NOWRDC Project #114- Cornell University

Right Wind:
Resolving Protected Species Space-Use Conflicts in Wind Energy Areas

Final Report

Prepared for the National Offshore Wind Research and Development Consortium

Mel Schultz (Program Manager)

Laura C. Ganley[1], Aaron N. Rice[3], Megan Ryder[1],

Carly Campbell, Ian Spooner[2], Jessica V. Redfern[1]

New England Aquarium[1], LAUTEC US[2], and Cornell University[3]

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Notice:

Abstract

The distribution of the critically endangered North Atlantic right whale (*Eubalaena glacialis*) overlaps with offshore wind lease areas along the U.S. Atlantic coast. Wind energy developers are required to mitigate impacts to these animals. Informed mitigation requires an understanding of the spatial and temporal distribution of right whales. Our research included nine tasks: 1) develop predictive models of right whale distribution; 2) estimate uncertainty in right whale predictions; 3) develop financial risk assessment scenarios; 4) determine the model's ability to forecast right whale distribution; 5) develop a commercialization/marketing strategy; 6) assess financial risk; and 7) analyze economic tradeoffs; 8) develop a decision support framework; and 9) deploy a commercialization strategy. To complete these tasks, we built density surface models that successfully predicted right whale distribution and estimated uncertainty in right whale predictions. We identified tradeoffs between financial costs to renewable energy developers and protected species conservation by coupling an offshore wind energy construction simulation with our density surface model to quantify the number of right whales exposed to pile-driving noise under ten financial risk scenarios, with costs assigned to each of the financial risk scenarios. We then built an interactive prototype decision support app to demonstrate the tradeoff analysis, and showcased the app at a stakeholder workshop attended by employees of Orsted and Equinor.

Keywords: North Atlantic right whale, offshore wind energy, financial risk, economic trade-off

Acknowledgments

We would like to extend our thanks to the many people that were involved in the collection of the data (aerial and acoustic) that are the basis of our Right Wind analyses. We are grateful to Benjamin Healy and Matthew Griswold for their efforts in scheduling and planning the financial risk scenarios; and to Nick Zenkin for his vision and leadership in helping create this project. We would also like to thank our Right Wind Project Advisory Board for their helpful comments throughout the project.

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List of Abbreviations

Acronym/Abbreviation	Definition
AIC	Akaike's Information Criterion
BBC	Big Bubble Curtain
BOEM	Bureau of Ocean Energy Management
DBBC	Double Big Bubble Curtain
DSM	Density Surface Model
ESA	Endangered Species Act
ESW	Effective Strip Width
GAMs	Generalized Additive Models
HLV	Heavy Lift Vessel
ICOADS	International Comprehensive Ocean–Atmosphere Data Set
IHA	Incidental Harassment Authorization
ITA	Incidental Take Authorization
MA/RI	Massachusetts/Rhode Island
MARUs	Marine Autonomous Recording Units
MassCEC	Massachusetts Clean Energy Center
MMPA	Marine Mammal Protection Act
MODIS	Moderate Resolution Imaging Spectrometer
NARWC	North Atlantic Right Whale Consortium
NASA	National Aeronautics and Space Administration
NBMCT	The New Bedford Marine Commerce Terminal
NCEI	National Center for Environmental Information U.S.
NEAq	New England Aquarium
NEFSC	Northeast Fisheries Science Center
NOAA	National Oceanographic and Atmospheric Administration
PSO	Protected Species Observer
QA/QC	Quality Assurance/Quality Control
REML	Restricted Maximum Likelihood
Right whale	North Atlantic Right Whale
RMSE	Root Rean Squared Error
SST	Sea Surface Temperature
WEA	Wind Energy Area

Executive Summary

Renewable energy resources are a critical component of a low-carbon future. Offshore wind energy plays a role in reducing our dependence on petroleum-based fuels, and thus reduces emissions of greenhouse gases. Construction, operation, and decommissioning of offshore wind energy projects is time-consuming and expensive; thus, extensive planning is required.

Numerous wind energy development projects are planned in U.S. Atlantic Coast waters. These waters are inhabited by many species that could be impacted by the development of wind energy. The distribution of the critically endangered North Atlantic right whale (*Eubalaena glacialis*), hereafter right whale, overlaps with proposed wind energy development areas. The Massachusetts/Rhode Island wind energy area (MA/RI WEA), the focus area for our project, overlaps with a recently repatriated right whale habitat (O'Brien et al., 2022). Most scientific studies on the impact of wind energy construction on marine mammals have taken place in European waters and focused on small marine mammals. The effects of wind energy on large whales (including right whales) are unknown (Kraus et al., 2019). Thus, an overarching objective of our study is to develop a computational tool that will quantify the costs associated with minimizing interactions between construction activities and right whales.

Throughout the project we simultaneously assessed the financial tradeoffs between right whale mitigation measures and their conservation value while also developing a commercialization strategy for a prototype tool that we developed allowing users to virtually interact with the results of our tradeoff analysis. To assess the financial tradeoffs between right whale mitigation measures and their conservation value we first built a density surface model (DSM) to predict right whale density in the MA/RI WEAs. We used aerial survey data collected by the New England Aquarium (NEAq) between 2011-2020 to fit the model. We used the DSM to estimate the number of right whales exposed to sound levels associated with Level A and B takes during pile driving activities under 10 mitigation scenarios. Mitigation scenarios included combinations of *Seasonal Restrictions* and *Additional Noise Attenuation Systems.* Seasonal restrictions can be used to shift construction activities to seasons when the least number of animals are predicted to be present. Noise Attenuation Systems (e.g., the Big Bubble Curtains (BBC) and Double Big Bubble Curtains (DBBC) considered here) reduce the radial distance that pile-driving noise travels. We estimated the change in the predicted number of right whales exposed to sound levels associated with Level A and B takes between each mitigation measure scenario and the *Early Start and Late Finish Seasonal Restriction scenario* (hereafter "change in takes") because this scenario represents the longest period allowed for pile driving under a seasonal pile driving restriction. We used the results of our tradeoff analysis to develop the R Shiny Decision Support App prototype. This app was built to offer a user friendly and interactive tool to engage interested parties with the key results of our tradeoff analysis.

To develop a commercialization strategy for the decision-support tool prototype we focused on utilizing pre-established experience, relationships, and platforms. After identifying the target audience, we outlined a strategy for the utilization of social media, conferences, community engagement, and infographics. We also presented our Decision Support App prototype to a group of ten colleagues from Orsted and Equinor at a stakeholder engagement workshop. We received valuable feedback during this workshop which we incorporated to further improve the App prototype.

Introduction

The distribution of the critically endangered North Atlantic right whale (*Eubalaena glacialis*) overlaps with offshore wind lease areas along the U.S. Atlantic coast. In the last decade, right whales have undergone widespread distribution shifts, abandoning some historically important habitats and repatriating others (O'Brien et al., 2022). The timing of right whale occurrence in these habitats has also shifted (Pendleton et al., 2022). These widespread changes in right whale habitat use make predicting right whale occurrence at fine spatial and temporal scales difficult. Even though predicting right whale habitat use is challenging, wind energy developers are required to mitigate impacts to marine mammals. Informed mitigation requires an understanding of the spatial and temporal distribution of right whales. Right whales are federally protected under the Endangered Species Act and the Marine Mammal Protection Act (MMPA). Due to the possible impacts of wind energy development construction activities on right whales, permitting through Incidental Take Authorizations (ITA) and Incidental Harassment Authorizations (IHA) are a necessary component of any offshore wind development along the U.S. Atlantic coast. These permits exempt wind energy developers from a small number of Level B harassment takes but developers must mitigate, monitor, and report on impacts to marine mammals.

One example of an offshore wind construction activity that could impact right whales is pile-driving. Pile-driving is used to repeatedly strike a monopile turbine foundation with a hammer until the monopile is secured to the seabed. As the hammer strikes the pile, some of this kinetic energy is transferred into underwater noise which can injure the auditory system of right whales within several kilometers of the pile.

Currently, right whale mitigation for wind energy development is informed by a combination of density estimates (Roberts et al. 2016), historical monthly occurrence data, and real-time monitoring (e.g., Cornell's www.listenforwhales.org). Right whale density is currently estimated at large spatial and temporal scales, and over the entire eastern seaboard. Estimates of density at smaller spatial and temporal scales will likely be more useful for understanding the impacts of wind energy development on right whales. Additionally, regional approaches to estimating habitat use may provide more precise estimates because the drivers of right whale distribution vary by habitat. Real-time monitoring can limit risks to whales that are detected while work is underway. However, real-time monitoring only detects a portion of the whales that are present and some whales will go undetected. In addition, mitigation measures that rely on real-time monitoring are reactionary and do not help with planning development activities. Changes due to scheduling delays can result in monetary losses for wind energy developers. Changes in right whale distribution increase the risks associated with offshore development for both the whales and wind developers.

Right Wind is a three-phase project, with the ultimate goal of **developing a computational tool and environmental compliance service that can be used to avoid or mitigate impacts to marine protected species (such as right whales) and reduce financial risks to wind energy**

developers. To achieve our ultimate goal, we initially developed ecological models (i.e., occupancy models) that predict the probability of right whale occurrence to gain an in-depth understanding of right whale occurrence patterns. However, for these models to accurately predict and forecast whale occurrence, more survey effort and whale sightings are needed. Therefore, we pivoted in Phase 2 to develop DSMs. DSMs have the added advantage of using data from line transect surveys to estimate spatial and temporal variation in animal density, rather than the probability of occurrence (as in occupancy models). Variations in density are estimated as a function of environmental conditions. We used our DSMs to estimate the number of right whales exposed to sound levels associated with Level A and B takes during pile driving activities under 10 mitigation scenarios. Mitigation scenarios included combinations of *Seasonal Restrictions* and *Additional Noise Attenuation Systems.* Seasonal restrictions can be used to shift construction activities to seasons when the least number of animals are predicted to be present. Noise Attenuation Systems (e.g., the Big Bubble Curtains and Double Big Bubble Curtains considered here) reduce the radial distance that pile-driving noise travels. We estimated the change in the predicted number of right whales exposed to sound levels associated with Level A and B takes between each mitigation measure scenario and the *Early Start and Late Finish Seasonal Restriction scenario* (hereafter "change in takes") because this scenario represents the longest period allowed for pile driving under a seasonal pile driving restriction.

Finally, we developed an R Shiny Decision Support App prototype to offer a user friendly and interactive tool to engage interested parties with the key results of this trade-off analysis. It provides a method by which developers and interested parties can better understand the relationship between construction timing, mitigation measures, and the predicted impacts to right whales in the MA/RI WEAs. We showcased our prototype app at a stakeholder workshop attended by colleagues from Orsted and Equinor.

Methods

Task 1: Develop Predictive Models of Right Whale Distribution

Occupancy models estimate changes in species occurrence over time while accounting for imperfect detection. We will estimate the probability of right whale occurrence using multi-season occupancy models (Mackenzie and Royle, 2005). Using this approach will allow us to estimate changes in right whale occurrence at sites (i.e., 4.6-by-4.6 km grid cells) in the southern New England region over time (Figure 1). This grid cell size was selected to conform with the resolution of the satellite environmental data products that will be used in our occupancy models. We will use the occupancy models to estimate the probability of right whale occupancy, colonization, persistence, and detection in the MA/RI WEA and surrounding waters. Occupancy estimates are the probability that a grid cell is occupied at a given time. Colonization estimates are the probability that whales will enter an empty grid cell, while persistence estimates are the probability that whales will remain in an already occupied grid cell. Detection probability is the probability that a whale that is present is observed during a survey.

Whale occurrence is influenced by a number of biological and oceanographic variables. Fitting occupancy models with environmental covariates helps us understand the conditions that influence species distribution patterns and how the influence of each environmental condition may change seasonally. Using environmental covariates also enables predictions of species distributions throughout our study area (e.g., regions between the aerial survey transect lines) using broad-scale, spatially-contiguous, environmental data layers such as interpolated sea surface temperature (SST), deep-water temperatures or primary production.

Multiple studies suggest that uncertainty in predicted marine mammal occurrence can be reduced through the incorporation of multimodal survey data (Clark et al., 2010; George et al., 2013; Kraus et al., 2016). However, this hypothesis has not yet been rigorously tested. To test this hypothesis and attempt to reduce uncertainty in our modeled estimates, we will fit occupancy models using aerial survey, acoustic survey, and combined data sources. By using both datasets, we anticipate a reduction in uncertainty through an increase in the frequency of surveys. Detection range during wildlife surveys varies depending on the survey platform/modality and environmental conditions. Due to this modality-dependent range, a multi-scale occupancy model is required to develop the combined aerial and acoustic survey model (Nichols et al., 2008). Using multi-scale occupancy models will allow us to simultaneously estimate right whale occupancy and detection probability at the larger spatial scale of the acoustic detection range and the smaller spatial scale of the aerial survey detection range. Additionally, the predictive ability of oceanographic covariates may vary by spatial scale and can be assessed using this method. For example, at the larger spatial scale (i.e., the acoustic scale), *C. finamrchicus* may be an indicator of right whale occupancy. Oceanographic fronts, which may aggregate *C. finmarchicus* into the concentrated patches required to elicit right whales feeding behavior, may be a better predictor of right whale occupancy at the smaller spatial scale (i.e., the grid cells used for summarizing the aerial survey data).

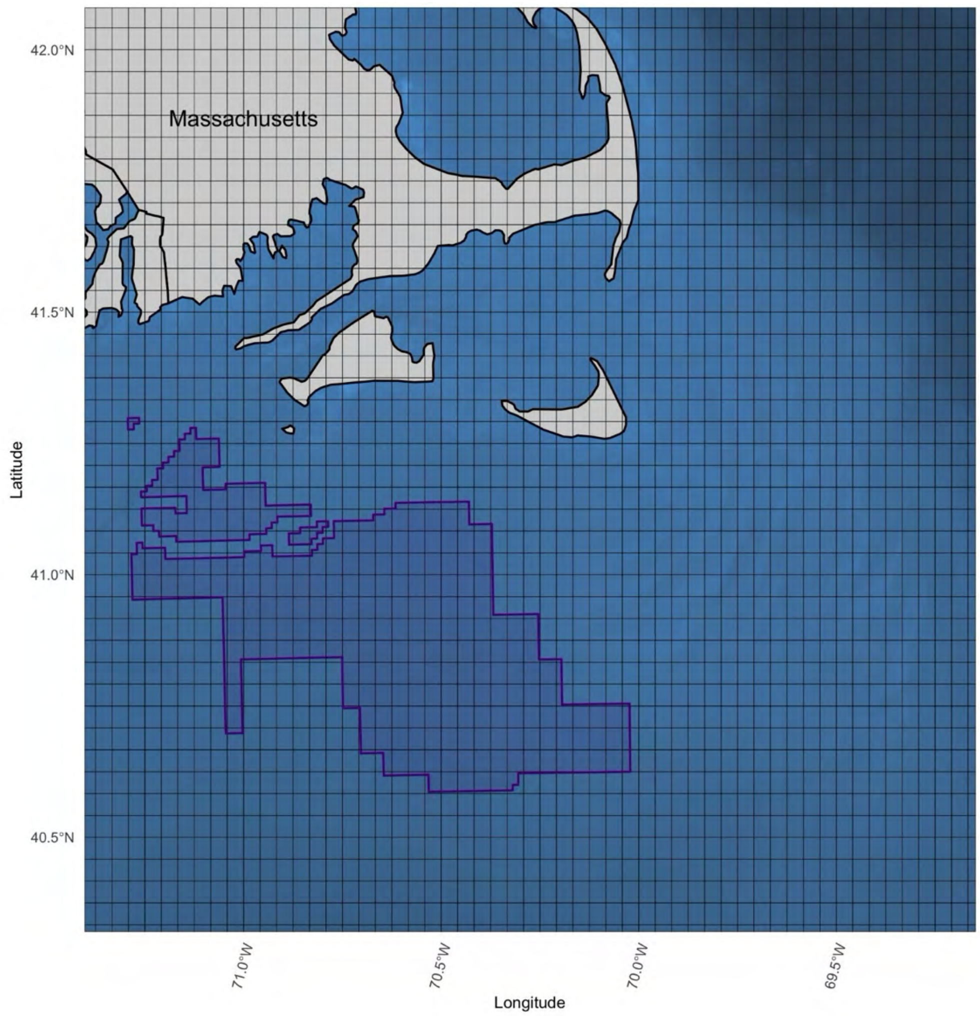


Figure 1: Southern New England with a 4.6-by-4.6 km grid overlay. The probability of right whale occupancy will be estimated by grid cell. The Massachusetts and Rhode Island Wind Energy Area is outlined in purple.

Task 1 is subdivided into two subtasks. The first subtask (1.1) is combining the visual and acoustic data set of right whale occurrence in the MA/RI WEA. The second subtask (1.2) is to develop the ecological probability models.

1.1 Combine visual and acoustic data of right whale occurrence in the MA/RI WEA

1.1.1 Visual detections of right whales

The NEAq has been conducting aerial surveys in and around the MA/RI WEA from 2011 through the present (Figures 2 and 3). These surveys have been funded by MassCEC, the Bureau of Ocean Energy Management (BOEM), and wind energy developers. A gap in funding resulted in no aerial surveys in 2016. The aerial survey team aims to fly two general line-transect aerial surveys every month but the realized effort is weather dependent. General surveys are comprised of twelve north-south tracklines evenly spaced at approximately six nautical miles (nm). Eight survey options are available: each option shifts all 12 tracklines 0.75 nm east or west, but maintains the six nm spacing between tracklines. Survey options were selected at random before each survey. Surveys were conducted in Cessna Skymasters O-2A (2011-March 2021) or Partenavias P68C (April 2021-present) at an altitude of 1,000 feet (ft) and a ground speed of 100 knots (kts). Our analyses require data that has undergone the extensive QA/QC process conducted by the North Atlantic Right Whale Consortium (NARWC). Therefore, our analyses only use data collected through 2021.

We subset the aerial survey data to ensure only general surveys conducted under specific conditions are used in the analyses (i.e., good visibility, Beaufort sea states less than or equal to 3, and effort conducted only on the north–south tracklines; Figure 2). This subset of the aerial survey effort and sightings data were summarized in 4.6 km x 4.6 km grid cells.

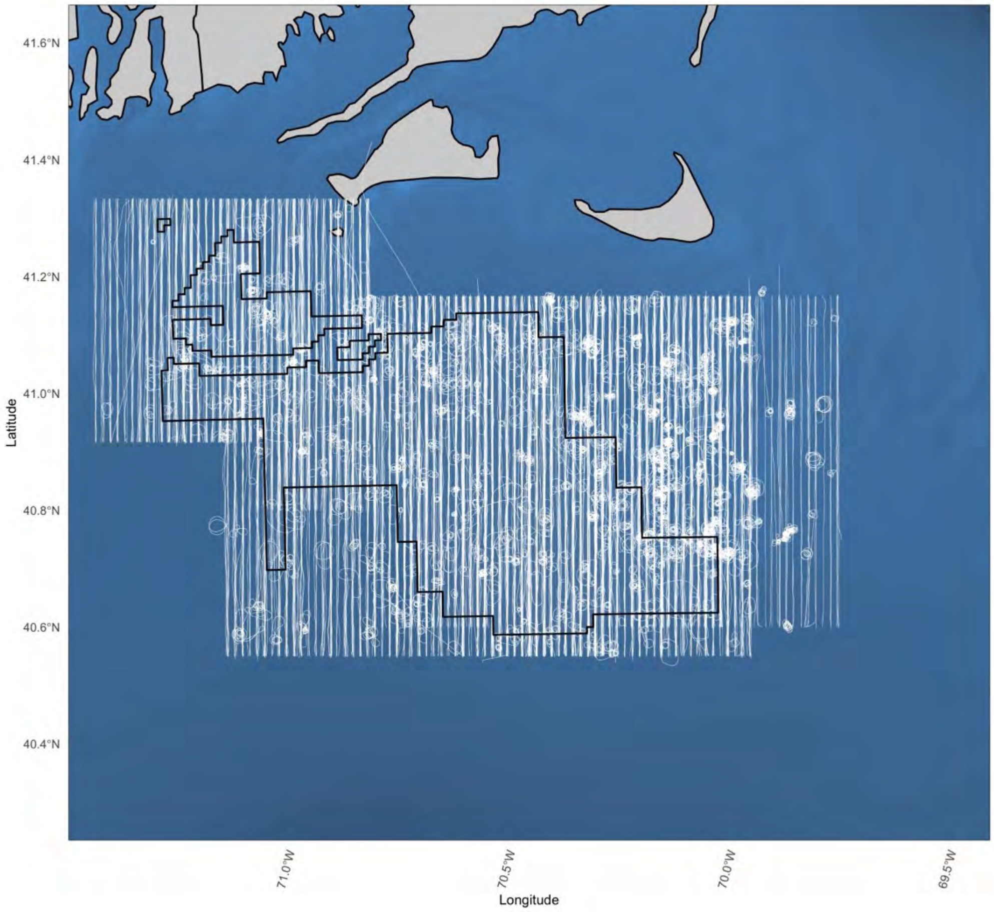


Figure 2: Aerial survey tracklines (white) flown between 2011 and 2021. The effort data used to make this figure has been put through the data processing code developed to remove aerial survey effort data conducted in low visibility and/or high Beaufort sea states. We also removed effort conducted on transits between transects (i.e., cross-legs). Aerial surveys were flown by the New England Aquarium in and around the Massachusetts and Rhode Island Wind Energy Areas (black outline).

1.1.2 Acoustic detections of right whales

Acoustic surveys were conducted using a network of marine autonomous recording units (MARUs) by the Cornell Lab Center for Conservation Bioacoustics. These surveys were funded by MassCEC. Bottom-mounted MARUs were deployed from November 2011 through March 2015 and recorded continuously during their deployment (Figures 3 and 4). The MARUs were suspended 3 meters above the seafloor. We used upcalls to determine right whale presence. The MARU detection range varies by the amount of background noise (Estabrook et al., 2022). Under median (50^{th} percentile) noise conditions in the right whale communication frequency band (upcalls, 71-224 Hz), the detection range is estimated to be 8 km. Under low (5th percentile) noise conditions, the detection range is estimated to be 22 km (Figure 4; (Estabrook et al., 2022).

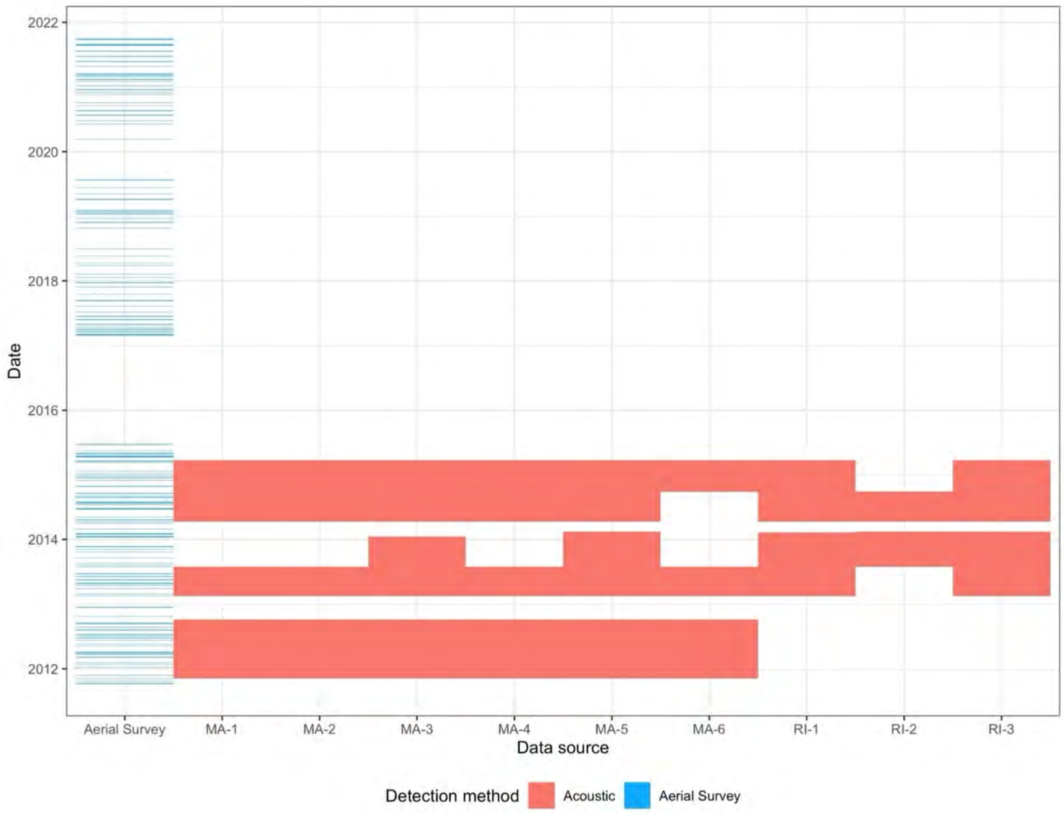


Figure 3: Temporal overlap in survey modalities. The New England Aquarium conducted aerial surveys approximately twice a month from 2011 to 2021, no surveys occurred in 2016. The Cornell Lab conducted acoustic surveys using nine marine autonomous recording units (MARUs) from 2011 through 2015. Blue bars represent the days aerial surveys were conducted. Orange bars represent the time periods that each MARU was recording. MARUs continuously record while deployed and therefore are represented by large chunks of orange.

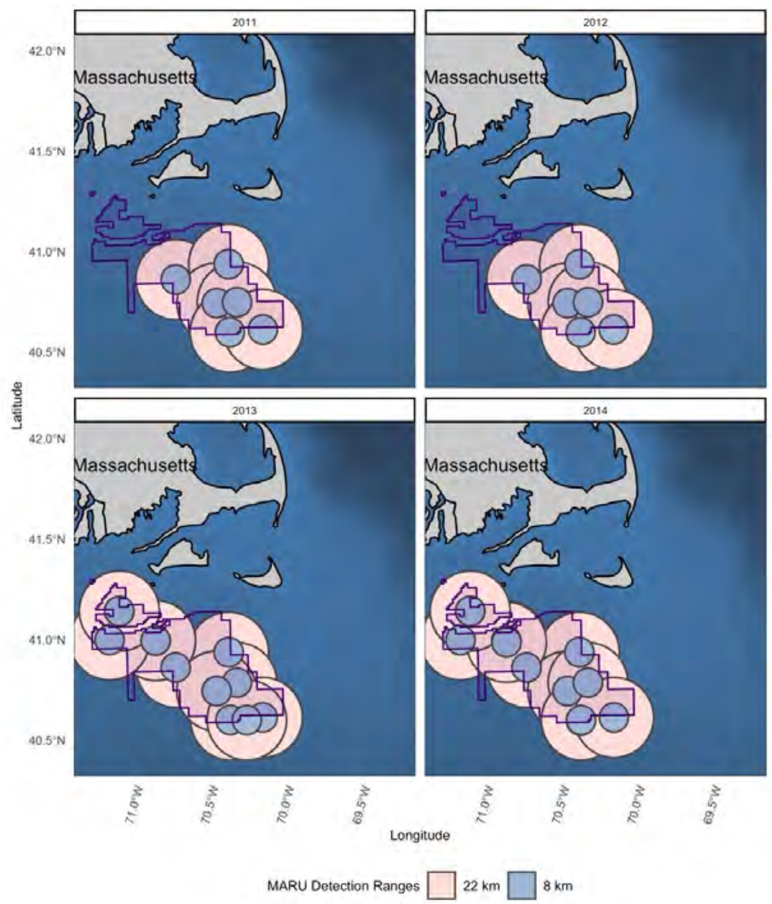


Figure 4: Distribution of marine autonomous recording units (MARUs) by year. Acoustic detection range is dependent on ambient noise levels. Under low noise conditions the detection range is 22 km (pink circles), under mid-level noise conditions the detection range is 8 km (blue circles). The Massachusetts and Rhode Island Wind Energy Area is outlined in purple.

1.1.3 Combination and comparison of aerial and acoustic detections of right whales

O'Brien et al. (2022) estimated seasonal right whale abundance using aerial survey data. The abundance estimates represent the average abundance for any given day within the season. For example, a spring abundance estimate of 24 right whales would be interpreted as: on the average spring day we would expect 24 right whales to be present in the survey area. To compare the aerial and acoustic survey datasets, we began with a qualitative comparison of a 30-day moving average of right whale upcalls to the estimates of right whale abundance by O'Brien et al. (2022). Additionally, we extracted right whales observed by the aerial surveys that were within the detection range of the MARUs. Finally, we used a Spearman correlation to determine the relationship between aerial survey data and acoustic data. Spearman correlations were used because the data are non-normally distributed. First, we determined the correlation between estimated right whale abundance and the number of upcalls detected during the same time period. However, there may not be a direct relationship between the number of right whales and the number of upcalls because a single whale can generate multiple calls. Therefore, we also compared right whale abundance to the proportion of days that at least one right whale upcall was detected.

1.2 Ecological Probability Models

1.2.1 Analysis plan

We fit our first model with aerial survey data from 2011 – 2021 (hereafter referred to as the "Aerial Model"). We used SST, bathymetry, chlorophyll *a* as oceanographic predictors. Beaufort sea state and Julian day were used as predictors of the probability of detection. Oceanographic front data will be used in the Aerial Model but will not be included until Phase 2. This model will be compared to:

- Acoustic Model: A model fit using acoustic data from 2011 – 2015 with SST, bathymetry, chlorophyll *a,* and modeled *C. finmarchicus* as environmental covariates.
- Aerial and Acoustic Model: A model fit using both the aerial survey and acoustic data with SST, bathymetry, chlorophyll *a,* and modeled *C. finmarchicus* as environmental covariates.
- Aerial and Zooplankton Model: A model fit using aerial survey data from 2011 – 2017 with the original environmental covariates and modeled *C. finmarchicus.* This model will not include data from 2018 – 2021 because *C. finmarchicus* data are only available through 2017.

We compared right whale occupancy models run under a number of scenarios (Table 1), in which we varied the temporal scale (i.e., months within a season) used to fit the model. The temporal scale selected for our final model is dependent on the number of surveys within a site during each season. Typically, at least three repeat surveys within a site during each season are the minimum required for model convergence. In addition, precise occupancy estimates rely on repeated surveys of a site during the season. We tested a number of temporal scales to determine how the precision of our estimates changes as we increase the resolution of the temporal scale (Table 1). For example, initially we ran the model with four three-month seasons every year; other scenarios included 12 one-month seasons. We also varied the number of iterations used in the Markov Chain. Increasing the number of iterations may increase the likelihood of model convergence but it also can drastically increase the model run time.

1.2.2 Oceanographic Covariates

We wrote code in R (R Core Team, 2022), MATLAB (The MathWorks, Inc., 2022), and the *m_map* toolbox (Pawlowicz, 2020) to aggregate the oceanographic covariates in the same 4.6 km spatial resolution as the aerial survey data. SST and chlorophyll *a* data were collected by the

Moderate Resolution Imaging Spectrometer (MODIS) instrument on the Aqua satellite between 2011 and 2021. Satellite data were downloaded as monthly 4.6 km resolution Level 3 coverages from the National Aeronautics and Space Administration (NASA) Ocean Color web. We obtained bathymetric data from the National Center for Environmental Information (NCEI) U.S. Coastal Relief Model. We also met with oceanographers at the NOAA Northeast Fisheries Science Center (NEFSC) who supplied us with oceanographic frontal data. Both the *C. finmarchicus* dataset and the oceanographic fronts were processed according to our temporal and spatial modeling resolutions.

Table 1: Modelling scenarios and trial strategies. Each scenario will be run in multiple trials. Trials may vary by the data included to fit the model, environmental and detection covariates, and the number of iterations, chains, and burn-in period. Trials that have been run during phase 1 have been assessed for convergence using Gelman-Rubin statistics.

Scenario	Trial #	Model	Years	Temporal Resolution	Environmental Covariates	Detection Covariates	Model Run?	Convergence	# Iterations	# Chains	Burn-in	Time to Run
Aerial Model	1	Multi-season occupancy model	2012-2021	4-3 Month Seasons	SST, Chlorophyll *a*, Bathymetry	Beaufort sea state, julian day	Yes	No	240,000	3	0	51.9 hours
	2	Multi-season occupancy model	2012-2021	4-3 Month Seasons	SST, Chlorophyll *a*, Bathymetry	Beaufort sea state, julian day	In progress	N/A	480,000	3	0	Power Outage
	3	Multi-season occupancy model	2012-2021	3-4 Month Seasons	SST, Chlorophyll *a*, Bathymetry	Beaufort sea state, julian day	Yes	No	240,000	3	0	18.2 hours
	4	Multi-season occupancy model	2012-2021	12 - 1 Month Seasons	SST, Chlorophyll *a*, Bathymetry	Beaufort sea state, julian day	In progress	N/A		3		Power Outage
	5	Multi-season occupancy model	May - October 2012-2021	2 - 3 Month Seasons	SST, Chlorophyll a, Bathymetry	Beaufort sea state, julian day	Yes	No - run longer	120,000	3	0	22.6 hours
	6	Climatological model	2012-2021	TBD	SST, Chlorophyll a, Bathymetry	Beaufort sea state, julian day	No	N/A	N/A	N/A		N/A
Aerial and Zooplankton Model	1	Multi-season occupancy model	2012-2017	4-3 Month Seasons	*Calanus finmarchicus*, SST, Chlorophyll *a*, Bathymetry	Beaufort sea state, julian day	Yes	No - run longer	240,000	3	0	71.63 hours
	2	Multi-season occupancy model	2012-2017	2 - 2 Month Seasons 24-46	*Calanus finmarchicus*, SST, Chlorophyll *a*, Bathymetry	Beaufort sea state, julian day	Yes	No - run longer	120,000	3	0	5.2 hours
Aerial and Acoustic Model	1	Multi-Scale occupancy model	2012-2021	TBD	SST, Chlorophyll a, Bathymetry	Beaufort sea state, julian day	No	N/A	N/A	N/A	N/A	N/A
Acoustic Model	1	Multi-season occupancy model	2012-2015	TBD	*Calanus finmarchicus*, SST, Chlorophyll *a*, Bathymetry	TBD	No	N/A	N/A	N/A	N/A	N/A

1.2.3 Modeling methods

We fit occupancy models with JAGS (Plummer, 2003) using the *R2jags* package (Su and Yajima, 2021) in R. We used vague priors (i.e., normally distributed with a mean = 0 and a variance = 0.1). The number of chains, iterations, and burn-in varied by modeling scenario (Table 1). We visually checked for model convergence by assessing traceplots and Gelman-Rubin statistics (Gelman et al., 2004). Inference on parameters was made using 95% Bayesian credible intervals. Distributions of parameter estimates that did not overlap 0 at the 95% credible interval were considered to be extremely likely to have an effect while distributions of estimates that did overlap 0 at the 95 % credible interval were not considered further.

1.2.4 Occupancy Model Validation

We used the acoustic survey data to validate the models fit with visual survey data. Our initial methods for model validation used a Spearman correlation to determine the relationship between the probability of mean habitat use estimated using the Aerial Model over the entire study area and three different metrics summarizing habitat use based on the acoustic survey data: 1) the number of days when at least one upcall was detected; 2) the proportion of recording days when an upcall was detected; 3) the number of recording days when an upcall was detected.

Task 2: Estimate Uncertainty in Right Whale Predictions

2.1: Estimates of uncertainty in right whale predictions

To measure the estimated uncertainty in our Right Wind models, we wrote code in R to estimate and map lower and upper 90% credible intervals for the probability of colonization and persistence. In addition, we wrote code that maps the difference in the upper and lower credible intervals. These maps clearly visualize the variation in the precision of the predictions over space and time.

Task 3: Develop Financial Risk Assessment Scenarios

We have researched the impact of noise on right whales, public IHAs (including those for the Vineyard Wind I and South Fork Wind Farm projects), and the various mitigation measures that developers can utilize to maintain compliance with their IHAs. We developed three pile-driving impact scenarios. To create the scenarios, we have designed a hypothetical offshore wind farm and determined the foundation installation methods for this farm, where all qualities of the farm and the installation methods reflect business-as-usual (hereafter referred to as the "*Early Start and Late Finish* scenario") at the time of this report (fall 2022). Then, we adapted this baseline into two new scenarios which vary only in their foundation installation timeline and methods.

The hypothetical farm contains 70 turbines with an assumed 10.3-meter diameter monopile foundation and transition piece (Figure 5). The foundation diameter is reflective of industry trends towards larger wind turbines.

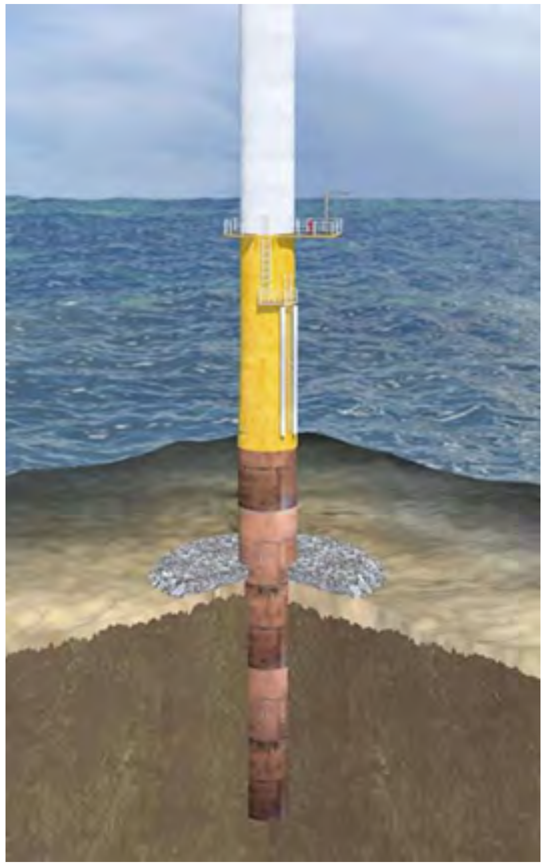


Figure 5: Computer rendering of a monopile installed into the seabed. This image shows the monopile with a transition piece installed atop it and scour protection installed where the monopile meets the subsea surface.

The farm's location is an important aspect of the financial assessment of these scenarios because the varying characteristics of farm location such as water depth, piling target depth, and soil profile inform the durations of campaign activities, which have a direct relationship with overall campaign duration and associated financial cost. The location and layout of the farm aimed to satisfy three objectives:

1. Reflective of a foundation installation campaign in the MA/RI WEA
2. Overlapping with both the acoustic and the aerial survey data used to generate the models
3. Nonspecific to any one or handful of ongoing projects/developers

For the purposes of generating the mitigation scenarios, we selected one sample location, centered at 40°47'09.6"N 70°48'43.2"W, southwest of the MA/RI WEA. This area, shown in Figure 6, has been excluded from the MA/RI WEA due to its role as a munition disposal site; for our purposes, we assume this area is feasible for development. The farm layout follows the one nautical mile grid layout endorsed by the Coast Guard and observed by all developers within the MA/RI WEA, as shown with bathymetric contours in Figure 7. All piles are installed by impact pile-driving, and per expectation of NOAA, each pile will be installed with two methods of noise attenuation, one of which is a BBC.

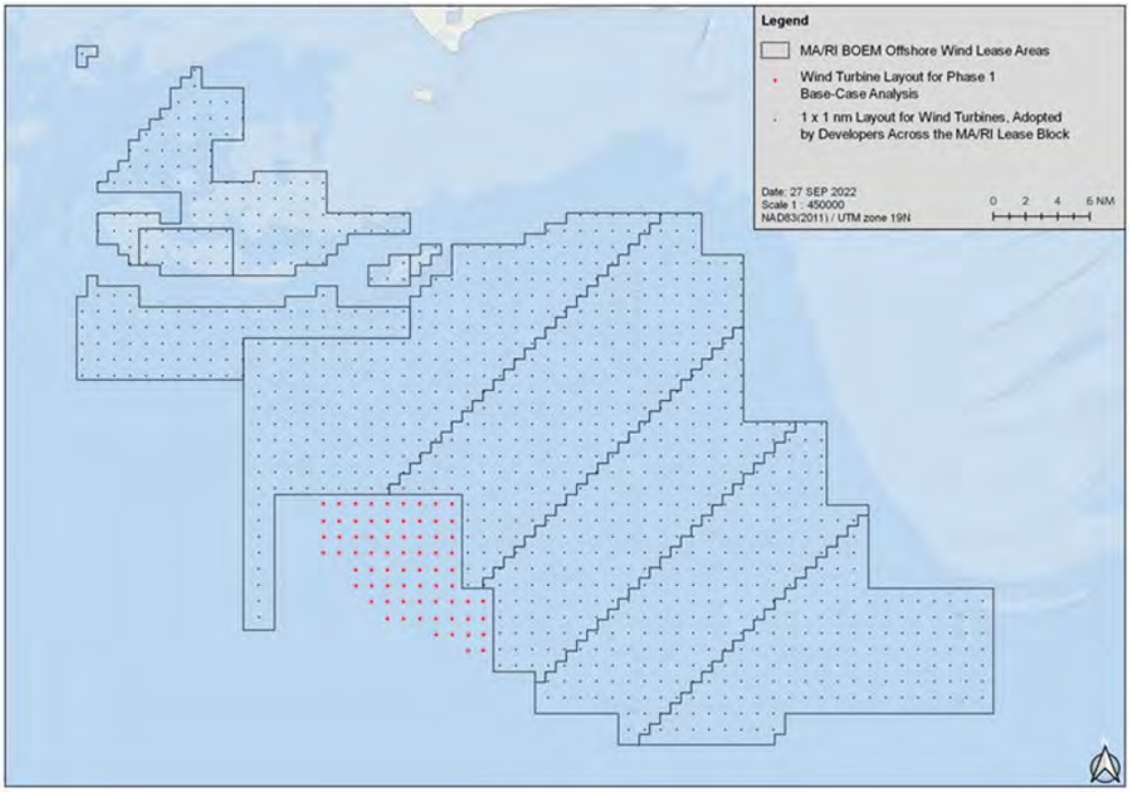


Figure 6: Simulated windfarm in the MA/RI Wind Energy Area. Dots show a one nautical mile grid turbine layout within the WEA and the layout of the 70-position hypothetical farm for which the foundation installation schedule in this report was built.

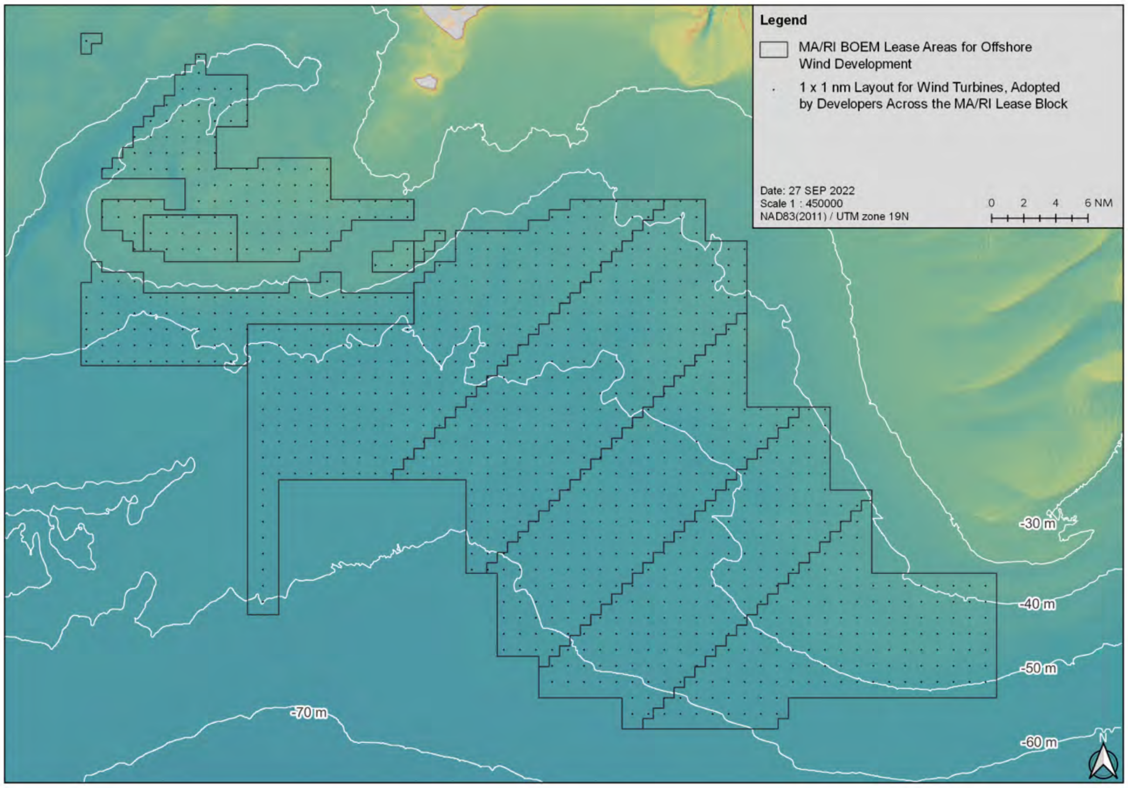


Figure 7: One nautical mile grid layout inside the Massachusetts and Rhode Island Wind Energy Area with bathymetric contour lines. This whole area will be sampled in the Monte Carlo simulation in the next phase of the project.

We assumed that a conventional heavy lift vessel (HLV) is conducting pile-driving, as opposed to a jack-up vessel. The vessel will install the foundations in batches with the ability to load out five monopiles and transition pieces and install these before returning to port. The New Bedford Marine Commerce Terminal (NBMCT) was selected as the marshalling port due to its optimal location for serving the whole MA/RI WEA. It is assumed that the HLV will follow the traffic separation scheme before taking a direct path of transit to the farm location (Figure 8). Thus, using an average transit speed of 6 knots and approximate transit distance of 145 km from the NBMCT to the center of the project area, transit time was estimated to be 13 hours.

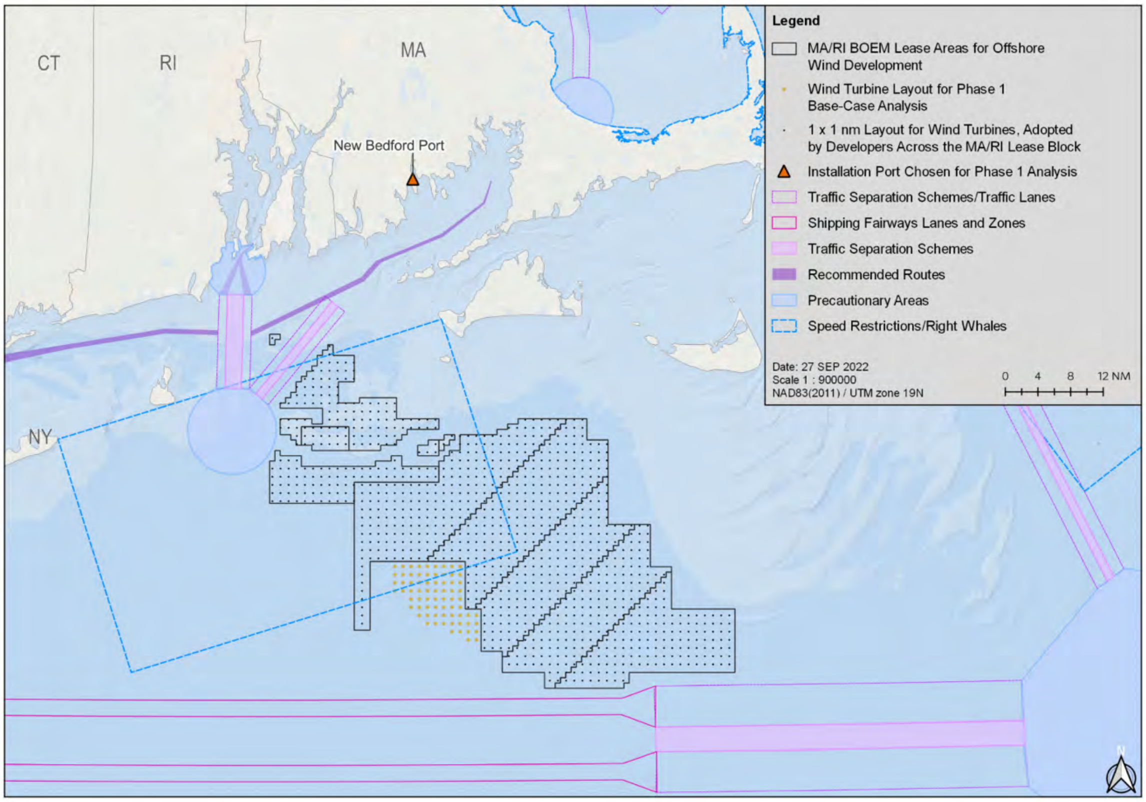


Figure 8: The Massachusetts and Rhode Island Wind Energy Area, one nautical mile grid layout, and the traffic separation schemes for the installation vessel. The vessel will transit from the New Bedford Port to outside the northwest corner of the block, then transit through the Wind Energy Area to the farm location.

Task 4: Determine the Models' Ability to Forecast Right Whale Distributions

Task 4 is subdivided into two subtasks. The first subtask (4.1) is determining oceanographic variables that best predict whale occurrence. The second subtask (4.2) is determining the best spatial and temporal scales for forecasts.

Occupancy models estimate changes in species occurrence over time while accounting for imperfect detection. However, as indicated in our results for Task 1.1, we were not able to get an occupancy model to converge. Occupancy models require multiple surveys of each site (grid cell) within the time period of interest. The low number of repeat site visits per season likely prevented our models from converging. Because the model did not converge, it cannot be used for decision-making or forecasting. Therefore, to complete Task 4, we fit DSMs. Like occupancy models, DSMs account for imperfect detection, but they have the added advantage of estimating spatial and temporal variation in animal density, rather than the probability of occurrence (as in occupancy models). Variations in density are estimated as a function of environmental conditions.

Aerial surveys

To account for changes in altitude and the aerial survey platform, the dataset used in Task 4 is slightly different than the dataset used in Task 1, the aerial survey methods for Task 4 are as follows. Whale sightings were collected during aerial surveys, flown approximately twice monthly, in Southern New England between 2011 and 2020 (Figure 2). Aerial surveys were flown at a ground speed of 185 km/h and an altitude of 305 m, in a Cessna Skymaster 337 O-2A aircraft. Trackline effort and environmental conditions were recorded every 2-5 seconds. Two observers, one on either side of the aircraft, scanned their field of view for whales. Sightings were recorded when they were perpendicular to the aircraft. Marks on the wing struts were used to record the estimated distance of the sighting from the trackline. When right whales were sighted, the plane diverted from the trackline to obtain photo-identification data for monitoring use of the area by individual whales.

Data preparation

To use the aerial survey data in DSMs, sections of aerial survey tracklines with uninterrupted survey effort were separated into approximately 4.6 km segments. In particular, we determined how many 4.6 km segments were contained in the uninterrupted survey effort. If the remaining effort was ≤ 2.3 km long, we randomly selected one segment to include the target 4.6km of effort and the remaining amount of effort. If the remaining effort was ≥ 2.3 km, we randomly selected one segment to have a target distance equal to the remaining amount of effort. If the entire section of uninterrupted survey effort was < 4.6 km, it was treated as a single segment. We then summed the point-to-point distances to make segments totaling each target distance. However, the sum of the point-to-point distances was not always equal to the target distance. To avoid biasing the segment lengths, we randomly determined if the segment should be slightly longer or shorter than the target distance. We also summarized the number of whale sightings and the number of whales in a group for each segment.

To estimate whale density, we used a multi-step modeling approach. The first step included fitting a detection function and estimating the effective strip width. The details of this process can be found in O'Brien et al., (2022). Because these surveys were flown in closing mode (i.e., the team diverted from the trackline to obtain photographs of individual whales), some whales were observed when the plane was not on the trackline. To adhere to the assumptions of distance sampling, the detection function was fit only with whales sighted from the trackline (Figure 9). In contrast, the spatial model (described below) was fit with all animals regardless of whether the animal was detected when the plane was on or off the trackline. The *Distance* package in R was used to fit a detection function with a hazard rate model (Miller et al., 2019; R Core Team, 2022). The second step in the modeling process included fitting generalized additive models (GAMs) to capture the relationship between the number of whales observed on a segment and oceanographic predictor variables (described below). We used a tweedie distribution and fit the models using the *dsm* package in R (Miller et al., 2013; R Core Team, 2022). Parameter estimates were optimized using restricted maximum likelihood (REML). Thin plate regression splines were used to model the relationship between individual environmental variables and right whale density. Relationships between whale density and interactions between variables were modeled using tensor splines. Density (*D*) was estimated as:

$$D_i = (n_i/L_i) * \tfrac{1}{2}(ESW) * g(0)$$

Where *n* is the number of animals on segment *i* and *L* is the length of the segment (km). *ESW* is the effective strip half width estimated from the detection function. We assumed perfect detection on the trackline (i.e., g(*0*) = 1). An offset was used in the GAMs to include the natural log of the effective area searched.

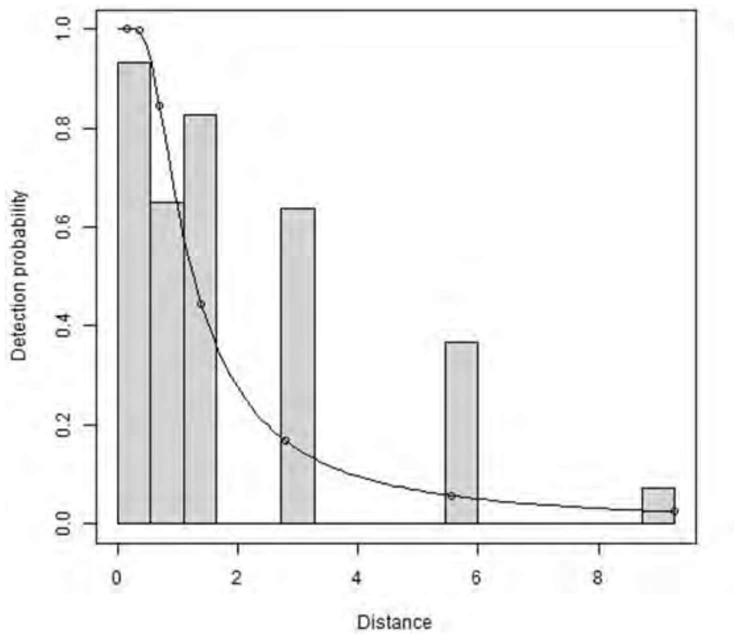


Figure 9: Right whale detection function derived from aerial survey data collected between 2011 and 2020. The line is the fitted detection function. The gray bars represent the number of sightings at each distance (km).

We assessed model fit by visually inspecting q-q plots and using the root mean squared error (RMSE). We compared models using the receiver operating characteristic curve (AUC) and Akaike's Information Criterion (AIC score). Models with larger AUC values have a better fit, while lower AIC scores indicate models with more support. Ultimately, we used AIC scores to determine the model with the most support to predict right whale density. To ensure extrapolation errors did not occur in our density predictions, we visually inspected histograms of the environmental data used for model fitting against the environmental data used to make predictions.

Variance was estimated using the methods outlined by Miller et al. (2022). Because we did not use predictor variables to model our detection function, we used the delta method to propagate the uncertainty in detectability into the GAMs. We then used a multivariate normal distribution to simulate 10 samples using the GAM parameters (β) and covariance matrix. For each eight-day period we calculated the predicted abundance for each grid cell 10 times (i.e., one abundance estimate per grid cell for each of the β samples). We then used the Welford method to summarize the seasonal average density and variance for each grid cell.

4.1 Oceanographic variables that best predict whale occurrence and the best spatial and temporal scales for forecasts.

We used DSMs to model whale density as a function of oceanographic variables (Table 1). Right whales have been observed over a wide range of depths and their preferred depths vary by habitat. In the Gulf of Maine right whales regularly occur in waters 100 to 200 m deep. However, in Cape Cod Bay, which is a prolific spring feeding ground, right whales occur in waters that are only 18 to 60 m deep. We used 0.00083° resolution depth data from the Northeast Coastal Relief Model V154 as a predictor variable in our DSMs. We calculated the distance from each segment midpoint to the 30, 40, and 50 m isobath using the marmap package in R (Pante and Simon-Bouhet, 2013; R Core Team, 2022). Right whales primarily feed on *Calanus finmarchicus* (Mayo and Marx, 1990); in the absence of right whale prey data suitable for our study, we used chlorophyll a concentration as it is an indicator of primary production, which should be broadly indicative of secondary production and the zooplankton species, such as *C. finmarchicus*, that are targeted by right whales. We used Aqua MODIS Global Mapped Chlorophyll data sampled at eight-day intervals at a 4 km spatial resolution (NASA Ocean Biology Processing Group, 2017). In Cape Cod Bay, abundance of *C. finmarchicus* and *Centropages typicus*, a second right whale food source, were found to be correlated with salinity (DeLorenzo Costa et al., 2006). We obtained four-day salinity data on a 1/4° grid from the Multi-Mission Optimally Interpolated Sea Surface Salinity Global Dataset V1(IPRC/SOEST, 2021). Previous studies have found the winter distribution of right whales to be largely determined by SST, although the mechanism for this influence is unclear (Pendleton et al., 2012). We obtained daily SST data on a 0.01 ° grid from the GHRSST Level 4 MUR Global Foundation Sea Surface Temperature Analysis (v4.1) (NASA/JPL, 2015). All oceanographic variables were standardized on a 4.6 km grid, over eight-day periods. Oceanographic data were associated with the midpoint of each trackline segment. We created eight-day, 4.6 km prediction grids, over the spatial extent of the prediction box (Figure 10).

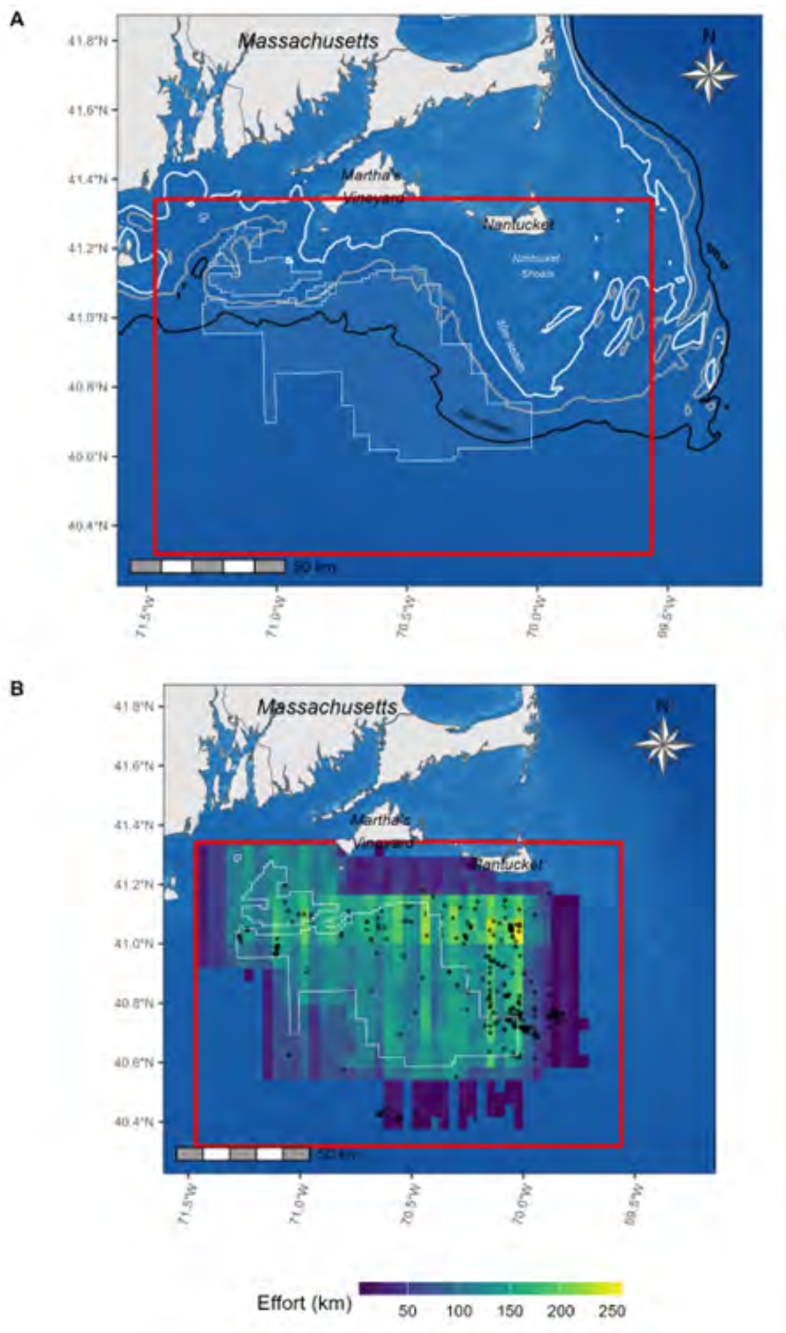


Figure 10: Right whale modeled density in the the southern New England study area. A) Bathymetry of project area, with relevant isobaths in white, grey, and black. B) The New England Aquarium aerial survey effort (km), summarized in 4.6 km grid cells. Black dots represent right whale sightings made during aerial surveys. The Massachusetts / Rhode Island Wind Energy Area is outlined in white. The density prediction area is outlined in red.

4.1.2 Best spatial and temporal scales for forecasts

To determine the model's ability to forecast right whale distributions, we fit a model for the years 2011 through the end of 2020. We then used that model to make predictions for 2021 through July of 2022. We visually compared the model predictions with the distribution of right whales observed by the aerial surveys.

Task 5: Develop Commercialization/Marketing Strategy

Task 5 is subdivided into four subtasks. The first subtask (5.1) is developing an effective marketing plan. The second subtask (5.2) is drafting several pieces of social media content. The third subtask (5.3) is drafting an industry-grade white paper that highlights the project and its proposed findings and recommendations. The fourth and final subtask (5.4) is to present at a major offshore wind conference.

To develop an effective marketing plan, we first identified the target audience. Next, we assessed what resources and outlets were already accessible to the team, such as social media outlets and conference opportunities. This also includes the extensive scientific and industry networks of the NEAq, Cornell University, and LAUTEC. Example text and social media posts were drafted on the basis of previous marketing experience and the message we hope to convey to each of our networks.

We drafted an industry-grade white paper to fulfill subtask 5.3. The content of this draft can be found in Appendix A.

Task 6: Assess Financial Risk; and Task 7: Analyze Economic Tradeoffs

To determine the tradeoffs between the financial costs of mitigation measures and their conservation benefit, we developed a wind energy construction simulation. In the simulation, 10.3diameter monopile foundations and transition pieces are installed 1 nm apart across the WEAs (Figure 11A). We assume monopile foundations would be constructed using an industry standard piling technique. This method involves dropping a hammer onto the monopile foundations to drive them into the stable seabed.

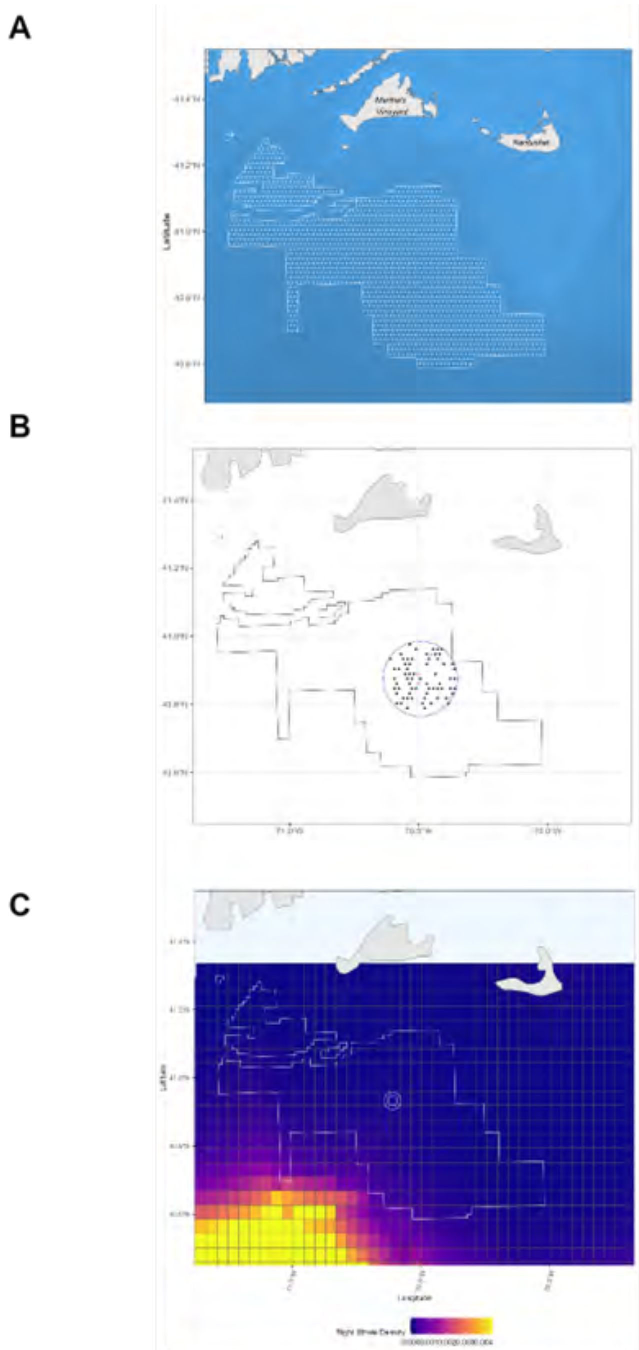


Figure 11: Schematic of tradeoff simulation. A) Simulated windfarm layout for the Massachusetts/Rhode Island Wind Energy Areas (white outline) with hypothetical turbines (white circles) spaced 1 nautical mile apart. B) 70 randomly chosen turbines within the circular buffer (blue circle) and five turbines (pink dots) randomly chosen for pile-driving in the first eight-day period of the simulation. C) shows right whale density summarized by grid cell for a single eight day period (C). The white circles indicate the Level A take ranges using 10 and 12 dB of noise attenuation.

Noise transmitted during pile driving is expected to have the biggest impact on cetaceans that communicate with low frequency sounds when compared to other potential wind energy construction impacts (Madsen et al., 2006). Pile driving sound transmission is dependent on several factors including seasonal variation in oceanographic conditions, bathymetry, substrate, pile material and diameter, and the energy of the pile driving hammer (Bailey et al., 2010). The U.S. MMPA defines Level A harassment as any act of pursuit, torment, or annoyance which has the potential to injure a marine mammal or marine mammal stock in the wild (NMFS, 2024). Level B harassment is defined as any act of pursuit, torment or annoyance which has the potential to disturb a marine mammal or marine mammal stock in the wild by causing a disruption of behavioral patterns, including, but not limited to, migration, breathing, nursing, breeding, feeding, or shelter. Acoustic exposure thresholds for Level A and B harassment are defined for protected species. Acoustic thresholds are used to quantify the size of the area surrounding the pile-driving that would encompass Level A and B take zones. Animals found within these zones would be exposed to acoustic thresholds surpassing what is considered a Level A or B take. Sound levels exceeding these thresholds within the zone result in a "take" of the protected species. The allowable number of takes are defined in projects permits.

To quantify the impact of wind energy development on right whales, we used predictions from our DSM to calculate the number of whales that would occur within Level A and B take zones, which means the whales could be exposed to sound levels associated with Level A and B takes (Figure 11C; hereafter, referred to as the predicted number of whales exposed to sound levels associated with Level A and B takes). We selected right whale density predictions from the eight-day period corresponding to the installation of the five selected turbines. To propagate variation in the density estimates through the tradeoff analysis we calculated the predicted number of whales exposed to sound levels associated with Level A and B takes ten times (i.e., one for each of the ten density estimates we calculated per grid cell per eight-day period). Density predictions may be missing for a grid cell if environmental data was missing for that eight-day period. We replaced these missing values with the average density prediction for that grid cell from the previous and post eight-day period. If the previous and post eight-day period also had missing values the density prediction was replaced with the monthly average for that grid cell. If the monthly average was also missing, the density was replaced with the seasonal average for that grid cell. We calculated the mean and variance of the ten density estimates to quantify the predicted number of whales exposed to Level A and B takes. We summed the predicted number of whales exposed to Level A and B takes over the development period to determine the predicted number of whales exposed to takes in each campaign.

The radial distance of Level A and B take ranges can be reduced using noise mitigation systems like BBCs. Compressed air is forced through holes in a hose, lying in a circle on the seafloor around the construction site, emitting a bubble curtain into the water column. A DBBC consists of two hoses lying on the seafloor. The noise attenuation, and therefore the radial distances of the take ranges, for BBCs can vary depending on the volume of compressed air, the size and spacing of the holes in the hose, the distance from the hose to the pile-driving location, current direction and speed, and water depth (Bellmann et al., 2020). BBCs have been optimized for up to 15 dB of noise attenuation and DBBCs have been optimized for up to 18 dB of noise attenuation (Hydrotechnik Lubeck, 2022). In our simulation, we assume a BBC attenuates noise up to 10 dB and a DBBC would attenuate noise up to 12 dB. To determine the radial distances of Level A and B take ranges we compiled data from the literature (Denes et al., 2019; Kusel et al., 2022; Limpert et al., 2024; Powered by Orsted & Eversource, 2024; Pyc et al., 2018; South Fork Wind, LLC, Powered by Orsted and Eversource, 2021). We found large variation in reported radial distances of Level A and B take ranges, dependent on the area, season, and underwater noise and exposure modeling vs. sound field verification estimates (Level A 10 dB mean = 3.53 km, SD = 1.81; Level A 12 dB mean = 3.98 km, SD = 2.00; Level B 10 dB mean = 4.48 km, SD = 1.99; Level B 12 dB mean = 3.77 km, SD = 0.81). Therefore, we decided to restrict our analysis to data from underwater noise and exposure modeling for the WEAs during the summer months (Kusel et al., 2022; Limpert et al., 2024; Pyc et al., 2018). We used the compiled data to calculate the median radial distance for Level A and B take ranges assuming 10 dB and 12 dB of noise attenuation (Table 2).

Table 2: Summary of pile-driving window, noise attenuation, and Level A and B take ranges (radial distance) for each mitigation scenario used in the tradeoff analysis.

Mitigation scenario	Pile-driving window	Noise attenuation	Level A radial distance	Level B radial distance
No Seasonal Restriction	January-December	10 dB	2.74 km	6.07 km
Early Start and Late Finish	May-December	10 dB	2.74 km	6.07 km
Early Start and Late Finish and Additional Noise Attenuation	May-December	12 dB	1.60 km	2.74 km
No Seasonal Restriction and Additional Noise Attenuation	January-December	12 dB	1.60 km	2.74 km
Late Start Seasonal Restriction	June-December	10 dB	2.74 km	6.07 km
Early Finish Seasonal Restriction	May-November	10 dB	2.74 km	6.07 km
Late Start and Early Finish Seasonal Restriction	June - November	10 dB	2.74 km	6.07 km
Additional Noise Attenuation and Late Start Seasonal Restriction	June-December	12 dB	1.60 km	2.74 km
Additional Noise Attenuation and Early Finish Seasonal Restriction	May-November	12 dB	1.60 km	2.74 km
Additional Noise Attenuation and Late Start and Early Finish Seasonal Restriction	June-November	12 dB	1.60 km	2.74 km

Monopile locations were spaced 1 nm apart, throughout the prediction box, and then clipped to the WEAs (Figure 11A). We began the simulation by randomly choosing one monopile location in the WEAs. We assumed the average area of a wind energy development campaign is approximately 675 km^2 (NOAA, 2021), therefore we drew an 473 km^2 circular buffer around the randomly chosen monopile location (Figure 11B). We assumed a hypothetical wind energy developer plans to drive 70 monopiles within the circular buffer; for context, the number of turbines varies by project but in the WEAs the numbers range from 62 – 130 (Kusel et al., 2024;

BOEM, 2024). For each eight-day period throughout the year, we randomly chose five of the 70 turbines from within the circular buffer that had adequate weather for pile driving one turbine in one day. We assumed two hours were required to drive a monopile. Weather was considered adequate for pile driving when the mean wind speed was at or below 15 m/s at 100 m above mean sea level for two hours and visibility was greater than 2 km (Figure 12). Pile driving could only occur during daylight hours, which varied monthly. Wind conditions were derived from the hourly Copernicus Era5 re-analysis dataset (IPRC/SOEST, 2021). The 100 m-u component and the 100 m-v component of wind were downloaded and combined ($w_s = \mathrm{sqrt}(u^2 + v^2)$) to estimate average hourly wind speed for 2018 in the WEAs. To determine days with visibility conditions adequate for pile driving, monthly visibility conditions were evaluated using the International Comprehensive Ocean–Atmosphere Data Set (ICOADS) database (Freeman et al., n.d.). For each month, we calculated the percentage of days that were subject to visibility less than 2 km using local ship-based observations collected between 2013-2024. We then took the monthly average of these percentages and randomly assigned the corresponding proportion of low visibility days to our dataset (Table 3).

Within our wind energy development simulation, we consider ten mitigation scenarios (Table 2). The *No Seasonal Mitigation* scenario assumes pile-driving can occur throughout the year and requires 10 dB of noise attenuation via a BBC. The *No Seasonal Mitigation and Additional Noise Attenuation* scenario assumes pile-driving can occur throughout the year and requires an additional noise attenuation device (i.e., a DBBC) that results in 12 dB of noise attenuation.

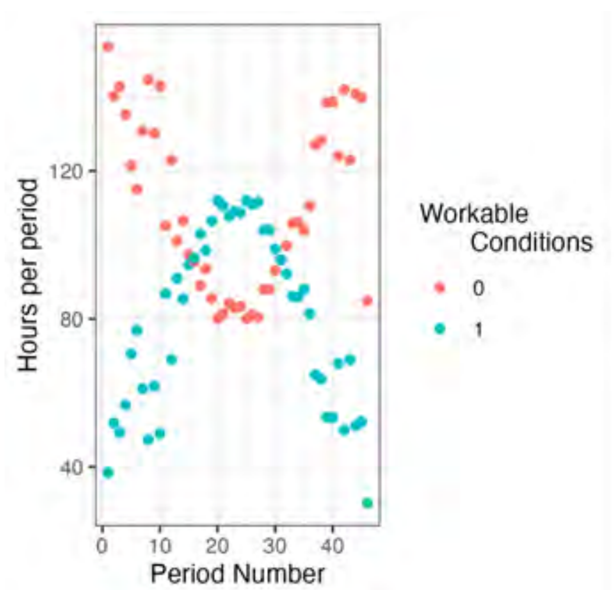


Figure 12: Simulated average number of workable hours for windfarm construction. Construction day is modeled over an eight day period in the Massachusetts/Rhode Island Wind Energy Areas, when wind and daylight are considered. Workable hours are shown in teal, non-workable hours are shown in pink.

Table 3: Percentage of days with visibility less than 2 km according to the International Comprehensive Ocean–Atmosphere Data Set (ICOADS) database. Data used in our analysis were collected between 2013-2024 and averaged monthly. The 2013-2024 time period was chosen to avoid overly skewing the data with historic conditions while also overlapping with the years aerial survey data collection occurred.

Month	Average number of days with weather data	Standard deviation of number of days with weather data	Average number of days with poor visibility	Standard deviation of number of days with poor visibility	Percentage of days with poor visibility
January	8.92	3.60	1.11	0.33	12.46
February	7.00	3.91	2.00	1.41	28.57
March	8.70	3.16	1.17	0.41	13.41
April	9.82	3.52	1.43	0.79	14.55
May	11.36	3.38	2.25	1.39	19.80
June	13.91	3.51	2.56	1.51	18.37
July	11.36	2.77	2.44	1.24	21.51
August	13.55	3.21	2.17	1.17	16.00
September	15.73	3.66	3.50	2.59	22.25
October	15.18	4.51	1.50	0.55	9.88
November	9.36	3.35	1.00	0.00	10.68
December	7.64	4.11	1.40	0.55	18.33

The seasonal restriction scenarios maintain the single BBC (i.e., 10 dB noise attenuation), but change the piling schedule. The *Early Start and Late Finish Seasonal Restriction* scenario assumes piling cannot occur from January 1 through April 30(National Marine Fisheries Service, 2020, p. 7). In the *Late Start Seasonal Restriction* scenario, pile driving occurs from June 1 through December 31. In the *Early Finish Seasonal Restriction* scenario, pile driving occurs from May 1 through November 30. Finally, in the *Late Start and Early Finish Seasonal Restriction* scenario, pile driving occurs from June 1 through November 30. Scenarios labeled with "*Additional Noise Attenuation*" use the piling schedule defined previously and require an additional noise attenuation device (i.e., a DBBC), resulting in 12 dB of noise attenuation.

We assume a daily cost rate of $805,000 in 2018. This cost includes a HLV ($765,000), project resources ($20,000), and two guard vessels ($10,000 each). These costs were based on the literature (Maienza et al., 2020; Myhr et al., 2014; Quintana, 2016) and adjusted for inflation. We also include a yearly cost of mobilization ($30M) (Ioannou et al., 2020). To determine the cost of each scenario we multiply the campaign duration by the daily cost rate and add the yearly mobilization cost~~s~~. We assume a cost of $2M for a DBBC (Beelen et al., 2025).

We submitted the results of the tradeoffs analysis (Task 6) into a scientific manuscript. After approval from the NOWRDC technical committee we submitted the manuscript on August 4, 2025 to the peer-reviewed, high impact scientific journal, nature climate change. The draft is currently undergoing the review process at the journal.

Task 8: Develop Decision Support Framework

We developed a prototype of an R Shiny Decision Support App to offer a user friendly and interactive tool to engage interested parties with the key results of our tradeoff analysis. The prototype app provides a method by which developers and interested parties can better understand the relationship between construction timing, mitigation measures, and the predicted impacts to right whales in the MA/RI WEAs (Appendix B). The framework also represents a prototype for future scenario planning and mitigation assessments, written in a flexible coding language that can be easily modified. The backend is written in R Studio, and the user interface is suitable for those who are not familiar with R or other coding languages. We designed the user interface to guide an individual through key background information and then the necessary steps to generate a wind farm simulation from our pre-calculated scenarios. The tool incorporates interactive buttons that lead the individual through each webpage, with options to view the full tradeoffs manuscript (pending submission and publication). We incorporated additional features, such as a floating button on each page that allows the user to offer feedback to our team, and a tab to provide web-links where the user can access further information about the impacts of offshore wind on whales and how these impacts are monitored and mitigated. This Decision Support Prototype currently exists on a local server at NEAq, and could be adapted in the future for other offshore wind projects, or alternative trade-off analyses.

Task 9: Deploy Commercialization Strategy

The strategy for commercialization of this tool was largely focused on the value it would bring to the offshore wind farm development companies in the United States. This would be accomplished through the marketing strategy defined in Task 5 as well as further stakeholder engagement via a workshop where the tool was reviewed and commented on by teams at local offshore wind developers. The team hosted an online Stakeholder Engagement Workshop with all developers in the northeast United States invited and Equinor and Orsted in attendance.

Results

Task 1: Develop Predictive Models of Right Whale Distribution

1.1 Combine visual and acoustic data set of right whale occurrence in MA/ RI WEA.

Visual Detections of Right Whales

Between 2011 and 2021, 490 right whales were observed during the aerial surveys. From 2011 through 2015, right whale presence, as indicated by the number of whales counted by the aerial survey team (i.e., the number of whales observed during aerial surveys regardless of the amount of aerial survey effort), peaked in the winter and spring, consistent with historical whaling data from this habitat (Allen, 1908) (Figures 13 and 14). Beginning in 2017, right whales were also detected by the aerial survey team in the summer and fall months (Figures 13 and 14). Right whale presence, as detected with aerial surveys, now occurs in southern New England in all seasons (Figures 13, 14, and 15). The spatial distribution of right whale detections by the aerial survey team varied by year (Figure 15). In general, right whale detections were spread from east to west across the northern part of the survey area in 2012, 2015, 2017, and 2021. However, concentrations of right whale detections occurred on the eastern side of the survey area in 2013, 2014, 2018, and 2019.

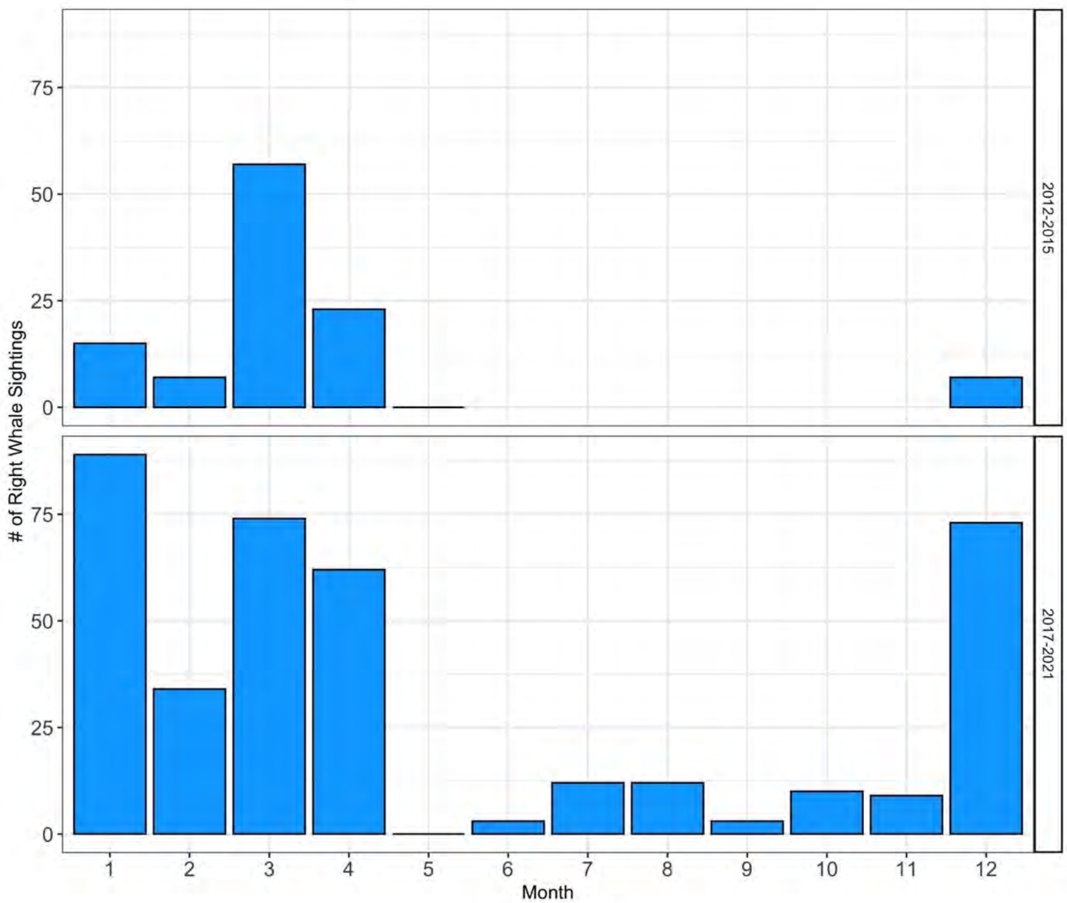


Figure 13: The number of right whale sightings detected by aerial survey by month for two time periods (2012-2015 and 2017-2021). Right whales were not detected by aerial surveys in the summer and fall months during the 2012-2015 time period, but were detected in all seasons during the 2017-2021 time period. No aerial surveys were conducted in 2016. Right whale sightings in this figure are not corrected for monthly variations in effort.

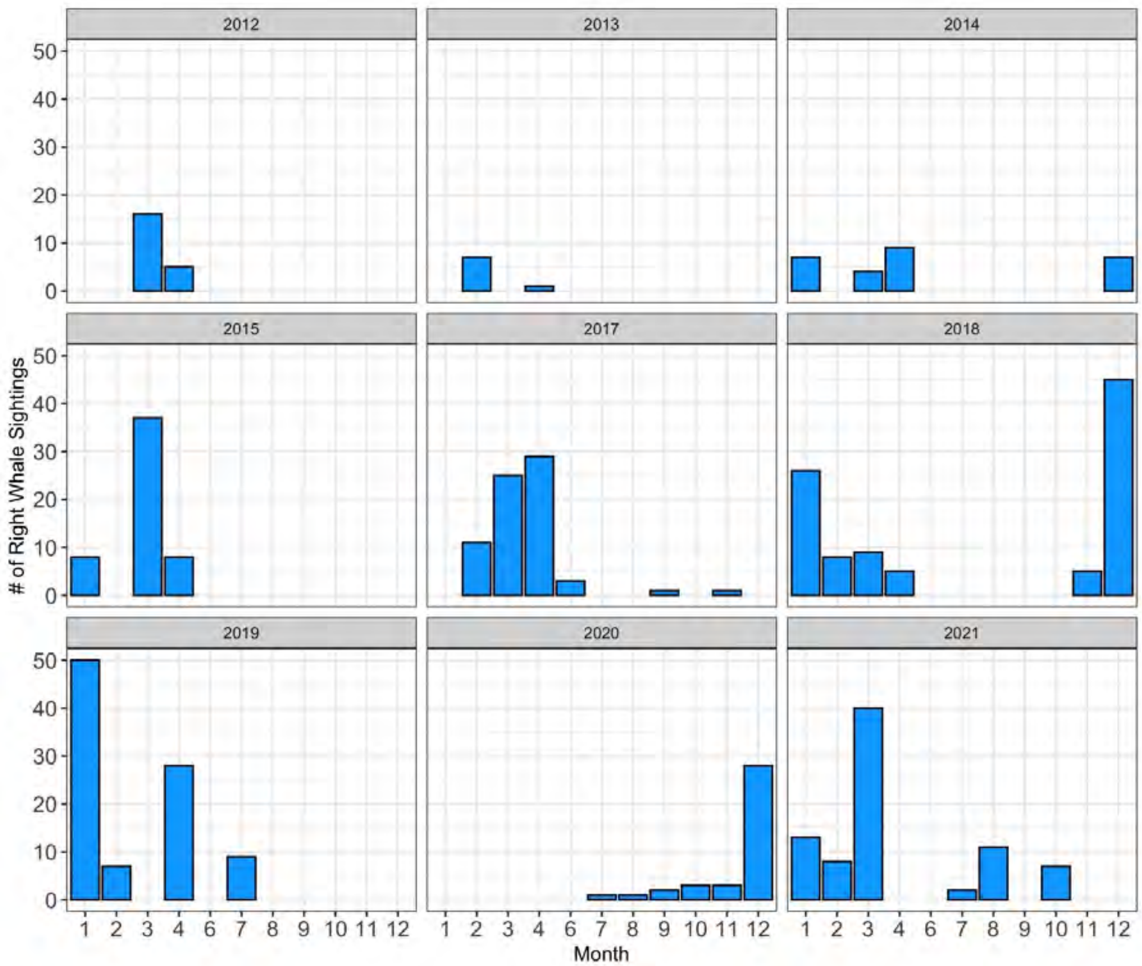


Figure 14: The number of right whale sightings detected by aerial survey by month for each year. No aerial surveys occurred in 2016. Right whale sightings in this figure are not corrected for monthly variations in effort. Note: there were no right whale sightings in May of any year.

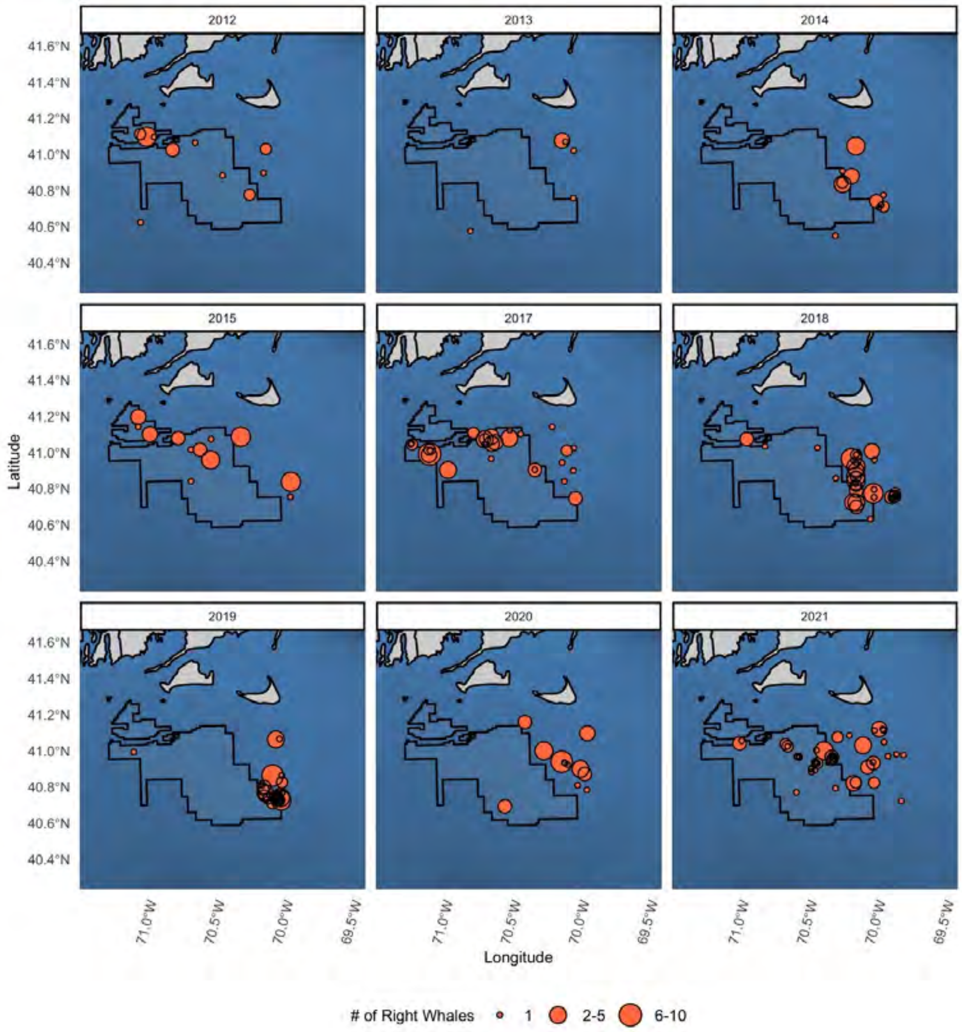


Figure 15: Right whales detected during New England Aquarium aerial surveys, faceted by year. No aerial surveys occurred in 2016. The black outline defines the Massachusetts and Rhode Island Wind Energy Areas.

Acoustic detections of right whales

A total of 6,894 days of audio recordings were collected between 2011 and 2015, with over 40,000 right whale upcalls detected. The number of right whale upcalls were the highest during the winter and spring and increased over the years with a peak in February 2015 (11,092 upcalls, Figures 16 and 17). There may not be a direct relationship between the number of right whale upcalls and the number of whales present because of variability in the number of upcalls produced by individual whales (e.g., some whales may call frequently, while other whales do not call at all). Therefore, we summarized upcalls using a variety of metrics, including the number of upcalls and the proportion of the MARU recording days with at least one upcall (Figure 18). Winter 2013 had the highest proportion of recording days with at least one upcall. Right whales were detected in all seasons (Figures 16 and 18). The spatial distribution of right whale detections by the acoustic surveys varied by year (Figure 19).

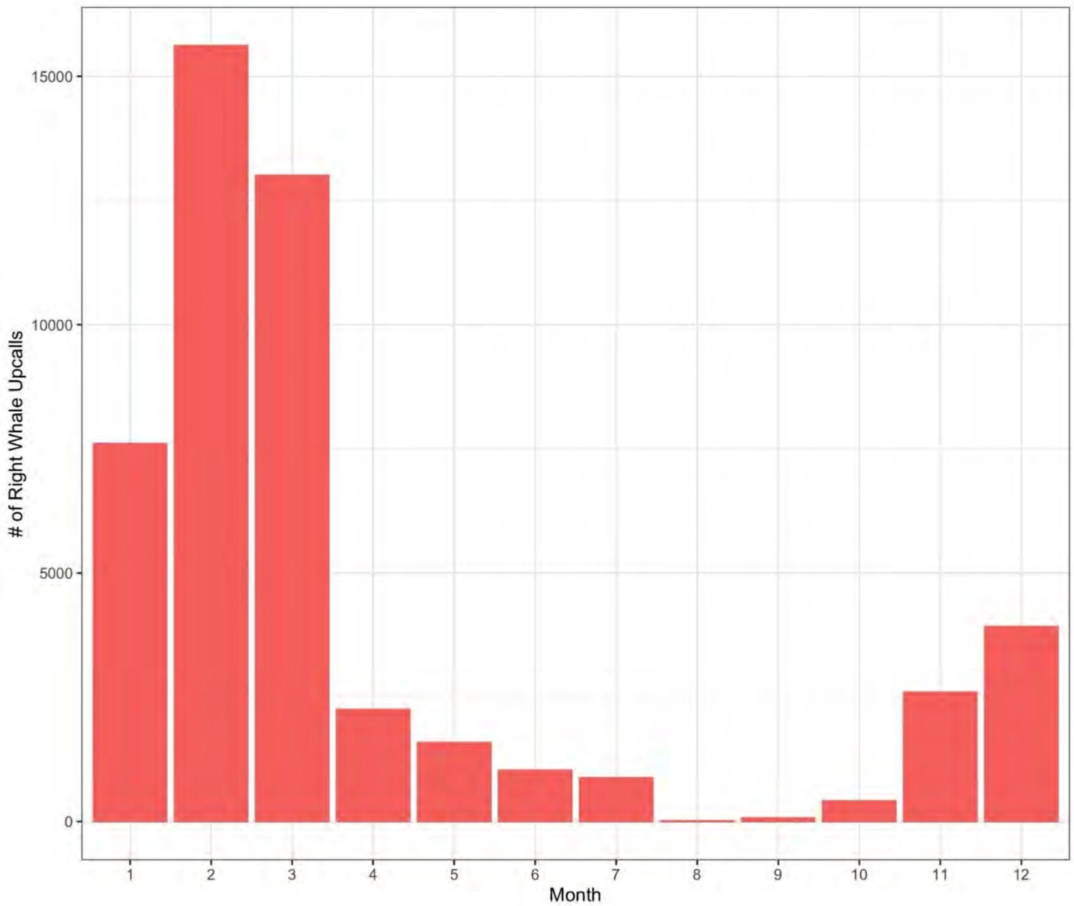


Figure 16: The number of right whale upcalls detected by marine autonomous recording units (MARUs) by month for 2011-2015. Right whale upcalls in this figure are not corrected for monthly variations in effort.

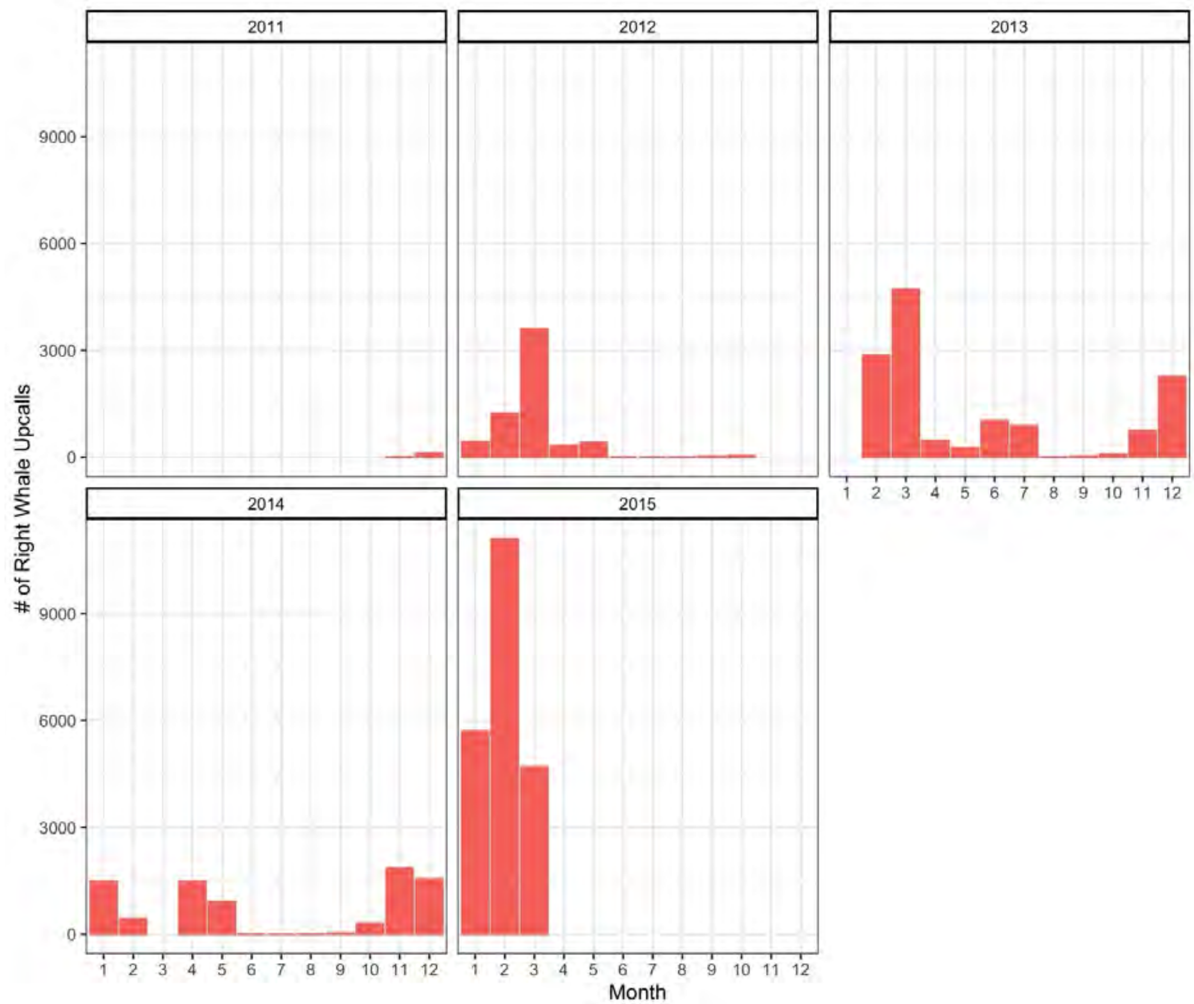


Figure 17: The number of right whale upcalls detected by marine autonomous recording units (MARUs) by month for each year. Right whale upcalls in this figure are not corrected for monthly variations in effort.

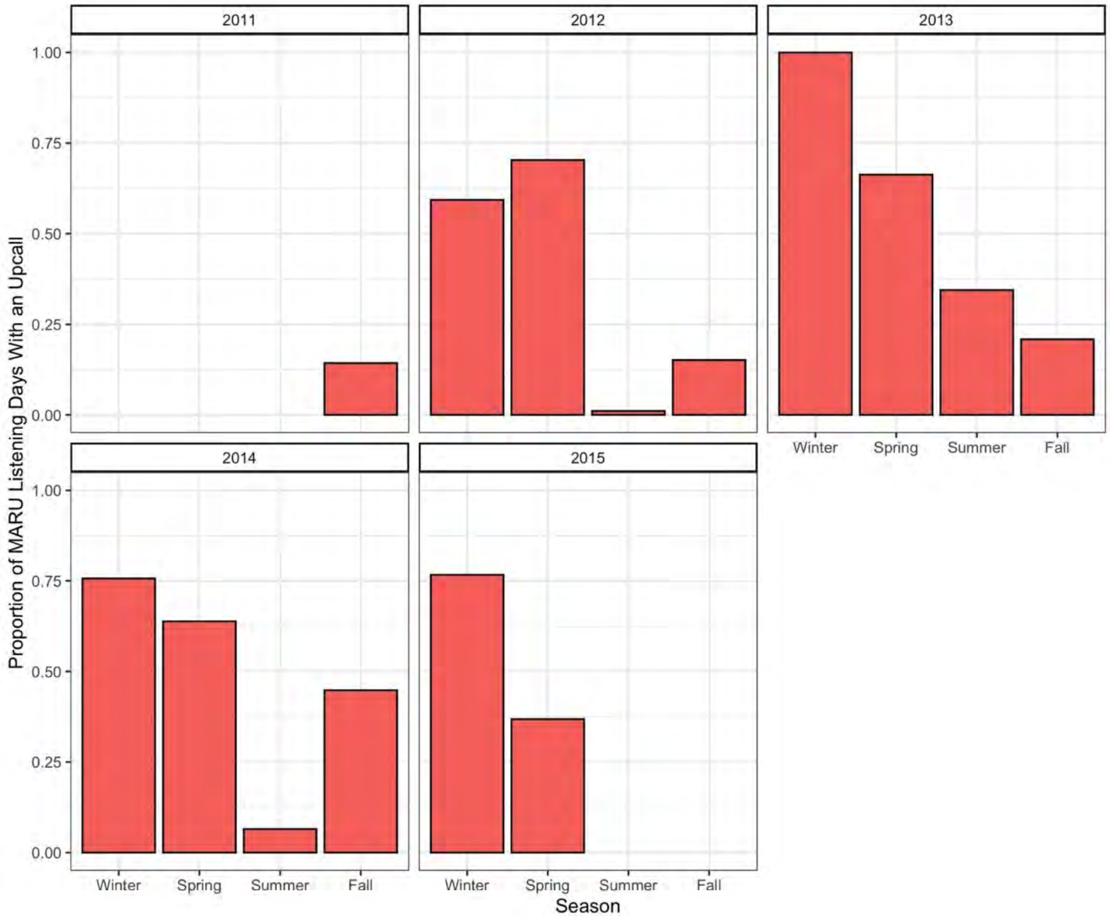


Figure 18: The proportion of Marine Autonomous Recording Unit (MARUs) deployment days with a recorded right whale upcall for each season of each year. December is considered a winter month for the following year (i.e. December 2012 is part of "Winter 2013").

Combination and comparison of aerial and acoustic detections of right whales

The aerial and acoustic survey data were collected at different spatial scales and coverage (Figure 20). Because of the difference in spatial coverage between the two survey modalities we would not expect all of the right whales observed by the aerial survey team to be detected by the MARUs, and vice versa. Between 2011 and 2015, four sightings of seven right whales were made by the aerial survey team within the detection range of MARUs under low-level noise conditions (22 km MARU detection range) (Figure 21B, 21D, 21F). One sighting of two right whales was made by the aerial survey team within the detection range of MARUs under median-level noise conditions (8 km MARU detection range) (Figure 21A, 21C, 21E). We determined that in some instances there were right whale upcalls under low- and median-level noise conditions, and no sightings by the aerial survey team. Surprisingly, the MARUs under the low-level noise condition detection range (22 km) that corresponded with most of the right whale sightings made by the aerial survey team had relatively few right whale upcall detections (Figure 21B). Additionally, the only MARU under median-level noise conditions (8 km detection range) that corresponded with right whale sightings made by the aerial survey team also had relatively few right whale upcall detections (Figure 21A).

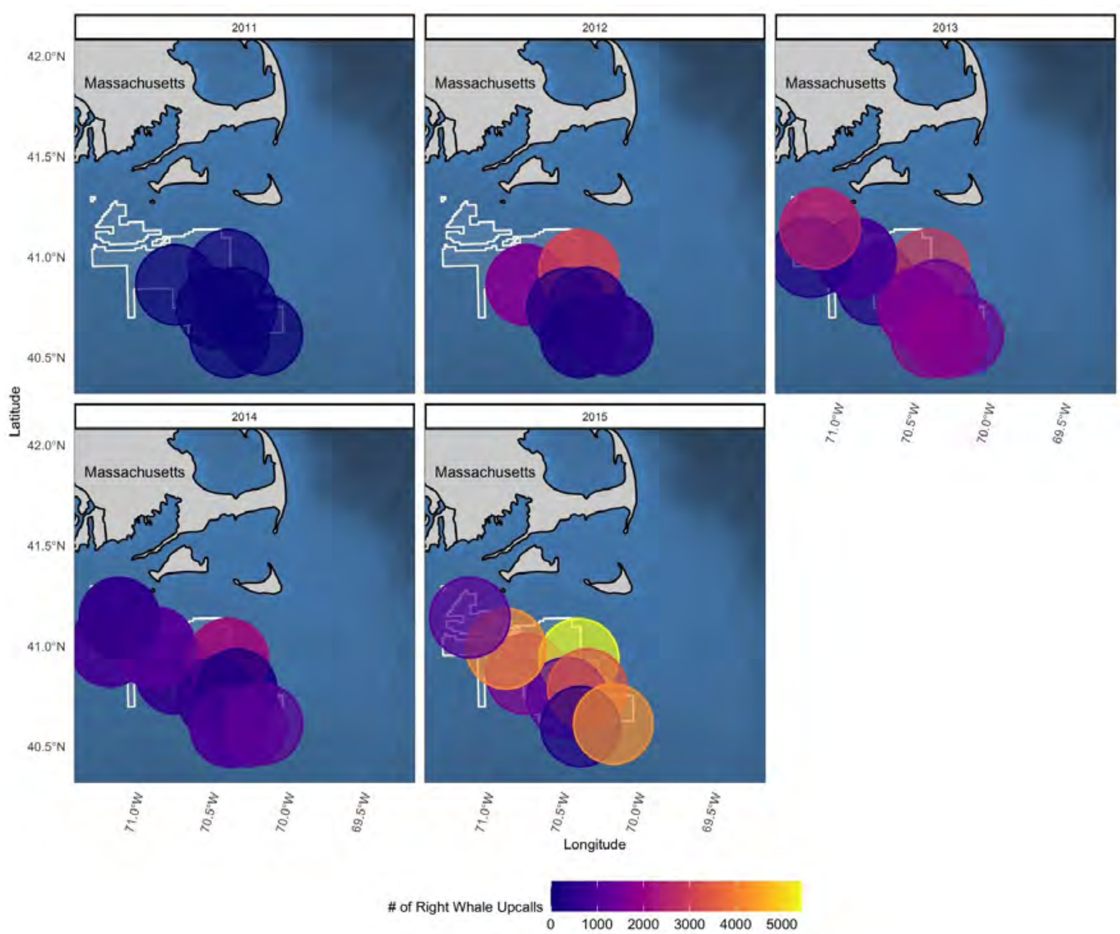


Figure 19: The number of right whale upcalls detected by marine autonomous recording units (MARUs) in the Massachusetts and Rhode Island Wind Energy Areas (white outline) by year. Circle size represents the detection range (22 km) of MARUs under low noise conditions.

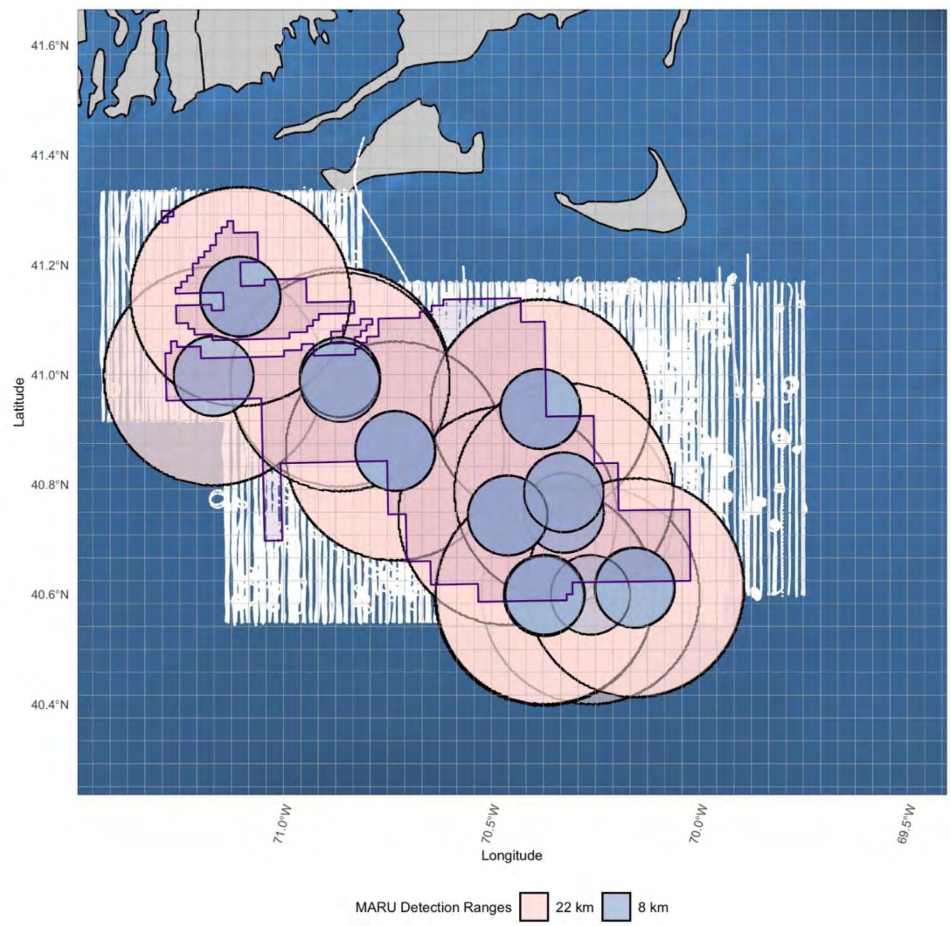


Figure 20: Aerial survey effort and marine autonomous recording units (MARUs) detection range under low- and mid-level noise conditions. Pink circles indicate the detection range of MARUs under low-level noise conditions (22 km). Blue circles indicate the detection range of MARUs under mid-level noise conditions (8km). Aerial survey effort is represented by white lines. The gray 4.6-by-4.6km grid was used to summarize aerial survey and environmental data. The Massachusetts and Rhode Island Wind Energy Area is outlined in purple.

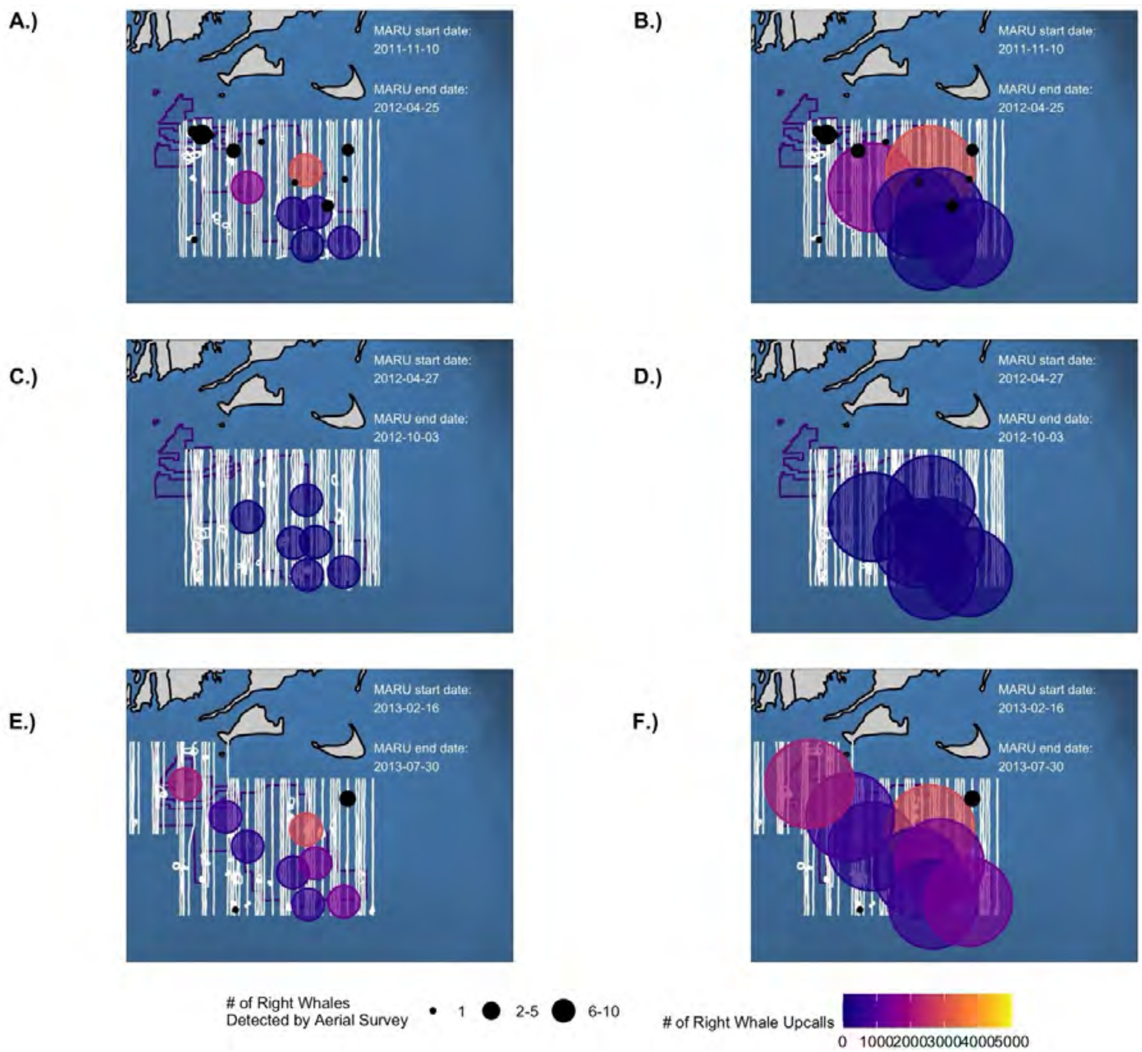


Figure 21: The number of right whale upcalls detected by marine autonomous recording units (MARUs) in the Massachusetts and Rhode Island Wind Energy Areas (purple outline). Right whale upcalls are compared to the number of right whale sightings made by the aerial survey team during the time of MARU deployment. Circle size for left-side figures (A, C, E) represents the detection range (8 km) of MARUs under median-level noise conditions. Circle size for right-side figures (B, D, F) represents the detection range (22 km) of MARUs under low-level noise conditions. The number of right whale upcalls at each MARU is represented by color. Aerial survey effort is represented by white lines, and black circles indicate the number of right whales sighted by the aerial survey team during the MARU deployment.

To qualitatively determine the relationship between the aerial and acoustic survey datasets we compared a 30-day moving average of right whale upcalls to estimates of right whale abundance from aerial surveys derived by O'Brien et al. (2022) (Figure 22). Generally, the seasonal trends of the two survey modalities mimic each other. However, the increase in right whale upcalls can be offset before or after aerial survey abundance estimates indicate an increase in right whale habitat use.

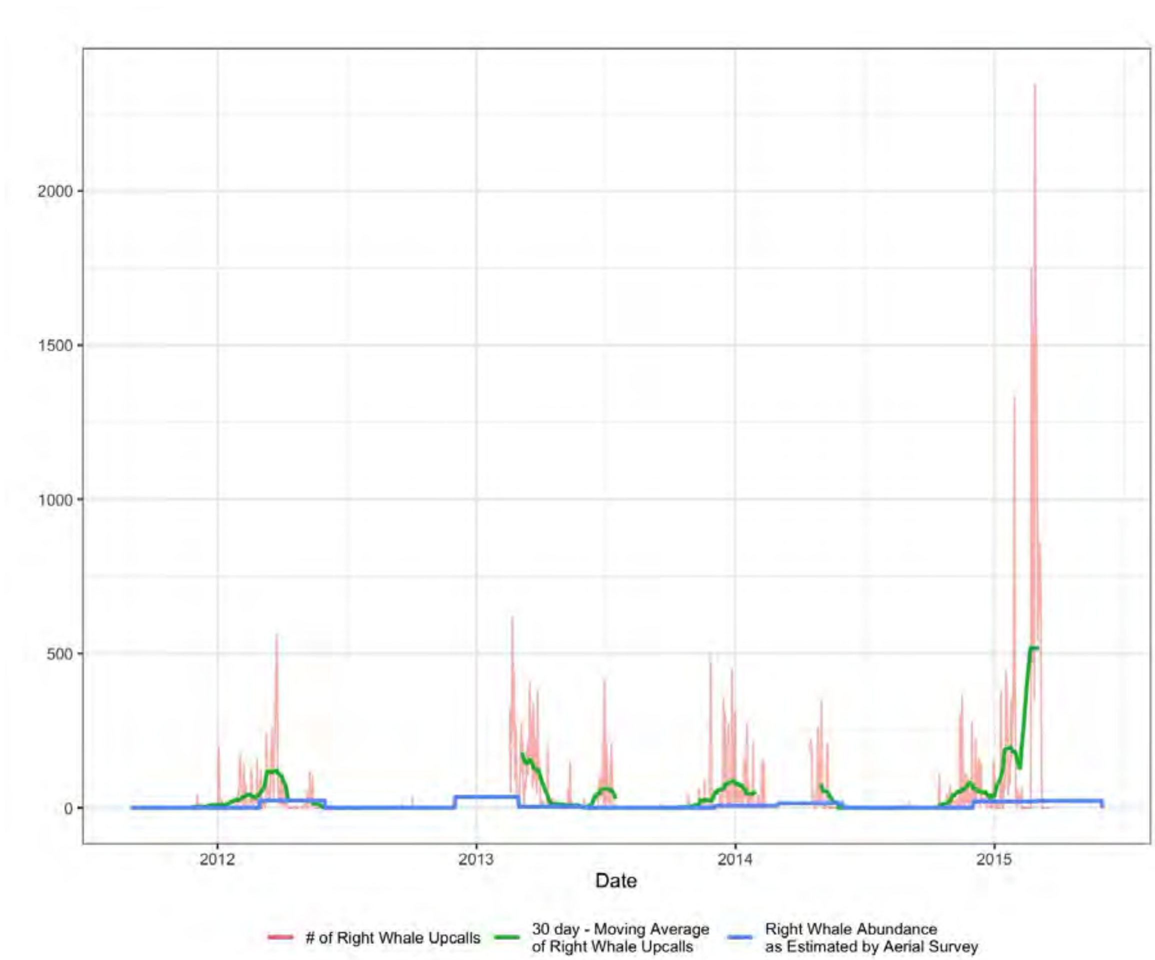


Figure 22: Qualitative comparison of the number of right whale upcalls detected by marine autonomous recording units (MARUs) (pink), a 30-day moving average of right whale upcalls (green), and right whale abundance estimated from aerial survey data (blue). Discontinuations in the upcall moving average (green line) result from time without deployed MARUs.

We found a significant positive correlation between the number of right whale upcalls and the right whale abundance estimates (Figure 23A; rho = 0.457, p < 2.2e-16). We also found a significant positive relationship between the proportion of days in which at least one upcall was detected and right whale abundance (Figure 23B; rho = 0.88, p = 0.0006). However, the relationship between right whale acoustic and aerial survey data seem to vary by season (Figure 23). In future phases of this project, we will explore and quantify these seasonal differences.

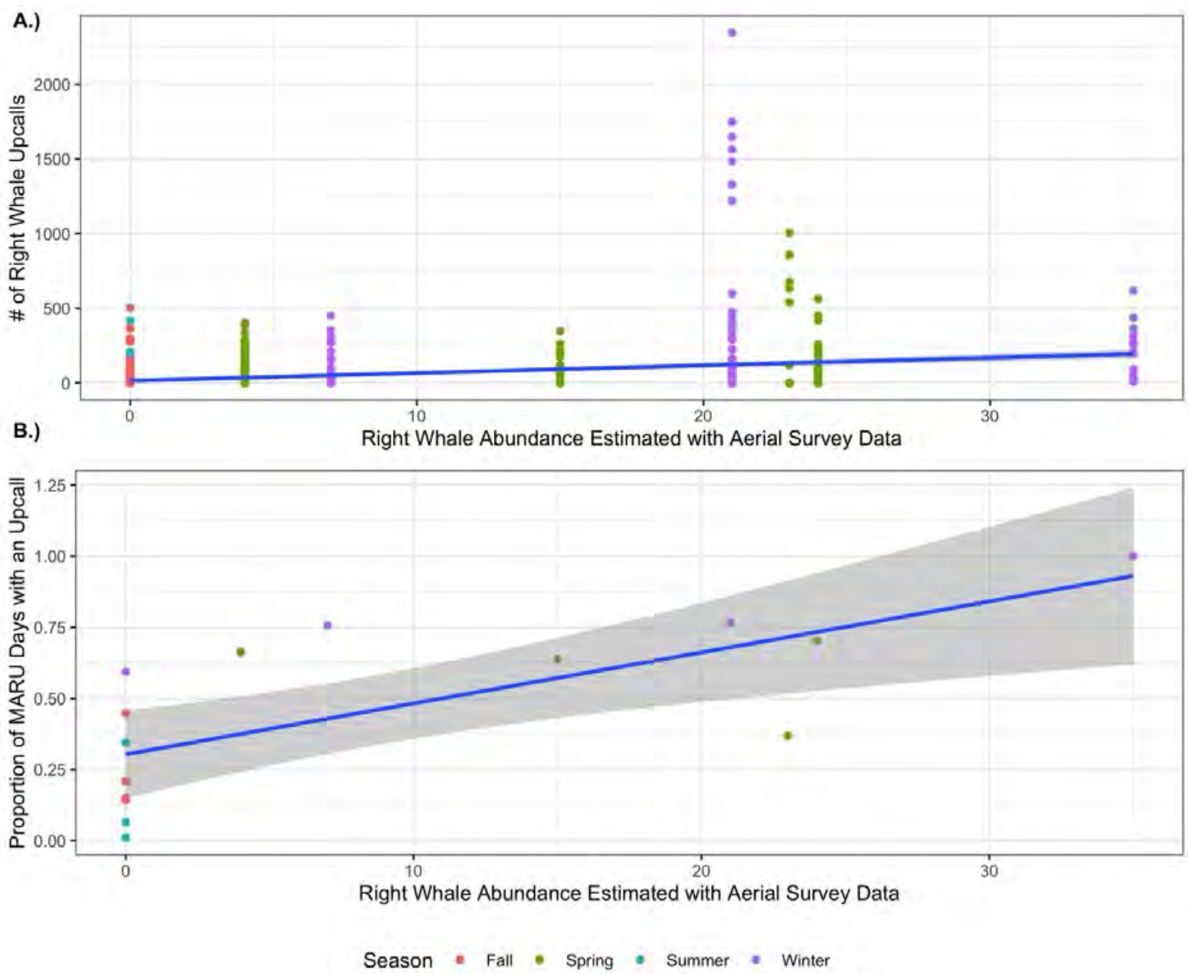


Figure 23: Spearman correlation showing the significant positive relationship between right whale abundance estimated comparing aerial and acoustic survey data. (A) the number of right whale upcalls detected on the marine autonomous recording units (MARUs), (B) the proportion of days in which the MARUs detected at least one upcall. Points are colored by season.

1.2 Ecological Probability Models

In our first Aerial Model trial (four three-month seasons), not all of our oceanographic variables converged (Rhat > 1.1; Table 1). The low number of repeat site visits per season is likely inhibiting the variables from converging (Figure 24). Because some of the variables did not converge, this model is not yet ready to be used for decision-making. However, the results from this model are indicative of what we expect to produce after we refine the models in Phase 2 of Right Wind (discussed below).

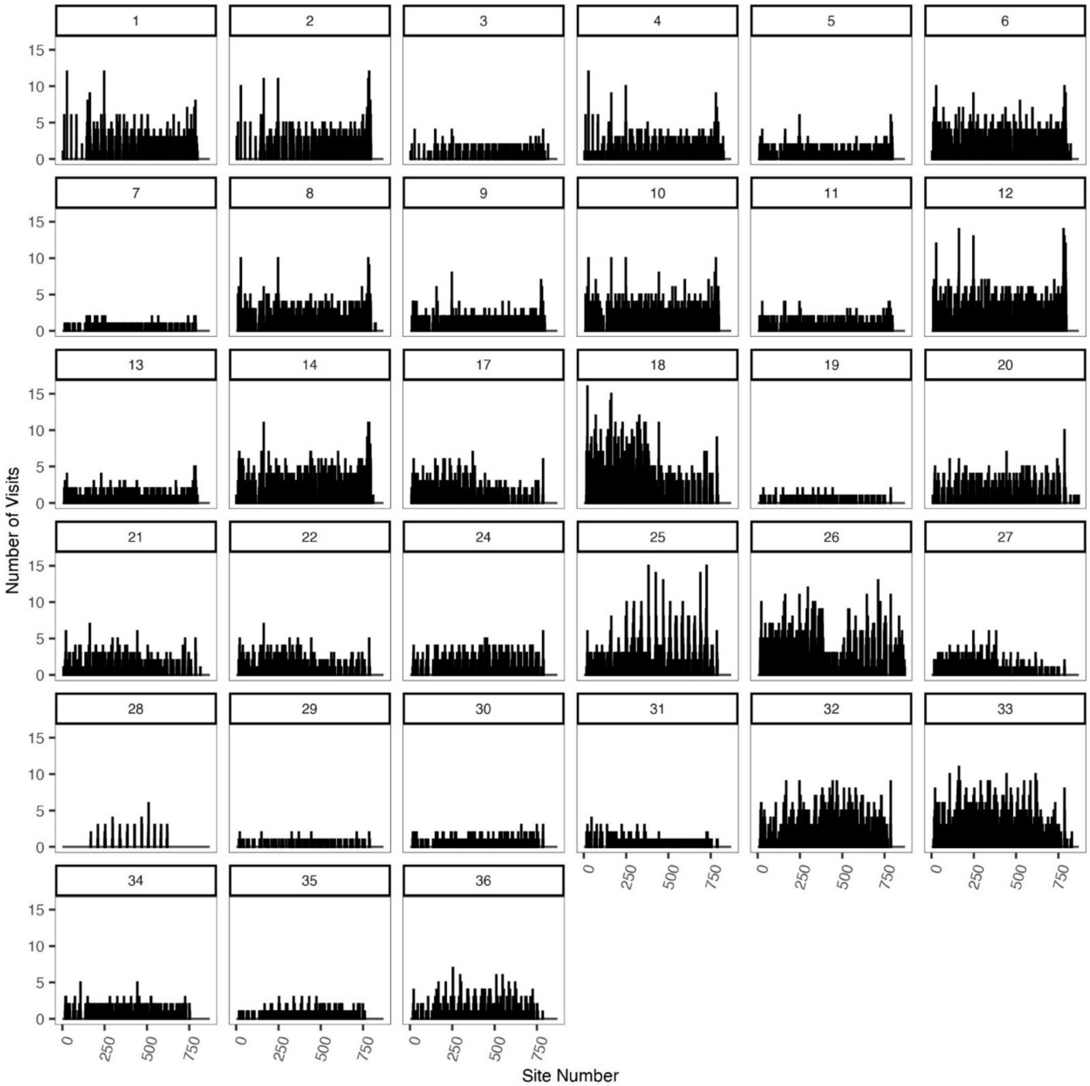


Figure 24: The number of aerial surveys at each site (black bars) facetted by three-month season. There are 36 three-month seasons between 2012 and 2021. The low number of repeat visits to each site in seasons 29, 30, 31, 34, and 35 may have prohibited Aerial Model trial 1 from converging.

The probability of occupancy maps show variations in occupancy probability in time and space that coincide with our understanding of right whale habitat use in southern New England. For example, the probability of occupancy in 2021 is predicted to be relatively high throughout the study area in the spring (Figure 25). The probability of occupancy decreases in the summer months; however, there are still areas south of Nantucket (Nantucket Shoals) with relatively high probability of occupancy. During the fall and winter months the probability of occupancy and the spatial area with high probabilities on the Shoals increases. However, the estimates of the probability of colonization and persistence do not show any variation in time or space and are likely suffering from the lack of model convergence (Figures 26 and 27). The mean probability of occupancy over the entire spatial and temporal study indicates that winter habitat use in southern New England by right whales is higher than spring, summer, and fall habitat use (Figure 28). Winter habitat use also appears to be increasing over the time series. Although we have not yet quantitatively tested for this increase, an increase in winter and spring abundance was quantified by O'Brien et al. (2022).

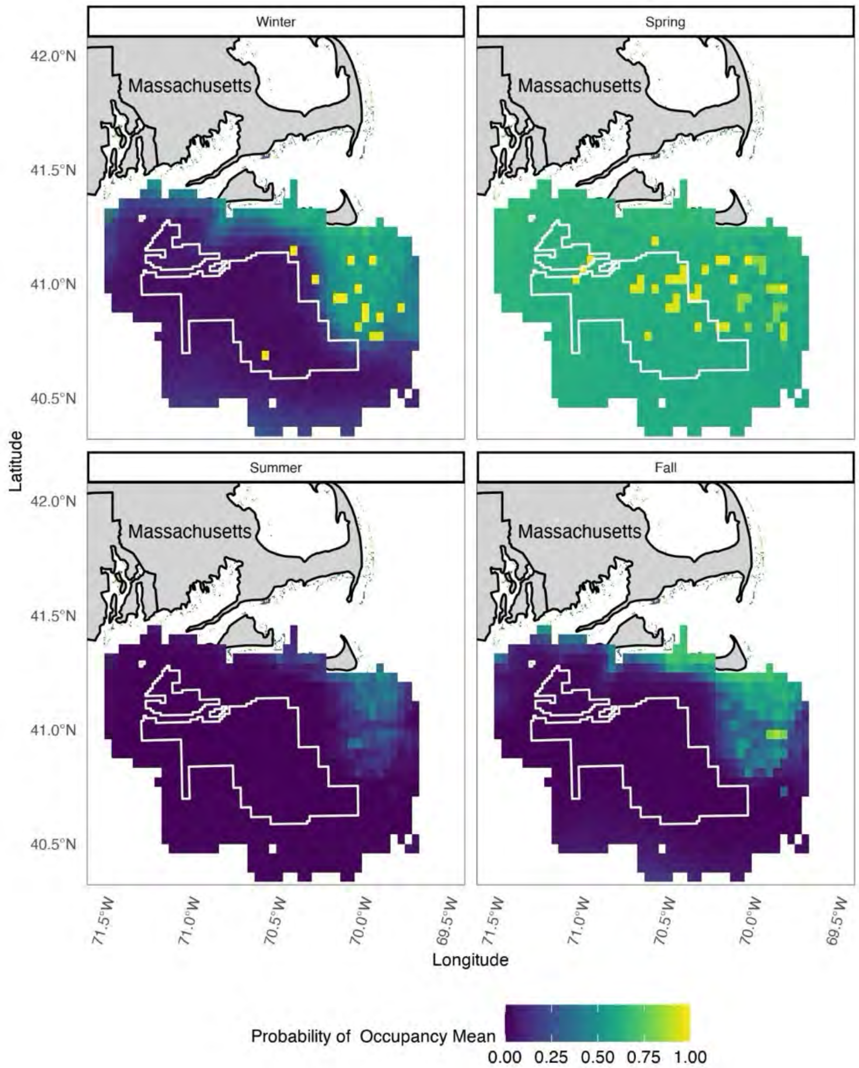


Figure 25: Predicted probability of occupancy in 2021 estimated using Aerial Model trial 1 (four three-month seasons). This model did not converge, and maps should not be used in decision-making. The Massachusetts and Rhode Island Wind Energy Areas is outlined in white.

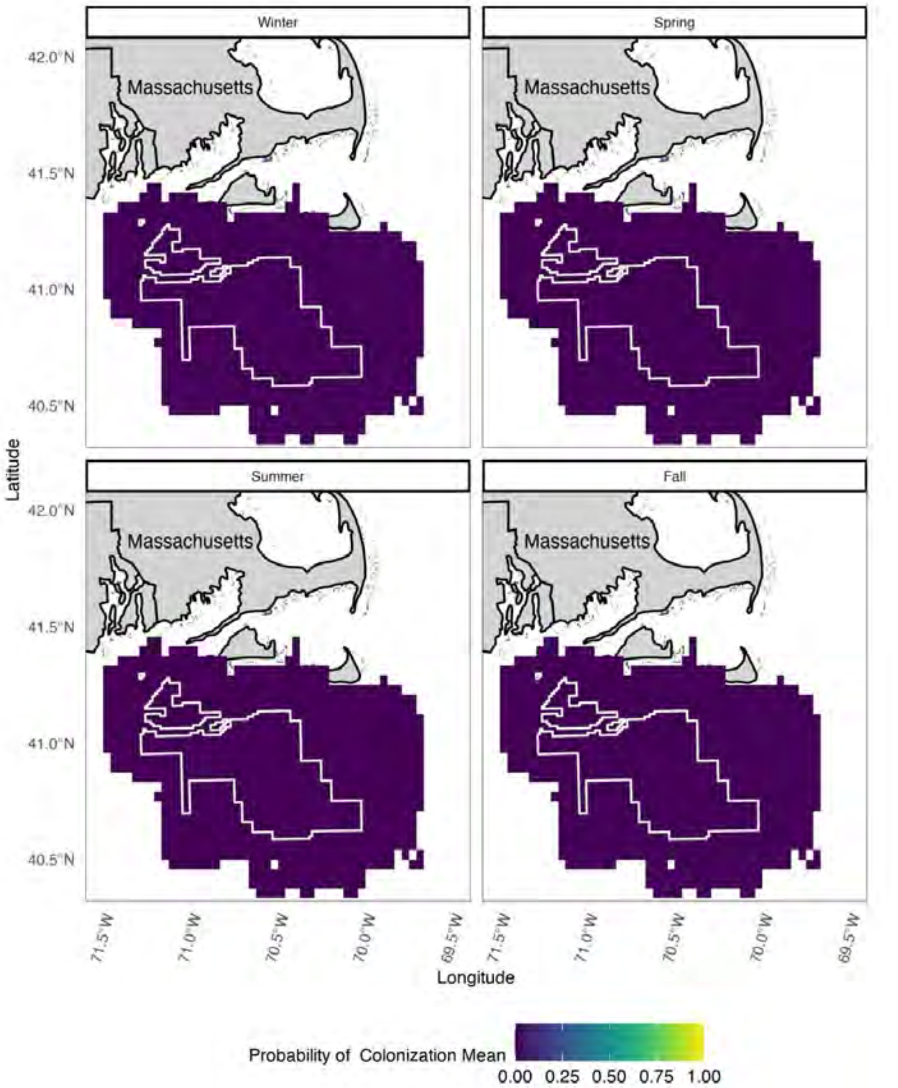


Figure 26: Predicted probability of right whale colonization in 2021 estimated using Aerial Model trial 1 (four three-month seasons). This model did not converge, and maps should not be used in decision-making. The Massachusetts and Rhode Island Wind Energy Areas is outlined in white.

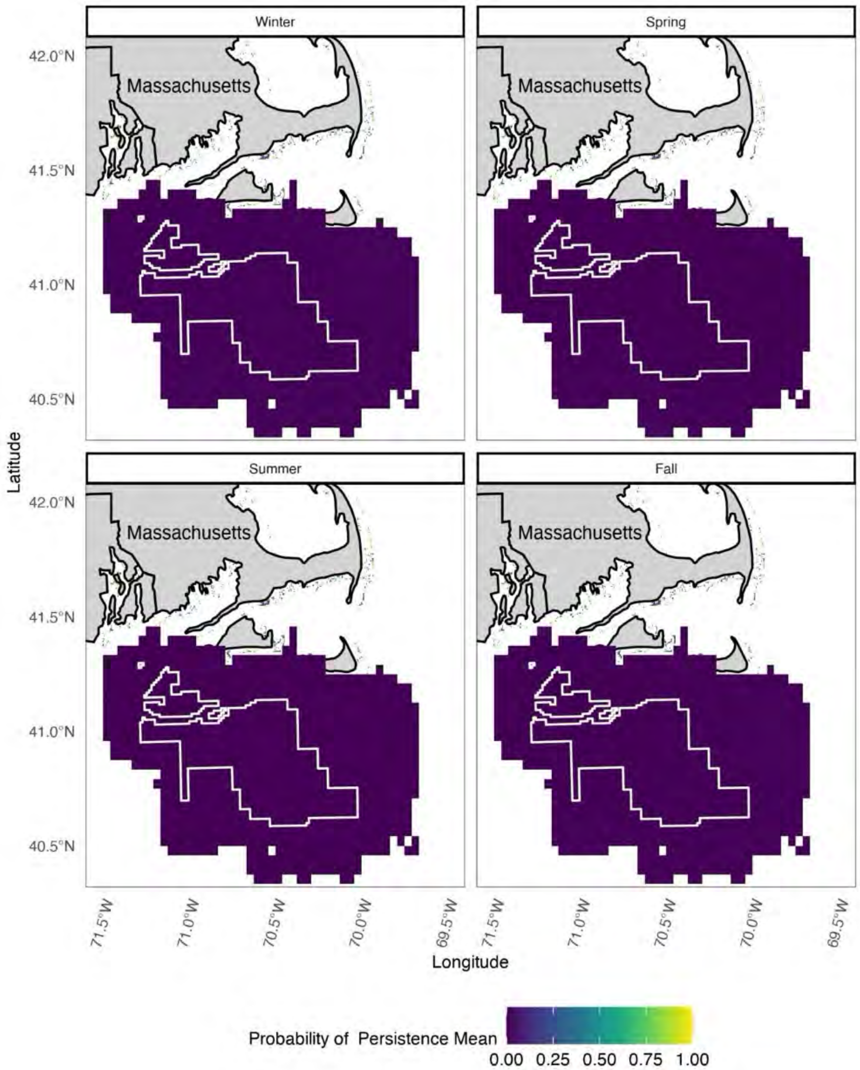


Figure 27: Predicted probability of right whale persistence in 2021 estimated using Aerial Model trial 1 (four three-month seasons). This model did not converge, and maps should not be used in decision-making. The Massachusetts and Rhode Island Wind Energy Areas is outlined in white.

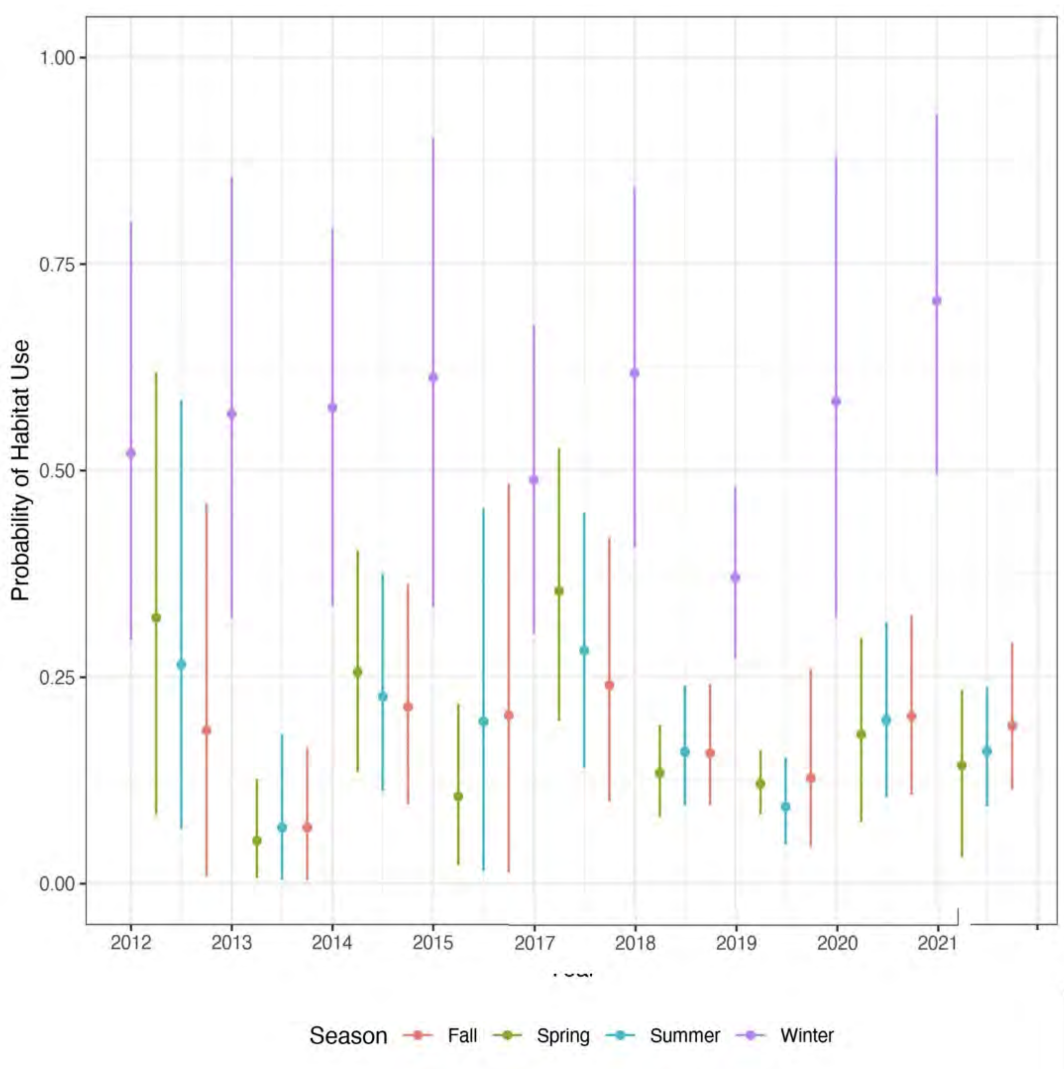


Figure 28: Estimated probability of habitat use over the entire study area for each year estimated using the Aerial Model trial 1. Points are the mean probability of occupancy and vertical lines represent the lower and upper credible intervals.

The pertinent months for wind energy construction in the MA/RI WEA are May through October. Therefore, we ran an Aerial Model, inclusive of those months, with two three-month seasons (trial 5). May, June, and July are defined as "early-summer" while August, September, and October are defined as "late-summer". Not all of our oceanographic variables converged in this model; however, it was run with a low number of iterations in the Markov Chain and all variables may converge when we increase the iterations (Rhat > 1.1, Table 1). The probability of occupancy maps show variations in occupancy probability in time and space that coincide with our understanding of right whale habitat use in southern New England during the summer months (Figure 29). For example, the probability of occupancy in early-summer 2021 is predicted to be high over the eastern (Nantucket Shoals), and northern regions of the study area

(Nantucket Shoals). In the late-summer months of 2021, the area with high probability of occupancy is reduced, but the northern and eastern sides of the study area have high probability of occupancy relative to the rest of the MA/RI WEA. Mean estimates of probability of habitat use are higher in the late-summer than the early-summer (Figure 30); however, the large credible intervals make it difficult to discern a difference between the two seasons.

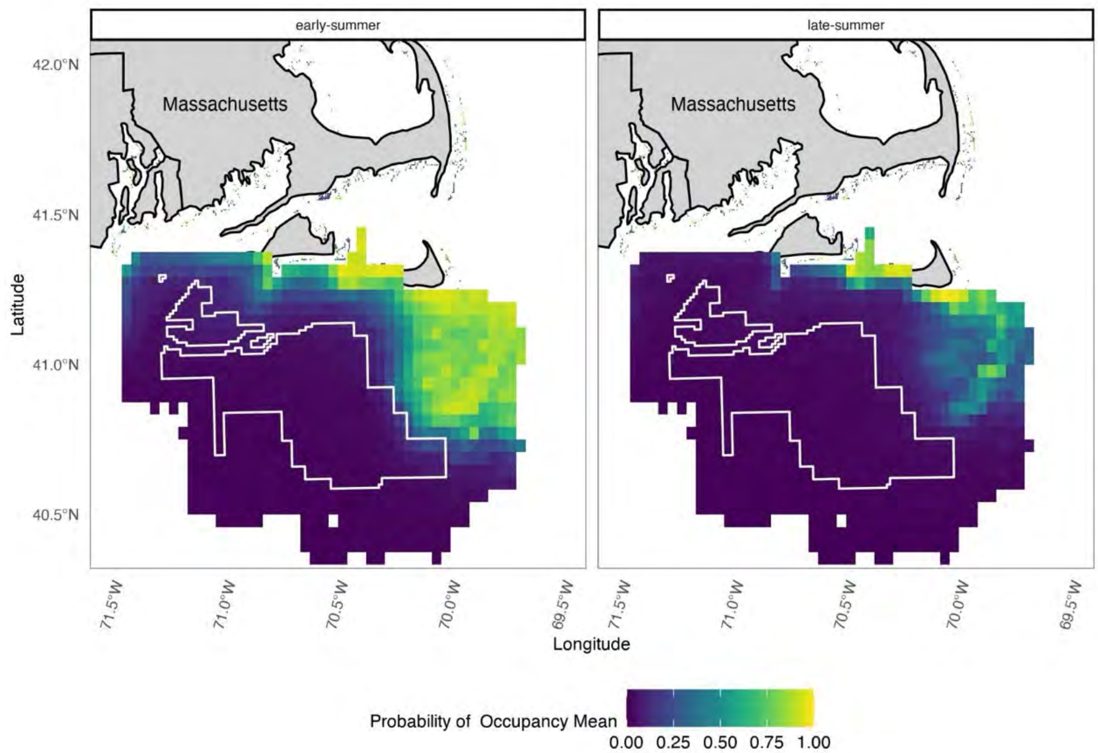


Figure 29: Predicted probability of occupancy in 2021 estimated using Aerial Model trial 5 (May – October, two three-month seasons). This model did not converge, and maps should not be used in decision-making. The Massachusetts and Rhode Island Wind Energy Areas is outlined in white.

Occupancy Model Validation

We used the acoustic survey data to validate our Aerial Model trial 1 (four three-month seasons). A Spearman Correlation found no significant relationship between modeled estimates of mean habitat use and the number of right whale upcalls (Figure 31A; rho = 0.173, p = 0.552), or the number of days with at least one right whale upcall (Figure 31B; rho = 0.252, p = 0.382). There was a significant positive relationship between the proportion of days with an upcall and modeled estimates of mean habitat use (Figure 31C; rho = 0.556, p = 0.04). However, there are likely seasonal differences in this relationship.

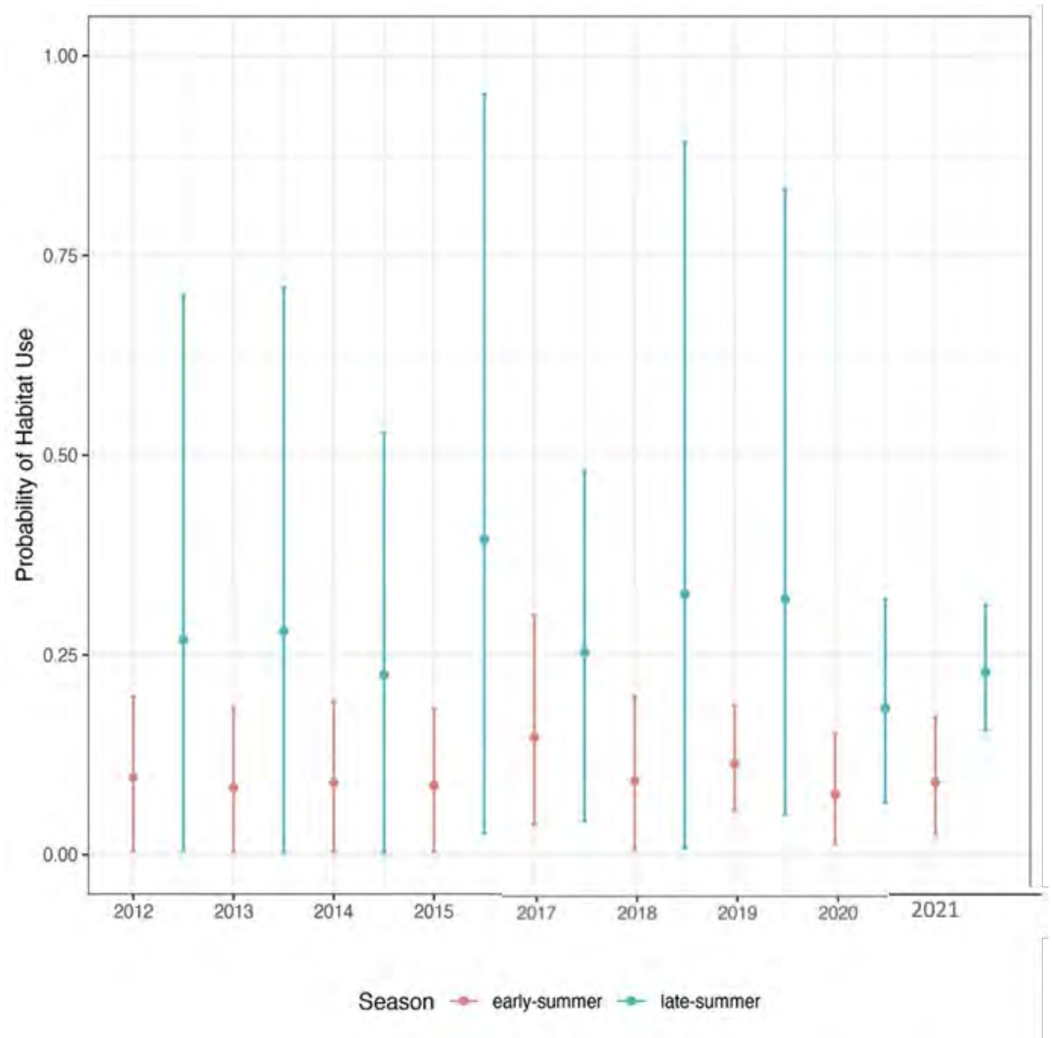


Figure 30: Estimated probability of habitat use over the entire study area for each year estimated using the Aerial Model trial 5 (May – October, two three-month seasons). Points are the mean probability of occupancy and vertical lines represent the lower and upper credible intervals.

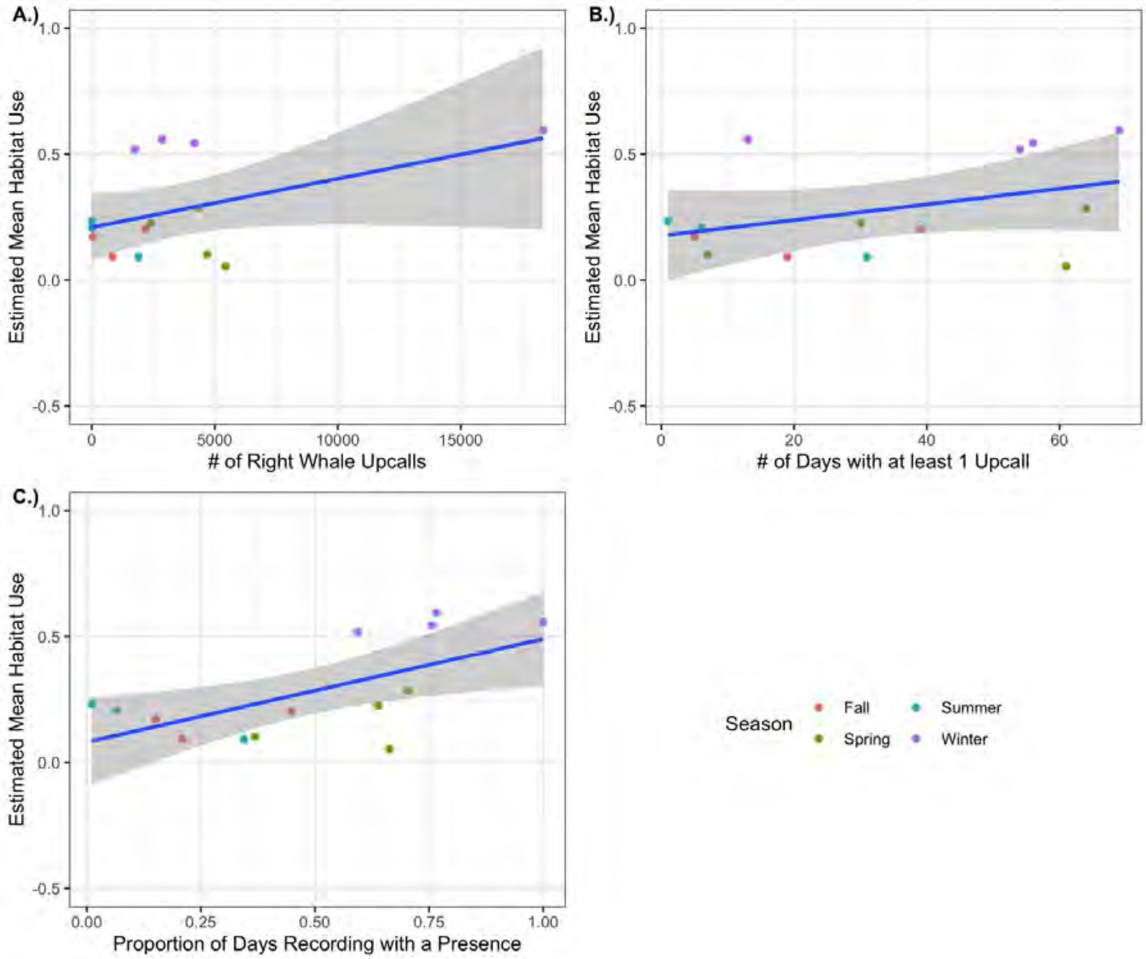


Figure 31: Acoustic data were used to validate the results from the Aerial Model trial 1 (four three-month seasons). Estimated mean habitat use was not significantly related to A.) the number of right whale upcalls, or B.) the number of days with at least one upcall. The estimated mean habitat use was significantly related to C.) the proportion of recording days with at least one upcall. Points are colored by season.

Task 2: Estimate Uncertainty in Right Whale Predictions

2.1 Estimates of uncertainty in right whale predictions

Maps of the lower and upper credible intervals for both colonization and persistence estimated using the Aerial Model trial 1 (four three-month seasons) show variation in time and space (Figures 32-35). In general, models had high confidence (lower uncertainty) where whales had a low probability of occurring and had lower confidence (higher uncertainty) where whales had a high probability of occurring. High uncertainty is common in estimates of marine mammal distributions and our project will explore ways to reduce this uncertainty.

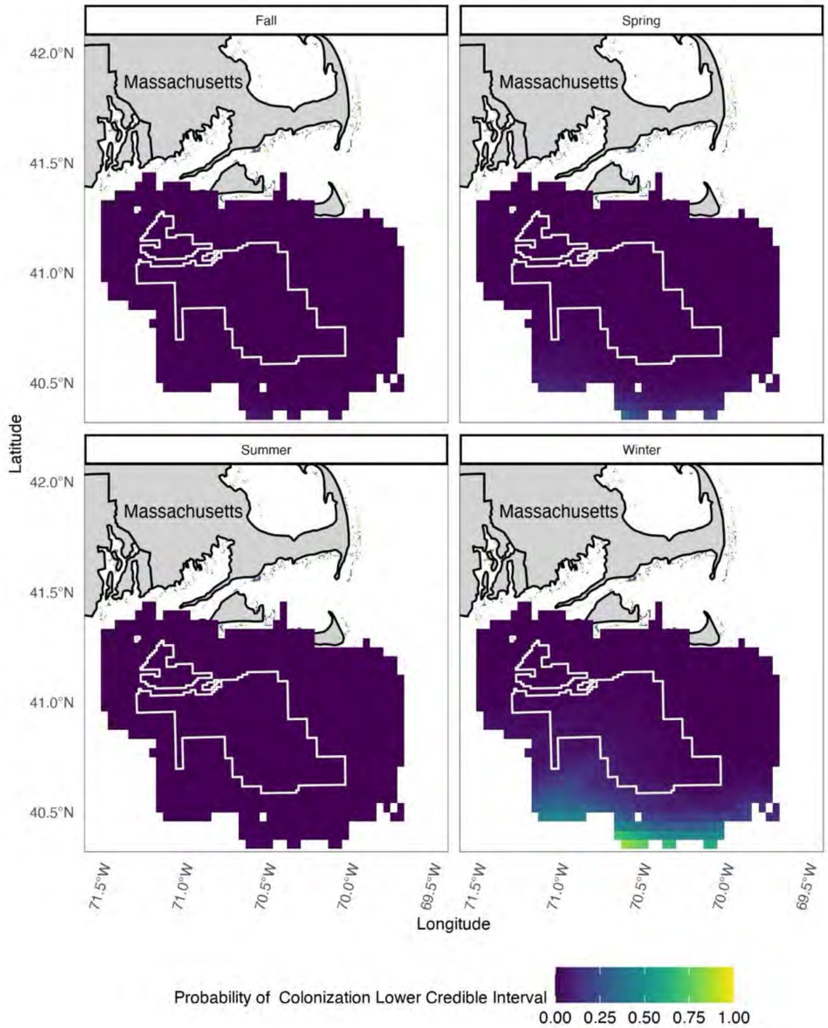


Figure 32: Lower Credible Intervals for predicted probability of colonization in 2021 estimated using Aerial Model trial 1 (four three-month seasons). This model did not converge, and maps should not be used in decision-making. The Massachusetts and Rhode Island Wind Energy Areas is outlined in white.

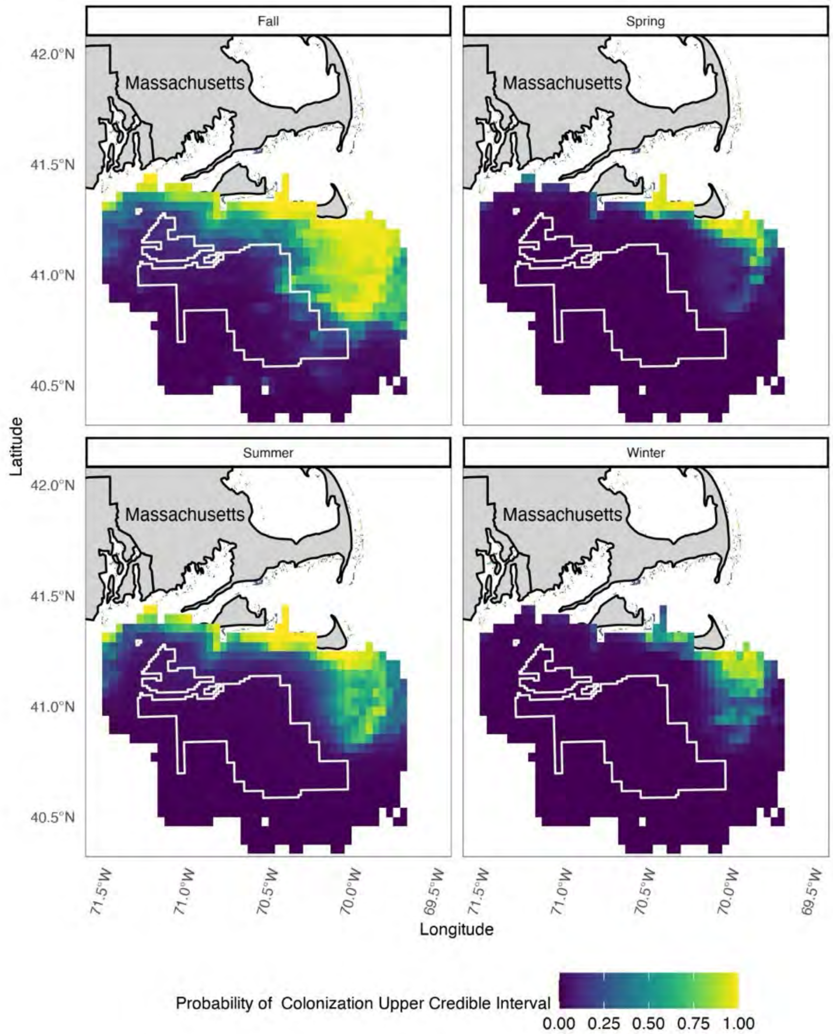


Figure 33: Upper Credible Intervals for predicted probability of colonization in 2021 estimated using Aerial Model trial 1 (four three-month seasons). This model did not converge, and maps should not be used in decision-making. The Massachusetts and Rhode Island Wind Energy Areas is outlined in white.

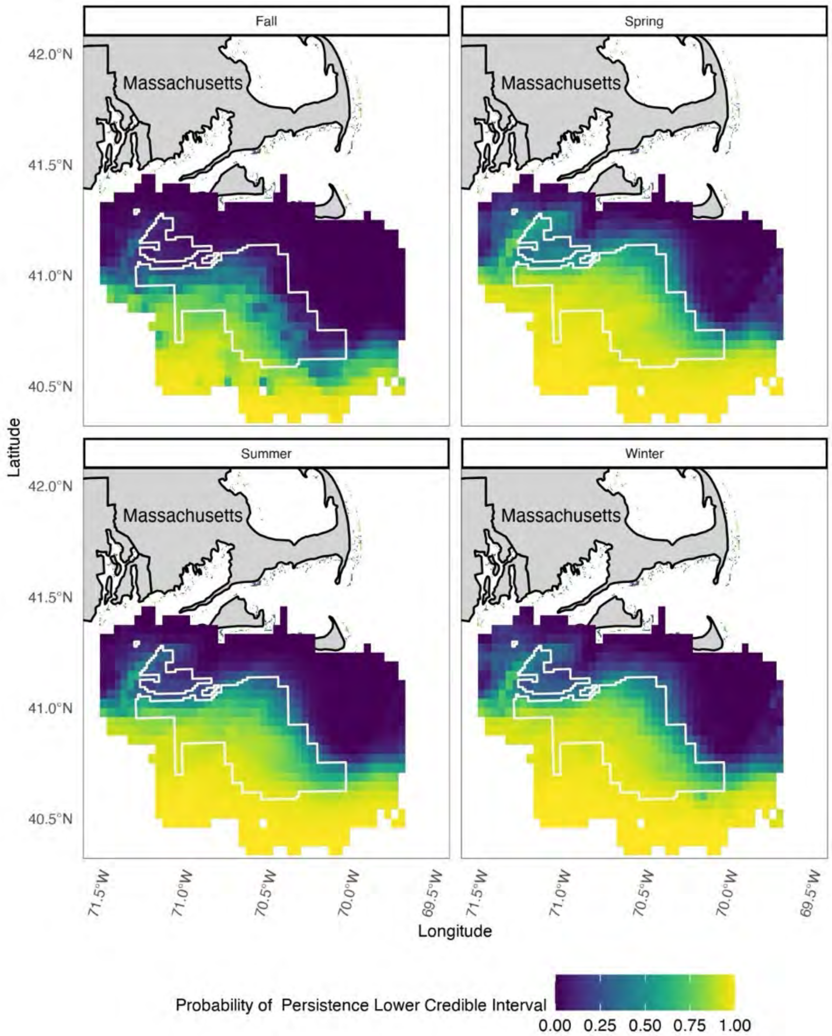


Figure 34: Lower Credible Intervals for predicted probability of persistence in 2021 estimated using Aerial Model trial 1 (four three-month seasons). This model did not converge, and maps should not be used in decision-making. The Massachusetts and Rhode Island Wind Energy Areas is outlined in white.

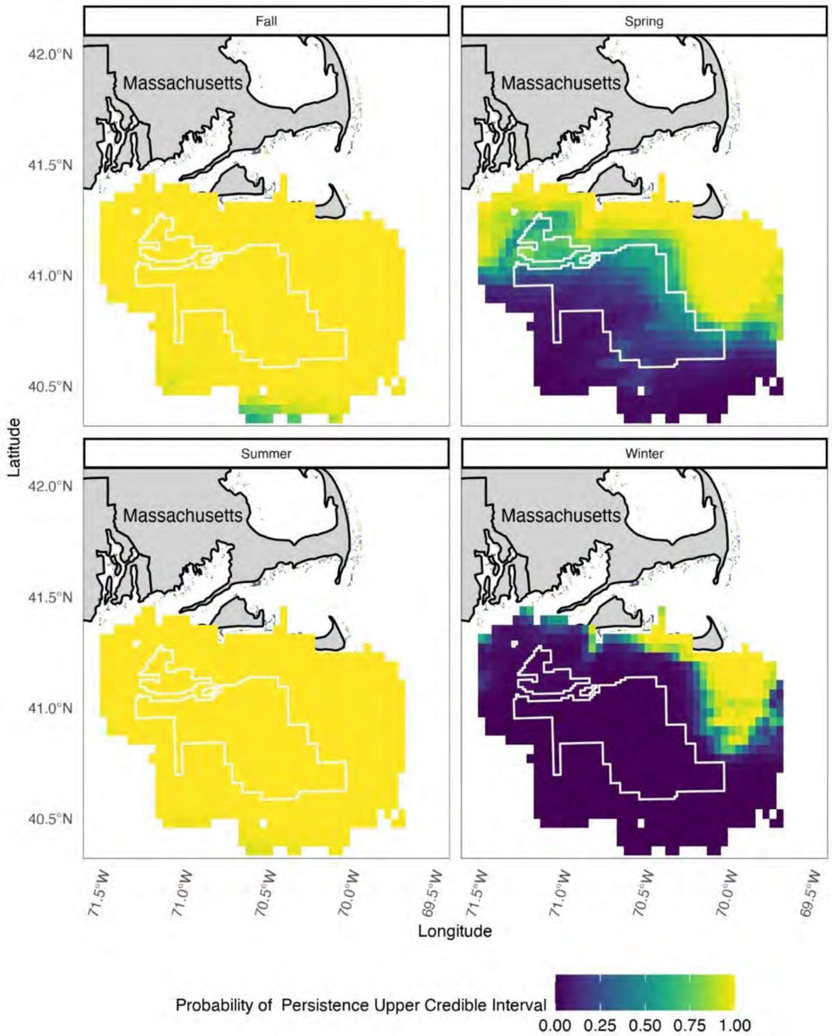


Figure 35: Upper Credible Intervals for predicted probability of persistence in 2021 estimated using Aerial Model trial 1 (four three-month seasons). This model did not converge, and maps should not be used in decision-making. The Massachusetts and Rhode Island Wind Energy Areas is outlined in white.

The Aerial Model trial 1 (four three-month seasons) estimated mean habitat use more precisely for seasons with relatively lower probability of habitat use, especially after 2016. Large variability in the mean probability of occupancy over the entire spatial and temporal study area makes discerning trends difficult (Figure 25). The Aerial Model trial 5 (two three-month seasons) had greater precision for early-summer estimates than late-summer estimates (Figure 30). Precision in late-summer estimates increases in later years of the time series.

2.2 Presentation of whale modelling results at Stakeholder workshop/panel/conference

Dr. Laura Ganley presented work from Right Wind at the International Ecological Modeling Conference in Toronto, Canada, in April 2023, at the National Offshore Wind Research and Development Symposium, in Brooklyn NY, in December 2023, at the New York Regional Species Distribution Modeling Discussion Group at the American Museum of Natural History in November 2023; at the Bureau of Ocean Energy Management (BOEM) Ocean Sciences Meeting, in New Orleans Louisiana in February 2024, at the North American Congress for Conservation Biology's meeting in Vancouver Canada in June 2024, to the Project WOW covariates subgroup in April 2025, and has submitted an abstract to the NARWC to present at the annual meeting in New Bedford, Massachusetts in October 2025. LAUTEC applied to present the Right Wind Project at the American Clean Power (ACP) conference in October 2023. Although we were rejected to present at the ACP conference, members of LAUTEC were still able to attend in October 2023 and verbally share the project's intentions while networking and meeting with developers or other members of the offshore wind supply chain.

The NEAq, LAUTEC US, and Cornell University collaborated to write a joint press release introducing Right Wind to the public. The press release was approved by the National Offshore Wind Research and Development Consortium. With the help of Teak Media + Communication, our joint press release reached 4.1 million people between June 4 and June 13, 2022, with a publicity value of $44,200.

Task 3: Develop Financial Risk Assessment Scenarios

3.1: Financial Risk Assessment Scenarios

Assuming two hours of suitable pile driving weather within a single day is required to complete the installation of a single turbine (NOAA 2021, Siddagangaiah et al., 2022), and five turbines can be installed per eight-day period, we determined that a construction campaign aiming to drive 70 turbines would span 14 eight-day periods under all mitigation scenarios. This campaign duration assumes that multiple piles can be driven in a single day.

3.2: Presentation of risk assessment scenarios results at Stakeholder workshop/panel/conference

The goal of this subtask was to increase exposure of the project to relevant stakeholders and interested parties. The joint press release introducing Right Wind to the public opened a communication channel between LAUTEC and offshore wind developers, and we received interest in the project from developers through this channel.

We used internal LAUTEC funding sources to send Nick Zenkin, former Research and Development Manager, Grace Pacelle, and Carly Campbell to the International Partnering Forum

(IPF), held in Atlantic City, New Jersey from April 26th – April 28th, 2022. This offshore wind energy conference, hosted by the Business Network of Offshore Wind, involved three days of networking with industrial and academic partners from around the world. We attended a panel entitled "Automated Real-Time Marine Mammal Observations: Recent Advancements in Technology" and shared with attendees our preliminary insights from this project and received great interest in its future development and results.

Additionally, Nick Zenkin presented at the American Clean Power Conference on October 21st. The American Clean Power Association published Mr. Zenkin's recorded presentation, "Right Wind: Resolving Protected Species Space-Use Conflicts in Wind Energy Areas," on an online database for all in attendance to view. The presentation outlines the project methodology and risk assessment scenarios, explaining the importance to the industry and environmental stakeholders. Some notable political figures in attendance at the conference included Secretary Deb Haaland, Senator Edward Markey, Massachusetts Governor Charlie Baker, and BOEM Director, Amanda Lefton. Senior management from GE, Equinor, Vestas, Vineyard Wind, EnBW, Orsted, Mayflower Wind, Shell, Atlantic Shores, and Avangrid Renewables were also in attendance.

3.3: Presentation of case studies and risk assessment scenarios to the Consortium and Advisory Board

On Wednesday, June 8th, 2022 and Wednesday, September 28th, 2022, the Right Wind team presented our preliminary modelling results and risk assessment scenarios to the NOWRDC Project Advisory Board. The advisory board provided valuable feedback that we have incorporated in this report and will incorporate in future analyses.

Task 4: Determine the Models' Ability to Forecast Right Whale Distributions

4.1 Oceanographic variables that best predict whale occurrence and the best spatial and temporal scales for forecasts.

4.1.1 Oceanographic variables that best predict whale occurrence

We tested the ability of ten DSMs, to predict right whale density (Table 4). The model with the most relative support included salinity, an interaction between SST and the eight-day period, and an interaction between the distance to the 30 m isobath and the eight-day period (Table 4). This model also had the highest AUC and explained 33.4% of the deviance (AUC = 0.89, Table 4). There was a significant non-linear relationship between right whale density and all the variables in the model (i.e., $p < 0.05$ for each covariate; Figure 36). We found seasonal patterns in right whale density over all the years (Figure 37). During the winter, right whale density was highest along the 30 and 40 m isobaths, and on Nantucket Shoals (Figure 38 and 39). Right whale density was high throughout the study area during spring, particularly along the 30 and 40 m isobaths, but density also increased between winter and spring in the southwest portion of the prediction area. Density decreased during summer but remained high along the eastern side of the 30 m isobath and on Nantucket Shoals. Densities were lowest in the fall and suggested that right whales would be found along the 30 m isobath. In general, these seasonal patterns were well represented within each year, with some notable exceptions. For example, the pattern of higher density in the summer months along the eastern side of the 30 m isobath and on Nantucket Shoals began in 2014 and predicted density was particularly high on Nantucket Shoals in 2017 and 2019 (Figure 37 and 38).

Table 4: Density surface models were used to relate aerial survey data, collected between 2011 and 2020, to oceanographic variables. The model with the lowest Akaike Information Criterion (AIC) score was chosen as the model with the most relative support. We used Area Under the Receiver Curve (AUC) and root mean squared error (RMSE) as a test of goodness-of-fit. Models with RMSE values between 0 and 1 are considered to fit sufficiently.

Model	leave_out_begin	AIC	AUC	RMSE	TSS
Distance to 30m isobath*period, period*SST, Salinity	All years	1,965.22	0.89	0.55	0.68
Distance to 40m isobath*period, period*SST, Salinity	All years	1,967.27	0.89	0.55	0.67
Depth, Period*SST, Salinity	All years	1,973.33	0.88	0.55	0.66
Distance to 30m isobath with depth*period, SST*period, Salinity	All years	1,976.32	0.87	0.55	0.62
Distance to 30m isobath with depth, period*SST, Salinity	All years	2,021.98	0.83	0.55	0.54
Distance to 40m isobath, SST, Salinity, CHL	All years	2,036.73	0.81	0.55	0.53
Distance to 40m isobath, SST	All years	2,039.31	0.80	0.55	0.51
SST, Salinity, CHL	All years	2,047.50	0.78	0.55	0.48
SST	All years	2,051.04	0.76	0.55	0.46
Distance to 40m isobath	All years	2,110.98	0.66	0.56	0.27

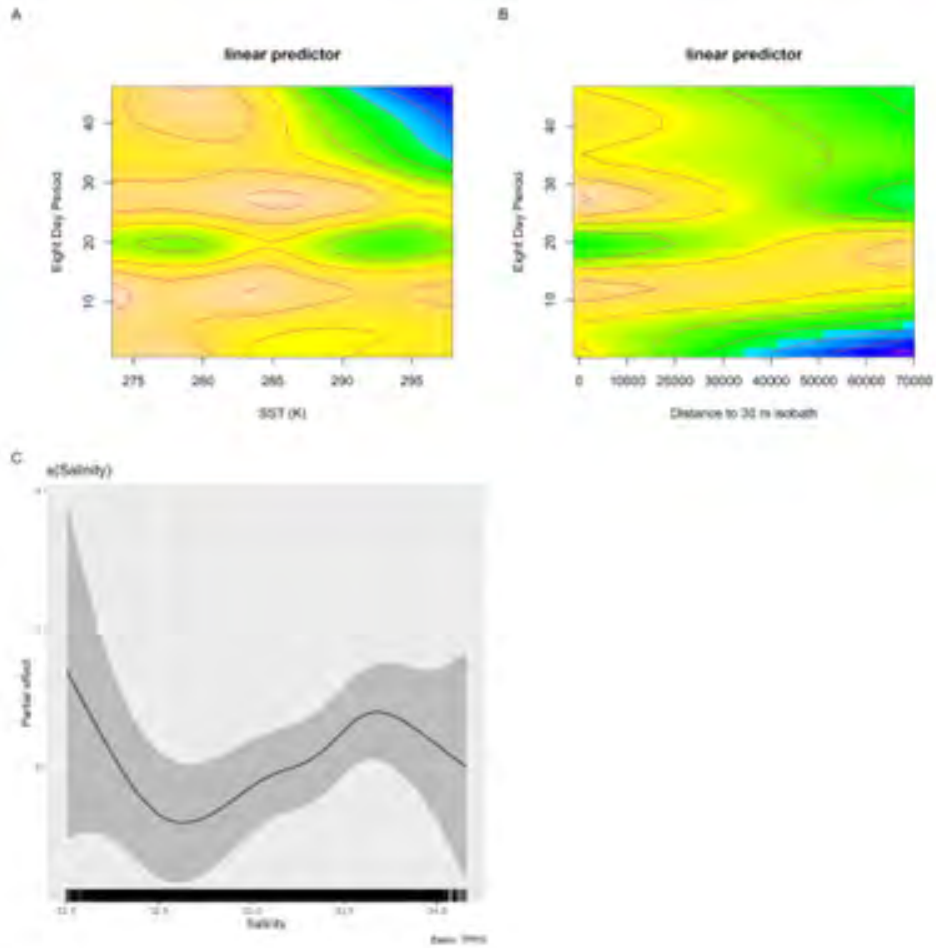


Figure 36: Visualizations of fitted values from the model with the most support for the relationship between right whale density and the interaction between time of year (eight-day period) and (A) sea surface temperature (SST) and (B) distance to the 30 m isobath. Partial effects of (C) salinity on right whale density according to the model with the most support. The gray shading represents 95% confidence intervals for the mean effect.

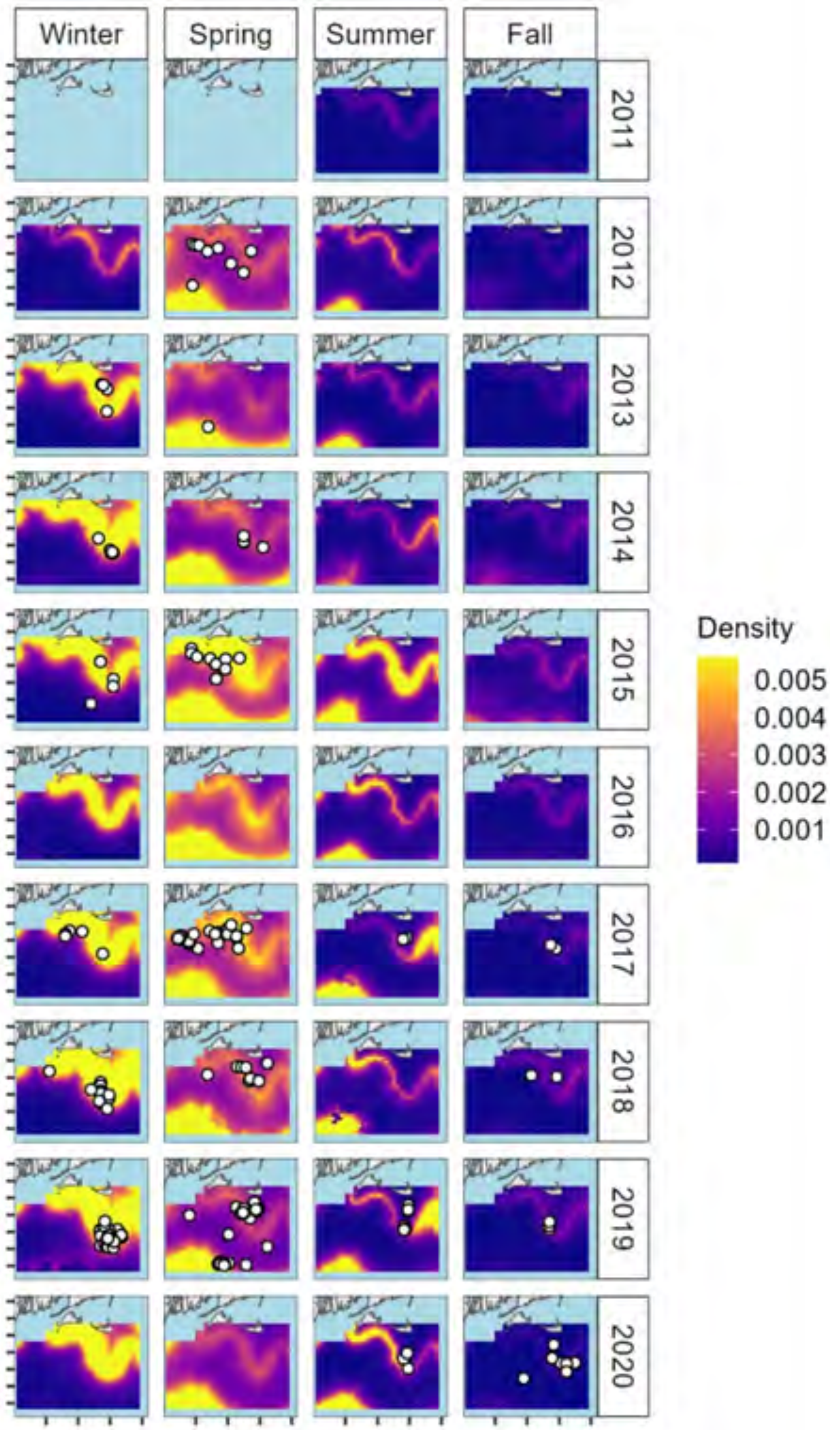


Figure 37: Right whale density predictions per 1 km^2 from the density surface model fit with aerial survey data collected between 2011 and 2020. Panels show the annual seasonal average density based on predicted eight-day densities. White dots show right whale sighting locations from the aerial surveys.

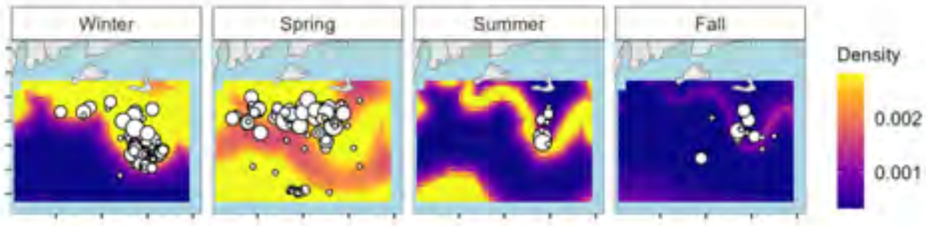


Figure 38: Seasonally averaged right whale density predictions from the density surface model fit with aerial survey data collected between 2011 and 2020. Density ranges were selected to encompass all values within the 25 and 75% quantiles. White dots show right whale sighting locations from the aerial surveys.

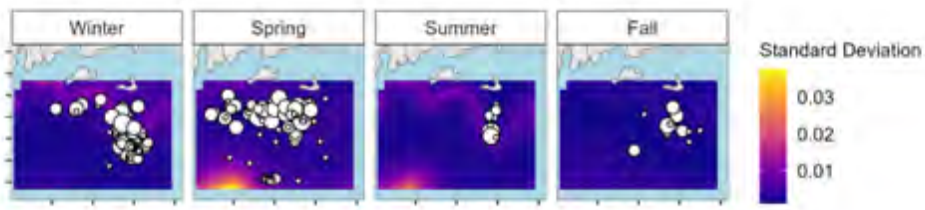


Figure 39: Seasonally averaged right whale density prediction standard deviations from the density surface model fit with aerial survey data collected between 2011 and 2020. Standard deviation ranges were selected to encompass all values within the 25 and 75% quantiles. White dots show right whale sighting locations from the aerial surveys.

4.1.2 Best spatial and temporal scales for forecasts

We fit the model with the most support with data from 2011-2020 and then used the model to generate predictions for 2021 and 2022 (Figure 37). A visual comparison of right whales observed by the NEAq aerial survey team and right whale density predictions for 2021 and 2022 showed relatively good agreement.

Task 5: Develop Commercialization/Marketing Strategy

By implementing the following comprehensive marketing plan, we aim to raise awareness of our Marine Mammal and Weather Downtime Scheduling Tool within the offshore wind industry. Our goal is to establish our solution as the go-to resource for developers committed to environmentally responsible construction practices, particularly the conservation of right whales. Through social media, conferences, community engagement, and informative infographics, we will connect with our target audience and drive positive change in the industry.

Target Audience

Our primary target audience includes offshore wind project managers, construction managers, environmental consultants, offshore wind developers, marine and logistics coordinators, regulatory authorities, marine biologists, conservation organizations, and environmental agencies. Additionally, we aim to engage with local communities, colleges, and the broader public to promote awareness about the topic.

General Message

The tool will help users to create project schedules that prioritize the conservation of right whales and minimizes downtime during installation and construction. This comprehensive marketing plan outlines strategies for promoting our solution through social media, conference participation, community engagement, infographics, and more.

Social Media Strategy

We will utilize platforms such as LinkedIn, Instagram, and Facebook to share updates, success stories, and industry insights (Figures 40, 41). This strategy will include sharing updates about the tool uses, awareness about the topic, infographics, and more.

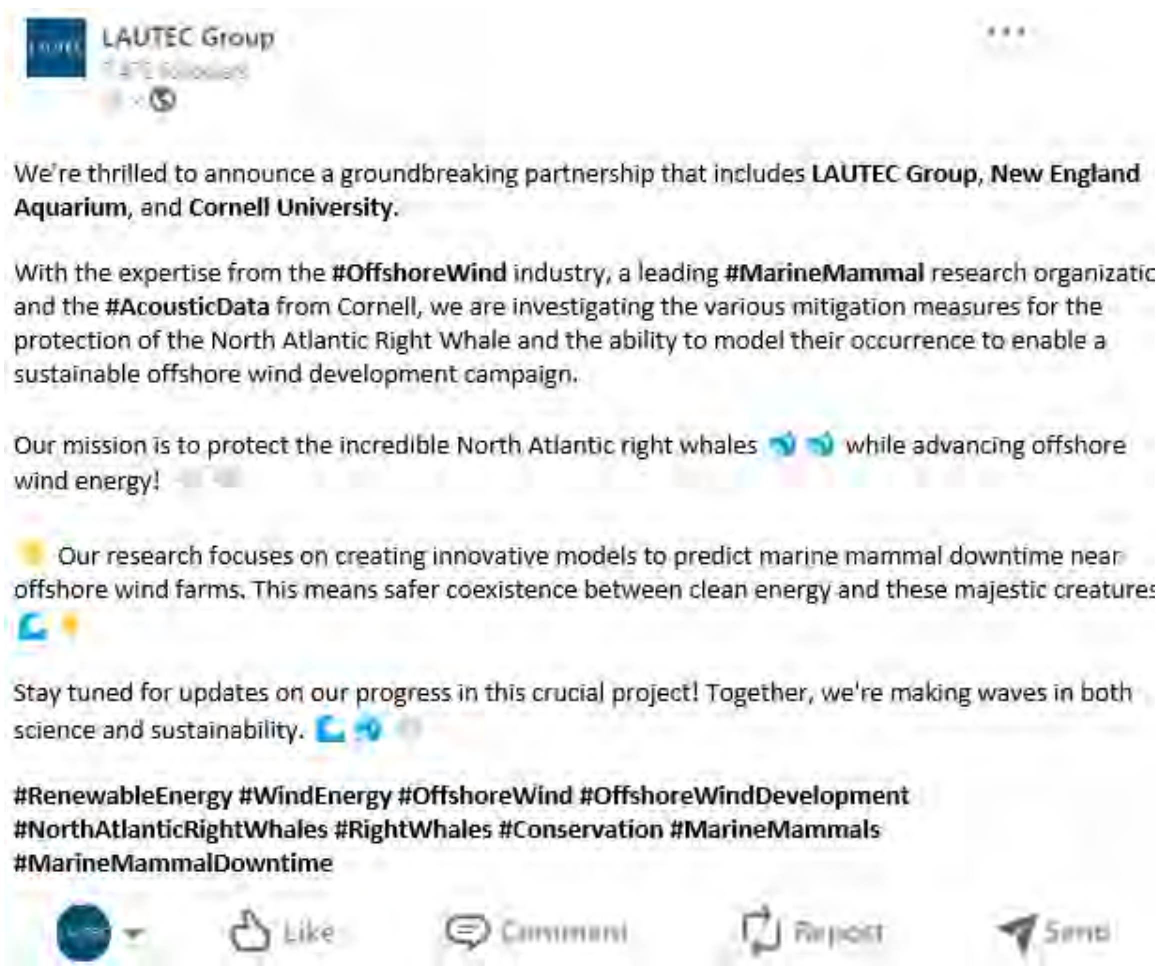
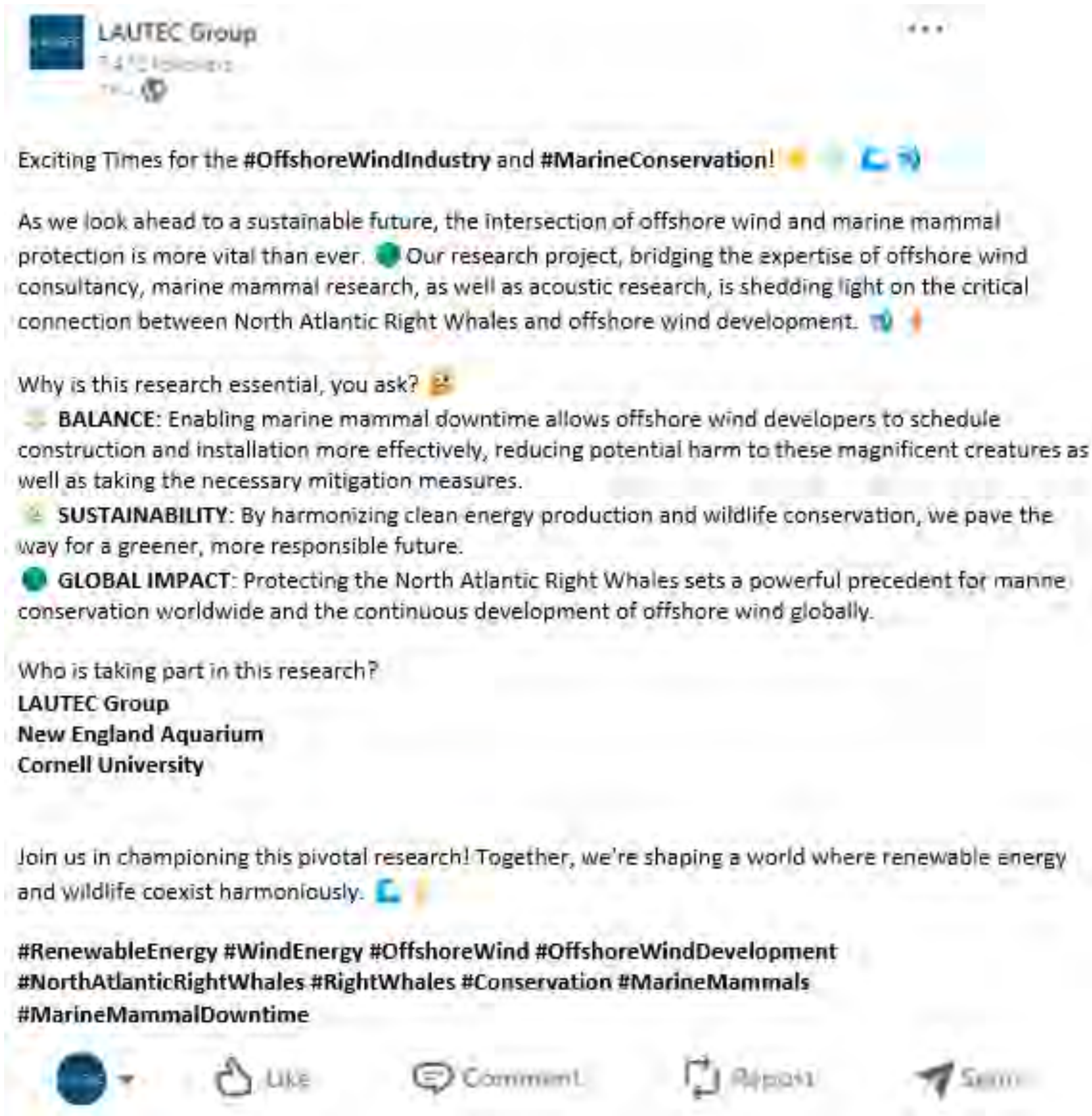


Figure 40: A sample draft of a LinkedIn social media post to raise awareness about the project.



LAUTEC Group

Exciting Times for the **#OffshoreWindIndustry** and **#MarineConservation**!

As we look ahead to a sustainable future, the intersection of offshore wind and marine mammal protection is more vital than ever. Our research project, bridging the expertise of offshore wind consultancy, marine mammal research, as well as acoustic research, is shedding light on the critical connection between North Atlantic Right Whales and offshore wind development.

Why is this research essential, you ask?
BALANCE: Enabling marine mammal downtime allows offshore wind developers to schedule construction and installation more effectively, reducing potential harm to these magnificent creatures as well as taking the necessary mitigation measures.
SUSTAINABILITY: By harmonizing clean energy production and wildlife conservation, we pave the way for a greener, more responsible future.
GLOBAL IMPACT: Protecting the North Atlantic Right Whales sets a powerful precedent for marine conservation worldwide and the continuous development of offshore wind globally.

Who is taking part in this research?
LAUTEC Group
New England Aquarium
Cornell University

Join us in championing this pivotal research! Together, we're shaping a world where renewable energy and wildlife coexist harmoniously.

#RenewableEnergy #WindEnergy #OffshoreWind #OffshoreWindDevelopment #NorthAtlanticRightWhales #RightWhales #Conservation #MarineMammals #MarineMammalDowntime

Like Comment Repost Send

Figure 41. Sample draft of a LinkedIn social media post to raise awareness about the project.

Conferences

Attending offshore wind industry conferences, expos, and seminars will allow us to spread the word about the tool and showcase live demonstrations and presentations about our tool's capabilities. We will benefit from attending these conferences by connecting– with potential clients, industry experts, and regulatory bodies to build relationships and establish credibility within the industry. Furthermore, these insights can be used to continuously develop the tool to better help the user.

Community Engagement

Community engagement is vital to raise awareness and demonstrate that offshore wind can be developed responsibly. We will collaborate with local communities, colleges, environmental organizations, and marine research institutions to build trust and garner local support. Furthermore, we will be hosting information sessions both in-person and virtually to educate the public and/or stakeholders about the importance of responsible offshore wind construction practices and the role our tool plays in it.

Infographics and Visual Content

We will create visually appealing infographics and videos that explain the tool's benefits, its role in right whale conservation, and its ease of use. These materials will be used in social media campaigns, conferences or tabling opportunities.

Task 6: Assess Financial Risk; and Task 7: Analyze Economic Tradeoffs

Allowing pile driving in all months increases the predicted number of right whales exposed to Level A takes regardless of noise attenuation (*No Seasonal Restriction* = 283% increase; *No Seasonal Restriction and Additional Noise Attenuation* = 30% increase; Figure 42) when compared to the *Early Start and Late Finish Seasonal Restriction scenario*. Shorter pile-driving seasons further reduces risk (*Late Start* = 8%, *Early Finish* = 10%, and *Late Start and Early Finish* = 44% decrease in right whales exposed to Level A takes) when compared to the seasonal restrictions in the *Early Start and Late Finish Seasonal Restriction scenario*. If a second bubble curtain is used, the risk reduction is large and similar among pile-driving options that include a seasonal restriction (*Late Start and Additional Noise Attenuation* = 68%, *Early Finish and Additional Noise Attenuation* = 70%, and *Late Start and Early Finish and Additional Noise Attenuation* = 81% decrease in right whales exposed to Level A takes). A second bubble curtain incurs an additional $2M cost to development over the *Early Start and Late Finish Seasonal Restriction scenario* (Beelen et al., 2025).

The change in risk for exposure to Level B takes was similar to Level A takes (Figure 42). One difference was that allowing pile driving in all months while using a second bubble curtain reduced the predicted number of right whales exposed to Level B takes *(No Seasonal Restriction and Additional Noise Attenuation* = 38% reduction*)* when compared to the *Early Start and Late Finish Seasonal Restriction scenario*, however we found large variability and often an increase in the predicted number of right whales exposed to noise levels above the Level B take threshold (Figure 42).

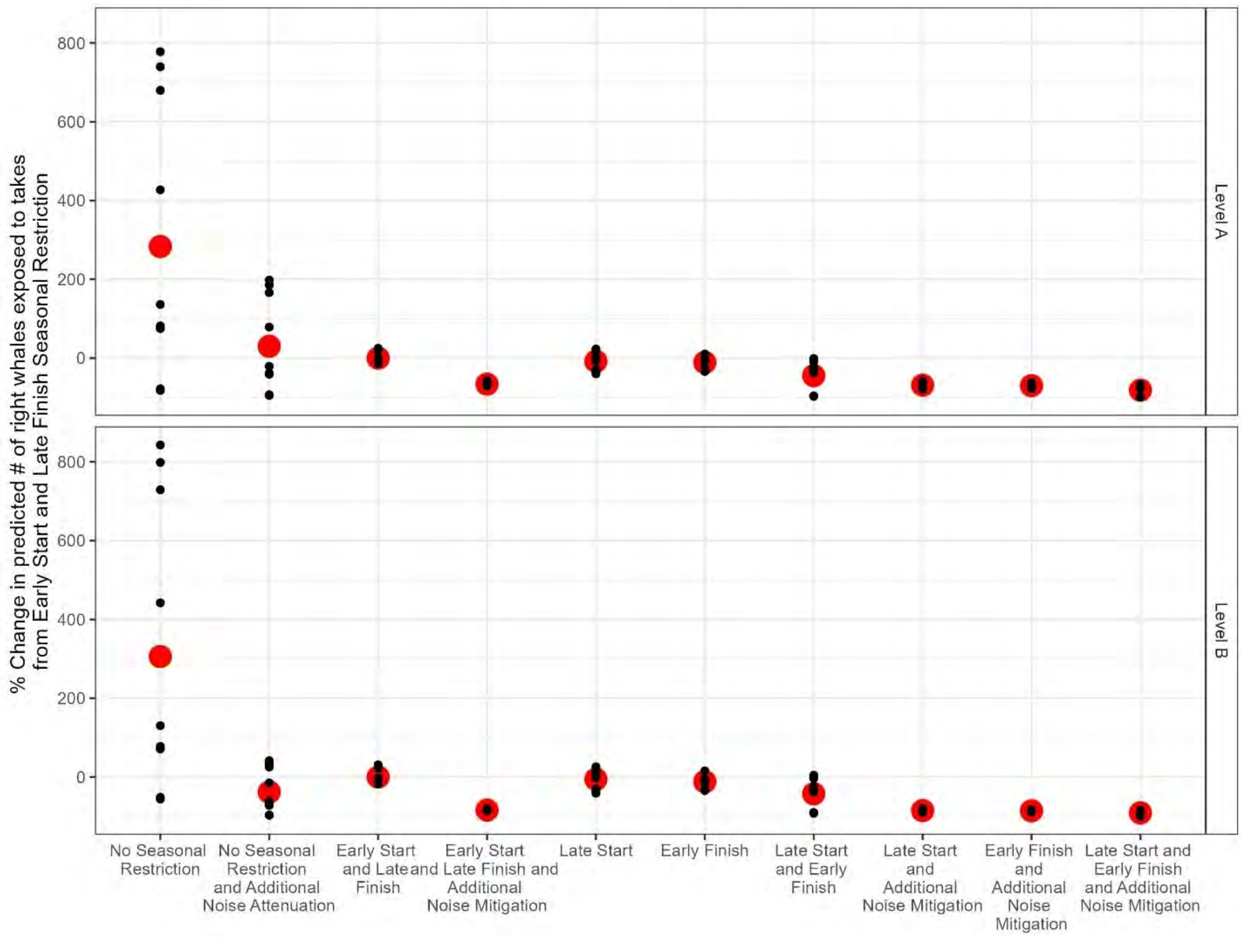


Figure 42: The predicted number of right whales exposed to Level A and B takes for the mitigation scenarios. Red circles indicate the % change in the mean predicted number of right whales exposed to sound levels associated with Level A and Level B takes when compared to the mean from the Early Start and Late Finish scenario. Black dots show the % change in the predicted number of takes for each of the 10 development campaigns within each scenario.

The magnitude of variation around the predicted number of right whales exposed to takes depends on the time of year that pile-driving took place (Figs. 43 and 44) and the location of the wind farm within the WEAs. In 2018, standard deviations of right whale density estimates were high in the winter months (Figure 45), when right whale abundance was high. The higher standard deviations during this time period leads to relatively high variation in the predicted number of right whales exposed to takes for the *No Seasonal Restriction scenario* (Figure 42), which is the only scenario that allows pile driving during the winter months. In comparison, density estimates in the WEAs in the summer and fall were more precise, when right whale abundance was lower, resulting in increased precision in the predicted number of right whales exposed to takes (Figure 42). There was also high variation in the predicted number of right whales exposed to takes in the winter months depending on the spatial location of the wind farm (e.g., wind farms in the SW portion of the WEAs would have much lower right whale density than wind farms in the NW portion of the WEAs).

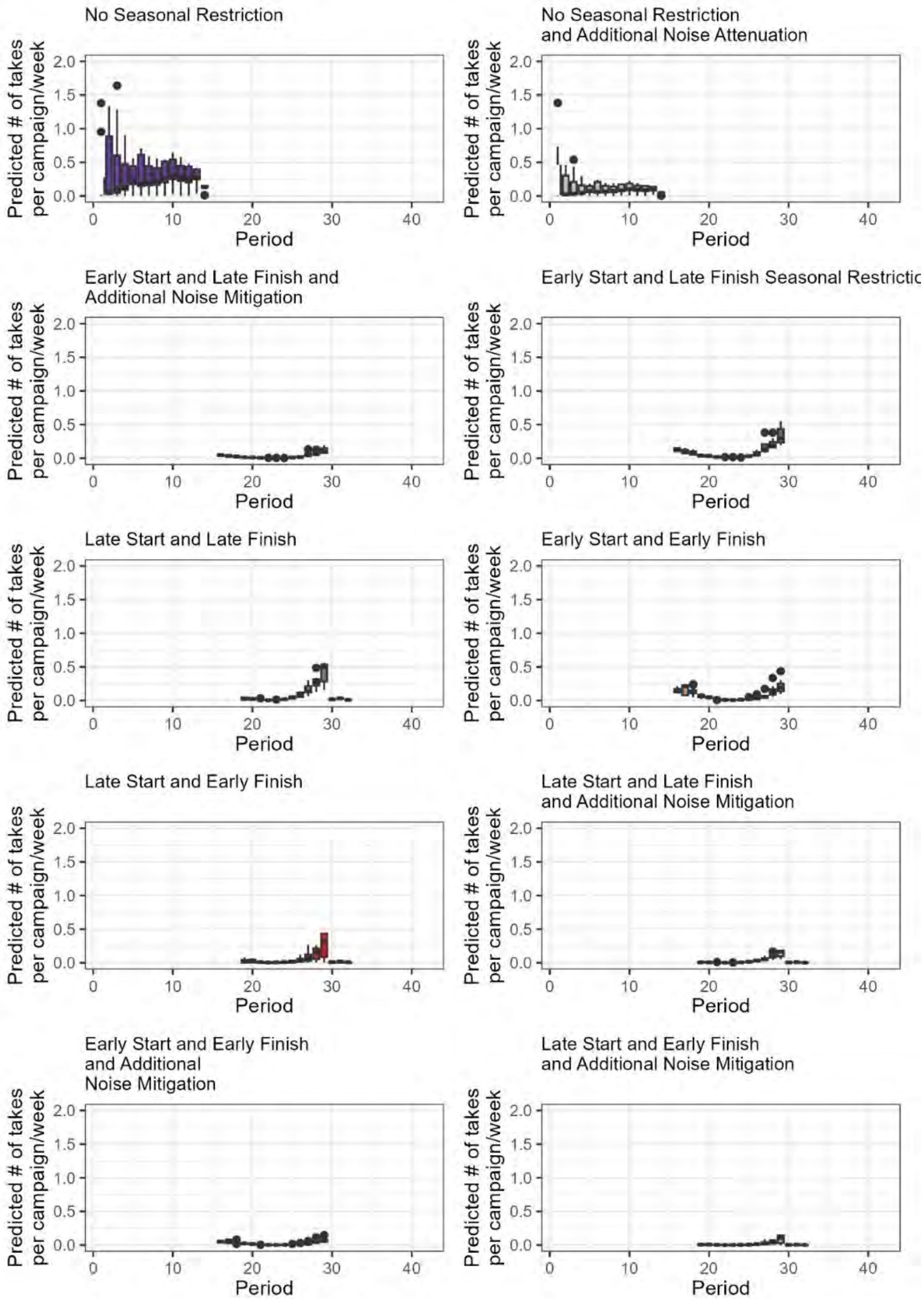


Figure 43: The predicted number of noise exceedances above the Level A Take regulatory threshold that a campaign would use in each eight day period.

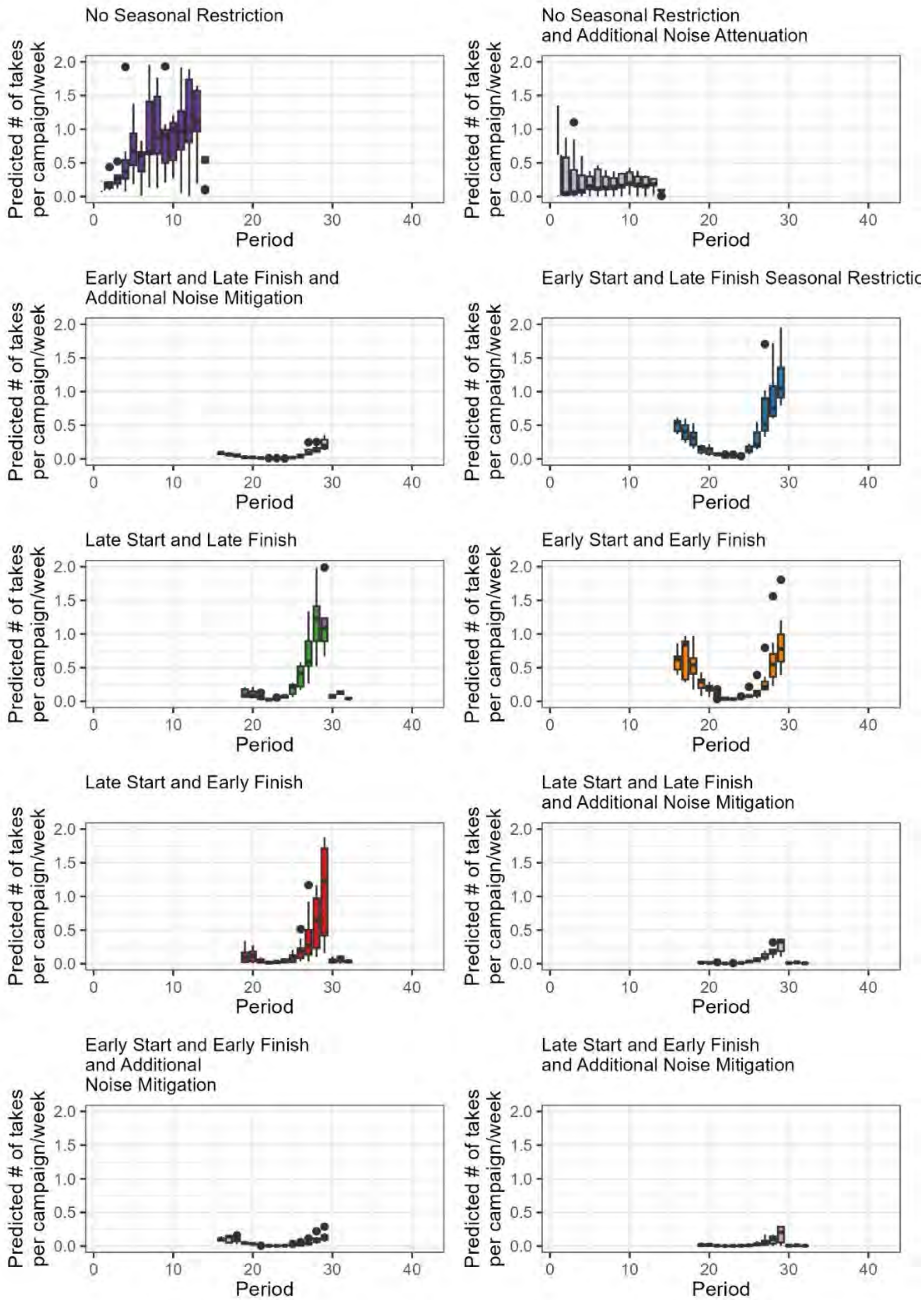


Figure 44: The predicted number of noise exceedances above the Level B Take regulatory threshold that a campaign would use in each eight day period.

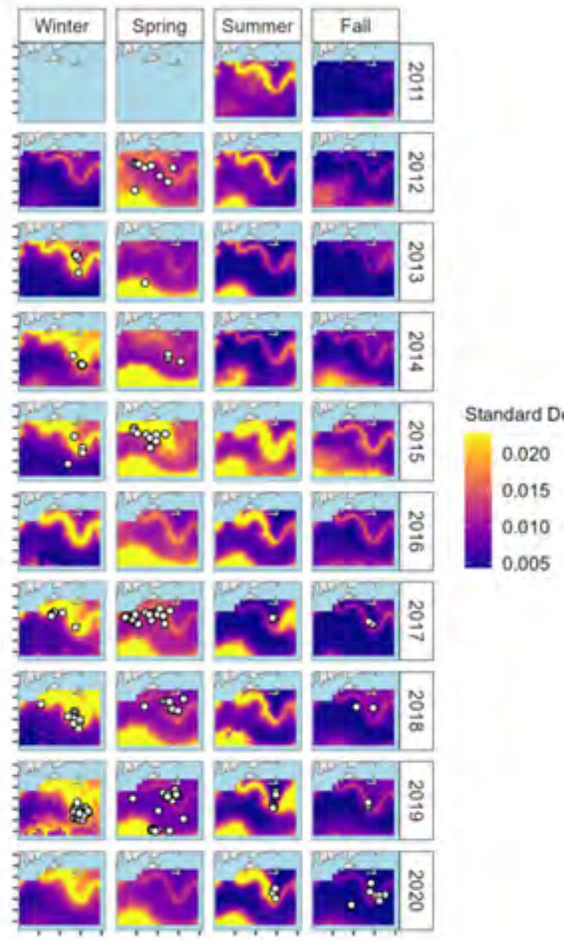


Figure 45: Seasonally averaged right whale standard deviation of density predictions for each year from the density surface model fit with aerial survey data collected between 2011 and 2020. Density ranges were selected to encompass all values within the 25 and 75% quantiles. White dots show right whale sighting locations from the aerial surveys.

Task 8: Develop Decision Support Framework

We developed an interactive R Shiny Decision Support App prototype which allows interested users to interact with our tradeoff analysis results (Appendix B).

Task 9: Deploy Commercialization Strategy

After the completion of the Support Prototype, the team began its deployment of its previously created commercialization strategy, including engaging with potential clients, ongoing industry needs, and future use cases. The team implemented an outreach effort to all major offshore wind developers in the northeast region of the United States. Unfortunately, due to major layoffs at most developers we received a very low level of interest. Despite these challenges the team was able to host a Stakeholder Engagement Workshop to present our Decision Support App prototype to a group of ten colleagues from Orsted and Equinor. The workshop was hosted online and involved a presentation of the project and a detailed walk through of the Decision Support Tool prototype, followed by Q&A from the developer teams. In general, the feedback from the developers was positive and they saw value in a tool like this supporting their development and construction efforts. Feedback on the prototype was well received by the project team and suggestions were implemented where possible.

Discussion

Developing offshore renewable energy resources will help meet increasing energy demand, and has the potential to increase economic growth, mitigate climate change, and help achieve a thriving Blue Economy. To achieve ecosystem sustainability, which is an integral part of a Blue Economy, the impacts of offshore development on vulnerable species must be minimized. Ideally, wildlife mitigation measures would be optimized to yield maximum conservation value while incurring minimal financial burden.

We developed a framework for a tradeoff analysis that allows the assessment of development costs and conservation benefits associated with measures to mitigate potential impacts of wind energy development on wildlife. Previous tradeoff analyses have used marine spatial planning to assess the impacts of where WEAs are sited and when construction should occur on wildlife conservation (Best and Halpin, 2019; White et al., 2024, 2012). Our analysis allows for a detailed assessment of the impacts of wind farm *construction* on wildlife conservation. In the USA, the permitting process quantifies the number of animals exposed to possibly harmful impacts by counting the number of Level A and B takes. As such, we use exposure to Level A and B takes as our measure of conservation value. While our case study required several simplifying assumptions (discussed below), our framework allows interested parties to adjust the assumptions, determine the conservation impacts of their actions, and minimize the costs of development.

Under the assumptions used in our simulation, we found that it is possible to minimize the costs of wind energy development and maximize right whale conservation. We identified several scenarios where increased right whale protections came with minimal or no additional financial costs. We found that both achieving additional noise attenuation, explored in our simulations through adding a second bubble curtain, and seasonal restrictions on pile-driving, reduced the number of whales predicted to be exposed to Level A takes when compared to the *Early Start and Late Finish Seasonal Restriction scenario* (Figure 42). A second bubble curtain used with seasonal pile-driving restrictions provides the most conservation benefit for right whales and results in a cost increase of $2M over the *Early Start and Late Finish Seasonal Restriction scenario* due to the cost of the additional noise attenuation devices (Beelen et al., 2025). This additional $2M is only 2% of the cost of the *Early Start and Late Finish Seasonal Restriction scenario*. Seasonal pile-driving restrictions, without the use of a second bubble curtain, also offer more conservation value than the *Early Start and Late Finish Seasonal Restriction scenario* with no added financial costs. Our analysis shows that pile-driving with no seasonal restrictions results in large increases in the number of right whales predicted to be exposed to Level A and B takes because of the seasonal whale occurrence patterns as indicated by our DSM (Figure 38 and 39).

The possibility for mitigation measures to extend pile-driving into a second year of development is an important financial consideration for wind energy developers. Extending a development campaign into a second year would result in an estimated minimum $30M cost increase due to mobilization costs alone[47]. In our simulation, even under the most limiting *Seasonal Restriction* scenarios (i.e., the *Late Start and Early Finish Seasonal Restriction scenario*), the construction of an average sized development campaign can be completed within one year. Therefore, the financial cost of *Seasonal Restriction* scenarios is equal to the E*arly Start and Late Finish Seasonal Restriction scenario*. Under the assumptions in our simulation, it is possible to pile drive 70 turbine foundations in a single year under the *Seasonal Restriction* scenarios. There is a risk that a campaign could extend into a second year because of work stoppages caused by unusually inclement weather, whale detections made by Protected Species Observers (PSOs), limited visibility that inhibits necessary monitoring by PSOs, or issues with supply chain and vessel mobilization. Right whale detections made from the pile-driving vessel trigger a mandated work stoppage until PSOs confirm they have not detected a right whale from the vessel for at least 30 minutes (National Oceanic and Atmospheric Association, n.d.). We have not included these delays in our analysis, and these stoppages will likely increase the length of the construction season. However, seasonal restrictions in pile-driving help to reduce the possibility of a work stoppage for right whales because of their seasonal patterns of occurrence, as inferred from our DSM.

Exceedance of the legally permitted takes during offshore wind development can result in additional delays and costs due to necessary operational adjustments, permit modifications, or project shutdowns (NOAA 2024). Identifying cost-effective solutions to minimize right whale exposure to Level A and B takes during project development therefore represents a strategy that both protects marine mammals and reduces the risk of future project delays. Project delays and unexpected costs may also result from supply chain complications, material cost increases, and changes in the political landscape (Hansen et al., 2024). For current wind energy development projects, these complications have resulted in costs ranging from $50 million a week to $600 million total (McDermott, 2025). In this context, the cost of mitigation to reduce impacts on critically endangered species is minimal. Additionally, we did not include the financial value of individual right whales, provided through ecosystem services or their intrinsic value, in our tradeoff analysis. The financial value of right whales would further justify the cost of mitigation measures to reduce potential impacts.

Our tradeoffs framework is widely applicable to other species, sectors within the Blue Economy, and mitigation scenarios. The conceptual power of our framework comes from simulating construction while also quantifying the number of whales exposed to Level A and B takes.

However, the ability to conduct the analysis is contingent upon the availability and amount of the data required to fit a species distribution model and an understanding of the effectiveness of the mitigation measure. For example, since the WEAs were designated in 2011, there has been relatively consistent aerial survey effort to monitor the use of the area by marine mammals. These surveys also incur a financial cost (approximately $500,000/year), albeit minimal relative to the other costs we have detailed in our analyses. Lower levels of survey effort will decrease the precision in density estimates, thereby reducing the utility of the results.

Humans are increasingly looking to the ocean for sources of renewable energy to mitigate the broad and chronic impacts of climate change. While offshore wind energy development presents an opportunity to reduce global greenhouse gas emissions and slow climate change, it is also part of the increasing trend toward industrialization of the world's oceans, which may have local and acute impacts on wildlife. It is important to understand the human-wildlife conflicts that result from development and how they can be moderated. To achieve a thriving Blue Economy, namely one that balances economic growth with sustainable practices, more quantitative tools that assess the tradeoffs between wildlife conservation and ocean industries are required.

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Using right whale density estimates to assess the financial risk of protected species mitigation measures to wind energy development

Laura C. Ganley[1], Daniel E. Pendleton[2], Ian Spooner[3], Aaron Rice[4], Orla O'Brien[1], Jessica V. Redfern[1]

1 Anderson Cabot Center for Ocean Life, New England Aquarium, Boston Ma, USA

[2] Whale Ecology Branch, Protected Species Division, NOAA Northeast Fisheries Science Center, Woods Hole, MA~~a~~, USA

3 LAUTEC US, Boston, MA, USA

4 K. Lisa Yang Center for Conservation Bioacoustics, Cornell Lab of Ornithology, Cornell University, Ithaca, NY, USA

Abstract:

Climate change is profoundly impacting ecosystems worldwide. Offshore wind energy is an important tool for reducing fossil fuel use and greenhouse gas emissions. However, wind energy development, intended to mitigate the impacts of climate change, may have negative impacts on large baleen whales. To mitigate these potential negative consequences, we need a detailed understanding of whale distribution. Right whale density estimates are necessary to assess the financial risk of right whale mitigation measures to wind energy development in the U.S. We develop fine spatial and temporal resolution right whale density models for the Massachusetts/Rhode Island Wind Energy Areas. We found that salinity, the interaction between sea surface temperature and eight-day period, an interaction between the distance to the 30 m isobath and eight-day period, and the interaction between the 40 m isobath and eight-day period were the best predictors of right whale density (AIC = 4812.22; AUC = 0.91; 64% explained deviance). We then use general expectations of marine mammal downtime to assess the financial risk of three right whale mitigation scenarios. The baseline scenario, which assumes construction starts on May 1st and extends until completion of 70 monopile foundations, has an estimated cost of \$215,150,000. For the second scenario the construction start date moves to June 1st and has an estimated cost of \$378,780,000. In the third scenario, we assumed a second Big Bubble curtain would be implemented, resulting in a cost of \$235,150,000. Preliminary economic tradeoff analyses (see our phase two report) combine predictions from our model and the financial risk assessment. Future work will be done to finalize the economic tradeoff analysis approach. Through our project, we intend to contribute to responsibly developing offshore wind energy, while conserving right whales and successfully mitigating climate change.

Keywords: density surface model, renewable energy development, right whale, financial risk

Introduction

Climate change is profoundly impacting ecosystems worldwide, and these effects are expected to continue and, in some cases, amplify over the next century (Intergovernmental Panel On Climate Change, 2023). Marine ecosystems are experiencing unprecedented warming, reductions in sea ice coverage and dissolved oxygen levels, ocean acidification, sea level rise, and weakening circulation patterns (i.e. Atlantic Meridional Overturning Circulation)(Garcia-Soto et al., 2021). These changes to the physical environment can lead to changes in the abundance, phenology, and distribution of animals at higher trophic levels. For example, thermal changes have led to increased mortality and reduced recruitment of Atlantic cod *Gadus morhua* (Pershing et al., 2015), and declining prey availability and reduced reproductive success in both southern right whales (*Eubalaena australis*) and the critically endangered North Atlantic right whale (*Eubalaena glacialis*) (Meyer-Gutbrod et al., 2021; Vermeulen et al., 2023). Significant shifts in migratory timing, related to changes in the timing of warming and sea ice dynamics, has been observed in several cetacean species (Pendleton et al., 2022; Ramp et al., 2015; Shuert et al., 2022; van Weelden et al., 2021). Changes in animal distribution resulting from climate change that are most relevant to this study are poleward shifts to follow preferred water temperatures for many fish stocks and cetaceans (Lucey and Nye, 2010; Nye et al., 2009; van Weelden et al., 2021). For example, a climate induced poleward shift in right whale distribution resulted in a mass human-caused mortality event (Davies and Brillant, 2019).

Mitigating climate change is one of the biggest conservation issues of our time. Offshore wind energy is an important tool for reducing fossil fuel use and greenhouse gas emissions. The US is on track to have 27 GW deployed by 2025 (The White House, 2023) with a Biden administration goal of deploying 30 GW by 2030 (The White House, 2022). While, there are still considerable knowledge gaps surrounding the impacts of offshore wind energy development on wildlife (Allison et al., 2019; Kraus et al., 2019) negative impacts can include habitat loss and increased risk of collision mortality with turbines. For example, several studies have documented decreased occurrence of harbor porpoise (*Phocoena phocoena*), from baseline levels, during the construction of offshore wind farms (Benhemma-Le Gall et al., 2021; Brandt et al., 2018; Haelters et al., 2015). In addition, loons (*Gavia spp.*) were displaced from offshore wind farms after construction resulting from both turbines and the increased vessel traffic required to maintain the turbines (Mendel et al., 2019). Collision mortality with wind turbines for birds and bats has been widely documented (Allison et al., 2019; Lloyd et al., 2023; Loss et al., 2013).

Wind energy, intended to mitigate the impacts of climate change, may have negative impacts on large baleen whales. Historically, southern New England (the area south of Nantucket and Martha's Vineyard), was a prolific whaling ground, dating back to the 1600's, with right whales, sperm whales (*Physeter macrocephalus*), and humpback whales (*Megaptera novaeangliae*) being the primary targets (Reeves et al., 1999). Small numbers of right whales were documented in southern New England during the 20th century, but habitat suitability models, developed for the early 2000s, indicated the area could be an important right whale feeding habitat (Pendleton et al., 2012). Aerial surveys, specifically designed to monitor the area prior to wind energy development, began in 2011 (Leiter et al., 2017; Stone et al., 2017), and in 2013, the Bureau of Ocean Energy Management (BOEM) designated two areas in southern New England (i.e. the Massachusetts/Rhode Island Wind Energy Areas (MA/RI WEAs)) for offshore wind development. These surveys documented a number of cetacean species that are afforded protection by the Endangered Species Act and/or the Marine Mammal Protection Act, including the critically endangered right whale, which has increased in abundance in the area since the surveys began (O'Brien et al., 2022). We are currently at a crossroad where we need to figure out how to responsibly develop offshore wind and conserve right whales.

To mitigate the potential negative consequences of wind energy development, we need a detailed understanding of whale distribution. This understanding can be obtained using species distribution models. While distribution models have been developed for cetacean species on the U.S. East Coast (Roberts et al., 2016), these models capture coast-wide habitat relationships that may miss important distribution patterns and environmental features at smaller scales. Determining the appropriate spatial and temporal scale for modeling requires balancing what might be biologically relevant for the species with factors that are relevant for conservation management. For example, a study comparing the effects of grid cell size on nine species found that model accuracy and the agreement of range location declined as grid cell size increased, and that species range size is an important consideration when choosing grid cell size (Seo et al., 2009). However, regional habitat models for cetaceans, designed to test the impact of spatial scale on species-environment relationships, have ambiguous conclusions (Becker et al., 2010; Jaquet and Whitehead, 1996; Redfern et al., 2008). For example, Redfern et al., (2008) found that the relationship between four dolphin species and their environment did not vary with spatial scale; the authors hypothesized that domains of scale exist wherein the species-environment relationship does not change. In contrast, Jaquet and Whitehead found that the relationship between sperm whales and their environment were only apparent at large spatial scales (Jaquet and Whitehead, 1996).

Right whale density estimates are necessary to assess the financial risk of right whale mitigation measures to wind energy development in the U.S. Currently, estimates of right whale density are available as monthly averages over long-time periods and are made using models developed for the entire U.S. east coast (Roberts et al., 2016). The goal of our study is to develop fine spatial and temporal resolution models for the MA/RI WEAs using the long time series of systematic aerial survey data collected by the New England Aquarium and combine those estimates with the financial risk assessment in a tradeoff analysis. In this report we use general expectations of marine mammal downtime to assess the financial risk of three right whale mitigation scenarios. We have conducted preliminary economic tradeoff analyses (see our phase two report) that combine predictions from our model and the financial risk assessment. In the remainder of this project, we will finalize the economic tradeoff analysis approach. Through our project, we intend to contribute to responsibly developing offshore wind energy, while conserving right whales and successfully mitigating climate change

Methods

Aerial surveys and data preparation

Whale sightings were collected during aerial surveys, flown approximately twice monthly, in Southern New England between 2011 and 2023 (Figure 1). Three types of surveys were flown: General, Directed, and Condensed. General surveys were standardized line-transect surveys flown on a monthly basis. Twelve north-south tracklines were evenly spaced at approximately 6 nautical miles (nm). One of eight survey options was randomly selected prior to each survey. Each option shifts all 12 tracklines 0.75 nm east or west, while maintaining the 6 nm spacing. Directed surveys were flown in areas of known right whale aggregations. These surveys followed line-transect protocols, but the area surveyed and number of lines varied based on the location of the right whale aggregations. Condensed surveys were standardized line-transect surveys but were comprised of 10-12 tracklines spaced 3 nm apart. Aerial surveys were flown at a ground speed of 185 km/h and an altitude of 305 m, in either a Cessna Skymaster 337 O-2A or a Partenavia P68 aircraft. Data indicating trackline effort were recorded every 2-5 seconds. Two observers, one on either side of the airplane, scanned their field of view for marine mammals, sea turtles, vessels, and fishing gear. Sightings were recorded when they were perpendicular to the airplane. Marks on the wing struts or an inclinometer were used to record information about the distance of the sighting from the trackline. When right whales were sighted, the plane diverted from the trackline to obtain photo-identification data.

To use the aerial survey data in density surface models (DSMs), sections of aerial survey tracklines with uninterrupted survey effort were separated into approximately 4.6 km segments. We determined how many 4.6 km segments were contained in the uninterrupted survey effort. If the remaining effort was ≤ 2.3 km long, we randomly selected one segment to include the target 4.6km of effort and the remaining amount of effort. If the remaining effort was ≥ 2.3 km, we randomly selected one segment to have a target distance equal to the remaining amount of effort. If the entire section of uninterrupted survey effort was < 4.6 km, it was treated as a single segment. We then summed the point-to-point distances to make segments totaling each target distance. However, the sum of the point-to-point distances was not always equal to the target distance. To avoid biasing the segment lengths, we randomly determined if the segment should be slightly longer or shorter than the target distance. We also summarized the number of whale sightings and the number of whales in a group for each segment.

To estimate right whale density, we used a multi-step modeling approach. The first step included fitting a detection function and estimating the effective strip width. The details of this process can be found in (O'Brien et al., 2022). Briefly, we used the *Distance* package in R to fit a detection function using data from 2011-2023 using a hazard rate model (R Core Team, 2022) (Miller et al., 2019). The effective strip width was estimated at 0.72 km. The second step in the modeling process included fitting generalized additive models (GAMs) to capture the relationship between the number of right whales observed on a segment and oceanographic predictor variables (described below). GAMs were estimated using the *dsm* package in R (Miller et al., 2013). We used a tweedie distribution in these models. Parameter estimates were optimized using restricted maximum likelihood (REML). Thin plate regression splines were used to model the relationship between individual environmental variables and right whale density. Relationships between right whale density and interactions between variables were modeled using tensor splines. Density (D) was estimated as:

$$D_i = (n_i/L_i) * \tfrac{1}{2}(ESW) * g(0)$$

Where n is the number of animals on segment *i* and *L* is the length of the segment (km). *ESW* is the effective strip half width estimated at 0.72 km. We assumed perfect detection on the trackline (i.e., g(*0*) = 1). An offset was used in the GAMs to include the natural log of the effective area searched.

Oceanographic predictors of right whale density

We used DSMs to model right whale density as a function of oceanographic variables. All the oceanographic variables were standardized on a 4.6 km grid, over eight-day periods. Oceanographic data were associated with the midpoint of each trackline segment.

Right whales have been observed over a wide range of depths, but the preferred depths vary by habitat. In the Gulf of Maine, right whales regularly occur in waters 100 to 200 m deep. However, in Cape Cod Bay, which is a prolific spring feeding ground, right whales occur in waters that are only 18 to 60 m deep. We used 0.00083° resolution depth data from the Northeast Coastal Relief Model V1 (National Geophysical Data Center, 1999) as a predictor variable in our DSMs. It is also possible that bathymetric features (e.g., isobaths), which cause thermal fronts and aggregate zooplankton, have a stronger influence than depth on right whale distributions. We calculated the distance from each segment midpoint and the center of each oceanographic grid cell to the 30, 40, and 50 m isobath using the *marmap* package in R (Pante and Simon-Bouhet, 2013).

Right whales primarily feed on *Calanus finmarchicus.* Chlorophyll *a* concentration can be used as a proxy for phytoplankton, the prey of *C. finmarchicus.* We used Aqua MODIS Global Mapped Chlorophyll data sampled at eight-day intervals and a 4 km spatial resolution (NASA Ocean Biology Processing Group, 2017).

In Cape Cod Bay, abundance of *C. finmarchicus* and *Centropages typicus,* a second right whale food source, were found to be correlated with salinity (DeLorenzo Costa et al., 2006). We obtained four-day salinity data on a 1/4° grid from the Multi-Mission Optimally Interpolated Sea Surface Salinity Global Dataset V1 (IPRC/SOEST, 2021).

Previous studies have found the winter distribution of right whales to be largely determined by sea surface temperature (SST), although the mechanism for this influence is unclear (Pendleton et al., 2012). We obtained daily SST data on a 0.01 ° grid from the GHRSST Level 4 MUR Global Foundation Sea Surface Temperature Analysis (v4.1) (NASA/JPL, 2015).

We created eight-day, 4.6 km prediction grids, over the spatial extent of the combined aerial survey and acoustic effort (Figure 1). We assessed model fit by visually inspecting q-q plots and using the root mean squared error (RMSE). We compared models using the receiver operating characteristic curve (AUC; Fawcett, 2006) and Akaike's Information Criterion (AIC score). Models with larger AUC values have a better fit, while lower AIC scores indicate models with more support. Ultimately, we used AIC scores to determine the model with the most support. We used the model with the most support to predict right whale density over our prediction grids. To ensure extrapolation errors did not occur in our density predictions, we visually inspected histograms of the environmental data used for model fitting against the environmental data used to make predictions.

Variance was estimated using the methods outlined by (Miller et al., 2022). Because our detection function model did not have any predictor variables, we were able to use the delta method to propagate the uncertainty in detectability into the GAM. We then extracted 10 posterior samples, with a multivariate normal assumption, from the GAM parameters (β) and covariance matrix. For each eight-day period we calculated the predicted abundance for each grid cell 10 times (i.e., one abundance estimate per grid cell for each of the β samples). We then used the Welford method to summarize the variance for each grid cell at each time period.

Model Validation

We used the acoustic survey data to validate the models fit with visual survey data. Acoustic surveys were conducted using a network of marine autonomous recording units (MARUs) by the Cornell Lab Center for Conservation Bioacoustics. These surveys were funded by the Massachusetts Clean Energy Center. Bottom-mounted MARUs were deployed from November 2011 through March 2015 and recorded continuously during their deployment. The MARUs were suspended 3 meters above the seafloor. We used upcalls to determine right whale presence. The MARU detection range varies by the amount of background noise (Estabrook et al., 2022). Under median (50^{th} percentile) noise conditions in the right whale communication frequency band (upcalls, 71-224 Hz), the detection range is estimated to be 8 km. Under low (5^{th} percentile) noise conditions, the detection range is estimated to be 22 km (Estabrook et al., 2022). We used a Spearman correlation to determine the relationship between right whale density and the number of right whale upcalls for each eight-day period that acoustic data were available.

Assessing financial risk

We compare three wind energy development scenarios: one baseline scenario (i.e., business as usual) and two right whale mitigation scenarios. The baseline scenario reflected a realistic schedule for the foundation installation campaign and assumes that pile-driving begins on May 1st, 2025. The schedule includes both weather downtime and general expectations for marine mammal downtime (MMD). The second scenario shifts the start date of the monopile installation campaign back one month, from May 1st to June 1st, 2025, and excludes December as a feasible pile-driving month. The third scenario utilizes an additional method of noise attenuation during pile driving, in the form of a second bubble curtain working with the first bubble curtain to further enhance noise attenuation and shrink the harassment zones surrounding the piles.

Technical Assumptions

The hypothetical wind farm contains 70 turbines with an assumed 10.3-meter diameter monopile foundation and transition piece. The foundation diameter is reflective of industry trends towards larger wind turbines—the largest foundations to be installed in the next few years are of this size. Monopile foundations will be constructed using an industry standard piling technique. This method involves dropping a hammer onto the monopile foundations to drive them into the stable seabed. It is this specific activity that results in the most noise and will be delayed should a right whale or other marine species be sighted near a construction site.

Other logistical assumptions we have used in the calculation of downtime include a 12-hour workable day for each day of the year, no piling in the months of January through April and little to no knock-on impact on the rest of the project activity durations. The 12-hour working day is based on the current regulation that piling activities cannot occur during nighttime hours. Current regulations also state that piling of this nature is restricted during the winter season, January 1 through April 30th. Our downtime calculations only consider the activities associated with the installation of foundations, including the activity of lifting and hammering the monopile to completion. The foundation campaign is isolated to accurately calculate the additional downtime from wind, waves, and marine mammals. As a stand-alone campaign, it is assumed that there is no impact to other campaign durations, specifically turbine and array cable installation, in the context of a full construction schedule.

In keeping with methods used by developers to generate installation schedules, we used Primavera P6 to create a schedule with activity durations that are appropriate for the site of interest. Primavera P6 is an industry standard project scheduling tool, similar to an Excel spreadsheet. The advantage of P6 is that individual activities can be defined with logical, temporal links to one another. Changing the date of one activity will shift all the activities in the chain, which allows for detailed planning analysis to be conducted.

For each of the three foundation installation scenarios, the downtime and assumptions were defined and assessed to estimate the financial risks and costs associated with each schedule. Weather downtime was determined through LAUTEC's weather downtime modeling tool ESOX. ESOX is a probabilistic model that has been trained by over a decade of data from offshore wind projects and decades of regional weather data. ESOX generates weather downtime results for multiple cases, including: the best weather year, the P30 case, the P50 case, the P90 case, and the worst weather year. The P50 case is representative of annual average weather at a particular location, and is typically the weather condition that is considered when building a project schedule. The P30 case is usually too optimistic, while the P90 is too conservative. ESOX provides weather downtime as a combination of both downtime due to adverse weather causing a stall in installation activities and downtime due to the nighttime pile-driving restriction. For a monopile installation to commence, a window with both daylight and compatible weather is required. As pile-driving requires daylight so that protected species observers can monitor for marine mammal presence, pile-driving is put on standby overnight until the daylight window returns the following morning. The durations from the Primavera P6 schedule were used as inputs into the ESOX model, with the output being the project schedule, inclusive of the total downtime due to adverse weather and the nighttime pile-driving restriction. The four construction durations for each of the three scenarios were then assigned a cost. Additionally, the cost of all vessels and mobilization were estimated on top of the total daily cost.

Cost Assumptions

Many cost assumptions were necessary due to the nascent offshore wind industry in the US, the quickly changing prices in the global offshore wind economy, and the varying approaches to a logistical setup for foundation installation. Regardless of the above conditions, the largest cost element for this part of foundation installation is the use of a Heavy-Lift Vessel (HLV). We have also selected to include the cost of project resources, and two guard vessels. It is assumed that the same HLV performing the installation will also sail to port to load out batches of components and bring those components back to the offshore site. The costs associated with these vessels alongside project resources can be viewed in Table 2. These costs were utilized in conjunction with the campaign durations to determine the total daily costs for a P30, P50, P50+MMD, and P90 downtime scenario.

Results

Aerial surveys and data preparation

The aerial surveys used in this analysis occurred over 211 days. We chopped 105,443 km of aerial survey data into 22,979 segments, with the majority (86.8%) between 4 and 5 km. The remaining segments were approximately equally divided into segments <4km (5.78%) and >5km (7.41%). Right whales were sighted on 183 of the 18,488 chopped segments. In total, there were 446 right whale sightings of 810 individuals with an average of 3.67 right whales per sighting.

Oceanographic predictors of right whale density

We tested seven DSMs to predict right whale density (Table 1). The model with the most relative support included salinity, an interaction between SST and the eight-day period, an interaction between the distance to the 40 m isobath and the eight-day period, and an interaction between the distance to the 30 m isobath and the eight-day period (AIC = 4812.22; Table 1, Figures 2,3,4, and 5). This model also had the highest AUC (AUC = 0.91; Table 1) and explained 64% of the deviance.

There was a significant non-linear relationship between right whale density and all the variables in the model (i.e., $p < 2e\text{-}16$ for each covariate). Right whale density decreased as salinity increased until salinity reached ~32.6 psu. Right whale density increased at salinity values between ~32.6 and 33.6 psu, and then decreased at salinity values higher than 33.6 psu (Figure 2). The relationship between right whale density and SST depends on the time of year (Figure 3). There is relatively high right whale density at relatively low SSTs and low right whale density at high SSTs early in the year. However, by the end of the year, right whale density is highest in the middle of the SST range. The relationship between right whale density and the distance to the 40 m isobath is also dependent on the time of year (Figure 4). Early in the year, right whale density is highest close to the isobath and decreases as distance to the isobath increases. However, in the middle of the year, density is evenly spread throughout distance ranges to the isobath. By the end of the year, density is high and evenly distributed across all measured distances. The relationship between right whale density and the distance to the 30 m isobath is also dependent on the time of year (Figure 5). The relationship between right whale density and distance to the 30 m isobath was similar to that of the 40 m isobath except in the middle of the year right whale density was higher at greater distances from the 30 m isobath, and later in the year right whale densities were lower at greater distances from the 30 m isobath.

We used our model to generate right whale density predictions for each eight-day period from 2011 through 2023. Example prediction maps showing the monthly mean of the eight-day periods for 2019 and 2021 can be found in Figure 6. In the winter and spring of both years, predicted right whale density is highest along the 30 and 40 m isobaths (i.e. the northeast corner of the prediction box). Predicted density decreases during the summer months, however, densities are still predicted to be greater than 0 southwest of Nantucket along the 30 and 40 m isobath. In the fall months predicted density increases again, predominantly in the northeast corner of the prediction box. Density predictions tightly aligned with right whale sightings made during New England Aquarium aerial surveys.

Variance

Uncertainty in the density estimates can arise from several components of the modeling process including detectability, the smooths used in the GAMs, and variability in environmental covariates. We estimated uncertainty for each of the components and propagated this uncertainty through the analysis. Our detection function was estimated without covariates, as in O'Brien et al., 2022. Therefore, detectability did not vary spatially, as such the delta method was used to estimate the uncertainty (CV = 0.13). We then propagated the estimated uncertainty in the detection function with the uncertainty in the GAM component (CV = 0.25), the estimated CV for the combined components was 0.29.

Validation

We found a significant positive correlation between the number of right whale upcalls and the right whale density estimates (rho = 0.45, p =$1.0e^{-07}$).

Assessing financial risk

The goal of this financial risk assessment was to define the associated costs of three foundation installation scenarios that offshore wind developers may encounter. It is important to note that the exact assumptions presented in the assessment will be different from project to project and depend on factors such as number and type of vessels utilized, contractual obligations, and location. The methodology and results presented can be tailored to each project by adjusting these assumptions as necessary.

Costs and Financial Risks

The baseline scenario assumes construction starts on May 1st and extends through the spring, summer and fall months until completion of 70 monopile foundations. Without weather considerations, the ESOX simulation for the base case took 117 days. When considering the most likely P50 weather downtime scenario in addition to the estimated MMD, the campaign duration becomes 230 days. The estimated cost of a P50 plus MMD case for the baseline scenario is $215,150,000.

For the second and third scenarios, the general assumptions above remain the same, except the construction start date moves from May 1st to June 1st in the second scenario. This scheduling change has the potential to impact campaign duration and average duration per position because of the risk of a split campaign across multiple years when weather downtime and MMD are taken into account. Concomitantly, the possibility of a split campaign affects the total daily cost. We found that under the second scenario, a P90 and a P50 weather scenario plus MMD resulted in a split campaign and, therefore, a higher cost than the same downtime cases for the baseline scenario. The estimated cost of a P50 plus MMD case for the second scenario is $378,780,000. The durations and total costs for the baseline and second scenarios can be found in Tables 3 and 4, respectively.

In the third scenario, we assumed a second Big Bubble curtain would be implemented to reduce the noise attenuation of the foundation piling activities. The addition of a bubble curtain has no impact on the duration of the piling activity compared to the baseline scenario because it is assumed that the bubble curtain installation campaign will occur prior to foundation installation. While there is no impact to the schedule, it is estimated that the cost for a bubble curtain for one installation season (May – December) would be approximately 20 million USD. This cost is added on top of the baseline scenario costs as seen in Table 5. The estimated cost of a P50 plus MMD case for Scenario three is $235,150,000.

Discussion

We have successfully developed a right whale density surface model for the MA/RI WEAs at spatial and temporal scales that are biologically relevant, but also applicable to wind energy developers attempting to estimate the financial risk associated with their construction projects. In addition, we estimated the financial risk associated with three wind energy development scenarios, while considering potential weather downtime and general expectations for marine mammal downtime. We have conducted preliminary economic tradeoff analyses (see our phase two report) that combine predictions from our model and the financial risk assessment. Future work will include finalizing the economic tradeoff analysis approach. Through our project, we intend to contribute to responsibly developing offshore wind energy, while conserving right whales and successfully mitigating climate change

The best oceanographic predictors of right whale occurrence in the MA/RI WEAs were salinity, an interaction between distance to the 40 m isobath and time of year, an interaction between distance to the 30 m isobath and time of year, and an interaction between SST and time of year. Salinity gradients, a proxy for density gradients, indicate a stratified water column. The vertical surfaces in stratified water columns can coalesce hyper-concentrated patches of zooplankton, a requirement for right whale foraging behavior. Bowhead whales (*Balaena mysticetus*), a species with similar foraging behaviors to right whales, have been documented feeding along salinity gradients concurring with large congregations of zooplankton (Moore et al., 1995). Other studies have found salinity to be an indicator of right whale habitat (Baumgartner and Mate, 2005), and correlated with *C. finmarchicus* biomass (Sorochan et al., 2019).

Pendleton et al. 2012 found support for the hypothesis that right whale habitat preferences are dynamic. Our results lend further support to this argument. We found that the effect of SST, distance to the 40 m isobath, and distance to the 30 m isobath changes depending on the time of year. Our SST results mirror those of Pendleton et al. 2012 who found that right whale sightings, in the same but larger geographical region, were associated with temperatures below 4 °C in the winter, and between 4 and 12 °C in the spring. The relationship between right whale density and distance to the 30 and 40 m isobaths was dependent on time of year. Pendleton et al. 2012 also found the relationship between bathymetry and habitat use to be dependent on time of year, in the same but larger geographical region. In Southern New England, the 30 and 40 m isobaths outline the Nantucket Shoals, which has strong tidal flow over the sloping bathymetry of the isobaths. This coupling of tidal flow and bathymetry often generates internal waves that can cause shoaling of the pycnocline and associated zooplankton layers that may persist for hours (e.g. Lai et al., 2010). These habitat preferences, which vary based on the time of year, may reflect, in part, the complicated life cycle of *C. finmarchicus*, in addition to the seasonal variations in right whale behavior (e.g., migrating vs. foraging).

We were able to estimate the costs incurred by adding mitigation techniques (i.e., the second and third scenarios) during wind energy construction. The work presented here represents an important step for understanding the financial risks that come with right whale mitigation during wind energy development. Renewable energy is an important component of meeting global goals to reduce the effects of climate change after decades of fossil fuel usage. However, renewable energy cannot be developed at the expense of wildlife conservation. To successfully develop renewable energy and protect wildlife, we must work with stakeholders to develop tools that can be used to explore trade-offs between the financial risks to renewable energy development and wildlife conservation strategies.

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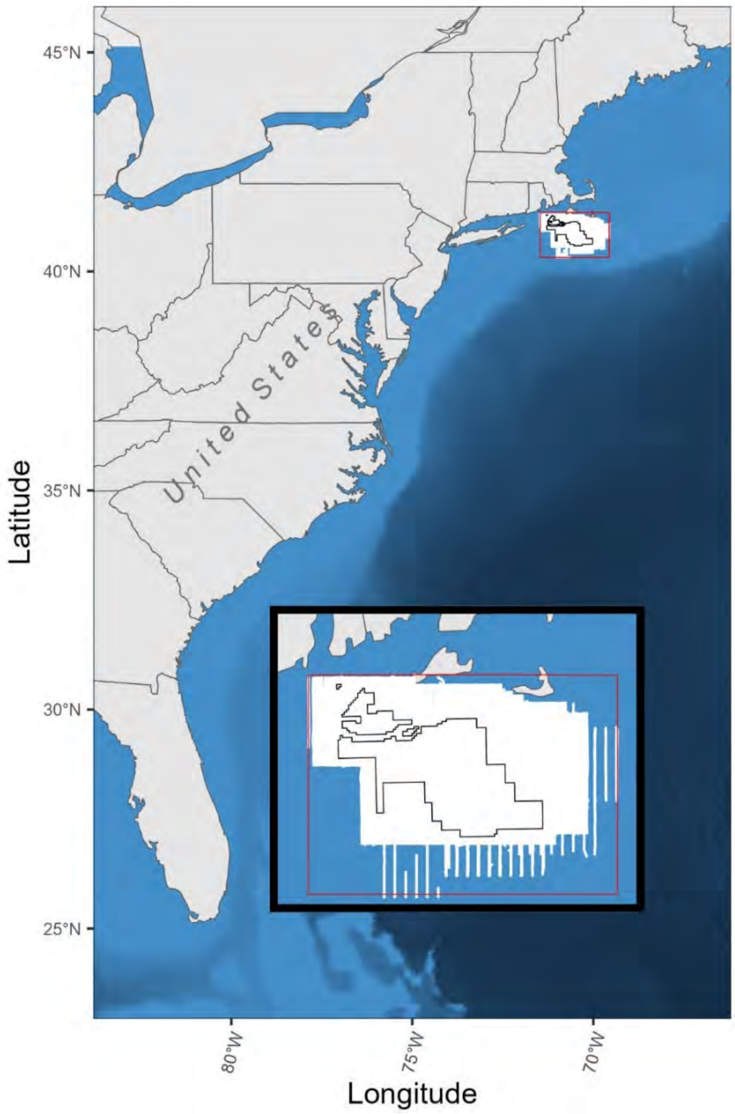


Figure 1: Aerial survey effort used to predict right whale density. White lines are tracklines flown by the New England Aquarium aerial survey team between 2011 – 2022. The area to be predicted over is outlined in red. The Massachusetts / Rhode Island Wind Energy Area is outlined in black.

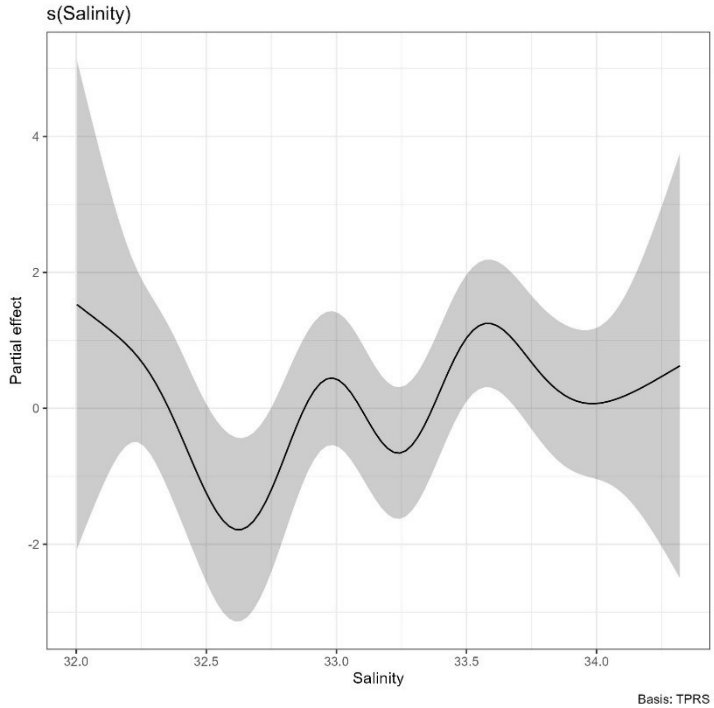


Figure 2: Partial effects of salinity on right whale density according to the model with the most support. The gray shading represents 95% confidence intervals for the mean effect. The distribution of the data is represented by the ticks at the bottom of each plot.

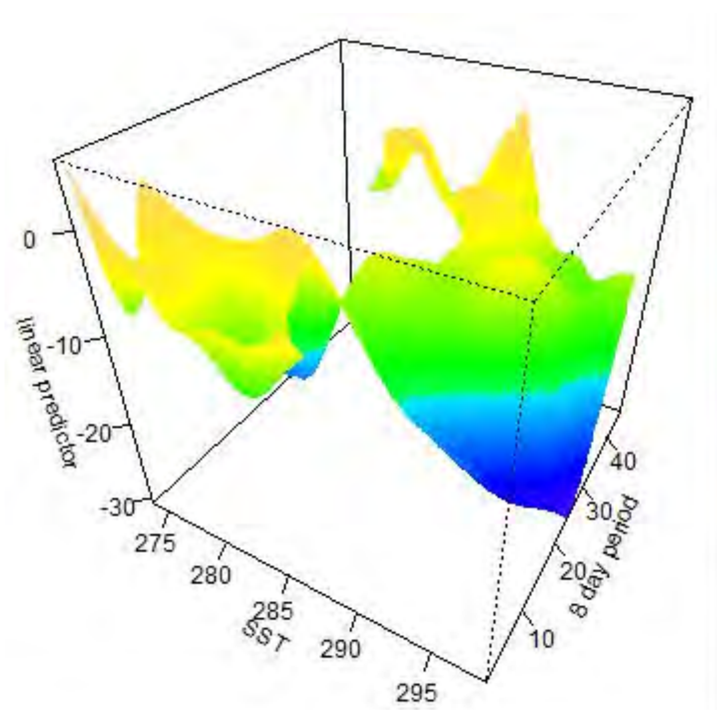


Figure 3: Partial effects of the interaction between sea surface temperature (SST) and time of year (eight-day period) on right whale density according to the model with the most support.

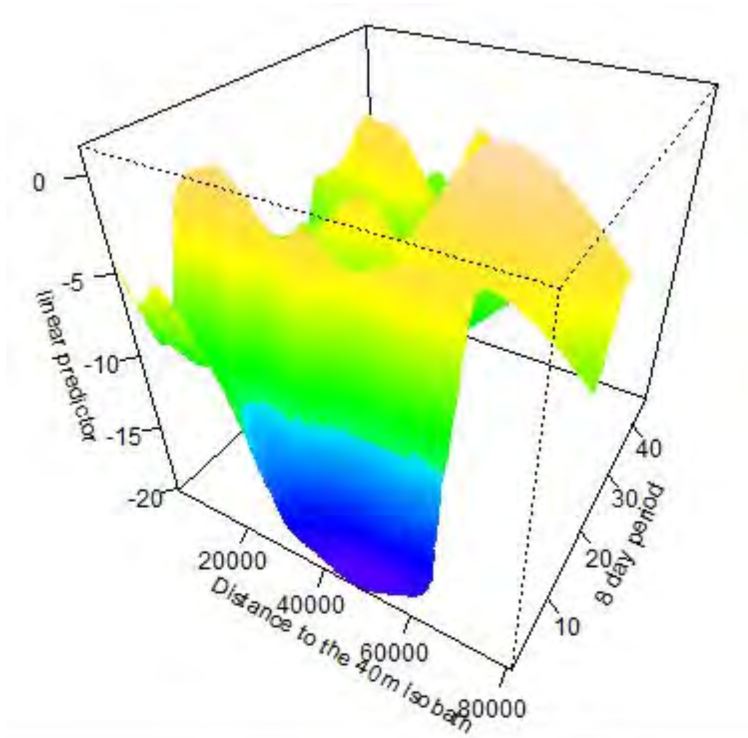


Figure 4: Partial effects of the interaction between distance to the 40 m isobath and time of year (eight-day period) on right whale density according to the model with the most support.

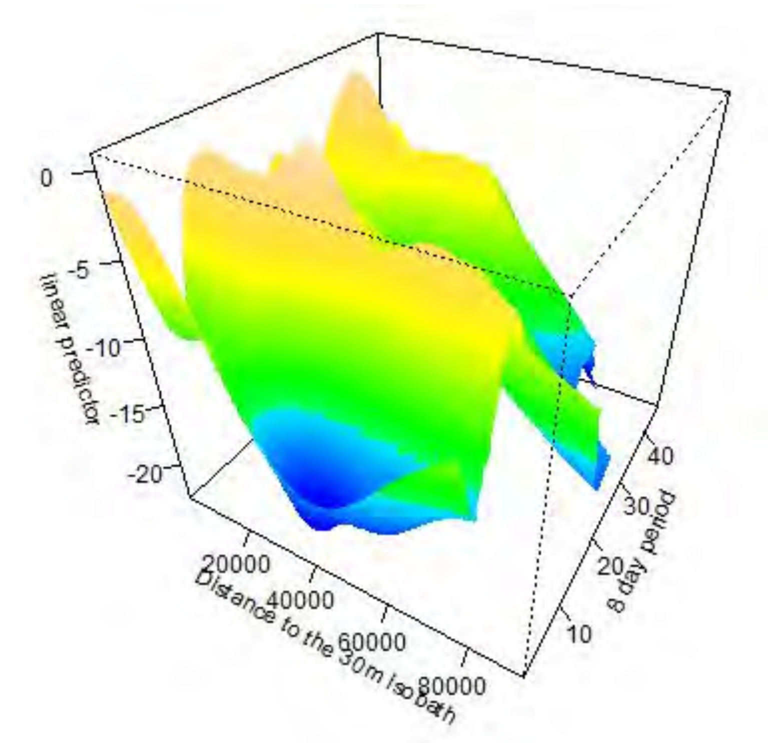
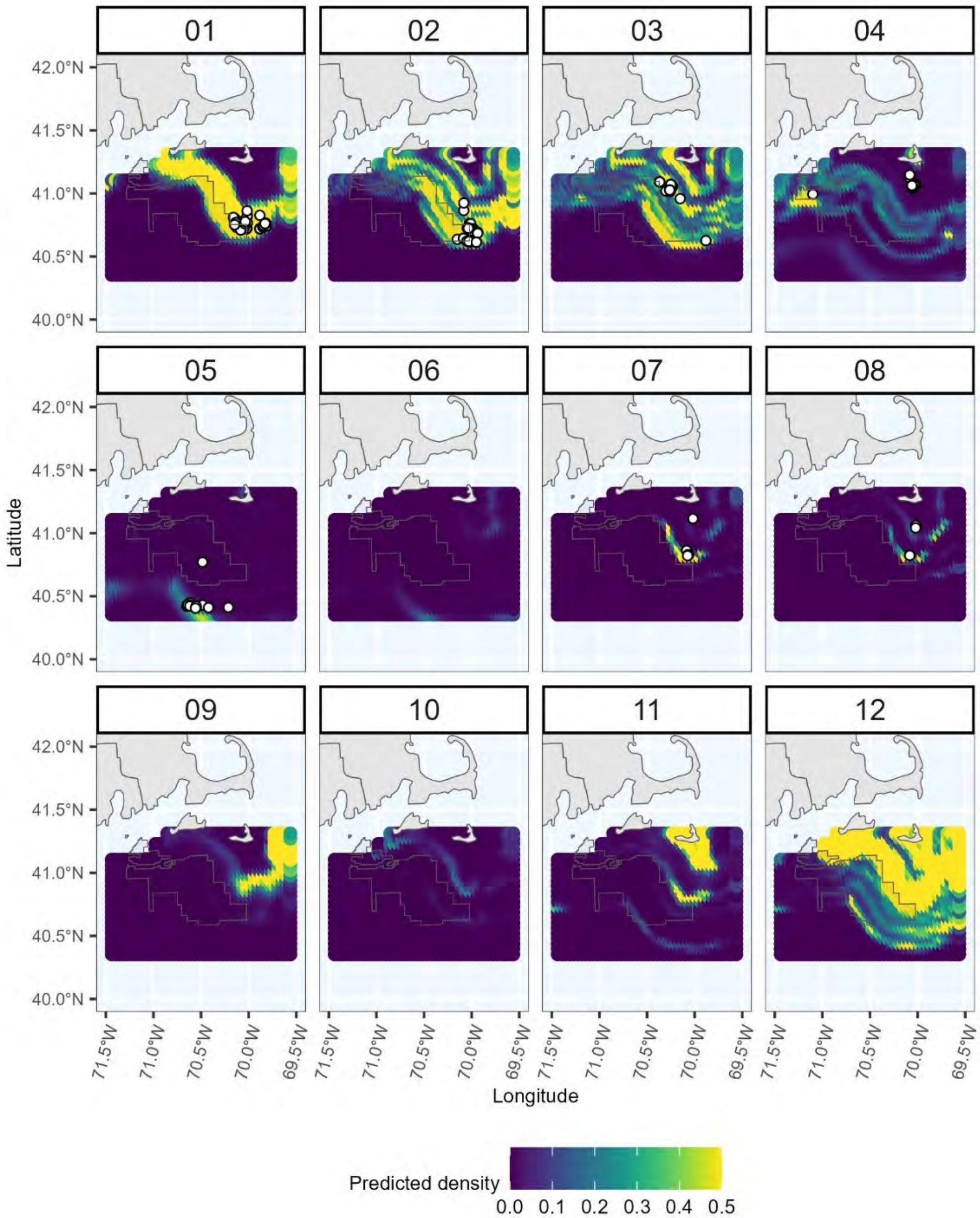


Figure 5: Partial effects of the interaction between distance to the 30 m isobath and time of year (eight-day period) on right whale density according to the model with the most support.

a.)



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Longitude
Predicted density
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0.3
0.4
0.5

b.)

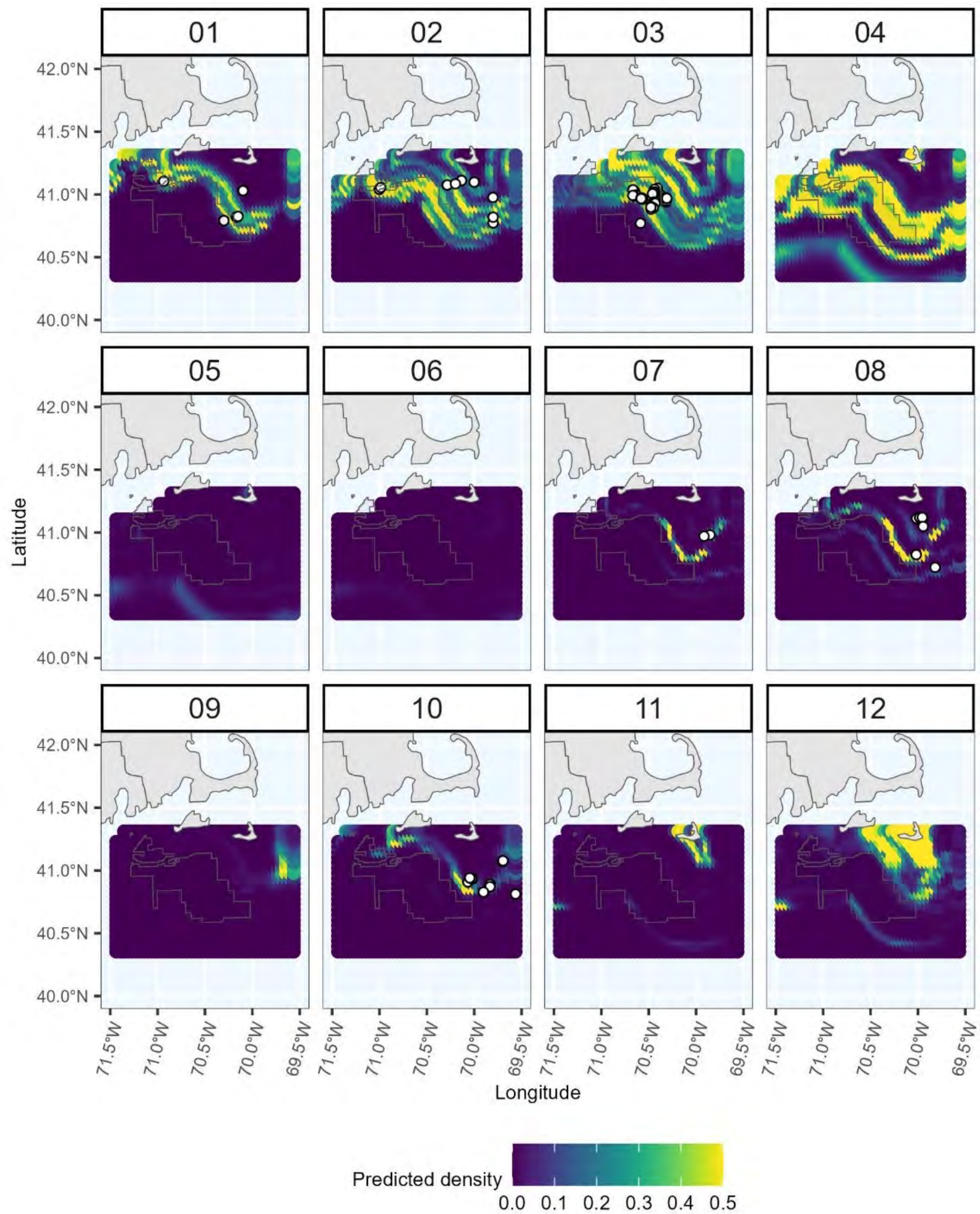

Figure 6: Eight-day right whale density predictions for the Massachusetts / Rhode Island Wind Energy Area prediction box summarized by month for (a) 2019 and (b) 2021. White dots are right whale sightings made by the New England Aquarium's right whale aerial survey team. Each dot represents one right whale. There were no New England Aquarium aerial surveys from September-December 2019 November-December 2021.

Table 1: Density surface models used to predict right whale density. The model with distance to the 30 m isobath dependent on time of year, distance to the 40 m isobath dependent on the time of year, sea surface temperature (SST) dependent on the time of year, and salinity had the lowest Akaike Information Criterion (AIC) score and is the model with the most support. This model also had the highest Area Under the Receiver Curve (AUC). We used root mean squared error (RMSE) as a test of goodness-of-fit. Models with RMSE values between 0 and 1 are considered to fit sufficiently.

Model	AIC	AUC	RMSE
Distance to 30m isobath*period, Distance to 40m isobath*period, period*SST, Salinity	4,812.22	0.91	0.62
Depth, Period*SST, Salinity	5,204.85	0.87	0.78
Distance to 40m isobath, SST, Salinity, CHL	5,736.32	0.80	0.84
SST, Salinity, CHL	5,842.56	0.79	0.85
Distance to 40m isobath, SST	5,888.72	0.77	0.86
SST	6,012.15	0.76	0.86
Distance to 40m isobath	6,282.31	0.60	0.87

Table 2: The vessel and resource costs associated with our baseline scenario, which is a generic foundation installation campaign that assumes one heavy lift vessel (HLV) and two guard vessels.

Package	Activity	Cost (USD)
Foundations	Foundation HLV	$765,000
General	Project Resources	$20,000
General	Guard Vessel 1	$10,000
General	Guard Vessel 2	$10,000

Table 3: The campaign durations and total costs for the baseline scenario. The values for an ideal, no weather case is provided. The P30 weather case represents the best case, P50 represents the most likely weather downtime case, and P90 the worst case. P50+MMD represents the most likely weather case and a general expectation for marine mammal downtime. Additionally, the start and end dates for each weather case are provided to show whether there is a risk for the campaign to continue into the following year due to time of year restrictions.

	Campaign Duration [days]	Avg Duration Per Position [Hours]	Total Daily Cost	Mobilization	Total Cost		Start Date	End Date	Split Campaign
Excluding Weather	117	40	$ 94,185,000.00	$30,000,000.00	$ 124,185,000.00		1/May/25	26/Aug/25	No
P30	208	71	$167,440,000.00	$30,000,000.00	$ 197,440,000.00		1/May/25	25/Nov/25	No
P50	213	73	$171,465,000.00	$30,000,000.00	$ 201,465,000.00		1/May/25	30/Nov/25	No
P90	238	81	$191,590,000.00	$30,000,000.00	$ 221,590,000.00		1/May/25	25/Dec/25	No
P50+MMD	230	80	$185,150,000.00	$30,000,000.00	$ 215,150,000.00		1/May/25	17/Dec/25	No

Table 4: The campaign durations and total costs for the second scenario, in which there is a month shift in start date. The values for an ideal, no weather case is provided. The P30 weather case represents the best case, P50 represents the most likely weather downtime case, and P90 the worst case. P50+MMD represents the most likely weather case and a general expectation for marine mammal downtime. Additionally, the start and end dates for each weather case are provided to show whether there is a risk for the campaign to continue into the following year due to time of year restrictions.

	Campaign Duration [days]	Avg Duration Per Position [Hours]	Total Daily Cost	Mobilization	Total Cost		Start Date	End Date	Split Campaign
Excluding Weather	117	40	$ 94,185,000.00	$30,000,000.00	$ 124,185,000.00		1/Jun/25	26/Sep/25	No
P30	208	71	$167,440,000.00	$30,000,000.00	$ 197,440,000.00		1/Jun/25	26/Dec/25	No
P50	209	71	$168,245,000.00	$30,000,000.00	$ 198,245,000.00		1/Jun/25	27/Dec/25	No
P90	238	81	$191,590,000.00	$60,000,000.00	$ 251,590,000.00		1/Jun/25	25/May/26	Yes
P50+MMD	396	138	$318,780,000.00	$60,000,000.00	$ 378,780,000.00		1/Jun/25	30/Oct/26	Yes

Table 5: The campaign durations and total costs for the third scenario, where a second bubble curtain is added. The values for an ideal, no weather case is provided. The P30 weather case represents the best case, P50 represents the most likely weather downtime case, and P90 the worst case. P50+MMD represents the most likely weather case and a general expectation for marine mammal downtime. Additionally, the start and end dates for each weather case are provided to show whether there is a risk for the campaign to continue into the following year due to time of year restrictions.

	Campaign Duration [days]	Avg Duration Per Position [Hours]	Total Daily Cost	Mobilization	Total Cost		Start Date	End Date	Split Campaign
Excluding Weather	117	40	$ 94,185,000.00	$30,000,000.00	$ 144,185,000.00		1/May/25	26/Aug/25	No
P30	208	71	$167,440,000.00	$30,000,000.00	$ 217,440,000.00		1/May/25	25/Nov/25	No
P50	213	73	$171,465,000.00	$30,000,000.00	$ 221,465,000.00		1/May/25	30/Nov/25	No
P90	238	81	$191,590,000.00	$30,000,000.00	$ 241,590,000.00		1/May/25	25/Dec/25	No
P50+MMD	230	80	$185,150,000.00	$30,000,000.00	$ 235,150,000.00		1/May/25	17/Dec/25	No

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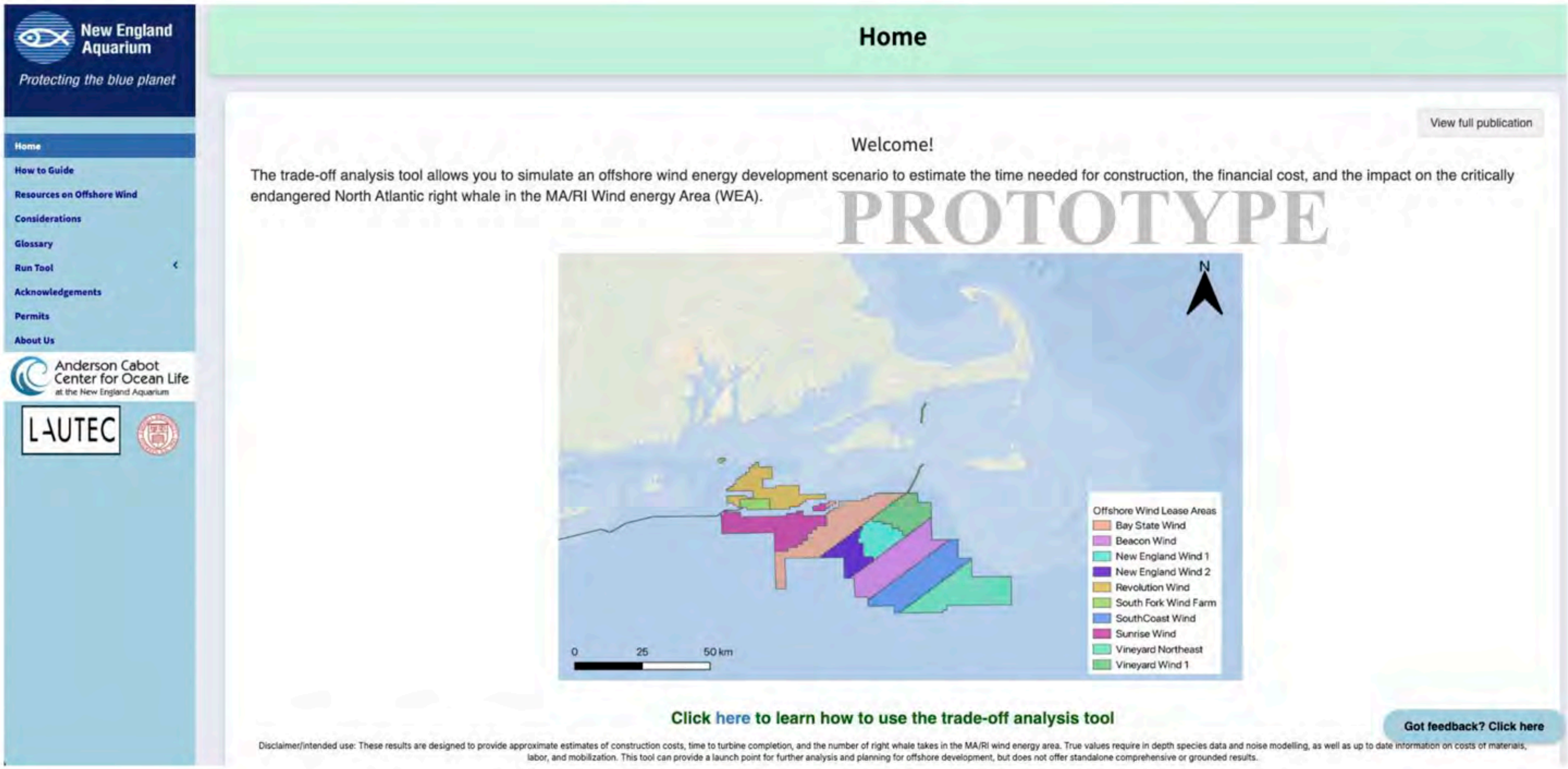
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Welcome!
The trade-off analysis tool allows you to simulate an offshore wind energy development scenario to estimate the time needed for construction, the financial cost, and the impact on the critically endangered North Atlantic right whale in the MA/RI Wind energy Area (WEA).
PROTOTYPE
N
Offshore Wind Lease Areas
Bay State Wind
Beacon Wind
New England Wind 1
New England Wind 2
Revolution Wind
South Fork Wind Farm
SouthCoast Wind
Sunrise Wind
Vineyard Northeast
Vineyard Wind 1
0
25
50 km
Click here to learn how to use the trade-off analysis tool
Got feedback? Click here
Disclaimer/intended use: These results are designed to provide approximate estimates of construction costs, time to turbine completion, and the number of right whale takes in the MA/RI wind energy area. True values require in depth species data and noise modelling, as well as up to date information on costs of materials, labor, and mobilization. This tool can provide a launch point for further analysis and planning for offshore development, but does not offer standalone comprehensive or grounded results.


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The trade-off analysis tool can be used to select an area for a new wind farm within the Rhode Island and Massachusetts wind energy area, choose the number of turbines to drive, and select a mitigation scenario. The current tool allows the user to choose from pre-defined mitigation scenarios to understand how placement, turbine number, and mitigation strategy impact the time required to complete pile driving, the financial cost, and impacts on right whales
Key Tips
1. Select your parameters for your offshore wind development in chronological order (Step 1, Step 2, Step 3).
2. Only click once per selection box – the tool can take a few minutes to load.
3. The tool includes pre-defined mitigation scenarios for you to choose from, contact us at lganley@neaq.org if you have questions about tailored scenarios.
4. We advise that you include a comparison to the business-as-usual scenario (May - December) and no mitigation scenario as a reference.
5. The more scenarios included in the analysis, the longer the tool will take to load.
6. Click here for a glossary of key analysis terms
Got feedback? Click here
Click here to check out data considerations and run the tool


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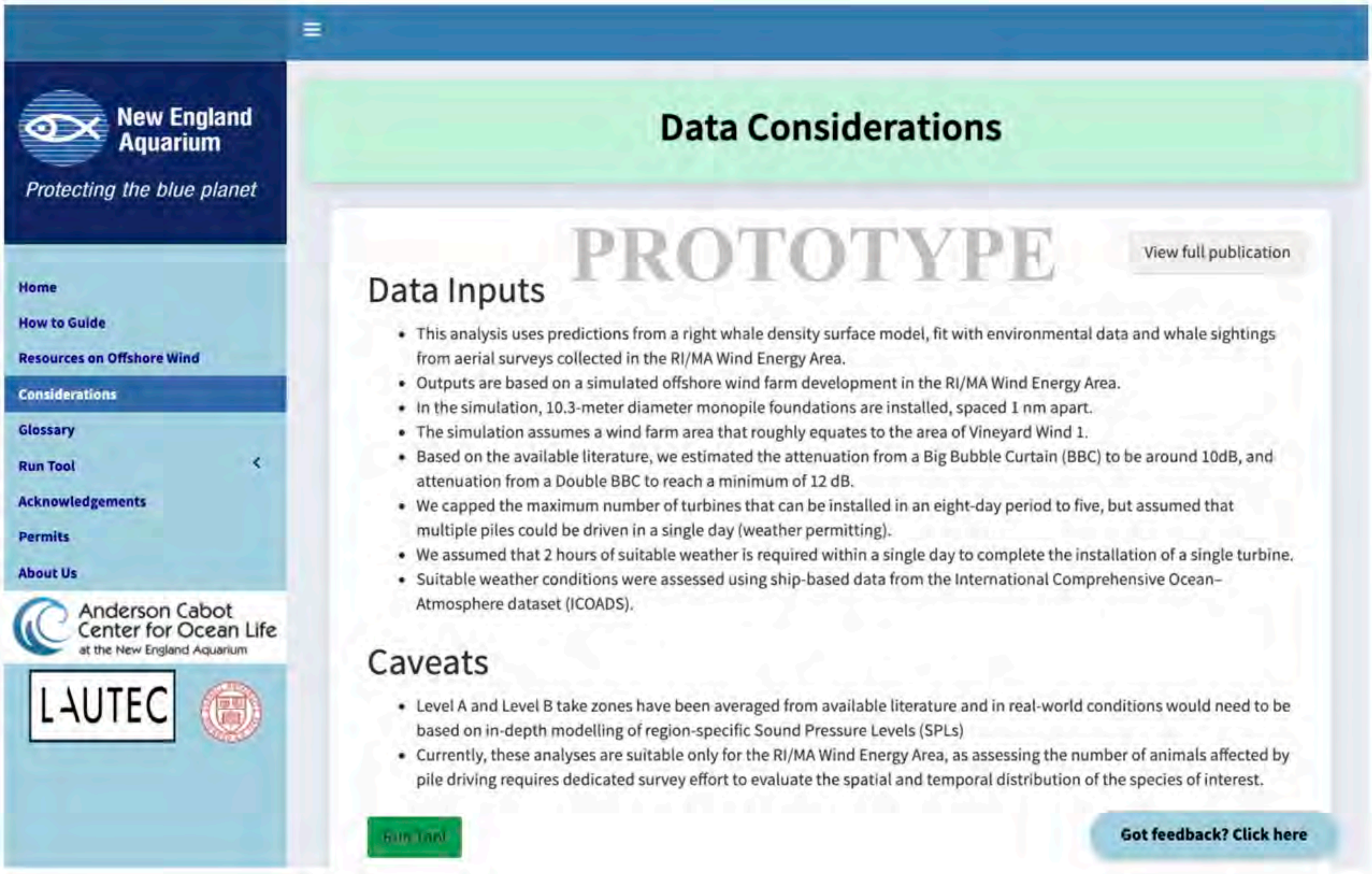
How is offshore wind regulated in U.S Waters?
The Bureau of Ocean Energy Management (BOEM) is responsible for authorizing offshore wind development in federal waters. The National Oceanic and Atmospheric Administration (NOAA) is responsible for ensuring that offshore wind development adheres to certain regulatory processes that aim to protect marine species. These processes fall under the legal jurisdiction of the Marine Mammal Protection Act (MMPA) and the Endangered Species Act (ESA).
How are marine mammals legally protected from the potential impacts of offshore wind development?
Marine mammals are legally protected by the MMPA and the ESA. The MMPA prohibits, with certain exceptions, the "take" of marine mammals in U.S waters by U.S citizens. The MMPA defines "take" as to harass, hunt, capture or kill, or to attempt to harass, hunt, capture or kill any marine mammal. See this link to find out more about Level A and Level B harassment, and how they are characterized.
What are the known impacts of noise from offshore wind construction on marine mammals?
As stated on the NOAA website, there are no known links between large whale deaths and offshore wind development activities. Click here for more information from NOAA on the known impacts of wind energy on whales. You can also click here to visit the New York State Environmental Technical Working Group page for more background information on offshore wind and whales.
Got feedback? Click here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Data Inputs
This analysis uses predictions from a right whale density surface model, fit with environmental data and whale sightings from aerial surveys collected in the RI/MA Wind Energy Area.
Outputs are based on a simulated offshore wind farm development in the RI/MA Wind Energy Area.
In the simulation, 10.3-meter diameter monopile foundations are installed, spaced 1 nm apart.
The simulation assumes a wind farm area that roughly equates to the area of Vineyard Wind 1.
Based on the available literature, we estimated the attenuation from a Big Bubble Curtain (BBC) to be around 10dB, and attenuation from a Double BBC to reach a minimum of 12 dB.
We capped the maximum number of turbines that can be installed in an eight-day period to five, but assumed that multiple piles could be driven in a single day (weather permitting).
We assumed that 2 hours of suitable weather is required within a single day to complete the installation of a single turbine.
Suitable weather conditions were assessed using ship-based data from the International Comprehensive Ocean–Atmosphere dataset (ICOADS).
Caveats
Level A and Level B take zones have been averaged from available literature and in real-world conditions would need to be based on in-depth modelling of region-specific Sound Pressure Levels (SPLs)
Currently, these analyses are suitable only for the RI/MA Wind Energy Area, as assessing the number of animals affected by pile driving requires dedicated survey effort to evaluate the spatial and temporal distribution of the species of interest.
Run Tool
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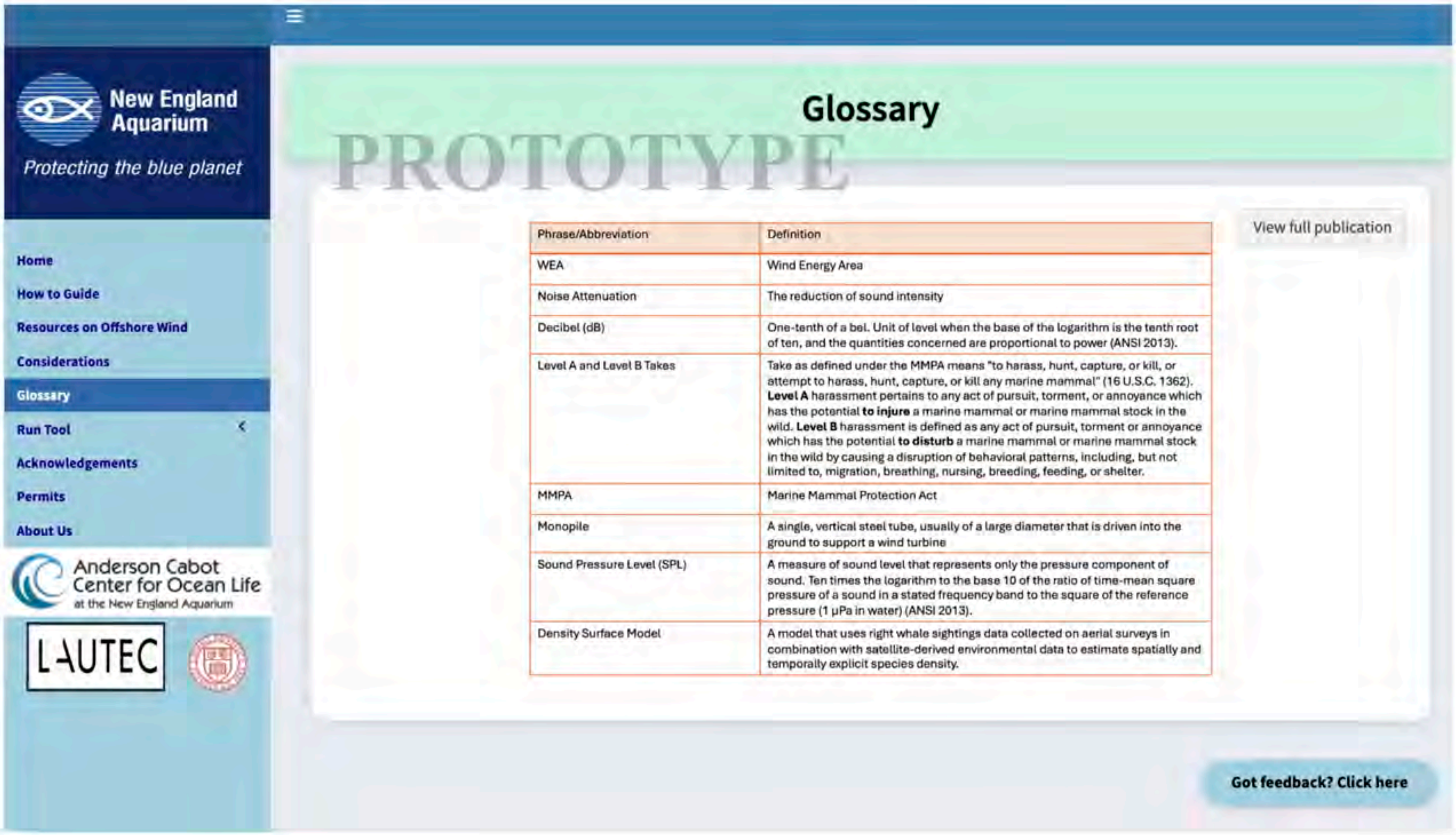

Glossary

Phrase/Abbreviation	Definition
WEA	Wind Energy Area
Noise Attenuation	The reduction of sound intensity
Decibel (dB)	One-tenth of a bel. Unit of level when the base of the logarithm is the tenth root of ten, and the quantities concerned are proportional to power (ANSI 2013).
Level A and Level B Takes	Take as defined under the MMPA means "to harass, hunt, capture, or kill, or attempt to harass, hunt, capture, or kill any marine mammal" (16 U.S.C. 1362). **Level A** harassment pertains to any act of pursuit, torment, or annoyance which has the potential **to injure** a marine mammal or marine mammal stock in the wild. **Level B** harassment is defined as any act of pursuit, torment or annoyance which has the potential **to disturb** a marine mammal or marine mammal stock in the wild by causing a disruption of behavioral patterns, including, but not limited to, migration, breathing, nursing, breeding, feeding, or shelter.
MMPA	Marine Mammal Protection Act
Monopile	A single, vertical steel tube, usually of a large diameter that is driven into the ground to support a wind turbine
Sound Pressure Level (SPL)	A measure of sound level that represents only the pressure component of sound. Ten times the logarithm to the base 10 of the ratio of time-mean square pressure of a sound in a stated frequency band to the square of the reference pressure (1 μPa in water) (ANSI 2013).
Density Surface Model	A model that uses right whale sightings data collected on aerial surveys in combination with satellite-derived environmental data to estimate spatially and temporally explicit species density.


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Step 1: Design Offshore Wind Farm
Select Location in the Wind Energy Area:
Central
2. Choose the number of turbines within the wind farm:
70 Turbines
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Step 1: Design Offshore Wind Farm
Select Location in the Wind Energy Area:
South
2. Choose the number of turbines within the wind farm:
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70 Turbines
Click here for next step
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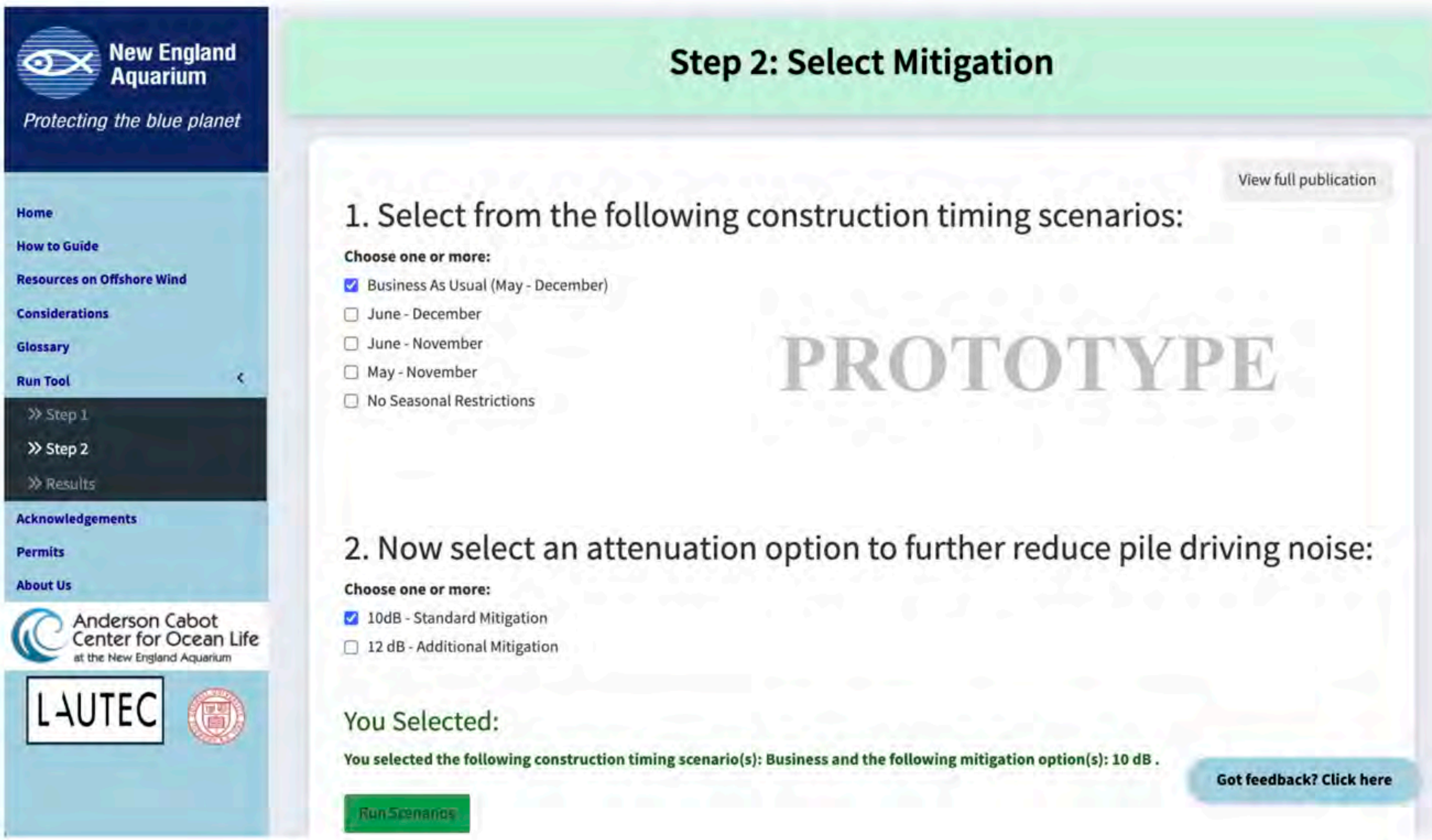
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Step 2: Select Mitigation
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1. Select from the following construction timing scenarios:
Choose one or more:
Business As Usual (May - December)
June - December
June - November
May - November
No Seasonal Restrictions
PROTOTYPE
2. Now select an attenuation option to further reduce pile driving noise:
Choose one or more:
10dB - Standard Mitigation
12 dB - Additional Mitigation
You Selected:
You selected the following construction timing scenario(s): Business and the following mitigation option(s): 10 dB .
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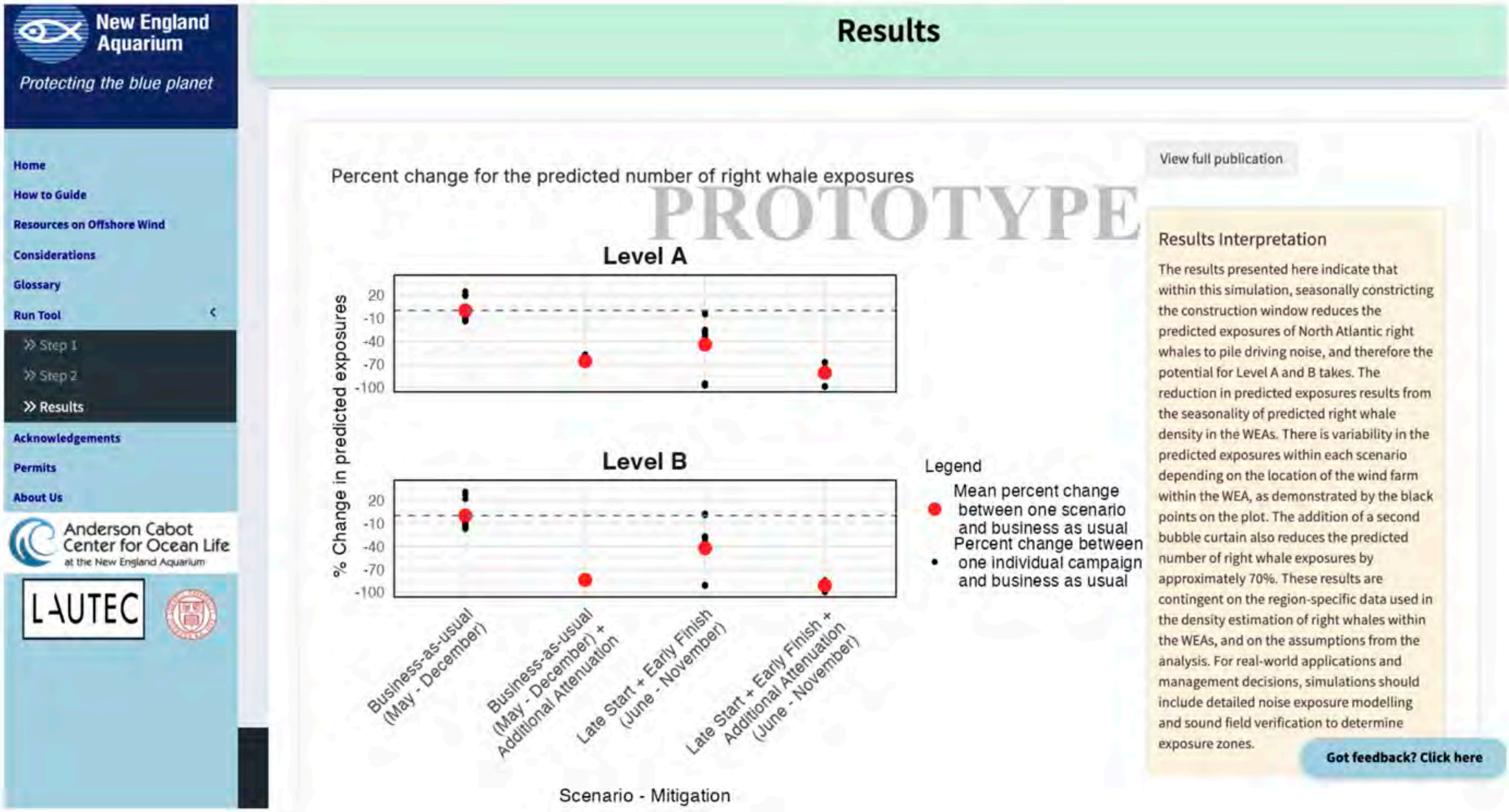
Run Scenarios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Percent change for the predicted number of right whale exposures
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Level A
Level B
% Change in predicted exposures
20
-10
-40
-70
-100
Business-as-usual (May - December)
Business-as-usual (May - December) + Additional Attenuation
Late Start + Early Finish (June - November)
Late Start + Early Finish + Additional Attenuation (June - November)
Scenario - Mitigation
Legend
Mean percent change between one scenario and business as usual
Percent change between one individual campaign and business as usual
Results Interpretation
The results presented here indicate that within this simulation, seasonally constricting the construction window reduces the predicted exposures of North Atlantic right whales to pile driving noise, and therefore the potential for Level A and B takes. The reduction in predicted exposures results from the seasonality of predicted right whale density in the WEAs. There is variability in the predicted exposures within each scenario depending on the location of the wind farm within the WEA, as demonstrated by the black points on the plot. The addition of a second bubble curtain also reduces the predicted number of right whale exposures by approximately 70%. These results are contingent on the region-specific data used in the density estimation of right whales within the WEAs, and on the assumptions from the analysis. For real-world applications and management decisions, simulations should include detailed noise exposure modelling and sound field verification to determine exposure zones.
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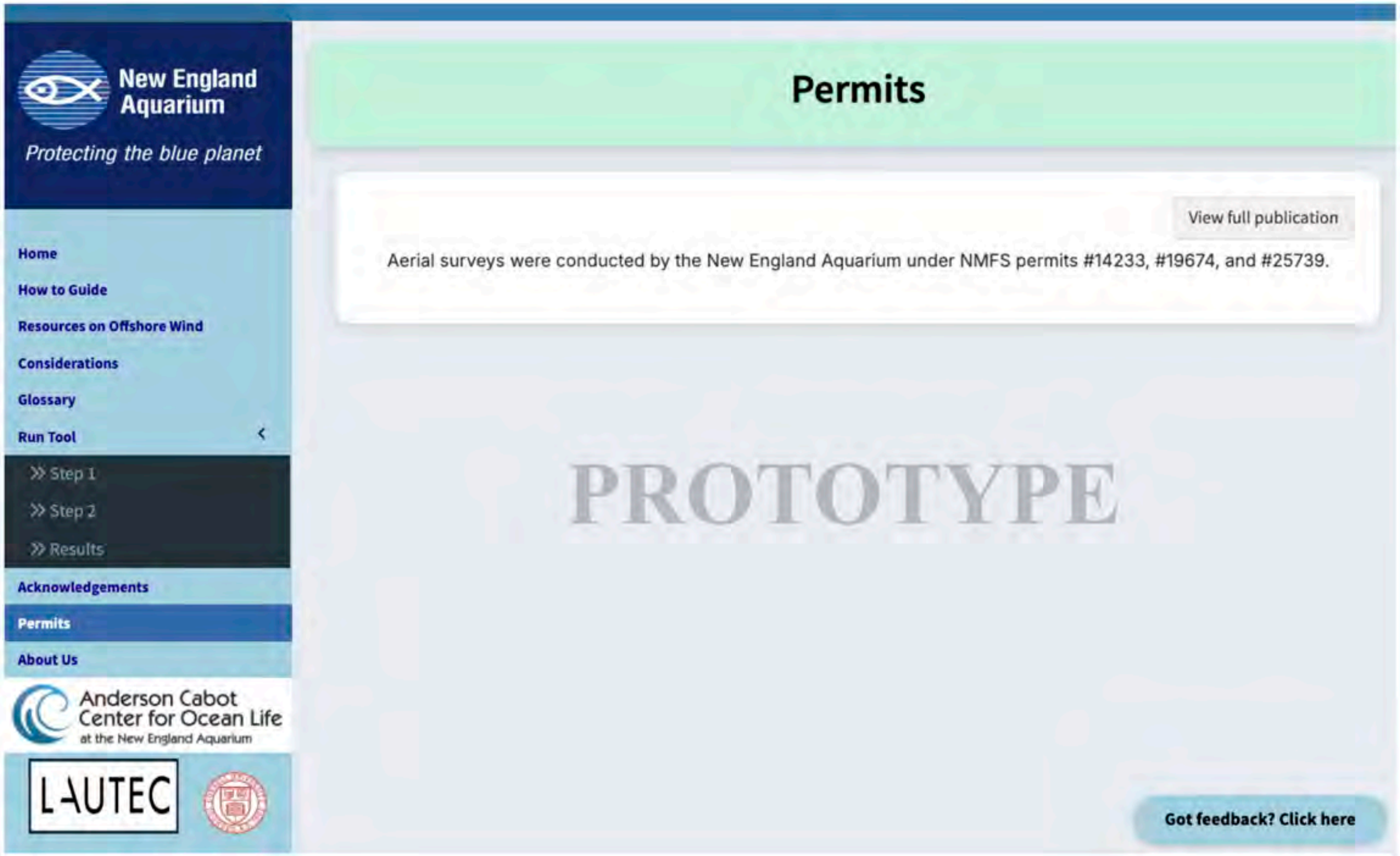
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Aerial surveys were conducted by the New England Aquarium under NMFS permits #14233, #19674, and #25739.
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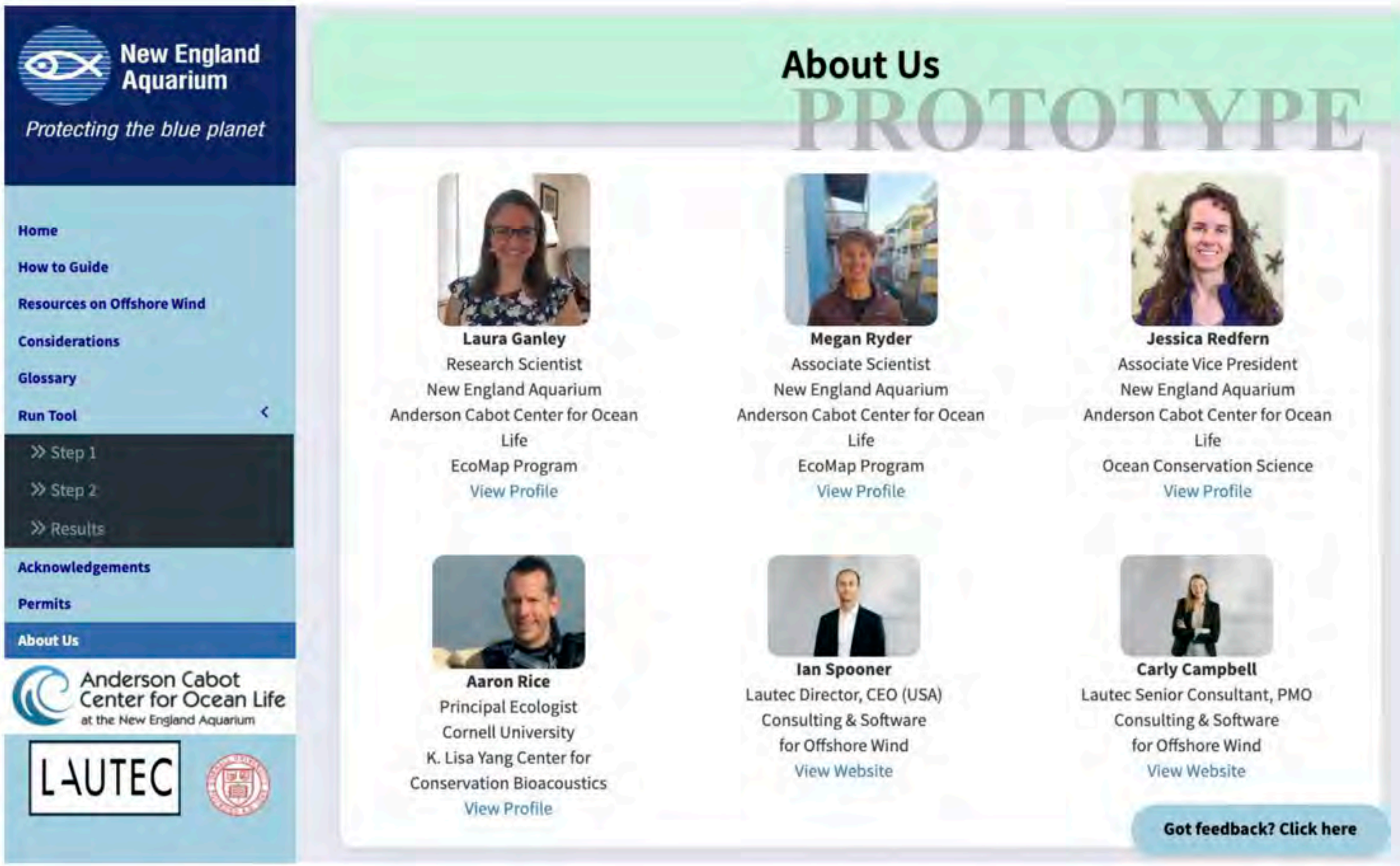
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Laura Ganley
Research Scientist
New England Aquarium
Anderson Cabot Center for Ocean Life
EcoMap Program
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Megan Ryder
Associate Scientist
New England Aquarium
Anderson Cabot Center for Ocean Life
EcoMap Program
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Jessica Redfern
Associate Vice President
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