

Marine mammal density models for the U.S. Navy Atlantic Fleet Training and Testing (AFTT) study area for the Phase IV Navy Marine Species Density Database (NMSDD)

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1. Introduction

In the United States (U.S.), national laws protect marine mammals. The Marine Mammal Protection Act (MMPA) prohibits intentional or incidental killing, injuring, or harassment of marine mammals and specifies the circumstances and rules under which permits may be issued for such activities. The Endangered Species Act (ESA) prohibits harm to species threatened with extinction and requires conservation of their habitat; currently, the National Oceanic and Atmospheric Administration (NOAA) lists 28 marine mammal species under the ESA (<https://www.fisheries.noaa.gov/species-directory/threatened-endangered>). The National Environmental Policy Act (NEPA) specifies a process by which U.S. national government agencies must evaluate the potential environmental effects of their actions, consider alternatives, and conduct public reviews. Agency actions that involve decisions to issue permits under the MMPA or ESA are usually subject to this process.

The U.S. Navy is responsible for compliance with a suite of federal environmental and natural resources laws and regulations intended to conserve marine ecosystems and maintain populations of marine species. Such species include marine mammals such as cetaceans and pinnipeds, which are designated for special protection by the MMPA. Over the past decade, to assist in environmental planning and in compliance with the MMPA and other relevant laws and regulations, the Navy has funded the Marine Geospatial Ecology Laboratory (MGEL) at Duke University to develop density surface models (DSMs) (Hedley and Buckland 2004; Miller et al. 2013) for extant species of marine mammals for several regions. DSMs relate the absolute density (individual animals per square kilometer) of species of interest observed during line transect surveys to ecologically relevant oceanographic covariates such as sea surface temperature. After models are fitted, they can be used to predict maps of species density from maps of the covariates.

Using surveys conducted by collaborating colleagues at NOAA's National Marine Fisheries Service (NMFS, or NOAA Fisheries), other government agencies, and several academic and independent research institutions, we developed and published a foundational suite of density models and maps for the U.S. east coast and Gulf of Mexico (Roberts et al. 2016b) and the Navy's wider Atlantic Fleet Training and Testing (AFTT) area (Mannocci et al. 2017a) for over 30 taxa. The Navy then applied the resulting density maps to the development of its AFTT Phase III Environmental Impact Statement (EIS), which documented

effects on marine mammal populations predicted to occur during training and testing activities initially planned for a five-year period that would start at the end of 2018 (<https://www.nepa.navy.mil/AFTT-Phase-III/>). In compliance with the MMPA, the Navy then obtained a Letter of Authorization (LOA) from NOAA Fisheries permitting these activities from November 14, 2018 through November 13, 2023 (83 FR 57076).

Following that founding effort, the Navy initiated the five-year project “Marine Mammal Density Gap Assessments and Update for the AFTT Study Area”, a Cooperative Agreement (#N62470-15-2-8003) with us to prepare revised density models and maps using newly available data and methodology, for use in future Navy environmental planning and compliance actions. These activities would be documented principally in a new AFTT Phase IV EIS and five-year LOA that would take effect when the Phase III LOA expired. Accordingly, in the Base Year (2015-2016), Option Year 1 (2016-2017), and Option Year 2 (2017-2018) of the Cooperative Agreement, we acquired and integrated a large quantity of additional marine mammal survey data and prepared updated models for 22 taxa for the Atlantic coast, known as the East Coast region in many of our reports (Roberts et al. 2016a, 2017, 2018).

At that time, the Navy planned to utilize the 22 updated models to develop the Phase IV EIS, along with additional updates to be made during Option Years 3 and 4. However, in summer of 2018, near the end of Option Year 2, the John S. McCain National Defense Authorization Act for Fiscal Year 2019 amended the MMPA and extended the maximum time period for regulations related to military readiness from five to seven years. The Navy subsequently obtained a revised LOA for the AFTT Phase III analysis with a new end date of November 13, 2025 (84 FR 70712). Given these additional two years, the Navy requested that we prepare a new set of updated models that incorporated additional marine mammal surveys beyond what we had utilized so far, using the latest methodological improvements available for density surface modeling. Accordingly, the focus of Option Years 3 and 4 of the original five-year Cooperative Agreement, spanning parts of calendar years 2018-2020, was to update our modeling workflow and database of surveys, and then develop a single density model as a means to test the new methods and data.

We selected the North Atlantic right whale (NARW) as the species to be updated, as it is one of most critical conservation concerns within the AFTT study area. This effort dovetailed with a strong interest from NOAA Fisheries, which sought specific model improvements to assist with its management of fishery interactions with right whales. During Option Year 3 and the first half of Option Year 4, we completed development of this new model, known as NARW model version 9 (Roberts et al. 2020). We finished out Option Year 4 by implementing additional updates to the NARW model (versions 10 and 11) based on feedback from NMFS and other stakeholders. We also updated our uncertainty estimation workflow to use the latest methodology (Miller et al. 2022) developed by the “DenMod” Working Group (<https://denmod.wp.st-andrews.ac.uk/>) and released the updated uncertainty estimates as NARW model version 11.1 (Roberts et al. 2021).

To facilitate completion of a full suite of density models under this new methodology with a final set of new survey data, the Navy extended the project via a follow-on Cooperative Agreement (#N62470-20-2-2011) that ends in 2023. The objective of this agreement is to produce a full suite of new density models for all extant marine mammal species for the East Coast (EC), Gulf of Mexico (GOM), and AFTT study areas, using the updated methodology and surveys conducted through 2020. New models were developed by Duke MGEL for the East Coast and AFTT study areas, and by NOAA Southeast Fisheries Science Center (SEFSC) for the Gulf of Mexico as part of the Gulf of Mexico Marine Assessment Program for Protected Species (GoMMAPPS) partnership (<https://www.boem.gov/gommapps>). The combined results were released to the Navy as the AFTT Phase IV Navy Marine Species Density Database (NMSDD) and to the general public on the OBIS SEAMAP Model Repository (<https://seamap.env.duke.edu/models/>). This report documents the models developed by Duke MGEL for the East Coast and AFTT study areas, and the production of the NMSDD. The SEFSC models of the Gulf of Mexico are documented by Rappucci et al. (2022), including models of sea turtles developed as part of GoMMAPPS that were also incorporated into the NMSDD.

2. Methods

2.1. Study areas

As with the Phase III analysis, the AFTT study area boundary was delineated by the Navy.

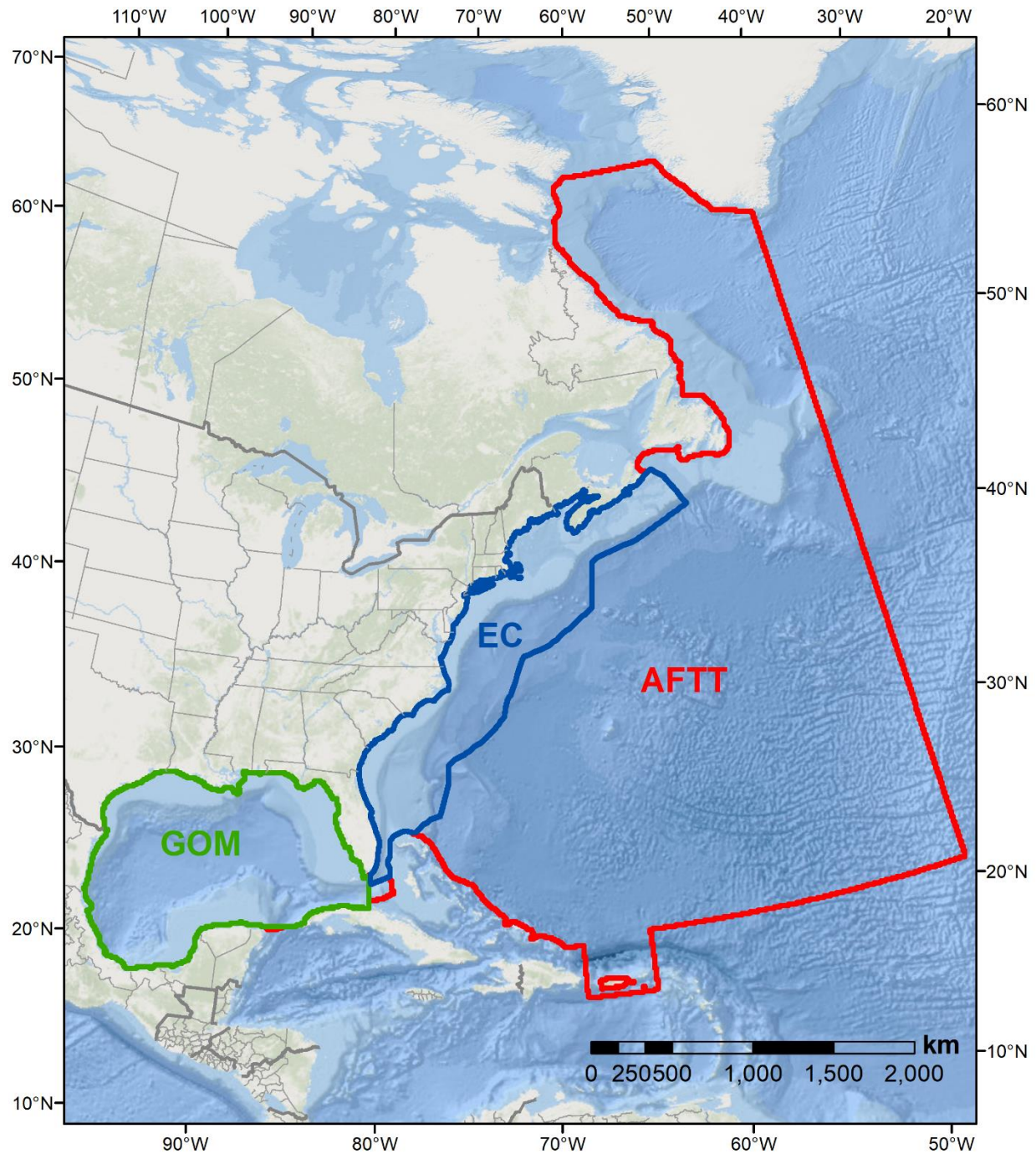


Figure 1. Study areas. The map uses the Albers equal area projection developed for the analysis.

While the waters of the continental U.S. have been heavily surveyed for marine mammals, and portions of Canada and western Greenland have also received some coverage, the rest of the AFTT remains largely unsurveyed. Continuing the strategy established in the Phase III analysis (Roberts et al. 2015), we split off the well-surveyed regions and modeled them separately from the wider AFTT study area. Because NOAA Fisheries placed many species that occur in both the North Atlantic and Gulf of Mexico into separate stocks under the MMPA, and to allow for possibility that species-environment relationships differ between stocks, we split the well-surveyed portion of the AFTT at 80.5°W into two analysis regions, the Gulf of Mexico (GOM) and East Coast (EC) (Figure 1).

For the EC and the northern half of the GOM, both regions where extensive marine mammal surveys were conducted, region-specific models were developed from the surveys within the region. MGEL developed models for the EC using methods evolved from the Phase III EC analysis (Roberts et al. 2016b). SEFSC developed models for the GOM using similar methods; these are known as the GoMMAPPS models (Rappucci et al. 2022). Although SEFSC's GoMMAPPS models only utilized data collected in the northern half of the Gulf of Mexico (i.e., in U.S. waters), SEFSC and MGEL modelers determined that the best approach for estimating density for the southern Gulf of Mexico for the Phase IV analysis was to extrapolate the GoMMAPPS models there, rather than extrapolating the AFTT-wide model, because of the substantial changes to species abundance and oceanographic features observed during GoMMAPPS as compared to prior years (Rappucci et al. 2022). So, while in Phase III the GOM study area encompassed only the northern half of the Gulf of Mexico, in Phase IV, it encompassed the entire Gulf of Mexico (Figure 1).

In the remainder of the AFTT study area, beyond the EC and GOM regions, surveying was relatively sparse. Several broad-scale surveys were completed in Canada (Lawson and Gosselin 2009, 2011, 2018) and western Greenland (Heide-Jørgensen et al. 2010; Hansen and Heide-Jørgensen 2013; Hansen et al. 2019) but these surveys were not made available for our use. Throughout much of the rest of the AFTT, almost nothing was available. Therefore, as in Phase III, we developed parsimonious models designed to extrapolate well across this largely-unsurveyed area, using the methods established by Mannocci et al. (2017a). Throughout this report, we refer to these as the "AFTT models".

This report documents the methods and results for MGEL's EC and AFTT models, as well as the approach we used to overlay the EC, GOM, and AFTT models' predictions to populate the NMSDD. For more information about the development of the GOM models, please see Rappucci et al. (2022).

2.2. Surveys

An overriding goal of our study was to maximize the number of marine mammal species modeled with density surface models rather than cruder methods. Meeting this goal required many sightings, thus many surveys. Using the Navy's pioneering NODE studies from the AFTT Phase II EIS as our baseline (Department of the Navy 2007a, b, c), we searched bioinformatics databases and the literature for aerial and shipboard visual line-transect surveys conducted throughout the AFTT between 1992, the year of the first survey used in the AFTT Phase II analysis, and 2020. We only considered surveys that used two or more observers and adhered to the requirements of distance sampling methodology (Buckland et al., 2001). For the AFTT-wide models, to boost sampling across the full ranges of environmental covariates and thereby reduce the need for extrapolation in environmental space, we also solicited surveys from teams that had surveyed regions of the Caribbean and central and eastern North Atlantic, as done in the Phase III analysis. We acquired the original survey data files, transformed them into a common database schema, and aggregated them into a geodatabase.

To define the EC region, we manually delineated a polygon that enclosed the surveys conducted along the coast of North America from the southern tip of Florida north to the Laurentian Channel at the entrance to the Gulf of St. Lawrence. We included near-shore waters but excluded most estuaries, bays, and sounds south of New Jersey, where the bottlenose dolphin is the only cetacean species that regularly occurs in those inshore waters. We estimated densities of estuarine bottlenose dolphin stocks of specific interest to the Navy with a separate methodology, documented in detail by Kot and Roberts (2022).

2.3. Modeled taxa

To facilitate straightforward use of our results within the U.S. regulatory framework, which requires estimating incidental takes at the species or stock level, we sought to model density on a per-species basis for each analysis region. This required that all sightings have fully resolved taxonomic identifications, but some species were difficult for observers to tell apart, resulting in a nontrivial fraction of sightings that were not fully resolved. We handled these ambiguous sightings differently based on their degree of ambiguity.

2.3.1. Ambiguous sightings resolved to a pair of species

The least ambiguous sightings resolved the identification to a pair of species, e.g., "fin or sei whale". When there were a substantial number of these for a pair of species, plus a substantial number of fully resolved sightings (a.k.a. definitive sightings)

for both, and the literature or exploratory analysis suggested the two species exhibit different spatiotemporal distributions, we classified the ambiguous sightings into one species or the other using the cforest classifier (Hothorn et al. 2006), an elaboration of the classic random forest classifier (Breiman 2001). We trained the classifier on the fully resolved sightings, using the species ID as the response variable, and environmental variables, day of year, or group size as predictor variables, depending on the species. We used the default parameters for cforest, with 1000 trees (fewer were used when memory limitations impeded analysis). We applied receiver operating characteristic (ROC) curve analysis to select a threshold for classifying the probabilistic result of the classifier into one species or the other. For the classification threshold, we selected the value that maximized the Youden index (Perkins and Schisterman 2006). We assessed the classifier's performance at predicting the fully resolved sightings using the area under the ROC curve (AUC) and Cohen's kappa (K) statistics. We then classified the ambiguous sightings as one species or the other by processing the predictor values observed for the sightings through the classifier. We only performed these classifications for surveys that occurred in the EC and GOM regions; surveys that occurred outside these regions—e.g., those conducted by European organizations—reported relatively few ambiguous sightings of this kind.

A special case of sightings resolved to a pair of species concerned four “sei or Bryde's whale” sightings reported by SEFSC in the 1990s. Three of these were collected while observers were on effort; for the other, observers were off effort. All four were south of Cape Hatteras, an area where baleen whale sightings other than North Atlantic right whale are very rare, but where some species are believed to overwinter beyond the continental shelf. In Phase III, out of an abundance of caution, we included all four ambiguous sightings (including the off-effort sighting) in both the sei whale model and the Bryde's whale model. While the sei whale model included many other sightings, the Bryde's whale model only included the four ambiguous sightings, which yielded a mean abundance of 7 whales, reflecting the extreme rarity of the species in the area. Subsequently, Rosel et al. (2021) reviewed multiple lines of evidence, including our model, and concluded that “Overall, the evidence to date indicates Bryde's whales are extremely rare in U.S. waters of the western North Atlantic.” They pointed out that passive acoustic monitoring has not recorded whale call types associated with any type of Bryde's whale along the east coast, but sei whales have been regularly recorded. Lacking any more recent possible evidence of Bryde's whales in the EC study area, and given the expert opinions of Rosel et al., our conclusion is that the ambiguous sightings from the 1990s were sei whales, and in Phase IV, we only included them in the sei whale model. (For Phase IV, we excluded the sighting that was off effort.) We now believe Bryde's whale is effectively absent from our East Coast study area and have not prepared an EC model for this species for Phase IV. We consider the Phase III Bryde's whale model retired, and no longer recommend its use.

For other sightings resolved to a pair of species, when we lacked enough fully resolved sightings to build a classifier, or when we could not establish a plausible claim that the two species exhibit sufficiently different spatiotemporal distributions, we modeled the two species together as a guild that included both the ambiguous and the fully resolved sightings of both species. This occurred for the *Kogia* (dwarf and sperm whales) and the *Globicephala* (pilot whales).

2.3.2. Ambiguous sightings resolved to a genus or family

The next most ambiguous type of sightings resolved the identification to a genus or family of more than two species. This occurred for the *Ziphiidae* family (beaked whales), for which the number of “unidentified Mesoplodon” or “unidentified beaked whale” sightings dominated the number of fully resolved sightings. Because of this problem, in Phase III we modeled all beaked whales other than northern bottlenose whale (*Hyperoodon ampullatus*) in a single guild (Roberts et al. 2016b). Observers asserted there was little chance of mistaking the northern bottlenose whale for one of the others. For Phase IV, NOAA Northeast Fisheries Science Center (NEFSC) and SEFSC contributed the Atlantic Marine Assessment Program for Protected Species (AMAPPS) surveys, which were not available for Phase III. During AMAPPS, NOAA undertook a concerted effort to boost the taxonomic precision of beaked whale sightings relative to prior surveys. Separately, the University of North Carolina Wilmington (UNCW) team revisited all beaked whale sightings they had collected since 2010 to try to fully identify them from photographs taken of each sighted group (McLellan et al. 2018). The AMAPPS and UNCW efforts collectively resulted in a large increase in sightings identified to the genus or species level, relative to unidentified sightings, as compared to sightings reported by the surveys used in Phase III. This allowed us for the Phase IV EC model to split the “beaked whales” guild into three successor models that have higher taxonomic resolution: Cuvier's beaked whale (*Ziphius cavirostris*) was modeled as a single species using its fully resolved sightings, “Mesoplodont beaked whales” were modeled as a guild that included the fully resolved sightings of the *Mesoplodon* genus plus sightings of “unidentified Mesoplodon”, and an “unidentified beaked whales” guild was modeled from the “unidentified beaked whale” sightings. As in Phase III, northern bottlenose whale was modeled as a single species using its fully resolved sightings.

This splitting of the “beaked whales” guild was only feasible for the EC study area. In the Gulf of Mexico, very few beaked whale sightings were fully resolved and SEFSC continued to model the “beaked whales” guild that included all of them (Rappucci et al. 2022). For the AFTT-wide model, which included surveys from the EC, GOM, Caribbean, and Mid-Atlantic Ridge, we faced the same problem and therefore continued to model the “beaked whales” guild. Therefore, for development of the Phase IV EIS and other environmental planning, we have delivered in the NMSDD both the three new EC models and also the “beaked whales” guild. Predictions for the three new models are only available in the EC region, while predictions for the “beaked whales” guild are only available outside of the EC region.

A similar level of sighting ambiguity occurred for seals (*Phocidae*). In the EC region, two species, harbor seal and gray seal, occur regularly and two others, harp seal and hooded seal, occur only occasionally (Haverkamp et al. 2023). The only fully resolved sightings were of harbor seal and gray seal, and these were dominated by the number of “unidentified seal” sightings. Given the strong overlap between harbor seal and gray seal habitats, we elected to model all seals as a single guild, as we did in Phase III.

2.3.3. *Sightings too ambiguous to use*

Finally, the most ambiguous sightings indicated only that an “unidentified dolphin” or “unidentified whale” was sighted, often with a size qualifier, e.g., “unidentified large whale”. We omitted these sightings from our analysis. Although these sightings comprised only 9.8% of the total reported, with the remaining 90.2% being fully resolved, they may have resulted in an underestimation of density on account of animals being present and sighted but not included in the model (see Section 3.1 for further discussion).

2.4. *Modeling workflow*

The models in both the well-surveyed EC and poorly-surveyed AFTT analysis regions followed the generic two-stage density surface modeling workflow (Figure 2) outlined by (Miller et al. 2013). In the first stage of the model, called detection modeling, we used traditional distance sampling (Buckland et al. 2001) to model the detectability of observed objects (marine mammals, in this case) and correct the survey data for imperfect detection. To account for substantial differences in detectability across survey platforms and programs, we first organized the observations hierarchically according to platform, program, and other important factors and fitted detection functions to groups of observations contained by branches of the hierarchy. Then, using findings reported by our collaborating survey institutions or from the literature, we applied additional corrections to account for the possibility that observers may miss sightings directly on the trackline, either because animals were submerged and unavailable for detection—a problem known as availability bias—or because they were simply hard to detect despite being at the surface—known as perception bias. Although NOAA AMAPPS and GoMMAPPS used two-team survey protocols that would allow us to estimate perception bias ourselves, we preferred to use estimates already prepared from these data by NOAA (Palka et al. 2021; Rappucci et al. 2022). Finally, we split the survey transects into segments and applied the detection functions and corrections to produce the records used to fit the second stage of the models.

In the second stage, referred to as spatial modeling, we used generalized additive models (GAMs) (Hastie and Tibshirani 1990; Wood 2006) to model the counts of individuals sighted on the survey segments from environmental covariates observed at the segments, as well as, occasionally, space and time. For certain species, to allow species-environment relationships to differ regionally or seasonally (e.g., for right whales that migrated to southern calving grounds vs. those that overwintered at the northern feeding grounds), we split the data into independent regional and seasonal models, based on what was known of the species’ ecology and what patterns we observed in the data. After selecting the best candidate models for each region and season, determined by examining goodness-of-fit statistics, diagnostic plots, total abundance estimates, and spatiotemporal patterns in density predictions, we predicted them across a time series of gridded maps of covariates (e.g., images of sea surface temperature, and so on), to produce a corresponding time series of maps of mammal density and model uncertainty. We then summarized the maps according to the Navy’s needs for the NMSDD. To estimate and summarize uncertainty, we used the approach described by Miller et al. (2022). (Although these prediction and uncertainty estimation steps are represented by independent green boxes in Figure 2, they are not considered separate “stages” under DSM methodology. They are considered part of the second stage, the spatial model.)

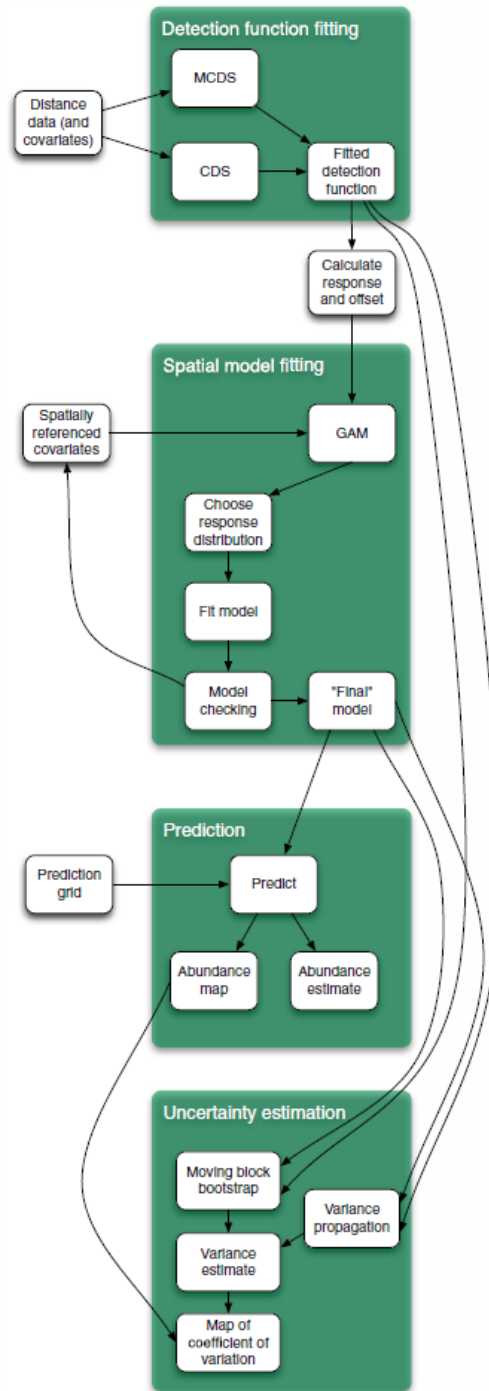


Figure 2. Generic density surface modeling workflow, reproduced from Figure 6 of Miller et al. (2013).

2.4.1. Detection functions

For line transect surveys, detection functions estimate the probability of detecting an animal given the perpendicular distance to it from the trackline, as well as other conditions affecting detection probability, such as the sea state or the weather. Buckland et al. (2001) recommended that at least 60-80 observations be used to fit a detection function, but noted that as few as 40 might be adequate for some purposes. The “DenMod” Working Group subsequently investigated this question, reaffirmed

that there is not a hard-and-fast minimum number of observations needed, and showed real-world examples in which a function for one taxon fitted to 45 observations achieved a better goodness of fit than a function for a different taxon fitted to 176 observations. In any case, marine mammals are rare enough that Buckland et al.'s recommendation often cannot be met with the observations obtained from a single survey. The typical workaround is to pool observations from multiple surveys or taxa until sufficient observations are obtained.

With that idea in mind, we arranged the surveys available for our analysis into tree-like “detection hierarchies”, as diagrammed under the “Detection Functions” sections of the accompanying taxon-specific reports. We defined separate hierarchies for aerial surveys and shipboard surveys. For each, we first clustered the surveys into small groups that we judged were most likely to have the most similar detection characteristics, informed by descriptions of their survey protocols and consultations with the observer teams. Next, we clustered the groups according to how similar *the groups* were, forming a smaller number of groups containing a larger number of surveys, and repeated this process until we had a single group of all surveys at the top of the hierarchy. (In the diagrams, the top of the hierarchy appears on the left, and the bottom on the right.)

Given the large number of surveys in our analysis and the large number of taxa we modeled, it was infeasible to develop taxon-specific detection hierarchies for every taxon. We did so when we judged that the taxon's detectability differed in important respects from others such that pooling should be avoided (e.g., for harbor porpoise) and we had enough observations of that taxon such that pooling with others was not necessary. Occasionally, we also developed taxon-specific hierarchies for taxa that had similar detectability to others but for which we had so many observations that pooling with other species provided little benefit (e.g., for North Atlantic right whale).

When we could not develop taxon-specific detection hierarchies, we pooled taxa with similar detection characteristics to allow the fitting of multi-species detection functions (e.g., for large whales), following common practice in NOAA's models (Barlow and Forney 2007; Palka et al. 2021; Rappucci et al. 2022). We consulted the literature and observer teams to determine appropriate pools. For these multi-taxon pools, when sufficient counts of each taxon were available, we tested the taxonomic identification as a categorical covariate in the detection function, to account for differences between them. Occasionally, we had too few observations of a taxon to allocate it with its own level of the covariate and had to group it with others, again consulting the literature and observers for advice on taxon similarity. Also, when taxa were observed frequently enough to be allocated their own level but statistical tests indicated no significant difference between the levels, we usually grouped them together into a single level (e.g. fin and sei whales). If, after all of this, there was still no statistically significant difference between the species or species groups, we removed the taxonomic covariate from the detection function.

For each hierarchy, at each node, we tallied the number of observations of the modeled taxon that were reported by all surveys under that node. When a suitable number of observations existed under a node, typically 70 or more, we fitted a detection function specific to those surveys. If not enough were available, we ascended the hierarchy until we reached a node that contained enough surveys to fit a detection function.

Although certain large surveys such as the NOAA North Atlantic Right Whale Sighting Survey (NARWSS) program occasionally reported enough observations to fit detection functions on a per-survey basis, exploratory analysis showed that per-survey detection functions fitted to a series of very similar surveys almost always achieved poorer fits than a single detection function fitted to all of them together, especially when the pooled set of observations were large enough to allow additional covariates to be utilized in a multiple covariate distance sampling (MCDS) formulation. For this reason, we rarely fitted detection functions on a per-survey basis.

For each detection function, we attempted several formulations and selected the one with the lowest Akaike information criterion (AIC). We tested both conventional distance sampling (CDS) and MCDS formulations. For CDS, we tested key functions based on the recommendations of Thomas et al. (2010): hazard rate and half normal key functions with no adjustments, hazard rate with second and fourth order polynomial adjustments, half normal with second and third order cosine adjustments, and half normal with a fourth order Hermite polynomial adjustment. For MCDS, when data were available, we tested covariates such as the sea state as assessed on the Beaufort scale, other ocean and weather conditions, glare, the observer's subjective estimate of the quality of observation conditions, and the season. When data were combined from multiple survey programs, we tested the program or vessel or aircraft that was used, when possible. For multi-year programs for which we had a specific reason to suspect interannual differences not addressed by other covariates, we tested year as a covariate. Not all covariates were tested for all taxa, and covariates that produced obvious ill effects were discarded. Unlike in Phase III, we generally did not limit the number of covariates allowed in a detection function according to the number of observations available. Instead, based on advice from collaborating distance sampling experts at the University of St. Andrews, we relaxed that restriction and eliminated candidate detection functions from contention when the standard error of any covariate

coefficient exceeded the estimate for the coefficient, indicating that the influence of that covariate was not supported statistically. We fitted all detection functions using the R *mrds* package version 2.2.5.

Several aerial survey programs measured vertical angles to sightings using marks on windows or wing struts, resulting in “heaping” of distance values (Buckland et al. 2001), typically at 10° increments. For these, we fitted detection functions to the heaps, using cutpoints that were halfway between the heaped values (Buckland et al. 2001). Several aerial programs also suffered from an inadequate view of the survey trackline due to having flat windows, or, more rarely, to observers not focusing attention adequately on the trackline. This latter problem occurred mainly with the NOAA NARWSS program, which had the primary objective of finding and photographing right whales rather than conducting abundance surveys; NARWSS observers were trained to scan most frequently at “one mile out from the trackline” (T.V.N. Cole, pers. comm.), resulting in missed detections of small species along the trackline. For these surveys, we applied left truncation (Buckland et al. 2001).

The accompanying taxon-specific reports for the EC document the detection hierarchies and proxy species that were used, and the detection functions that were fitted along with statistical diagnostics. The AFTT models mostly reused the same detection functions; those that were reused are omitted from the taxon-specific reports for the AFTT.

For beaked and sperm whales, for two surveys conducted by Marine Conservation Research, we used acoustic detections collected by a towed hydrophone rather than visual observations. For these taxa, passive acoustic monitoring provides advantages over visual observation, such as being able to operate at night and having less availability bias. The taxon-specific reports for beaked and sperm whales provide more information about our use of these passive acoustic surveys.

2.4.2. *Perception and availability bias corrections*

An important assumption of distance sampling is that objects that occur at distance 0 (directly along the survey trackline) are always detected (Buckland et al. 2001). This is known as the $g(0)=1$ assumption, signifying that the probability of detection, g , at distance 0 is 1. When this assumption is violated and $g(0)<1$, density will be biased low—that is, the number of animals present will be underestimated—unless the bias is corrected.

On surveys for marine animals, this bias generally occurs in two ways (Marsh and Sinclair 1989). On visual surveys, *perception bias* occurs when animals are not detected by the observer team because they are hard to see—e.g. because they are small or otherwise inconspicuous. *Availability bias* occurs because the animals are not available to be seen, even though they are present—e.g. because they are submerged. The two biases are often assumed to be independent, and modelers typically estimate a $g(0)$ for each—i.e. $g(0)_{\text{perception}}$ as the probability that an animal at the surface will be sighted if it is at distance 0, and $g(0)_{\text{availability}}$ as the probability that an animal along the trackline will be at the surface while it is within visual range—and then multiply the detection function by each one, reducing the integrated probability of detection accordingly. Alternatively, the counts of detected animals for each observation can be divided by each one, inflating the counts to account for animals that were “missed”. We took this alternative approach to facilitate the use of sighting-specific $g(0)$ estimates.

To ensure the biases are independent of the surveying process, appropriate field methods must be used to ensure animals do not respond to the survey platform before they are sighted. On aerial surveys, this is achieved by flying at sufficiently high speed or altitude, so that the animals do not have a chance to respond before observers are close or are not disturbed by the presence of the aircraft high above. On shipboard surveys, it is accomplished by enabling observers to scan far ahead of the vessel, e.g. by positioning them as high as possible and equipping them with binoculars.

A recommended approach for assessing perception bias is to utilize an independent observer or multiple observer teams and match up the sightings reported by each to characterize how frequently sightings were missed. The most commonly-used variations of this approach are known generally as *mark recapture distance sampling* (MRDS; Burt et al. 2014). Many of the shipboard surveys available for our analysis used one of these variations. Most of the aerial surveys did not, owing to the logistical difficulty of carrying sufficient personnel in a small aircraft or the budgetary challenge of affording a suitable aircraft and so many observers. The main exceptions were the NOAA AMAPPS aerial surveys, which carried two independent observer teams on de Havilland Twin Otter aircraft. Prior to AMAPPS, the NEFSC broad-scale marine mammal abundance surveys used the same aircraft but a single observer team, and employed a “circle-back” method to characterize detection probability by making multiple observations of sighted groups by the same team (Palka 2006).

Because of this heterogeneity we used a single-team approach for our analysis. For all surveys we only used effort and sightings from the team that our collaborators designated as the primary team. Then, to correct for perception bias, we consulted

our collaborators and searched the literature for studies that had estimated it, selected estimates that best matched according to the platform, species, and surveyor organization or location, and applied the various estimates to the appropriate surveys after fitting detection functions using traditional single-team methodology. We relied mainly on perception bias corrections estimated by Palka et al. (2021) for the NEFSC and SEFSC AMAPPS programs. We caution that it is possible that perception bias on non-AMAPPS programs was different than what was estimated for AMAPPS, particularly for aerial surveys, as the other programs often used different aircraft, flew at different altitudes, and were staffed by different personnel. Of particular concern are that many programs flew Cessna 337 Skymasters, which had flat windows, while NOAA flew de Havilland Twin Otters, which had bubble windows, which likely afforded a better view of the transect line and therefore might have required less of a correction than the Skymasters. Correcting the other programs using NOAA's AMAPPS estimates as we have done is likely to yield less bias than leaving them uncorrected, but we urge all programs to undertake their own efforts to estimate perception bias, as resources allow.

To estimate availability bias for aerial surveys, we surveyed the literature for dive data and used Laake et al.'s (1997) estimator to calculate survey-program-specific corrections, discussed in more detail in the next section. For shipboard surveys, for all taxa other than beaked and sperm whales, we assumed that availability bias would be negligible (i.e. $g(0)_{\text{availability}} = 1$) due to the ships operating at slow speeds during the surveys, which afforded diving animals sufficient time to surface before they moved out of view. For beaked and sperm whales, we utilized availability bias corrections from the literature to correct visual surveys, and derived a correction for acoustic surveys, as discussed in the taxon-specific reports for those taxa.

2.4.2.1. Availability bias corrections for aerial surveys

Availability bias for aerial surveys depends on a number of factors. Important considerations include the diving patterns of species of interest, the size and behavior of the group, the speed and altitude of the aircraft, and the field of view available to the observer (as determined by the aircraft windows, obstructions, etc.). Because availability bias can vary considerably based on these factors, we attempted to account for as many as feasible in the time available for this project.

To do this, we relied on the approach of Laake et al. (1997), as formulated by Robertson et al. (2015):

$$a(x) = \frac{\bar{s}}{\bar{s} + \bar{d}} + \frac{\bar{d} \left[1 - e^{-t(x)/\bar{d}} \right]}{\bar{s} + \bar{d}} \quad (1)$$

Here, $a(x)$ is the availability bias correction factor at perpendicular distance x ; the value $a(0)$ is the $g(0)_{\text{availability}}$ that we sought to estimate. \bar{s} and \bar{d} are average surface and dive intervals for the species, and $t(x)$ is the time that a parcel of water at distance x remains in view of the observer. Under this approach, the first fraction $\left(\frac{\bar{s}}{\bar{s} + \bar{d}} \right)$ represents the probability that the animal is at the surface when it enters the observer's field of view, and the second fraction represents the probability that it is submerged but will surface while within the field of view as the observer passes over. Please see Laake et al. (1997) for further details.

We obtained surface and dive intervals from diving studies in the literature. We were interested in availability at $x=0$, so we needed to estimate $t(0)$, the total time-in-view on the trackline at perpendicular distance zero. We derived this parameter from the speed and altitude of the survey. Below, we first discuss the estimation of $t(0)$ and then the application of surface and dive intervals and resulting availability estimates.

Estimation of $t(0)$

We based our estimates of $t(0)$ on results reported by Robertson et al. (2015), who estimated availability corrections for bowhead whales sighted from de Havilland Twin Otters flown at a target altitude of 305 m (1000 ft) altitude and speed of 220 km h⁻¹ (119 knots). To do this, they fitted linear models to the times an object was in view forward and aft of perpendicular as a function of perpendicular distance, using field data collected by trained marine mammal observers. To obtain this training data, they flew trial passes by a static structure placed at randomly determined perpendicular distances. They asked observers to execute their "normal" search pattern and recorded the times the object first came into view, passed perpendicular, and passed out of view behind the plane. Under these conditions, their procedure estimated that at the mean speed (62.31 m s⁻¹) and altitude (305 m) of the analysis, the total time-in-view on the trackline $t(0)$ was 37.78 s, based on a search sector spanning 37.4° forward to 121.2° aft, also estimated by the model.

To adapt this result to each of the surveys used in our analysis, which occurred at different speeds and altitudes, we used the expression:

$$t(0) = t_R(0) \frac{v_R}{v} \frac{h}{h_R} \quad (2)$$

where $t(0)$ was the survey-specific value we sought to estimate, $t_R(0)$ was Robertson's time-in-view estimate at distance 0 (37.78 s), v_R and h_R were the speed (62.31 m s⁻¹, or 121.1 kts) and altitude (305 m, or 1001 ft), respectively, of Robertson's experiment, and v and h were the speed and altitude, respectively, of our focal survey. This approach assumed that $t(0)$ would scale linearly with altitude (e.g. doubling altitude would double time-in-view) and inverse-linearly with speed (e.g. doubling speed would halve time-in-view). Table 1 shows our results.

Table 1. $t(0)$ estimates for aerial surveys used in our analysis.

Altitude (m)	Speed (kts)	$t(0)$ (s)	Surveys
183	95	28.90	VAMSC and Riverhead Maryland DNR
183	110	24.96	NEFSC pre-AMAPPS; NEFSC and SEFSC AMAPPS
229	100	34.36	NARWSS 2003-2016
229	110	31.23	SEFSC pre-AMAPPS
229	120	28.63	NJ-DEP
305	87	52.60	VAMSC VA CZM and Navy VACAPES
305	100	45.76	NARWSS 2017-2019, NEAq, NYS-DEC/TT, all SEUS NARW, UNCW
305	110	41.60	HDR

We caution that our approach, although based on empirical results, assumed that Robertson's results, which involved a specific organization, aircraft type, and survey protocol, were a reasonable proxy to use for our surveys when scaled using the method we described. Although no empirical analyses similar to Robertson's were available in the literature for our surveys, our results may be compared to those of D. Palka (pers. comm.), who developed similar availability corrections for the AMAPPS surveys, which used similar aircraft to Robertson, and possibly some of the same personnel, but flew at a lower altitude and slower speed. Palka's analysis assumed a hemispherical, forward-facing field of view and based $t(0)$ estimates on the maximum forward distance animals were sighted for the 2010-2013 AMAPPS surveys (sometimes the maximum perpendicular distance was used instead). For fin, sei, and right whales, which were analyzed as a guild for the purpose of deriving $t(0)$, Palka reported a maximum distance of 1490 m. Under the assumed field of view, this is the along-track distance that a parcel of water directly below the plane would be sufficiently visible to an observer to allow them to sight a large whale. To obtain this result, Palka assumed an altitude of 183 m and 105 kts¹. For comparison, when we rescaled Robertson's results using the method above, we obtained $t(0) = 26.15$ s and a distance of 1412 m, which differs by less than 7% of Palka's result.

Surface and dive intervals, and estimation of availability corrections

To determine taxon-specific surface and dive intervals—the \bar{s} and \bar{d} parameters of the availability bias correction factor equation shown above—we consulted dive studies in the literature. In particular, we consulted Palka et al. (2021), who had recently surveyed the literature and located surface and dive intervals for many species. For species other than the North Atlantic right whale, the intervals available were for a single adult individual. To account for the influence of group size on availability, we applied the group availability estimator of McLellan et al (2018), also used by Palka et al. (2021), on a per-sighting basis to estimate the availability of the group:

$$a(0)_{group} = 1 - (1 - a(0)_{individual})^{GroupSize} \quad (3)$$

¹ Although Palka (pers. comm.) used a speed of 105 kts for the AMAPPS surveys, in our analysis we used 110 kts, the speed consistently reported in the AMAPPS annual reports. This discrepancy is currently unresolved but can be clarified for future models, with Palka's assistance.

We caution that this method assumes that individuals in a group dive asynchronously, and that this assumption can lead to an underestimation of density and abundance if diving is actually synchronous. Please see McLellan et al (2018) for an exploration of this effect. So that this approach may be improved in the future, we encourage future studies of diving behavior to quantify the synchronicity of diving by individuals in groups. If the degree of synchronicity can be characterized, or the overall availability of groups to otherwise be estimated, our models can be updated to account for this knowledge.

For the North Atlantic right whale, considerably more diving information was available than for other species, and we developed corrections that took into account geographic location and group composition. Please see the accompanying taxon-specific report for the right whale for details.

2.4.3. Splitting of survey transects into segments

After fitting detection functions and determining perception and availability bias corrections, it was necessary to split survey transects into the segments that would form the training data for the spatial model. We based the segment length on the spatial resolution of the analysis. As with Phase III, the Navy requested that density predictions be provided on a grid at a spatial resolution no coarser than 10x10 km, when possible. NOAA expressed interest in a higher resolution to improve the utility of model predictions in non-military management applications, particularly those that required predictions near shore. For Phase IV, we increased the resolution of the EC models to 5x5 km. For the AFTT models, which were primarily of interest to the Navy and which did not approach shore except in the EC and GOM regions (where the EC and GOM models' predictions would be used instead), we retained the 10x10 km resolution of Phase III. Therefore, for the EC models we generated segments with a target length of 5 km, and for the AFTT models, 10 km, using the following procedure:

For each survey, we iterated through the sequence of points that defined the transects, finding sections of continuous survey effort and splitting them into segments. Here, we defined a “continuous section” of survey effort as a sequence of on-effort transect points for which there were 1) no changes in the covariates (e.g., Beaufort sea state) used in the survey’s detection function, 2) no off-effort gaps of 2 h or more, and 3) no stretch of trackline of the target segment length (5 km for EC, 10 km for AFTT) for which 1/3 or more of it was off-effort (i.e., 1.667 km for EC, 3.333 km for AFTT). We then split each continuous section into equal-length on-effort segments, as follows:

First, the number of segments N was computed by dividing the continuous section's length by the target segment length (5 km or 10 km) using integer division. If the remainder was less than half the target segment length, then the remainder was distributed evenly among the N segments, resulting in N equal-length segments that were all slightly larger than the target length. Otherwise, the number of segments was increased by 1 and their length was computed by dividing the continuous section's length by $N+1$, resulting in $N+1$ equal-length segments that were all slightly smaller than the target length. Under no circumstances was a segment ever longer than 1.5 times the target segment length. A very small number of short, spatiotemporally-isolated segments occurred and were preserved, so long as they were longer than 1 km. (Segments shorter than 1 km were dropped from the analysis.)

The segments generated for each model varied according to the covariates used in the detection functions, the time range of data utilized in the model, and the specific conditions excluded from the model (e.g. high sea states). The accompanying taxon-specific reports summarize the segments used to fit each model.

2.4.4. Spatial models

For each modeled taxon, after fitting detection functions and obtaining corrections for perception and availability bias, we estimated the count of animals present and the area effectively surveyed for each segment, accounting for the factors influencing detectability described above. These two values—the count of animals and the area effectively surveyed—served as the response variable and offset, respectively, for the spatial regression models fitted during the second stage of modeling.

2.4.4.1. Statistical framework

In this section, we outline more formally the statistical framework used to fit each spatial model. Let i be the index into the set of detection functions fitted for the model, and j be the index into the set of segments obtained from the surveys pooled

for that detection function, after splitting up their transects as described above. For each detection function i , for each segment j , we computed the number of individuals observed, inflated by the observation-specific bias correction:

$$n_{ij} = \sum_r \frac{s_{ijr}}{\hat{g}_{0ijr}} \quad (4)$$

where s_{ijr} was the group size reported for observation r at the segment and \hat{g}_{0ijr} was the estimated bias correction for observation s_{ijr} . We then computed the effective area surveyed at the segment:

$$A_{ij} = (\hat{p}_i(z_{ijLEFT}) + \hat{p}_i(z_{ijRIGHT}))w_i l_{ij} \quad (5)$$

where $\hat{p}_i(z_{ijLEFT})$ was the probability of detection estimated by detection function i given the detectability covariates z_{ijLEFT} observed by the left observer, and $\hat{p}_i(z_{ijRIGHT})$ was the same for the right observer. w_i was the half-width of the transect (i.e. the detection function's right truncation distance minus left truncation distance, if any), and l_{ij} was the length of the transect. (For many surveys, the detectability covariates were the same for both observers, in which case the expression simplified to $A_{ij} = 2\hat{p}_i(z_{ij})w_i l_{ij}$.) We then fitted a log-link generalized additive model (GAM) (Hastie and Tibshirani 1990; Wood 2017):

$$\mathbb{E}(n_{ij}) = A_{ij} \exp[\beta_0 + \sum_k f_k(z_{ijk})] \quad (6)$$

where the segment's effective area A_{ij} was an offset, β_0 was an intercept, and each $f_k(z_{ijk})$ was a smoothed function of the spatial model covariate k (e.g., sea surface temperature) with the value z_{ijk} for the segment.

We fitted and predicted GAMs in R with the `mgcv` package version 1.8-36. For smoothed terms, we used thin-plate regression splines with shrinkage smoothers (`bs="ts"`) (Marra and Wood 2011). We used the Tweedie distribution (Miller et al. 2013), with automatic selection of the power parameter (`family="tw()"`). We used restricted maximum likelihood (REML) (Wood 2011) for smoothness selection and to compare candidate model goodness of fit. After model fitting, if a covariate p-value was greater than 0.05 or its estimated degrees of freedom were less than 0.85 (resulting in its estimated confidence limits enclosing 0 throughout the range of the covariate), we removed the covariate from the model and refitted it. We discuss additional details, including covariate selection and model prediction, summarization, and uncertainty estimation, in later sections of this report.

2.4.4.2. Spatial model covariates

Table 2 lists the covariates we prepared for the Phase IV spatial models. To be usable for our model, covariates needed to be: 1) plausibly correlated with cetacean habitat (ideally, reported as such in the literature); 2) available as gridded surfaces spanning the study area; 3) available for period 1998-2019, and ideally 1992-2020; 4) available at 25 km spatial resolution or higher; and 5) available at least at monthly contemporaneous resolution. In Phase III, we used daily resolution out of a principled desire to use the highest temporal resolution available. During Option Years 3-4 of the Cooperative Agreement, we reevaluated that decision by comparing North Atlantic right whale models fitted with daily resolution to those with monthly resolution. Goodness of fit statistics indicated better performance for monthly resolution, so we proceeded with that for the Phase IV models. We caution that we lacked the time to perform a comprehensive sensitivity analysis across all taxa we modeled, and that different species or ecosystems might show different results.

We favored products in which the covariate producer solved any gap-filling problems, as is done with Level 4 remote sensing products and by ocean models. Our preference was for oceanographers and similar experts to handle this job, using expertise they specifically developed for the products in question. After downloading each product, we resampled it to the model's grid, filled any remaining gaps with Laplacian interpolation, and prepared monthly contemporaneous (per-month, per-year) and climatological (per-month, all years) mean grids. Using the resampled grids, we extracted covariate values for survey segments as follows. First, we matched the segments to the resampled grids using the appropriate ranges of dates. (For example, to extract the monthly contemporaneous chlorophyll covariate, we matched all segments from January 2010 to the monthly chlorophyll grid for January 2010, all February 2010 segments to the February 2010 grid, and so on). Next, for each grid to which some segments had been matched, we overlaid the segments' centroids on the grid using GIS and extracted the value of the cell under each centroid using linear interpolation. We proceeded through all of the segments and covariates until each segment had both a contemporaneous and a climatological value for each covariate.

Table 2. Candidate covariates for the spatial models. All covariates were resampled or averaged to the spatial and temporal resolutions and coordinate system of the modeled region (EC or AFTT). Checkmarks indicate which regions covariates were applied to. Following Mannocci et al. (2017a), the AFTT used a subset of the EC’s covariates. Following Roberts et al. (2016b), most EC models tested both contemporaneous and climatological formulations of covariates, while the AFTT models always used climatological formulations, following Mannocci et al. (2017a). All distances were calculated using a fast-marching algorithm that accounted for the shortest paths around islands and peninsulas.

Type	Covariates	Resolution	Time Range	EC	AFTT	Description
Spatial	x, y	5 km		✓		Easting (m) and northing (m) representing geographic location in the projected coordinate system of the analysis
Static	Depth, Slope	30 arc sec		✓	✓	Seafloor depth (m) and slope, derived from SRTM30-PLUS global bathymetry (Becker et al. 2009).
	DistToShore, DistTo125m, DistTo300m, DistTo1500m	30 arc sec		✓		Distance (km) to the closest shoreline, excluding Bermuda and Sable Island, and various ecologically relevant isobaths, derived from SRTM30-PLUS
	DistToCan, DistToSmt, DistToCanOrSmt	30 arc sec		✓	✓	Distance (km) to the closest submarine canyon, seamount or either one; derived from the Harris et al. (2014) geomorphology
	Fetch_50km	30 arc sec		✓		Mean distance (km) to shore averaged over 16 radial directions, limited to a maximum of 50 km
Physical oceanographic	SST_CMC	0.2°, daily	1992-2020	✓	✓	Sea surface temperature (SST) (°C) from GHR SST Level 4 CMC0.2deg and CMC0.1deg (Brasnett 2008; Canada Meteorological Center 2012, 2016; Meissner et al. 2016)
	DistToFront063, DistToFront105, DistToFront207,	0.2°, daily	1992-2020	✓	✓	Distance to front in daily CMC_SST images detected with the Canny (1986) edge detection algorithm with MGET (Roberts et al. 2010); three parameterizations tested
	BotT_HYCOM, SSS_HYCOM, BotS_HYCOM, UV_HYCOM	0.08°, 3-hour	1994-2020	✓		Bottom temperature (°C), sea surface and bottom salinity (PSU), and current speed (m s^{-1}) from the HYCOM GOFS 3.1 3-hourly ocean model (Chassignet et al. 2009)
	TKE, EKE	0.25°, daily	1993-2019	✓	✓	Total kinetic energy (TKE) and eddy kinetic energy (EKE) ($\text{m}^2 \text{s}^{-2}$) derived from Aviso Ssalto/Duacs global gridded reprocessed geostrophic currents, produced and distributed by Copernicus Marine Service (doi: 10.48670/moi-00148)
	CurrentSpeed, SLASDev	0.25°, daily	1993-2019		✓	Current speed (m s^{-1}) and standard deviation in sea level anomaly (m), derived from Aviso/Duacs global gridded L4 sea surface heights
	DistToAEddy, DistToCEddy, DistToEddy, DistToAEddy30, DistToCEddy30, DistToEddy30, DistToAEddy90, DistToCEddy90, DistToEddy90,	0.25°, daily	1994-2019	✓		Distance (km) to closest mesoscale eddy edge, for three polarity (anticyclonic, cyclonic, or both) and age (at least 7, 30, and 90 days) combinations, for eddies from the Aviso Mesoscale Eddy Trajectory Atlas (META2.0), produced by Ssalto/Duacs and distributed by AVISO+ with support from CNES, in collaboration with Oregon State Univ. with support from NASA, using the method of Schlax and Chelton (2016), based on Chelton et al. (2011)
	WindSpeed	0.25°, 6-hour	1992-2020	✓		Wind speed (m s^{-1}) from the CCMP V2 L3 surface wind vectors (Atlas et al. 2011; Wentz et al. 2015)

Biological	Chl	4 km, monthly	1998-2020	✓	✓	Chlorophyll <i>a</i> concentration (mg m^{-3}) from Copernicus GlobColour (Garnesson et al. 2019) provided by Copernicus Marine Service (CMEMS product code OCEANCOLOUR_GLO_CHL_L4_REP_OBSERVATIONS_009_082)
	PP_VGPM	4 km, monthly	1998-2020	✓	✓	Net primary productivity ($\text{mg C m}^{-2} \text{ day}^{-1}$) from the Vertically Generalized Production Model (VGPM) (Behrenfeld and Falkowski 1997)
	PP_EVGPM	4 km, monthly	1998-2020	✓		Net primary productivity ($\text{mg C m}^{-2} \text{ day}^{-1}$) from the "Eppley" VGPM (Eppley 1972; Morel 1991; Behrenfeld and Falkowski 1997)
	PP_CbPM	4 km, monthly	1998-2020	✓		Net primary productivity ($\text{mg C m}^{-2} \text{ day}^{-1}$) from the Carbon-based Production Model (CbPM) (Behrenfeld et al. 2005; Westberry et al. 2008)
	PP_CAFE	4 km, monthly	1998-2020	✓		Net primary productivity ($\text{mg C m}^{-2} \text{ day}^{-1}$) from the Carbon, Absorption, and Fluorescence Euphotic-resolving (CAFE) model (Silsbe et al. 2016)
	MnkEpi, MnkEpiUMeso, MnkEpiULMeso, MnkULMeso, MnkLMeso, Zoo_SEAPODYM	1/12°, daily	1998-2019	✓		Micronekton biomass, expressed as wet weight (g m^{-2}), for five combinations of depth zones, and zooplankton biomass, expressed in carbon (g C m^{-2}), from SEAPODYM (Lehodey et al. 2008, 2015), provided by Copernicus Marine Service (10.48670/moi-00020)
	EpiMnkPB, EpiMnkPP, PkPB, PkPP	0.25°, 7-day	1998-2013		✓	Micronekton biomass, expressed as wet weight (g m^{-2}), and productivity ($\text{g m}^{-2} \text{ day}^{-1}$), and zooplankton biomass, expressed in carbon (g C m^{-2}), from the prior version of SEAPODYM, used in AFTT models for consistency with the Phase III methodology

For the EC, we compared models formulated with contemporaneous covariates to those with climatological covariates. For the AFTT, to improve model transferability and reduce the chance for spurious extrapolations, we only used a subset of the covariates, and only in climatological formulations. Both of these approaches were consistent with our strategy for Phase III. We discuss model formulation and selection procedures for the two regions in the following sections of this report.

2.4.4.3. EC models

In the EC region, which was relatively well surveyed compared to the AFTT-wide region, our goal was to closely reproduce the spatiotemporal patterns in marine mammal density revealed by the surveys. Although there was notable seasonal heterogeneity in survey effort (Figure 3), particularly beyond the continental shelf break, most physical oceanographic and biological covariates were sampled across a wide range of values in all seasons. Accordingly, for the EC models we adopted a modeling strategy that did not strongly constrain model complexity. (Such constraints typically include limiting models to only a few covariates or limiting covariate relationships to only a few degrees of freedom. We did use these constraints in the AFTT models, as discussed in Section 2.4.4.4 below.)

Prior to fitting models for each taxon, we investigated its seasonality by reviewing the literature and examining the sightings available in our surveys. Under the assumption that the taxon would exhibit different behaviors in different seasons, and therefore different relationships to the environment—e.g. whales on summer feeding grounds might prefer cold, productive waters, while those on winter calving grounds might prefer warmer, calmer waters—we split the year into seasonal strata when all of the following were true: 1) the literature suggested that the taxon exhibits seasonality in which its relationship to the environment is expected to be different during different parts of the year; 2) we had sufficient survey coverage and sightings to model at least one of the seasons effectively; and 3) the spatial pattern in the sightings resembled the expectation described by the literature. We defined seasons that were specific to the taxon modeled, rather than using the same seasonal definitions for all taxa. For convenience, we defined seasons with month boundaries; higher precision might be possible for some taxa

(e.g. they might initiate migration to feeding grounds within the same two-week period) but detecting this was beyond the scope of this project. If any of the aforementioned conditions were false, we defined a single “year-round” stratum that encompassed all months.

While investigating seasonality, we also investigated the spatial distribution of the taxon. When the known ecology of the taxon indicated that it either 1) exhibited ecologically different behaviors in different parts of the study area—e.g., in winter, some right whales calve in the southeast while others overwinter in the Gulf of Maine—or 2) was typically absent from an area—e.g., Atlantic white-sided dolphins do not occur south of Cape Hatteras in summer—or 3) there was reason to believe a taxon was present but we lacked the survey data to confidently model its density, we split the study area into regional strata. Otherwise, we defined a single study-area-wide stratum. As with seasons, regional strata were specific to the modeled taxon, rather than being common across all taxa.

During this investigation, we also examined the survey effort conducted and sightings reported by year and consulted the literature for knowledge on population trends, range shifts, data collection issues, and other information that would prompt us to limit the range of years used to fit models for the taxon. In general, we modeled most taxa with data collected from 1998-2020, or 1998-2019 when covariate selection procedures (see below) determined that the most effective covariates were those only available through 2019 (see Time Range column of Table 2). Taxa that were modeled using shorter eras included the North Atlantic right whale (October 2003 - September 2020), humpback whale (December 2001 - November 2020), and the Cuvier’s, Mesoplodont, and unidentified beaked whales (January 2010 - December 2019). Please see the accompanying taxon-specific reports for more information.

After defining the model’s focal era and splitting the year into seasons and the study area into regions, as appropriate, we modeled these seasonal-regional strata independently. For models with a large number of sightings, we fitted a GAM that allowed a relatively large number of smoothed covariates, without strong limitations on their degrees of freedom. We refer to this approach as a “full density surface model”. For models with between 20-40 sightings, we fitted a more parsimonious GAM, typically with just one or two covariates, sometimes limiting the degrees of freedom of relationships to maintain ecological plausibility. We refer to this approach as a “limited density surface model”. For models with less than 20 sightings, we developed a pseudo-design-based abundance estimate by fitting a GAM with no covariates and thereby obtaining a uniform density surface. We refer to this approach as a “stratified model”.

Full density surface models

The R *mgcv* package commonly used to fit GAMs implements a single-step, shrinkage-based covariate selection method in which the full set of candidate covariates can be tested in one model fitting run, and those that are not statistically effective are “shrunk” out of the model (Marra and Wood 2011). This provides substantial practical benefits over older multi-step approaches, such as forward or backward covariate selection, and we endeavored to take advantage of it in our covariate selection procedure. However, even though maximizing prediction accuracy was more important than developing models that could be interpreted to explain species-habitat relationships, we still wanted to obtain models that yielded ecologically plausible relationships, if possible. For several covariates, such as distance to fronts or primary productivity, we had several formulations of the covariate, developed using different underlying methods or parameterizations, and we were reluctant to introduce all of them into the same model, in case *mgcv* encountered trouble dealing with many numbers of highly correlated covariates. Also, if more than one of them was retained, we would have a hard time justifying it conceptually, or at least determining whether such a result was a plausible ecological effect. Also, fitting models with 10s of covariates required substantial memory and run times, making such an approach intractable with the hardware available to us.

One alternative was to fit and rank all possible combinations of covariates, as was done by Mannocci et al. (2017a) for the Phase III AFTT models, eliminating combinations that included multiple formulations of the same variable—e.g., those with more than one of the three SST fronts covariates, or more than one of the four primary productivity covariates—or variables that represented similar underlying processes—e.g. distance to eddy and eddy kinetic energy. Even after such combinations were eliminated, there were still over 1000 candidate models to be fitted in the worst case, which was still impractical.

To reduce the computation time required to select covariates, we adopted a two-step procedure, with the first step designed to identify a smaller number of candidate covariates to be tested in all combinations by the second step. We decided that each combination in the second step would, in general, maximally include:

- Depth and SST: always included, on the basis that they are widely correlated with many ecological processes
- 3 additional dynamic covariates, one from each of three families:

- Additional physical water properties: bottom temperature, surface salinity, bottom salinity
- Dynamic physical features: distance to SST fronts, distance to eddies, TKE, or EKE
- Biological: chlorophyll, primary productivity, zooplankton biomass, or micronekton biomass
- Zero or more additional covariates, included in special situations:
 - Fetch or distance to shore: for certain shelf-inhabiting species
 - Slope: for species that forage at the continental shelf break or slope
 - Distance to bathymetric features: for species known or suspected to have associations with these features
 - Wind speed: a proxy for surface roughness, mainly used for calving right whales, following Good (2008)
 - x,y: bivariate smooth of spatial location, used to address residual spatial variation (Miller et al. 2013)
 - Additional bivariate interactions were tested in certain situations when additive univariate relationships did not sufficiently capture a taxon's distribution
 - Additional spatial and temporal covariates were used in the North Atlantic right whale and humpback whale models; please see the accompanying taxon-specific reports for details

In the first step, for each of the three families of dynamic covariates, we fitted a model for each covariate in the family that included that covariate plus depth and SST, and then ranked the models within each family by REML score. This identified the covariates within each family likely to have the most predictive power, once the important influences of depth and temperature were addressed. We also did this for certain optional covariates (e.g., bathymetric features). For each taxon, we only considered covariates that were appropriate given its primary habitat. For example, for species that primarily inhabited the continental shelf, such as the North Atlantic right whale, we did not consider the distance to eddy covariates, as mesoscale eddies primarily occur beyond the continental shelf and decohere over the shelf. Similarly, for species that primarily inhabit waters beyond the shelf, such as beaked whales, we did not consider distance to shore.

In the second step, we fitted and ranked all combinations of models that included the first- or second-ranked covariate from each family, discarding those of lower rank. Fitting this smaller set of candidate final models was tractable on our computational infrastructure. In general, we performed the two-step procedure once for the contemporaneous covariates, and a second time for climatological covariates, so we could evaluate which offered better performance, similar to what was done for Phase III. Contemporaneous covariates account for both seasonal and interannual variability, while climatological covariates only account for seasonal variability; see Mannocci et al. (2017b) for additional discussion. For the Phase IV models, we always limited the climatological-covariate model's segments to those used in the contemporaneous-covariate model, making the models directly comparable by REML score and other goodness of fit statistics. This did not result in any loss of data, as all full DSMs were developed from surveys starting in 1998, the earliest year for which all covariates were available, or later. If climatological-covariate models performed better and we had restricted the final year of the model to 2019 because contemporaneous covariates were not available for 2020, we eliminated contemporaneous-covariate models from contention and refitted the climatological-covariate models to surveys through 2020 unless there was not any survey data available for 2020 for the taxon, in which case we retained 2019 as the final year.

After fitting the full set of candidate final models, we ranked them by REML score, predicted them across the time series of years and months used to fit them, inspected the results, and selected one as our “best” estimate of density for the taxon. This involved some subjective evaluation, informed by both the models' statistical performance (as assessed through various diagnostics shown in the accompanying taxon-specific reports), the spatiotemporal noisiness of the predictions, our judgment of how well the predictions matched well-established findings from the literature, and a comparison of total abundance predicted by our model to that estimated in the NOAA Stock Assessment Reports. We also assessed the degree of univariate and multivariate extrapolation across model covariates using the NT1 and ExDet statistics (Mesgaran et al. 2014; Bouchet et al. 2020) and either avoided covariates for which excessive extrapolation occurred or Winsorized relationships to well-sampled ranges (Dixon 1960) to avoid such extrapolation while retaining the covariates. In the case of blue, fin, humpback, sei, and North Atlantic right whales, we also qualitatively evaluated the match-up between summarized density predictions and summaries of passive acoustic monitoring results from Davis et al. (2020) and newer results yet to be published. (We gratefully acknowledge G. Davis and coauthors for making these data available for this comparison.) Assuming the subjective evaluation did not reveal important concerns among the top candidate models, we selected the model with the lowest REML score, which almost always also had the lowest AIC, and often explained the most deviance.

After selecting the best model, we summarized the predictions as follows. The Navy requested climatological summaries of density (known in the community as “densitologies”) at a monthly time step—i.e., for each taxon, the Navy wanted 12 maps, one for each month, with each estimating the climatological mean density for the taxon during that month. To confidently summarize the predictions at a monthly time step, we required: 1) evidence in the literature of the taxon shifting distribution

seasonally, 2) sufficient survey coverage, both spatially and temporally, to detect the shift, and 3) a spatial pattern in the sightings and the resulting monthly summaries that resembled the expectation described by the literature. If all of these conditions were met, we produced monthly summaries. If any were not, we produced a single seasonal summary that spanned all the months of the season. For taxon modeled with only one year-round season, this resulted in a single, static year-round prediction.

Note that the decision to summarize monthly rather than seasonally/year-round was independent of the decision made at model fitting time of whether to split the year into two or more seasonal models rather than using a single, year-round model. Both decisions were based in part on how well a species' migratory patterns were known. The taxa that used two or more seasonal models all exhibited relatively well-known migratory patterns and were thus all summarized monthly. Several taxa that used year-round models were also well-known and summarized monthly. See Section 3.1 and Table 9 for a summary, and the accompanying taxon-specific reports for detailed discussion for each taxon.

To summarize uncertainty, we computed and summarized empirical variance with the approach of Miller et al. (2022), using the analytic method outlined in Appendix A of that publication (also known as Supplement 7), yielding a map of the Coefficient of Variation (CV) for each of the 12 climatological prediction maps, or in the case of taxa not summarized monthly, a single CV map for the season or entire year. For taxa summarized monthly, if the final model used contemporaneous covariates, monthly CV maps represented the uncertainty that would result if a random year was selected from among those predicted, accounting both for interannual variability in dynamic covariates and for uncertainty in model parameter estimates. If the final model used climatological covariates, the predictions for a given month were the same for every year, and monthly CV maps only represented uncertainty in model parameter estimates. For taxa summarized seasonally or year-round, for contemporaneous-covariate models the seasonal or year-round CV map represented the uncertainty that would result if a random month of a random year was selected, accounting both for interannual and intra-annual variability in dynamic covariates as well as uncertainty in model parameter estimates. For climatological-covariate models, the seasonal or year-round CV map represented the uncertainty that would result if a random month was selected, accounting both for intra-annual variability in dynamic covariates and uncertainty in model parameter estimates.

Limited density surface models

For models with 20-40 sightings, we fitted a density surface model in which we limited the number of covariates used—typically just one or two—and occasionally the degrees of freedom in the fitted relationships, and sometimes only considered climatological covariates. The covariate and model selection procedures were specific to the taxon in question, and usually driven by what was known of its ecology. The accompanying taxon-specific reports provide details of these procedures. We summarized these limited models the same way as for the full models discussed above, except in the case of Clymene dolphin, for which we used AIC-weighted model averaging to combine multiple models (please see the accompanying Clymene dolphin report for details).

Stratified models

For models with less than 20 sightings, we judged it not possible, or at least inadvisable, to fit a traditional density surface model. Nor was it possible to make proper design-based abundance estimates using traditional distance sampling, because the aggregate surveys provided very heterogeneous coverage that did not together constitute a proper systematic survey design. For cases like this, to provide the Navy and other interested parties with at least a rough estimate of density, we built a “stratified model” by fitting a GAM with no covariates, under the assumption that density would be distributed uniformly within the stratum. This assumption, if true, would mean we would obtain similar density estimates for the stratum under any sampling design, and therefore it would not matter if there was some heterogeneity in sampling within it. However, we strongly caution that this assumption did not hold for the other, more-common species we successfully modeled with traditional density surface modeling, as evidenced by the non-uniform patterns in density predicted by those species' models.

That said, when the results of more common species are viewed at a very coarse, ecoregional scale, discrete patterns generally appear, such as beaked whales occurring along the slope and in abyssal waters but not over the shelf, or cold-water species such as Atlantic white-sided dolphin very rarely occurring south of the Gulf Stream. Thus, we offer this simplified approach of estimating uniform density within such ecoregions as a rough-and-ready substitute for density surface models. As more data are collected and the habitats of rare species be better characterized, more taxa will be able to be modelled with density surface models, as occurred in this project, in which we were able to switch several species modeled with stratified models in Phase III to limited DSMs in Phase IV (see Section 3.4).

2.4.4.4. *AFTT models*

In the EC and GOM analysis regions—the well-surveyed portions of the AFTT study area—we and colleagues at SEFSC developed relatively complex models designed to closely reproduce spatiotemporal patterns in marine mammal densities. To estimate densities for the areas beyond the EC and GOM, where there was very little survey data available to us, we developed parsimonious models designed to produce plausible extrapolations of marine mammal density. These are called the “AFTT models”.

Given the generality of the AFTT models, and because the EC models were given a higher priority during the Phase IV modeling cycle, our approach for the AFTT models was not to rebuild them from scratch as we did with the EC models, but instead to update the AFTT models from Phase III using the new survey data and methods developed for Phase IV. Accordingly, we regenerated the AFTT models’ survey segments using the new detection functions fitted for Phase IV, replacing existing segments that were remodeled and adding new segments for the surveys added since Phase III, including some additional surveys in the Caribbean and the central and eastern North Atlantic (although incorporating new surveys for the AFTT-wide model was not a priority of this project). We maintained the same 10 km spatial resolution for the AFTT in Phase IV that we used in Phase III. Using the statistical framework developed for the Phase IV EC models, including the updated uncertainty estimation methodology, we refitted the final AFTT models selected in Phase III by Mannocci et al. (2017a). That is, for most taxa, we did not redo the covariate selection procedure conducted for Phase III, but instead refitted, re-predicted, and re-summarized the final Phase III model using the updated survey segments developed for Phase IV. For several taxa, we did redo the selection procedure after noting a deficiency in the resulting model or predictions. These cases are noted and discussed in the accompanying taxon-specific reports for the AFTT models.

We caution that it is possible that because the segments changed, different covariates could have been selected, had we redone the selection procedure from scratch. Given more time, we would have tested this. However, given the parsimonious approach of the AFTT models, which was designed to focus on the strongest relationships likely to be the most transferrable to unsurveyed regions, we did not believe the risk was high that the new data would yield strongly differing results.

As with Phase III, following Mannocci et al. (2017a), climatological covariates were used for all AFTT models, and most models were summarized at a year-round time step. For AFTT models that were summarized monthly, the predictions for a given month were the same for every year, and monthly CV maps represented uncertainty in model parameter estimates but not temporal variability, similar to the EC models that used climatological covariates. For AFTT models summarized seasonally or year-round, the seasonal or year-round CV map represented the uncertainty that would result if a random month was selected, accounting both for uncertainty in model parameter estimates and intra-annual variability in dynamic covariates, but not interannual variability.

2.5. *Production of the Phase IV NMSDD*

The Phase IV NMSDD is an ArcGIS geodatabase containing the density predictions and accompanying metadata in the format desired by the Navy. After density predictions were produced, reviewed, and finalized, we produced the NMSDD and delivered it to the Navy. The NMSDD containing the final model predictions was dated 11 June 2022. We subsequently updated this NMSDD with metadata for all feature classes, with an updated date of 25 July 2022.

In the NMSDD, the density predictions are given as polygon feature classes. All feature classes appear under the AFTT feature dataset. For taxa summarized monthly, there are 12 feature classes per taxon, named `TAXON_monthXX` where `TAXON` is the name of the modeled taxon and `XX` is a two-digit month. Within `TAXON`, spaces and dashes are replaced by underscores; apostrophes are removed. `XX` is 01 through 12. For taxa summarized year-round, there is only a single layer, named `TAXON_annual`.

Each feature class is in the Albers Equal Area coordinate system defined for the Phase III analysis and used again in Phase IV (central meridian: -78.0, standard parallel: 27.333333, standard parallel 2: 40.666666, latitude of origin: 34.0, datum: WGS 1984). While in Phase III we resampled the final predictions into an equirectangular coordinate system (a.k.a. “geographic projection” in ArcGIS parlance), in Phase IV we delivered predictions in the native Albers system used by the underlying density models.

2.5.1. Production process

We produced each prediction for each modeled taxon with the following procedure. First, using a polygon feature class of 10x10 km grid cells representing the extent of the full AFTT model, we populated all of the cells using that taxon's AFTT model, or set them to null if there was no AFTT model. Next, if there was an EC model for the taxon, we replaced the AFTT cells in the EC region with EC cells, wherever the EC cells had a prediction. The EC cells were 5x5 km and precisely aligned with the AFTT cells, so typically each AFTT cell was replaced by 4 EC cells, except along certain edges of the EC study area. Then, if there was a GOM model, we replaced the AFTT cells of the GOM with the GoMMAPPS model's hexagonal cells. Finally, for the "AFTT", "EC", or "GOM" polygon strata defined in the NMSDD, we filled any slivers shoreward of the modeled regions using a spatial extrapolation procedure.

For certain GoMMAPPS models, predictions were missing from several cells, apparently because the covariate surfaces that SEFSC used to predict the models were missing values, e.g., from clouds. We filled these with a spatial interpolation procedure before overlaying them onto the AFTT predictions.

For Chesapeake Bay and estuaries south of it, we first consulted the literature and species experts to determine which species were present in the estuaries. Our consultations indicated that bottlenose dolphins were the only cetacean that regularly inhabits these estuaries. We obtained estimates for bottlenose dolphin density for these estuaries as described in an accompanying report by Kot and Roberts (2022). We assumed that density was zero in these estuaries for all other taxa, including seals. We caution that in recent years, harbor seals have been regularly observed inhabiting lower Chesapeake Bay from November to April, and gray seals were also sighted very occasionally (Ampela et al. 2021; Jones and Rees 2022). Therefore, if seals are species of concern in Chesapeake Bay, we recommend that Navy derive density estimates from some other source than our Chesapeake Bay stratum of the NMSDD. We recommend that future updates to the AFTT NMSDD (e.g. for the AFTT Phase V EIS) re-examine how best to account for seals in Chesapeake Bay, e.g. by incorporating local abundance studies similar to what was done for estuarine bottlenose dolphins by Kot and Roberts (2022). Finally, manatees are marine mammals that may also inhabit some of the more southerly estuaries but our analysis did not include manatees, as they were not designated by the Navy to be a focal species for this cooperative agreement.

For estuaries north of Chesapeake Bay, we obtained density estimates for all taxa, including bottlenose dolphin and seals, from the EC models, spatially extrapolating them as necessary into the estuaries.

2.5.2. Fields of the NMSDD

Table 3. Fields of the AFTT Phase IV NMSDD.

Field	ArcGIS data type	Description
UID	LONG	A unique ID for each Navy EIS study area; always 1000 for all features.
SPECIES	TEXT	Common name of the modeled taxon (e.g. "Fin whale").
SPECIES_2	TEXT	Scientific name for the modeled taxon. For taxa that are individual species, this is the genus and species. For guilds it is the finest taxonomic name that encompasses all species in the guild (e.g. "Ziphiidae" for beaked whales, "Globicephala spp." for pilot whales).
MONTH_NUMB	LONG	Month number. Ranges from 1 to 12 for _monthXX layers; NULL for _annual layers.
MONTH_NAME	TEXT	Month name. "January", "February", and so on for _monthXX layers; null for _annual layers.
STUDY	TEXT	A shorthand citation for the data source; always "Duke Density Project 2022" for all features.
STRATUM	TEXT	The model that was used to predict the feature—either AFTT, EC, or GOM—or, in the case of estuaries, the name of the estuary. For estuaries, you can look up the procedure used to produce estimates for bottlenose dolphins in the

Field	ArcGIS data type	Description
		accompanying report. For other taxa, we assumed their density was 0 in all features designated in the database as estuaries.
MODEL_TYPE	TEXT	Specifies how we obtained the density value for the feature: <ul style="list-style-type: none"> Assumed absent – density was assumed to be zero External study – density was obtained from an external study Habitat-based density model – density was predicted from a DSM Not modeled – density was not modeled; it and uncertainty are null Spatial extrapolation – density was extrapolated from nearby cells Uniform density model – density was obtained from a stratified model
DENSITY	DOUBLE	Estimated density for the feature, as individuals km ⁻² .
UNCERTAINTY	DOUBLE	Coefficient of variation (CV) that estimates the uncertainty of the DENSITY estimate, given temporal variability addressed by the model and the uncertainty in the model's parameter estimates. Unitless. Please see preceding sections for details of how this was estimated and what it represents.
UNCER_QUAL	TEXT	Qualitative uncertainty for the predicted density: <ul style="list-style-type: none"> AFTT model – the feature was predicted by the AFTT model and all of the covariates were within the range used to fit the model. However, caution is advised: the feature has higher qualitative uncertainty than if it was predicted by a regional model, although no environmental extrapolation occurred. AFTT model out of range – the feature was predicted by the AFTT model and one or more covariates were beyond the range used to fit the model. Additional caution is warranted than above because the prediction represents an extrapolation of environmental relationships. Assumed absent – we assumed the density was zero and therefore that the CV is also zero. Not modeled – density and CV not modeled and left null. Regional model – the feature was predicted by a regional model.
AREA_SQKM2	DOUBLE	Estimated area of the feature, in km ² . Typically 25 km ² for cells of the EC model, 36-40 km ² for hexes predicted by the GOM model, and 100 km ² for cells predicted by the AFTT model. Can be larger for estuarine strata or smaller for cells bordering land or the edge of the AFTT study area.
ABUNDANCE2	DOUBLE	Estimated abundance of the feature, in individual animals, computed as DENSITY multiplied by AREA_SQKM2.
MODEL_VERS	TEXT	Model version number. An arbitrary string containing our internal version numbers of the model(s) used to produce the prediction. This is intended to be used by us for our own debugging.

3. Results and Discussion

3.1. EC models

In the EC area, we expanded our collaboration to include 11 surveyor institutions who collectively contributed 2,985,700 linear km of aerial and 111,900 km of shipboard survey effort (Table 4, 5, 6). Survey effort beyond the continental shelf was heavily biased toward summer, as was the case in Phase III, but coverage did improve in winter and spring (Figure 3). For the

first time, we incorporated a towed passive acoustic monitoring survey (MCR SOTW Acoustical). This survey was used in models for sperm whales and beaked whales. Please see their accompanying taxon-specific reports for more information.

In total, 69,817 sightings were available in the region with taxonomic identifications sufficiently precise for our modeling effort (Table 7). Dolphins and porpoises were sighted most frequently, followed by large whales. The majority of sightings of large whales, dolphins, and porpoises retained for analysis were fully-taxonomically-resolved, while the majority of medium and small whale sightings retained were ambiguous, mainly owing to the difficulty of fully identifying beaked whales, dwarf and pygmy sperm whales (*Kogia* species), pilot whales, and other “blackfish” species. Seals were similarly difficult to identify.

The surveys reported 2,730 ambiguous sightings resolved to a pair of species that we subsequently classified to one or the other. All but four were classified using the random forest classification model fitted to definitive sightings (see Section 2.3.1). We built classification models for four cases of ambiguous sightings. For three cases—“fin or sei whale”, “Atlantic spotted or bottlenose dolphin”, and “Atlantic white-sided or short-beaked common dolphin”—we used a suite of environmental variables and day of year as predictors. For the fourth—“melon-headed or pygmy killer whale”—we used group size. Across all cases, the AUC statistic of the classifiers ranged from 0.949-0.998 and the K statistic ranged from 0.721-0.960, indicating all classifiers performed well. For details of the classification models, please see the accompanying taxon-specific reports.

A further 7,563 sightings, comprising 9.8% of the total sightings reported, were too ambiguous or otherwise unable to be classified to one of the taxa we modeled, and were omitted from the analysis (Table 8). As a result, our models may have slightly underestimated density. However, ambiguous sightings often occurred at farther distances than definitive sightings, and the influence of distance on the difficulty of making a definitive sighting was addressed by the detection modeling procedure.

In total, we developed models for 26 species and 5 guilds, comprising 7 large whale models, 6 beaked and sperm whale models, 6 large delphinoid models, 12 small delphinoid models, and one pinniped model (Table 9). For each of the guilds, too few fully-resolved sightings were reported to build a classifier from them. The “Mesoplodont” guild comprised the four *Mesoplodon* species that occur in the EC (Stanistreet et al. 2017). The “unidentified beaked whales” guild comprised unidentified beaked whales that were determined by observers to be either one of the four *Mesoplodons* or Cuvier’s beaked whale (*Ziphius cavirostris*), but not northern bottlenose whale (*Hyperoodon ampullatus*). The “dwarf and pygmy sperm whales” guild comprised two species, *Kogia sima* and *Kogia breviceps*, respectively. The “pilot whales” guild comprised two species, short-finned pilot whale (*Globicephala macrorhynchus*) and long-finned pilot whale (*Globicephala macrorhynchus*). Finally, the “seals” guild comprised two common species—harbor seal (*Phoca vitulina*) and gray seal (*Halichoerus grypus*)—but probably included two other rare species—harp seal (*Pagophilus groenlandicus*) and hooded seal (*Cystophora cristata*)—for which no definitive sightings were reported but which do occur occasionally in the region (Haverkamp et al. 2023).

Most models were developed for the period 1998-2020 but not earlier, so that biological covariates derived from satellite ocean color data first available in fall of 1997 could be used. Several models extended only through 2019, in order to take advantage of certain covariates available only through that year. Models for humpback whale and North Atlantic right whale started in the early 2000s, when relatively consistent survey coverage was initiated in the Gulf of Maine and the southeast U.S., which was important for our use of temporal covariates in their models (see their accompanying reports for details). Models for beaked whales other than northern bottlenose whale started in 2010, owing to the better species identifications available starting that year. Finally, the model for false killer whale, a rare species for the region, started in 1995, to take advantage of a sighting reported that year.

Of the 31 models, 19 were implemented as full density surface models, 4 were limited density surface models, and 8 were stratified models (see Section 2.4.4.3). Seven models used climatological covariates, 12 used contemporaneous covariates, 4 were “mixed”, with at least one seasonal or regional stratum that used climatological and another that used contemporaneous, and 8 did not use any covariates (these were the stratified models). Together, relative to Phase III, these results represented a reduction in the number of stratified models, an increase in the number of full density surface models, and an increase in models using contemporaneous covariates vs. other types. We discuss these changes in Section 3.4.

We summarized predictions from 12 models into monthly climatological density surfaces, 18 models into year-round surfaces, and 1 model—Atlantic spotted dolphin—with a “mixed” scheme, in which the continental shelf was summarized monthly and area beyond the shelf was summarized year-round. Further discussion of our rationale for deciding on the summarization for each taxon, as well as all other modeling details, can be found in the accompanying taxon-specific reports.

Table 4. Survey programs contributed by collaborators operating within the EC region. Length is the cumulative linear distance observers were on effort. Not all programs were used in all models, and the transects used (and thus the total length) vary by model, according to the observation conditions (e.g. sea state) accepted for each model's detection functions. Please see the EC taxon-specific reports for details. Institution and program names and references are given in Table 5 and Table 6.

Platform	Institution	Program	Period	Length (1000 km)
Aerial	FWRI	SEUS NARW EWS	2003-2020	680.3
	HDR	Navy Norfolk Canyon	2018-2019	12.8
	NEAq	CNM	2017-2020	1.8
	NEAq	MMS-WEA	2017-2020	37.7
	NEAq	NLPSC	2011-2015	43.3
	NEAq	SEUS NARW EWS	2003-2010	235.8
	NEFSC	AMAPPS	2010-2019	90.6
	NEFSC	NARWSS	2003-2020	505.8
	NEFSC	Pre-AMAPPS	1995-2008	71.2
	NJDEP	NJEBS	2008-2009	11.4
	NYS-DEC/TT	NYBWM	2017-2020	86.0
	SEFSC	AMAPPS	2010-2020	116.7
	SEFSC	MATS	1995-2005	34.7
	SEFSC	SECAS	1992-1995	8.5
	UNCW	MidA Bottlenose	2002-2002	18.3
	UNCW	Navy Cape Hatteras	2011-2017	37.9
	UNCW	Navy Jacksonville	2009-2017	93.1
	UNCW	Navy Norfolk Canyon	2015-2017	15.4
	UNCW	Navy Onslow Bay	2007-2011	49.1
	UNCW	SEUS NARW EWS	2005-2008	114.6
	VAMSC	MD DNR WEA	2013-2015	15.9
	VAMSC	Navy VACAPES	2016-2017	19.6
	VAMSC	VA CZM WEA	2012-2015	21.5
	WLT/SSA/CMARI	SEUS NARW EWS	2003-2020	663.7
			Total	1992-2020
Shipboard	MCR	SOTW Acoustical	2019-2019	3.8
	MCR	SOTW Visual	2012-2019	9.4
	NEFSC	AMAPPS	2011-2016	16.5
	NEFSC	Pre-AMAPPS	1995-2007	18.5
	NJDEP	NJEBS	2008-2009	13.7
	SEFSC	AMAPPS	2011-2016	16.9
	SEFSC	Pre-AMAPPS	1992-2006	33.1
			Total	1992-2019
Grand Total			1992-2020	3097.6

Table 5. Collaborating institutions who contributed surveys in the EC region (see Table 4).

Institution	Full Name
FWRI	Fish and Wildlife Research Institute (FWRI) of the Florida Fish and Wildlife Conservation Commission (FWC)
HDR	HDR, Incorporated
MCR	Marine Conservation Research
NEAq	New England Aquarium
NEFSC	NOAA Northeast Fisheries Science Center
NJDEP	New Jersey Department of Environmental Protection
NYS-DEC/TT	New York State Department of Environmental Conservation and TetraTech, Incorporated
SEFSC	NOAA Southeast Fisheries Science Center
UNCW	University of North Carolina Wilmington
VAMSC	Virginia Aquarium & Marine Science Center
WLT/SSA/CMARI	Wildlife Trust / Sea to Shore Alliance / Clearwater Marine Aquarium Research Institute

Table 6. Descriptions and references for surveys in the EC region (see Table 4).

Program	Description	References
AMAPPS	Atlantic Marine Assessment Program for Protected Species	Palka et al. (2017, 2021)
CNM	Northeast Canyons Marine National Monument Aerial Surveys	Redfern et al. (2021)
MATS	Mid-Atlantic Tursiops Surveys	None available
MD DNR WEA	Aerial Surveys of the Maryland Wind Energy Area	Barco et al. (2015)
MidA Bottlenose	Onshore/Offshore Surveys for Bottlenose Dolphins	Torres et al. (2005)
MMS-WEA	Marine Mammal Surveys of the MA and RI Wind Energy Areas	Quintana-Rizzo et al. (2021); O'Brien et al. (2022)
NARWSS	North Atlantic Right Whale Sighting Surveys	Cole et al. (2007)
Navy Cape Hatteras	Aerial Surveys of the Navy's Cape Hatteras Study Area	McLellan et al. (2018)
Navy Jacksonville	Aerial Surveys of the Navy's Jacksonville Study Area	Foley et al. (2019)
Navy Norfolk Canyon	Aerial Surveys of the Navy's Norfolk Canyon Study Area	McAlarney et al. (2018); Cotter et al. (2019)
Navy Onslow Bay	Aerial Surveys of the Navy's Onslow Bay Study Area	Read et al. (2014)
Navy VACAPES	Aerial Survey Baseline Monitoring in the Continental Shelf Region of the VACAPES OPAREA	Mallette et al. (2017)
NJEBS	New Jersey Ecological Baseline Study	Geo-Marine, Inc. (2010); Whitt et al. (2015)
NLPSC	Northeast Large Pelagic Survey Collaborative Aerial Surveys	Leiter et al. (2017); Stone et al. (2017)
NYBWM	New York Bight Whale Monitoring Surveys	Zoidis et al. (2021)
Pre-AMAPPS	Pre-AMAPPS Marine Mammal Abundance Surveys	Mullin and Fulling (2003); Garrison et al. (2010); Palka (2006)
SECAS	Southeast Cetacean Aerial Survey	Blaylock and Hoggard (1994)
SEUS NARW EWS	Southeast U.S. Right Whale Early Warning System Surveys	Gowan and Ortega-Ortiz (2014)
SOTW	R/V Song of the Whale Surveys	Ryan et al. (2013)
VA CZM WEA	Virginia CZM Wind Energy Area Surveys	Mallette et al. (2014, 2015)

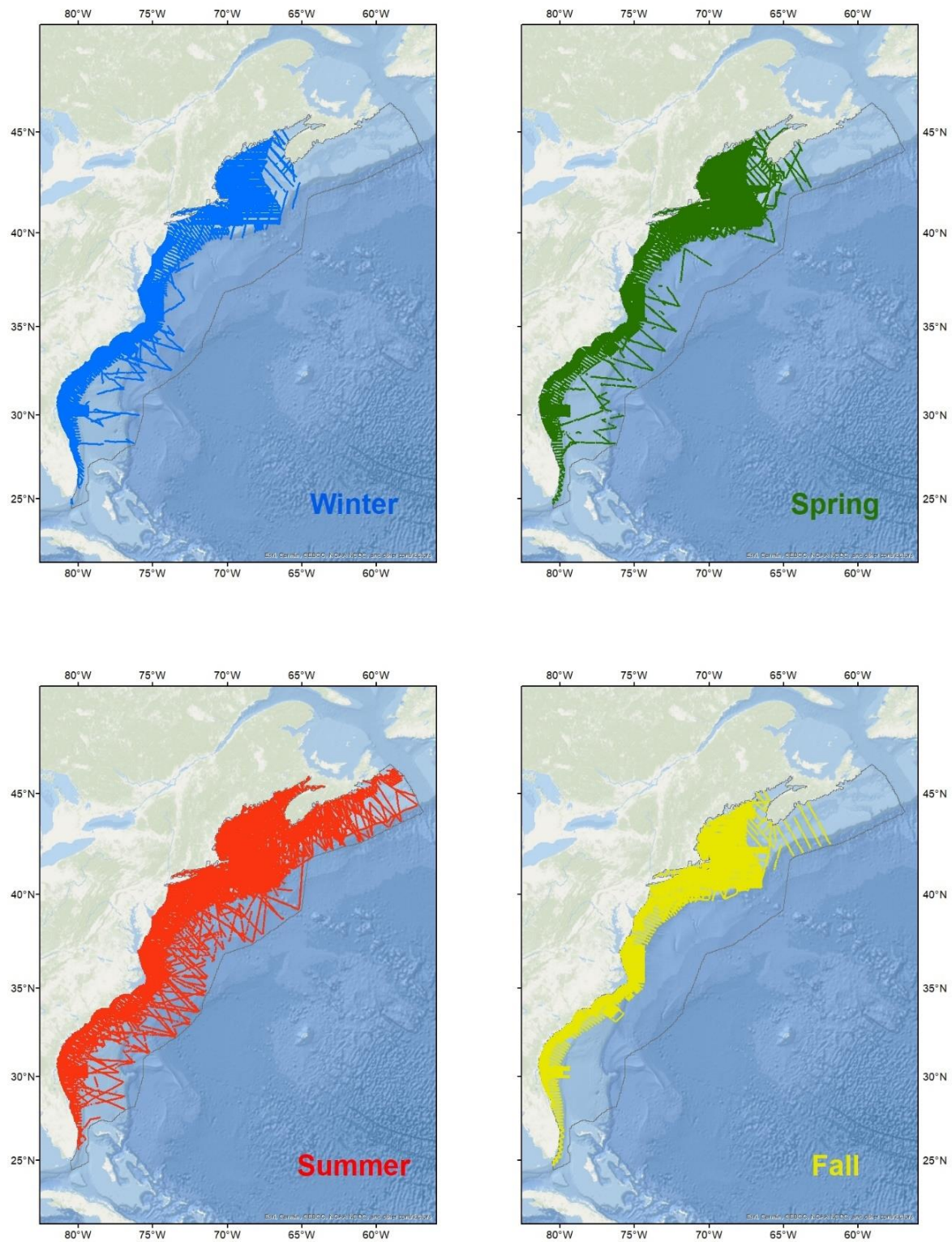


Figure 3. Tracklines of on effort surveys in the EC region by season. Winter (Jan-Mar) (top left panel) tracklines are shown in blue, Spring (Apr-Jun) (top right panel) tracklines are shown in green, Summer (Jul-Sept) (bottom left panel) tracklines are shown in red and Fall (Oct-Dec) (bottom right panel) tracklines are shown in yellow.

Table 7. Taxa modeled in the EC region, arranged in the taxonomic groupings of Roberts et al. (2016b). Notes: (1) We classified these ambiguous sightings as the modeled taxon from environmental, day of year, or group size covariates (see Section 2.3.1). (2) In the EC, we counted ambiguous “Bryde’s or sei whale” sightings as sei whales (see Section 2.3.1). (3) We modeled these species as a guild; too few fully resolved sightings were reported to build a classifier from them. (4) This was manually classified as an Atlantic spotted dolphin after review.

Group	Modeled taxon	Identification reported by observer	Sightings	Note
Baleen whales	Blue whale <i>Balaenoptera musculus</i>	Blue whale	26	
	Common minke whale <i>Balaenoptera acutorostrata</i>	Common minke whale	1,997	
	Fin whale <i>Balaenoptera physalus</i>	Fin whale	2,960	
		Fin or sei whale	612	1
		Total	3,572	
	Humpback whale <i>Megaptera novaeangliae</i>	Humpback whale	4,707	
	North Atlantic right whale <i>Eubalaena glacialis</i>	North Atlantic right whale	4,699	
	Sei whale <i>Balaenoptera borealis</i>	Sei whale	1,152	
		Bryde’s or sei whale	3	2
		Fin or sei whale	266	1
		Total	1,421	
Beaked and sperm whales	Cuvier’s beaked whale <i>Ziphius cavirostris</i>	Cuvier's beaked whale	252	
	Dwarf and pygmy sperm whales (guild) <i>Kogia spp.</i>	Dwarf sperm whale	37	
		Pygmy sperm whale	29	
		Dwarf or pygmy sperm whale	105	
		Total	171	3
	Mesoplodont beaked whales (guild) <i>Mesoplodon spp.</i>	Blainville's beaked whale	6	
		Gervais' beaked whale	19	
		Sowerby's beaked whale	48	
		True's beaked whale	11	
		Mesoplodon spp.	153	
		Total	237	3
	Northern bottlenose whale <i>Hyperoodon ampullatus</i>	Northern bottlenose whale	10	
	Sperm whale <i>Physeter macrocephalus</i>	Sperm whale	1,208	
	Unidentified beaked whales <i>Ziphiidae</i>	Unidentified beaked whale	263	3
Large delphinoids	False killer whale <i>Pseudorca crassidens</i>	False killer whale	8	
	Killer whale <i>Orcinus orca</i>	Killer whale	9	
	Melon-headed whale <i>Peponocephala electra</i>	Melon-headed whale	4	
		Melon-headed or pygmy killer whale	6	1
		Total	10	

Group	Modeled taxon	Identification reported by observer	Sightings	Note
Small delphinoids	Pilot whales (guild) <i>Globicephala spp.</i>	Long-finned pilot whale	3	3
		Short-finned pilot whale	250	
		Long-finned or short-finned pilot whale	1,480	
		Total	1,733	
	Pygmy killer whale <i>Feresa attenuata</i>	Pygmy killer whale	1	1
		Melon-headed or pygmy killer whale	6	
		Total	7	
	Risso's dolphin <i>Grampus griseus</i>	Risso's dolphin	1,633	
Small delphinoids	Atlantic spotted dolphin <i>Stenella frontalis</i>	Atlantic spotted dolphin	1,372	4
		Atlantic spotted or bottlenose dolphin	58	
		Atlantic or pantropical spotted dolphin	1	
		Total	1,431	
	Atlantic white-sided dolphin <i>Lagenorhynchus acutus</i>	Atlantic white-sided dolphin	2,088	1
		Atlantic white-sided or short-beaked common dolphin	1,212	
		Total	3,300	
	Clymene dolphin <i>Stenella clymene</i>	Clymene dolphin	28	
	Common bottlenose dolphin <i>Tursiops truncatus</i>	Common bottlenose dolphin	7,713	1
		Atlantic spotted or common bottlenose dolphin	122	
		Total	7,835	
	Fraser's dolphin <i>Lagenodelphis hosei</i>	Fraser's dolphin	2	
	Harbor porpoise <i>Phocoena phocoena</i>	Harbor porpoise	4,350	
	Pantropical spotted dolphin <i>Stenella attenuata</i>	Pantropical spotted dolphin	30	
	Rough-toothed dolphin <i>Steno bredanensis</i>	Rough-toothed dolphin	28	
	Short-beaked common dolphin <i>Delphinus delphis</i>	Short-beaked common dolphin	2,676	1
		Atlantic white-sided or short-beaked common dolphin	444	
		Total	3,120	
	Spinner dolphin <i>Stenella longirostris</i>	Spinner dolphin	5	
	Striped dolphin <i>Stenella coeruleoalba</i>	Striped dolphin	468	
	White-beaked dolphin <i>Lagenorhynchus albirostris</i>	White-beaked dolphin	24	
Pinnipeds	Seals (guild) <i>Phocidae</i>	Gray seal	183	3
		Harbor seal	356	
		Unidentified seal	1,659	
		Total	2,198	
All	Grand Total		69,817	

Table 8. Ambiguous sightings omitted from the analysis. For identifications that were resolved to a pair of species, such as “Atlantic white-sided or white-beaked dolphin”, we either lacked the sightings necessary to attempt a habitat-based classification, or the sighting occurred in habitat occupied by both species, making habitat-based classification inconclusive. For the rest, the reported identifications were too generic for classification.

Identification reported by observer	Sightings
Atlantic white-sided or white-beaked dolphin	3
Atlantic white-sided, white-beaked, or common bottlenose dolphin	1
Bottlenose or Risso's dolphin	3
Bottlenose or rough-toothed dolphin	1
Common dolphin, Bottlenose, or <i>Stenella</i> sp.	49
Common dolphin or <i>Stenella</i> spp.	1
Pantropical or Atlantic spotted dolphin	14
Sei, blue, or fin whale	2
Unidentified <i>Balaenoptera</i> spp.	6
Unidentified baleen whale	89
Unidentified cetacean	75
Unidentified delphinid	1065
Unidentified dolphin	1440
Unidentified large dolphin	12
Unidentified large whale	1269
Unidentified medium whale	35
Unidentified odontocete	2869
Unidentified porpoise or dolphin	331
Unidentified cetacean	71
Unidentified small cetacean	3
Unidentified small delphinid	5
Unidentified small whale	112
Unidentified <i>Stenella</i> spp.	103
Unidentified whale	4
Total	7,563

Table 9. Model fitting and summarization details for EC models. Some models did not run January-December, thus included only part of the first and last year of the Era listed. “Mixed” covariates means one seasonal or regional stratum used climatological covariates, another used contemporaneous. “Mixed” summarization means one regional stratum was summarized monthly, another was year-round. Abundance shown is for the months and region most directly comparable to NOAA Stock Assessment Reports; some were too complicated to summarize here. Please see the accompanying taxon-specific reports for complete details.

Group	Modeled taxon	Model Fitting				Summarization	
		Era	Seasons	Model Type	Covariates	Summarized	Abundance
Baleen whales	Blue whale	1998-2020	1	Limited DSM	Climatological	Year-round	33
	Common minke whale	1998-2019	2	Full DSM	Mixed	Monthly	3,765
	Fin whale	1998-2020	1	Full DSM	Climatological	Monthly	3,956
	Humpback whale	2002-2020	2	Full DSM	Mixed	Monthly	1,760
	North Atlantic right whale	2003-2020	3	Full DSM	Mixed	Monthly	See report
	Sei whale	1998-2020	1	Full DSM	Contemporaneous	Monthly	859
Beaked and sperm whales	Cuvier’s beaked whale	2010-2019	1	Full DSM	Climatological	Year-round	4,710
	Dwarf and pygmy sperm whales (guild)	1998-2019	1	Full DSM	Contemporaneous	Year-round	7,585
	Mesoplodont beaked whales (guild)	2010-2019	1	Full DSM	Contemporaneous	Year-round	5,413
	Northern bottlenose whale	1998-2020	1	Stratified	None	Year-round	122
	Sperm whale	1998-2019	1	Full DSM	Climatological	Monthly	5,578
	Unidentified beaked whales (guild)	2010-2019	1	Full DSM	Climatological	Year-round	2,655
Large delphinoids	False killer whale	1995-2020	1	Stratified	None	Year-round	138
	Killer whale	1998-2020	1	Stratified	None	Year-round	73
	Melon-headed whale	1998-2020	1	Stratified	None	Year-round	618
	Pilot whales (guild)	1998-2019	1	Full DSM	Contemporaneous	Year-round	See report
	Pygmy killer whale	1998-2020	1	Stratified	None	Year-round	68
	Risso's dolphin	1998-2019	1	Full DSM	Climatological	Monthly	28,187
Small delphinoids	Atlantic spotted dolphin	1998-2020	1	Full DSM	Mixed	Mixed	40,807
	Atlantic white-sided dolphin	1998-2020	1	Full DSM	Contemporaneous	Monthly	61,718
	Clymene dolphin	1998-2020	1	Limited DSM	Climatological	Year-round	8,576
	Common bottlenose dolphin	1998-2019	1	Full DSM	Contemporaneous	Monthly	68,493
	Fraser's dolphin	1998-2020	1	Stratified	None	Year-round	658
	Harbor porpoise	1998-2020	2	Full DSM	Contemporaneous	Monthly	66,810
	Pantropical spotted dolphin	1998-2020	1	Limited DSM	Contemporaneous	Year-round	1,398
	Rough-toothed dolphin	1998-2020	1	Limited DSM	Contemporaneous	Year-round	1,009
	Short-beaked common dolphin	1998-2019	1	Full DSM	Contemporaneous	Monthly	141,617
	Spinner dolphin	1998-2020	1	Stratified	None	Year-round	880
	Striped dolphin	1998-2019	1	Full DSM	Contemporaneous	Year-round	56,618
	White-beaked dolphin	1998-2020	1	Stratified	None	Year-round	128
Pinnipeds	Seals (guild)	1998-2019	2	Full DSM	Contemporaneous	Monthly	See report

3.2. GOM models

Rappucci et al. (2022) provide complete documentation on the GoMMAPPS models; please see their report for details. SEFSC split the Gulf of Mexico into two analysis regions: the shelf and the oceanic. The shelf region was modeled exclusively from aerial surveys conducted from 2011-2018, covering all four seasons and totaling 34,000 linear km of effort. The oceanic region was modeled exclusively from shipboard surveys conducted from 2003-2018 and totaling 39,000 linear km of effort.

In total, models were developed for 10 species of cetaceans and 3 guilds. The “pygmy and dwarf sperm whales” guild comprised the same two *Kogia* species as the EC. The “beaked whales” guild comprised three species: Cuvier’s beaked whale (*Ziphius cavirostris*), Blainville’s beaked whale (*Mesoplodon densirostris*), and Gervais’ beaked whale (*Mesoplodon europaeus*). The “blackfish” guild comprised four small whale species: false killer whale (*Pseudorca crassidens*), killer whale (*Orcinus orca*), melon-headed whale (*Peponocephala electra*), and pygmy killer whale (*Feresa attenuata*). All of these species are rare, and those within each guild are difficult to distinguish from each other. SEFSC also developed models for four species of sea turtle: green (*Chelonia mydas*), Kemp’s ridley (*Lepidochelys kempii*), leatherback (*Dermochelys coriacea*), and loggerhead (*Caretta caretta*).

SEFSC built all GoMMAPPS models as “full density surface models”, insofar as they did not restrict models *a priori* to a smaller number of covariates when sighting counts were low, but instead utilized their full suite of covariates and relied on model selection procedure to determine model parsimony. All dynamic candidate covariates were contemporaneous; of the 13 cetacean models, all but one retained at least one dynamic covariate; the spinner dolphin model retained only static covariates.

All GoMMAPPS models were summarized by SEFSC into mean monthly density surfaces. Predictions for the model with only static covariates were the same every month, and therefore we consider this a “year-round” model, even though SEFSC delivered 12 identical monthly surfaces for it. For the *Kogia* model, SEFSC only made predictions for the months of April through November, owing to a lack of sightings in winter, which was possibly due to poor sighting conditions, and led SEFSC to distrust their model’s predictions for those months. We consulted SEFSC and NOAA Office of Protected Resources (Ben Laws) for advice on how to obtain predictions for the months of December through March. A collective decision was made to average the predictions from the two months of November and April and used the resulting mean surface for December-March.

Two species—common bottlenose dolphin and Atlantic spotted dolphin—inhabit both the shelf and the oceanic regions and were modeled separately in each region. For the purpose of our report—e.g., above and in Table 12—we have counted the two regional models for each species as a single model. For the NMSDD, for each species, we merged SEFSC’s shelf and oceanic predictions for each month into a single layer.

3.3. AFTT models

For the AFTT, where our objective was to update the models developed for Phase III without redoing them completely from scratch (see Section 2.4.4.4), we retained 1992 as our starting year but extended our ending year to 2020, the most recent year for which any survey data were available. From this 1992-2020 period, our collaborators contributed over 3 million linear km of aerial effort—more than 3x what was available for the Phase III models—and 241,000 km of shipboard effort—30% more than was available for Phase III. Most of the increase came from the EC region, but some additional data were added from the Caribbean (the REMMOA 2017 survey), Europe (the SAMM 2011-2012 surveys), and from various other locations around the North Atlantic basin, including several cross-basin transits (SOTW 2004-2018). These data from outside the EC and GOM regions (Table 10, 11; Figure 4) still formed a small fraction of the total data available but helped widen the ranges of sampling of environmental covariates.

As in Phase III, we fitted 26 species models and 4 guild models: pilot whales, dwarf and pygmy sperm whales, seals, and beaked whales. As in Phase III, this last guild included all beaked whales except northern bottlenose whale, and was built from all beaked whale sightings, including ambiguous or unidentified beaked whale sightings, except those definitively identified as northern bottlenose whale. In general, we refitted the same models that were selected in Phase III, using the same climatological covariates, resulting in 16 full density surface models, 8 limited density surface models, and 6 stratified models. We adjusted the surveys used to fit some of the models, based on the introduction of new data in the wider North Atlantic basin and also recognizing that the AFTT model would not be used to fill the southern half of the GOM region, as was done in Phase III. Finally, we adjusted the construction and summarization of the AFTT model for North Atlantic right whale (used for predictions outside the EC area) to provide predictions seasonally rather than year-round, reflecting the species’ rarity in Canada in winter.

Table 10. Surveys contributed by institutions operating around the North Atlantic basin that were used in the AFTT-wide models to improve the sampled ranges of environmental covariates. Length is the cumulative linear distance observers were on effort. MCR's surveys do not include those already included in the EC region (Table 4). Not all programs were used in all models, and the transects used (and thus the total length) vary by model, according to the observation conditions (e.g. sea state) accepted for each model's detection functions. Please see the AFTT taxon-specific reports for details.

Region	Platform	Institution	Program	Period	Length (1000 km)
Caribbean	Shipboard	SEFSC	Caribbean	1995, 2000	8.4
	Aerial	U. of La Rochelle	REMMA	2008, 2017	38.7
Europe	Shipboard	Multiple partners	SCANS-II	2005	17.9
	Shipboard	Multiple partners	CODA	2007	9.6
	Aerial	U. of La Rochelle	SAMM	2011-2012	60.6
Mid-Atlantic Ridge	Shipboard	Norway Institute of Marine Research	MAR-ECO	2004	2.4
Basin-wide	Shipboard	MCR	SOTW	2004-2018	22.3

Table 11. Descriptions and references for survey programs from around the North Atlantic basin (Table 10) that were used in the AFTT models to improve the ranges of environmental covariates.

Program	Description	References
CODA	Cetacean Offshore Distribution and Abundance in the European Atlantic	Hammond et al. (2009)
MAR-ECO	Census of Marine Life Mid-Atlantic Ridge Ecology Program	Waring et al. (2008)
REMMA	REcensement des Mammifères marins et autre Mégafaune pélagique par Observation Aérienne	Mannocci et al. (2013); Laran et al. (2019)
SAMM	Suivi Aérien de la Mégafaune Marine	Pettex et al. (2014)
SCANS-II	Small Cetaceans in the European Atlantic and North Sea	Hammond et al. (2013)
SEFSC Caribbean	Caribbean abundance survey; Windwards Humpback Cruise	Mullin (1995); Swartz and Burks (2000)
SOTW	R/V Song of the Whale Surveys	Ryan et al. (2013)

3.4. Phase III models vs. Phase IV models

Table 12 summarizes the changes from Phase III to Phase IV for various model characteristics. The overall changes that occurred were different in each region. In the EC, we incorporated a very large amount of additional survey data contributed by both continuing and new collaborators, with total aerial effort increasing by 2,139,000 linear km, or 255%, and shipboard effort by 54,000 km, or 93%. The biggest increase resulted from the incorporation of the southeast U.S. North Atlantic right whale early warning system surveys (SEUS NARW EWS), which together totaled 1,579,800 km of the added aerial effort. These contributions were essential to modeling the critically endangered right whale, and also helpful for the humpback whale, but were generally not utilized in other models, as they only recorded large whale sightings and were geographically restricted to a region not inhabited by other large whales. The program that provided the broadest overall impact was NOAA AMAPPS. While AMAPPS only contributed about 207,300 km of the additional aerial effort and 33,400 km of the shipboard effort, it was the only program to estimate perception bias, which provided crucial corrections needed to estimate absolute abundance. AMAPPS was also the only program to cover the entire U.S. Exclusive Economic Zone (EEZ) and provided coverage in all four seasons. New contributions from New England Aquarium, the partnership of New York State Department of Environmental Conservation and TetraTech, HDR, UNCW, and the Virginia Aquarium & Marine Science Center provided critical boosts to seasonal coverage of the Mid-Atlantic Bight and Navy OPAREAs.

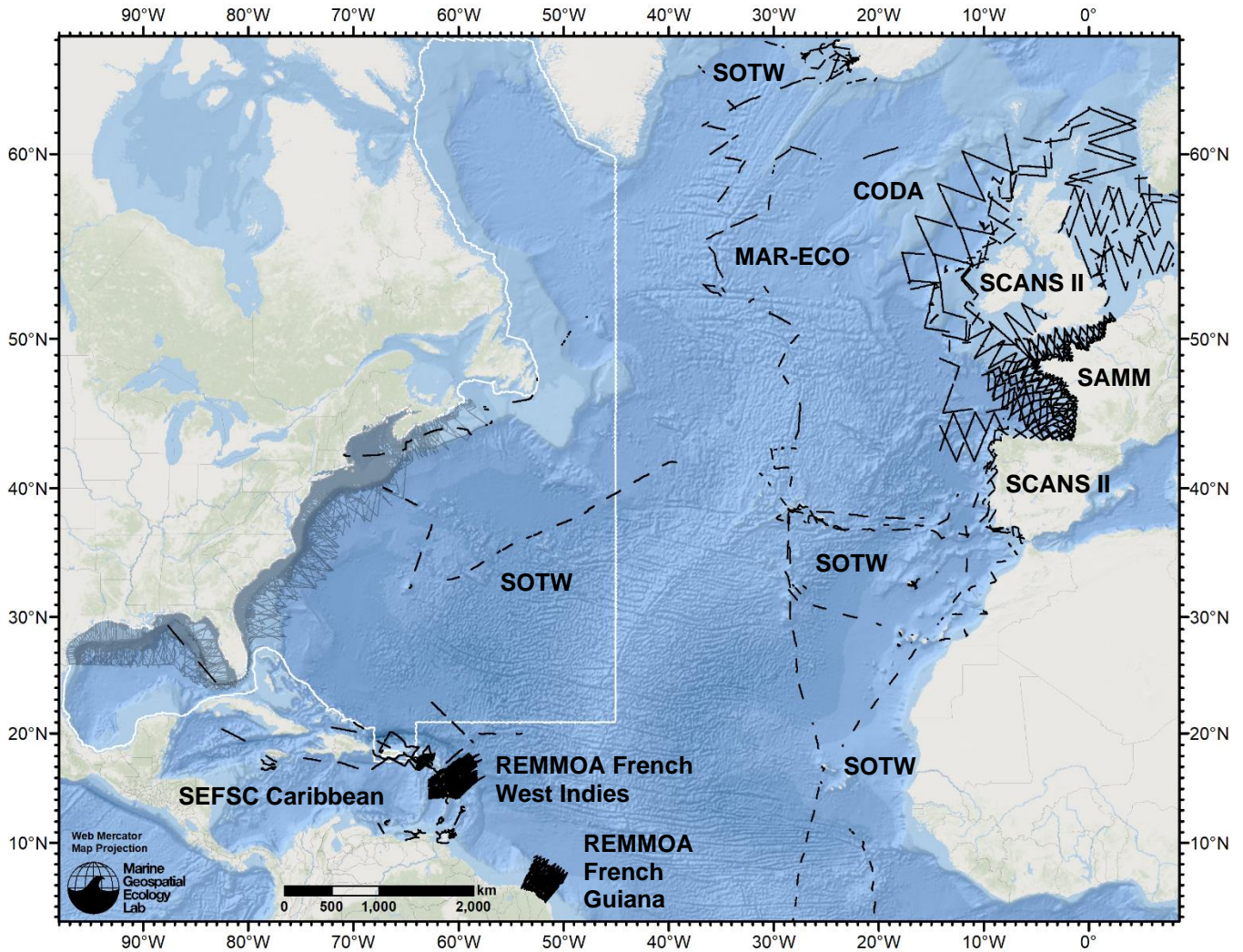


Figure 4. Surveys outside the EC and GOM regions that were considered in fitting models for the AFTT region (heavy lines). EC and GOM surveys also shown for reference (faint lines).

The additional survey effort and sightings allowed us to split the Phase III beaked whales model into three models of higher taxonomic precision, to reduce the number of stratified models from 13 to 8, to increase the number of taxa modeled with full DSMs from 16 to 19, and to switch the summarization of one taxon (seals) from seasonal to monthly density surfaces. An interesting outcome in the EC was that the number of models fitted with contemporaneous covariates increased from 5 to 12 and mixed covariates increased from 2 to 4, driven by a switch in selection of climatological covariates to contemporaneous covariates. The number of models fitted with climatological covariates only decreased from 9 to 7, but this reduction was partially offset by a shift from stratified models in Phase III to climatological-covariate models in Phase IV.

We can think of several possible reasons for this change. First, we acknowledge that for some models the decision to use contemporaneous covariates rather than climatological covariates was not made strictly on the basis of goodness of fit statistics, so it is possible we biased the results by preferring contemporaneous covariates when the statistics indicated roughly equal performance (e.g. similar deviance explained). However, we do not believe that this can fully explain the large increase in contemporaneous-covariate models. Another possibility relates to the change from daily resolution in contemporaneous covariates in Phase III to monthly resolution in Phase IV. In our temporal resolution comparison test for the North Atlantic right whale, we found that monthly covariates yielded better goodness of fit statistics than daily covariates, suggesting that broad seasonal changes were more important than daily changes, at least for that species. It may be that implementing this change *en masse* for Phase IV yielded better fitting contemporaneous models for many species, enough to advantage them over

climatological models. Finally, it may be that the increased selection of contemporaneous covariates reflects increased interannual variability driven by climate change, which has been implicated in recent cetacean habitat shifts (Meyer-Gutbrod et al. 2021; Chavez-Rosales et al. 2022; Thorne et al. 2022). Climatological covariates, by definition, average out interannual variations and thus models built from them will suffer when an interannual trend causes a habitat shift. Finally, we note that the increased selection of contemporaneous covariates did not result simply from an increase in the duration of time considered: although we shifted the end year from 2014 to 2019 or 2020 for most models, we also shifted the starting year from 1992 to 1998, thus most Phase IV models considered a similar duration of time (~23 years) as the Phase III models. So if interannual variability—e.g. a warming trend—is the reason for the increased selection of contemporaneous covariates, it suggests that greater variability has occurred in recent years, consistent with SST observations of the EC region (Pershing et al. 2015). In any case, our analysis was not focused on testing the performance of covariates nor on detecting species range shifts, so we urge caution with this interpretation of our results.

Even greater changes in modeling outcomes occurred in the GOM region. In the GOM, NOAA SEFSC was the only conductor of broad scale line transect surveys suitable for density modeling. We collaborated with SEFSC to adapt their GoMMAPPS models to the Navy's needs, rather than building our own duplicative models from SEFSC's data. SEFSC's approach, after observing "large scale shifts in both spatial distribution and abundance of marine mammals related to changes in physical oceanography" during the GoMMAPS program (Rappucci et al. 2022) was to focus their models on a recent range of years for which 71% less aerial data and 50% shipboard data were available, as compared to our Phase III models. This, combined with differences in methodology, resulted in only 10 species-specific models, compared to the 17 we developed for Phase III. For the difference of seven, the new "blackfish" guild accounted for four; Fraser's dolphin and rough-toothed dolphin, which were not modeled in GoMMAPPS because of lack of sightings, accounted for two; and fin whale was the last, now judged to be absent from the GOM, with the last sighting occurring in the early 1990s. With better seasonal surveying than we had in Phase III, SEFSC elected to fit full DSMs to all models, exclusively with contemporaneous covariates, and summarize them all monthly. (For one model, spinner dolphin, all dynamic covariates were discarded and only static covariates were retained; we counted this model as being summarized year-round, as the predictions did not change from month to month.)

In principle, the use of contemporaneous covariates and summarization to monthly density surfaces is an improvement over Phase III. However, we note that SEFSC did not test climatological covariates, nor did they require predictions to match prior knowledge of migratory movements in order to summarize monthly, as we did for the EC (see Section 2.4.4.3). Thus, we cannot say for certain that these decisions would have been made under our methodology, but we defer to SEFSC as experts for the GOM ecosystem. Another important improvement with GoMMAPPS was, similar to AMAPPS, the GoMMAPPS surveys estimated perception bias, and SEFSC's models corrected for it. In Phase III, we had to rely on perception bias estimates made on surveys from outside the region. Finally, although SEFSC did not discuss this directly in their GoMMAPPS report, we note that the two shelf models (common bottlenose dolphin and Atlantic spotted dolphin) were built exclusively from data collected after the Deepwater Horizon oil spill in 2010. Therefore, models for these species are likely to reflect the full consequences of the oil spill on their populations, which were substantial (Schwacke et al. 2015, 2017). Our Phase III models stopped in 2009, and therefore did not account for any effects of the oil spill. For the offshore GoMMAPPS models, about 19,000 km of effort occurred before the oil spill (in 2003, 2004, and 2009), while about 19,600 km occurred after it (in 2017-2018). Therefore, models for the offshore taxa also reflect the effects of the oil spill, at least partially.

The Phase IV AFTT models, while benefitting from the large addition of survey data, did not change significantly from Phase III in terms of the summary characteristics shown in Table 12. The apparent lack of change resulted from our deliberate strategy to simply update the Phase III AFTT models without making major methodological changes or redoing the model selection procedure; see Sections 2.4.4.4 and 3.3 for further discussion. This is not to say that the models did not change at all—most detection functions and all spatial models were refitted, resulting in updated species-environment relationships for the covariates in each model—only that the changes that did occur are not of the type that are summarized by Table 12. Interested readers can compare the taxon-specific reports from Phase III to those from Phase IV to learn more about the changes.

We caution that, as with Phase III, the Phase IV AFTT models do not incorporate any data north of the Laurentian Channel, and therefore are unable to provide full taxonomic coverage for species that inhabit the northern waters of the AFTT. For example, the bowhead whale and the beluga whale are two cetacean species known to inhabit these northern waters. Surveys exist for parts of these waters, e.g., for Labrador (Lawson and Gosselin 2011, 2018) and western Greenland (Heide-Jørgensen et al. 2010; Hansen and Heide-Jørgensen 2013; Hansen et al. 2019), but thus far we have been unable to secure a collaboration that would allow us to utilize them. This should remain an objective for the Phase V AFTT modeling effort.

Table 12. Summary of important model characteristics in Phase III vs. Phase IV for the three regional modeling areas. In the EC, nearly all models considered surveys only as old as 1998 or a later year; a few considered surveys as old as 1992. GOM Phase IV shipboard effort was estimated; SEFSC did not list total shipboard effort in their GoMMAPPS report (Rappucci et al. 2022). GOM data shown here is only for cetaceans; sea turtles are not included here. AFTT effort includes surveys from the EC and GOM, in addition to those incorporated specifically for the AFTT models.

Region	Characteristic	Metric	Phase III	Phase IV	Change $\pm\%$
EC	Surveys	Years considered	1992-2014	1998-2020	
		Aerial effort (1000 km)	837	2,986	255
		Shipboard effort (1000 km)	58	112	93
	Model taxonomic resolution	Species	25	26	8
		Guild	4	5	0
	Model type	Full DSM	16	19	19
		Limited DSM	0	4	
		Stratified	13	8	-38
	Model covariates	Climatological	9	7	-22
		Contemporaneous	5	12	140
		Mixed	2	4	100
		None	13	8	-38
	Summarization	Monthly	11	12	9
		Seasonal	1	0	-100
		Year-round	17	18	6
		Mixed	0	1	
GOM	Surveys	Years considered	1992-2009	2003-2018	
		Aerial effort (1000 km)	117	34	-71
		Shipboard effort (1000 km)	78	39	-50
	Model taxonomic resolution	Species	17	10	-41
		Guild	2	3	50
	Model type	Full DSM	11	13	18
		Limited DSM	5	0	-100
		Stratified	3	0	-100
	Model covariates	Climatological	9	0	-100
		Contemporaneous	3	12	300
		Static	4	1	-75
		None	3	0	-100
	Summarization	Monthly	0	12	
		Year-round	19	1	-95
AFTT	Surveys	Years considered	1992-2014	1992-2020	
		Aerial effort (1000 km)	972	3,027	211
		Shipboard effort (1000 km)	186	241	30
	Model taxonomic resolution	Species	26	26	0
		Guild	4	4	0
	Model type	Full DSM	16	16	0
		Limited DSM	8	8	0
		Stratified	6	6	0
	Model covariates	Climatological	24	24	0
		None	6	6	0
	Summarization	Monthly	3	3	0
		Seasonal	2	3	50
		Year-round	25	24	-4

3.5. Layers in the Phase IV NMSDD

In total, we populated the Phase IV NMSDD with layers for 39 taxa (Table 13): 8 baleen whale layers, 7 beaked and sperm whale layers, 7 large delphinoid layers, 12 small delphinoid layers, 1 pinniped layer, and 4 sea turtle layers. 26 taxa were summarized at monthly temporal resolution in at least one region and thus were rendered in the NMSDD with 12 monthly layers per taxon. The remaining 13 taxa were summarized at year-round resolution and thus were rendered as a single layer. More taxa are summarized monthly in Phase IV than in Phase III, owing mainly to SEFSC's decision to summarize all GoMMAPPS models monthly, whereas in Phase III we summarized all GOM taxa year-round (Table 12).

Several other important differences from the Phase III NMSDD may be noted. As discussed in Section 2.3.1, the baleen whale that inhabits the GOM was determined to be a separate species, Rice's whale (*Balaenoptera ricei*), and the Bryde's whale (*Balaenoptera brydei*) was also determined to be absent from the EC. The Phase IV NMSDD contains layers for both species, with Rice's whale absent in the EC and AFTT, and Bryde's whale absent in the EC and GOM. Also, after consultation with SEFSC, we determined the fin whale is absent from the GOM and set Phase IV GOM density to zero accordingly. The last confirmed fin whale sighting was reported in the early 1990s (Roberts et al. 2016b), and all sightings by SEFSC since that time have either confirmed to be or assumed to be Rice's whale (L. Garrison, pers. comm.).

In the EC region, as discussed in Section 2.3.2, we were able to split up the Phase III "Beaked whales" model for Phase IV into three models of higher taxonomic precision: Cuvier's beaked whale, Mesoplodont beaked whales, and Unidentified beaked whales. SEFSC was unable to do this for the GOM, owing to having too many sightings not resolved to the genus level, nor were we confidently able to do it for the AFTT-wide model, for the same reason. The Phase IV NMSDD layers reflect this situation. The three NMSDD layers of higher taxonomic prediction only contain predictions in EC region; in the GOM and AFTT regions, density values are left null. Conversely, for the "Beaked whales" layer, the cells of the EC are null, while predictions are provided for the GOM and AFTT regions.

A similar situation exists for the rarer of the large delphinoids: false killer whale, killer whale, melon-headed whale, and pygmy killer whale. In Phase III, in the GOM, we utilized over 78,000 km of shipboard surveys going back to 1992 and were able to develop separate models for these four species (Roberts et al. 2016b). As discussed in the previous section, for the GoMMAPPS models, SEFSC utilized only 39,000 km of surveys (Table 12) and accumulated markedly fewer sightings, and instead modeled these species together as a "Blackfish" guild. Thus, the Phase IV NMSDD contains the four species layers with the cells of the GOM set to null and predictions available for the EC and AFTT, and also a Blackfish layer with predictions available for the GOM and cells of the EC and AFTT set to null.

For two species of small delphinoids, Fraser's dolphin and rough-toothed dolphin, SEFSC did not obtain enough sightings to build GoMMAPPS models. In the Phase IV NMSDD, for these species we have populated the GOM cells with predictions from the AFTT model. These are the only two species for which the GOM cells were populated from non-GoMMAPPS models.

Finally, the GoMMAPPS effort produced models for four species of sea turtle. In the Phase IV NMSDD, these layers are populated for the GOM but are left as null in the EC and AFTT. These species do occur in the latter two regions but modeling them was beyond the scope of MGEL's Phase IV effort. However, a collaboration led by A. DiMatteo and L. Sparks produced sea turtle density surface models for the EC region for Phase IV (DiMatteo et al. 2023). These models were delivered to the Navy for incorporation into the Phase IV NMSDD via a separate process.

Table 13. Layers in the Phase IV NMSDD. Absent means the species did not occupy the region and density and uncertainty were set to zero. Blank cells mean the region was not predicted by a model, and left with null values (see Section 3.5 for explanations).

Group	NMSDD Layer	Resolution	Model Used to Populate Region			Temporal Summarization in Region		
			EC	GOM	AFTT	EC	GOM	AFTT
Baleen whales	Blue_whale	Year-round	EC	Absent	AFTT	Year-round	Year-round	Year-round
	Brydes_whale	Year-round	Absent	Absent	AFTT	Year-round	Year-round	Year-round
	Common_minke_whale	Monthly	EC	Absent	AFTT	Monthly	Year-round	Year-round
	Fin_whale	Monthly	EC	Absent	AFTT	Monthly	Year-round	Monthly
	Humpback_whale	Monthly	EC	Absent	AFTT	Monthly	Year-round	Seasonal
	North_Atlantic_right_whale	Monthly	EC	Absent	AFTT	Monthly	Year-round	Seasonal
	Rices_whale	Monthly	Absent	GOM	Absent	Year-round	Monthly	Year-round
	Sei_whale	Monthly	EC	Absent	AFTT	Monthly	Year-round	Seasonal
Beaked and sperm whales	Beaked_whales	Monthly		GOM	AFTT		Monthly	Year-round
	Cuviers_beaked_whale	Year-round	EC			Year-round		
	Dwarf_and_pygmy_sperm_whales	Monthly	EC	GOM	AFTT	Year-round	Monthly	Year-round
	Mesoplodont_beaked_whales	Year-round	EC			Year-round		
	Northern_bottlenose_whale	Year-round	EC	Absent	AFTT	Year-round	Year-round	Year-round
	Sperm_whale	Monthly	EC	GOM	AFTT	Monthly	Monthly	Year-round
	Unidentified_beaked_whales	Year-round	EC			Year-round		
Large delphinoids	Blackfish	Monthly		GOM			Monthly	
	False_killer_whale	Year-round	EC		AFTT	Year-round		Year-round
	Killer_whale	Year-round	EC		AFTT	Year-round		Year-round
	Melon_headed_whale	Year-round	EC		AFTT	Year-round		Year-round
	Pilot_whales	Monthly	EC	GOM	AFTT	Year-round	Monthly	Year-round
	Pygmy_killer_whale	Year-round	EC		AFTT	Year-round		Year-round
	Rissos_dolphin	Monthly	EC	GOM	AFTT	Monthly	Monthly	Year-round
Small delphinoids	Atlantic_spotted_dolphin	Monthly	EC	GOM	AFTT	Mixed	Monthly	Year-round
	Atlantic_white_sided_dolphin	Monthly	EC	Absent	AFTT	Monthly	Year-round	Monthly
	Clymene_dolphin	Monthly	EC	GOM	AFTT	Year-round	Monthly	Year-round
	Common_bottlenose_dolphin	Monthly	EC	GOM	AFTT	Monthly	Monthly	Year-round
	Frasers_dolphin	Year-round	EC	AFTT	AFTT	Year-round	Year-round	Year-round
	Harbor_porpoise	Monthly	EC	Absent	AFTT	Monthly	Year-round	Year-round
	Pantropical_spotted_dolphin	Monthly	EC	GOM	AFTT	Year-round	Monthly	Year-round
	Rough_toothed_dolphin	Year-round	EC	AFTT	AFTT	Year-round	Year-round	Year-round
	Short_beaked_common_dolphin	Monthly	EC	Absent	AFTT	Monthly	Year-round	Year-round
	Spinner_dolphin	Monthly	EC	GOM	AFTT	Year-round	Monthly	Year-round
	Striped_dolphin	Monthly	EC	GOM	AFTT	Year-round	Monthly	Year-round
	White_beaked_dolphin	Year-round	EC	Absent	AFTT	Year-round	Year-round	Year-round
Pinnipeds	Seals	Monthly	EC	Absent	AFTT	Monthly	Year-round	Year-round
Sea turtles	Green_turtle	Monthly		GOM			Monthly	
	Kemps_ridley_turtle	Monthly		GOM			Monthly	
	Leatherback_turtle	Monthly		GOM			Monthly	
	Loggerhead_turtle	Monthly		GOM			Monthly	

4. Accompanying taxon-specific reports

As mentioned above, this main report is accompanied by taxon-specific reports that document the EC and AFTT models for each modeled taxon. The GOM models, from the GoMMAPPS project, are individually documented in Appendices F (marine mammals) and G (sea turtles) of Rappucci et al. (2022). Also, the accompanying report by Kot and Roberts (2022) documents how we obtained density estimates of bottlenose dolphins for the various estuaries requested by the Navy that were beyond the spatial extent of the EC and GOM models. Together, these documents comprise several thousand pages of maps, plots, tables, statistical output, and narrative text describing modeling decisions and interpreting model results.

5. Manuscripts in preparation

To further document this work and subject it to formal peer review, we are preparing two journal publications. The first will focus on the EC regional models, describing the methodology and presenting results for those models. While this manuscript is in preparation, it may be cited:

Roberts JJ, Yack TM, Cañadas A, Fujioka E, Curtice C, Halpin PN, Barco SG, Boisseau O, Chavez-Rosales S, Cole TVN, Cotter MP, Cummings EW, Davis GE, DiGiovanni RA, Garrison LP, Gowan TA, Jackson KA, Kenney RD, Khan CB, Lockhart GG, Lomac-MacNair KS, McAlarney RJ, McLellan WA, Mullin KD, Nowacek DP, O'Brien O, Pabst DA, Palka DL, Quintana-Rizzo E, Redfern JV, Rickard ME, White M, Whitt AD, Zoidis AM (in prep) Habitat-based density surface models for marine mammals of the U.S. Atlantic.

The second publication will focus on the development of and results for the North Atlantic Right Whale spatial model, a species of critical conservation concern which had the most complex internal seasonal and regional structure of all the taxa we modeled. A citation is not yet available for this publication.

6. Planned updates

During the write-up of the accompanying taxon-specific reports, after all models had been finalized, reviewed by collaborators and species experts, delivered to the Navy in the NMSDD, and released to the public, we discovered minor mistakes in two taxa:

- In the data we received from NOAA NEFSC, a sighting of 160 dolphins on 30 June 2016 reported by observers on the HB 16-03 shipboard survey was miscoded as “Dolphin, Unid. Spotted” but should have been coded “Dolphin, Spinner”. Our spinner dolphin model included the HB 16-03 survey but not the miscoded sighting, and therefore underestimated spinner dolphin density. We discovered the problem when cross-checking our results against NEFSC’s Reference Document for NOAA’s 2016 summer abundance estimates (Palka 2020). NEFSC confirmed the problem and instructed us to correct the identification in their data file. We estimate that if the spinner dolphin model is refitted and this sighting is included, it will boost abundance by 200-400 in the “Offshore Gulf Stream and South” stratum.
- In our model for killer whale, we accidentally excluded the NEFSC AJ 99-02 shipboard survey of the northern Gulf of Maine from the analysis. This survey sighted two groups of killer whales, totaling 10 individuals. We estimate that if the killer whale model is refitted and this survey is included, it will boost abundance by 8-12 in the “Shelf North of Nantucket Shoals” stratum.

We anticipate that we will update these two models to correct these problems sometime in 2023, ideally before submitting the publication on the EC models. When this happens, we will also update the taxon-specific reports and the OBIS SEAMAP model repository and the Mapper application for these two species. At the Navy’s request, we can also release an update to the NMSDD and update the Navy’s web services.

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