138, US
E-mail: robinson@pacific.deas.harvard.edu

Advanced integrated systems for the prediction of operational activities in the ocean are under development and prototypes are being implemented. Such systems are essential for REA/REP and are generally required to be interdisciplinary, modular and of hierarchical complexity. Systems are flexible, based on a variety of platforms and sensors, coupled deterministic and stochastic models, and interdisciplinary data assimilation schemes. They must be able to deal with powerful, intermittent synoptic events. The representation and attribution of errors and the development of quantitative predictive skill measures together represent a major research focus. Uncertainties must be quantitatively described and transferred from the environment all the way through the system for specific applications, e.g. from the environment through acoustics and signal processing for sonar operations and Tactical Decision Aids. Illustrations will be presented for the ASCOT-01 and ASCOT-02 predictive skill experiments, the PRIMER experiment and the summer 2003 AOSN-II experiment in Monterey Bay.

1 Introduction

Research advances in interdisciplinary ocean science have led to the emergence of new dynamical concepts in which non-linear interdisciplinary processes are now known to occur on multiple interactive scales in space and time with bi-directional feedbacks. Such processes, importantly, can be dominated by strong sporadic events that are intermittent in both space and time. Understanding specific non-linear dynamics of known events and identification of important as yet unknown multi-scale interactive processes provides a framework for realistic understanding and prediction of the interdisciplinary coastal ocean.

A system approach that synthesizes theory, data and numerical computations is essential for rapid and efficient progress. The concept of Ocean Observing and Prediction Systems for field and parameter estimations has recently crystallized with three major components: (i) an observational network: a suite of platforms and sensors for specific tasks; (ii) a suite of interdisciplinary dynamical models; and, (iii) data management, analysis and assimilation schemes. A generic Ocean Observing and Prediction System and the Harvard Ocean Prediction System (HOPS) are illustrated in Figure 1. The schematic of the generic Ocean Observing and Prediction System (Fig. 1a) depicts the linkages among the components of a prediction system as well as the feedbacks for model improvement, adaptive modeling and adaptive sampling. The HOPS schematic (Fig. 1b) represents a multi-variate coupled physical-biological-acoustical system that is actively used for real-time operations and ocean forecasting.

Applications of existing Ocean Observing and Prediction Systems are illustrated in this paper from the projects: Advanced Distributed Adaptive Predictive Tidy System for the ocean (ADAPTS); Assessment of Skill for Coastal Ocean Transients (ASCOT); Uncertainties and Interdisciplinary Transfers Through the End-To-End System (UNITES); Autonomous Ocean Sampling Networks-II (AOSN-II).

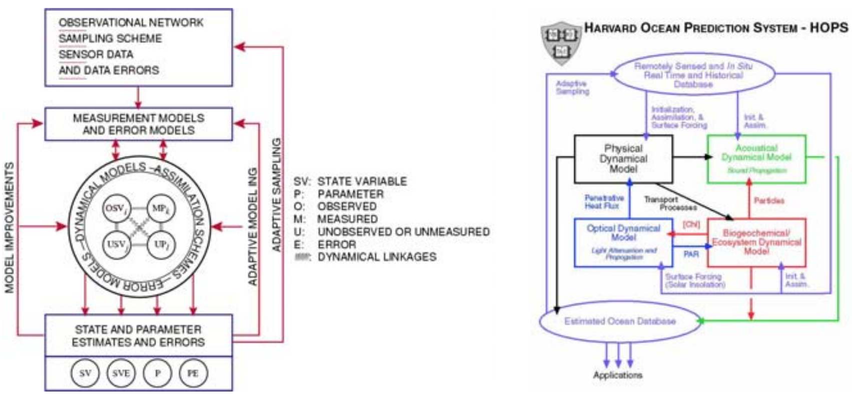


Figure 1 – illustration of a generic Ocean Observing and Prediction System (left – a) and the Harvard Ocean Prediction System (HOPS) (right – b)

2 ADAPTS[1]

Ocean Forecasting in a Distributed Computing Environment

The ADAPTS project, Rapid Real-Time Interdisciplinary Ocean Forecasting: Adaptive Sampling and Adaptive Modeling in a Distributed Environment, is developing the use of a distributed computing environment and the coupling of physical and biological oceanographic modeling with ocean acoustics to provide more effective and efficient real-time interdisciplinary ocean forecasting for naval and maritime operations, pollution control, fisheries management, etc. The advanced data assimilation and adaptive modeling methods integral to the ocean prediction system require significant computation and data storage resources. Grid computing technologies (Globus, Sun Grid Engine, Condor) and grid storage solutions with domain specific support (DODS etc.) are employed with a web portal interface to provide transparent remote or local computing and data access to help satisfy the computational and storage needs and to allow the ocean scientist/forecaster to focus on the research/operational task and not the management of the forecasting mechanism. Figure 2a is a schematic of the distributed computing environment and infrastructure for real-time interdisciplinary ocean forecasting and Figure 2b is a schematic of the HOPS Error Subspace Statistical Estimation (ESSE) procedure for data assimilation and error forecasting. ESSE is a four-dimensional multivariate estimation scheme for physical-biogeochemical-acoustical fields and parameters that aims to capture and forecast the dominant uncertainties, i.e. the error subspace, and assimilate all relevant data in order to control and reduce errors. It is currently based on a singular value decomposition of the minimum error variance update and on an adaptive, stochastic ensemble scheme for the forecast of the largest errors.

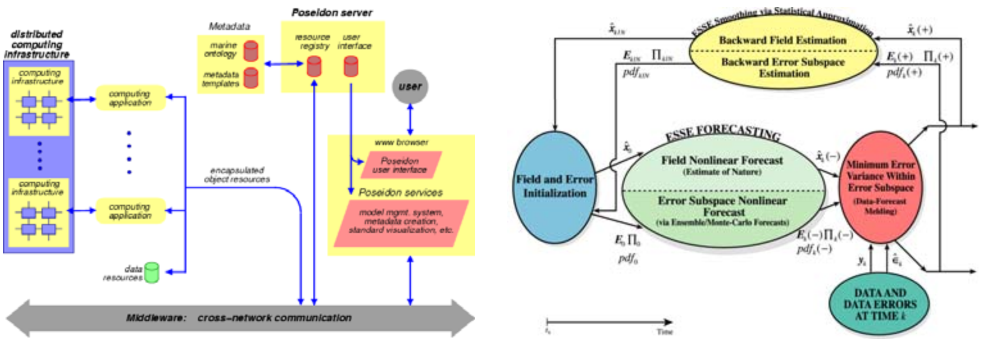


Figure 2 – schematic of (a) the distributed computing environment and infrastructure for real-time interdisciplinary ocean forecasting and (b) the Error Subspace Statistical Estimation procedure

Real-time adaptive modeling

Automated objective adaptive modeling allows for the optimal use of approximate models for rapidly evolving ocean dynamics. Adaptive biological modeling requires that a model change in response to ecosystem functioning, with respect to scientific objectives and according to data availability from field observations. Changes can be made to model structure, equations, and/or parameter values. Seasonal successions in food web structure and ecosystem shift due to climate change and anthropogenic stress require subsequent adaptation from numerical models. Physical and biological models can be adaptively coupled in multiple ways: (1) an (adaptive) physical model can drive multiple biological models when there is no way to ascertain *a priori* which is best for a given case; or, (2) an adaptive physical model and an adaptive biological model may proceed in parallel, independently adapting and driving each other. Figure 3 schematizes the coupling of physical and biological models.

[1] The project formerly known as LOOPS/Poseidon.

Figure 3 – adaptive coupling of physical and biological models – a single physical model drives multiple biological models (left) or physical and biological models adapt in parallel (right)

3 Predictive skill

Ocean states that are initially close often separate rapidly over time. Quantitative studies and methodologies are needed for quantifying the theoretical predictability. The predictability limit is the theoretical time necessary for two slightly different true ocean states to become undistinguishable from two arbitrarily chosen states. It depends on the true ocean processes under consideration and is a function of the initial uncertainty. The ability of a system to predict certain ocean phenomena is the predictive capability of the system for those phenomena. The system predictive capability is ultimately limited by predictability. Before the predictability limit is reached, other sources of error (quality and quantity of data, forcings, model structures and parameters, initialization and assimilation schemes, etc.) limit the predictive capability.

The Assessment of Skill for Coastal Ocean Transients (ASCOT) project is a series of real-time Coastal Predictive Skill (CPSE) and Rapid Environmental Assessment (REA) experiments and simulations focused on quantitative skill evaluation, carried out by the Harvard Ocean Prediction System group in collaboration with the NATO SACLANT Undersea Research Centre. ASCOT-01 was carried out in Massachusetts Bay and the Gulf of Maine in June 2001. ASCOT-02 took place in May 2002 in the Corsican Channel near the island of Elba in the Mediterranean Sea. Figure 4 presents the HOPS modeling domains utilized during the ASCOT exercises.

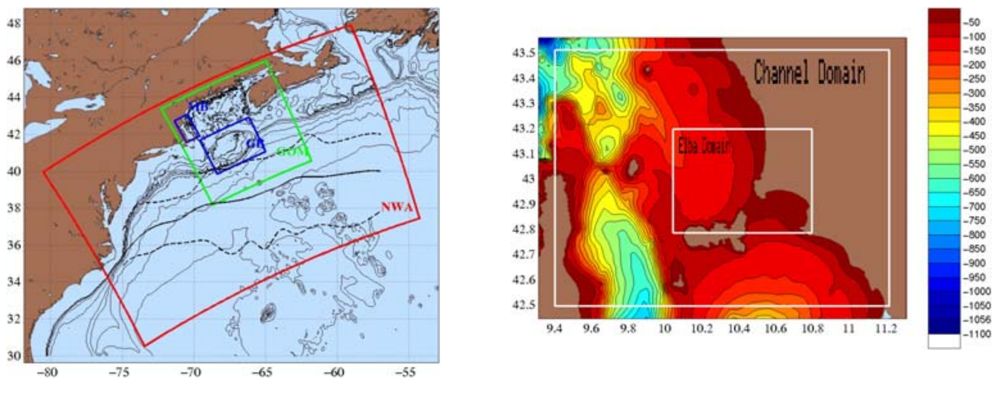


Figure 4 – HOPS modeling domains for the ASCOT-01 (left) June 2001 and ASCOT-02 (right) May 2002 experiments.

Skill of the operational forecasts is measured using the metrics, Root-Mean-Square Error (RMSE) and Pattern Correlation Coefficient (PCC). These numbers are computed model level by model level or on depth surfaces, and as a volume average. Perfect values of the RMSE and PCC are, respectively, zero and one. The metrics RSME and PCC are defined by:

$$\mathrm{RMSE} \equiv \sqrt{(T^f - \hat{T})^T (T^f - \hat{T})} \equiv \left\| T^f - \hat{T} \right\|_2, \text{ and } \mathrm{PCC} \equiv \frac{(T^f - T^b)^T (\hat{T} - T^b)}{\left\| T^f - T^b \right\|_2 \left\| \hat{T} - T^b \right\|_2}$$

where $\hat{T}$ denotes the true ocean, T^f its forecast, T^b a background field vector (e.g. large-scale field, climatological field, etc.), and $\|\,.\,\|_2$ the vector $_2$ norm. A classic measure of skill is to compare the RMS and PCC of the forecast with those of the initial conditions (persistence). If the RMSE of the forecast is smaller than that of the IC, the forecast has RMS-skill or beats persistence. Similarly, if the PCC of the forecast is larger than that of the IC, the forecast has PCC-skill or has better patterns than persistence. The units of the RMSE are those of the quantity being evaluated. PCC is non-dimensional.

The ASCOT-01 skill metrics have been determined by defining the initialization survey (6-8 June 2001) (nowcast) fields as "persistence", the forecast from the end of the assimilation of the initialization survey data as the "forecast", and the verification survey fields (15-20 June) as the "verification". RMS and PCC are calculated only in regions where the non-dimensional objective analysis expected observation errors are estimated to be less than or equal to 0.3. The statistics are computed at constant depths determined by important features in the vertical structure of the verification fields, e.g. depth of the mixed layer, center of the thermocline and deep (quiescent) conditions. Additional intermediate depths have been added for completeness.

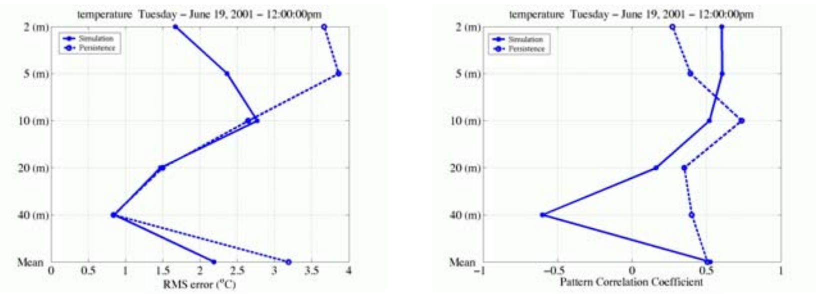


Figure 5 – ASCOT-01 temperature RMS error (left) and Pattern Correlation Coefficient (right)

The comparison of forecast and persistence to verification for ASCOT-01 is shown in Figure 5 (RMS Error and PCC) for temperature. The statistics of the forecast fields are shown as solid lines while persistence is shown as dotted. The bottom point in Figure 5 indicates the mean value of the points above. For both RMS Error and PCC, the forecast is clearly better than persistence for temperature in the upper water column. Below the center of the thermocline (10m), the values are essentially identical. In the mean, forecast RMS errors are lower by approximately 1^{o}C. Temperature mean PCC values are approximately the same for the forecast and persistence.

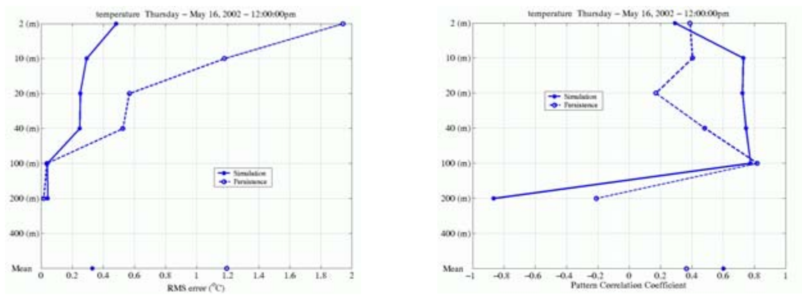


Figure 6 – ASCOT-02 temperature RMS error (left) and Pattern Correlation Coefficient (right)

The ASCOT-02 comparison of forecast and persistence to verification for 15 May is shown in Figure 6. For temperature RMS error, the forecast for 16 May is clearly superior to persistence above the pycnocline (40m). Below that depth, the results are nearly identical. The mean temperature forecast RMS error is approximately 0.85^{o}C lower than that of persistence. The temperature forecast PCC is larger than the persistence PCC above the center of the thermocline (20m), but is lower below. Additional results from these experiments can be found at the web sites: http://people.deas.harvard.edu/~leslie/ASCOT01/index.html and http://people.deas.harvard.edu/~leslie/ASCOT02/index.html.

4 Mini-HOPS

Although available ocean forecast schemes include a broad range of scales, they usually cannot account accurately for higher frequency ocean phenomena (sub-mesoscale to small scale) due to the uncertainty of the forcing fields and initial phase of high frequency phenomena. At present, to overcome this uncertainty, extensive oceanographic data collection is required, which is very expensive and is generally not feasible to obtain on a sustained and substantial basis. The Mini-HOPS concept is designed to locally solve the accurate representation of the sub-mesoscale synopticity through rapid real-time assimilation of high-resolution data in a high-resolution local nested model domain. This approach produces locally more accurate oceanographic field estimates and short-term ocean forecasts and improves the impact of local field high-resolution data assimilation.

For MREA03, each domain survey was designed to be completed within an inertial period (app. 13 hours). The small domains were initialised from a regional HOPS run. Inertial motion and sub-mesoscale features were identified from the collected data and assimilated into the small domains following a progressive pattern (from west most domain to the east most domain) on a cyclic basis. The mini-HOPS protocol produced short-term forecasts (24-48 hours) with hourly resolution. Over-sampling was carried out so redundancy exists to evaluate the accuracy and persistency of the sub-mesoscale, short-term forecasts. Additional information is available in E. Coelho and A.R. Robinson, “NATO Tactical Ocean Modeling: the mini-HOPS strategy in the MREA03 field trial”, in this volume.

5 End-to-End System

The littoral environment can be highly variable on multiple scales in space and time, and sonar performance is affected by these inherent variabilities. Uncertainties arise in estimates of oceanic and acoustic fields from imperfect measurements (data errors), imperfect models (model errors), and environmental variabilities not explicitly known. A conceptual basis has been developed to achieve the following: i) generic methods to efficiently characterize, parameterize, and prioritize system variabilities and uncertainties arising from regional scales and processes; ii) error, variability and uncertainty models for the end-to-end system and it’s components to address forward and backward transfer of uncertainties; and, iii) transfers of uncertainties from the acoustic environment to the sonar and its signal processing in order to effectively characterize and understand sonar performance and predictions. In order to accomplish these objectives, an end-to-end system approach is necessary.

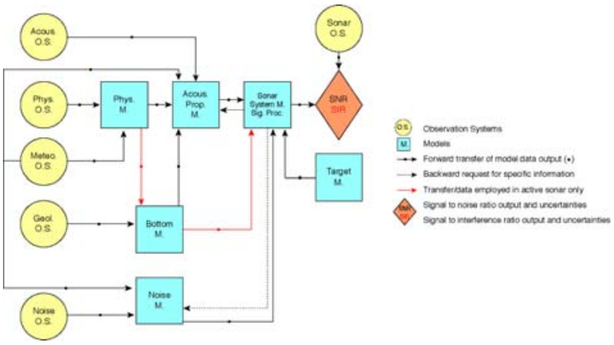


Figure 7. Schematic diagram of the end-to-end system (model point of view).

Figure 7 schematizes the end-to-end system from the model point of view, where models are used to represent each of the coupled dynamics (boxes) and also the linkages to observation systems (circles). An effort was made to make the diagram exact but as simple as possible. The diagram illustrates the forward transfer of information, including uncertainties, in terms of observed, processed and model data (dots on arrows) and products and applications (diamond). The system concept encompasses the interactions and transfers of information with feedback from: i) observing systems, the information being physical-acoustical-bottom-noise-meteorological-sonar data, ii) coupled dynamical models, the information being physical-acoustical-bottom-noise-sonar state variables and parameters, and, iii) sonar equation models, the information being parameters in sonar equations.

The estimation of ocean physical and acoustical fields has been carried out as a single coupled data assimilation problem for identical-twin experiments using PRIMER data. Environmental fields and their dominant uncertainties are predicted using ESSE and transferred to acoustical fields and uncertainties using an ensemble of acoustic propagation model simulations. The resulting coupled dominant uncertainties define the error subspace. The physical and acoustical data are then assimilated such that the total error variance in the error subspace is minimized.

In the identical twin experiment shown here the “true” ocean is a model simulation that assimilates real physical data. After 5 days, a snapshot of the “true” ocean is taken and the corresponding “true” sound-speed field is input to the acoustical coupled-normal-mode model. The acoustical model provides the “true” TL field on day 5. Different synthetic physical and acoustical data were coarsely sampled from this “true” physical-acoustical ocean. These data sets were assimilated using ESSE. Sequential processing of observations is utilized and it was verified that the order of the assimilation (ocean physics before acoustics, or vice-versa) does not matter. In Figures 8-9, the synthetic physical data are coarsely sampled temperature and salinity measurements: 2 CTD profiles are taken across the shelfbreak front, along a PRIMER acoustical path. The acoustical data are simulated towed-receiver TL data along the same path. An ESSE ensemble of 79 members is used for prior error estimate.

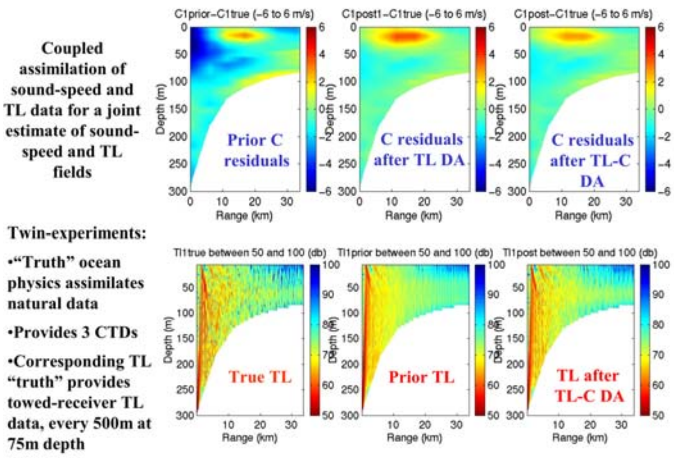


Figure 8. Coupled physical-acoustical filtering via ESSE along one of the Shelfbreak-PRIMER acoustic path (top row, C-residuals; bottom row TL fields).

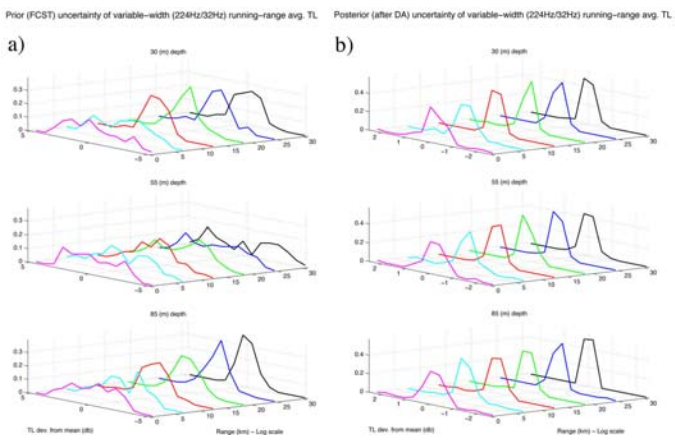


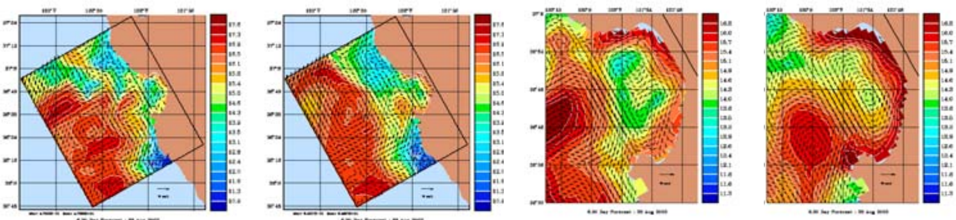
Figure 9. PDF estimates of broadband TL as a function of range and depth, along a PRIMER acoustic path: (a) Prior PDF (predicted by ESSE); (b) Posterior PDF (after ESSE assimilation).

The assimilation results for the sound-speed and continuous-wave TL fields are shown in Figure 8. The sound-speed (C) residuals are before assimilation (prior fields), after assimilation of the TL data, and after assimilation of both the TL and C data. The true TL, prior TL (i.e. the mean or forecast) and posterior TL (after assimilation of both TL and C data) are shown in the bottom row. Although the sub-sampled data are limited, the posterior C and TL are substantially closer to the true C and TL than the priors. The posterior ESSE ensemble properties (error covariances, etc, not shown) importantly estimate the uncertainty reduction as a result of the coupled data assimilation. To simulate the transfer uncertainties to a broadband sonar system (TL term in a sonar equation), the ensemble of single-frequency TL realizations are processed, using a variable-width running-range average. The prior and posterior histograms of deviations from the mean broadband TL (i.e., the error PDF estimates) are shown in Figure 9. The prior PDFs are found to be depth and range dependent (Fig. 9a). Near the depth (55 m) of the main wave-guide, the predicted error standard deviation is relatively constant with range and relatively large, around 3 to 4 (db). Above (30 m) and below (85 m), standard deviations tend to decrease with range (down to 2 db), leading to a higher PDF peak. After assimilation (Fig. 9b), the uncertainties are reduced to ± 1db and are more Gaussian at all depths.

The end-to-end system encompasses the interactions and transfers of information with feedback from observing systems, coupled dynamical models that result in sonar performance predictions. The linkages and feedback among these different components are now being developed. The end-to-end framework is designed to support the individual components, environmental as well as non-environmental uncertainties (system related) so that an assessment of the dominant mechanism of uncertainty as it affects the SNR/SIR can be identified. The ability to assess the importance of the individual uncertainty components in the sonar performance prediction along within its aggregate uncertainty can be an invaluable tool in the development of tactical guidance.

6 AOSN-II

The AOSN-II 2003 Monterey Bay Field Experiment brought together physical oceanographers, AUV engineers, marine biologists and dynamical modelers. This diverse group studied Monterey Bay using dynamical ocean circulation models and observational tools such as satellites, airplanes, ships, drifters, buoys, autonomous underwater vehicles, and undersea gliders. The researchers used these tools to observe and predict the upwelling and movement of cold, nutrient-rich water that occurs off Monterey Bay during the summer months. These upwelling events create blooms of marine plankton that support the abundant fisheries and other wildlife in and around the bay.



Nowcast Forecast Nowcast Forecast

Figure 10. Example HOPS products from AOSN-II: a nowcast and 2-day forecast of temperature for the complete data domain and a zoom on Monterey Bay

During the AOSN-II experiment, the Harvard HOPS team achieved the following: 23 sets of real-time nowcasts and forecasts of temperature, salinity and velocity were released between 4 August and 3 September; 10 sets of real-time ESSE forecasts, comprised of a total of 4323 ensemble members, were issued over the same time period; adaptive sampling recommendations for ship and glider observations were suggested on a routine basis; a web site (http://www.deas.harvard.edu/~leslie/AOSNII/index.html) was developed for daily distribution of field and error forecasts, scientific analyses, data analyses, special products and control-room presentations; and, data from ships (Pt. Sur, Martin, Pt. Lobos), gliders (WHOI and Scripps) and aircraft SST were assimilated within 24 hours of their appearance on the data server. Figures 10 and 11 are examples of HOPS products for the AOSN-II experiment.

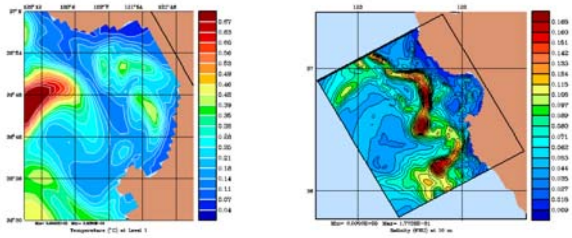


Figure 11. Example HOPS ESSE products from AOSN-II: two-day forecast of model error for temperature in the Monterey Bay zoom and for salinity in the complete data domain.

7 Summary and conclusions

Advanced systems for adaptive sampling and adaptive modeling in a distributed computing environment have been developed and implemented. Using these systems in real-time forecast exercises, quantitative predictive skill, as measured by RMS Error and Pattern Correlation Coefficient has been achieved significantly in the dynamic upper ocean. The use of coupled physical-acoustical data assimilation via the ESSE data assimilation process has demonstrated the ability to transfer environmental uncertainties through acoustic propagation and signal processing to sonar performance. An integrated ocean observing and prediction system was utilized for a predictive skill experiment in Monterey Bay and the California Current System in Summer 2003 and disseminated numerous forecasts in real-time.

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References

1. Abbot P. and Dyer I., Sonar Performance Predictions Based on Environmental Variability, In “Acoustic Variability, 2002”. N.G. Pace and F.B. Jensen (Eds.), SACLANTCEN. Kluwer Academic Press, 611-618 (2002).
2. Chin-Bing S.A., Kink D.B. and Boyd J.D., The Effects of Ocean Environmental Variability on Underwater Acoustic Propagation Forecasting, *Oceanography and Acoustics: Prediction and Propagation Models* (A.R. Robinson and D. Lee, editors), American Institute of Physics Press, New York (1994).
3. Evangelinos C., Chang R., Lermusiaux P.F.J. and Patrikalakis N. Rapid Real-Time Interdisciplinary Ocean Forecasting using Adaptive Sampling and Adaptive Modeling and Legacy Codes: Component Encapsulation using XML, In ``*Computational Science - ICCS 2003, International Conference on Computational Science 2003''*, P.M.A. Sloot, D. Abramson, A. Bogdanov, J.J. Dongarra, A. Zomaya, Y. Gorbachev (Eds.). Springer, *Lecture Notes in Computer Science*, 2660, 375-384 (2003).
4. Lermusiaux, P.F.J. and C.-S. Chiu. Four-dimensional data assimilation for coupled physical-acoustical fields. In “Acoustic Variability, 2002”. N.G. Pace and F.B. Jensen (Eds.), Saclantcen. Kluwer Academic Press, 417-424 (2002).
5. Lermusiaux P.F.J., C.-S. Chiu and A.R. Robinson. Modeling Uncertainties in the Prediction of the Acoustic Wavefield in a Shelfbreak Environment. Proceedings of the 5th ICTCA, May 21-25, 2001, in “Theoretical and

Computational Acoustics 2001", E.-C. Shang, Q. Li and T.F. Gao (Eds.), World Scientific Publishing Co., 191-200 (2002).
6. Lermusiaux, P.F.J., A.R. Robinson, P.J. Haley, Jr. and W.G. Leslie. Advanced Interdisciplinary Data Assimilation: Filtering and Smoothing via Error Subspace Statistical Estimation. *Proceedings of Oceans 2002 IEEE/MITS Conference*, 795-802 (2002).
7. Robinson A.R., Lermusiaux P.F.J., and Sloan N.Q., Data Assimilation. In THE SEA: The Global Coastal Ocean, Volume 10: Processes and Methods (K.H. Brink and A.R. Robinson, eds.), John Wiley and Sons, NY, 541-594 (1998).
8. Robinson, A.R., P. Abbot, P.F.J. Lermusiaux and L. Dillman. Transfer of uncertainties through physical-acoustical-sonar end-to-end systems: A conceptual basis. Acoustic Variability 2002. N.G. Pace and F.B. Jensen (Editors), Saclantcen. Kluwer Academic Press, 603-610 (2002).
9. Robinson, A.R., P.F.J. Lermusiaux, P.J. Haley, Jr. and W.G. Leslie. Predictive Skill, Predictive Capability and Predictability in Ocean Forecasting. *Proceedings of* O*ceans 2002 IEEE/MITS Conference*, 787-794 (2002).
10. Robinson, A.R. and P.F.J. Lermusiaux (2004). Prediction Systems with Data Assimilation for Coupled Ocean Science and Ocean Acoustics, Proceedings of the Sixth International Conference on Theoretical and Computational Acoustics (A. Tolstoy, *et al*., editors), World Scientific Publishing. [In press].