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Environmental and Statistical Performance Mapping Model for Underwater Acoustic Detection Systems

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Environmental and Statistical Performance Mapping Model for Underwater Acoustic Detection Systems

A Dissertation

Submitted to the Graduate Faculty of the
University of New Orleans
in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy
in
Engineering and Applied Science
Physics

by

Pamela Jackson McDowell

B.S. Louisiana Tech University, May 1981
M.S. University of New Orleans, May 2001

May, 2010

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Abstract

This manuscript describes a methodology to combine environmental models, acoustic signal predictions, statistical detection models and operations research to form a framework for calculating and communicating performance. This methodology has been applied to undersea target detection systems and has come to be known as *Performance Surface* modeling. The term *Performance Surface* refers to a geo-spatial representation of the predicted performance of one or more sensors constrained by all-source forecasts for a geophysical area of operations. Recent improvements in ocean, atmospheric and underwater acoustic models, along with advances in parallel computing provide an opportunity to forecast the effects of a complex and dynamic acoustic environment on undersea target detection system performance. This manuscript describes a new process that calculates performance in a straight-forward ‘sonar-equation’ manner utilizing spatially complex and temporally dynamic environmental models. This performance model is constructed by joining environmental acoustic signal predictions with a detection model to form a probabilistic prediction which is then combined with probabilities of target location to produce conditional, joint and marginal probabilities. These joint and marginal probabilities become the scalar estimates of system performance. This manuscript contains two invited articles recently accepted for publication. The first article describes the *Performance Surface* model development with sections on current applications and future extensions to a more stochastic model. The second article is written from the operational perspective of a Naval commanding officer with co-authors from the active force. *Performance Surface* tools have been demonstrated at the Naval Oceanographic Office (NAVOCEANO) and the Naval Oceanographic Anti-Submarine Warfare (ASW) Center (NOAC) in support of recent naval exercises. The model also has recently been a major representation for the ‘performance’ layer of the Naval

Meteorological and Oceanographic Command (NAVMETOCOM) in its Battlespace on Demand strategy for supporting the Fleet with oceanographic products.

Keywords: Underwater Acoustics, Anti-Submarine Warfare, Performance Surface, Sonar Performance, Statistical Performance Modeling

Chapter 1 Introduction

Background

A core mission for the U.S. Navy is to conduct Anti-Submarine Warfare (ASW). The motivation for this work originated from a report requested by Congress in 1997 to assess the current capability of the U.S. Navy to perform the ASW mission. To prepare this assessment many data sources that impact the Navy's ASW program were gathered. One such source was the Ship ASW Readiness/Effectiveness Measurement (SHAREM) exercise program. SHAREM exercises are fleet events conducted by Commander Surface Warfare Development Group in forward areas to assess the performance of Navy systems against realistic targets in realistic environments. A set of these SHAREM exercises, termed 'Site-Specific SHAREM Exercises', were supported by the Naval Oceanographic Office (NAVO) with co-incident environmental and transmission loss measurements. While results from these exercises produced a quantitative field measured accounting of ASW performance, there was little connection made to system and/or environmental factors which could be used to explain past and predict future overall ASW performance. This inability to effectively predict overall ASW performance over operationally significant spatial and temporal scales led to an ONR sponsored research effort (McDowell and Gough, 2000) which initiated this research. The objective was to develop a framework to connect environmental variability to ASW performance in ways that could account for unexpected detection results.

From the tactical and operational point of view, the single most critical metric of sonar performance is Range of Detection (Koopman, 1946), meaning the horizontal distance from the

sonar at which the target becomes apparent as a target and is correctly declared a target. This metric is a random variable that depends on many factors, some deterministic and measurable, some deterministic and immeasurable, and some random. The central problem of sonar performance prediction has been to convert a heterogeneous collection of specialist's models describing sources of acoustic energy in the ocean environment, acoustic energy propagation in the ocean, ocean variability, ocean boundary variability, sonar apertures, signal processing, machine and human decision processes into an expression of Expected Range of Detection, at least, and at best a complete probability distribution of detection conditional on range. Interim stages of analysis produce estimates of probability of detection conditional on all the variables faced by the sonar engineer, the tactician, and the strategic planner.

The advantage of the methodology developed under this project is that it provides a theoretical framework for assessing a variety of assertions about sonar performance and its relationship with the environment, tactics, sonar design and employment, and many other issues. A simple model of the framework is depicted in Figure 1.

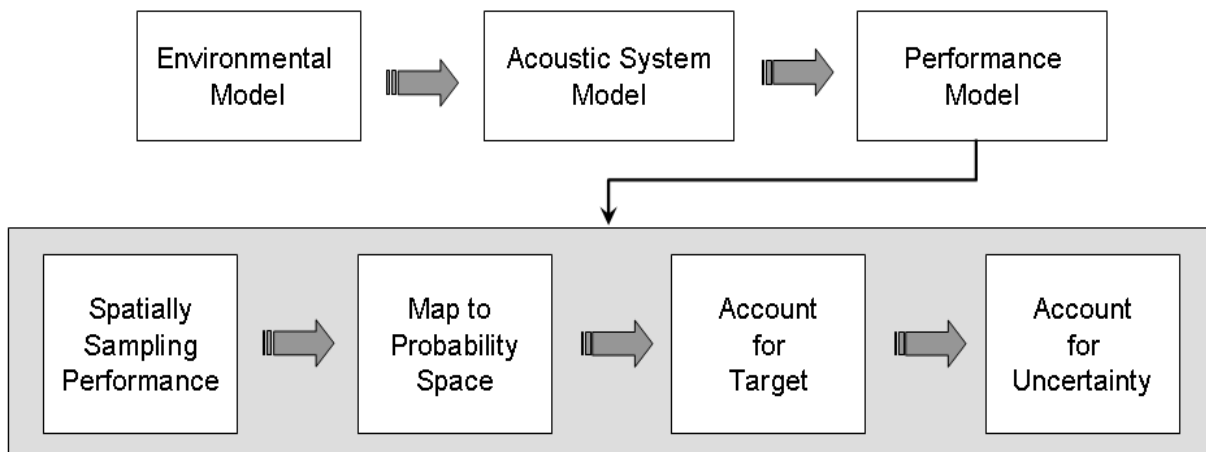


Figure 1 Performance Model Framework

A typical Naval Tactical Decisions Aid (TDA) system (represented in the upper row middle box of Figure 1 as ‘Acoustic System Model’), takes as input an Environmental Model (represented by the upper row right box) of ocean surface, water column sound speed, and bottom properties. Traditionally, the Acoustic System Model or TDA consists of acoustic models, some embedded environmental databases, and system signal processing models, and is used to make predictions of point-to-point sonar performance in terms of Signal Excess. The new concept was to take a step beyond, utilize the accepted TDA models to produce a large number of these predictions over the entire operational area and temporal time scale, combine these with a probabilistic detection model, a probabilistic target location distribution, and conditional probability methods in order to produce a model of ASW performance that carries the full range of detection probability over the entire operational space. In the time since the work began notable advances have been made in oceanographic forecast models, acoustic propagation models, statistical ambient noise climatology, and TDA computational speed. These advances have made the computation of Performance Surface estimates not only operationally viable but better able to capture the complex and dynamic nature of the acoustic ASW problem.

Description of Embedded Articles

This manuscript contains two invited journal articles recently accepted for publication in the Journal of Underwater Acoustics. The two articles are founded on *Performance Surface* as a tool that can be used to provide operational insight for Navy commanders conducting ASW operations. This performance model, in its present form, was developed by the author, however both articles have valued contributions by co-authors from Navy command institutions, Navy

active force, and industry. The first article “Performance Surface: Development, Current Use and Future Improvements” by McDowell, Gough, Miller, and Keenan, describes the model development, some of its output, puts in the context of its intended usage, and introduces options for future extension. The second paper “Performance Surface as a Tool for Increasing ASW Proficiency” by Miller, McDowell, and Holton is written from a Navy operational perspective. CDR Anthony Miller, a Ph.D. graduate of the Naval Post Graduate School, has served as the commanding officer for the Naval Oceanography ASW Center. This paper describes ways that his Naval Oceanography ASW Team (NOAT) officers have used this modeling tool to provide strategic guidance to Fleet decision-makers in both experimental exercises and real-world events.

Following this introduction, Chapter 2 defines *Performance Surface*, describes the inputs, methodology, and examples of typical results. Chapter 3 contains the invited journal article “Performance Surface: Development, Current Use and Future Improvements”. This paper describes the early development and motivation for this research. Various *Performance Surface* types are described. A small set of current uses are presented. Finally a future extension of this methodology is described where a stochastic approach of replacing each component of the sonar equation with probability density functions is presented. Chapter 4 contains the second article, “Performance Surface as a Tool for Increasing ASW Proficiency”. This paper is based on uses of *Performance Surface* products from the perspective of a Navy officer providing guidance of high level operational commanders. Operations Research can be described, in part as providing quantitative options or guidance for evaluating alternative courses of action (COAs) in complex environments (Moore and Kimbal, 1951). *Performance Surface* estimates are presently used to evaluate various operational scenarios such as optimal allocations of sensors, sensor placement,

and optional routing to name a few. Examples of operational uses are discussed in this paper. Strengths and weaknesses are presented. Chapter 5 summarizes with, a brief step by step description of the method, followed by a discussion of the impact of the work from an operational and research perspective. Future and on-going work resulting from this research is discussed.

Chapter 2 Method

Performance Surface Overview

Performance Surface is a geo-spatial representation of relative performance of a sonar system.

The process begins, depicted graphically in Figure 2, with an environmental model of the ocean.

An adequate model of the ocean environment consist of bathymetry, geophysical bottom

properties, water column properties that effect acoustic propagation. Additionally,

characterization of the surrounding signal interferers, ambient noise and clutter are required.

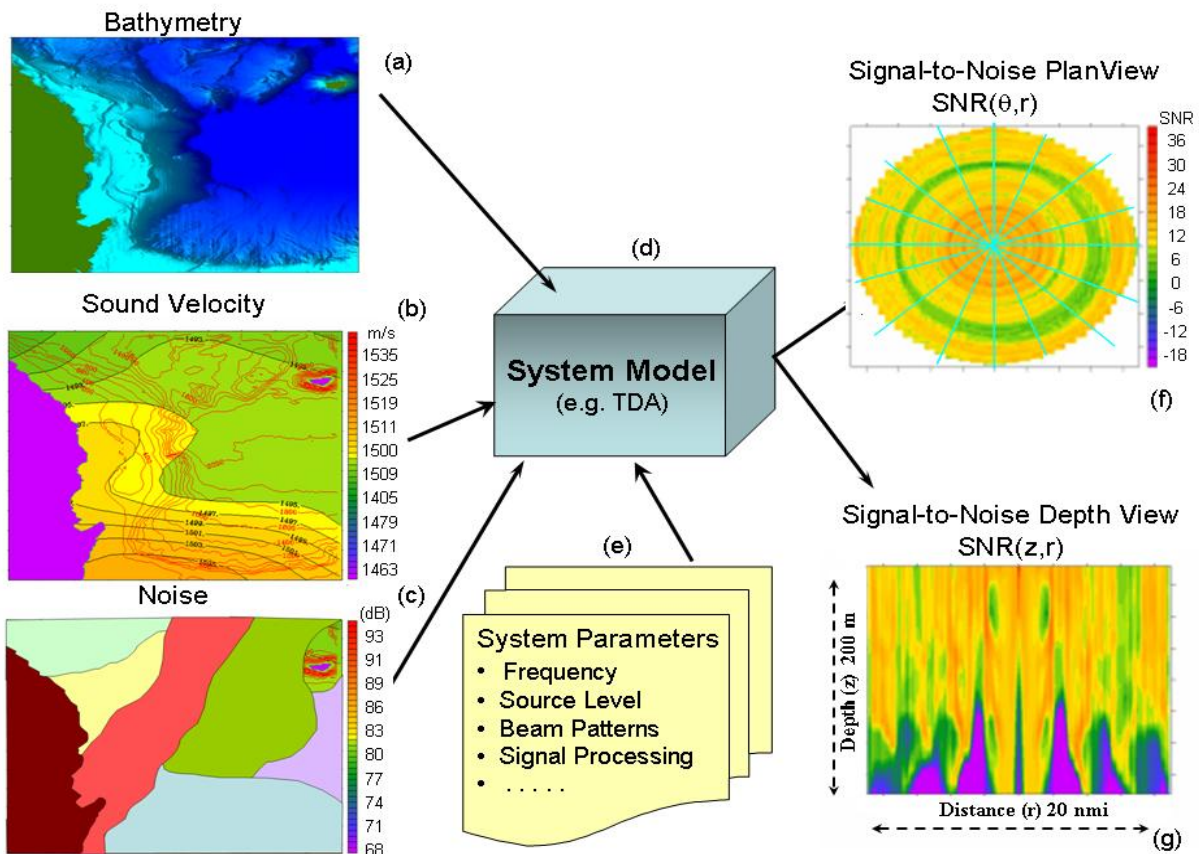


Figure 2 Combining Environmental Parameters (a) bathymetry,(b) sound velocity, (c) noise, and (e) system parameters, with , (d) Sound Propagation and System Models to predict, (f) Plan View of SNR(θ,r) and (g) Vertical Depth View of SNR(z,r)

The current Navy Tactical Decision Aid (TDA) systems perform the function of combining environmental models with system parameters to calculate estimates of Signal-to-Noise ratio (SNR). Panel (f) of Figure 2 represents SNR in a top-down (plan view) of SNR at a single depth, as a functions of range (r), and radial bearing (θ). Panel (g) of Figure 2 depicts a depth view of the east-looking radial and west-looking radial showing SNR as a function of range (r), and depth (z).

To represent performance well, care must be taken in preparing an accurate characterization of the environmental factors. The Naval Oceanographic Office and the Naval Research Laboratory have devoted much effort and attention to developing and improving these models and databases. Because the environment is such an important component of the process, the next section focuses on some of these models and their potential impact on the resulting performance estimates.

Environmental Modeling

Fundamental to this technique is having an accurate representation of the underlying environmental conditions. Initially, the oceanographic model used to characterize the sound velocity structure over a significantly sized operational area (i.e. 100 X 100 nmi) was the Modular Ocean Data Assimilation System (MODAS) developed by Fox et al. (2001). MODAS is a global model that assimilates in situ salinity and temperature profiles, sea surface height (SSH) and sea surface temperature measurements to construct synthetic profiles and predict the subsurface. This model performed best when the area was either easy to characterize with static climatology or when extensive oceanographic measurements were made. Figure 3 shows an area

with a spatially variable environment. The dots indicate the places where performance predictions are calculated. This level of performance sampling is far greater than that typically done by on-scene acoustic analysts. However the spatial complexity indicated by the bathymetry alone, as depicted here with the contour overlays, suggests a potential for performance variations that could be missed with the standard analysis.

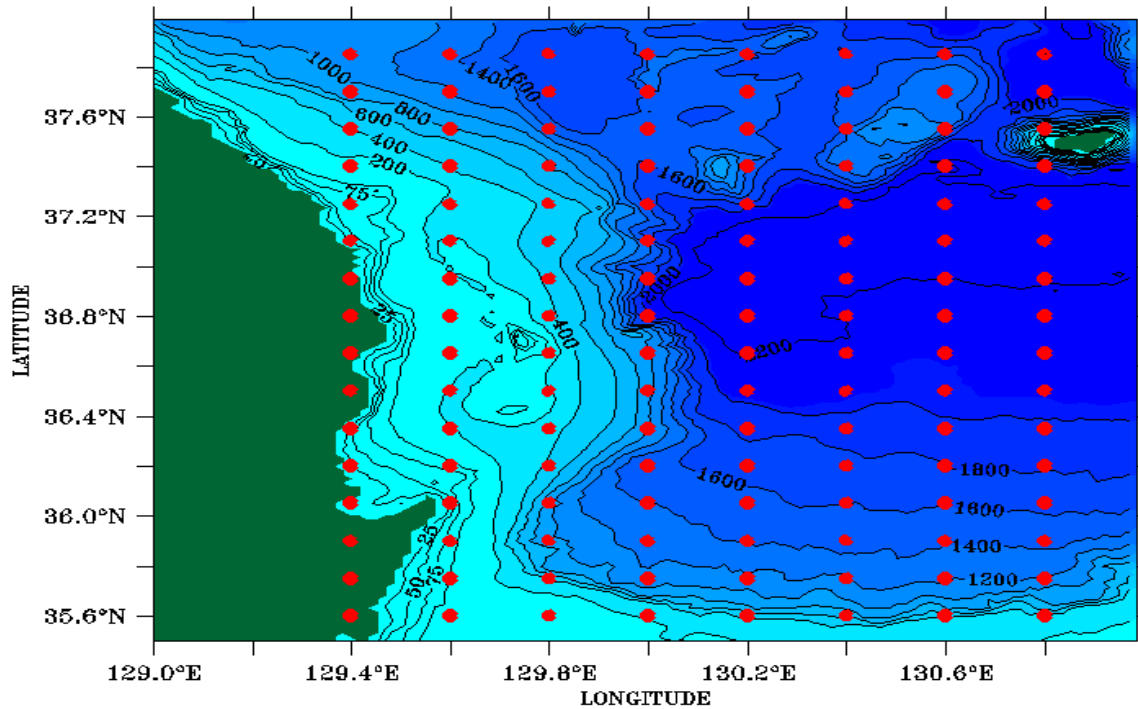


Figure 3 Oceanographic area with varying bathymetry shown by contours (and shades of blue) with overlay points to indicate sonar performance sampling positions

MODAS predictions are made routinely over much larger areas, however, in this example 16 days of sound speed field estimates are used to calculate performance for an arbitrary sonar system. The MODAS model is a climatology-type model, but the assimilation of in-situ measurements of sea surface height (SSH), sea surface temperature (SST), and/or any available oceanographic profile measurements provide a benefit over static historical climatology

databases. With these inputs a more dynamic picture of the ocean environment emerges.

In this example SSH and SST measurements were incorporated.

The resulting modeled sound speed fields show significant variability across the geographic area as indicated by Figure 4 and Figure 5. Both graphics show the spatial extent of a changing ocean sound velocity over a 16 day period in winter season where the major changes occur in the middle area near land. The most significant changes occur from February 17 to the February 22.

Figure 4 shows sound velocity in meters at a shallow water depth of 20 meters.

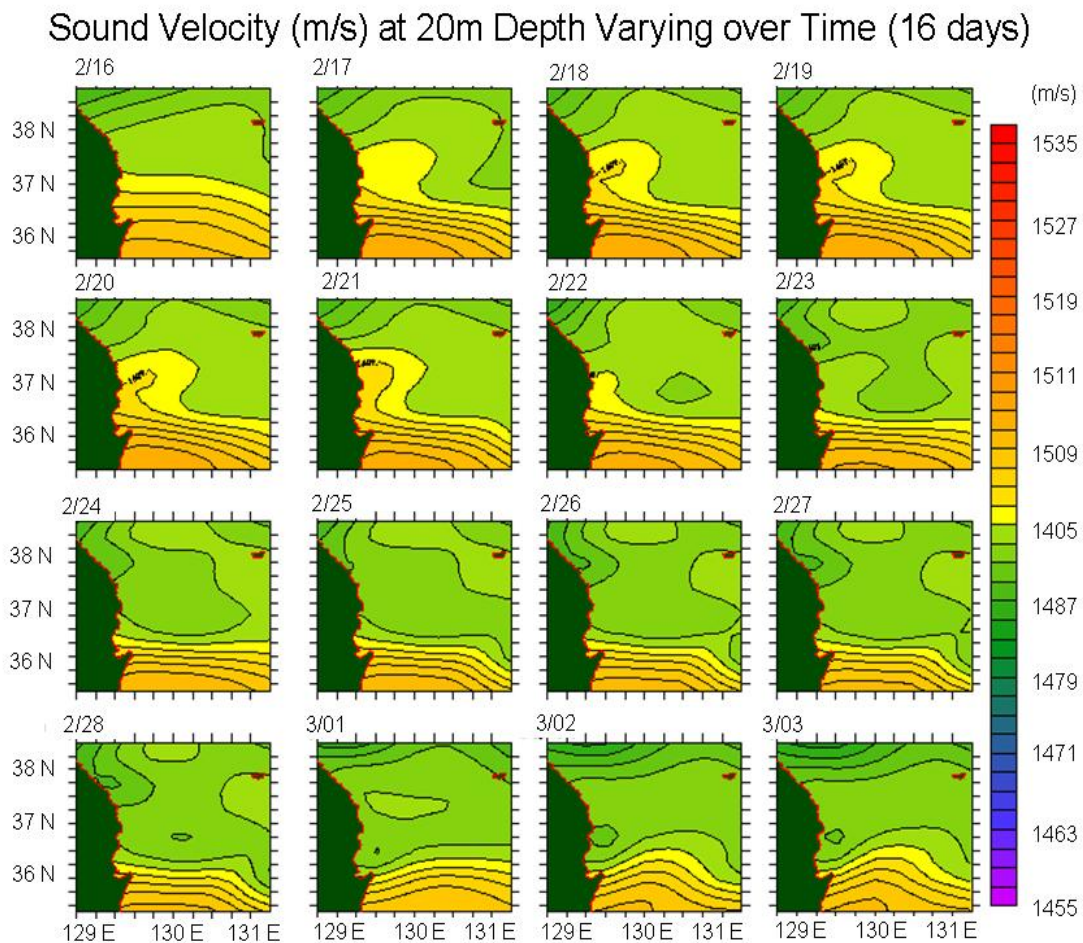


Figure 4 MODAS predicted sound speed at 20 meter depth over 16 days (2/16 – 3/03).

Figure 5 is a similar depiction of sound velocity for a water depth of 130 meters where again the graphics show oceanographic changes in sound velocity over the 16 day period of the experiment. It can be noted that the major dynamics are seen about latitude 37 N for both the shallow 20 meter, and deeper 130 meter depths.

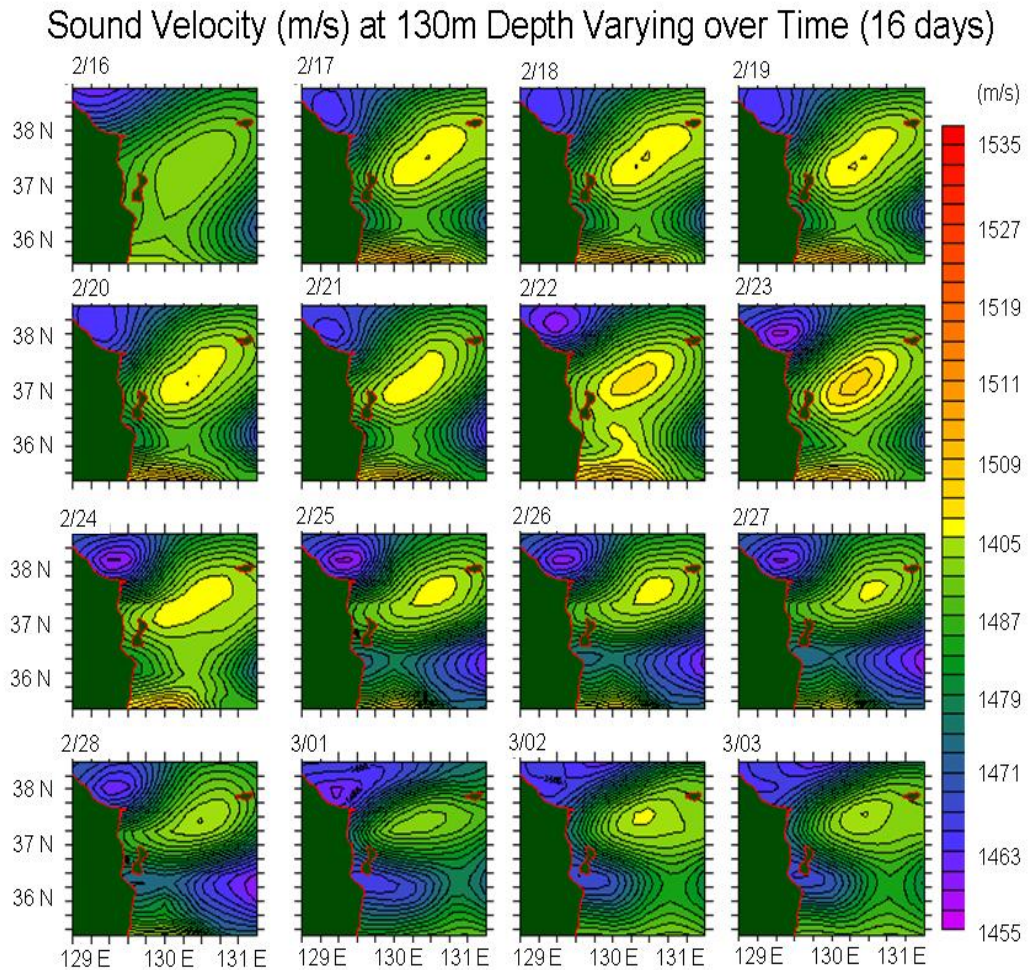


Figure 5 MODAS sound velocity predictions at 130 meter depth over 16 days(2/16 – 3/03).

As one might suspect, the resulting acoustic predictions arising from this environmental model vary greatly over this region. Figure 6 and Figure 7 show plan views of the SNR vs. Radial at the corresponding depths of 20 and 130 meters shown earlier. Inspection of these results indicate that the environment supports good detection results for the sensor against a target operating at

20 meters in the northern portions of the region. Performance degrades somewhat at the mid latitudes then further degradation as the target moves south still operating at shallow depths. While these depictions can mislead the analyst, in that at this point only SNR is presented, they can however communicate a relative spatial effect.

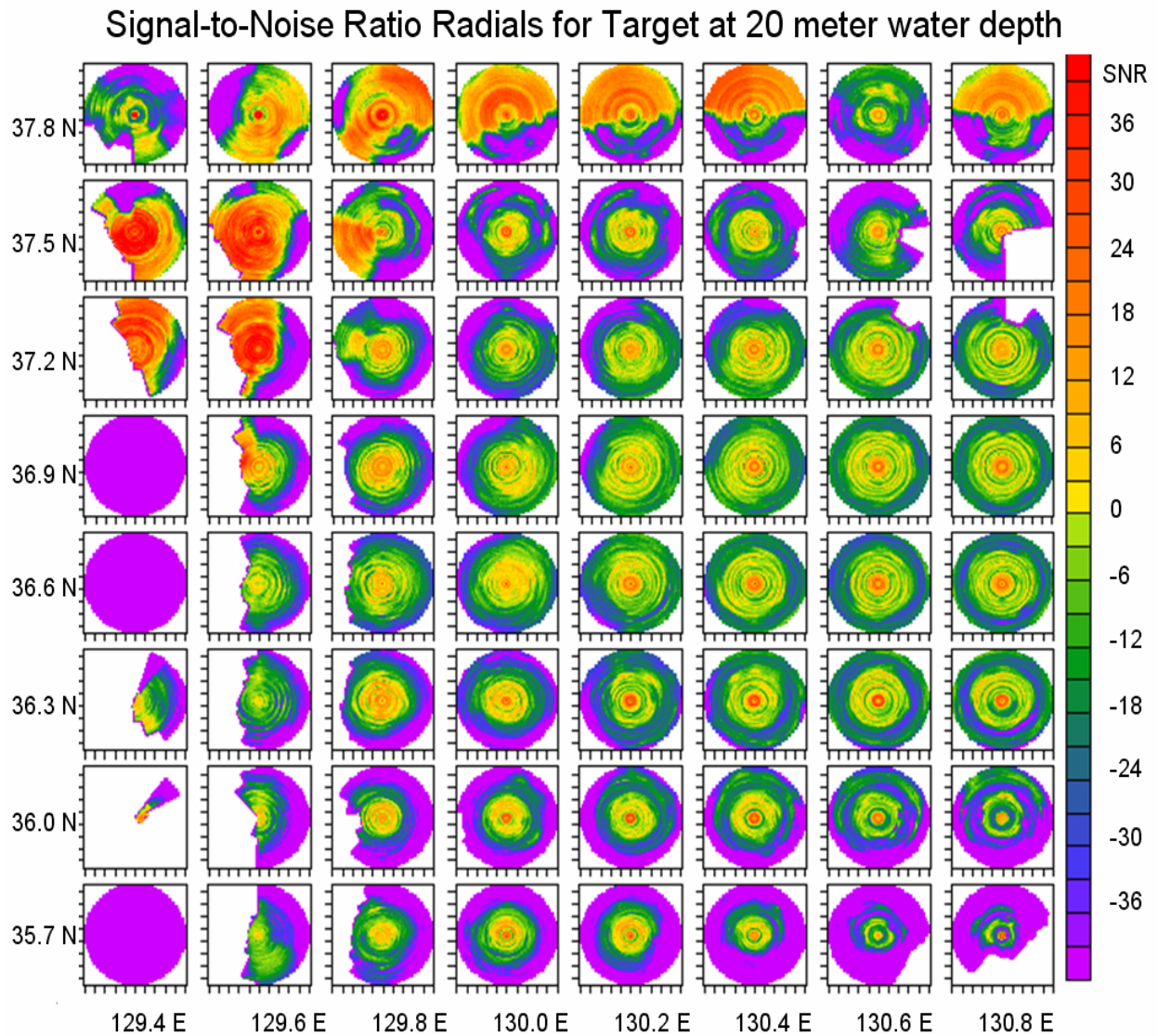


Figure 6 SNR vs. Radial for Target at 20 meter water depth

Figure 7 shows a similar view for the performance against a deep target operating at 130 meters. Notice that the performance story has changed. The target now operating in the northern area is

less detectable than before. SNR is relatively better and more consistent in the middle portions of the exercise area, although performance over the entire area, as measured only by SNR, has also degraded compared to the previous shallow target.

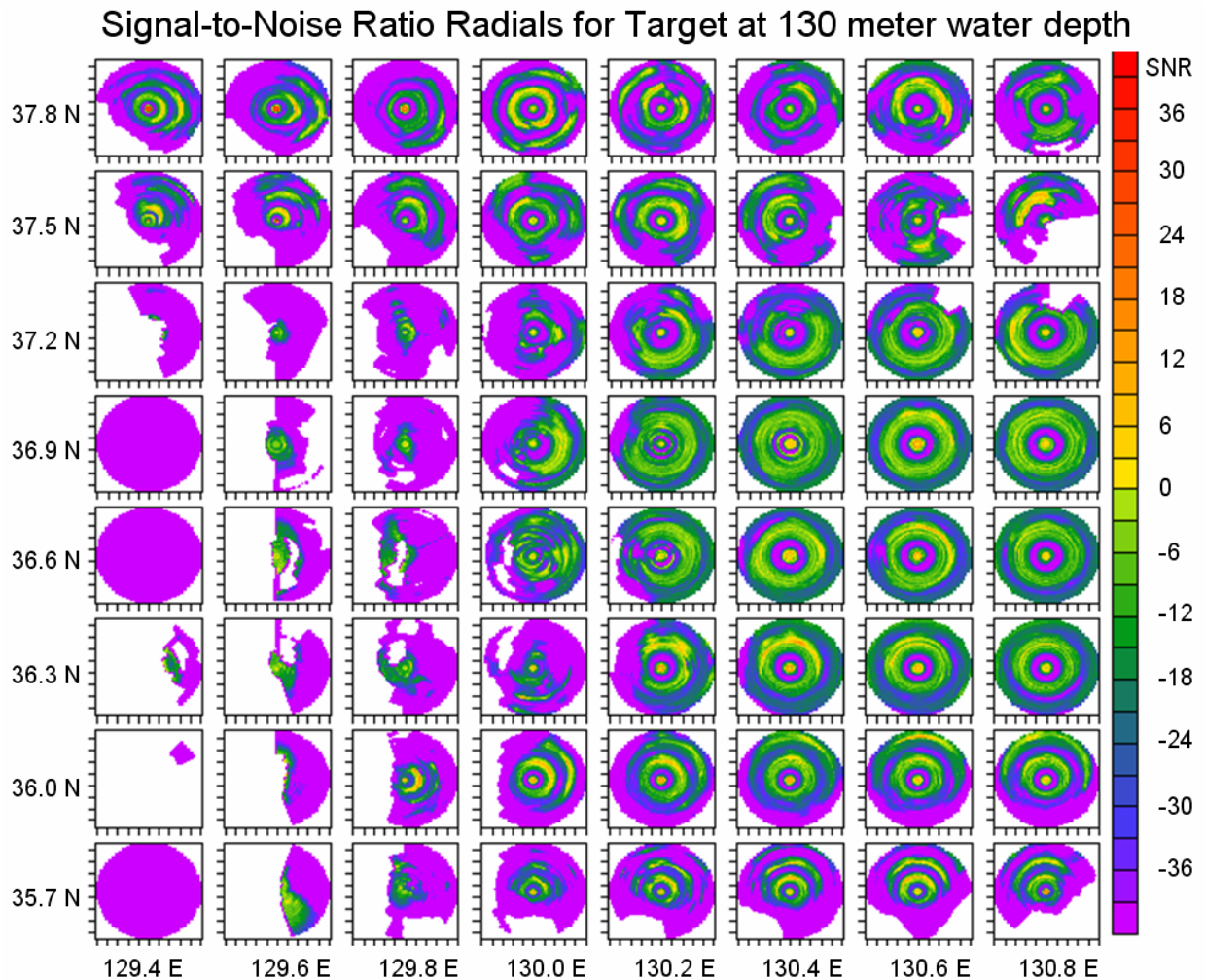


Figure 7 SNR vs. Radial for Target at 130 meter water depth

To get a better sense of the environmental effects on acoustic detection sensors, it is helpful to use depictions that show performance over depth. Figure 8 is one such graphic. As described earlier in Figure 2, a depth view is created by taking a cut across the mid latitude for each radial and plotting the depth extent which shows a view from the center to the east and from the center

to the west. This view captures the effect that causes the ‘perceived good’ performance for the sensor operating against the shallow target in the north. There appears to be a small surface duct present in this region resulting in trapped energy, long ranges and high SNR. However, counting on this level of performance which is implied by the SNR or TDA Signal Excess radial plots can be problematic for two reasons. One reason is climatological models like MODAS can easily miss-represent the oceanographic dynamics of the upper water column. A second reason for caution is the statistical nature of sonar performance. Taking the next steps in creating *Performance Surfaces* by applying a statistical detection model gives additional insight to address some of these issues.

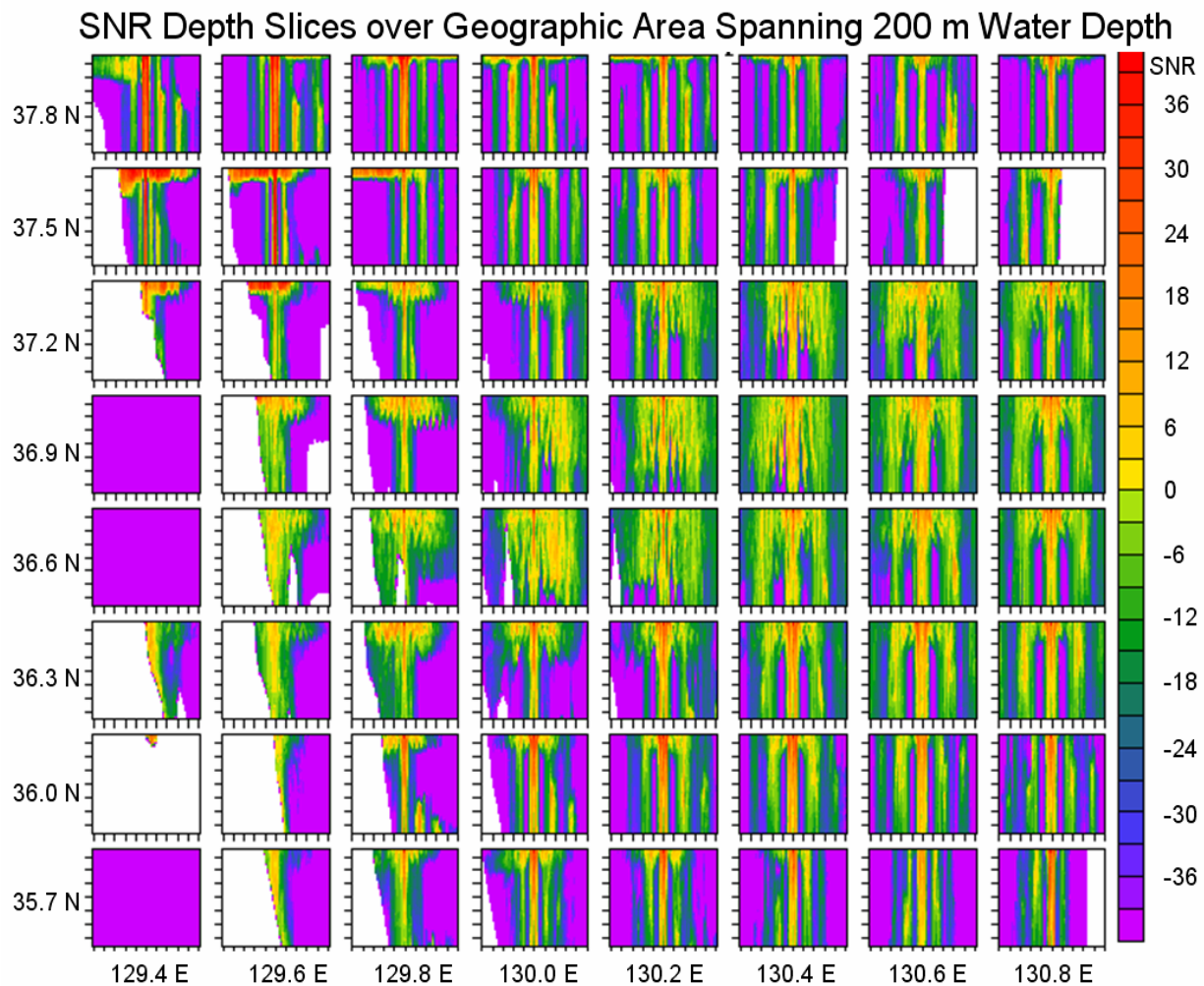


Figure 8 SNR Depth View Multiples over Computational Region

In the radial plan-view graphics (Figure 6 and 7) the depths of these SNR radials are chosen to represent where a target would likely operate. These SNR depictions are typical of single-point performance runs that an ASW analyst would make. However due to time constraints or the potential lack of awareness for the spatial variability only a handful of these predictions would be generated. Performance changes due to the underlying dynamic environment which could be used to inform maneuver tactics can easily be lost. Increased sampling over the geographic area as depicted in Figures 6, 7, and 8 provide a more complete picture of the changing environment and its effect on relative performance.

Recent Improvements in Environmental Modeling

The *Performance Surface* methodology to this point demonstrates the potential impact of a dynamic ocean environment and the need to adequately sample this environment. Before moving to the next step in the process, mention should be made of the improved oceanographic models currently available. The Navy Coastal Ocean Model (NCOM), based on the Princeton Ocean Model (POM) (Blumberg and Mellor, 1983), developed by Barron et al. (2002) at the Naval Research Laboratory is a physics-based ocean model that provides 1/8 degree resolution forecast predictions. These innovations that capture spatial and temporal dynamics of the ocean sound speed structure at scales of tactical significance have made Performance Surface products increasingly important. Figure 9 shows an example sound speed field from NCOM that illustrates the detailed structure that can be routinely modeled and forecast.

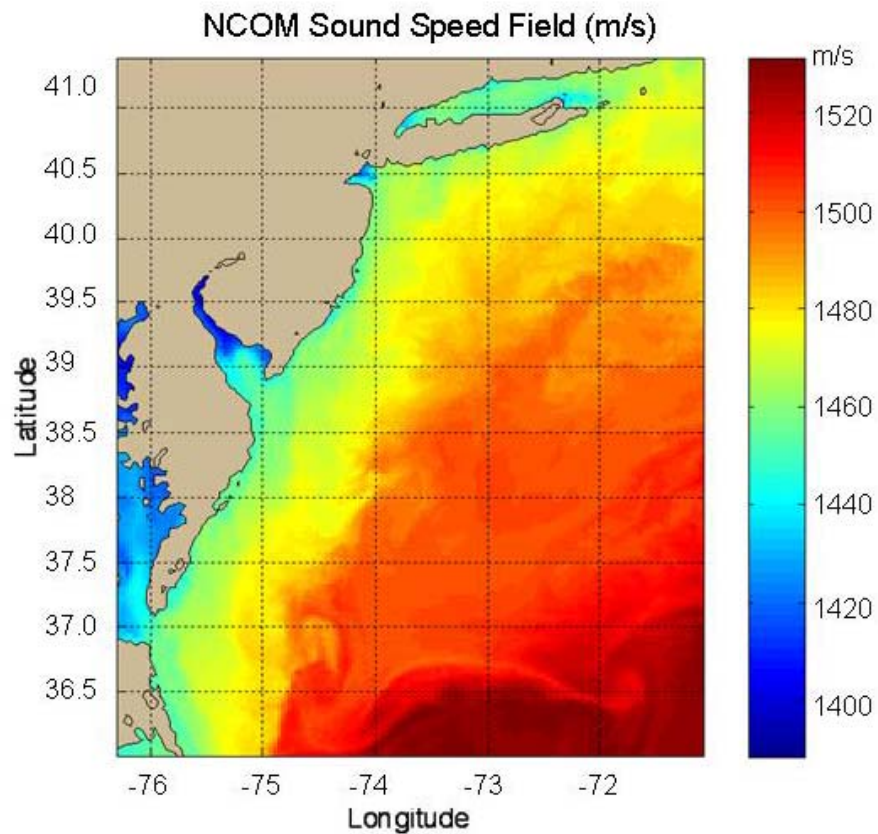


Figure 9 Example NCOM sound speed field. Color scale is sound speed in m/s.

Gridded calculations of Performance

Traditional Navy performance models are used to calculate single point-to-point signal excess estimates in the standard sonar equations for passive and active systems

$$\text{Passive: } \text{SNR} = S - \text{NL} + \text{DI} = \text{SL} - \text{TL} - \text{NL} + \text{DI} \quad (1)$$

$$\text{Active: } \text{SNR} = \text{SL} - \text{TL1} + \text{TS} - \text{TL2} - (\text{RL} + \text{NL}) + \text{DI} \quad (2)$$

Where:

SNR = Signal-to-Noise Ratio,

S = Signal Level

NL = Noise Level

DI = Array Gain

SL = Source Level

TL = Transmission Loss

TL1 and TL2 = Transmission Loss to and from the Target for Active SONAR

TS = Target Strength

RL = Reverberation Level

While these models give an estimate of local performance, calculations are generally limited to single point-to-point, radial predictions that inherently assume that a target is always present. Multiple points are sometimes calculated to get a spatial sense of performance but typically not done in a systematic way to provide an overall estimate of the environmental effects. Our first departure from the traditional approach is that calculations are made on a finely spaced grid covering the entire area of operation. Figure 10 illustrates this process.

Sampling Performance over Area of Interest

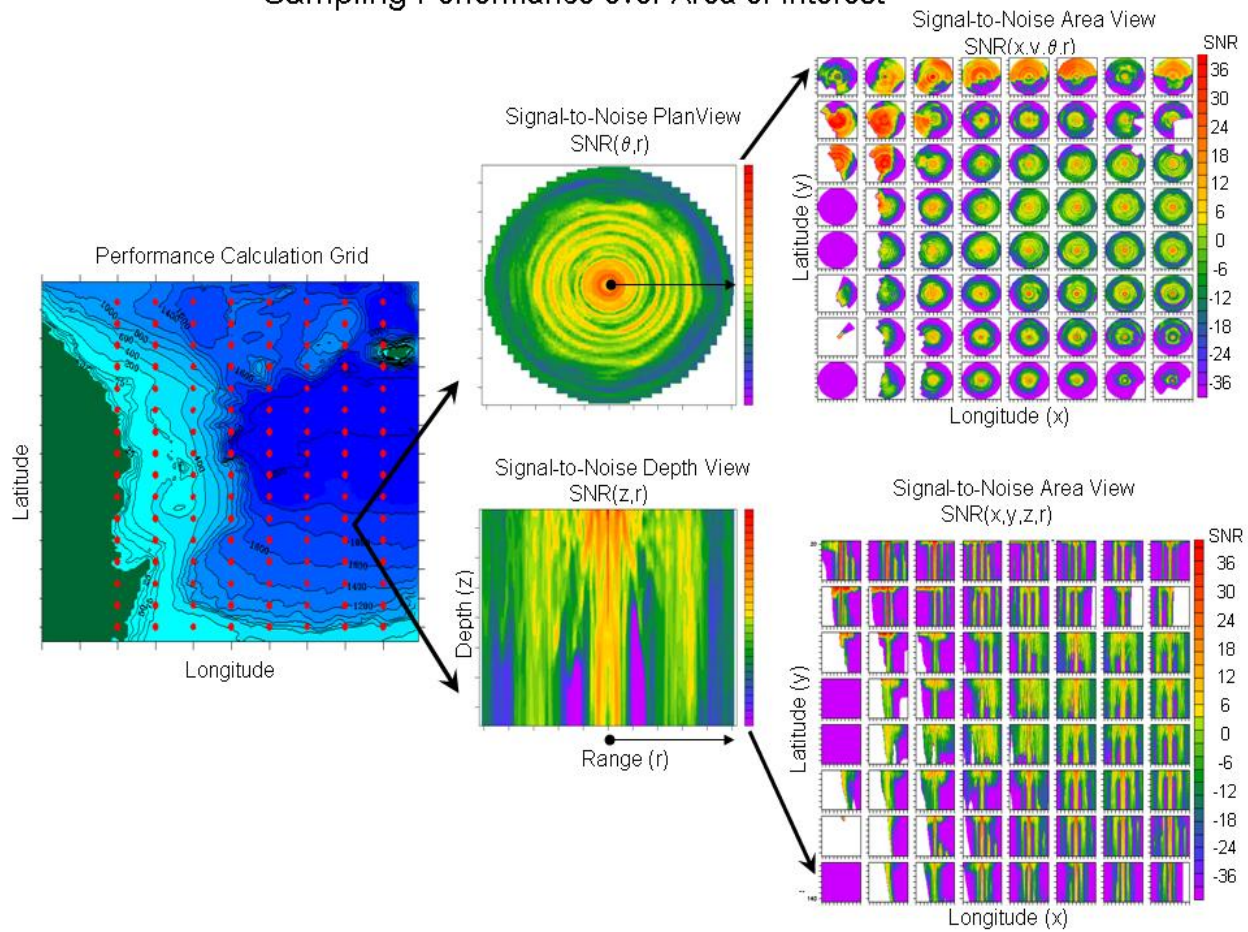


Figure 10 Repeating SNR calculations over area of interest

Signal-to-Noise (SNR) calculations are made on a uniformly spaced grid along multiple radials across the geographic area of interest. Figure 10 shows a typical sample grid starting at the left panel. From these geographic locations, calculations of SNR are formed as a function of location (x,y) , Range (r) , Radial for Bearing Angle (θ) , and Depth (z) . The two graphics at the right represent the repeated calculations over the geographic area to form an array of SNR (x,y,r,θ,z) .

Another limitation in the standard usage of many Navy TDA models is that after calculation of SNR, a detection threshold is applied, and only Signal Excess values are presented to the operator with no insight as to the shape of the assumed detection model or the effect of higher SNR on probability of detection. Additionally even more information is lost by only passing positive Signal Excess values above the threshold with no distinction in level. This threshold is typically 50 % and results are displayed giving the impression that detection is assured.

Accounting for Uncertainty

Up to this point in the process, standard performance modeling has been employed with the added improvements of using high resolution oceanographic models and increased performance sampling. A major strength of our *Performance Surface* process and a departure from the standard ASW modeling is the framework for capturing uncertainty. Uncertainty associated with sonar performance can be grouped into three categories. The first category is kinematical parameters associated with source, receiver, and target, such as range, bearing, heading, speed, and relative depth. The second category is the environmental uncertainty. Even with the notable improvement in ocean modeling describe earlier, the variability of the environment is such that complete knowledge is unlikely. The third category of uncertainty is that embedded with the signal processing associated with sonar display. The sonar display lights a pixel and marks the screen when the voltage level of a detector circuit exceeds a threshold. The probabilities that marks appear on the display are determined by the statistical distributions of the signal and noise. These distributions are greatly affected by the properties and variability of the ocean

environment (Kinsler and Frey, 1982). The sonar designer attempts to account for this by building a detector that maximizes performance for known distributions of noise and signal.

Probability theory provides methods for accounting for these categories of uncertainty. A detection model can be used to transform SNR to a sonar performance metric Probability of Detection (P_d). This is used to account for the uncertain nature of the signal and noise distributions as they affect the signal detector.

This probability metric is conditional on a target being present, $P(D|T)$. To account for incomplete knowledge of the target kinematics a joint probability can be formed by using some distribution of target location. As an example, a Performance Surface estimate for sonar position at location (X, Y) would be the probability detecting a target within a given range (R) . In this case the target distribution, $P(T)$ would be represented as uniformly distributed about the point (X, Y) . The conditional probability $P(D|T)$ would be transformed to a joint probability, $P(D,T)$ thus accounting for the uncertainty of target location ($P(T)$).

$$P(D,T) = P(D|T) * P(T) \quad (3)$$

Then these joint probability estimates are summed to form marginal probabilities over the uncertain parameters. Similarly uncertain environmental parameters can be included by extending the marginal probability to include multiple forecasts and/or ensembles.

Applying Detection Model

Continuing the Performance Surface process, from the point of extensive sampling of the SNR versus range, azimuth and depth, to a target, on a finely spaced grid, a detection model or Receiver Operator Characteristic (ROC) curve is applied. This is a detection model of performance that relates conditional probability of detection, probability of false alarm and signal-to-noise ratio. This process is depicted in Figure 11.

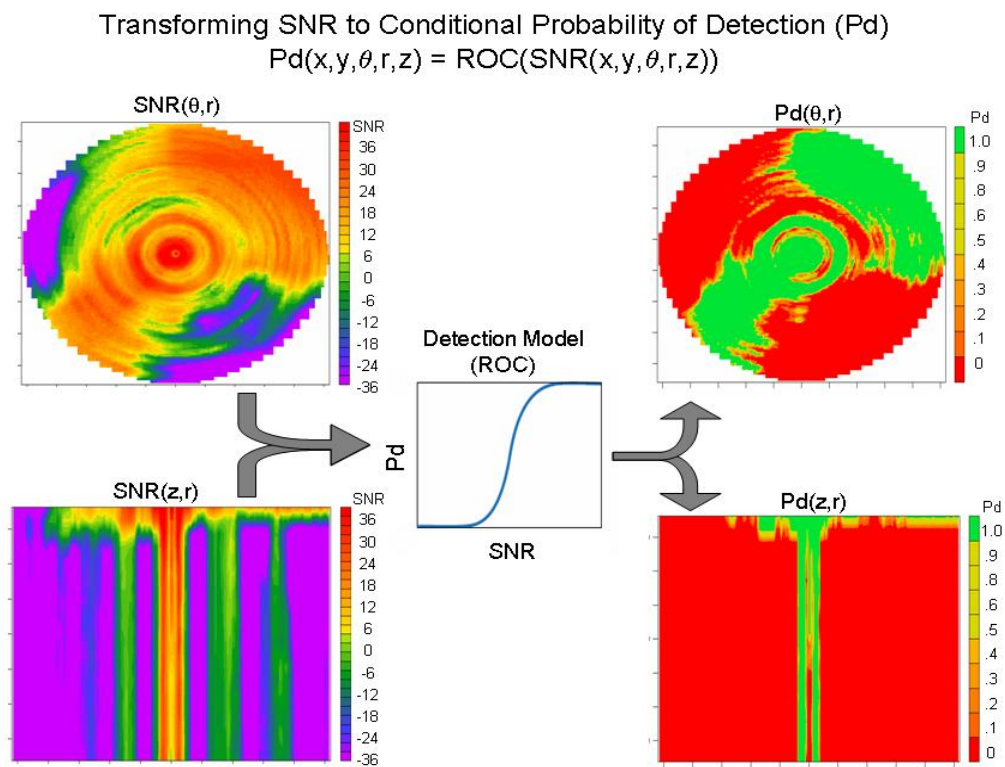


Figure 11 Transforming SNR to Conditional Probability of Detection using ROC Detection Model

Peterson et al. (1950) introduced the approach for relating SNR to Probability of Detection in the early 1950s by applying statistical decision theory to the problem of operator performance and derived a model of how operators performed detection tasks on radar screens in terms of signal to noise ratio. They developed ROC curves that mapped the probability of making a detection given the target is present to the signal-to-noise ratio. Robertson of Bell Laboratories (Robertson, 1999) later derived a set of ROC curves which have been used extensively to relate SNR to conditional probability of detection.

The ROC model originally used in this work was a closed-form approximation to Robertson's detection characteristics introduced by Albersheim (1999). Albersheim simplified Robertson's work for computing the signal to noise power ratio (S/N) at which a signal is detectable in the presence of random noise to a simple function of three parameters with an error less than 0.2 dB. The equation is a function of the conditional probability of detection, $P(D|T)$; probability of false alarm, ($P(D|T')$ or P_{fa}); and the number of independent samples, M . Albersheim's formulation is given here;

$$SNR = -5 \log_{10} M + \left(6.2 + \frac{4.54}{\sqrt{M + 0.44}}\right) \log_{10} (A + 0.12 AB + 1.7 B)$$

where

$$A = \ln \frac{0.62}{P_{fa}} \tag{4}$$

$$B = \ln \frac{Pd}{1 - Pd} = \ln Pd - \ln(1 - Pd)$$

While Albersheim's model was used in initial work because of its computational simplicity, more system specific ROC curves have been applied in recent work.

There are many ROC models for explaining underlying noise probability distributions or causal mechanisms. A simple example is a threshold model, where there is certain dismissal if signal-to-noise ratios fall below a given threshold, and certain detection when above the threshold. Other models developed in the 1950s found that observed detection behaviors, including uncertainty, could be explained and quantified. One such estimator of performance is the probability of true detection, which we define as the joint probability of an operator declaring a target at X, and a target is present at X, ($P(D,T)$). This measure can be represented in terms of the probability matrix illustrated in Table-1.

	Target Present T	Target Absent T'
Declare D	<i>True Detection:</i> Declare and Present P(D,T)	<i>False Alarm:</i> Declare and Absent P(D,T')
Not Declare D'	<i>False Dismissal:</i> Not Declare and Present P(D',T)	<i>True Dismissal:</i> Not Declare and Not Present P(D',T')

Table 1 Probability of Detection Definitions Matrix: The probabilities are measures on the sets associated with the joint conditions of operator action and objective target conditions represented in the matrix.

This calculation of the Joint Probability of Detection is the next step in the *Performance Surface* model. To form this estimate, assumptions about the target location are made. The broadest assumption is made here in that the location of the target is unknown and thus assumed to be uniformly distributed within the range of the sensor. This assumption results in a uniformly spaced Probability of Target ($P(T)$) in rectangular coordinates, linearly increasing in a Cartesian coordinate system. Reconstructed data from field exercises have shown this to be a reasonable assumption.

Once these Joint Probability estimates are calculated, they are summed to a Marginal Probability scalar value and plotted as map as shown in Figure 12. These scalar values of Marginal Probability, color contoured to form a map display, represent the information we know as well as the information we don't know. This step is very important in that often the underlying assumptions of the performance estimate are overlooked or forgotten. In many if not most cases the exact position of the receiving array is unknown. This is accounted for here calculating the marginal probability by summing the joint probabilities over ranges and bearings of uncertainty. The exact position of the target is rarely known. This can be handled by marginalizing over depths that the target is expected to cover. Environmental uncertainty is always present. This can also be accounted for by including forecast and ensemble environments in the estimate.

Marginal Probability of Detection *Performance Surface*

$$P(D) = P(D|x,y,z=z') = \sum_{\theta,r} P(D|x,y,z',\theta,r)P(\theta)P(r)$$

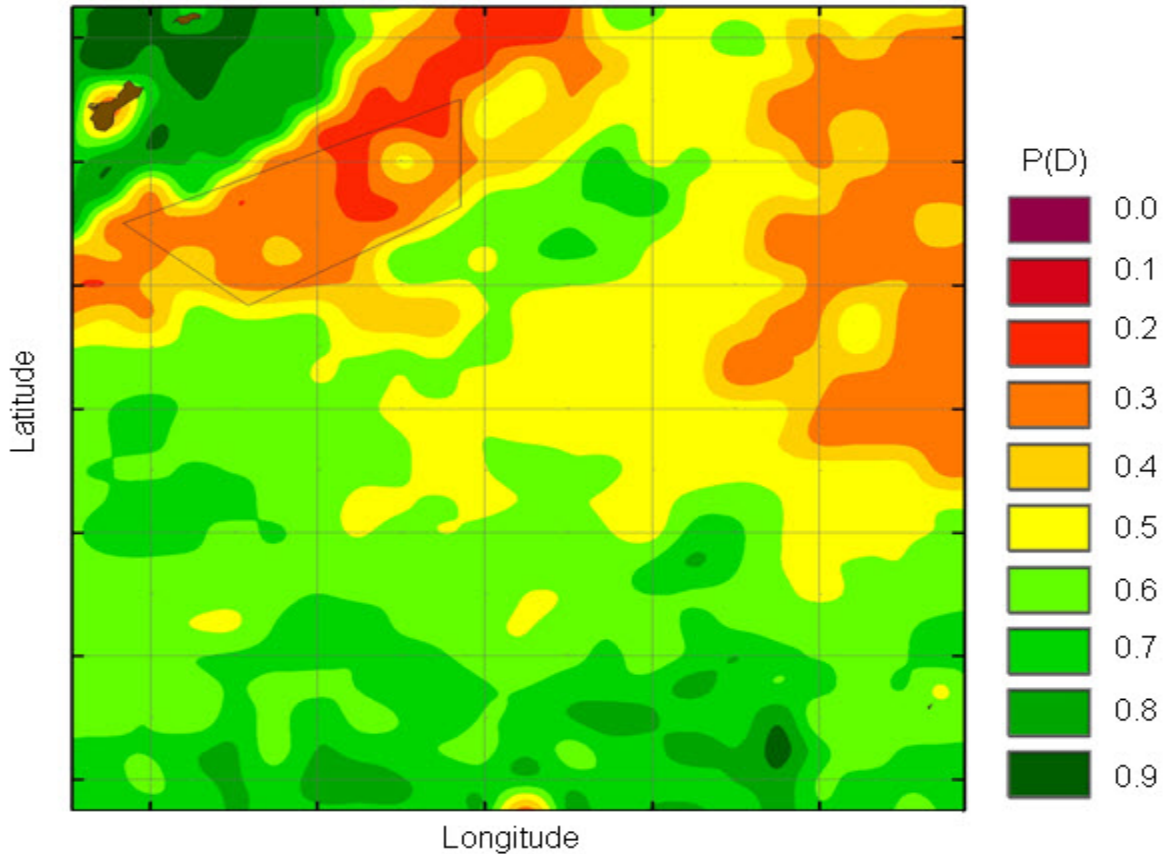


Figure 12 Underwater Acoustic Detection *Performance Surface*

This introduction describes the performance estimate most generally used, i.e. the scalar value of the Marginal Probability of Detection. The *Performance Surface* however can be any metric that adequately captures system performance. Examples of such estimates are briefly described here.

Expected Range is a metric calculated by integrating the conditional probability of detection vs. range curve. This is a robust estimate much like the classic lateral range curve, with the notable difference being the marginalization over the uncertainties of bearing and depth. The performance metrics of Lateral Range and Sweepwidth were first introduced by Koopman

(1951) and generally applied to visual search problems. This metric and the *Expected Range* metric share the property of relating probability of detection to range. The metric is calculated by integrating the probability of detection curves over range and bearing at given depths. Figure 13 shows an example of two Expected Range Performance Surface maps for target at different depth

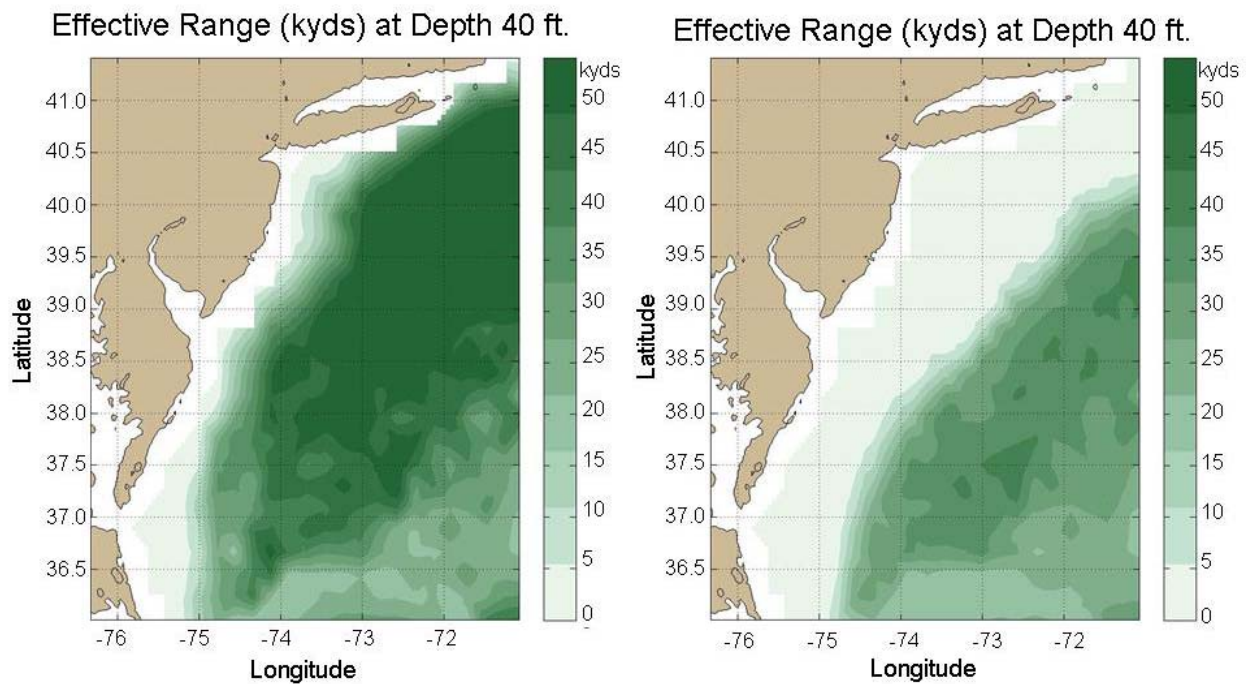


Figure 13 Effective Range Performance Surfaces for 2 Target Depths

Two metrics were developed at the urging of users needing to answer specific questions. The two metrics *Near-Continuous Range* and *Maximum Detectable Range* were designed to address propagation path questions. The resulting Performance Surface graphics are depicted in Figure 14. The left panel, *Near-Continuous Range* captures ranges over which probability of detection exceeds a threshold (typically .5) allowing for some small user defined drop-out intervals. These drop-out tolerances are set in such a way as to minimize complete loss of target

holding. This type of propagation is typically in areas that support good bottom-bounce performance.

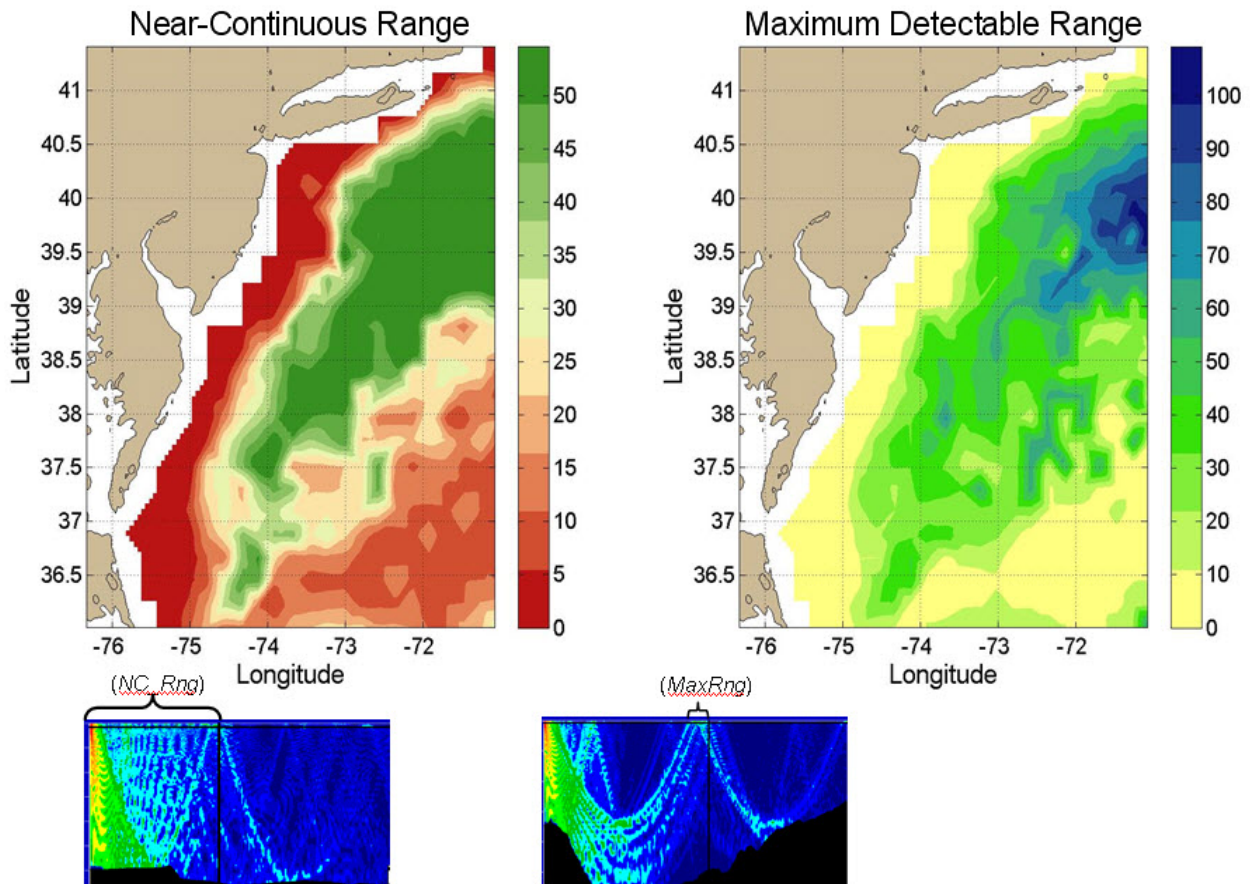


Figure 14 *Near Continuous Range* (with example acoustic full-field plot) and *Maximum Detectable Range* (with example acoustic full-field plot)

Maximum Detectable Range is the second requested metric. This Performance Surface type is shown in the right panel of Figure 15. This metric was designed to capture the maximum range at which the probability of detection crosses a threshold and remains above for a user-specified duration. This metric is very useful in capturing areas where Convergence Zone (CZ) performance is likely. The user-specified duration is set for a period to provide enough time for a detection to be called.

Figure 15 depicts another type of metric that provides insight and guidance as to optimum sensor depth placement. This metric, Best Passive Sensor Depth, presents this information in two forms as illustrated in Figure 15.

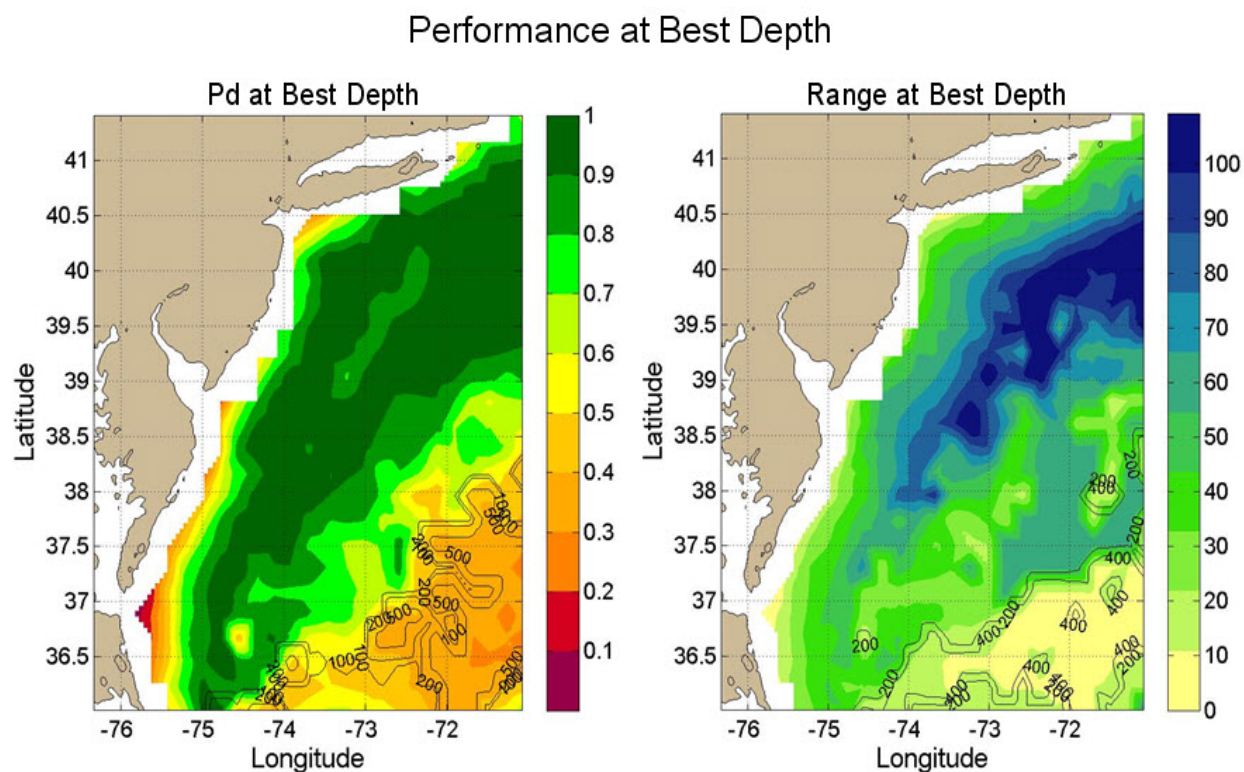


Figure 15 Performance at Best Depth for Pd and Range

The left panel shows the maximum probability of detection (color scale) for the geographic location, with overlaid contours of the depth at which this performance occurs. Likewise the right panel shows the longest ranges for the geographic location with overlaid contours of the corresponding depth. This metric is useful for maximizing passive sensor performance.

This concludes the introduction to Performance Surface methodology. The next two chapters contain articles from the Journal of Underwater Acoustics describing some to the current usages.

Chapter 3

Performance Surface: Development, Current Use and Future Improvements

Abstract

The term Performance Surface refers to a geo-spatial representation of the predicted performance of one or more sensors constrained by all-source forecasts for a geophysical area of operations. Recent improvements in ocean, atmospheric and underwater acoustic models, along with advances in parallel computing provide an opportunity to forecast the effects of a complex and dynamic acoustic environment on ASW system performance. This paper describes a process that calculates sonar performance in a straight-forward ‘sonar-equation’ manner utilizing spatially complex and temporally dynamic environmental models. This deterministic ‘sonar-equation’ performance model is combined with a Receiver Operating Characteristics (ROC) detection model, and broad target assumptions to form conditional, joint and marginal probabilities. These joint and marginal probabilities become the scalar estimates that form the current Performance Surface model. On-going work that extends the deterministic sonar equation, representing each component as stochastic distributions, is also presented. Performance Surface tools have been demonstrated at the Naval Oceanographic Office (NAVOCEANO) and the Naval Oceanographic ASW Center (NOAC) in support of recent naval exercises. An operational example will be shown to illustrate current use with realistic sonars, targets, and environment.

Introduction

An essential mission for the U.S. Navy is to conduct Anti-Submarine Warfare (ASW), and an essential mission for the Naval Oceanography Program is to understand and forecast how the ocean environment will affect ASW operations and tactics at a specific place and time. Over the past five years Naval Oceanography has accelerated efforts to operationalize emerging skills in ocean observations, forecasts, and system performance prediction to create new products to advise naval decision makers. This paper documents one aspect of this emerging operational capability: the sonar *Performance Surface*.

Since the submarine crises of World War II, and the Cold War up until the early 1990s, the United States has invested heavily in understanding sonar performance in the ocean. Although much progress was made, the difficulties posed by uncertainties in ocean, target and system conditions has meant that performance prediction has had limited operational utility. Now, in the early 2000s, the cumulative advances in computing capacity, algorithms and codes over decades of public and private investment, advanced sensing technologies from space such as altimeters and radiometers, and *in situ* sensors such as Argo floats and sea gliders, plus global communications networks that allow real-time measurement of the global ocean, all mean that the ocean can now be forecast on operational time scales. Rather than a static data base of ocean conditions, which may or may not be dynamically consistent and stable, a daily dynamic data base of ocean conditions can be delivered to planners and warfighters that has the advantage of incorporating all available oceanographic information (Barron, 2006). Furthermore, in forecast mode the information can be used to drive planning cycles and fleet movement to take advantage of that knowledge. These ocean data bases, Navy Coastal Ocean Model (NCOM) are published

and distributed daily, to be used by fleet planners to feed on-scene Tactical Decision Aids (TDAs) as needed in operational areas.

Work sponsored by the Office of Naval Research (McDowell and Gough, 2010) provided a framework for producing ASW performance assessments utilizing TDA type sonar prediction and probabilistic detection models over tactically significant spatial scales. In general TDAs are used to produce point-to-point Signal Excess (SE) analyses, or multiple radials from a single point. These predictions are often made about several points around the given or projected sensor position. This work was a method that generated sonar predictions in all directions at uniformly spaced grid locations across the entire operational area. These predictions were combined with a detection model to produce a geo-spatial ASW performance assessment.

The *Performance Surface* model, as presented in this paper, builds on the ONR work by incorporating the real-time ocean forecasts (Rhodes and Hurlburt, 1999) produced daily by the Naval Oceanographic Office (NAVOCEANO), adding a target location distribution, utilizing adaptations to current TDAs for large area predictions, and including a statistical spatial noise model as introduced by Mire (Mire and Pflug, 2010). This noise model provides a spatial representation of ambient noise across large geographic regions, seasons and environmental conditions. Single point mean omni-directional noise levels, varying at each geospatial grid point are used as input to the current *Performance Surface* model. However, these noise products additionally provide probability distributions. These statistical distribution fields can be used in the next generation of stochastic *Performance Surface* models that are discussed in the last section of this paper. The *Performance Surface* approach uses accepted TDA models to produce

a large number of sonar predictions over the entire operational space and temporal scales, combine these with a probabilistic detection model, and a probabilistic target location distribution to create a model of ASW performance that carries the full range of detection probability over the course of an ASW event.

The *Performance Surface* model is described in terms of the development and performance measures chosen to represent ASW capability. The scalar values calculated as performance estimates are described. The process for computing and generating the *Performance Surface* maps are detailed, and finally various types of *Performance Surface* maps are shown along with a discussion of operational usage. A real-world problem, where fleet asset allocation and movement are in question, is shown. This example will set up a specific sonar / target configuration and the resulting *Performance Surface* results. Finally, a detailed description of the next generation of a stochastic *Performance Surface* model is addressed. A step-by-step method describes a process where each component of the sonar equation is accounted for as a probabilistic distribution and combined in a way to better represent observed sonar performance.

Performance Surface Description

Performance Surface is generally defined here as a geospatial representation of system performance. Mathematically, the *Performance Surface* is a scalar field consisting of a scalar performance estimate associated with every point of a connected geo-spatial domain. The domain almost always (we know of no exceptions) represents a volume of an environment associated with a naval task, say an ocean volume or atmospheric volume. Any point, O , within the domain may be taken as the origin of a cylindrical coordinate system such that any other

point $x = (r, \theta, z)$ where r represents a radial distance from the origin, θ an angular deflection from the reference direction, and z the depth or elevation below or above the reference horizontal plane represented by $z=0$. The performance measure can be any scalar estimate that represents the sonar system's capability at O with regard to detecting an undersea target at all x . It should be noted that there is no reason one might not have a more general vector field of performance, and indeed such fields are produced on the way to the scalar representation, but as an historical accident the scalar fields drew initial display and question-answering attention, and as such were named *performance surfaces* because of their topology. These might also be named *Performance Fields*.

Estimating Sonar Performance in the Ocean

Since the 1940s the standard method for computing sonar performance in the ocean is called the *Sonar Equation*. It has many forms and expressions, but at its core it computes an estimate of signal-to-noise or signal-to-interference ratio for a pair of points in the environment using a decibel, i.e., logarithmic, representation of terms that contribute to the quantitative expression of the signal or noise through a particular sensor. The value is compared to a model of performance that relates probability of detection, probability of false alarm and signal-to-noise ratio. We refer to this detection model as a *Receiver Operating Characteristic* (ROC) model, although some practitioners maintain that this phrase is reserved only for a projection of the function onto the probability-of-detection versus probability-of-false-alarm plane with signal-to-noise represented as a parameter producing a family of curves (McDonough and Whalen, 1995). One reason for our picturing ROC as a surface is to emphasize the unity of the model over three dimensions without

parameterization or projection.

There are many ROC models, depending on the practitioner’s preference for explaining underlying noise probability distributions or causal mechanisms. Perhaps the simplest is a threshold model, wherein there is certain dismissal if signal-to-noise ratios fall below a given threshold, and certain detection when above the threshold. More nuanced models developed when, in the 1950s, practitioners applied emerging statistical decision theory (Wald, 1967) to the problems of human and machine detection performance of signals embedded in noise and found that observed detection behaviors, including uncertainty, could be explained and quantified in that way. One such estimator of performance is the probability of *true detection*, which we define as the joint probability of an operator declaring a target at x , *and* a target is present at x , ($P(D,T)$). This measure can be represented in terms of the probability matrix illustrated in Table 1.

	Target Present T	Target Absent T'
Declare D	<i>True Detection:</i> Declare and Present P(D,T)	<i>False Alarm:</i> Declare and Absent P(D,T')
Not Declare D'	<i>False Dismissal:</i> Not Declare and Present P(D',T)	<i>True Dismissal:</i> Not Declare and Not Present P(D',T')

Table 1 Probability of Detection Definitions Matrix: The probabilities are measures on the sets associated with the joint conditions of operator action and objective target conditions represented in the matrix.

The joint probability is estimated *a priori* by combining the Conditional Probability of Detecting a Target ($P(D|T)$ or P_d) computed by the TDA and the Probability of a Target present ($P(T)$) which is designated by the analyst. When the analyst has no prior knowledge of the target

location it is represented as a uniform, or maximum-entropy distribution over the domain.

$$\text{Joint Probability: } P(D,T) = P(D|T) \times P(T) \quad (1)$$

The Conditional Probability of Detecting a Target is derived from calculating Signal-to-Noise Ratio (SNR) then mapping to P_d through the use of a ROC curve. An approach of relating SNR to Probability of Detection introduced by Peterson (Peterson and Birdsall, 1954) in the early 1950s applied statistical decision theory to the problem of operator performance and derived a model of how operators performed detection tasks on radar screens in terms of signal to noise ratio. They developed ROC curves that mapped the probability of making a detection given the target is present to the signal to noise ratio. Robertson (1967) of Bell Laboratories later derived a set of ROC curves which have been used extensively to relate SNR to conditional probability of detection.

The ROC model originally used in this work was a closed-form approximation to Robertson's detection characteristics introduced by Albersheim (1981). Albersheim simplified Robertson's work for computing the signal to noise power ratio (S/N) at which a signal is detectable in the presence of random noise to a simple function of three parameters with an error less than 0.2 dB. The equation is a function of the conditional probability of detection, $P(D|T)$; probability of false alarm, ($P(D|T')$ or P_{fa}) and the number of independent samples, M . Albersheim's formulation is given here;

$$SNR = -5 \log_{10} M + (6.2 + \frac{4.54}{\sqrt{M + 0.44}}) \log_{10} (A + 0.12 AB + 1.7 B)$$

where

$$A = \ln \frac{0.62}{Pfa} \tag{2}$$

$$B = \ln \frac{Pd}{1 - Pd} = \ln Pd - \ln(1 - Pd)$$

While Albersheim's model was used in initial work because of its computational simplicity, more system specific ROC curves have been applied in recent work.

Signal-to Noise Ratio (SNR), represented in dB, is defined as,

$$SNR = S - NL \tag{3}$$

where the received signal (S) intensity present at the hydrophone is the difference between the sound emitted from the underwater target or Source Level (SL) intensity, and the losses accrued as the sound travels to the receiving hydrophone or Transmission Loss.

$$S = SL - TL \tag{4}$$

Our sonar system consists of an array of hydrophones where some gain against a directional noise field can be obtained through beamforming. This gain is accounted for by convolving the spatial beam pattern against a directional noise field to observe a *beam noise*. For performance prediction it is unwieldy to attempt to construct beam noise estimates computationally this way. In practice it is accepted to either apply observed beam noise distributions, or make a simplifying assumption of isotropic noise. In the latter case it is assumed that all contributions to the omnidirectional noise term are equal from all directions, then spatial gain can be represented by a term, DI (Directivity Index) or AG (Array Gain). Thus the SNR for a passive sonar becomes,

$$SNR_{BF} = S - NL + DI = SL - TL - NL + DI \tag{5}$$

SNR for the active sonar is similarly derived with the additional contributions from two-way transmission loss, target strength (TS), and reverberation (RL).

$$\text{SNR}_{\text{BF}} = \text{SL} - \text{TL1} + \text{TS} - \text{TL2} - (\text{RL} + \text{NL}) + \text{DI} \quad (6)$$

Given assumptions of target-receiver positions, environmental databases, and system signal processing parameters, Tactical Decision Aids (TDA), are employed as the computational engines to calculate SNR vs. Range and bearing.

Figure 16 depicts the conversion from SNR to Conditional Probability of Detection, Pd. In the left-hand panel 16 radials of SNR vs. Range are plotted from a central latitude-longitude position. A spline algorithm blends the radial for smoother visual presentation. The colors from purple to red represent SNR values of -40 to $+40$ dB. From this example, a radial oriented toward North-East, shows very little signal loss in range, while a radial toward the South goes from SNR values near 40 dB down to SNRs less than -40 dB. These azimuthal variations are due to environmental factors such as bathymetry, sound speed and bottom type. The middle panel is an example of a typical ROC curve where the Probability of False Alarm is held constant at 10^{-5} , the X-axis is SNR and the Y-axis is Pd. Each value of SNR from the left panel is mapped to a conditional probability of detection value and re-plotted in the right panel. The color scale here goes from red, Pd=0, to green, Pd=1.

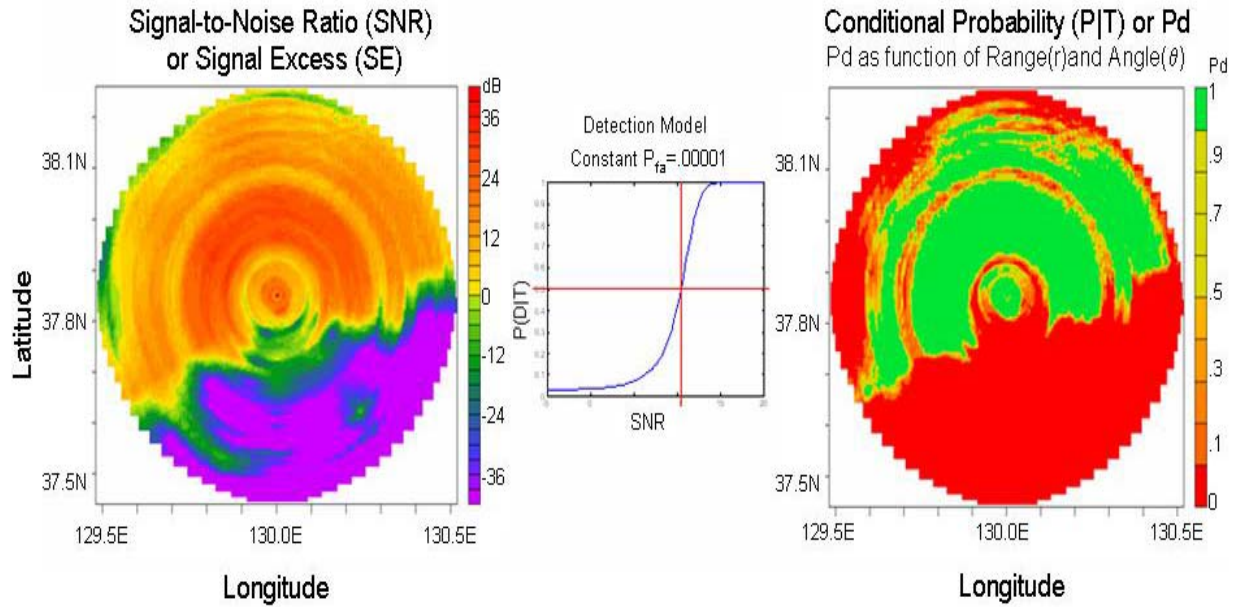


Figure 16 Illustration of mapping SNR conditional on a target present at the spatial coordinates (r,θ) to conditional probability of detection, $P(D|T)$. The underlying spatial domain of the SNR field is retained and the resulting scalar performance map represents a conditional field of performance referenced to the origin.

Having computed the conditional probability of detection vs. range along many radials centered at a geospatial grid point location, we combine this with a target density probability $P(T)$, to form joint probability values. In the case where the Target's position azimuthally is unknown yet given to be present within a range, R , the Probability of Target Present $P(T)$ is defined as a uniform distribution over the area out to range R , $(P(T(R)))$. These joint probability values are summed to form marginal probability scalar estimates of performance. These scalars are interpreted to represent relative system performance at a given geospatial point for stated detection conditions. Equations 7 and 8 show this process.

$$P(D) = P(D,T(R)) = P(D|T) * P(T(R)) \quad (7)$$

$$P(D) = \int_{Area} P(D,T(R)) da \quad (8)$$

An example of this process, carried out over a large geographic area, of uniformly space grid point is illustrated by Figure 17.

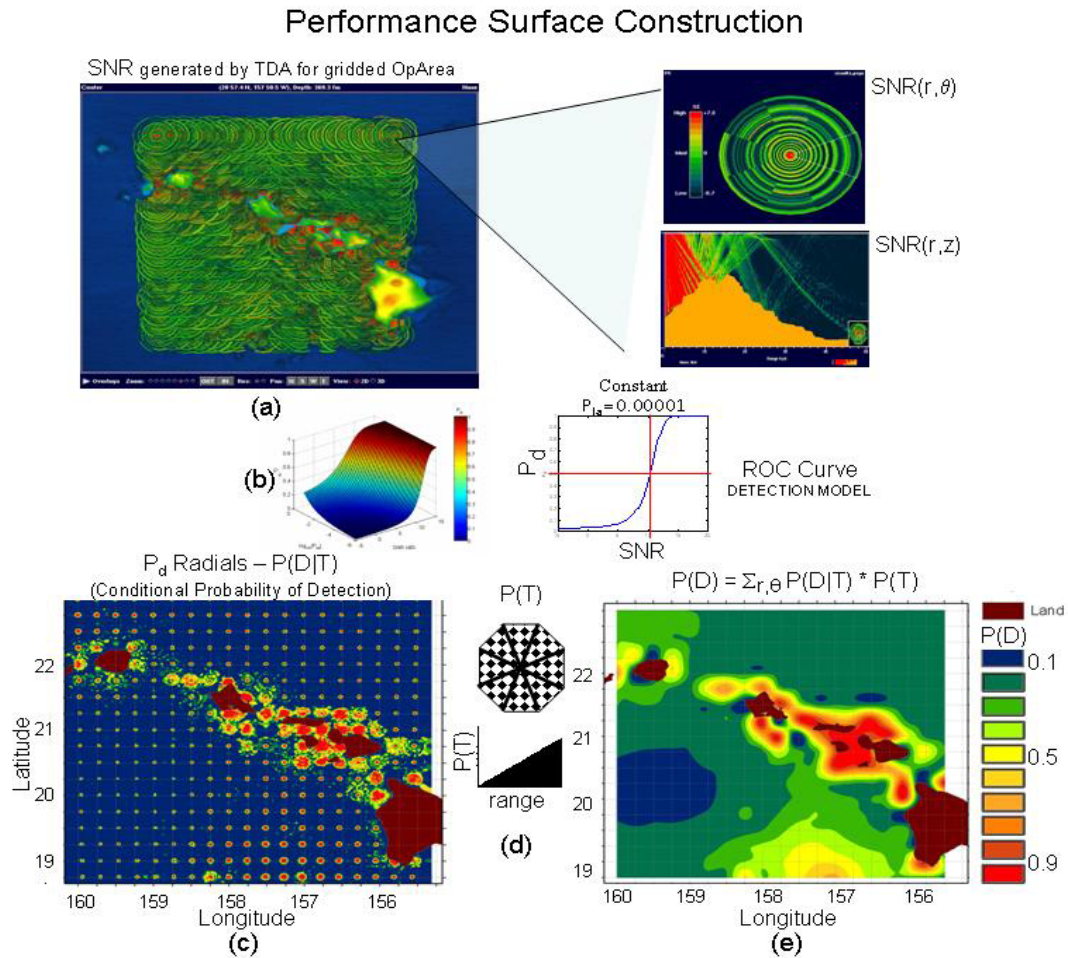


Figure 17 Process of computing Performance Surface: (a) the overall area of operation is partitioned into a regular grid which serves as multiple points of origin for sonar performance calculations, the expanded view to the right shows the outcome of the calculation for a single point of origin mapped onto range and azimuth for a single depth, indicating non-isotropic performance in signal-to-noise ratio; also, signal-to-noise ratio along a single radial is shown for all range and depth; (b) a non linear transform is applied to create a performance grid on conditional probability of detection given target present, shown here as a “small-multiple” plot over the area; (c) are the conditional probability of detection radials resulting from the detection model transformation (d) represents the uniform target present distribution which is combined with the conditional probabilities to form joint probabilities; (e) the joint probabilities are resolved to marginal probabilities of detection and plotted as a single surface.

The upper row of plots show estimates of SNR calculated at each geospatial grid point where the x-axis is longitude and the y-axis is latitude. The top left-hand panel is the output display of SNR vs. Range radials centered at a latitude-longitude location. The panel in the upper right is a blow-up on one of those SNR vs. Range depictions with the upper showing SNR vs. Range from a plan-view and the lower showing a vertical slice of a single radial.

The center plots in Figure 17 represent the ROC detection model where the left panel depicts a family of ROC curves as a function of SNR, Conditional Probability of Detection (P_d), and Probability of False Alarm (P_{fa}). The right panel of one ROC curve where some a constant P_{fa} is fixed and an SNR estimate can be mapped to a conditional probability of detection.

The bottom left panel shows the result of this mapping which produces conditional probability of detection versus range for each radial at each geospatial grid point. The final right plot is the final scalar value of the joint probability of the conditional probability weighted by the uniform distribution of a target present within a specified range. The color scale here from blue to red represent probability of detection values from 0 to 1. The blue in the middle left area indicating poor detection performance is in this case due to a cold core eddy, while the yellow to red, or good performance, in the south is due to warmer water entering the area. It is important to understand the parameters and constraints bounding these performance maps. These parameters, sensor depth, target depth, and range to which the probabilities are integrated, should always accompany the graphics when presented to the operational user. Additionally sensor and target specific parameters are also stated in order to provide user with information relevant to the given task.

Examples of Performance Surface Types

‘Probability of Detecting Target within Range’, is one of the primary *Performance Surface* maps used operationally. An example of the current ‘Probability of Detecting Target within Range’ *Performance Surfaces* is depicted in the lower right panel of Figure 17. The color scale ranges from red to green represent 0 to 1 probability of detection respectively. This type of graphic is used to relay information to the decision maker considering asset allocation or movement across the area. The colors are interpreted as the probability of detecting a target within the given range, for specified target-receiver depths. Note in the color scale that yellow is assigned to 0.5 probability. This “0.5” or 50 % probability is the threshold that most TDAs present. The TDA implication is that 50% and above will result in detection and below 50% will result in a missed detection. An alternative explanation is that half of the detections are made above this value, and half are made below. The *Performance Surface* representation is distinguished from current TDA presentations in that the full range of Pd are presented and further the probability of target present is included. Albeit the target distribution in this case is uniformly distributed, with the only assumption being that a target is present within the stated range, with knowledge of a more likely target location, a different distribution could easily be included in the present framework.

As described earlier, *Performance Surface* can be any scalar estimate that presents a relative measure of ASW capability. The estimate described in detail to this point is the Probability of Detection for Target within Range. Other performance estimates that are currently generated are ‘Maximum Detectable Range’, ‘Near-Continuous Range’, ‘Best Passive Depth’, and ‘Effective

Range'. These estimates and the resulting *Performance Surface* maps are used to provide insight to relative system performance, acoustic propagation characteristics (i.e. convergence zone, bottom bounce), and sensor placement alternatives. These types of *Performance Surface* map outputs are described here.

'*Maximum Detectable Range*' is the maximum range at which the conditional probability of detection exceeds a threshold (generally "0.5") and remains above for some range tolerance (i.e. 4 kyds). The 'conditional probability of detection' vs. range curves at each grid location are collapsed to a single representative curve. An algorithm then determines the maximum range where this curve crosses the stated threshold value. In addition to the threshold crossing the curve must remain above long enough given by the 'range tolerance' to provide a 'detection opportunity'. This 'range tolerance' or 'detection opportunity' has been defined by operational users. These maps provide insight into determining areas where extended ranges due to convergence zone (CZ) propagation are likely.

'*Near-Continuous Range*', is defined as the range starting at 0, where the conditional probability of detection crosses a threshold (generally "0.5") and remains with some allowable drop-out tolerance (i.e. 2 kyds). This metric can capture areas where good bottom-bounce propagation is expected. Knowledge of areas where bottom-bounce propagation paths are likely can be used to aid decisions enabling many navy missions. Areas where longer 'Near Continuous' ranges are likely can suggest asset spacing for screens and barriers.

'*Effective Range*' is the scalar result of collapsing the conditional probability of detection vs. range curves down to one then integrating over range at each grid location. This is a good

estimate for comparing different sensors across the full range of the SNR predictions. This is a common estimate for the stochastic Performance Surface model, described in the final section of this paper.

'Best Passive Sensor Depth' is the depth at each grid point where the maximum joint probability of detecting a target within range occurs, along with the probability value at that depth. The metric is used to optimize passive receiver depth. The value of this map is illustrated in the operational example described in the next section. The plot in the right panel is a *'Best Passive Sensor Depth'* map where the colors still refer to the joint probability as described before. However these colors now represent the best performance across all (or selected) sensor depths and the contours denote the depth.

Current Operational Use

The Naval Oceanography ASW Center (NOAC) combined with NAVOCEANO Subject Matter Expert (SMEs) analysts form an operational support team called the ASW Reach-Back Cell (RBC). This RBC was established in September 2006 with a mission to “provide an asymmetric warfighting advantage for ASW forces through the application of oceanographic sciences”.

Performance Surface is one of the tools used to demonstrate the impact of the environment on system capability (Miller, McDowell and Holton 2010). Performance Surface maps have been tested extensively with Navy Fleet exercises primarily through the RBC. Large Fleet exercises where Performance Surface products have been utilized include SHARKHUNT-05, RIMPAC-06, USWEX-07, and RIMPAC-08. Performance Surface maps have been used routinely as standard products since USWEX-07.

The *Performance Surface* products are used routinely to provide guidance and environmental insight to mission planners and theater commanders. Figure 18, Figure 19 and Figure 20 illustrate three examples. For any given mission, ASW assets are often scarce. Effective and efficient use and allocation of these resources is critical. Performance Surface products can be easily used to compare sensor options. Figure 18 shows 2 sensors operating against the same threat and environmental conditions. The active sensor, shown in the upper left panel, exhibits good performance against a shallow target throughout the region. The lower left panel shows the performance of the same sensor when the same threat is operating deep. The two panels on the upper and lower right show performance for a passive sensor against the shallow and deep targets respectively.

Comparing Sensor Performance P(D), for Asset Allocation (Sensors Operating against shallow and deep Target within 20 kyds)

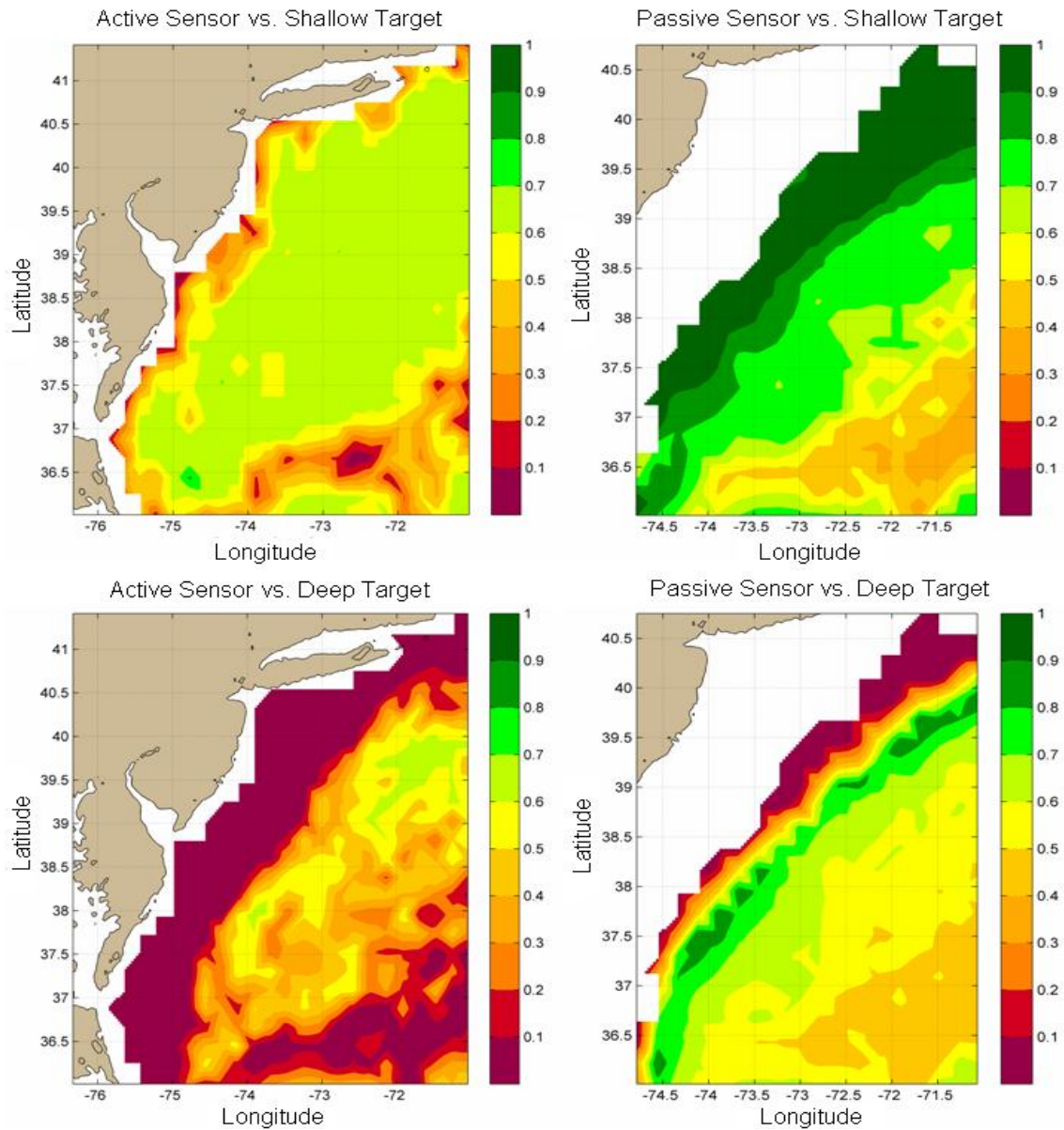


Figure 18 Comparison of performance of active and passive assets vs. shallow and deep threats operating within a 20 kyd range

The Performance Surface graphics shown in Figure 19 illustrate how performance can vary temporally. The two frames shown were produced from environmental models 6 hours apart.

This figure shows the improvement in performance in the northern area associated with the

forecasted oceanographic changes. Temporal changes of this level are frequently encountered. Significant environmental changes over as little as 3 hour periods have been seen in some areas.

Probability of Detection P(D), Varying over Time (6 Hours)

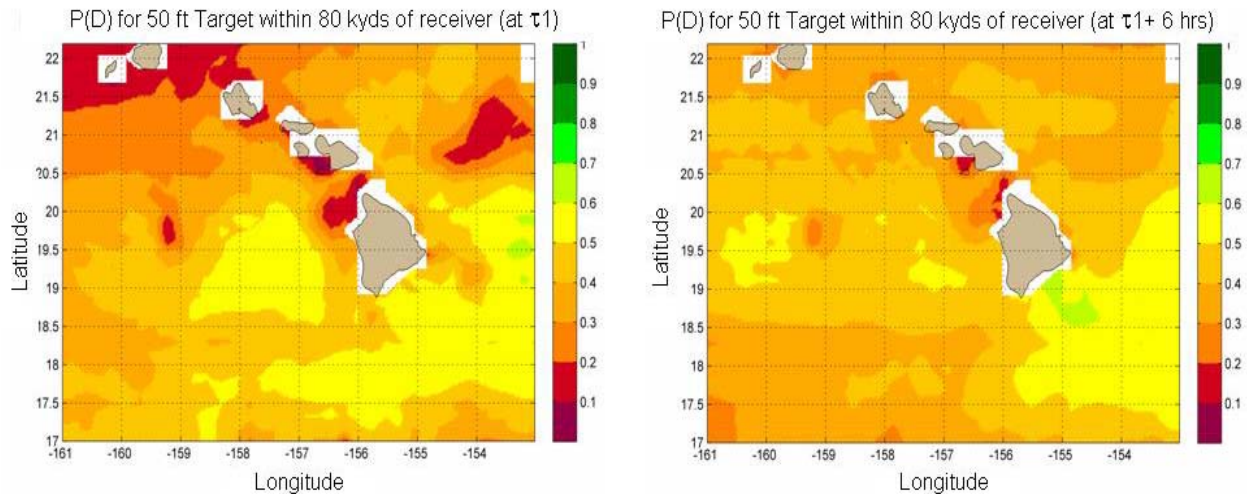


Figure 19 Active sensor performance show significant degradation over two time periods varying from Tau-1 in panel (a) to Tau-1 + 6 hours later in right panel

A final example of how Performance Surface products are used operationally is shown in Figure 20. For passive predictions and natural outcome of the modeling is the varying sensor performance over depth. While typically performance products are generated at requested sensor depths, an additional output can be produced to provide additional insight and possibly alternative guidance. Figure 20 shows a graphic of the Best Passive Sensor Depth metric. The two graphics on the left show performance for a passive sensor, detecting a shallow target operating at 200 and 400 ft. respectively. The larger panel on the right shows the performance when the sensor is located at a depth that maximizes the probability of detection (Pd). The colors indicate Pd and the contours indicate the associated depth. This is not used to suggest excessive movement of the sensor up or down, rather as information the can be used to exploit depth advantages throughout the area when appropriate.

Best Passive Sensor Depth Performance P(D), Compared to Constant Sensor Depth against a Target at 50 ft.

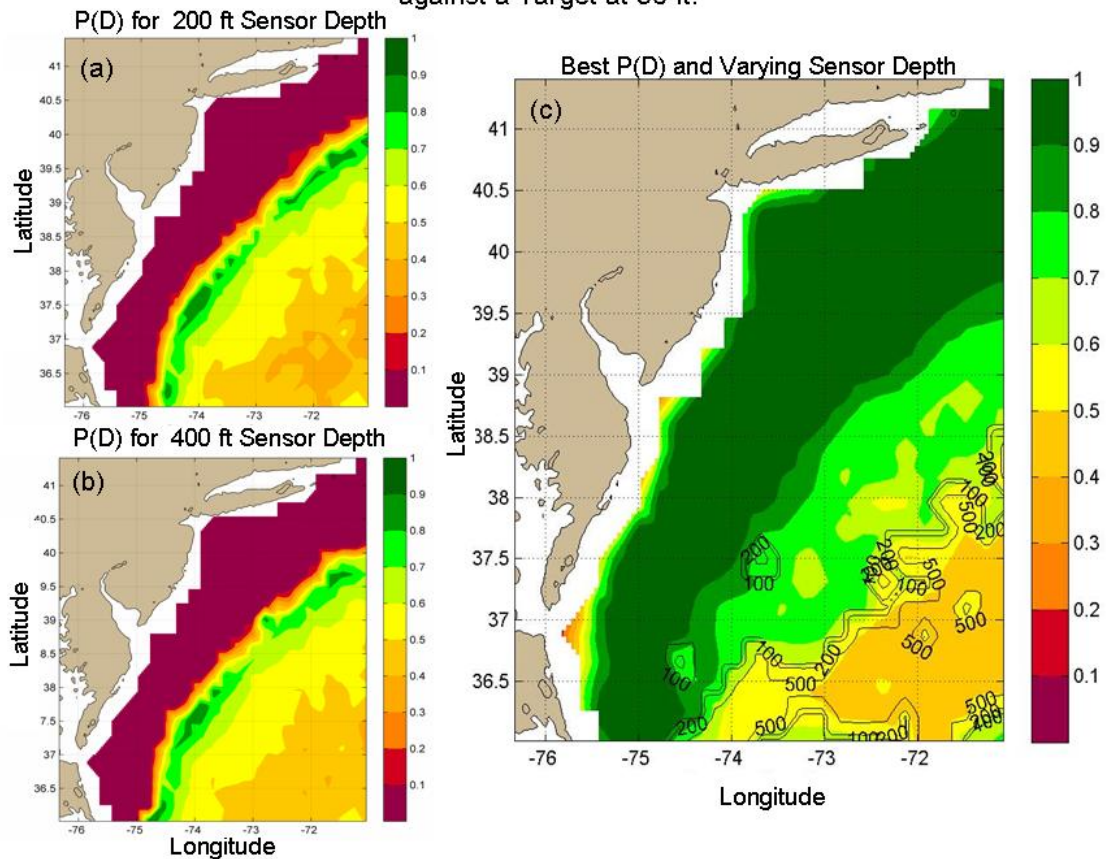


Figure 20 Best Passive Sensor Depth map depicted in larger right panel (c) compared with performance for single sensor depths at (a) 200 ft and (b) 400 ft.

Future and On-Going Improvements, A Stochastic Performance Surface Model

The present *Performance Surface* model is as described earlier, a deterministic combination of the terms of the sonar equation with the addition of an SNR to P_d detection model and a target location distribution. This implies exact knowledge, or assumptions, of values for each term of the sonar equation. The reality of trying to predict actual ASW performance leads to the acknowledgement that these quantities are rarely, if ever, known exactly and should more appropriately be described stochastically as probability density functions.

The signal to noise ratio can be expressed as a convolution of probability distributions of each term:

$$PDF_{SNR} = PDF_{SL} \otimes PDF_{(N-DI)} \otimes PDF_{TL} \quad (9)$$

This is illustrated in Figure 21. The figure shows a Gaussian distribution for a notional source level centered about 130 dB and a Gaussian distribution for a notional TL distribution centered on $-20\log_{10}(\text{range})$, where range is expressed in meters. Heuristically, the standard deviation of the example is set to 0.02 dB. The TL distribution for ranges sampled at 1, 5, 10, 15, and 20 nm are illustrated in varying colors. The convolution of the notional source level distribution with the notional TL distributions produces received level distributions. The 1 nm TL curve is centered about -65 dB: when the 130 dB peak source level curve is convolved with the 1 nm TL curve the resulting distribution is centered about 65 dB.

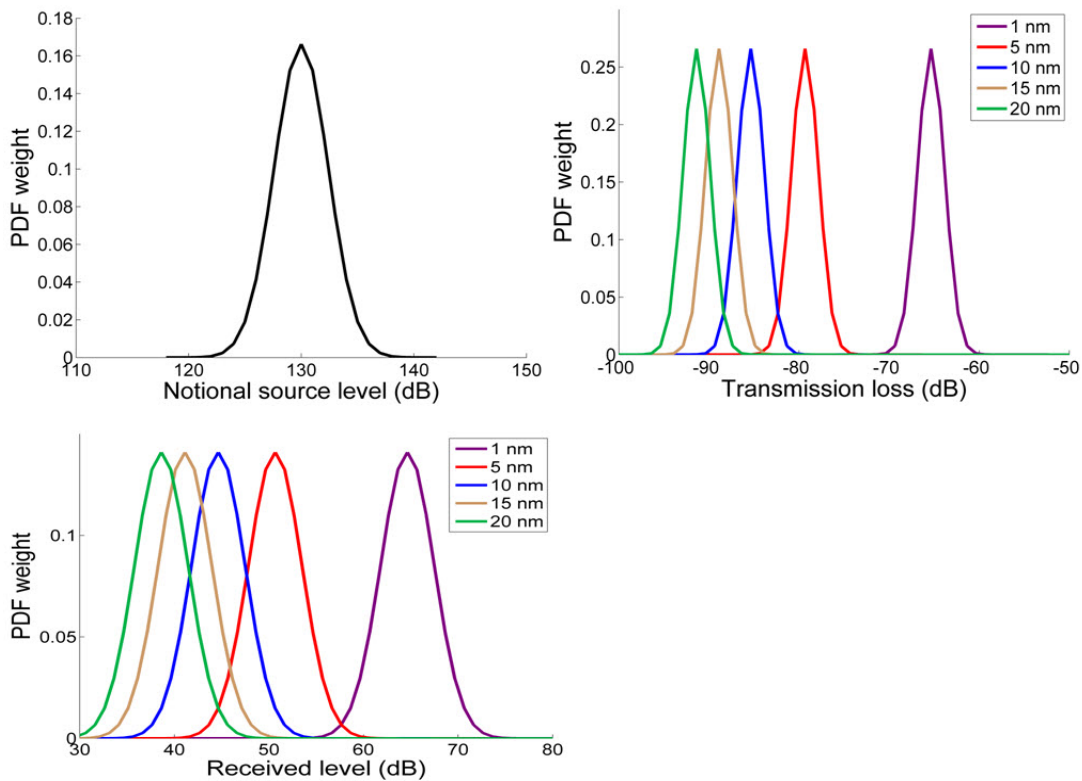


Figure 21 Convolution of source level and TL to compute received level

In Figure 22 the ambient noise is convolved with the received level. The ambient noise was derived from McCarty (McCarty, 2006). Matlab scripts modified the Newhall (Newhall et al., 1995) beam noise probability distributions for wind noise. The shipping level contribution is centered about 70 dB and the wind at 57 dB with an assumed 10 dB array directivity index. After application of the McCarty-Newhall algorithm the effective noise peaks about 53 dB. When the received level is convolved with $-N(x)$ the probability distributions for the SNR are obtained as a function of range. Thus, the peak received level of 65 dB when convolved with the noise peaked at 53 dB yields a 1 nm SNR curve peaked about 12 dB. These curves are probability density functions that integrate to unity.

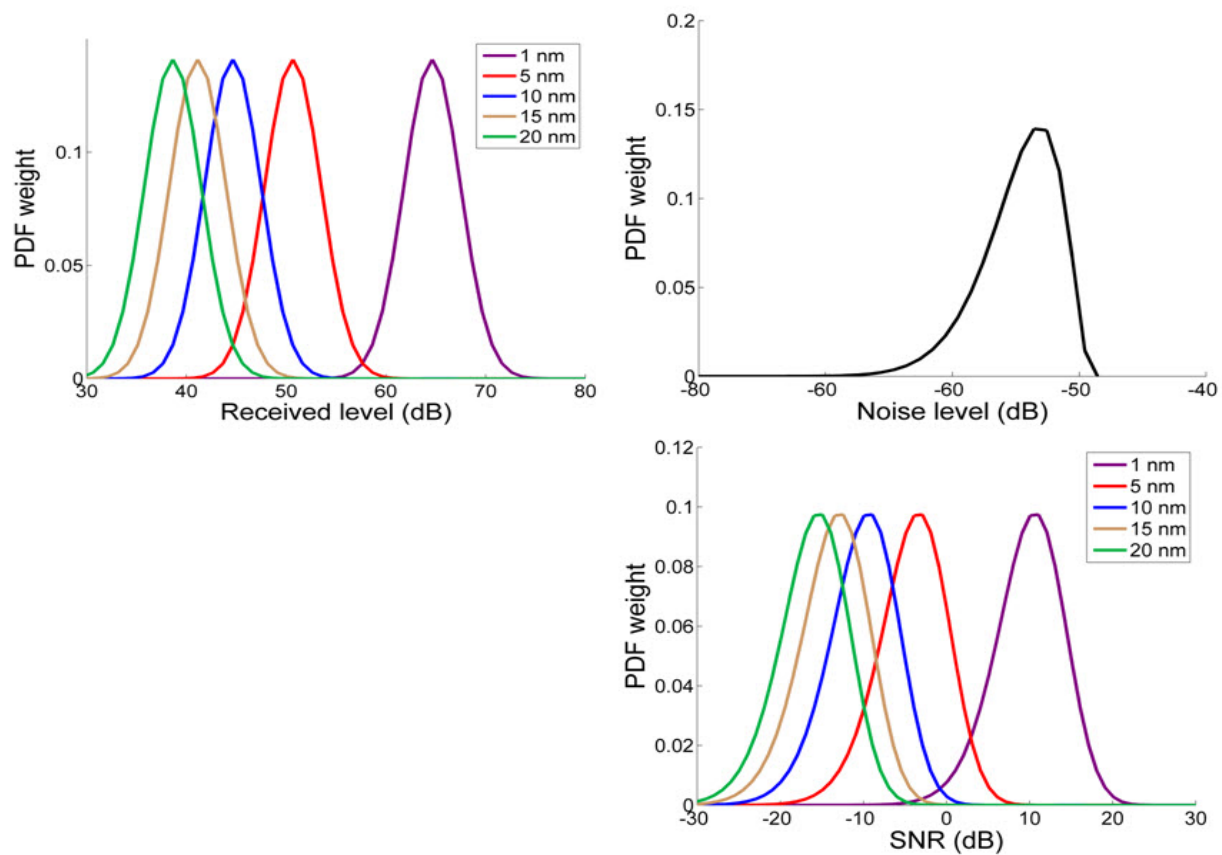


Figure 22 Convolution of received level with noise to compute signal to noise ratio

To compute the conditional probability a target is declared, given the target is present, equation (11) needs to be evaluated:

$$P(\text{declare target}|\text{target present}) = \text{PDF}_{\text{SNR}} \times P(\text{PD}(\text{target present})|\text{SNR}) \quad (10)$$

The probability of detection is the product of the SNR probability distribution function calculated in equation (9) with the probability of detection given the target is present and given a signal to noise ratio. Albersheim's equation is used to relate the SNR to PD given the target is present. For an active system the number of pings could be considered the number of independent samples. Albersheim assumes random noise described by a Gaussian process. For a passive system, because the noise is not correlated, the bandwidth-time product represents the number of independent samples.

Figure 23 shows the process of computing conditional probability vs. range from SNR probability density functions. The upper left panel is a plot of SNR probability density functions for the 5 ranges indicated in the legend (1, 5, 10, 15 and 20 nmi). The upper right is the ROC curve. The lower left panel is a plot the same probability density function after the ROC transformation. Note the brown, 15 nm SNR curve which was centered about -12 dB is greatly reduced in amplitude, whereas the purple, 1 nm SNR curve which was centered about 11 dB is virtually unchanged. The lower right panel is the total detection probability for a given range is then the integral over all SNR values for the probability curve corresponding to that range.

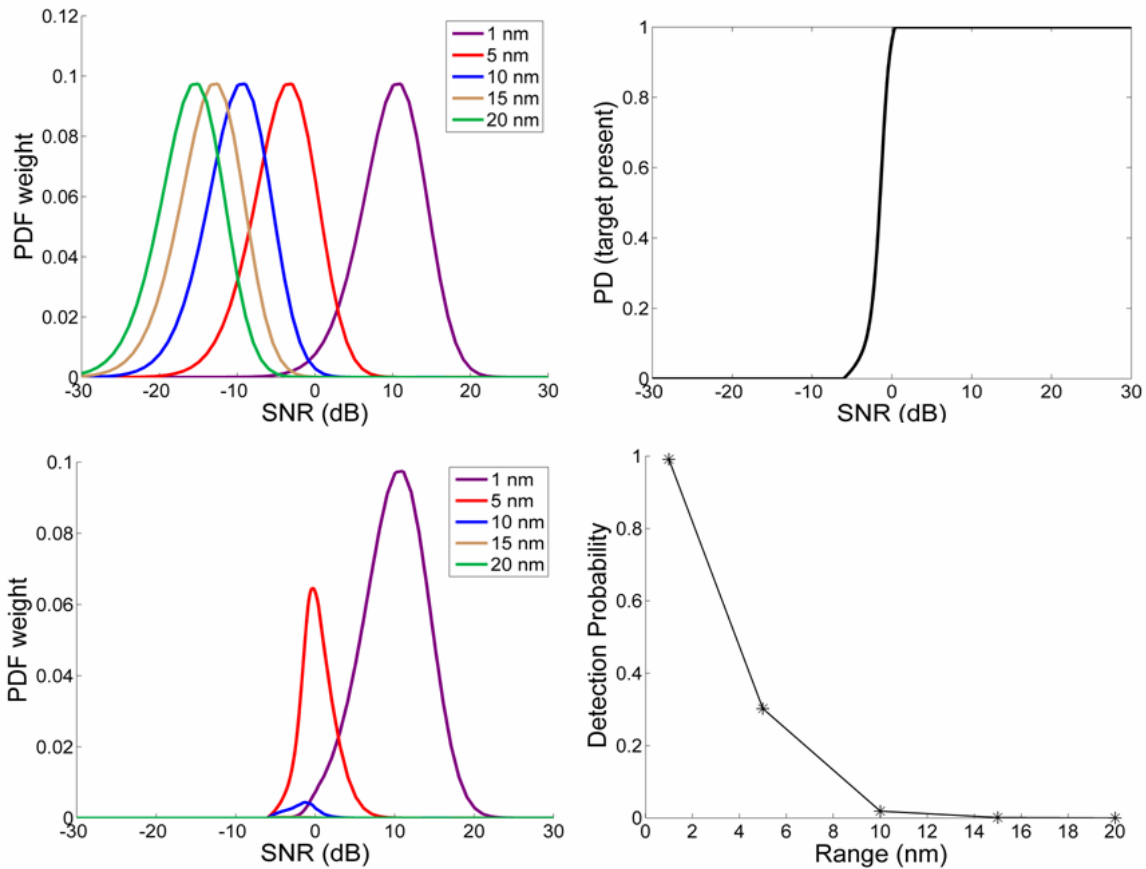


Figure 23 Conversion of signal to noise ratio to probability of detection given target present

At this point the conditional probability of detection has been derived from stochastic representations of each component of the sonar equation.

Conclusions

The nature of the *Performance Surface* continues to be a work in progress, highly informed by our operational customers, the science and engineering community and a rigorous program of field measurements and assessments. This paper describes products currently being published, as well as an approach to future products, and a strategic or philosophical framework for future tools. This framework suggests that *Performance Surfaces* should explicitly account for all we

know and don't know about the ocean volume, all we know and don't know about the target, and all we know and don't know about systems and weapons. There may be many approaches to satisfying these criteria being developed across various technical disciplines (machine learning for example) but our specific approach now is to represent all our variables as distributions that represent the set of plausible conditions. Within this framework those values which are known or admit only a single valued solution are represented by delta-function distributions. The uncertainty vanishes for these distributions. Many of the distributions are taken on sets of model trials made on varying initial or boundary conditions taken on ensembles of model results. These ensembles are available to us partly because of the massive computational effort represented in computing ocean models and estimating acoustic fields over their domain. We then apply the calculus of distributions to standard performance models, such as a sonar equation in the case of ASW, to estimate plausible distributions of signal-to-noise ratios. The distributions contain all the known information, and as distributions continue to represent the spreads of uncertainty.

Acknowledgements

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Chapter 4

Performance Surface as a Tool for Increasing ASW Proficiency

Abstract

Frequently, meteorology and oceanography (METOC) professionals have sought to characterize the physical environment and its impact on the performance of ASW sensors in the context of a plan which has already been developed by the decision-maker's staff. In the past, limitations on processing power and the lack of a reliable ocean forecast model have made it difficult for METOC personnel to accurately characterize the variability of the ocean environment for the purpose of predicting acoustic ASW sensor performance. Advancements in ocean modeling and computing systems have enabled the development of acoustic performance surface maps (AcPS Maps) that can characterize the performance of several acoustic sensors over a wide geographical area and over several time intervals, allowing for a meaningful comparison of the efficacy of various sensors at the warfighter's disposal. This capability makes the performance surface a tool which can improve the operational planning process and help mission planners fully exploit variations in the physical environment when building an ASW plan. AcPS Maps can be produced for several time periods of interest based on forecast model output from the Navy Coastal Ocean Model (NCOM), allowing for a characterization of future sensor performance. By producing performance surfaces for multiple sensors against a threat, one can quickly determine whether acoustic advantage lies with active or passive prosecution and determine where and when certain platforms will be most effective. This paper addresses methods to bring these and other uses of performance surface into every phase of the planning process to enhance ASW tactical advantage.

Introduction

Anti-Submarine Warfare (ASW) is a thinking game, much like a long, slow game of chess. It is extremely difficult to acoustically detect a submerged submarine even under the best of conditions. Noise produced by the submarine varies greatly in both frequency and intensity as equipment lineup, course, and speed change. The underwater environment constantly changes, as fluctuations in surface winds, solar heating, ocean currents, and thermal gradients cause wide variations in the acoustic transmission properties of the water mass. Even when the ocean environment is relatively static, the movement of the submarine itself can cause significant changes in exploitable transmission paths for acoustic sensors. Ambient noise levels in the ocean vary greatly as shipping density and biologic activity fluctuate spatially and temporally. Meteorological activity can also significantly affect acoustic propagation paths and ambient noise levels. A heavy storm can cause disturbances in the surface layer, causing mixed layer depths to increase significantly, while simultaneously increasing ambient noise levels due to wind and rain. The result could be either improved or degraded acoustic sensor performance depending upon the acoustic sensors employed or the acoustic frequency of interest. With so many environmental variables affecting the performance of acoustic systems, it is very difficult to predict how various ASW systems will perform in a given place and time.

Several technologies have been developed since the 1980s that attempt to predict reliably the acoustic capabilities of various SONAR systems. Tactical decision aids (TDA) such as Personal Computer - Interactive Multi-sensor Analysis Trainer (PC-IMAT) and SONAR

Tactical Decision Aid (STDA) can predict acoustic sensor performance with input from several oceanographic databases developed by the Naval Oceanographic Office (NAVO). These systems rely upon several assumptions entered by the operator to approximate the several factors affecting the acoustic properties of a given target, such as acoustic reflectivity (i.e., target strength), operating depth, target aspect, acoustic source levels and environmental noise. With very accurate inputs, these TDA can produce acoustic detection range predictions of reasonable accuracy. A significant limitation of these TDA, however, is that these technologies allow planners to analyze only single geographical points at discrete time references, and provide little information on levels of variability in space and time around the point being studied. They also require significant processing power and a large amount of time to calculate sufficient numbers of points to reasonably characterize the acoustic properties of an area.

Current doctrine at the Naval Mine and Anti-Submarine Warfare Center (NMAWC), the center for development of ASW and mine-warfare tactics and doctrine for the U.S. Navy, emphasizes recognition of the ocean environment as a dynamic fluid and discarding the notion of the “range of the day” when attempting to quantify the performance of ASW sensors. The development of acoustic performance surface (AcPS) technology as a joint venture between the Naval Oceanographic Office (NAVO) and the Naval Oceanography ASW Center, Stennis Space Center (NOAC SSC) supports this doctrine by more accurately depicting the ASW battlespace as a spatially and temporally dynamic environment. Much as a surveyor or scout would exhaustively study and characterize a terrain environment for suitability of deploying ground forces for maximum effect, the AcPS allows an ASW commander to truly understand how the whole environment in which he or she intends to deploy ASW forces can change in space and

time over the course of a campaign. By fully understanding the variability of an entire battlespace, rather than only discretely defined points within that battlespace, and the resultant impact of the operating environment on the available resources and systems employed, the commander and staff can develop more meaningful courses of action (COA) from which to choose that which will more likely result in mission success.

In developing such COA, three distinct thought exercises must be used. First, consider how the environment affects our own sensors. Next, consider how the environment affects the adversary's sensors. Finally, and probably most difficult, consider how the environment affects the adversary's behavior – his tactics. With a great deal of time and research, an experienced analyst can identify most of the individual factors that will affect acoustic propagation conditions and with sufficient processing capabilities, can use existing TDA to characterize an operating area (OPAREA) for ASW suitability. However, in the constraints of a short decision cycle, and the constantly changing environmental conditions inherent in an operational scenario, it will be difficult to perform this analysis effectively over a wide geographical area. The performance surface provides a superb tool to use as a starting point in completely and accurately characterizing an area for ASW operations.

Performance Surface Maps Defined

By definition, a *Performance Surface* (PS) Map is any graphical depiction of the performance of a given system over a geospatially and temporally (x, y, z and t) defined area. These maps are intended to be a fused view that depicts, in easy to understand terms, the overall result of the complex interactions of several factors on a particular combat system. The acoustic Performance Surface map (AcPS Map) depicts the sum effect of several complex oceanographic factors on a

particular acoustic sensor for a given threat scenario, and is a useful tool for identifying water masses with relatively “good” acoustics and those with relatively “bad” acoustics for ASW prosecution. Figure 24 shows a basic representation of an AcPS Map.

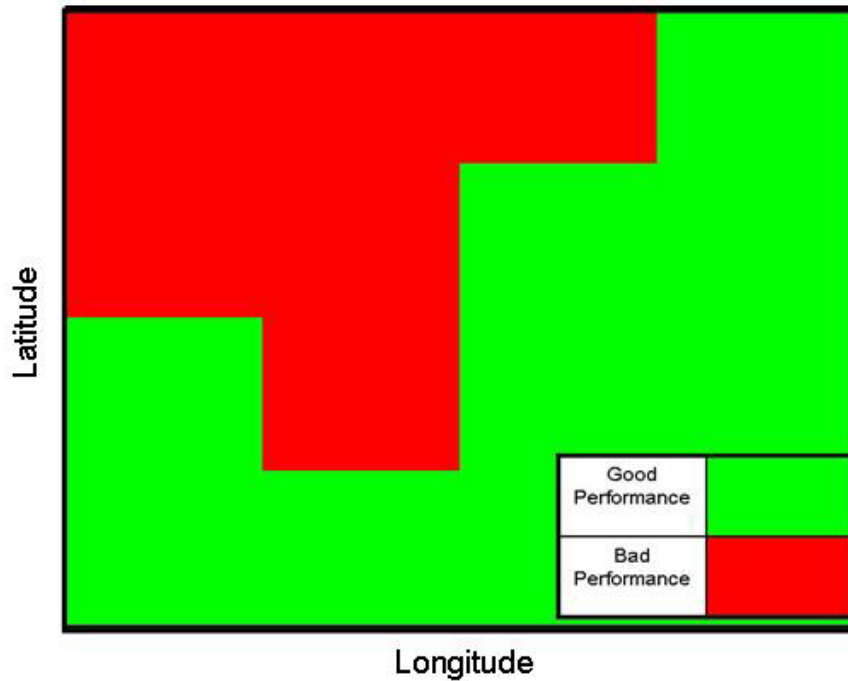


Figure 24 Generic Performance Surface or AcPS Map

The AcPS Map provides the warfighter with a visual representation of how well a particular acoustic sensor will perform against a threat at a given time in a given environment. The AcPS Map consists of thousands of acoustic transmission loss calculations performed on a grid within a particular area of interest. An acoustic transmission loss calculation is based on the active and passive sonar equations.

$$\text{Active: } \text{SNR} = \text{SL} + \text{TS} - \text{RD} - \text{NL} + \text{DI} - 2\text{TL}$$

$$\text{Passive: } \text{SNR} = \text{SL} - \text{TL} - \text{NL} + \text{DI}$$

Where:

SNR = Signal to Noise Ratio

SL = Source Level of the acoustic signal

TL = Transmission Loss suffered by the signal from source to receiver

TS = Target Strength. The reflectivity of a target to active SONAR transmissions.

NL = Environmental Noise.

RD = Recognition Differential. The ability of an average SONAR operator to detect an acoustic contact with 50% probability.

DI = Directivity Index. Amount of directivity of a SONAR system.

Using STDA, each calculation is performed in three polar dimensions (r, T, z) at hundreds of geospatial coordinates in the area of interest. The resultant SNR vector values for each radial about the discrete coordinates are averaged and converted to a scalar value of probability of detection (Pd) at each grid point. The various probabilities of detection are then assigned a discrete color value and smoothed using a geospatial software application (i.e. GIS) to produce a graphic representation of probability of detection for a given sensor location (see Figure 25).

More detail about this process is discussed in McDowell and Gough (2010).

Performance Surface Construction

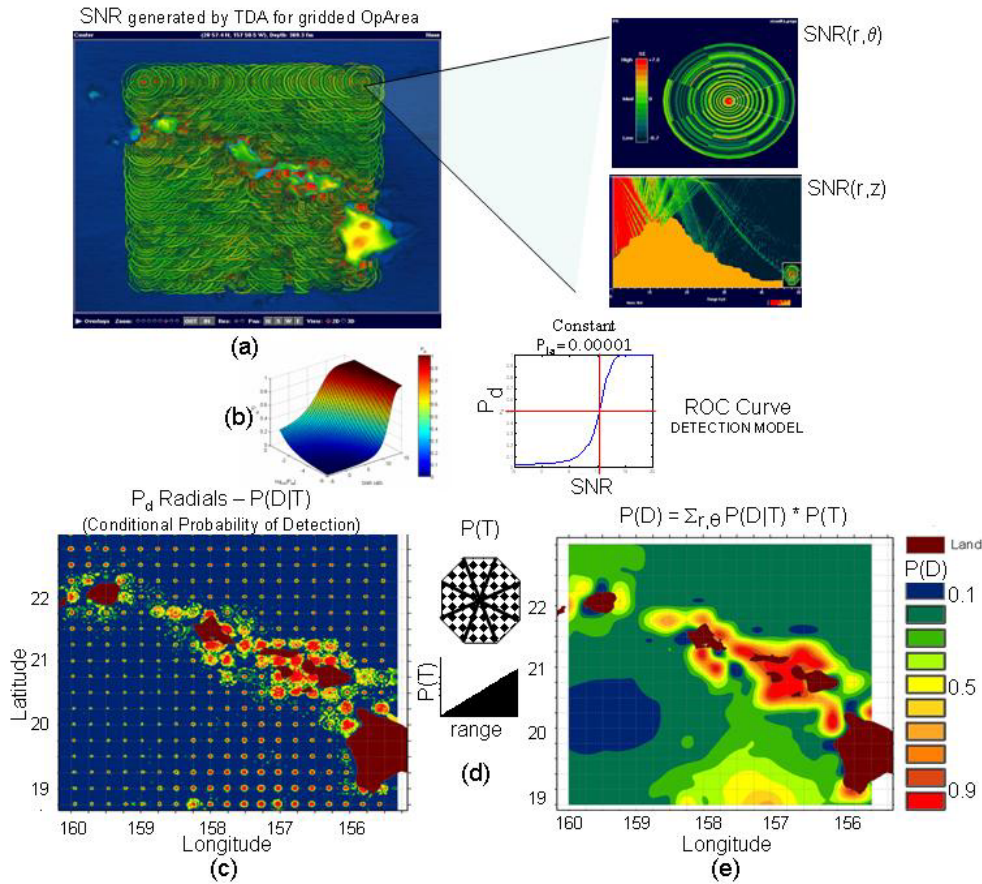


Figure 25 Process of computing Performance Surface: (a) the overall area of operation is partitioned into a regular grid which serves as multiple points of origin for sonar performance calculations, the expanded view to the right shows the outcome of the calculation for a single point of origin mapped onto range and azimuth for a single depth, indicating non-isotropic performance in signal-to-noise ratio; also, signal-to-noise ratio along a single radial is shown for all range and depth; (b) a non linear transform is applied to create a performance grid on conditional probability of detection given target present, shown here as a “small-multiple” plot over the area; (c) are the conditional probability of detection radials resulting from the detection model transformation (d) represents the uniform target present distribution which is combined with the conditional probabilities to form joint probabilities; (e) the joint probabilities are resolved to marginal probabilities of detection and plotted as a single surface.

The AcPS Map is well suited to identify areas of acoustic opportunity and vulnerability; however, it should not be misconstrued to indicate acoustic “coverage” of an area of interest by a particular sensor. Additionally, AcPS Maps are calculated using several inputs of environmental

elements, target characteristics and own-ship sensor characteristics to predict a sensor's ability to discern a target at a fixed distance. The degree of uncertainty in these estimates will have implications on the AcPS Map's ability to accurately reflect probability of detection of a target at a given range. Despite these limitations, the AcPS Map remains the most straightforward and efficient way to depict relative acoustic sensor performance over a large geographic area. In the next section, some examples of ASW planning scenarios will be discussed for which AcPS Map applications are particularly suited.

Use of Performance Surface techniques in ASW analysis

Performance surface is not a singular tool to provide all answers to the ASW operator and decision-maker. However, it is uniquely suited to answer a number of questions very well and quickly. Additional analysis can be done by military and civilian subject matter experts at the ASW NOAC SSC Reachback Cell (ASW RBC) or aboard ship by Naval Oceanography ASW Teams (NOAT) analysts. Using local TDAs tools such as PC-IMAT or STDA, deployed staff oceanographers and ASW analysts can provide ASW planners with a relatively complete picture analysis of the environment and its effects on ASW acoustic sensors in a moderately short period of time. The primary advantage of the AcPS Map over other TDAs currently in use is that the AcPS Map characterizes an entire battlespace for a particular parameter of interest, rather than only at discrete points that may be arbitrarily chosen by an inexperienced analyst.

As has been previously discussed, the acoustic environment of the ocean changes rapidly in both space and time. Only a very thorough analysis of those factors which introduce a high degree of variability in ocean conditions in both space and time will sufficiently characterize an area's

suitability for ASW operations. As is evident in any study of statistical analysis, two key components of success for identifying trends in a physical property are accurate data and proper sampling. For example, Figure 26 denotes an arbitrary waveform depicting the relationship between the range from an arbitrary sensor to the target with acoustic SNR that the associated SONAR system detects. Note how the undersampled case is unable to properly characterize the associated waveform due to the paucity of data, whereas the oversampled case, which is sampled at twice the frequency, much more accurately reflects the variability in SNR at the range of interest. Likewise, acoustic analysis using single point modeling for “range of the day” metrics often employed with current TDA usage is unable to properly characterize the spatially and temporally dynamic ASW environment of interest. As an example, the “range of the day” metric associated with the acoustic sensors of interest could easily miss the effects of environmental temporal and spatial variability which are commonly present and dominated adequate characterization of the ASW battlespace. The much more thorough sampling of the battlespace inherent in the AcPS Map analysis, shown in panels (a) and (c) of Figure 25 allows the analyst to readily identify and further analyze features prevalent in the ASW battlespace being considered and develop plans accordingly. The following sections discuss some significant oceanographic considerations that the AcPS Map is well suited to address.

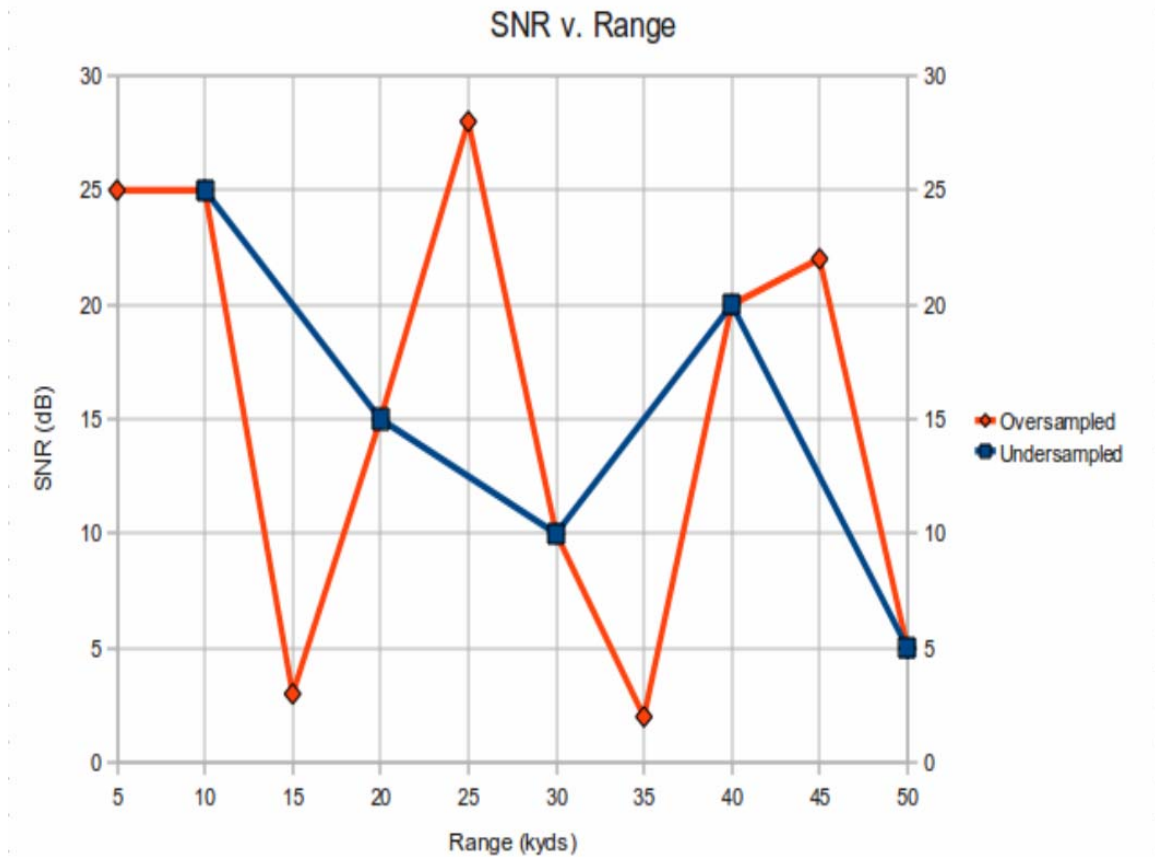


Figure 26 Sampling SNR vs. Range

Temporal Variability in Acoustic Conditions

AcPS Map analysis makes temporal variations in acoustic sensor performance readily evident to the ASW analyst. Diurnal heating and cooling of the surface mixed layer has a significant impact upon acoustic propagation in the resultant surface duct, a phenomenon known as the “afternoon effect”. PS Map techniques can help an acoustic analyst identify areas where the ocean forecast indicates significant degradation in sonic layers through the time frame of interest during an ASW operation Figure 27 shows an area where the surface duct layer experiences a high degree of diurnal cooling and reduced surface mixing over

a 12 hour period and the resultant decrease in detection potential in certain parts of the area of interest for an arbitrary active sensor against a target operating in the surface duct. This information can be used by an analyst to recommend operating in an area of less variability or to identify time periods where the performance of the available acoustic system can be maximized.

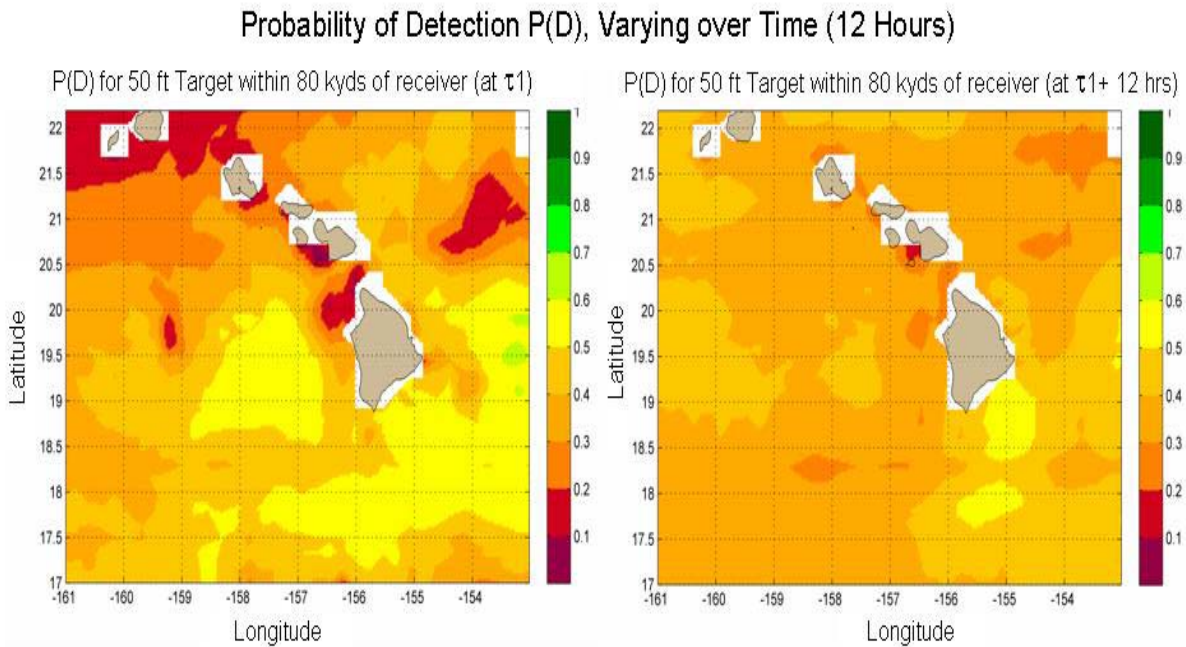


Figure 27 Performance Varying over 12 Hours

Sensor Comparison and Asset Allocation

The ASW RBC can produce PS Maps for both passive and active sensors against a given target in a given water space. Since the environmental parameters used for both sets of transmission loss calculations are the same, the result is a true apples-to-apples comparison between different sensors over a broad expanse of water space. In Figure 28 the four panels depict the performance of several active and passive acoustic sensors available to the mission planner. Because each of these views is produced using the same input parameters for both the environment and the target geometry (i.e. depth, aspect, etc.), the panels provide a true

comparison of relative sensor performance over a wide geographic area, allowing a mission planner to choose an OPAREA that will maximize the performance of all available acoustic sensors.

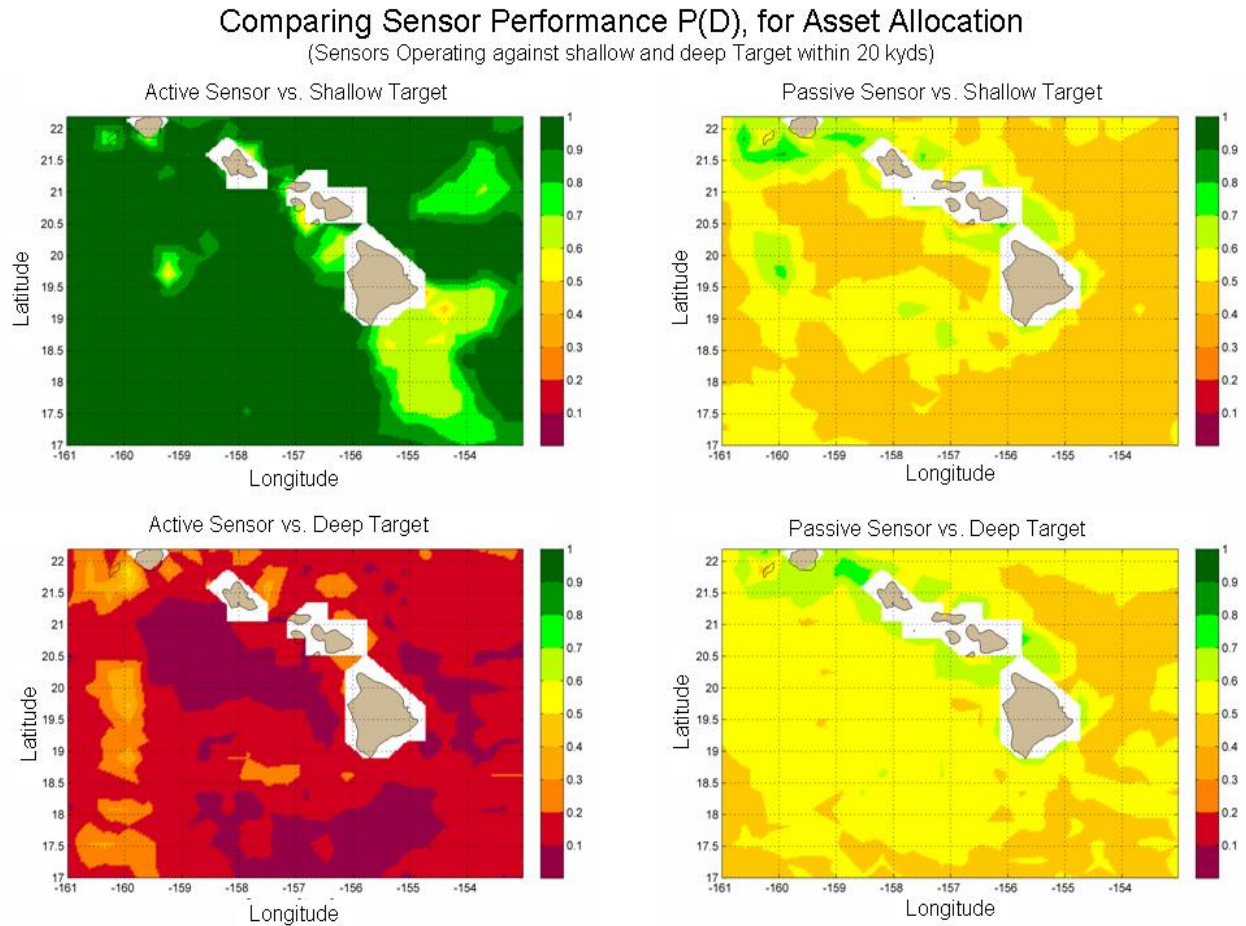


Figure 28 Performance for different sonar systems. The left panels are result from an active system vs. a shallow (top) and deep (bottom) target. The right panels are for a passive sensor vs. a shallow (top) and deep (bottom) target.

Determining Optimal Array Depth

Once search boxes are assigned, the performance surface map can be a valuable tool in recommending the optimal towed array depth. Significant improvements in detection potential can be achieved wherever the search box is located by optimizing search depth. In order to accomplish this, the acoustic sensor performance is calculated for a fixed target depth and

multiple receiver depths. A simple algorithm is then run on all those performance surface outputs to pick out the highest probability of detection (Pd) at each grid point. That probability of detection field is color shaded on the map and the depth for each is contoured over the color shading, as shown in Figure 29. Note that by towing the passive sensor at the depth prescribed by the contours in panel (c), the area of optimum sensor performance is greater than that indicated in panels (a) or (b). No other analysis technique currently used is able to replicate this capability.

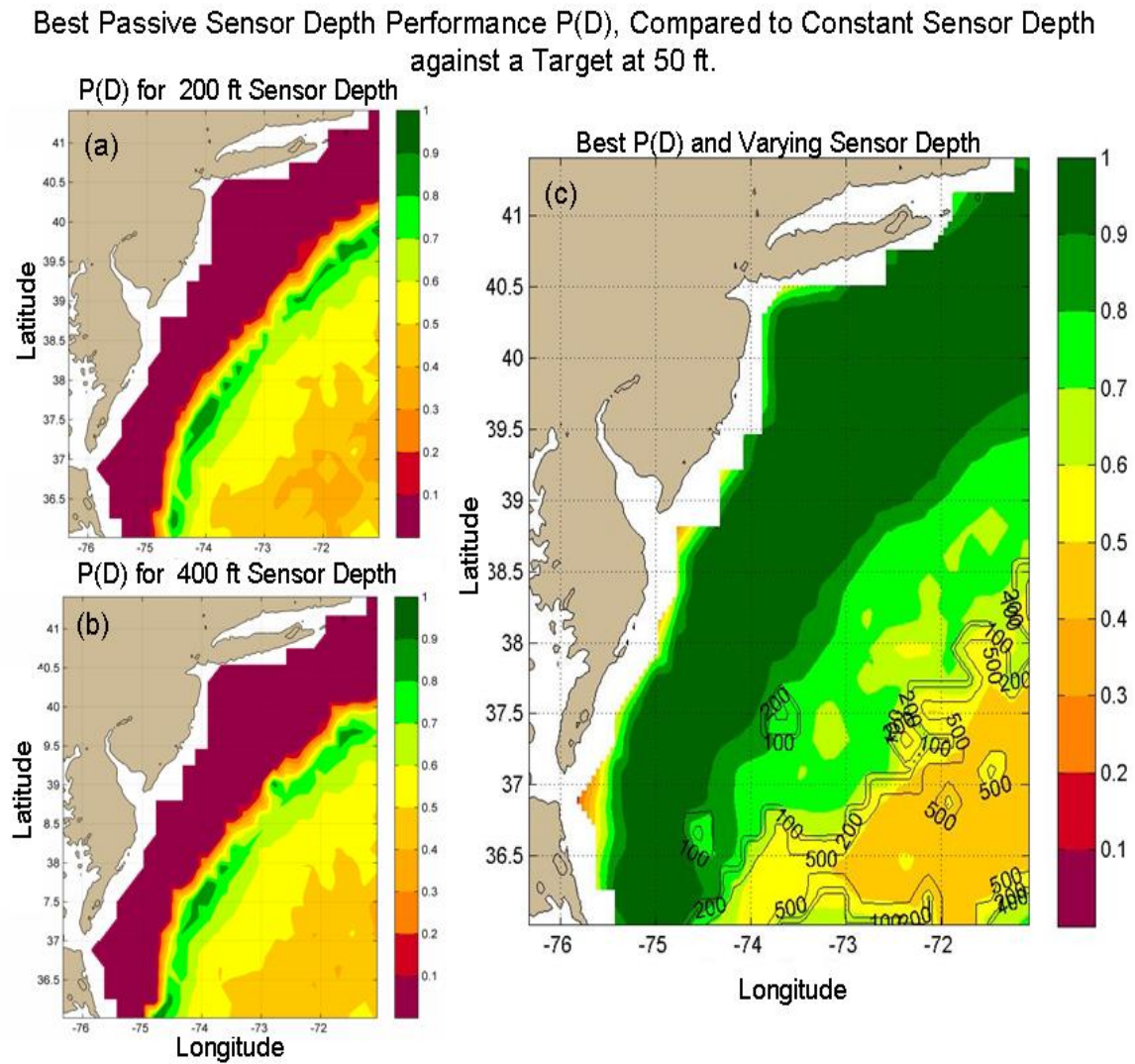


Figure 29 Optimum Sensor Depth

Identifying Areas for Further Analysis and Water Sampling

Since the performance surface algorithms, in these cases, use a range-weighted radial averaging scheme to reflect a uniformly distributed target, the performance measure represented by a single scalar value at each grid point does not show directional information. There is no problem with this approach in areas where the performance does not change significantly over a short horizontal distance. However, in areas where there is a gradient in performance, the analyst must realize that the performance surface map is not necessarily representing the full range of acoustic complexity in these areas. In order to determine the oceanographic and acoustic structure in the water column, an analyst must produce detailed acoustic transmission loss plots in these areas to gain a full understanding of this structure and its resultant impacts on the tactical situation. In Figure 30 the circled portion of the AcPS map indicates an area of degraded acoustic performance (i.e. significant performance gradient). Figure 30 shows an example ‘Maximum Detectable Range’ AcPS Map view of the performance of an arbitrary passive sensor against a shallow target. A casual observation shows that the performance of the sensor degrades when operating in the southwest portion of the area of interest.

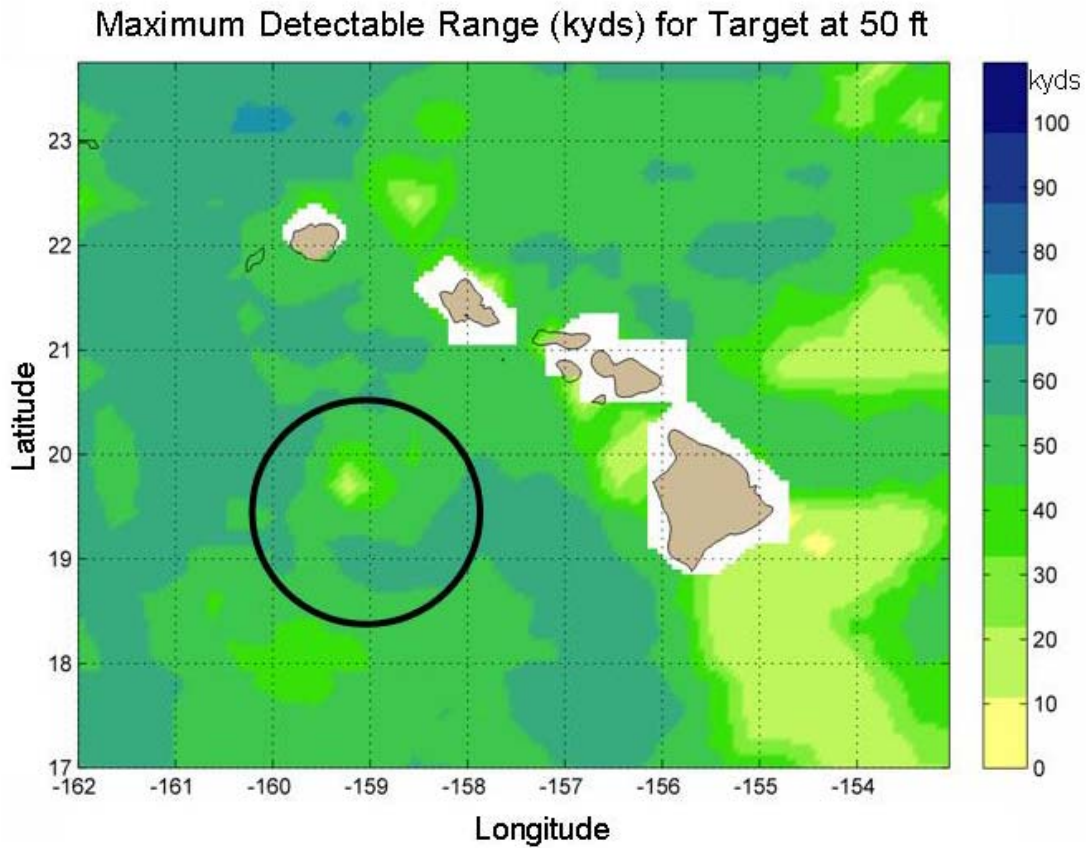


Figure 30 Varying Performance used to advise additional sampling

Further investigation reveals that this is due to the presence of several seamounts of sufficient height to disrupt the long-range convergence zone path, as shown by a bathymetric chart depicted in Figure 31. The AcPS Map technique readily displays the sum effect of these seamounts on an acoustic sensor of interest, allowing the analyst to further investigate other Course of Action (COA) options as needed.



Figure 31 Bathymetric Variability determined as cause for performance degradation

While this may at first seem to be a weakness of performance surface, rather than a strength, it should be noted that the performance surface gives a quick view of performance over a wide area. Without this product, numerous appropriately selected single point transmission loss runs would be required to characterize the acoustic environment over the area, which would demand a great deal of the on-scene analysis time. With performance surface, the areas which require detailed study are immediately identified, thereby reducing the number of calculations required. Additionally, areas of strong acoustic performance gradients as shown on an AcPS map may indicate transition zones which the oceanographic models may not handle well. This should alert the on-scene analyst to contact the ASW RBC for recommendations so that water sampling

resources can be employed in such a way that their data will most effectively improve the ocean forecast which will in turn improve the acoustic forecast.

Other Assets Required for Success

While the performance surface is a very good tool for gaining a quick understanding of the acoustic environment, it is not intended to answer every question alone. The Naval Oceanography ASW Center (NOAC) provides Naval Oceanography ASW Teams, or NOATs, with specific expertise in tactical oceanography to ASW commanders (ASWC) to interpret various data and oceanographic products in order to completely characterize the environment and make actionable recommendations to the warfighter which will improve the effectiveness of an ASW prosecution. In order to do this well, analysts must have a complete understanding of the environment and its effects on sensor performance, a good knowledge of the capabilities and limitations of own force and adversary assets, tactical expertise, and critical thinking skills.

Stand-alone tools for Analysis Forward

The performance surface gives the analyst a large-area view of the predicted acoustic sensor performance, but it does not explain why the performance is good or poor. It is important for the analyst to understand why the performance is good or poor for three reasons. First, “why” is the most frequent question the ASW planners receive from watchstanders and decision-makers. It is essential that they understand the environmental impacts on sensor performance and be able to articulate their reasoning in order to build and maintain credibility. Second, they must understand the propagation paths and how they respond to environmental factors in order to make the best recommendations on asset placement, sensor employment, and force movement. Finally, they should have a good understanding of environmental and acoustics basics in order to assess the accuracy of the PS Map depiction. If it does not make sense according to sound

acoustic principles, the NOAT will know that they need to contact the ASW RBC for further explanation. When this occurs, the ASW RBC may be able to provide an explanation for why something unexpected is occurring or they may determine that the ocean model is not handling the situation well.

To achieve this understanding, a tactical decision aid, such as PC-IMAT or STDA, which can produce full-field acoustic propagation loss plots is required. These tools allow an on-scene analyst to address uncertainty in PS Map depictions by creating full-field acoustic propagation loss plots and acoustic path availability analysis that are not readily evident in the PS Map view. These tools allow the analyst to create graphics that fully explain the oceanographic factors that contribute to changes in acoustic sensor performance in an operating area.

In addition to the information produced by a tactical decision aid, other products from the ASW RBC are helpful in completing the environmental and acoustic picture for interpreting the AcPS Map. Domain-wide sonic layer depth and cut-off frequency graphics are produced daily by automated post-processing of the NCOM model output. These products readily show which frequencies will be ducted throughout the operating area. Bottom slope, composition and loss graphics produced with local TDA or by the ASW RBC are also valuable in assessing bottom bounce availability and reliability. These additional tools are a vital complement to the AcPS map to give the ASW analyst a complete understanding of the total effect of several factors influencing the performance of acoustic ASW systems.

For an anti-submarine warfare commander (ASWC) planning cell to effectively plan operations, the NOAT must also address how environmental conditions will change over time. Due to the computing resources required and the length of time needed to run the transmission loss calculations, along with time-zone differences between the ASW RBC and deployed team, there is usually a later oceanographic model run available by the time the performance surface products are delivered. Also due to this lengthy processing time, performance surface is typically only run for one time instance (τ) for each model run. The acoustic subject matter experts provide an assessment of how conditions will change, but the NOAT can use the TDA and later taus of a more recent model run to analyze “what-if” scenarios and provide more effective long range planning guidance.

Brain storming – scenario development

As discussed previously, knowledge of the environment is not enough for the NOAT to effectively augment a warfighting staff. It is the marriage of tactical and environmental knowledge that enables the decision superiority which leads to ASW superiority. First the team must determine what the adversary forces are and what blue assets are available. Reliable passive search tonals and target strength for active prosecution must be determined, usually through liaison with acoustic intelligence (ACINT) if available or from staff intelligence personnel. Since ASW is rarely the primary mission, constraints placed upon asset placement and employment by other mission areas must be balanced against any ASW plans. The ASWC, Anti-Surface Warfare Commander (ASUWC), and Air Defense Commander (ADC), share most of the same platforms for both surface and air. In addition, if strike warfare is a coincident mission, then distance from the aircraft carrier to the strike objective is of primary concern. Close liaison with staff Material Department is absolutely necessary so that the NOAT may stay abreast of any degradation of

sensors or engineering plants that place restrictions on the search and prosecution capabilities of any platform in the strike group. A host of other information may also need to be gathered, such as start time, end time, and time duration requirements for a transit, availability of maritime patrol aircraft, and any geographic constraints.

After this initial information is collected, sitting the team down as a group for a brainstorming session can be a very useful beginning to sketch out some possible courses of action. Good communication with the ASW RBC will also allow the ASW RBC and non-deployed NOAT members to do this type of brainstorming at the NOAC and forward recommended options to the NOAT afloat. The brainstorming must begin by describing the oceanographic and general acoustic conditions in the operating area. The performance surface is a superb tool for providing an overview of these acoustic conditions. Then the group will discuss the strengths and weaknesses of the adversary submarine in this environment and consider their historical tactics to determine their possible actions. The next step is to consider how to use the assets available, within the constraints imposed, to counter possible adversary actions. By using this group brainstorming approach, many more possibilities can be discovered than one person working alone would usually devise. If the brainstorming has been done at the ASW RBC, the plans are sent out to the NOAT, where further refinement to the changing situation can be made and the best recommendations possible are made to the decision maker.

Extensive oceanographic and tactical expertise

In order to provide effective support to ASW decision makers, the NOAT must have an extensive understanding of ocean structure, how ocean features change over time, and how those features affect acoustic propagation. This knowledge is essential to understanding how different

placement of platforms and their sensors will change their sensor performance. They must also have a good working knowledge of the sonar equation. This knowledge must be deep enough to allow an understanding of which sonar equation terms can be changed by the actions of the strike group. They must also know how to mitigate the performance degrading effects of those terms which cannot be changed.

A solid understanding of the capabilities, limitations, and operating characteristics of both own-force and adversary assets is necessary in order to determine how the environment will affect them. The NOAT must have knowledge of every mission area and what will be required of each platform in executing that mission in order to determine how other tasking will affect the ASW plan. They must also have a firm understanding of current ASW tactics to enable them to formulate recommended plans which are executable.

Continuous, aggressive, and thought-provoking training

A strong training program is an absolute necessity to develop personnel with the level of oceanographic, acoustic, and tactical expertise required to provide this type of support. Multiple hours of training each week must be conducted on oceanography and own-force and adversary tactical topics. Critical thinking skills are more difficult to develop, but are essential to this process. Frequent group discussions of scenarios and practice at building recommended courses of action are used to build and reinforce these thinking skills.

Conclusions

The PS Map is a valuable tool for addressing the complex ASW challenges of today. With the advent of high-end diesel electric submarine threats worldwide, the ASW threat is as important to national security as it has ever been. This trend has highlighted the need for the Navy to find innovative ways to win the ASW fight. The performance surface is a promising tool for that purpose. Properly used, it allows an experienced oceanographic analyst to understand the combined effect of a host of disparate environmental factors on the performance of various ASW sensors and develop meaningful COA to minimize risk to mission and maximize opportunities for success. It also gives the analyst a clear and concise graphic product that can help identify areas of high and low acoustic variability. With the recent advances in computing power that have made these time-consuming calculations possible, the PS Map has become the premier tool for oceanographic analysis for ASW.

Chapter 5 Conclusions

The goal of this research was to develop a methodology for computing and communicating detection system performance in a way that includes the effects of dynamic physical environments, system and target kinematics, signal processing, and the inherent associated uncertainties. This research has led to the development of a new performance modeling framework that provides the user with more insight into the environmental effects on underwater detection systems. The model brings together advances in ocean modeling, acoustic modeling, and parallel computing with statistical modeling, probability theory, and operations research to a common picture for the user to support the high level operational decision-maker.

The method begins with advances in environmental modeling that include higher spatial fidelity, extended forecast and ensemble estimates of uncertainty. New in this methodology is a framework to include these uncertainties in an estimate of performance that can be easily interpreted and exploited by the user.

The next step in the process is sampling SNR over the environment at a much higher fidelity than previously done, taking advantage of advances in high-speed parallel computing assets. To this point typical application of the standard performance tools has been to sample at single point or at points scattered over the region hoping to capture gradients or anomalies. The effect of this sampling strategy often results in identifying environmental feature that can be used to achieve system positioning advantage. The *Performance Surface* model has been used as a target and a metric for recent work in smarter, more efficient methods for environmental sampling that take into account the affected detection system. These research efforts, termed adaptive sampling,

have been explored recently through the Office of Naval Research’s Rapid Transition Program projects.

Once SNR over the region has been calculated, a detection model is applied to convert SNR to conditional probability of detection. This conditional probability is joined with an assumption of the target position to form a joint probability estimate. These joint probability estimate are then summed to include the parameters of uncertainty. As discussed in Chapter 3, uncertainty can also be accounted for stochastically by representing each component of the sonar equation with probability density functions. Stochastic modeling shows promise as an approach to represent the unknowns inherent to the undersea detection problem. Figure 32 depicts a graphical overview of the approach.

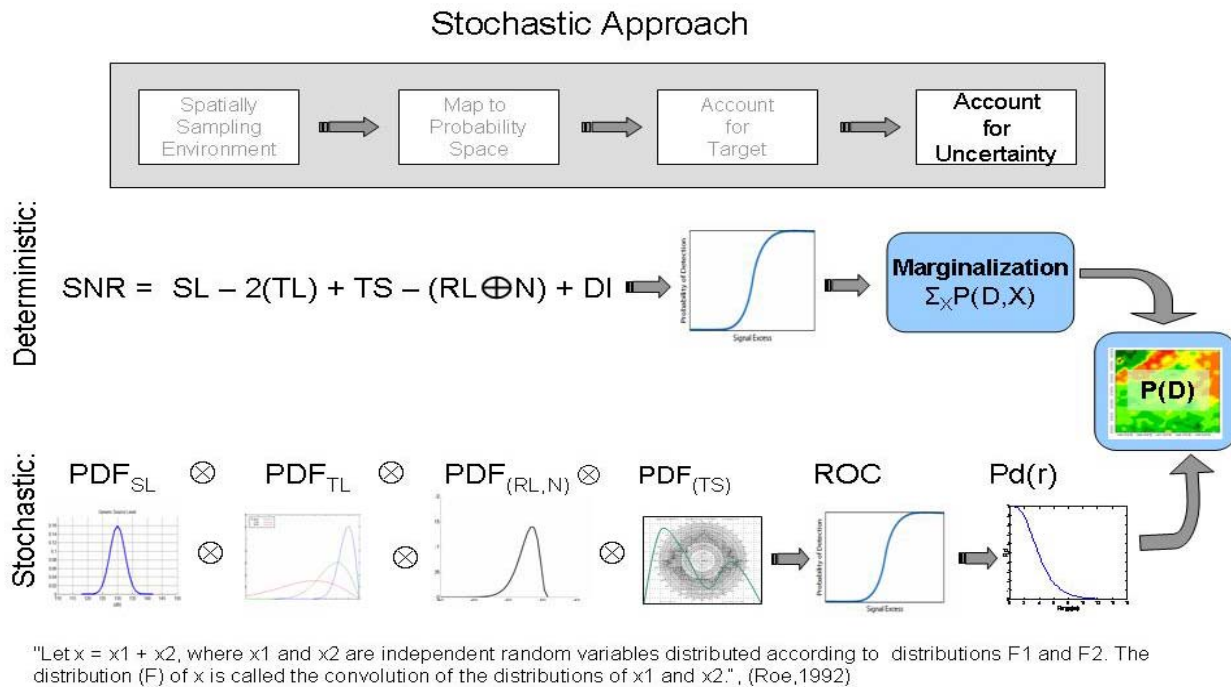


Figure 32 Extending current model to a fully stochastic model in order to include uncertainty for each component of sonar equation.

This summarizes the process for the most common Performance Surface metric, joint probability of detection estimates marginalized over unknown parameters. However Chapter 3 also presents other metrics that can be calculated and presented in a similar manner. Some of these metrics such as *Expected Range*, an extension of Lateral Range and Sweepwidth, are classic measures of performance that have been used in some form since the 1940's. Other metrics, such as *Near-Continuous Range* were specifically designed for very narrow questions. A clear strength of this methodology is the flexibility to pose different questions, and provide rapid, quantifiable answers in an intuitive form.

The ASW *Performance Surface* Model has been used extensively to support numerous Navy Fleet exercises. Chapter 4 describes a number of operational problems where this methodology has been successfully applied. This methodology has also been applied to other non-ASW Navy mission areas supported by the Naval Meteorology and Oceanography Command. The *Performance Surface* methodology itself has been used as first example of 'Performance Tier' of the Naval Meteorology and Oceanography Command's four tier ' Battlespace on Demand' (BonD) approach for delivering products to the Fleet.

Numerous research efforts have been initiated in connection to this work. The Oceanographer of the Navy and the Office of Naval Research have and continue to make substantial investments in additional research efforts that support, improve and validate *Performance Surface* efforts and associated modeling. Much of this work, presently in its beginnings, is underway at the Naval Research Laboratory, the Applied Research Laboratory at the University of Texas, the Applied Physics Laboratory at the University of Washington and other Industry researchers.

In closing, the goal of this research was to develop a model to provide operational decision-maker with an effective assessment of a given system within a complex environment. The result has been a modeling framework that combines high fidelity dynamic environmental forecasts, advanced acoustic system prediction models, and probability theory to form quantitative metrics for easy evaluation. The success of the work, to this point, can be seen in its routine usage and the new research that it continues to generate.

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Appendices

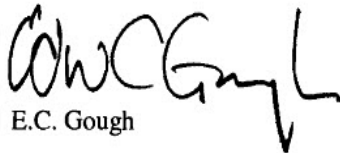
Appendix 1 Journal Article Co-Author Authorization Letters

To: Dean of Graduate School
University of New Orleans
New Orleans, LA

Dear Dean of Graduate School,

As a co-author of the paper "Performance Surface: Development, Current Use and Future Improvements", I hereby give my permission and 'grant authority' to Pamela J. McDowell and the University of New Orleans to include this article in it's present form, as part of the dissertation manuscript entitled "Environmental and Statistical Performance Mapping Model for Underwater Acoustic Detection Systems".

Respectfully,

A handwritten signature in black ink, appearing to read "E.C. Gough". The signature is stylized and written in a cursive-like font.

E.C. Gough

Date: 3-19-10

To: Dean of Graduate School
University of New Orleans
New Orleans, LA

Dear Dean of Graduate School,

As a co-author of the paper "Performance Surface: Development, Current Use and Future Improvements", I hereby give my permission and 'grant authority' to Pamela J. McDowell and the University of New Orleans to include this article in its present form, as part of the dissertation manuscript entitled "Environmental and Statistical Performance Mapping Model for Underwater Acoustic Detection Systems".

Respectfully,



CDR Henry A. Miller, Ph.D.

Date: 16 MAR 2010

To: Dean of Graduate School
University of New Orleans
New Orleans, LA

Dear Dean of Graduate School,

As a co-author of the paper "Performance Surface: Development, Current Use and Future Improvements", I hereby give my permission and 'grant authority' to Pamela J. McDowell and the University of New Orleans to include this article in its present form, as part of the dissertation manuscript entitled "Environmental and Statistical Performance Mapping Model for Underwater Acoustic Detection Systems".

Respectfully,

A handwritten signature in cursive script that reads "Ruth E. Keenan". The signature is written in black ink and is positioned above the printed name.

Ruth E. Keenan

Date: March 17, 2010

To: Dean of Graduate School
University of New Orleans
New Orleans, LA

Dear Dean of Graduate School,

As a co-author of the paper "Performance Surface as a Tool for Increasing ASW Proficiency", I hereby give my permission and 'grant authority' to Pamela J. McDowell and the University of New Orleans to include this article in its present form, as part of the dissertation manuscript entitled "Environmental and Statistical Performance Mapping Model for Underwater Acoustic Detection Systems".

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Respectfully,



LT Jeremy W. Holton

Date: 17 March 2010

Appendix 2 Journal Article Title Pages

Performance Surface: Development, Current Use and Future Improvements

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Performance Surface as a Tool for Increasing ASW Proficiency

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Pamela McDowell was born in Shreveport, Louisiana on May 13, 1960. She received a bachelor of science degree in Chemical Engineering in 1981 from Louisiana Tech University. In 1991 she received a master of science degree from the University of New Orleans. She began doctorate studies while working as a environmental acoustics scientist for the Naval Research Laboratory. Her research interests have included Experimental Arctic studies, environmental acoustics, signal processing, and statistical performance modeling.