Identifying priority areas to enhance monitoring of cetaceans in the Northwest Atlantic Ocean

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IDENTIFYING PRIORITY AREAS TO ENHANCE MONITORING OF CETACEANS IN THE NORTHWEST ATLANTIC OCEAN

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ABSTRACT

Gomez, C., Konrad, C.M., Vanderlaan, A., Moors-Murphy, H.B., Marotte, E., Lawson, J., Kouwenberg, A-L., Fuentes-Yaco, C., Buren, A. 2020. Identifying priority areas to enhance monitoring of cetaceans in the Northwest Atlantic Ocean. Can. Tech. Rep. Fish. Aquat. Sci. 3370: vi + 103 p.

Species Distribution Models (SDM) were used to predict seasonal suitable habitat of cetaceans during spring (2 species), summer (10 species), and autumn (7 species) in eastern Canadian waters off Nova Scotia, and Newfoundland and Labrador. Available cetacean sightings data from 1975-2015 was compiled from the Department of Fisheries and Oceans Canada (DFO), the Ocean Biogeographic Information System (OBIS), the North Atlantic Right Whale Consortium (NARWC), the Whitehead Lab at Dalhousie University, and the Environment and Climate Change Canada (Canadian Wildlife Service) Eastern Canada Seabirds at Sea (ECSAS) program. As proxies for prey availability, we selected five predictor environmental variables for our SDM: ocean depth, compound topographic index, sea surface temperature, areas of persistently high chlorophyll-a concentration, and regional chlorophyll-a magnitude. Habitats with high suitability in this report are interpreted as areas where cetacean monitoring efforts may be prioritized, and results can help direct future survey efforts. While the SDM developed are informative, this report also illustrates that our results do not necessarily provide a fully accurate representation of the current distribution of cetaceans in the region and thus their use in marine spatial planning processes should be accompanied by complimentary approaches such as acoustic and visual validation of the SDM results as well as additional monitoring and modeling efforts. This study represents a significant initiative in eastern Canada to highlight key areas for cetacean monitoring efforts in waters off Nova Scotia, and Newfoundland and Labrador. Future efforts will focus on improving these models to facilitate the inclusion of cetaceans in marine spatial planning processes that are currently underway.

RÉSUMÉ

Gomez, C., Konrad, C.M., Vanderlaan, A., Moors-Murphy, H.B., Marotte, E., Lawson, J., Kouwenberg, A-L., Fuentes-Yaco, C., Buren, A. 2020. Identifying priority areas to enhance monitoring of cetaceans in the Northwest Atlantic Ocean. Can. Tech. Rep. Fish. Aquat. Sci. 3370: vi + 103 p.

On a utilisé des modèles de répartition des espèces afin de prédire l'habitat convenable saisonnier de cétacés pendant le printemps (deux espèces), l'été (dix espèces) et l'automne (sept espèces) dans les eaux de l'est du Canada, au large de la Nouvelle-Écosse et de Terre-Neuve-et-Labrador. On a compilé les données d'observation de cétacés recueillies de 1975 à 2015 par le ministère des Pêches et des Océans (MPO), le Système d'information biogéographique des océans (OBIS), le North Atlantic Right Whale Consortium (NARWC), le laboratoire Whitehead de l'Université Dalhousie et le programme Suivi des oiseaux de mer de l'est du Canada (SOMEC) d'Environnement et Changement climatique Canada (Service canadien de la faune). À titre d'indicateurs de la disponibilité de proies, on a choisi cinq variables environnementales prédictives pour les modèles de répartition des espèces utilisés, soit la profondeur de l'océan, l'indice topographique composé (CTI), la température à la surface de la mer, la superficie des zones où la concentration de chlorophylle a est toujours élevée, et l'ampleur de la concentration régionale de chlorophylle a. On considère que les milieux hautement convenables cernés dans le présent rapport sont des zones qui pourraient être prioritaires en matière d'efforts de suivi des cétacés. Les résultats figurant dans ce rapport permettront d'orienter les futures activités de relevé. Les modèles de répartition des espèces conçus sont informatifs, mais le rapport illustre également que les résultats obtenus ne fournissent pas nécessairement une représentation entièrement exacte de la répartition actuelle des cétacés dans la région. Par conséquent, l'utilisation de ces modèles dans le cadre de processus de planification spatiale marine devrait être combinée à des approches complémentaires, comme des activités de validation visuelle et acoustique des résultats issus des modèles, ainsi que des activités de suivi et de modélisation supplémentaires. L'étude en question représente une importante initiative menée dans l'est du Canada, qui vise à cerner les zones clés pour les activités de suivi des cétacés dans les eaux au large de la Nouvelle-Écosse et de Terre-Neuve-et-Labrador. Les futures activités, qui seront axées sur l'amélioration des modèles, permettront de faciliter l'inclusion des cétacés dans les processus de planification spatiale marine en cours.

INTRODUCTION

Cetacean effort-based surveys (e.g., line-transect surveys) have been conducted in only a quarter of the world's ocean surface (Kaschner et al. 2012), thus knowledge on cetacean distribution and density in many areas is generally limited. In Canada, the distribution and seasonal occurrence of cetaceans in most of the Northwest Atlantic Ocean (NWAO; waters off Nova Scotia, and Newfoundland and Labrador) is poorly understood (Breeze et al. 2002, Gomez and Moors-Murphy 2014). There is generally limited information available from effort-based surveys in most areas of eastern Canada (e.g., Lawson and Gosselin 2009, DFO 2019). This knowledge gap limits our ability to effectively monitor, manage and mitigate the impacts of human activities on cetacean species occurring in eastern Canadian waters, and has important implications for the monitoring and recovery of species at risk. Lack of information on cetacean distribution has limited their inclusion in network analyses related to the identification and delineation of Ecologically and Biologically Significant Areas (EBSAs) and Marine Protected Areas (MPA) in eastern Canada (e.g., King et al. 2013, DFO 2014). Therefore, information on cetaceans has been under-represented when identifying areas for protection.

During past DFO Canadian Science Advisory Secretariat (CSAS) processes related to spatial planning off eastern Canada, Species Distribution Models (SDMs) were recommended as an important tool for combining available opportunistic cetacean sightings data and relevant environmental data to predict suitable habitat for these species (King et al 2013). Cetacean sightings and environmental predictors have successfully been used in the development of SDMs for cetaceans in other regions (Ainley et al. 2012, Gregr 2011, Pendleton et al. 2012, Bombosch et al. 2014, Roberts et al. 2016). Consequently, a series of efforts prior to this report were conducted to implement SDM for a selection of cetacean species. A first effort by Gomez and Moors-Murphy (2014) implemented Maximum Entropy (MaxEnt) models for northern bottlenose (*Hyperoodon ampullatus*) and Sowerby's beaked whales (*Mesoplodon bidens*) using five environmental variables: ocean depth, seafloor slope, seafloor aspect, sea surface temperature and Chlorophyll-a concentration. This first effort provided significant recommendations to further refine these approaches, including the inclusion of a more comprehensive dataset of cetacean sightings and improved environmental predictors. Gomez et al. (2017) implemented these recommendations and proposed a SDM framework to update the datasets and methods as part of an iterative, adaptive process to identify suitable habitat for cetaceans. They implemented this framework to predict priority areas for enhanced blue whale (*Balaenoptera musculus*) and northern bottlenose whale monitoring efforts in eastern Canada. Cetacean sighting records were compiled to provide information on cetacean occurrence, and broad-scale environmental data were assembled, including datasets acquired via satellite remote sensing. The modeling framework and datasets compiled by Gomez et al. (2017) were used by Moors-Murphy et. al (2019) to predict suitable habitat for blue whales. The SDM outputs from Moors-Murphy et al. (2019), in combination with additional sources of information, were then used to identify important blue whale habitat in the Northwest Atlantic (Lesage et al. 2018).

Building upon these previous efforts in the NWAO, this report developed SDMs to predict seasonal suitable habitat for several cetacean species in the NWAO, with the goal of identifying and providing recommendations on areas where increased cetacean monitoring should be prioritized. This paper follows similar methods proposed by Gomez et al. (2017), while expanding the number of species considered, updating the boundaries of the study area, and improving the modelling framework. Further refining and validation of the SDM results will be necessary to continue the process of understanding the distribution of cetaceans in eastern Canada.

MATERIALS AND METHODS

The NWAO study area

The study area is situated in the Northwest Atlantic, encompassing waters off Nova Scotia, and Newfoundland and Labrador in eastern Canada. The NWAO comprises a continental shelf of varying breadth, characterized by complex topography including shallow banks, basins and submarine canyons, and bounded by convoluted coastlines and deep ocean basins (Breeze et al. 2002, Zwanenburg et al. 2002). In this study, the NWAO was delineated in the north by the northern tip of Labrador and in the south by the Fundian (or Northeast) Channel (Figure 1). Shallow coastal areas (waters <50m depth) as well as the enclosed areas of Bay of Fundy and the Gulf of St Lawrence are characterized by very different ecosystem dynamics compared with the rest of the NWAO (Araújo & Bundy 2012, Zwanenburg et al. 2002) and were not considered in this study. Very deep waters (>3000m) were also excluded from the study area as there were very few sightings off the continental shelf .

Cetacean data

This manuscript follows the proposed framework and modelling procedures developed by Gomez et al. (2017). This study used long-term cetacean catch and sightings data available and assembled in Gomez et al. (2017) from several sources: sightings databases from the Department of Fisheries and Oceans Canada (DFO) Maritimes region (MacDonald et. al. 2017), and Newfoundland and Labrador regions, the Ocean Biogeographic Information System (OBIS; http://www.iobis.org/), the North Atlantic Right Whale Consortium (NARWC; http://www.narwc.org/), the Whitehead Lab at Dalhousie University (http://whitelab.biology.dal.ca/), and the Environment and Climate Change Canada (Canadian Wildlife Service) Eastern Canada Seabirds at Sea (ECSAS) program (Gjerdrum et al. 2012). The data obtained from DFO, OBIS and NARWC are compilations of sightings from a variety of sources including governmental, non-governmental organizations, academia and industry, using aerial- and vessel-based platforms. Note that sightings data from these sources are not always effort corrected and distribution patterns based on these opportunistic sightings data are biased by when and where survey activities were conducted.

Locations of cetacean sightings (or catches, in some cases) from all sources were merged. Quality control checks included discarding all records outside of our study area and removing redundant records (identical species, day, month, latitude and longitude). The dataset does not include dead animal, stranding, entanglement or entrapment data.

The dataset encompasses records obtained during the whaling (catches or sightings, prior to 1975) and post-whaling periods (sightings only, 1975-2015). However, for all subsequent analyses in this study, only sightings of free-swimming whales, obtained during the post-whaling period (1975-2015), were used (Figure 1; N = 110,890).

The data used in this study were extracted from the various databases listed above in 2016 and do not reflect any updates or corrections to the databases that have occurred since that time. The majority of sighting records extracted were from summer (June to August; N = 76,399), followed by autumn (September to November; N = 29,464), spring (March to May; N = 4,113), and winter (December to February; N = 914). Unfavorable weather and reduced visual effort in winter, spring, and autumn likely account for smaller number of sighting records in these seasons compared to summer.

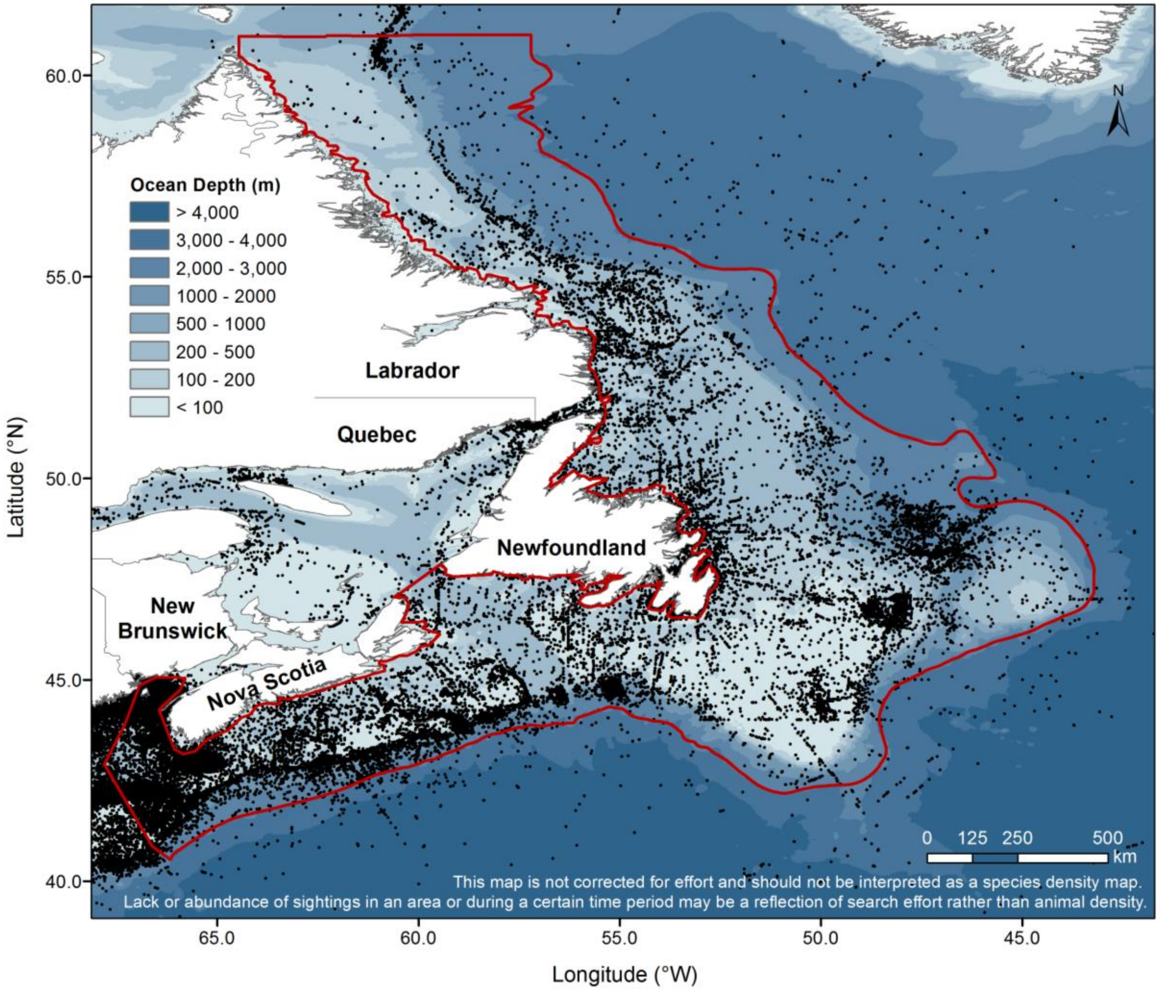


Figure 1. Sightings of free-swimming cetaceans collected during the post-whaling period (1975 – 2015). A total of 110,890 records are contained within the study area (red line). Sources: Department of Fisheries and Oceans Canada (DFO, Maritimes Region and Newfoundland and Labrador Region databases), the North Atlantic Right Whale Consortium (NARWC), the Ocean Biogeographic Information System (OBIS), the Whitehead Lab at Dalhousie University, and the Environment and Climate Change Canada (Canadian Wildlife Service) Eastern Canada Seabirds at Sea (ECSAS) program.

Environmental data

A fundamental component of SDM is the selection of a suite of predictor variables that exhibit a spatial and temporal relationship with the location records for the species of interest, and thus, are useful to predict suitable habitat. Information on prey is an ideal predictor variable (e.g. Pendleton et al. 2012); however, information on the spatial and temporal distribution of cetacean prey is limited. Thus, as in previous studies with limited prey data (e.g., Gregr 2011, Roberts et al. 2016), we selected a suite of environmental variables that likely serve as proxies for prey availability (Table 1):

1) Ocean depth (Figure 2)
2) Compound Topographic Index (CTI; Figure 2)
3) Sea Surface Temperature (SST; Figure 3)
4) Persistence of high chlorophyll-a concentration (CHL_{pers}; Figure 4)
5) Regional chlorophyll-a concentration magnitude (CHL_{magn}; Figure 5)

Areas of persistently high chlorophyll-a concentration (CHL_{pers}; Figure 4) and regional chlorophyll-a magnitude (CHL_{magn}; Figure 5) were derived by identifying and mapping phytoplankton-rich zones using satellite imagery to provide an indication of primary productivity (see Fuentes-Yaco et al. 2015 and Gomez et al. 2017 for a detailed description of methods). The study area was subdivided into neritic (50m-600m depth) and oceanic (> 600m depth) regions. These regions were further subdivided into north and south sections following the boundaries of divisions 3 and 4 of the Northwest Atlantic Fisheries Organization (NAFO, Figure 4), as well as distinct bathymetric and hydrographic features (Devred et al. 2007, 2009, Longhurst 2007). Each one of these four large geographical regions has unique marine communities and food web systems (Devred et al. 2007, 2009, Longhurst 2007, NAFO 2014). For each of the regions, and for each season, we computed CHL_{pers} and CHL_{magn}. For 2003-2014, CHL_{pers} was calculated as a percentage of weekly composite images that a pixel's value was above the region's median value (in the same composite image) plus a half standard deviation. CHL_{magn} was the average of the median chlorophyll-a concentrations for the weekly composite images. To account for the time-lag for primary productivity to transfer to top predators (Croll et al. 2005, Jaquet 1996, Wong 2012), the SDMs from a given season used CHL data from that season (CHL_{pers} and CHL_{magn}) and for the season prior (lagged CHL_{pers} and CHL_{magn}). For example, the spring SDMs used CHL data for spring and winter.

Shallow coastal areas in the ocean (< 50m depth) typically contain a mixture of a constituents with different optical properties such as phytoplankton, other suspended particulates and yellow substances (Morel & Prieur 1977). In addition, shallow waters are also influenced by the depth of the water column, and by the nature of the bottom. Consequently, these areas require detailed and customized algorithms to identify concentrations of chlorophyll-a (IOCCG 2000), which was not applied in this study. Thus shallow coastal areas were excluded from the analyses.

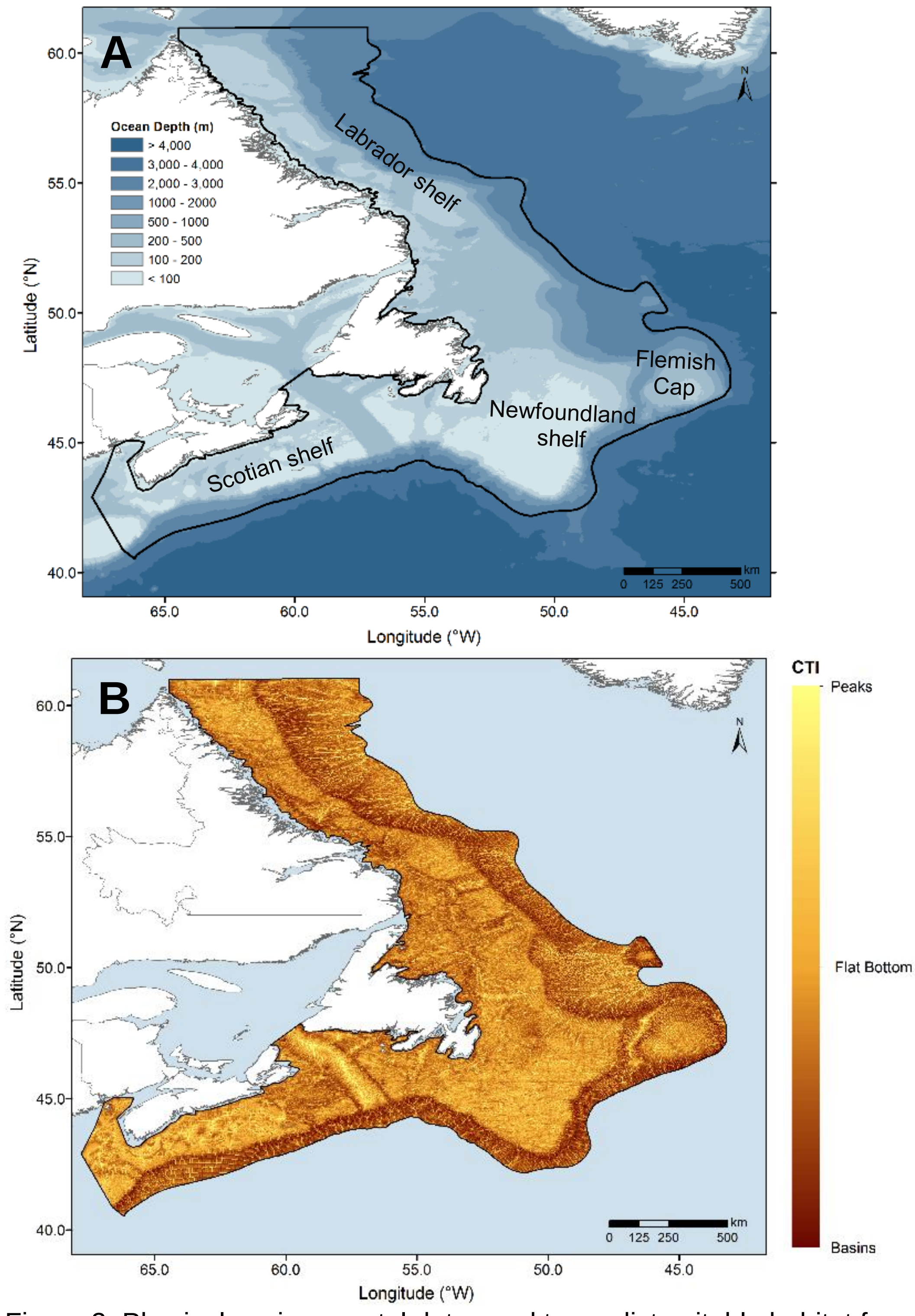


Figure 2. Physical environmental data used to predict suitable habitat for cetaceans in the study area (outlined in black): (A) ocean depth and (B) compound topographic index (CTI). CTI is derived from ocean depth (Evans et al. 2014) and represents peaks (high values of CTI), basins (low values), and flat surfaces (intermediate values; Gessler et al. 1995, Moore et al 1991, Andersen et al. 2013).

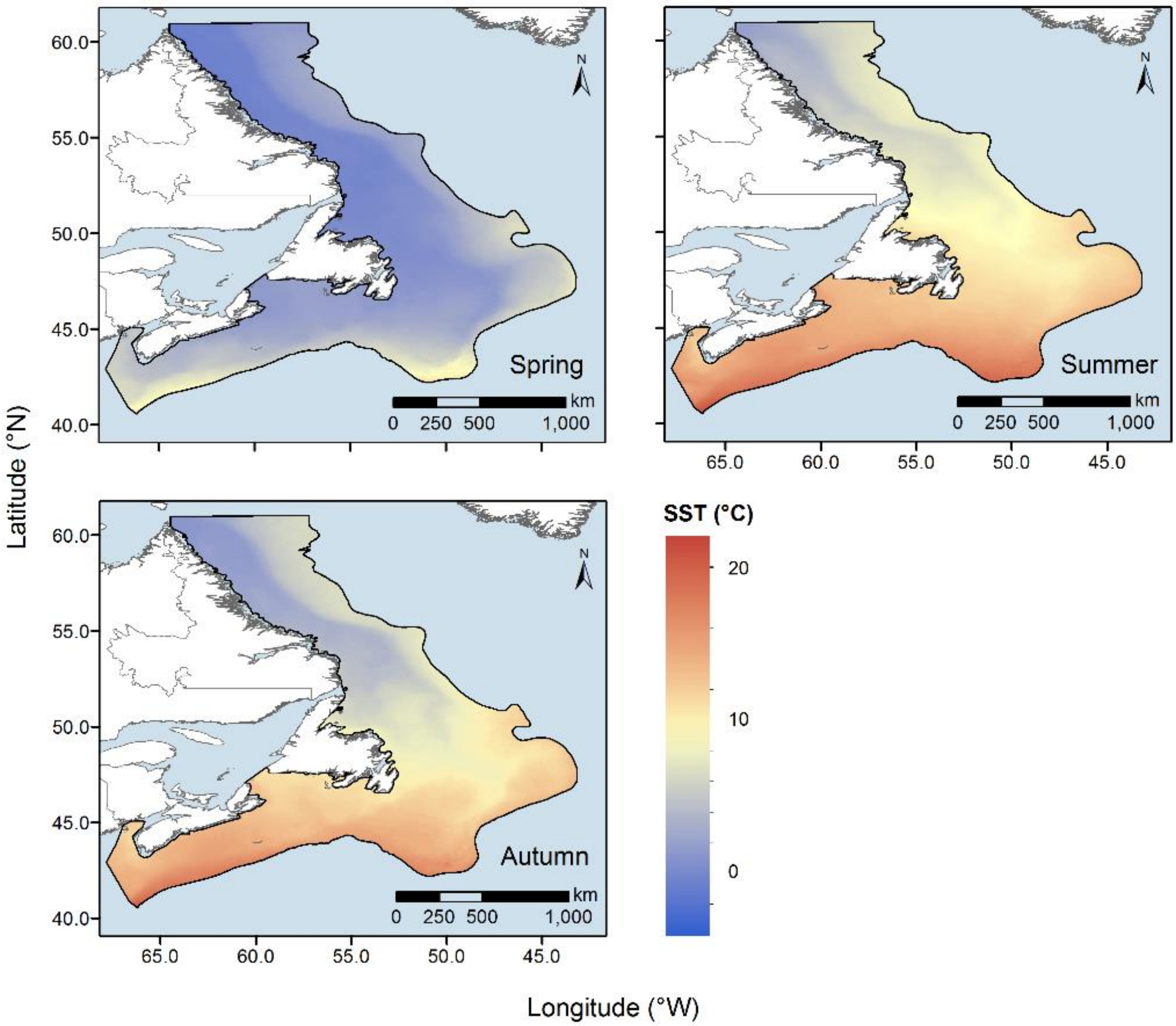


Figure 3. Average sea surface temperature (°C) during spring, summer and autumn, used to predict suitable habitat for cetaceans in the study area (outlined in black). Seasonal climatologies were derived from semi-monthly composites for 2003 to 2014.

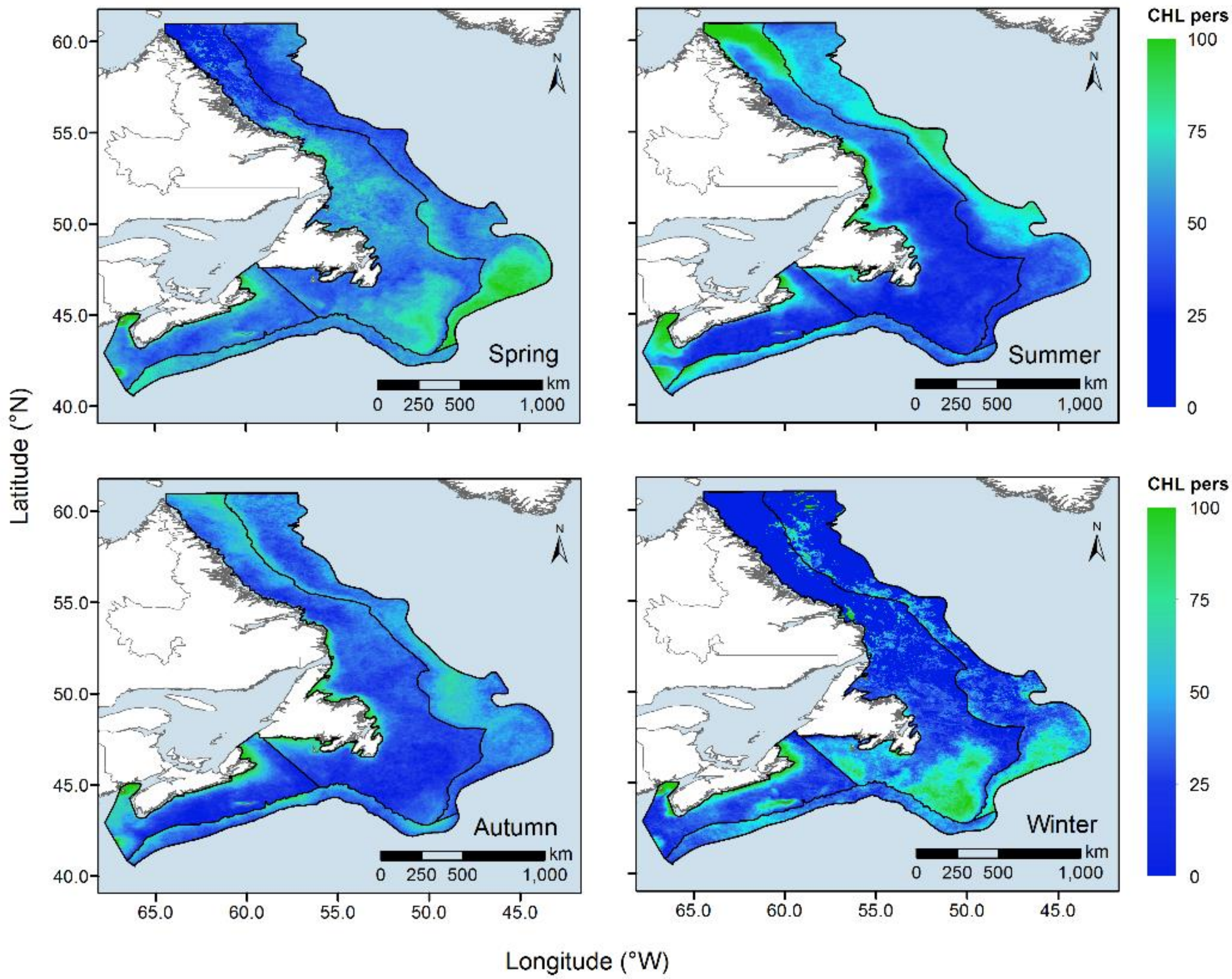


Figure 4. Persistence of high chlorophyll-a concentration (CHL_{pers}) during spring, summer, autumn and winter, used to predict suitable habitat for cetaceans in the study area (outlined in black). Black lines show the subdivision of the study area into regions: neritic (50m-600m depth) and oceanic regions (> 600m depth), which were further divided into North and South (see Figure 5). CHL_{pers} values were calculated as a percentage of time periods that the pixel's value was above the region's median value (in the same time period) plus a half standard deviation (see Fuentes-Yaco et al. 2015 for detailed description of the methods). Seasonal climatologies were derived from weekly composites for 2003 to 2014 (see Fuentes-Yaco et al. 2015).

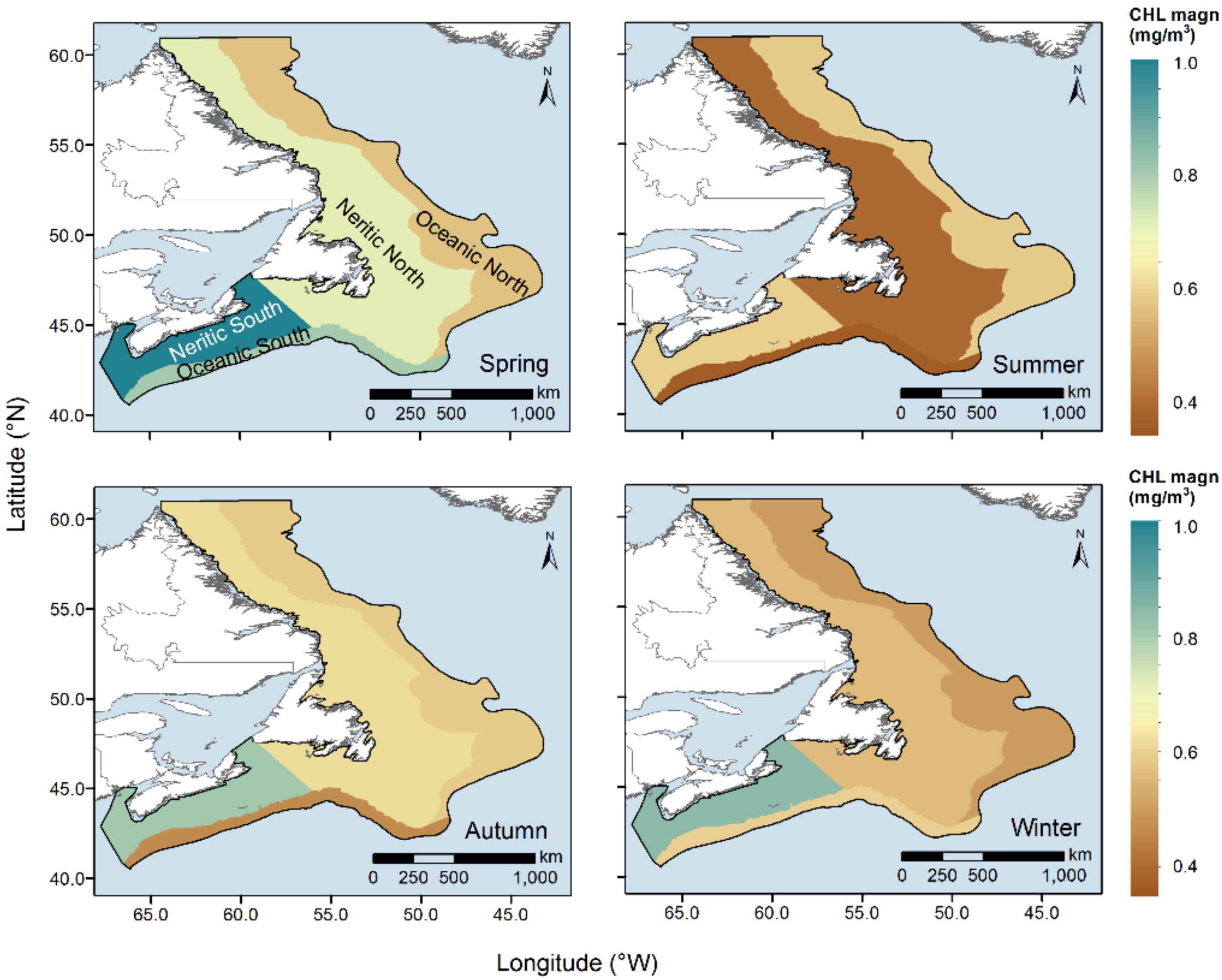


Figure 5. Regional chlorophyll-a concentration magnitude (CHL_{magn}) during spring, summer, autumn and winter, used to predict suitable habitat for cetaceans in the study area (outlined in black). These values correspond to the average of the median chlorophyll-a concentration calculated to obtain the transformed chlorophyll indicators. Seasonal climatologies were derived from weekly composites for the 2003 to 2014 period (see Fuentes-Yaco et al. 2015). The study area was subdivided into neritic (between 50m and 600m depth) and oceanic (> 600m depth). Neritic and oceanic regions were further divided into North and South.

Table 1. Environmental layers selected to predict the distribution of cetaceans in the NWAO. Seasonal values were derived from weekly composites for CHL_{pers} and CHL_{magn}, and from semi-monthly composites for SST, for 2003-2014. All environmental layers were processed to have the same geographic extent and cell size (1.5 km), and converted to an ASCII raster grid format.

Variable	**Units**	**Temporal resolution**	**Native Spatial resolution**	**Source**
Ocean depth	metres	Static	1 km	Oceans and Coastal Management Division, Maritimes Region, DFO, Bedford Institute of Oceanography
Compound topographic index (CTI)	unitless	Static	1 km	Calculated using the Geomorphometry and Gradient Metrics Toolbox version 2.0 in ArcGIS (Evans et al. 2014)
Sea surface temperature (SST)	degrees Celsius	Seasonal	1.5 km	Derived from images from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument on the Aqua satellite
Persistence of high chlorophyll-a concentration (CHL_{pers})	percentage	Seasonal	1.5 km	Derived from images from MODIS Aqua satellite (Fuentes-Yaco *et al.* 2015)
Regional chlorophyll-a concentration (CHL_{magn})	milligrams/ metre^3	Seasonal	1.5 km	Derived from images from MODIS Aqua satellite (Fuentes-Yaco *et al.* 2015)

All environmental layers were processed to have the same geographic extent and cell size (1.5 km), and converted to an ASCII raster grid format using ArcGIS 10. Before running SDMs, we investigated correlation between the environmental variables, using the variance inflation factor (VIF; Zuur et al. 2010). An environmental variable's VIF is a measure of collinearity – how much of that variable's variation is explained by all other variables. In accordance with Zuur et al. (2010), we considered VIF values less than three to denote that the environmental variables do not exhibit collinearity and thus are relevant to use in the SDMs. CHL_{magn} was not included in the VIF calculations as it is comprised of only one value per unique region (Figure 5).

Implementing SDMs to model habitat suitability

We used SDMs to integrate information on the location of cetaceans with environmental variables to predict areas of suitable habitat, which are to be interpreted as priority areas for monitoring species in the NWAO. We used MaxEnt software (version 3.3.3k; Phillips et al. 2006), implemented using the 'maxent' function from the R package 'dismo' (Hijmans et al. 2017), to build each SDM because this tool performs well compared to other approaches when using species presence-only data (sightings data without associated effort) and when sample size is relatively small (Elith et al.

2006, Pearson et al. 2007, Tittensor et al. 2009). In multiple studies, MaxEnt has been used to exploit opportunistically collected data that lacks true absences, to predict important cetacean habitat (e.g., Ainley et al. 2012, Gregr 2011, Pendleton et al. 2012, Bombosch et al. 2014).

MaxEnt incorporates the presence locations for the species being modelled and a set of environmental data predictors across the study area (subsequently referred to as the landscape). The presence locations used include only one record of the target species per environmental grid cell. For each grid cell across the study area, the model calculates a probability of presence of an individual of the species of interest in that cell, relative to other cells in the landscape (Phillips et al. 2006, Merow et al. 2013), referred to as a relative occurrence rate (ROR). However, when assumptions of random sampling are not met, as is the case in our study, these ROR values are better interpreted as indices of predicted habitat suitability (Merow et al. 2013). To determine ROR values, MaxEnt contrasts environmental conditions at locations of species presence to conditions at a sample of background point locations within the landscape (Fithian & Hastie 2013). Background points are randomly selected from the landscape, unless a list of background points is supplied (for details, see section below: 'background points based on non-TGS').

To allow comparison between results for different species, we used raw ROR values to calculate indices that ranged between 0 and 100 for the grid cells; the value assigned to each grid cell was the sum of that pixel's raw ROR and the RORs of all pixels of equal or lesser values, multiplied by 100. We used this cumulative index to generate habitat suitability maps as indicators of priority areas to target future monitoring efforts. High values indicate areas of predicted suitable habitat, where the target species is most likely to occur and thus these areas should be considered priority monitoring areas (Merow et al. 2013). The MaxEnt run settings are provided in Table 2.

Evaluation of MaxEnt model performance

The Area Under the Receiver Operating Curve (AUC) metric was used to evaluate the ability of the SDMs to discriminate correctly between sites associated with cetaceans' presence and the sample of points from the landscape (Phillips et al. 2006). For this, we selected the cross-validation option in MaxEnt as recommended in Merow et al. (2013) (Table 2) and we used the AUC to investigate the probability that a randomly-chosen cetacean presence location was ranked higher than a randomly-chosen location in the landscape. An AUC value close to 1.0 indicates that the SDM has good discriminatory power; a value less than or equal to 0.5 indicates that the model prediction is no better than random (Fielding & Bell 1997).

Table 2. MaxEnt run settings used to build SDMs for cetaceans in the NWO. Settings were selected following Phillips et al. (2006) and Merow et al. (2013).

Variable	Setting	Comments
Random Seed	Yes	
Max Number of Background Points	10000	A sample of point locations from the landscape to represent the environmental conditions in the study area, selected randomly or based on a supplied list of non-target group species sightings, if applicable.
Regularization Multiplier	1	Reduces model over-fitting.
Output Grids	None	
Maximum Iterations	5000	Allows the model adequate opportunity for convergence.
Convergence Threshold	0.00001	
Replicated Run Type	Crossvalidate	Assesses uncertainty in model predictions; it incorporates all available sightings, making better use of smaller datasets. Occurrence data is randomly split into a number of equally-sized groups, and models are created leaving out each group in turn. The left-out groups are then used for model evaluation.
Number of Replicates	100	Number of runs for each species. Averages of the results from all model replicates are used to generate habitat suitability maps.
Output Type	Raw	Relative occurrence rate, from which we calculated cumulative output values that we used to generate maps of predicted habitat suitability. Cumulative values do not rely on post-processing assumptions and are useful when illustrating potential species range boundaries.
Alternate estimates of variable importance	Jacknife	Each predictor variable is excluded in turn, and a model is created with the remaining variables. A model is also created using each variable in isolation. This is in addition to the model created using all variables.

Sampling bias correction

Bias in the sampling effort within a study area can influence SDMs reliability and quality (Bystriakova et al. 2012, Fourcade et al. 2014). There are two types of sampling bias in this study: 1) cetacean records may be overrepresented in regions with high sampling efforts (e.g. in the Gully MPA or Bay of Fundy, where dedicated cetacean fieldwork has occurred for many years); and 2) cetacean records in suitable habitat may be absent due to lack of survey effort. We cannot correct for sampling biases directly, because most cetacean sightings gathered for this study were from opportunistic surveys and we do not have a measure of survey effort. Instead, we applied two methods to indirectly account for these biases: 1) mixed random-systematic sampling of target group species (TGS) to account for overrepresentation in areas of high effort and 2) using background points based on records of non-target group species (non-TGS) to account for absences due to lack of effort (Gomez et al. 2017). These methods, as well as the SDM strategy used in this study, are summarized in Figure 6.

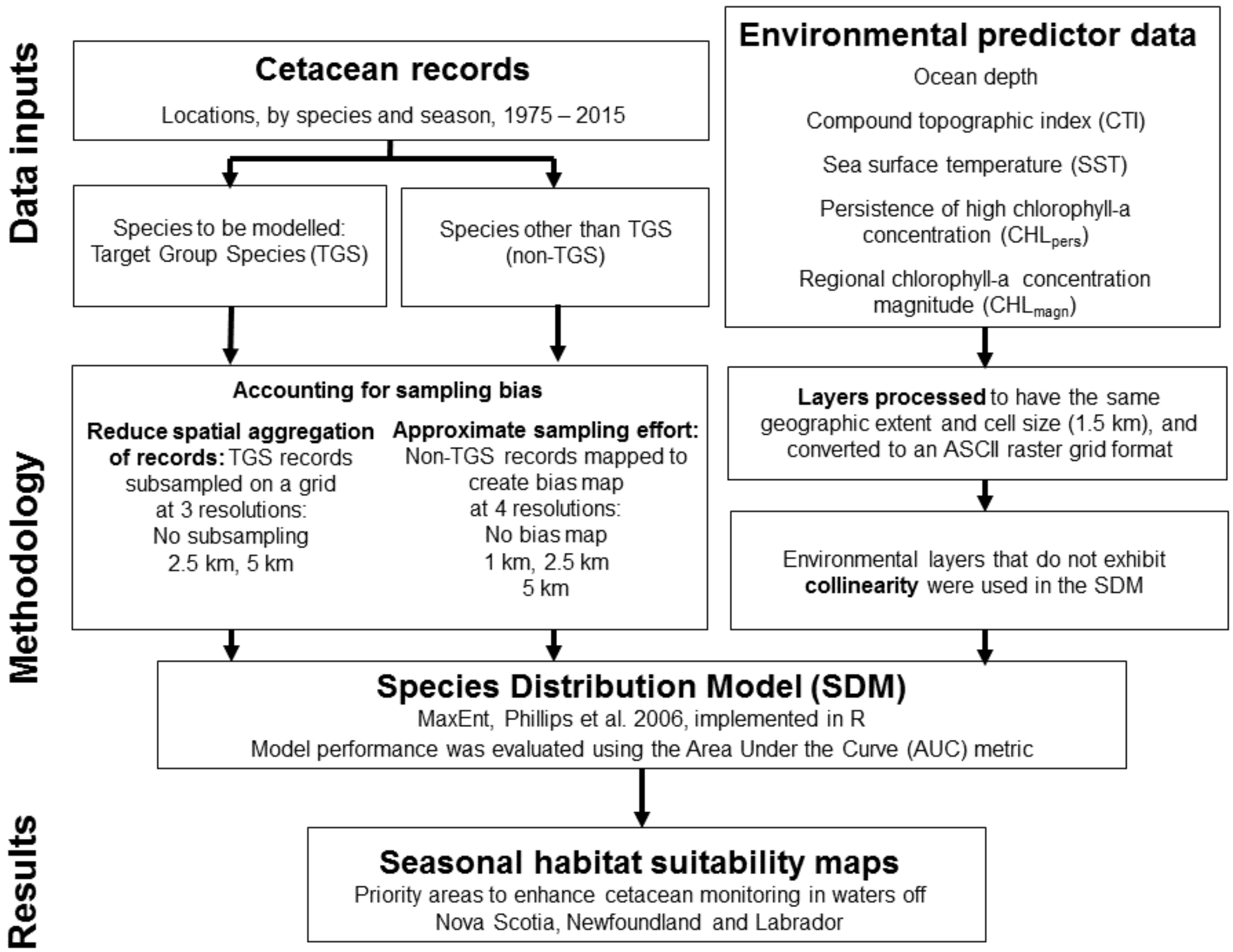


Figure 6. Summary of the SDM approach used to integrate information on the location of cetaceans and environmental variables to predict suitable habitat and priority monitoring areas for cetaceans in the NWAO.

Mixed random-systematic sampling of TGS – We refer to the cetacean species being modeled as the TGS (Tables 3 to 5). MaxEnt discards redundant TGS records that occur in the same grid cell of the environmental predictor raster layers (1.5 km resolution); however, it may still over-represent regions with high sampling efforts (Kadmon et al. 2004), especially if those regions of high effort are larger than the resolution of the environmental predictors. Thus, we replicated the SDMs after further reducing spatial aggregation of records; for each applicable season, we randomly subsampled one TGS record per grid cell on a 2.5 km and on a 5 km grid (e.g., Fourcade et al. 2014) and generated a SDM for each of these subsampled sets of records (Table 4). These models were in addition to a SDM with no subsampling (in all models, only one record of the target species within any given environmental grid cell was included). For each season, SDMs were only built for species with at least 450 records (prior to subsampling) in that season as model implementation encountered errors at sample sizes below this count. For all species, sample sizes in winter were too low to implement SDMs (Table 3 and Table 4).

Background points based on non-TGS – When sampling effort across the study area cannot be reliably estimated, but many sightings of species other than one being modeled are available, these sightings can guide the selection of background points (Merow et al. 2013). If these other species, hereafter termed non-TGS, were observed using the same techniques as the TGS, then, based on the assumption that the TGS would have been observed if present, non-TGS sightings can serve as surveyed points (Merow et al. 2013). By selecting background points from surveyed locations, we exclude areas with no known survey effort from the landscape used to train the model. In this study, non-TGS comprised all free-swimming cetaceans except the TGS. Non-TGS includes cetaceans that were not identified to species (e.g. unknown dolphin). For each combination of species and season that we analysed, we generated three lists of ‘surveyed’ background points (corresponding to environmental predictor variable grid cells): generally, points that were within a 1 km, 2.5 km or 5 km radius of a non-TGS record (Table 5). We will subsequently refer to these lists of background grid cells as bias maps. We created models based on each of these bias maps and one where background points were selected without reference to non-TGS records, to examine the effect of how strictly the landscape is restricted.

SDMs were generated for 12 species in each season for which these species had sufficient sample size (Table 3), using each combination of TGS subsampling resolution and background points (Tables 4 and 5). In this document we present results for ten species; North Atlantic right whales and northern bottlenose whales were not included as independent SDM studies are underway for these species.

Spatial correlation of habitat suitability

To assess the correspondence between all the habitat suitability maps generated for each species, we assessed their spatial correlation using the Pearson’s rank correlation coefficient (*r*) (Quinn & Keough, 2002).

Consolidated priority areas to target monitoring efforts

SDM quantitative outputs were divided in 4 arbitrary categories in Gomez et al. 2017: high (100 to 60%), moderate (60 to 40%), low (40 to 10%) and very low (<10%) suitability. When appropriate, areas of high suitability (60-100%) from all scenarios of sampling bias correction (bias maps and subsampling) may be combined into one map per species. Consolidated outputs in this report indicate priority areas where monitoring efforts may be targeted.

Table 3. Counts of sighting records for free-swimming cetacean species observed in the study area from 1975 to 2015, by season. Seasons for which a given species had enough records (n > 450) to implement the SDM are bolded and highlighted in green. Counts are prior to any subsampling or the removal of additional records of the same species within the same environmental grid cell. *Northern bottlenose whales and North Atlantic right whales, highlighted in grey, were not included in this report as independent efforts are underway for those species.

		Records			
Taxon	**Species**	**Spring**	**Summer**	**Autumn**	**Winter**
Baleen Whales	Blue whale	32	222	51	10
	Fin whale	286	**6413**	**2666**	79
	Sei whale	125	**631**	405	9
	Minke whale	264	**5737**	**1171**	38
	Humpback whale	**463**	**10455**	**4066**	73
	North Atlantic right whale*	195	13997	8055	17
Medium & Large Toothed Whales	**Sperm whale**	119	**766**	223	31
	Pygmy sperm whale	0	1	0	0
	Northern bottlenose whale*	198	2352	169	28
	Blainville's beaked whale	0	0	1	0
	Cuvier's beaked whale	2	1	1	0
	Gervais' beaked whale	0	1	0	0
	Sowerby's beaked whale	0	53	2	0
	Beluga	0	9	4	0
	Killer whale	73	214	72	11
	Long-finned pilot whale	**874**	**3208**	**933**	118
	False killer whale	1	1	3	0
Dolphins & Porpoises	Atlantic spotted dolphin	0	3	0	0
	Atlantic white-sided dolphin	254	**3098**	**1039**	64
	Bottlenose dolphin	54	176	56	20
	Short-beaked common dolphin	48	**1513**	**690**	100
	Risso's dolphin	8	72	44	0
	Striped dolphin	0	118	8	0
	White-beaked dolphin	24	**579**	163	6
	Harbour porpoise	250	**20600**	**6928**	31
	Other/Unknown	843	6179	2714	279
Total		**4113**	**76399**	**29464**	**914**

Table 4. Counts of sighting records for the target cetacean species, by season, used in the Species Distribution Models. Counts represent the number of sightings after subsampling (if any) and the removal of additional records of the same species within the same environmental grid cell. The counts are shown as a range in some cases as a result of randomization in the subsampling process. Counts include only free-swimming cetaceans observed in the study area from 1975 to 2015.

		Subsampling grid		
Season	**Species**	**None**	**2.5 km**	**5 km**
Spring	Humpback whale	355	333-335	312-313
	Long-finned pilot whale	542	416-421	363-366
Summer	Fin whale	2308	1908-1923	1471-1477
	Sei whale	434	399-401	327-329
	Minke whale	1727	1429-1436	1093-1102
	Humpback whale	3304	2730-2757	2073-2078
	Sperm whale	582	529-532	451-453
	Long-finned pilot whale	2229	1930-1940	1643-1644
	Atlantic white-sided dolphin	1811	1510-1530	1185-1192
	Short-beaked common dolphin	1073	986-992	856-858
	White-beaked dolphin	455	431-433	383-387
	Harbour porpoise	2329	1569-1584	868-883
Autumn	Fin whale	1229	982-990	710-715
	Minke whale	661	563-567	446-447
	Humpback whale	1685	1450-1453	1154-1157
	Long-finned pilot whale	702	620-625	567-569
	Atlantic white-sided dolphin	697	587-594	486-487
	Short-beaked common dolphin	525	494-496	451-454
	Harbour porpoise	1117	745-747	401-405

Table 5. Number of background points used in the SDMs for each target group species (TGS) by season. A maximum of 10,000 background points (Table 2) were randomly selected from environmental predictor variable grid cells in the study area with records of non-target group cetacean species (non-TGS) observed in each season from 1975 to 2015. These background points were used to create a bias map of ‘surveyed’ cells for the SDMs, at three different resolutions (Figure 6). For SDMs without a bias map, 10,000 background points were randomly selected from across the entire study area, uninformed by non-TGS observations. At 1 and 2.5 km bias map resolutions, less than 10,000 background points were used because a smaller selection of predictor variable grid cells overlap with a non-TGS observation at those resolutions.

		Bias map resolution		
Season	**Target group species**	**1 km**	**2.5 km**	**5 km**
Spring	Humpback whale	558	3477	10000
	Long-finned pilot whale	550	3329	10000
Summer	Fin whale	5073	10000	10000
	Sei whale	5333	10000	10000
	Minke whale	5145	10000	10000
	Humpback whale	4797	10000	10000
	North Atlantic right whale	5141	10000	10000
	Sperm whale	5297	10000	10000
	Long-finned pilot whale	4944	10000	10000
	Atlantic white-sided dolphin	5111	10000	10000
	Short-beaked common dolphin	5187	10000	10000
	White-beaked dolphin	5316	10000	10000
	Harbour porpoise	4890	10000	10000
Autumn	Fin whale	2489	10000	10000
	Minke whale	2530	10000	10000
	Humpback whale	2325	10000	10000
	North Atlantic right whale	2336	10000	10000
	Long-finned pilot whale	2458	10000	10000
	Atlantic white-sided dolphin	2489	10000	10000
	Short-beaked common dolphin	2489	10000	10000
	Harbour porpoise	2401	10000	10000

RESULTS

Predictor variable contributions and model performance

As proxies for prey availability, we selected five predictor environmental variables for our SDMs: ocean depth, compound topographic index, sea surface temperature, areas of persistently high chlorophyll-a concentration, and regional chlorophyll-a magnitude. These environmental variables did not exhibit collinearity (VIFs < 3; Table 6) and thus all were used in the SDMs.

There were sufficient sighting records to produce SDMs for two cetacean species during spring, ten during summer, and seven during autumn (excluding North Atlantic right whales and northern bottlenose whales; Table 3). Mean AUC values in all scenarios of sampling bias correction were larger than 0.58, indicating that all model predictions are better than random, and often AUC values were greater than 0.70, indicating that many SDMs have good discriminatory power (Tables 7-25).

SDM results using different bias maps and subsampling grids are reported in Figures A1-A19. As observed in Gomez et al. (2017), in general, maps that did not incorporate a bias file and included the total set of TGS sighting records (no subsampling) predicted a more conservative proportion of priority habitat compared with models that did utilize the bias files, and subsampled cetaceans records, which illustrate a more conservative prediction. This is represented by low correlation values in the different scenarios of bias correction (Table A1 - A20). We consider all outputs from these scenarios of sampling bias correction to be reasonable predictions in which to target monitoring efforts. We therefore used a precautionary approach by combining outputs from all scenarios of sampling bias correction to indicate consolidated priority areas where monitoring efforts may be targeted (Figures 8-12, 15,16,18, 21, 22).

The relative contribution of each environmental variable to the SDM are presented in Tables 7-25. Mean relative contributions of the predictor environmental variables to these SDMs varied by species and season. Ocean depth, SST and summer CHL_{pers} often contributed the most to the SDM (Tables 7-25). However, the relative contributions of environmental predictors varied substantially in some cases, depending on the bias map and subsampling grid used (Tables A1-A19).

Sightings maps and predicted habitat suitability maps

Given that all models predictions are better than random, it was considered appropriate to combine areas of high suitability (60-100%) from all scenarios of sampling bias correction (bias maps and subsampling) across all seasons into one map per species. These consolidated outputs indicate priority areas where monitoring efforts may be targeted. For each species, maps of sightings and predicted areas of high priority are presented in Figures 7-22. Maps of sightings are accompanied by information on the species' residency in the NWAO (migratory or resident), conservation status, and known prey preferences (as reviewed by Gomez and Moors-Murphy 2014; see Appendix 1 and 2 in that document).

The following information summarizes general patterns in the predicted distribution of cetaceans for all scenarios of sampling bias correction:

- Priority areas for monitoring fin whales (Figure 8) and minke whales (Figures 10) were, in general, predicted across most of the study area when accounting for all different scenarios of sampling correction, although the deep water areas and Flemish cap had overall lower predictions.

- Priority areas for monitoring sei whales included primarily the Scotian Shelf, Bay of Fundy, north area of the Labrador shelf, and the Flemish cap (Figure 9).

- Priority areas for monitoring humpback whales were predicted on the Scotian Shelf, the Newfoundland Shelf, and a portion of the Labrador shelf (Figure 11).

- Priority areas for monitoring sperm whales included primarily deep water of the Scotian, Newfoundland and Labrador shelf edges, and a portion of the Bay of Fundy (Figure 12).

- Priority areas for monitoring long-finned pilot whales were predicted in the Scotian Shelf, and deep water areas in the offshore margins of the Newfoundland and Labrador shelves, including several submarine canyons and basins (Figure 15).

- Priority areas for monitoring Atlantic white-sided dolphins included the Scotian Shelf, the Bay of Fundy, the Newfoundland shelf, and deeper waters of the Labrador shelf and the Laurentian Channel (Figure 16).

- Priority areas for monitoring short-beaked common dolphins included the Scotian Shelf, deep water areas in the offshore margins of the Scotian Shelf, and south of the Newfoundland shelf (Figure 8). Predictions were very low for the Labrador region.

- Priority areas for monitoring white-beaked dolphins included the Bay of Fundy, the Newfoundland and Labrador shelves, and excluded deep-water areas of the shelf edges in most cases (Figure 21).

- Priority areas for monitoring harbour porpoises included, in particular, the Bay of Fundy and the northern area of the Scotian Shelf, Newfoundland shelf and Labrador shelf edge (Figure 22).

Interpreting results from this report

This study represents an important initiative in eastern Canada to highlight key areas for cetacean monitoring in waters off Nova Scotia, and Newfoundland and Labrador. High priority areas in this report are interpreted as areas where cetacean monitoring efforts should be prioritized. In this context, SDM results can direct future survey and monitoring efforts for particular cetacean species (see also Gomez et al. 2017).

Our predictions do not represent the current distribution of cetaceans in the region because this is beyond the objectives of this report and is beyond the scope of our model's evaluation capabilities (Gomez et al. 2017). Our aim was to capture general conditions that may direct where to focus monitoring efforts. We used cetacean sightings from 1970-2015, and dynamic environmental predictors (CHL and SST) that use seasonal averages across multiple years. Therefore, persistent patterns over time (between 1975 and 2015) are the main patterns expected to be captured by these models. Further, SDM results presented here are not the same as species density maps; rather, they portray predicted suitable habitat based on environmental characteristics and sightings data that are not always derived from effort based surveys. Consequently, the use of the SDM outputs in marine spatial planning process should be accompanied by complimentary approaches such as acoustic and visual validation of the SDM results as well as additional modeling efforts already available for the area. The discussion section provides some examples on how to interpret SDM outputs for these purposes.

All SDM outputs for the various scenarios of sampling bias correction in the appendices (Figures A1 – A19) are reasonable predictions (mean AUC values > 0.58). Consequently, areas that are consistently predicted as having high suitability across all scenarios are potential areas in which to target monitoring efforts.

Table 6. Variance inflation factor (VIF) values indicating lack of collinearity between environmental variables: ocean depth, CTI, SST, and CHL_{pers} (note: CHL_{magn} was not included in this analysis, because it has only four values; see Figure 5). VIF < 3 denote environmental variables that do not exhibit collinearity with the other variables and thus are relevant to use in the SDMs (Zuur et al. 2010).

Environmental Variable	**Spring SDMs**	**Summer SDMs**	**Autumn SDMs**
Ocean depth	1.45	1.14	1.15
CTI	1.06	1.06	1.07
SST	1.66	1.33	1.11
CHL_{pers}	1.58	1.19	2.07
Lagged CHL_{pers}	1.66	1.24	2.32

Blue whale (Atlantic population)

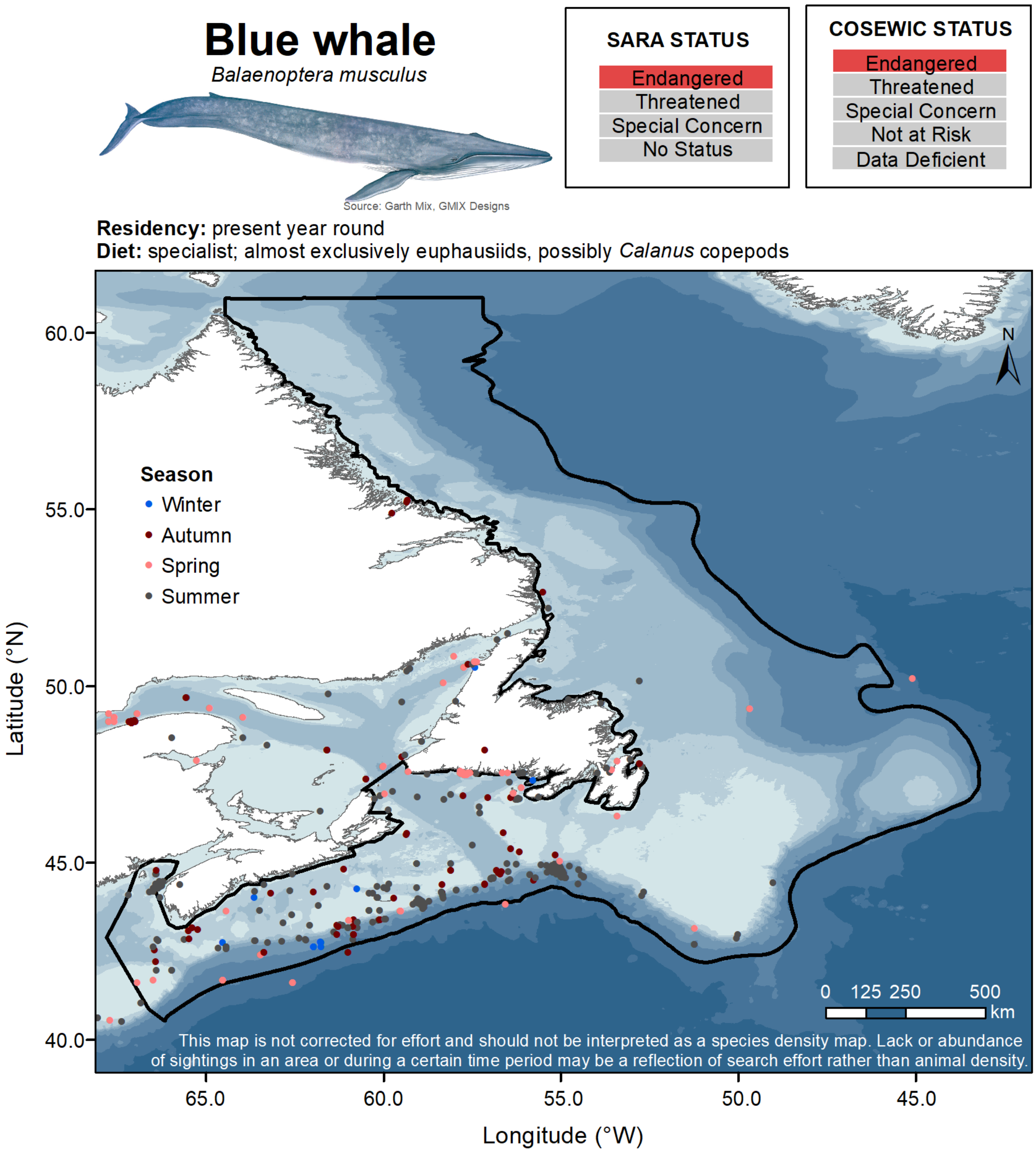
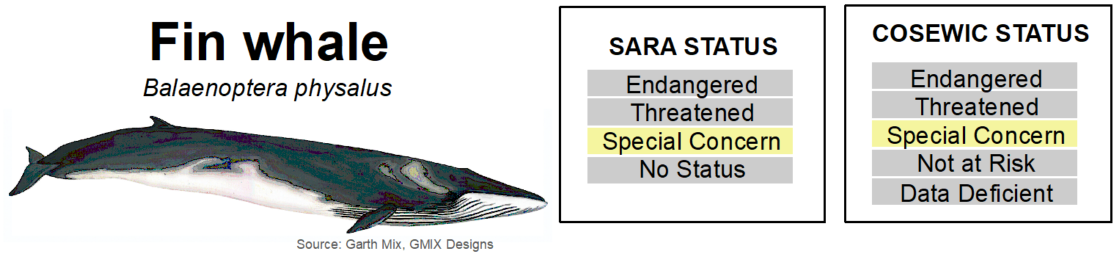


Figure 7. Sightings of blue whales by season, collected from 1975 through 2015 (n = 315, within study area outlined by black line, see Table 3).

Fin whale (Atlantic population)



Residency: migratory
Diet: generalist; small pelagic fish (e.g. herring, capelin), large zooplankton, small pelagic squid

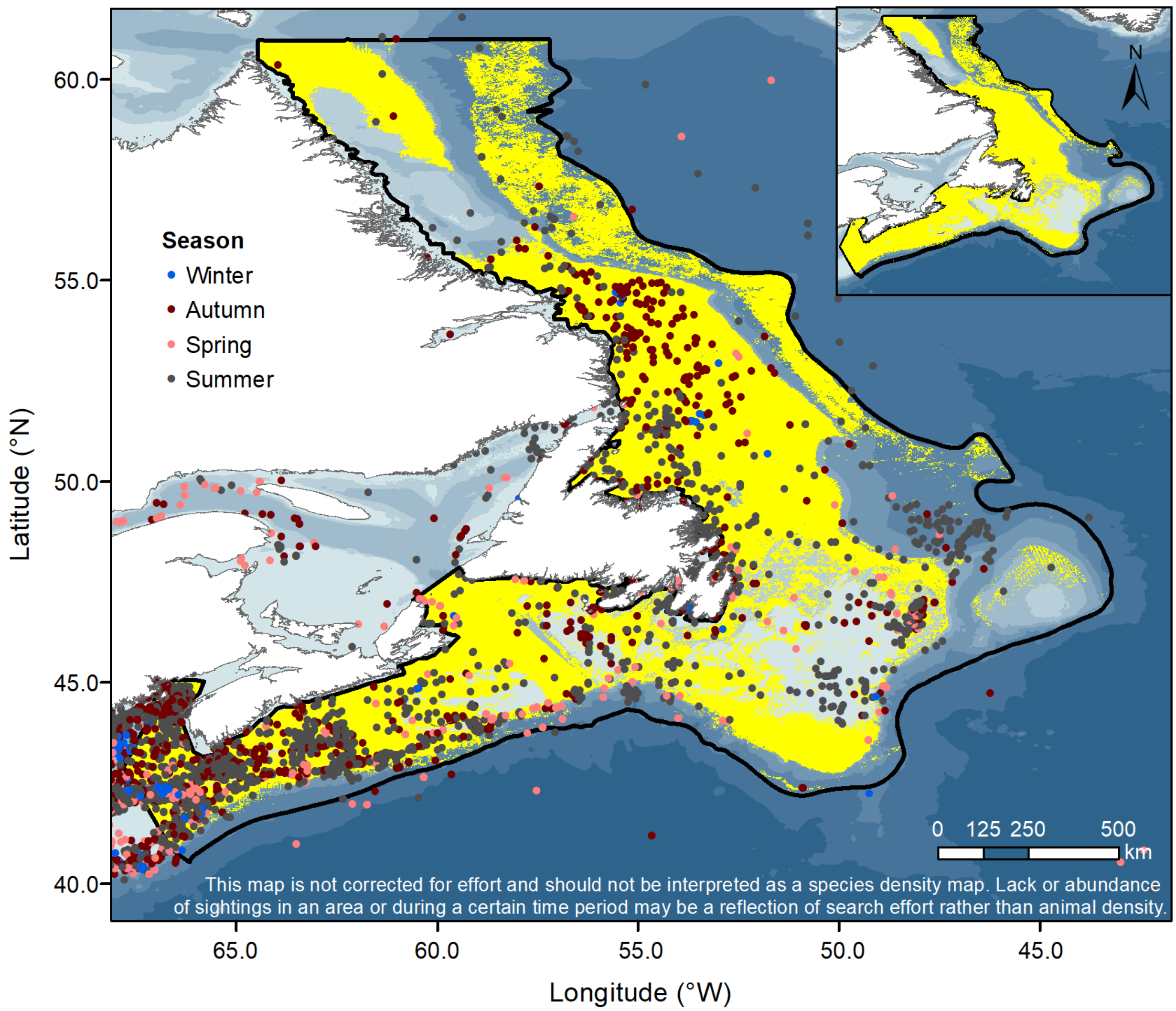


Figure 8. Sightings of fin whales by season, collected from 1975 through 2015 (n = 9444, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during summer and autumn. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 7. Relative contribution of each environmental variable to the fin whale summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDMs that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		**Mean Environmental Variable Contribution**							**AUC**	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	4.4	14.2	0.4	31.4	34.4	0.5	14.7	0.81	0.04
	1 km	26.3	23.7	2	4.1	3.3	7.6	33	0.6	0.06
	2.5 km	9	12.3	0.5	8.2	18.3	2.6	49.1	0.67	0.06
	5 km	6.1	9	0.6	12.8	22.6	2.3	46.4	0.7	0.06
2.5 km	**none**	5.4	17.1	0.2	23.4	39.9	0.7	13.3	0.81	0.04
	1 km	41	41.3	1.9	0.1	2.3	7.2	6.1	0.58	0.06
	2.5 km	16.5	16.5	0.6	11.5	21.1	2.4	31.3	0.64	0.06
	5 km	9.9	11	0.9	12.9	26.6	2.4	36.2	0.68	0.06
5 km	**none**	6.6	20.5	0.4	15.2	44.1	1.4	11.8	0.79	0.05
	1 km	21.6	34.7	3.5	2.2	2.5	4.6	30.8	0.6	0.07
	2.5 km	37.1	32.9	3	2.9	14.2	2	7.8	0.61	0.07
	5 km	17.1	16.9	1.2	4.2	38.4	1.7	20.5	0.64	0.07

Table 8. Relative contribution of each environmental variable to the fin whale autumn species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDMs that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		**Mean Environmental Variable Contribution**							**AUC**	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	10.2	9.7	0.4	40.2	8.7	28.6	2.1	0.87	0.04
	1 km	40.4	9.1	1.6	2.8	4.5	37.8	3.7	0.64	0.07
	2.5 km	14.6	7.2	1.2	7.6	7.5	57	5	0.73	0.07
	5 km	11.6	5.5	0.8	9.1	6.6	61.9	4.5	0.76	0.07
2.5 km	**none**	13.3	11.3	0.8	42.4	7.9	22.1	2	0.87	0.04
	1 km	65.1	15.3	2.3	0.2	1	11.1	5	0.6	0.08
	2.5 km	23.5	7.5	1.3	10.4	6.4	46.6	4.4	0.69	0.08
	5 km	15.3	6.1	1	12.2	9.6	52	3.8	0.73	0.08
5 km	**none**	18.6	17.4	0.5	37.3	7.2	17.5	1.5	0.85	0.05
	1 km	39.2	31	1.8	0.6	0.4	21.2	5.6	0.61	0.1
	2.5 km	55.4	12.9	3.2	6.3	3.1	11.6	7.5	0.62	0.09
	5 km	36.5	7.2	1.3	9.3	9.8	30.9	5	0.68	0.09

Sei whale (Atlantic population)

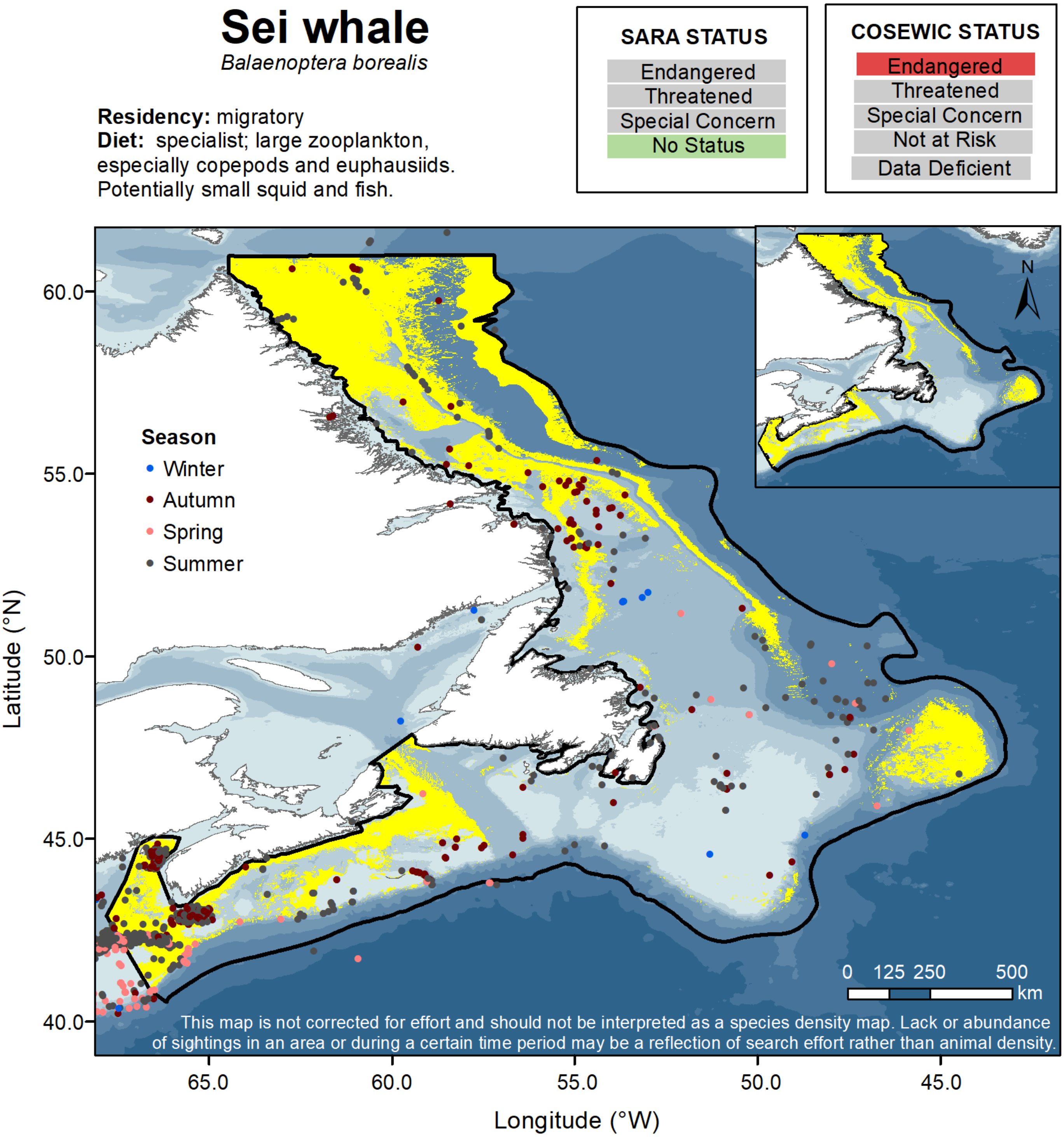


Figure 9. Sightings of sei whales by season, collected from 1975 through 2015 (n = 1170, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during summer. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 9. Relative contribution of each environmental variable to the sei whale summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	9	9.2	0.6	22.2	37.2	1.9	19.8	0.87	0.07
	1 km	8.1	16.9	1.4	0.2	17.6	15.4	40.4	0.73	0.1
	2.5 km	13.4	11.7	0.9	5.8	24.3	6.3	37.6	0.76	0.1
	5 km	13.9	11.7	0.6	14.4	20.4	4.7	34.3	0.79	0.1
2.5 km	**none**	10.2	8.3	0.6	18.8	38.6	1.8	21.8	0.86	0.08
	1 km	10.7	14.6	0.8	0.4	15.9	15.5	42.1	0.72	0.1
	2.5 km	14.7	10.2	1	5.3	23.6	6.5	38.8	0.75	0.1
	5 km	13.9	10.7	0.7	13.7	20.5	5	35.5	0.79	0.1
5 km	**none**	9.8	10.6	0.6	35	20.6	2.9	20.5	0.84	0.08
	1 km	5.6	19.5	0.7	0.4	14.8	14.5	44.5	0.70	0.11
	2.5 km	12.5	14.5	0.4	0.9	27.3	6.8	37.6	0.72	0.11
	5 km	13.7	12.5	0.7	7.1	24.7	5.2	36.1	0.76	0.11

Minke whale (Atlantic population)

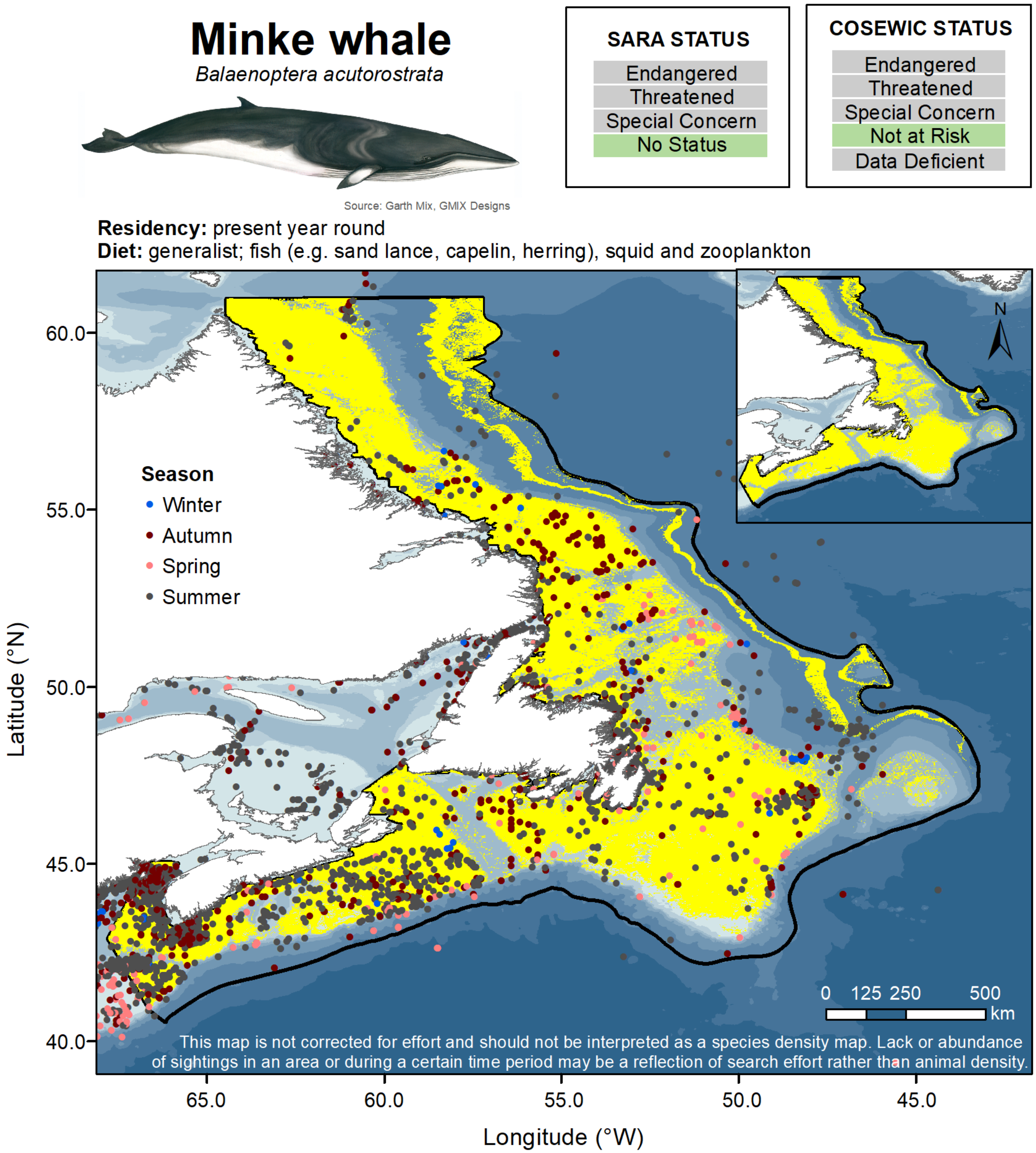


Figure 10. Sightings of minke whales by season, collected from 1975 through 2015 (n = 7210, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during summer and autumn. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 10. Relative contribution of each environmental variable to the minke whale summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	Bias Map	Ocean depth	SST	CTI	Lagged CHL magn	CHL magn	Lagged CHL pers	CHL pers	mean	sd
none	none	13.5	8.6	0.6	5	53.4	0.9	18.1	0.84	0.04
	1 km	36.7	11.4	2.7	2.1	24.4	14.4	8.4	0.66	0.06
	2.5 km	22	9.1	2.5	7.8	14.6	4.5	39.6	0.72	0.06
	5 km	13.6	8.7	0.9	8.6	20.3	4	43.8	0.75	0.06
2.5 km	none	13.3	8.9	0.6	5.9	51.2	0.6	19.5	0.83	0.05
	1 km	38.7	9.9	2.9	0.2	36.4	10.2	1.8	0.63	0.06
	2.5 km	28.7	8.6	2.6	4.7	19.2	3.6	32.6	0.7	0.06
	5 km	16.9	8.3	0.8	6.9	24.1	3.9	39.2	0.73	0.06
5 km	none	21	10.8	0.3	1.9	54.6	1.3	10	0.82	0.06
	1 km	30.4	9	2.6	0.1	48.2	2.8	6.9	0.62	0.08
	2.5 km	41.3	11.9	4.2	4.8	27.8	2.6	7.3	0.66	0.07
	5 km	28.8	9.6	1.7	4.8	30.2	3.1	21.8	0.69	0.07

Table 11. Relative contribution of each environmental variable to the minke whale autumn species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	Bias Map	Ocean depth	SST	CTI	Lagged CHL magn	CHL magn	Lagged CHL pers	CHL pers	mean	sd
none	none	13.7	9.4	0.4	18.9	10.3	43.7	3.7	0.86	0.06
	1 km	35	41.5	8.2	1.5	1.7	9.8	2.3	0.61	0.09
	2.5 km	11.2	15.5	2.8	1.7	1.8	63.7	3.4	0.71	0.09
	5 km	6.1	11.2	1.9	1.6	3.1	71.4	4.6	0.74	0.09
2.5 km	none	17.3	11.3	0.8	10.5	15.2	41.4	3.4	0.85	0.06
	1 km	34	38.4	10.5	8.1	5.7	2.3	0.9	0.58	0.1
	2.5 km	15.8	19.7	2.3	1	2.7	54.1	4.3	0.68	0.1
	5 km	8.5	13.1	2.5	1.2	3.9	67	3.8	0.72	0.1
5 km	none	21.8	14.3	0.5	13	13.4	34.4	2.5	0.83	0.07
	1 km	16	19.6	8.7	33.3	13.6	6.1	2.9	0.58	0.11
	2.5 km	28.9	32.7	3.2	1.5	1.5	29.6	2.6	0.61	0.11
	5 km	15.7	18.7	2.2	2	2.7	55	3.7	0.66	0.11

Humpback whale (Atlantic population)

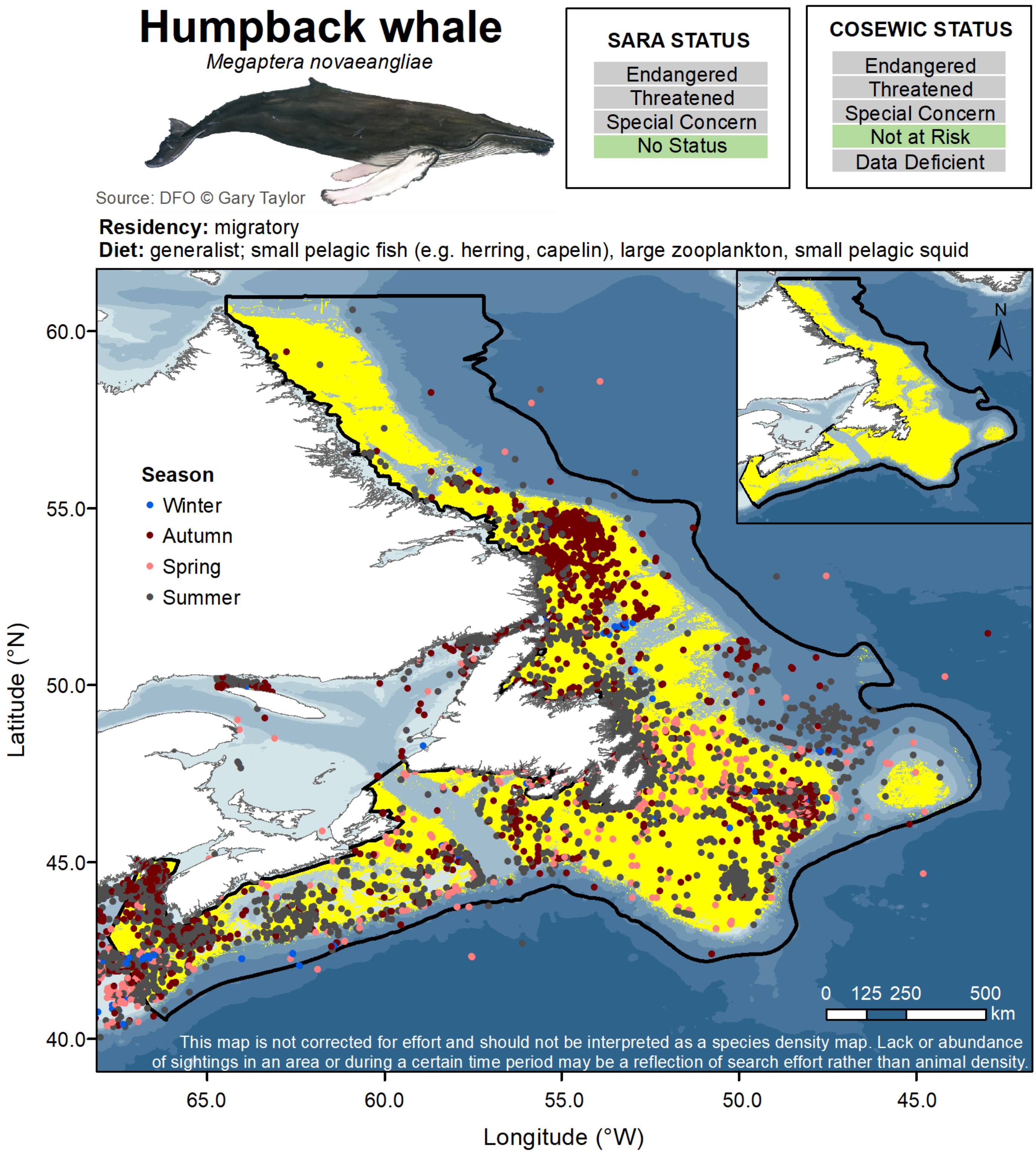


Figure 11. Sightings of humpback whales by season, collected from 1975 through 2015 (n = 15057, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during spring, summer and autumn. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 12. Relative contribution of each environmental variable to the humpback whale spring species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	Bias Map	Ocean depth	SST	CTI	Lagged CHL magn	CHL magn	Lagged CHL pers	CHL pers	mean	sd
none	none	39.8	32.8	4.9	3.9	5.6	9.3	3.7	0.8	0.07
	1 km	18.6	60.5	1.8	2.7	12.1	3.6	0.7	0.64	0.11
	2.5 km	28.1	57.1	3.8	1.6	3.4	4.2	1.8	0.71	0.1
	5 km	35	49.5	3.5	1.5	2	5.1	3.3	0.72	0.1
2.5 km	none	43.9	33.8	4.9	5.9	2.1	5.8	3.5	0.8	0.08
	1 km	24.8	48.2	1.8	4.1	18.4	2.3	0.4	0.65	0.11
	2.5 km	31.7	48.4	4.1	1.2	9.3	3.7	1.7	0.72	0.1
	5 km	38.8	42.1	3.1	1.8	7.5	4.2	2.5	0.72	0.11
5 km	none	41.6	34.5	4	5.3	2.2	9.3	3.1	0.8	0.08
	1 km	18.4	53.7	2.3	3.4	19.1	2.7	0.4	0.67	0.11
	2.5 km	26.7	52.6	3.7	1.7	10.6	3.1	1.5	0.72	0.11
	5 km	34.3	45.9	3.3	1.8	8.5	3.8	2.4	0.72	0.1

Table 13. Relative contribution of each environmental variable to the humpback whale summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	Bias Map	Ocean depth	SST	CTI	Lagged CHL magn	CHL magn	Lagged CHL pers	CHL pers	mean	sd
none	none	35.6	23.1	0.9	5.8	19.7	1.4	13.6	0.77	0.03
	1 km	41.4	29.2	1.4	8.1	7.4	8.8	3.7	0.63	0.04
	2.5 km	45.8	31.6	1.7	0.8	3.3	10.2	6.6	0.68	0.04
	5 km	44.4	20.9	1.6	1.0	2.0	6.7	23.4	0.69	0.04
2.5 km	none	38.8	24.3	0.8	13.5	6.6	2.1	13.9	0.77	0.04
	1 km	32.7	8.3	0.8	33.1	15	6.6	3.4	0.63	0.05
	2.5 km	47.2	31.8	1.6	1.9	6.9	7.9	2.8	0.67	0.05
	5 km	47.5	23	1.5	0.1	7.7	6.3	13.9	0.68	0.05
5 km	none	41.6	30.3	0.7	5	7.1	2.3	13.1	0.76	0.05
	1 km	22.6	3.8	0.7	46.4	9.6	2.1	14.8	0.67	0.05
	2.5 km	40.9	14.1	0.9	28	10.8	4.4	0.9	0.66	0.05
	5 km	47.1	27.1	1.0	0.3	17.4	5.0	2.0	0.66	0.05

Table 14. Relative contribution of each environmental variable to the humpback whale autumn species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	22.2	26.8	0.1	1.9	17	30.5	1.5	0.83	0.04
	1 km	27.1	62.1	2.5	3.5	0.1	1.5	3.3	0.64	0.06
	2.5 km	30.9	57.8	1.0	0.9	0.1	6.2	3.0	0.74	0.05
	5 km	27.6	45.1	0.5	1.2	0.7	21.3	3.6	0.76	0.05
2.5 km	**none**	23.3	28	0.1	2.2	18.1	27.2	1.1	0.83	0.04
	1 km	22.8	53.4	3.1	15.6	1.2	0.7	3.2	0.65	0.07
	2.5 km	30.1	60.5	1.0	0.7	0.1	4.5	3.0	0.73	0.06
	5 km	30.9	51.1	0.8	1.0	0.1	12.3	3.8	0.74	0.06
5 km	**none**	22.5	37.4	0.2	1.0	22	15.7	1.1	0.82	0.05
	1 km	13.1	33.8	2.3	39.2	3.1	2.7	5.7	0.68	0.07
	2.5 km	24.7	51.1	1.4	13.2	1.0	1.9	6.7	0.72	0.07
	5 km	32.3	57.4	0.4	0.5	0.1	3.8	5.5	0.72	0.06

Sperm whale

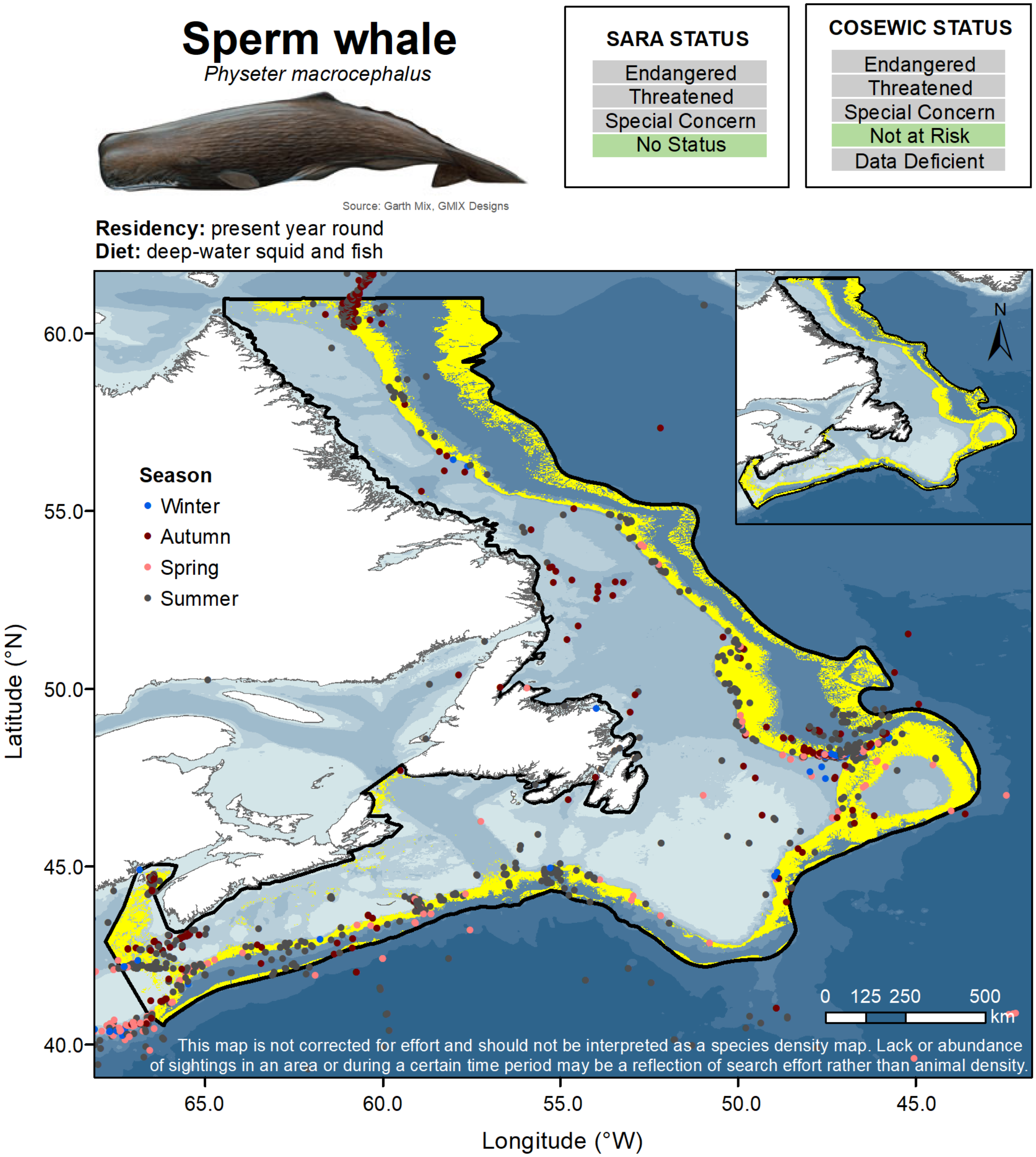


Figure 12. Sightings of sperm whales by season, collected from 1975 through 2015 (n = 1139, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during summer. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 15. Relative contribution of each environmental variable to the sperm whale summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDMs that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	44.3	11.9	6.6	14.9	10	5.3	7.1	0.87	0.06
	1 km	80.3	8.5	2.1	3.3	2.1	2.6	1.2	0.81	0.07
	2.5 km	75.6	10.2	3.8	1.2	3.3	3.9	2	0.82	0.07
	5 km	69.6	12.2	4.2	0.1	6.1	4.4	3.5	0.82	0.07
2.5 km	**none**	47.9	10.4	5.5	11.5	11.5	6	7.1	0.86	0.06
	1 km	78.3	7.9	2.1	6.4	1.9	2.1	1.2	0.81	0.07
	2.5 km	76	8.2	3.9	4.3	2.7	3.6	1.4	0.81	0.08
	5 km	70.5	10.4	4.1	3.2	5.3	3.7	2.8	0.82	0.07
5 km	**none**	49.2	7.6	4.3	7.8	18.1	7.1	5.9	0.85	0.06
	1 km	72.4	7.7	1.2	12.6	1.4	2.3	2.4	0.8	0.08
	2.5 km	72.6	6.4	3.4	10.9	2.7	3.2	0.8	0.8	0.08
	5 km	68.7	7	3.8	11	4.8	3.3	1.4	0.8	0.08

Sowerby's beaked whale

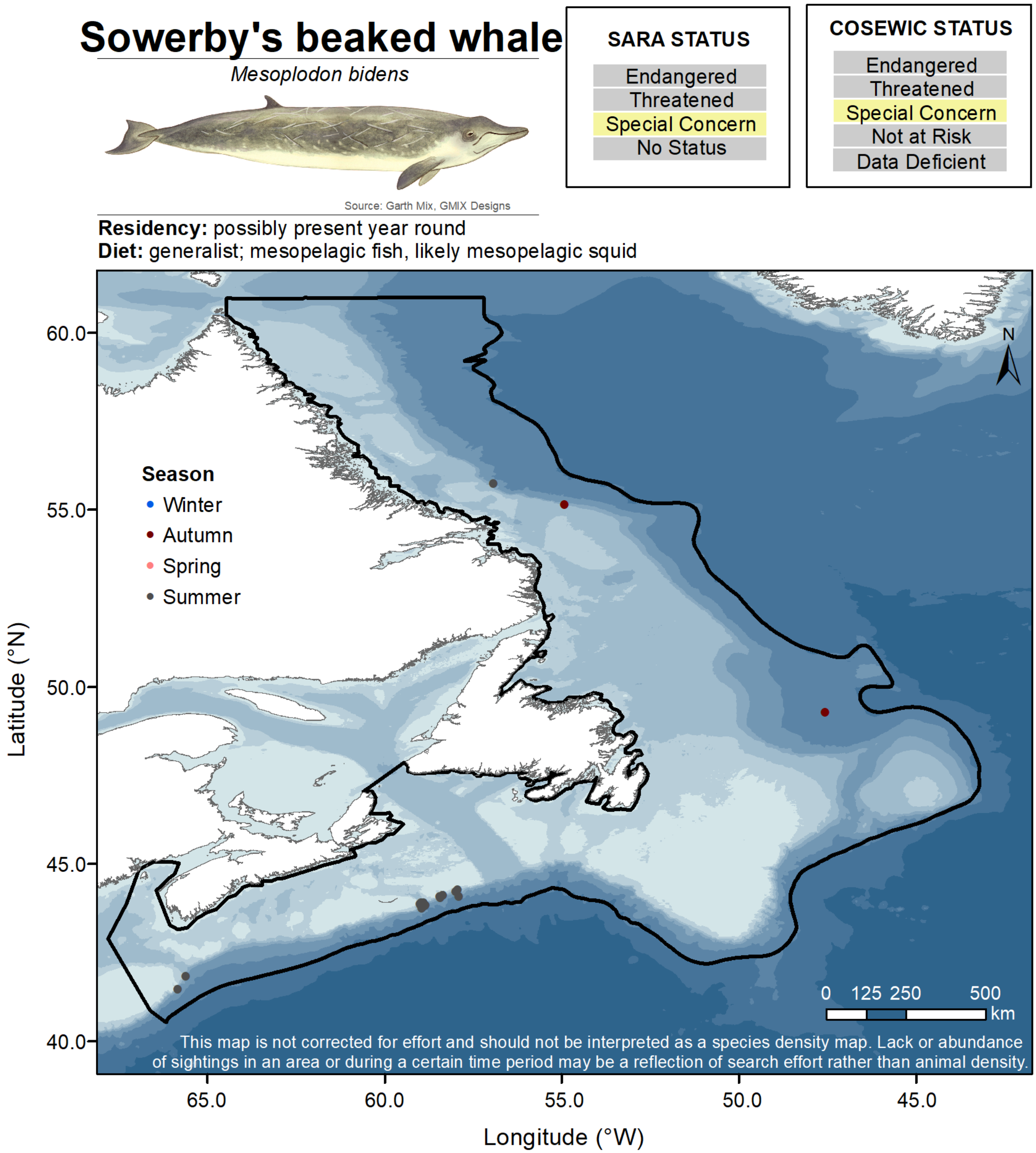


Figure 13. Sightings of Sowerby's beaked whales by season, collected from 1975 through 2015 (n = 55, within study area outlined by black line, see Table 3).

Killer whale (Atlantic population)

Killer whale

SARA STATUS
Endangered
Threatened
Special Concern
No Status

COSEWIC STATUS
Endangered
Threatened
Special Concern
Not at Risk
Data Deficient

Residency: present year round
Diet: herring and other fish species

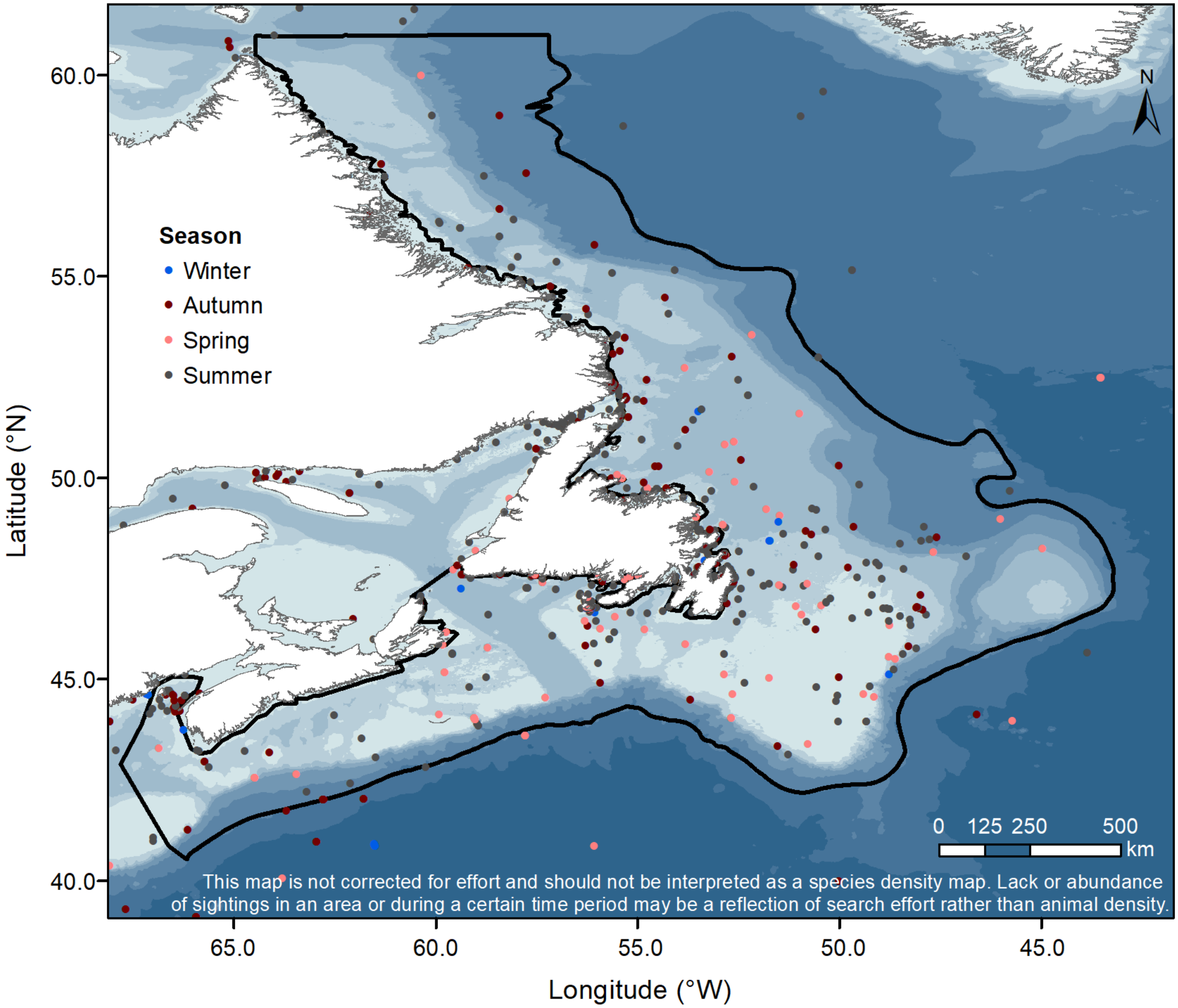


Figure 14. Sightings of killer whales by season, collected from 1975 through 2015 (n = 370, within study area outlined by black line, see Table 3).

Long-finned pilot whale (Atlantic population)

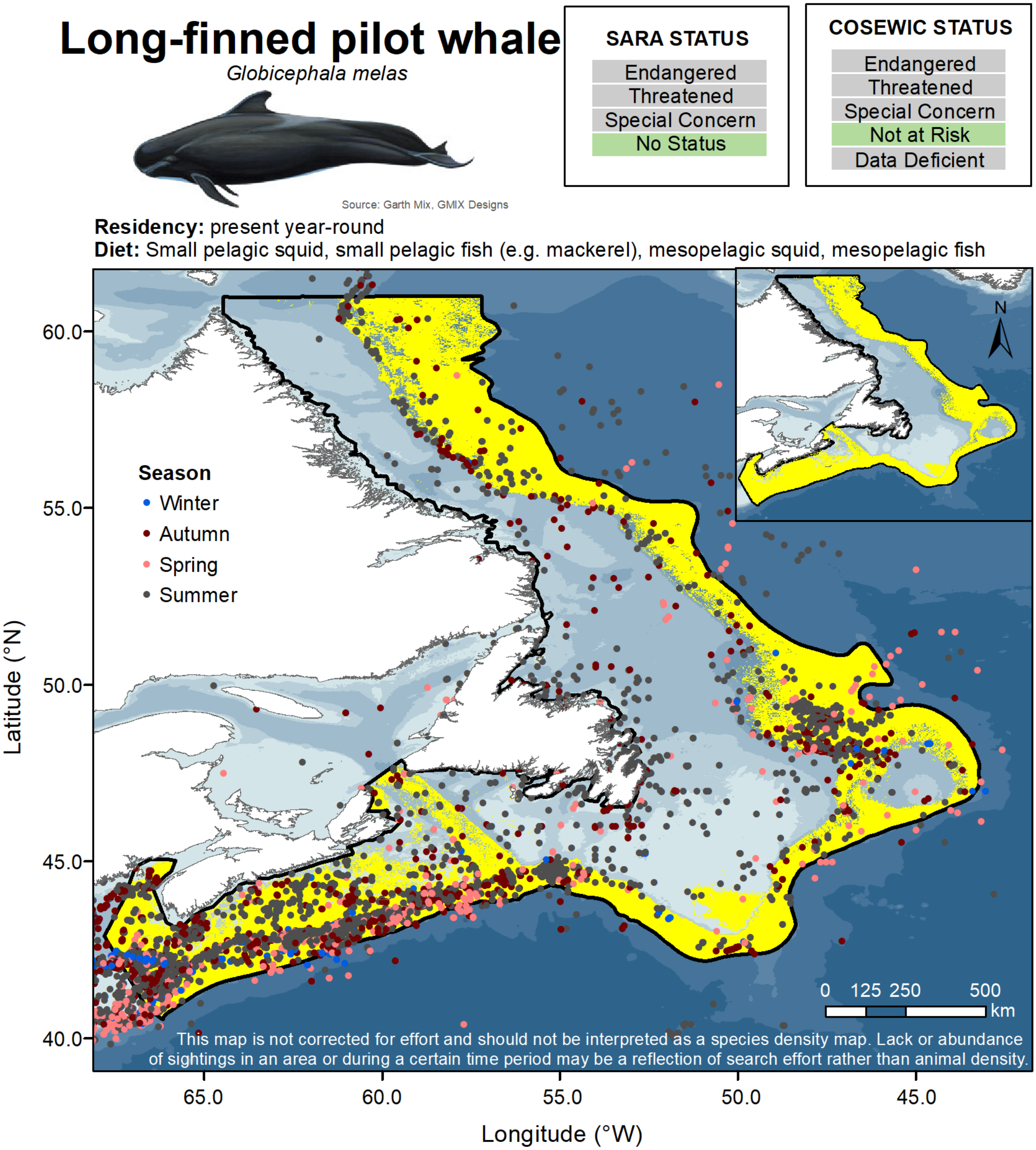


Figure 15. Sightings of long-finned pilot whales by season, collected from 1975 through 2015 (n = 5133, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during spring, summer and autumn. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 16. Relative contribution of each environmental variable to the long-finned pilot whale spring species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDMs that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	13.3	25.9	7.8	3.6	47.2	0.9	1.3	0.89	0.05
	1 km	33.1	23.6	10.4	3.9	8.8	8.3	12	0.65	0.09
	2.5 km	26	27.9	8.7	2.4	17.1	6.2	11.8	0.78	0.08
	5 km	24.5	27.3	9.7	4	19.1	5.3	10.1	0.81	0.08
2.5 km	**none**	11.1	28.1	9.1	2.9	46.1	0.6	2.0	0.88	0.06
	1 km	33.8	25.6	11.4	5.5	4.2	8.2	11.3	0.65	0.1
	2.5 km	28.3	29.6	8.4	3.9	13.7	6.3	9.8	0.75	0.09
	5 km	25.6	29.2	10.3	4.1	18.2	4.3	8.3	0.78	0.09
5 km	**none**	9.5	29.2	8.1	2.3	47.3	1.0	2.6	0.87	0.06
	1 km	37.6	23.4	12.2	7.3	3.0	7.2	9.3	0.65	0.11
	2.5 km	32.2	29.5	7.1	4.1	12.4	6.9	7.8	0.73	0.1
	5 km	26.6	32.7	8.0	4.6	15.5	5.4	7.1	0.76	0.09

Table 17. Relative contribution of each environmental variable to the long-finned pilot whale summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDMs that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	8.9	33.3	3.5	46.7	2.4	3.1	2.0	0.78	0.04
	1 km	31	21.6	0.6	1.6	0.5	1.7	42.9	0.71	0.04
	2.5 km	41.7	41.8	2.1	1.3	1.2	1.9	10	0.71	0.05
	5 km	36.4	50	2.5	1.2	4.8	1.5	3.5	0.7	0.05
2.5 km	**none**	9.7	31.8	2.3	44.5	4.5	3.8	3.3	0.78	0.05
	1 km	31.8	15.7	0.5	2.6	0.8	1.6	46.9	0.7	0.05
	2.5 km	45.1	36.3	1.6	0.9	2.0	2.5	11.6	0.7	0.05
	5 km	41.5	44.9	2.6	0.4	4.5	2.2	3.9	0.69	0.05
5 km	**none**	11.1	32.9	2.1	41.7	5.2	3.9	3.2	0.77	0.05
	1 km	32.4	11	0.6	2.3	0.9	1.9	50.8	0.71	0.05
	2.5 km	52	26.6	0.9	1.8	1.7	2.9	14	0.69	0.06
	5 km	49.5	34.7	2.5	0.3	4.8	2.4	5.7	0.68	0.06

Table 18. Relative contribution of each environmental variable to the long-finned pilot whale autumn species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDMs that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	Bias Map	Ocean depth	SST	CTI	Lagged CHL magn	CHL magn	Lagged CHL pers	CHL pers	mean	sd
none	none	19.4	48.5	2.9	5	5.4	4.6	14.2	0.81	0.07
	1 km	51.5	16.6	1.3	2.5	2.4	22.8	2.9	0.78	0.06
	2.5 km	60.8	26.1	2.3	2.9	3.7	1.3	3.0	0.8	0.07
	5 km	62.2	29	3.5	2.4	0	0.9	2.0	0.79	0.07
2.5 km	none	23.4	42.7	4.1	5.9	4.0	5.6	14.4	0.81	0.07
	1 km	54.7	11.9	1.4	2.9	1.4	25.9	1.8	0.78	0.07
	2.5 km	65.8	20.7	2.6	2	4.0	1.7	3.3	0.79	0.07
	5 km	66.1	24.2	4.1	2.3	0.1	0.8	2.3	0.78	0.07
5 km	none	19.7	42.4	7.9	4.6	5.9	3.5	16	0.8	0.08
	1 km	51.1	12	1.4	2.6	2.6	27.8	2.4	0.78	0.07
	2.5 km	59.2	19.3	2.3	2.3	11.2	3.8	1.7	0.79	0.08
	5 km	63.8	22.7	4.0	2.1	4.9	0.9	1.7	0.77	0.08

Atlantic white-sided dolphin (Atlantic population)

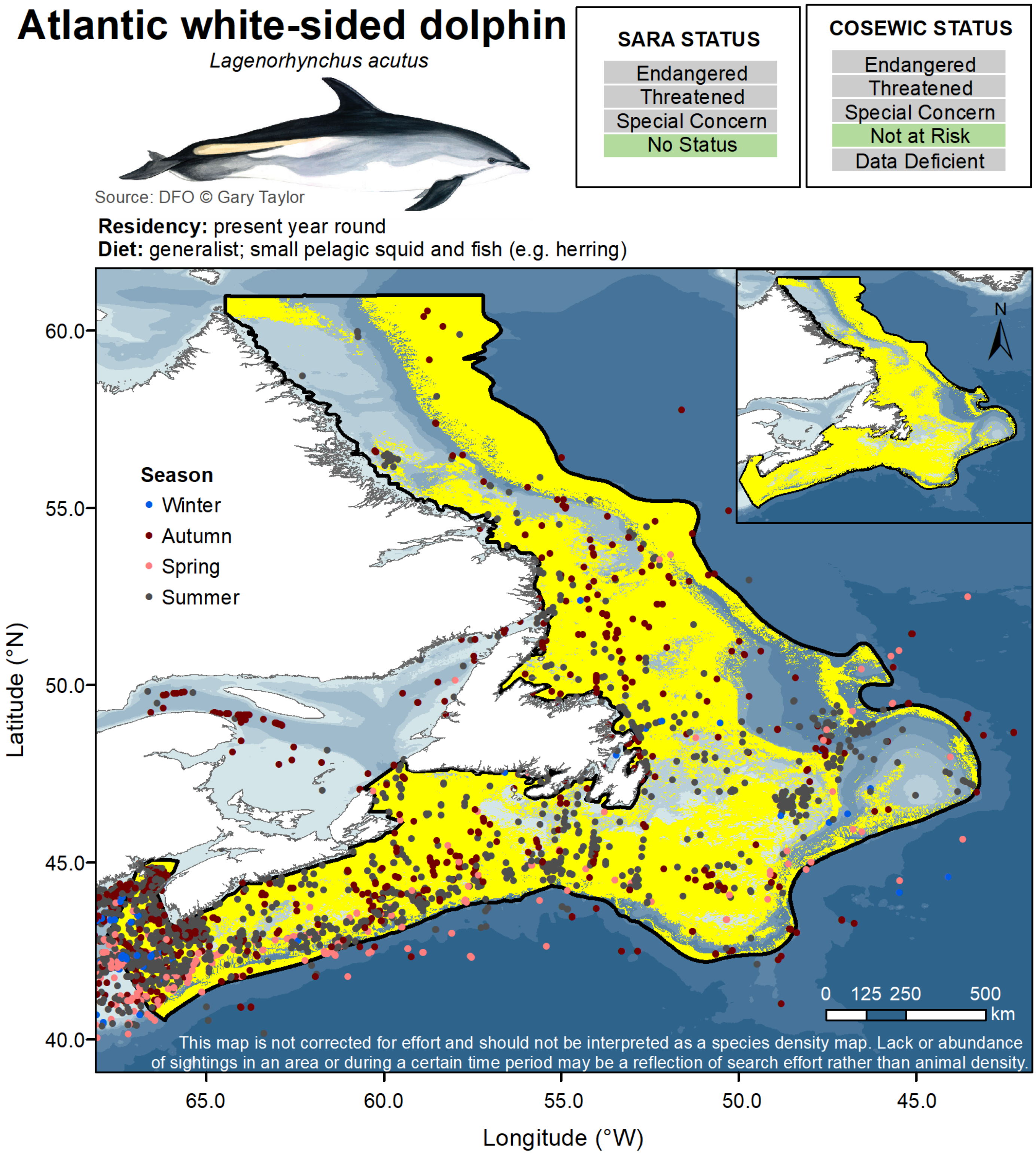


Figure 16. Sightings of Atlantic white-sided dolphins by season, collected from 1975 through 2015 (n = 4455, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during summer and autumn. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 19. Relative contribution of each environmental variable to the Atlantic white-sided dolphin summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDMs that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	4.9	20.3	0.6	44.6	10.3	1.3	18	0.82	0.04
	1 km	5.3	9.9	2.5	19.7	1.2	50.4	10.8	0.61	0.06
	2.5 km	11.5	16.4	1.2	15.9	1.0	19.1	34.8	0.66	0.06
	5 km	8.6	13.5	1.0	19.6	1.9	11.8	43.6	0.69	0.06
2.5 km	**none**	5.2	18.2	0.3	41.5	14.4	2.8	17.7	0.81	0.05
	1 km	6.4	9.4	1.6	18.7	4.4	49.1	10.3	0.59	0.07
	2.5 km	14.3	17.3	1.2	16.5	1.6	21.9	27.2	0.65	0.07
	5 km	9.9	12.3	0.9	19.8	3.7	13.4	40	0.68	0.07
5 km	**none**	5.6	22.8	0.3	38	17.5	2.8	12.8	0.8	0.05
	1 km	5.7	5.7	3.4	8.5	14.5	26.6	35.6	0.61	0.07
	2.5 km	13.8	17.3	2.6	22.1	0.9	29.8	13.4	0.61	0.07
	5 km	12.1	15.9	0.7	22.6	3.4	16.4	28.9	0.64	0.07

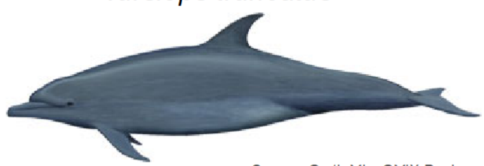
Table 20. Relative contribution of each environmental variable to the Atlantic white-sided dolphin autumn species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDMs that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	3.6	6.0	0.5	44.2	7.2	35	3.5	0.83	0.07
	1 km	19.4	21.2	2.9	0.8	5.1	15	35.7	0.62	0.09
	2.5 km	7.9	24.6	1.8	4.5	2.3	45.8	13	0.7	0.09
	5 km	4.8	19	1.2	7.2	5.4	54.7	7.7	0.74	0.09
2.5 km	**none**	5.0	6.6	1.0	35.4	13.9	34.5	3.6	0.81	0.08
	1 km	28.1	21.4	2.3	1.6	4.3	4	38.3	0.61	0.1
	2.5 km	10.8	26.8	2.2	6.0	3.0	36.4	14.9	0.68	0.1
	5 km	6.5	20.5	1.2	7.6	6.8	48.7	8.7	0.71	0.1
5 km	**none**	6.2	8.6	0.6	13.7	39.6	28.3	3.0	0.79	0.08
	1 km	19.4	22.1	2.8	2.7	3.1	16.9	32.9	0.61	0.12
	2.5 km	11.9	48	2.9	5.5	1.7	16	13.9	0.63	0.11
	5 km	6	33.5	2.5	5.8	6.9	34.7	10.6	0.67	0.1

Bottlenose dolphin (Atlantic population)

Bottlenose Dolphin

Tursiops truncatus



Source: Garth Mix, GMIX Designs

SARA STATUS
Endangered
Threatened
Special Concern
No Status (highlighted)

COSEWIC STATUS
Endangered
Threatened
Special Concern
Not at Risk (highlighted)
Data Deficient

Residency: present year round
Diet: miscellaneous fish (e.g. cod, herring, sardines), small squid

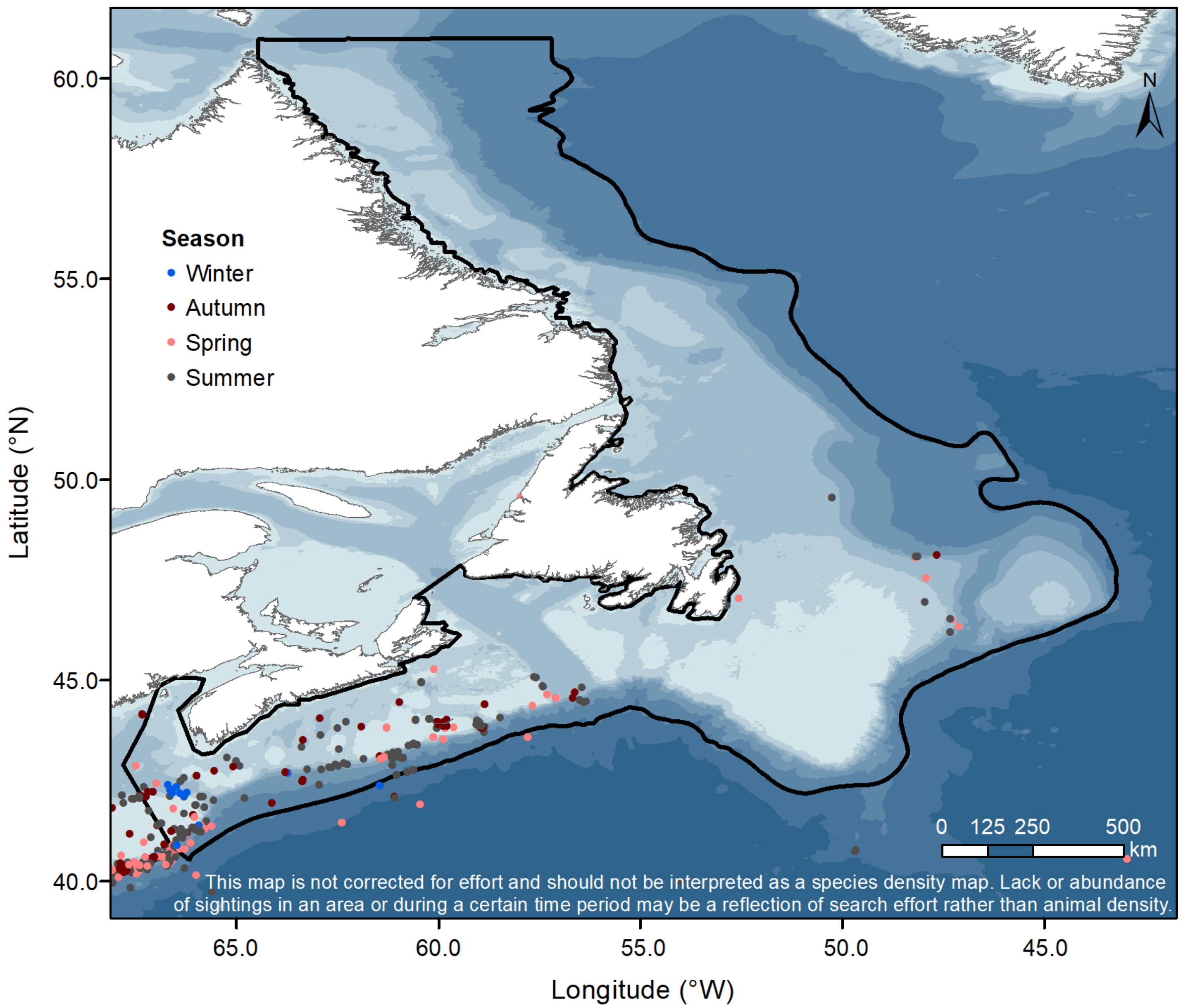


Figure 17. Sightings of bottlenose dolphins by season, collected from 1975 through 2015 (n = 306, within study area outlined by black line, see Table 3).

Short-beaked common dolphin (Atlantic population)

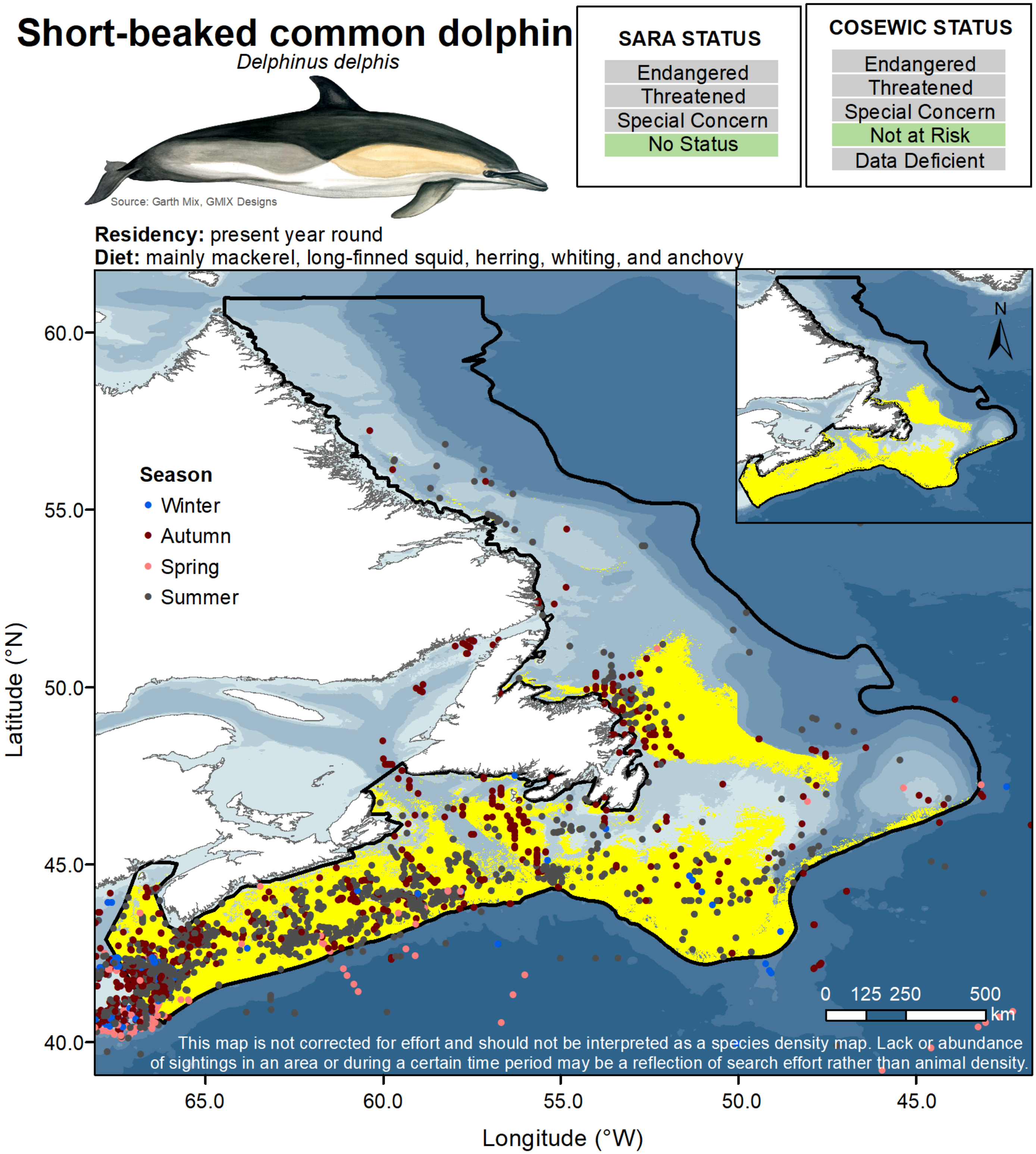


Figure 18. Sightings of short-beaked common dolphins by season, collected from 1975 through 2015 (n = 2351, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during summer and autumn. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 21. Relative contribution of each environmental variable to the short-beaked common dolphin summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	Bias Map	Ocean depth	SST	CTI	Lagged CHL magn	CHL magn	Lagged CHL pers	CHL pers	mean	sd
none	**none**	8.5	30.8	3.2	54	0.2	1.4	1.9	0.83	0.05
	1 km	1.5	51.9	4.0	1.8	5.6	0.8	34.5	0.72	0.06
	2.5 km	1.1	70.5	10.4	4.6	0.5	2.9	9.9	0.71	0.06
	5 km	1.0	74.8	9.2	5.1	0.1	6.1	3.6	0.71	0.07
2.5 km	**none**	8.0	31.4	2.7	54.2	0.4	1.5	1.7	0.83	0.05
	1 km	1.6	52.1	3.0	1.5	4.9	0.9	36.1	0.72	0.06
	2.5 km	1.0	71.7	8.7	4.5	0.5	3.4	10.2	0.71	0.06
	5 km	1.0	77.9	7.8	4.0	0.2	6.3	2.9	0.71	0.07
5 km	**none**	7.6	35.1	2.9	50.6	1.2	1.2	1.3	0.83	0.06
	1 km	2.0	48	1.6	1.2	5.9	1.4	40	0.72	0.06
	2.5 km	1.0	71.3	5.9	3.6	1.0	2.8	14.5	0.7	0.07
	5 km	0.8	80.3	5.0	3.4	0.2	7.4	3.0	0.69	0.07

Table 22. Relative contribution of each environmental variable to the short-beaked common dolphin autumn species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	Bias Map	Ocean depth	SST	CTI	Lagged CHL magn	CHL magn	Lagged CHL pers	CHL pers	mean	sd
none	**none**	20.4	25	0.5	10.5	32.1	7.8	3.8	0.84	0.06
	1 km	11.2	27	0	2.6	0.3	57.1	1.8	0.78	0.06
	2.5 km	17.8	51	0.3	2.0	0.3	23.8	4.8	0.77	0.07
	5 km	19.3	59.6	0.7	1.5	0.5	12.5	5.9	0.76	0.08
2.5 km	**none**	18.2	25.8	0.6	14.2	30.4	7.5	3.2	0.83	0.06
	1 km	11.6	26.6	0	2.4	0.3	56.8	2.3	0.78	0.06
	2.5 km	18	49.4	0.5	2.2	0.4	24.8	4.8	0.77	0.07
	5 km	20.1	58.3	1.1	1.2	0.4	13.7	5.2	0.76	0.08
5 km	**none**	17.9	28.1	0.5	17.3	24.5	7.6	4.1	0.83	0.06
	1 km	11.3	26.4	0	2.6	0.3	57.1	2.3	0.77	0.07
	2.5 km	16.9	49.5	0.4	2.0	0.3	25.1	5.8	0.76	0.08
	5 km	18.4	60.8	0.4	1.2	0.6	14	4.6	0.75	0.08

Risso's dolphin (Atlantic population)

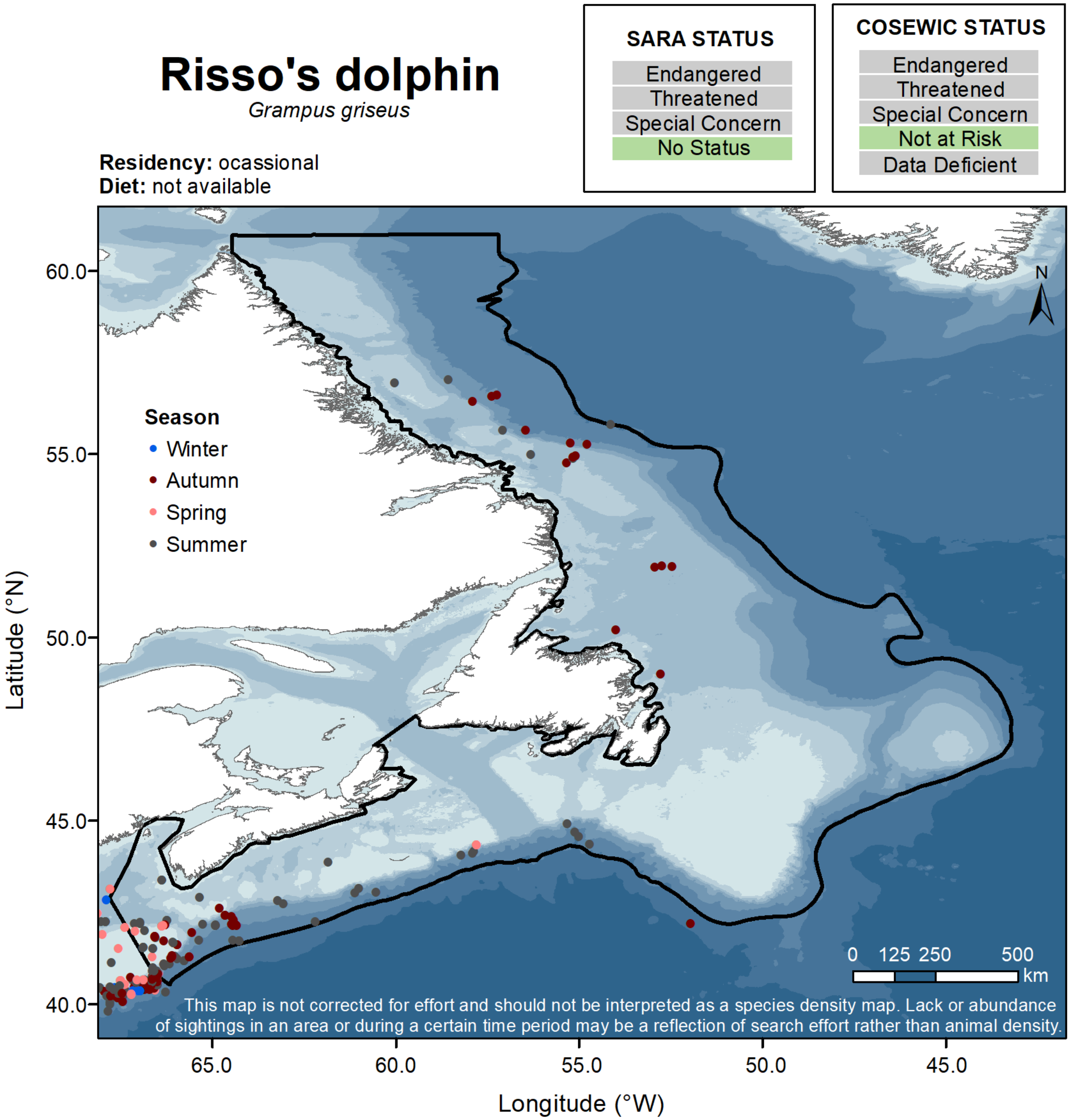


Figure 19. Sightings of Risso's dolphins by season, collected from 1975 through 2015 (n = 124, within study area outlined by black line, see Table 3).

Striped dolphin (Atlantic population)

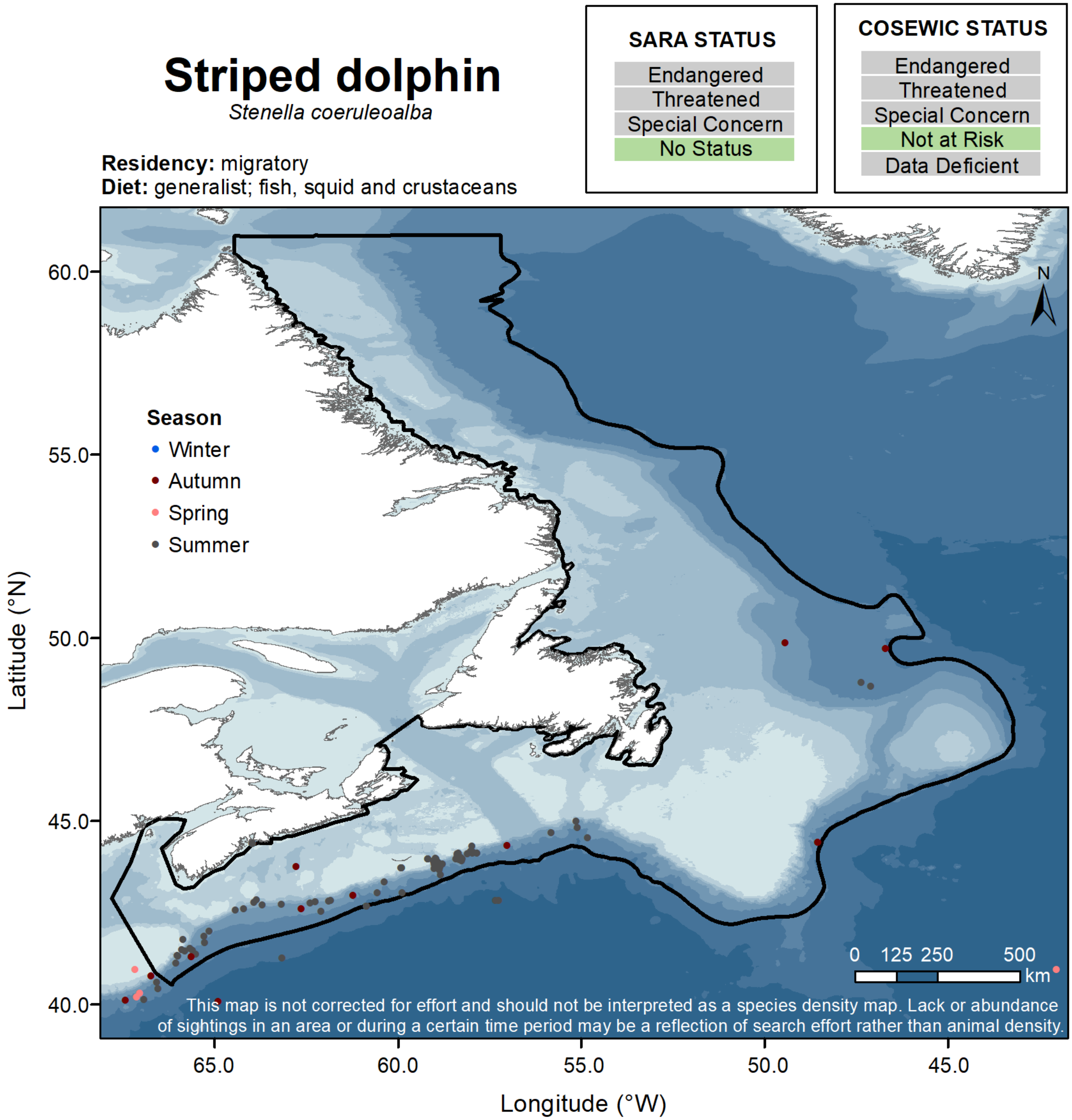


Figure 20. Sightings of striped dolphins by season, collected from 1975 through 2015 (n = 126, within study area outlined by black line, see Table 3).

White-beaked dolphin (Atlantic population)

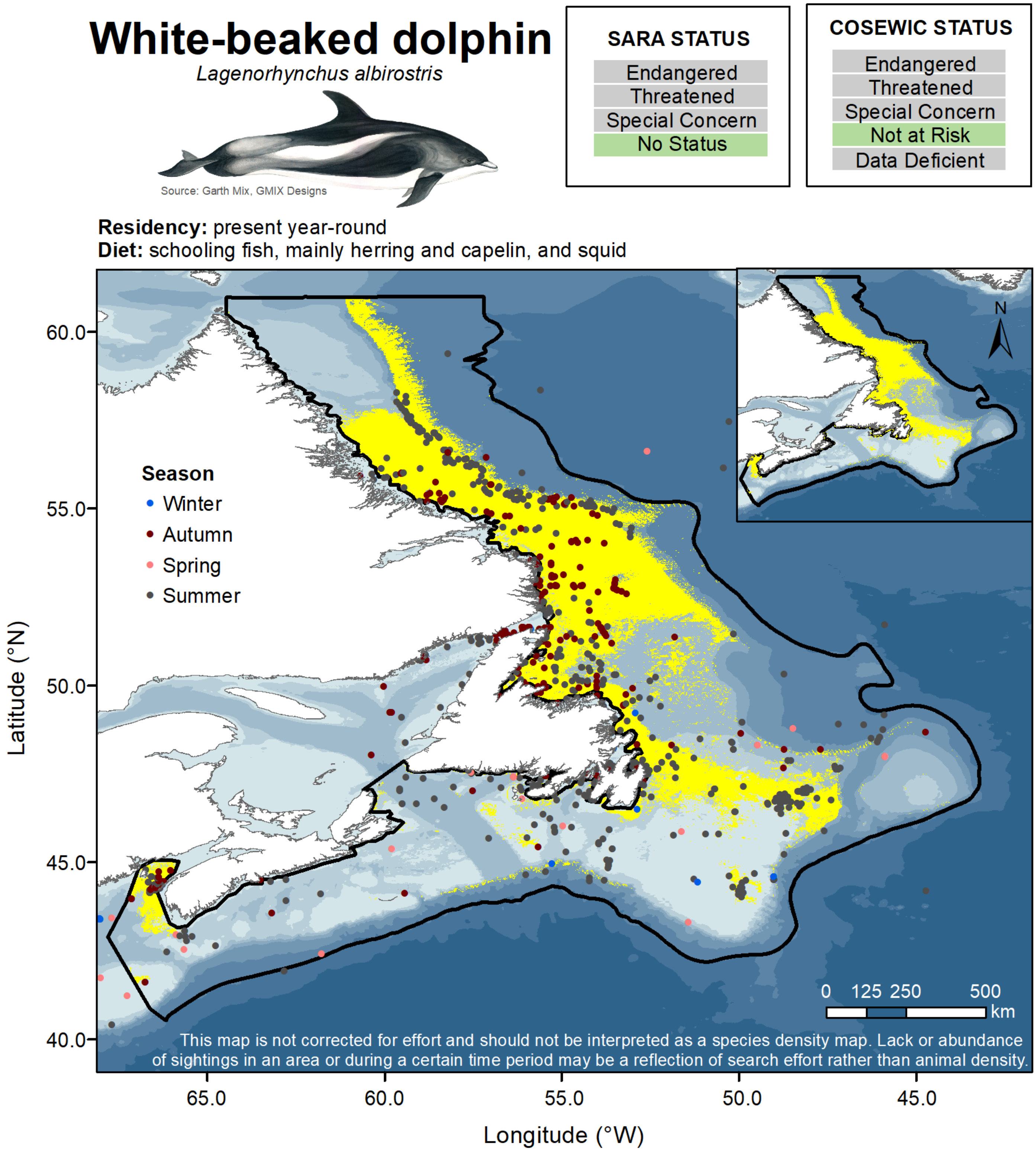


Figure 21. Sightings of white-beaked dolphins by season, collected from 1975 through 2015 (n = 772, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during summer. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 23. Relative contribution of each environmental variable to the white-beaked dolphin summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	**Bias Map**	**Ocean depth**	**SST**	**CTI**	**Lagged CHL magn**	**CHL magn**	**Lagged CHL pers**	**CHL pers**	**mean**	**sd**
none	**none**	28.1	41.9	6.1	0.3	1.3	4.1	18.3	0.82	0.07
	1 km	6.3	26.6	1.3	53.2	6.3	2.5	3.8	0.86	0.05
	2.5 km	7.6	59.2	2.1	15.4	6.8	4.6	4.3	0.84	0.06
	5 km	8.7	71.8	2.8	1.5	4.7	5.1	5.5	0.83	0.06
2.5 km	**none**	27.6	43.9	7.0	0.3	1.4	4.1	15.8	0.82	0.07
	1 km	5.3	21.1	1.1	61.3	6.7	1.5	3.0	0.86	0.05
	2.5 km	8.2	48.7	2.1	28.4	5.7	3.6	3.4	0.84	0.06
	5 km	7.9	72.3	3.1	3.1	5.8	4.1	3.7	0.82	0.06
5 km	**none**	31	44.9	5.3	0.4	2.2	3.6	12.5	0.82	0.07
	1 km	5.2	18.5	1	66.3	6.7	1.0	1.3	0.86	0.05
	2.5 km	6.8	39.4	2.1	40.3	7.1	2.2	2.1	0.84	0.06
	5 km	7.0	60.8	2.6	17	7.1	3.0	2.5	0.81	0.07

Harbour porpoise (Atlantic population)

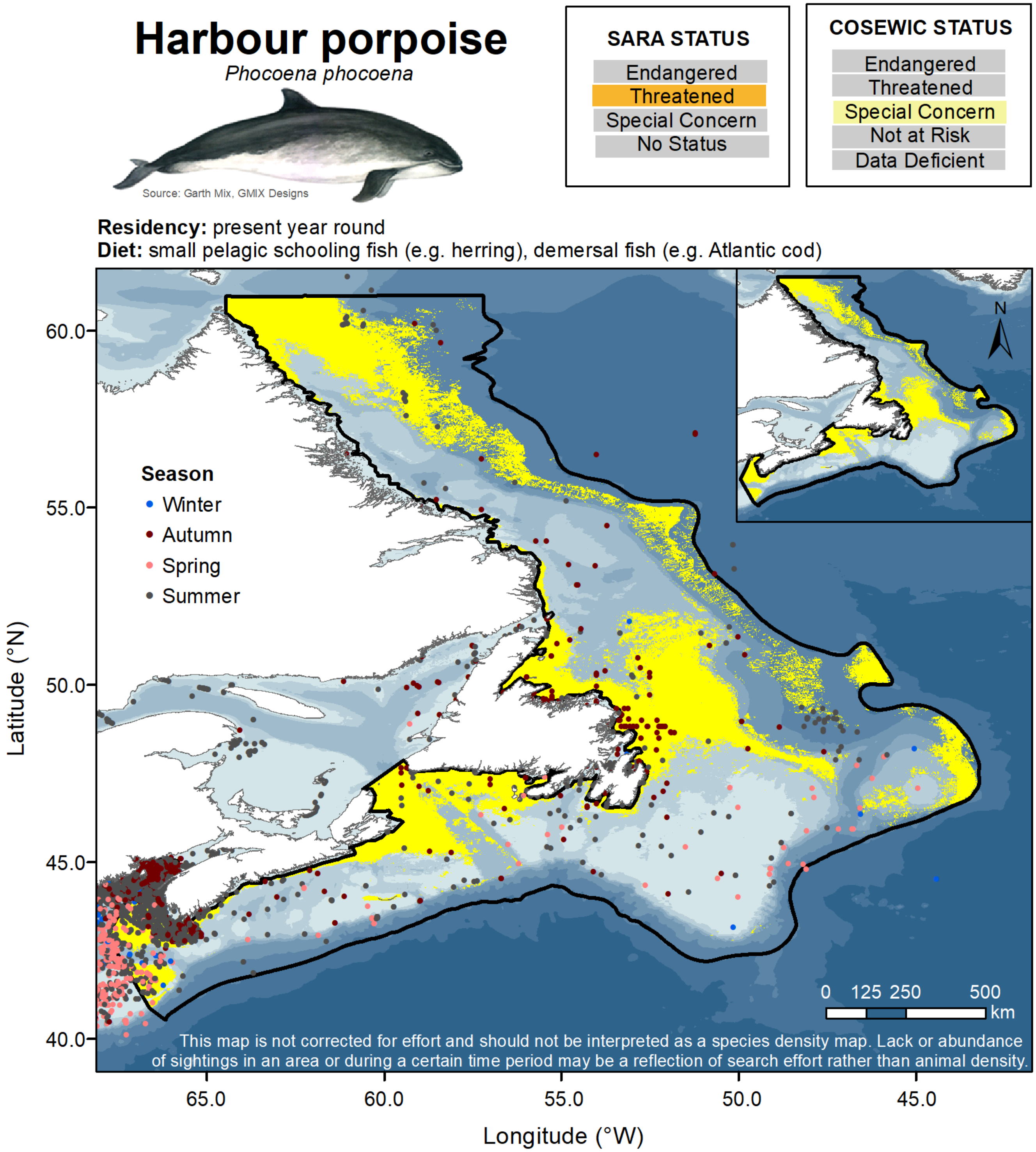


Figure 22. Sightings of harbour porpoises by season, collected from 1975 through 2015 (n = 27809, within study area outlined by black line, see Table 3). Yellow indicates consolidated SDM outputs: areas with high (60-100%) relative occurrence rate for any scenarios of sampling bias correction (bias maps and subsampling) during summer. SDM outputs indicate priority areas where monitoring efforts may be targeted.

Table 24. Relative contribution of each environmental variable to the harbour porpoise summer species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	Bias Map	Ocean depth	SST	CTI	Lagged CHL magn	CHL magn	Lagged CHL pers	CHL pers	mean	sd
none	none	1.4	2.7	0.9	10.1	53.3	1	30.6	0.88	0.02
	1 km	0.1	20.5	0.1	6.4	14.6	2	56.3	0.77	0.04
	2.5 km	0	15	0.3	8.5	15.4	1.2	59.5	0.85	0.03
	5 km	0.1	13.5	0.3	11.1	17.6	1.3	56	0.86	0.03
2.5 km	none	1.8	4	0.5	5.5	54.2	0.9	33.1	0.9	0.03
	1 km	1.2	25.4	0.5	6.8	17.1	1.1	47.8	0.76	0.04
	2.5 km	0.1	18.5	0.2	4.7	22.4	1	53.1	0.85	0.04
	5 km	0.2	15.3	0.3	6	25.2	0.9	52.2	0.87	0.04
5 km	none	2.1	6.6	1.3	5.3	51.6	1.1	32	0.9	0.04
	1 km	9.6	27.1	1	5	17.5	2.9	37	0.76	0.06
	2.5 km	1.5	23.1	0.9	3.8	26	2.3	42.4	0.82	0.06
	5 km	0.4	18.7	0.8	7.9	26.3	1.2	44.7	0.85	0.05

Table 25. Relative contribution of each environmental variable to the harbour porpoise autumn species distribution model for each model scenario. Contributions and area under the curve (AUC) values were averaged across model runs (n = 100). AUC values greater than 0.70 indicate SDM that have good discriminatory power. Variables with a mean contribution of at least one third (≥ 33), or fifth (≥ 20) are highlighted in dark and light grey, respectively.

Grid Resolution		Mean Environmental Variable Contribution							AUC	
Subsampling	Bias Map	Ocean depth	SST	CTI	Lagged CHL magn	CHL magn	Lagged CHL pers	CHL pers	mean	sd
none	none	4.3	6.0	0.1	22.2	10	54.1	3.3	0.93	0.02
	1 km	2.0	14.9	0.8	3.2	5.8	66.6	6.8	0.76	0.05
	2.5 km	1.7	11	0.7	7.0	5.1	70	4.5	0.89	0.03
	5 km	1.1	9.2	0.5	4.4	5.9	72.3	6.6	0.91	0.03
2.5 km	none	4.0	5.2	0.8	24.3	4.7	54.6	6.4	0.93	0.03
	1 km	3.0	22.8	1.2	7.6	3.1	55.1	7.2	0.75	0.06
	2.5 km	1.4	13.4	1.3	5.5	3.9	67.7	6.9	0.87	0.04
	5 km	2	11.9	0.8	4.7	7.0	63.9	9.6	0.9	0.04
5 km	none	5.7	8.7	2.4	11.7	18.4	45.4	7.7	0.91	0.05
	1 km	10.6	45.1	4.1	3.2	3.1	16.8	17	0.73	0.08
	2.5 km	3.6	28.8	1.2	1.2	9.5	47.2	8.4	0.83	0.07
	5 km	2.0	22.5	0.8	3.8	9.1	51.5	10.3	0.87	0.06

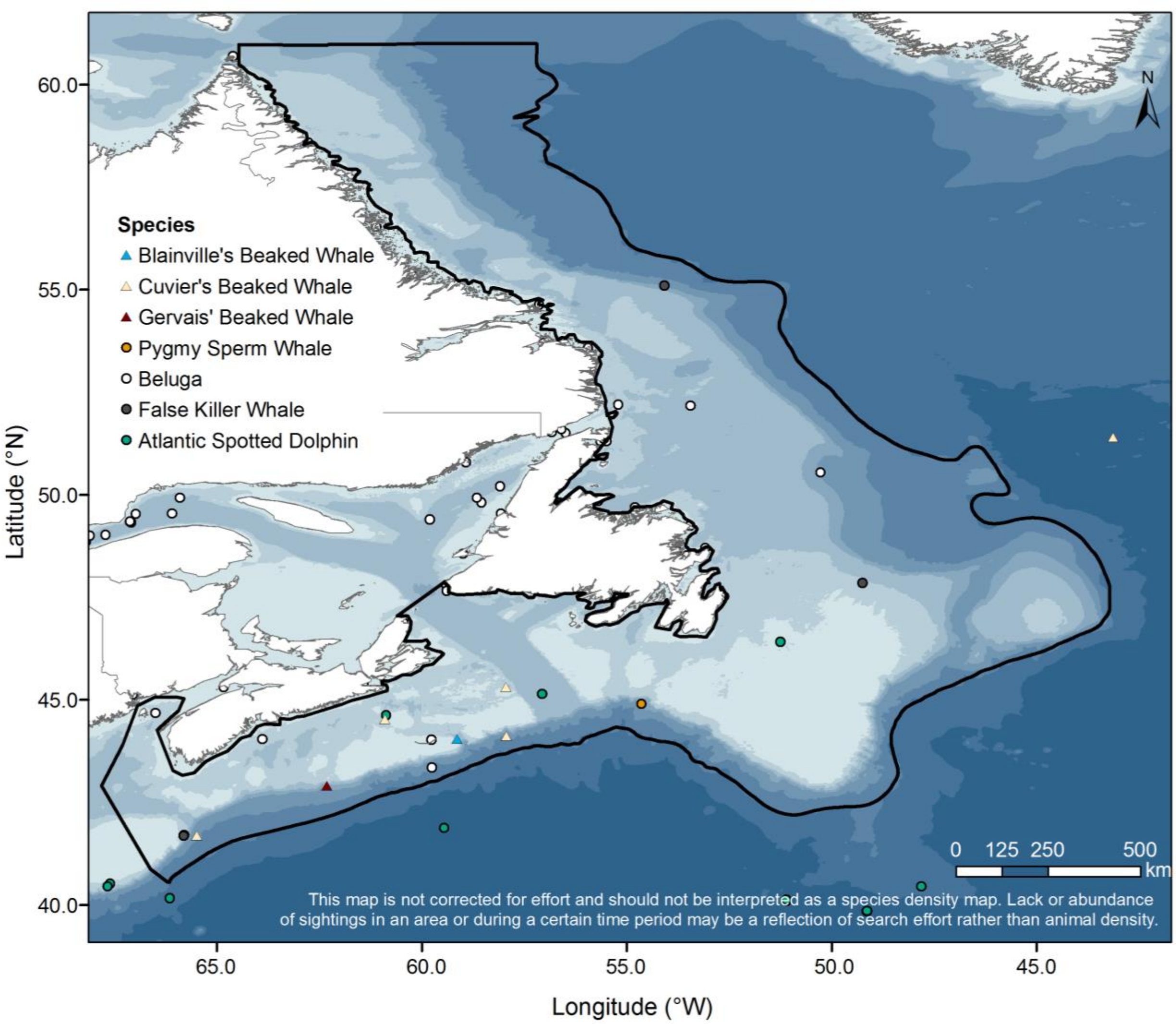


Figure 23. Sightings of cetacean species that were rarely observed in the study area (outlined by black line), collected from 1975 through 2015 (sightings within study area: total n = 28, range: 1-13). Belugas may belong to either St. Lawrence Estuary or Arctic populations, thus COSEWIC status varies from Special Concern to Endangered while SARA status is Endangered or Not Assessed. Gervais' beard whales and Atlantic spotted dolphins have not been assessed by COSEWIC or SARA, while the remaining four species are considered Not at Risk by both COSEWIC and SARA.

DISCUSSION

Long-term cetacean sightings data from government, non-government, academic, and industry sources were assembled for this project. When there were sufficient numbers of sightings by species and season, we developed SDMs for each species using a set of environmental variables to predict priority areas in eastern Canadian waters off Nova Scotia, and Newfoundland and Labrador. This section provides general information about these SDMs, and some recommendations on how to interpret and use these spatial outputs.

SDM results: indicators of priority areas for increased cetacean monitoring efforts

Environmental data used to model species distributions should ideally be collected in the same time frame as the sightings data, to best reflect conditions experienced by the observed animals and thus allow the development of dynamic spatial planning tools (Hazen et al. 2018). Given the lack of sightings data from effort-based surveys on a monthly and seasonal time-period in the study area, the sightings data in the SDM were consolidated by season, across years. Thus, we correspondingly used an amalgamation of dynamic environmental data (SST, CHL_{pers} and CHL_{magn}, by season) collected from 2003-2014 (during which 41% of cetacean sightings in the study area were collected), to explore general patterns of species' preferred habitat conditions. In some cases, the relative importance of environmental predictors for a given species varied by season (Tables 7-25). Seasonal variation is not surprising as our study area is characterized by marked seasonality, which induces changes in the spatial and temporal availability of resources (Fuentes-Yaco et al. 2015) and thus can change cetacean habitat preferences across seasons (Lambert et al. 2017). The relative importance of environmental predictors also varied by species (Tables 7-25). Cetacean species have different ecological requirements, which are partially reflected in the relative contribution of environmental predictors to the SDMs.

In particular, ocean depth contributed to the SDM predictions for fin whale, minke whale, humpback whale, sperm whale, and long-finned pilot whale (Tables 7-25). Ocean depth has been identified as important in predicting the distribution of cetaceans in previous SDM studies (e.g. Abgrall 2009, Mannocci et al. 2015). For instance, Abgrall (2009) highlighted the importance of ocean depth in predicting the distribution of baleen whales in waters off Newfoundland, particularly in areas characterized by deep water and steeper seabed slopes (Abgrall 2009). Deep water and steep topography were also often identified as the most important variables explaining the presence of deep diving whales, such as sperm whales and northern bottlenose whales (Moors-Murphy 2014, Gomez et al. 2017). Ocean depth has been important in the process of defining cetacean hotspots in many ecosystems (e.g., Cañadas et al. 2005, Hooker et al. 1999, MacKay et al. 2016) and thus it is an important predictor to be considered in SDM studies. Ocean depth contributed significantly more to cetaceans' habitat preferences than CTI (which was used here as a measure of topography). CTI is derived from ocean depth, but represents different habitat characteristics. CTI reflects peaks, basins and flat surfaces of the ocean floor. Those characteristics may be relatively less important in predicting cetacean habitat compared with ocean depth in our models. Alternatively, CTI may not emerge as an important feature because the scale it was calculated on may not be the scale relevant to the animals.

SST provided significant contributions to the SDMs for harbour porpoise, white-beaked dolphins, Atlantic white-sided dolphins, short-beaked common dolphins, long-finned pilot whale, humpback whales, fin whales, and minke whales. SST is an important predictor of diversity and abundance of marine life (Worm et al. 2003, Morato et al. 2010, Pirotta et al. 2011, Whitehead et al. 2010) and provides information about dynamic thermal mesoscale processes that can potentially be linked to cetacean distribution. For example, SST maps highlight areas related to increased biological productivity and aggregated prey, particularly at persistent thermal fronts where higher food densities are found, leading to predictable feeding locations for many marine species (Podesta et al. 1993, Etnoyer et al. 2006). Such areas in our study area include regions where warm waters from the Gulf Stream meet the cold waters from the Labrador current. SST, therefore, captures important seasonal and spatial processes that are important for cetaceans and cetacean prey distribution. For species with sufficient data available, further investigation may also reveal patterns at a finer temporal scale (e.g., daily SST have proven to be important predictors for harbor porpoises, Gilles et al. 2016).

Predictors related to chlorophyll-a provided significant contributions to the SDMs for fin whales, sei whales, minke whales, long-finned pilot whale, short-beaked common dolphins, harbour porpoise, and Atlantic white-sided dolphins. Areas with relatively high chlorophyll-a concentration have been used in other SDM studies to locate biological hotspots (Palacios et al. 2006, Kobayashi et al. 2011) and as a proxy for the amount of primary production, which is important for predicting cetacean distribution (Jaquet & Whitehead 1996, Ferguson et al. 2006, Mannocci et al. 2015). Regional CHL_{magn} also captures the distinctiveness of geographic regions shown in Figure 5, which are characterized by unique marine communities and food web systems (Devred et al. 2007, 2009, Longhurst 2007). Cetaceans were not among the marine species used to characterize these regions; however, the relatively high contribution of regional CHL_{magn} suggests that this partitioning is important to understanding spatial ecology for some cetacean species.

Interpreting results for marine spatial planning purposes

An AUC value close to 1.0 indicates that the SDM has good discriminatory power, whereas a value ≤0.5 indicates that the model prediction is no better than random (Fielding & Bell 1997). With most AUC values indicating relatively good model performance (>0.70 for most model runs; Tables 7-25), our SDMs can be interpreted as areas to prioritize cetacean monitoring in waters off Nova Scotia, Newfoundland and Labrador regions. The following are important considerations for using outputs of this report:

- Cetacean sighting records compiled in this work were largely collected through platforms of opportunity rather than systematically. Therefore, sampling effort was often not recorded. Areas, seasons, and species with low sampling effort are underrepresented, and it is possible that important habitats may not be captured in this report's predictions. The lack of highly suitable habitat in some cases may be the result of a lack of effort and not necessarily low suitability.

- The use of all non-TGS in the bias files assumes that all of the surveys record all species types. Some surveys may not record all species even when present and therefore, the bias file is likely missing non-TGS records. One consideration in future approaches may be to limit the non-TGS records to surveys that may be similar in nature and species types that may be similar to the focal species.

- AUC values reflect the probability of having a higher predicted suitability value in a randomly chosen presence cell compared with a randomly chosen absence cell (Elith et al. 2006). This is problematic for SDMs that lack true absence data (Lobo et al. 2008), and there is a lack of alternatives to evaluate model performance for this type of presence-only approach (Merow et al. 2013), although see Muscarella et al 2014 and Cobos et al 2019). However, AUC values are considered reliable to compare models generated for a single species in the same area and the same predictors (Fourcade et al. 2014).

- SDMs in this study used seasonal averages, and cetacean data from 1975-2015. SDMs do not take into account monthly or inter-annual variations in the distribution of cetaceans, and more recent cetacean sightings data (e.g., from 2016 to present) are available. They also do not capture fluctuations in environmental conditions that impact cetacean prey or long-term changes in environmental conditions (e.g., climate change). This limits their availability to be used in dynamic spatial management efforts.

- There is additional uncertainty associated with using environmental predictors from shorter time frames compared with the cetacean sightings. This limitation may have implications for our predictions as there are large scale changes that have occurred in the NWAO that are not captured due to environmental predictors available for more recent time frames.

- There are likely additional environmental predictors not included in this study that may impact cetacean prey. Inclusion of cetacean prey, or better predictor variables as proxies for cetacean prey, would likely improve predictions as more data becomes available.

- This report used MaxEnt due to the nature of the available cetacean sightings, which were largely opportunistic for most of the species. However there are other approaches, such as those that also allow to estimate pseudo absences. Thus, we recommend testing other algorithms to compare outputs and ultimately improve predictions of suitable habitat for these species.

- SDM outputs sometimes vary considerably under the different sampling bias correction. When background points are selected randomly from within the study area (i.e. without a bias map), MaxEnt is expected to predict wider ranges of suitable habitat (Merow et al. 2013). In our case, and in Gomez et al. (2017), the opposite pattern was observed: predictions seemed to be more restricted when bias maps were not included. In these models without bias maps, there is also a trend that the Scotian Shelf – an area of relatively high densities of sightings (due at least in part to greater presence of vessels/observers in this area) – is deemed more highly suitable than in models with a bias map. Despite this variation, all SDM outputs presented in the scenarios of sampling bias correction are reasonable predictions with which to target monitoring efforts (Figures A1-A19). We therefore combined all the different models into one all-inclusive predictive output.

- How would the inclusion of human drivers (e.g. offshore development, shipping) that may result in the avoidance of areas or degradation of habitat (seasonally or at some point during the study period) by some species affect these models?

Due to the reasons listed above (and summarized in Gomez et al. 2017), results in this report do not represent a complete and current distribution of cetaceans in the region. Thus, its use in marine spatial planning processes should be accompanied by complimentary approaches. For example, important habitat for blue whales in the Northwest Atlantic was identified using a combination of approaches related to blue whale distribution and krill aggregation (observed or predicted) (Plourde et al. 2016, Lesage et al. 2018, Moors-Murphy et. al 2019), including the SDM approach described in this report. Consequently, SDM predictions presented in this report should not be used on their own. Rather, outputs should be used together with other sources of information (such as: prey distribution, tagging data, detections from acoustic monitoring, other data on cetacean occurrence, and other modeling efforts already available for the area) to delineate important habitat. The use of multiple sources of information in Lesage et al. (2018), in addition to SDM predictions, represents a good framework in which to properly use the outputs of this report in marine spatial planning processes.

Recommendations for future work

Gomez et al. 2017 provide an extensive list of recommendations to improve the approach and predictions illustrated in this report. Here we highlight some of those key recommendations that should be taken into consideration when conducting further SDM exercises for cetaceans.

Sightings data collection and management: A significant amount of effort was put into collating cetacean sighting records from multiple sources/databases, removing duplicate data and quality checking the sightings data. In some cases, existing sightings records were not included in this study because they were not captured in the databases from which the data used here were extracted. Ensuring that existing DFO cetacean sightings databases capture all known sightings records within the study area would facilitate future data gathering and modelling efforts. This is especially important in the case of sightings in areas for which there currently exist few records, such as deep off-shelf waters. For example, records from marine mammal observers onboard offshore seismic vessels from seismic surveys occurring off Nova Scotia in 2013 and 2014 (LGL 2013, 2014) could be included in the SDM to have a better representation of deep-water areas. Further, a centralized cetacean sightings database that captures data from all regions in a standardized way and removes duplicate or inaccurate data to ensure that data extracted is of the highest quality possible would greatly facilitate modelling efforts.

Model validation using new sightings data: Validation of model results can be conducted by using sighting records obtained from more recent cetacean surveys in eastern Canada (e.g., the North Atlantic International Sightings Survey (NAISS) conducted in 2016; Lawson and Gosselin 2020) or more recent North Atlantic right whale survey efforts that have been occurring since 2017; DFO 2019). Until the SDMs models in this report are validated with independent datasets such as these, particularly in areas with low sighting efforts, the SDM results should be used primarily to direct monitoring efforts.

Updating models using new data: New sightings data can be used not only to validate these SDMs, but also to update them. When enough data becomes available, the models may be able to account for monthly or inter-annual variations in the distribution of cetaceans and potentially investigate long-term fluctuations in environmental conditions that may impact cetacean prey.

Use of acoustic data on cetacean presence: Incorporating cetacean acoustic detection data into SDM is highly recommended. Some of this data is already available and includes occurrence data from autumn, winter and spring, which typically have less visual-based effort relative to summer (Lesage et al. 2018). With these data, we can more closely examine areas highlighted as suitable in the SDM, and we can do so across all seasons.

Incorporating better predictors: Future SDM efforts will likely benefit by including additional predictor data layers such as thermal fronts, prey distribution or human drivers. Selecting useful predictors may depend on the species whose distribution is being modelled, and the model’s intended use (Kenchington et al. 2019). The approach presented in this report was for multiple species, but future single-species studies should examine individual species ecology to select meaningful environmental predictors for the target species. The importance of carefully selecting biologically meaningful variables is evidenced by Fourcade et al. (2017), who show that SDMs that use variables with no biological relevance can be misleadingly classified as good or even excellent using common evaluation measures. Incorporating better predictors will be also relevant in in the context of climate change as species will shift their distribution in responses to changes in temperature (Greenan et al. 2019).

Use of additional satellite-derived information: Satellite-derived information can be further explored and utilized to fully take advantage of its ability to improve environmental predictors. Fuentes-Yaco (com pers) proposed the use of satellite-derived information on selected wavelengths to better understand the spatial and temporal distribution of marine species. Fuentes-Yaco et al. (in press) is producing specific Moderate Resolution Imaging Spectroradiometer (MODIS) products at a spatial resolution of 250m per pixel that can be applied for this purpose. Preliminary tests using this dataset have given promising results (Fuentes-Yaco and Clay 2018). The mechanisms of visual foraging by cetaceans to find prey patches, and the role of colour vision has been explored in multiple studies (Griebel and Peich 2003, Dugan et al. 2015, Fasick and Robinson 2016, Cronin et al. 2017). Remote detection of whales from space (Fretwell et al. 2014) and of whales' prey, zooplankton, is also currently being developed and explored (Trudnowska et al 2015; Basedow et al 2019). Before they can be applied to modelling species distributions, these approaches must be improved using more advanced sensors such as the Visible and Infrared Imager/Radiometer Suite (VIIRS) (https://oceancolor.gsfc.nasa.gov/data/viirs-snpp/) and the Ocean and Land Colour Instrument (OLCI) (https://oceancolor.gsfc.nasa.gov/data/olci-s3a/).

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APPENDIX - SPECIES DISTRIBUTION MODEL RESULTS

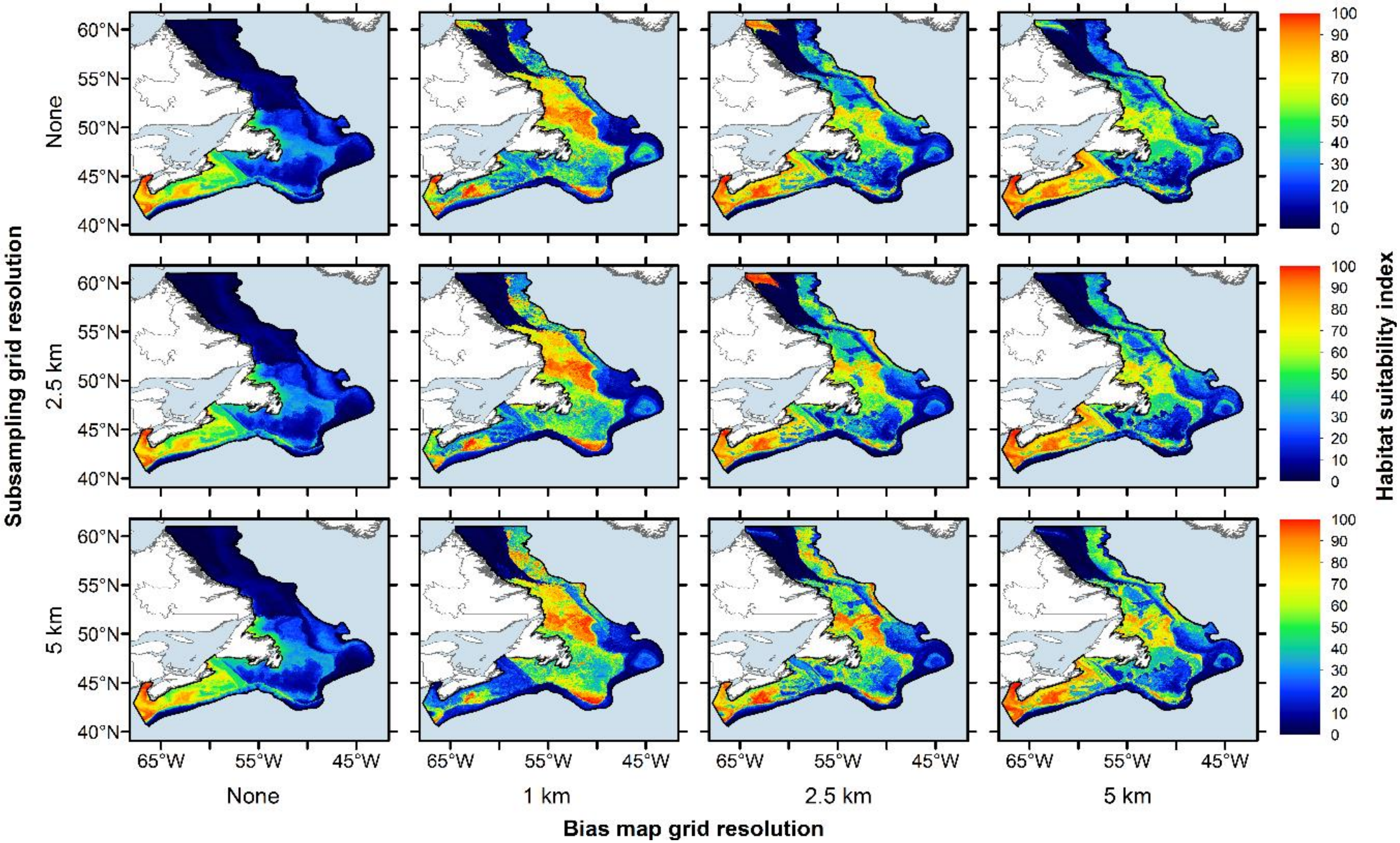

Figure A 1. Habitat suitability index for fin whale during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

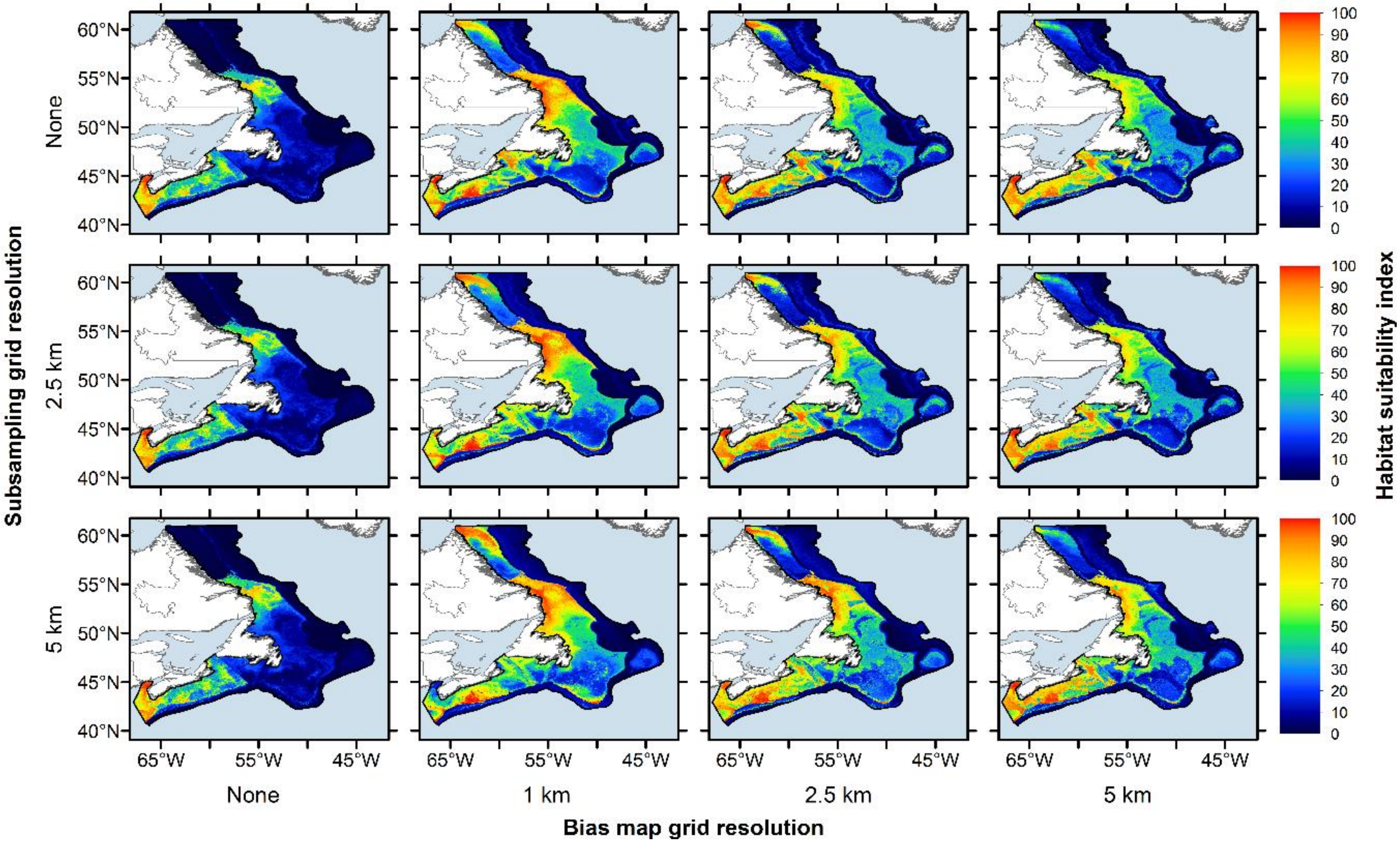

Figure A 2. Habitat suitability index for fin whale during autumn, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in autumn from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 1. Pearson's correlation between for the 12 summer SDMs for fin whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	1.00	0.99	0.38	0.25	0.05	0.66	0.57	0.45	0.78	0.75	0.67
	2.5km		1.00	0.99	0.38	0.25	0.06	0.66	0.58	0.46	0.78	0.76	0.69
	5 km			1.00	0.38	0.26	0.07	0.65	0.58	0.47	0.78	0.76	0.69
1 km	none				1.00	0.91	0.78	0.78	0.79	0.78	0.69	0.69	0.71
	2.5km					1.00	0.94	0.61	0.67	0.84	0.54	0.63	0.69
	5 km						1.00	0.45	0.54	0.79	0.36	0.47	0.56
2.5 km	none							1.00	0.96	0.78	0.93	0.88	0.86
	2.5km								1.00	0.85	0.86	0.84	0.86
	5 km									1.00	0.71	0.80	0.88
5 km	none										1.00	0.96	0.90
	2.5km											1.00	0.97
	5 km												1.00

Table A 2. Pearson's correlation between the 12 models for the autumn SDMs for fin whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.99	0.75	0.71	0.58	0.80	0.81	0.79	0.86	0.86	0.85
	2.5km		1.00	0.99	0.76	0.71	0.59	0.80	0.82	0.79	0.86	0.87	0.85
	5 km			1.00	0.77	0.73	0.61	0.80	0.82	0.80	0.86	0.86	0.85
1 km	none				1.00	0.98	0.89	0.91	0.93	0.92	0.89	0.90	0.91
	2.5km					1.00	0.95	0.88	0.90	0.91	0.85	0.86	0.88
	5 km						1.00	0.77	0.80	0.86	0.73	0.75	0.80
2.5 km	none							1.00	0.99	0.93	0.97	0.96	0.94
	2.5km								1.00	0.96	0.96	0.97	0.96
	5 km									1.00	0.91	0.93	0.96
5 km	none										1.00	0.99	0.96
	2.5km											1.00	0.98
	5 km												1.00

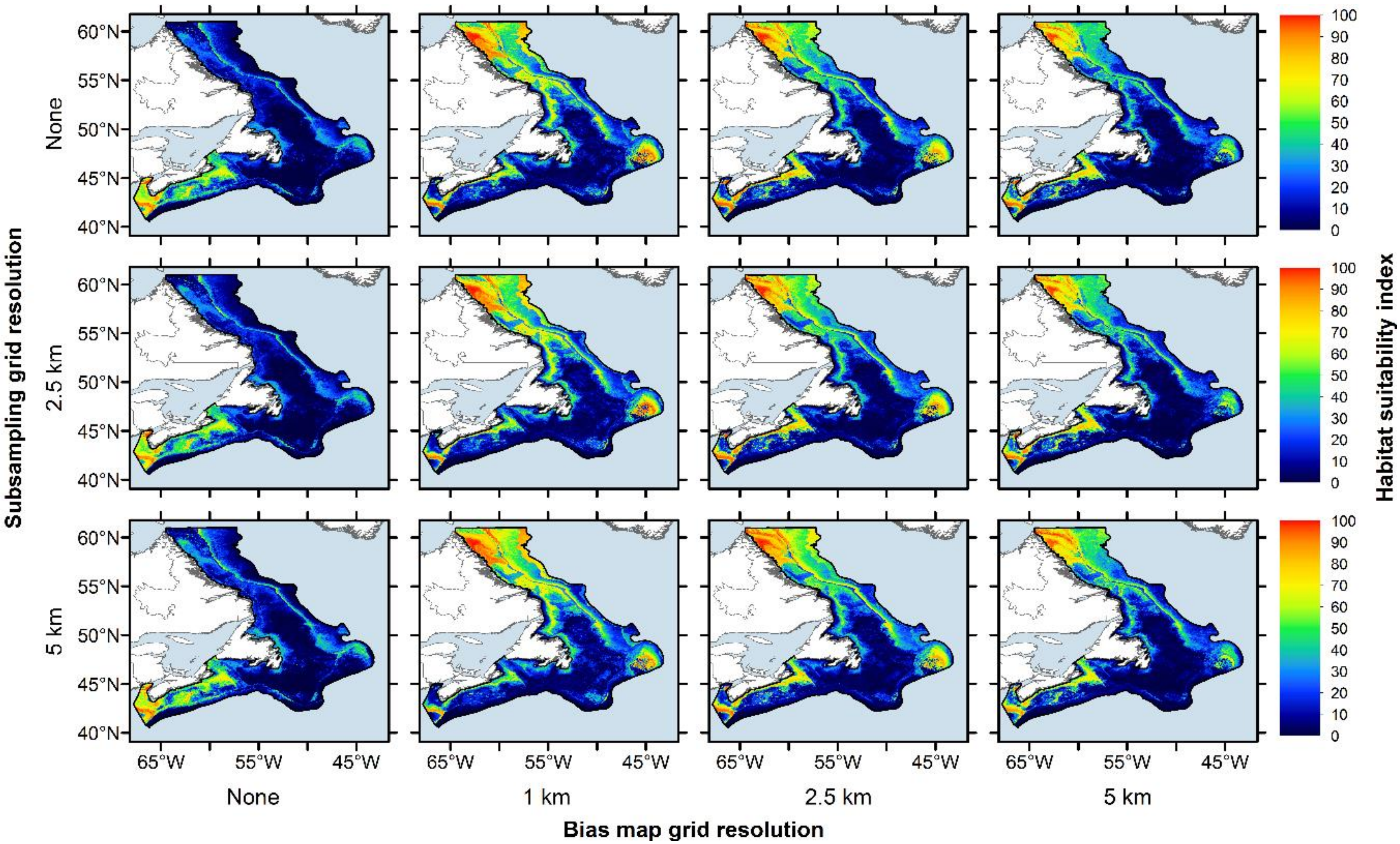

Figure A 3. Habitat suitability index for sei whale during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 3. Pearson's correlation between the 12 models for the summer SDMs for sei whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.99	0.53	0.50	0.47	0.61	0.60	0.56	0.63	0.62	0.59
	2.5km		1.00	0.99	0.55	0.52	0.49	0.63	0.62	0.58	0.65	0.64	0.60
	5 km			1.00	0.54	0.52	0.49	0.63	0.62	0.59	0.65	0.64	0.61
1 km	none				1.00	1.00	0.98	0.97	0.97	0.96	0.93	0.94	0.95
	2.5km					1.00	0.99	0.95	0.96	0.97	0.92	0.94	0.95
	5 km						1.00	0.92	0.94	0.96	0.88	0.90	0.93
2.5 km	none							1.00	1.00	0.97	0.98	0.99	0.98
	2.5km								1.00	0.98	0.98	0.99	0.99
	5 km									1.00	0.95	0.96	0.98
5 km	none										1.00	1.00	0.98
	2.5km											1.00	0.99
	5 km												1.00

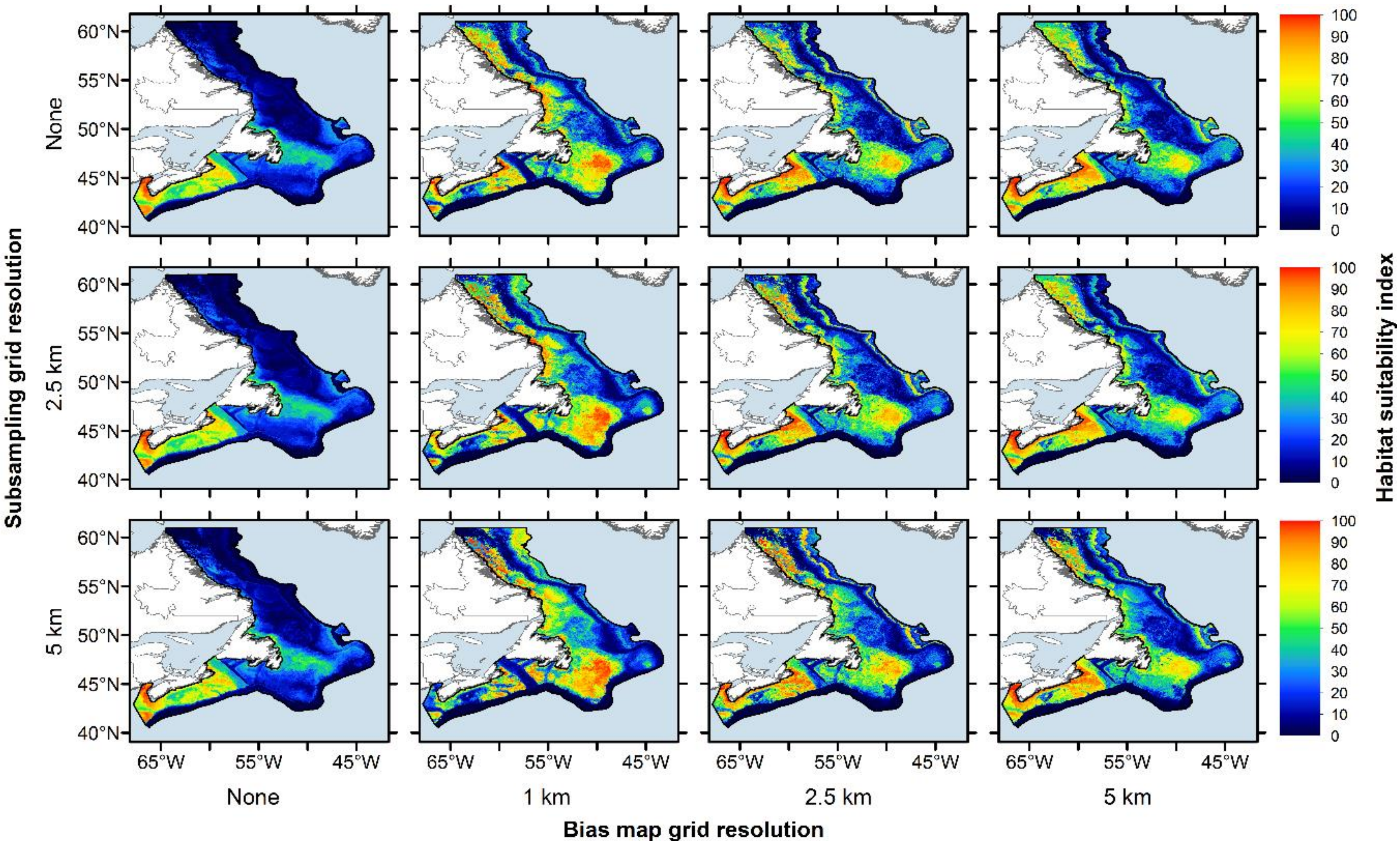

Figure A 4. Habitat suitability index for minke whale during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

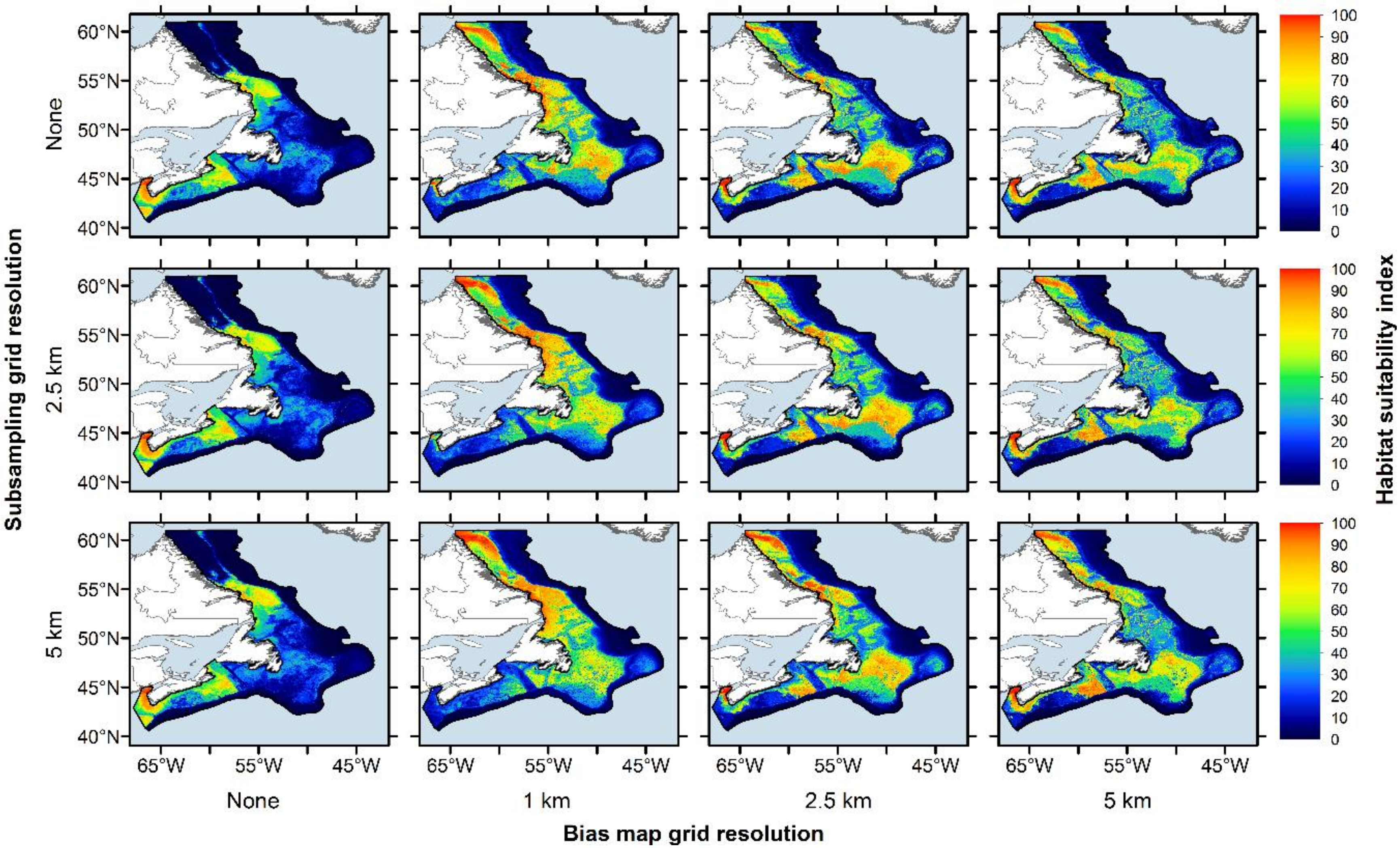

Figure A 5. Habitat suitability index for minke whale during autumn, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in autumn from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 4. Pearson's correlation between the 12 models for the summer SDMs for minke whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.0	0.99	0.99	0.53	0.44	0.32	0.73	0.70	0.63	0.77	0.75	0.74
	2.5km		1.0	0.99	0.54	0.45	0.33	0.73	0.70	0.63	0.77	0.76	0.74
	5 km			1.0	0.54	0.46	0.35	0.73	0.70	0.65	0.77	0.75	0.75
1 km	none				1.0	0.96	0.84	0.87	0.90	0.87	0.8	0.82	0.83
	2.5km					1.0	0.92	0.79	0.85	0.86	0.70	0.74	0.79
	5 km						1.0	0.62	0.72	0.81	0.51	0.55	0.70
2.5 km	none							1.0	0.98	0.9	0.96	0.96	0.93
	2.5km								1.0	0.95	0.94	0.94	0.96
	5 km									1.0	0.83	0.85	0.94
5 km	none										1.0	0.99	0.92
	2.5km											1.0	0.93
	5 km												1.0

Table A 5. Pearson's correlation between the 12 models for the autumn SDMs for minke whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.98	0.47	0.43	0.37	0.56	0.55	0.51	0.59	0.58	0.58
	2.5km		1.00	0.99	0.48	0.45	0.38	0.57	0.56	0.51	0.60	0.59	0.59
	5 km			1.00	0.48	0.46	0.41	0.55	0.55	0.52	0.58	0.58	0.58
1 km	none				1.00	0.98	0.93	0.88	0.91	0.92	0.81	0.83	0.84
	2.5km					1.00	0.97	0.83	0.86	0.90	0.76	0.80	0.82
	5 km						1.00	0.74	0.78	0.85	0.67	0.72	0.75
2.5 km	none							1.00	0.99	0.94	0.96	0.95	0.93
	2.5km								1.00	0.96	0.93	0.94	0.93
	5 km									1.00	0.89	0.92	0.94
5 km	none										1.00	0.98	0.95
	2.5km											1.00	0.98
	5 km												1.00

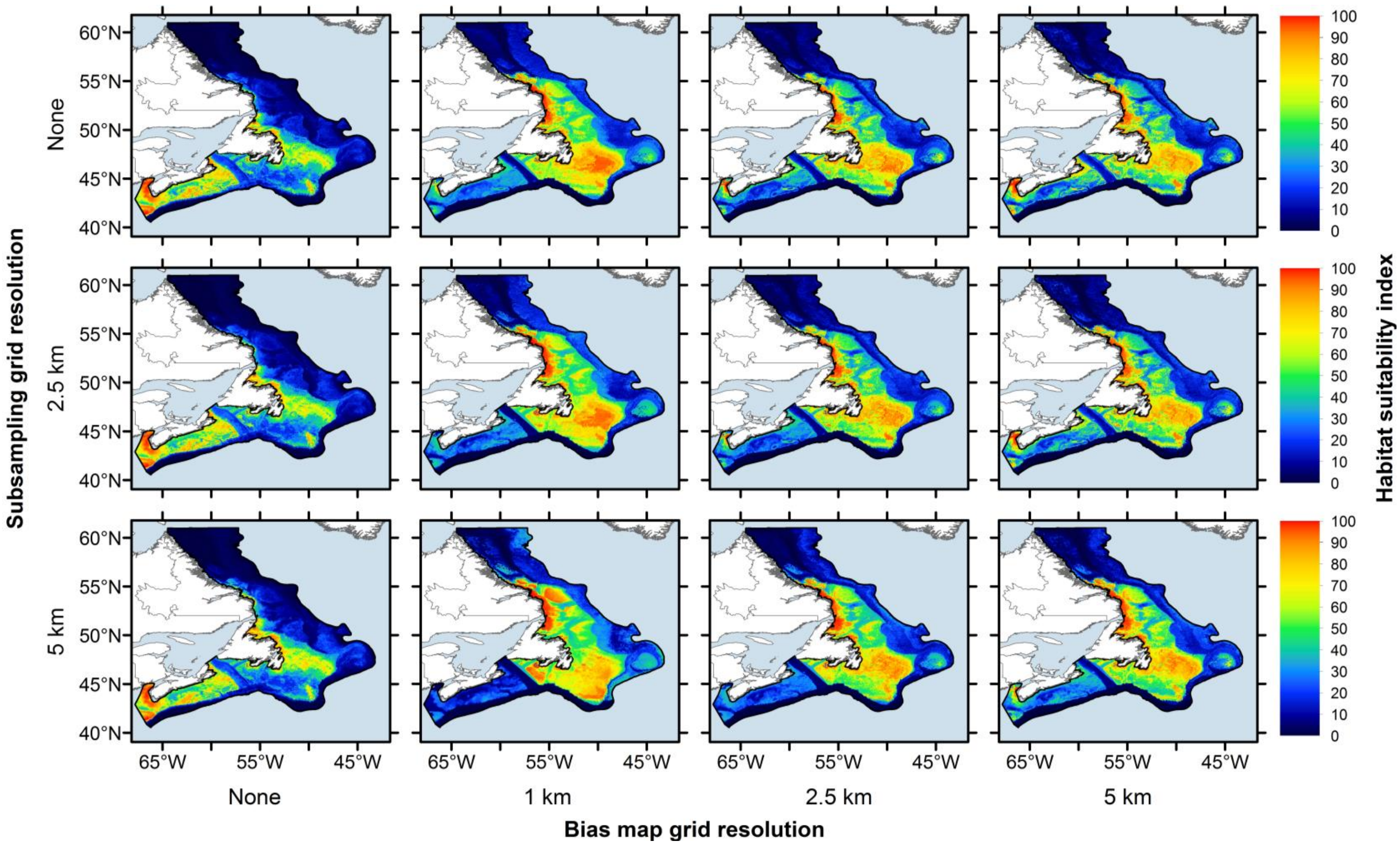

Figure A 6. Habitat suitability index for humpback whales during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

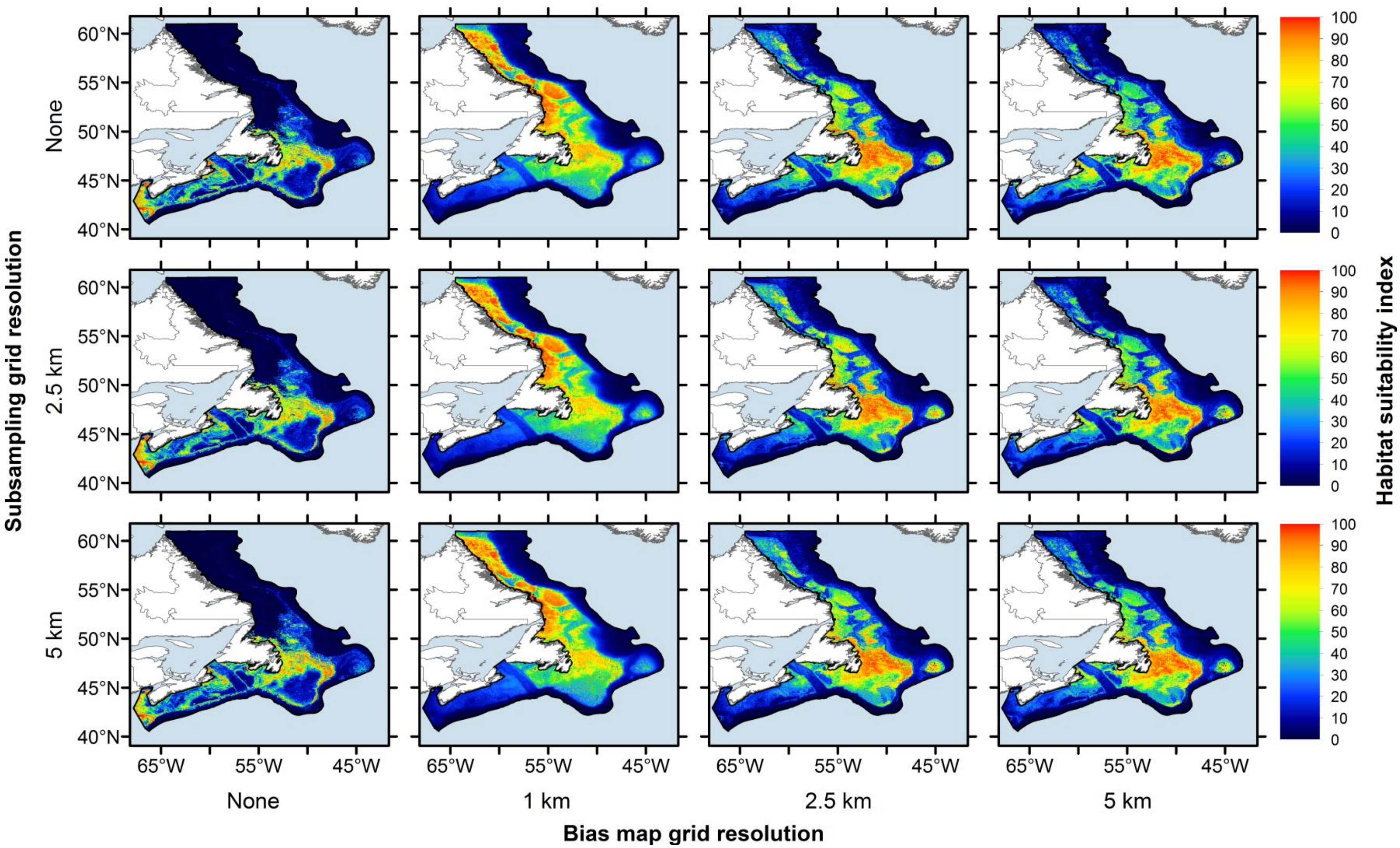

Figure A 7. Habitat suitability index for humpback whales during spring, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in spring from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

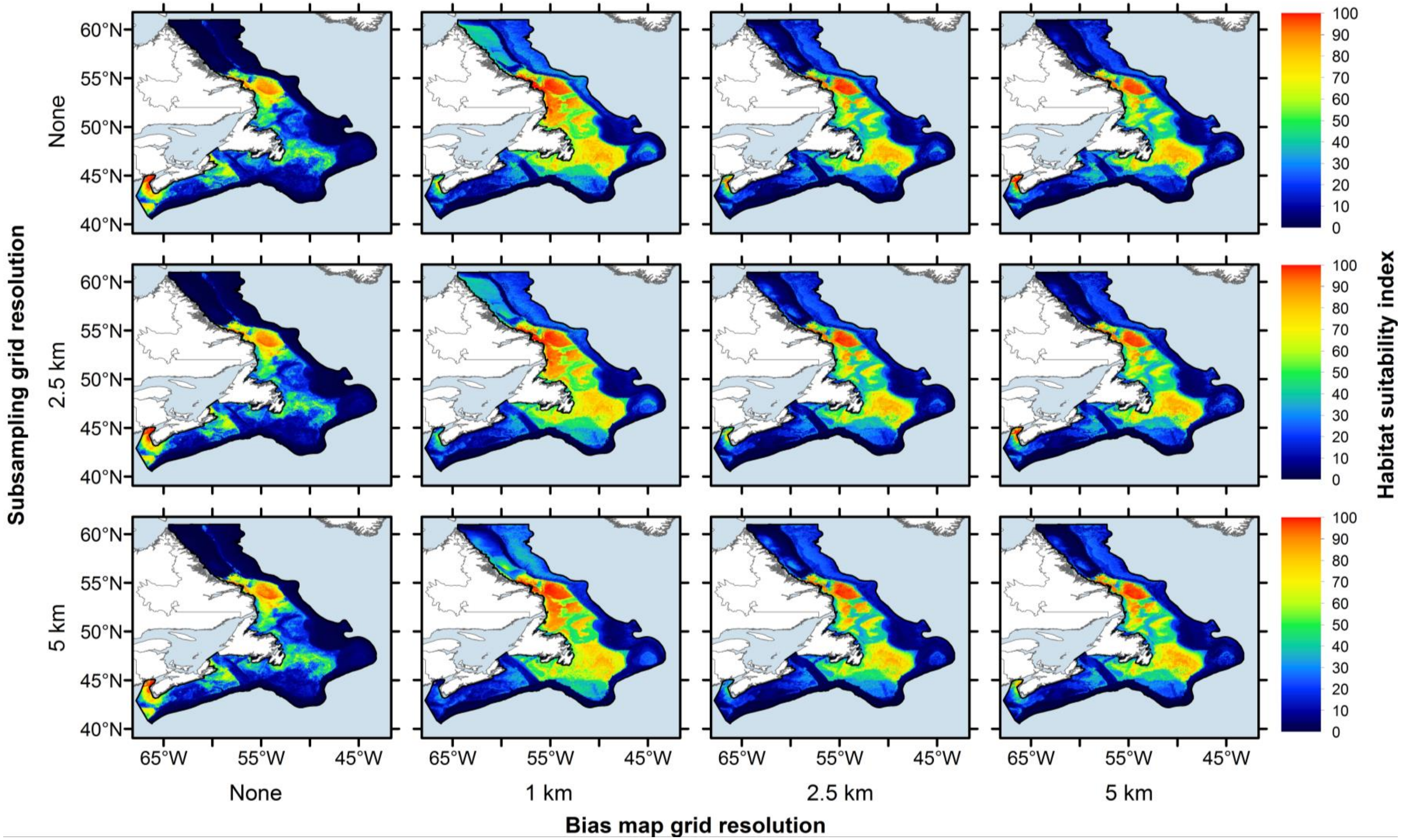

Figure A 8. Habitat suitability index for humpback whales during autumn, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in autumn from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 6. Pearson's correlation between the 12 models for the spring SDMs for humpback whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.98	0.18	0.15	0.14	0.52	0.47	0.48	0.64	0.61	0.58
	2.5km		1.00	0.98	0.21	0.18	0.17	0.55	0.51	0.52	0.67	0.65	0.61
	5 km			1.00	0.21	0.18	0.18	0.55	0.51	0.53	0.67	0.65	0.62
1 km	none				1.00	1.00	0.99	0.79	0.83	0.81	0.70	0.74	0.76
	2.5km					1.00	1.00	0.77	0.82	0.80	0.67	0.71	0.74
	5 km						1.00	0.76	0.81	0.79	0.67	0.71	0.73
2.5 km	none							1.00	0.99	0.99	0.97	0.98	0.98
	2.5km								1.00	0.99	0.95	0.97	0.97
	5 km									1.00	0.95	0.97	0.98
5 km	none										1.00	0.99	0.98
	2.5km											1.00	0.99
	5 km												1.00

Table A 7. Pearson's correlation between the 12 models for the summer SDMs for humpback whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.98	0.54	0.47	0.32	0.63	0.60	0.51	0.73	0.69	0.60
	2.5km		1.00	0.99	0.55	0.49	0.34	0.65	0.61	0.53	0.74	0.70	0.62
	5 km			1.00	0.60	0.52	0.38	0.68	0.65	0.58	0.77	0.74	0.66
1 km	none				1.00	0.98	0.91	0.96	0.98	0.97	0.92	0.94	0.96
	2.5km					1.00	0.95	0.93	0.95	0.97	0.88	0.91	0.94
	5 km						1.00	0.83	0.87	0.92	0.76	0.81	0.88
2.5 km	none							1.00	0.99	0.95	0.97	0.98	0.96
	2.5km								1.00	0.97	0.95	0.97	0.98
	5 km									1.00	0.90	0.93	0.97
5 km	none										1.00	0.99	0.95
	2.5km											1.00	0.97
	5 km												1.00

Table A 8. Pearson's correlation between the 12 models for the autumn SDMs for humpback whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.99	0.67	0.65	0.61	0.73	0.71	0.68	0.78	0.76	0.73
	2.5km		1.00	0.99	0.67	0.65	0.62	0.73	0.71	0.68	0.78	0.76	0.74
	5 km			1.00	0.69	0.68	0.65	0.76	0.74	0.71	0.80	0.78	0.76
1 km	none				1.00	0.99	0.95	0.93	0.93	0.92	0.91	0.92	0.91
	2.5km					1.00	0.97	0.92	0.93	0.93	0.89	0.91	0.92
	5 km						1.00	0.91	0.93	0.95	0.87	0.90	0.93
2.5 km	none							1.00	0.99	0.97	0.99	0.99	0.98
	2.5km								1.00	0.99	0.97	0.98	0.99
	5 km									1.00	0.94	0.96	0.98
5 km	none										1.00	0.99	0.98
	2.5km											1.00	0.99
	5 km												1.00

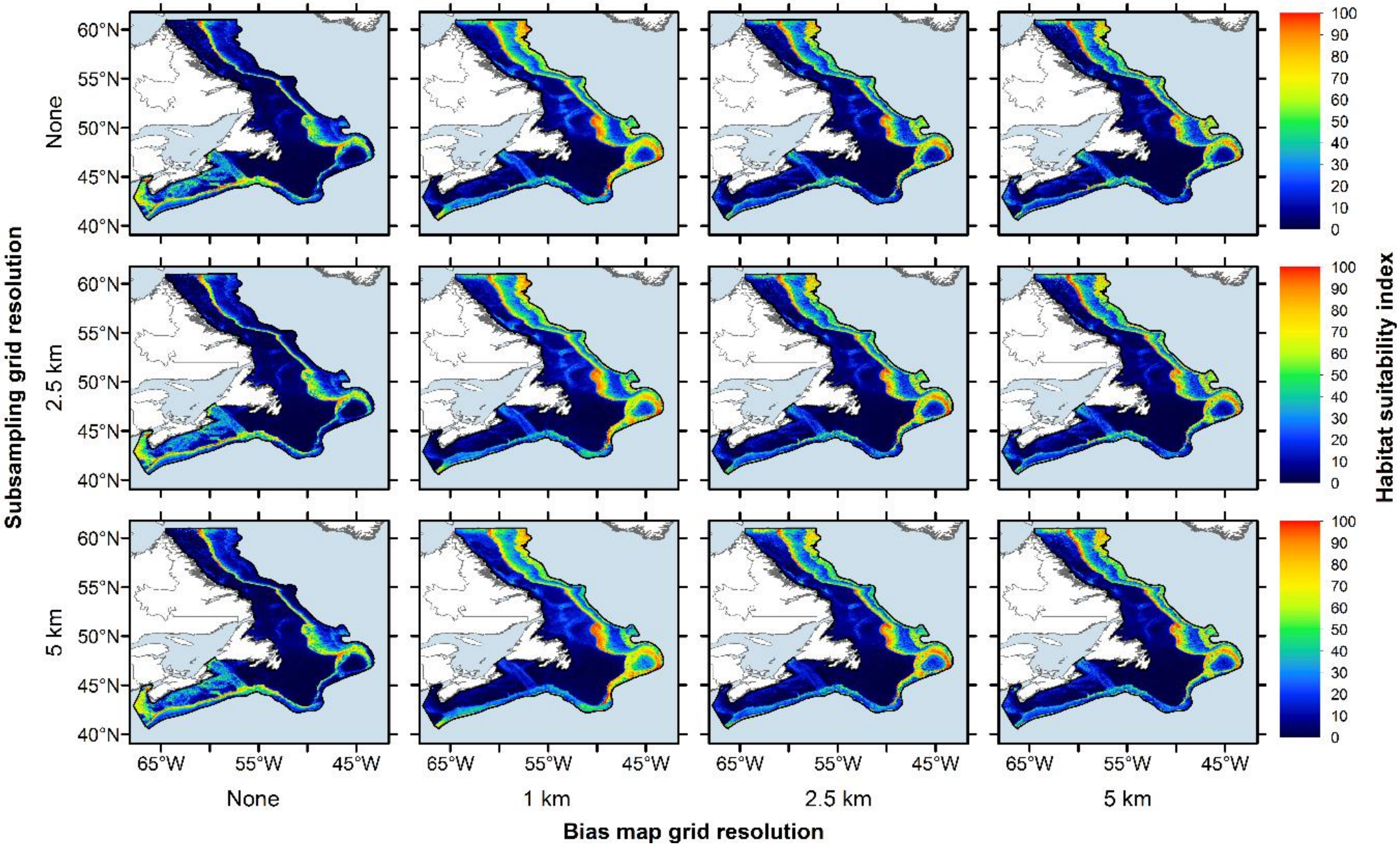

Figure A 9. Habitat suitability index for sperm whale during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 9. Pearson's correlation between the 12 models for the summer SDMs for sperm whales.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.99	0.53	0.50	0.47	0.61	0.60	0.56	0.63	0.62	0.59
	2.5km		1.00	0.99	0.55	0.52	0.49	0.63	0.62	0.58	0.65	0.64	0.60
	5 km			1.00	0.54	0.52	0.49	0.63	0.62	0.59	0.65	0.64	0.61
1 km	none				1.00	1.00	0.98	0.97	0.97	0.96	0.93	0.94	0.95
	2.5km					1.00	0.99	0.95	0.96	0.97	0.92	0.94	0.95
	5 km						1.00	0.92	0.94	0.96	0.88	0.90	0.93
2.5 km	none							1.00	1.00	0.97	0.98	0.99	0.98
	2.5km								1.00	0.98	0.98	0.99	0.99
	5 km									1.00	0.95	0.96	0.98
5 km	none										1.00	1.00	0.98
	2.5km											1.00	0.99
	5 km												1.00

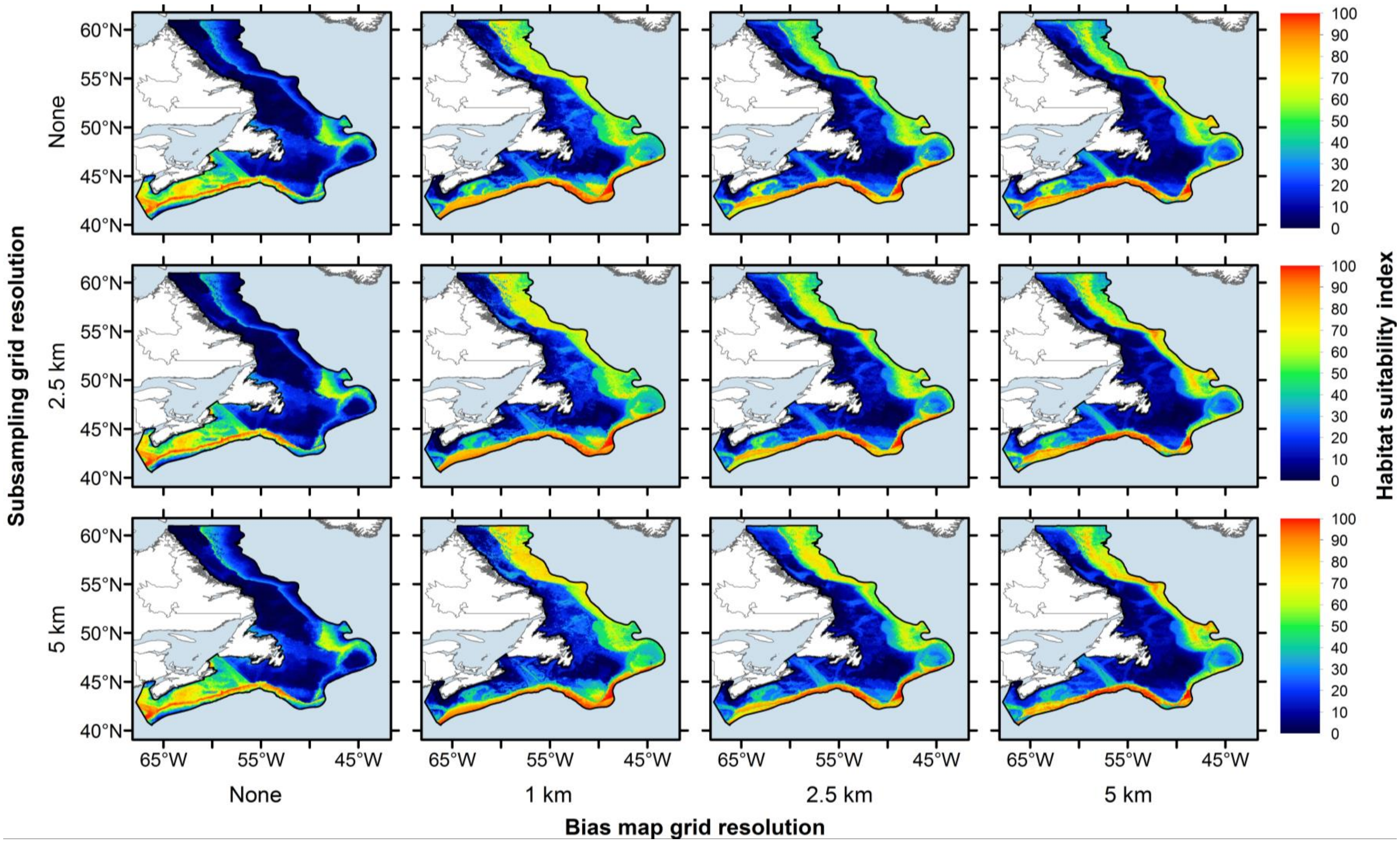

Figure A 10. Habitat suitability index for long-finned pilot whales during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

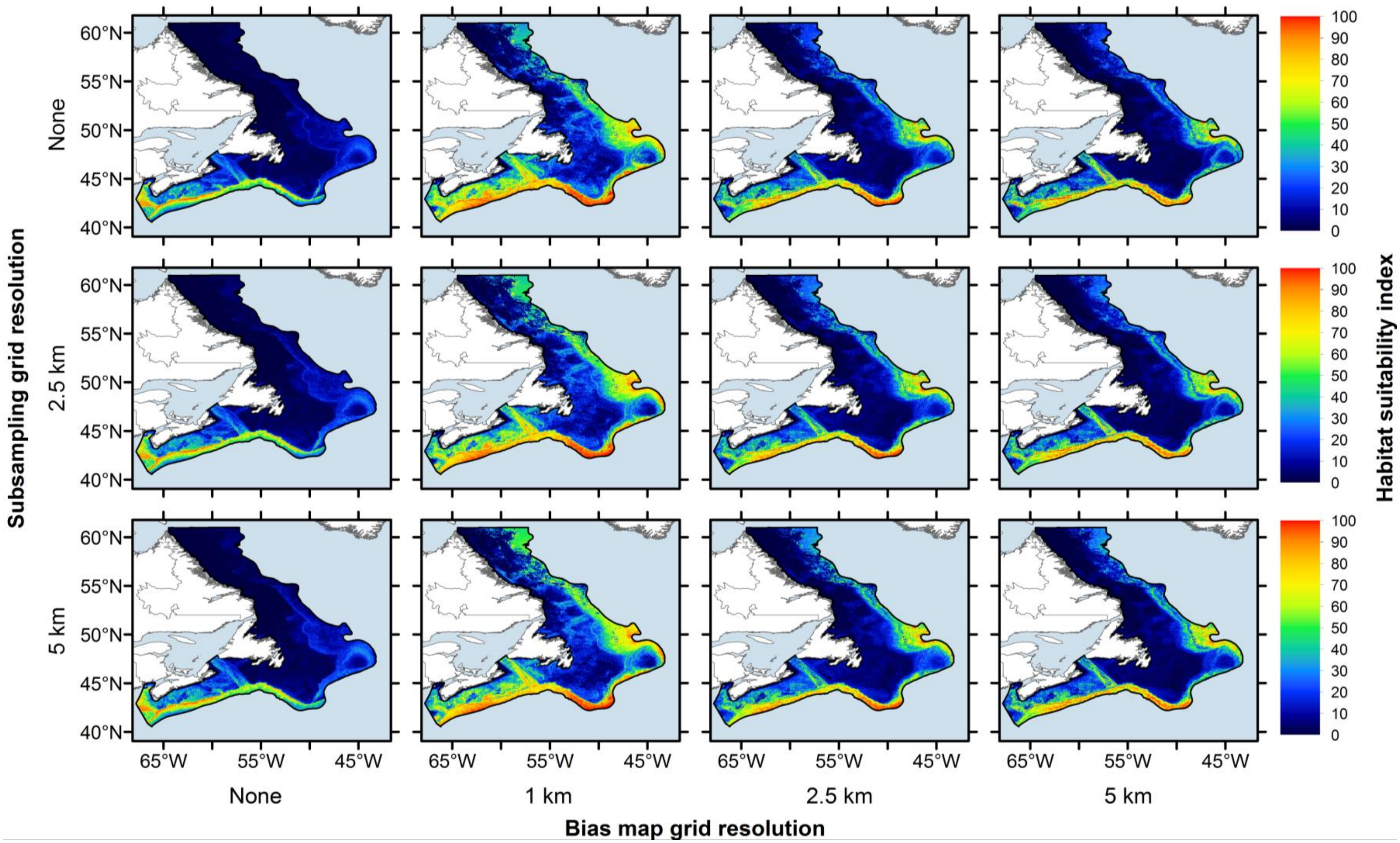

Figure A 11. Habitat suitability index for long-finned pilot whales during spring, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in spring from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

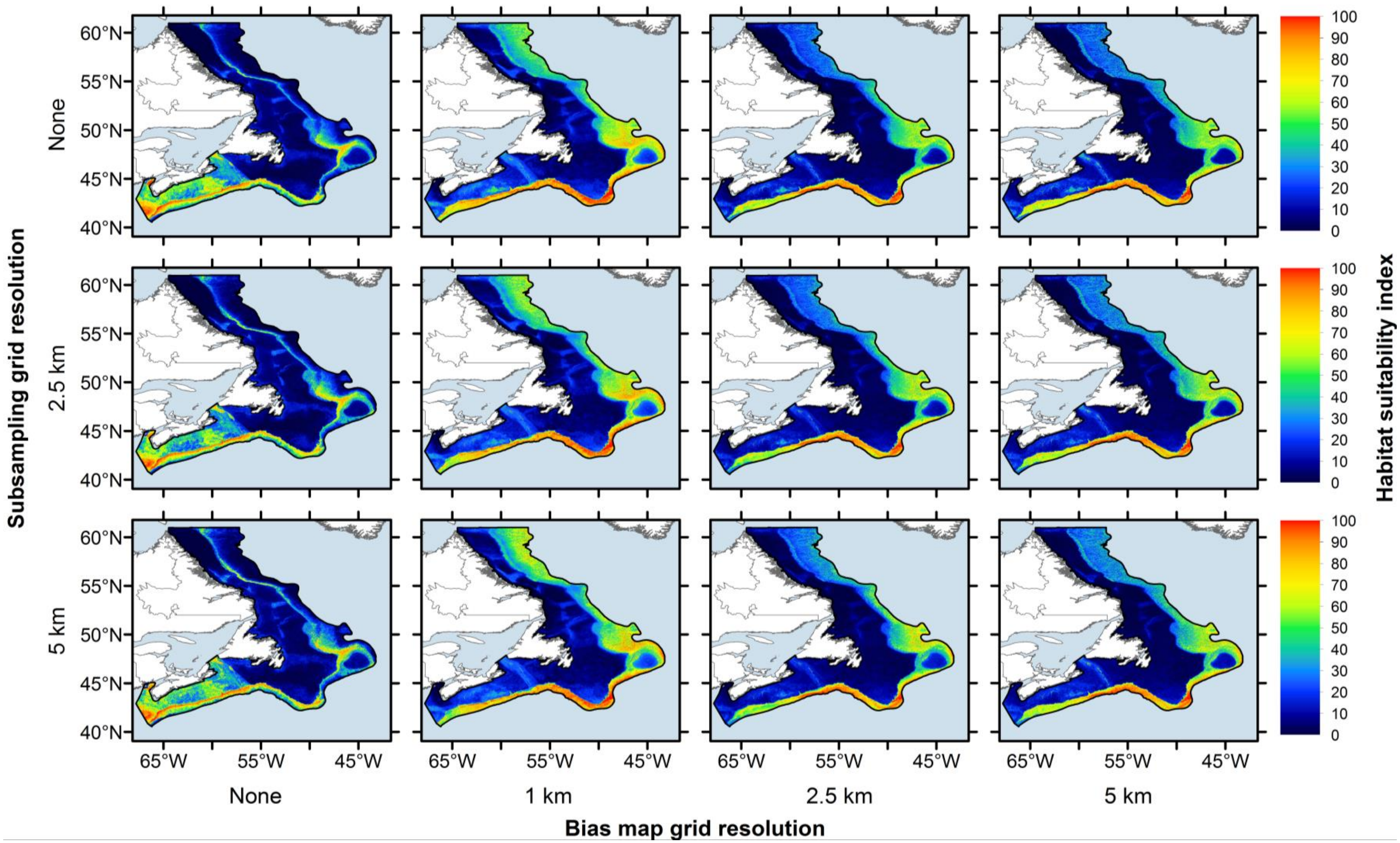

Figure A 12. Habitat suitability index for long-finned pilot whales during autumn, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in autumn from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 10. Pearson's correlation between the 12 models for the spring SDMs for long-finned pilot whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.98	0.71	0.67	0.64	0.73	0.68	0.66	0.76	0.72	0.69
	2.5km		1.00	0.99	0.72	0.68	0.66	0.73	0.69	0.67	0.76	0.74	0.70
	5 km			1.00	0.72	0.68	0.66	0.73	0.70	0.68	0.76	0.74	0.71
1 km	none				1.00	0.99	0.98	0.93	0.92	0.92	0.90	0.90	0.90
	2.5km					1.00	1.00	0.93	0.93	0.93	0.89	0.91	0.91
	5 km						1.00	0.91	0.92	0.93	0.88	0.90	0.91
2.5 km	none							1.00	0.99	0.97	0.98	0.98	0.97
	2.5km								1.00	0.99	0.97	0.98	0.98
	5 km									1.00	0.95	0.96	0.98
5 km	none										1.00	0.99	0.97
	2.5km											1.00	0.99
	5 km												1.00

Table A 11. Pearson's correlation between the 12 models for the summer SDMs for long-finned pilot whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.99	0.41	0.36	0.26	0.53	0.48	0.41	0.58	0.54	0.47
	2.5km		1.00	0.99	0.38	0.33	0.24	0.50	0.45	0.39	0.55	0.51	0.45
	5 km			1.00	0.40	0.35	0.26	0.51	0.46	0.40	0.56	0.52	0.46
1 km	none				1.00	0.99	0.97	0.94	0.95	0.94	0.89	0.89	0.89
	2.5km					1.00	0.98	0.93	0.94	0.94	0.87	0.88	0.89
	5 km						1.00	0.89	0.91	0.93	0.84	0.85	0.87
2.5 km	none							1.00	0.99	0.97	0.97	0.95	0.94
	2.5km								1.00	0.99	0.96	0.96	0.95
	5 km									1.00	0.94	0.95	0.95
5 km	none										1.00	0.99	0.97
	2.5km											1.00	0.99
	5 km												1.00

Table A 12. Pearson's correlation between the 12 models for the autumn SDMs for long-finned pilot whale.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.98	0.98	0.49	0.45	0.41	0.51	0.47	0.43	0.55	0.52	0.49
	2.5km		1.00	0.98	0.53	0.48	0.44	0.54	0.51	0.46	0.58	0.55	0.52
	5 km			1.00	0.51	0.47	0.43	0.52	0.49	0.45	0.56	0.54	0.51
1 km	none				1.00	0.99	0.98	0.97	0.97	0.96	0.96	0.97	0.97
	2.5km					1.00	0.99	0.95	0.96	0.96	0.95	0.96	0.96
	5 km						1.00	0.94	0.95	0.95	0.93	0.94	0.95
2.5 km	none							1.00	1.00	0.99	0.99	0.99	0.99
	2.5km								1.00	0.99	0.98	0.99	0.99
	5 km									1.00	0.98	0.98	0.99
5 km	none										1.00	1.00	0.99
	2.5km											1.00	1.00
	5 km												1.00

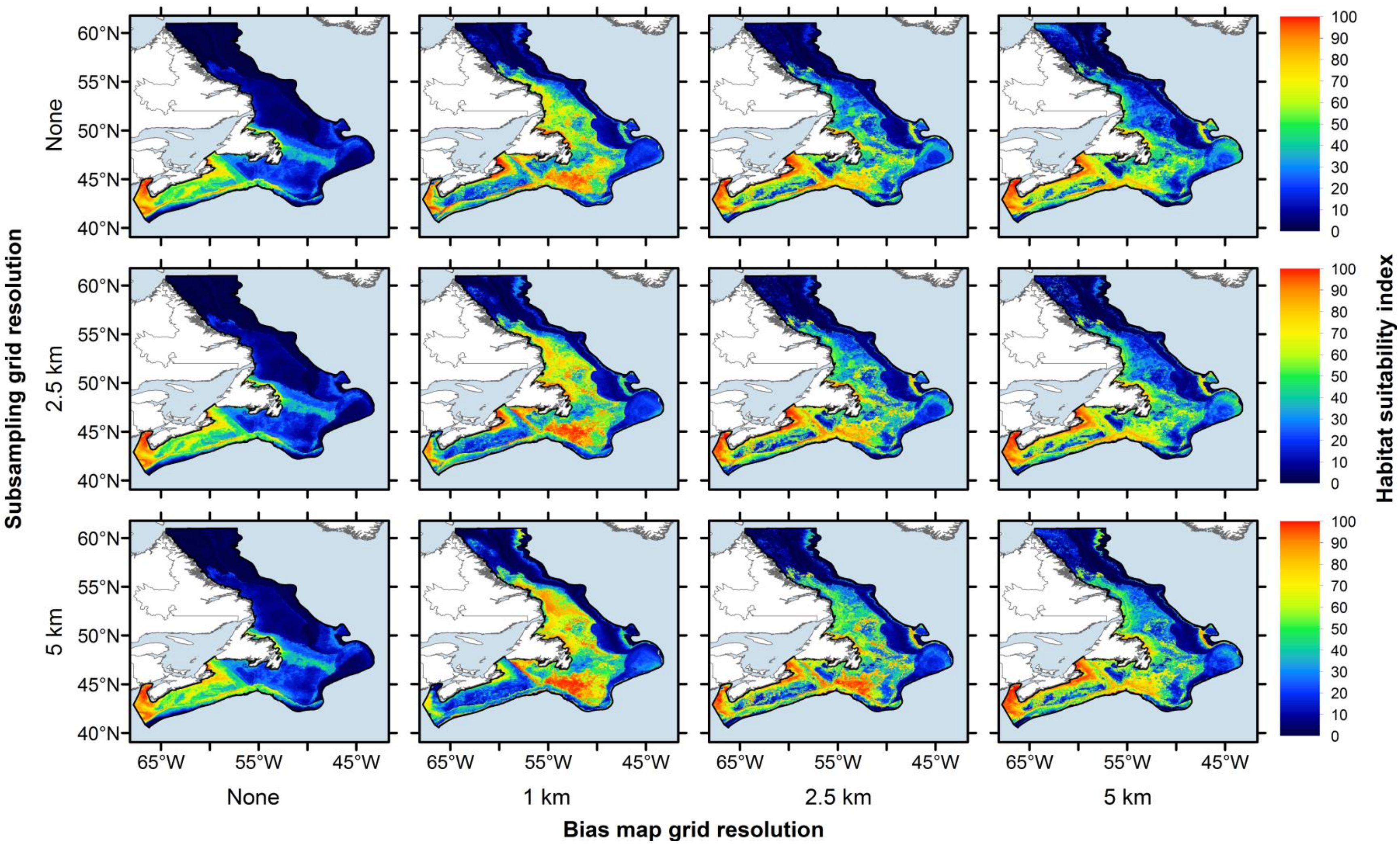

Figure A 13. Habitat suitability index for Atlantic white-sided dolphin during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

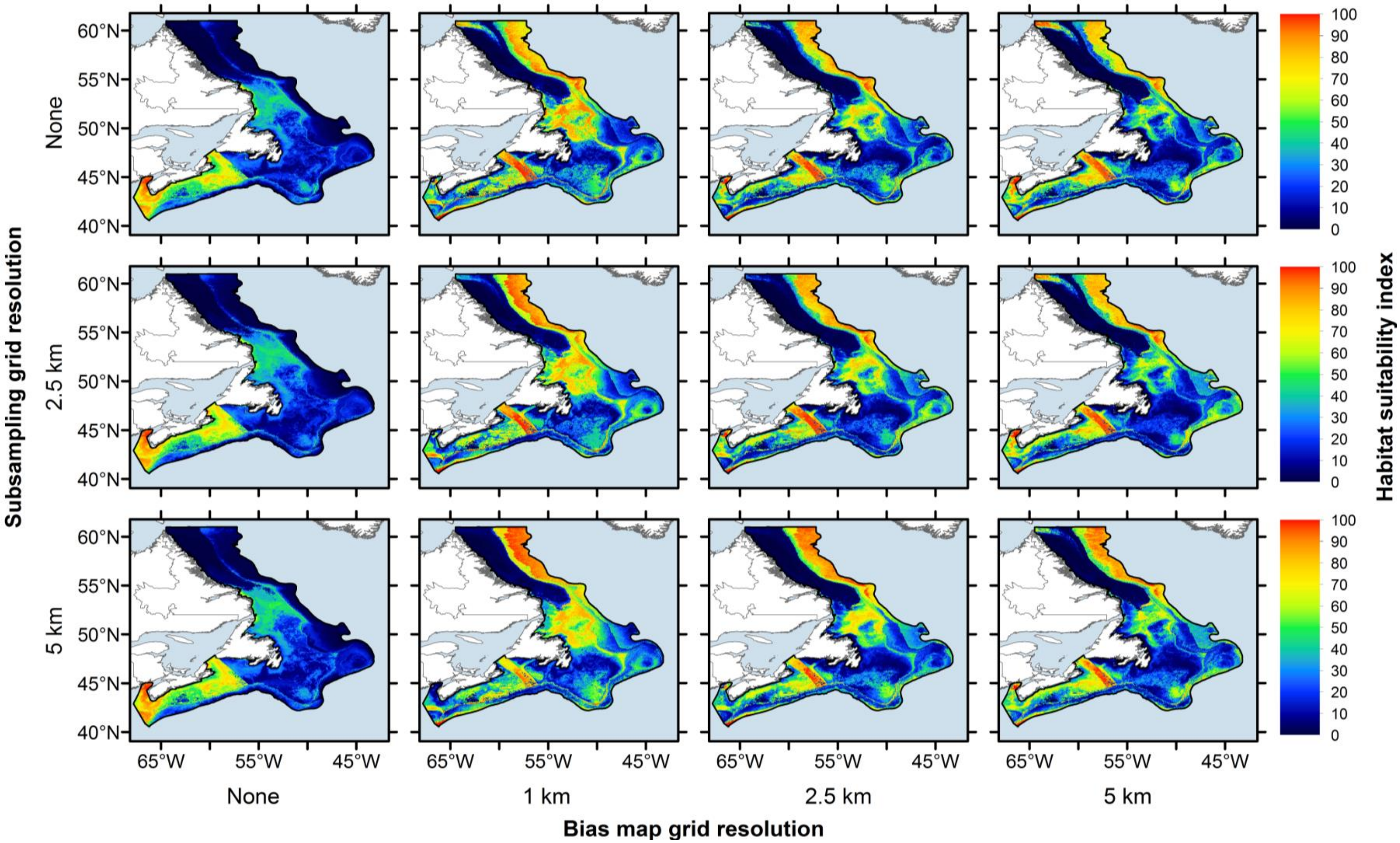

Figure A 14. Habitat suitability index for Atlantic white-sided dolphin during autumn, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in autumn from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 13. Pearson's correlation between the 12 models for the summer SDMs for Atlantic white-sided Dolphin.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.99	0.55	0.41	0.22	0.78	0.73	0.63	0.84	0.82	0.77
	2.5km		1.00	0.99	0.55	0.41	0.22	0.78	0.74	0.64	0.84	0.82	0.77
	5 km			1.00	0.55	0.42	0.23	0.78	0.74	0.65	0.84	0.83	0.78
1 km	none				1.00	0.96	0.84	0.86	0.88	0.88	0.77	0.80	0.82
	2.5km					1.00	0.93	0.77	0.82	0.86	0.66	0.71	0.76
	5 km						1.00	0.60	0.66	0.77	0.47	0.54	0.64
2.5 km	none							1.00	0.98	0.92	0.95	0.95	0.94
	2.5km								1.00	0.96	0.93	0.95	0.95
	5 km									1.00	0.84	0.88	0.94
5 km	none										1.00	0.99	0.94
	2.5km											1.00	0.97
	5 km												1.00

Table A 14. Pearson's correlation between the 12 models for the autumn SDMs for Atlantic white-sided Dolphin.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.98	0.99	0.27	0.24	0.17	0.28	0.26	0.21	0.35	0.30	0.29
	2.5km	0.98	1.00	0.98	0.26	0.24	0.16	0.27	0.26	0.20	0.33	0.29	0.28
	5 km	0.99	0.98	1.00	0.26	0.24	0.17	0.27	0.25	0.21	0.33	0.29	0.28
1 km	none	0.27	0.26	0.26	1.00	0.96	0.90	0.90	0.89	0.88	0.82	0.82	0.83
	2.5km	0.24	0.24	0.24	0.96	1.00	0.96	0.86	0.89	0.90	0.75	0.80	0.83
	5 km	0.17	0.16	0.17	0.90	0.96	1.00	0.81	0.84	0.89	0.67	0.73	0.80
2.5 km	none	0.28	0.27	0.27	0.90	0.86	0.81	1.00	0.97	0.94	0.93	0.92	0.93
	2.5km	0.26	0.26	0.25	0.89	0.89	0.84	0.97	1.00	0.96	0.89	0.93	0.93
	5 km	0.21	0.20	0.21	0.88	0.90	0.89	0.94	0.96	1.00	0.85	0.89	0.94
5 km	none	0.35	0.33	0.33	0.82	0.75	0.67	0.93	0.89	0.85	1.00	0.97	0.93
	2.5km	0.30	0.29	0.29	0.82	0.80	0.73	0.92	0.93	0.89	0.97	1.00	0.96
	5 km	0.29	0.28	0.28	0.83	0.83	0.80	0.93	0.93	0.94	0.93	0.96	1.00

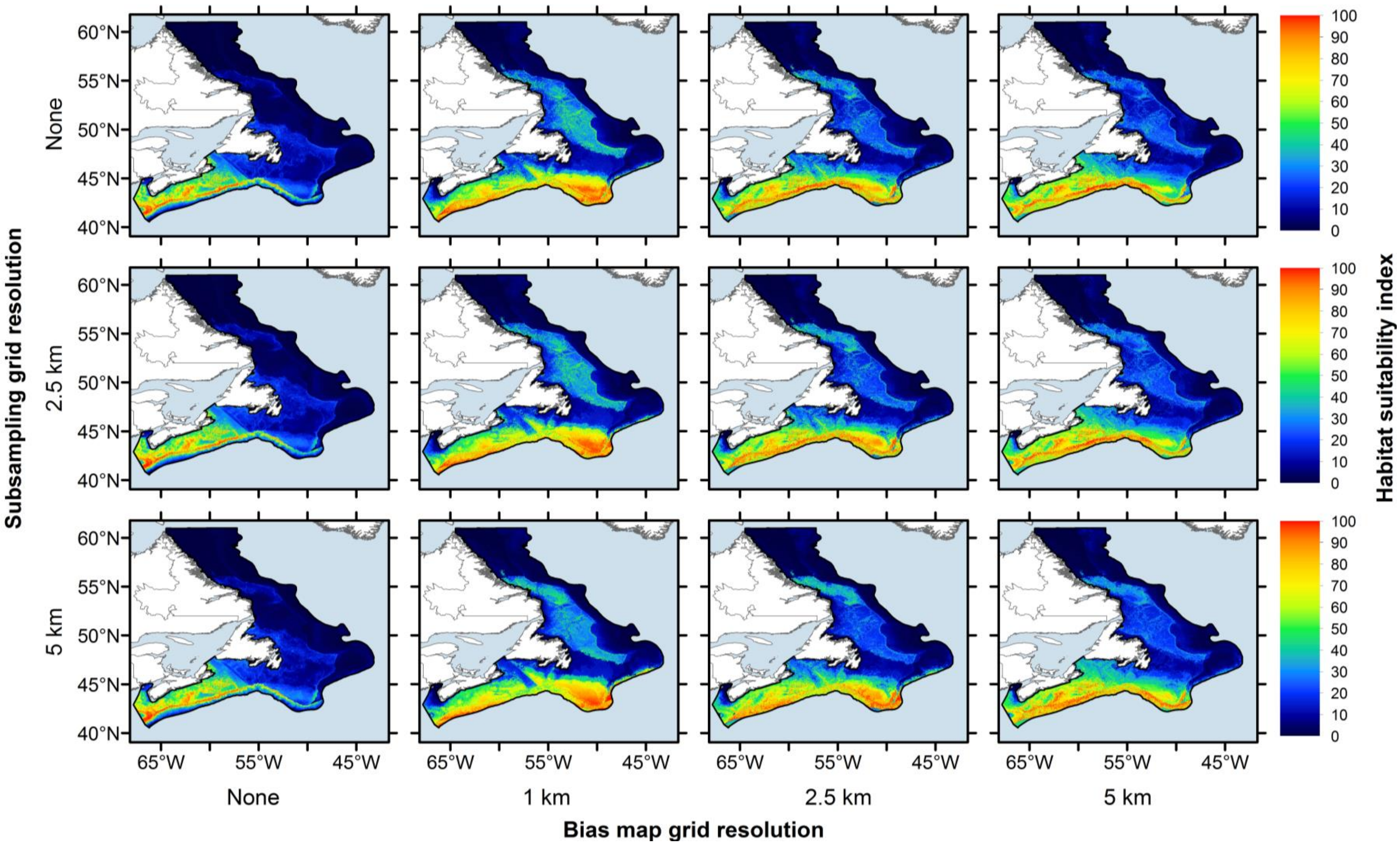

Figure A 15. Habitat suitability index for short-beaked common dolphin during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

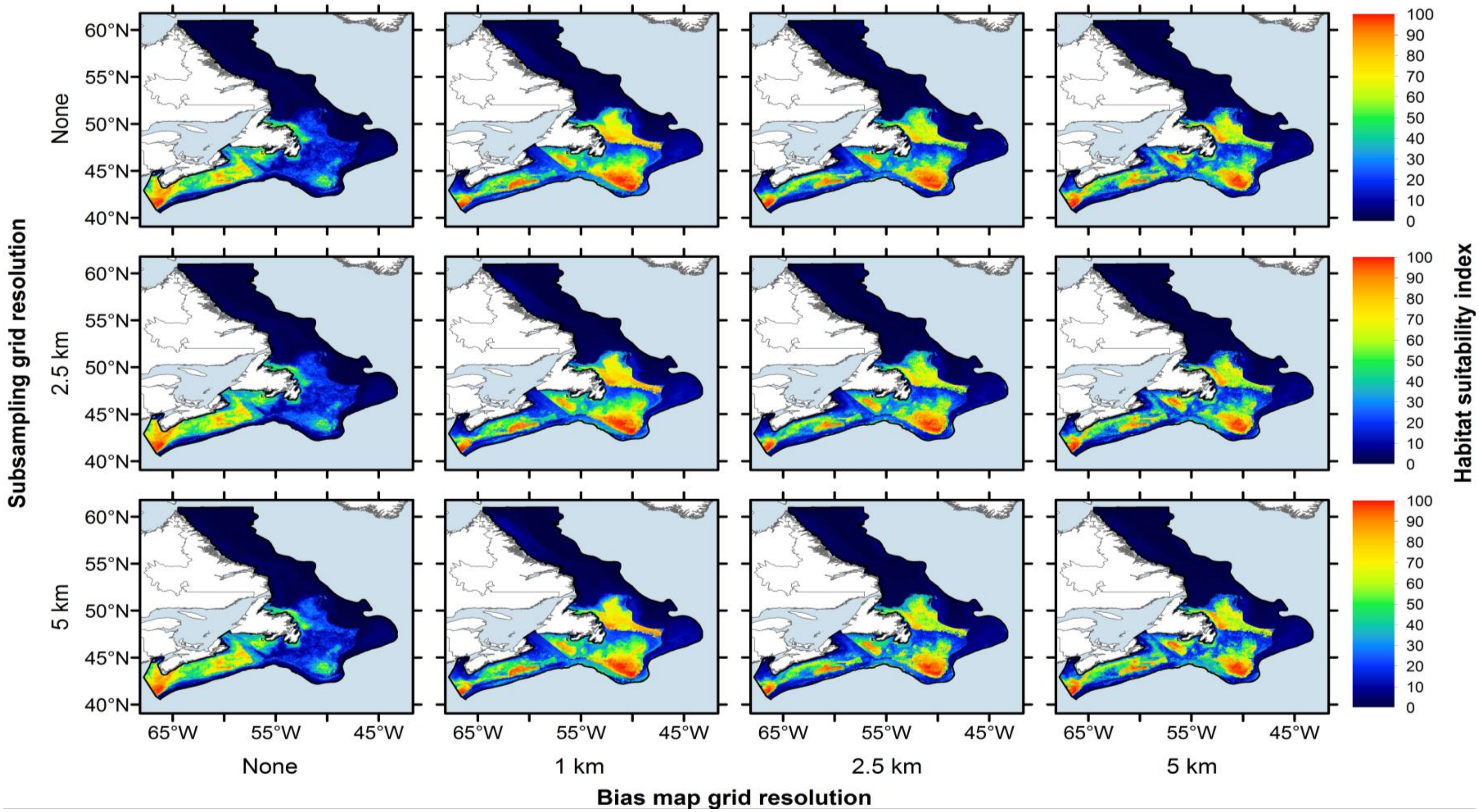

Figure A 16. Habitat suitability index for short-beaked common dolphin during autumn, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in autumn from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 15. Pearson's correlation between the 12 models for the summer SDMs for short-beaked common dolphin.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	1.00	0.99	0.62	0.60	0.55	0.78	0.77	0.70	0.87	0.85	0.82
	2.5km		1.00	0.99	0.62	0.60	0.55	0.78	0.77	0.70	0.87	0.85	0.82
	5 km			1.00	0.63	0.61	0.57	0.79	0.77	0.72	0.87	0.86	0.83
1 km	none				1.00	1.00	0.97	0.94	0.94	0.95	0.87	0.89	0.90
	2.5km					1.00	0.98	0.93	0.94	0.95	0.86	0.88	0.90
	5 km						1.00	0.89	0.91	0.95	0.81	0.84	0.87
2.5 km	none							1.00	0.99	0.97	0.97	0.97	0.97
	2.5km								1.00	0.98	0.95	0.97	0.97
	5 km									1.00	0.91	0.93	0.96
5 km	none										1.00	1.00	0.98
	2.5km											1.00	0.99
	5 km												1.00

Table A 16. Pearson's correlation between the 12 models for the autumn SDMs for short-beaked common dolphin.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.99	0.60	0.58	0.57	0.64	0.62	0.62	0.74	0.72	0.72
	2.5km		1.00	0.99	0.60	0.58	0.57	0.64	0.62	0.62	0.73	0.71	0.71
	5 km			1.00	0.62	0.60	0.59	0.65	0.64	0.64	0.75	0.73	0.74
1 km	none				1.00	1.00	1.00	0.97	0.97	0.96	0.93	0.93	0.93
	2.5km					1.00	1.00	0.96	0.96	0.96	0.92	0.93	0.93
	5 km						1.00	0.96	0.96	0.96	0.92	0.92	0.92
2.5 km	none							1.00	1.00	0.99	0.97	0.97	0.96
	2.5km								1.00	0.99	0.96	0.97	0.96
	5 km									1.00	0.96	0.97	0.96
5 km	none										1.00	1.00	0.99
	2.5km											1.00	0.99
	5 km												1.00

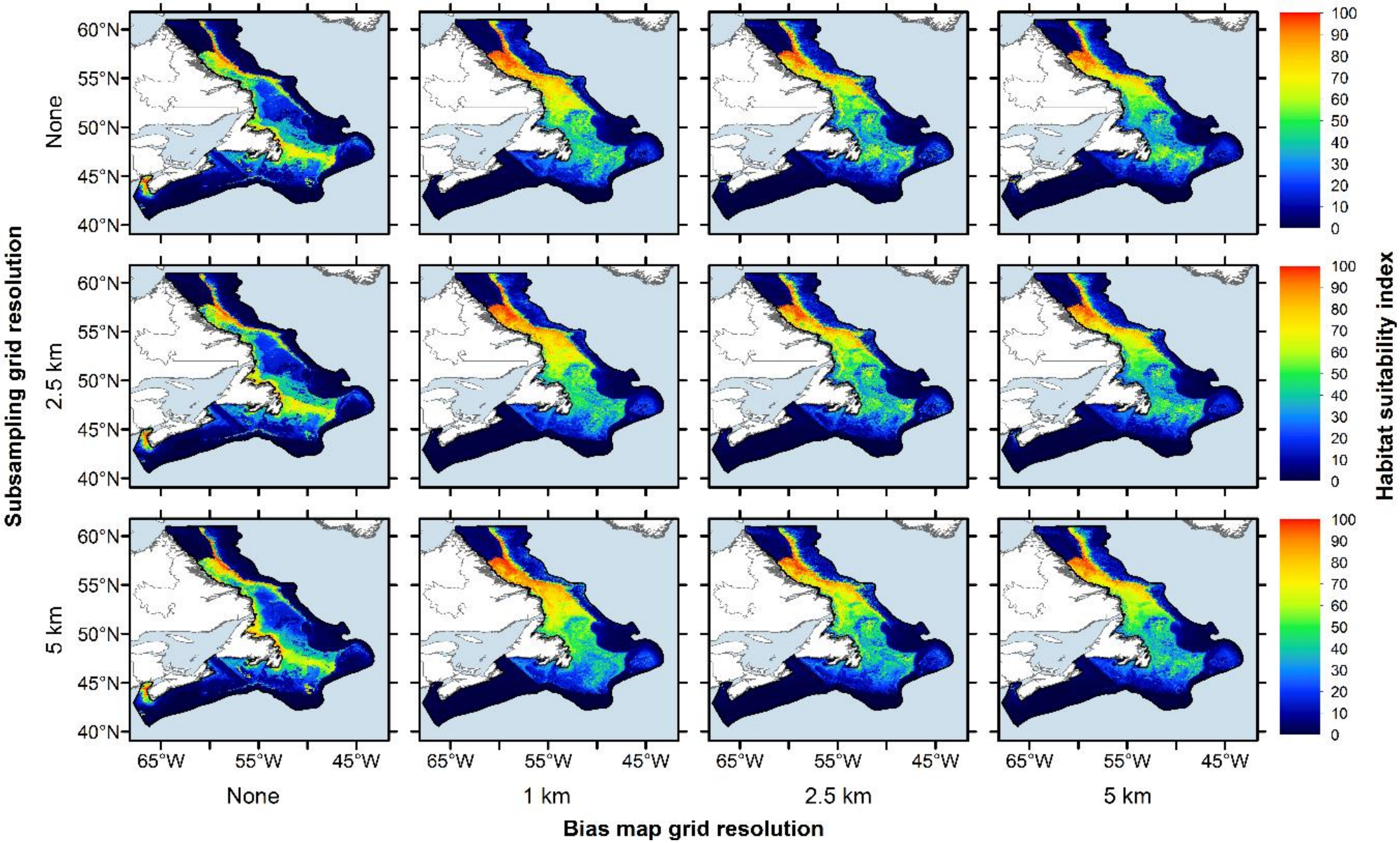

Figure A 17. Habitat suitability index for white-beaked dolphin during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 17. Pearson's correlation between the 12 models for the summer SDMs for white-beaked dolphin.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.97	0.71	0.70	0.69	0.74	0.73	0.72	0.77	0.75	0.75
	2.5km		1.00	0.98	0.70	0.69	0.67	0.73	0.71	0.71	0.75	0.73	0.73
	5 km			1.00	0.71	0.70	0.70	0.72	0.72	0.72	0.74	0.74	0.74
1 km	none				1.00	1.00	0.98	0.96	0.97	0.96	0.96	0.97	0.97
	2.5km					1.00	0.99	0.95	0.96	0.96	0.95	0.96	0.97
	5 km						1.00	0.94	0.95	0.97	0.93	0.95	0.96
2.5 km	none							1.00	1.00	0.98	0.98	0.98	0.98
	2.5km								1.00	0.99	0.98	0.98	0.98
	5 km									1.00	0.96	0.97	0.98
5 km	none										1.00	1.00	0.99
	2.5km											1.00	0.99
	5 km												1.00

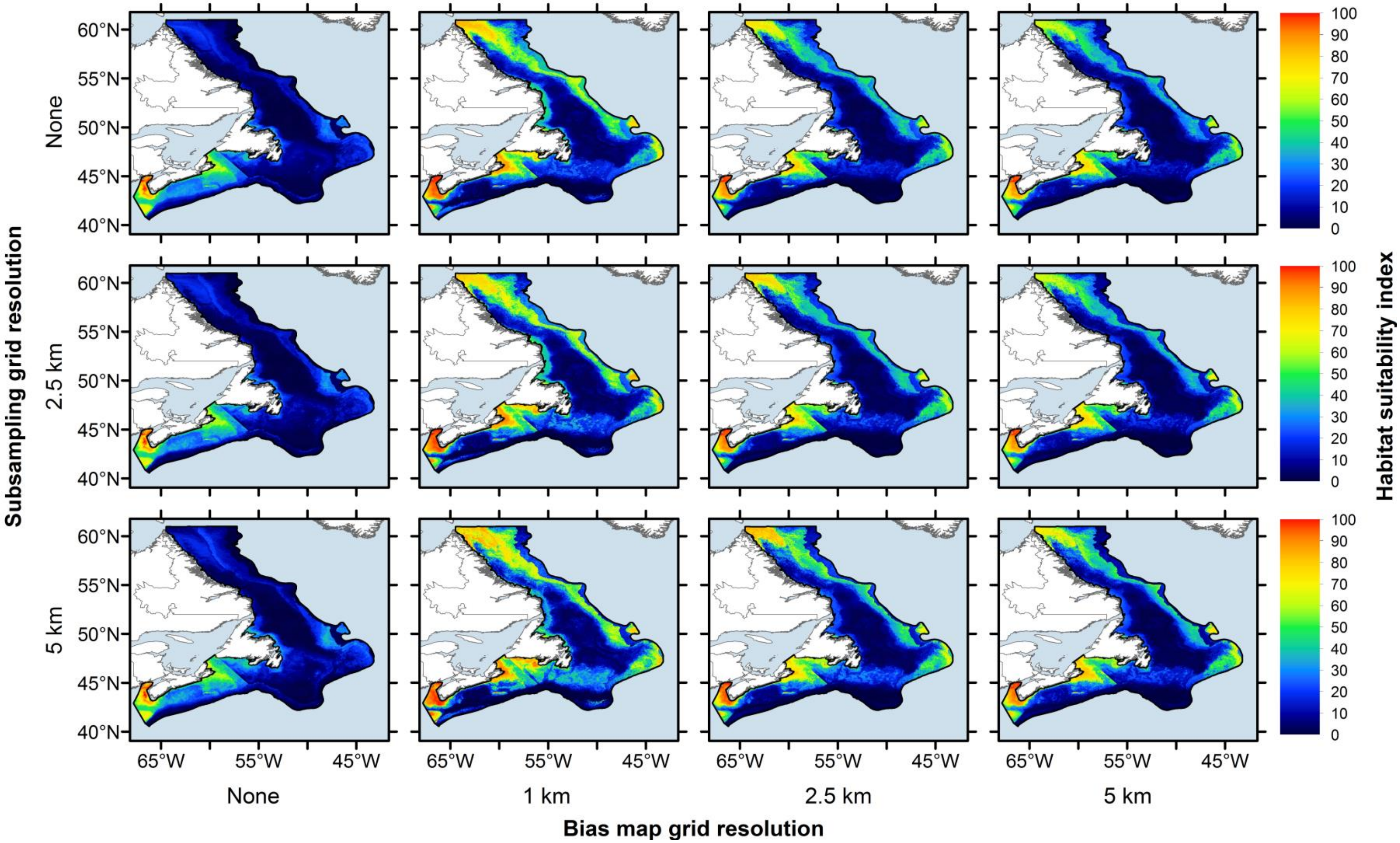

Figure A 18. Habitat suitability index for harbour porpoise during summer, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in summer from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

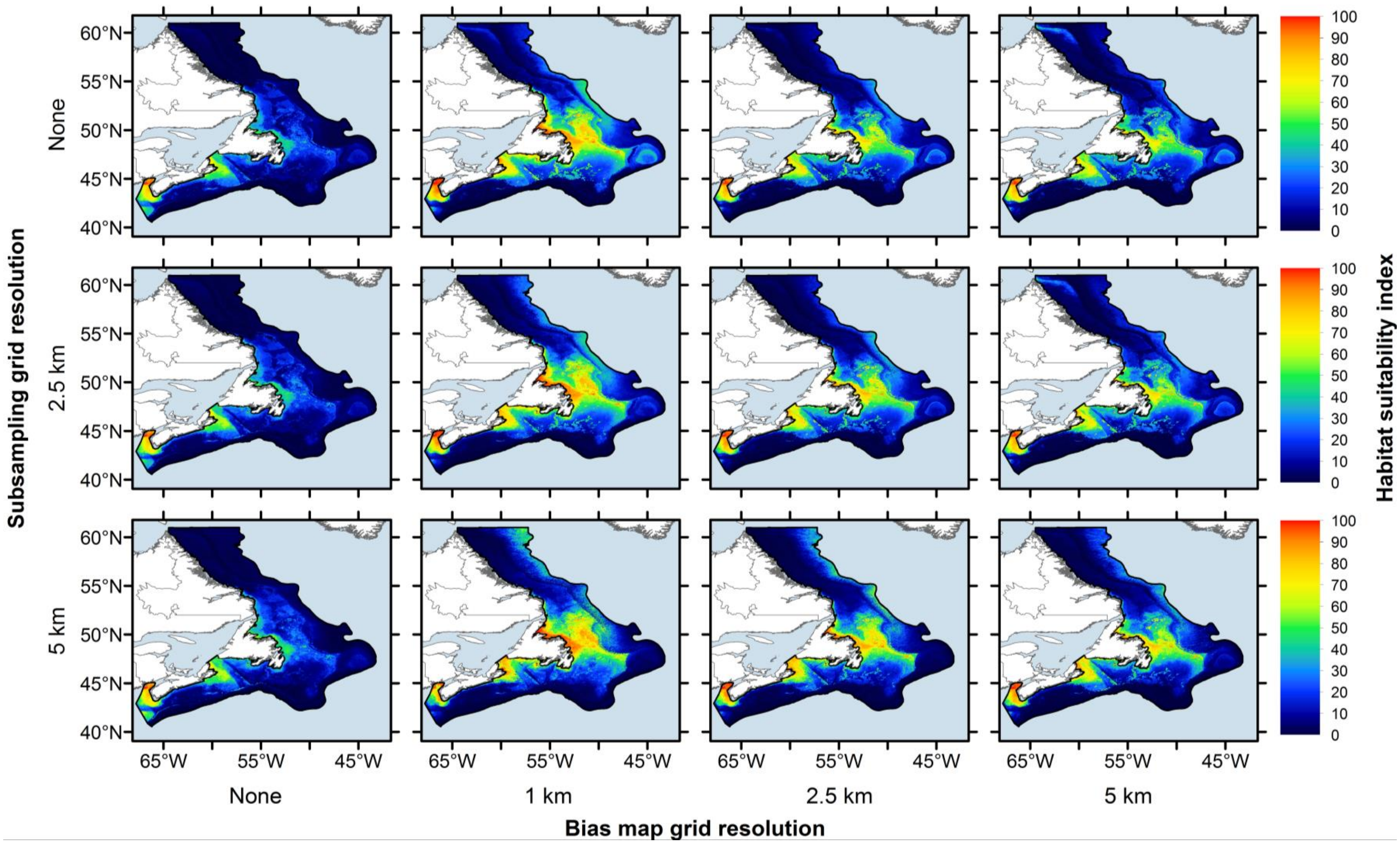

Figure A 19. Habitat suitability index for harbour porpoise during autumn, based on the averaged relative occurrence rate output from the MaxEnt models. Within the study area (black outline), the model used the geographic locations of sightings in autumn from 1975 to 2015. Models were run for 12 combinations of subsampling grid resolution and bias map grid resolutions.

Table A 18. Pearson's correlation between the 12 models for the summer SDMs for harbour porpoise.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.98	0.62	0.64	0.59	0.69	0.69	0.66	0.75	0.75	0.73
	2.5km		1.00	0.99	0.63	0.64	0.60	0.69	0.69	0.66	0.75	0.75	0.73
	5 km			1.00	0.58	0.61	0.58	0.65	0.65	0.63	0.71	0.72	0.70
1 km	none				1.00	0.99	0.92	0.97	0.96	0.95	0.96	0.95	0.94
	2.5km					1.00	0.96	0.96	0.96	0.96	0.95	0.95	0.95
	5 km						1.00	0.89	0.91	0.95	0.90	0.91	0.92
2.5 km	none							1.00	0.99	0.97	0.99	0.98	0.97
	2.5km								1.00	0.99	0.99	0.99	0.98
	5 km									1.00	0.97	0.97	0.98
5 km	none										1.00	1.00	0.99
	2.5km											1.00	0.99
	5 km												1.00

Table A 19. Pearson's correlation between the 12 models for the autumn SDMs for harbour porpoise.

Bias map		None			1 km			2.5 km			5 km		
	Subsampling	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km	none	2.5km	5km
none	none	1.00	0.99	0.98	0.78	0.78	0.76	0.83	0.82	0.75	0.85	0.85	0.82
	2.5km		1.00	0.99	0.79	0.79	0.77	0.84	0.83	0.76	0.85	0.86	0.83
	5 km			1.00	0.80	0.80	0.79	0.83	0.83	0.77	0.84	0.85	0.84
1 km	none				1.00	1.00	0.98	0.97	0.97	0.93	0.94	0.95	0.94
	2.5km					1.00	0.97	0.94	0.97	0.96	0.90	0.92	0.95
	5 km						1.00	0.85	0.91	0.96	0.80	0.84	0.91
2.5 km	none							1.00	0.99	0.92	0.98	0.98	0.95
	2.5km								1.00	0.96	0.96	0.97	0.98
	5 km									1.00	0.88	0.91	0.97
5 km	none										1.00	0.99	0.94
	2.5km											1.00	0.96
	5 km												1.00