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A spatial conservation prioritization approach for protecting marine birds given proposed offshore wind energy development

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A B S T R A C T

There are currently no offshore wind energy developments (OWEDs) in North America, although numerous OWEDs have been proposed along the Atlantic Coast. Development pressure has been a catalyst for marine spatial planning (MSP) to identify suitable areas for OWED. However, integrating complex ecological information to guide OWED siting remains a substantial challenge. We developed spatial distribution models of marine birds from aerial surveys that we conducted from 2010 to 2012 throughout a 3800 km^2 area off the coast of Rhode Island. For seven groups of marine birds, we constructed either a density surface model or a presence–absence model that incorporated relevant environmental covariates. We integrated our spatial models, along with uncertainty, using spatial conservation prioritization (SCP) software. This identified sites with high marine bird conservation priority that aided evaluation of proposed OWED sites. We found that shallow nearshore waters had the highest conservation priority overall, but we also detected key offshore areas of high priority. Hypothetical OWEDs placed in conservation priority areas significantly reduced the overall distribution of focal species. Currently proposed OWED sites are located in areas of relatively low conservation priority and so would not substantially reduce the overall distribution of marine birds. This SCP approach when combined with quantitative models of bird distribution given relevant environmental covariates provides a robust framework that satisfies the principles of ecosystem-based MSP. Thus, this combined SCP-distribution modeling framework should be extremely helpful to decision makers as they evaluate proposed siting locations of OWEDs in the context of a dynamic marine system.

1. Introduction

There is increasing interest in the ecological consequences of offshore wind energy development (OWED), particularly on marine birds (Langston, 2013). This is in part due to the substantial increase in the number of OWEDs in Europe, where energy production has increased from 5 MW in 1993 to 4995 MW in 2012 (EWEA, 2013), and the consequent potential cumulative impacts on marine ecosystems. In North America, no OWEDs have been constructed, although there are several projects in the planning stages on the Atlantic continental shelf (US Department of Energy, 2011). Due to the potential for large-scale OWED in the eastern United States, several states have developed marine spatial plans (MSPs) including Massachusetts (Massachusetts Final Ocean Plan, 2009), North Carolina (Street et al., 2005) and Rhode Island (Rhode Island Ocean Special Area Management Plan, 2010). Recently, ecosystem-based MSPs have been proposed as a more rigorous framework (Foley et al., 2010) to ensure the ocean's ecological resources are protected in the face of future development by maintaining: (i) native species and diversity, (ii) habitat diversity and heterogeneity, (iii) populations of key species, and (iv) connectivity. Few examples exist that have integrated complex ecological information to evaluate various siting and development proposals for both marine and terrestrial spatial planning, therefore this rigorous approach remains a significant challenge (Polasky et al., 2008).

Marine birds include a diverse assemblage of key species from a variety of foraging guilds that may be negatively affected by large-scale OWEDs as a result of: (i) direct mortality from collision with turbine blades, (ii) turbines acting as barriers to migratory or daily movements that increase overall energy expenditure of individuals (barrier effect), or (iii) turbines displacing birds from important foraging and resting areas within the footprint of the development (Desholm and Kahlert, 2005; Petersen et al., 2006; Larsen and Guillemette, 2007; Masden et al., 2009; Langston, 2013). However, potential impacts on marine bird populations are still not thoroughly understood as interactions between OWEDs and marine birds have only been studied for a limited number of species at a few sites over the past decade. Current empirical evidence suggests

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that collision and barrier effects are minimal for marine birds and likely do not result in negative impacts to marine bird populations (Desholm and Kahlert, 2005; Masden et al., 2012). Yet, there is considerable uncertainty regarding the effects of displacement of marine birds from OWEDs. Some monitoring studies documented decreased densities of marine birds following OWED construction (Petersen et al., 2011), whereas other studies found some species habituate to the structures over time and return to pre-construction densities (Leonhard et al., 2013). In contrast, other studies have not found any changes in the density of some species of marine bird after the construction of OWEDs (Petersen et al., 2006; Vanermen et al., 2012). One primary issue with most OWED evaluation studies is that recent power analyses have revealed critical weaknesses in the current approaches used to evaluate displacement, with many studies not having adequate statistical power to detect changes even when declines are in excess of 50% (Maclean et al., 2013). In addition, investigators often develop statistical models that ignore important factors such as spatial autocorrelation and environmental conditions at the time of survey, which can impact the conclusions from displacement studies (Pérez Lapenã et al., 2010, 2011, 2012).

One approach to minimize the potential effects of OWEDs displacing marine birds under such uncertainty is an "impact avoidance approach" (Moilanen, 2012), which suggests a precautionary approach by siting OWEDs outside of conservation priority areas until the direct and indirect effects of OWEDs on marine birds, and marine bird population demographics are better understood. This is a refinement of the approach that Bright et al. (2008) undertook to map avian sensitivities to onshore wind facilities in Scotland to guide conservation planning. To our knowledge, no previous studies have integrated such an impact avoidance approach with an ecosystem-based MSP to evaluate proposed OWED scenarios while explicitly considering conservation priorities.

Species distribution models (SDMs) based on systematically collected survey data can provide robust estimates of the spatial distribution of animals, including marine birds (Clarke et al., 2003; Certain et al., 2007; Nur et al., 2011; Oppel et al., 2012; Winiarski et al., 2013) and thus could be used to inform biologists and regulators about important areas for marine birds. As a model-based approach, SDMs can incorporate environmental covariates to determine the relationships of biotic and abiotic variables to species' distributions (Miller et al., 2013). Occupancy or abundance can then be predicted from these models across the surveyed region to create maps that highlight important areas to the species or taxa in question. However, the number of species' distribution maps (and associated model uncertainty maps) that need to be reviewed to decide where to locate or evaluate a proposed OWED can quickly become complex and overwhelming, thus making it difficult to identify areas of conservation priority without a robust integrated approach.

Here we model distributions of marine birds off the coast of southern New England using two SDM approaches: density surface modeling (DSM; Miller et al., 2013) and presence–absence modeling (PAM; Guisan and Thuller, 2005). DSMs and PAMs were used to predict the distribution of marine birds across the Rhode Island Ocean Special Area Management Plan (RI OSAMP, 2010). We then integrated these predictions (and associated model uncertainties) using spatial conservation prioritization (SCP) software (Zonation; Moilanen et al., 2005) to identify sites with high conservation priority to marine birds to satisfy the requirements of ecosystem-based MSP. This approach has been applied to the development and evaluation of marine protected areas (Leathwick et al., 2008; Delavenne et al., 2012; Oppel et al., 2012), but to our knowledge has not been used to guide siting decisions of OWEDs to minimize risk to marine animals, including marine birds.

2. Methods

2.1. Study area

We conducted surveys in the Rhode Island OSAMP study area, which encompassed approximately 3800 km^2 in Rhode Island Sound, Block Island Sound, and portions of the Inner Continental Shelf, an area currently designated for a large-scale OWED (Fig. 1; Winiarski et al., 2012). Mean water depth in the study area is 34.9 m ± 9.9 (SD), with approximately 8% of the area <20 m deep and 86% between 20 and 50 m deep.

2.2. Aerial-based line transect surveys

We used aerial line-transects (Camphuysen et al., 2004; Winiarski et al., 2013) to survey marine birds throughout our study area. We conducted 41 aerial surveys from 20 October 2010 to 22 July 2012. All aerial surveys occurred from 0900 to 1500 h to ensure that birds had completed their post-dawn movements, but had not yet begun their pre-sunset movements from feeding to roosting areas. We conducted surveys along 24 transect lines oriented perpendicular to the coast that were spaced 3 km apart, with an average transect length of 46.3 km ± 12.3 km (SD) (min = 7.8 km, max = 58.0 km) (Fig. 1; top left panel). Locations of the 24 transects were determined using the survey design tool in program Distance 6.1 (Thomas et al., 2010) which randomly offset a grid of transect lines over the study area. Transects terminated approximately 1 km from the coast, as the plane was required by the Federal Aviation Administration (FAA) regulations to increase flight altitude to over 305 m elevation over land. Each transect was surveyed once per month, with every third transect surveyed during each flight to ensure that transects throughout the study area were surveyed each flight. We conducted all aerial surveys from a twin-engine Cessna Skymaster aircraft that flew at an altitude of 76 m above mean sea level at a constant speed of 160 km/h when wind speed was less than 35 km/h or waves were <1.2 m tall. Two observers on each survey flight were located in seats behind the pilot and co-pilot (one on each side of the plane) and each observer recorded all birds observed on their side of the plane within three distance bins out to 1000 m (A = 44–163 m, B = 164–432 m and C = 433–1000 m; note observers could not see beneath the plane from 0 to 44 m). A clinometer was used to mark set angles with black tape on the aircraft's wing struts delineating the three distance bins. Observers used their unaided eyes to detect individuals or flocks, identifying species when possible or to an avian guild (e.g., alcid species) when necessary. Birds were recorded as either on the water or in flight. Observers recorded sightings to the nearest second on a digital voice recorder. Each observer had a digital stopwatch that was synchronized with a global positioning system (GPS; Garmin model No. 496) which recorded the aircraft's position every 2 s. Due to the orientation of the transect lines and the position of the sun, glare affected observers on sunny days on some transect lines when surveying from north to south. If glare compromised the detection of birds on one side of the plane, that observer went "off" survey.

2.3. Environmental variables

Explanatory variables in the SDMs included available abiotic and biotic factors that are known determinants of marine bird distributions based on previous marine bird research (Tremblay et al., 2009; Wakefield et al., 2009; Oppel et al., 2012; Winiarski et al., 2013). We included six abiotic explanatory variables: latitude (y) and longitude (x; both transformed into meters from the center of the region of interest 41.17°N and 71.34°W), distance to nearest

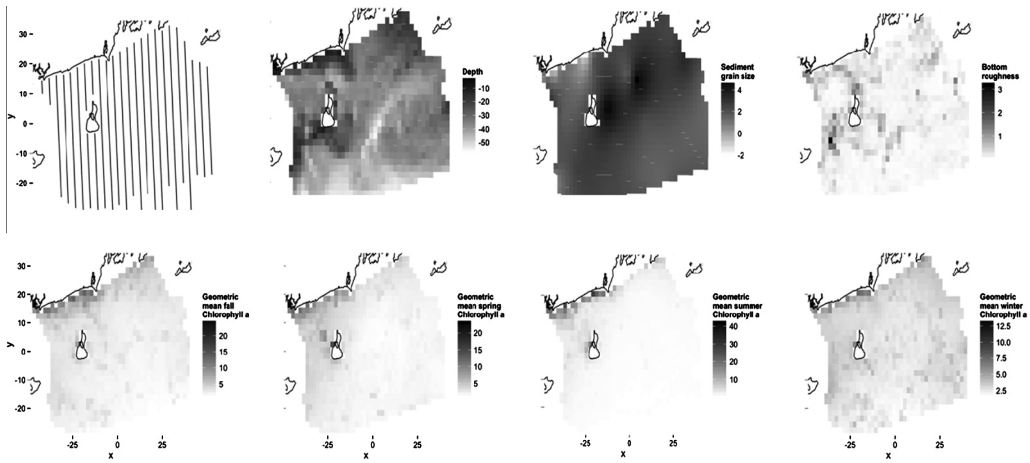

Fig. 1. Top row left to right: the twenty-four-aerial transects surveyed from 20 October 2010 to 22 July 2012 overlaid on a map of the study area; spatial distribution of water depth; spatial distribution of sediment grain size; spatial distribution of bottom roughness. Bottom row left to right: spatial distributions of the geometric mean of chlorophyll *a* for fall, spring, summer and winter (2010–2011 and 2011–2012 combined) during the period when surveys were conducted.

land (*distancelandkm*; Fig. 1), water depth (*depthm*; NOAA, 2013a), sediment median grain size (*phimedian*; NOAA, 2013b) and bottom roughness (*roughness*; LaFrance et al., 2010). We also included the seasonal geometric mean of surface chlorophyll *a*, which is a known proxy for primary productivity, calculated using the chlorophyll *a* surface concentration over a 10-year period (2002–2012) from the Aqua MODIS satellite (NOAA, 2013c). For species modeled in the summer; we included the geometric means of summer and spring chlorophyll (*gchl_summer*, *gchl_spring*) and for species most abundant in winter we included the geometric means of winter and fall chlorophyll (*gchl_winter*, *gchl_fall*).

2.4. Spatial distribution modeling

During aerial surveys, we were able to accurately and consistently identify three bird species: common loon (*Gavia immer*) common eider (*Somateria mollissima*) and northern gannet (*Morus bassanus*). Other species were more difficult to identify to species, so we categorized these species into the following taxonomic groups: alcids (razorbill [*Alca torda*], common murre [*Uria aalge*], and dovekie [*Alle alle*]), terns (common [*Sterna hirundo*], roseate [*Sterna dougallii*], and least [*Sternula antillarum*]), scoters (black [*Melanitta americana*] surf [*Melanitta perspicillata*], and white-winged [*Melanitta fusca*]), and storm-petrels (Wilson's [*Oceanites oceanicus*] and Leach's [*Oceanodroma leucorhoa*]). For each species distribution model, or species group distribution model, we developed models for the season in which they were most abundant (Table 1). Alcids, common eiders, northern gannets, scoters and common loons were more abundant in winter and storm-petrels and terns were most abundant in summer (Table 1, Winiarski et al., 2012). For each species or group, we first attempted to fit a DSM; however, for common eiders and scoters, this was not possible due to small numbers of observations with a heavy skew in flock size (see Section 3.1 for further explanation). When fitting a DSM was not possible, we modeled binary presence or absence.

2.4.1. Density surface modeling

Constructing DSMs was a two-step approach (Hedley and Buckland, 2004; Miller et al., 2013). First, abundances were estimated from line transect data using distance sampling methods (Buckland et al., 2001). Second, a generalized additive model (GAM; e.g., Wood, 2006) was fitted to those abundances with explanatory variables provided by spatially referenced environmental covariates. Abundances were calculated per *segment*: transects were split into contiguous sections (segments) within which there was not a large change in density or environmental covariate values. Here each segment was 2270 m long and 1912 m wide.

2.4.1.1. Controlling for imperfect detection. Rather than assume that detectability was certain, observers recorded distance to each individual or flock. Distance sampling methodology (Buckland et al., 2001, 2004) can then be used to adjust the counts to take into account changes in detectability due to distance from the observer (and possible other covariates, see below). Modeling took the form of fitting a detection function which describes the drop-off in detectability with increasing observation distance from the plane, assuming that detection was certain at zero distance (in our case bin A = 44–163 m). Analyses were performed in the Distance package (Miller, 2012) for R (R Development Core Team, 2012). Both half-normal and hazard-rate detection functions were fitted to

Table 1
Model results for the seven species or species groups including the season modeled, best selected model with smooth terms (as selected by the procedure outlined in Section 2.4), deviance explained, number of survey segments in the model and model type (density surface model (DSM) or presence–absence model (PAM)). The selected model column indicates whether a term has been included as a smooth function (with *s()*) and the associated effective degrees of freedom (this is the number after the covariate name(s) which indicates the complexity of the smooth function). Model selection details are given in Appendix A.

Species or group	Season modeled	Selected model	Deviance explained (%)	Number of segments	Model type
Alcids	Winter	s(*gchl_winter*, 1.53) + s(*distancelandkm*, 2.38) + s(*gchl_fall*, 2.97)	6.67	2067	DSM
Common eider	Winter	*depthm* + $s(x, y, 3.94)$	37.87	2067	PAM
Northern gannet	Winter	s(*depthm*, k = 5.9) + $s(x, y, 12.2)$	48.32	1179	DSM
Common loon	Winter	s(*gchl_long*, 3.6) + *depthm* + $s(y, 2.53)$	35.87	2019	DSM
Storm-petrels	Summer	*depthm* + $s(y, 4.03)$	11.18	1836	DSM
Scoters	Winter	s(*depthm*, 2.49) + $s(x, y, k = 6.10)$	26.78	2067	PAM
Terns	Summer	s(*depthm*, 3.27) + $x + y$	35.81	1836	DSM

the line transect data and covariates (group size and observer identity) were available for inclusion in the detection function. AIC was then used to select between candidate detection functions. Note that no adjustment for imperfect detection was made when a presence/absence model was used.

Having fitted a detection function, the probability of detection $\hat{p}_j$ for a given segment j could be estimated (Buckland et al., 2001) by integrating the detection function over the observation window (44–1000 m) and dividing through by this interval (the *truncation distance*, 956 m). c_{r_j} are possible covariates (in addition to distance) affecting detectability of a given species. If covariates were included in the detection function then $\hat{p}_j$ may be considered a function of those covariates. In the analysis presented here, the group size as a covariate as we believed that this might affect the detectability of a group. Again, AIC was used to select whether covariates should be included.

Note that fitting a detection function will only adjust the counts to account for effects of distance and other observed covariates on detectability; it is possible that there are other reasons that the counts in a given segment are incorrect. One potential source of bias is that smaller birds are much more difficult to observe (especially when flock size is small). Since we cannot quantify the relative difference in detectability for smaller birds (since we do not observe them), we interpret with caution the abundance estimates for these more difficult to detect bird species.

2.4.1.2. Density surface models. Estimated marine bird abundance was modeled per species or species group in a given segment, j, as a sum of smooth functions of the k explanatory variables (z_{jk}) using a generalized additive model (GAM) with the general formulation:

$$E[n_j] = a_j\hat{p}_j \, exp\left(\beta + \sum_{k=1}^{K} f_k(z_{jk})\right) \quad \text{where } n_j \sim \text{Negative Binomial}(\theta),$$

where a_j is an offset (the area of the segment, taking into account one/two-sided transects), β is an intercept parameter and f_k are smooth functions involving the K explanatory variables (see Section 2.4.3, below). The θ parameter of the negative binomial distribution was estimated during model fitting (Appendix A).

2.4.2. Presence/absence models

If it was not possible to fit a DSM to a particular marine bird species or species group's data (see below), we modeled probability of presence (occupancy) instead. The model took a similar form to the DSM, above, but observations were categorized as 1 (presence; i.e., $n_j > 0$) or 0 (absence; i.e., $n_j > 0$) with the response (probability of presence, P_j) modeled as binomial. The corresponding GAM had the following form:

$$E[\hat{\mu}_j] = \log \text{it}^{-1}\left(\beta + \sum_{k=1}^{K} f_k(z_{jk})\right) \quad \text{where } P_j \sim \text{Binomial}(1, \hat{\mu}_j),$$

where β is an intercept and f_k are smooths of the K explanatory variables.

2.4.3. Smooth terms

The smooth terms (the f_ks) were modeled using thin plate regression splines (Wood, 2003). Since the smooth terms were penalized, only the maximum basis size needed to be set and further wigglyness was suppressed by optimizing smoothing parameters that control the influence of a penalty term. Smoothing parameter selection was performed via REstricted Maximum Likelihood (REML; Wood, 2011). Both DSMs and PAMs were fitted using the dsm package (Miller, 2013) for R (R Development Core Team, 2012).

For each species or species group, univariate smooths of all covariates and a bivariate smooth of spatial location were included in the "base" model. Covariate selection then proceeded via two mechanisms: (*i*) an extra penalty for each smooth which allowed smooth terms to be completely removed from the model during fitting (Wood, 2011) and (*ii*) (approximate) p-values to select which smooth terms were significant (Wood, 2006).

2.4.4. Prediction and variance estimation

Once a spatial model was selected, species or species group abundance was predicted over a grid of 920 predictive cells that encompassed the flight transects and the sea between transects with the study area boundaries (each cell was 2 km^2; our "landscape"). Environmental covariate data were available for each prediction cell. The variance of abundance in each grid cell and the overall abundance estimate were obtained by the variance propagation method of Williams et al. (2011) when DSMs were used and no covariates were included in the detection function. This method incorporated uncertainty from the estimation of the detection function parameters as well as from the GAM by including an additional term in the model representing the uncertainty in the probability of detection (see also Miller et al. (2013), Appendix B). When there were covariates in the detection function, uncertainty from the GAM and detection function were combined using the delta method (Seber, 1982). For the PAMs, we used standard GAM confidence intervals (Wood, 2006). The coefficient of variation was then calculated for each prediction grid cell in the study area using the predicted abundance and the standard error for the given cell.

2.5. Identification of marine bird conservation priority areas

To identify potentially important marine bird conservation priority areas in our study area, we used the spatial conservation prioritization software Zonation (v. 3.1.0; Moilanen et al., 2005; Lehtomäki and Moilanen, 2013). Zonation is a quantitative methodology to identify important areas for multiple species while simultaneously maintaining connectivity between sites. The algorithm prioritizes the landscape by ranking all grid cells using a hierarchical process. First, the grid cells with the lowest biodiversity rank are removed from the landscape, while minimizing the marginal loss of overall biodiversity rank (Moilanen et al., 2005). Then the biodiversity rank for each remaining cell is recalculated, accounting for how much of the cumulative distribution remains for each species, before removing the cell with the next lowest diversity rank from the landscape. At each stage, losses are minimized and the remaining biodiversity rank is maximized. Recording the order of cell removal from the landscape produces a ranking of conservation priority from the least important (first cell removed from the landscape) to the most important (the last cell remaining on the landscape). We used the "core area" prioritization definition of marginal loss in Zonation, which prioritized the inclusion of high-quality locations for all species' layers without boundary quality penalties, and used a boundary length penalty of 0.1 to retain larger areas on the landscape instead of smaller isolated areas (Moilanen et al., 2005; Moilanen, 2007). Uncertainty in our SDMs was incorporated by subtracting an uncertainty surface, thus emphasizing areas of higher SDM certainty. We used coefficient of variation of each SDM prediction estimate to build our uncertainty surface and used the default Zonation uncertainty preset (uncertainty parameter alpha = 1). Further mathematical details regarding Zonation and the Zonation workflow are presented by Moilanen et al. (2005), Moilanen (2007) and Lehtomäki and Moilanen (2013). The main output from Zonation consists of a conservation priority-ranked map of the study area, representing the ranking of all cells across the landscape and species' performance curves which show the proportion of distribution remaining on the landscape as cells are removed during the prioritization process. Note that the proportion of distribution remaining at 0.90 of the landscape lost represents how much of that species or species' group overall distribution is included in those areas ranked in highest 10% for marine bird conservation priority in the study area.

2.6. Evaluating hypothetical OWEDs sited in marine bird conservation priority areas

To evaluate a worst-case scenario of the potential impact of OWEDs on seabirds, we assumed 100% displacement of marine birds away from turbines for this section of the analysis. Available empirical evidence suggests that long-term displacement from OWEDs varies by species of seabirds and may often be <100% (Leonhard et al., 2013). After our initial marine bird SCP, we performed two SCPs, each SCP with a hypothetical OWED in a high ranking marine bird conservation priority area. This included one SCP with a 70 km^2 development area sited west of Block Island and one SCP with a 70 km^2 development area sited east of Long Island, NY. The hypothetical OWEDs were the first areas removed during the SCP process (in our initial SCP lowest ranked biodiversity cells were the first cells removed from the landscape), which allowed us to evaluate species' performance curves based on the specific siting location of the hypothetical development. If hypothetical OWEDs were sited in an area that contained a significant proportion of a species' distribution, then we would expect the performance curve to have an initial sharp decrease due to the initial removal of the hypothetical development area (each ca. 0.04 of the total study area).

2.7. Evaluating currently designated OWED areas

Currently, two different areas are designated for OWED in our study area including a relatively small wind development (i.e., 5 turbines, 30 MW) off of the coast of Block Island, Rhode Island in state waters (referred to as the "Block Island Renewable Energy Zone") and a much larger area of federal lease blocks between Block Island and Martha's Vineyard, Massachusetts, which were recently auctioned by the federal Bureau of Ocean Energy Management to an offshore wind energy developer (potentially up to 200 turbines, 1000 MW, referred to as the "Area of Mutual Interest" between these two states; see Fig. 3 top left panel). Again, if these two OWED areas were sited in an area on the landscape that contained a significant proportion of a species' distribution, then we would expect the performance curve to have an initial sharp decrease in distribution remaining due to the initial removal of the designated OWED areas (each ca. 0.20 of the total study area). We also ran an additional SCP applying a weighting value to each individual species or species' groups based on a species concern index value (see Furness et al. (2013)) that was a function of a given species' or species' group disturbance and/or displacement sensitivity and conservation status. Based on Furness et al. (2013), common loon had the highest displacement sensitivity weighting (27), followed by scoters (24), common eider (16), alcids (14), terns (9), northern gannet (2) and storm-petrels (2). Note these values presented in Furness et al. (2013) are based on the results of OWED monitoring in European waters as well as basic ecological knowledge of the species in question, as no OWEDs currently exist in US waters.

3. Results

3.1. Marine bird species distribution models

We were able to develop DSMs for common loon, northern gannet, terns, alcids, and storm-petrels. We were unable to adequately fit DSMs for common eider and scoters because the abundance of these two species were characteristically clumped with most areas having no birds and a few areas with large flocks. Therefore, we constructed PAMs for common eider and scoters and DSMs for the other species or species groups (Table 1). DSMs and PAMs typically included water depth in the final model, and most species or species groups had higher abundances or higher probabilities of occurrence in nearshore waters, particularly common loon, common eider, scoters and terns (Fig. 2; top panels and Table 1). Alcids, northern gannet and storm-petrels were widespread across the study area, with alcids more abundant southwest of Block Island and in the eastern portion of the study area, northern gannets slightly more abundant offshore in those waters southwest of Long Island, NY, and storm-petrels more abundant in deeper offshore waters (Fig. 2; top row). Again, water depth was an important driver of the distribution of these species and species groups (Table 1). Model uncertainty was highest in areas closest to shore and furthest from shore, which can be attributed to lower sampling effort in those portions of the study area (Fig. 2; bottom row).

3.2. Spatial conservation prioritization of marine bird SDMs

3.2.1. Marine bird conservation priority areas

Marine bird conservation priority ranking was highest in the western portion of our study area in nearshore, shallow waters southwest of Block Island, east and southeast of Long Island, and the south west coast of mainland RI, but was also high in an offshore area in which water depths were significantly deeper than surrounding offshore areas (diagonal line east of Block Island) and in some areas furthest from shore in the western portion of our study area (Fig. 3a, left side). Lowest ranked conservation priority areas included mainly offshore areas in the eastern portion of the study area, where marine bird densities and presence were predicted to be relatively low for our 7 guilds (Fig. 3a). Proposed OWED areas had highest conservation priority ranking in the southern section of the AMI area and Block Island Renewable Energy Zone and lowest conservation priority ranking in the northern section of the AMI area (Fig. 3a).

Performance curve shape for individual species or species' groups in this initial base prioritization was driven by their distribution across the study area (Fig. 3a, right side). Species or species groups that were widespread or distributed farther offshore in our study area (storm-petrels, common loons, alcids and northern gannets) lost a higher proportion of their overall distribution as cells were removed from the landscape (Fig. 3a). This differed from those species or species' groups that tended to have a more limited distribution that was restricted to nearshore habitats including scoters, common eider and terns – these species lost a much lower proportion of their overall distribution as cells were removed from the landscape (Fig. 3a). Species such as scoters, common eider and alcids that occurred at highest densities or had the highest probability of presence in nearshore waters or in those waters southwest of Block Island and east of Long Island where the conservation priority ranking was highest lost less of their distribution even when 0.90 of the landscape was removed (Fig. 3a, right panel).

3.2.2. Effects of hypothetical OWEDs on marine bird SCP

If OWEDs were placed in waters west of Block Island or east of Long Island, then the spatial pattern of the marine bird

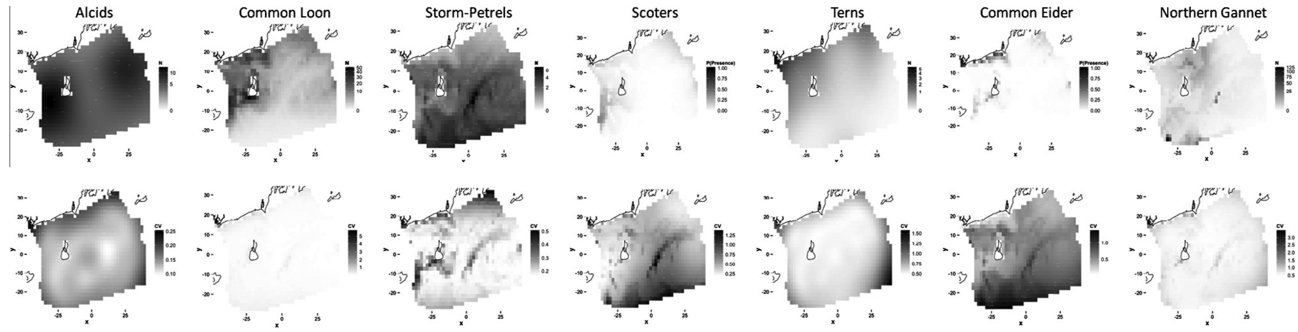

Fig. 2. Density surface models or presence–absence models of marine bird species or species groups (see Table 1 for type of model) observed during aerial surveys off the coast of Rhode Island. Top panels are predictive plots with the darker colors indicating higher predicted abundance or probability of presence. Bottom panels are model uncertainty (coefficient of variation) for the predicted surface with darker colors indicating greater model uncertainty.

conservation priority rankings was very similar to that from our initial prioritization (Fig. 3b and c, left side), although the individual species or species' group performance curves differed from our initial SCP and depended on siting location on the landscape (Fig. 3b and c, right side). These two hypothetical OWEDs had the greatest negative effect on the performance curves of those species or species' groups that were distributed nearshore (Fig. 3b and c). Placing the hypothetical OWED east of Long Island had a dramatic effect on the performance curve of scoters, as this area had the highest probability of presence for scoters (Fig. 3b). This effect was minimal when the hypothetical OWED was placed just west or north of Block Island, where the probability of scoter presence was lower (Fig. 3c).

3.2.3. Effects of current OWED designated areas on marine bird SCP

The Block Island Renewable Energy Zone and the Area of Mutual Interest were both located in areas of relatively low conservation priority based on our SCP, although portions of the southern section of the Area of Mutual Interest did have a relatively high conservation priority ranking (Fig. 3d). When we removed these two proposed OWED areas first during the SCP, conservation priority ranking was very similar to the ranking found with the initial SCP (Fig. 3d, left side). Individual species or species' group performance curves exhibited few differences between the SCP with the current OWED designated areas removed during the SCP and our initial SCP (Fig. 3a and d, right side). However, there were some exceptions. For storm-petrels, when 0.20 of the landscape was removed, 0.74 of their distribution remained, which represented a 0.10 decrease compared with our initial SCP (Fig. 3a and d). In contrast, common loon and northern gannet had an increase in the proportion of their distributions remaining (0.04 and 0.02, respectively) when 0.20 of the landscape was removed compared with our initial SCP (Fig. 3a and d).

3.2.4. Effects of current OWED designated areas on marine bird SCP when weighting species vulnerability to OWED

When we removed the two currently designated OWED areas (Block Island Renewable Energy Zone and the Area of Mutual Interest) first from the SCP and included a weighting for each individual species or species group based on displacement sensitivity and conservation status (Furness et al., 2013), there was higher conservation priority ranking of areas in shallower waters, nearer the shore and lower conservation priority ranking of areas in offshore waters than compared with the initial SCP (Fig. 3a and e, left side). Areas with high conservation priority ranking increased around Block Island (especially southwest of Block Island), east of Long Island and south of the Rhode Island coastline, while cells with low conservation priority ranking increased in the western portion of the study area furthest from shore and in the deeper waters southeast of Block Island (Fig. 3e).

Removal of the two proposed OWEDs and including no weighting for species or species groups did not substantially change the distribution of species or species groups relative to the initial prioritization (Fig. 3a and d, left side), whereas including the weightings for individual species or species group substantially affected the performance curve shape of certain species or species groups (Fig. 3a and e, right side). For example, common loon, alcids and terns had an increase in the proportion of their distributions remaining (0.17, 0.14 and 0.11, respectively) with 0.80 of the landscape removed (with a species weighting), compared to the prioritization with no species weighting (Fig. 3d and e). Storm-petrels and northern gannet had a decrease in the proportion of their distributions remaining (0.08 and 0.16, respectively) with 0.80 of the landscape removed (with a species weighting), compared to the prioritization with no species weighting (Fig. 3d and e). Scoters and common eider showed no change in their remaining distributions when 0.80 of the landscape was removed (Fig. 3d and e).

4. Discussion

We developed SDMs for seven species or species' groups of marine birds common to our study area and used SCP software to identify areas of marine bird conservation priority based on overall marine bird biodiversity. We then evaluated how placement of hypothetical OWEDs in conservation priority areas changed conservation priority ranking and individual species or species' group performance curves. We found that currently proposed OWEDs areas follow an "impact avoidance approach" (Moilanen, 2012) in that they are in areas of relatively low ranking conservation priority, and these areas rank even lower when marine bird taxa are weighted based on their sensitivity to displacement by OWED. Our analyses were limited to marine birds, but such a SCP approach facilitates the integration of ecological information across taxa and trophic levels (Ballard et al., 2012), thus allowing the principles of ecosystem-based marine spatial planning to be met.

4.1. Marine bird conservation priority areas

The use of Zonation to conduct the SCP allowed us to (a) integrate our SDMs (DSMs, PAMs) of marine birds and the associated model uncertainty into the site assessment process, (b) identify conservation priority areas in our study area, and then (c) use this information to quantitatively assess how the location of OWEDs affects marine birds. SCP of marine birds (or other taxa) across the landscape requires robust models of the distribution species or taxa of interest. In our example, we used DSMs to estimate distribution and abundance for several species or species groups of

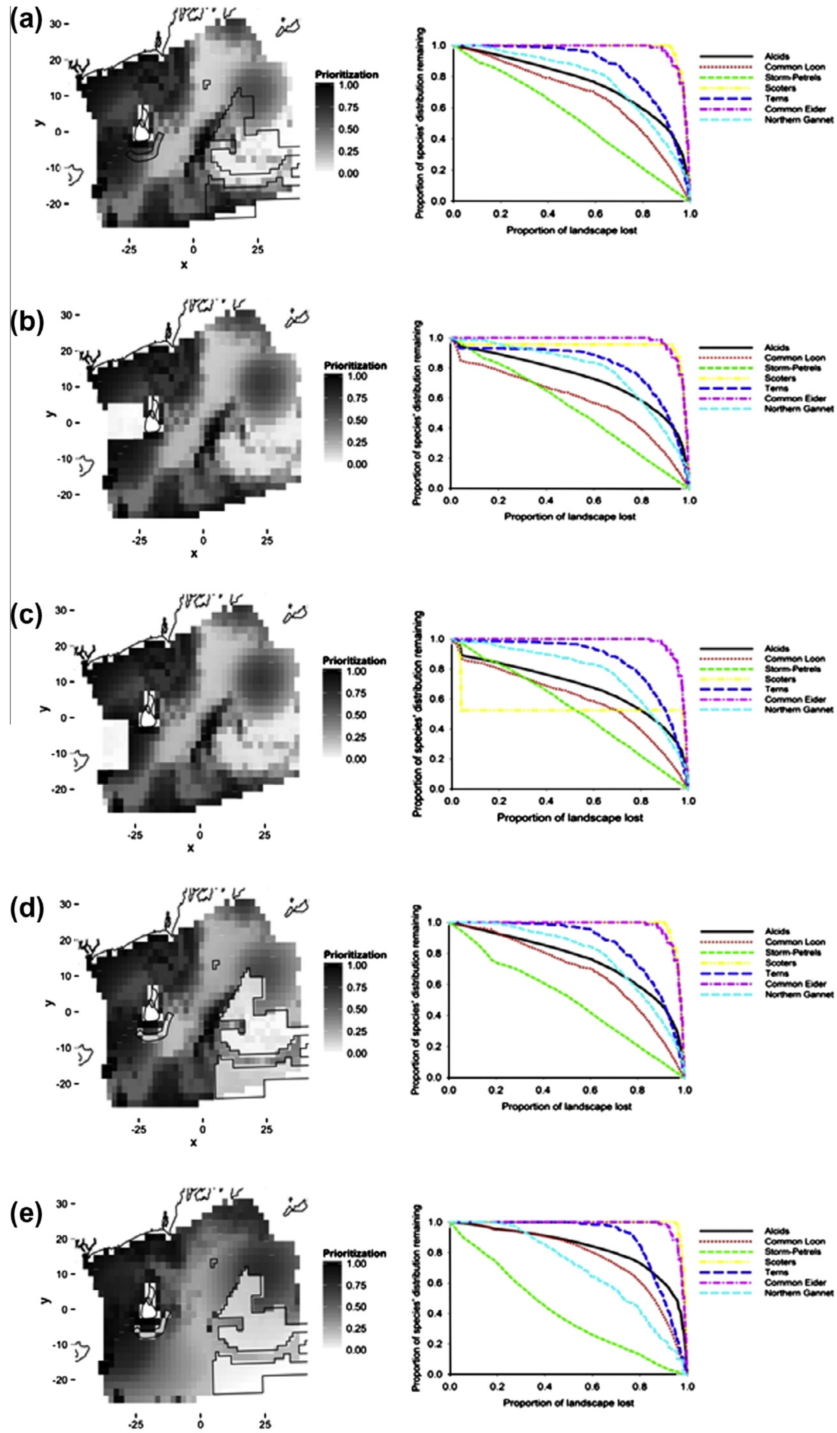

Fig. 3. Marine bird conservation prioritization maps (left panels) and associated marine bird performance curves (right panels) that were generated using Zonation software (Moilanen, 2012). Five different prioritizations include: (a) initial base prioritization with our 7 modeled marine bird taxa, (b and c) initial prioritization but with two different hypothetical OWEDs (light rectangles) removed from the landscape (each OWED was ca. 4% of the overall study area), (d) initial prioritization but with currently designated OWED areas (polygons with black borders) removed (ca. 20% of the overall study area) and (e) same as (d) but with a displacement sensitivity weightings given to each marine bird taxa from Furness et al. (2013). Darker cells on prioritization maps represent higher ranked areas of conservation priority. Performance curves that stay relatively flat with increasing loss of landscape represent species that are restricted to a small number of highly ranked areas, whereas those performance curves that linearly decrease with increasing loss of landscape represent species that tend to be uniformly distributed or distributed further offshore in lower ranking areas. Note that in (b and c) the performance curves that show a sharp decrease in proportion of distribution remaining suggest the hypothetical OWEDs occur in areas of highly ranked conservation priority for the species or species group (e.g., scoters). Note that in (d) no performance curves exhibit a sharp decrease with the initial removal of the currently designated OWED areas from the landscape. Note that in (e) the weighting of species or species' groups based on displacement sensitivity results in a prioritization with higher ranking of nearshore areas, as offshore areas are now removed earlier from the landscape as they have a lower biodiversity value and that performance curve shape differs from (d) based on the displacement sensitivity weightings.

marine birds, and occupancy-based models (i.e., PAMs) for others. Most species or species' groups had highest densities in nearshore waters, although storm-petrels and northern gannet were found in highest densities in offshore waters. Similar spatial patterns of marine birds were found in the nearshore and offshore areas of the New York Bight (Kinlan et al., 2012).

Not surprisingly, SCP of our SDMs ranked the highest conservation priority areas as those nearshore waters off of Rhode Island's mainland coast and those waters southwest of Block Island, RI and east of Long Island, NY. These areas have been previously shown to be important for marine birds based on satellite telemetry and other surveys (Loring et al., in press; Winiarski et al., 2013). These waters are strongly influenced by significant freshwater input from the Connecticut River and have high tidal velocities, both of which likely attract a high diversity and density of prey eaten by marine birds (Mau et al., 2007; Codiga and Ullman, 2010). Our SPCs were limited to marine birds, although they are broadly relevant because marine bird distributions overlap with those of other top marine predators (Le Corre and Jaquemet, 2005; Ainley et al., 2009; Ballard et al., 2012) and the diet of marine birds encompasses a wide range of lower trophic level marine organisms (Litzow et al., 2000; Ainley et al., 2009).

4.2. Improved siting of OWEDs

Spatial conservation prioritization combined with quantitative SDMs provides a user friendly decision support tool and a robust framework for integrating ecological information about many taxa into the OWED siting process, and the means to emphasize the importance of single species that are of conservation concern (i.e., threatened or endangered). Development or evaluation of marine protected areas has previously used marine bird SDMs and a spatial conservation prioritization approach (Oppel et al., 2012; Ballard et al., 2012), but to our knowledge has not been used to compare competing OWED siting options. Siting of large-scale OWEDs could potentially become more streamlined if conflicts over siting decisions are reduced by involving stakeholders in a transparent SCP process and if OWEDs are proposed in areas of low conservation priority ranking. We showed how placement of OWEDs in areas of high conservation priority ranking resulted in a sharp initial decrease in the performance curves for particular marine bird species or species' groups and that minor adjustments in the location of OWEDs can be evaluated and can have remarkably different effects on marine birds.

If currently proposed OWEDs are constructed in our study area, then our analyses suggest that the species or species groups of marine birds we were able to model will not be substantially affected. For example, when the proposed OWED locations were removed from the landscape this did not result in large decreases in the performance curves. This result occurred because the currently proposed OWED areas are not in areas of high ranking conservation priority for marine birds (although, portions of the southern section of the Area of Mutual Interest did have a relatively high conservation priority ranking). Weighting of marine birds in the SCP based on their displacement sensitivity and conservation priority from Furness et al. (2013) increased the conservation priority ranking of nearshore waters. However, further development of displacement sensitivity weightings (Furness et al., 2013) are needed because they are currently based on relatively few OWED monitoring studies in Europe that were all conducted in relatively shallow waters. Increased monitoring of European OWEDs and future monitoring of OWEDs in US waters will lead to more accurate estimates of displacement sensitivity for species or species' groups of marine birds. It is possible that OWED will actually create habitat for some marine bird species (we assume in our study that development leads to a complete loss of habitat) and it has recently been found that some marine bird species may habituate to the offshore wind energy development after a few years of being displaced from the developed footprint (Leonhard et al., 2013). SCP maps could also be used to determine maintenance and construction routes for ships, which have also been shown to displace marine birds (Schwemmer et al., 2011). It is important to emphasize that some areas will always be ranked as having low conservation priority because the ranking is relative to the biodiversity values of the overall study area. Therefore, it is important for regulators to balance the importance of models for guiding conservation planning with other available information. These low ranking areas may still be potentially important for certain species. For example, some offshore waters in our study area were ranked low conservation priority, but these sites had relatively high predicted abundances of storm-petrels.

4.3. Advantages and disadvantages of SCP

SCP software packages, such as Zonation, have previously been used to make real-world conservation decisions in terrestrial, riverine, marine and urban environments (Kremen et al., 2008; Leathwick et al., 2008; Lehtomäki et al., 2009; Leathwick et al., 2010; Bekessy et al., 2012; Delavenne et al., 2012). We chose to use Zonation because it does not require individual conservation targets to be defined *a priori* for each biodiversity feature of interest and it allows for a combination of different types of SDMs (Moilanen et al., 2005; Kukkala and Moilanen, 2013; Lehtomäki and Moilanen, 2013) which in our case was essential given the diversity of marine birds. SCP is transparent for stakeholders and has a strong scientific basis. Software such as Zonation can also prioritize very large high resolution datasets (e.g., as it has been applied to areas with 30 million effective grid cell sizes; Kukkala and Moilanen, 2013), which is important for large-scale spatial planning. Zonation can also incorporate information about connectivity in the environment, which could be particularly important for central place foragers, such as colonial-nesting birds during the breeding season. In our case, we assumed that marine birds could easily move across the different habitats in our study area (Arponen et al., 2012; Kukkala and Moilanen, 2013).

There are, of course, limitations and potential shortcomings to SCP software. As with any sophisticated software package, practitioners must develop a conceptual understanding of the analysis and the software that takes time. Well-designed aerial surveys for marine birds and the development of the SDMs is time intensive and expensive, and requires skilled biologists who can accurately conduct the surveys and who have expertise in conducting and knowledge of spatial statistics. Poor input models or taxonomically limited models will lead to SCPs that are inaccurate and potentially meaningless (Lehtomäki and Moilanen, 2013). Building reliable input models is difficult due to the highly dynamic nature of the marine environment, and this inevitably leads to spatial models that often have low predictive power (Oppel et al., 2012; Winiarski et al., in press). Improving the predictive power of DSMs is a complicated matter: maintaining generality in the model and avoiding overfitting to outlying data is essential. Bias incurred from incomplete detection can be accounted for using distance sampling methods, although improving the quality of the observational data is most important and recent advances in high-speed, digital imaging are promising if the costs are reduced (Buckland et al., 2012). Replication of survey effort makes it possible to evaluate whether patterns are "one offs" or reflect the true distribution of birds in the area over time. In general, long-term multi-year surveys of marine birds are needed so that spatial distribution models incorporate inter-annual variability, and so provide the foundation for more accurate conservation planning in the context of a dynamic marine system.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.biocon.2013.11.004.

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