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

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Document Version 1.1 – 2015-06-19

This document should be cited:

Roberts JJ, Mannocci L, Halpin PN (2015) Marine mammal density models for the U.S. Navy Atlantic Fleet Training and Testing (AFTT) study area for the Phase III Navy Marine Species Density Database (NMSDD). Document version 1.1. Report prepared for Naval Facilities Engineering Command, Atlantic by the Duke University Marine Geospatial Ecology Lab, Durham, North Carolina.

1. Introduction

In the United States, national laws protect cetaceans. 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 ESA lists 27 marine mammal species (http://www.nmfs.noaa.gov/pr/species/esa/listed.htm). 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.

To evaluate the potential effects of proposed activities on marine mammal populations, permit applicants, regulators, and other stakeholders require a detailed understanding of the spatiotemporal distributions of these populations. To facilitate spatiotemporally-explicit descriptions of marine mammal distributions in U.S. waters, government organizations such as the National Marine Fisheries Service (NMFS) have conducted visual line-transect surveys of marine mammals for over 35 years, yielding two parallel modeling efforts. One effort, prompted by the regulatory framework imposed by the MMPA and ESA, applied distance sampling methodology (Buckland et al., 2001) to estimate the abundance of marine mammal species within large geographic strata (e.g. CeTAP, 1982; Mullin and Fulling, 2003, 2004; Palka 2006, 2012). The other effort, driven by a desire to describe marine mammal habitats at a fine spatiotemporal scale, developed statistical regression models that related the presence of marine mammal species to environmental correlates such as sea surface temperature and then predicted the models across the seascape using gridded maps of the correlates, yielding fine-scale maps of habitat suitability (e.g. Best et al., 2007; Good, 2008; Hamazaki, 2002; Waring et al., 2001).

Neither effort has proved entirely satisfactory for managing marine mammal populations in the U.S. The regulatory framework requires that proposals for actions that could harm or disturb marine mammals estimate the number of individual animals that would be affected. The abundance studies estimated the number of individuals present in large geographic areas, but they assumed they are distributed homogeneously within each area. In contrast, the habitat suitability studies modeled spatial variability at fine resolutions, but produced estimates that used relative or unit-less scales (e.g. ranging from 0 to 1) that cannot be used to estimate counts of affected individuals.

The last decade as seen a unification of these two approaches into a two-stage method known as density surface modeling (DSM) (Hedley and Buckland, 2004; Miller et al., 2013). In this method, traditional distance sampling is coupled to a regression model, allowing absolute density (individuals km^{-2}) to be modeled from spatiotemporally-varying correlates, yielding gridded maps of absolute density. NMFS applied this method in several studies of the Pacific (e.g. Ferguson et al., 2006; Becker et al., 2012, 2014). The U.S. Navy applied it in the western North Atlantic and Gulf of Mexico in the 2007 Navy OPAREA Density Estimates (NODE) studies (DON, 2007a-c), the only studies of this kind for these regions.

A challenge with DSM is that a large number of sightings are needed to fit the regression model. While a traditional geographically-stratified abundance estimate can sometimes be made for a single survey that obtained just a handful of marine mammal sightings, a DSM estimate typically requires that many surveys be aggregated in order to obtain sufficient sightings. For example, in their model of beaked whales in the eastern tropical Pacific, Ferguson et al. (2006) aggregated six years of surveys to obtain 90 sightings of Cuvier's beaked whale and 106 of *Mesoplodon* beaked whales. This problem is exacerbated if the modeler desires to fit different models for different regions or seasons under the presumption that different behaviors occur in those places and times, e.g. that whales on summer feeding grounds exhibit different environmental preferences than those on winter calving grounds. Finally, some species may just be so rare or infrequently detected that they cannot be modeled with the DSM approach.

The Navy faced all of these problems with its NODE studies, despite aggregating many surveys (Table 1). Here, we present new marine mammal density models for the Navy's Atlantic Fleet Training and Testing (AFTT) study area that are a marked improvement over the NODE effort. In the years that have passed since the NODE models were developed, many additional surveys have been conducted, particularly along the U.S. east coast. These include additional NOAA surveys as well as a large number of non-NOAA surveys funded by the Navy and state administrative agencies (Table 4). By incorporating all of these we were able to obtain 80% more hours of shipboard effort and 605% more hours of aerial effort than was available when the NODE models were built. For certain species, we also utilized several European surveys of waters beyond the AFTT, all conducted after the NODE studies, as well as two NOAA surveys of the Caribbean (Table 5 and section 2.3.4.3). The availability of additional remote sensing and ocean modeling products allowed us to consider additional dynamic environmental covariates in our spatial models (we considered 13, the NODE studies considered 2). Finally, we controlled for the influence of sea state, group size, availability bias, and perception bias on the probability of making a sighting (the NODE studies were not able to control for these).

Table 1

Surveys utilized and marine mammal taxa modeled by the U.S. Navy (DON, 2007a-c). All surveys were conducted by NMFS. Seasonal DSMs split the data into two or more seasons and modeled them separately. Year-round DSMs fitted a single model to all of the data. Stratified models were used when insufficient sightings were available to fit a DSM. Unmodeled taxa were so rare that the Navy did not attempt any kind of model. The large number of stratified models and unmodeled taxa illustrate the difficulty of obtaining enough sightings to fit DSMs, even when many surveys are aggregated.

			Taxa modeled with:			
Study area	Aerial surveys	Shipboard surveys	Seasonal DSMs	Year-round DSMs	Stratified Models	Unmodeled taxa
East coast north	4	0	1	5	10	5
East coast south	8	9	4	6	7	11
Gulf of Mexico	16	11	4	6	8	0

2. Methods

2.1. Surveys and study area

An overriding goal of our study was to maximize the number of marine mammal stocks modeled with DSMs rather than stratified models. Meeting this goal required many sightings, thus many surveys. Using the Navy's pioneering NODE studies as our baseline, we searched bioinformatics databases and the literature for aerial and shipboard visual line-transect surveys conducted in mainland U.S. waters of the Gulf of Mexico and North Atlantic between 1992, the year of the first survey used in the Navy's analysis, and 2014. We only considered surveys that used two or more observers and adhered to the requirements of distance sampling methodology (Buckland et al., 2001).

We acquired the original survey data files, aggregated them into a common geodatabase, and manually delineated a study area encompassing the total area surveyed (Fig. 1). We included near-shore waters but excluded estuaries and many bays. South of Delaware, bottlenose dolphins are the only cetacean species that regularly occurs in estuaries and bays. We produced these estimates with a separate methodology; please see the accompanying report titled "Estimates of bottlenose dolphin density for estuaries in the AFTT area for the Phase III NMSDD".

The MMPA requires that impacts to marine mammals be estimated on a per-stock basis, where a stock is defined as "a group of marine mammals of the same species or smaller taxa in a common spatial arrangement, that interbreed when mature" (16 U.S.C. § 1362). NMFS bears responsibility for defining stocks and has placed many species that occur in both the North Atlantic and Gulf of Mexico into separate stocks. Pursuant to the need for per-stock estimates, and to allow for the 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), and designated the area outside as the AFTT analysis region (Fig. 1).

In the EC and GOM analysis regions—the well-surveyed portions of the AFTT—we fitted relatively complex models designed to closely reproduce spatiotemporal patterns in cetacean density. Beyond these areas—what we called the AFTT analysis region, where we had very little survey effort—we fitted parsimonious models designed to produce plausible extrapolations of marine mammal density. We describe these modeling processes in detail in following sections.

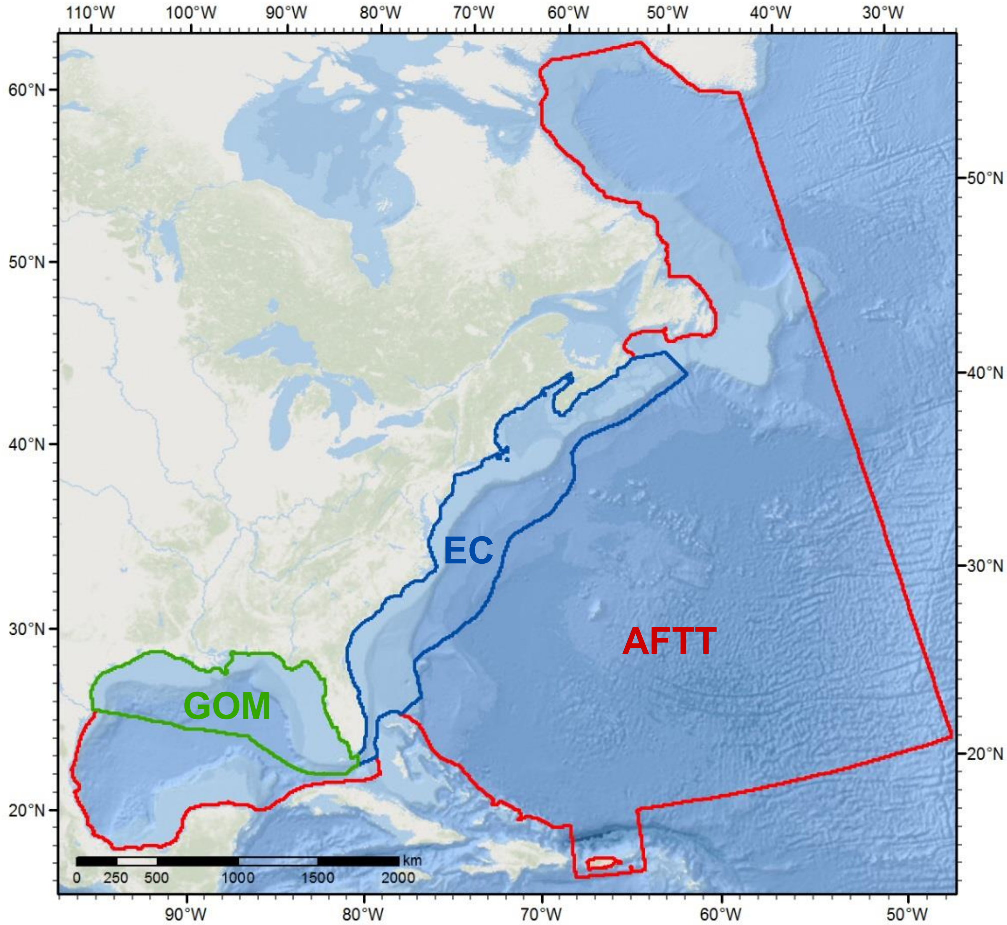

Fig 1. Study areas. The map uses the Albers equal area projection developed for the analysis.

2.2. Modeled taxa

To facilitate straightforward use of our results within in the U.S. regulatory framework, 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 (Table 6).

We handled these ambiguous sightings differently based on their degree of ambiguity. 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 for both, and the literature or exploratory analysis suggested the two 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. 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.

When we lacked enough fully-resolved sightings to build a classifier, or 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).

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 "*Mesoplodon* spp." or "*Ziphiidae* spp." sightings dominated the number of fully-resolved sightings. We modeled all of these as a single "beaked whales" guild. This also occurred for seals, for which the number of "unidentified seal" sightings dominated the number of fully-resolved sightings. We modeled all seals as a single guild. Table 7 lists the guilds and the counts of sightings that compose them.

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 were a clear minority compared to the fully-resolved sightings, they resulted in an underestimation of density on account of animals being present and sighted but not included in the model.

2.3. Modeling workflow

The models in both the well-surveyed (EC and GOM) and poorly-surveyed (AFTT) analysis regions followed the generic DSM workflow (Fig. 2) outlined by Miller et al. (2013), using the formulation described in that paper as "DSM with covariates at the observation level".

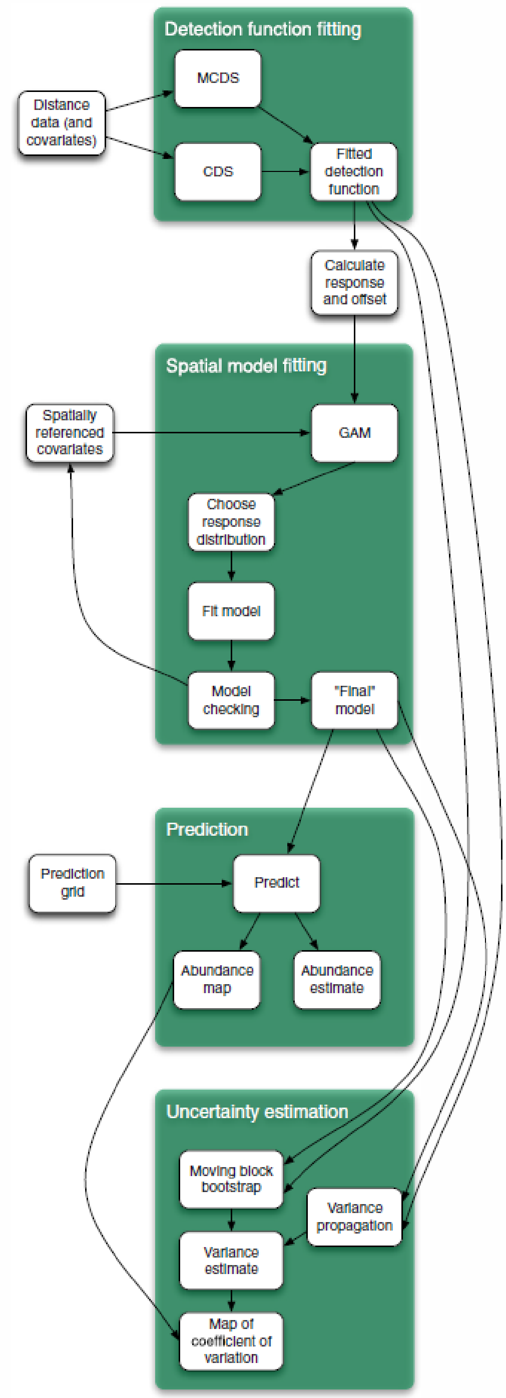

Fig 2. Generic density surface modeling workflow, reproduced from Fig. 6 of Miller et al. (2013).

2.3.1. Splitting of survey transects into segments

This workflow first required the survey transects to be split into segments. The Navy requested that density predictions be provided at 10 km scale, therefore we sought to obtain segments of this length. 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 off-effort gaps of 1 h or more, and 2) no stretch of 15 km for which 1/3 or more of it was off-effort. 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 10 km (the target segment length) using integer division. If the remainder was less than 5 km, then the remainder was distributed evenly among the N segments, resulting in N equal-length segments that were all slightly larger than 10 km. 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 10 km. Under no circumstances was a segment ever longer than or equal to 15 km. A very small number of short, spatiotemporally-isolated segments occurred and were preserved, so long as they were longer than 1 km.

For the surveys used to fit the EC models, this procedure yielded 106,813 segments with a mean length of 9.95 km (SD=0.89 km). For the segments used to fit the GOM models, it yielded 19,988 segments of 9.75 km (SD=1.56 km). For the AFTT models, which included all of the segments in the EC and GOM plus, in some cases, those from the European Atlantic, the mid-Atlantic ridge and the Caribbean, it yielded 130,436 segments of 9.92 km (SD=1.02 km).

2.3.2. Detection functions

For each modeled taxon, we then used a two-stage model (first two green boxes of Fig. 2) to model the count of animals per 10 km survey segment using a Horvitz-Thompson-like estimator (Marques and Buckland 2003; Miller et al. 2013). In the first stage, we fitted taxon-specific detection functions using single-observer methodology. Buckland et al. (2001) recommended that at least 60-80 sightings be used to fit a detection function. Ideally, separate detection functions would be fitted to each survey, to account for survey-specific biases in detectability. But marine mammal surveys rarely obtain enough sightings to achieve that under Buckland et al.'s recommendation. The typical workaround is to pool sightings from multiple surveys or "proxy" species until sufficient sightings are obtained.

With that idea in mind, we arranged the surveys in two "detection hierarchies", one for shipboard surveys and one for aerial surveys (the hierarchies are diagrammed in the accompanying taxon-specific reports for the EC and GOM regions). Each hierarchy first clustered the surveys into small groups that we judged were most likely to have the most similar detection characteristics. For example, shipboard surveys conducted by NOAA on the research vessel Oregon II were placed into four groups: Oregon II Atlantic, Oregon II Gulf of Mexico Shelf, Oregon II Gulf of Mexico Oceanic, and Oregon II Caribbean. Next we clustered the groups according to how similar *they* 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 for that platform type (labelled All Boats and All Planes).

For each modeled taxon, at each node of the hierarchy we tallied the number of sightings reported by all surveys under that node. When a suitable number of sightings 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 to a node that contained more surveys and tried again. If we ascended very high in the hierarchy—typically to the nodes that were the children of the top "all surveys" node—without obtaining sufficient sightings, we pooled "proxy" species into that branch of the hierarchy and started over. For example, when modeling humpback whales, too few humpback sightings were obtained from shipboard surveys to fit humpback-specific detection functions, despite pooling many years of surveys. To compensate, we added sightings of all other baleen whales as proxies for humpbacks, which allowed us to fit several shipboard detection functions. For proxy species, we consulted the literature and species experts and selected species that displayed similar size, behaviors, and other characteristics that affect detectability.

For each detection function, we attempted a number of formulations and selected the one with the lowest Akaike information criterion (AIC). We tested both CDS and MCDS formulations. For CDS, we tested hazard rate and half normal key functions with no adjustments, hazard rate with second and forth order polynomial adjustments, half normal with second and third order cosine adjustments, and half normal with a forth order Hermite polynomial adjustment. For MCDS, we tested as covariates the group size (number of sighted animals), the Beaufort sea state, the observer's subjective estimate of the quality of observation conditions (or sun glare, if quality was not available), the survey, and the vessel or aircraft that was used. Not all covariates were tested for all taxa, and covariates that produced obvious ill effects were discarded.

Although certain large surveys such as the NOAA NARWSS program occasionally reported enough sightings 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 sightings were large enough to allowed a covariate to be utilized in an MCDS formulation. For this reason, we rarely fitted detection functions on a per-survey basis.

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 not having a belly observer or bubble 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 along the trackline. For these surveys, we applied left truncation (Buckland et al. 2001).

The accompanying taxon-specific reports for the EC and GOM regions document the detection hierarchy and proxy species that were used, and the detection functions that were fitted along with statistical diagnostics. The AFTT models used the same detection functions documented there.

We fitted all detection functions using the R *mrds* package version 2.1.10.

2.3.3. Probability of detection along the trackline, g(0)

Distance sampling methodology assumes that the probability of detecting objects that lie along the trackline (i.e. at distance 0) is 1. This is often called the "g(0)=1" assumption. Unfortunately this assumption often does not hold for surveys of marine mammals. Marine mammals dive; while submerged, they are unavailable to be detected at the surface. Marine mammals may also be difficult for observers to perceive, due to their size, coloration, or failure to display obvious visual cues. These two problems are known as *availability bias* and *perception bias* and result in an underestimation of abundance unless they are accounted for.

A preferred way to account for them is to utilize two independent teams of observers. Unfortunately most of the surveys used in our study only used one team. If we restricted our analysis to only the dual-team surveys, we would have had to discard at least 80% of the survey effort. This would severely limit the number of SDMs we could attempt, leaving us to fit stratified density estimates for most taxa, providing little improvement over the Navy's NODE studies.

Instead, we retained all surveys and used a single-team methodology; for surveys that used two teams, we only incorporated the sightings from the primary team. To address perception and availability bias, we consulted the literature to obtain estimates of the value of g(0) that incorporated these biases. The accompanying taxon-specific reports for the EC and GOM regions document the g(0) values and sources. The AFTT models used the same g(0) values documented there.

2.3.4. Spatial models, prediction, and uncertainty estimation

After fitting detection functions and obtaining estimates of g(0), we calculated for each segment the estimated count of animals present and the area effectively surveyed, 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 for the spatial regression models fitted during the second stage of the analysis. Here, we had different objectives in the well-surveyed EC and GOM regions and the poorly-surveyed AFTT region. In the EC and GOM, our goal was to closely reproduce the spatiotemporal patterns in marine mammal density revealed by the surveys. In the AFTT, our goal was to produce plausible extrapolations of marine mammal density where little or no surveying was performed.

2.3.4.1. Spatial model covariates

The spatial models correlated the count of animals present on survey segments to environmental covariates plausibly related to marine mammal distributions (Table 2), in a statistical regression framework. The models for the EC and GOM regions utilized a different suite of covariates than the models for the AFTT region, as described in the following sections. We did not use purely geospatial covariates (e.g. longitude or latitude) or temporal covariates (e.g. year or day of year), due to the patchy distribution of survey effort. All gridded products were rescaled to a 10 km resolution using bilinear interpolation.

Table 2

Covariates considered in spatial models. Not all covariates were considered in all spatial models (see text).

Type	Predictor	EC & GOM	AFTT	Description
Physiographic	Depth	X	X	From SRTM30-PLUS global bathymetry (Becker et al., 2009)
	Slope	X	X	Computed from SRTM30-PLUS
	DistToShore	X		Distance to shore, not including Bermuda
	DistTo125m, DistTo300m, DistTo1500m	X		Distance to isobaths that delineate various ecologically relevant geomorphic features
	DistToCanyon	X		Distance to submarine canyon, from Harris et al. (2014) geomorphology
	DistToCanyonOrSeamount	X	X	Distance to submarine canyon or seamount, from Harris et al. (2014)
SST & Winds	SST	X	X	Taken from GHRSST CMC 2.0 L4 SST (Brasnett, 2008)
	DistToFront	X	X	Distance to closest SST front detected in CMC SST using Canny (1986) edge detection operator; tested several alternative formulations
	WindSpeed	X		30-day running mean of NCDC 1/4° Blended Sea Winds (Zhang et al., 2006); only used for calving right whales
SSH & Currents	TKE	X		Total kinetic energy derived from AVISO 1/4° DT-MADT geostr. currents
	EKE	X	X	Eddy kinetic energy derived from AVISO 1/4° DT-MSLA geostr. currents
	CurrentSpeed		X	Absolute current speed derived from AVISO 1/4° DT-MADT geostr. curr.
	SLAStDev		X	Climatological standard deviation of sea surface height anomalies, derived from AVISO 1/4° DT-MADT sea surface height
	DistToEddy, DistToAEddy, DistToCEddy	X		Distance to ring of closest geostrophic eddy having any/anticyclonic/cyclonic polarity, from a new eddy database produced by D. Chelton and colleagues using a revision of the Chelton et al. (2011) eddy detection algorithm; we tested eddies at least 9, 4, and 0 weeks old
Biological	Chl1	X	X	GSM merged SeaWiFS/Aqua/MERIS/VIIRS 9km daily chl-a concentration (Maritorena et al. 2010), smoothed with 3D Gaussian smoother to reduce data loss to < 10%; tested two smoothing formulations
	VGPM	X	X	Behrenfeld and Falkowski (1997) vertically generalized primary prod. model (VGPM) at 8-day, 9km resolution, trilinear-interpolated to daily resolution; also tested 45 and 90 day running cumulative sums
	PkPP, PkPB	X	X	Weekly zooplankton potential production and potential biomass from the SEAPODYM ocean model (Lehodey et al 2010)
	EpiMnkPP, EpiMnkPB	X	X	Weekly epiplelagic micronekton potential production and potential biomass from the SEAPODYM ocean model (Lehodey et al 2010)

2.3.4.2. EC and GOM spatial models

Prior to fitting models for each taxon, we investigated its seasonality, 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 calving grounds would prefer warmer, calmer waters—we split the year into seasons 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. 3) The spatial pattern in the sightings resembled the expectation described by the literature.

If all of these conditions were true, we split the year into two or more seasons. For convenience, we used 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 these conditions were false, we fit a single "year-round" model. In the GOM region, we always used year-round models; none of the taxa there were reported to undertake large seasonal movements, and we lacked sufficient survey coverage during different parts of the year to detect more subtle movements.

After investigating seasonality and, when appropriate, splitting the data into seasonal strata, we investigated the spatial distribution of the taxon during each season. 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. right whales calving and overwintering, Fig 3.), or 2) was typically absent from an area (e.g. sperm whales do not occur on the continental shelf of the Gulf of Mexico, Fig 4.), or 3) there was reason to believe a taxon was present but we lacked the survey data to confidently model its density (Fig. 3), we split the study area into sub-regional strata.

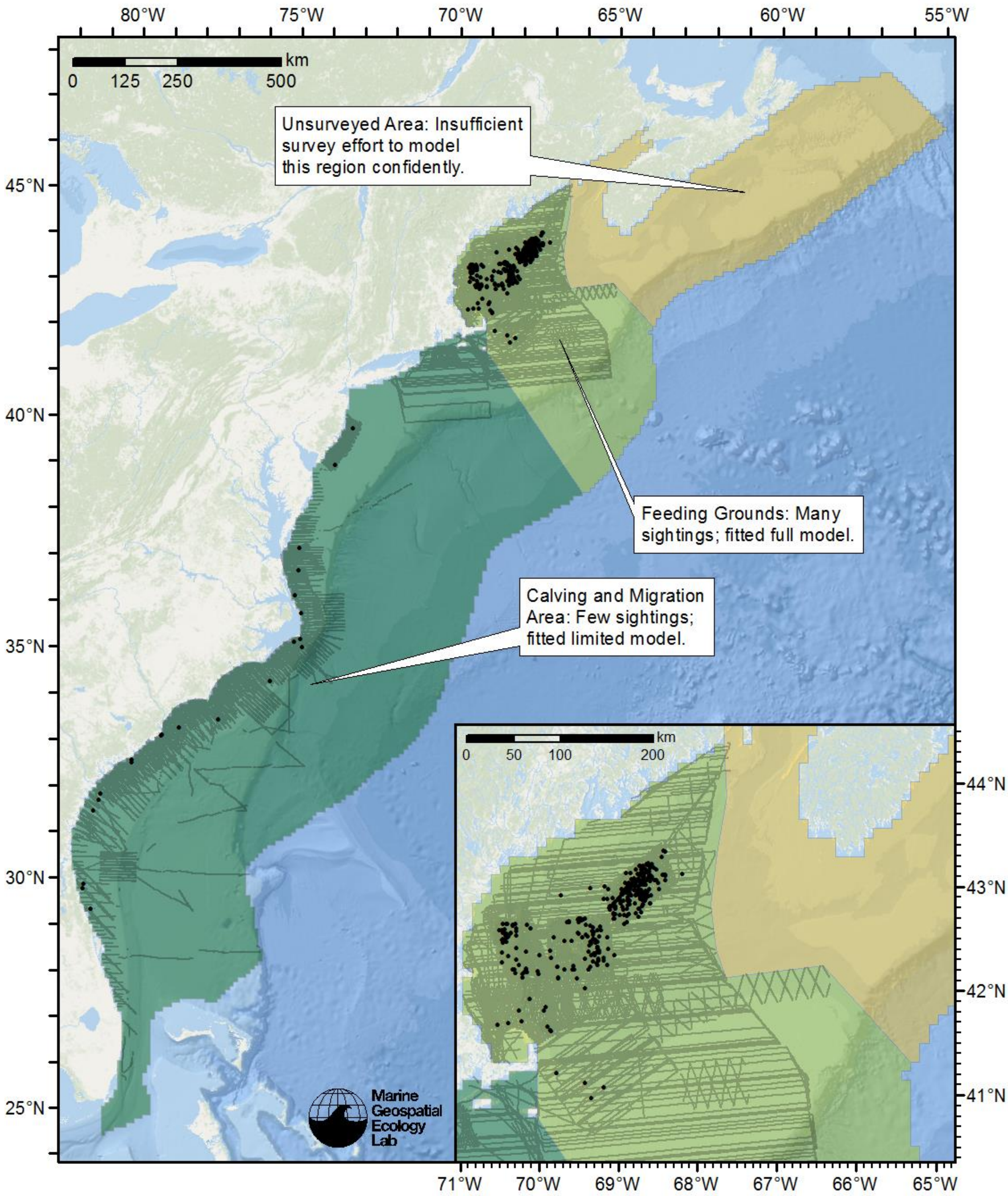

Fig 3. Schematic for the EC North Atlantic right whale winter season (November-February) model, showing an example in which we split the study area on the basis of sub-units of the population likely exhibiting different relationships to the environment (right whales overwintering on the feeding grounds vs. those on the calving grounds). This model also shows an example of where we suspected a species was present—Canadian waters, in this case—but lacked the survey effort to model it confidently.

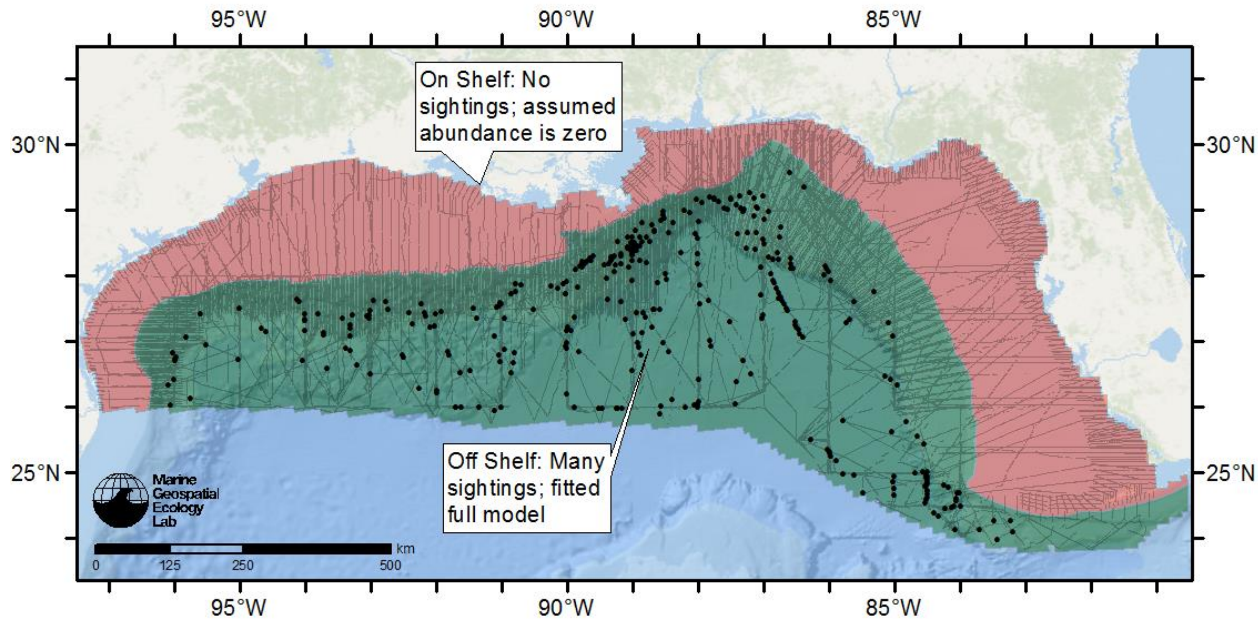

Fig 4. Schematic for the GOM sperm whale year-round model, showing an example in which we split the study area on the basis of the taxon not occupying part of the area— the continental shelf, in this case.

After splitting the seasonal and sub-regional strata, as appropriate, we fitted generalized additive models (GAMs) to the data in each stratum. When a relatively large number of sightings were available for a stratum (we used our judgement and did not develop a specific criterion here), we fitted a multivariate model that considered a full suite of candidate covariates from Table 2. When a moderate number of sightings were available (typically 20-40) we fitted a univariate model. For some taxa we tested many covariates and selected the one that explained the most deviance; for others, we selected a specific covariate based on the ecology of the taxon. Finally, when few sightings were available (typically less than 20), we fitted a model with no covariates, which ultimately resulted in what we termed a “stratified model” in the Introduction of this paper—a model that assumed that density was distributed uniformly throughout the modeled sub-region. The accompanying taxon-specific reports for the EC and GOM describe how each taxon was modeled.

In multivariate and univariate models, we only considered the subset of covariates from Table 2 that were appropriate for ecology of the taxon and for the sub-region of interest. For example, mesoscale eddies shed from the Gulf Stream or Gulf of Mexico Loop Current rarely maintain coherence over the continental shelf; we only used the “distance to eddy” covariates in models of off-shelf sub-regions.

When a model included dynamic oceanographic covariates (i.e. any of those from Table 2 that were not physiographic), we fitted three parallel models. The first model tested 8-day climatological formulations of the covariates developed from a long time series of daily or weekly observations. The climatologies captured regular seasonal variability but not inter-annual variability or ephemeral variations such as mesoscale eddies. Because the climatological images were not missing any data, we were able to fit these models to the entire set of survey segments, with no data loss.

The second model tested daily contemporaneous (a.k.a. “time resolved”) formulations of the covariates (e.g. daily SST on the dates the surveys were conducted). In this model, the values for a given segment were extracted from the oceanographic images produced for the date of that segment, at daily resolution for SST, winds, SSH, currents, and Chl covariates, and 8-day resolution for VGPM, and weekly resolution for PkPB, PkPP, EpiMnkPB, and EpiMnkPP. The contemporaneous covariates allowed models to capture a full range of temporal patterns—inter-annual, seasonal, and ephemeral—but suffered from data loss, typically due to clouds, or because satellites had not been aloft for the entire 1992-2014 study period. When covariates were not available for segments, we discarded them from the model. This problem was particularly acute in the Gulf of Mexico, in which approximately 68% of the survey effort occurred prior to the availability of biological covariates, which depended on the launch of the SeaWiFS sensor (Fig. 6).

The third model tested climatological covariates but was restricted to the contemporaneous model's segments, to permit goodness-of-fit statistics to be directly compared between these two models. To distinguish between the first and third models, we called them the "climatological all-segments" (or simply "climatological") model and the "climatological same-segments" model, with the latter referring to the same segments as the contemporaneous model.

To mitigate the data loss problem, we usually fitted each of the three models with several formulations, progressively including more covariates, potentially allowing for more explanatory power at the cost of higher data loss. The first formulation included just physiographic covariates; no contemporaneous or climatological-same-segments models were necessary in this case. The second formulation added SST and wind covariates; these data were available for the entire 1992-2014 study period, resulting in relatively little loss of survey data. The third formulation added SSH and currents covariates; these were available for 1993-2013. The fourth formulation added biological covariates; these were available from late 1997 to 2013 or 2014, depending on the covariate, resulting in loss of substantial survey data, particularly in the Gulf of Mexico.

We fitted all models using the R *mgcv* package (Wood and Augustin, 2002; Wood, 2006). All covariates were continuous; we used thin-plate splines with shrinkage (`bs="ts"`). Following Forney (2000) and a subsequent series of cetacean density studies published by the NOAA Southwest Fisheries Science Center (SWFSC) which sought to preserve the ecological interpretability of functional relationships, we limited the number of degrees of freedom to 4. (The SWFSC papers typically limited functional relationships to 3 degrees of freedom; we included an additional d.f. as a compromise with other modelers who did not believe in limiting the degrees of freedom this way.) We used a shrinkage approach to selecting covariates for the models: 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 assumed the Tweedie distribution and allowed mgcv to estimate the Tweedie p parameter (`family=tw()`). We used the REML optimization method (Wood, 2011).

After fitting all of the formulations (typically 4) for each of the three models (climatological all-segments, contemporaneous, and climatological same-segments), we selected for each of the three models the formulation that explained the most deviance. The Density Models section of the accompanying taxon-specific reports for the EC and GOM provide full documentation of each of the three selected models. The Model Comparison section of the reports summarizes the performance of each model formulation. After selecting the three final models, we produced predictions, as follows.

For the climatological-all-segments and climatological-same-segments models, we predicted the models on each of the 8-day climatological periods spanned by the season. For example, for a taxon modeled with single season (year-round) models, there were 46 8-day predictions (the last one spanning less than 8 days). For the contemporaneous models, we predicted the models at a 1-day time step across the time period for which both survey data and covariates were available. For example, for Gulf of Mexico sperm whales, modeled with single-season models, the contemporaneous model with physiographic, SST, and current covariates explained the most deviance. The covariates were available from 1993-2014, while the survey data were available from 1992-2009; therefore the prediction period was all days of 1993-2009, comprising 6209 daily predictions.

After producing the predictions for the three models, we inspected them and the model diagnostics, and selected one of the three as our "best" estimate of density for the taxon. This was a subjective procedure, informed by both the models' statistical performance, the spatiotemporal noisiness of the predictions, how much survey data were lost by the contemporaneous covariates, and our judgment of how well the predictions matched well-established findings from the literature. All else being equal, we selected the model that explained the most deviance, while keeping in mind that the climatological all-segments and contemporaneous models were often not directly comparable, by virtue of the latter being fitted to a subset of the segments used to fit the former.

After selecting the best model we summarized the predictions, as follows. The Navy requested climatological predictions at a monthly time step—i.e., for each taxon, the Navy wanted 12 predictions, 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. Table 8 lists what was done for each taxon.

As noted previously, for sub-regional strata for which there were insufficient sightings to build a multivariate or univariate regression model, we built a so-called "stratified model" by fitting a model with no covariates. We predicted this model across the sub-region, resulting in the same density estimate at all locations.

For comparison to other modeling efforts, such as those from the NOAA stock assessment reports (SARs), we produced total abundance estimates for each season by computing the mean density of all pixels in the study area and multiplying by its area. Caution should be exercised when comparing our abundance estimates to NOAA's, as our study area and seasons often differed from NOAA's.

In tandem with the final density and abundance predictions, we also produced uncertainty estimates, as follows. First, when predicting each of the models, we produced standard error (SE) images paired with the density images using the `se.fit=TRUE` parameter to the mgcv `predict()` function. We then averaged these similar to how we averaged the density images, producing mean SE images at monthly or seasonal resolution, as appropriate, and computed corresponding coefficient of variation (CV) images.

To estimate CVs that expressed how close our total abundance estimates were to the actual abundance of the modeled taxa, we applied the "delta method" described by Miller et al. (2013), Appendix B, section 3.2.

We caution that our SEs and CVs underestimate the true uncertainty of our models, as they only reflect the uncertainty of the spatial modeling step of the workflow. Traditionally, uncertainty estimates for cetacean density models also incorporate the uncertainty of the detection functions and the g(0) estimates. For our complex study, which incorporated two platforms, many disparate surveys, and several g(0) estimates per model, the only viable method described in the literature for integrating these additional sources of uncertainty was bootstrapping. But with over 100,000 segments and thousands of predictions (in the case of models having contemporaneous covariates), bootstrapping was computationally prohibitive with the time and resources we had available. This remains an important priority for future work.

2.3.4.3. AFTT spatial models

Estimating cetacean densities in the AFTT area required predicting beyond the surveyed regions (geographical extrapolation) and, in some cases, predicting beyond the range of environmental covariates; this second type of 'environmental' extrapolation is more speculative (Mannocci et al. 2015). To increase the reliability of our extrapolations in the AFTT area we (1) incorporated survey data from various regions of the North Atlantic, (2) carefully selected candidate environmental covariates and (3) designed parsimonious habitat models. Furthermore, we developed a qualitative index of uncertainty to differentiate geographical *versus* environmental extrapolation in the AFTT area.

In EC and GOM, line-transect surveys mainly occurred within 200 nautical miles from the shore. To compensate for the lack of survey coverage in offshore waters which comprise most of the AFTT area, we considered the incorporation of survey data from other regions of the North Atlantic basin, including the Caribbean, the European Atlantic and the mid-Atlantic ridge (Fig. 7). After examining taxon-environment relationships in these different regions, and with support from species experts, decisions were made to incorporate survey data from outside the EC and GOM. These decisions were made on a per-taxon basis and are reported in the accompanying reports for the AFTT models).

To reduce the amount of environmental extrapolation, we carefully selected candidate environmental covariates (Table 2). Specifically, we favored covariates with a broad range of values covered by the surveys (for example we avoided distances from the coast or isobaths) and considered biological covariates with direct effects on cetacean distributions. In the AFTT models, all covariates were monthly climatologies and consequently only climatological models were developed. We believe the climatological resolution is more appropriate to fit habitat models in the AFTT area than the contemporaneous resolution for three main ecological reasons. First, because of the close coupling between space and time in the pelagic marine environment (Haury et al. 1978), it is meaningful to consider a large temporal scale when modeling cetacean habitats at a large spatial scale. Second, correlating cetacean distributions with average environmental conditions (*i.e.* using climatological covariates), is more likely to provide generic relationships that would extrapolate well outside of surveyed regions. Third, increasing evidence for cultural transmission in whale and dolphin societies (Rendell and Whitehead 2001) advocates for an inter-generational knowledge of areas where environmental conditions are on average favorable, providing support for the use of climatological variables in habitat models. For similar reasons, climatological covariates have previously been used to develop extrapolations in other pelagic regions (Mannocci et al. 2015). Therefore, we only fitted climatological models in the AFTT area.

We relied on a multivariate regression approach similar to the one used to provide density predictions in the EC and GOM, but with a slightly different modeling philosophy. For each modeled taxon, seasonal or year-round models were built (decisions are reported in the accompanying reports for the AFTT models), but a single GAM was developed to predict densities across the entire AFTT area. Parsimonious models were fitted to model smooth ecological relationships and provide generic predictions. This included limiting models to 4 predictor variables and 3 degrees of freedom with a similar philosophy to that described in Mannocci et al. (2015). For each taxon, models with all possible combinations of 4 non-correlated covariates were fitted and the model with the lowest value of the Akaike criterion was retained. For taxa with fewer available sightings (in general less than 100), univariate models were fitted (*e.g.* Clymene dolphin modeled with SST only) or models with a limited number of covariates were fitted (*e.g.* white beaked dolphin modeled with 2 covariates). All models were fitted in the R *mgcv* package with the same user-defined parameters as in the EC and GOM models.

The retained model was used to predict monthly climatologies of densities. Predictions were delivered to the Navy at a monthly time step when support for the monthly variations was present in the literature or following expert recommendations. In most cases monthly climatologies of densities were subsequently averaged on a year-round or seasonal basis to obtain mean prediction maps (these per-taxon decisions are reported in the accompanying documentation). For taxa for which less than 5 sightings were reported the Gulf of Mexico, a post-hoc procedure was applied to affect a zero density to pixels in the entire Gulf of Mexico (including non U.S waters).

For taxa for which insufficient sightings were available and for North Atlantic right whale, we produced a so-called "stratified" model rather than a spatial model. (Because the North Atlantic right whale has a very limited present-day distribution compared to its historical range, fitting a habitat model to sightings from the East Coast and extrapolating it to the AFTT area would most probably result in an overestimation of their current distribution and abundance. Therefore, a stratified model was developed to produce a density estimate for this species that reflects the present-day distribution.) For each taxon, an area of assumed presence was delimited using the presented environmental covariates as well as latitude based on information from the literature (see the accompanying taxon-specific reports for the AFTT). A stratified density estimate was provided in this area and the taxon was assumed to be absent in the rest of the AFTT area.

Abundance estimates were produced for the entire AFTT area by computing the densities of all pixels in the study area and multiplying its area. No attempt was made to estimate the uncertainty associated with these abundance estimates and caution is warranted when interpreting them, especially because they may obtained by some degree of environmental extrapolation (see the following section).

Despite our efforts to minimize it, there were some cases in which environmental extrapolation could not be avoided in order to provide predictions in the entire AFTT area. To reflect the various quality of predictions in the AFTT area, we provided monthly maps of qualitative uncertainty to differentiate: (1) surveyed regions (*i.e.* the EC and the GOM where quantitative uncertainty was estimated from the models fitted in these two regions), (2) areas where we extrapolated beyond the surveyed regions and (3) areas where we extrapolated beyond the covariate ranges. A highest uncertainty is associated with this later type of environmental extrapolation. Mean (seasonal or year round) maps of qualitative uncertainty were computed from the monthly maps (if environmental extrapolation was performed in a pixel for one month, the mean map showed environmental extrapolation in this pixel). Future research should focus on developing a qualitative index of uncertainty based on biogeographic provinces (*i.e.* assigning a higher uncertainty to our extrapolations in biogeographic provinces where no survey effort was available).

2.4. Production of the Phase III NMSDD

The Phase III NMSDD is an ArcGIS geodatabase containing the density predictions in the format and with the metadata desired by the Navy. After density predictions were produced, reviewed, and finalized, we produced the NMSDD and delivered it to the Navy. The final version of the NMSDD for this project was dated 25 January 2015. A minor revision was delivered on 18 February 2015; this revision provided predictions for a small number of polygons that were missing values in the 25 January 2015 version.

In the NMSDD, the density predictions are given as polygon feature classes. All feature classes appear under the AFTT feature dataset. They are 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. There are always 12 feature classes for each taxon. In the case where we did not produce predictions at a monthly time-step (i.e. we only produced seasonal or year-round predictions), the values of each layer will be the same for each month of the season (or for the entire year, for year-round models).

Each feature class uses the WGS 1984 equirectangular coordinate system (a.k.a. "geographic projection" in ArcGIS parlance) and spans the exact extent of the AFTT study area polygon provided by the Navy (PhaseIII_StudyArea_20140828.shp) in August 2014. We gridded that polygon into square cells ~0.0988° on a side; cells of this size cover approximately 100 km^2 (the target scale for predictions) at 34°N (a latitude roughly within the Navy VACAPES area, biased south a bit on to reduce error in the Gulf of Mexico). We excluded Chesapeake Bay and estuaries south of it from the grid (including in the Gulf of Mexico), leaving these as irregular polygons.

2.4.1. Production process

We produced each monthly prediction for each modeled taxon as follows. First, we produced raster predictions for the appropriate seasonal AFTT, EC, and GOM models for the taxon. (If we did not fit an EC or GOM model because the taxon was absent from that area (e.g. harbor porpoises in the GOM), we did not produce an EC or GOM prediction, for obvious reasons.) These rasters utilized a common Albers equal area projection optimized for the AFTT and a 10x10 km cell size and were snapped such that the EC and GOM rasters precisely covered a subset of the AFTT cells.

Next, we overlaid the cells predicted by the AFTT model with those predicted by the two regional models, except in certain circumstances. If we fitted a DSM for the EC or GOM, we always overlaid the AFTT predictions with it. If we did not fit a model at all for a region (e.g. harbor porpoises in the GOM), we did not overlay the AFTT predictions for that region. Finally, for certain taxa, if we fitted a stratified model for the EC or GOM but a DSM for the AFTT, we did not overlay the AFTT predictions with those from the stratified model. For example, for *Kogia* whales, we were able to fit a DSM for the AFTT and GOM but not the EC. We could only fit a stratified model for the EC. In this case, we did not overlay the AFTT predictions with those from the stratified EC model.

The result of the procedure above was a single density raster for that taxon and month. Next, we spatially extrapolated the edges of this raster five cells outward by applying five times in succession the ArcGIS Analyst Focal Mean tool with a 3x3 rectangular neighborhood. We did not overwrite the original density values with the results of the Focal Mean tool; we only used it to fill in five cells around the extent of the original prediction.

Then, to obtain density values for all NMSDD polygon features, except those of Chesapeake Bay and estuaries south of it, we sampled the spatially-expanded density raster at the polygons' centroids using bilinear interpolation. Throughout this process, we preformed the geoprocessing steps necessary to determine the source model that produced the prediction used for each polygon feature.

For estimates 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 or seal species that regularly inhabits these estuaries. (Manatees are marine mammals that may also inhabit some of these estuaries but our analysis did not include manatees.) We obtained estimates for bottlenose dolphin density for these estuaries as described in an accompanying report dedicated specifically to this topic. We assumed that the density of all other taxa was zero in these estuaries.

For estuaries north of Chesapeake Bay, we obtained estimates for all taxa including bottlenose dolphin via spatial extrapolation (by sampling the density raster that was expanded by 5 cells with the Focal Mean tool). In a future version of our models, we may replace these with estuary-specific estimates, should any become available in the scientific literature or elsewhere.

2.4.2. Fields of the NMSDD

Table 3

Fields of the NMSDD polygon feature classes.

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.
MONTH_NAME	TEXT	Month name (e.g. “January”, “February”, and so on).
STUDY	TEXT	A shorthand citation for the data source; always “Duke Density Project 2014” 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 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: • Assumed absent – we assumed the density was zero • External study – we obtained the density from an external study; this was only done for estuaries • Habitat based density model – we predicted the density from a DSM • Spatial extrapolation – the value was spatially extrapolated from nearby cells • Uniform density model – we predicted the density from a stratified model
DENSITY	DOUBLE	Predicted density for the feature, as individuals km^{-2}.
UNCERTAINTY	DOUBLE	Coefficient of variation (CV) that estimates how close the predicted density is to the true density. Unit-less. Only available when the STRATUM is EC or GOM or an estuary for which a CV was available; null otherwise (e.g. when STRATUM is AFTT). Note when STRATUM is EC or GOM, the CV only reflects the uncertainty of the spatial model; it does not incorporate other known sources of uncertainty, such as the detection functions or

		g(0) estimates.
UNCER_QUAL	TEXT	Qualitative uncertainty for the predicted density: • AFTT model – the feature was predicted by the AFTT model and all of the covariates were within the range used to fit the model, but caution is warranted because the feature was beyond the well-surveyed EC and GOM areas, and therefore the prediction represents a geographic extrapolation of relationships that occurred there. Because of this, no CV is given by the UNCERTAINTY field. • 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 beyond that above, because not only did the prediction occur beyond well-surveyed areas, it also represents an extrapolation of environmental relationships that occurred there. No CV is given by the UNCERTAINTY field. • Assumed absent – we assumed the density was zero and cannot offer a CV with the UNCERTAINTY field (but suspect that CV is also zero). • Regional model – the uncertainty of the predicted density is represented quantitatively by the CV given by the UNCERTAINTY field.
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. Surveys

In the EC and GOM areas, we established a collaboration with five surveyor organizations and aggregated 954,000 linear km (5250 h) of aerial and 136,000 linear km (8675 h) of shipboard survey effort (Table 4, Figs. 5, 6). To this, for consideration in the AFTT models, we added 15,000 linear km of aerial and 39,000 linear km of shipboard survey effort from other regions of the North Atlantic (Table 5; Fig. 7). For all surveys, we excluded segments in which observers were “off effort”, and those that paralleled the shoreline, occurred in estuaries or other areas beyond our study area, or were initiated in response to reports of animals (e.g. flights directed at whales entangled in fishing gear).

Table 4

Visual line-transect survey programs used in density analysis for the EC and GOM areas. Most programs comprised several surveys; for brevity we do not list them all here. Note that the 2010-2014 AMAPPS surveys were not included; NOAA did not start providing these surveys to us until February 2015, which was too late to be incorporated into our models. Surveyors: NEFSC = NMFS Northeast Fisheries Science Center, NJDEP = New Jersey Department of Environmental Protection, SEFSC = NMFS Southeast Fisheries Science Center, UNCW = University of North Carolina at Wilmington, VAMSC = Virginia Aquarium and Marine Science Center. Length and hours are the cumulative linear distance and duration observers were on effort.

Region	Platform	Surveyor	Survey program	Period	Length (1000 km)	Hours	Reference
EC	Aerial	NEFSC	Marine mammal abundance surveys	1995-2008	70	412	Palka, 2006
			Right Whale Sighting Survey (NARWSS)	1999-2013	432	2330	Cole et al., 2007
			NARWSS harbor porpoise survey	1999	6	36	T.V.N. Cole, pers. comm.
		NJDEP	NJ Ecological Baseline Study	2008-2009	11	60	Geo-Marine, Inc., 2010
		SEFSC	Mid-Atlantic Tursiops Surveys (MATS)	1995, 2004-5	35	196	L. Garrison, pers. comm.
			Southeast Cetacean Aerial Surveys (SECAS)	1992, 1995	8	42	Blaylock and Hoggard, 1994
		UNCW	Cape Hatteras Navy surveys	2011-2013	19	125	Read et al., 2014
			Jacksonville Navy surveys	2009-2013	66	402	Read et al., 2014
			Marine mammal surveys, 2002	2002	18	98	Torres et al., 2005
			Onslow Bay Navy surveys	2007-2011	49	282	Read et al., 2014
			Right whale surveys, 2005-2008	2005-2008	114	586	W.M. McLellan, pers. comm.
		VAMSC	VA Wind Energy Area surveys	2012-2014	9	53	Mallette et al., 2014
			Total:	1992-2014	837	4622	
	Shipboard	NEFSC	Marine mammal abundance surveys	1995-2004	16	1143	Palka, 2006
		NJDEP	NJ Ecological Baseline Study	2008-2009	14	836	Geo-Marine, Inc., 2010
		SEFSC	Marine mammal abundance surveys	1992-2005	28	1731	Mullin and Fulling, 2003
			Total:	1992-2009	58	3710	
GOM	Aerial	SEFSC	GOMEX92-96	1992-1996	27	152	Blaylock and Hoggard, 1994
			GulfCet I	1992-1994	50	257	Davis and Fargion, 1996
			GulfCet II	1996-1998	22	124	Davis et al., 2000
			GulfSCAT 2007	2007	18	95	L. Garrison, pers. comm.
			Total:	1992-2007	117	628	
	Shipboard	SEFSC	Oceanic CetShip	1992-2001	49	3102	Mullin and Fulling, 2004
			Shelf CetShip	1994-2001	10	707	Fulling et al., 2003
			Marine mammal abundance surveys	2003-2009	19	1156	Mullin, 2007
			Total:	1992-2009	78	4965	

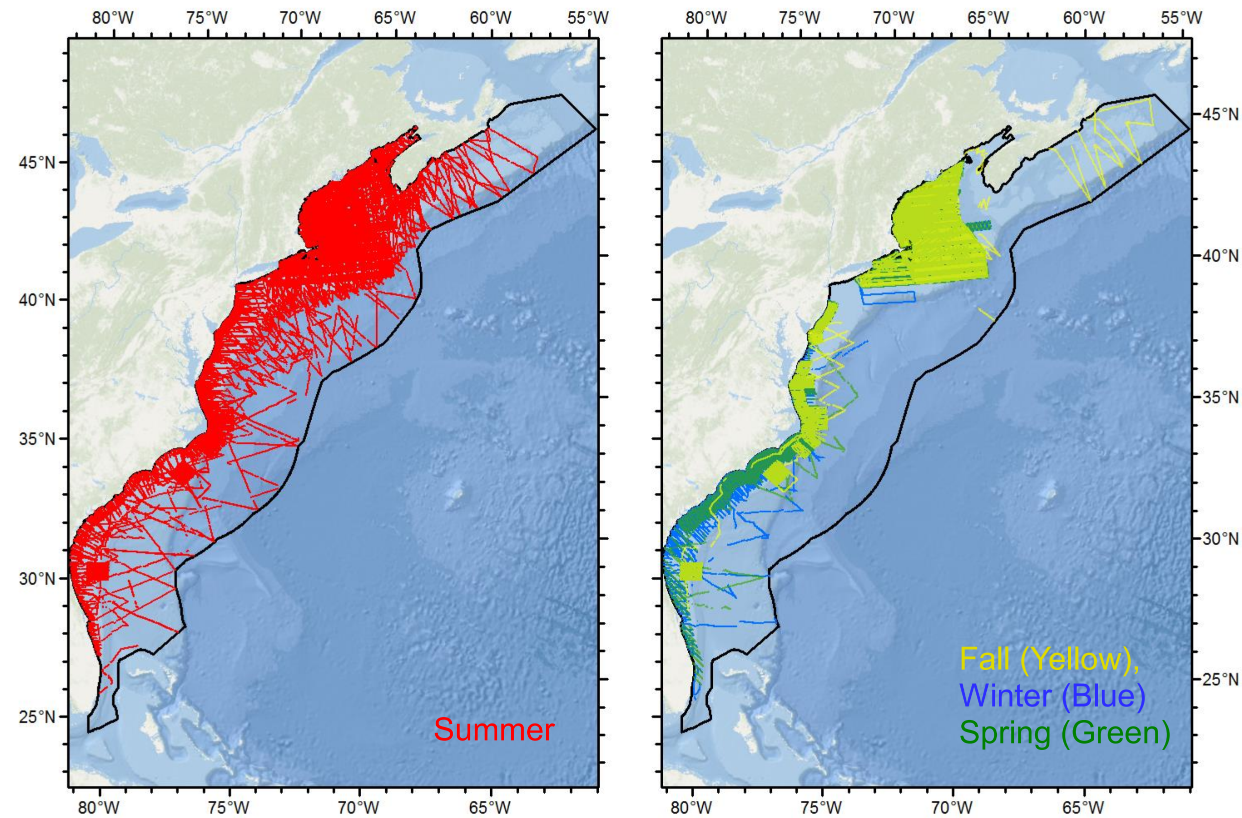

Fig 5. Tracklines of surveys utilized in the EC region. Summer (left panel) is shown separately from the other seasons (right panel) to highlight the the seasonal bias in survey effort off the continental shelf.

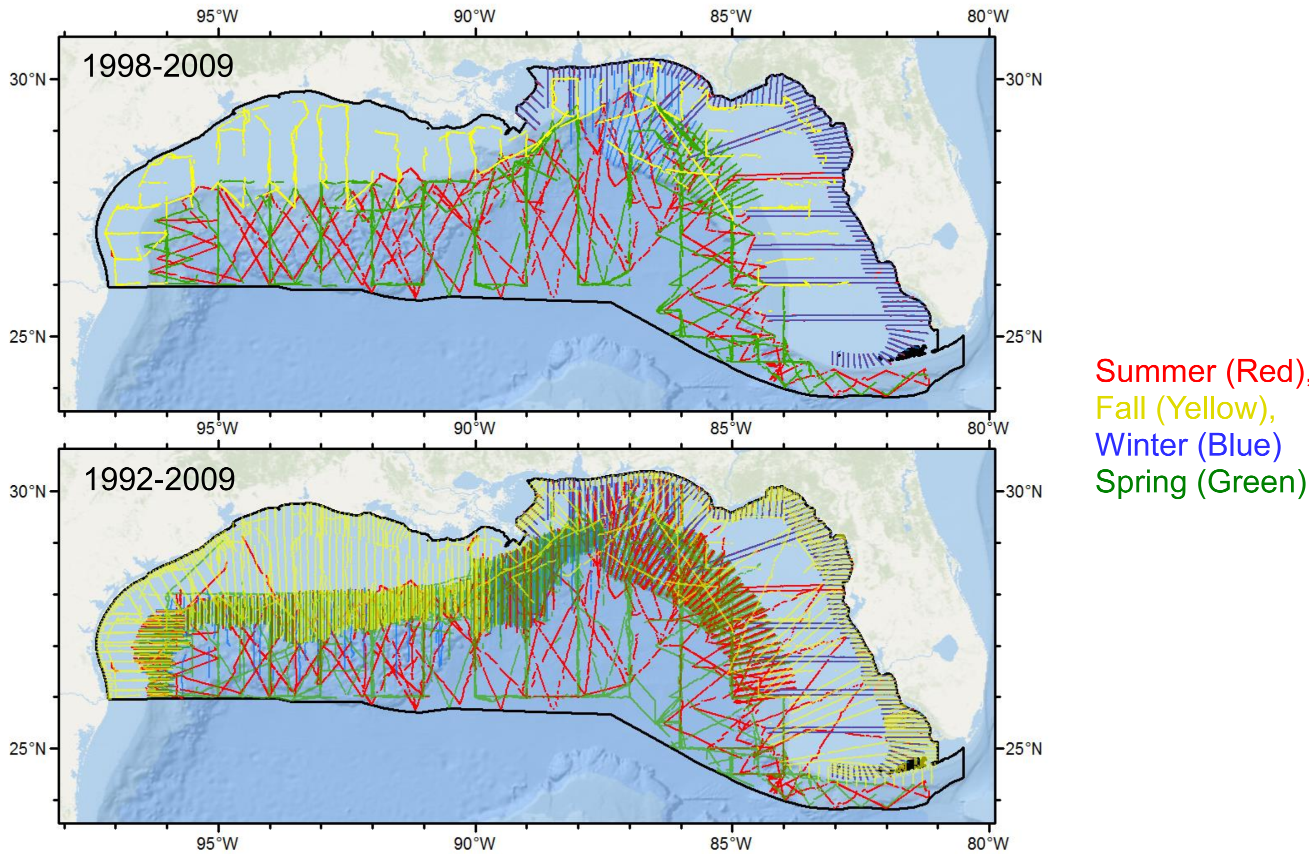

Fig 6. Tracklines of surveys utilized in the GOM region. The data from 1998 and later (upper panel) only contitute 32% of the data from 1992 and later (lower panel), highlighting the age bias in the data available in the GOM. Note also the seasonal biases, e.g. the western continental shelf was only surveyed in fall; the off-shelf area was mainly surveyed in spring and summer.

Table 5

Surveys considered by the AFTT models, in addition to those considered by the EC and GOM models.

Region	Platform	Surveyor	Survey program	Period	Length (linear km)	Reference
Caribbean	Shipboard	NOAA	Marine mammal visual and acoustic surveys in the eastern and southern Caribbean Sea, Puerto Rico and the Virgin Islands	January – March 1995, February – April 2000	8,975	Swartz et al 2001, 2002
	Aerial	University of La Rochelle	REcensement des Mammiferes Marins et autre megafaune pelagique par Observation Aerienne (REMMOA) in the French Antilles	February – March 2008	8,275	Mannocci et al. 2013

	Aerial	University of La Rochelle	REcensement des Mammiferes Marins et autre megafaune pelagique par Observation Aerienne (REMMOA) in French Guiana	September – October 2008	7,014	Mannocci et al. 2013
European Atlantic	Shipboard	Multiple European partners	Small Cetacean Abundance in the North Sea and adjacent waters-II (SCANS-II)	July 2005	17,942	Hammond et al. 2013
	Shipboard	Multiple European partners	Cetacean Offshore Distribution and Abundance in the European Atlantic (CODA)	July 2007	9,584	Hammond et al. 2009
Mid Atlantic Ridge	Shipboard	Mid-Atlantic Ridge Ecology Program (MAR-ECO)	Mid-Atlantic Ridge Ecology Program (MAR-ECO)	June – July 2004	2,424	Waring et al. 2008

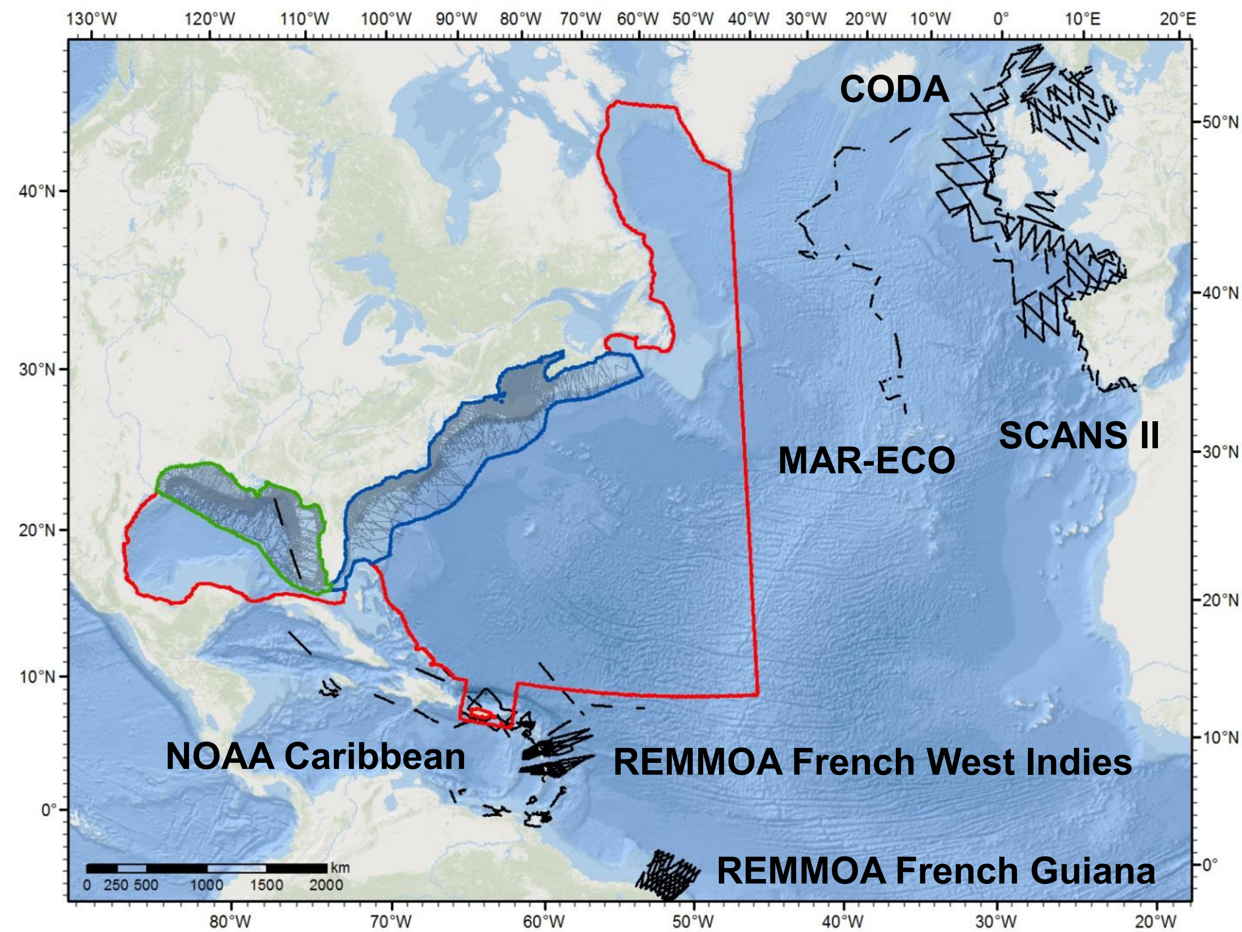

Fig 7. Surveys outside the GOM and EC regions that were considered in fitting models for the AFTT region.

3.2. *Modeled taxa*

Dolphins and porpoises were sighted most frequently, followed in the EC by large whales and in the GOM by medium and small whales (Table 6). The large majority of large whale, dolphin, and porpoise sightings 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 identifying pilot whales, beaked whales, and *Kogia* species. Between 7-29% of cetacean sightings (depending on taxonomic group and location) were too ambiguous to be retained for analysis, resulting in an underestimation of abundance.

Seals were only sighted in the EC region. Approximately two-thirds of all seal sightings were the ambiguous "unidentified seal". No seal sightings were omitted due to ambiguity.

Table 6

Sightings retained and omitted, by region and taxonomic group. Fully-resolved sightings had a complete species identification. Retained ambiguous sightings were classified to a species, or used in a guild model (see text). Omitted sightings were too ambiguous to be used in the analysis (e.g. "large whale") and resulted in an underestimation of abundance. The last column roughly characterizes the potential underestimation.

		Sightings retained			
Region	Taxonomic group	Fully-resolved	Ambiguous	Sightings omitted	Omitted/ retained ratio (%)
EC	Large whales	8248	658	1125	13%
	Medium and small whales	897	1023	137	7%
	Dolphins and porpoises	11074	944	3475	29%
	Seals	503	1057	0	0%
GOM	Large whales	378	8	38	10%
	Medium and small whales	205	271	44	9%
	Dolphins and porpoises	3347	165	503	14%

The sighted species comprised eight large whale, 14 medium and small whale, 12 dolphin, one porpoise, and at least two seal species (Table 7). Of these, we modeled 26 with species-specific models and grouped the rest into four guilds, for a total of 30 modeled taxa. For each of the guilds, too few fully-resolved sightings were reported to build a classifier from them. The "beaked whales" guild comprised five species in the EC and three in the GOM. The "*Kogia* whales" guild comprised two species in both regions. The "pilot whales" guild comprised two species. Only short-finned pilot whales occur in the GOM, but because we lacked the sightings necessary to build a classification model for the ambiguous sightings in the EC, we were forced to leave the ambiguous EC sightings unclassified, making an AFTT-wide short-finned-pilot-whale model intractable. Thus, although we only modeled the "pilot whales" guild for the Navy's NMSDD, model users may safely assume that predictions in the Gulf of Mexico are all of short-finned pilot whales. Finally, the "seals" guild comprised at least two species—gray seals and harbor seals—but probably included other species (e.g. harp seals) for which no definitive sightings were reported.

We built classifiers for four cases of ambiguous sightings that resolved taxonomic identifications to pairs of species. 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 a predictors. For the fourth—"melon-headed or pygmy killer whale"—we used group size and longitude. Across all cases, the AUC statistic of the classifiers ranged from 0.94-1.00 and the K statistic ranged from 0.61-0.79, indicating all classifiers performed well. Other details of these models may be found in the accompanying taxon-specific reports for the EC and GOM regions.

Three other cases of ambiguous sightings we handled specially. First, for sightings of "spotted dolphin", which could be either Atlantic spotted dolphin or pantropical spotted dolphin, we lacked sufficient sightings of pantropical spotted dolphins to build a classification model. These all occurred in a northerly part of the EC region near sightings of Atlantic spotted dolphins, so we treated them as such. Sightings of "Bryde's or sei whale" in the EC also lacked sufficient fully-resolved sightings to be classified. Bryde's whales are very rare in this region and the ESA lists sei whales as endangered. As a precautionary measure, we included these ambiguous sightings in both species' models. Given the rarity of these species, we preferred to avoid underestimating them (e.g. by omitting the ambiguous sightings from our analysis), so that parties using our models to estimate impacts to these populations would avoid underestimating those impacts. Finally, we classified GOM sightings of "Bryde's or sei whale" and "*Balaenoptera* spp." as Bryde's whales, following Maze-Foley and Mullin (2006), who believed that all of these were Bryde's whales.

Table 7

Modeled taxa, with counts of sightings reported in the EC and GOM regions. As with Table 6, we ordered the taxa in four groups: large whales, medium and small whales, dolphins and porpoises, and seals. Notes: (1) We classified these ambiguous sightings as the modeled taxon from environmental, day of year, or group size covariates (see text). (2) In the EC, we counted ambiguous "Bryde's or sei whale" sightings in both the Bryde's whale and sei whale models, as a precautionary measure (see text). (3) In the GOM, we classified ambiguous "Bryde's or sei whale" and "*Balaenoptera* spp." sightings as Bryde's whales, following Maze-Foley and Mullin (2006). (4) We modeled these species as a guild; too few fully-resolved sightings were reported to build a classifier from them. (5) Only short-finned pilot whales occur in the GOM, but we did not build a short-finned pilot whale model for the NMSDD (see text). (6) We lacked sufficient pantropical spotted dolphin sightings to fit a classification model for these ambiguous sightings; they all occurred in a northerly area near sightings of Atlantic spotted dolphins, so we treated them as such. (7) For harbor porpoises and seals, we restricted the analysis to data collected when the Beaufort sea state was 2 or less, following Hammond et al. (2013).

			Sightings		
Modeled taxon	Identification reported by observer		EC	GOM	Note
Blue whale	Blue whale		8		
Bryde's whale	Bryde's whale			17	
	Bryde's or sei whale		4	4	2,3
	Balaenoptera spp.			4	3
		Total:	4	25	
Fin whale	Fin whale		1690	1	
	Fin or sei whale		410		
		Total:	2100	1	
Humpback whale	Humpback whale		2732		
Minke whale	Minke whale		1031		
North Atlantic right whale	North Atlantic right whale		1634		
Sei whale	Sei whale		585		
	Bryde's or sei whale		4		2
	Fin or sei whale		232		1
		Total:	821		
Sperm whale	Sperm whale		501	360	
Beaked whales (guild)	Blainville's beaked whale		3	2	
	Cuvier's beaked whale		46	22	
	Gervais' beaked whale		3	1	
	Sowerby's beaked whale		14		
	True's beaked whale		3		
	Mesoplodon spp.		137	42	
	Mesoplodon or *Ziphius* spp.		20	49	

	Total:	226	116	4
False killer whale	False killer whale	2	19	
Killer whale	Killer whale	4	16	
Kogia whales (guild)	Dwarf sperm whale	4	16	
	Pygmy sperm whale	3	41	
	Dwarf or pygmy sperm whale	24	167	
	Total:	31	219	4
Melon-headed whale	Melon-headed whale	4	25	
	Melon-headed or pygmy killer whale		4	1
	Total:	4	29	
Northern bottlenose whale	Northern bottlenose whale	4		
Pilot whales (guild)	Long-finned pilot whale			
	Short-finned pilot whale	86	50	5
	Long-finned or short-finned pilot whale	823		
	Total:	909	50	4
Pygmy killer whale	Pygmy killer whale		18	
	Melon-headed or pygmy killer whale		9	1
	Total:		27	
Atlantic spotted dolphin	Atlantic spotted dolphin	795	312	
	Atlantic spotted or bottlenose dolphin	33	35	1
	Atlantic or pantropical spotted dolphin	10		6
	Total:	838	347	
Atlantic white-sided dolphin	Atlantic white-sided dolphin	1670		
	Atlantic white-sided or short-beaked common dolphin	596		
	Total:	2266		
Bottlenose dolphin	Bottlenose dolphin	4603	1733	
	Atlantic spotted or bottlenose dolphin	54	116	1
	Total:	4657	1849	
Clymene dolphin	Clymene dolphin	11	78	
Fraser's dolphin	Fraser's dolphin	2	5	
Harbor porpoise	Harbor porpoise	2018		7
Pantropical spotted dolphin	Pantropical spotted dolphin	17	719	
Risso's dolphin	Risso's dolphin	721	282	
Rough-toothed dolphin	Rough-toothed dolphin	11	51	
Short-beaked common dolphin	Short-beaked common dolphin	938		
	Atlantic white-sided or short-beaked common dolphin	251		1
	Total:	1189		
Spinner dolphin	Spinner dolphin	2	71	
Striped dolphin	Striped dolphin	195	92	
White-beaked dolphin	White-beaked dolphin	12		
Seals (guild)	Gray seal	31		
	Harbor seal	472		
	Unidentified seal	1057		

Total:	1560	4,7

3.3. Density models produced for the NMSDD

Of the 30 taxa we modeled, only four were modeled with purely stratified models: blue whale, false killer whale, Fraser's dolphin, and northern bottlenose whale (Table 8). These were all species with so few sightings (Table 7) that we could not attempt even a univariate spatial model, except false killer whale, for which we attempted univariate models in the GOM but every variable was dropped, indicating either a truly homogeneous distribution or that our covariates do not correlate well with patterns in false killer whale distribution.

Five other taxa included a stratified model for at least one season or sub-region: fin whale, minke whale, sei whale, killer whale, and seals. For fin whales, the stratified model was in the GOM. Although this sighting was extralimital, our methodology was to fit models for all on-effort sightings that were reported. In the case of extralimital sightings, this was done to account for the very low but non-zero probability of encountering animals beyond their usual range. Fin whales were the only case for which this occurred. Please see the accompanying taxon-specific report for fin whales in the Gulf of Mexico for more discussion.

For minke whales, we lacked sufficient survey effort to confidently model their off-shelf distribution south of the Gulf Stream in winter. For sei whales, too few sightings were reported in winter to fit a DSM, presumably because by that time nearly all of the whales have departed the surveyed feeding grounds for unsurveyed breeding grounds. For killer whales, which exhibit a circumglobal distribution but comprise several ecotypes with different ecology (Forney and Wade, 2006), we lacked sufficient sightings to confidently model them in the greater AFTT area, although we did fit a univariate spatial model in the GOM to account for their off-shelf distribution there. Finally, for seals, we encountered difficulty fitting a reasonable DSM in the greater AFTT area, so we opted for a stratified model there.

The AFTT models for nearly all of the 30 modeled taxa utilized surveys from outside the AFTT region: 25 utilized surveys from the Caribbean, 12 utilized the mid-Atlantic ridge survey, and 8 utilized surveys from Europe.

Thanks to the increased amount of survey data available, this project yielded an improvement over the pioneering NODE studies (DON 2007a-c) in the number of taxa modeled and the spatiotemporal resolutions of the resulting predictions. We provided models for all taxa, while the NODE studies left 5 unmodeled in the NODE "east coast north" and 11 unmodeled in the NODE "east coast south" study areas. The NODE studies modeled 7-10 taxa with stratified models, depending on the region; we modeled only 4 taxa with stratified models. Finally, the NODE studies produced seasonal predictions for 6 taxa in the EC: 5 with DSMs developed by the NODE authors and 1 derived from the literature (North Atlantic right whales). We produced monthly predictions in the EC region for 11 taxa and seasonal predictions for 1 (seals).

In contrast, the NODE study for the Gulf of Mexico produced seasonal DSMs for 4 taxa while we produced none. As noted in section 2.3.4.2, our research suggested that none of the species there were reported to undertake large seasonal movements, and we lacked sufficient survey coverage during different parts of the year to detect more subtle movements. Our philosophy in this situation was to fit year-round DSMs. In contrast, the philosophy of the NODE studies was to fit separate seasonal models whenever sufficient data were available, using the same season definitions for all species.

3.4. Differences between the NMSDD and regional (EC and GOM) predictions produced for other users

We are making the EC and GOM predictions developed as part of this project available for independent regional use outside of our contract with the Navy. These regional predictions, sometimes known as the "CetMap" or "CetSound" models, may be released and maintained in several locations, including but not limited to our own websites, the NOAA CetSound website, the NOAA/BOEM Marine Cadastre website, and the data portals for regional planning bodies such as the Northeast Regional Ocean Council (NROC) and the Mid Atlantic Regional Ocean Council (MARCO).

The predictions that appear in the Navy's NMSDD differ from these stand-alone regional predictions in two important respects. First, the NMSDD was produced as a geodatabase of polygon feature classes, as described in section 2.4, while the stand-alone regional predictions are being made available as GIS-compatible rasters. The NMSDD uses an equirectangular coordinate system (a.k.a. a "geographic projection" in ArcGIS parlance), while the stand-alone regional rasters use the Albers equal area projection in which the analysis was performed. Within the EC and GOM regions, the NMSDD contains a grid of polygons that closely but not exactly matches the EC and GOM rasters; please see section 2.4 for details. Finally, the units of the NMSDD predictions are individuals / km^2, while the units of the regional rasters are individuals / 100 km^2.

Second, the values of the regional cells for certain taxa are different in the NMSDD, as follows. In the NMSDD, for certain taxa for which we able to fit a DSM for the AFTT but not for one of the nested regions (due to not having sufficient sightings in the region), we predicted the regional cells with the AFTT DSM rather than the stratified model we developed for the region. For example, for *Kogia* whales, we were able to fit a DSM for the AFTT and GOM but not the EC. We could only fit a stratified model for the EC. In the NMSDD, we predicted the EC cells using the AFTT DSM rather than the stratified EC model, which we are releasing as an independent stand-alone model for *Kogia* in the EC.

This situation occurred mainly for taxa that were common in the GOM but rare in the EC, for which we used the AFTT model to predict the EC cells in the NMSDD but also developed stand-alone stratified models for the EC. In our view, both predictions—those from the AFTT DSM in the NMSDD, and those from the regional stratified models that we're releasing stand-alone—are suitable for management of marine mammals. At the present time we do not recommend one over the other for non-Navy users who are only concerned with activities occurring in EC or GOM regions; either are OK for these users, although we may revise our view in the future. For the Navy, which is specifically concerned with the entire AFTT area, we recommend the NMSDD predictions be used to minimize edge effects that result when overlaying stratified regional models onto DSMs for the AFTT region.

4. Accompanying taxon-specific reports

As mentioned above, this main report is accompanied by reports that document the EC, GOM, and AFTT models for each modeled taxon. These reports begin with the words "East Coast", "Gulf of Mexico", and "AFTT", respectively. Together, they comprise several thousand pages of maps, plots, tables, statistical output, and narrative text describing certain modeling decisions and interpreting the results. For bottlenose dolphins specifically, there is also a report documenting how we obtained density estimates for the various estuaries requested by the Navy that were beyond the spatial extent of our EC and GOM models.

We delivered the final versions of these reports to the Navy in June of 2015.

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 and GOM regional models, describing the methodology through section 2.3.4.2 of this report and presenting results for the EC and GOM models. While this manuscript is in preparation, it may be cited:

> Roberts JJ, Best BD, Mannocci L, Halpin PN, Palka DL, Garrison LP, Mullin KD, Cole TVN, McLellan WM (in prep) Habitat-based cetacean density models for the Northwest Atlantic and Northern Gulf of Mexico.

The second will focus on development of and results for the AFTT spatial models, elaborating particularly on section 2.3.4.3 of this report. While this manuscript is in preparation, it may be cited:

> Mannocci L, Roberts JJ, Miller DL, Halpin PN (in prep) From surveyed to unsurveyed areas: extrapolating cetacean densities in the offshore North Atlantic.

Table 8

Summary of models developed. Regional abundances are the mean for the specified season and are given only for the EC and GOM models. The CVs estimate how close the abundance estimates are to the true abundances, but only account for the uncertainty in the spatial model. They do not account for other known sources of uncertainty, such as in the detection functions or g(0) estimates (see section 2.3.4.2). For the segments used in the AFTT model, see Table 6 and Fig 7. EC = east coast, GOM = Gulf of Mexico, CAR = Caribbean, MAR = Mid-Atlantic Ridge, EU = Europe.

Modeled taxon	Region	Season	Months	Model type	Prediction resolution	Regional abundance	CV	Segments used in AFTT model
Blue whale	AFTT	Year-round		Stratified	Year-round			EC MAR EU
Bryde's whale	AFTT	Year-round		DSM	Year-round			EC GOM CAR MAR
	GOM	Year-round		DSM	Year-round	66	0.24	
Fin whale	AFTT	Year-round		DSM	Monthly			EC GOM CAR
	EC	Year-round		DSM	Monthly	4633	0.08	
	GOM	Year-round		Stratified	Year-round	9	1.01	
Minke whale	AFTT	Year-round		DSM	Year-round			EC GOM CAR MAR EU
	EC	Winter	Nov-Mar	DSM	Monthly	740	0.23	
		Summer	Apr-Oct	DSM & stratified	Monthly	2112	0.05	
Humpback whale	AFTT	Winter	Dec-Mar	DSM	Seasonal			EC GOM CAR
	EC	Winter	Dec-Mar	DSM	Monthly	205	0.16	
	AFTT	Summer	Apr-Nov	DSM	Seasonal			EC GOM CAR
	EC	Summer	Apr-Nov	DSM	Monthly	1637	0.07	
North Atlantic right whale	AFTT	Year-round		DSM	Year-round			EC: depth<200m & lat 25-50°N
	EC	Winter	Nov-Feb	DSM	Monthly	535	0.45	
		Spring	Mar-Apr	DSM	Monthly	416	0.12	
		Summer	May-Jul	DSM	Monthly	379	0.07	
		Fall	Aug-Oct	DSM	Monthly	334	0.25	
Sei whale	AFTT	Winter	Nov-Mar	Stratified	Seasonal			EC
		Summer	Apr-Oct	DSM	Seasonal			EC GOM CAR MAR
	EC	Winter	Dec-Mar	Stratified	Monthly	98	0.25	
		Spring	Apr-Jun	DSM	Monthly	627	0.14	
		Summer	Jul-Sep	DSM	Monthly	717	0.30	
		Fall	Oct-Nov	DSM	Monthly	37	0.19	
Sperm whale	AFTT	Year-round		DSM	Year-round			EC GOM CAR MAR

	EC	Year-round	DSM	Monthly	5353	0.12	
	GOM	Year-round	DSM	Year-round	2128	0.08	
Beaked whales (guild)	AFTT	Year-round	DSM	Year-round			EC GOM CAR MAR
	EC	Year-round	DSM	Year-round	14491	0.17	
	GOM	Year-round	DSM	Year-round	2910	0.16	
False killer whale	AFTT	Year-round	Stratified	Year-round			EC GOM CAR
	GOM	Year-round	Stratified	Year-round	3204	0.36	
Killer whale	AFTT	Year-round	Stratified	Year-round			EC GOM CAR MAR EU
	GOM	Year-round	DSM	Year-round	185	0.41	
Kogia whales (guild)	AFTT	Year-round	DSM	Year-round			EC GOM CAR
	GOM	Year-round	DSM	Year-round	234	0.19	
Melon-headed whale	AFTT	Year-round	DSM	Year-round			EC GOM CAR
	GOM	Year-round	DSM	Year-round	6733	0.30	
Northern bottlenose whale	AFTT	Year-round	Stratified	Year-round			EC: SST<22°C & depth>2000m & distance to canyons <100km
Pilot whales (guild)	AFTT	Year-round	DSM	Year-round			EC GOM CAR EU MAR
	EC	Year-round	DSM	Year-round	18977	0.11	
	GOM	Year-round	DSM	Year-round	1981	0.18	
Pygmy killer whale	AFTT	Year-round	DSM	Year-round			EC GOM CAR
	GOM	Year-round	DSM	Year-round	2126	0.30	
Atlantic spotted dolphin	AFTT	Year-round	DSM	Year-round			EC GOM CAR
	EC	Year-round	DSM	Year-round	55436	0.32	
	GOM	Year-round	DSM	Year-round	47488	0.13	
Atlantic white-sided dolphin	AFTT	Year-round	DSM	Year-round			EC GOM CAR MAR EU
	EC	Year-round	DSM	Monthly	37180	0.07	
Bottlenose dolphin	AFTT	Year-round	DSM	Year-round			EC GOM CAR
	EC	Year-round	DSM	Monthly	97476	0.06	
	GOM	Year-round	DSM	Year-round	138602	0.06	
Clymene dolphin	AFTT	Year-round	DSM	Year-round			EC GOM CAR
	GOM	Year-round	DSM	Year-round	11000	0.16	

Fraser's dolphin	AFTT	Year-round		Stratified	Year-round			EC GOM CAR: SST>22°C & depth>200m
	EC	Year-round		Stratified	Year-round	492	0.76	
	GOM	Year-round		Stratified	Year-round	1665	0.73	
Harbor porpoise	AFTT	Year-round		DSM	Year-round			EC GOM CAR
	EC	Winter	Nov-May	DSM	Monthly	17651	0.17	
		Summer	Jun-Oct	DSM	Monthly	45089	0.12	
Pantropical spotted dolphin	AFTT	Year-round		DSM	Year-round			EC GOM CAR
	GOM	Year-round		DSM	Year-round	84014	0.06	
Risso's dolphin	AFTT	Year-round		DSM	Year-round			EC GOM CAR
	EC	Year-round		DSM	Monthly	7732	0.09	
	GOM	Year-round		DSM	Year-round	3137	0.10	
Rough-toothed dolphin	AFTT	Year-round		DSM	Year-round			EC GOM CAR
	GOM	Year-round		DSM	Year-round	4853	0.19	
Short-beaked common dolphin	AFTT	Year-round		DSM	Year-round			EC GOM CAR MAR EU
	EC	Year-round		DSM	Monthly	139104	0.13	
Spinner dolphin	AFTT	Year-round		DSM	Year-round			EC GOM CAR
	GOM	Year-round		DSM	Year-round	13485	0.24	
Striped dolphin	AFTT	Year-round		DSM	Year-round			EC GOM CAR MAR EU
	EC	Year-round		DSM	Year-round	75657	0.21	
	GOM	Year-round		DSM	Year-round	4914	0.17	
White-beaked dolphin	AFTT	Year-round		DSM	Year-round			EC MAR EU
Seals (guild)	AFTT	Year-round		Stratified	Year-round			EC: depth<1000m & lat>35°N
	EC	Winter	Sep-May	DSM	Seasonal	15002	0.17	
		Summer	Jun-Aug	DSM	Seasonal	98747	0.55	

6. Acknowledgments

This project would not be possible without the contributions of many individuals and organizations. Above all, we acknowledge the work of those who collected, processed, and shared marine mammal and remote sensing observations with us. Thank you for the opportunity to analyze the data you produced; we hope you find this project a satisfactory outcome of your efforts.

Many thanks to colleagues who shared data, reviewed portions of our work, provided valuable advice, or answered technical questions, including: Susan Barco, Suzanne Bates, Eric Beals, Elizabeth Becker, Beatriz Calmettes, Marthajane Caldwell, Dudley Chelton, Danielle Cholewiak, Tim Cole, Peter Corkeron, Megan Ferguson, Erik Fields, Karin Forney, Lance Garrison, Tim Gowan, Jim Hain, Patrick Lehodey, Phil Hammond, Jolie Harrison, Leila Hatch, Dave Johnston, Beth Josephson, Christin Khan, Erin LaBrecque, Claire Lacey, Gwen Lockhart, Stéphane Maritorena, Bill McLellan, David L. Miller, Doug Nowacek, Joel Ortega-Ortiz, Richard Pace, Debi Palka, Rui Prieto, Andy Read, Denise Risch, Jooke Robbins, Rob Schick, Michael Schlax, Doug Sigourney, Melissa Soldevilla, Joy Stanistreet, Len Thomas, Kim Urian, Sofie Van Parijs, Danielle Waples, Amy Whitt, and Simon Wood.

Benjamin D. Best developed data processing infrastructure for integrating the many surveys used in this analysis into a standard database schema. Although Ben did not contribute to the writing of this report, his work helping prepare the data for analysis was essential and he will share coauthorship on our first journal publication.

Thanks to Meghan Rickard, who assisted with our literature review, and also to our colleagues at MGEL who also assisted with data processing, including Jesse Cleary, Corrie Curtice, and Ei Fujioka.

Funding for this project was provided by United States Fleet Forces Command and was managed on their behalf by Naval Facilities Engineering Command Atlantic. Initial development of some aspects of this analysis was funded by NASA (Grant/Cooperative Agreement Number NNX08AK73G).

The VAMSC aerial surveys were funded by the Virginia Coastal Zone Management Program at the Department of Environmental Quality through Task 1 of Grant NA12NOS4190027 and Task 95.02 of Grant NA13NOS4190135 of the U.S. Department of Commerce, National Oceanic and Atmospheric Administration, under the Coastal Zone Management Act of 1972, as amended.

The altimeter products used in this analysis were produced by Ssalto/Duacs and distributed by Aviso, with support from Cnes (http://www.aviso.altimetry.fr/duacs/). The satellite chlorophyll data were obtained from the Ocean Color MEaSUREs project at UCSB (http://wiki.icess.ucsb.edu/measures/Products). D. Chelton and colleagues provided us preliminary results from a revision of their 2011 eddy detection algorithm, applied to the "Duacs 2014" Aviso data.

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