Updated Marine Species Density Models for the Arctic Study Area

Final Report v3

Tina M. Yack, Jason J. Roberts, Jesse Cleary, Ana Cañadas, and Patrick N. Halpin

Marine Geospatial Ecology Lab, Duke University

Submitted to:

Naval Facilities Engineering Systems Command Atlantic
for U.S. Fleet Forces Command under
Contract No. N62470-23-2-0006

May 2026

Prepared by

Tina M. Yack, Jason J. Roberts, Jesse Cleary, Ana Cañadas, Patrick N. Halpin

Marine Geospatial Ecology Lab
Duke University

Suggested Citation:

Yack, T.M., J.J. Roberts, J. Cleary, A. Cañadas. and P.N. Halpin. 2026. Updated Marine Species Density Models for the Arctic Study Area. Final Report v3. Prepared for U.S. Fleet Forces Command. Submitted to Naval Facilities Engineering Systems Command Atlantic, Norfolk, Virginia, under Cooperative Agreement number N62470-23-2-0006. May 2026.

Table of Contents

List of Tables

List of Figures

Acronyms and Abbreviations

AIC	Akaike Information Criterion
AMM	Arctic marine mammal(s)
ARCWEST	Arctic Whale Ecology Study
ARMR	Arctic Region Military Readiness
ASAMM	Aerial Survey of Arctic Marine Mammals
BOEM	Bureau of Ocean Energy Management
BS	Beaufort Sea
BWASP	Bowhead Whale Aerial Survey Project
CAP	Cetacean Aggregation Protocol
CDS	Conventional Distance Sampling
CHAOZ	Chukchi Acoustic, Oceanography, and Zooplankton
COMIDA	Chukchi Offshore Monitoring in Drilling Area
CV	Coefficient of Variation
DFO	Fisheries and Oceans Canada
DSM	Density Surface Model
EB	Eastern Bering
EC	Eastern Chukchi
esw	Effective strip half-width
Esri	Environmental Systems Research Institute
EEZ	Economic Exclusive Zone
GAM	Generalized Additive Model
GIS	Geographic Information System
IWC	International Whaling Commission
MCDS	Multiple Covariate Distance Sampling
m	Meters
km	Kilometers
MML	Marine Mammal Laboratory
NMFS	National Marine Fisheries Service
NOAA	National Oceanic and Atmospheric Administration
NSIDC	National Snow and Ice Data Center

REML	Restricted Maximum Likelihood
SRTM	Shuttle Radar Topography Mission
SUP	Small unidentified pinniped(s)
UP	Unidentified pinniped(s)
US	United States of America
V	Version

1. Introduction

The Arctic is a dynamic and rapidly changing ecosystem. The annual cycle of sea ice melt and freeze-up structures much of the region's ecological function, and ongoing climate warming is occurring more rapidly here than in most other parts of the globe (Tynan and DeMaster 1997; Moore and Huntington 2008; Kovacs et al. 2011; Screen and Williamson 2017). In addition to supporting diverse marine mammal communities, the Arctic is increasingly used by humans for transportation, resource extraction, and military activities (Laidre et al. 2015). Because ecological processes in this system are strongly mediated by sea ice, the distribution of Arctic marine mammals (hereafter AMMs) reflects the interaction between species-specific life history requirements and the spatial and temporal availability of suitable habitat—particularly access to open (ice-free) water and productive foraging areas.

Despite decades of research on AMMs (Moore and Huntington 2008; Laidre et al. 2015), comprehensive, spatially explicit estimates of AMM density remain limited. This gap is increasingly consequential in a rapidly changing Arctic where sustainable management depends on understanding how human activities may affect individuals and populations across space and time. Quantifying distribution and abundance is therefore a critical component of effective conservation and environmental planning. In this report, we describe and model AMM abundance and distribution in the Chukchi Sea, Beaufort Sea (Alaskan and Canadian waters), and the Bering Strait regions. Our analyses draw on the long-term Aerial Survey of Arctic Marine Mammals (ASAMM) program conducted by the National Oceanic and Atmospheric Administration's (NOAA's) Marine Mammal Laboratory (MML), supplemented by surveys in the Canadian Beaufort Sea and Amundsen Gulf conducted by Fisheries and Oceans Canada (DFO), as well as shipboard surveys (ARCWEST and CHAOZ) led by NOAA's MML (Friday et al. 2016, Berchok et al. 2018).

Detailed results and discussion for each modeled species and guild are included in the accompanying taxon-specific reports. These reports comprise maps, plots, tables, statistical output, and narrative text describing modeling decisions and interpreting model results for each taxon.

1.1. Report Structure

This is the final report for the Arctic Density Modeling project completed for the United States (U.S.) Navy (Cooperative Agreement number N62470-23-2-0006). This report is structured as follows:

1. **Background** to the ecosystem and the problem we are addressing.
2. **Materials & Methods**
3. Summary of **Results**
4. **Future Work**
5. **Summary**
6. **Literature Cited**

Background

Many species of marine mammals occupy Arctic and sub-Arctic waters. Core Arctic species and sub-Arctic species exist, with the key distinction being whether the species depends on the Arctic ecosystem for all life history aspects or not (Laidre et al. 2008). In the western Arctic, the core Arctic marine mammals include bowhead whale (Balaena mysticetus), beluga whale (Delphinapterus leucas), walrus (Odobenus rosmarus), bearded seal (Erignathus barbatus), and ringed seal (Pusa hispida). (Note that polar bears (Ursus arctos) are also considered a core Arctic marine mammal (Laidre et al. 2008) but are not addressed by our analysis here, owing to the large majority of sightings occurring on land.) These core AMM species are categorized as follows: 1) ice-obligate, 2) ice-associated, and 3) sub-arctic species that seasonally migrate into Arctic waters (Moore and Huntington 2008). The sub-Arctic species include gray whale (Eschrichtius robustus), humpback whale (Megaptera novaeangliae), minke whale (Balaenoptera acutorostrata), fin whale (Balaenoptera physalus), harbor porpoise (Phocoena phocoena), spotted seal (Phoca largha), ribbon seal (Histriophoca fasciata), harp seal (Pagophilus groenlandicus), and hooded seal (Cystophora cristata). For the sub-Arctic baleen whales, there is an important distinction; gray whales are thought to be seasonally resident in Arctic waters, while humpback, minke and fin whales are thought to be seasonally migrant (Moore 2016). Here we concentrate on ten species (four core Arctic, and six sub-Arctic), as well as two guilds. The ten species are: bowhead whale, beluga whale, gray whale, fin whale, humpback whale, minke whale, killer whale, harbor porpoise, walrus, and bearded seal; the two guilds are small unidentified pinnipeds (hereafter SUPs), and unidentified pinnipeds (hereafter UPs).

Because the Arctic is strongly structured by sea ice, marine mammal use of Arctic habitats is inherently dynamic in both space and time. As winter ice retreats and open water expands north of the Bering Strait, species redistribute in response to changing habitat availability and prey conditions. Interannual variability in ice extent, combined with long-term declines in annual ice cover (Walsh 2008; Jeffries et al. 2013), results in substantial variation in the timing and spatial extent of species' distributions. The magnitude of these shifts differs among species. Core Arctic species such as bowhead whales may show relatively constrained ranges, while sub-Arctic migrants such as gray whales can expand farther north and east in warmer years. Even among core Arctic species, northern range limits vary considerably; for example, beluga whales have been documented as far north as approximately 81°N (Suydam, Lowry, and Frost 2005; Suydam et al. 2001), whereas bowhead whales typically range to approximately 73°N (Citta et al. 2015). These shifting habitat boundaries in a rapidly changing climate complicate efforts to produce broad-scale, spatially explicit estimates of AMM density. To address this challenge, we incorporate a suite of dynamic environmental covariates into the modeling framework to capture temporal and spatial variability in habitat conditions.

Research on the ecology of AMMs has been ongoing since at least the 1970s, with foundational syntheses documenting species distribution, behavior, and subsistence management considerations (Burns et al. 1993). Much of the early and continuing work has focused on bowhead whales, driven by the dual imperatives of managing Indigenous subsistence harvests and evaluating potential impacts of offshore oil and gas development.

Within the U.S. Exclusive Economic Zone (EEZ), one of the longest-running monitoring efforts is the ASAMM project, initiated in 1979 under the Minerals Management Service and subsequently supported through interagency partnerships involving NOAA and the Bureau of Ocean Energy Management (BOEM) (Moore and Reeves 1993; Clarke et al. 2016). Components of ASAMM included the Bowhead Whale Aerial Survey Project (BWASP) and Chukchi Offshore Monitoring in Drilling Area (COMIDA) survey programs. More recently, aerial surveys in 2020 and 2021 were supported by the North Slope Borough in collaboration with NOAA's MML ensuring continuity of broad-scale monitoring in the Chukchi and Alaskan Beaufort Seas.

Complementary research has expanded our understanding of species-specific habitat use and movement patterns. Aerial surveys in the Canadian Beaufort Sea have provided comparable abundance and distribution data (Harwood et al. 2009). Satellite telemetry studies have revealed seasonal movement corridors and habitat associations for bowhead whales (Citta et al. 2015), beluga whales (Suydam, Lowry, and Frost 2005; Suydam et al. 2001), and walrus (Jay et al. 2012; Jay et al. 2017). Studies of ice-associated seals have documented haul-out behavior and responses to sea ice variability (Harwood et al. 2015), while shore-based point counts (George et al. 2004) and passive acoustic monitoring (Moore et al. 2006) have provided additional insight into seasonal occurrence and migration timing. Beyond dedicated marine mammal studies, large-scale oceanographic investigations in the Pacific Arctic (e.g., Grebmeier et al. 2006) have characterized changes in productivity, benthic–pelagic coupling, and Pacific water inflow dynamics. These physical and biological processes underpin the environmental covariates used in density surface models (DSMs) and help explain observed shifts in species distribution (e.g., Pendleton et al. 2020, Ashjian et al. 2010) (Figure 1).

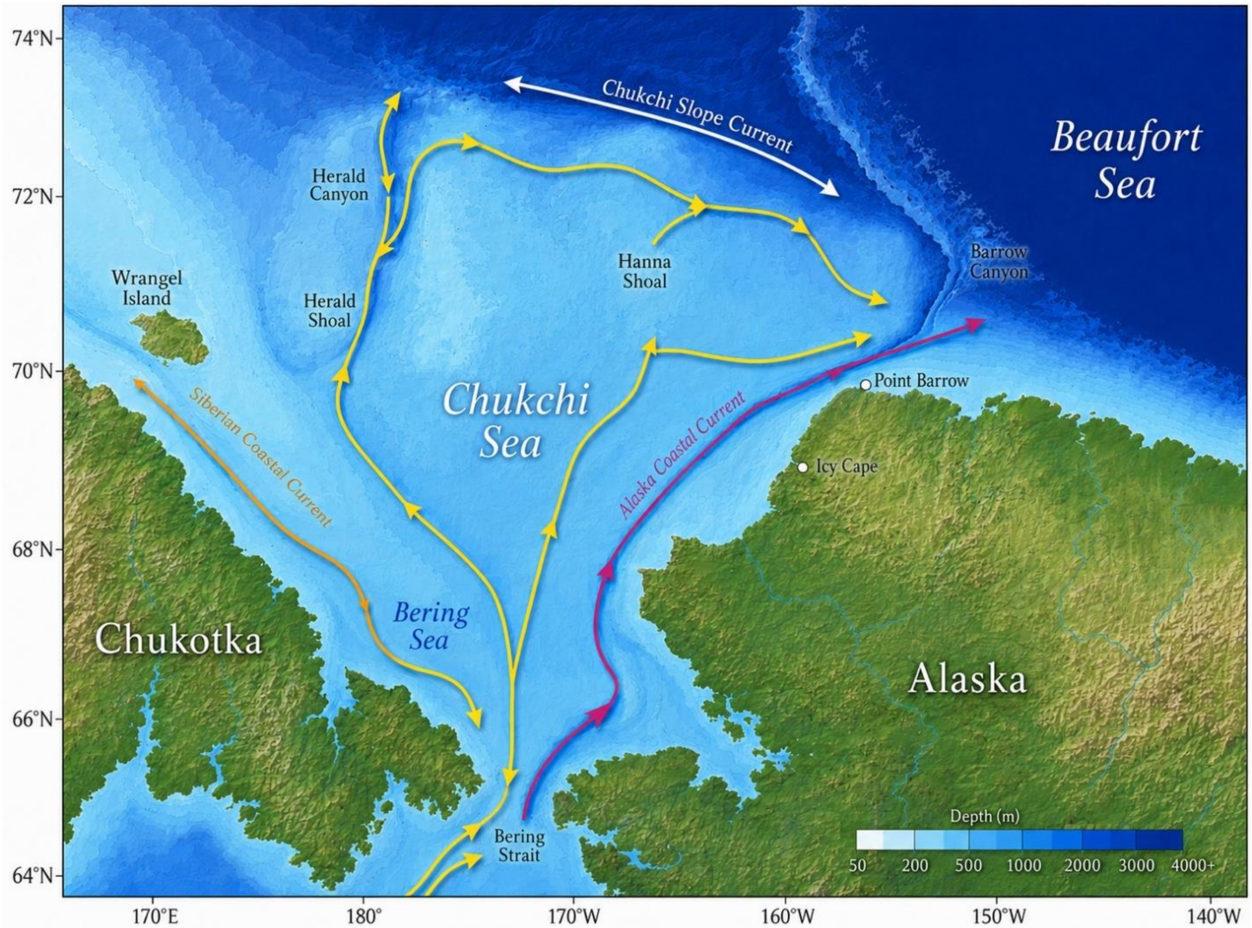

Figure 1. Background map. Key oceanographic features and circulation patterns in the Pacific Arctic study region, including the Bering Strait, Chukchi Sea, Beaufort Sea, Wrangel Island, Point Barrow, Hanna Shoal, Herald Shoal, Herald Canyon, and Barrow Canyon. Bathymetric shading illustrates the transition from shallow shelf waters to deeper slope and basin habitats, while arrows show generalized surface circulation features, including the Alaska Coastal Current, Siberian Coastal Current, Chukchi Slope Current, and Beaufort Gyre. Currents are shown schematically for geographic and ecological context and are not intended to represent modeled current velocities or exact trajectories. Note: Generated using AI.

Bowhead whales

Current understanding of bowhead whale distribution indicates that as winter sea ice recedes, individuals from the Bering–Chukchi–Beaufort stock migrate northward into the Arctic, passing near Point Barrow enroute to summer feeding grounds in the Canadian Beaufort Sea. As the season progresses into late summer and fall, whales begin a westward migration, feeding in nearshore waters of the Canadian and Alaskan Beaufort Seas east of Point Barrow. By autumn, they continue west past Point Barrow, dispersing into the Chukchi Sea before ultimately returning to the northern Bering Sea as sea ice advances (Moore and Reeves 1993).

Interannual variability can modify this seasonal pattern. A notable deviation occurred in 2019, when unusually warm ocean conditions and very low sea-ice extent were associated with few bowhead whales observed on the western Beaufort Shelf during the expected fall migration period, and the expected nearshore westward movement past Point Barrow was largely absent or substantially delayed (Ferguson et al. 2021; BOEM 2023). More recent acoustic studies suggest that bowhead whale migration timing and seasonal habitat use in the Pacific Arctic continue to be changing, including later departure from the western Beaufort Sea, increased summer presence in the Chukchi region, and evidence that some whales may remain north of the Bering Strait during winter in some years. Thus, rather than indicating a single anomalous year followed by a documented return to the historical pattern, the 2019 event appears consistent with broader interannual variability and ongoing shifts in bowhead whale phenology and distribution under changing sea-ice conditions.

Beluga whales

Beluga whales are a core, ice-associated Arctic species (Moore and Huntington 2008). In the ASAMM study area, three distinct stocks are present: the Eastern Chukchi Sea (EC), the eastern Beaufort Sea (BS), and the Eastern Bering Sea population (EB) (Hauser et al. 2017). The EC stock undertakes seasonal migrations between wintering areas in the Bering Sea and summer habitat in the Chukchi Sea, with distribution intricately linked to coastal habitats and sea-ice dynamics (Allen and Angliss 2014). Previous tagging work (Suydam, Lowry, and Frost 2005; Suydam et al. 2001) has documented broad-scale use of the study area by the EC and BS stocks, while more recent work has shown that the distribution and habitat features that predict habitat use differ both by stock and within stock by sex (Hauser et al. 2017, 2018). For example, Chukchi belugas respond strongly to the Barrow Canyon feature, while Beaufort belugas respond more to distance-to-shore and distance-to-ice-edge covariates (Hauser et al. 2017). Unfortunately, neither sex nor stock can be determined from aerial surveys; thus, stock-specific responses to habitat covariates may be more difficult to ascertain. We therefore modeled the EC and BS stocks together across the study area and produced a separate model for the EB stock for Norton Sound in June, when it is presumed that the entire EB stock is present in Norton Sound (Ferguson pers. comm.).

Walrus

Walruses are benthic foragers that often occur in large aggregations throughout the Arctic (Fay 1982). As a core ice-associated species, they have historically hauled out on both landfast and pack ice (Jay et al. 2012; Moore and Huntington 2008), with aggregations sometimes numbering in the tens of thousands (D. Clarke, Leidos Corporation, pers. comm.). Walruses typically overwinter in the Bering Sea and migrate northward into the Chukchi Sea as ice begins to break up in spring (Fay 1982; Jay et al. 2012). Recent telemetry and observational studies indicate that, as seasonal sea ice has declined, walruses are increasingly using coastal land haulouts in lieu of sea ice, particularly in late summer and fall (Fischbach et al. 2007; Jay et al. 2012, 2017). Peak abundance in the northeastern Chukchi Sea generally occurs in July and August, coinciding with areas of high benthic productivity (Dunton et al. 2005). By early fall (e.g., September), their distribution shifts southward, though walruses remain largely associated with shallow, coastal habitats (Jay et al. 2012). Observations also suggest increased use of open-water habitats with lower ice concentrations compared to historical conditions (Jay et al. 2012).

Gray whales

Gray whales are typically considered a sub-Arctic species that use Arctic habitats as sea ice recedes. They are benthic feeders that migrate into the Chukchi Sea as summer progresses and tend to concentrate in several known feeding hotspots, including the gray whale garden (west of Point Barrow), Hanna Shoal, and areas off Point Lay. Marine mammal occurrence in this region is strongly influenced by environmental and oceanographic conditions that structure prey availability and productivity (Escajeda et al. 2020). Gray whales are rarely seen east of Point Barrow.

Fin, humpback, and minke whales

Fin, humpback, and minke whales are considered sub-Arctic species that historically were rarely seen in Arctic habitats. However, as the Arctic has warmed in recent decades, sightings have become more frequent, and these species are expected to continue to expand northward if the warming trend continues (Moore and Huntington 2008). In the version (v) v1 modeling project (Schick et al. 2017), we modeled these as a guild, but with the added data incorporated for the project for v2 we were able to build species-specific models, an approach we carried forward for the v3 models documented here.

Harbor porpoises

Harbor porpoises are considered sub-Arctic but are known to range as far north as Point Barrow, Alaska, although high abundances typically occur in southern regions of the state (Muto et al. 2020). In the v1 modeling project (Schick et al. 2017), we lacked sufficient sightings to model them, but with the additional data incorporated for the v2 modeling project we obtained enough to fit a basic spatial model. For v3, documented here, we were able to fit a more complex spatial model.

Killer whales

Killer whales are increasingly observed in Arctic and sub-Arctic regions as sea ice declines and previously inaccessible habitats become available (Moore and Huntington 2008; Kovacs et al. 2011; Laidre et al. 2015). Two primary ecotypes occur within the broader study region, resident and transient killer whales, which differ markedly in genetics, behavior, and ecology (Ford et al. 1998; Baird 2000). Resident killer whales are primarily fish-eating and highly social, with approximately 1,920 individuals identified in the Eastern North Pacific Alaska Resident stock based on long-term photo-identification data (Young et al. 2023). Their range extends from Puget Sound through Southeast Alaska and into the Aleutian Islands, where they are typically associated with coastal and shelf waters supporting abundant prey resources, particularly salmon.

In contrast, transient killer whales are mammal-eating and occur in smaller, less stable social groups (Baird and Dill 1996; Ford et al. 1998). Approximately 450 individuals have been identified across the Aleutian Islands and Bering Sea, with an additional ~130 individuals documented in the Gulf of Alaska population based on photo-identification studies and stock assessment summaries (Young et al. 2023; Hanson et al. 2010). Although their distribution partially overlaps with that of resident whales, transients primarily prey on marine mammals, including seals, porpoises, and occasionally small cetaceans.

In recent decades, both resident and transient killer whales have been sighted farther north into the Bering, Chukchi, and Beaufort Seas, regions historically limited by sea ice. These movements correspond with loss of seasonal ice cover and extended open-water periods, allowing killer whales to exploit new foraging opportunities. This range expansion reflects a broader ecological shift in Arctic marine predator communities, potentially impacting native species like bowhead whales, belugas, and seals. In earlier (v1 and v2) modeling projects we lacked sufficient data to build a killer whale model but in the v3 model documented here we had enough sightings to develop a limited model.

Seals

Broad-scale summaries of pinniped distribution and abundance during the open-water season in the Arctic are more limited than those available for cetaceans, in part due to differences in survey focus and detectability. While the ASAMM survey extends back several decades, from the start it has focused on large whales. Thus, the intensity of collection and identification of seal sightings has varied over the duration of the survey. In addition, most Arctic seals are small and the ASAMM planes fly at high altitudes (Ferguson and Clarke 2013), making identification of these sightings difficult, more so as weather and sighting conditions degrade. Thus, when seals are seen during ASAMM, they tend to be lumped into one of two sighting categories, stratified by size: 1) small unidentified pinnipeds; and 2) unidentified pinnipeds. The species that comprise these two groups include walrus, bearded seal, ringed seal, and spotted seal. Some span both, e.g., a juvenile walrus could be in the “small unidentified” category, while an adult could be in the “unidentified” category. Bearded seals, because of their unique morphology (big body, small head) tend to be easier to fully identify than other Arctic ice-seal species. There have been aerial surveys for ringed and bearded seals in the Alaskan Beaufort Sea (Burns and Harbo 1972, Burns et al. 1981); however, most of the spatial modeling done for these species occurred in the Bering Sea (Bengtson et al. 2005, Conn et al. 2013, Conn et al. 2014, Ver Hoef et al. 2014). And while these surveys have been conducted, they are typically conducted during the winter-ice period, as opposed to the summertime open-water period. Consequently, there have been few attempts to quantify the distribution and abundance of Arctic ice-seals during the ice-free period over broad scale areas. (See Aerts et al. (2013) for an example of a fine-scale analysis of selected ice-seal species.)

1.2. Objective

The objective of this work was to rebuild Arctic marine mammal density models used for the Navy Marine Species Density Database (NMSDD) by integrating newly available survey data and environmental covariates with those used previously and building new density models from scratch. Our approach was to build statistically rigorous DSMs that link aerial and shipboard survey observations to dynamic habitat predictors, explicitly quantify uncertainty, and evaluate extrapolation beyond surveyed areas. We prioritized modeling choices that ensured consistency with our previous density modeling cycles while also incorporating newly available improvements in data and methodology, with an aim to support current and future environmental compliance activities undertaken by the Navy. Because habitat availability in the Arctic is strongly influenced by interannual variability and long-term trends in sea ice and other oceanographic phenomena, the modeling framework incorporates dynamic environmental covariates and is structured to accommodate future updates as new survey data and environmental products become available.

2. Methods

Here we describe the species observation datasets and analytical framework used to develop updated DSMs. We begin with the primary aerial survey dataset in the region, followed by supplemental aerial and shipboard surveys and then outline the analytical workflow.

Aerial Survey Data (ASAMM)

The primary dataset consists of multi-decade aerial surveys currently conducted under the Aerial Survey of Arctic Marine Mammals (ASAMM), previously known as the Bowhead Whale Aerial Survey Project (BWASP) and the Chukchi Offshore Monitoring in Drilling Area (COMIDA) program. Although originally focused on bowhead whales, ASAMM has consistently recorded sightings of all Arctic marine mammals (AMMs) observed in the Chukchi and Alaskan Beaufort Seas.

Surveys were flown during the open-water season (June–October) using either Aero Turbo Commander or de Havilland Twin Otter aircraft, typically at altitudes of 305–457 m. Aircraft were equipped with bubble windows to ensure unobstructed views of the trackline, and photography was conducted when feasible. Surveys followed standard line-transect distance sampling protocols (Buckland et al. 2001) and covered a consistent set of survey blocks across the Chukchi and Beaufort Seas, particularly during July–October. Detailed descriptions of survey design and methods are available in Moore and Reeves (1993), Ferguson and Clarke (2013), and Clarke et al. (2016). In addition, ASAMM conducted a dedicated survey of Norton Sound in June 2017 targeting the eastern Bering Sea beluga whale population.

Canadian Beaufort Sea Aerial Surveys (DFO)

We incorporated four years (2007-2010) of aerial strip-transect surveys conducted by Fisheries and Oceans Canada (DFO) in the Canadian Beaufort Sea and Amundsen Gulf (Harwood et al. 2009). These surveys were not included in the v1 models (i.e., Schick et al. 2017). Unlike ASAMM, DFO surveys used systematic strip transects (Caughley 1977), recording all sightings within 1,000 m of the trackline but not measuring perpendicular distances. As a result, detection functions could not be estimated for these surveys, and detection probability was assumed to be 1 within the strip.

DFO surveys were flown using a de Havilland Twin Otter aircraft at approximately 305 m altitude (152 m under low ceilings), with transects spaced approximately 20 km apart. Because sightings of large whales and belugas were the only species made available for our use, these surveys were incorporated only into models for those species.

Shipboard Line-Transect Surveys (ARCWEST and CHAOZ)

Shipboard visual surveys from the Arctic Whale Ecology Study (ARCWEST; 2013–2016) (Friday et al. 2016) and the Chukchi Acoustic, Oceanography, and Zooplankton (CHAOZ; 2010–2012) (Berchok et al. 2019) programs were also incorporated. Both were conducted by NOAA's Alaska Fisheries Science Center MML. These surveys followed standard line-transect distance sampling protocols (Buckland et al. 2001), facilitating integration into detection and density surface modeling. Surveys were conducted during daylight hours so long as the sea was not too rough (Beaufort wind force scale ≤ 5). Observers rotated through standardized watch periods and recorded horizontal angles and reticle measurements to estimate perpendicular distance to sighted animals. Additional data collected included species identity, group size (best, low, high estimates), sighting cue, and environmental conditions.

Analytical Workflow

Density surface modeling followed a five-step process:

1. **Data review and standardization**
   Survey datasets were screened, cleaned, and harmonized across platforms to ensure consistency in effort, sightings, and environmental covariates.
2. **Detection function modeling**
   Taxon-specific detection functions were fitted to line-transect data to account for imperfect detectability and to estimate effective strip half-width (esw). Multiple covariate distance sampling approaches were evaluated where appropriate.
3. **Spatial density modeling**
   Generalized Additive Models (GAMs) were fitted to model variation in animal density as a function of spatial, temporal, and environmental covariates. Smoothing parameters were estimated using restricted maximum likelihood (REML).
4. **Spatial prediction**
   Fitted relationships were used to generate taxon-specific density predictions across the Arctic Study Area on a standardized grid.
5. **Model evaluation and validation**
   Model diagnostics included residual analysis, evaluation of extrapolation in environmental space, and comparison with independent passive acoustic monitoring data provided by NOAA MML where available.

2.1. Study Area

The study area was redefined for this modeling round by the U.S. Navy. The Navy's Arctic Region Military Readiness (ARMR) Study Area (Figure 2) encompassed an expansive circumpolar region. The data available were insufficient to model the full ARMR region, and our goal was to model the extent plausible based on what data could be acquired, with an emphasis on U.S. waters. As such, the model study area is a subcomponent of the ARMR study area. We were able to expand the model study area from v1 and v2 density models in this modeling round given the addition of shipboard data.

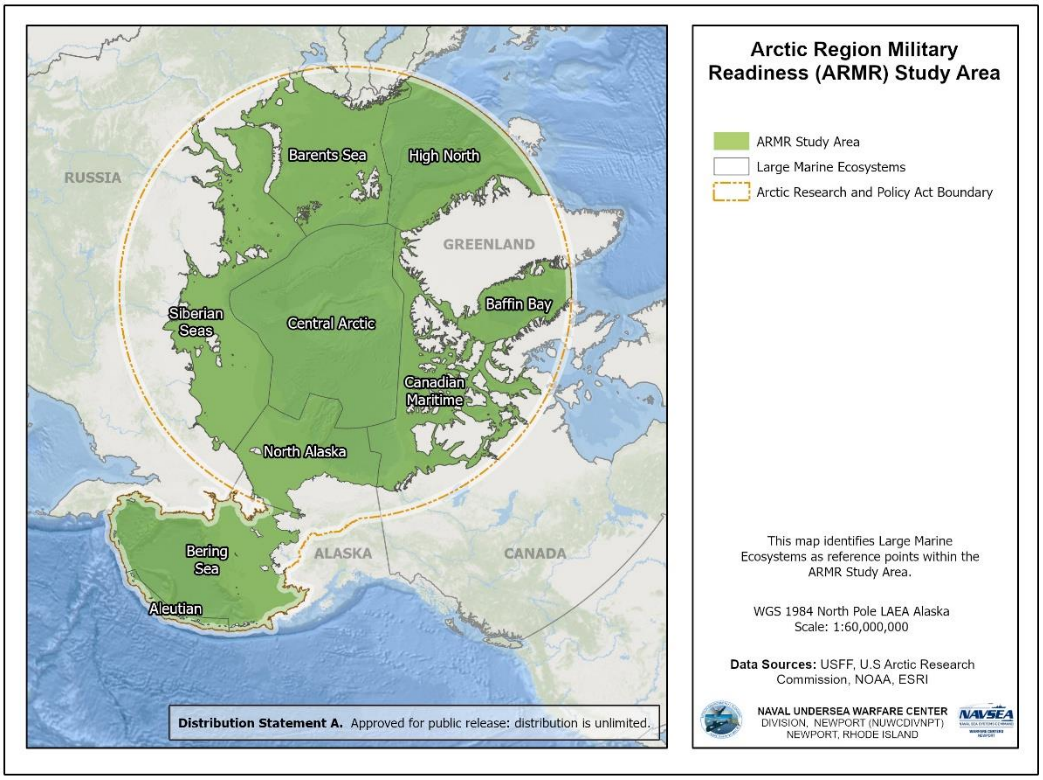

Figure 2 Arctic Region Military Readiness (ARMR) Study Area

We defined an Albers Equal Area coordinate system appropriate for density modeling, then delineated a Study Area (Figure 3) that encompassed the available surveys, with a grid cell size of 10km. We made model predictions across the entire area for all species except the Eastern Bering Sea Beluga whale model, which was restricted to only Norton Sound in June (Figure 4), and the Walrus model which was confined to a smaller study area due to unrealistic extrapolations (Figure 5).

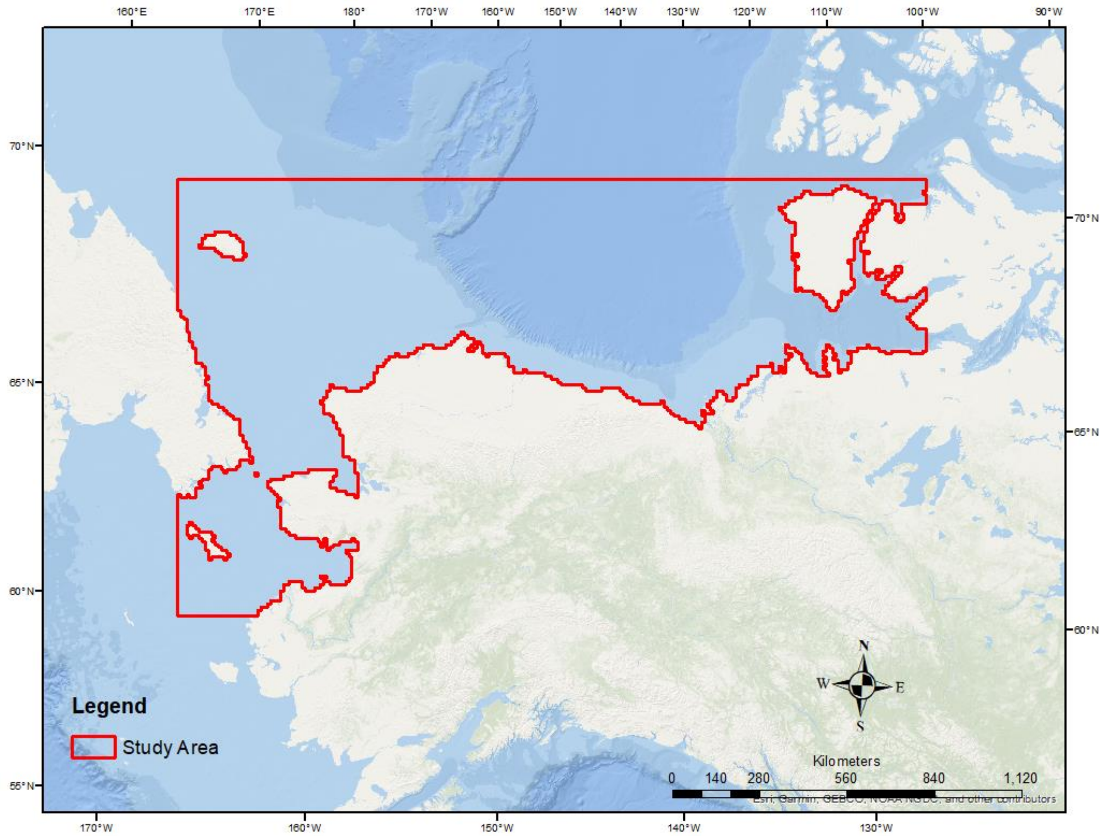

Figure 3. Arctic modeling study area. The map uses the Albers Equal Area projection developed for the analysis.

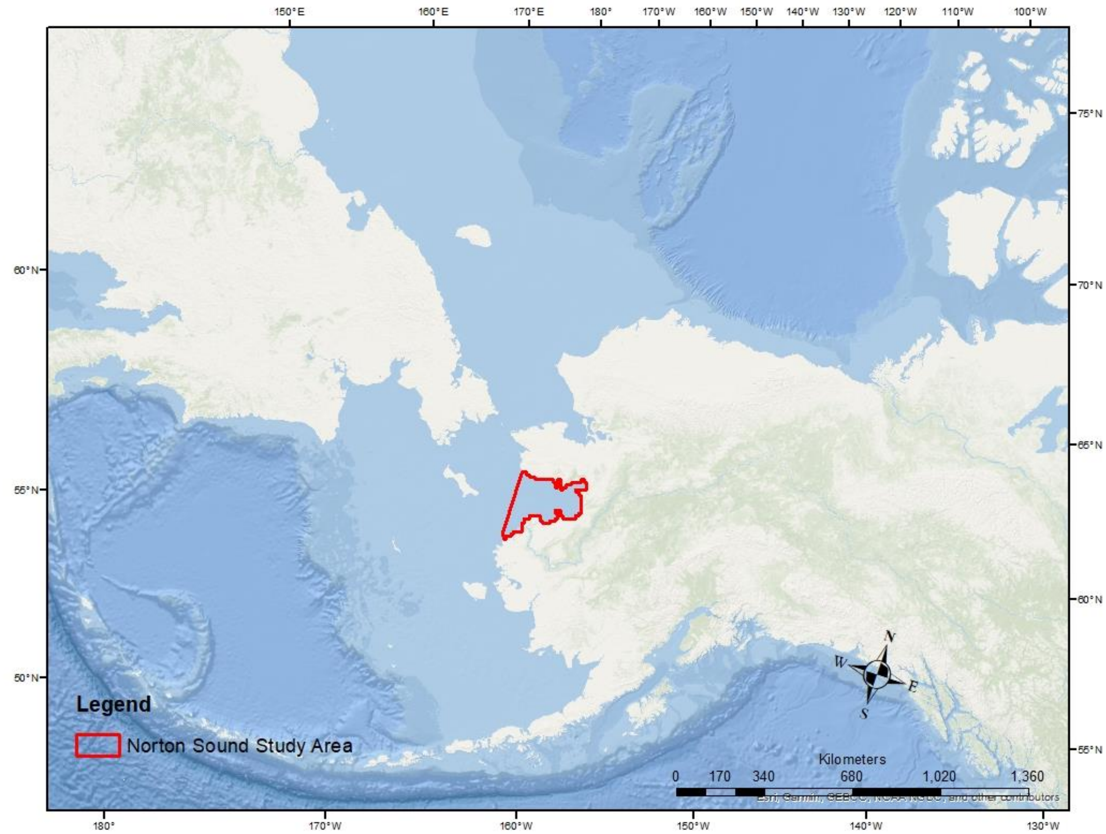

Figure 4. The Norton Sound Study Area for the Eastern Bering Sea Beluga whale model.

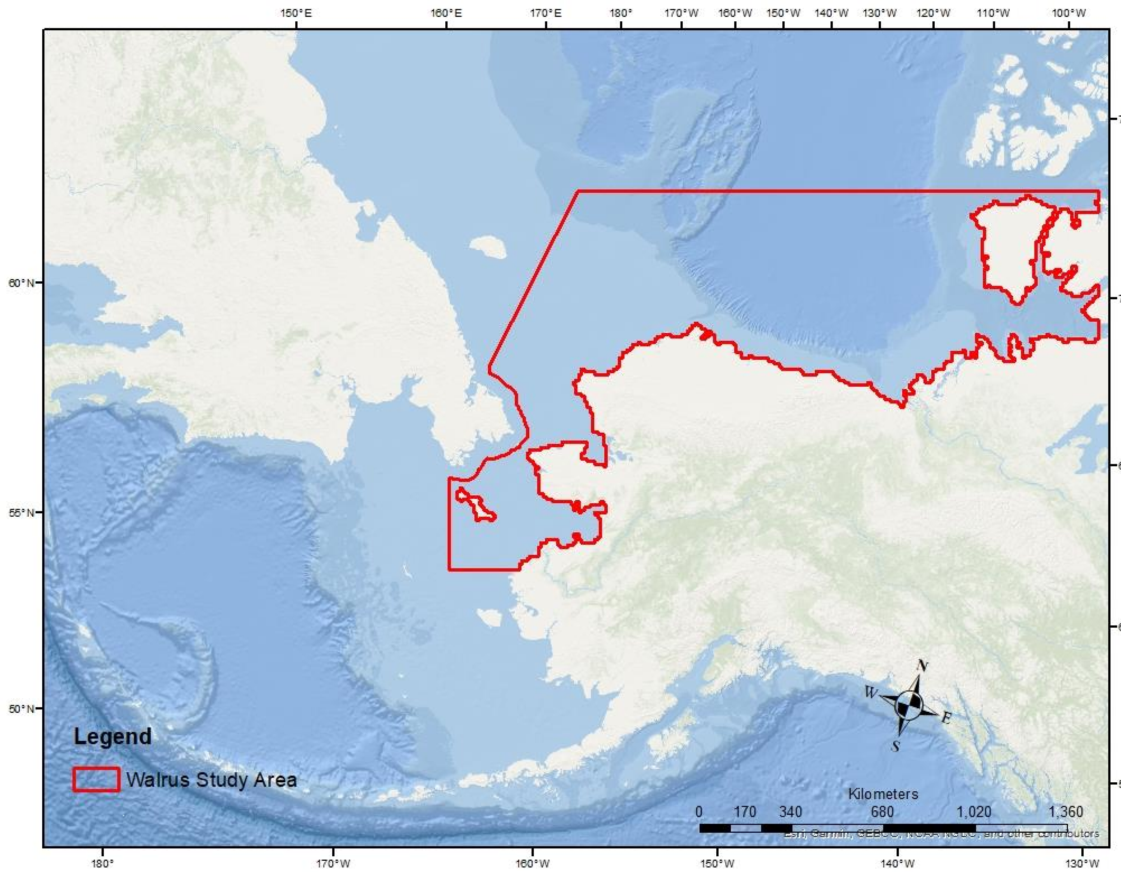

Figure 5. The Study Area for the Walrus model.

2.2. Data Summary

ASAMM has been active since 1979, with the most recent survey occurring in 2021. For this analysis, we restricted the dataset to a more recent subset spanning 2008–2021 for three primary reasons. First, because model outputs are intended to support Navy training and testing activities in the near future, density estimates that reflect contemporary ("modern-day") conditions are preferred. Second, the Arctic ecosystem has undergone rapid environmental change over recent decades (Moore and Huntington 2008), and restricting the analysis to recent years reduces the risk of fitting species–environment relationships that are no longer representative of current conditions. Finally, ASAMM survey protocols were updated beginning in 2008, resulting in more consistent observation methods and species identification compared to earlier years.

Survey coverage during this period included a consistent set of blocks across the Chukchi and Beaufort Seas during July–October, with more limited spatial coverage in June (Western block only). Canadian waters were surveyed only in August, both by ASAMM (2019) and DFO (2007–2010), with slight differences in spatial extent between these efforts. In addition, ASAMM conducted a dedicated survey of Norton Sound, Alaska, in June 2017, which was used to model the Eastern Bering Sea beluga population.

From 2018–2021, ASAMM occasionally used a modified survey approach referred to as Cetacean Aggregation Protocols (CAPs; Ferguson et al. 2015). This protocol was implemented under conditions of high cetacean density and resulted in a combination of "passing mode" and circling observations. These data streams were used differently in model development, with passing-mode observations contributing to encounter rate estimation and circling observations informing group size and species composition.

In addition to ASAMM, supplemental datasets were incorporated where available. DFO aerial surveys contributed observations for large whales and belugas within the Canadian Beaufort Sea, while shipboard surveys from ARCWEST and CHAOZ expanded spatial and temporal coverage and provided additional environmental covariate information. Differences in survey design among these datasets were accounted for within the modeling framework (see Methods).

Relative to previous modeling efforts (e.g., v2 modeling cycle; Canadas et al. 2023), the present analysis incorporates more recent years of data (2020–2021) and includes shipboard survey data from ARCWEST and CHAOZ, increasing both spatial and temporal coverage of observations.

The study area and transects available for modeling are shown in Figure 6, and survey effort by platform is summarized in Table 1. Monthly survey effort is shown in Figures 7–11, and yearly summaries by month are provided in Table 2.

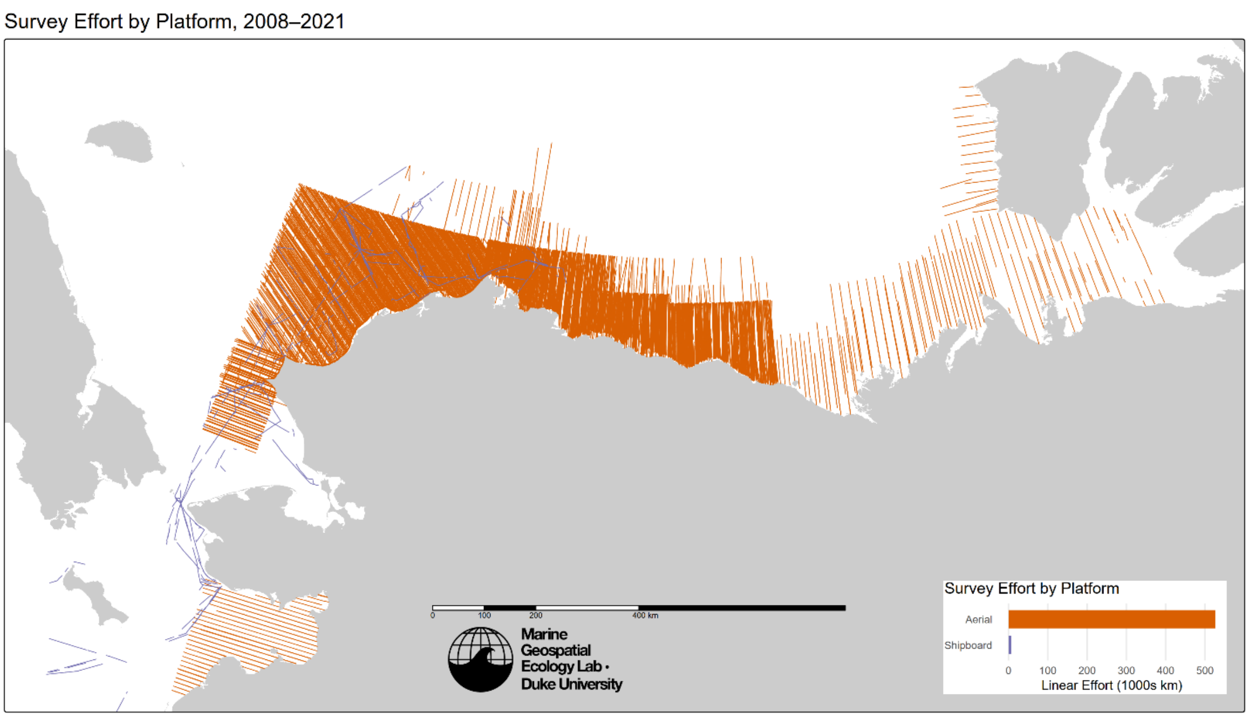

Figure 6 Survey effort by platform, 2008-2021. Aerial survey transects are shown in orange; shipboard survey transects are shown in blue.

Survey Effort by Platform, 2008–2021, June

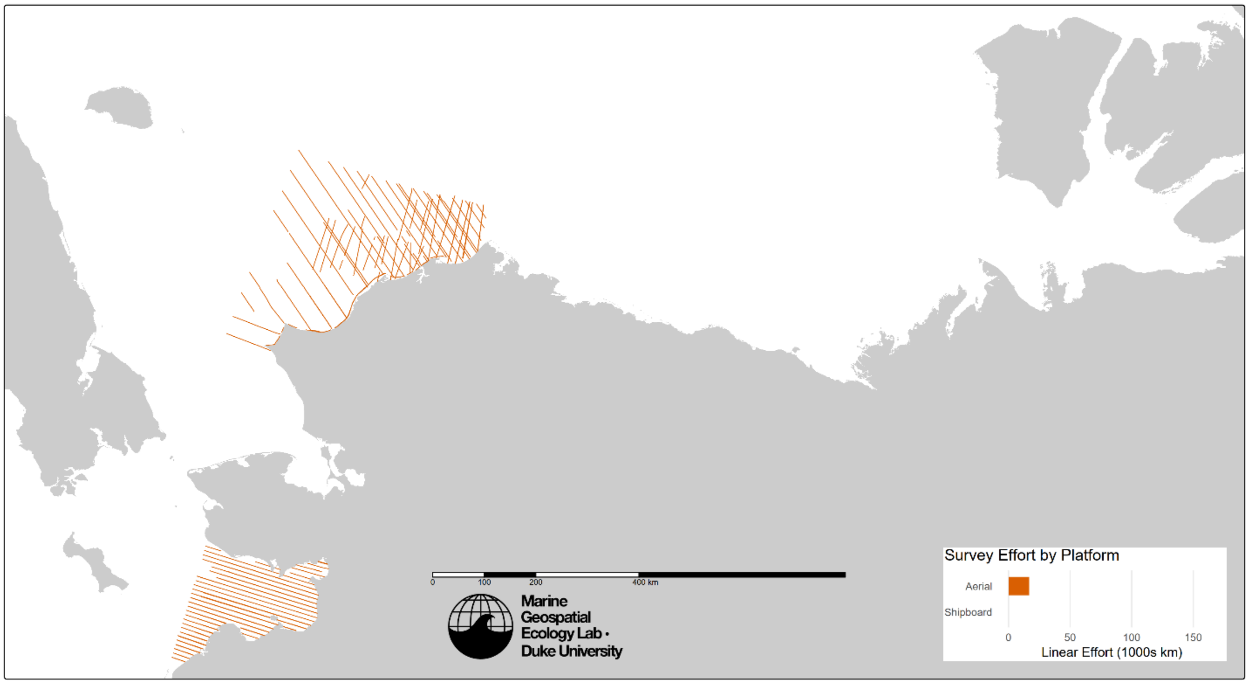

Figure 7 Survey transects during June.

Survey Effort by Platform, 2008–2021, July

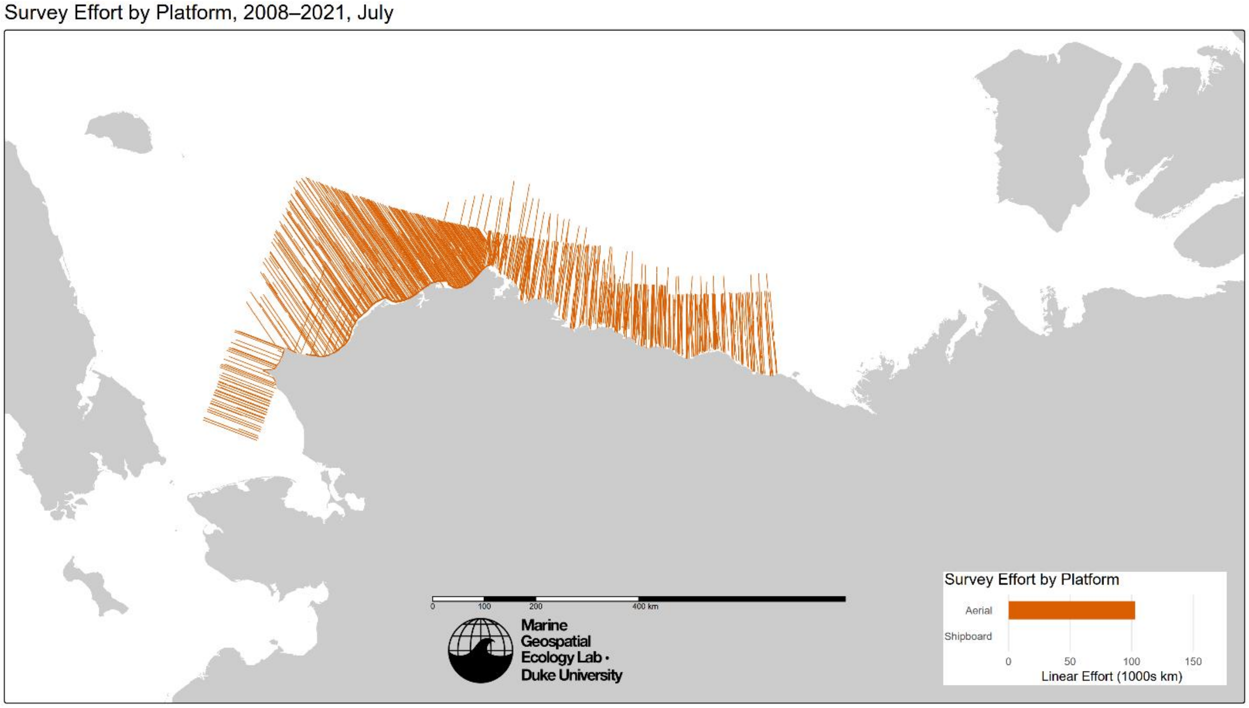

Figure 8 Survey transects during July.

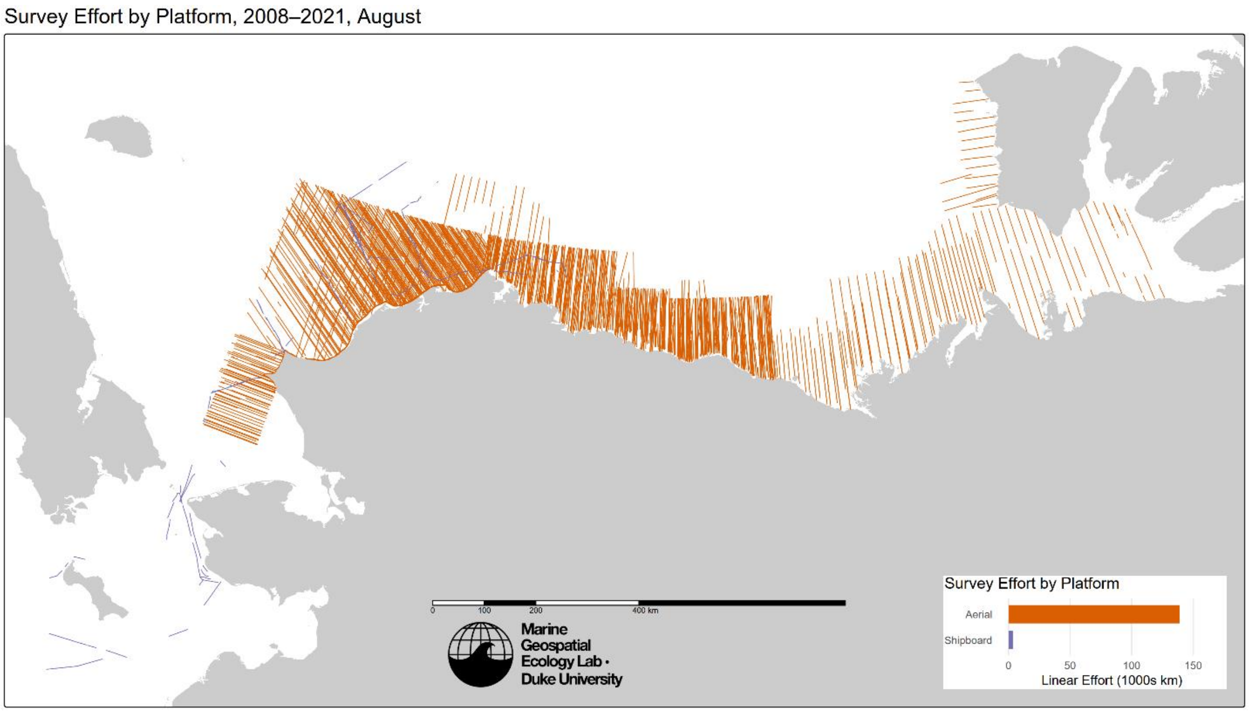

Figure 9 Survey transects during August.

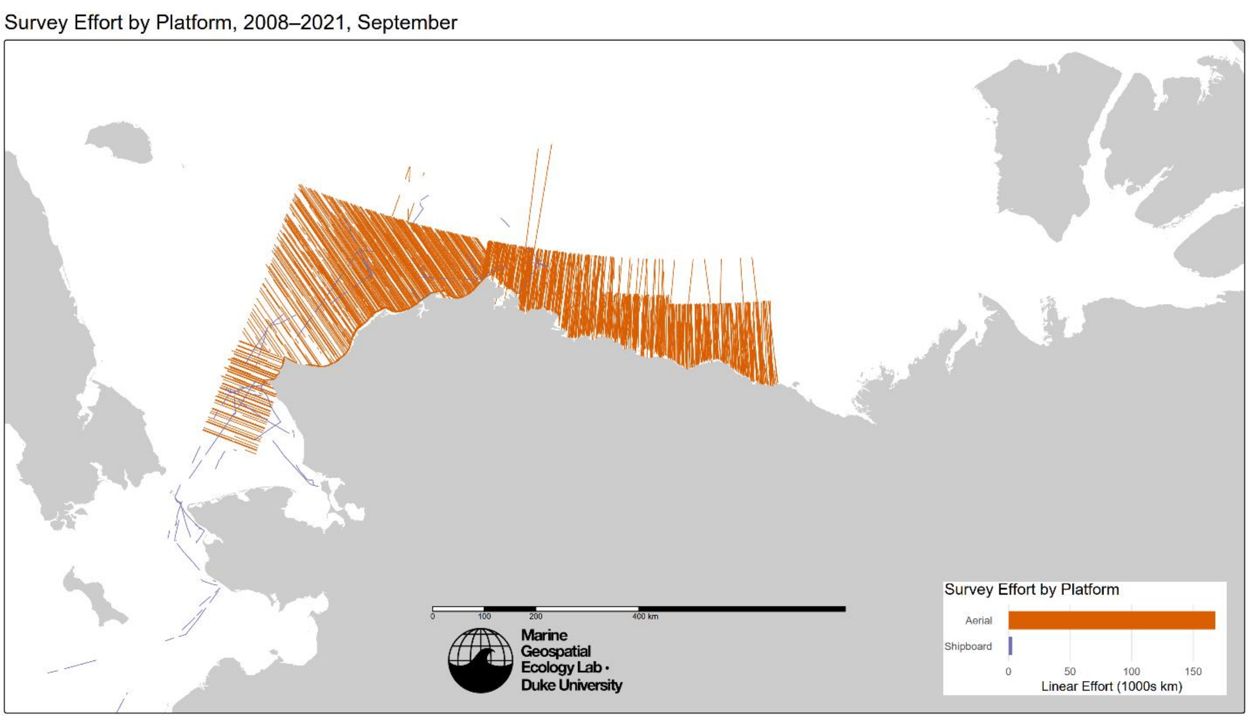

Figure 10. Survey transects during September.

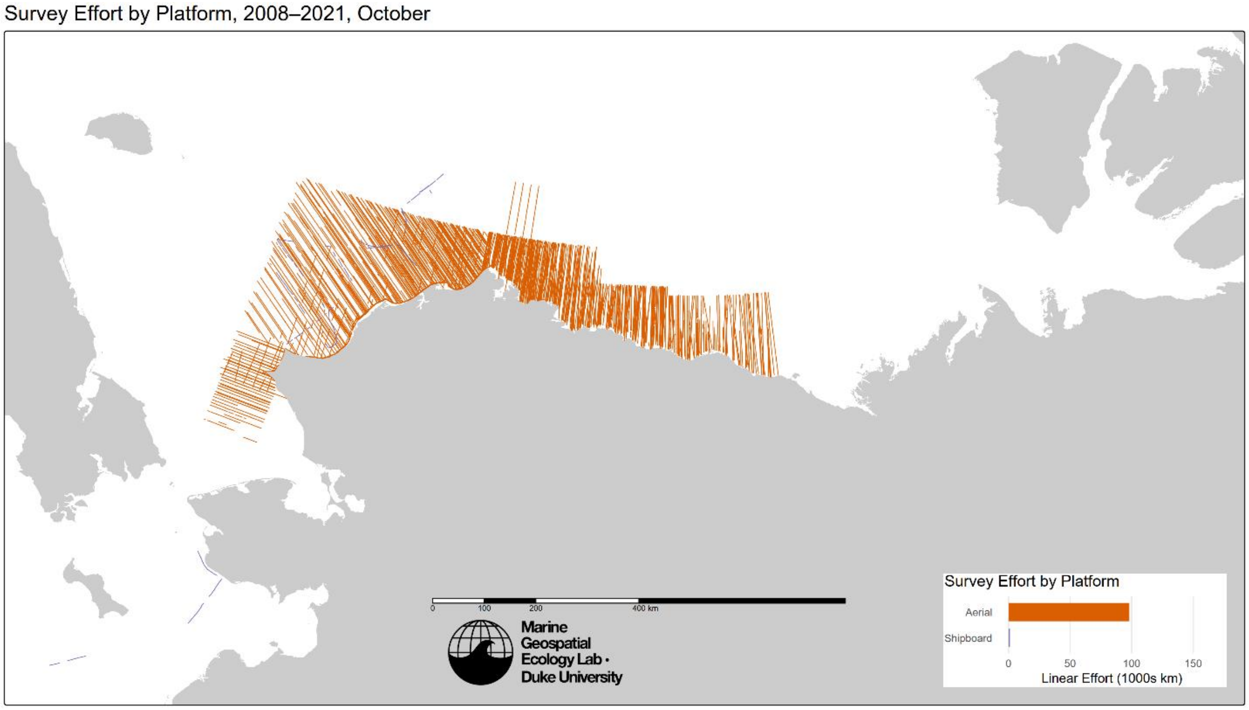

Figure 11. Survey transects during October.

Table 1.Summary of survey effort, by platform, 2008-2021

Institution	Period	Effort (1000s km)
Aerial		
DFO	2008–2010	9.4
MML	2008–2021	532.4
Shipboard		
MML	2010–2015	7.7
All		549.6

Table 2. Summary of survey effort during 2008-2021 split out over each of the 5 main survey months. Values are in km and represent the cumulative on-effort distance covered on the trackline.

Year	***June***	***July***	***August***	***September***	***October***	***Total***
2008	2,748	787	5,428	6,809	6,486	**22,257**
2009	1,108	4,585	3,543	11,762	7,449	**28,446**
2010		6,901	3,569	8,421	5,296	**24,188**
2011	4,006	4,419	9,046	16,872	4,110	**38,454**
2012	360	12,951	15,781	11,849	10,279	**51,219**
2013		8,584	14,219	12,331	2,757	**37,891**
2014		9,334	11,307	11,956	9,606	**42,203**
2015		7,711	11,773	19,112	10,997	**49,593**
2016		13,367	15,487	17,451	10,002	**56,307**
2017		13,634	15,368	16,169	8,517	**53,688**
2018		11,306	11,498	14,551	7,432	**44,786**
2019		9,357	16,723	16,966	12,603	**55,649**
2020				2,305	2,025	**4,330**
2021				4,190	1,623	**5,813**
Total	**8,222**	**102,937**	**133,740**	**170,744**	**99,184**	**514,826**

Below we summarize the data available for use in the models. Table 3 provides the sighting summaries of groups for each modeled taxon, and Table 4 provides the yearly sighting summaries by taxon. Following the tabular summaries, we show the spatial extent of species-specific effort and sightings (Figures 12-24). The off-effort segments of tracks are not included.

Table 3. Summary of sightings of groups during 2008-2021.

Sightings represent the cumulative number of groups and individuals sighted while on-effort.

Species or Guild	**Sightings total (Groups)**	**Sightings total (Individuals)**
Bearded Seals	**633**	**674**
Beluga Whales (EC_B)	**5,652**	**18,025**
Beluga Whales (EB)	**720**	**1,817**
Bowhead Whales	**3, 098**	**7,935**
Fin whales	**107**	**196**
Gray Whales	**1,658**	**4,424**
Harbor porpoise	**59**	**86**
Humpback whales	**84**	**159**
Killer whale	**15**	**97**
Minke whale	**38**	**48**
Small Pinnipeds	**10,547**	**21,799**
Unidentified Pinnipeds	**1,395**	**1,939**
Walrus	**4,975**	**83,983**
Total	**25,883**	**141,182**

Table 4. Summary of sightings of groups by species and year during 2008-2021 for all Arctic surveys. Sightings represent the cumulative number of groups sighted while on-effort for a given year and may include sightings outside of the modeled study area boundary.

Years	Bowhead whales	Beluga whales	Fin whales	Gray whales	Humpback whales	Minke whales	Harbor porpoise	Killer whales	Walrus	Bearded seals	Small unidentified pinnipeds	Unidentified pinnipeds	Total
2008	156	187	0	26	0	0	0	0	73	64	0	197	703
2009	126	151	0	101	1	0	1	0	410	69	455	130	1,444
2010	140	72	0	51	0	0	7	0	209	7	293	71	850
2011	55	206	54	121	85	5	28	3	719	100	871	68	2,318
2012	232	454	9	138	44	6	0	6	418	31	984	165	2,491
2013	219	355	15	154	64	5	6	5	416	76	767	188	2,273
2014	253	780	6	231	7	2	0	1	268	7	916	119	2,593
2015	241	517	13	102	5	6	2	1	393	21	1,123	177	2,605
2016	499	335	2	205	4	8	6	3	688	16	1,280	127	3,174
2017	334	1,105	13	222	6	4	2	2	653	81	1,725	86	4,237
2018	278	506	46	173	38	3	12	2	737	70	497	48	2,410
2019	358	1,481	12	144	10	5	0	4	845	81	1,600	166	4,707
2020	209	151	0	5	0	0	0	0	20	9	87	2	483
2021	87	231	0	2	0	0	0	0	30	19	214	1	584
Total	**3,187**	**6,531**	**170**	**1,675**	**264**	**44**	**64**	**27**	**5,879**	**651**	**10,812**	**1,545**	**30,872**

Bowhead Whales

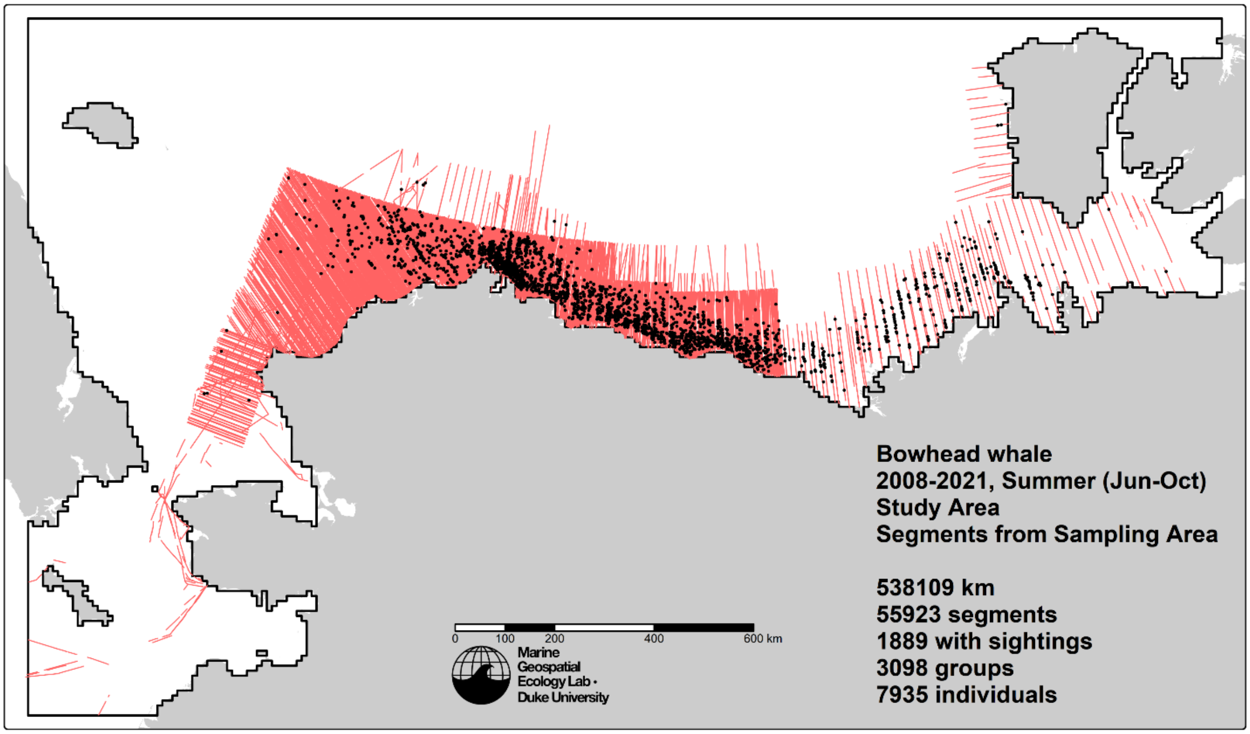

Figure 12. All on-effort sightings of bowhead whales (Balaena mysticetus) in the study area.

.

Beluga Whales

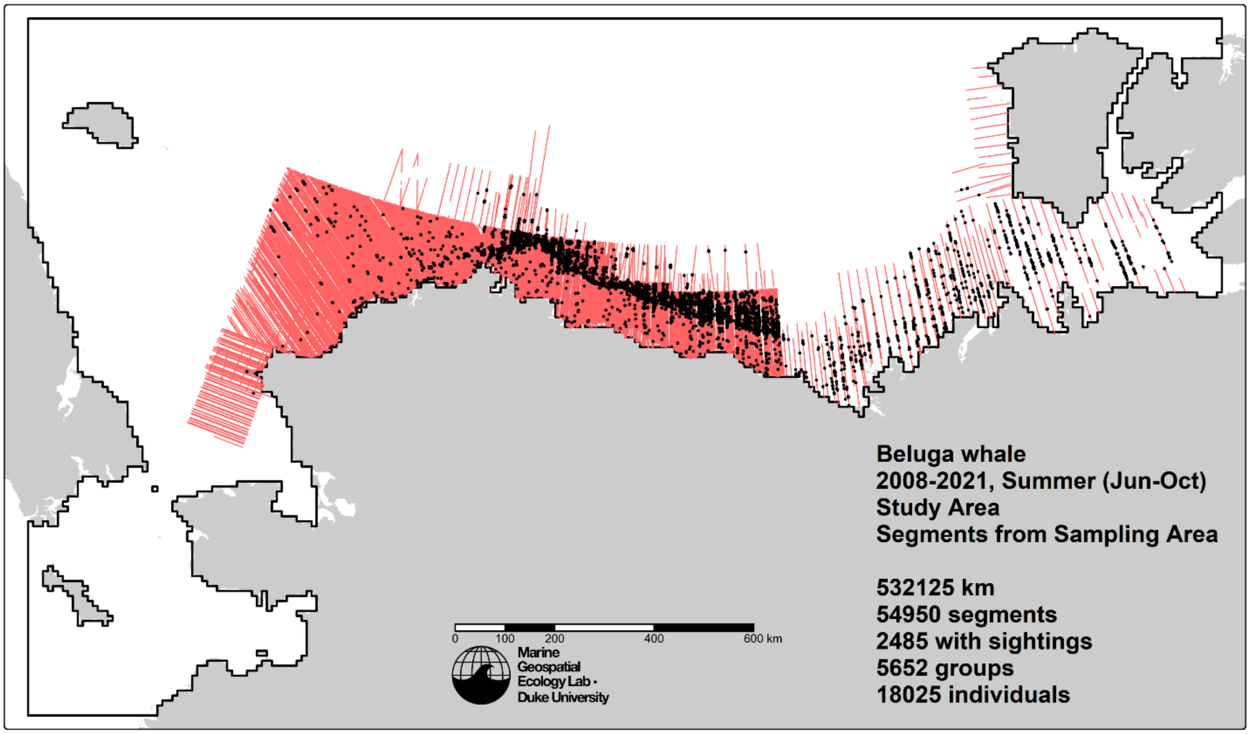

Figure 13. All on-effort sightings of Eastern Chukchi and Beaufort Sea beluga whales (Delphinapterus leucas) in the study area.

.

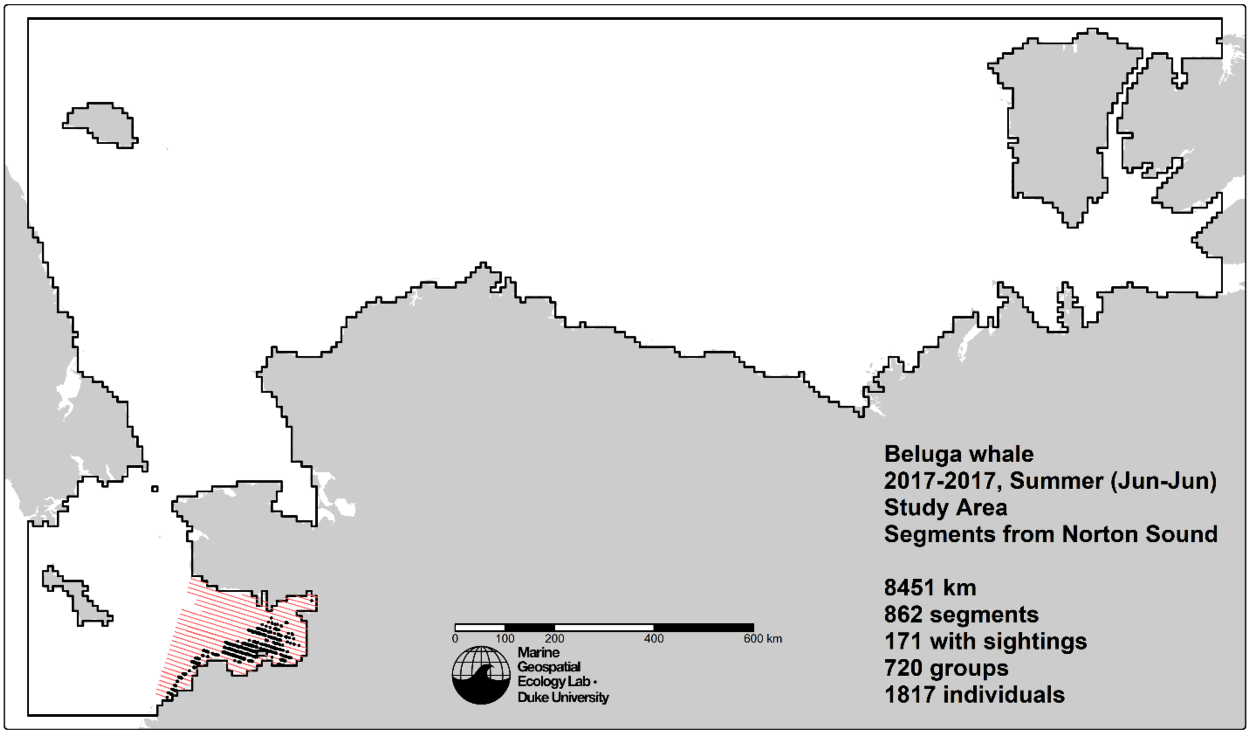

Figure 14. All on-effort sightings of Eastern Bering Sea beluga whales (Delphinapterus leucas) in Norton Sound.

Fin Whales

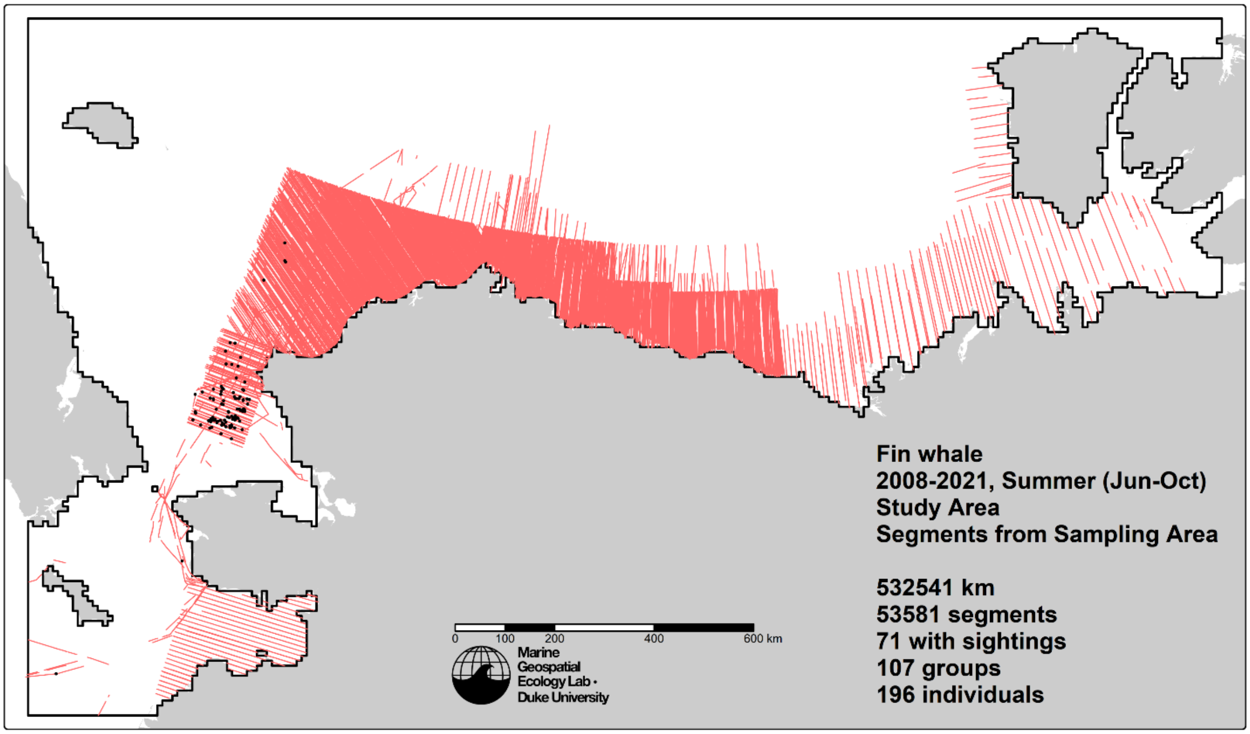

Figure 15. All on-effort sightings of fin whales (Balaenoptera physalus) in the study area.

Gray Whales

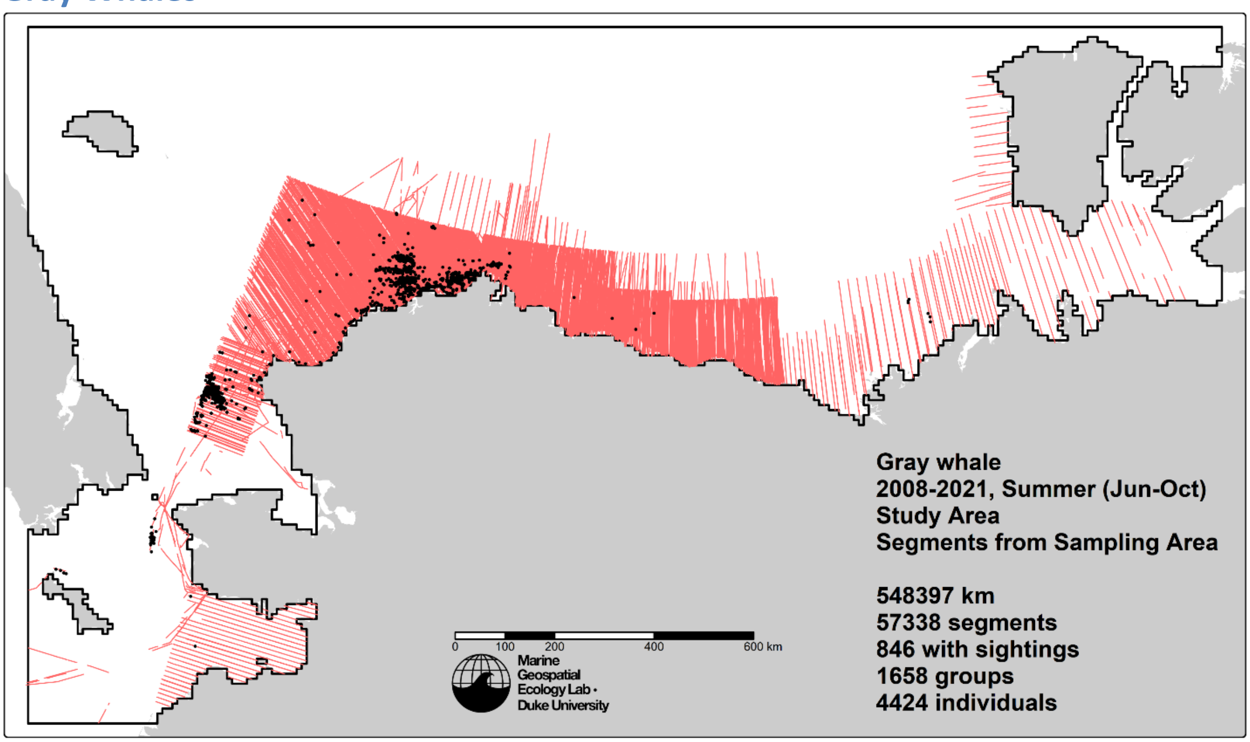

Figure 16. All on-effort sightings of gray whales (Eschrichtius robustus) in the study area.

.

Humpback Whales

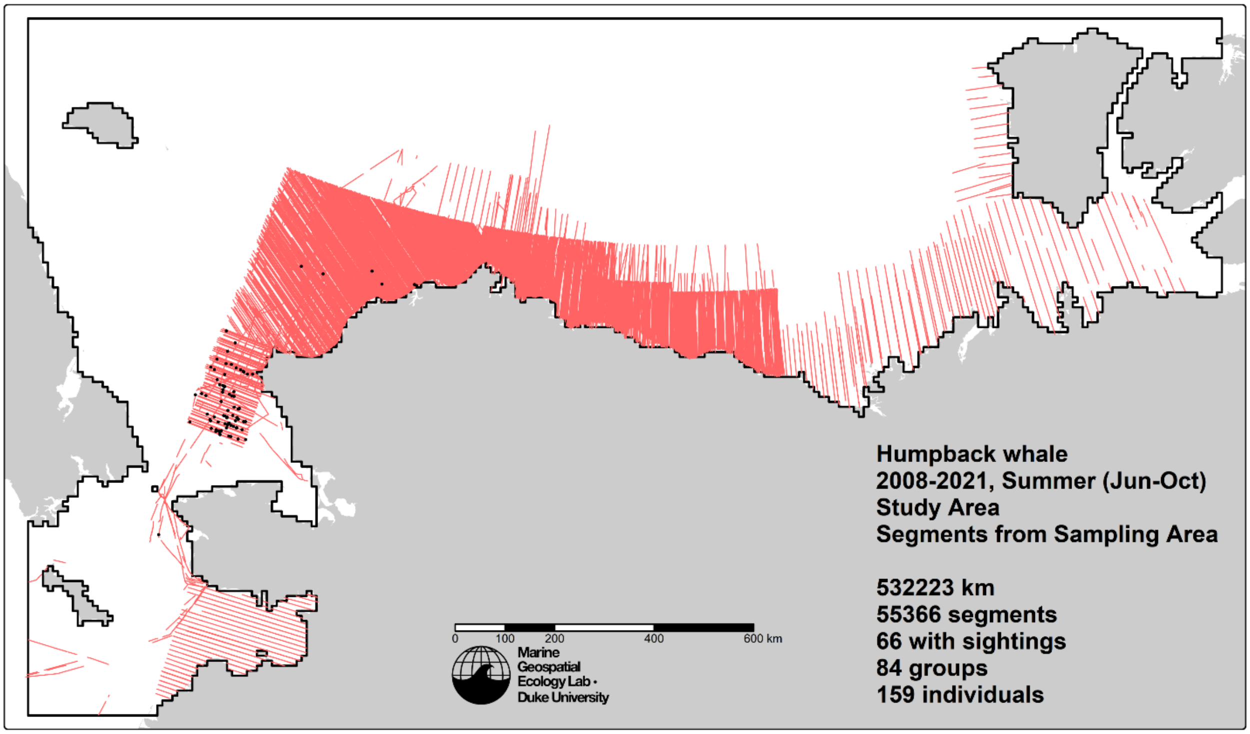

Figure 17. All on-effort sightings of humpback whales (Megaptera novaeangliae) in the study area.

Minke Whales

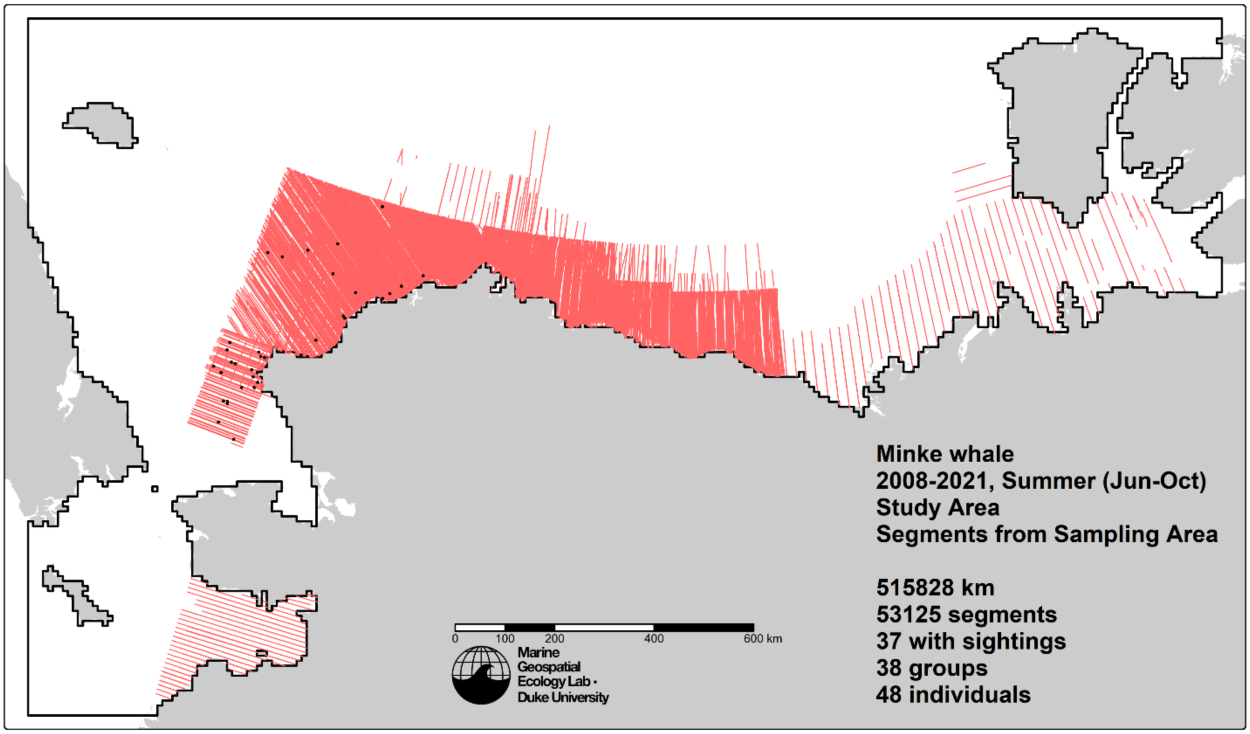

Figure 18. All on-effort sightings of minke whales (Balaenoptera acutorostrata) in the study area.

Harbor porpoises

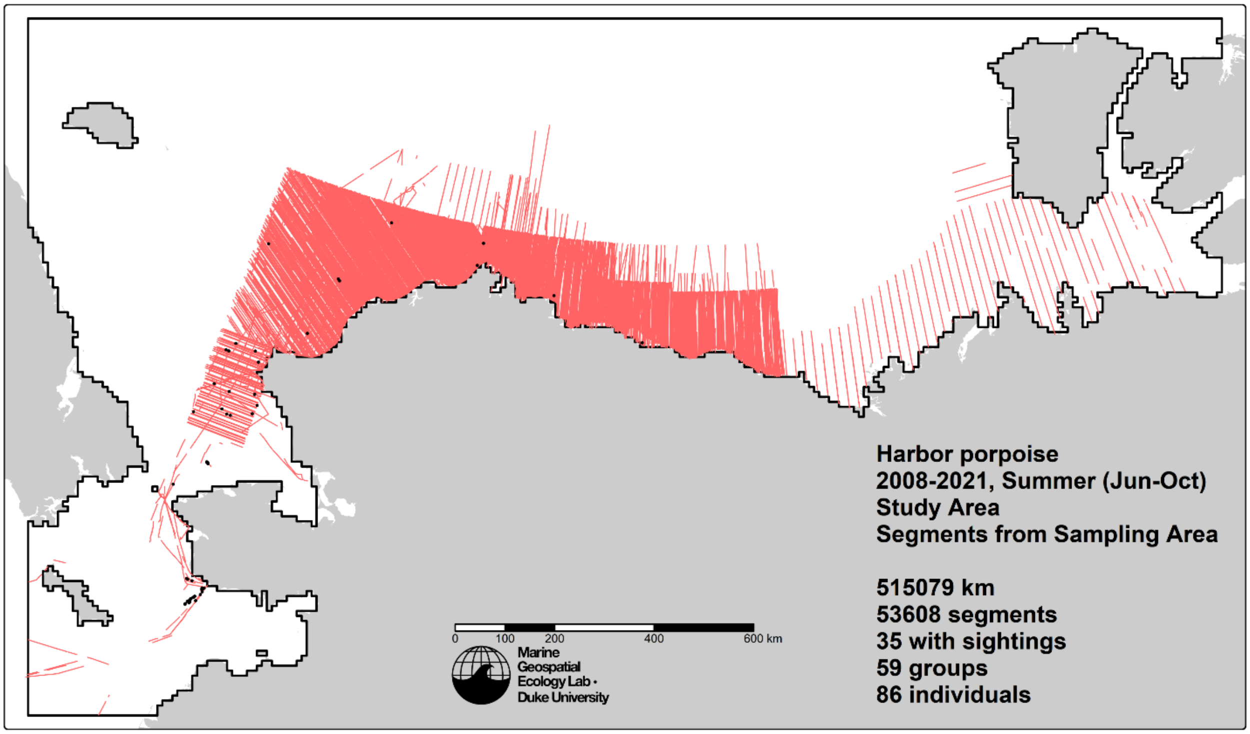

Figure 19. All on-effort sightings of harbor porpoises (Phocoena phocoena) in the study area.

Killer Whales

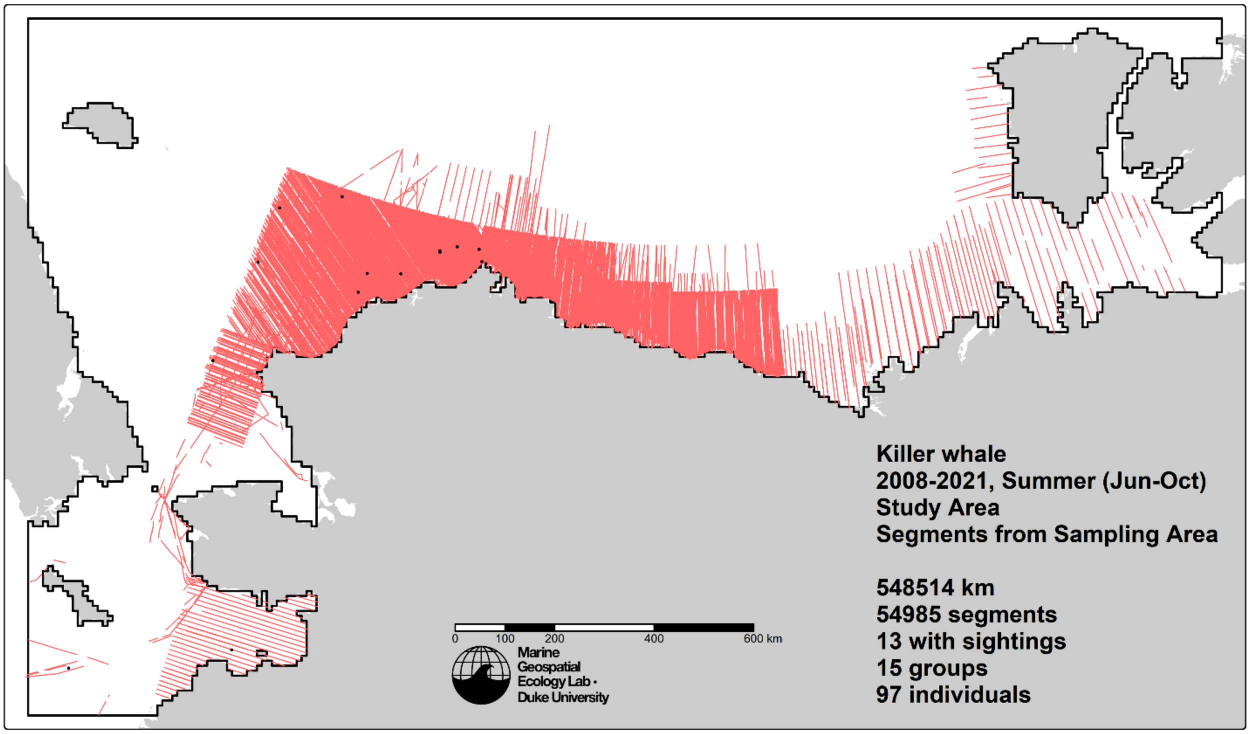

Figure 20. All on-effort sightings of killer whales (Orcinus orca) in the study area.

Walrus

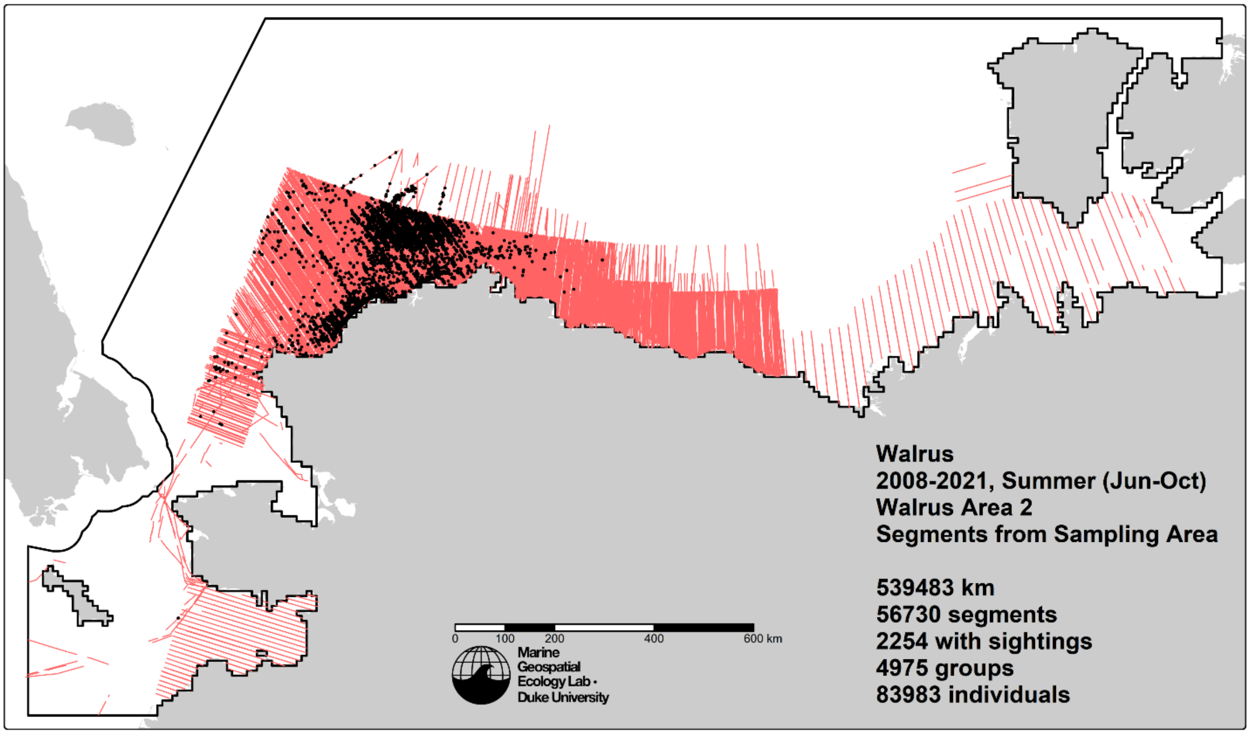

Figure 21. All on-effort sightings of walrus (Odobenus rosmarus) at sea in the Walrus study area.

Bearded Seals

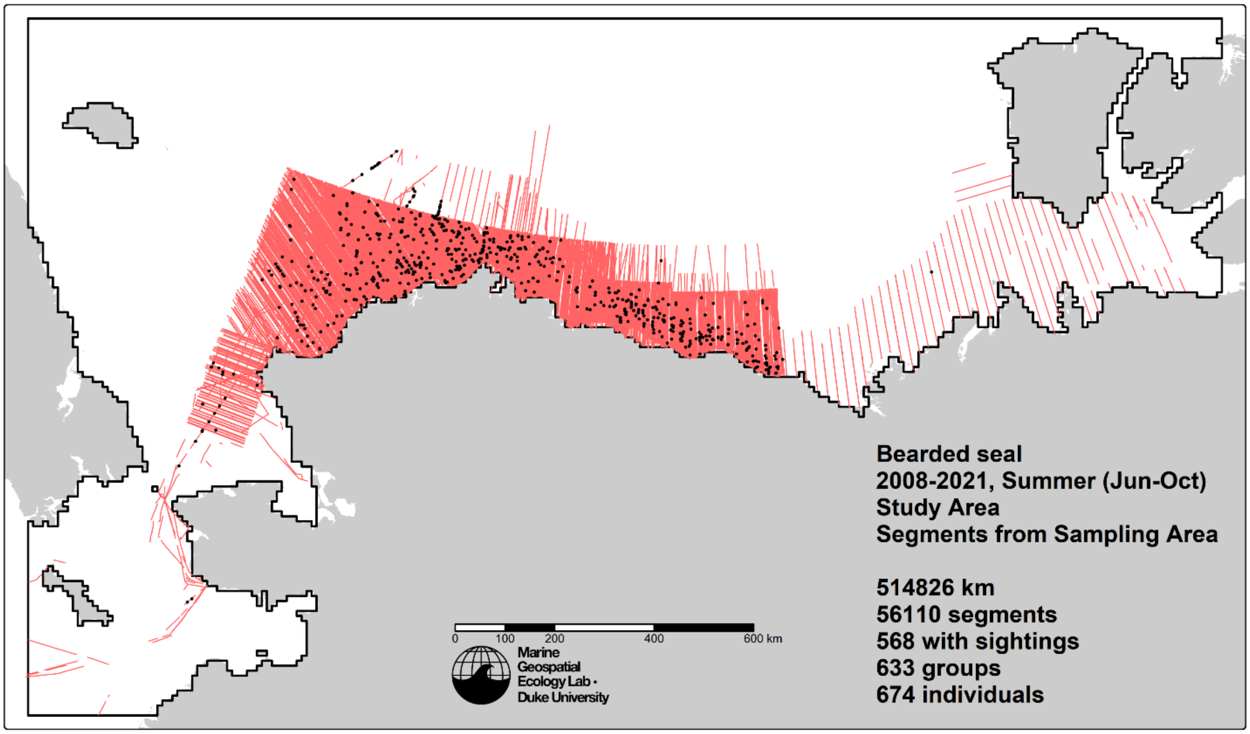

Figure 22. All on-effort sightings of bearded seals (Erignathus barbatus) at sea in the study area.

Small Unidentified Pinnipeds

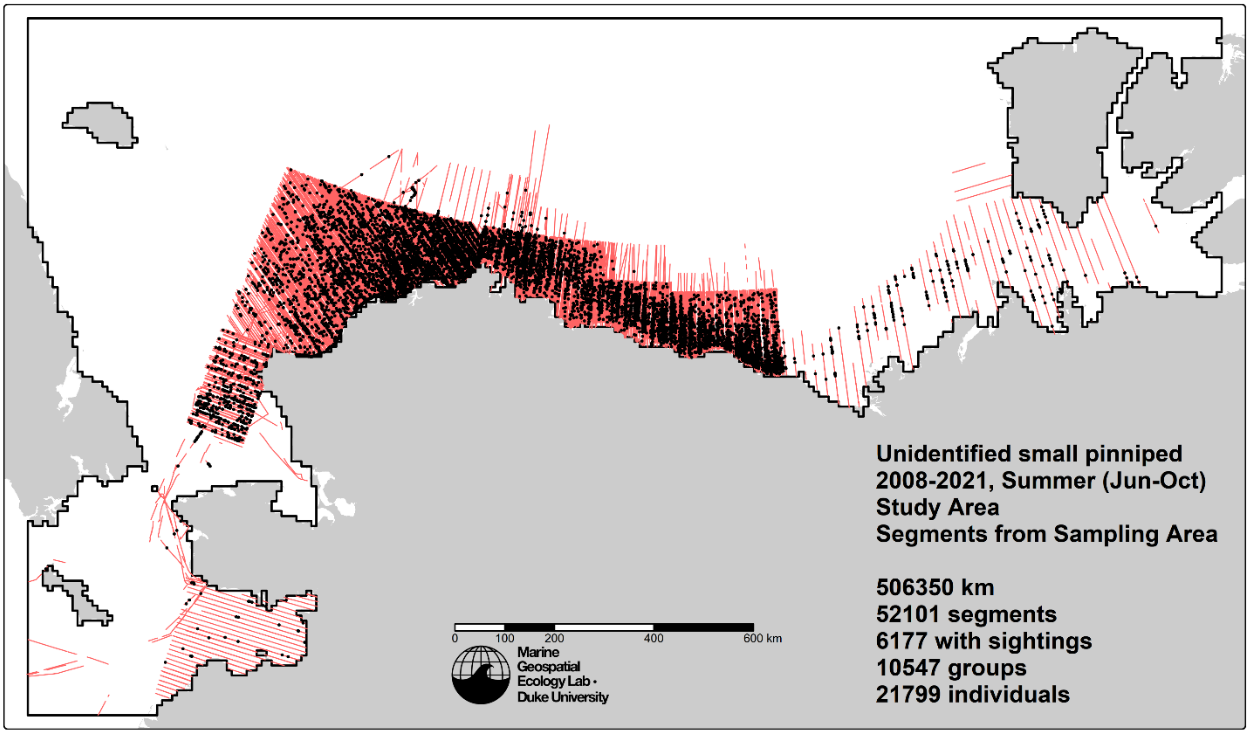

Figure 23. All on-effort sightings of small pinnipeds at sea in the study area. Pinnipeds were not recorded during the DFO surveys in 2007-2010.

Unidentified Pinnipeds

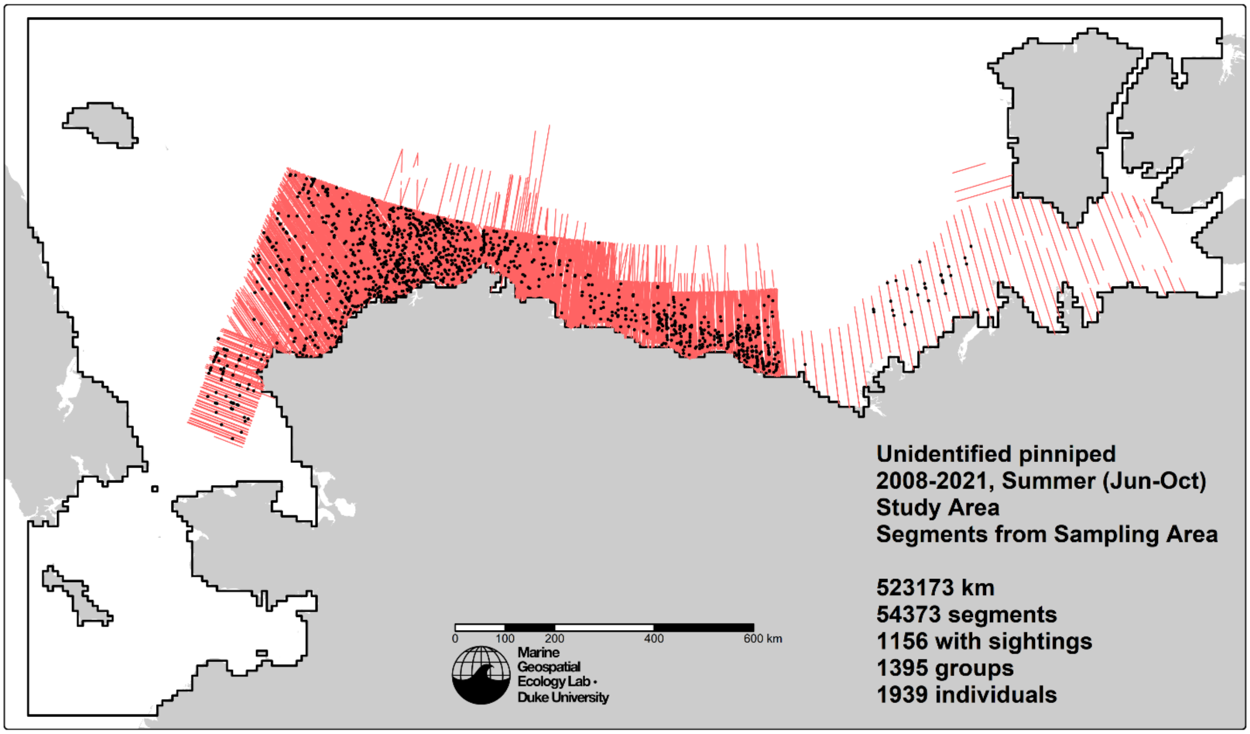

Figure 24. All on-effort sightings of unidentified pinnipeds at sea in the study area. Pinnipeds were not recorded during the DFO surveys in 2007-2010.

2.3. Data Cleaning

The data provided by our collaborators at MML and DFO (including ARCWEST and CHAOZ data) were in exceptionally good condition. To be consistent with previously established workflows for density products delivered to the Navy, we followed the data preparation process outlined in Roberts et al. (2016). We used a custom-built ArcMap plug-in that allowed for screening of the ASAMM data at a daily basis. This allowed us to load one day's worth of survey effort, along with the sightings, and on a transect-by-transect basis, check and flag errors. Most errors were small and included such things as going off-effort late or resuming a transect early. For example, when the plane breaks from the transect to circle a group of large whales, observers mark the breakpoint with a time- and location-stamp. It is crucial that these break points be marked as accurately as possible. In most cases, these “break-transect” and “resume-transect” points were consistently and correctly marked; however, in a few instances we detected and fixed anomalies.

Throughout the data cleaning phase, the modeling team reviewed the events that had been flagged and resolved them. When more complicated cases arose, we contacted MML collaborators to review them and incorporate their suggested changes. We kept detailed processing notes that described the steps we used to work through the data. An example of a more complicated case occurred when the plane circled a sighted group for an extended period. Depending on the size of the group and the time spent circling, the observers occasionally detected additional sightings while circling. Based on how far these additional groups were from the initial sighting that led to breaking transect, and whether the species were similar or different, we either counted the additional groups as part of the initial group or excluded them from the analysis. Sometimes this required additional input from collaborators.

2.4. Overall workflow of the analytical process

In the first stage of the model, called detection modeling (Figure *25*), 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 key 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. 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 (Figure *25*), 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. After selecting the best candidate models, 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 marine 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 *25*, they are not considered separate "stages" under DSM methodology. They are considered part of the second stage, the spatial model.)

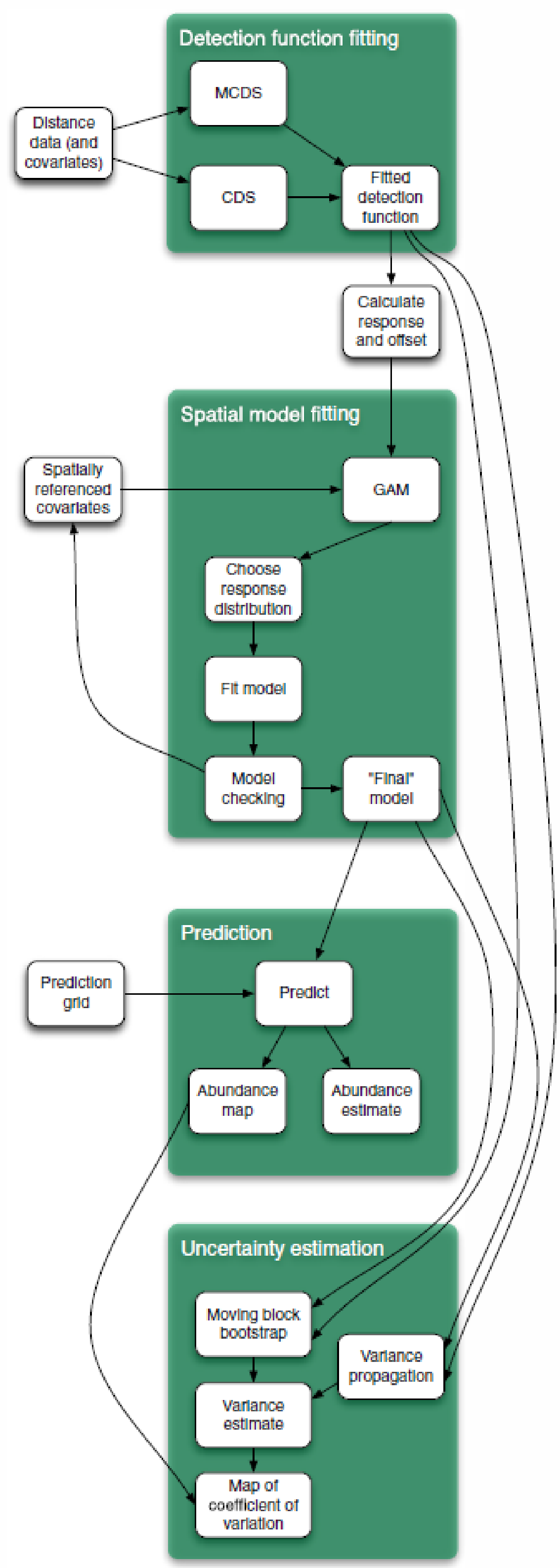

Figure 25. Generic density surface modeling workflow, reproduced from Figure 6 of Miller et al. (2013).

2.5. Data Modeling -- 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, 2015) recommended a minimum of 60–80 observations for fitting detection functions, though they noted that sample sizes as low as 40 may sometimes be acceptable. The Navy-funded "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.

We were able to develop taxon and guild specific hierarchies for all models for aerial and shipboard surveys separately, however for some species there were insufficient sightings to break the hierarchy down further (e.g., by airframe: Aero Commander and Twin Otter). For the DFO strip transect survey of Canadian waters, for which we had no sighting distances to build a detection function, we assumed detection probability was 1 within the defined strip and discarded sightings beyond it. Finally, species specific detection functions were also applied to Norton Sound segments for models that used these segments.

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 Multiple Covariate Distance Sampling (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. In some instances, we also tried a gamma function. The gamma form is a flexible alternative for situations in which detection counts drop off near distance 0, indicative of poor visibility under the aircraft. It can accommodate asymmetric detection shapes, allowing for a sharp peak near the trackline and a gradual decline at greater distances. This flexibility makes it useful when detection probabilities do not conform well to the more commonly used half-normal or hazard-rate key functions.

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, (see Table 5). Not all covariates were tested for all taxa, and covariates that produced obvious ill effects were discarded. We fit all detection functions using the R mrds package version 3.0.1.

The accompanying taxon-specific reports document the detection hierarchies that were used, and the detection functions that were fitted along with statistical diagnostics.

2.5.1 Covariates used

Table 5 summarizes the covariates evaluated during detection function modeling. Because several covariates represented alternative encodings or closely related measures of the same underlying condition, we organized them into groups of correlated covariates. To avoid redundancy and multicollinearity, only one covariate from each group was included in any given detection function formulation. For example, *Visibility*, *VisImpCode*, and *VisibilityCode* represent related measures of observation conditions; therefore, only one of these variables was considered in a single candidate model.

Table 5. Covariates at the effort levels tested in the detection functions.

Covariate	Description	Type	Platform	Values
Weather Code	Nubosity	factor	Plane	Clear / Partly cloudy / Cloudy
VisImpCode	Impediment of visibility	factor	Plane	Fog / Glare / Haze / Precip / Ice on window / Low ceiling / none
Visibility	Visibility in km	numeric	Both	1-20
VisibilityCode	Visibility category (km)	factor	Plane	<1 / 1-2 / 2-3 / 3-5 / 5-10 / Unlimit.
IceCode	Description of Ice	factor	Plane	broken floe/floe/frazil/grease/new/new + broken floe/no ice/pack/pack/floe/shorefast
Ice	Percent coverage of ice (%)	numeric	Plane	0-100%
Beaufort	Sea state (from Beaufort scale)	numeric	Both	0-6
Swell	Swell Height (ft)	numeric	Ship	0-10
Windspeed	Windspeed (kts)	numeric	Ship	0-35
GlareCode	Glare Description	factor	Ship	None=0, Diffuse = 1, <10% = 2, <50% =3, <75%=4, >= 75% = 5
CloudCover	Percentage of cloud cover	factor	Ship	Clear = 0, 25%=1, 26-50% =2, 51-75%=3, 75% = 4

2.6 Perception and availability bias corrections

A fundamental assumption of distance sampling is that objects located at distance zero, directly along the survey trackline, are detected with certainty (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 the observer team does not detect animals 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. $g(0)_{perception}$ as the probability that an animal at the surface will be sighted if it is at distance 0, and $g(0)_{availability}$ 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 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."

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, so that the animals do not have a chance to respond before observers are close, or altitude, so they 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.

Perception bias is commonly assessed using independent observers or multiple observer teams whose sightings are compared to quantify missed detections. The most commonly-used variations of this approach are known generally as *mark recapture distance sampling* (MRDS; Burt et al. 2014).

All the surveys in our analysis used a single observer team, precluding our use of MRDS methodology. Instead, 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.

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, we assumed that availability bias would be negligible (i.e., $g(0)_{availability} = 1$) 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.

2.6.1 Availability bias corrections for aerial surveys

Availability bias for aerial surveys depends on several 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):

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

Here, $a(x)$ is the availability bias correction factor at perpendicular distance *x*; the value $a(0)$ is the $g(0)_{availability}$ 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.

Surface and dive interval information was obtained from published diving studies. To evaluate availability at distance zero, we estimated $\boldsymbol{t(0)}$, the total time an animal remains within view along the trackline at perpendicular distance zero. This parameter was calculated from the survey speed and altitude. We first describe the estimation of $\boldsymbol{t(0)}$and then the application of surface and dive intervals to derive availability estimates.

2.6.2 Estimation of $\boldsymbol{t(0)}$

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) and speed of 220 km h^{-1} (119 knots). To do this, Robertson et al. (2015) fit 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, observers flew trial passes by a static structure placed at randomly determined perpendicular distances. Observers were then asked 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, the authors' 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 6 shows our results.

Table 6. $t(0)$ estimates for aerial surveys used in our analysis.

Altitude (m)	Speed (kts)	$t(0)$ (s)	Surveys
305	108	42.37	NOAA MML ASAMM Twin Otter Surveys
381	120	47.63	NOAA MML ASAMM Aero Commander Surveys

2.6.3 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. 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:

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

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 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 can otherwise be estimated, our models can be updated to account for this knowledge.

The application of the group availability bias estimator to pinnipeds led to a clear underestimation of abundance. The estimator is intended to be applied to an accurate estimate of a group's size, to estimate the probability of a group of that size being missed. However, the vast majority of pinniped sightings were collected with the ASAMM survey protocol, which employed "passing mode" for pinnipeds. Under passing mode, observers did not circle the sighted group to obtain an accurate estimate of group size after animals had been given a chance to surface. Instead, the aircraft passed by without breaking to circle, and the observer recorded their best estimate of animals they saw at the surface at the time the sighting was made. This differed from the "closing mode" used for cetaceans, which were circled and given a chance to surface, to ensure accurate group size estimates.

Given the surface and dive intervals we assumed for pinnipeds (Table 8.), the probability that an individual would be at the surface when the aircraft passed by was low. In a group of more than 1 individual, this probability would apply to every individual independently, and a proportionally sized fraction of the group would be submerged and not counted, regardless of the group's size, assuming dive behavior was asynchronous and independent of group size. The group availability bias estimator does not correct for this problem: it is not an estimator of the correct size of a group given how many individuals were instantaneously sighted, it is an estimator of the probability that at least one individual will be at the surface given the group's correct size. Therefore, to correct for the underestimation of pinniped group sizes, we omitted the application of the group availability bias estimator and instead applied the availability bias correction factor for a single animal to the entire group, regardless of size.

The perception bias corrections used for aerial surveys are shown in Table 7, surface and dive intervals used to calculate aerial survey availability bias are shown in Table 8, and bias corrections for shipboard surveys are shown in Table 9.

Table 7. g(0) used for Aerial Surveys.

Species	Surveys	Group Size	g0.P	g0.P.source
Bowhead whale	All	All	0.727	Ferguson 2021
Beluga whale	All	All	0.565	Marcoux et al. 2025
Bearded seal	All	All	0.181	Palka et al. (2017): NEFSC
Fin whale	All	< 3	0.67	Palka et al. (2021): NEFSC
Fin whale	All	>= 3	1	Assumed
Gray whale	All	< 3	0.67	Palka et al. (2021): NEFSC
Gray whale	All	>= 3	1	Assumed
Humpback whale	All	< 3	0.67	Palka et al. (2021): NEFSC
Humpback whale	All	>= 3	1	Assumed
Harbor porpoise	All	<=25	0.56	Palka et al. (2021): SEFSC
Harbor porpoise	All	> 25	0.99	Caretta et al. (2000)
Killer whale	All	Any	0.54	Palka et al. (2021): NEFSC: pilot whales
Minke whale	All	All	0.62	Palka et al. (2021): NEFSC
Walrus	All	<50	0.49	Heide-Jørgensen et al. (2014)
Walrus	All	>=50	1	Assumed
Unidentified Pinnipeds	All	All	0.181	Palka et al. (2017): NEFSC
Unidentified Small Pinnipeds	All	All	0.181	Palka et al. (2017): NEFSC

Table 8. Surface and Dive Intervals Used to calculate Aerial Survey Availability Bias.

Species	Surface Interval (s)	Dive Interval (s)	Source
Bowhead whale (summer)	66.6	394.2	Robertson et al. (2015): Table II
Bowhead whale (autumn)	78.9	542	Robertson et al. (2015): Table II
Beluga whale	287.2	425.2	Marcoux et al. (2025): Table II
Bearded seal	84	396	Hamilton et al. (2018)
Fin whale	51.74	173.49	Palka et al. (2017)
Gray whale	49.8	190.8	Wursig (1983) Table I
Humpback whale	144.55	175.55	Palka et al. (2017)
Harbor porpoise	49	64	Palka et al. (2017)
Killer whale	5	47.33	Miller et al. (2010)
Minke whale	26.76	116.37	Palka et al. (2017)
Walrus	72	312	Wiig et al. (1993)
Unidentified Pinnipeds	198	78.9	Vance et al. (2021)
Unidentified Small Pinnipeds	198	78.9	Vance et al. (2021)

Table 9. g(0) used for Shipboard Surveys, g0.P is perception bias and g0.A is availability bias.

Species	Group Size	g0.P	g0.P.source	g0.A	g0 A.source
Bowhead whale	Any	0.48	Palka et al. (2021): NEFSC	1	Assumed
Beluga whale	NA	NA	NA	NA	NA
Bearded seal	Any	0.85	Reay (2005)	1	Assumed
Fin whale	Any	0.48	Palka et al. (2021): NEFSC	1	Assumed
Gray whale	Any	0.48	Palka et al. (2021): NEFSC	1	Assumed
Humpback whale	Any	0.39	Palka et al. (2021): NEFSC	1	Assumed
Harbor porpoise	Any	0.52	Palka et al. (2021): NEFSC	1	Assumed
Killer whale	<= 20	0.6415	Garrison et al. (in prep.)	1	Assumed
Killer whale	>20	1	Garrison et al. (in prep.)	1	Assumed
Minke whale	Any	0.48	Palka et al. (2021): NEFSC	1	Assumed
Walrus	Any	0.85	Reay (2005)	1	Assumed
Unidentified Pinnipeds	Any	0.85	Reay (2005)	1	Assumed
Unidentified Small Pinnipeds	Any	0.85	Reay (2005)	1	Assumed

2.7 Splitting 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 the AFTT Phase IV models, the Navy requested that density predictions be provided on a grid at a spatial resolution no coarser than 10x10 km, when possible. Therefore, for the Arctic models we generated segments with a target length of 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 for which 1/3 or more of it was off-effort (i.e., 3.333 km). 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 (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 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.

2.8 Spatial models

For each modeled taxon, we first fit detection functions and applied corrections for perception and availability bias. We then estimated the number of animals present and the effective area surveyed for each segment, accounting for the detectability factors 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.

2.8.1 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 the 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:

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

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:

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

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):

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

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 1.9.3 (Wood 2017). For smoothed terms, we used thin-plate regression splines with shrinkage smoothers (`bs="ts"`) (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.

2.8.2 Spatial model covariates

Table 10 lists the covariates we prepared for the 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 the period 2008-2021; 4) available at 25 km spatial resolution or higher; and 5) available at least at monthly contemporaneous resolution.

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) 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 June 2010 to the monthly chlorophyll grid for June2010, all July 2010 segments to the July 2010 grid, etc.). Next, for each grid to which some segments had been matched, we overlaid the segments' centroids on the grid using geographic information systems (GIS) and extracted the value of the cell under each centroid using linear interpolation. We proceeded through all segments and covariates until each segment had a climatological value for each covariate.

Table 10. 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. All distances were calculated using a fast-marching algorithm that accounted for the shortest paths around islands and peninsulas.

Type	Covariates	Resolution	Description
Spatial	x, y	10 km	Easting (m) and northing (m) representing geographic location in the projected coordinate system of the analysis
	Lat, Long		Latitude and Longitude representing geographic location as angular units (an alternative to x, y)
Static	Depth, Slope	30 arc sec	Seafloor depth (m) and slope, derived from SRTM30-PLUS global bathymetry (Becker et al. 2009).
	DistToShore, DistToBS, DistToBS2, DistTo35m, DistTo100m, DistTo125m, DistTo150m, DistTo300m, DistTo1500m, DistTo200m, DistTo2500m	30 arc sec	Distance (km) to the closest shoreline, Distance to Bering Strait (km) as geographic feature and Distance to Bering Strait 2 (km) with (-) south of BS and {+) north of BS is modified version that distinguishes locations north vs. south of the strait to better capture ecological differences between the Chukchi and Bering Sea regions and various ecologically relevant isobaths, derived from SRTM30-PLUS
	DistToCan,	30 arc sec	Distance (km) to the closest submarine canyon; derived from the Harris et al. (2014) geomorphology
Bottom-Type	GVL, SND, MUD, GRZ, HardVsSoft, CRB, OCBN	10km	Bottom Type Covariates: Gravel, Sand, Mud, Grain size, Hard vs. Soft bottom type, Carbonate, and Organic carbon provided by Chris Jenkins at dBSEABED (University of Colorado).
Physical oceanographic	SST, BotT, SSS, BotS, u, v, MLD, WSPD	0.083°, monthly	from the GLORYS12V1 product is the CMEMS global ocean eddy-resolving (1/12° horizontal resolution, 50 vertical levels) reanalysis covering the altimetry (1993 onward)

Biological	Chl, NPPV, PHYC	0.25°, monthly	1998-2021	Chlorophyll *a* concentration (mg m^{-3}), Net primary production, and Phytoplankton carbon concentration from CMEMS Global Ocean Biogeochemistry Hindcast — dataset cmems_mod_glo_bgc_my_0.25deg_P1M-m
National Snow and Ice	DistToIce, IceConc	10 km, monthly	1998-2021	Distance to the nearest ice edge (m) and Sea-ice concentration per grid cell (%, 0–100) computed from NSIDC ice-extent GeoTIFFs.

2.8.3 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, Wood 2017). 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.

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 models with and without spatial terms in a second step. We decided that each combination in the second step would, in general, maximally include:

- Depth: always included, on the basis that it is widely correlated with many ecological processes
- 3-5 additional dynamic covariates, one or more from each of three families:
    - Additional physical water properties: sea surface temperature, bottom temperature, surface salinity, bottom salinity
    - Dynamic physical features: distance to ice, ice concentration
    - Biological: chlorophyll, primary productivity, phytoplankton
- Zero or more additional covariates, included in special situations:
    - 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.
- Additional bivariate interactions were tested in certain situations when additive univariate relationships did not sufficiently capture a taxon's distribution.
- Bottom-type covariates, for species that forage benthically or are otherwise associated with benthic habitat.
- Distance to Bering Strait, mainly for species that migrate through it.

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 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 influence of depth was addressed. We also did this for certain optional covariates (e.g., bathymetric features and bottom-type).

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 to obtain a set of final candidates. For each of these we tried variants with and without an XY bivariate term, to account for deviance not explained by the environmental covariates. Fitting this smaller set of candidate final models was tractable on our computational infrastructure. During this stage we also evaluated the covariate coverage and adjusted Winsorization (Dixon 1960) and transformations of covariates as needed. We then refitted the top models with the adjusted Winsorization values and evaluated the results again.

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. For most species we also qualitatively evaluated the match-up between summarized density predictions and summaries of passive acoustic monitoring results from J. Crance and C. Berchok (NOAA AFSC MML) (We gratefully acknowledge J. Crance and C. Berchok 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 5 maps, one for each month that was modeled, with each estimating the climatological mean density for the taxon during that month.

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). This produced maps of the coefficient of variation (CV) for each of the five monthly prediction surfaces. The uncertainty represented in the CV depends on the type of model and prediction summary. For models based only on static or climatological covariates, the monthly CV maps primarily represent uncertainty in the fitted density surface model parameter estimates. For models using contemporaneous dynamic covariates and summarized across multiple years, the monthly CV maps also reflect interannual variability in predicted density associated with year-to-year variation in those dynamic covariates. Thus, the contemporaneous-model CV maps represent both model-parameter uncertainty and variability among annual predictions for a given month, whereas climatological-model CV maps represent model-parameter uncertainty for the corresponding monthly prediction surface.

2.8.4 Limited density surface models

For the killer whale model, which had limited sightings, we fitted a density surface model in which we limited the number of covariates used. The covariate and model selection procedures were specific to and driven by what was known of its ecology. The accompanying taxon-specific report provides details of this procedure. We summarized this model the same way as for the full models discussed above. The beluga whale EB Norton Sound model was also a limited model as it only included spatial (XY) terms and was only produced from and predicted for one year (2017) and month (June).

3. NMSDD Production

The NMSDD is an Esri file 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 were dated 02 March 2026.

In the NMSDD, the density predictions are given as polygon feature classes. All feature classes appear under the Arctic feature dataset. For taxa summarized monthly, there are 5 feature classes per taxon, named `TAXON_`*`monthXX`*`_Arctic` 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 `06` through `10`.

Each feature class is in the Albers Equal Area coordinate system defined for the Arctic 2026 analysis (central meridian: -145.0, standard parallel: 64.0, standard parallel 2: 72.0, latitude of origin: 68.0, datum: WGS 1984).

3.1 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 Arctic 2026 model, we populated all the cells using that taxon's model, or set them to null and specified 'Not Modeled' if there was no model. Finally, for the polygon strata defined in the NMSDD, we filled any slivers shoreward of the modeled regions using a spatial extrapolation procedure and specified these polygons as "Spatial extrapolation".

3.2 Fields of the NMSDD

Table 11 shows the fields provided in the NMSDD.

Table 11. Fields of the 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.
SEASON	TEXT	NA
STUDY	TEXT	A shorthand citation for the data source; always "Duke Density Project 2025" for all features.
STRATUM	TEXT	NA
MODEL_TYPE	TEXT	Specifies how we obtained the density value for the feature: • 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.

Field	ArcGIS data type	Description
		• 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	NA
AREA_SQKM	FLOAT	Estimated area of the feature, in km2, using the World Cylindrical Equal Area projection (WKID: 54034). 100 km2 for most cells predicted by the Arctic model. It can be larger for estuarine strata or smaller for cells bordering land or the edge of the study area.
ABUNDANCE	DOUBLE	Estimated abundance of the feature, in individual animals, computed as DENSITY multiplied by AREA_SQKM.
AREA_SQKM2	FLOAT	Estimated area of the feature, in km2 using the custom Albers Equal Area projection used by the models. 100 km2 for most cells predicted by the Arctic model. It can be larger for estuarine strata or smaller for cells bordering land or the edge of the 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.

4. Summarized Results

In total, we developed models for 10 species and 2 guilds, comprising 5 large whale models, 3 large delphinid models, 1 small delphinoid model, and 4 pinniped models (Table 12).

Most models were developed for the period 2008 - 2021 except the beluga whale EB model which was for the year 2017 only.

Of the 13 models, 11 were implemented as full DSMs, one was a limited density surface model, and one was a spatial (XY) model.

We summarized predictions from 12 models into monthly climatological density surfaces for June-October, and 1 model—beluga whale EB— into a single monthly surface (June), when the entire EB Beluga population is expected to be in the Norton Sound study area. 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 12. Model fitting and summarization details for Arctic models.

Group	Modeled taxon	Model Fitting			Summarization	
		Era	Model Type	Covariates	Summarized	Abundance
Baleen whales	Bowhead whale	2008-2021	Limited DSM	Contemporaneous	Monthly	9,562
	Fin whale	2008-2021	Full DSM	Contemporaneous	Monthly	1,316
	Gray whale	2008-2021	Full DSM	Contemporaneous	Monthly	9,774
	Humpback whale	2008-2021	Full DSM	Contemporaneous	Monthly	204
	Minke whale	2008-2021	Full DSM	Contemporaneous	Monthly	510
Large delphinids	Beluga whale B and EC	2008-2021	Full DSM	Contemporaneous	Monthly	52,196
	Beluga whale EB	2017	XY only	Spatial	Monthly (June)	11,313
	Killer whale	2008-2021	Limited DSM	Contemporaneous	Monthly	119
Small delphinoids	Harbor porpoise	2008-2021	Full DSM	Contemporaneous	Monthly	4,423
Pinnipeds	Bearded seal	2008-2021	Full DSM	Contemporaneous	Monthly	20,124
	Walrus	2008-2021	Full DSM	Contemporaneous	Monthly	140,800
	Unidentified small pinniped	2008-2021	Full DSM	Contemporaneous	Monthly	288,680
	Unidentified pinniped	2008-2021	Full DSM	Contemporaneous	Monthly	58,655

4. Future Work

Though we have generated predicted density models for these 11 species and multi-species guilds, there is scope for improvement and expansion of the analysis. While we successfully added shipboard surveys and an additional year of aerial survey effort, there are additional surveys we could not obtain either because the data was not yet ready or we did not receive permission. We will keep working toward acquiring this data for future modeling efforts (Table 13). NOAA conducted their first comprehensive aerial survey of ice seals (bearded, ringed, spotted and ribbon) in the Arctic from April-June 2025 to study their abundance and distribution in the Bering, Chukchi and Beaufort Seas, we will aim to acquire this for future modeling efforts.

Table 13. Survey data potentially available for future efforts.

Status	Survey Name	Survey Start	Survey End
Requested but not received	2019 DFO Aerial	7/21/2019	8/02/2019
Will be available for future	2019 and 2022 Eastern Bering Sea Beluga Whale Aerial Abundance Survey (NOAA AFSC)	6/20/2022	7/02/2022
Requested but not received	IWC Power Cruises	TBD	TBD
Will request	NOAA 2025 Aerial Ice Seal Survey	4/4/2025	6/10/2025

5. Summary

This work provides updated marine species DSMs for Arctic marine mammals within the Arctic Region Military Readiness (ARMR) Study Area, including the Chukchi Sea, Beaufort Sea (U.S. and Canadian waters), and the Bering Strait. Using aerial survey data from the Aerial Surveys of Arctic Marine Mammals (ASAMM) program, supplemental Canadian Beaufort surveys, and recent shipboard surveys (ARCWEST and CHAOZ), we modeled the distribution and abundance of 10 focal species and two pinniped guilds during the open-water season (June–October) for 2008–2021. Detection functions were developed using line-transect distance sampling methods with corrections for perception and availability bias, and spatial models were fitted using generalized additive models (GAMs) to relate observed counts to dynamic and static environmental covariates. Resulting density predictions and associated uncertainty estimates were summarized for delivery in the

Navy's NMSDD framework. These updated models incorporate recent survey data, improved bias corrections, expanded spatial coverage, and improved covariate selection, providing spatially explicit abundance estimates to support regulatory compliance, environmental planning, and adaptive management in a rapidly changing Arctic ecosystem.

References

Aerts, Lisanne A M, Alexandra E McFarland, Bridget H Watts, Kate S Lomac-MacNair, Pamela E Seiser, Sheyna S Wisdom, Alex V Kirk, and Carissa A Schudel. 2013. "Marine Mammal Distribution and Abundance in an Offshore Sub-Region of the Northeastern Chukchi Sea During the Open-Water Season." *Cont. Shelf Res.* 67: 116–26.

Allen, B M, and R P Angliss. 2014. "BELUGA Whale (Delphinapterus Leucas): Eastern Chukchi Sea Stock." NOAA-TM-AFSC-301. US Department of Commerce, National Oceanic; Atmospheric Administration.

Ashjian, Carin J, Stephen R Braund, Robert G Campbell, John C George, Jack Kruse, Wieslaw Maslowski, Sue E Moore, et al. 2010. "Climate Variability, Oceanography, Bowhead Whale Distribution, and Iñupiat Subsistence Whaling Near Barrow, Alaska." *Arctic* 63 (2): 179–94.

Baird, R. W. 2000. *The Killer Whale: Foraging Specializations and Group Hunting*. In *Cetacean Societies: Field Studies of Dolphins and Whales*. University of Chicago Press.

Baird, R. W., and Dill, L. M. 1996. Ecological and social determinants of group size in transient killer whales (*Orcinus orca*). *Behavioral Ecology*, 7(4): 408–416.

Becker, Jeroen J., David T. Sandwell, William H. F. Smith, John Braud, Brian Binder, Jennifer Depner, David Fabre, et al. 2009. "Global Bathymetry and Elevation Data at 30 Arc Seconds Resolution: SRTM30_PLUS." *Marine Geodesy* 32 (4): 355–71.

Bengtsont, John L, Lisa M Hiruki-Raring, Michael A Simpkins, and Peter L Boveng. 2005. "Ringed and Bearded Seal Densities in the Eastern Chukchi Sea, 1999–2000." *Polar Biol.* 28 (11): 833–45.

Berchok, C.L., J.L. Crance, and P.J. Stabeno. 2019. Chukchi Sea Acoustics, Oceanography, and Zooplankton Study: Hanna Shoal Extension (CHAOZ-X) and Arctic Whale Ecology Study (ARCWEST) Supplemental Report. OCS Study BOEM 2019-024. Marine Mammal Laboratory, Alaska Fisheries Science Center, NMFS, NOAA, 7600 Sand Point Way NE, Seattle, WA 98115-6349.

Berchok, C.L., J.L. Crance, E.C. Garland, J.A. Mocklin, P.J. Stabeno, J.M. Napp, B.K. Rone, A.H. Spear, M. Wang, and C.W. Clark. 2015. Chukchi Offshore Monitoring In Drilling Area (COMIDA): Factors Affecting the Distribution and Relative Abundance of Endangered Whales and Other Marine Mammals in the Chukchi Sea. Final Report of the Chukchi Sea Acoustics, Oceanography, and Zooplankton Study, OCS Study BOEM 2015-034. National Marine Mammal Laboratory, Alaska Fisheries Science Center, NMFS, NOAA, 7600 Sand Point Way NE, Seattle, WA 98115-6349.

Bravington, M. V., Miller, D. L., & Hedley, S. L. (2018). Reliable variance propagation for spatial density surface models. arXiv preprint arXiv:1807.07996.

Buckland, Stephen T., David R. Anderson, Kenneth P. Burnham, Jeffrey L. Laake, David L. Borchers, and Len Thomas. 2001. *Introduction to Distance Sampling: Estimating Abundance of Biological Populations.* Oxford: Oxford University Press.

Buckland, Stephen T, Eric A Rexstad, Tiago A Marques, and Cornelia S Oedekoven. 2015. *Distance Sampling: Methods and Applications*. Methods in Statistical Ecology. Springer International Publishing.

Burns, John J, and Samuel J Harbo. 1972. "An Aerial Census of Ringed Seals, Northern Coast of Alaska." *Arctic* 25 (4): 279–90.

Burns, John J, Jon Jerome Montague, and Cleveland J Cowles. 1993. *The Bowhead Whale*. Allen Press.

Burns, John J, Lewis H Shapiro, and Francis H Fay. 1981. "Ice as Marine Mammal Habitat in the Bering Sea." In *The Eastern Bering Sea Shelf: Oceanography and Resources*, edited by Calder John A Hood Donald W, 2:781–97. University of Washington Press.

Caughley, G. 1977. Sampling in aerial survey. J. Wildl. Manage. 41: 605-615.

Citta, John J, Lori T Quakenbush, Stephen R Okkonen, Matthew L Druckenmiller, Wieslaw Maslowski, Jaclyn Clement-Kinney, John C George, et al. 2015. "Ecological Characteristics of Core-Use Areas Used by Bering–Chukchi–Beaufort (BCB) Bowhead Whales, 2006–2012." *Prog. Oceanogr.* 136: 201–22.

Clarke, Janet T, Amy S Kennedy, and Megan C Ferguson. 2016. "Bowhead and Gray Whale Distributions, Sighting Rates, and Habitat Associations in the Eastern Chukchi Sea, Summer and Fall 2009–15, with a Retrospective Comparison to 1982–91." *Arctic* 69 (4): 359–77.

Conn, Paul B, Brett T McClintock, Michael F Cameron, Devin S Johnson, Erin E Moreland, and Peter L Boveng. 2013. "Accommodating Species Identification Errors in Transect Surveys." *Ecology* 94 (11): 2607–18.

Conn, Paul B, Jay M Ver Hoef, Brett T McClintock, Erin E Moreland, Josh M London, Michael F Cameron, Shawn P Dahle, and Peter L Boveng. 2014. "Estimating Multispecies Abundance Using Automated Detection Systems: Ice-Associated Seals in the Bering Sea." *Methods Ecol. Evol.* 5 (12): 1280–93.

Dunton, Kenneth H, Jonathan L Goodall, Susan V Schonberg, Jacqueline M Grebmeier, and David R Maidment. 2005. "Multi-Decadal Synthesis of Benthic–pelagic Coupling in the Western Arctic: Role of Cross-Shelf Advective Processes." *Deep Sea Res. Part 2 Top. Stud. Oceanogr.* 52 (24): 3462–77.

Escajeda, E., Stafford, K. M., Woodgate, R. A., & Laidre, K. L. (2020). Variability in fin whale (Balaenoptera physalus) occurrence in the Bering Strait and southern Chukchi Sea in relation to environmental factors. *Deep Sea Research Part II: Topical Studies in Oceanography*, 104782.

Fay, Francis H. 1982. *Ecology and Biology of the Pacific Walrus, Odobenus Rosmarus Divergens Illiger*. *N. Am. Fauna*. US Fish & Wildlife Service.

Ferguson, Megan C, and Janet T Clarke. 2013. "Estimates of Detection Probability for BWASP Bowhead Whale, Gray Whale, and Beluga Sightings Collected from Twin Otter and Aero Commander Aircraft, 1989 to 2007 and 2008 to 2011." NMFS-AFSC-261. US Department of Commerce, National Oceanic & Atmospheric Administration.

Ferguson, M. C., Clarke, J. T., et al. 2015. *Aerial surveys of Arctic marine mammals in the Chukchi Sea, 2008–2011*. NOAA Technical Memorandum NMFS-AFSC-XXX. U.S. Department of Commerce.

Ferguson, M.C. 2020. Bering-Chukchi-Beaufort Seas bowhead whale (*Balaena mysticetus*) abundance estimate from the 2019 aerial line transect survey. SC/68B/ASI/09 International Whaling Commission 2020.

Ferguson, M.C., J.T. Clarke, A.A. Brower, A.L. Willoughby, S.R. Okkonen (2021) Ecological variation in the western Beaufort Sea. In: The Bowhead Whale, pp. 365-379. Elsevier.

Fischbach, A. S., Monson, D. H., & Jay, C. V. 2007. *Enumeration of Pacific walrus carcasses on beaches of the Chukchi Sea in Alaska following a mortality event, September 2007*. U.S. Geological Survey Open-File Report 2007–1291.

Ford, J. K. B., Ellis, G. M., Barrett-Lennard, L. G., Morton, A. B., Palm, R. S., and Balcomb, K. C. 1998. Dietary specialization in two sympatric populations of killer whales (*Orcinus orca*) in coastal British Columbia and adjacent waters. *Canadian Journal of Zoology*, 76: 1456–1471.

Ford, J. K. B., Ellis, G. M., and Balcomb, K. C. 2000. *Killer Whales: The Natural History and Genealogy of Orcinus orca in British Columbia and Washington*. UBC Press.

Friday, N.A., P.J. Clapham, C.L. Berchok, J.L. Crance, A.N. Zerbini, B.K. Rone, A.S. Kennedy, P.J. Stabeno, J.M. Napp, and A. Spear. 2016. *Arctic Whale Ecology Study (ARCWEST): Use of the Chukchi Sea by endangered baleen and other whales (Westward Extension of the BOWFEST) Annual Report.* Submitted to the Bureau of Ocean Energy Management under IAA M12PG00021 (AKC 108). National Marine Mammal Laboratory, Alaska Fisheries Science Center, NOAA Fisheries, Seattle, WA

George, J Craig, Judy Zeh, Robert Suydam, and Christopher Clark. 2004. "Abundance and Population Trend (1978–2001) of Western Arctic Bowhead Whales Surveyed Near Barrow, Alaska." *Mar. Mamm. Sci.* 20 (4): 755–73.

Grebmeier, Jacqueline M, Lee W Cooper, Howard M Feder, and Boris I Sirenko. 2006. "Ecosystem Dynamics of the Pacific-Influenced Northern Bering and Chukchi Seas in the Amerasian Arctic." *Prog. Oceanogr.* 71 (2): 331–61.

Hanson, M. B., Baird, R. W., Ford, J. K. B., et al. 2010. Species and stock identification of killer whales in Alaskan waters using mitochondrial DNA and microsatellite markers. NOAA Technical Report.

Harwood, Lois A, J Auld, A Joynt, and Sue E Moore. 2009. "Distribution of Bowhead Whales in the SE Beaufort Sea During Late Summer, 2007–2009." *DFO Can. Sci. Advis. Sec. Res. Doc* 111.

Harwood, Lois A, Thomas G Smith, James C Auld, Humfrey Melling, and David J Yurkowski. 2015. "Seasonal Movements and Diving of Ringed Seals, Pusa Hispida , in the Western Canadian Arctic, 1999–2001 and 2010–11." *Arctic* 68 (2): 193–209.

Hauser, Donna W, Kristin L Laidre, Harry L Stern, Sue E Moore, Robert S Suydam, and Pierre R Richard. 2017. "Habitat Selection by Two Beluga Whale Populations in the Chukchi and Beaufort Seas." *PLoSOne* 12 (2): e0172755.

Hauser, D. D., Laidre, K. L., Stern, H. L., Suydam, R. S., & Richard, P. R. 2018. Indirect effects of sea ice loss on summer-fall habitat and behaviour for sympatric populations of an Arctic marine predator. Diversity and Distributions, 24(6), 791-799.

Hedley, Sharon L, and Stephen T Buckland. 2004. "Spatial Models for Line Transect Sampling." *JABES* 9 (2): 181–99.

Heide-Jørgensen, Mads Peter, Kristin Laidre, Sabrina Fossette, Marianne Rasmussen, Nynne Nielsen, and Rikke Hansen. 2014. "Abundance of Walruses in Eastern Baffin Bay and Davis Strait." *NAMMCO Scientific Publications* 9: 159–71.

Jay, Chadwick V, Anthony S Fischbach, and Anatoly A Kochnev. 2012. "Walrus Areas of Use in the Chukchi Sea During Sparse Sea Ice Cover." *Mar. Ecol. Prog. Ser.* 468: 1–13.

Jay, Chadwick V, Rebecca L Taylor, Anthony S Fischbach, Mark S Udevitz, and William S Beatty. 2017. "Walrus Haul-Out and in Water Activity Levels Relative to Sea Ice Availability in the Chukchi Sea." *J. Mammal.* 98 (2): 386–96.

Jeffries, Martin O, James E Overland, and Donald K Perovich. 2013. "The Arctic Shifts to a New Normal." *Phys. Today* 66 (10): 35–40.

Kovacs, Kit M, Christian Lydersen, James E Overland, and Sue E Moore. 2011. "Impacts of Changing Sea-Ice Conditions on Arctic Marine Mammals." *Mar. Biodivers.* 41 (1): 181–94.

Laidre, Kristin L, Harry Stern, Kit M Kovacs, Lloyd Lowry, Sue E Moore, Eric V Regehr, Steven H Ferguson, et al. 2015. "Arctic Marine Mammal Population Status, Sea Ice Habitat Loss, and Conservation Recommendations for the 21st Century." *Conserv. Biol.* 29 (3): 724–37.

Laidre, Kristin L, Ian Stirling, Lloyd F Lowry, Øystein Wiig, Mads Peter Heide-Jørgensen, and Steven H Ferguson. 2008. "Quantifying the Sensitivity of Arctic Marine Mammals to Climate-Induced Habitat Change." *Ecol. Appl.* 18 (sp2): s97–125.

Marra, G., and S. N. Wood. 2011. Practical variable selection for generalized additive models. *Computational Statistics & Data Analysis* 55(7):2372–2387. https://doi.org/10.1016/j.csda.2011.02.004

Miller, P. J. O., A. D. Shapiro, and V. B. Deecke. 2010. *The diving behaviour of mammal-eating killer whales (Orcinus orca): variations with ecological, not physiological, factors.* Canadian Journal of Zoology 88:1103–1112.

Miller, David L, M Louise Burt, Eric A Rexstad, and Len Thomas. 2013. "Spatial Models for Distance Sampling Data: Recent Developments and Future Directions." *Methods Ecol. Evol.* 4 (11): 1001–10.

Miller, David L, Elizabeth A Becker, Karin A Forney, Jason J Roberts, Ana Cañadas, and Robert S Schick. 2022. Estimating uncertainty in density surface models

Moore, Sue E. 2016. "Is It 'Boom Times' for Baleen Whales in the Pacific Arctic Region?" *Biol. Lett.* 12 (9).

Moore, Sue E, and Henry P Huntington. 2008. "Arctic Marine Mammals and Climate Change: Impacts and Resilience." *Ecol. Appl.* 18 (sp2): s157–165.

Moore, Sue E, and Randall R Reeves. 1993. "Distribution and Movement." *The Bowhead Whale*. Society for Marine Mammalogy, 313–86.

Moore, Sue E, Kathleen M Stafford, David K Mellinger, and John A Hildebrand. 2006. "Listening for Large Whales in the Offshore Waters of Alaska." *Bioscience* 56 (1): 49–55.

Muto, M. M., V. T. Helker, B. J. Delean, R. P. Angliss, P. L. Boveng, J. M. Breiwick, B. M. Brost, M.F. Cameron, P. J. Clapham, S. P. Dahle, M. E. Dahlheim, B. S. Fadely, M. C. Ferguson,L.W. Fritz, R. C. Hobbs, Y. V. Ivashchenko, A. S. Kennedy, J. M. London, S. A. Mizroch,R. R. Ream, E. L. Richmond, K. E. W. Shelden, K. L. Sweeney, R. G. Towell, P. R. Wade,J.M. Waite, and A. N. Zerbini. 2020. Alaska marine mammal stock assessments, 2019. U.S. Dep.Commer., NOAA Tech. Memo. NMFS-AFSC-404, 395 p.

Pendleton, D. E., Holmes, E. E., Redfern, J. V., & Zhang, J. (2020). *Using modelled prey to predict the distribution of a highly mobile marine mammal*. Diversity and Distributions, 26(11), 1612–1626.

Roberts, Jason J, Benjamin D Best, Laura Mannocci, Ei Fujioka, Patrick N Halpin, Debra L Palka, Lance P Garrison, et al. 2016. "Habitat-Based Cetacean Density Models for the U.S. Atlantic and Gulf of Mexico." *Sci. Rep.* 6: 22615.

Robertson, Frances C, Koski William R, John R Brandon, Tannis A Thomas, and Andrew W Trites. 2015. "Correction Factors Account for the Availability of Bowhead Whales Exposed to Seismic Operations in the Beaufort Sea." *Journal of Cetacean Research and Management* 15: 35–44.

Schick, Robert S, Jason J Roberts, Scott A Eckert, Patrick N Halpin, Helen Bailey, Fei Chai, Lei Shi, and James S Clark. 2013. "Pelagic Movements of Pacific Leatherback Turtles (*Dermochelys Coriacea*) Highlight the Role of Prey and Ocean Currents." *Movement Ecology* 1 (1): 1–14.

Schick, R.S., J.J. Roberts and P.N. Halpin. 2017. Marine Species Density Models for the Arctic Environmental Impact Statement (EIS) Study Area. Final Report. Prepared for Fleet Forces Command. Submitted to Naval Facilities Engineering Command Atlantic, Norfolk, Virginia, under Contract No. N62470-15-D-8006, Task Order TO11 issued to HDR, San Diego, California. October 2017.

Screen, James A, and Daniel Williamson. 2017. "Ice-Free Arctic at 1.5 °c?" *Nat. Clim. Chang.*

Simpkins, Michael A, Lisa M Hiruki-Raring, Gay Sheffield, Jacqueline M Grebmeier, and John L Bengtson. 2003. "Habitat Selection by Ice-Associated Pinnipeds Near St. Lawrence Island, Alaska in March 2001." *Polar Biol.* 26 (9): 577–86.

Suydam, Robert S, Lloyd F Lowry, and Kathryn J Frost. 2005. "Distribution and Movements of Beluga Whales from the Eastern Chukchi Sea Stock During Summer and Early Autumn." North Slope Borough Department of Wildlife Management.

Suydam, Robert S, Lloyd F Lowry, Kathy J Frost, Greg M O'Corry-Crowe, and Danny Pikok. 2001. "Satellite Tracking of Eastern Chukchi Sea Beluga Whales into the Arctic Ocean." *Arctic* 54 (3): 237–43.

Tynan, Cynthia T, and Douglas P DeMaster. 1997. "Observations and Predictions of Arctic Climatic Change: Potential Effects on Marine Mammals." *Arctic* 50 (4): 308–22.

Ver Hoef, Jay M, Michael F Cameron, Peter L Boveng, Josh M London, and Erin E Moreland. 2014. "A Spatial Hierarchical Model for Abundance of Three Ice-Associated Seal Species in the Eastern Bering Sea." *Stat. Methodol.* 17: 46–66.

Walsh, John E. 2008. "Climate of the Arctic Marine Environment." *Ecol. Appl.* 18 (sp2): s3–22.

Wood, Simon N, Mark V Bravington, and Sharon L Hedley. 2008. "Soap Film Smoothing." *J. R. Stat. Soc. Series B Stat. Methodol.* 70 (5): 931–55.

Wood, S.N. 2011. Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. Journal of the Royal Statistical Society (B) 73(1):3-36

Wood, S.N. 2017. Generalized Additive Models: An Introduction with R (2nd edition). Chapman and Hall/CRC.

Young, N. C., Muto, M. M., Helker, V. T., Angliss, R. P., et al. 2023. *Alaska Marine Mammal Stock Assessments, 2022*. NOAA Technical Memorandum NMFS-AFSC-474. U.S. Department of Commerce.