



NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

**QUANTIFYING THE VALUE OF ENVIRONMENTAL
SOURCES AND OCEANOGRAPHIC FORECASTS
IN UNDERSEA WARFARE DECISION-MAKING**

by

Joseph Cantwell

September 2023

Thesis Advisor:

Co-Advisor:

Second Reader:

Eva Regnier

Jefferson Huang

Jeffrey E. Kline

Approved for public release. Distribution is unlimited.

This project was funded in part by the NPS Naval Research Program.

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE			<i>Form Approved OMB No. 0704-0188</i>	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC, 20503.				
1. AGENCY USE ONLY (Leave blank)		2. REPORT DATE September 2023	3. REPORT TYPE AND DATES COVERED Master's thesis	
4. TITLE AND SUBTITLE QUANTIFYING THE VALUE OF ENVIRONMENTAL SOURCES AND OCEANOGRAPHIC FORECASTS IN UNDERSEA WARFARE DECISION-MAKING			5. FUNDING NUMBERS NPS-23-N094-A	
6. AUTHOR(S) Joseph Cantwell				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			10. SPONSORING / MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. This project was funded in part by the NPS Naval Research Program.				
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.			12b. DISTRIBUTION CODE A	
13. ABSTRACT (maximum 200 words) This thesis explores the critical role of oceanographic forecasting in enhancing the United States Navy's undersea warfare (USW) mission, with a focus on passive sound navigation and ranging (SoNAR) techniques for detecting enemy submarines. Through a comparative analysis of two forecasting sources, one based on daily numerical modeling and the other on historical climatological data, the study assesses their impact on decision outcomes. Surprisingly, the research reveals that climatology offers comparable, if not slightly more reliable results than numerical forecasting, challenging conventional assumptions. The findings emphasize the importance of tailored environmental source selection and forecasting parameters in USW operations, potentially leading to improved mission success. Furthermore, the study suggests the need for further experiments in other regions and evaluating the impact of forecasting source on other USW decisions and the inclusion of classified ambient noise databases to enhance future decision-making processes in USW.				
14. SUBJECT TERMS acoustic, oceanographic, forecasting, environmental, submarine, detection, undersea warfare, decision-making, decisions, operational, tactical, METOC, FNMOC, adversary, sound velocity, sound velocity profile, temperature, salinity, depth, frequency, range, bearing, transmission loss, bottom depth, passive, SoNAR, HYCOM, GDEM, GOFS, reanalysis			15. NUMBER OF PAGES 75	
			16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT UU	

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. Z39-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release. Distribution is unlimited.

**QUANTIFYING THE VALUE OF ENVIRONMENTAL SOURCES AND
OCEANOGRAPHIC FORECASTS IN UNDERSEA WARFARE
DECISION-MAKING**

Joseph Cantwell
Lieutenant Commander, United States Navy
BSBA, Hawai'i Pacific University, 2010
MBA, Baylor University, 2013
MHA, Baylor University, 2013

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

**NAVAL POSTGRADUATE SCHOOL
September 2023**

Approved by: Eva Regnier
Advisor

Jefferson Huang
Co-Advisor

Jeffrey E. Kline
Second Reader

W. Matthew Carlyle
Chair, Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

This thesis explores the critical role of oceanographic forecasting in enhancing the United States Navy's undersea warfare (USW) mission, with a focus on passive sound navigation and ranging (SoNAR) techniques for detecting enemy submarines. Through a comparative analysis of two forecasting sources, one based on daily numerical modeling and the other on historical climatological data, the study assesses their impact on decision outcomes. Surprisingly, the research reveals that climatology offers comparable, if not slightly more reliable results than numerical forecasting, challenging conventional assumptions. The findings emphasize the importance of tailored environmental source selection and forecasting parameters in USW operations, potentially leading to improved mission success. Furthermore, the study suggests the need for further experiments in other regions and evaluating the impact of forecasting source on other USW decisions and the inclusion of classified ambient noise databases to enhance future decision-making processes in USW.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

I.	INTRODUCTION.....	1
A.	UNDERSEA WARFARE MISSION	1
B.	RESEARCH QUESTION	2
C.	CHAPTER OVERVIEW	2
II.	BACKGROUND	5
A.	SONAR AND THE ACOUSTIC ENVIRONMENT	5
B.	OCEANOGRAPHIC FORECASTING.....	6
1.	HYbrid Coordinate Ocean Model	6
2.	Global Ocean Forecast System	7
3.	Generalized Digital Environment Model.....	7
4.	Other Numerical Modeling Systems	8
C.	SIGNIFICANCE OF STEALTH.....	8
D.	TACTICAL DECISION AIDS	9
E.	FORECASTING SOURCE DILEMMA	10
III.	EXPERIMENTAL DESIGN.....	13
A.	DEFINING DESIGN POINTS IN THE CONTEXT OF NOLH	13
B.	DESIGN “S” – STARTING CONDITIONS BLUE	13
C.	DESIGN “R” – FACTORS RELATED TO RED.....	15
D.	DESIGN “T”—TARGET DATE-TIME.....	19
IV.	IMPLEMENTATION OF EXPERIMENTAL DESIGN.....	21
A.	OPERATIONAL AREA	21
B.	SIMULATED OCEANOGRAPHIC ENVIRONMENT	22
C.	DECISION POLICY AND DETERMINATION OF SEARCH DEPTH.....	22
1.	Decision Policy.....	22
2.	Determination of Search Depth (z^*).....	22
D.	BUILDING TL FILES AND TL DETERMINATION FOR EACH Z^*	24
1.	Building TL Files for Each Target Date-Time	24
2.	TL Determination for Each z^*	25
E.	DETERMINATION OF DETECTION.....	26
V.	ANALYSIS	29

A.	INITIAL DATA STRUCTURE.....	29
B.	DATA CLEANING.....	31
1.	Handling Missing Data.....	31
2.	Addressing Unrealistic Transmission Loss.....	31
C.	DATA TRANSFORMATION	31
D.	EXPLORATORY DATA ANALYSIS (EDA) AND MODELING	33
1.	Descriptive Statistics of Key Variables in Final Dataset	33
2.	Analysis of z^*	34
3.	Analysis of TL at z^*	38
4.	Analysis of Detection.....	44
VI.	CONCLUSION AND RECOMMENDATIONS.....	49
A.	RECOMMENDATIONS FOR FUTURE RESEARCH.....	49
	LIST OF REFERENCES	51
	INITIAL DISTRIBUTION LIST	55

LIST OF FIGURES

Figure 1.	Multiple factors influencing undersea sound propagation.....	6
Figure 2.	Combining environmental parameters and system parameters with sound propagation and system models to predict undersea battlespace. Adapted from McDowell (2010).....	10
Figure 3.	Depiction of a typical sound velocity profile.....	11
Figure 4.	Initial starting conditions in design “S” without depth constraints (17 locations).....	14
Figure 5.	Initial starting conditions in design “S” that meet depth constraints (14 locations)	14
Figure 6.	Final starting conditions in Design “S” (16 locations)	15
Figure 7.	Scatterplot matrix—design “R” factors	17
Figure 8.	Depiction of Blue/Red locations from design “S” crossed with design “R” (16 by 17 or 272 Red locations).....	18
Figure 9.	Scatterplot matrix—design “T” (jittered)	20
Figure 10.	Depth of operating area.....	21
Figure 11.	Schematic of z^* determination for HYCOM, GDEM, and GOFS reanalysis.....	23
Figure 12.	Schematic of process to build transmission loss files.....	25
Figure 13.	Description of detection determination.....	27
Figure 14.	Comparative histograms— z^*	35
Figure 15.	Comparative boxplots— z^* by forecast lead times	36
Figure 16.	Partition tree—HYCOM z^*	37
Figure 17.	Partition tree—GDEM z^*	37
Figure 18.	Comparative histograms—TL at z^*	39
Figure 19.	Comparative boxplots—TL at z^* by forecast lead time	40
Figure 20.	Partition tree model—HYCOM TL at z^*	41

Figure 21.	Partition tree model—GDEM TL at z^*	42
Figure 22.	Map of Blue locations with detection rates and bottom depth.....	46
Figure 23.	Detection rates by bottom depth at Blue’s location	47

LIST OF TABLES

Table 1.	Description of factors for starting conditions Blue – design “S”	13
Table 2.	Description of factors related to Red—design “R”	16
Table 3.	Summary statistics for crossed NOLH design (“S” by “R”)	19
Table 4.	Description of factors related to forecast target date-time—design “T”	19
Table 5.	Portion of final dataset filtered for design point number 880 (nine rows per design point).....	30
Table 6.	Target date-time hour values and associated forecast lead times	30
Table 7.	Restructured final dataset filtered for design point number 880 (seven rows per design point)	32
Table 8.	Description of variable names in the restructured final dataset.....	33
Table 9.	Descriptive statistics for key factors in final dataset	34
Table 10.	Parameter estimates for regression models—HYCOM TL at z^* and GDEM TL at z^*	43
Table 11.	Parameter estimates for logistic regression models—HYCOM Detection and GDEM Detection.....	44

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

COAMPS	coupled ocean-atmosphere mesoscale prediction system
dB	decibels
DT	detection threshold
EDA	exploratory data analysis
GDEM	generalized digital environmental model
GOFS	global ocean forecast system
HYCOM	hybrid coordinate ocean model
Hz	hertz
LE	ambient noise
MOODS	master oceanographic observation data set
NaN	not-a-number
NAVGEN	naval global environmental model
NOLH	nearly orthogonal Latin hypercube
NSPE	Navy standard parabolic equation
RASE	root absolute squared error
SL	source level
SoNAR	sound navigation and ranging
SV	sound velocity
SVP	sound velocity profile
TDA	tactical decision aids
TL	transmission loss
USN	United States Navy
USW	undersea warfare
z*	search depth

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

The United States Navy's (USN) undersea warfare (USW) mission is an integral component of our nation's comprehensive defense strategy. The USW mission includes military operations conducted within, or originating from, the undersea domain. Submarines use sound navigation and ranging (SoNAR) to monitor the undersea environment, which is vital for detecting, tracking, and engaging enemy submarines and surface vessels as well as avoiding detection by adversaries. Since sound propagation between source and receiver is determined largely by the undersea environment, reliable oceanographic forecasting, including predictions of temperature and salinity, provides increased knowledge of the undersea environment to the operator and consequently contributes to the effectiveness and success of naval operations in the undersea domain. USW operators can utilize their knowledge of the underwater environment to gain a strategic "acoustic advantage" (Gardner 1996, p. 42).

This thesis conducts a comparative analysis of two commonly used forecast sources: one that is updated daily using numerical modeling and another that is based on historical climatological data. Using modeling and simulation, this thesis explores whether a forecast choice led to observable and significant differences in decision outcomes or if the variations stemming from each distinct forecast are negligible. The experiment pertains specifically to a decision policy related to increasing the probability of detecting and tracking enemy submarines using passive SoNAR techniques. Ultimately, this study attempts to gain insights regarding the critical decision-making aspect of forecast selection in submarine operations, where precision and reliability are of paramount importance in the complex undersea environment.

The thesis's ultimate objective is to equip commanders and operators with a comprehensive understanding of which oceanographic forecasting source is the most valuable for the USW mission and how each may improve outcomes based on tactical and operational decisions. Strategic decisions regarding which environmental sources and oceanographic forecasting parameters to use, integrated with operational and tactical planning, may lead to better decisions and improve mission success.

One may expect the value of numerical forecasting models to decline as forecast lead times increase away from target (forecasted) date-times. Also, it may be expected for a forecast model to be more accurate than a historical climatological data source or for the value to change significantly across various seasons. None of these assumptions and expectations are observed in this experiment.

In the context of the experiment, where the decision policy aimed to enhance detection rates through choice of search depths for passive SoNAR, it was evident that climatology offers comparable if not slightly more reliable results compared to numerical forecasting. This experiment did not explore whether the result is generalizable to more complex USW decisions, such as tracking a detected submarine and theater USW. In addition, the geographic location of the modeling area and the time period included in the study may lack variability compared to other regions of the world. It may be valuable to conduct a similar experiment in a different region to assess whether results differ significantly. For example, perhaps the historical data driven Global Digital Environmental Model (GDEM) is more reliable near the coastlines of the United States where historical climatology data may be more reliable. It is recommended to repeat a similar experiment in a region that is more distant from the United States coastal areas.

Also, incorporating classified ambient noise (LE) databases into subsequent simulations and modeling experiments can shed light on how varying levels of LE affect transmission loss (TL) during passive search operations. This can provide valuable insights for future mission planning and decision-making processes.

Reference

Gardner WJR (1996) *Anti-Submarine Warfare* Volume 11 (Brassey's Ltd, London, England).

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to the United States Navy and the Medical Service Corps for providing me with the invaluable opportunity to participate in the esteemed Operations Research program at the Naval Postgraduate School. I am deeply thankful for the opportunity.

I extend my appreciation to the dedicated professors who played an instrumental role in shaping me into an Operations Research analyst.

A special thank you goes out to my diverse and supportive cohort, who exemplified the essence of teamwork, ensuring that no one was left behind.

I am indebted to my trusted co-advisors, Dr. Eva Regnier and Dr. Jefferson Huang, whose unwavering support and constant availability were essential to the completion of this thesis. Without their guidance and expert advice, this thesis would not have been possible. I am grateful for the challenges they presented, pushing me to work harder and providing direction every step of the way.

I would like to acknowledge Dr. Jeffrey Kline, my second reader, for his invaluable feedback, which significantly contributed to the refinement and improvement of the final thesis document.

Special thanks go to Dr. Susan Sanchez for initially presenting this intriguing thesis opportunity and for her assistance in designing experiments to support this research.

I am grateful to Dr. Patricia Jacobs for her voluntary support, valuable time, and wisdom, which greatly contributed to the successful completion of this thesis.

I would like to express my appreciation to CDR Pamela Tellado, the METOC and USW Programs Officer at NPS, for graciously mentoring me in an unfamiliar domain.

My gratitude extends to Mr. Steve Upton from the SEED (Simulation Experiments & Efficient Designs) Center for Data Farming, whose support and expertise were essential in the data collection process that supported this thesis.

I also want to thank Dr. Tetyana Margolina, from the Oceanography Department, for her invaluable subject matter expertise and clarity whenever needed.

I recognize that time is a precious and limited resource for all of us, and I am deeply appreciative of the time and effort generously provided by all those mentioned above as well as many others whose contributions are immeasurable.

Above all, I dedicate this thesis to my beautiful and supportive wife, Roma Cantwell. Her unwavering patience and support throughout this challenging process have been most valuable, and I am forever grateful for her presence in my life.

I. INTRODUCTION

A. UNDERSEA WARFARE MISSION

The United States Navy's (USN) undersea warfare (USW) mission is an integral component of the nation's comprehensive defense strategy. This mission encompasses military operations conducted within, or originating from, the vast undersea domain, which includes the world's oceans and their complex underwater environments. The 2022 National Defense Strategy outlined the pressing challenges posed by adversarial nations, underscoring their persistent and evolving threats in all domains to include the realm of USW. Moreover, this strategic document emphasized the imperative recognition that our adversaries, most notably the People's Republic of China and Russia, are rapidly enhancing their capabilities in USW and related domains. These advancements introduce a dynamic landscape with continuous challenges, particularly concerning the deterrence of potential conflicts and the management of escalating risks. The resulting complexity may likely lead to unpredictable paths in the event of hostilities, placing a spotlight on the critical endeavor of deterring Russia's acute potential for limited nuclear use in a regional conflict. This challenge is accentuated by Russia's nuclear capable submarines, heightening the importance and complexity of USW operations (National Defense Strategy 2022).

The United States submarine force's primary mission is to establish and maintain superiority while also enabling the combat lethality and any other desired effects derived from, and within, the undersea domain (e.g., safeguarding U.S. interests, securing sea lines of communication, and deterring potential adversaries) (United States Fleet Forces Command, n.d.). Submarines are essential national security assets, providing stealthy and highly mobile platforms capable of executing and supporting a wide range of military operations. Their missions include but are not limited to strategic deterrence, Indications and Warning, USW, Surface Warfare, precision strike, mining, Subsea and Seabed Warfare, and enabling Special Operations Forces (Commander, Submarine Forces n.d.).

This thesis explores Sound Navigation and Ranging (SoNAR), which is a crucial function in support of most submarine missions USW forces use sonar to monitor the

undersea environment, and therefore underwater sound propagation, which is vital for detecting, tracking, and engaging enemy submarines and surface vessels, as well as avoiding detection by adversaries. USW forces use both passive SoNAR, listening for radiated noise from a submarine or surface ship, and active sonar, the transmission of sound to “bounce” off a potential target and return to the transmitting ship. Predicting these systems’ performance based on the undersea acoustic environment becomes a critical element of undersea warfare.

B. RESEARCH QUESTION

This thesis’ central research question is which undersea environmental forecast should be used by submarine force to enhance their situational awareness within the undersea battlespace. Specifically, it investigates the optimal choice of forecast type to be integrated with Tactical Decision Aids (TDA) for commanders and operators. Should submarines rely on forecasts generated by high-speed computers and their algorithms, which use real-time, high-resolution data, or is it sufficient to rely on historical climatological data to drive tactical decisions?

In pursuit to provide answers for the research question, the analysis seeks to ascertain whether the forecast choice leads to observable and significant differences in decision outcomes or if the variations stemming from each distinct forecast are negligible. Ultimately, this study attempts to gain insights regarding the critical decision-making aspect of forecast selection in submarine operations, where precision and reliability are of paramount importance in the complex undersea environment.

C. CHAPTER OVERVIEW

Chapter II provides an overview of SoNAR and its crucial role within the acoustic environment of USW operations is provided. This chapter provides important background information and describes the relationship between SoNAR and the acoustic environment. Additionally, it explains the diverse forecast sources available, which play a pivotal role in supporting decision-making processes in conjunction with TDAs.

Chapters III and IV discuss separate elements of the methodology utilized for this thesis. Chapter III outlines the experimental design and provides a comprehensive understanding of the thoughtfully constructed framework that supports the research. Subsequently, Chapter IV describes the implementation of the experimental design and how the design was effectively executed to facilitate the modeling and simulation efforts that drive this thesis.

Chapter V provides a summary of the analysis of results. In this chapter, an overview is given describing the data preparation and cleaning procedures that prepared the dataset for a comprehensive analysis. The analysis in Chapter 5 provides insights to the research findings.

Chapter V concludes the thesis and summarizes key findings and their implications. Additionally, Chapter V provides recommendations for future research within this critical domain.

THIS PAGE INTENTIONALLY LEFT BLANK

II. BACKGROUND

Prior to discussing the relationship between SoNAR and the acoustic environment, it is important to emphasize the critical role of SoNAR in USW operations. SoNAR is an essential technology used by USW forces for monitoring the undersea environment and understanding underwater sound propagation. Its significance lies in its ability to detect, track, engage enemy submarines and surface vessels, and avoid detection by adversaries. SoNAR is an indispensable function that supports a wide array of submarine missions.

A. SONAR AND THE ACOUSTIC ENVIRONMENT

SoNAR is an indispensable tool in submarine operations, serving critical functions such as monitoring, navigation, communication, and the detection and tracking of both friendly and adversarial submarines and surface vessels. As mentioned, SoNAR detection methods are broadly categorized into two types: active and passive. Active detection involves emitting sound signals, known as “pinging,” and analyzing the returning echoes. In contrast, passive detection relies solely on acoustic listening. For the scope of this thesis, our analysis is centered exclusively on passive SoNAR detection.

The behavior of sound in water depends on sound velocity (SV) (Etter 1991). SV is determined by water temperature, salinity, and pressure, all of which are influenced by depth. Variations in these variables significantly affect sound propagation. Beyond SV, other factors influence undersea sound propagation. These other factors include ocean floor depth, bottom sediment composition, the emission frequency from the source (designated as Red in this thesis), and the relative bearing and range of the receiver (designated as Blue in this thesis), all of which directly contribute to transmission loss (TL) from the source to the receiver (Red to Blue), as illustrated in Figure 1.

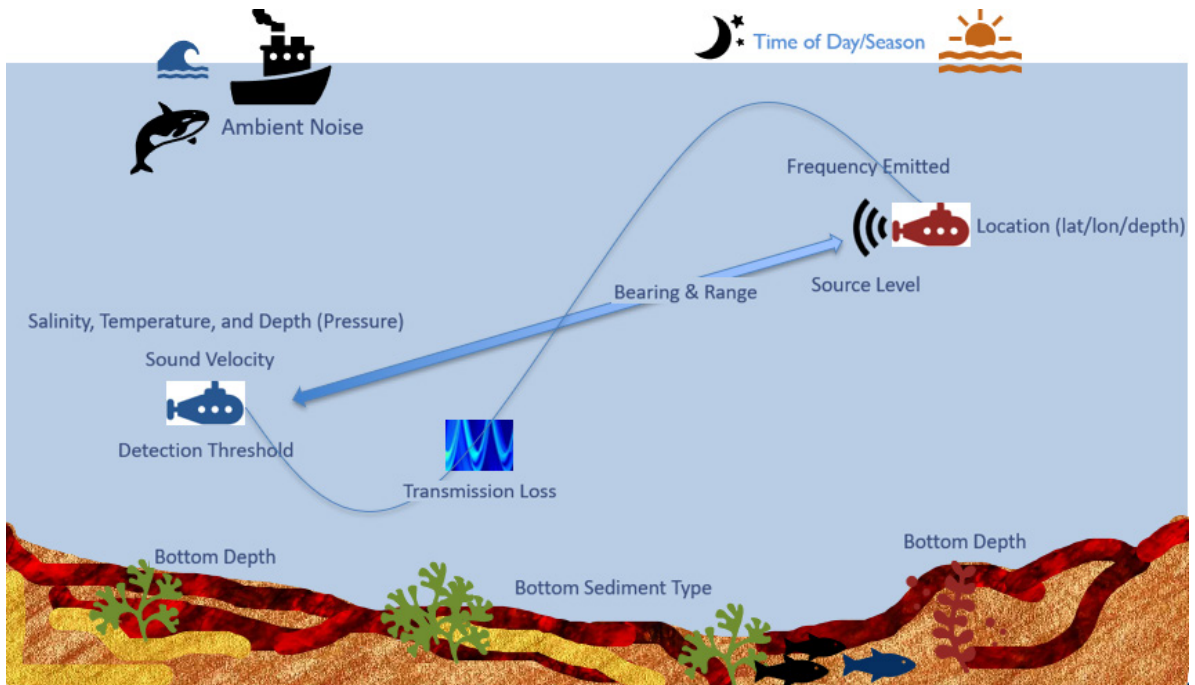


Figure 1. Multiple factors influencing undersea sound propagation.

B. OCEANOGRAPHIC FORECASTING

Since sound propagation between source and receiver is determined largely by the undersea environment, reliable oceanographic forecasting, including predictions of temperature and salinity, provides increased knowledge of the undersea environment to the operator and consequently contributes to the effectiveness and success of naval operations in the undersea domain. USW operators can utilize their knowledge of the underwater environment to gain a strategic “acoustic advantage” (Gardner 1996, p. 42).

1. HYbrid Coordinate Ocean Model

The global HYbrid Coordinate Ocean Model (HYCOM) is a gridded numerical model forecasting system that supports submarine tactical decision making. The Fleet Numerical Meteorology and Oceanography Centers provide HYCOM oceanographic forecasts to the Fleet in the form of three-dimensional data. These three-dimensional HYCOM forecasts consist of predicted ocean salinity and temperature across different depths for latitude and longitude coordinates across the globe. HYCOM forecasts are

available with lead times up to 180 hours in 3-hour increments. Submarines must reduce their depths closer to the surface to enable the ability to download HYCOM forecasts.

2. Global Ocean Forecast System

HYCOM forecasts are incorporated in the Global Ocean Forecast System (GOFS). GOFS 3.1 is based on the $(1/12.5)^\circ$ ($\sim .08^\circ$) horizontal resolution global HYCOM model and uses the Navy Coupled Ocean Data Assimilation system for assimilation of data (Metzger et al. 2020). The latest version of GOFS, GOFS 3.5, is based on the $(1/25)^\circ$ horizontal resolution HYCOM model (Cummings 2005). GOFS is run daily by the Navy DOD Supercomputing Resource Center in Stennis Space Center, Mississippi, and returns a zero-hour nowcast forecast through a seven-day forecast each day (Naval Research Laboratory n.d. GOFS 3.1). This thesis leverages the GOFS 3.1 and its associated HYCOM forecasts to support the experimental modeling and simulation.

A reanalysis integrates data from various sources, including ocean observations, satellite measurements, and numerical models that become available after the time the forecast is issued. The GOFS reanalysis therefore provides the closest match to the ground truth, against which the performance of forecasting models can be evaluated (Metzger et al. 2020).

3. Generalized Digital Environment Model

Another forecast often leveraged by USW decision makers is the Generalized Digital Environment Model (GDEM). GDEM is a global gridded ocean temperature and salinity climatology model that has been utilized by the USN since its initial development in 1975 (Carnes 2009). The main source of historical data for GDEM is the Master Oceanographic Observation Data Set (MOODS) that includes more than 4.5-million profiles of temperature and salinity that have been collected since 1920 (NOAA NCEI n.d.). The United States Naval Oceanographic Office maintains and continuously updates the MOODS database. Unlike HYCOM forecasts, GDEM information is readily available onboard submarines, so there is no need to reduce depth to obtain GDEM information.

In the latest version of GDEM, GDEM Version 4.0, the temperature and salinity profile dataset used to calculate climatology was created by combining profiles from the Navy's MOODS unclassified profile archive (Bauer 1982), the 2005 World Ocean Database (Boyer et al. 2002) and delayed-mode Apex temperature and salinity profiles downloaded from the U.S. Global Ocean Data Assimilation Experiment server (Carnes 2010). The location (latitude/longitude) resolution for GDEM is at .25° intervals with depths that include 78 points on a variable scale from the surface of the ocean (0 meters depth) down to 6,600 meters maximum in depth (Barlow 2019). Like HYCOM, GDEM is often utilized to support USW decision-making in conjunction with Tactical Decision Aids (TDAs). This thesis leverages GDEM Version 4.0 to support the experiment.

4. Other Numerical Modeling Systems

Other numerical modeling systems exist, such as a global weather prediction system named Navy Global Environment Model (NAVGEM) and a hydrostatic regional ocean model referred to as the Coupled Ocean-Atmosphere Mesoscale Prediction System (COAMPS). These models provide environmental information related to the ocean surface, including wind, currents, and waves (Naval Research Laboratory n.d. Marine Meteorology). However, these models were not considered in the modeling and simulation conducted for this thesis.

C. SIGNIFICANCE OF STEALTH

The significance of stealth cannot be overstated for submarines. It serves as a critical means to avoid detection, thereby enhancing survivability, while contributing to overall strategic deterrence. It is crucial for the USN submarine force to maintain an effective but stealthy presence amid hostility (National Research Council, 1997). During missions where Blue aims to detect Red, it is most likely undesirable for Blue to compromise their stealth in order to obtain HYCOM oceanographic forecast transmissions by coming near the surface. Fortunately, in situations where obtaining new oceanographic forecasts might be high risk and challenging, Blue can rely on historical GDEM climatology information to inform tactical decisions that may increase their likelihood to detect Red.

The ability to detect enemy submarines while preserving stealth is vital for the success of USW missions and the protection of friendly forces. Accurate oceanographic forecasting enhances the probability to detect potential threats, provides early warning, and enables timely deployment of proactive defensive measures. By leveraging reliable forecasts, the USW mission can maintain an edge in situational awareness, optimize response times, and ensure the safety of its submarines and surface vessels.

D. TACTICAL DECISION AIDS

A TDA is a decision support tool designed to assist USN commanders and operators in making informed and effective decisions during various operational scenarios. TDAs for USW combine information from onboard sensors and external inputs to generate a comprehensive undersea battlefield overview, identify potential risks, convey crucial data to friendly forces, and to promptly revise mission strategies (RTO Lecture Series 227 2005).

Figure 2 serves as a visual representation of the inputs and outputs that TDAs typically encompass. Within the context of our experiment, a significant focal point revolves around analysis of the impact of SV variations. SV is intrinsically linked to sound velocity profiles (SVPs), and can be derived from forecasts (e.g., GDEM or HYCOM) that predict a variety of target date-times. A target date-time represents the date-time for which the forecast is predicting. The outcomes stemming from these dynamic SV variations may substantially influence the complex undersea acoustic environment and are central to our research objectives.

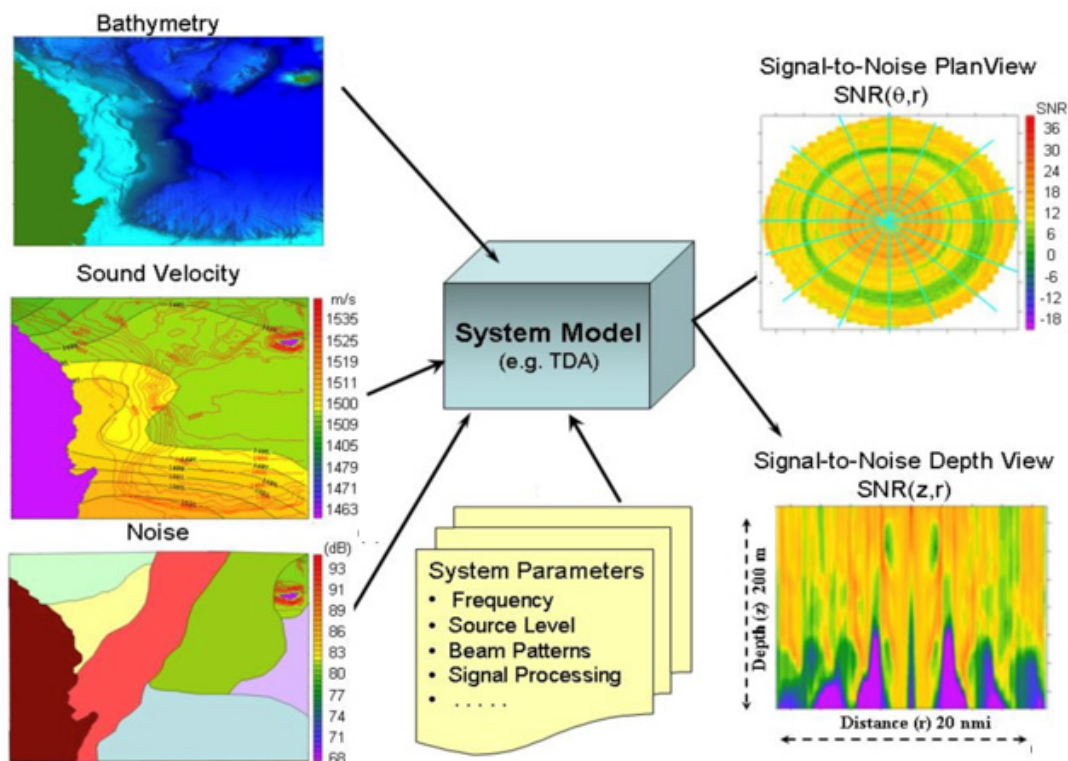


Figure 2. Combining environmental parameters and system parameters with sound propagation and system models to predict undersea battlespace. Adapted from McDowell (2010).

TDA in support of USW incorporate the Navy Standard Parabolic Equation (NSPE) model to simulate how sound waves propagate in the ocean. The NSPE model is a widely used computational tool for predicting underwater sound propagation and TL in range-dependent ocean environments (Holmes 1992). The NSPE calculation involves evaluating the acoustic energy loss as sound propagates from the source (Red) at a given sound frequency to calculate TL between Red and Blue. Input parameters including source, position, frequency, and environmental variables directly influence the NSPE model's outcomes and ultimately influence decision recommendations and output from any associated TDA.

E. FORECASTING SOURCE DILEMMA

Figure 3 provides a visual representation of a typical SVP. The SVP in Figure 3 represents an SVP obtained from experimental data associated with this thesis. These

profiles typically exhibit slight variations, and generally fall within the range of 1,450 m/s to 1,540 m/s. However, small fluctuations in SV can exert a substantial influence on ocean sound propagation (Breshkovsky et al. 2002).

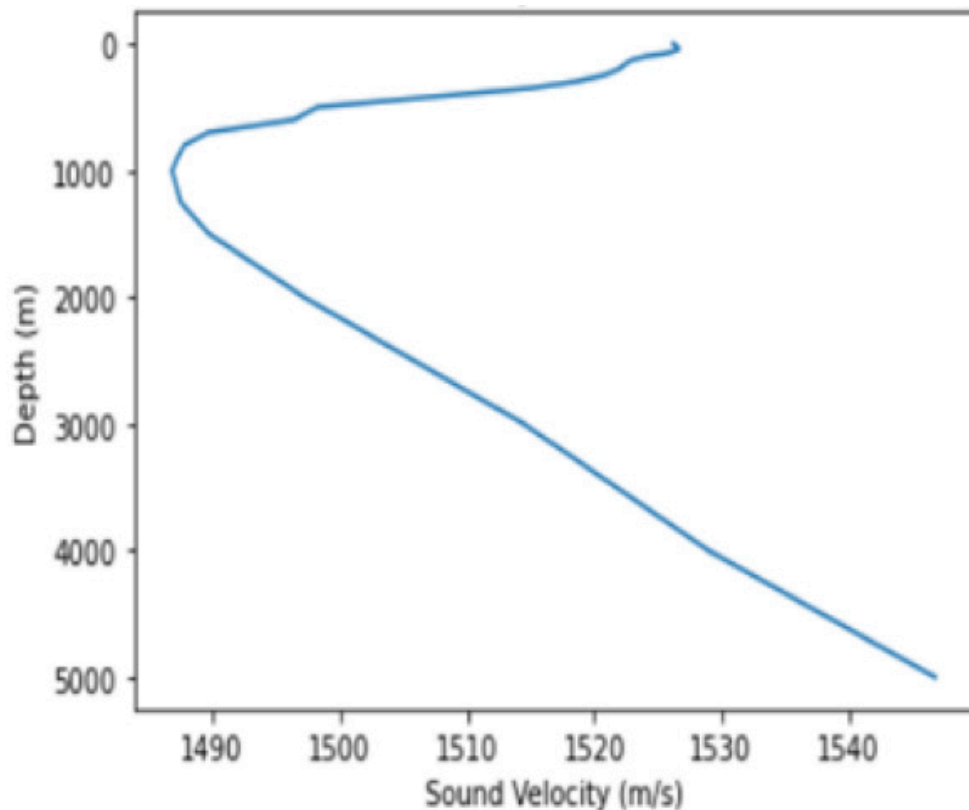


Figure 3. Depiction of a typical sound velocity profile

GDEM and HYCOM forecasts offer varying temperature and salinity levels, each suggesting potentially different search depth decisions based on specific latitude and longitude coordinates' acoustic environment. Consequently, one forecast source may yield superior outcomes compared to the other, or their value might be virtually indistinguishable.

In addition to relying on forecasts, submarine operators have the option to conduct real-time measurements to calculate SV at their specific location. Methods like utilizing expendable bathythermograph devices to measure temperature as a function of depth or

velocimeters to measure SV directly can be employed (Etter 1991). However, this thesis does not consider real-time measurement alternatives.

This thesis conducts a comparative analysis using GOFS 3.1 reanalysis as the baseline against its corresponding HYCOM forecasts, and historical data derived from GDEM Version 4.0. Reanalysis is the process of combining historical weather observations with past short-range weather forecasts using modern forecasting models, resulting in globally consistent and complete datasets (ECMWF 2023). The specific focus of this thesis lies in comparing GDEM forecasts and the full spectrum of HYCOM forecasts, encompassing lead times of up to 165 hours. Through this exploration, the goal is to discern which of these forecasting models and environmental information sources, if any, offer the highest utility in informing critical mission-related decision-making. This experiment pertains specifically to a decision policy related to increasing the probability of detecting and tracking enemy submarines using passive SoNAR techniques.

The ultimate objective is to equip commanders and operators with a comprehensive understanding of the intrinsic value of both GDEM and HYCOM forecasts. Strategic decisions regarding which environmental sources and oceanographic forecasting parameters to use, integrated with operational and tactical planning, may lead to better outcomes and improve mission success.

Furthermore, by quantifying the value of specific environmental forecasts and their associated parameters, this research may enhance future modeling efforts while informing decision-makers in the field of USW.

III. EXPERIMENTAL DESIGN

To support the objectives of this thesis, a carefully structured experimental design was selected. The chosen approach, a crossed Nearly Orthogonal Latin Hypercube (NOLH) design, represents a robust methodology for efficiently exploring a complex parameter space. By minimizing correlation and effectively exploring a representative sample of the parameter space, the NOLH design can save time and cost in research and development projects (Cioppa et al. 2007). Our design of experiments crossed three distinct NOLH designs: factors related to Blue locations, factors related to Red, and factors pertaining to forecast target date-times.

A. DEFINING DESIGN POINTS IN THE CONTEXT OF NOLH

Central to the experimental design are “design points.” In the context of an NOLH design, a design point specifies unique combinations of factors, i.e., a distinct scenario or configuration within the simulated environment. The careful selection of design points ensures a comprehensive exploration of the parameter space, allowing us to comprehensively study factors’ interactions and their influence on outcomes.

In the forthcoming sections, an in-depth description of each of the three designs employed in this modeling and simulation experiment is provided. Each NOLH design was initially constructed using an NOLH design Excel spreadsheet (Sanchez 2011).

B. DESIGN “S” – STARTING CONDITIONS BLUE

The first NOLH specifies Blue’s geographical coordinates based on latitude (degrees North) and longitude (degrees East). The factors of this space-filling NOLH design, denoted as design “S,” are described in Table 1.

Table 1. Description of factors for starting conditions Blue – design “S”

Factor Name	Units	Min	Max	Type
Blue_Lat	Degrees	35	41	Continuous
Blue_Lon	Degrees	-76	-60	Continuous

To ensure Blue's safety, it is imperative to consider specific challenges posed by shallow littoral waters, especially those locations with maximum depths less than 50 meters (Joubert 2004). In this experiment, a cautious assumption is made that Blue does not operate in areas less than 150 meters deep, mitigating concerns about any potential submarine mishap due to shallow water operating conditions. Consequently, any initial conditions within design "S" that fall within the shallow regions or on land must be excluded.

Initially, design "S" consisted of 17 points (Figure 4), but through the removal of points in these shallow or land areas, the starting conditions for Blue were refined to produce 14 design points (Figure 5).

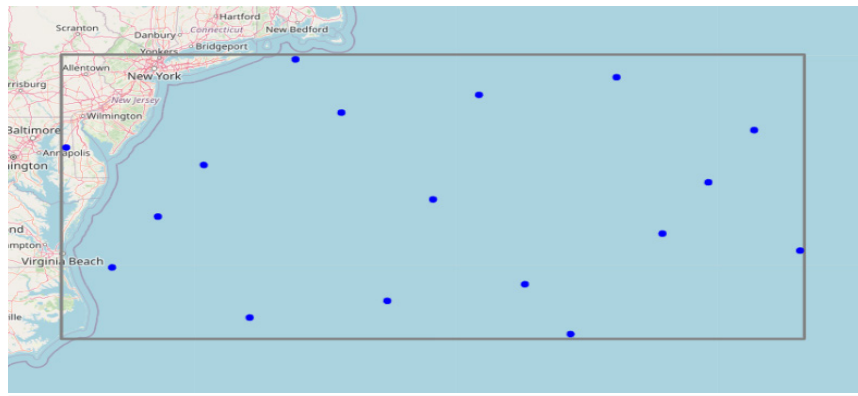


Figure 4. Initial starting conditions in design "S" without depth constraints (17 locations)

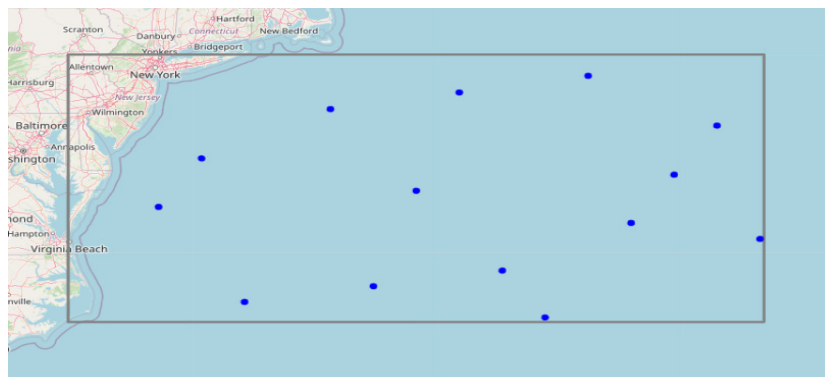


Figure 5. Initial starting conditions in design "S" that meet depth constraints (14 locations)

Examination of the 14 initial starting conditions that satisfied the depth constraints (Figure 5) revealed two noticeable regions with significant vacant spaces exist within the modeling area. Consequently, we manually introduce two additional Blue locations strategically positioned to fill these voids. The resulting outcome is presented in Figure 6, depicting the locations of the definitive and final set of 16 design points constituting design “S.”

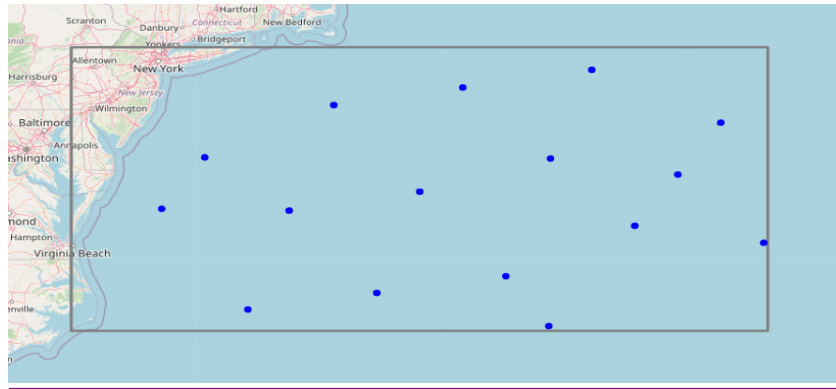


Figure 6. Final starting conditions in Design “S” (16 locations)

C. DESIGN “R” – FACTORS RELATED TO RED

The second experimental design introduced in this experiment, denoted as design “R,” comprises 17 distinct design points, each characterized by factors associated with Red. These factors encompass critical parameters that affect undersea TL between source and receiver, such as the bearing of Blue from Red (ranging from 0 to 359 degrees), the range of Blue from Red (spanning 200 meters to 200,000 meters), the operating depth of Red (expressed as a percentage of its maximum operating depth), and the frequencies emitted by Red (ranging logarithmically from Log 10 to Log 5000 Hz). The details regarding the factors defining design “R” are outlined in Table 2.

Table 2. Description of factors related to Red—design “R”

Factor Name	Units	Min	Max	Type
bearing	Degrees	0	359	Discrete (integer)
range	Meters	200	200,000	Discrete (integer)
depth	Percent	0	100	Dicsrete (integer)
freq	Hz	Log 10	Log 5,000	Continuous

The scatterplot matrix of the factors from design “R” is depicted in Figure 7. This scatterplot illustrates the space filling properties associated with the NOLH design.

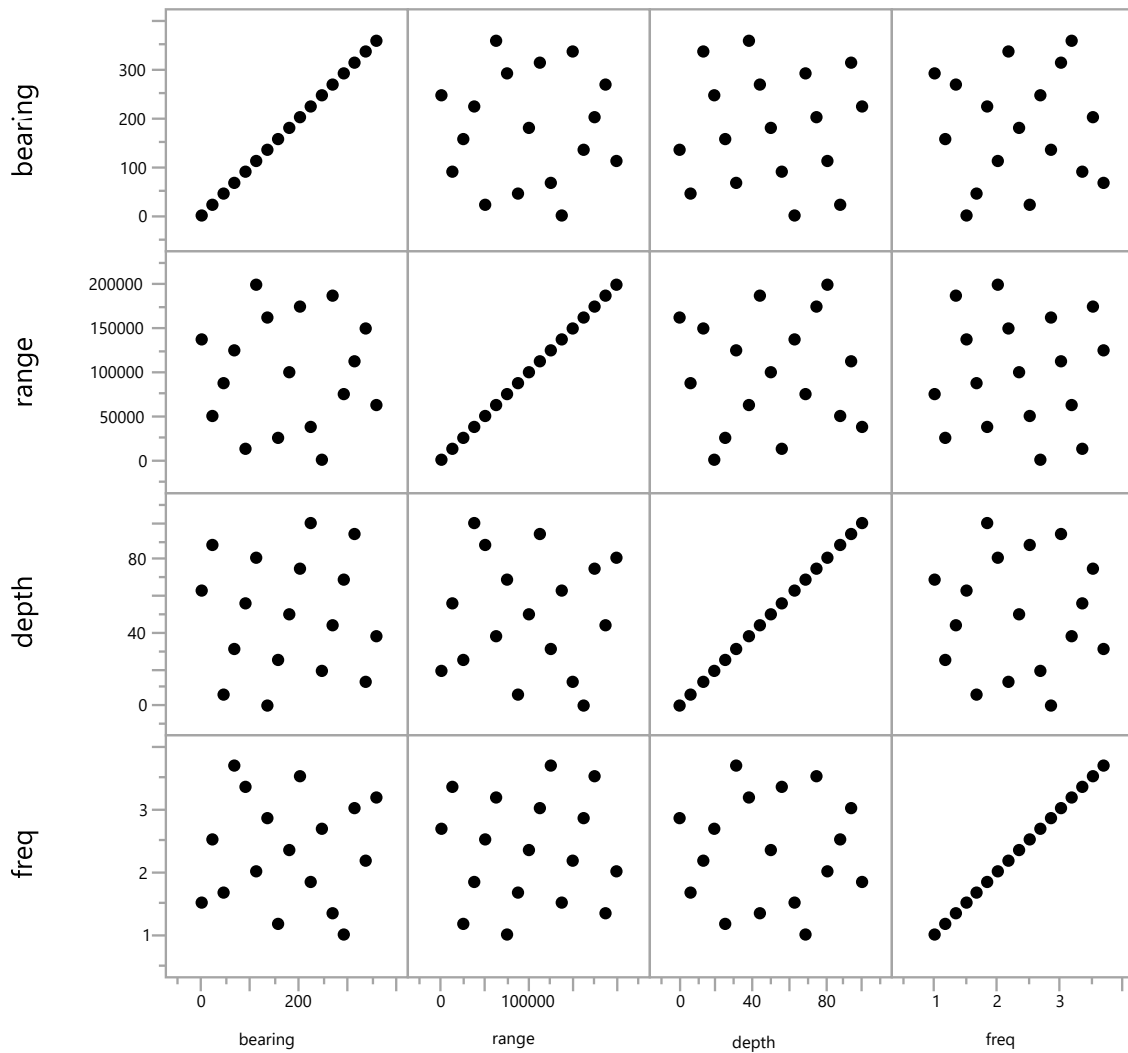


Figure 7. Scatterplot matrix—design “R” factors

Design “R” was crossed with design “S” yielding 272 paired locations for Blue and Red, based on the factors “bearing” and “range” in design “R” alongside Blue locations from the initial design “S.” A constraint for this pairing is that all Red locations, as was the case with Blue locations in design “S,” are in water of at least 150 meters in depth and fall within the defined modeling area.

A depth validation step identified that 50 of the 272 Red locations failed to meet the constraints; 21 of these positions were at elevations greater than -150 meters, and 29 were situated outside the modeling area. To ensure all Red locations in the crossed “S” by

“R” design met the depth and modeling area conditions, the bearing of these 50 Red locations was adjusted by 180 degrees. This modification enabled all points to meet the specified constraints.

The final crossed design, denoted as “S” by “R,” consists of 272 design points whose locations of Red and Blue are depicted in Figure 8.

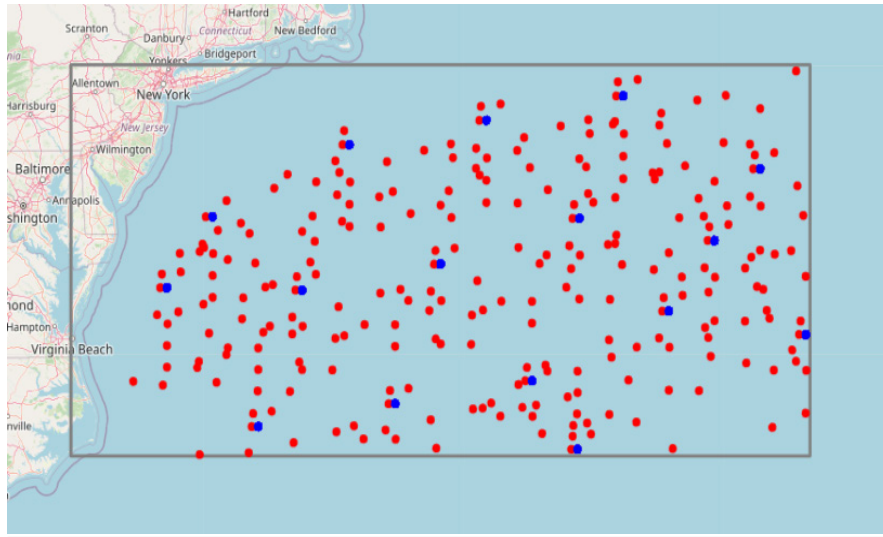


Figure 8. Depiction of Blue/Red locations from design “S” crossed with design “R” (16 by 17 or 272 Red locations)

Summary statistics for the final crossed “S” by “R” design are provided in Table 3. The Red locations (“sourceLatitude” and “sourceLongitude”) were inferred from the range and bearing row values from design “R.”

Table 3. Summary statistics for crossed NOLH design (“S” by “R”)

	moving_point_lat	moving_point_lon	range	bearing	freq	fixed_point_depth	sourceLatitude	sourceLongitude
count	272.000000	272.000000	272.000000	272.000000	272.000000	272.000000	272.000000	272.000000
mean	37.860156	-66.889062	54.049803	175.558824	910.588235	498.006584	37.774024	-66.876094
std	1.628105	4.169611	33.093290	110.306033	1376.717185	309.619734	1.485410	4.078633
min	35.100000	-73.925000	0.107991	0.000000	10.000000	0.000000	35.016392	-74.655401
25%	36.731250	-70.231250	27.078834	89.000000	50.000000	250.000000	36.589686	-70.279434
50%	37.818750	-66.518750	54.049676	180.000000	220.000000	500.000000	37.771758	-66.516396
75%	38.906250	-63.803125	81.020518	269.000000	1050.000000	750.000000	38.949510	-63.382793
max	40.537500	-60.100000	107.991361	359.000000	5000.000000	1000.000000	40.906845	-60.087794

D. DESIGN “T”—TARGET DATE-TIME

The third and final NOLH design produced for this experiment is referred to as design “T” and is comprised of 257 design points. The factors include year, month of year, day of month, and time of day and represent forecast target date-times (Table 4).

Table 4. Description of factors related to forecast target date-time—design “T”

Factor Name	Units	Type	Categories
Year	Year	Categorical	2019, 2020, 2021, 2022
Month of Year	Month	Categorical	1, 2, 3, 4, 5...12
Day of Month	Day	Categorical	1, 2, 3, 4, 5...31
Time of Day	Hour	Categorical	00, 03, 06, 09, 12, 15, 18, 21

The scatterplot matrix of design “T” is illustrated in Figure 9. The design points are well distributed among the parameter space due to the NOLH design.

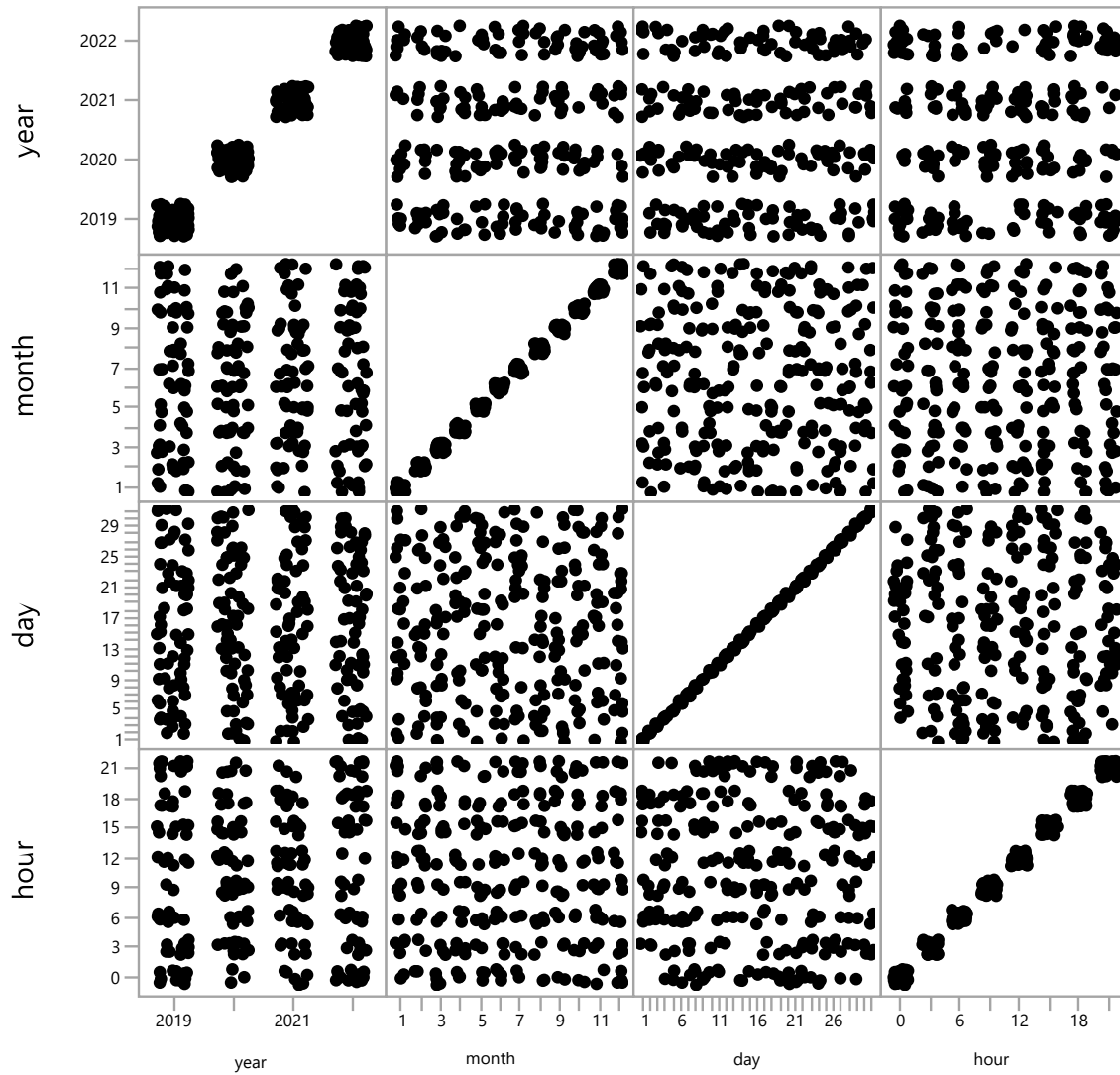


Figure 9. Scatterplot matrix—design “T” (jittered)

The 257 design points of design “T” was crossed with the 272 design points from the crossed “S” by “R” design and resulted in 69,904 design points in the final experimental design.

IV. IMPLEMENTATION OF EXPERIMENTAL DESIGN

A. OPERATIONAL AREA

The experimental design serves as the foundation for the modeling and simulating of Blue's ability to detect Red within a predefined operational area. The three designs, "S," "R," and "T" (Figures 7, 8, and 9) demonstrate the space-filling properties of each design. Due to the NOLH design, each of these designs are a good representation of the sample space. The predefined operational area consisted of a specific area in the North Atlantic Ocean, within the following parameters: 35 to 41 degrees North latitude and -76 to -60 degrees East longitude as briefly alluded to in Section III B (Design "S"—Starting Conditions Blue). The topographic map in Figure 10 portrays the bottom depth of the experiment's operating area.

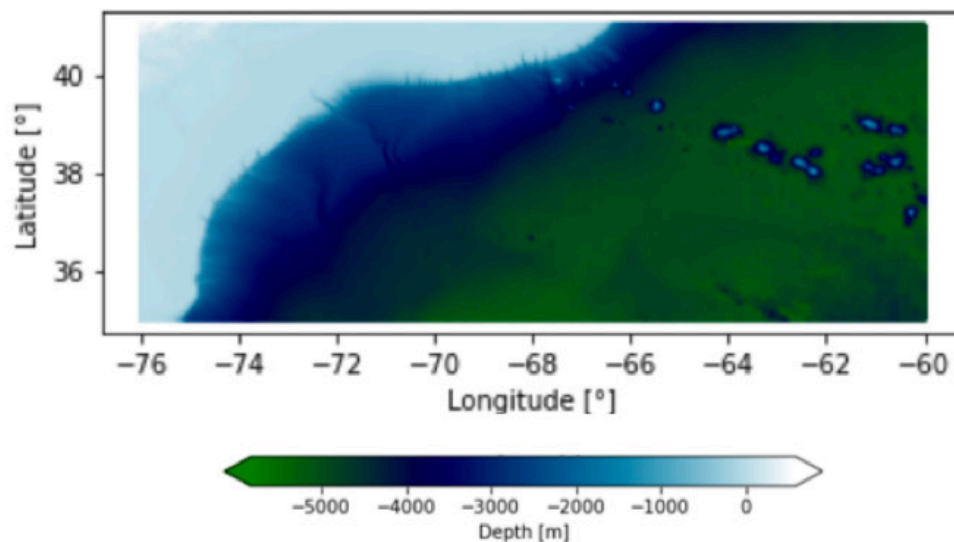


Figure 10. Depth of operating area

This modeling area holds significant importance, not solely due to its location overlapping the territorial waters and Economic Exclusive Zone of the United States but also because of the sea mounts depicted in Figure 10. These underwater formations may potentially create challenging blind spots that could hinder Blue's capacity to detect Red

and are located in an area of strategic interest (Harding 2022). The average bottom depth at the 272 Red locations in the experimental design is 4,130 meters and the average bottom depth at the 16 Blue locations is 3,899 meters.

B. SIMULATED OCEANOGRAPHIC ENVIRONMENT

This experiment relied on an extensive collection of oceanographic variables derived from GDEM, HYCOM, and GOFS reanalysis forecasts as its foundation to simulate the ever-changing oceanographic environment. These oceanographic variables are used to produce SVPs associated with each of the 257 target date-times in the experimental design.

C. DECISION POLICY AND DETERMINATION OF SEARCH DEPTH

This experiment's scenario is based on a simulated mission involving a friendly submarine (Blue) in search of an adversary (Red) at an unknown location. Blue must detect Red by utilizing passive SoNAR techniques in which the search depth of Blue is selected following a decision policy based on the oceanographic environment at Blue's location (latitude and longitude).

1. Decision Policy

The decision policy's objective is to maximize the likelihood of Blue detecting Red using passive sonar, given that Red's depth is unknown. To achieve this, the decision policy suggests positioning the submarine or its acoustic sensors at a search depth (z^*) that corresponds to the depth of minimum SV within the forecast SVP based on Blue's precise location at the target date-time represented by each design point. This decision policy is supported by Ferla and Porter's Receiver Depth Selection for Passive Sonar Systems, in which they concluded that if Red's depth is unknown, then the sensor should be placed at the depth of the minimum SV in given location (Ferla & Porter 1991).

2. Determination of Search Depth (z^*)

For each design point in this experiment, the simulated outcomes of the decision policy are based on SVP files generated from monthly GDEM, plus HYCOM forecasts

with seven distinct lead times. The outcomes were assessed and compared to evaluate their value in operational decision making.

Figure 11 portrays the schematic diagram that describes the determination of the search depth (z^*) for Blue based on the decision policy. This z^* determination is made for each forecast available within this experiment (HYCOM with associated forecast lead times and GDEM) to include a z^* based on GOFS reanalysis for comparison).

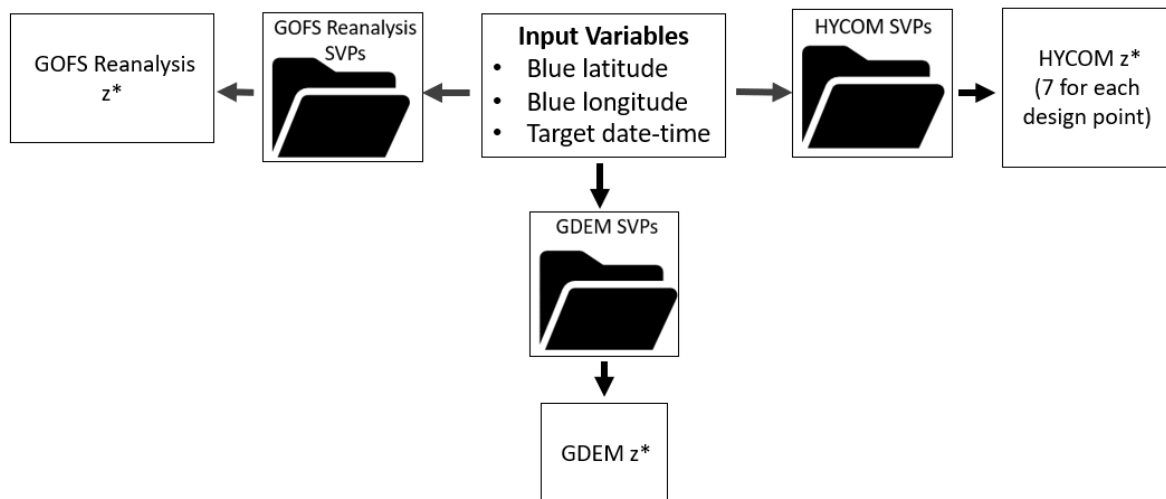


Figure 11. Schematic of z^* determination for HYCOM, GDEM, and GOFS reanalysis

The geographical coordinates of Blue's location from each design point and associated target date-times are used to find their associated SVP and return the minimum SV within that location's SVP for each forecast. Each SVP file consisted of an SV for each of the following forty depths in meters: 0, 2, 4, 6, 8, 10, 12, 15, 20, 25, 30, 35, 40, 45, 50, 60, 70, 80, 90, 100, 125, 150, 200, 250, 300, 350, 400, 500, 600, 700, 800, 900, 1000, 1250, 1500, 2000, 2500, 3000, 4000, 5000. A Python function is utilized to find the z^* based on quadratic interpolation of the SVs available for each of the 40 depths. In the absence of interpolation, the z^* will be derived from only one of the 40 depths that are included in each SVP file. This function interpolated the SV within a given SVP for depths at every integer from 0 up to 5000 meters of ocean depth.

For each design point's target date-time and associated Blue location, seven z^* are obtained based on HYCOM forecasts, each tied to the available forecast lead times ("tau_lead_time" variable) with forecast lead times segmented in 24-hour increments, ranging from +00 hours to +144 hours based on each design point's target date-time. For example, if the first available forecast lead time is 21 hours, the max forecast lead time would be +165. This ensures a robust analysis of the optimal depth for Blue across a range of forecast scenarios, with specific focus on how the forecasts evolve as the lead time progresses.

For each design point's target date-time and associated Blue location, one z^* value is obtained based on GDEM's monthly SVP prediction for the associated Blue location.

Finally, for each design point's target date-time and associated Blue location, one distinct z^* value is returned based on the GOFS reanalysis.

D. BUILDING TL FILES AND TL DETERMINATION FOR EACH Z^*

1. Building TL Files for Each Target Date-Time

Two main inputs are required to build TL files for each target date-time (Figure 12). The two inputs are the GOFS reanalysis SVPs for each target date-time and the associated factors related to the initial design "R" (bearing from Blue to Red, Red depth and Red's emission frequency). The output from NSPE is represented by a TL file for each target date-time.

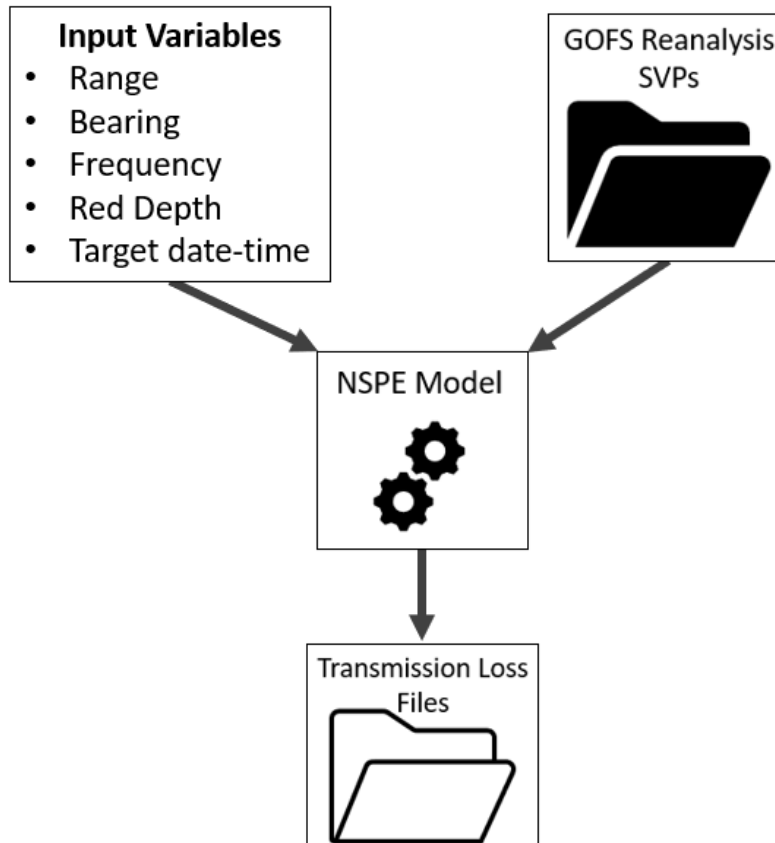


Figure 12. Schematic of process to build transmission loss files

GOFS reanalysis is considered the most accurate salinity and temperature conditions near the specified target date-time (Naval Research Laboratory n.d. GOFS 3.1). Therefore, the GOFS reanalysis output is used as the oceanographic environment input for NSPE model when generating the TL files for this experiment.

2. TL Determination for Each z^*

A Python function is utilized to obtain TL associated with each forecasted z^* value for each target date-time. The function uses a weighted linear interpolation of the TL values that are available in each TL file at interval depths listed in the NSPE output file (weighted based on nearest depth above and nearest depth below for a given z^* value). For each design point, TL is calculated for each of the seven z^* based on HYCOM, the single z^* based on GDEM, and the single z^* based on GOFS reanalysis.

E. DETERMINATION OF DETECTION

Detection determination is based on the TL values for each of the z^* associated with each design point, i.e., the seven z^* derived from various HYCOM forecast times, the single z^* value obtained from the GDEM, and the z^* value obtained from the GOFS reanalysis. To determine whether the Red submarine is detected or not utilizes a formula rooted in the passive SoNAR principles, as described in Figure 13. To facilitate the analysis of the impact of factors included in the experimental design, certain parameters are held constant in the detection calculations. Specifically, LE is maintained at a level of 60 dB, which is a bit less than common LE levels related to transiting shipping vessels (65 dB at 300 Hz) and LE related to six-foot surface waves (66 dB) (Federation of American Scientists 2023). Additionally, the difference between source level (SL) and detection threshold (DT) or (SL–DT) remain fixed at 150 dB, representing SL at a fixed 170 dB and DT at a fixed 20 dB. Utilizing these fixed values in conjunction with the TL value for each z^* enables the calculation of detection outcomes, where ‘yes’ is denoted as 1 and ‘no’ as 0, for every entry within the dataset. This calculation adheres to the passive SoNAR equation, where detection is confirmed only when:

$$(SL - DT) - LE > TL$$

Blue's ability to detect Red is strictly based on the passive SoNAR equation where detection occurs iff:

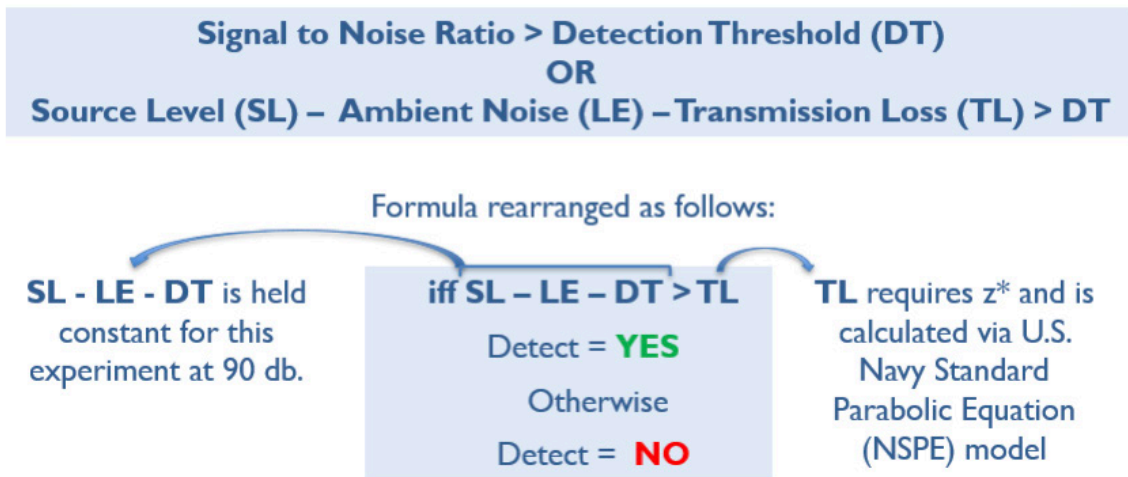


Figure 13. Description of detection determination

In actual USW operations, the consistent presence of background noise, otherwise known as LE, increases the difficulties of detecting a submarine and makes it so that detection is never certain. This is why the detection of submarines is usually referred to as probabilistic rather than certain (Stockholm International Peace Research Institute 1974). However, for the sake of simplification, detection is treated as binary “yes” or “no” outcomes in this experiment to support this thesis.

THIS PAGE INTENTIONALLY LEFT BLANK

V. ANALYSIS

A. INITIAL DATA STRUCTURE

The final dataset only includes design points with target date-times from the years 2021 and 2022, which reduces the size of the original design from 69,904 design points to a total of 34,816 design points. These are evenly distributed between the years 2021 and 2022, with 17,408 design points each. Notably, the absence of data from 2019 and 2020 had no detrimental impact on space-filling characteristics of the design.

As described in Chapter 3, Section C, there are nine z^* for each of the 34,816 design points. These z^* consist of seven derived from varying HYCOM forecast times, one obtained using GDEM historical information, and one derived from GOFS reanalysis. Consequently, the result is a comprehensive data frame containing 34,816 sets of nine data points, totaling 313,344 rows of data.

Table 5 presents a representative example of one set of nine rows within the final dataset, corresponding to the original design point—number 880 of the 17,408 design points from 2021. The first ten columns (excluded from Table 5 example) represent factors from the initial design of experiments (S by R by T), with the column “re_dp” serving as a reference to the original design point, such as 880 in this case.

Table 5. Portion of final dataset filtered for design point number 880 (nine rows per design point)

re_dp	tau_lead_time	ts3z_data_type	zstar	min_sound_speed	TL_at_zstar	detection
880	3	GOFS31Re	1151.0	1485.5	90.4	0
880	3	HYCOM	1133.0	1486.4	89.6	1
880	27	HYCOM	1133.0	1486.4	89.6	1
880	51	HYCOM	1137.0	1486.1	89.2	1
880	75	HYCOM	1209.0	1485.8	88.0	1
880	99	HYCOM	1128.0	1485.4	92.5	0
880	123	HYCOM	1165.0	1485.7	93.3	0
880	147	HYCOM	1234.0	1486.1	92.6	0
880	0	GDEM	1202.0	1491.0	90.0	0

Table 6 illustrates the forecast lead time values in hours (“tau_lead_time”) and their association with the target date-time hours of each design point. The GOFS zero-hour forecast is issued once a day (once every 24 hours) and is valid at the hour 12Z of each day. Subsequent forecasts follow at 24-hour intervals from the first forecast time. So, for target times at 12Z, the available lead times are 0, 24, 48, hours etc. The available lead times corresponding to their target date-time hours are depicted in Table 5.

Table 6. Target date-time hour values and associated forecast lead times

Target Date-time Hour Value	Forecast Lead Time ("tau_lead_time")						
00	12	36	60	84	108	132	156
03	15	29	53	77	101	125	149
06	18	42	66	90	114	138	162
09	21	45	69	93	117	141	165
12	00	24	48	72	96	120	144
15	03	27	51	75	99	123	147
18	06	30	54	78	102	126	150
21	09	33	57	81	105	129	153

B. DATA CLEANING

Several data cleaning steps were performed to ensure the quality and integrity of the final dataset.

1. Handling Missing Data

Upon initial review of the final dataset, it was observed that NSPE encountered challenges in calculating TL at z^* for a subset of rows in which there was no data. Specifically, 37,324 rows (11,072 associated with 2021 design points and 26,252 associated with 2022 design points) out of the initial 313,344 rows were affected. This accounted for approximately 11.9% of the dataset. To maintain data integrity, all rows containing NaN (Not-a-Number) values were removed, resulting in a reduced dataset consisting of 276,020 rows.

2. Addressing Unrealistic Transmission Loss

Another issue discovered during data inspection pertained to TL output for design points emitting a frequency of 720 Hz. Regardless of other factors, all design points with this specific frequency exhibited an unrealistically high TL exceeding 400 dB. No other rows reached over 400 dB in TL in the entire dataset. Perhaps this was related to an anomaly within the NSPE model in the determination of TL associated with a 720 Hz emitting frequency. Given this inconsistency, all rows associated with a frequency of 720 Hz were excluded from the dataset. This led to the removal of 18,176 rows, with 8,960 originating from 2021 data and 9,216 from 2022 data. Consequently, the total count of rows in the dataset decreased from 276,020 to 257,844, representing approximately 82.3% of the original dataset that remained.

C. DATA TRANSFORMATION

The dataset was transformed to facilitate a comparative analysis of the TL, z^* , and detection rates for HYCOM, GDEM, and GOFS reanalysis across varying forecast lead times. Instead of the previously described nine-row sets, the dataset was restructured into sets of seven rows for each design point. During this transformation, these four columns were removed: “ts3z_data_type,” “zstar,” “TL_at_zstar,” and “detection.” In their place,

new columns were introduced, including “GOFSRe_zstar,” “HYCOM_zstar,” “GDEM_zstar,” “GOFSRe_TL,” “HYCOM_TL,” “GDEM_TL,” “GOFSRe_detection,” “HYCOM_detection,” and “GDEM_detection.” This transformation can be observed in Table 7, which displays the revised representation of design point 880 from the 2021 data. It is noteworthy that GOFS reanalysis (GOFSRe) and GDEM-related data points remain constant throughout their respective columns, while HYCOM-related data points vary due to changes in HYCOM forecasts based on forecast lead times (“tau_lead_time”).

Table 7. Restructured final dataset filtered for design point number 880
(seven rows per design point)

re_dp	tau_lead_time	HYCOM_TL	GOFSRe_TL	GDEM_TL	HYCOM_zstar	GOFSRe_zstar	GDEM_zstar	HYCOM_detection	GOFSRe_detection	GDEM_detection
880	3	89.597273	90.420882	90.036215	1133.0	1151.0	1202.0	1	0.0	0.0
880	27	89.597273	90.420882	90.036215	1133.0	1151.0	1202.0	1	0.0	0.0
880	51	89.175534	90.420882	90.036215	1137.0	1151.0	1202.0	1	0.0	0.0
880	75	87.978297	90.420882	90.036215	1209.0	1151.0	1202.0	1	0.0	0.0
880	99	92.514208	90.420882	90.036215	1128.0	1151.0	1202.0	0	0.0	0.0
880	123	93.251676	90.420882	90.036215	1165.0	1151.0	1202.0	0	0.0	0.0
880	147	92.558259	90.420882	90.036215	1234.0	1151.0	1202.0	0	0.0	0.0

Finally, two additional columns were incorporated into the dataset: “bottom_depth_blue” and “bottom_depth_red.” These variables capture the ocean’s depth at Blue’s and Red’s locations, respectively. The bottom depths were obtained by Google maps using an Application Programming Interface key with each of the sets of latitude and longitude coordinates. Additionally, the columns “year,” “month,” “day,” and ‘hour’ were reintroduced, which were originally part of the experiment’s initial design but were subsequently transformed into the “valid_date_time” format. This reintroduction enables a comprehensive examination of the individual factors for years, months, days, and hours. For a detailed overview of variable names in the final dataset, refer to Table 8.

Table 8. Description of variable names in the restructured final dataset

Variable Name	Description
re_dp	Ordered reanalysis of design points (years 2021 and 2022 from original design of experiments)
moving_point_lat	Latitude (degrees) at Blue's location from Design "S"
moving_point_lon	Longitude (degrees) at Blue's location from Design "S"
range	Range (nm) of Blue to Red from Design "R"
bearing	Bearing (degrees) of Blue to Red from Design "R"
freq	Frequency (Hz) emitted by Red from Design "R"
fixed_point_depth	Depth (m) of Red from design "R"
sourceLatitude	Latitude (degrees) at Red's location based on bearing and range from Design "R"
sourceLongitude	Longitude (degrees) at Red's location based on bearing and range from Design "R"
valid_date_time	Forecast target date-time with Year, Month, Day and Hour derived from Design "T"
tau_lead_time	Forecast lead time based on target date-time ("valid_date_time")
HYCOM_zstar	Search depth (m) with HYCOM forecast for target date-time and lead time based on decision policy
GOFsRe_zstar	Search depth (m) with GOFs zero-hour forecast for target date-time and lead time based on decision policy
GDEM_zstar	Search depth (m) with GDEM information for target date-time and lead time based on decision policy
HYCOM_TL	Transmission Loss (db) at associated HYCOM z* based on GOFs zero-hour forecast
GOFsRe_TL	Transmission Loss (db) at associated HYCOM z* based on GOFs zero-hour forecast
GDEM_TL	Transmission Loss (db) at associated HYCOM z* based on GOFs zero-hour forecast
HYCOM_detection	HYCOM detection, binary (either 1 or 0) where detect YES = 1 and detect NO = 0
GOFsRe_detection	GOFs zero-hour detection, binary (either 1 or 0) where detect YES = 1 and detect NO = 0
GDEM_detection	GDEM detection, binary (either 1 or 0) where detect YES = 1 and detect NO = 0
bottom_depth_blue	The ocean's depth (m) at Blue location
bottom_depth_red	The ocean's depth (m) at Red location
year	Year value from target date-time (Design "T")
month	Month value from target date-time (Design "T")
day	Day value from target date-time (Design "T")
hour	Hour value from target date-time (Design "T")

D. EXPLORATORY DATA ANALYSIS (EDA) AND MODELING

The exploratory data analysis (EDA) employs a range of statistical techniques to examine variables within the final dataset. Our EDA began with an examination of descriptive statistics, and a particular emphasis on key output variables derived from the design of experiments, including z^* , TL at z^* , and detection values for each forecast source. These output variables are the primary focus of the analysis. Additionally, modeling was conducted to gain insights into important factors that influence z^* , TL at z^* , and likelihood of detection based on environmental predictions from HYCOM and GDEM.

1. Descriptive Statistics of Key Variables in Final Dataset

Table 9 provides a comprehensive overview of descriptive statistics for the output variables. Notably, the detection proportion across various sources exhibit remarkable similarity, with GDEM exhibiting the highest detection rate at 33.65 % (55,496 out of

164,974), closely trailed by the GOFS reanalysis at 32.80 % (54,096 out of 164,974), and HYCOM at 32.42 % (53,470 out of 164/974).

Table 9. Descriptive statistics for key factors in final dataset

	HYCOM_TL	GOFSRe_TL	GDEM_TL	HYCOM_zstar	GOFSRe_zstar	GDEM_zstar	HYCOM_detection	GOFSRe_detection	GDEM_detection
mean	96.570	95.931	95.593	1077.345	1069.739	998.285	0.324	0.328	0.336
std	19.898	16.879	16.875	280.704	266.138	247.600	0.468	0.469	0.473
min	46.916	48.890	52.492	0.000	0.000	603.000	0.000	0.000	0.000
25%	87.820	87.697	87.496	845.000	854.000	708.000	0.000	0.000	0.000
50%	94.302	94.152	94.021	1149.000	1124.000	1074.000	0.000	0.000	0.000
75%	101.587	101.529	101.156	1304.000	1284.000	1226.000	1.000	1.000	1.000
max	398.957	235.919	199.029	1692.000	1658.000	1313.000	1.000	1.000	1.000

2. Analysis of z^*

The EDA of the z^* derived from each forecast consists of histograms to compare the distributions of z^* and comparative boxplots to compare the variability for the z^* across forecast lead times. Additionally, this section models z^* as response variables to determine factor importance and drivers of z^* .

a. Histograms of z^*

Figure 14 provides histograms that represent the distribution of z^* for each of the forecasts and the reanalysis (HYCOM, GDEM, and GOFS reanalysis) in the final dataset.

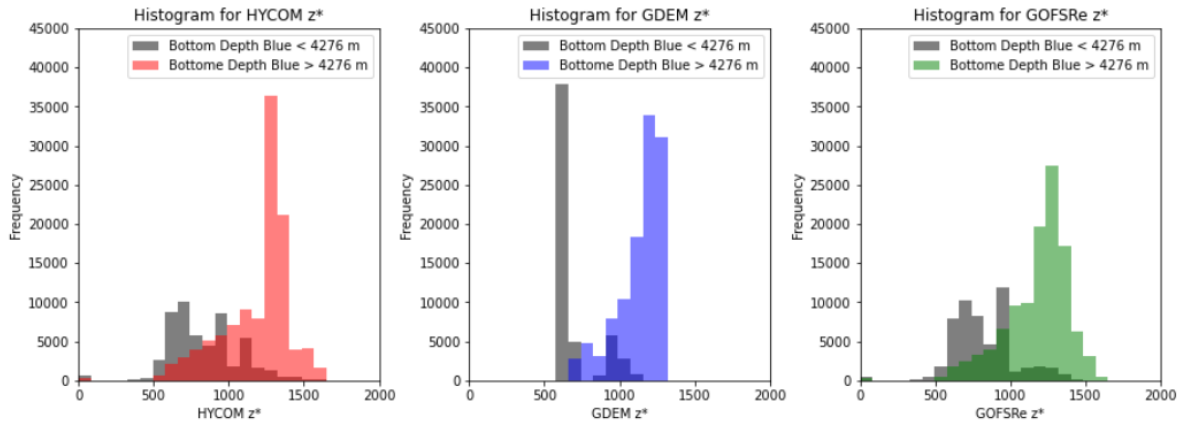


Figure 14. Comparative histograms— z^*

When comparing the z^* distributions for each source, it appears that GFS reanalysis and HYCOM are very closely related with similar outliers. However, the GDEM z^* distribution has no major outliers and is a very tight range of depths compared to the other two z^* distributions. This may be due to less variability with historical oceanographic information provided by GDEM. Each of the three z^* distributions appear to be bimodal. The histograms in Figure 14 suggest that the bimodal distribution is attributed to the bottom depth of Blue. The mode for bottom depth Blue is 4,276 meters and any z^* associated with a bottom depth less than the mode of 4,276 m are depicted in black.

b. z^* by Forecast Lead Times

Figure 15 presents boxplots illustrating the distribution of z^* across forecast lead times based on HYCOM and GDEM. The whiskers in these boxplots extend to 1.5 times the Interquartile Range (IQR). Notably, for HYCOM z^* , specific forecast lead times of 3 hours, 27 hours, 66 hours, and 147 hours exhibit strikingly long whiskers that extend towards 0 meters in depth. Lead times 3, 27, and 147 are all related to target date-time hour 1500 Z. This translates to 1100 Eastern Standard Time zone. This observation suggests that forecast lead times that are predicting the oceanographic environment at 1100 EST may display unusual data distributions, with skewed interquartile ranges, compared to the other forecast lead times.

The boxplots for GDEM and HYCOM z^* demonstrate no notable trend as a function of forecast lead time. This is an unexpected result. One would believe that as forecast lead times increase, that there would be greater variation in the boxplots, especially those z^* values related to HYCOM forecasting.

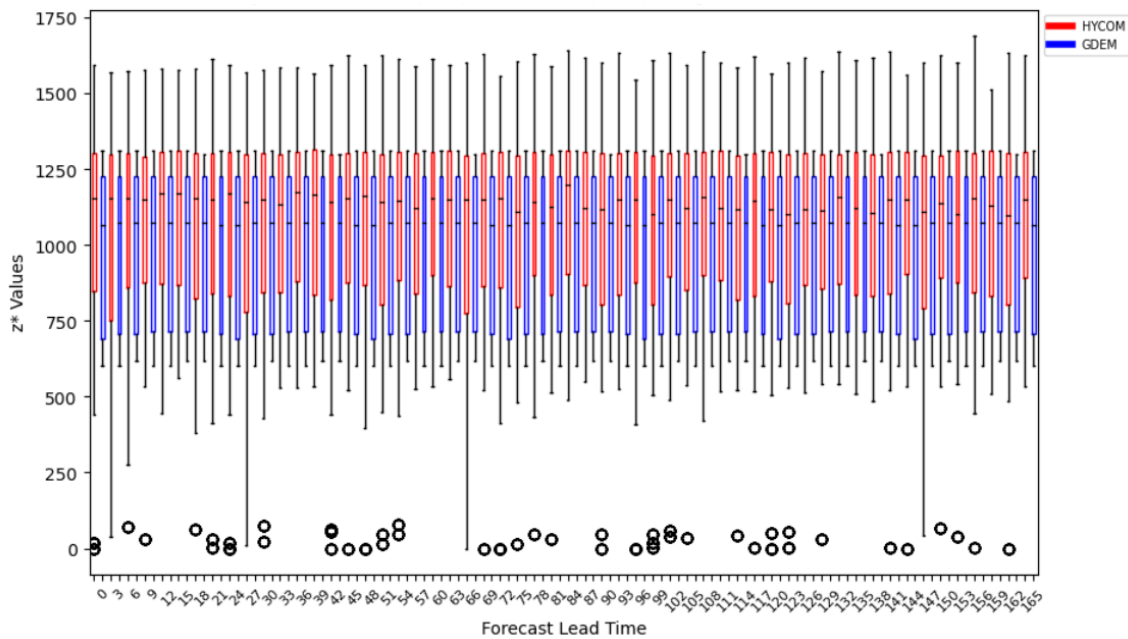


Figure 15. Comparative boxplots— z^* by forecast lead times

c. *Drivers of z^**

Two separate partition trees are employed to investigate the factors influencing the response variables HYCOM z^* and GDEM z^* (Figures 16 and 17). The following factors are considered for these two partition trees: range, log(frequency), Red depth, month, day, hour, forecast lead times, bottom depth at Red location, bottom depth at Blue location. R-squared values are utilized to determine when to no longer split the partition tree into more leaves. If a split of the partition tree does not increase the R squared value more than .1, then the partition tree is pruned back to the previous split.

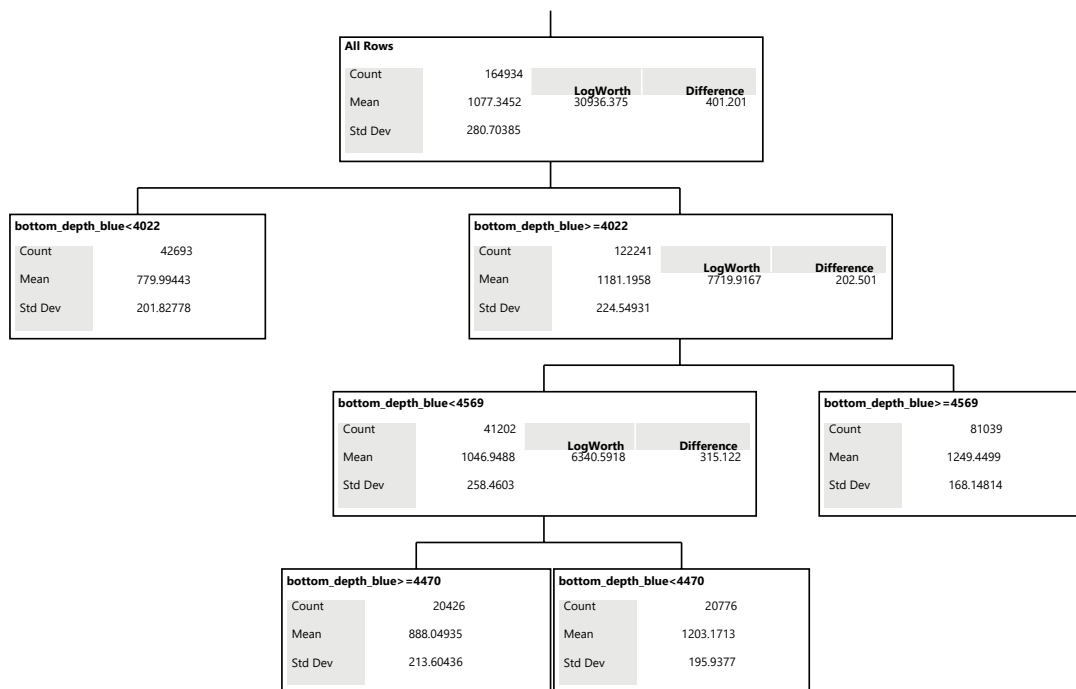


Figure 16. Partition tree—HYCOM z^*

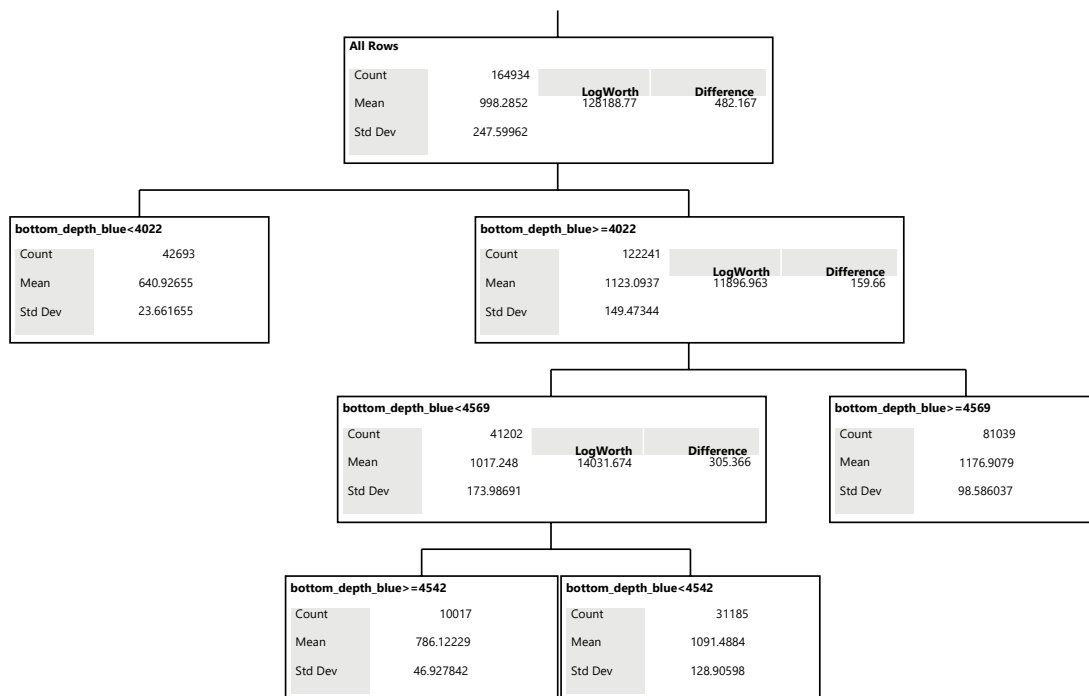


Figure 17. Partition tree—GDEM z^*

Overall, the depth of the ocean at Blue's location appears to be the only significant factor from our design of experiments that affected z^* for both GDEM and HYCOM related z^* . In fact, it was the only factor identified in the partition tree for both response variables. This result matches intuition, as the depth of the ocean affects the associated SVP at each location of Blue. As the depth of the ocean at Blue's location increases, the z^* tends to increase. This finding was also depicted by the bimodal histograms in Figure 14.

The partition tree model for HYCOM z^* response variable has an R-squared value of 0.557, with an associated Root Absolute Squared Error (RASE) of 187 meters. In contrast, the partition tree model for GDEM z^* response variable explained the variability in z^* remarkably well, yielding a higher R-squared value of 0.866 and a lower RASE of 91 meters.

3. Analysis of TL at z^*

The EDA of the TL at z^* derived from each forecast consists of histograms to compare the binned frequency distributions of TL at z^* and comparative boxplots to compare TL at z^* and their variability across forecast lead times. Additionally, the modeling conducted in this section uses TL at z^* as response variables to determine factor importance and drivers of TL at z^* for each respective forecast.

a. Histograms of TL at z^*

Figure 18 presents a comparative analysis of histograms, illustrating the distribution of TL at z^* extracted from each distinct forecast source: HYCOM, GDEM, and GOFS reanalysis. Upon examination, it becomes apparent that the TL at z^* distributions for each forecast source resembles a unimodal distribution with a primary mode just less than 100 dB. When viewing the summary statistics for each TL at z^* , the median values are extremely close for each forecast's associated TL at z^* (94.3 dB for HYCOM, 94.0 dB for GDEM, and 94.2 dB for GOFS reanalysis) as well as the mean values (96.6 dB for HYCOM, 95.6 dB for GDEM, and 95.9 dB for GOFS reanalysis).

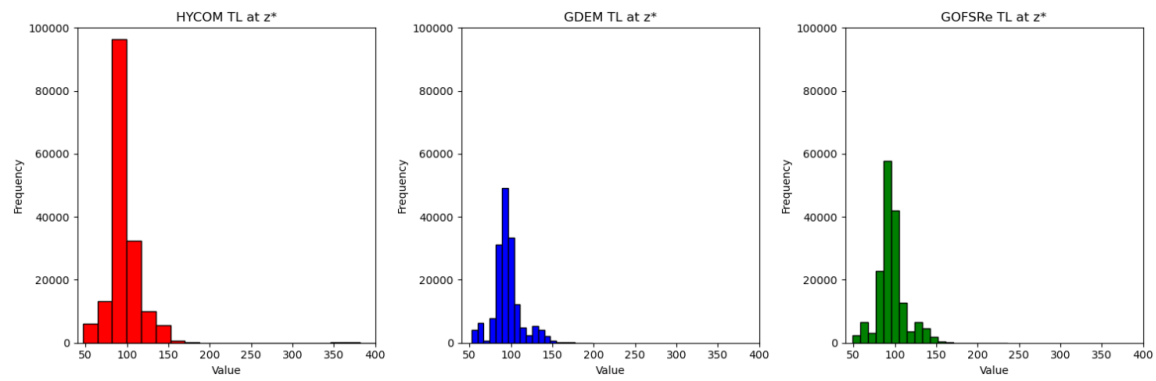


Figure 18. Comparative histograms—TL at z^*

b. TL at z^* by forecast lead time

Figure 19 provides a visual representation through comparative boxplots, showcasing the TL at z^* across various forecast lead times for HYCOM and GDEM forecasts. What stands out is the remarkable consistency in the presence of outliers across the different forecast lead times within each plot. Across the spectrum of forecast lead times examined, these outliers demonstrate a surprising degree of stability. This observation suggests that certain outlier behaviors persist consistently throughout all forecast lead times considered for HYCOM related TL at z^* . It implies that HYCOM's oceanographic forecast prediction does fluctuate with longer forecast times and remains consistent even as forecast lead times increase.

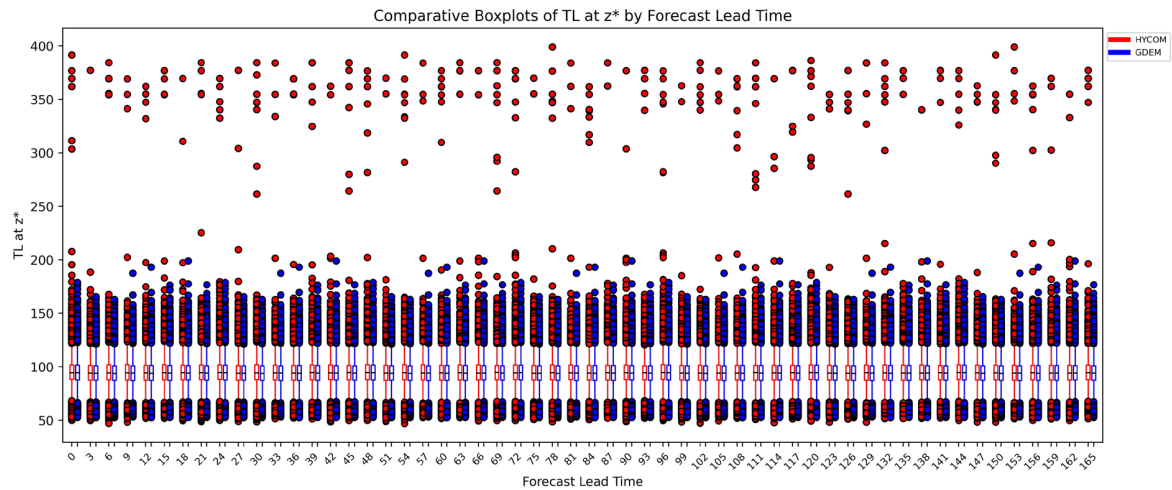


Figure 19. Comparative boxplots—TL at z^* by forecast lead time

*c. Drivers of TL at z^**

(1) Partition trees for HYCOM TL at z^* and GDEM TL at z^*

Two separate partition trees are employed to investigate the factors influencing the response variables HYCOM TL at z^* and GDEM TL at z^* (Figures 20 and 21).

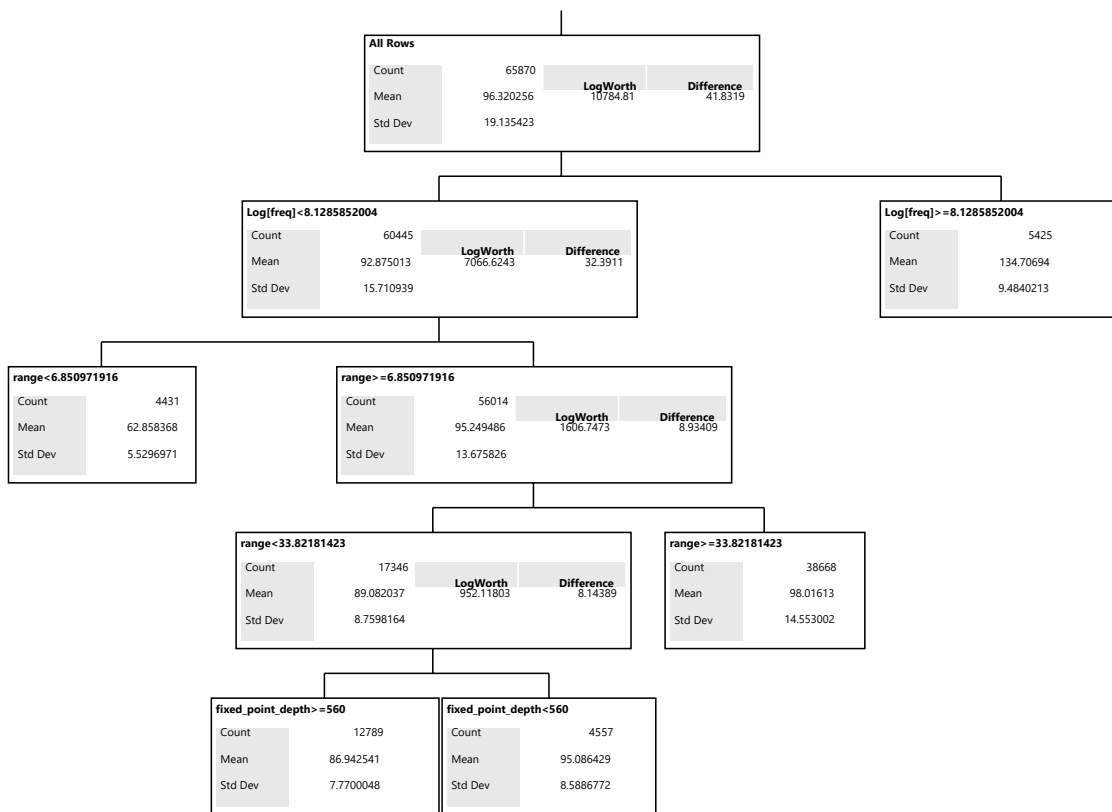


Figure 20. Partition tree model—HYCOM TL at z^*

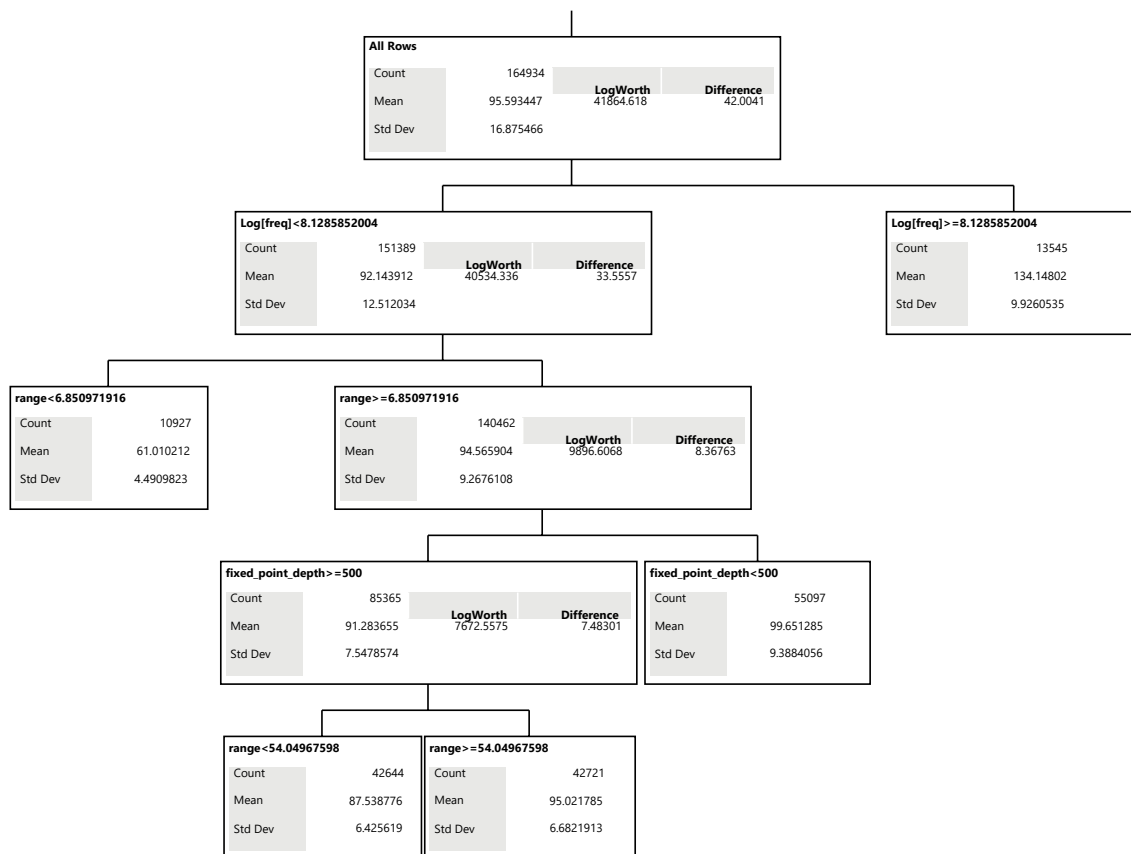


Figure 21. Partition tree model—GDEM TL at z^*

The best partition tree for each TL at z^* response variable occurs after four splits of the partition tree. Any further splits only increase the R-squared value by less than .01, adding little value to the model. Based on the R squared values for each of these partition trees, the GDEM TL at z^* partition tree (R squared value of .79) appears to model the observed data better than the HYCOM TL at z^* partition tree (R squared value .59).

Furthermore, each of the response variables for TL at z^* split on a combination of the same factors (frequency, range, and Red depth). This implies that frequency, range, and Red depth have similar influence for the TL at z^* regardless of which source was used to support the decision policy. Both models split on the same values of frequency first (~3,412 hz), followed by the same values of range (~6.9 nm). This suggests that frequency is the most significant factor influencing TL at z^* followed by range. It is interesting that frequency was suggested to be more significant than range, because intuitively it seems

that range will be the most influential driver of TL at z^* . The depth of Red (“fixed_point_depth”) is the other factor considered in both partition trees but split at different Red depth levels.

(2) Regression Model for HYCOM TL at z^* and GDEM TL at z^*

The results of the regression models for both HYCOM TL at z^* and GDEM TL at z^* are each depicted in Table 10.

Table 10. Parameter estimates for regression models—HYCOM TL at z^* and GDEM TL at z^*

Response HYCOM TL at z^*					Response GDEM TL at z^*				
Term	Estimate	Std Error	t Ratio	Prob> t	Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	77.570101	0.216071	359.00	<.0001*	Intercept	70.681739	0.165703	426.56	<.0001*
range	0.2641668	0.00131	201.71	<.0001*	range	0.284578	0.001004	283.35	<.0001*
Log[freq]	2.6392532	0.022927	115.12	<.0001*	Log[freq]	2.9569501	0.017582	168.18	<.0001*
fixed_point_depth	-0.00576	0.000149	-38.59	<.0001*	fixed_point_depth	-0.00674	0.000114	-58.88	<.0001*
bottom_depth_red	-0.000546	6.815e-5	-8.01	<.0001*	bottom_depth_red	-0.000866	5.226e-5	-16.56	<.0001*
bottom_depth_blue	-0.000707	5.336e-5	-13.24	<.0001*	bottom_depth_blue	0.0005963	0.000041	14.57	<.0001*

The results of the two regression models in Table 10 reveal some key insights. Both models exhibit strong statistical significance, as evidenced by the remarkably low p-values across all predictor variables. The parameter estimates for range, frequency, Red depth, bottom depth at Blue’s location, and bottom depth at Red’s location are significant in both models, indicating their importance in explaining the variation in TL at z^* . Interestingly, the models share similar parameter estimates, suggesting that the relationship between these predictor variables and TL at z^* is comparable for both GDEM and HYCOM.

However, a distinction arises in the goodness of fit, with the GDEM TL at z^* model demonstrating a notably higher R-squared value of 0.38 compared to the R-squared value of 0.24 for the HYCOM TL at z^* model. This suggests that the GDEM model explains a larger proportion of the variance in TL at z^* than the HYCOM model, highlighting its greater predictive power. Overall, while the predictor variables hold similar importance in both models, the GDEM TL at z^* model outperforms the HYCOM TL at z^* model in terms of its ability to explain the observed variance. This may be due to the lack of outliers in the GDEM TL at z^* as depicted in Figure 19.

4. Analysis of Detection

a. Drivers of detection

The binary response variables HYCOM detection and GDEM detection are each modeled using a logistic regression model. In each of the regression models for HYCOM detection and GDEM detection, several predictor variables are examined to understand their impact on the probability of detection (1 for detection and 0 for no detection). The summary of the parameter estimates for each model are illustrated in Table 11.

Table 11. Parameter estimates for logistic regression models—HYCOM Detection and GDEM Detection

<i>Parameter Estimates – HYCOM Detection</i>				
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	1.62101935	0.0297222	2974.5	<.0001*
range	-0.0392085	0.0002356	27697	<.0001*
Log[freq]	-0.1352353	0.0032054	1779.9	<.0001*
fixed_point_depth	0.00224849	2.2777e-5	9745.5	<.0001*
bottom_depth_red	-0.0001704	1.0638e-5	256.61	<.0001*
bottom_depth_blue	-0.0001214	8.6189e-6	198.34	<.0001*
<i>Parameter Estimates – GDEM Detection</i>				
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	1.96306437	0.0301279	4245.5	<.0001*
range	-0.0405955	0.0002412	28320	<.0001*
Log[freq]	-0.1826069	0.0032414	3173.6	<.0001*
fixed_point_depth	0.00239742	2.3075e-5	10795	<.0001*
bottom_depth_red	2.69548e-5	1.0841e-5	6.18	0.0129*
bottom_depth_blue	-0.0003437	8.725e-6	1551.9	<.0001*

The “range” variable has a negative coefficient in both models, implying that an increase in range is associated with a decrease in the log-odds of detection. This is intuitive and suggests that as the range from Blue to Red increases, the likelihood of detection decreases.

The “Log [freq]” variable also shows negative coefficients in both models, intuitively suggesting that higher frequency values correspond to a decrease in the log-odds of detection. This indicates that higher frequency values are less favorable for detection outcomes.

The “fixed_point_depth” variable has positive coefficients in both models, indicating that an increase in Red depth is associated with an increase in the log-odds of detection. This suggests that increased Red depths are more favorable for detection.

Interestingly, the “bottom_depth_red” variable exhibits different patterns in the two models. The HYCOM model has a negative coefficient ($p = < 0.0001$), suggesting that increasing “bottom_depth_red” is associated with a decrease in detection odds. However, in the GDEM model, it has a positive coefficient with a p-value of 0.0129, indicating a potential positive impact on detection odds.

Lastly, “bottom_depth_blue” shows a negative coefficient in both models, indicating that higher “bottom_depth_blue” values are associated with a decrease in detection odds. To help visualize how detection rates are influenced by the bottom depth at Blue’s location, a map of Blue’s locations and associated depths in meters, along with the detection rates for each location is depicted in Figure 22. It is apparent that deeper depths at Blue’s location are generally associated with lower detection rates.

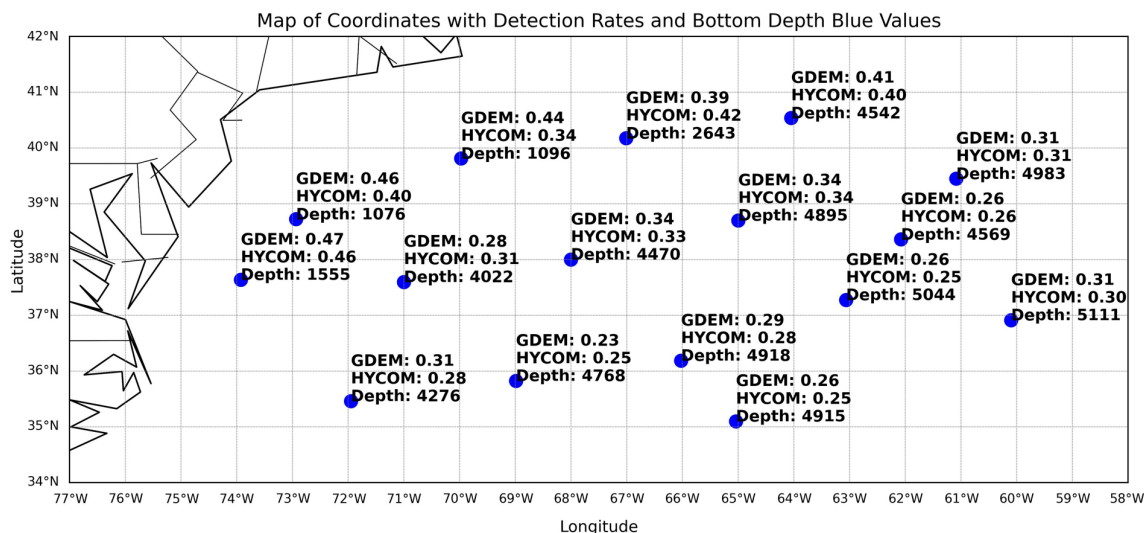


Figure 22. Map of Blue locations with detection rates and bottom depth

Figure 23 further emphasizes that as bottom depth at Blue’s location increases, detection rates have a decreasing trend for both HYCOM detection rates and GDEM detection rates. Notice that as depth decreases, GDEM detection rates become increasingly higher than HYCOM detection rates.

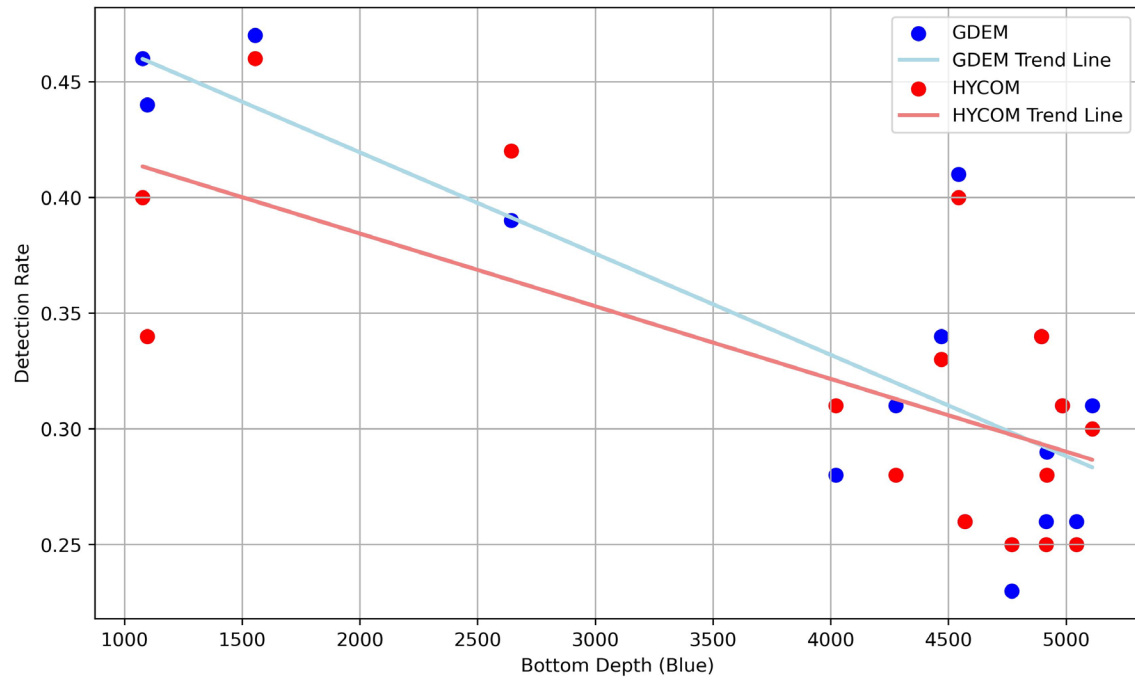


Figure 23. Detection rates by bottom depth at Blue's location

THIS PAGE INTENTIONALLY LEFT BLANK

VI. CONCLUSION AND RECOMMENDATIONS

This thesis's primary objective is to evaluate which forecasting models and environmental information sources, if any, are most valuable in informing critical mission-related decision-making.

One may expect forecasting models such as HYCOM to vary and/or degrade as forecast lead times move farther away from target date-times. Also, it may be expected for a forecast model to be more accurate than a historical climatological data source. Additionally, it may be that forecasts based on monthly historical averages may change as the target date-times move away from the middle of the month. Perhaps, deviating much more in the beginning and end of months when compared to the middle of the month. One may expect that forecasts change significantly across various seasons. None of these assumptions and expectations were observed in this experiment.

In the context of the experiment, where the decision policy aimed to operate at the point of minimum SV in the SVP to enhance detection rates through passive SoNAR techniques, it is evident that GDEM offers comparable, if not slightly more reliable results compared to HYCOM forecasting. Based on the analysis of results from this experiment, especially considering detection rate as a measure of effectiveness, there is no substantial difference identified between the two forecasting sources, indicating that HYCOM does not appear to be a superior information source compared to GDEM in this scenario.

A. RECOMMENDATIONS FOR FUTURE RESEARCH

Similar experiments with alternative decision-making contexts and criteria should also be considered. For instance, decisions to optimize Blue's tracking decisions in submarine scenarios, rather than solely prioritizing initial detection. More complex decisions involving optimization of multiple sensor placement within a designated operating region, or incorporating active SONAR detection techniques alongside passive methods could possibly better exploit HYCOM forecasts.

The geographic location of this modeling area may lack variability compared to other regions of the world. It may be valuable to conduct a similar experiment in a different

region to assess whether results differ significantly. For example, perhaps GDEM is more reliable near the coastlines of the United States where historical climatology data may be more reliable. It is recommended to repeat a similar experiment in a region that is more distant from the United States coastal areas.

Also, incorporating classified LE databases into subsequent simulations and modeling experiments can shed light on how varying levels of LE affect TL during passive search operations. This could provide valuable insights for future mission planning and decision-making processes. These diverse avenues for exploration could potentially advance our understanding of the utility of oceanographic forecasts and contribute to more effective underwater surveillance.

LIST OF REFERENCES

- Barlow J (2019) Global Ocean Sound Speed Profile Library (GOSSPL), an Rdata resource for studies of ocean sound propagation. NOAA-TM-NMFS-SWFSC-612, U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Marine Fisheries Service, Southwest Fisheries Science Center, La Jolla, CA, <https://repository.library.noaa.gov/view/noaa/19838>
- Bauer R (1982) Functional Description: Master Oceanographic Data Set (MOODS). Report, Compass Systems Inc, San Diego, CA.
- Boyer TP, Stephens C, Antonov JJ, Conkright ME, Locarnini, RA, O'Brien TD, Garcia HE (2002) *World Ocean Atlas 2001 Volume 2: Salinity*. In S. Levitus, Ed., NOAA Atlas NESDIS 50, US Government Printing Office, Washington, DC.
- Carnes MR (2009) Description and Evaluation of GDEM-V 3.0 (No. NRL/MR/7330-09-9165). Report, Naval Research Lab, Oceanographic Data Bases Division, Stennis Space Center, Hancock County, MS.
- Carnes MR (2010) Validation Test Report for GDEM4. Report, Naval Research Lab, Oceanographic Data Bases Division, Stennis Space Center, MS.
- Cioppa TM, Lucas TW (2007) Efficient nearly orthogonal and space-filling Latin hypercubes. *Technometrics*. 49(4): 468–479.
- Commander Submarine Forces (n.d.) Commander's Intent 4.0. Accessed 07/10/2023, <https://www.csp.navy.mil/Portals/2/documents/about/commandersintent4.0.pdf>
- Cummings JA (2005) Operational Multivariate Ocean Data Assimilation. *Quarterly Journal of the Royal Meteorological Society*. 131(613): 3583–3604.
- ECMWF (2023) Fact sheet: Reanalysis. Accessed 09/08/2023, <https://www.ecmwf.int/en/about/media-centre/focus/2023/fact-sheet-reanalysis>
- Etter PC (1991) *Underwater Acoustic Modeling: Principles, Techniques and Applications* (The American Institute of Physics Press, Elsevier, New York).
- Federation of American Scientists. (n.d.) Fundamentals of Naval Weapons Systems. Accessed 09/04/2023, <https://man.fas.org/dod-101/navy/docs/fun/index.html>
- Ferla J, Porter M (1991) Receiver Depth Selection for Passive Sonar Systems. *Journal of the Acoustical Society of America*, 90(1).
- Gardner WJR (1996) *Anti-Submarine Warfare* Volume 11 (Brassey's Ltd, London, England).

- Harding J (2022) Exploring the operational significance of transmission loss predictions using a high-fidelity acoustic model for the Arctic Ocean (No. NPS-MA-22-001). Master's thesis, Naval Postgraduate School.
- Holmes ES (1992) Use of the Navy Standard Parabolic Equation Model for Broadband Applications. *OCEANS 92 Proceedings, Mastering the Oceans Through Technology*, 37–41.
- Joubert PN (2004) Some Aspects of Submarine Design, Part 1: Hydrodynamics. Report, Department of Defence, Defence Science and Technology Organization, Canberra, Australia.
- McDowell P (2010) Environmental and statistical performance mapping model for underwater acoustic detection systems. Doctoral dissertation, University of New Orleans, <https://scholarworks.uno.edu/td/1157>
- Metzgar EH, Barron CN, Mehra A (2020) Validation Test Report for the Global Ocean Forecast System 3.5 – 1/25° HYCOM/CICE with Tides. Report, Naval Research Laboratory, Stennis Space Center, Hancock County, MS.
- National Research Council (1997) *Technology for the United States Navy and Marine Corps, 2000–2035: Becoming a 21st-Century Force: Volume 6: Platforms* (The National Academies Press, Washington, DC).
- Naval Research Laboratory (n.d.) Global Ocean Forecast System (GOFS) 3.1. Accessed 07/16/2023, <https://www7320.nrlssc.navy.mil/dynamic/gofs/gofs.php>
- Naval Research Laboratory (n.d.) Marine Meteorology. Accessed 05/25/2023, <https://www.nrl.navy.mil/marine-meteorology>
- NOAA National Centers for Environmental Information (NCEI) (n.d.) Metadata for Dataset ID gov.noaa.nodc:9600094. Accessed 06/20/2023, <https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.nodc:9600094>
- Regnier E, Margolina T, Upton S (2023) Assessing the Value of Extended-Range Meteorological and Oceanographic (METOC) forecasts in Tactical Decision-Making for the Theater ASW Fight. Draft Naval Postgraduate School Technical Report.
- RTO Lecture Series 227 (2005) Tactical Decision Aids and Situational Awareness (Les aides à la prise de décisions tactiques et la connaissance de la situation des forces). Report, NATO Research and Technology Organisation, Neuilly-sur-Seine, France.
- Sanchez SM (2011) NOLH designs spreadsheet. Accessed 05/20/2023, <http://harvest.nps.edu>

Stockholm International Peace Research Institute (1974) *Tactical and Strategic Antisubmarine Warfare* (MIT Press, Cambridge, MA).

United States Fleet Forces Command (n.d.) About Us – Mission. Accessed 07/18/2023, <https://www.sublant.usff.navy.mil/UWDC/About-Us/Mission>

U.S. Department of Defense (2022) 2022 National Defense Strategy. Strategy document.

Water Encyclopedia (n.d.) Sound Transmission in the Ocean. Accessed 08/10/2023, <http://www.waterencyclopedia.com/Re-St/Sound-Transmission-in-the-Ocean.html>

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
Fort Belvoir, Virginia
2. Dudley Knox Library
Naval Postgraduate School
Monterey, California



DUDLEY KNOX LIBRARY

NAVAL POSTGRADUATE SCHOOL

WWW.NPS.EDU

WHERE SCIENCE MEETS THE ART OF WARFARE