Chapter 12: Predicting the offshore distribution and abundance of marine birds from shipboard surveys, using a hierarchical community distance sampling model

Final Report to the Department of Energy Wind and Water Power Technologies Office, 2015

Holly F. Goyert[1]*, Beth Gardner[1], Rahel Sollmann[1], Richard R. Veit[2], Andrew T. Gilbert[3], Emily E. Connelly[3], Kathryn A. Williams[3]

[1] North Carolina State University, Department of Forestry and Environmental Resources, Raleigh, NC
[2] City University of New York, College of Staten Island, Department of Biology, New York, NY
[3] Biodiversity Research Institute, Portland, ME
*This chapter is under review for publication in a peer-reviewed journal

Project webpage: *www.briloon.org/mabs*

Suggested citation: Goyert HF, Gardner B, Sollmann R, Veit RR, Gilbert AT, Connelly EE, Williams KA. 2015. Predicting the offshore distribution and abundance of marine birds from shipboard surveys, using a hierarchical community distance sampling model. In: Wildlife Densities and Habitat Use Across Temporal and Spatial Scales on the Mid-Atlantic Outer Continental Shelf: Final Report to the Department of Energy EERE Wind & Water Power Technologies Office. Williams KA, Connelly EE, Johnson SM, Stenhouse IJ (eds.) Award Number: DE-EE0005362. Report BRI 2015-11, Biodiversity Research Institute, Portland, Maine. 42 pp.

Chapter 12 Highlights

Prediction of seabird densities across the study area by season, based on an incorporation of environmental data into a multi-species modeling approach

Context[1]

A broad geographic and temporal scale of analysis is required to assess exposure to wildlife from proposed development projects. Unlike several other chapters in Part IV of this report that utilize approaches for combining boat and digital aerial survey data, Chapter 12 focuses on using data from a single, well understood survey method to describe abundance patterns. Standardized boat-based surveys with distance estimation are a well-established method of obtaining density data for wildlife.

Project collaborators developed a community distance sampling (CDS) model for seabirds using data from the first boat survey (Chapter 11). Building on this novel multi-species approach, Chapter 12 analyzes data from 15 boat surveys and incorporates remotely-collected environmental covariate data into the hierarchical modeling structure. This approach accounts for imperfect detection to estimate "true" abundance, and predicts seabird distributions by season to help identify important habitat use areas and patterns.

Study goal/objectives

Evaluate potential exposure of the marine bird community to offshore development by: 1) quantifying the detectability of 40 avian species to predict their seasonal abundance across the study area; and 2) identifying ecological drivers of distribution and abundance, both within and among species.

Highlights

- Abundance and species composition varied across the study area, as well as by season.
- Distance to shore was generally the most common significant predictor of abundance.
- Estimated abundance was highest in the winter, and for most species was higher in the second (2013-14) than first (2012-13) winter of surveys. Species richness was also higher in the second winter.
- High species density and diversity also occurred in spring and fall, suggesting that migratory and overwintering species dominate the region's species composition.
- Although species abundance and richness was generally lower during the summer, members of some protected species were present during the summer, largely closer to the shore.

Implications

Identifying areas more or less suitable for development involves prioritizing areas rich in abundant species, as well as important areas for species of concern (such as terns) that may be vulnerable even at low numbers.

---

[1] For more detailed context for this chapter, please see the introduction to Part III of this report.

Abstract

Proposed offshore wind energy development on the Atlantic Outer Continental Shelf has brought attention to the need for baseline studies of marine birds. We compiled line transect data from 15 shipboard surveys (June 2012 to April 2014), along with associated remotely-sensed habitat data, in the lower Mid-Atlantic Bight off the coast of Delaware, Maryland, and Virginia. We used observations from 40 marine bird species to inform a hierarchical community distance sampling model that estimated the seasonal detection and abundance of marine birds in the study area. We hypothesized that avian benthivores (bottom-feeders) respond more to static covariates that characterize seafloor variability, and that piscivores (fish-eaters) respond primarily to dynamic covariates that quantify surface productivity. Treating each season separately, we included six oceanographic parameters to estimate seabird abundance: three static (distance to shore, slope, sediment grain size), and three dynamic covariates (sea surface temperature, salinity, primary productivity). We compared the variation in species-specific and community-level responses to these habitat features, including for rare and protected species, and predicted the abundance for each species across the study area. Our hypothesis was partially supported by our results, but there was wide interannual, seasonal, and interspecies variation in habitat relationships. We found that abundance and diversity was highest for overwintering species. These results show the importance of quantifying detection and determining the ecological drivers of a community's distribution and abundance, within and among species, for evaluating the potential exposure of marine birds to offshore development.

Introduction

Proposed offshore energy development in the United States over the last decade has brought increased public attention to potential species-level impacts of anthropogenic activities on marine life (Caldow et al. 2015; Winiarski et al. 2014). We present a method of examining species- and community-level exposure of marine birds to potential development within wind energy areas (WEAs) in federal U.S. waters on the Atlantic Outer Continental Shelf. Identifying important habitat for marine communities of mammals, fish, and birds presents one of the most effective mitigation techniques for wind energy development's effects on wildlife: that is, avoiding, 'hotspots', defined as locations where high diversity and densities of sensitive species persist (Marques et al. 2014). Characterizing hotspots of seabird communities is important in assessing potential impacts from offshore development, particularly because as meso-predators, marine birds are useful indicators of environments that support high biodiversity (Lascelles et al. 2012).

The dynamic nature of pelagic marine communities is important to consider in siting offshore development, since marine predators locate prey in an environment characterized by exceptionally high spatial and temporal variability (Davoren et al. 2010; Fauchald et al. 2011). However, "enduring" features of the seafloor (e.g., shelf margins) can also drive the persistence or predictability of hotspots (Santora and Veit 2013). Our primary objective was to quantify the spatial and temporal variability of marine bird abundance and its relationship with habitat covariates in the offshore waters in and around the three WEAs located in the lower Mid-Atlantic Bight, off the coasts of Delaware (DE), Maryland (MD), and Virginia (VA; Figure 12-1).

We evaluated seasonal species abundance and community composition using two years of shipboard surveys and recently-developed hierarchical community distance sampling (HCDS) models (Chapter 11; Sollmann et al. in review). The high rates of identification in shipboard surveys make them a reliable method of documenting species richness for identifying important bird areas (Camphuysen et al. 2004; Smith et al. 2014). Increasing interest in quantifying species richness, as a measure of biodiversity, has spurred the development of community models in the field of ecology (Royle and Dorazio 2008). We use site-specific covariates in a hierarchical distance sampling model to estimate the abundance of multiple species (Royle et al. 2004), all within a single community model (Chapter 11; Sollmann et al. in review). Distance sampling accounts for imperfect detection to estimate 'true' (as opposed to relative) abundance (Buckland et al. 1993). In community models, certain parameters are shared and informed by all species, which improves the predictive power of rare species, because "borrowing strength" from the rest of the community renders the model robust to spurious covariate effects (Madon et al. 2013). Accurately representing the breadth of environmental variability across the study area is one of the most important factors in predicting the distribution and abundance of seabirds to unsampled areas, for assessing their potential post-construction displacement (Lapeña et al. 2011). Our approach enables us to incorporate infrequently detected species that may otherwise be excluded from modeling efforts, and thus we make use of the full shipboard survey dataset in analyzing species abundance and habitat relationships.

Seasonality in species richness or abundance is an important factor in determining when it is possible to minimize disturbance from the construction of wind facilities (Bailey et al. 2014). In our study area, breeders (e.g., pelicans, terns) and southern hemisphere winterers (e.g., storm-petrels) are generally present during the North Atlantic summer (see Table 12-1 for Latin names). Migratory and pelagic species that range throughout the region include ospreys, phalaropes, jaegers, fulmars and shearwaters. Overwintering, nonbreeding species in the region include northern breeders such as Northern Gannets, grebes, cormorants, gulls, loons, sea ducks, and alcids (e.g., murres).

Generally, these species fall into three feeding categories: piscivores (fish-eaters, e.g., Northern Gannets), planktivores (e.g., storm-petrels) or benthivores (bottom-feeding divers, e.g., sea ducks). Sea ducks such as scoters sometimes feed on fish and plankton, but primarily rely on more sessile benthic prey such as mollusks (Loring et al. 2014). The spatial and temporal patterns of marine birds at-sea are largely determined by these foraging ecologies, which factors into the cumulative impacts of disturbance, displacement, or collision risk from offshore wind energy development (for review, see Bailey et al. 2014; Langston 2013).

We hypothesized that habitat use would correspond to the foraging ecology of different species groups. We expected static seafloor characteristics to have a larger effect on benthivores (e.g., scoters), and dynamic sea surface characteristics (e.g., related to currents, etc.) to have a stronger effect on piscivores and planktivores (hereafter referred to as surface-feeders). Using the HCDS approach (Chapter 11; Sollmann et al. in review), we evaluate the relationships of species abundance with static and dynamic oceanographic parameters. The results of this study provide seasonal information on community composition and habitat use in the lower Mid-Atlantic Bight. We predict the distribution and abundance of seabirds for the purpose of minimizing effects to those populations from offshore wind energy development.

Methods

Marine bird data collection
From June 2012 to April 2014, we collected shipboard data on 15 surveys that lasted 4-5 days each. Two surveys were conducted in each year and season, defined as spring (Mar-May), summer (Jun-Aug), fall (Sep-Nov), and winter (Dec-Feb). We chartered a 55-ft vessel, which departed from the ports of Ocean City, MD and Virginia Beach, VA to transit 12 transects across the Atlantic Outer Continental Shelf (Figure 12-1). Two pairs of observers alternated 2-h shifts collecting standard line-transect data using distance sampling (Buckland et al. 1993). While the recorder entered data into the program dLOG (R.G. Ford Consulting, Inc.), and regularly updated changes in environmental conditions (Beaufort sea state, etc.), the observer scanned the horizon, focusing on one forward quadrant on either side of the vessel. We continuously recorded the species, count, distance, and angle to seabird observations (see Appendix 12A and Chapter 6 for more details on data collection methods).

Data analysis
We implemented a set of HCDS models to estimate abundance and flock size while accounting for imperfect detection (Chapter 11; Royle et al. 2004; Sollmann et al. in review). Because HCDS requires

spatial replication, we split the 12 tracklines for each survey into segments that averaged approximately 4 km, each of which is considered an individual 'site' in the model (Equation 1). We used seabird data observed up to one km perpendicular to the track line, beyond which there were few observations identified to species. We calculated mean habitat values per segment for six remotely-sensed covariates downloaded from online databases (Appendix 12A): three static (distance to shore, 'Dst'; seafloor slope, 'Slp'; sediment grain size, 'Grn') and three dynamic (daily sea surface temperature [SST], 'Sst'; daily salinity, 'Sal', monthly chlorophyll anomaly, 'Chl'). Sediment grain size ranged from fine to coarse sandy substrate, and is a proxy for variations in benthic prey assemblages (Loring et al. 2013). Chlorophyll anomaly is an index of high or low phytoplankton density, or extreme values of primary productivity at the sea surface (Santora and Veit 2013). Additional information on covariates may be found in Appendix 12A.

In a community model, multiple species are combined into one analysis that encompasses both abundant and uncommon species (Royle and Dorazio 2008). Here, we defined the marine bird community as a guild composed of species that are known to cohesively use marine habitat (we list those included in the community models in Table 12-1). Because scoters were largely identified to genus, as opposed to species, we removed them from the community model and treated them as a single group in a separate 'scoter' model (made up of White-winged Scoters, Black Scoters, and Surf Scoters; Table 12-2, Appendix 12A). We separated analyses by season to accommodate temporal changes in species composition resulting from migratory patterns, and to allow species-level covariate effects to vary independently by season for breeders and nonbreeders. Therefore, we present the results from one distance sampling model for scoters during the nonbreeding seasons when scoters were present in the area (first year: Nov 2012 – Mar 2013; second year: Oct 2013 – Apr 2014). We also present the results of one HCDS model for each of seven seasons (first year summer, fall, and winter, Jun 2012 – Jan 2013; second year spring, summer, fall, and winter, Mar 2013 – Feb 2014). There were at least five species with a single detection in each season of the second year (observed number of flocks = 1), which we removed to avoid problems with model convergence.

The sampling unit of analysis was an observation of a 'flock' containing one or more individuals. The model included two components that estimated (1) abundance of flocks (number of seabird clusters) based on distance sampling, and (2) flock size for each species to calculate total abundance (number of individuals). For the first component, we fit either a half-normal or negative exponential detection function on the observed distances to a flock, selecting the best-fitting distance function by computing Bayesian p-values using Freeman-Tukey fit statistics (Gelman et al. 2014). We also report this measure of goodness of fit for flock abundance and flock size.

Due to overdispersion, which is common in seabird counts (Zipkin et al. 2014), we assumed that the flock abundance, N_{ij}, of species i at site j followed a Negative Binomial distribution. We modeled the variation in mean abundance of flocks, λ_{ij}, as a function of the covariates such that:

$$N_{ij} \sim Negative\ Binomial(\lambda_{ij}, r)$$

$$\log(\lambda_{ij}) = \alpha_{0,i} + \log(site\ length_j) + \tag{1}$$

$$\alpha_{1,i}Dst_j + \alpha_{2,i}Slp_j + \alpha_{3,i}Grn_j + \alpha_{4,i}Sst_j + \alpha_{5,i}Sal_j + \alpha_{6,i}Chl_j$$

where we included the log of the length of each segment as an offset in the model to standardize for slight variations in the true survey tracks (see Appendix 12A). Each parameter (e.g., $\alpha_{0,i}...\alpha_{6,i}$) was species-specific, governed by a hyperdistribution. For example, each species i had an intercept $\alpha_{0,i}$, such that:

$$\alpha_{0,i} \sim Normal(\mu_{\alpha 0}, \sigma_{\alpha 0})$$

where the hyperparameters of these distributions, here $\mu_{\alpha 0}$ and $\sigma_{\alpha 0}$, are shared and informed by all species within the model. This allowed us to (1) retain species with few detections that would have otherwise been discarded from analysis, and (2) compare habitat use by each species to the overall mean community response. We modeled the observed flock sizes, $\boldsymbol{F}_i$, a vector of flock sizes for each species i, as an outcome of a zero-truncated Poisson – Negative Binomial mixture model, which allowed us to accommodate overdispersion, but with limits due to small sample sizes (Appendix 12A).

To predict to areas between and around the sampled transects, we first established a grid that contained the study area (Figure 12-1) based on the data layer with the coarsest spatial resolution (chlorophyll at 4 km). Daily covariate values made up the finest temporal resolution used in the model input, therefore, we used data from the midpoint of each season to predict overall abundance of flocks on that day (spring: 15 Apr, summer: 15 Jul, fall: 15 Oct, winter: 15 Jan). For example, we predicted the abundance for fall 2012 using the posterior mean parameter estimates and data from Oct 2012 for chlorophyll anomaly, and 15 Oct 2012 for SST and salinity. We implemented the HCDS models in a Bayesian framework using the package "rjags" to run the software JAGS (Plummer 2003) in program R version 2.15.3 (R Development Core Team 2013). We diagnosed convergence on three parallel chains that ran for 30,000 iterations (Gelman et al. 2014).

Results

For the community models, we analyzed 40 marine bird species that fell into 11 taxonomic families (Table 12-1). Community composition differed between years (Table 12-3): there were 29 species observed in the first year (15 summer, 22 fall, 16 winter) and 35 observed in the second year (18 spring, 11 summer, 16 fall, 21 winter). The separate scoter group models included the three aforementioned species, White-winged, Black, and Surf Scoters, which were observed during the nonbreeding season (Table 12-2).

Overall patterns of estimated and predicted abundance for the entire community in most seasons reflect the influence of the shoreline, to which most species adhered closely (Figure 12-2, Figure 12-3). Exceptions to this pattern included several spring migrant species that were predicted in higher numbers offshore, such as Common Terns and Red Phalaropes, some wintering alcids (e.g., Dovekies), and Wilson's Storm-petrels in summer (Figure 12-4). Only in the fall of the first and second year did a covariate (grain size or distance to shore, respectively) have a strong effect on the entire community (Table 12-4), which was generally driven by the more abundant species (Table 12-3). Coefficient of variation (CV) maps (Figure 12-5) were calculated for the estimated number of flocks to show

uncertainty relative to the predicted mean in flock abundance. In the case of scoters, the higher CV towards the edge of the Outer Continental Shelf was due to sparse data and estimated flock abundances close to zero in these areas (Figure 12-3).

Bayesian p-values (Table 12-5) indicated that the Negative Binomial distribution was a good fit for abundance for all species. Mean estimated flock sizes for each species corresponded closely to mean observed flock sizes (Table 12-1), although variation in the overdispersion of flocks produced poor fit statistics for a few of these models (Table 12-5), likely due to few observed flocks (small sample size) but large variation in the observed flock size that we could not adequately model. For the detection function, the half-normal distribution fit the first year summer community, while the negative exponential function fit the other seasons and the scoter observations (Table 12-5). As expected, we found that detection was significantly lower at higher Beaufort sea states (Table 12-4). Additionally, more conspicuous species such as Northern Gannets were detectable at farther distances than scoters (Appendix 12B).

To evaluate our hypothesis, we compared species (Figure 12-6, Figure 12-7) and community-level (Table 12-4) effects on the surface-feeding community to group-level habitat effects on scoters (benthivores, Figure 12-8, Table 12-6); responses were not consistent between species, seasons or years, as described below. In many cases, the community mean for the coefficient of distance to shore was not significantly different from zero (Table 12-4) but the species-specific parameter was significant (Figure 12-6, Figure 12-7). The three dynamic covariates (SST, salinity, and chlorophyll) were also significant predictors in many models, although their effects varied by species (Figure 12-7) and were much more important in some seasons (e.g., SST in the first fall) than others. During the fall of 2012, the surface-feeding community as a whole was associated with fine sediment grain size, which was driven by Royal Terns, Common Terns, Laughing Gulls, Northern Gannets, and Double-crested Cormorants; in fall 2013, the entire community was likely to be close to shore, driven by 13 of the 16 species (the main exception being Cory's Shearwater).

We focus primarily on winter models below, due to the high abundance and species diversity within the study area in this season. For details on the distribution and abundance of species in response to covariate effects in the spring, summer, and fall, see Appendix 12B and Figure 12-7.

Winter
In the nonbreeding season across both years (2012-2014), scoter abundances had a significant relationship with distance to shore (a static covariate) and to high primary productivity (i.e., chlorophyll anomaly, a dynamic covariate; Figure 12-8). During the first year (2012-13), two static covariates (gentle slope and fine sediment) were strong predictors of scoter abundance but not of the wintering surface-feeding community. Additionally, scoter abundance was not associated with the dynamic covariate SST, but several wintering surface-feeders abundances were (Bonaparte's Gull, Manx Shearwater, Common Loon, Great Black-backed Gull, and Dovekie; Figure 12-6). In the second year (2013-14), scoter abundances were not related to those same two static covariates as in the year prior (slope and grain size), but they did associate with cold water, a dynamic covariate. During that same second year winter, surface-feeder abundances were not significantly correlated with sediment grain size but several

surface-feeding species (Northern Gannets and three larids: Bonaparte's Gulls, Herring Gulls, and Ring-billed Gulls) were positively related with gentle slopes. The surface-feeders that associated with cold water in the second year winter were Northern Gannets, Herring Gulls, and Razorbills. Salinity was significantly lower in the second year summer, fall, and winter than in the first (Figure 12-9). Mean SST also contrasted sharply between winters; values used in model fit (i.e., along the sampled survey transects) were considerably warmer in the second year (mean 12.3 ± 2.8°C) compared to the first year (7.7 ± 2.8°C).

Among surface-feeders (Figure 12-6), Northern Gannets had higher estimated abundances close to shore (both years), as did Red-throated Loons; the same was true only for Year 2 for Common Loons. SST and primary productivity drove loon habitat partitioning in the first year, when Common Loons associated with higher SST, and Red-throated Loons associated with higher primary productivity. Alcids were observed farther from shore (i.e., closer to the continental shelf edge), particularly Atlantic Puffins (Year 1) and Razorbills (Year 2). Bonaparte's Gull abundances showed variable responses from the first to second year: in Year 1, they were associated with warm water and proximity to shore, while in Year 2 they associated with low salinity over gentle slope, further from shore. In the second year, Northern Gannets associated with gentle slope and cold water. Alcids also associated with cold water, specifically Dovekies (Year 1) and Razorbills (Year 2). With respect to chlorophyll anomaly (primary productivity), Dovekie abundances were negatively associated (Year 1), and Razorbills positively (Year 2). In the first year winter, Dovekie abundances had a positive relationship with cold water and low primary productivity, which resulted in higher winter 2013 predictions along the Atlantic Outer Continental Shelf (Figure 12-4). Horned Grebes also were estimated to have higher abundances in areas of higher primary productivity. Manx Shearwaters, which are northern breeders, had estimated higher abundance in warmer waters (Year 1).

Discussion

Marine bird abundance estimates revealed that some species adhered closely to the shoreline (e.g., scoters), and were more common in the Delaware and Maryland WEAs, while some species showed pelagic distributions (e.g., during migration), and were more common in the Virginia WEA. By accounting for reduced detectability of scoters, which were present during the nonbreeding season, their estimated abundance was comparable to that of the more common surface-feeding species (e.g., Northern Gannet, Bonaparte's Gulls, and Common Loons in the spring, fall, or winter; Wilson's Storm-petrel, Laughing Gulls, Common Terns and Royal Terns in the summer). The HCDS model allowed us to include rare or elusive species, so as to directly compare habitat use in distinct seabird groups to the entire seabird community, and to document within- and between-species variability across seasons. The results show some consistencies with our hypothesis that the distribution of scoters would relate more to static covariates (distance to shore, slope, sediment grain size), compared to dynamic covariates (SST, salinity, chlorophyll anomaly), which we expected to drive the community of surface-feeders.

In line with our hypothesis, during the first year nonbreeding season (2012-2013), overwintering benthivores (scoters) showed significant relationships with static covariates characterizing seafloor variability (slope, sediment grain size), to which the wintering surface-feeders did not respond.

Furthermore, scoter abundances were not associated with the dynamic covariate SST, which was a significant predictor of the abundance of wintering surface-feeders. Scoters are known to adhere closely to the shoreline, where they have easier access to benthic prey at shallower depths (Loring et al. 2014). In our study area, primary productivity was high along the coast, which could explain the association between this dynamic covariate and high scoter abundance. However, during the second year winter season (2013-2014), scoter abundance was positively related to cold water (a dynamic covariate), and not significantly related to static covariates characterizing seafloor variability (slope, sediment grain size), unlike the first year. During that same second year winter, surface-feeders did not respond to sediment grain size, as we would expect, but a few species did respond to gentle slope. SST in the second year was significantly warmer compared to the first year, which could be due to eddies from the Gulf Stream off the Atlantic Outer Continental Shelf (Shealer 2001), or to variation in the North Atlantic Oscillation (Veit and Manne 2015), and may have influenced scoter selection of relatively colder water. This, along with the lack of an association with static seafloor characteristics, may also reflect dynamic movements of scoters in response to unstable sandy sediment (Dalyander et al. 2013) or ephemeral secondary productivity (zooplankton) and benthic prey resources in the second year (Loring et al. 2014).

Distance to shore dominated as one of the most consistent predictors of seabird distributions in our study area. Since it is an easily quantifiable metric for predicting abundance, distance to shore presents a useful foundation on which to base marine spatial planning efforts, but not to the exclusion of the other static and dynamic covariates that drive seabird abundance in this region. For example, northerly-migrating Common Tern abundance in the spring of 2013 had a positive relationship with warm water and low primary productivity, which led to predicted pre-breeding spatial distributions far from shore. Their positive association with fine sediment also resulted in a prediction of high Common Tern abundances at the center of the VA WEA in the spring (Figure 12-4). Considering that sediment grain size is a static covariate, we did not expect it to have a strong effect on the surface-feeding community, as occurred during the spring and first year fall. However, fine grain size correlated positively with proportion of sand, and terns are known to forage over sandy shoals that provide good habitat for high quality forage fish such as sandlance (*Ammodytes* spp.; Goyert 2015; Robards et al. 2000). Further research should investigate whether such a pattern in sediment grain size reflects the distribution of prey, and whether it is likely to persist during the migratory season from year to year, particularly in the WEAs.

We observed 'hotspots' around the mouth of the Delaware and Chesapeake Bay (for example, high richness and abundance of loons, razorbills, gannets, terns, gulls, scoters and others), which were likely driven by a salinity front and high primary productivity. This suggests that future efforts to assess the potential cumulative impacts of offshore wind energy development and shipping-channel traffic on seabird movements and populations may want to closely examine these regions (Chapter 1; Schwemmer et al. 2010). Productivity in our study area ranged from 1-5 mg m^{-3}, which corresponds to the lower end of the longer-term chlorophyll values that had strong positive effects on Common Loons in a study by Winiarski et al. (2013). Productivity relationships with loon abundance varied depending on the season. However, Red-throated Loons were consistently located closer to shore and in areas over colder water than Common Loons, which matched where productivity was generally higher in our study

area (Powers and Cherry 1983). The fact that Dovekies associated with low primary productivity seems counterintuitive, but is likely a function of their distribution away from the highly productive coastline and over the outer edge of the shelf, where cold upwelled water can produce high concentrations of zooplankton (i.e., secondary productivity; Lieske et al. 2014; Veit and Guris 2009). Studies have shown that in the Northwest Atlantic, top-down forcing (negative predator-prey associations) occurs in subarctic waters under low productivity conditions, whereas bottom-up control (resource limitation inducing positive predator-prey relationships) dominates in waters off the east coast of the US where there is relatively higher primary or secondary productivity and species richness (Frank et al. 2007).

Observed species richness was highest in the second year winter and first year fall. High species diversity also extended to the spring, suggesting that migratory and overwintering species dominate the region's species composition. It is important that management considerations include the risk of displacement of nonbreeders that use this habitat while passing through the study area. For example, the procellarids and hydrobatids observed in our study were likely to be observed far from shore, associating with warm Gulf Stream water on the Atlantic Outer Continental Shelf (e.g., Wilson's Storm-petrels; Figure 12-4; Watson et al. 2013). Depending on climate patterns (e.g., the North Atlantic Oscillation), the region may continue to see increasing trends in the abundance of Cory's shearwaters, which reflects their northerly movement with increasingly warmer water along the US East Coast since 2009 (R.R. Veit, unpublished data).

While species abundance and richness was generally lower during the summer (breeding season for Northern Hemisphere species), some federally and state-listed Threatened or Endangered species were present in the region during that time of year (U.S. Fish & Wildlife Service, Delaware Division of Fish & Wildlife, Maryland Wildlife and Heritage Service, Virginia Department of Conservation and Recreation's Division of Natural Heritage). Examples include Roseate Terns (listed in DE, MD, VA, and federally in the USA), Least Terns (DE, MD), Common Terns (DE, MD), Forster's Terns (DE), and Royal Terns (MD). These species were primarily observed nearshore during summer months, while Common Terns were additionally abundant offshore in the spring, which corresponds to the pre-breeding migratory season (Appendix 12B). Studies have suggested that the foraging and breeding behavior of terns places them at risk of collision with offshore wind facilities (e.g., flying within rotor-height during repeated trips through facility footprints to feed chicks at the nest; Bradbury et al. 2014; Everaert 2014). The community distance sampling model enabled us to accommodate these relatively rare species. For example, in the fall, we had only 21 detections of Common Terns in the first year, and 6 in the second year, which might prohibit fitting a fully parameterized distance sampling model to those data. By combining data across species, we were able to estimate fall abundance for Common Terns and estimate their relationships with habitat features, improving our understanding of their distributions. This is particularly important because, while much focus on the exposure of terns to offshore wind energy development has been during the breeding season, we found their exposure to potential development within the Virginia WEA to be highest during the migratory period.

We also accounted for variation in detection, which is important in making comparisons between different species across time (Royle and Dorazio 2008). For example, Northern Gannets are large, white

birds that contrast sharply against a deep blue ocean, and thus their detection probability is higher than less conspicuous species like smaller dark scoters. This results in differences between observed and estimated abundance that varies by species. After estimating detection and habitat relationships as well as abundance of marine birds in this study, future research should evaluate the types of risk that these populations face, as well as other conditions that were outside the sampling frame of the shipboard survey. For example, additional understanding of nocturnal movements and distributions of marine species under different weather conditions would be useful for informing further risk potential. In using our data to identify areas that may be more or less suitable for development, the decision-making process should prioritize further research within areas with high abundance and species richness, as well as areas with target species of concern (e.g., terns) that may be vulnerable even at low numbers.

In summary, species within the seabird community off the coasts of Delaware, Maryland, and Virginia show relatively high variability in their abundance and response to habitat covariates, which we were able to quantify reliably using HCDS. Although it has been suggested that a two-year study can capture much of the spatiotemporal variation in environmental conditions (Kinlan et al. 2012), our study had high variability across seasons from one year to the next. In planning for the potential construction of static structures (wind facilities) in a dynamic environment, it is important to consider that the distribution of hotspots is likely to change over a range of fine to coarse spatiotemporal scales. Considering that the operation of wind facilities can span decades, our study quantifies relatively short-term intra- and inter-annual volatility in the region. Further research is required to provide complementary information on the potential effects of long-term climatological cycles (e.g., North Atlantic Oscillation) or climate change on the exposure of marine animals to offshore energy development. Therefore, two years may provide baseline information on the seasonality of spatial trends, but it is likely not enough to quantify longer-term persistence, volatility, or vulnerability (Bailey et al. 2014).

Literature cited

Bailey, H., Brookes, K., Thompson, P., 2014. Assessing environmental impacts of offshore wind farms: lessons learned and recommendations for the future. Aquatic Biosystems 10, 8.

Bradbury, G., Trinder, M., Furness, B., Banks, A.N., Caldow, R.W.G., Hume, D., 2014. Mapping seabird sensitivity to offshore wind farms. PLoS ONE 9, e106366.

Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., 1993. Distance Sampling: Estimating Abundance of Biological Populations. Chapman and Hall, London.

Caldow, C., Monaco, M.E., Pittman, S.J., Kendall, M.S., Goedeke, T.L., Menza, C., Kinlan, B.P., Costa, B.M., 2015. Biogeographic assessments: A framework for information synthesis in marine spatial planning. Marine Policy 51, 423-432.

Camphuysen, C.J., Fox, A.D., Leopold, M.F., Petersen, I.K., 2004. Towards standardised seabirds at sea census techniques in connection with environmental impact assessments for offshore wind farms in the U.K. Royal Netherlands Institute for Sea Research, Texel.

Dalyander, P.S., Butman, B., Sherwood, C.R., Signell, R.P., Wilkin, J.L., 2013. Characterizing wave- and current- induced bottom shear stress: U.S. middle Atlantic continental shelf. Continental Shelf Research 52, 73-86.

Davoren, G., Garthe, S., Montevecchi, W., Benvenuti, S., 2010. Influence of prey behaviour and other predators on the foraging activities of a marine avian predator in a Low Arctic ecosystem. Marine Ecology Progress Series 404, 275-287.

Everaert, J., 2014. Collision risk and micro-avoidance rates of birds with wind turbines in Flanders. Bird Study 61, 220-230.

Fauchald, P., Skov, H., Skern-Mauritzen, M., Hausner, V.H., Johns, D., Tveraa, T., 2011. Scale-dependent response diversity of seabirds to prey in the North Sea. Ecology 92, 228-239.

Frank, K.T., Petrie, B., Shackell, N.L., 2007. The ups and downs of trophic control in continental shelf ecosystems. Trends in Ecology & Evolution 22, 236-242.

Gelman, A., Carlin, J.B., Stern, H.S., Dunson, D.B., Vehtari, A., Rubin, D.B., 2014. Bayesian Data Analysis, Third Edition. Taylor & Francis, New York, NY, USA.

Goyert, H.F., 2015. Foraging specificity and prey utilization: evaluating social and memory-based strategies in seabirds. Behaviour 152, 861-895.

Kinlan, B.P., Zipkin, E.F., O'Connell, A.F., Chris, C., 2012. Statistical analyses to support guidelines for marine avian sampling: final report. U.S. Department of the Interior, Bureau of Ocean Energy Management, Office of Renewable Energy Programs. OCS Study BOEM 2012-101. NOAA Technical Memorandum NOS NCCOS 158, Herndon, VA.

Langston, R.H.W., 2013. Birds and wind projects across the pond: A UK perspective. Wildlife Society Bulletin 37, 5-18.

Lapeña, B.P., Wijnberg, K.M., Stein, A., Hulscher, S.J.M.H., 2011. Spatial factors affecting statistical power in testing marine fauna displacement. Ecological Applications 21, 2756-2769.

Lascelles, B.G., Langham, G.M., Ronconi, R.A., Reid, J.B., 2012. From hotspots to site protection: Identifying Marine Protected Areas for seabirds around the globe. Biological Conservation 156, 5-14.

Lieske, D.J., Fifield, D.A., Gjerdrum, C., 2014. Maps, models, and marine vulnerability: Assessing the community distribution of seabirds at-sea. Biological Conservation 172, 15-28.

Loring, P.H., Paton, P.W.C., McWilliams, S.R., McKinney, R.A., Oviatt, C.A., 2013. Densities of wintering scoters in relation to benthic prey assemblages in a North Atlantic estuary. Waterbirds 36, 144-155.

Loring, P.H., Paton, P.W.C., Osenkowski, J.E., Gilliland, S.G., Savard, J.-P.L., McWilliams, S.R., 2014. Habitat use and selection of black scoters in southern New England and siting of offshore wind energy facilities. The Journal of Wildlife Management 78, 645-656.

Madon, B., Warton, D.I., Araújo, M.B., 2013. Community-level vs species-specific approaches to model selection. Ecography 36, 1291-1298.

Marques, A.T., Batalha, H., Rodrigues, S., Costa, H., Pereira, M.J.R., Fonseca, C., Mascarenhas, M., Bernardino, J., 2014. Understanding bird collisions at wind farms: An updated review on the causes and possible mitigation strategies. Biological Conservation 179, 40-52.

Plummer, M., 2003. JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling, In Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003). March, pp. 20-22.

Powers, K.D., Cherry, J., 1983. Loon migrations off the coast of the Northeastern United States. The Wilson Bulletin 95, 125-132.

R Development Core Team, 2013. R: A language and environment for statistical computing, Version 2.15.3. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org

Robards, M.D., Willson, M.F., Armstrong, R.H., Piatt, J.F., 2000. Sand lance: a review of biology and predator relations and annotated bibliography. USDA Forest Service, Pacific Northwest Research Station, Portland, OR.

Royle, J.A., Dawson, D.K., Bates, S., 2004. Modeling abundance effects in distance sampling. Ecology 85, 1591-1597.

Royle, J.A., Dorazio, R.M., 2008. Hierarchical Modeling and Inference in Ecology: The Analysis of Data from Populations, Metapopulations and Communities. Elsevier Science, Burlington, MA USA.

Santora, J., Veit, R., 2013. Spatio-temporal persistence of top predator hotspots near the Antarctic Peninsula. Marine Ecology Progress Series 487, 287-304.

Schwemmer, P., Mendel, B., Sonntag, N., Dierschke, V., Garthe, S., 2010. Effects of ship traffic on seabirds in offshore waters: implications for marine conservation and spatial planning. Ecological Applications 21, 1851-1860.

Shealer, D.A., 2001. Foraging behavior and food of seabirds, In Biology of Marine Birds. eds E.A. Schreiber, J. Burger, pp. 137-177. CRC Press, New York, NY.

Smith, M.A., Walker, N.J., Free, C.M., Kirchhoff, M.J., Drew, G.S., Warnock, N., Stenhouse, I.J., 2014. Identifying marine Important Bird Areas using at-sea survey data. Biological Conservation 172, 180-189.

Sollmann, R., Gardner, B., Williams, K.A., Gilbert, A.T., Veit, R.R., in review. A community distance sampling model to investigate the abundance and distribution of seabirds. Methods in Ecology and Evolution.

Veit, R., Guris, P., 2009. Recent increases in alcid abundance in the New York Bight and New England Waters. New Jersey Birds 34, 83-87.

Veit, R.R., Manne, L.L., 2015. Climate and changing winter distribution of alcids in the Northwest Atlantic. Frontiers in Ecology and Evolution 3.

Watson, H., Hiddink, J., Hobbs, M., Brereton, T., Tetley, M., 2013. The utility of relative environmental suitability (RES) modelling for predicting distributions of seabirds in the North Atlantic. Marine Ecology Progress Series 485, 259-273.

Winiarski, K., Miller, D., Paton, P., McWilliams, S., 2013. Spatially explicit model of wintering common loons: conservation implications. Marine Ecology Progress Series 492, 273-283.

Winiarski, K.J., Miller, D.L., Paton, P.W.C., McWilliams, S.R., 2014. A spatial conservation prioritization approach for protecting marine birds given proposed offshore wind energy development. Biological Conservation 169, 79-88.

Zipkin, E.F., Leirness, J.B., Kinlan, B.P., O'Connell, A.F., Silverman, E.D., 2014. Fitting statistical distributions to sea duck count data: Implications for survey design and abundance estimation. Statistical Methodology 17, 67-81.

Figures and tables
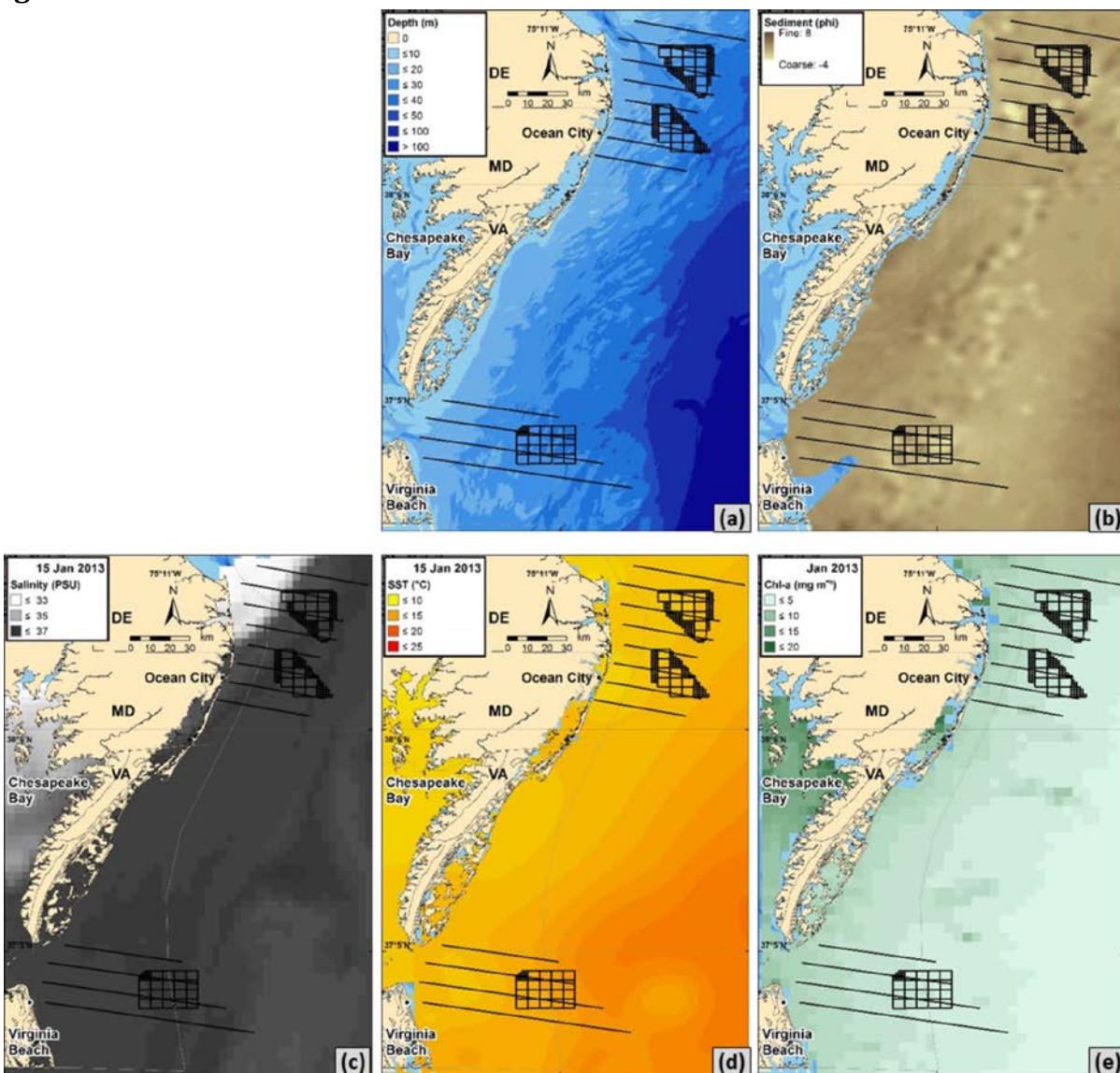
Figure 12-1. Study area and example covariate data. Transects were placed 10 km apart and ran perpendicular to the shoreline, covering federal waters greater than 5 km from the shore and extending out to a length of approximately 35-90 km. Black lines represent boat transects, black grids represent WEAs, and habitat covariates represent (a) bathymetry, distance to shore and slope, (b) sediment grain size (increases in phi units correspond to decreases in size; i.e., coarse to fine sand), (c) 15 Jan 2013 predictive salinity, (d) 15 Jan 2013 predictive sea surface temperature, and (e) Jan 2013 chlorophyll concentration used for model fit and predictions.
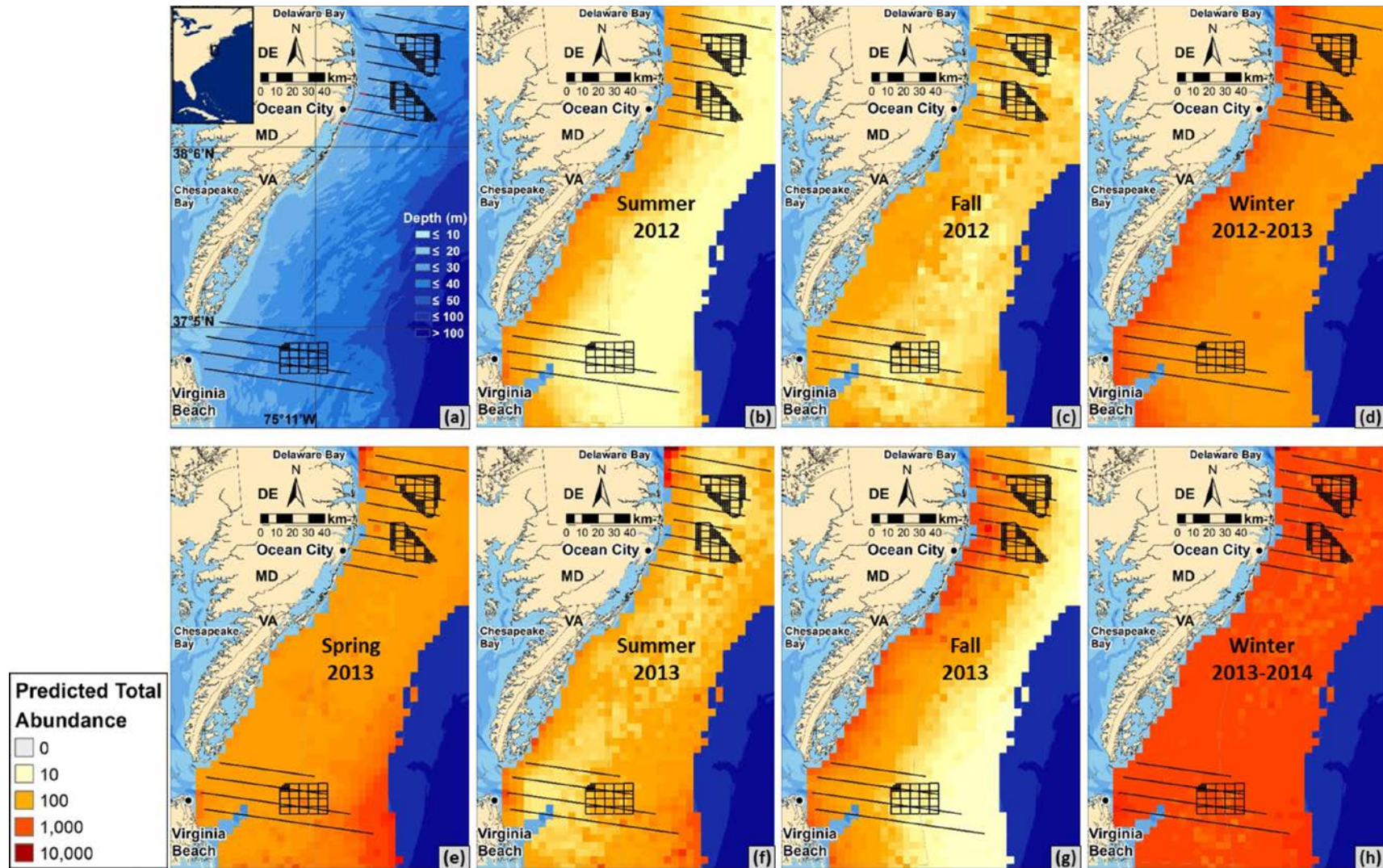
Figure 12-2. Study area (a) and predicted total abundance maps for the first (top) and second (bottom) year in (b, f) summer, (c, g) fall, (d, h) winter (right column), and (e) spring. Abundance maps (b-h) include all species in each seasonal community model (except scoters, which were modeled separately). Each map shows the posterior mean predicted total abundance across the study area: the expected number of flocks multiplied by flock size for each species, then summed across all species. Black lines represent boat transects, red transect segments in (a) delineate the MD extensions, black grids represent WEAs.
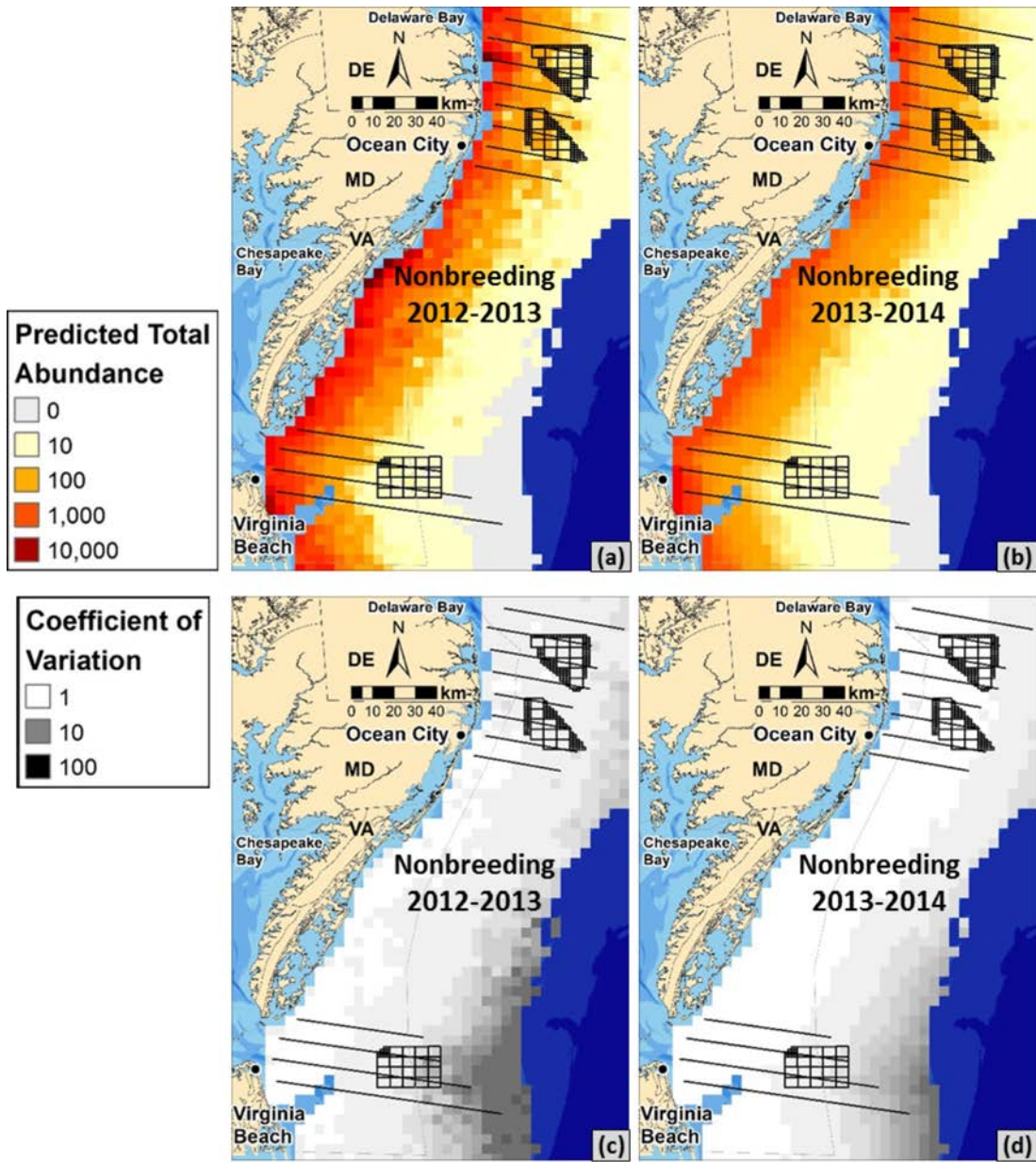
Figure 12-3. Total abundance (top) for scoters during the nonbreeding season, predicted to 15 Jan 2013 (first year, left) or 15 Jan 2014 (second year, right). The coefficient of variation (CV) maps below were derived only for the abundance of flocks, not total abundance. The higher CV towards the edge of the Outer Continental Shelf coincided with sparse data and estimated flock abundances close to zero in the areas farther away from the coastline. Black lines represent boat transects, black grids represent WEAs.
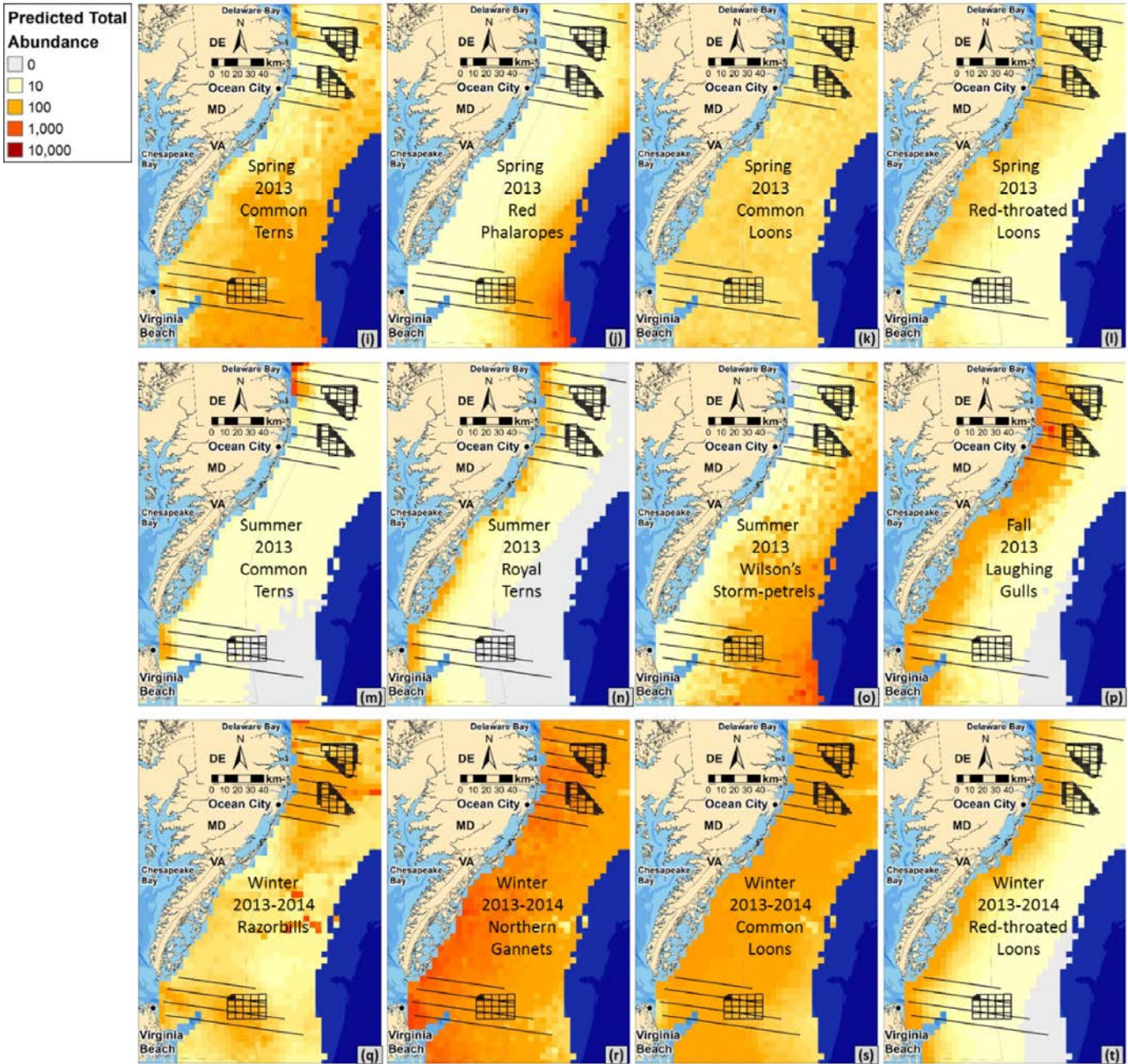
Figure 12-4. Predicted total abundance for selected species per season. The distribution of some of the most abundant species selected from each season, predicted to (a-b) summer 2012 (15 Jul), (c-d) fall 2012 (15 Oct), and (e-h) winter 2013 (15 Jan), as well as (i-l) spring 2013 (15 Apr), (m-o) summer 2013 (15 Jul), (p) fall 2013 (15 Oct), and (q-t) winter 2014 (15 Jan). Selected species include Common Terns (a, i, m), Royal Terns (b, n), Bonaparte's Gulls (c), Razorbills (e, q), Dovekies (f), Common Loons (g, k, s), Red-throated Loons (h, l, t), Red Phalaropes (j), Wilson's Storm-petrels (o), Laughing Gulls (d, p), and Northern Gannets (r).
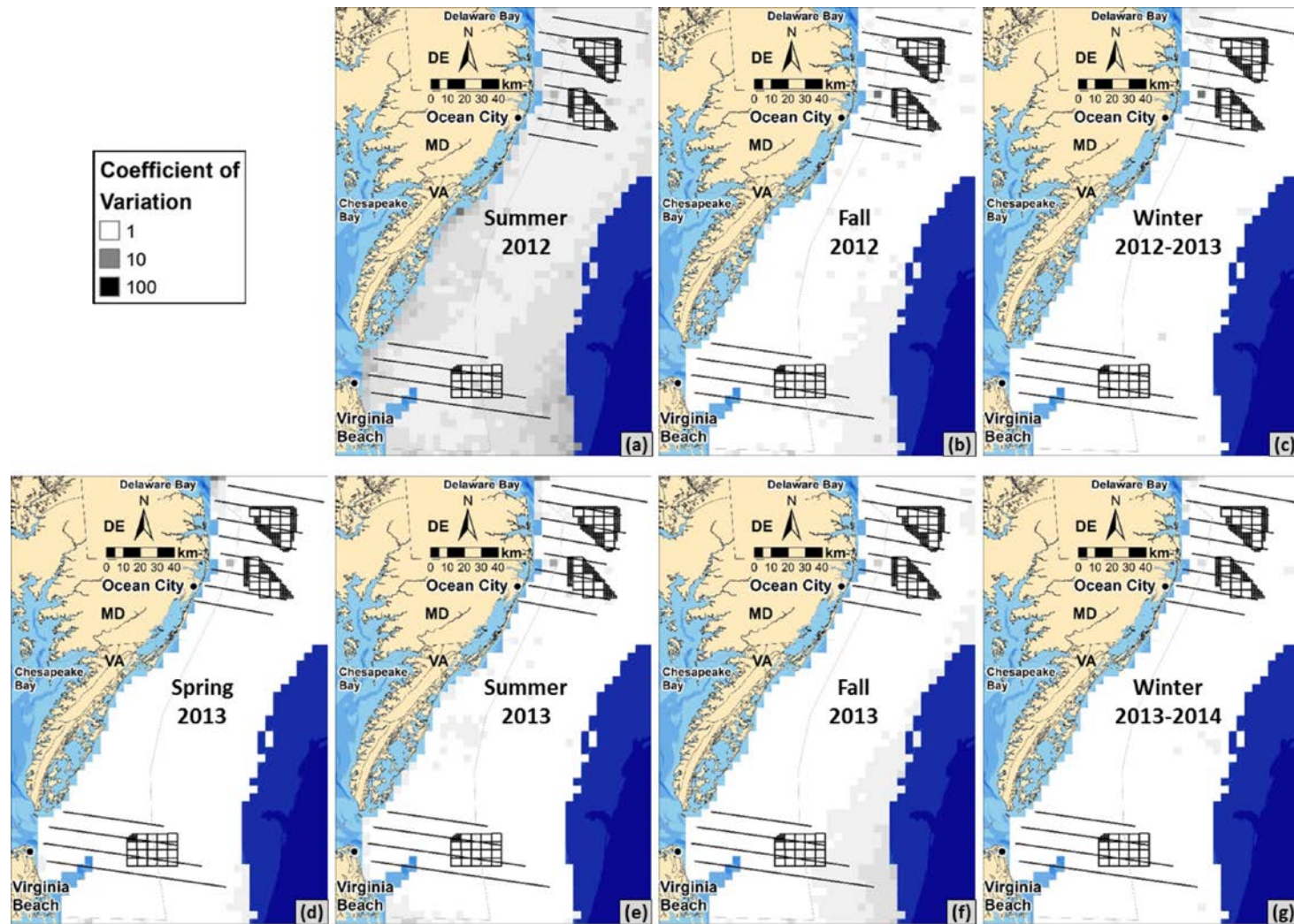
Figure 12-5. Coefficient of variation (CV) maps for abundance of flocks in the first (top) and second (bottom) year (a, e) summer, (b, f) fall, (c, h) winter (right column), and (d) spring. These figures include all species in each seasonal community model (to the exclusion of scoters, which were modeled separately) and predicted to the mid-point of the season as described in the text.
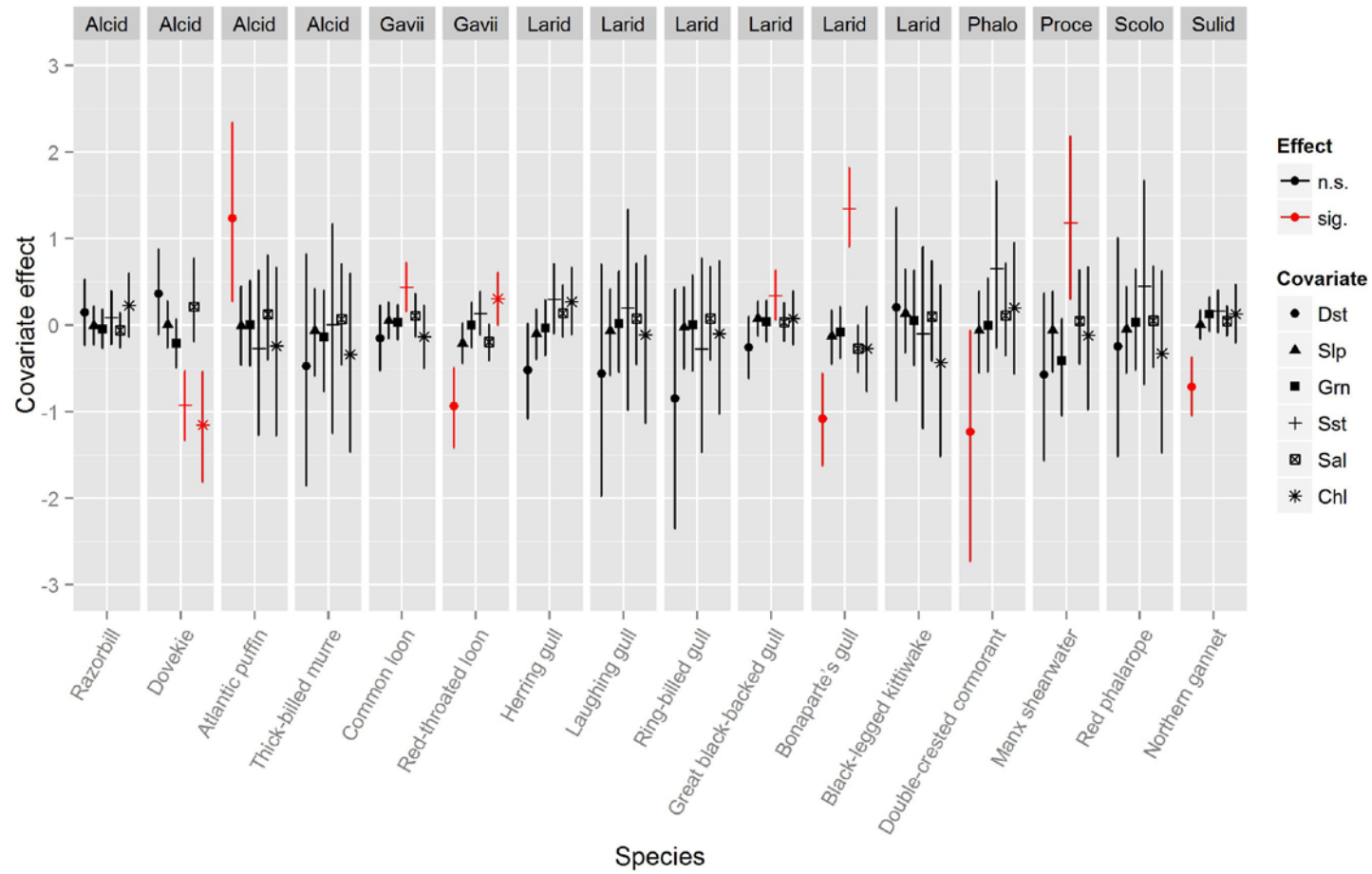
(a)
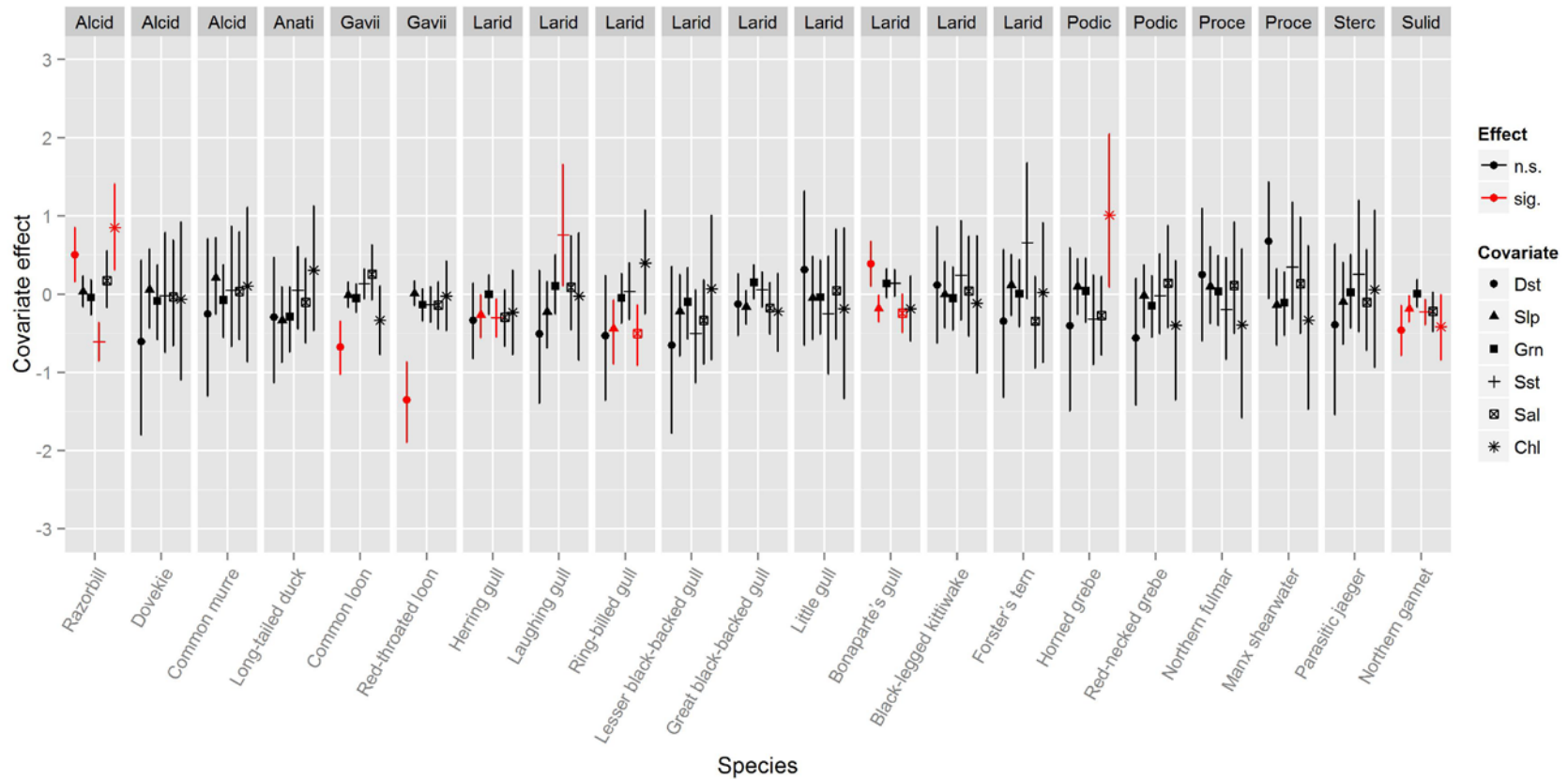
(b)

Figure 12-6. First (a) and second (b) year effects of habitat covariates on each species in the winter community model (excluding scoters). Error bars (Bayesian credible intervals) in red indicate which parameter estimates (on the log scale) were significantly different from zero; n.s. = not significant, sig. = significant, Dst = distance to shore, Slp = slope of the seafloor, Grn = sediment grain size, Sst = sea surface temperature, Sal = salinity, Chl = chlorophyll anomaly. Species are ordered by family (see Table 12-1 for abbreviations). Covariate effects are relative to study-specific habitat values, where negative responses indicate associations with proximity to shore, gradual slope, coarse sediment grain size, cold water, low salinity, and low primary productivity; positive responses indicate dependence on distance away from shore, steep slope, fine sediment grain size, warm water, high salinity, and high primary productivity.

(a)

(b)

(c)

(d)

(e)

Figure 12-7. First year summer (a), and fall (b), and second year spring (c), summer (d), and fall (e) effects of habitat covariates on each species in the community models.
Error bars (Bayesian credible intervals) in red indicate which parameter estimates (on the log scale) were significantly different from zero; n.s. = not significant, sig. = significant, Dst = distance to shore, Slp = slope of the seafloor, Grn = sediment grain size, Sst = sea surface temperature, Sal = salinity, Chl = chlorophyll anomaly. Species are ordered by family (see Table 12-1 for abbreviations). Covariate effects are relative to study-specific habitat values, where negative responses indicate associations with proximity to shore, gradual slope, coarse sediment grain size, cold water, low salinity, and low primary productivity; positive responses indicate dependence on distance away from shore, steep slope, fine sediment grain size, warm water, high salinity, and high primary productivity.

Figure 12-8. Habitat effects for scoters during the nonbreeding season (Nov 2012 - Mar 2013, and Oct 2013 – Apr 2014). Error bars (Bayesian credible intervals) in red indicate which parameter estimates (on the log scale) were significantly different from zero; n.s. = not significant, sig. = significant, Dst = distance to shore, Slp = slope of the seafloor, Grn = sediment grain size, Sst = sea surface temperature, Sal = salinity, Chl = chlorophyll anomaly, Anati = anatid family. Covariate effects are relative to study-specific habitat values, where negative responses indicate associations with proximity to shore, gradual slope, coarse sediment grain size, cold water, low salinity, and low primary productivity; positive responses indicate dependence on distance away from shore, steep slope, fine sediment grain size, warm water, high salinity, and high primary productivity.
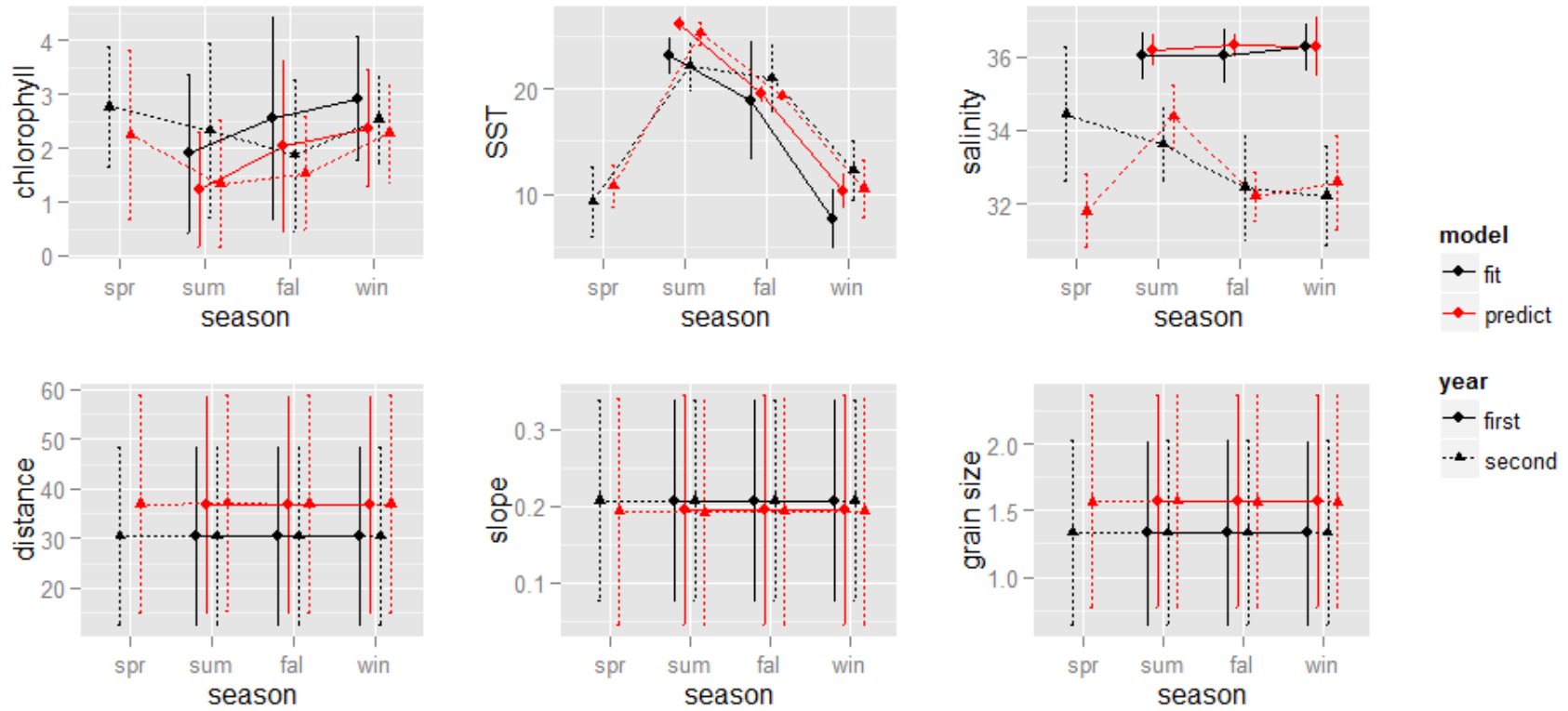
Figure 12-9. Comparison of mean covariate values and standard deviations (bars) used in model fit (along transects) and prediction (entire study area) for the first and second year, across each season (spr = spring, sum = summer, fal = fall, win = winter). Dynamic covariates are shown in the top row and static covariates in the bottom row.

Table 12-1. Seasonal flock size for each species in the community models, including Latin names and taxonomic family. "Observed" and "estimated" refer to the sampled area along transects, by season (across two surveys), where "Obs." is the mean of the observed flock sizes, and "Estim." is the estimated posterior mean for flock size.

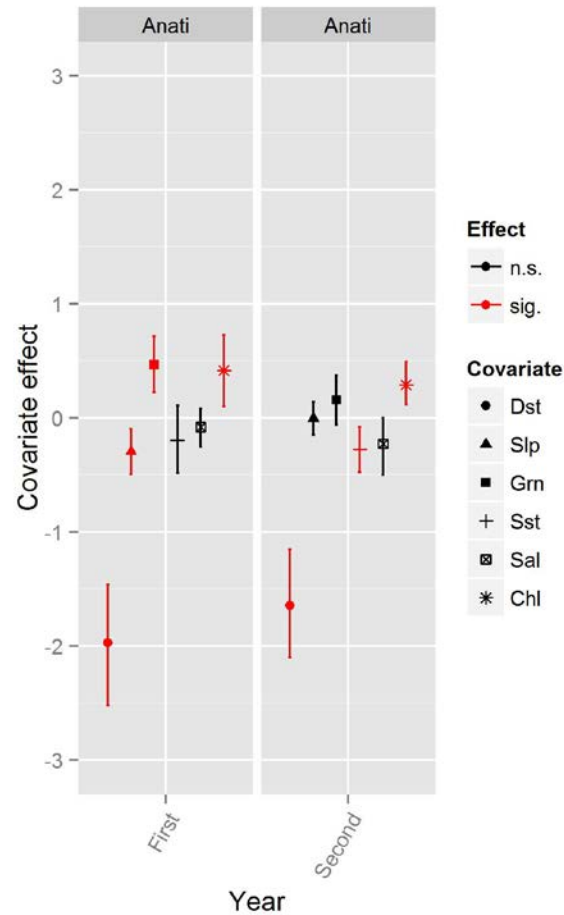| Common Name	Latin Name	Family	2012 Summer		2012 Fall		2012-13 Winter		2013 Spring		2013 Summer		2013 Fall		2013-14 Winter	
			Obs.	Estim.	Obs.	Estim.	Obs.	Estim.	Obs.	Estim.	Obs.	Estim.	Obs.	Estim.	Obs.	Estim.
Razorbill	*Alca torda*	Alcidae					2.5	2.5	2.1	2.1					3.1	3.2
Dovekie	*Alle alle*	Alcidae					1.9	2.0	1.0	1.0					1.0	1.2
Atlantic Puffin	*Fratercula arctica*	Alcidae					1.8	1.8								
Common Murre	*Uria aalge*	Alcidae													1.3	1.4
Thick-billed Murre	*Uria lomvia*	Alcidae					1.0	1.6								
Long-tailed Duck	*Clangula hyemalis*	Anatidae													2.7	2.7
Red-breasted Merganser	*Mergus serrator*	Anatidae							8.0	7.8						
Common Loon	*Gavia immer*	Gaviidae	1.0	1.2	2.0	2.1	1.5	1.5	1.5	1.5	2.0	2.0	1.2	1.5	5.0	5.4
Red-throated Loon	*Gavia stellata*	Gaviidae			1.5	1.5	1.3	1.3	1.3	1.3					1.6	1.6
Wilson's Storm-petrel	*Oceanites oceanicus*	Hydrobatidae	1.8	2.1	1.0	1.1			1.0	1.0	1.6	1.7				
Herring Gull	*Larus argentatus*	Laridae	1.0	2.0	1.1	1.1	1.2	1.3	1.5	1.6			1.7	1.8	2.4	2.5
Laughing Gull	*Leucophaeus atricilla*	Laridae	1.4	1.5	1.3	1.3	1.0	1.6	1.3	1.3	1.6	1.7	3.5	3.5	1.3	1.4
Ring-billed Gull	*Larus delawarensis*	Laridae			1.0	1.2	1.0	1.4					1.0	1.0	1.6	1.6
Lesser Black-backed Gull	*Larus fuscus*	Laridae			1.0	1.1									1.3	1.4
Great Black-backed Gull	*Larus marinus*	Laridae	1.2	1.4	1.2	1.2	1.3	1.3	1.5	1.5	1.1	1.2	1.5	1.5	1.4	1.4
Little Gull	*Hydrocoloeus minutus*	Laridae													1.0	1.2
Bonaparte's Gull	*Chroicocephalus philadelphia*	Laridae			9.1	8.6	3.0	2.9	1.0	1.0					15.4	14.9
Black-legged Kittiwake	*Rissa tridactyla*	Laridae			1.0	1.1	1.0	1.3					1.0	1.0	1.4	1.4
Sabine's Gull	*Xema sabini*	Laridae			1.0	1.2										
Black Tern	*Chlidonias niger*	Laridae	1.5	1.8	1.2	1.2										
Least Tern	*Sternula antillarum*	Laridae							1.3	1.4						
Caspian Tern	*Hydroprogne caspia*	Laridae											1.5	1.5		
Roseate Tern	*Sterna dougallii*	Laridae	1.0	2.0												
Forster's Tern	*Sterna forsteri*	Laridae			3.7	3.6									7.4	7.1
Common Tern	*Sterna hirundo*	Laridae	4.7	5.5	3.6	3.7			4.3	4.4	1.9	2.0	6.0	6.0		
Royal Tern	*Thalasseus maximus*	Laridae	1.5	1.6	2.0	2.0					1.3	1.4	1.6	1.7		
Osprey	*Pandion haliaetus*	Pandionidae									1.0	1.5				
Brown Pelican	*Pelecanus occidentalis*	Pelecanidae	2.0	2.5	2.0	2.0					2.0	2.1	1.5	1.5		
Double-crested Cormorant	*Phalacrocorax auritus*	Phalacrocoracidae	5.0	6.0	24.4	23.1	1.0	1.3	53.7	52.2			88.6	87.6		
Horned Grebe	*Podiceps auritus*	Podicipedidae													1.1	1.1
Red-necked Grebe	*Podiceps grisegena*	Podicipedidae													1.1	1.1
Northern Fulmar	*Fulmarus glacialis*	Procellariidae													1.4	1.4
Cory's Shearwater	*Calonectris diomedea*	Procellariidae	1.0	1.2	1.3	1.4					1.5	1.6	1.0	1.0		
Great Shearwater	*Puffinus gravis*	Procellariidae	1.1	1.2							1.1	1.2				
Sooty Shearwater	*Puffinus griseus*	Procellariidae							6.0	6.0						
Manx Shearwater	*Puffinus puffinus*	Procellariidae	1.0	1.5	1.0	1.2	2.3	2.2	1.0	1.0	1.6	1.7	1.0	1.0	2.3	2.3
Red Phalarope	*Phalaropus fulicaria*	Scolopacidae					3.0	2.4	74.7	72.7						

Common Name	Latin Name	Family	2012 Summer		2012 Fall		2012-13 Winter		2013 Spring		2013 Summer		2013 Fall		2013-14 Winter	
			Obs.	Estim.	Obs.	Estim.	Obs.	Estim.	Obs.	Estim.	Obs.	Estim.	Obs.	Estim.	Obs.	Estim.
Red-necked Phalarope	*Phalaropus lobatus*	Scolopacidae			2.2	2.2							2.3	2.3		
Parasitic Jaeger	*Stercorarius parasiticus*	Stercorariidae			1.0	1.1			1.0	1.0			1.0	1.0	1.0	1.2
Northern Gannet	*Morus bassanus*	Sulidae	1.0	1.5	2.8	2.9	3.6	3.7	1.9	2.0			2.8	2.9	7.4	7.5

Table 12-2. First and second year abundance of scoters during the nonbreeding season (8 surveys). "Observed" and "estimated" refer to the sampled area along transects, by season (across four surveys), where "Obs." is the raw count of individuals, and "Estim." is the estimated posterior mean for total abundance. "Predict." is the posterior mean for the total abundance predicted to the 15 Jan 2013 (first year) or 15 Jan 2014 (second year), over the entire study area (including unsampled areas). Three species make up the 'scoter' group: White-winged Scoters *Melanitta. fusca*, Black Scoters *M. nigra,* and Surf Scoters *M. perspicillata*.

Scoters	Nonbreeding abund.			Flock size	
	Obs.	Estim.	Predict.	Obs.	Estim.
First year (Nov 2012 – Mar 2013)	11990	90545.3	706723.8	24.4	24.7
Second year (Oct 2013 – Apr 2014)	4906	36572.1	305488.7	14.6	14.9

Table 12-3. Seasonal abundance for each species in the community models (excluding scoters). "Observed" and "estimated" refer to the sampled area along transects, by season (across two surveys), where "Obs." is the raw count of individuals, and "Estim." is the estimated posterior mean for total abundance. "Predict." is the posterior mean for total abundance predicted to a single day at the midpoint of each season, over the entire study area (including unsampled areas; see text for more details). Species are listed in order of decreasing total mean estimated abundance, averaged across the seven seasons. The five most abundant (estimated) species in each season are in bold. In the second year, there were at least five species with a single detection in each season (observed number of flocks = 1), which we removed to avoid problems with model convergence related to sparse observations.

Species	2012 Summer			2012 Fall			2012-13 Winter			2013 Spring			2013 Summer			2013 Fall			2013-14 Winter		
	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.
Northern Gannet	2	8.6	274.4	1227	**5728.1**	6308.5	2790	12503.9	**213891.6**	1041	**5768.1**	24305.9	NA	NA	NA	678	**3998.3**	47755.1	4148	**21795.7**	383298.0
Bonaparte's Gull	NA	NA	NA	372	**2200.1**	11285.2	282	1458.2	44000.0	6	65.2	798.1	NA	NA	NA	NA	NA	NA	5471	**38203.7**	704669.7
Common Loon	6	49.1	599.8	208	**1550.2**	3805.0	421	2520.1	**62373.2**	313	**3205.9**	57157.5	16	132.8	1134.6	27	142.2	2485.9	1586	**10688.2**	152887.8
Laughing Gull	106	**394.4**	11549.0	292	**2264.1**	26044.9	1	15.0	496.6	10	191.0	2518.2	289	**1847.5**	87989.4	804	**5862.7**	77448.1	20	176.8	1591.7
Double-crested Cormorant	5	62.5	1564.5	122	705.8	12127.5	4	31.1	921.5	161	2067.2	48545.5	NA	NA	NA	797	**5761.1**	84029.7	NA	NA	NA
Razorbill	NA	NA	NA	NA	NA	NA	375	3839.4	**63221.3**	23	530.9	1509.4	NA	NA	NA	NA	NA	NA	494	**3141.5**	89158.5
Common Tern	252	**1042.1**	19105.0	76	**852.9**	13205.1	NA	NA	NA	376	**3835.1**	105664.4	93	**797.9**	134278.6	36	469.7	2591.6	NA	NA	NA
Red-throated Loon	NA	NA	NA	19	147.7	484.1	277	1792.9	**34540.6**	259	**2541.1**	31648.4	NA	NA	NA	NA	NA	NA	404	**2461.2**	37633.2
Great Black-backed Gull	6	75.5	1715.0	71	516.5	4961.8	243	1641.3	33454.0	58	727.8	5260.7	14	100.4	1965.3	148	**1207.2**	18366.8	179	1263.7	20451.3
Wilson's Storm-petrel	319	**2041.4**	20385.2	5	63.3	699.9	NA	NA	NA	9	135.5	4027.9	290	**3120.8**	115828.5	NA	NA	NA	NA	NA	NA
Herring Gull	1	12.3	557.0	20	173.7	1668.6	73	592.5	10446.9	104	1106.2	25948.1	NA	NA	NA	101	**941.2**	12227.5	235	1707.9	30256.5
Red Phalarope	NA	NA	NA	NA	NA	NA	3	46.0	1023.9	224	**3559.0**	79819.2	NA	NA	NA	NA	NA	NA	NA	NA	NA
Dovekie	NA	NA	NA	NA	NA	NA	204	2681.1	**38556.3**	9	117.2	1860.9	NA	NA	NA	NA	NA	NA	2	19.6	400.8
Royal Tern	86	**422.6**	17971.6	86	502.5	4260.0	NA	NA	NA	NA	NA	NA	85	**730.2**	18995.6	57	384.1	2948.4	NA	NA	NA
Ring-billed Gull	NA	NA	NA	1	13.9	181.3	2	23.4	461.6	NA	NA	NA	NA	NA	NA	6	81.7	1375.1	62	612.3	12388.2
Sooty Shearwater	NA	NA	NA	NA	NA	NA	NA	NA	NA	60	642.1	45266.5	NA	NA	NA	NA	NA	NA	NA	NA	NA
Brown Pelican	4	34.2	1024.6	14	92.1	1402.2	NA	NA	NA	NA	NA	NA	79	**472.4**	11108.1	6	39.7	435.3	NA	NA	NA
Forster's Tern	NA	NA	NA	26	200.5	1035.8	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	52	381.2	3465.8
Manx Shearwater	2	13.4	488.8	1	15.8	311.6	16	163.9	5136.0	4	52.3	380.2	8	63.3	429.2	2	30.6	449.7	21	186.5	5783.7
Cory's Shearwater	5	60.7	1561.8	4	55.9	1946.4	NA	NA	NA	NA	NA	NA	29	245.8	2313.3	11	101.4	1004.8	NA	NA	NA
Red-necked Phalarope	NA	NA	NA	11	157.4	3104.7	NA	NA	NA	NA	NA	NA	NA	NA	NA	14	205.7	1198.5	NA	NA	NA
Red-breasted Merganser	NA	NA	NA	NA	NA	NA	NA	NA	NA	16	255.6	3383.7	NA	NA	NA	NA	NA	NA	NA	NA	NA
Long-tailed Duck	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	35	246.9	3902.5
Great Shearwater	20	**92.3**	377.2	NA	NA	NA	NA	NA	NA	NA	NA	NA	21	101.9	431.7	NA	NA	NA	NA	NA	NA
Black-legged Kittiwake	NA	NA	NA	3	3NA	342.4	3	32.3	996.3	NA	NA	NA	NA	NA	NA	3	24.8	361.2	14	100.8	1751.9
Black Tern	6	52.7	3289.2	6	58.0	617.2	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Parasitic Jaeger	NA	NA	NA	2	17.6	266.9	NA	NA	NA	3	44.3	1071.5	NA	NA	NA	2	24.7	478.9	2	20.4	361.6

Species	2012 Summer			2012 Fall			2012-13 Winter			2013 Spring			2013 Summer			2013 Fall			2013-14 Winter		
	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.	Obs.	Estim.	Predict.
Red-necked Grebe	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	14	101.9	1615.3
Lesser Black-backed Gull	NA	NA	NA	3	29.0	211.7	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	8	66.7	1610.3
Atlantic Puffin	NA	NA	NA	NA	NA	NA	14	94.6	3006.9	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Least Tern	NA	NA	NA	NA	NA	NA	NA	NA	NA	4	75.8	1871.8	NA	NA	NA	NA	NA	NA	NA	NA	NA
Horned Grebe	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	11	73.7	11049.9
Northern Fulmar	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	7	58.2	1446.8
Caspian Tern	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	3	38.8	289.0	NA	NA	NA
Common Murre	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	4	36.2	652.5
Osprey	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	2	21.7	50046.9	NA	NA	NA	NA	NA	NA
Little Gull	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	2	18.1	507.7
Thick-billed Murre	NA	NA	NA	NA	NA	NA	1	14.7	458.6	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Sabine's Gull	NA	NA	NA	1	13.4	320.6	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Roseate Tern	1	5.7	194.1	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Table 12-4. First and second year posterior summaries for the community-level parameters by season. SD is the standard deviation, 2.5% and 97.5% are the respective quantiles, Dst = distance to shore, Slp = slope of the seafloor, Grn = sediment grain size, Sst = sea surface temperature, Sal = salinity, Chl = chlorophyll anomaly, NB overdisp. is the Negative Binomial overdispersion parameter, and Beaufort sea state 3-6 are rough seas (as opposed to calm, 0-2). Parameters are presented on the log scale, and the posterior mean for covariates where the 95% Bayesian credible interval does not overlap zero are in bold italics; all SD terms (shaded) are greater than zero by necessity.

Component	Term	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Abundance	Intercept; $\mu_{\alpha0}$	*-4.8*	0.7	*-4.1*	0.5	*-2.6*	0.7	*-3.0*	0.6	*-3.2*	0.6	*-3.7*	0.5	*-2.5*	0.5
	Intercept SD; $\sigma_{\alpha0}$	2.3	0.6	1.7	0.4	2.6	0.6	2.1	0.4	1.8	0.5	1.7	0.4	2.0	0.4
	Dst, mean; $\mu_{\alpha1}$	-0.9	0.5	0.0	0.2	-0.4	0.3	0.3	0.2	-0.8	0.4	*-1.4*	0.3	-0.3	0.2
	Dst, SD; $\sigma_{\alpha1}$	1.5	0.4	0.7	0.2	0.8	0.2	0.8	0.2	1.2	0.4	0.7	0.2	0.6	0.2
	Slp, mean; $\mu_{\alpha2}$	-0.1	0.1	0.1	0.1	0.0	0.1	0.0	0.1	0.1	0.1	0.1	0.1	-0.1	0.1
	Slp, SD; $\sigma_{\alpha2}$	0.3	0.1	0.3	0.1	0.2	0.1	0.2	0.1	0.3	0.1	0.2	0.1	0.3	0.1
	Grn, mean; $\mu_{\alpha3}$	0.2	0.2	*0.3*	0.1	0.0	0.1	0.1	0.1	0.1	0.2	-0.2	0.1	0.0	0.1
	Grn, SD; $\sigma_{\alpha3}$	0.3	0.1	0.3	0.1	0.3	0.1	0.3	0.1	0.4	0.1	0.3	0.1	0.2	0.1
	Sst, mean; $\mu_{\alpha4}$	-0.3	0.3	-0.6	0.4	0.2	0.2	0.1	0.3	-0.3	0.3	-0.3	0.3	0.0	0.1
	Sst, SD; $\sigma_{\alpha4}$	0.6	0.2	1.8	0.4	0.7	0.2	1.2	0.3	0.7	0.3	1.0	0.3	0.5	0.1
	Sal, mean; $\mu_{\alpha5}$	0.1	0.2	0.2	0.1	0.0	0.1	0.0	0.2	-0.4	0.2	0.1	0.2	-0.1	0.1
	Sal, SD; $\sigma_{\alpha5}$	0.4	0.2	0.3	0.1	0.3	0.1	0.6	0.3	0.5	0.2	0.4	0.2	0.3	0.1
	Chl, mean; $\mu_{\alpha6}$	0.2	0.1	0.0	0.1	-0.1	0.2	0.0	0.1	-0.2	0.2	-0.3	0.2	0.0	0.2
	Chl, SD; $\sigma_{\alpha6}$	0.3	0.1	0.3	0.1	0.5	0.2	0.4	0.1	0.5	0.2	0.4	0.2	0.6	0.2
	NB overdisp.; r_N	*0.5*	0.1	*0.6*	0.1	*0.6*	0.0	*0.9*	0.1	*0.5*	0.1	*1.0*	0.1	*0.9*	0.1
Detection	Intercept; $\mu_{\beta0}$	*5.1*	0.2	*5.0*	0.1	*4.9*	0.1	*4.5*	0.1	*5.0*	0.1	*4.9*	0.2	*5.2*	0.1
	Intercept SD; $\sigma_{\beta0}$	0.5	0.2	0.4	0.1	0.4	0.1	0.4	0.1	0.4	0.1	0.4	0.2	0.2	0.1
	Beaufort 3-6; β_1	*-0.5*	0.1	*-0.3*	0.1	*-0.2*	0.0	*-0.1*	0.1	*-0.3*	0.1	-0.1	0.1	*-0.4*	0.0

Table 12-5. First and second year Bayesian p-values for the abundance and detection components of the models. Values close to 0.5 indicate good model fit. Value in bold indicate which detection function we selected to model abundance. In the case of the second-year spring and fall, the low fit statistic was due to our fitting a Poisson distribution to the flock size of two species with sparse data (< 20 observations) that had large variance-to-mean ratios: Double-crested Cormorants (fall, spring), Common Terns (fall) and Red Phalaropes (spring). We recalculated the fit statistic without those species, to evaluate the impact of just a few species with few observations, and found that this improved the Bayesian p-value (from the reported 0.0 to a value of 0.3, which is closer to the ideal of 0.5). HN = Half Normal, NE = Negative Exponential functions.

Year	Model	Abundance	Detection		Flock
			HN	NE	size
First	Community summer	0.50	**0.49**	0.37	0.52
	Community fall	0.51	0.89	**0.51**	0.11
	Community winter	0.50	0.92	**0.39**	0.61
	Scoter nonbreeding	0.49	0.89	**0.48**	0.75
Second	Community spring	0.52	0.72	**0.34**	0.01
	Community summer	0.50	0.73	**0.42**	0.44
	Community fall	0.48	0.93	**0.49**	0.00
	Community winter	0.49	0.90	**0.32**	0.60
	Scoter nonbreeding	0.51	0.78	**0.47**	0.63

Table 12-6. First and second year posterior summaries of the parameters for scoters during the nonbreeding season (4 surveys, Nov 2012 - Mar 2013 or Oct 2013 – Apr 2014). SD is the standard deviation, 2.5% and 97.5% are the respective quantiles, Dst = distance to shore, Slp = slope of the seafloor, Grn = sediment grain size, Sst = sea surface temperature, Sal = salinity, Chl = chlorophyll anomaly, NB overdisp. is the Negative Binomial overdispersion parameter, and Beaufort sea state 3-6 are rough seas (as opposed to calm, 0-2). Parameters are presented on the log scale, and the posterior mean for covariates where the 95% Bayesian credible interval (BCI) does not overlap zero are in bold italics.

Nonbreeding scoters		First year				Second year			
Component	Term	Mean	SD	2.5%	97.5%	Mean	SD	2.5%	97.5%
Abundance	Intercept; α_0	**-2.5**	0.2	-3.0	-2.1	**-2.3**	0.2	-2.7	-2.0
	Dst; α_1	***-2.0***	0.3	-2.5	-1.5	***-1.6***	0.3	-2.1	-1.1
	Slp; α_2	***-0.3***	0.1	-0.5	-0.1	0.0	0.1	-0.1	0.1
	Grn; α_3	***0.5***	0.1	0.2	0.7	0.2	0.1	-0.1	0.4
	Sst; α_4	-0.2	0.2	-0.5	0.1	***-0.3***	0.1	-0.5	-0.1
	Sal; α_5	-0.1	0.1	-0.2	0.1	-0.2	0.1	-0.5	0.0
	Chl; α_6	***0.4***	0.2	0.1	0.7	***0.3***	0.1	0.1	0.5
	NB overdisp.; r_N	***0.5***	0.1	0.4	0.7	***0.7***	0.1	0.5	1.0
Detection	Intercept; β_0	**5.0**	0.1	4.9	5.2	**5.0**	0.1	4.9	5.2
	Beaufort 3-6; β_1	***-0.3***	0.1	-0.3	-0.3	***-0.2***	0.1	-0.1	-0.2

Supplementary material

Appendix 12A. Supplementary information on methods

Covariate data collection

We considered eight habitat covariates as explanatory variables for variation in abundance. Five of the habitat covariates were static: distance to shore, bathymetry, and three seafloor features. We calculated distance to shore (km) as the distance to the nearest Delmarva shoreline (North or South regions[2]). We extracted a bathymetry data layer from the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center (NGDC) Coastal Relief Model (3-second, or 30-m resolution), using the spatial extent -76.1°W, 36.5°N to -74.4°W, 38.9°N[3]. Seafloor feature characteristics were derived by NOAA/NOS National Centers for Coastal Ocean Science (NCCOS, Kinlan et al. 2013) at a 370-m resolution and included: (1) seafloor slope (% rise) (2) predicted surficial sediment mean grain size (φ = -log2[mean grain diameter in mm]), and (3) predicted surficial sediment percent sand (%). On rare occasions (<0.01% of sites), sediment data contained missing values, which we imputed using the average from neighboring sites.

We used three dynamic habitat covariates: daily SST and salinity, and monthly chlorophyll. We downloaded the two daily data layers (1) one km SST (°C) from the Group for High-Resolution Sea Surface Temperature (GHRSST[4]) and (2) three km salinity (Practical Salinity Units, PSU) from the Global Navy Coastal Ocean Model (NCOM[5]). We downloaded monthly composites of 4-km chlorophyll concentration (mg/cubic m) from the Marine Geospatial Ecology Tools (Roberts et al. 2010) in ArcGIS 10.2, which accesses the OceanColor Level 3 Standard Mapped Image, via the National Aeronautics and Space Administration's (NASA) Goddard Space Flight Center (GSFC) Aqua satellite. We used monthly chlorophyll data because coastal satellite interference produced too many missing chlorophyll values at finer temporal resolution. Instead of using chlorophyll concentration, we calculated chlorophyll anomaly, by centering on the monthly mean of all sites, or effectively standardizing this covariate to a mean = 0 and a standard deviation < 2.

We conducted a preliminary analysis to select which covariates, at what spatiotemporal scale, were needed to quantify habitat suitability. This involved a tradeoff in selecting enough covariates to maximize variation, yet minimize overparameterization and co-linearity (Dormann et al. 2013). We evaluated co-linearity of these eight covariates by calculating Pearson's correlation coefficients and generalized variance inflation factors (GVIF, Zuur et al. 2010). As a result, this reduced our parameter space to include six covariates: three static (distance to shore, seafloor slope, sediment grain size) and three dynamic (SST, salinity, chlorophyll anomaly).

Due to slight survey-specific variation in the course-made-true (e.g., at the ends of each transect), we included the length of each segment as an offset in the model to standardize abundance by effort for

---

[2] pubs.usgs.gov/of/2010/1119/data_catalog.html

[3] maps.ngdc.noaa.gov/viewers/wcs-client/

[4] coastwatch.pfeg.noaa.gov/erddap/griddap/jplG1SST.html

[5] http://edac-dap3.northerngulfinstitute.org/erddap/griddap/US_East_3D_agg.html

each of the 1206 transect segments (each of which was considered an individual 'site' in the model). Eight of the 15 surveys (from March 2013 to February 2014) also included extensions of three transects farther west into Maryland state waters, with a total additional transect length of approximately 12 km per survey. Where track line segments (sites) crossed over multiple values of each habitat covariate, we calculated the mean value per segment. Therefore, we modeled seabird observations in each 4-km segment by fitting them to the corresponding segment-level mean SST and salinity value on their day of observation, and mean chlorophyll from their month of observation (e.g., Figure 12-1).

Modeling

Some seabird groups were only present during two surveys (e.g., during the summer or winter), which is one of the reasons why we analyzed each season separately in the community models; there were at least 5 species with a single detection in each season of the second year (observed number of flocks = 1), which we removed to avoid problems with model convergence related to lack of data. Scoters, on the other hand were present for the four surveys that comprised the nonbreeding season for Northern Hemisphere breeders. Therefore, the scoter models included the same surveys from the two winter seasons in the community models(Dec-Feb), but also included an adjacent survey from either shoulder season (fall and spring). We separated scoters from the community models for three reasons: (1) of all observations not identified to species in the dataset, > 90% were scoters, and 75% of all scoter observations were identified to the scoter genus, *Melanitta* spp., or to "non-White-winged Scoter", but not to species; (2) their flock sizes were larger than any other species in the community; (3) they are benthivores, whereas the rest of the community is composed primarily of surface-feeding piscivores and planktivores. Analyzing scoters separately allowed for estimates of their flock sizes and habitat responses to remain independent of the surface-feeding community, and avoid influences acting upon or arising from other species.

As described in Chapter 11, the sampling unit of analysis was an observation of a seabird 'flock', consisting of one or more individuals. First, we used observed distances to a flock to estimate the detection function that describes decline in detection probability with distance from the transect. To do so, we binned the observed distances into $k = 10$ distance categories of $w = 100$ m each, where b corresponds to the break points (we truncated the data at a maximum perpendicular distance of 1-km from the boat). Let p_{ijk} be the detection probability of species i at site j in distance bin k. Then, under a Gaussian (or half-normal) detection function,

$$p_{ijk} = \frac{\int_{b_k}^{b_{k+1}} \exp\left(-\frac{x^2}{2\sigma_{ij}^2}\right)dx}{w}.$$

We allowed the scale parameter σ_{ij} in the detection function to vary by species i and a binary indicator of sea state at site j. We classified Beaufort state as a 0 if the mean Beaufort state was 0-2 for a segment (calm seas), and as a 1 if mean Beaufort state was 3-6 for a segment (rough seas). . For example, a sea state of 6 represents wind velocities that reach up to 27 knots (38 mph or 14 m/s), thus the weather conditions were variable during sampling. These high wind periods also fall within the range at which offshore wind turbines can operate at maximum rated power (Jonkman et al. 2009). Accounting for sea

state accommodated reduced visibility due to increased wave height and occasions when observers switched platforms between calm and rough seas, following equipment safety protocol (Chapter 6).

We modeled the observed number of flock detections of species i at site j, n_{ij}, as an outcome of a Binomial random variable where N_{ij} is the true abundance of species i at site j, and $p.t_{ij}$ is the total detection probability ($p.t_{ij} = \sum_k p_{ijk}$) such that:

$$n_{ij} \sim Binomial(N_{ij}, p.t_{ij})$$

See text in Chapters 11 and 12 for further details on estimating flock abundance as a function of covariates. To model observed flock sizes, $\boldsymbol{F}_i$ (a matrix of $\sum_j N_{ij}$ by i flock sizes for each species i) we used a Poisson – Negative Binomial mixture model to accommodate overdispersion, but with limits due to small sample sizes. Through data exploration, we found that there was overdispersion of flock sizes for many species; however, there were also often very small sample sizes. Therefore, we set the threshold of the mixture to be 20 observed detections for each species in each season, and we fitted flock sizes to a Poisson distribution when those detections fell below this threshold, or a Negative Binomial distribution otherwise.

$$\boldsymbol{F}_i \sim \begin{cases} \text{zt Poisson}(\mu_i) & < 20 \text{ detections} \\ \text{zt Negative Binomial}(\mu_i, \rho_i) & \geq 20 \text{ detections} \end{cases}$$

Note that $\boldsymbol{F}_i$ is partially observed for each species, i.e., known for observed clusters and unknown for $\sum_j (N_{ij} - n_{ij})$ unobserved clusters of species i. We implemented a hyperparameter on mean flock size and on the dispersion parameter for all seasons except the summer of the first year, when flocks were more consistent in size. .

Using the package "rjags" (Plummer 2014) in program R version 2.15.3 (R Development Core Team 2013), we ran the software JAGS. We standardized the covariates for analysis to center them on a mean = 0, with a variance close to 1. We initialized three parallel Markov chains at different values and ran them for 30,000 iterations following a burn-in of 1,000 iterations. We checked for chain convergence visually (posterior density and trace plots), and quantitatively using the Gelman-Rubin statistic; this R-hat statistic indicated that chains converged as a measure of among-chain versus between-chain variance (R-hat < 1.1; Gelman et al. 2014).

Literature cited in Appendix 12A

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J., Münkemüller, T., McClean, C., Osborne, P.E., Reineking, B., Schröder, B., Skidmore, A.K., Zurell, D., Lautenbach, S., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36, 27-46.

Gelman, A., Carlin, J.B., Stern, H.S., Dunson, D.B., Vehtari, A., Rubin, D.B., 2014. Bayesian Data Analysis, Third Edition. Taylor & Francis, New York, NY, USA.

Jonkman, J.M., Butterfield, S., Musial, W., Scott, G., 2009. Definition of a 5-MW reference wind turbine for offshore system development. National Renewable Energy Laboratory, Golden, CO.

Kinlan, B.P., Poti, M., Drohan, A., Packer, D.B., Nizinski, M., Dorfman, D., Caldow, C., 2013. Digital data: Predictive models of deep-sea coral habitat suitability in the U.S. Northeast Atlantic and Mid-Atlantic regions. Downloadable digital data package. Department of Commerce (DOC), National Oceanic and Atmospheric Administration (NOAA), National Ocean Service (NOS), National Centers for Coastal Ocean Science (NCCOS), Center for Coastal Monitoring and Assessment (CCMA), Biogeography Branch. Released August 2013. Available at: http://coastalscience.noaa.gov/projects/detail?key=35.

Plummer, M., 2014. rjags: Bayesian graphical models using MCMC, R package version 3-13.

R Development Core Team, 2013. R: A language and environment for statistical computing, Version 2.15.3. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org

Roberts, J., Best, B., Dunn, D., Treml, E., Halpin, P., 2010. Marine Geospatial Ecology Tools: An integrated framework for ecological geoprocessing with ArcGIS, Python, R, MATLAB, and C++. http://mgel.env.duke.edu/mget

Zuur, A.F., Ieno, E.N., Elphick, C.S., 2010. A protocol for data exploration to avoid common statistical problems. Methods in Ecology and Evolution 1, 3-14.

Appendix 12B. Supplementary information on results

High levels of spatiotemporal variability were observed between species, for both detection and abundance. Highly conspicuous Northern Gannets, for example, had a higher detection probability than scoters (in rough seas during the first year winter/nonbreeding season, detection probability, p = 0.33 ± 0.012 SD for Northern Gannets and p = 0.23 ± 0.015 for scoters). Seasonal patterns of distribution and abundance by season are described in further detail below; winter patterns are described in the main text.

Spring

In the spring (2013, Figure 12-7c), Northern Gannets showed consistency with the second year winter associations (2013-14), as they were likely to be observed over high primary productivity, high salinity, and cold water areas, and were more likely to venture farther away from shore than in other seasons. With respect to alcids, Dovekies were observed far away from shore, and Razorbills associated with cold water, as in the second year winter. As for gaviids, Red-throated Loons were likely to be close to shore (as in the winter), over low primary productivity (unlike the first year winter) and cold water (unlike Common Loons in the first year winter). The procellarids and hydrobatids we observed during the spring were southern ocean breeders: Sooty Shearwaters were likely to stay far from shore, while Wilson's Storm-petrels associated with warm water and fine grain size. Red Phalaropes were observed away from the coast. Common Terns are larids that migrate northerly during the spring, and they were predicted to have higher abundances in low primary productivity and high SST (as in other offshore studies, Amorim et al. 2009; Goyert et al. 2014), as well as to fine sediment grain size (see discussion).

Summer

During the summer (2012-2013, Figure 12-7a, d), SST was significantly warmer than the other seasons. Warm water positively influenced the distribution of Royal Terns (Year 2), and negatively affected Great Shearwaters (both years) and Cory's Shearwaters (Year 2). The procellarids and hydrobatids we observed were likely to be far from shore (Year 1), and included southern breeders (Wilson's Storm-petrel, Great Shearwater), northern breeders (Manx Shearwater), and East Atlantic breeders (Cory's Shearwater). In the second year, Wilson's Storm-petrels were again far from shore, and associated with steep slope and low primary productivity. Low primary productivity also had a strong effect on Great Shearwaters (Year 2). Terns adhered closely to the shoreline, particularly Common Terns (Year 1), which are northern breeders, and Royal Terns (both years), which are local breeders. In the second year, Common Terns additionally associated with high primary productivity (similarly to a northerly nearshore study, Goyert 2014) and low salinity. Laughing Gulls were likely to be observed close to shore (Year 1), over high primary productivity (Year 2) and low salinity (Year 2), which led to high density predictions around the Delaware Bay. Brown Pelicans, which breed locally, were likely to be close to shore, over low primary productivity, low salinity, and fine sediment.

Fall

During the fall (Figure 12-7b, e) of the first year (2012), the surface-feeding community as a whole were positively associated with fine sediment grain size (Table 12-4), which was driven by Royal Terns, Common Terns, Laughing Gulls, Northern Gannets, and Double-crested Cormorants (Table 12-3). In the second year (2013), the entire community was likely to be close to shore, driven by 13 of the 16 species

(Table 12-4, Figure 12-7); distance to shore had no strong effect on Cory's Shearwater, which was the only species to respond differently from the rest of their community (its Bayesian credible interval did not overlap the community mean effect). Cory's Shearwaters and Common Loons were likely to be observed far from shore in the first year fall. In addition to their response to fine sediment, Royal Terns associated with proximity to shore (both years), high salinity (Year 2), and warm water (Year 2). In the first year, SST strongly affected many species in the community both positively and negatively. Wilson's Storm-petrels, Common Terns and Black Terns associated with warm water. Across both years, the species that associated with cold water were Northern Gannets (as in the winter and spring), Common Loons (unlike in the first year winter), Herring Gulls and Great Black-backed Gulls. Other larids and gaviids that associated with cold water in the first year were: Laughing Gulls, Black-legged Kittiwakes, Lesser Black-backed Gulls, Bonaparte's Gulls, Forster's Terns, and Red-throated Loons. In the second year fall, several species associated with low primary productivity: Northern Gannets (unlike in the spring), Laughing Gulls, Common Loons (like Red-throated Loons in the spring), Red-necked Phalaropes, and Cory's Shearwaters. Gaviid abundances were negatively related to low primary productivity, specifically Common Loons in the second year fall and Red-throated Loons in the spring (in contrast to the first year winter, when they associated with higher primary productivity). Primary productivity was lowest in the summer and second year fall.

Literature cited in Appendix 12B

Amorim, P., Figueiredo, M., Machete, M., Morato, T., Martins, A., Serrão Santos, R., 2009. Spatial variability of seabird distribution associated with environmental factors: a case study of marine Important Bird Areas in the Azores. ICES Journal of Marine Science 66, 29-40.

Goyert, H.F., 2014. Relationship among prey availability, habitat, and the foraging behavior, distribution, and abundance of common terns *Sterna hirundo* and roseate terns *S. dougallii*. Marine Ecology Progress Series 506, 291-302.

Goyert, H.F., Manne, L.L., Veit, R.R., 2014. Facilitative interactions among the pelagic community of temperate migratory terns, tunas and dolphins. Oikos 123, 1400-1408.