Environmental Acoustic Variability Characterization for Adaptive Sampling

J.P. Fabre,[1] C. Rowley,[2] G. Jacobs,[2] E. Coelho,[2]
C. Bishop,[3] X. Hong,[3] and J. Cummings[2]
[1]Acoustics Division
[2]Oceanography Division
[3]Marine Meteorology Division

Introduction: During shallow water antisubmarine warfare missions, environmental uncertainty significantly impacts Fleet asset performance. Oceanographic sensor availability, acoustic sensor coverage, and operational time limitations put constraints on efforts to observe large ocean areas. To address these challenges, NRL researchers have advanced and incorporated applied research technologies developed under several disciplines, to implement an adaptive sensor placement capability that, under certain assumptions, minimizes the uncertainty in forecasted information. The technologies incorporated include ocean data quality control, rapidly nested oceanographic modeling, data assimilation, ensemble representation of uncertainty, acoustic performance modeling, and Ensemble Transform Kalman Filter (ETKF) adaptive sampling.

Techniques: The relocatable Navy Coastal Ocean Model (NCOM) is currently being implemented and tested at the Naval Oceanographic Office (NAVOCEANO) to provide high-resolution local mesoscale ocean forecasts to support Fleet oceanographic and acoustic operations. Observations from local sensors including gliders and Fleet measurements are assimilated into NCOM using the NRL Coupled Ocean Data Assimilation (NCODA) system. Surface forcing is provided by the Coupled Ocean/Atmosphere Mesoscale Prediction System (COAMPS®) or the Navy's Operational Global Atmospheric Prediction System (NOGAPS), and the boundary conditions are provided by a global run of NCOM available at the NAVOCEANO. Multiple sources of error in the modeling process need to be considered, including errors associated with the initialization and boundary conditions of models, numerical approximations, modeling strategies, atmospheric forcing, impact of under-sampling in the assimilation process, and unresolved scales. There are multiple approaches to address these problems. This work focused on the application of Monte Carlo methods to producing ensemble based error estimates along with the predicted state variables. Monte Carlo methods have the advantage of simplicity in their formulation and have been used extensively by the meteorological community. The atmospheric Ensemble Transform (ET) approach[1] was adapted for ocean mesoscale applications and provides a self-calibrated ensemble generation technique, such that at each initialization time, the magnitudes of the ensemble spread are re-set to match the best estimate available of the analysis error variance field. Uncertainty in the atmospheric forcing of the ocean is accounted for by forcing each ocean ensemble member with atmospheric forecasts that are smoothly but randomly shifted in time.

The sample covariance of the ensemble of forecasts provides a 4-dimensional estimate of how the covariance of the error of the ensemble mean would evolve through time if no additional observations were taken. To predict how targeted observations would reduce the forecast error variance, the Ensemble Transform Kalman Filter[2,3] was applied to the ET ensemble. The ETKF rapidly evaluates the reduction in forecast error variance due to very large numbers of future feasible sensor deployments. The particular sensor deployment that, according to the ETKF, reduces forecast error variance more than any other proposed sensor deployment is deemed "optimal."

The acoustic properties of the ocean state are the most critical to Fleet operations. To create measures of forecast error directly related to these acoustic properties, each ensemble member is processed using the Navy Standard Parabolic Equation (NSPE) acoustic propagation model for multiple bearings at each grid point to compute transmission loss. Integrated acoustic coverage[4,5] is then computed to provide a wide area assessment of the uncertainty (due to the ocean model variability) of the acoustic performance over the area. Methods are then used to predict optimal sensor sampling to reduce uncertainty in areas where it is high. This guidance is provided to the sensor operators in a variety of formats, including waypoints for existing sensors, or sensor placement plans for each sensor to be deployed. Once the data is collected, it is fed back into the adaptive sampling system and the process is continued.

Demonstration: The adaptive sampling techniques described above were demonstrated during the Valiant Shield 07 (VS07) Fleet exercise in the eastern Pacific Ocean around Guam in the summer of 2007. Ensembles of oceanography (temperature, salinity, and sound speed) and acoustic coverage were provided daily for analysis. Variance of forecast temperature and acoustic performance over the ensemble were used as cost functions (Figs. 4 and 5) to drive the sensor placement algorithms for optimization of measurements for the purposes of reducing the error in the ocean predictions given all candidate sensor paths (Fig. 6).

This planning tool, currently being transitioned to NAVOCEANO, enables the Navy to employ assets in a way that reduces uncertainty in acoustic predictions, allowing the operational planner to maximize

the desired effect. This exciting effort has many applications beyond adaptive sampling, in that it provides estimates of the environmental uncertainty. This work also resulted in improvements to various capabilities, including the NSPE, which impacts many Navy applications.

[Sponsored by ONR and SPAWAR Rapid Transition Program]

References
[1] C.H. Bishop and Z. Toth, "Ensemble Transformation and Adaptive Observations," *J. Atmos. Sci.* **56**, 1748-1765 (1999).
[2] C.H. Bishop, B.J. Etherton, and S.J. Majumdar, "Adaptive Sampling with the Ensemble Transform Kalman Filter Part I: Theoretical Aspects," *Mon. Wea. Rev*. **129**, 420-435 (2001).
[3] G. Evensen, "The Ensemble Kalman Filter: Theoretical Formulation and Practical Implementation," *Ocean Dynamics* **53**, 343-367 (2003).
[4] S.M. Dennis and J.P. Fabre, "Characterization of the Range Dependence of an Ocean Environment to Reduce Acoustic Estimation Time," *IEEE Proceedings of Oceans 2007, Vancouver*, 2007. doi:10.1109/oceans.2007.4449371.
[5] J.P. Fabre, "Integrated Signal Excess as a Metric for Environmental Acoustic Assessment," *J. Acoust. Soc. Am.* **122**(5), 2942 (2007). ★
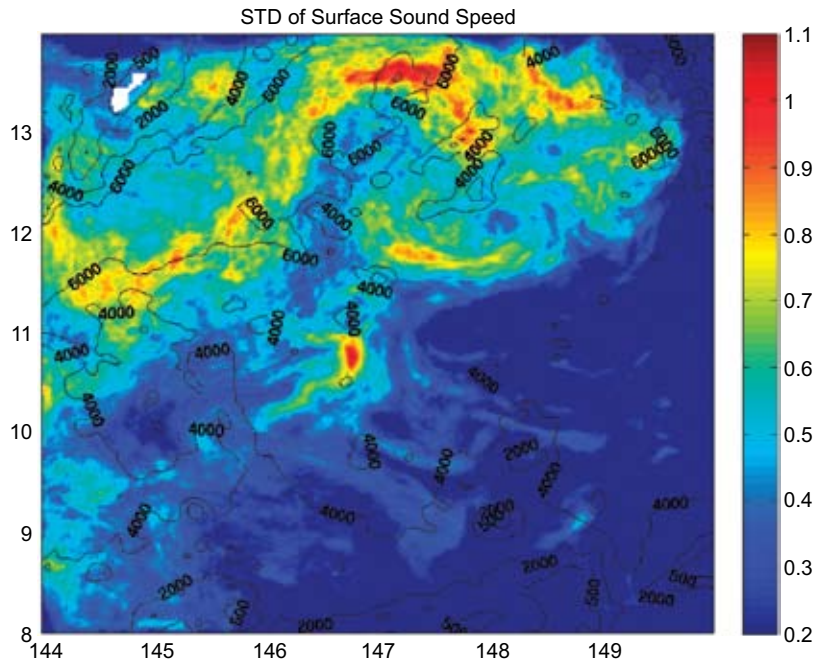
STD of Surface Sound Speed

FIGURE 4
Example of variance of sound velocity at the surface over the ensemble with bathymetry contours for the exercise area. Areas of greatest model uncertainty are shown in red.
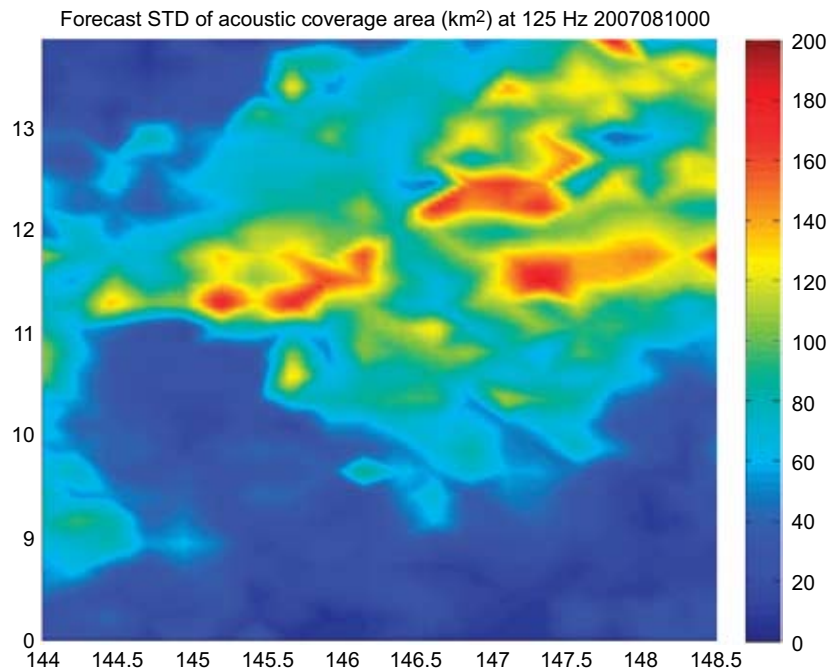
Forecast STD of acoustic coverage area (km2) at 125 Hz 2007081000

FIGURE 5
Example of acoustic coverage variance at a receiver depth of 100 m, over the ensemble for the exercise area, showing the areas of greatest acoustic performance uncertainty (red).

Optimal Glider Tracks on Summary Map for Day 09

Optimal Glider Tracks on Summary Map for Day 12
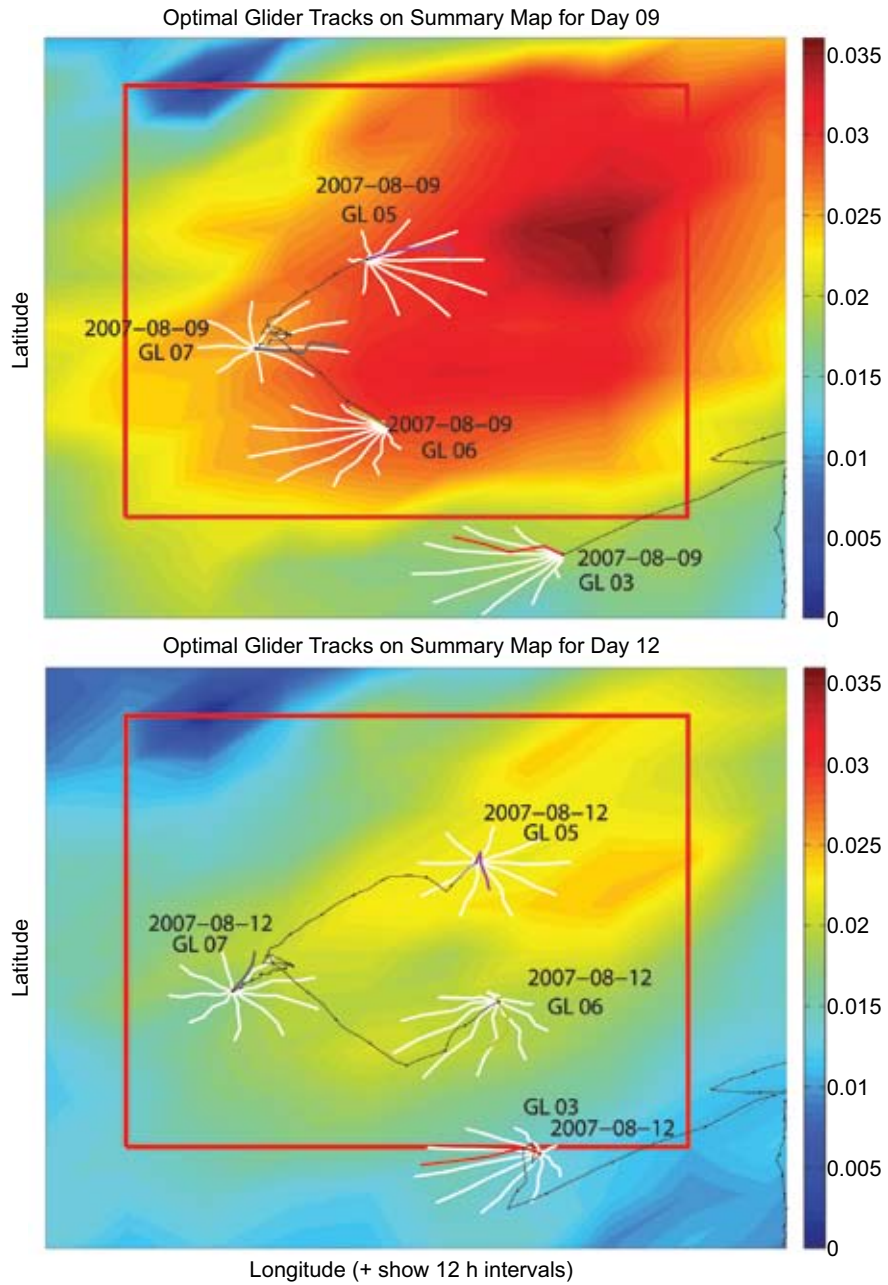
Longitude (+ show 12 h intervals)

FIGURE 6
Example of a scenario used to reduce model error in an area of high model uncertainty
(red box). The colors in the figure show the relative impact of observations in reducing the
predicted error at August 9 and 12, 2007. Between these two days, gliders were steered to-
ward locations with high predicted impact in reducing the model error. Data was assimilated
into the model and the impact of observations became smaller as the model forecast became
more accurate in the area of interest.