Atlantic Coast Wintering Sea Duck Survey 2008–2011

ATLANTIC COAST WINTERING SEA DUCK SURVEY, 2008-2011

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Cover: Black scoter along the south shore of the St. Lawrence Estuary near Trois-Pistoles, May 2009. Courtesy of Christine LePage, Canadian Wildlife Service, Quebec Region.

In Memoriam

This report is dedicated to our colleague and friend, Thom Lewis, who died in the line of duty, while training for aerial surveys. Thom was a passionate wildlife biologist whose love and knowledge of nature, easy-going humor, attention to detail, and commitment to waterfowl conservation is deeply missed. His example continues to inspire us.

Acknowledgements

Survey Crews

Year	Crew[*]	Pilot	Right seat observer
2008	North Coast	John K. Bidwell	Timothy P. White, Paul I. Padding, Holliday H. Obrecht
	South Coast	James S. Wortham	Matthew Perry, Terry S. Liddick
	3441	Mark D. Koneff, James S. Wortham	Terry S. Liddick
	4051	Carl F. Ferguson	Doug J. Forsell, Thomas E. Lewis
	4206	Fred H. Roetker	Timothy P. White
2009	Coast	Mark D. Koneff	Doug J. Forsell
	3306	Walt E. Rhodes	John W. Solberg
	3821	Terry S. Liddick	Fred H. Roetker, Holliday H. Obrecht
	4141	James S. Wortham, John K. Bidwell	Timothy P. White, Thomas E. Lewis
	4446	John K. Bidwell	Thomas E. Lewis
2010	3411	Walt E. Rhodes	M. Tim Jones
	3916	Terry S. Liddick	Holliday H. Obrecht, Nate J. Carle
	4121	James S. Wortham	Thomas E. Lewis
	4446	John K. Bidwell	Timothy P. White
	Mid-Coast Replicates	Mark D. Koneff	G. Scott Boomer, Paul I. Padding, Thomas E. Lewis
2011	3501	Walt E. Rhodes	Holliday H. Obrecht
	3906	James S. Wortham, Walt E. Rhodes	Stephen D. Earsom
	4116	James P. Bredy	Thomas E. Lewis
	4446	Mark D. Koneff	Timothy P. White

[*] Numbers indicate the latitude (degrees-minutes) of the northern-most transect in the crew area.

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1. Executive Summary

1.1 Background

In 2005, the Sea Duck Join Venture's Monitoring Working Group identified the development of a winter sea duck survey along the Atlantic coast of the United States/Canada as a high priority. Winter distributional data are necessary to assess threats to sea ducks from hunting, coastal development, and marine activities. Winter abundance estimates may also provide cost-effective, feasible indices of population size for some species.

Monitoring of sea ducks along the eastern seaboard has been limited in range and utility, and adequate estimates of abundance and trend are lacking. The Atlantic Flyway Sea Duck Survey, an aerial survey conducted between 1991 and 2002, consisted of a single track flown parallel to the coast, one-quarter mile offshore; the resulting data did not allow estimation of winter population sizes or the quantification of survey precision. Subsequent surveys, which included offshore areas, were conducted only in the mid-Atlantic, in the vicinity of the Chesapeake and Delaware Bays. To expand on these efforts and address the Sea Duck Joint Venture priority, the U.S. Fish & Wildlife Service conducted four years of exploratory survey work, aimed at developing a rigorously designed, coast-wide, offshore winter sea duck survey.

1.2 Survey design & analysis

The experimental survey was conducted along the Atlantic coast from the U.S.-Canadian border to Palm Beach, FL between January and March in 2008-11. The design of the survey varied over the four years in response to lessons learned from the data and logistical challenges. In all four years, crews flew transects east from the coastline, spaced every 5′ of latitude. Additional transects were placed over shoal areas thought to be important wintering locations, as well as within bays and sounds.

In this report, we present a model to estimate sea duck abundance, and the results of an analysis to identify survey strata based on observed densities, for five species of sea ducks: common eider *Somateria mollissima*, long-tailed duck *Clangula hyemalis*, white-winged *Melanitta fusca*, surf *M. perspicillata*, and black scoter *M. americana*. We include abundance and precision estimates under (1) the current systematic survey design and effort, (2) increased and decreased effort, and (3) several simulated reallocations of survey effort, based on the survey strata. We discuss future analyses and data collection that could reduce uncertainty and increase survey efficiency. Appendix 1 includes a detailed description of sea duck distributions, and a preliminary analysis of coastal characteristics associated with sea duck presence. Appendix 2 outlines modeling work that contributed to the development of the abundance models.

1.3 Abundance estimation

In fourteen of fifteen cases (five species, three years), the annual abundance estimates fall within two standard errors of the three-year mean abundance (Table 1). The coefficients of variation (CV) on single year estimates average 0.19 to 0.30, and the CVs for the three-year mean estimates range from 0.11 to 0.30. Under the current design, white-winged scoter estimates are the most imprecise, followed by black scoter and common eider. White-winged scoter abundance is low, making efficient estimation challenging; black scoter has the widest and most variable range, and common eider is the most highly (and variably) aggregated. Estimates were the least variable for long-tailed duck and surf scoter, the species that winter within the central portion of the survey's latitudinal range.

   Effort and stratification analyses suggest that we can achieve improvements in the efficiency of our estimates by modifying the survey design to sample more heavily in high density areas and by increasing the current effort. (Table 1 includes estimated CVs for stratification based on combined species densities, assuming the effort available in 2008-10.) Improving precision will also likely be achieved by (1) refining methods of data collection and introducing corrections for observation condition, observer, and count bias, (2) shortening transects that currently extend outside sea duck ranges and reallocating effort to high density areas, and (3) collecting additional data to refine the model assumptions, the characterization of flock size distributions, and our understanding of annual variation. Ultimately, specific survey objectives must be articulated, since optimal survey design will depend on the focal species, and the spatial and temporal scale of interest.

Table 1. Estimated total observable birds in the survey area by species and year, and the three-year mean (SE), for 2009-11; average annual coefficient of variation for survey as flown and for stratification assuming 5 crews.

	Common eider	Long-tailed duck	White-winged scoter	Surf scoter	Black scoter
2009 estimate	234,100	242,400	44,100	151,200	142,900
2010 estimate	299,600	253,800	55,200	118,300	380,700
2011 estimate	220,400	213,400	76,500	178,100	110,400
3-yr mean estimate (SE)	251,400 (43,400)	236,600 (25,700)	58,600 (11,100)	149,200 (17,100)	211,300 (63,800)
Average annual CV	0.29	0.19	0.33	0.19	0.30
Average annual CV, stratified design	0.22	0.14	0.23	0.15	0.27

1.4 Questions to consider for survey evaluation and to guide additional analyses.

   What management/research objectives should this survey inform (e.g., harvest regulation, offshore development planning, focused research on sea duck-habitat associations)?
   What priority species and areas need abundance estimates? At what temporal interval?
   What distributional data are needed? At what temporal and spatial scales?
   What information is missing?

2. Introduction

Concerns about the status of North American sea duck populations, and the lack of information about the species' ecology, habits, and distribution, led to the establishment of the Sea Duck Joint Venture (SDJV) in 1999. The SDJV quickly identified the need for monitoring programs targeted at sea ducks: established waterfowl surveys do not cover sea duck habitats, so population trends, critical areas, and potential threats are not well characterized (SDJV Prospectus, available at seaduckjv.org).

The SDJV convened the Sea Duck Monitoring Working Group in 2005, and the group included a winter sea duck survey off the Atlantic coast of the United States and Canada in a list of high priority surveys (Sea Duck Joint Venture 2007). Information on winter distributions will support the assessment of threats to sea ducks from hunting, coastal development, and marine activities. Winter abundance estimates may also provide cost-effective indices of population sizes. Previous efforts to monitor sea ducks along the eastern seaboard did not extend to offshore areas, provide estimates of precision, or cover the entire coast: the Atlantic Flyway Sea Duck survey, an aerial survey conducted from 1991 to 2002, consisted of a single track flown parallel to the coast, one-quarter mile offshore; later survey efforts were located only around the Chesapeake and Delaware Bays in the mid-Atlantic region. These efforts led the U.S. Fish & Wildlife Service (USFWS) to propose exploratory survey work aimed at developing an operational coast-wide winter sea duck survey.

In this report, we summarize data from the resulting surveys, conducted during the winters of 2008-11. The goal of the prerequisite surveys has been to design an operational survey to estimate population sizes of wintering sea ducks, assess yearly variation and trends in distribution and abundance, and determine habitat associations and areas of special significance. We focus the current analysis on survey design and modeling approaches for the estimation of winter abundance and associated measurement of precision. We present results for the five abundant species of primary conservation concern: American common eider *Somateria mollissima*, long-tailed duck *Clangula hyemalis*, and black *Melanitta americana*, surf *M. perspicillata*, and white-winged scoter *M. fusca*. (All species of sea ducks were surveyed, but for this report "all sea ducks" refers only to these five species.) Additional analytical work is reported in the appendices: Appendix1 describes the distribution of each species, interannual variation in distribution, and preliminary assessment of the relationship between occurrence, distance offshore, and bathymetry; Appendix 2 (Zipkin et al. *In press*) presents the statistical work that provides the analytical framework for abundance modeling. Analyses that quantify detection probabilities, the effect of observation conditions, and the magnitude of observer effects, all of which will likely result in modified abundance estimates, will be presented in a subsequent report.

3. Methods

3.1 Survey description

The surveys were conducted along the Atlantic coast from the U.S.-Canadian border ($44^\circ46'$ N) to Palm Beach, FL ($26^\circ56'$ N) between January and March, 2008-11. Survey crews, consisting of an observer and pilot-observer, flew fixed-wing aircraft at 110 knots and 70 m altitude. Each observer counted all sea ducks from the closest observable distance to the center line (~50 m) to 200 m on his side of the aircraft. Survey range and design, as well as the number of crews and their assignments, changed between the four years, based on lessons learned, logistics, and resources. Appendix 1 provides a description of the survey design and the annual changes. In 2008-10, there were five survey crews, but only four surveyed the primary east-west transects (three in 2008); in 2011, there were four crews, all flying east-west transects. In 2012, additional data were collected off the South Carolina and Georgia coasts, and around the mouth of the Chesapeake Bay. These data will be summarized in a subsequent report.

In this report, we analyze data from 2009-11 from the four primary survey crews. These crews flew east-west transects spaced systematically at intervals of five minutes of latitude (approximately 5 NM apart). Transects extended east from the coastline to the longer of two distances: 8 NM or the distance to 16 m depth. Transects ranged in length from one to 79 NM (average transect length was 16 NM with a standard deviation of 11 NM), as transects that span bays may be less than 8 NM, and longer transects parallel the shoreline in complicated coastal areas, such as Long Island Sound. After completing their entire set of transect lines, each crew flew north to their first east-west transect line and replicated every other transect from north to south. The replicate surveys were conducted approximately one week after the first surveys and do not duplicate the original track exactly, making the possibility of recounting the same individuals unlikely. Replicates were flown to compare spatial and temporal count variability and assess if distributions shifted over the survey period.

Due to the vagaries of field operations, transects and replicates differed somewhat between years. We use data from 253 unique transects (249 in 2009 and 252 in both 2010 and 2011) and 151 unique replicated transects (111 in 2009-10, 120 in 2011). Common eider and long-tailed duck models were fit only to the portions of the survey area in which they were found (93 transects and 44-46 replicates per year for common eider and 188-191 transects and 86-91 replicates per year for long-tailed duck). White-winged and surf scoter also do not winter south to the Georgia-Florida border, but species-specific scoter abundance was estimated using a two-stage procedure (described below) and, because this model includes black scoter, utilized the entire set of transects.

The data consist of observations along survey transects recording the (1) location, (2) species, and (3) number of birds seen at the location.   The three scoter species can be difficult to distinguish reliably in the field, leading to a large number of scoters identified only to genus (*Melanitta* spp.).

3.2 Analysis

3.2.1 Identification of regions of high use

We analyzed sea duck densities along the survey transects to delineate coastal regions that differentiate sea duck use and abundance, and to define strata for more efficient estimation. We applied a spatially constrained clustering algorithm to the log-transformed three-year average transect densities of each species (averages were weighted by area flown, see Appendix 1). A description of the algorithm, available in ArcGIS 10.1, and our application can be found in Appendix 1. To identify survey strata, we applied a multivariate version of the algorithm, and standardized the densities of each species (subtracting the mean and dividing by the standard deviation), so that the clustering weighted all species equally and did not favor the most abundant species. For this analysis and subsequent abundance estimates, we set the eastern range limit for all transects (except transects along Nantucket Shoals) to 15 NM from the coast, because no sea ducks were ever detected farther from the coastline: densities on long transects in shallow areas will be underestimated with the inclusion of survey miles well past the eastern boundary of the birds' ranges.

Our procedure for defining strata had four steps. First, we divided the coast into three areas, based on the southern range boundaries of (1) common eider and white-winged scoter, and (2) long-tailed duck and surf scoter. If the clustering algorithm is run on the full set of transects, using data for all five species, then the cluster breaks are dominated by the range edges (since they separate positive densities from zero values). The range break for the northern area, i.e., the southern boundary for common eider and white-winged scoter, was $40^{o}26'$N; the area north of this latitude included 99.96% of all common eider observed and 96.36% of all white-winged scoter (small numbers of white-winged scoter are sometimes seen with larger surf or black scoter flocks far south of their typical wintering range). The range break for the mid-coast, i.e., the southern boundary for long-tailed duck and surf scoter, was $35^{o}06'$N; the area north of this latitude included 99.97% of all long-tailed duck and 99.95% of all surf scoter. Second, we ran the multivariate clustering separately for the three areas, using densities from all five species in the northern area, three species in the mid-coast area (long-tailed duck, surf and black scoter), and using only black scoter in the southern area. Third, we compared the resulting breaks, along with the two pre-defined range boundaries, with the major cluster breaks calculated for each species (see Appendix 1, Fig A1.2-3, for these areas), identifying consistent breaks as stratum boundaries. And, fourth, we made minor changes to a few transects' cluster assignments to ensure spatially compact, logistically feasible survey strata.

3.2.2 Abundance model fitting

For the annual Waterfowl Breeding Population and Habitat survey, estimates of breeding waterfowl populations in the mid-continent of North America are calculated using a "design-based" model. (The survey is conducted jointly by the USFWS and the Canadian Wildlife Service, see USFWS 2012 for description and methods.) This approach assumes that transect counts are fixed, and, as a result, the underlying count distribution does not affect the estimated standard error (except through the magnitude of the count variance). Wintering sea ducks, however, unlike breeding birds, are not tied to a specific location, and constantly move in and out of the surveyed transect areas. In such a dynamic system, the particular shape of the highly right-skewed count distribution has a critical effect on the variance of the estimates, and needs to be considered in estimation of abundance and precision. Therefore, we have used a "model-based" procedure to estimate sea duck abundance. This approach requires that we make explicit assumptions about the observed count distributions, but also provides a flexible way to include the effect of covariates and to estimate annual and regional abundance by borrowing information from all the available data.

We derived a model to estimate sea duck abundance by considering the two components of the observation process: (1) an observer sees and identifies a group of birds, and (2) the observer estimates the number of birds in the group. This process is described mathematically as a marked point-process, where the groups represent the points and the group size is the mark. In this report, we identify the individual records in the data, or points, as "flocks" and the count associated with the record, or mark, as the "flock size," where the counts are restricted to the area within the transect boundary (i.e., our flocks and flock sizes are functions of the survey protocol and observer counting technique, not biological processes alone).

Appendix 2 (Zipkin et al., *In Press*) describes exploration of the best fitting marked point model to our data. We determined that the point process, i.e, the total number of flocks per transect, was best fit by the negative binomial distribution and the mark process was best described by a discretized log-normal distribution; these results held for all species and all years. But, while the discretized log-normal was the clear best choice among the distributions fit to the flock size data, it underestimated the mean flock size, because the empirical flock size distributions have a heavier right-tail than the log-normal.   Further research is needed to identify a better fitting distribution or determine if the data will fit this distribution when factors such as bird density (i.e., regional differences in bird abundance, which affect flock size), locational covariates, observer effects, or annual changes in social behavior are considered.

We used the model fitting results in Appendix 2 to guide specification of a sea duck abundance model. We model flock counts for each species using a negative binomial distribution with the mean of the distribution including region×year effects. Because of the lack-of-fit of the discretized log-normal in

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the right-tail, and the absence of an alternative distribution, we used a non-parametric bootstrap procedure (resampling flock sizes from our data) to characterize the flock size distribution, estimate flock sizes, and determine estimator standard errors.

We made two refinements to the basic model. For common eider and long-tailed duck, we included a zero-inflation term in the flock count model (i.e., fit the flock counts to a zero-inflated negative binomial model). The zero-inflation component allows our models to estimate the coastal range and location of suitable/unsuitable habitat as a function of two covariates, latitude and transect area (see, e.g., Zipkin et al. 2010), with the zero probability a quadratic function of latitude. The zero-component quantifies the probability that the species is present by latitude, adjusted for transect area, and, since year effects were not included, represents the average area for 2009-11. For eider, the fit of the zero-inflated model ranked higher than the simple negative binomial (Appendix 2). For long-tailed duck, an absence of the zero-component leads to underestimated abundance (as assessed by comparing observed and model-predicted counts), because there is a sharp drop in long-tailed duck abundance between southern and central Cape Cod (Fig A1.2C, Fig A1.5A), and this drop falls within one of our survey strata (inclusion of these transects in the stratum without the zero component reduces the stratum's mean flock count, so that estimated counts along the majority of the stratum's transects are too low).

We also modified our approach to estimate black, surf, and white-winged scoter abundance. A large proportion of scoters are not identified to species, and this proportion varies by region and year (due to observer experience, observation conditions, and scoter species composition). Thus, if unidentified scoters are not included in species-specific estimation procedures, we are likely to see large changes in scoter species estimates, due only to changes in identification. To estimate black, surf, and white-winged scoter abundance, we fit a hierarchical model with the following components: (1) the total scoter flock counts, N, are modeled with the negative binomial distribution, including region×year effects; (2) the number of identified black, surf, and white-winged scoter flocks and unidentified scoter flocks within each region-year are modeled by the multinomial distribution with parameters $(p_b\pi, p_s\pi, p_w\pi, 1 - \pi)$, conditional on N, where π is the proportion of scoter flocks that were identified to species for a given region-year, and (p_b, p_s, p_w) are the proportion of black, surf, and white-winged scoters in the region; and, (3) the flock sizes for each species are then estimated using a non-parametric bootstrap procedure selecting from the species, year, and region specific observed flock sizes. We did not include a zero-component in the combined scoter flock count model, because these species are found at variable abundance all along the coast and generic presence/absence is not a simple function of latitude.

Finally, we have treated replicate counts as new observations in these models. We made the assumption that replicate counts are independent of the original count because it is likely that the birds counted in the first replicate have moved outside of the transect area in the interval between replicates,

and because the plane is unlikely to fly the exact same track on the replicate. Positive correlation of replicate counts still result, because they occur close to the same location and are therefore being affected by the same covariates (we include latitude, region, year, and transect length in our modeling). We checked the effect of this assumption by exploring correlations among replicate counts and running the models for the first-replicate data only, and found no resulting bias and minimal changes to the estimates.

3.2.3 Estimation and bootstrapping

The complexity of the scoter flock count model required a modeling framework with the flexibility to build a specific hierarchical model and the OpenBUGS program for Bayesian analysis (Lunn et al. 2009) was therefore used to fit the scoter flock count model. For consistency, models for common eider and long-tailed duck were also fit using OpenBUGS. OpenBUGS uses Markov chain Monte Carlo (MCMC) simulation to estimate parameter values. We ran three chains with unique starting values for each model for 250,000 iterations after convergence, keeping one of every 250 values in order to remove evidence of autocorrelation between sampled values; this process resulted in 1,000 estimates of the parameter values for each chain.

To obtain flock count estimates and standard errors, we used the median value of each parameter estimate, along with our model covariates and indicator variables for region-year, to simulate 1,000 realizations of the species-specific flock counts on every transect within each region-year combination. Next, we selected flock sizes for the 1,000 simulated flock count datasets with a non-parametric bootstrap of our observed flock size data (subset by region-year). The sum of these flock sizes by region and year is an estimate of the total ducks present along the surveyed transects; the mean of these 1,000 bootstrap estimates is our final estimate for the total number of sea ducks for each species within the survey area and its estimated standard error is the standard deviation of the 1,000 bootstrap estimates. The total estimated number of ducks in each region and its standard error were calculated using the bootstrap totals multiplied by an expansion factor equal to the total area of the region, divided by the surveyed area. (See Fig 1, which illustrates the estimation and bootstrapping steps.)

To investigate the impact of survey effort on the precision of our estimates, we applied the bootstrapping procedure described above to a range of survey efforts, estimating total birds, the standard error, and the coefficient of variation for each year and species at five additional effort levels. The 2009-11 effort entailed surveying all transects once, and half a second time (effort=1.5). We estimated precision, measured by the annual average coefficient of variation, assuming effort of ½, ¾, 1, 2, and 3, corresponding to half the lines surveyed once, three-quarters surveyed once, all surveyed once only, all surveyed twice, and all surveyed three times, respectively. Note that, because replicates are treated as independent observations, this procedure is equivalent to adding new transect lines. Re-selecting current

transects simplifies the simulations, because transect area is needed for every new line, and the existing areas provide a representative sample for each survey strata.

Data:
Flock counts by transect
Area surveyed by transect
Latitude of transects

Zero-inflated Negative Binomial model fit with OpenBUGS
Prob[Present] = $\beta_o + \beta_1 \cdot$ latitude $+ \beta_2 \cdot$ latitude$^2 + \beta_3 \cdot$ 3-yr avg transect area
Flock count | Present = NB(λ_{it}, transect area$_t$)
λ_{it} = mean count for stratum i, year t

1,000 estimates of
$\beta_o, \beta_1, \beta_2, \beta_3, \lambda_{11}, \lambda_{21}, \ldots$
$\lambda_{S1}, \ldots \lambda_{13}, \lambda_{23}, \ldots \lambda_{S3}$
S = number of strata

Use median estimates, transect latitudes and surveyed areas to simulate flock counts for each transect from ZiNB model
Randomly select size for each simulated flock from regional flock size distribution
Calculate total ducks by expanding simulated counts to total area
Repeat 1,000 times

Mean and standard deviation of 1,000 estimates of Total Ducks

Alter areas, latitudes, replicates to simulate effort and allocation scenarios

Figure 1: Flowchart illustrating the steps in the estimation and bootstrapping procedure.

3.2.4 Stratification

The 2009-11 survey design consisted of systemically sampling transects spaced at roughly five nautical miles and replicating every second transect line. However, observed sea duck densities varied considerably by species and region. With a goal of improving the current survey design, we tested six different possible stratification scenarios. In each case, the total surveyed area (effort) was held constant, but the surveyed effort from transects replicated in low density regions was reapplied to regions of high density. These stratification scenarios allowed us to estimate the change in survey precision under different hypothetical survey designs.

We designed one stratification scenario for each individual species; a hypothetical survey design that would target the regions of high density specific to that species. Our sixth stratification design was based on overall sea duck densities for the five species of interest. This "five-species" stratification represents a more informed (i.e., more efficient) hypothetical survey for all target species, designed to

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concentrate survey effort on regions of overall high density with a goal of obtaining more precise abundance estimates.

Lastly, we investigated the effect of assigning the full five-crew effort that was available in 2009 and 2010 to the five-species stratification scenario. With the additional survey area provided by a fifth crew, we were able to simulate replicating all transects within the four high density regions (see below: strata 2, 4, 5, and 8), while adding a set of lines between the existing transects in stratum 2 and several lines in stratum 8 (added mileage varied slightly by year). Again, we applied the bootstrapping procedure above to estimate total birds, standard error, and coefficient of variation.

3.2.5 Power calculation

A decrease in wintering sea duck populations can result from a drop in the number of flocks, a drop in the sizes of the flocks, or, most likely, some combination of both. For example, large flocks might initially be unaffected by population declines, but decreasing population size would inevitably decrease their size; similarly, declining flock sizes will eventually result in fewer flocks. Power calculations necessarily depend on how both components of the abundance model are affected by changes in population size, and this is currently unknown. In particular, we do not know how the shape of the flock size distribution changes with changing population size and, because we are bootstrapping to estimate flock sizes, instead of making an assumption about the form of the flock size distribution, we have no flock size parameters to adjust. Given these limitations, we explored the survey's power to detect winter population declines for two cases: (1) decreases in the number, but not the size, of flocks, and alternatively, (2) decreases in the size, but not the number, of flocks. We calculated power for common eider, the species with the most variable abundance estimates, and long-tailed duck, the species with the least variable estimates, using the average parameter values for 2009-11 and assuming five-crew effort assigned according to the five-species stratification scenario.

To simulate changes in the number of flocks, we added a parameter representing proportional annual decline, $\Delta_{\text{No. of flocks}} > 0$, to the model, multiplying the mean of the negative binomial count component by $(1-\Delta_{\text{No. of flocks}})^t$, where t is the number of years the population has declined. To simulate changes to flock sizes, we decreased the size of all flocks used for the bootstrapping by multiplying by $(1-\Delta_{\text{Flock size}})^t$. When the percentage drop resulted in a non-integer flock size, we truncated the flock size and added the decimal value to the next smallest flock size, repeating the process until we reached the smallest flock size, when the decimal was dropped. This process shifts the flock size distribution to smaller values and ensures that a $100 \cdot \Delta\%$ drop in flock size corresponded to a $100 \cdot \Delta\%$ drop in the total number of birds counted in all flocks: if flock sizes are instead rounded, then for small to moderate

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percent declines, smaller flocks will not decrease in size at every time step and the average flock size decline is less than stated.

Before running the power calculations, we explored the effect of a decrease in the number of flocks versus a decrease in the size of flocks on the total number of birds. We ran 1,000 bootstrapped estimates of total birds for $t = 0$ (as described in section 3.2.3), followed by 1,000 bootstrapped estimates for $t = 1$, using $\Delta_{\text{No. of flocks}}$ and $\Delta_{\text{Flock size}}$ each selected from a uniform distribution between 0 and 0.2. We calculated the drop in the estimated total number of ducks ($\Delta_{\text{Total birds}}$) for the 1,000 pairs and fit a zero-intercept linear model to these values with decrease in number of flocks ($\Delta_{\text{No. of flocks}}$), decrease in flock size ($\Delta_{\text{Flock size}}$), and their interaction as explanatory variables to estimate the relationship between a decrease in number and/or size of flocks and the resulting decrease in total birds. Using the resulting parameter estimates, we calculated the mean percent decrease in total bird count for all combinations of decreases of 0, 1, 2, 5, 10, and 15% in the number and size of flocks.

We calculated the survey's power to detect population declines for annual decreases of 1, 2, 5, 10,and 15% in (1) the number of flocks and (2) the size of flocks by simulating 1,000 31-year time series of total birds for both scenarios using the 2009-11 average estimated parameter values for common eider and long-tailed duck. For each type of decline, time interval (2-30), and simulation, we fit a log-linear regression model to estimate the rate of population decline, $\Delta_{\text{Total birds}}$ (abundance $N(t) = N_o(1 - \Delta_{\text{Total birds}})^t$ in our formulation). This resulted in 1,000 estimated rates of decline, $\log(1 - \Delta_{\text{Total birds}})$, and associated confidence intervals for $\alpha = 0.05$ and 0.1, for each type of decline and time interval; the proportion of the 1,000 confidence intervals that fell entirely below zero is our estimate of the power to detect $\Delta_{\text{Total birds}} > 0$. For the case of decreasing flock counts, we also calculated the power to detect positive values of the parameter $\Delta_{\text{No. of flocks}}$, by fitting the simulated flock counts to the zero-inflated negative binomial model for each time interval and estimating the associated confidence intervals.

4. Results

4.1 Identification of survey strata

Using the clustering algorithm and four-step process described in section 3.2.1, we identified ten coastal regions that differed in individual and total sea duck density (Fig 2). Appendix 1 includes details for the species-specific regions and annual differences.   The range break for the northern species occurs at the boundary of strata 2 and 3; this is also a cluster break for long-tailed ducks. The range break for the mid-coast species occurs between strata 6 and 7 and is a cluster break for black scoter. The high-density strata that received extra effort at the expense of replication in the low-density strata are illustrated in Table 2.

Table 2: Six stratification scenarios. The stratification scenarios are represented by columns, and the column heading indicates the species targeted by the stratification effort. Shading indicates the high-density strata that received additional effort, with all low-density replicates reallocated to previously un-replicated transects in high density areas. Pluses indicate strata that received additional effort beyond that needed to replicate all transects; Minuses indicate strata that received additional effort that was insufficient to replicate all transects. The 5-species, 5-crew stratification sampled additional transects in the four strata shaded in the right-most column, with no strata receiving insufficient added effort (minus sign) and strata 2 and 8 receiving additional effort (plus sign).

	Stratum	Common eider	Long-tailed duck	White-winged scoter	Surf scoter	Black scoter	5-species
1	Maine & New England						
2	Cape Cod & Long Island Sound	+	+	+	−		
3	New Jersey coast						
4	Delaware Bay & DE/MD coast					+	−
5	Chesapeake Bay						−
6	Virginia coast & Pamlico Sound					+	
7	S. North Carolina coast						
8	Central South Carolina coast					+	
9	S. South Carolina/N. GA coast						
10	S. Georgia coast						

Figure 2: Ten sea duck strata identified by clustering analysis, color coded from high (red) to low (dark green) in total sea duck density. Numbers are the annual mean (SD) density for the neighboring region (birds/NM^2). Note that two strata in the mid-Atlantic have similar overall sea duck densities. The *ed central South Carolina region's high value is due to one especially large count. The region's density without this count is 20.8 (26.2). Black scoter regions in the south were identified with this value excluded.

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4.2 Abundance estimation

Table 3 reports the total birds estimated in the survey area by year and species, along with the three-year average. Table 4 includes the three-year averages for the ten regions. Note that the current methods and model do not account for detection, count bias, or observer effects. These numbers should be interpreted as the total number of ducks that crews would have counted, if they had surveyed all ten regions in their entirety, and should not be considered winter population estimates. Further analyses of the data to quantify observation effects are needed to build models that predict actual wintering population sizes.

Table 3: Estimated total observable birds in the survey area, estimated standard error, and coefficient of variation by species and year, along with the three-year mean values.

		2009	2010	2011	3-year mean
	Estimated total birds	234,106	299,624	220,383	251,371
Common eider	Est. standard error	72,492	91,907	58,973	43,394
	Coefficient of variation	0.31	0.31	0.27	0.17
	Estimated total birds	242,419	253,817	213,421	236,552
Long-tailed duck	Est. standard error	49,387	48,200	39,565	25,700
	Coefficient of variation	0.20	0.19	0.19	0.11
	Estimated total birds	44,076	55,183	76,525	58,595
White-winged scoter	Est. standard error	14,617	19,825	22,191	11,069
	Coefficient of variation	0.33	0.36	0.29	0.19
	Estimated total birds	151,158	118,346	178,105	149,203
Surf Scoter	Est. standard error	27,226	21,543	37,547	17,149
	Coefficient of variation	0.18	0.18	0.21	0.11
	Estimated total birds	142,902	380,695*	110,390	211,329
Black scoter	Est. standard error	26,178	187,167	26,040	63,778
	Coefficient of variation	0.18	0.49	0.24	0.30
	Estimated total birds	336,444	581,505	370,273	429,407
Scoter spp.	Est. standard error	50,701	193,883	66,261	70,950
	Coefficient of variation	0.15	0.33	0.18	0.17

*The 2010 black scoter estimate calculated excluding the large replicate value at 32°41′ is 138,247 (37,924) with a CV of 0.27. The resulting 3-year mean is 130,796 (16,971) with a CV of 0.13.

The annual estimates are all within two standard errors of the three-year mean, with the exception of the estimate for black scoter in 2010. The black scoter estimate is due to a few unusually large counts off the southern coast; this is reflected in the high standard error for black scoter in 2010. Estimates are the least variable for the long-tailed duck and surf scoter. Common eider, long-tailed duck, and black scoter estimates are highest in 2010 and lowest in 2011; white-winged and surf scoter estimates are highest in 2011 and lowest in 2009 and 2010, respectively.

The model estimates correspond well to the raw observed counts (data not shown): these counts, expanded by region to the total survey area for each species and year, are all well within one standard error of the model estimated total birds, as are the 3-year means for the expanded raw counts (231, 245, and 457 thousand, for common eider, long-tailed duck, and scoter spp., respectively). The model over-predicts slightly relative to the raw counts for common eider in all three years, and under predicts total scoters. These patterns may result from an interaction between the zero-inflation term (or lack thereof) and the stratum boundaries, as highlighted in the case of the long-tailed duck estimates. Further investigation is needed to develop the best stratification approach (e.g., post-stratifying by species) and form of the zero-inflation term, so as to minimize these effects.

Table 4: Estimated three-year mean abundance (estimated SE) in thousands, by survey region and species. 0.00 values indicate estimates in the single digits.

	Common eider	Long-tailed duck	White-winged scoter	Surf scoter	Black scoter	Scoter spp.
All Regions	251.4 (43.4)	236.6 (25.7)	58.6 (11.1)	149.2 (17.1)	211.3 (63.8)	429.4 (70.9)
1 Maine & New England	45.5 (6.3)	11.9 (2.9)	1.7 (1.0)	2.2 (0.5)	0.5 (0.2)	4.7 (1.3)
2 Cape Cod & Long Island Sound	205.8 (43.3)	194.6 (25.2)	55.2 (11.0)	66.0 (11.8)	32.6 (8.3)	155.4 (25.7)
3 New Jersey coast		2.7 (0.9)	0.08 (0.04)	0.1 (0.1)	0.3 (0.1)	1.8 (1.5)
4 Delaware Bay & DE/MD coast		0.8 (0.2)	0.7 (0.3)	47.7 (9.0)	34.0 (6.2)	84.6 (14.8)
5 Chesapeake Bay		25.4 (5.8)	0.8 (0.4)	30.3 (8.9)	4.0 (2.4)	37.9 (11.3)
6 Virginia coast & Pamlico Sound		1.2 (0.5)	0.01 (0.02)	2.8 (1.0)	19.5 (6.5)	23.6 (7.0)
7 Southern North Carolina coast				0.01 (0.01)	1.8 (0.7)	1.9 (0.8)
8 Central South Caroline coast			0.1 (0.2)	0.00 (0.01)	113.6 (62.5)*	112.2 (62.0)
9 S. SC coast & N. Georgia coast				0.00 (0.00)	3.2 (1.6)	3.3 (1.6)
10 southern Georgia coast			0.01 (0.01)	0.01 (0.01)	2.0 (2.4)	3.9 (4.2)

* Black scoter estimate excluding the large replicate value at $32^o41'$ in 2010 is 32.8 (12.5).

Species-specific scoter estimates also sum to slightly less than the total scoter estimate. This is due to the fact that we calculated the species-specific estimates using the observed species-specific flock size distributions, while the generic scoter estimates were calculated using all scoter flock sizes. Unidentified scoter flock sizes were somewhat larger than identified scoters (mean = 10.5, SD = 27.5 for unidentified scoters versus mean = 9.8, SD = 26.9 for identified scoters, omitting southern coast, where only black scoter are found) and this suggests that large, mixed flocks are more likely to be recorded as generic scoter. There were more unidentified scoters in 2011 (37% of all scoters seen, as compared to 15 and 16% for 2009 and 2010, respectively, Table 5). The increase was due to our decision to reclassify one new observer's scoter observations as generic, because his species composition differed substantially from the experienced pilot's. In this case, the model uses the regional species composition from the pilot-observer to estimate species-specific flock counts.

Table 5: Proportion of scoters identified by species and year.

	2009	2010	2011
White-winged scoter	0.07	0.05	0.17
Surf scoter	0.31	0.14	0.29
Black scoter	0.47	0.65	0.17
Total identified	0.85	0.84	0.63

The abundance model first estimates the number of flocks per transect, and then assigns each a size by sampling from the distribution of observed flock sizes. Figure 3 presents the distribution of flocks per transect by species and year for transects with flocks present (log-scale), along with the total number of flocks estimated for each year by the model, and the coefficient of variation of the estimate. The observed and model-estimated number of transects with no flocks, for each survey year and species, are close (the average percent difference in number of transects with no flocks, all species and years is 2.0%).

Total scoter flock counts are consistent between years and more skewed than eider or long-tailed duck counts, indicating many transects with few flocks and a few transects with many flocks. Since the scoter counts represent the sum of three species, one might expect the combined distribution to be less skewed than those for single species, if the species were distributed independently among transects. The higher skew would suggest the three species tend to concentrate in the same areas. The increased abundance of white-winged scoter in 2011 was due to more, larger flocks, and the high count of black scoter in 2010 was due to a few very large counts (Fig 3 and Fig 4, which plots the distribution of flock sizes by year and species).
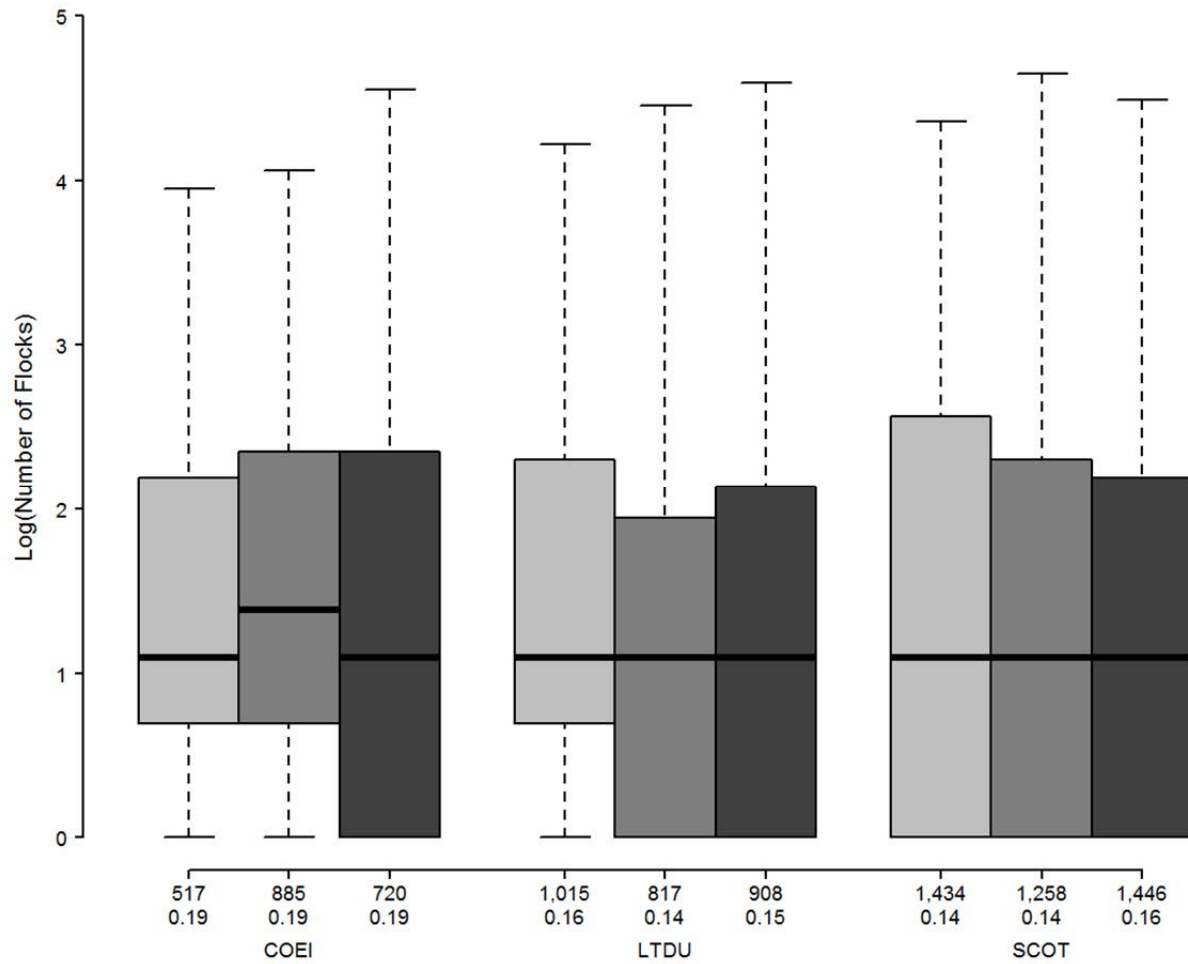
Figure 3: Flock count distributions by year and species (COEI = common eider, LTDU = long-tailed duck, and SCOT = scoter spp.). Scoter species are combined, because single species distributions are affected by the number of unidentified scoter flocks on each transect. The model assigns scoter-species to estimated flocks based on the proportion of each species' flocks in the region. Numbers below the boxplots are (1) the estimated number of flocks by year and species, based on the negative binomial model with zero-inflation (eider and long-tailed duck), region×year effects, and a transect area offset, and (2) the coefficient of variation of these estimates.
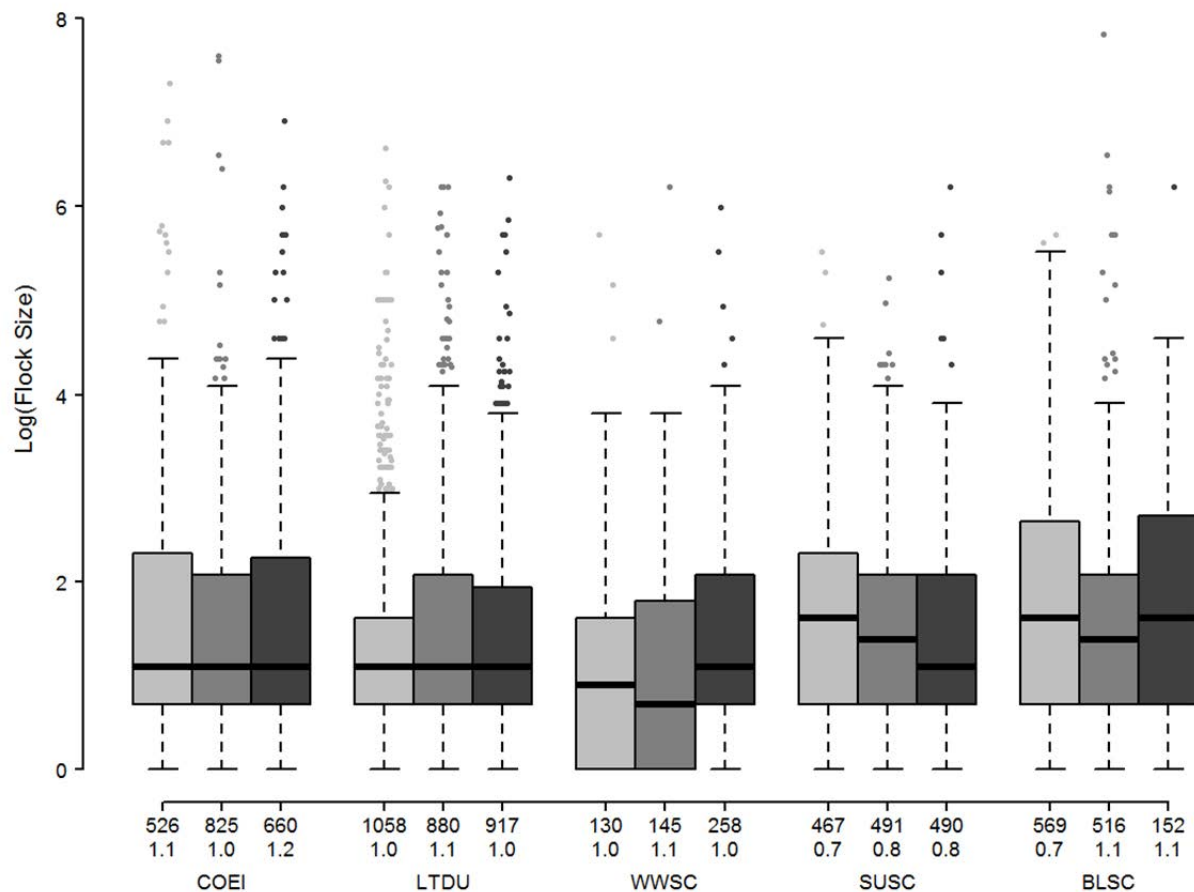
Figure 4: Boxplots of log[flock size] by year and species (WWSC = white-winged scoter, SUSC = surf scoter, BLSC = black scoter). Scoter species boxplots represent the distributions of flock sizes, for flocks identified to species. The numbers on the x-axis are the total number of flocks observed in each year, and below these are the variance to mean ration of the observed log[flock size] distribution.

The total number of eider flocks surveyed each year varied the most, as does our confidence in the flock count estimate (as measured by the CV, Fig 3). Transect flock counts for eider, however, are less skewed, as might be expected given their more concentrated range: Figure 5 illustrates the probability of transect occupancy as a function of latitude for eider and long-tailed duck. The eider range has a sharp boundary, although a few eiders are regularly counted south of the sharp drop (see also Table 4).
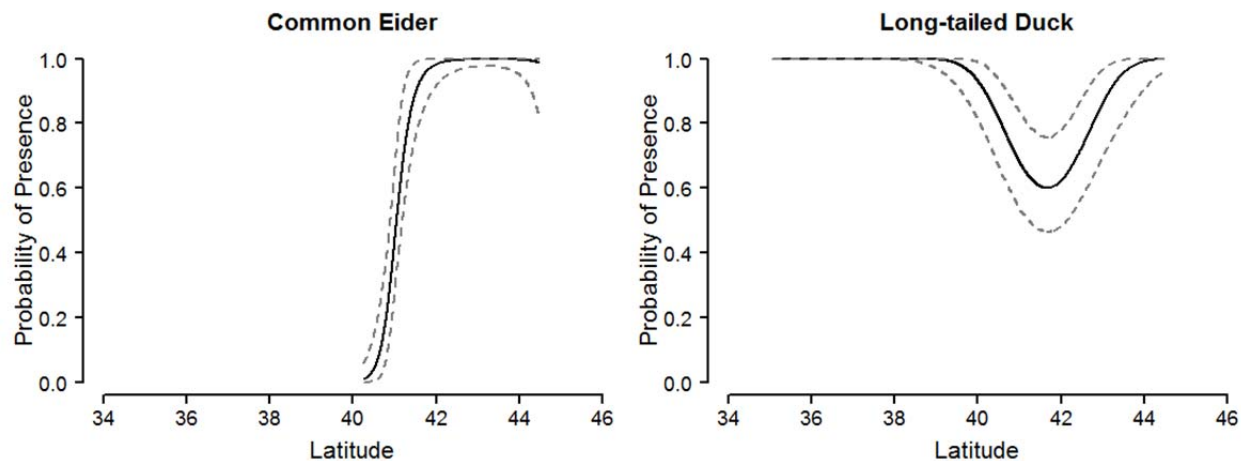
Figure 5: Estimated probability of presence by latitude for a transect of average area. Solid curves are the model estimated medians; the dashed lines encompass the 90% credible interval.

Long-tailed duck flock counts and flock sizes are less variable both within and between years, and our estimates of their abundances are correspondingly more precise (Figs 3-4, Table 3). The larger long-tailed duck estimate in 2010 was due to fewer, somewhat larger flock counts (Fig 3-4). Estimation of long-tailed duck probability of occurrence is dominated by the northern and eastern transects in stratum 2 (i.e., Cape Cod, Fig 5), which represent a sharp drop in long-tail abundance from the southern Cape. This result is due to the fact that we set the stratum boundary just north of Cape Cod, because this was identified as a stratum break for white-winged scoter and because it would result in a more "logical" stratum for survey crews and data management.

The flock size distributions for common eider and long-tailed duck are similar between species and years, but the differences are sufficient to impact the annual estimates. Scoter distributions are more variable, which, for white-winged and surf scoter in particular, may reflect variations among observers in species identification. Black scoter distributions are affected particularly by flock sizes along the southern coast, where they are not confused with the other two species. Their spatial distribution and patterns of aggregation over the four survey years have been highly variable (see Appendix 1), and this is reflected in the lower precision of the black scoter estimates.

4.3 Effect of effort and stratification on the precision of estimates

Under current survey effort, the annual species-specific coefficients of variation range from 0.18 to 0.49, and the CVs for the three-year means from 0.11 (long-tailed duck and surf scoter) to 0.30 (black scoter); abundance estimates for common eider, white-winged scoter, and black scoter are the most variable (Table 3). Figure 6A plots the average annual CVs, which measure the typical precision of the annual estimates, as a function of survey effort. The effort level in 2009-11 (1.5) is indicated on the plot (these

CVs are the averages of the three annual values reported in Table 3 for each species). The red dashed line on the figure indicates the effort value that would have been possible, if the five survey crews deployed in 2009-10 had all flown east-west transects, and effort that went to transects longer than 15 NM was reassigned.
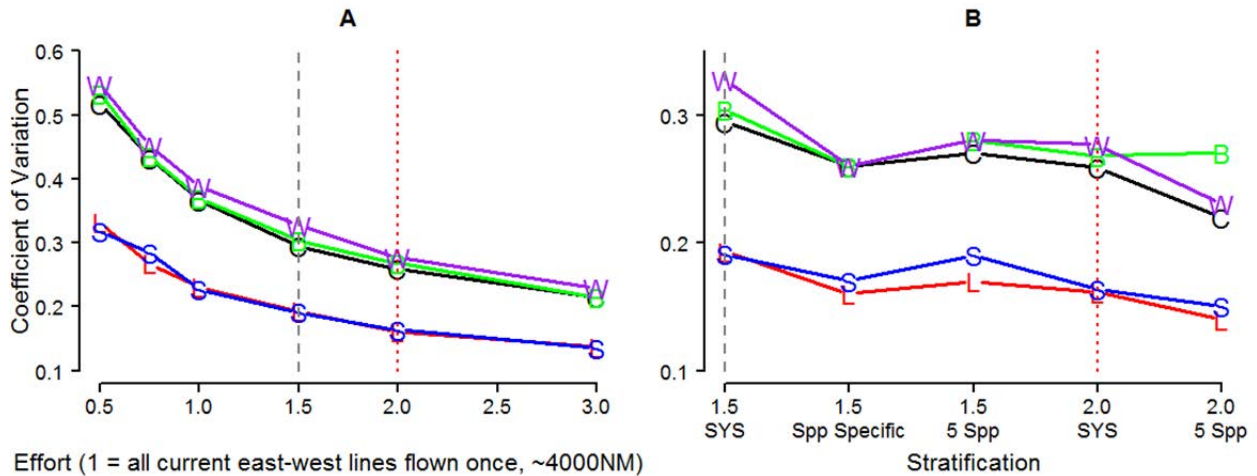
Figure 6: Average annual coefficient of variation versus (A) survey effort and (B) stratification scenario by species. W = WWSC, B = BLSC, C = COEI, S = SUSC, and L = LTDU. In 2009-11 survey effort was 1.5 (all lines flown once, half flown again). If the 5th survey crew were to be assigned "regular" survey lines, effort would be 2.0, indicated by the red dashed line. Dashed lines in (B) correspond to those in (A), and are included for reference, i.e., *1.5 SYS* and *2.0 SYS* refer to the current systematic scenario with survey effort equal to 1.5 and 2.0, respectively; *1.5 Spp Specific* refers to the individual species stratification at 1.5 effort; *1.5 5 Spp* refers to the five-species stratification at 1.5 effort; and, *2.0 5 Spp* refers to the five-species stratification with five crews. Note the different y-axis scales in A and B.

Table 6 and Figure 6B summarize the results of the stratification simulation on the precision of the annual total and regional estimates. The consequences of the species-specific stratifications are included only for the species itself, as a measure of the largest improvement likely under stratification with current effort. The five-species stratification under current effort (1.5 in Fig 6B) and five-crew effort (2.0 in Fig 6B) are also included.

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Table 6: Average annual coefficients of variation for the current survey design and effort (SYStematic), the five species-specific stratifications (COEI, LTDU, WWSC, SUSC, and BLSC STRATA), the five-species omnibus stratification (5 Spp STRATA) and the five-species stratification assuming five crews at current effort (5 Spp STRATA, 5 Crews). Shaded regions (Cape Code/Long Island, DE Bay, DE/MD coast, Chesapeake Bay, and Central SC coast) are the high density five-species strata. Shading under the species headings indicates high density strata by species. Red outlines denote the strata receiving additional effort under each scenario, dashed red outline indicate added effort that is insufficient to replicate all lines in the stratum (the two mid-Atlantic strata in the five-species case and the Cape Cod/Long Island stratum in the SUSC-specific stratification).

	Common eider				Long-tailed duck				White-winged scoter				Surf scoter				Black scoter			
	SYS	COEI STRATA	5 Spp STRATA	5 Spp STRATA, 5 Crews	SYS	LTDU STRATA	5 Spp STRATA	5 Spp STRATA, 5 Crews	SYS	WWSC STRATA	5 Spp STRATA	5 Spp STRATA, 5 Crews	SYS	SUSC STRATA	5 Spp STRATA	5 Spp STRATA, 5 Crews	SYS	BLSC STRATA	5 Spp STRATA	5 Spp STRATA, 5 Crews
Total area	**0.29**	**0.26**	**0.27**	**0.22**	**0.19**	**0.16**	**0.17**	**0.14**	**0.33**	**0.26**	**0.28**	**0.23**	**0.19**	**0.17**	**0.19**	**0.15**	**0.30**	**0.26**	**0.28**	**0.27**
Maine/New England	0.24	0.20	0.28	0.29	0.35	0.41	0.42	0.42	0.57	0.70	0.70	0.70	0.40	0.50	0.50	0.52	0.50	0.59	0.58	0.59
Cape Cod/Long Isl.	0.36	0.32	0.32	0.26	0.23	0.18	0.19	0.16	0.35	0.27	0.30	0.24	0.27	0.26	0.24	0.20	0.34	0.41	0.29	0.24
NJ coast					0.53	0.64	0.63	0.64	0.97	1.15	1.15	1.14	1.06	1.28	1.28	1.28	0.79	0.97	0.95	0.95
DE Bay, DE/MD coast					0.44	0.55	0.40	0.37	0.73	0.90	0.72	0.62	0.26	0.22	0.26	0.22	0.26	0.20	0.25	0.22
Chesapeake Bay					0.37	0.30	0.36	0.29	0.73	0.83	0.73	0.60	0.45	0.35	0.44	0.35	0.74	0.87	0.75	0.58
VA & Pamlico Sound					0.42	0.53	0.52	0.50	1.63	1.92	2.00	2.07	0.52	0.63	0.63	0.64	0.39	0.30	0.47	0.47
Southern NC coast													1.48	1.67	1.69	1.68	0.74	0.87	0.88	0.90
Central SC coast									1.30	1.61	1.17	1.09	1.60	1.91	1.34	1.34	0.52	0.38	0.46	0.43
s.SC & n. GA coast													2.58	3.19	3.03	3.10	0.68	0.81	0.83	0.81
Southern GA coast									1.47	1.52	1.58	1.48	1.38	1.75	1.64	1.62	1.40	1.63	1.60	1.64

Stratification improves the precision of the estimates in all cases: an average of two percentage points under the current effort, five-species stratification, four points under species-specific stratifications, and six points under the five-crew, five-species design (Table 6, Fig 6B). Improvements in precision for the coastwide abundance estimates and for high density regions come at the expense of precision in low density strata. Thus, the common eider estimate in stratum 1 (Maine/New England) and the black scoter estimate in stratum 6 (Virginia coast/Pamlico Sound) see CV increases under the five-species stratifications, because those strata do not receive extra effort under that stratification. These effects could be mitigated by increasing overall survey effort and applying that effort to species-specific high density strata.

Stratification improves precision most for the white-winged scoter estimates with the species-specific resulting in a CV drop of seven percentage points: from 0.33 to 0.26. The highest density white-winged scoter strata (Cape Cod/Long Island) received extra effort under all stratifications, with the five-crew, five-species stratification giving the best overall improvement (0.23). The 11 point improvement in stratum 2's CV, however, comes at the expense of stratum 1, which saw a 13 point increase in its CV.

Common eider, long-tailed duck, and black scoter have similar precision gains through stratification, with eider benefiting most from the five-species, five-crew stratification that concentrates survey effort around Cape Cod, and black scoter benefiting most from a species-specific stratification, which shifts effort south. Surf scoter see the smallest gains, as both the five-species, current effort and five-crew effort concentrate extra effort in around Cape Cod and South Carolina, and add relatively less effort to the mid-Atlantic strata, where surf scoter is most abundant.

4.4 Power

Power calculations for detecting $\Delta_{\text{Total birds}} > 0$ were essentially identical for equivalent decreases in $\Delta_{\text{No. of flocks}}$ and $\Delta_{\text{Flock size}}$ (results not shown). The zero-intercept linear model relating $\Delta_{\text{Total birds}}$ to $\Delta_{\text{No. of flocks}}$ and $\Delta_{\text{Flock size}}$ supported this result: a decrease in either the number or size of flocks results in the same proportional decrease in the total number of birds, while a simultaneous decrease in both number and size of flocks results in total birds decreasing by the sum of the two decreases, less their product (which is approximately equal to the summed declines, e.g., a one percent decline in both the number and size of flocks translates into a 1.99% decline in total number of birds). The standard error values for the parameters in the zero-intercept model are very close to one another in magnitude (within two percent) , which suggests that one avenue of decline does not produce more variability in the decline in total birds than the other.

Table 7 summarizes the results of the power analysis. Power to detect declines is higher for long-tailed duck than common eider, requiring, for example, about eight fewer years to detect a two

percent annual decline and one less year to detect a fifteen percent decline. For both species, more than 25 years are needed to detect annual declines of one percent, and about eleven to fifteen years to detect five percent declines. But, the smaller the annual decline, the larger the population size will be when the trend is detected: for example, a two percent annual decline should be detected when the population has dropped between 28% (long-tailed duck at 80% power, $\alpha = 0.1$) and 43% (common eider at 90% power, $\alpha = 0.05$), while a ten percent decline would be detected when the population had dropped 47-65%.

Power to detect a decline in the number of flocks is substantially higher than a decline in total birds. At 80% power, annual declines in number of common eider flocks will be detected three to eight years sooner than equivalent declines in total birds, and declines in long-tailed duck flocks two to seven years sooner. For both species, the time to detect a five percent decline in number of flocks is equivalent to the time to detect a ten percent decline in total birds. Thus, if more than half of the annual decline in total wintering population is manifest as a decline in the number of flocks, monitoring the number of flocks would provide a more sensitive metric for population trends than estimates of total birds.

Table 7: The number of years to detect a decline in total abundance ($\Delta_{Total\ birds} > 0$) and the number of flocks ($\Delta_{No.\ of\ flocks} > 0$) with 80% power and $\alpha = 0.1$ or 90% power and $\alpha = 0.05$ for common eider and long-tailed duck. The calculations for $\Delta_{Total\ birds}$ are based on a yearly decline in the number of flocks ($\Delta_{No.\ of\ flocks}$). Results based on a decline in the size of flocks ($\Delta_{Flock\ size}$) were the same. Power calculated using the average 2009-11 parameter values and assuming the five-crew, five-species stratified effort.

Yearly decline (%)	Years to ≥50% decline	$\Delta_{Total\ birds}$		$\Delta_{No.\ of\ flocks}$	
		80% at 0.1	90% at 0.05	80% at 0.1	90% at 0.05
		Common eider			
1	70	>31	>31	24	28
2	36	24	29	16	18
5	15	13	16	9	10
10	8	9	11	6	7
15	6	7	9	4	5
		Long-tailed duck			
1	70	27	>31	19	23
2	36	17	21	10	12
5	15	10	12	7	8
10	8	7	8	4	5
15	6	6	7	4	4

5. Discussion

5.1 Model performance and next steps for abundance estimation
Based on our previous analyses (Appendix 2), the close match between observed and estimated counts, and the flock count models' successful prediction of the number of zero-flock transects, we suggest that

the abundance model fits the data well and provides reasonable estimates of abundance. Bootstrapping the flock sizes should result in realistic standard error estimates that account for the extreme skew of the flock size distributions.

Because the model is sensitive to the flock size distribution, further data and analyses are needed to characterize these distributions and understand the factors that affect the weight of the tail (e.g., the relative effect of observer counting strategies versus bird behavior, and the extent to which these factors vary by observer, year, or species). Estimation accuracy and efficiency might also be increased, without additional effort or data, by accounting for both observer differences and observation conditions. Including local covariates for replicated transects may improve our description of the flock size distributions and weight areas with large flock counts appropriately.

Separating the observation process into the occurrence component (flock count) and the measurement component (flock size) allows us to improve our estimates by identifying the separate covariates that affect each component, and to adjust the survey protocol and design accordingly. It may ultimately be most efficient to collect the flock count and flock size data independently using different protocols (e.g., observers count flocks and cameras determine flock sizes) or to incorporate a double counting procedure for a sub-sample of transects (simultaneous counts and photos, or double observers with the second observer focused only on estimation of large flocks). Because the large flock counts have a disproportionate effect on the abundance estimate, improvements in detection are unlikely to improve survey efficiency relative to improvements in flock size measurement.

As a result of the impact of a few large flock counts on the 2010 BLSC abundance estimate, and the general variability of black scoter along the southern coast, we conducted intensive surveys along South Carolina and Georgia in 2011-12, replicating all lines and adding lines at 2.5NM intervals. We plan to analyze these data to better understand scoter distributions in this area, the distribution of flock counts and the factors affecting these counts, the relative advantages of increasing spatial coverage versus replicating lines, and the survey effort necessary to obtain sound black scoter abundance estimates.

Further analysis of the factors affecting scoter identification is also necessary: if the probability of identifying a scoter to species differs substantially by species, then some of our regional scoter estimates could be biased. The extent of this problem would depend on the magnitude of the differences in identification and the underlying species composition in the region. For the most part, the survey crews in 2008-11 consisted of observers with extensive experience with aerial waterfowl surveys and sea ducks, which should minimize the effect of inexperience on scoter speciation.

For highly aggregated count data, such as winter sea duck counts, the excess of zero values presents another modeling challenge. Although the zero-inflation component is an effective means to address this problem, (1) the covariates determining the probability of occurrence, (2) the functional form

of the relationship between these covariates and occurrence, and (3) the interaction of the zero-inflation formulation and the stratification (which essentially defines covariate 'regional indicator' variables for the negative binomial count component of the model), all affect model performance and the quality of the resulting estimates. Further research is needed to understand these interactions and develop methods to select appropriate stratum boundaries or adjust for boundaries that are selected based on multi-species or logistical considerations.

5.2 Improving precision through survey design changes

The effort and stratification analyses suggest that we can achieve meaningful improvements in the efficiency of our estimates by modifying the survey design to sample more heavily in high density areas and by increasing the current effort. The five-species stratification using five crews (the effort available in 2008-10) reduced overall CVs three to ten percentage points and improved the precision of some regional estimates substantially.

Estimates for long-tailed duck and surf scoter, species whose wintering areas fall within the central portion of the survey's latitudinal range, are the most precise. Estimates for these species show smaller precision gains under stratification than do estimates for the white-winged scoter and common eider, the species with the most variable estimates. The higher CVs for white-winged scoter and common eider are not surprising: white-winged scoter abundance is low, making efficient estimation challenging, and common eider is the most highly (and variably) aggregated of the five species. Black scoter CVs exhibited high inter-annual variability in precision (due to 2010) and small precision gains under the stratifications that we explored, which is expected given their wide and variable range.

As the distributions of the five species vary, so do the solutions to achieving more precise estimates. Estimation of long-tailed duck abundance would likely improve if the Nantucket Shoals transects were treated as a unique stratum. Precise eider estimates require concentrating effort from Long Island northward. In contrast, precise black scoter estimates necessitate more survey effort in the southern half of the survey area, likely at the expense of the other four species.

Power analysis suggests that the survey can detect large changes in abundance in relatively few years, and slow changes before overall population declines are large. Increasing survey precision in general or targeting stratification to species of concern (i.e., those likely to have the greatest annual declines) would improve the power to detect negative trends. A better understanding of the flock size distribution, and the relative effect of population size changes on number of flocks and flock sizes, would further improve the survey's power to detect trends, as well as our ability to estimate it correctly. If flock numbers decline more rapidly than flock sizes, then trends in the number of flocks may be an effective means of monitoring for population trend. Note, however, that our power analysis is preliminary, and

does not include realistic components such as variability in annual declines, which might affect power calculations.

One additional avenue of exploration for optimal design and stratification concerns the effect that changes in distributional patterns have on annual abundance estimates. In 2011, when the white-winged scoter estimate is the highest, we also recorded the lowest percentage of white-winged scoter on the Nantucket Shoal transects. Although the survey design appears to cover the eastern extent of the species wintering range, the larger 2011 estimate for white-winged scoter could be due in part to the birds' shift off the Shoals and inshore: because our sampling effort is necessarily greater nearer to land, such shifts might add variability to the annual abundance estimates. We plan to explore the effect of stratifying by distance from the coast, as well as latitude, to achieve appropriate estimates. A distance-to-coast sensitive stratification may also improve the precision on our estimates of black scoter abundance, as they are found farther offshore than the other species (Appendix 1).

We consider the strata used for the analyses in this report to be preliminary, with improvements possible as additional data and analyses of distributions are available. In general, long-term monitoring programs would benefit from a process of continual updating of survey strata, as new data are collected. Such an approach would not only improve estimator efficiency and reduce bias, but would also provide a method of tracking distributional shifts and understanding how species are responding to environmental and habitat changes.

The larger issue of annual variability due to shifts in and out of the survey area (e.g., to the Great Lakes, Canadian waters, or coastal areas inaccessible to survey aircraft) cannot be addressed by the current survey alone. It is worth noting that survey crews have not been able to enter the southwestern corner of Pamlico Sound, because the area is restricted airspace. In 2010, several satellite-tagged black scoters were in this area, and some annual variation in black and surf scoter abundance may be due to our inability to survey what we know to be an important area for wintering scoters. Observations from sea ducks outfitted with satellite transmitters may give insight into the frequency and scale of such shifts, and provide baseline data for development of a more comprehensive winter survey.

6. References

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Appendix 1

WINTERING SEA DUCK DISTRIBUTIONS ALONG THE ATLANTIC COAST OF THE UNITED STATES

1. Abstract

Monitoring data for sea ducks, which are limited, indicate that ten of the fifteen North American populations may be declining. These apparent trends, combined with the fact that sea duck life histories are among the most poorly documented of North American waterfowl, have led to concerns for sea duck populations, and questions about the impacts of human activities, such as hunting, as well as catastrophic events and environmental change. During the winter, thousands of sea ducks are found along the Atlantic coast of the United States, where they may be affected by proposed wind power development and the associated changes to marine traffic, aquaculture, sand mining, and other coastal development. Possible impacts are difficult to quantify, because traditional winter waterfowl surveys do not cover many of the marine habitats used by sea ducks. Thus, the United States Fish and Wildlife Service conducted an experimental survey of sea ducks from 2008-11 to characterize their winter distributions along the U.S. Atlantic coast. Each year, data were collected on eleven species of sea ducks on more than two hundred transects, stretching from Maine to Florida. In this paper, we describe distributions of five of these species: common eider *Somateria mollissima*, long-tailed duck *Clangula hyemalis*, white-winged scoter *Melanitta fusca*, surf scoter *Melanitta perspicillata*, and black scoter *Melanitta americana*. Densities of the two species with the most northerly distribution, white-winged scoter and common eider, were highest near Cape Cod and Nantucket. Long-tailed duck were most abundant around Cape Cod, Nantucket Shoals, and in Chesapeake Bay. Surf scoter also concentrated within Chesapeake Bay, however, they were additionally found in high densities in Delaware Bay, and along the Maryland/Delaware outer coast. Black scoter, the most widely distributed species, occurred at high densities along the South Carolina coast and the mouth of Chesapeake Bay. Spatial patterns of high density transects were consistent among years for all species except black scoter, which exhibited the most inter-annual variation in distribution. The distance from land, depth, and bottom slope where flocks were observed varied among species and regions, with over 75% of sea ducks observed in less than 20 m of water, closer than 4 NM from the coast and over seabed with slope shallower than 1°. Common eider and long-tailed duck were observed closer to shore and over steeper ocean bottoms than the three scoter species. Our results represent the first large scale quantitative description of winter sea duck distributions along the U.S. Atlantic coast, and should guide the development of sea duck monitoring programs and aid the assessment of potential impacts of ongoing and proposed offshore development.

2. Introduction

The fifteen species of North American sea ducks (Tribe *Mergini*) are the least understood group of waterfowl protected under the Migratory Bird Treaty Act (Bellrose 1980, Goudie et al. 1994, Sea Duck Joint Venture 2003, Sea Duck Joint Venture Management Board 2008). Monitoring data for these species are of limited scope and uncertain quality, and little is known about their distributions and habitat preferences (Zipkin et al. 2010). Available data suggest ten of the fifteen North American sea ducks have declining populations, but causes of the declines are not known (Goudie 1989, Caithamer et al. 2000, Sea Duck Joint Venture 2003).

Sea ducks exhibit delayed sexual maturity and have long life spans and low annual recruitment (Caithamer et al. 2000, Sea Duck Joint Venture 2003), making their population dynamics sensitive to adult survival and slow to recover from catastrophic events, environmental degradation, and anthropogenic impacts (Di Giulio and Scanlon 1984, Ohlendorf and Fleming 1988, Piatt et al. 1990, Guillemette and Larsen 2002, Larsen and Guillemette 2007). Sea duck populations are legally harvested (Krementz et al. 1996, Krementz et al. 1997, Caithamer et al. 2000) and human activity is expanding in both their northern breeding and coastal wintering areas. Along the U.S. Atlantic coast, an important sea duck wintering area, energy production (e.g., proposed wind farms), coastal development and engineering, sand mining, shipping, and aquaculture all have the potential to alter sea duck habitats and affect migrating and wintering birds.

Existing information on the distribution of sea ducks along the Atlantic coast comes from previous U.S. Fish and Wildlife Service (USFWS) surveys of near shore habitats (i.e., 0.25 NM from coast; Zipkin et al. 2010). These data do not lend themselves to estimation of intra-annual spatial or temporal variation, or provide information for offshore areas, where many sea ducks are observed to aggregate and where wind energy development is proposed.

The USFWS conducted several experimental offshore surveys of limited scope in the mid-Atlantic region during the 1990s and early 2000s; these efforts highlighted concerns about reliance on near shore surveys to monitor sea duck populations (M.D. Koneff, USFWS, unpublished data). To improve our understanding of offshore sea duck distribution, the USFWS initiated the Atlantic Coast Wintering Sea Duck survey in 2008. This experimental survey was aimed at developing an operational survey for all sea duck species wintering along the full extent of the U.S. Atlantic coast. The primary goals of the experimental survey were to estimate population sizes of wintering sea ducks, assess yearly variation and trends, and identify high concentration areas, as well as associations among sea duck occurrence and environmental features (Silverman et al. 2010, 2011, 2012). Identifying associations among sea duck occurrence and physical features (e.g., distance to land, water depth, bottom slope) is a

first step towards defining research efforts necessary to identify offshore resources that are critical for sea ducks. Clarifying relationships between critical resources and sea duck distribution and abundance (Morrison 2001) will provide a quantitative basis for understanding sea duck wintering ecology and movements, aid the design of monitoring programs, inform targeted conservation and management actions, and allow for the prediction of potential anthropogenic impacts. In this paper, we analyze data from the Atlantic Coast Wintering Sea Duck survey to characterize the winter distributions of five sea duck species – common eider *Somateria mollissima*, long-tailed duck *Clangula hyemalis,* white-winged scoter *Melanitta fusca*, surf scoter *Melanitta perspicillata*, and black scoter *Melanitta americana* – along the U.S. Atlantic coast, and to identify the relationships between sea duck occurrence and distance from land, water depth, and bottom slope.

3. Methods

3.1 Survey description

The Atlantic Coast Wintering Sea Duck survey was flown between late January and early March in 2008-11. The survey design varied among years with the 2008 design differing most substantially from the other years (Table A1.1). The design was changed in 2009 based on lessons learned in 2008 and consisted of east-west transects spaced at 5′ intervals of latitude (except in the northern part of the Chesapeake Bay where transects were spaced at 10′ intervals), extending east from the coastline to the longer of two distances: 8 NM or the distance to 16 m depth (hereafter, off-coast transects). Transects were also located at 5′ intervals over the Nantucket Shoals, and across major coastal bays and sounds (e.g., Chesapeake Bay, Delaware Bay, Cape Cod, and Long Island Sound, see Fig A1.1). In 2009-11, as feasible, crews flew transects from north to south, then returned north and replicated every other line, flying south. Surveys were conducted using USFWS fixed-winged aircraft flown at 110 knots and 70 m altitude. During surveys, an observer and pilot-observer counted all sea ducks and other aquatic birds along transects, from the closest observable distance to the center line (~50 m) to 200 m on their side of the aircraft.

Due to the vagaries of field operations, transects and replicates differed somewhat between years. In this report, we only included transects that were sampled consistently among years (e.g., same latitude and similar area surveyed in two or more years, Fig. A1.1). We present results for 2009-11 from 253 unique transects (249 in 2009 and 252 in both 2010 and 2011) and 151 unique replicated transects (111 in 2009-10, 120 in 2011), representing 170 off-coast transects placed according to the 8 NM/16 m depth design rule, nine transects placed to cover the Nantucket Shoals, three covering shoals off the North Carolina coast, and 71 transects spanning shore-to-shore across bays and sounds.

3.2 Sea duck observations

Pilot-observer and observer records were entered directly into laptop computers as sound files using software developed by the U.S. Fish and Wildlife Service (Hodges 2003). Each computer was linked to the aircraft global positioning system (GPS) unit, enabling simultaneous recording of both observations and their coordinates in linked sound and ASCII files. Locations recorded for each observation are not precise; rather they correspond to the location of the aircraft when an observation is recorded. Individual records include the (1) location and time, (2) species, and (3) number of birds seen along survey transects. In this paper, we refer to the individual records as "flocks" and the count associated with the record as the "flock size," although flock boundaries are not well-defined and the counts are restricted to the area within the transect boundary. The three scoter species can be difficult to identify in the field, leading to a large number of scoters recorded only to genus (*Melanitta* spp.). In addition to recording observations, the software records aircraft location at least every 15 seconds while surveying to form a track file or flight path (Hodges 2003).

Following each survey, observers transcribed the observation data from sound files to ASCII files and simultaneously attributed each observation record with appropriate geographic coordinates using another in-house software application (Hodges 2003). We post-processed the observation files and flight paths using scripts written in the R statistical computing environment (R Development Core Team 2011) and ArcGIS 10.0 (Environmental Systems Research Institute 2011). Processing included deleting bad GPS fixes and observations located far from transects (> 1 NM) or on land (> 0.5 NM inland), as well as correcting records (e.g., mistyped species codes, missing ending or starting locations, etc.).

3.3 Physical features and tides

We measured distance from land as the Euclidean distance between sea duck observations and the nearest edge of the Atlantic coastline obtained from the National Oceanic and Atmospheric Administration's (NOAA) Coastal Geospatial Data Project (NOAA 2010) using ArcGIS 10.0 (Environmental Systems Research Institute 2011). We extracted water depths from the United States Geological Survey digital elevation model (DEM) of the Atlantic Ocean obtained from the National Elevation Dataset (Gesch et al. 2002, Gesch 2007). We also used the DEM to create an interpolated surface of slope (i.e., the steepness of the ocean bottom based on changes in water depths, measured in degrees) for the Atlantic Ocean.

We characterized the tide cycle for each sea duck observation by dividing the off-coast areas of the survey into fourteen regions each comprised of 20 contiguous transects. We defined separate regions for transects in bays and over the Nantucket Shoals. To estimate the mean time of low tide within each region, we consulted NOAA's Center for Operational Oceanographic Products and Services (http://oceanservice.noaa.gov/programs/coops/); using the three coastal reporting stations that were

closest to the region's northern boundary, southern boundary, and center point, we calculated mean time of low tide by region and survey date. We then subtracted the mean low tide time from the time of each sea duck record in the region to estimate time since low tide. Flocks recorded within 1.5 hours of low tide were classified as occurring at low tide, those within 1.5 hours of high tide were classified as occurring at high tide; flocks observed 1.5 to 4.5 hours after low tide were classified as occurring during rising tide, while those between 7.5 and 10.5 hours after low were classified as occurring during falling tide.

3.4 Data analysis

3.4.1 Species distributions

We calculated sea duck densities for each transect by dividing total number of birds observed for each species by area surveyed. Area surveyed is the distance surveyed by each observer, multiplied by 150 m, the transect half-width (200 m) less the area under the plane that is not visible to observers (50 m). For transects replicated in a given year, we averaged densities across replicates, by summing all birds counted on both replicates and dividing by the replicated area. For species-specific scoter density calculations, unidentified scoters on individual transects were apportioned among the three species based on the composition of the identified scoters on a given transect and its northern and southern neighbors, extending north and south if none of the neighboring transects included speciated scoter records. (This calculation assumes that the probability of identifying scoters does not differ by species and deserves further investigation. However, the survey crews had substantial experience with aerial waterfowl observation and sea ducks; moreover, using only scoters identified to species did not alter our results.)

To define distinct geographical areas of high and low density for each of the five species (hereafter "density regions"), we applied a spatially constrained grouping algorithm available in ArcGIS 10.1 Spatial Statistics toolkit (ArcGIS 10.1 2012) to the three-year average densities for the 253 transects (area weighted average, as above, with two-year averages for some transects). The algorithm, called SKATER for Spatial 'K'luster Analysis by Tree Edge Removal (Assunção et al. 2006), identifies groups using a minimum spanning tree, based on (1) a spatial constraint matrix constructed from the transect locations and (2) transect densities, which represent the tree's node values. We defined transect neighbors using the "rook's case", where each transect's neighbors include those directly to the north and south, as well as any contiguous transect to the east or west. Transects located to the east or west that were not contiguous, but within 30-50 NM overwater or within 10-30 NM overland, were treated as half neighbors (weighted by 0.5, instead of 1 in the spatial constraint matrix). The algorithm calculates an R^2 value (sum of squares calculated using the group means divided by total sum of squares) and pseudo-F statistic for 2-15 groups, allowing selection of an "optimal" number of groups.

The method, as implemented, does not allow for specification of a minimum group size, so, in some instances, the optimal grouping resulted in small clusters. This problem is exacerbated by the high degree of right-skew present in the count data and can result in optimal groupings consisting of one large cluster and many 1-2 transect clusters. We therefore ran the clustering algorithm on log-transformed average annual densities. To handle zero values, counts were adjusted prior to transformation by adding 0.25, which is one half of the minimum "number" of birds needed to record a positive count. (We assume that if a bird is more than halfway within a transect, the bird would be counted and, if less than halfway within, the bird would not be counted: i.e., 0.5 or more is rounded to one bird, while less than 0.5 is rounded to zero birds). This correction resulted in variable densities for transects of different lengths with no birds: longer transects with no birds have smaller transformed densities than shorter transects with no birds.

For all species except black scoter, we identified a southern range limit and ran the spatial clustering only on data from transects north of this latitude. When low/no density southern transects are included, the clustering algorithm is dominated by the range edge and we learn less about the spatial patterns in the core of the species' winter range. We set the southern limit for the clustering analysis at the latitude below which less than 1% of the all birds of the species were counted for long-tailed duck, surf scoter, and common eider. Because a few white-winged scoters are sometimes seen quite far south of their main wintering areas in the company of surf and black scoter, we used a cutoff of 5% for white-winged scoter. The southern boundary we used for our analyses for common eider was 40°46′N latitude, for white-winged scoter it was 40°21′N latitude, and for long-tailed duck and surf scoter the southern boundary was 35°06′N latitude. In addition to identifying a southern range limit, we also established an eastern range limit, or distance from coast, in order to exclude unoccupied areas. We set the eastern range limit for all transects, except transects along Nantucket Shoals, to 15 NM from the coast since no sea ducks were detected this far from the coastline.

To provide a more detailed picture of density variation within and between the three-year average density regions, we ran the transformed three-year average densities through SKATER with no spatial constraints on cluster membership in order to classify transects into six density categories by species (1 = low to 6 = high) and overlaid these results on the density regions. The unconstrained SKATER algorithm is equivalent to *k*-means clustering (Hartigan and Wong 1979, Assunção et al. 2006) and the pseudo-F values represent the test statistic for a one-way analysis of variance (ANOVA) comparing within cluster sums of squares to between cluster values, with the highest F-value indicating the number of clusters with the lowest ANOVA p-value.

To explore annual variation, we created annual density regions for each species and compared these results to the regions based on the three-year average. We also ran the unconstrained clustering on

all three years of densities (un-averaged) simultaneously to define six density categories; we quantified interannual variation in density for each transect by subtracting its minimum density category value from its maximum. For example, if a given transect was assigned to cluster 6 (high density) in 2009 but to cluster 1 (low density) in 2011, the difference of 5 would indicate a large interannual change in density. We overlaid these density change values, which range from 0-5, on the three-year average density regions to identify the regions and species with more or less variable distributions.

3.4.2 Occurrence relative to physical features and tides
We measured distance from land, water depth, and bottom slope for each sea duck flock with the goal of comparing patterns among species and years. Such comparisons, however, are confounded by the change in coastal bathymetry with latitude: a shallow, gradual depth gradient along the southern coast is replaced by a steep, sharp drop in the north. To control for this pattern, we applied the unconstrained SKATER algorithm to classify the off-coast transects (i.e., excluding the Nantucket Shoal and bay transects) by three variables which characterize the transect profile: distance to 16 m depth, start depth at 0.25 NM from the coast (the point where survey protocol calls for the near shore start of each transect), and gradient (end depth – start depth / distance flown). We used the three resulting off-coast transect clusters (corresponding roughly to the northern, mid-, and southern coast), along with the Nantucket Shoals and bays/sounds, to define five "transect types" for our analyses of species-specific associations with the physical features, and annual changes in these associations.

We compared the distribution of the three variables (distance from land, water depth, and bottom slope), by species and transect type, to the characteristics of the surveyed transects: we determined the proportion of flocks within each transect type that were (1) greater or less than 4 NM from the land, (2) over bottom depths of 0-6 m, 6-12 m, 12-18 m, or greater than 18 m, and (3) over bottom slopes of less than 0.1 degrees, 0.1-0.5, 0.5-1.0, and greater than 1.0 degrees. We then calculated the proportion of surveyed area within these categories for each transect type. When the range of a species did not include all transects of a given type, we used only transects that overlapped the species range to calculate surveyed area (thus, surveyed areas, and the proportion surveyed in each distance, depth, and slope category, differ somewhat by species within transect type). We highlight categories where the proportion of flocks observed is greater than the proportion expected based on the available surveyed area, testing for significant patterns with simple chi-square goodness-of-fit tests.

We next compared the characteristics of the flock locations by species for each of the three variables and five transect types using one-way ANOVA, followed by Tukey's multiple comparisons test. Diagnostic plots showed residuals that were generally somewhat right-skewed, but results were not sensitive to outlying values.

We explored annual patterns in the distance, depth, and bottom slope associated with flock locations observed on the off-coast transects, controlling for transect type, using two-way ANOVA with year and transect-type as factors. Because none of the species are found in all three off-coast transect types – steep, moderate, and flat bottom gradients– in sufficient numbers, these comparisons were restricted to (1) steep and moderate gradient regions for common eider and long-tailed duck, (2) moderate and flat gradient regions for black scoters, and (3) moderate gradient for surf and white-winged scoters (i.e., one-way ANOVA with year as the factor was used for these two species). We checked ANOVA assumptions using standard diagnostic plots, which suggested the modeling approach was reasonable. We assessed model fit using the Akaike Information Criterion (AIC), comparing the model AIC to the null AIC, and determined the significance of individual year and transect-type effects by considering their associated p-values.

To explore whether variability in flock location characteristics might be explained by the tide cycle and time of observation, we estimated the effect of time and tide on distance, depth, and slope for each species using two-way ANOVA. Time of day was treated as a categorical variable, with two levels: morning (11:59 EST and earlier) and afternoon (12:00 and later; results for finer divisions of the day were the same as for two intervals; we also checked for patterns by plotting of the variables versus time of day). Because annual and transect-type differences might confound estimates of the time and tide effects, we fit these models using the residuals of the year/transect-type model. Models fit to the unadjusted variables gave similar results.

4. Results

During the four survey winters, crews observed eleven species of sea ducks: common eider, long-tailed duck, surf scoter, white-winged scoter, black scoter, common goldeneye *Bucephala clangula*, bufflehead *Bucephala albeola*, common merganser *Mergus merganser*, red-breasted merganser *Mergus serrator*, hooded merganser *Lophodytes cucullatus,* and harlequin duck *Histrionicus histrionicus*. Overall, for the five "focal" species, 168,675 birds (50,699 long-tailed duck; 41,234 black scoter; 33,842 common eider; 18,550 surf scoter; 5,475 white-winged scoter; and 18,875 unidentified scoters) were observed comprising 11,970 flocks with flock sizes in the transect area ranging from 1 to 5,000 individuals. For the transects included in the density analyses, 124,171 birds (32,271 long-tailed duck; 31,368 common eider; 28,602 black scoter; 14,584 surf scoter; 5,111 white-winged scoter; and 12,235 unidentified scoters) were observed comprising 9,565 flocks. Of these 9,565 flocks, 83% were located more than 0.25 NM from the coastline (60% of common eider flocks, 86% of long-tailed duck flocks, 92% of white-winged scoter flocks, 93% of both surf scoter and black scoter flocks).

Based on the three-year average densities for 2009-11, we identified twelve spatially distinct density regions for common eider ($r^2 = 0.76$, Fig A1.2A), two for white-winged scoter ($r^2 = 0.36$, Fig A1.2B), four for long-tailed duck ($r^2 = 0.42$, Fig A1.2C), three for surf scoter ($r^2 = 0.24$, Fig A1.2D), and fifteen for black scoter ($r^2 = 0.50$, Fig. A1.3). The ArcGIS implementation of the SKATER algorithm does not calculate the pseudo-F value for more than fifteen groups, while the optimal number of clusters for black scoter was likely greater. We therefore ran SKATER with the number of black scoter clusters set to greater than fifteen; the procedure resulted in fragmented, small groupings that did not provide any additional illumination into black scoter distribution.

Although there was some variability in the annual density regions, the optimal number and location of the clusters were similar among years for all five species (results not shown). For common eider, high densities were observed around Cape Cod and Maine coastal islands (Fig A1.4A). Common eider densities were consistent across years (Fig A1.4B, Fig A1.8A-C), with 42% of transects shifting less than two density categories (50% of the occupied transects, Table A1.2). Common eider had a compact distribution along the U.S. coast and only 17% of the surveyed transects in their range were unoccupied in all surveyed years (Table A1.2). Long-tailed duck were observed at highest densities around Cape Cod and the Nantucket Shoals, followed by Chesapeake Bay, Long Island Sound, and the Maine coast (Fig A1.5A). Their densities were second to common eider as the most consistent between years, with 28% of 192 transects (or 40% of occupied transects) shifting one or fewer density categories (Table A1.2, Fig 1.5B, Fig A1.9A-C).

White-winged scoter, the least abundant of the five species, had highest densities in Cape Cod Bay, over the Nantucket Shoals, and at the eastern end of Long Island (Fig A1.4C). Surf scoter was found at high densities within Chesapeake and Delaware Bays, and along the Maryland/Delaware coast with smaller areas of high density around Nantucket Island and the southern end of Pamlico Sound (Fig A1.5C). Black scoters have a wide range, with high densities along the South Carolina coast, in Pamlico Sound, at the mouth of Chesapeake Bay, and around Cape Cod, and variably high densities around Delaware Bay, interspersed with low densities between these regions (Fig A1.6).

The three scoter species have more variable annual densities than common eider and long-tailed duck (Fig A1.4D, Fig A1.5D, Fig A1.6, Fig A1.8D-F, Fig A1.9D-F) with only 13-16% of transects shifting one or fewer density categories (or 22-29% of occupied transects, Table A1.2). Fourteen to 21% of occupied transects shifted four or more categories (calculated from Table A1.2, removing unoccupied transects). Not unexpectedly, densities were more consistent in low density regions (Fig A1.4D, Fig A1.5D). Densities of black scoter were the most variable among years (Fig A1.6, Table A1.2), shifting from the mouth of the Chesapeake Bay and Pamlico Sound in 2009, south to the South Carolina coast and north to Cape Cod in 2010-11. In 2008, their distribution was intermediate between these patterns, with

high numbers in the mouth of the Chesapeake Bay, in Delaware Bay, and in Cape Cod, as well as along the south Georgia coast (results not shown). The three scoter species also had a higher percentage of unoccupied transects than common eider and long-tailed duck (33-44%, Table A1.2). This was likely a consequence of their lower overall abundance relative to the latitudinal extent of each species' winter range.

Using the bathymetry measurements, we identified three transect types, representing steep, moderate, or flat seabed profiles (Fig. A1.7). Table A1.3 presents the mean distance to 16 m depth, mean western start depth, and mean gradient for the three off-coast transect types, the Nantucket Shoals, and the bays and sounds. Although the three profile types were interspersed throughout the survey area, the steep profile was most common along the Maine coast and the outer coast of Cape Cod with transects starting at over 16 m depth, the cutoff depth for our survey design; the moderate profile occurred mostly south of Cape Cod to the southern boundary of North Carolina and the flat profile predominated south of North Carolina.

Over the four survey years, crews observed more than 75% of the sea ducks in depths of less than 20 m, within 4 NM of land, and over bottom slopes less than 1° (Table A1.4-5). Sea duck flocks were not distributed randomly along transects with respect to the covariates (Table A1.4; χ^2 test p-values were <0.001 in 44 cases, between 0.001-0.05 in five cases, and not significant in eight cases). When the last category (>18 m depth) was excluded, common eider, long-tailed duck, and white-winged scoter flocks were distributed randomly with respect to depth along the steep profile transects (p-values 0.36, 0.62, and 0.77, respectively), but this result did not hold for the other transect types.

In our comparisons among species, the results for distance from land were the strongest and most consistent across transect types: common eiders were found closest to shore, followed by long-tailed duck (Table A1.5, see also Table A1.4). Both species were closer to shore on steep profile transects than on moderate (Table A1.5). We also observed common eider over the steepest bottom slopes, followed by long-tailed duck. Differences among the species in depth were less significant, and vary by transect type: long-tailed duck were found in deeper water in areas with steep profiles, while this was not the case for common eider. The location of common eider and long-tailed duck flocks, as measured by distance from land and depth, were more variable than the scoters (bold font, Table A1.5).

The scoter species were significantly farther from shore than common eider and long-tailed duck, with no consistent differences between the three species (Table A1.4-5). Like common eider, white-winged scoter flocks were farther from shore, and in somewhat deeper waters, on moderate profile transects compared to steep profile transects. Both surf and black scoters were in deeper water on moderate profile transects than flat profile, but surf scoters were farther from shore in flat areas, while black scoters were closer. Overall, black scoter was found at the shallowest depths, and white-winged

scoter at the deepest. Scoters were also found, without distinction, over the flattest ocean bottom slopes. The bottom slopes underneath black scoter and long-tailed duck locations were the most variable of the five species (bold font, Table A1.5).

We found significant yearly differences in distance from land for all five species. Common eider, long-tailed duck, and white-winged scoter were farther from shore in 2011 (eider ΔAIC=19.4, 2011 effect p<0.001; long-tailed duck ΔAIC=3.0, 2011 effect p=0.02; white-winged scoter ΔAIC=24.1, 2011 effect p=0.01), and the results were consistent across transect types for common eider and long-tailed duck. Common eiders were typically in deeper water on moderate profile transects than on steep, except in 2011 (ΔAIC=5.9, p<0.1 all effects). The three scoter species were closer to shore in 2010 (black scoter ΔAIC=74.8, p<0.001; surf scoter ΔAIC=8.6, p<0.001; white-winged scoter ΔAIC=24.1, p=0.03). Black scoter distances varied by both year and transect type: typically closer to the coast on flat profile transects, their 2010 inshore shift occurred on moderate profile transects.

Our results show little effect of time of day and tidal cycle. These variables do not explain variability in distance and depth better than year and transect type, nor do they consistently explain variation not accounted for by year and transect type. There were no significant time or tide effects on distance from land for common eider and long-tailed duck (ΔAICs were negative). Black scoters were somewhat closer to shore during low tides and in the afternoon (ΔAIC=19.5, all p<0.04), and white-winged and surf scoters were nearer to shore in the morning (white-winged ΔAIC=3.1, p=0.03; surf ΔAIC=4.6, p=0.01). While some time and tide effects were significant for depth, these effects involved complicated interactions and no consistent main effects or patterns across species.

5. Discussion

The 2008-11 experimental sea duck survey conducted by the USFWS generated the largest and most comprehensive dataset available to characterize the winter distributions of common eider, long-tailed duck, white-winged scoter, surf scoter, and black scoter along the U.S. Atlantic coast. Our analyses provide the first quantitative description of important coastal regions, variation in density and abundance, and the characteristics of locations where sea ducks occur. These five species of sea ducks have overlapping distributions that concentrate in several critical regions, most particularly around Cape Cod, Nantucket Shoals, and the mouth of Chesapeake Bay (Fig A1.2-3). Nantucket Shoals is an especially important wintering area for long-tailed duck and white-winged scoter with over 43% of all observations for these species occurring on these nine transects (48% for long-tailed duck, and 14% for white-winged scoter). Regions of significance for individual species include the Maine coastal bays and islands for common eiders, the Chesapeake Bay for long-tailed duck, Long Island Sound for white-winged scoter,

the Maryland coast and Delaware Bay for surf scoter, and the Pamlico Sound and South Carolina coast for black scoter.

Despite substantial inter- and intrannual variation, high density transects and regions were similar between years. Black scoter shifted the most between high density regions, with large numbers in Delaware Bay in 2008, at the mouth of Chesapeake Bay in 2009 (and 2012, M.D. Koneff, W.E. Rhodes, personal communication) and the southern coast in 2010 and 2011. While it is not unexpected that the species with the largest winter range would exhibit the most annual variation in distribution, black scoter occurrence and abundance along the southern coast was particularly variable (Fig A1.6, only 8% of southern transects shifted one or fewer density categories). We have additional, more intensive survey data for the South Carolina and Georgia coasts from 2011-12, which, in combination with information from black scoter outfitted with satellite transmitters (Loring 2012, Sea Duck Joint Venture 2012) may provide further insight into this species' distribution along the southern coast.

The characteristics of sea duck locations were not random with respect to bathymetry and distance from land. Some of the patterns we observed likely resulted because transects were extended beyond the eastern range of the species. For example, the depth distributions of all three species found commonly along the steep profile transects (common eider, long-tailed duck, and white-winged scoter) were similar to the surveyed depth profile when the deepest offshore category is excluded. In the other areas where they co-occur, however, there were notable differences among the species in their distributions and association with the covariates: common eider was found more often in steeper areas nearer to shore, scoters in flatter areas farther from land, and long-tailed duck intermediate between these two. The differences likely reflect differences in preferred prey and substrate: common eider have been shown to concentrate over shallow reefs (Guillemette et al. 1993), surf and black scoter over sandy substrates (Stott and Olson 1973, Loring 2012), with long-tailed duck exhibiting the most varied habitat use (Stott and Olson 1973)

There were also substantial annual changes in location, and little evidence that time of observation or tidal cycle explained variation in distance from land or depth. It is important to note, however, that the survey was not designed to measure or control for time and tides, and the data may be insufficient to detect real effects. The causes of species-specific patterns of abundance associated with distance, depth, and slope, and annual changes in these patterns, remain to be explored and a full understanding will likely require more detailed and finer scale observations.

Data from this survey are being used by USFWS partners as part of offshore development planning. The results of the current analysis are essential to finalizing the design of an operational survey, as they provide the foundation for defining survey strata and anticipating annual variation in distributions. The physical covariate analysis will aid in specifying the survey's eastern boundary,

allocating survey effort relative to priority species, and building efficient models to estimate winter abundance. The patterns we observed suggest that any survey focused on abundance estimation for one of the five species will necessarily sacrifice information about the others, while an omnibus survey is unlikely to achieve the level of precision possible from more targeted monitoring efforts. Further consideration of annual changes in distribution and association with physical covariates, however, may assist in developing an efficient multi-species survey to estimate wintering population sizes. We view our preliminary assessment of associations among sea duck occurrence and the physical covariates examined as a first step toward specifying and testing hypotheses about critical resources exploited by sea ducks and modeling these relationships to improve survey design, estimation, and predictions about the effect of environmental change on these species.

6. Management Implications

To be justifiable, information from an operational Atlantic Coast Winter Sea Duck survey should address specific management or research objectives. Obvious objectives include unbiased, efficient population estimation for harvest and habitat management and the identification of concentration areas for environmental planning applications. The available experimental data, and a future operational survey, could also support critical research by informing development, and subsequent testing, of hypotheses about factors affecting sea duck wintering distributions (e.g., critical offshore resources utilized by sea ducks). Understanding mechanistic relationships would help refine survey design and improve model-based estimation procedures, and will be required to predict the effects of development activities or other environmental influences on critical resources and, ultimately, sea duck populations. Advancing this management-oriented research agenda is beyond the capacity of any individual agency or organization and will require broad and well-coordinated collaboration. Offshore planning envisioned by the evolving U.S. National Ocean Policy should provide further impetus for such collaboration.

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Table A1.1. Survey effort, 2008-11. In 2008, the coast was surveyed north only as far as Cape Cod, Massachusetts; the transects, which extended east from the coastline at 5 NM intervals, were flown as pairs with lengths of the pairs alternating between (i) 8 NM (the average distance to 6 m depth) and (ii) the greater of 14 NM (the average distance to 16 m depth) and the distance to 16 m depth; replication was planned, but only five replicates were completed, all over the Nantucket Shoals. In 2010, a fifth survey crew replicated transects within Chesapeake Bay and along the Maryland/Delaware coast; and in 2011, all transects along the South Carolina/Georgia coast were replicated (see Silverman et al. 2010, 2011, 2012 for more detailed description of study design). To replicate previous surveys conducted along the Atlantic coast (see Zipkin et al. 2010), additional survey observations were made on tracks flown parallel to the shore at 0.25 NM and 0.50 NM from the coast in 2008-10. Results from the extra 2010 and 2011 replicates, and the coastal track observations, are not included in this report. The number of transects and replicates reported in this table include some that were not used in the analyses (see text).

	2008	2009	2010	2011
Survey dates	4-25 Feb	31 Jan-18 Feb	23 Jan-2 Mar*	31 Jan-17 Feb
Northern extent	$42^{o}06'$N	$44^{o}46'$N	$44^{o}46'$N	$44^{o}46'$N
Southern extent	$26^{o}56'$N	$28^{o}26'$N	$28^{o}26'$N	$30^{o}21'$N
Number of crews	5	5	5	4
Number of transects	233	261	264	260
Number of replicates	5	133	199	134
Distance flown (NM) 1st replicate	3116	4170	4351	4374
Distance flown (NM) 2nd replicate	277	2176	2261	2148

*Survey period was protracted due to extreme weather conditions and aircraft mechanical problems, and because one crew flew more than two replicates.

Table A1.2. Percent of transects within each difference category, estimating inter-annual variation in transect densities, 2009-11. The first row is the percent of transects that had 0 densities in all years (hence have no change in density due to no birds being present).

	Species				
Difference	Common eider	Long-tailed duck	White-winged scoter	Surf scoter	Black scoter
All years 0 birds	17	31	33	44	42
0-1	42	28	15	16	13
2-3	39	36	43	30	33
4-5	2	6	10	9	12
Number of transects	84	192	94	192	253

Table A1.3. Mean (SD) of the bathymetry measurements for the three off-coast profile categories, Nantucket Shoals, and the Bays/Sounds.

Cluster type	Distance to 16 m depth (NM)	Start Depth (m)	Gradient (°)
Steep profile	1.0 (1.9)	16.7 (15.9)	7.4 (3.2)
Moderate profile	4.4 (2.6)	4.3 (5.4)	1.9 (1.1)
Flat profile	16.4 (6.2)	1.9 (2.0)	0.8 (0.2)
Bays and sounds	NA[a]	1.8 (4.4)	0.5 (1.8)
Nantucket Shoals	NA[b]	30.2 (19.5)	0.6 (0.9)

[a]Not calculated due to the shallow depths within the bay transects and the limited number of transects reaching this depth (7 transects).
[b]Not calculated because all transects' start depths were greater than 16 m.

Table A1.4. Proportion of flocks by distance, depth, and slope categories for each species and transect type. The proportion of the surveyed transect area within each category is included in bold. Surveyed areas were subset to the latitude range within which the species winters. Dark shading indicates categories where the proportion of flocks was at least 0.10 higher than the proportional survey area. The nine Nantucket Shoal and 71 Bay transects are summarized separately in (B) and (C) on the following page. Sample sizes are included in Table A1.5. Italics indicate a non-significant difference between the flock proportions and the proportion available in the surveyed area (all p-values > 0.1); the remaining distributions of flock locations are significantly different from the surveyed area (most p-values < 0.001, the largest is 0.02 for black scoters slope on flat profile transects).

A. Off-coast transects	Distance from land (NM)		Water depth (m)				Slope (°)			
	0.0-4.0	>4.0	0.0-6.0	6.1-12.0	12.1-18.0	>18.0	<0.1	0.1-0.5	0.51-1.0	>1.0
Steep Profile										
Common eider	0.99	0.01	0.33	0.16	0.27	0.24	0.03	0.18	0.24	0.55
White-winged scoter	0.96	0.04	0.18	0.18	0.18	0.46	0.04	0.50	0.39	0.07
Long-tailed duck	0.94	0.06	0.25	0.14	0.18	0.43		0.12	0.25	0.63
Surveyed area	**0.70**	**0.30**	**0.05**	**0.03**	**0.05**	**0.87**	**0.04**	**0.35**	**0.22**	**0.38**
Moderate Profile										
Common eider	0.99	0.01	0.12	0.18	0.43	0.27	*0.09*	*0.32*	*0.13*	*0.46*
Surveyed area	**0.77**	**0.23**	**0.06**	**0.07**	**0.10**	**0.77**	**0.13**	**0.33**	**0.17**	**0.38**
White-winged scoter	0.41	0.59	*0.07*	*0.11*	*0.07*	*0.75*	0.18	0.75	0.06	0.01
Surveyed area	**0.69**	**0.31**	**0.09**	**0.09**	**0.14**	**0.69**	**0.24**	**0.43**	**0.11**	**0.22**
Long-tailed duck	0.92	0.08	0.32	0.30	0.19	0.18	*0.26*	*0.54*	*0.12*	*0.08*
Surf scoter	0.75	0.25	0.16	0.32	0.45	0.07	0.41	0.54	0.03	0.03
Black scoter	*0.52*	*0.48*	0.09	0.34	0.52	0.05	0.46	0.48	0.04	0.01
Surveyed area	**0.52**	**0.48**	**0.10**	**0.17**	**0.37**	**0.36**	**0.32**	**0.51**	**0.09**	**0.08**
Flat Profile										
Long-tailed duck	0.88	0.13	0.63	0.08	0.21	0.08	*0.21*	*0.71*	*0.04*	*0.04*
Surf scoter	*0.50*	*0.50*	0.38	0.48	0.12	0.02	*0.38*	*0.62*		
Surveyed area	**0.52**	**0.48**	**0.25**	**0.22**	**0.27**	**0.26**	**0.40**	**0.53**	**0.06**	**0.01**
Black scoter	0.76	0.24	0.67	0.29	0.03	0.01	0.58	0.39	0.03	0.01
Surveyed area	**0.37**	**0.63**	**0.24**	**0.37**	**0.36**	**0.03**	**0.49**	**0.47**	**0.03**	**0.01**

B. Bays and Sounds	Distance from land (NM)		Water depth (m)				Slope (°)			
	0.0-4.0	>4.0	0.0-6.0	6.1-12.0	12.1-18.0	>18.0	<0.1	0.1-0.5	0.51-1.0	>1.0
Common eider	0.84	0.16	0.47	0.29	0.15	0.09	0.21	0.39	0.16	0.24
Surveyed area	**0.80**	**0.20**	**0.21**	**0.18**	**0.16**	**0.44**	**0.22**	**0.37**	**0.13**	**0.28**
White-winged scoter	0.71	0.29	0.27	0.33	0.17	0.24	0.29	0.54	0.10	0.07
Surveyed area	**0.81**	**0.19**	**0.21**	**0.18**	**0.17**	**0.45**	**0.22**	**0.38**	**0.13**	**0.27**
Long-tailed duck	0.74	0.26	0.35	0.40	0.16	0.09	0.34	0.42	0.10	0.14
Surf scoter	0.59	0.42	0.41	0.41	0.16	0.04	0.42	0.47	0.09	0.04
Black scoter	0.42	0.58	0.68	0.22	0.06	0.03	0.60	0.31	0.07	0.02
Surveyed area	**0.76**	**0.24**	**0.40**	**0.20**	**0.13**	**0.27**	**0.35**	**0.38**	**0.10**	**0.17**

C. Nantucket Shoals	0.0-8.0	>8.0	0.0-12.0	12.1-18.0	>18.0	<0.1	0.1-0.5	>0.51
Common eider	0.84	0.16	0.26	0.46	0.28	0.13	0.53	0.34
Long-tailed duck	0.20	0.80	0.10	0.17	0.73	0.45	0.40	0.15
White-winged scoter	0.08	0.92	*0.08*	*0.16*	*0.76*	0.48	0.45	0.08
Surveyed area	**0.14**	**0.86**	**0.08**	**0.11**	**0.81**	**0.26**	**0.45**	**0.29**

Table A1.5. Mean (SD) for coastal features associated with common eider, white-winged scoter, long-tailed duck, surf scoter, and black scoter flocks. Bold indicates species with a coefficient of variation (CV) greater than the mean CV. For example, the CV for common eider flocks' distance from land along the steep profile transects is 1.06, which is larger than the average CV for all species on the off-coast transects (0.85). Superscripts indicate species means that are significantly different (one-way ANOVA with all pairwise comparisons within transect types, overall $\alpha = 0.05$). For example, common eider flocks (a) were found at shallower locations on steep profile transects than long-tailed duck flocks (b), while white-winged scoter depths are not significantly different from common eider or long-tailed duck (ab).

A. Off-coast transects

	Distance (NM)	Water depth (m)	Slope (°)	# of Flocks
Steep Profile				
Common eider	**0.7 (0.8)[a]**	**13.2 (11.6)[a]**	1.7 (1.5)[b]	134
White-winged scoter	1.4 (1.0)[b]	17.1 (9.0)[ab]	0.6 (0.7)[a]	28
Long-tailed duck	**1.3 (1.5)[b]**	**22.6 (22.8)[b]**	1.9 (1.8)[b]	51
Moderate Profile				
Common eider	**1.2 (1.0)[a]**	16.1 (8.4)[b]	1.3 (1.4)[c]	95
White-winged scoter	4.1 (2.0)[d]	23.4 (9.7)[c]	0.3 (0.2)[ab]	85
Long-tailed duck	**1.9 (1.9)[b]**	**11.7 (9.1)[a]**	**0.4 (0.6)[b]**	236
Surf scoter	2.9 (2.0)[c]	12.0 (5.2)[a]	0.2 (0.2)[a]	153
Black scoter	4.0 (2.2)[d]	12.8 (4.8)[a]	**0.2 (0.3)[a]**	325
Flat Profile				
Long-tailed duck	**1.4 (1.8)[a]**	**7.3 (9.5)[ab]**	**0.3 (0.5)[b]**	24
Surf scoter	4.1 (2.5)[c]	8.6 (4.5)[b]	0.1 (0.1)[a]	42
Black scoter	**2.9 (2.5)[b]**	6.0 (4.0)[a]	**0.2 (0.4)[a]**	241

B. Bays and Sounds

	Distance (NM)	Water depth (m)	Slope (°)	# of Flocks
Common eider	**1.5 (1.8)[a]**	**8.7 (7.7)[b]**	0.9 (1.3)[c]	1616
White-winged scoter	**2.7 (2.2)[b]**	12.4 (8.4)[d]	0.3 (0.5)[a]	279
Long-tailed duck	**2.5 (2.0)[b]**	**9.7 (7.3)[c]**	**0.5 (1.0)[b]**	1657
Surf scoter	3.4 (2.1)[c]	8.3 (4.9)[b]	0.2 (0.3)[a]	1415
Black scoter	4.4 (2.6)[c]	6.7 (4.7)[a]	**0.2 (0.4)[a]**	672

C. Nantucket Shoals

	Distance (NM)	Water depth (m)	Slope (°)	# of Flocks
Common eider	**6.2 (6.1)[a]**	**16.7 (8.5)[a]**	0.5 (0.6)[c]	171
White-winged scoter	20.6 (7.6)[c]	27.2 (9.4)[c]	**0.2 (0.2)[a]**	143
Long-tailed duck	16.8 (8.5)[b]	23.5 (8.3)[b]	**0.3 (0.4)[b]**	1007

Figure A1.1. Location of Atlantic Coast Wintering Sea Duck surveys, 2009-11. The red lines represent off-coast transects, blue lines represent bay transects, dark green lines represent Nantucket Shoals, and light green represent the southern shoal lines.
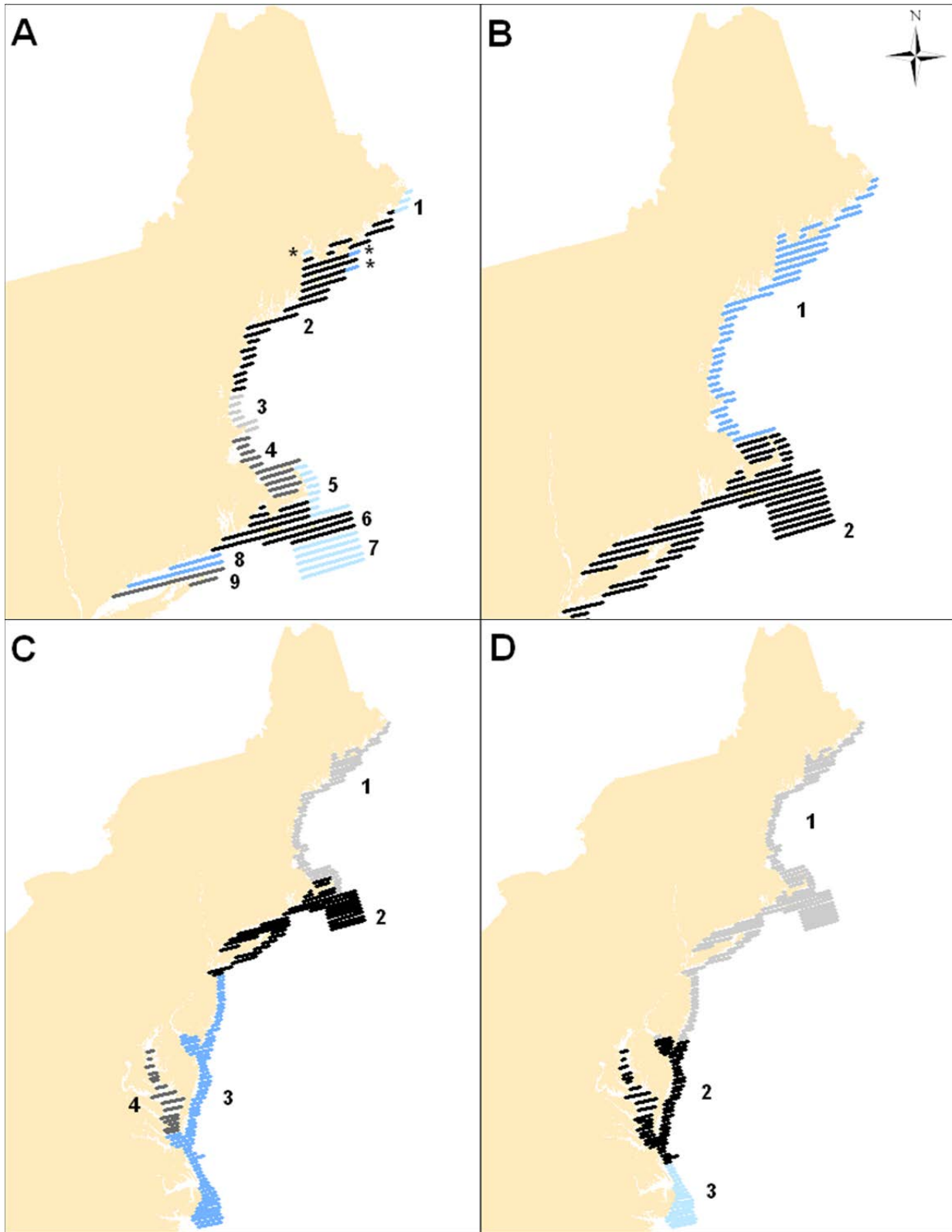
Figure A1.2. Three-year density regions for (A) common eider, (B) white-winged scoter, (C) long-tailed duck, and (D) surf scoter estimated using the SKATER algorithm. Regions are color coded based on density: black (high), dark grey, light grey, light blue, blue (low). Regions with "*" in panel (A) are low density regions defined by one transect within region 2 along the Maine coast.
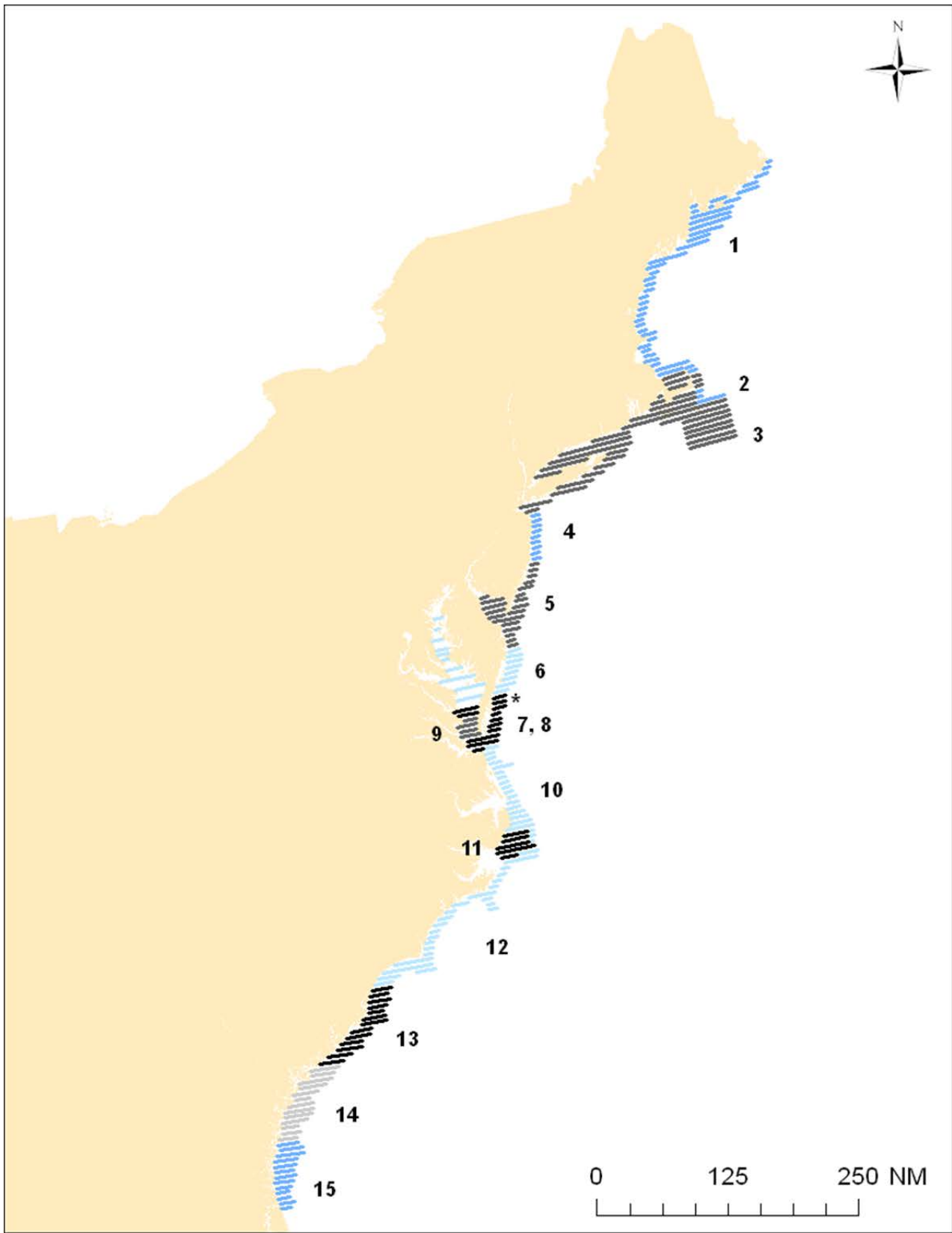
Figure A1.3. Three-year density regions for black scoter estimated using the SKATER algorithm. Regions are color coded based on density: black (high), dark grey, light grey, light blue, blue (low). Region 7 (*) is a high density region defined by two transects bordering regions 6 and 8 along Maryland's outer coastline.
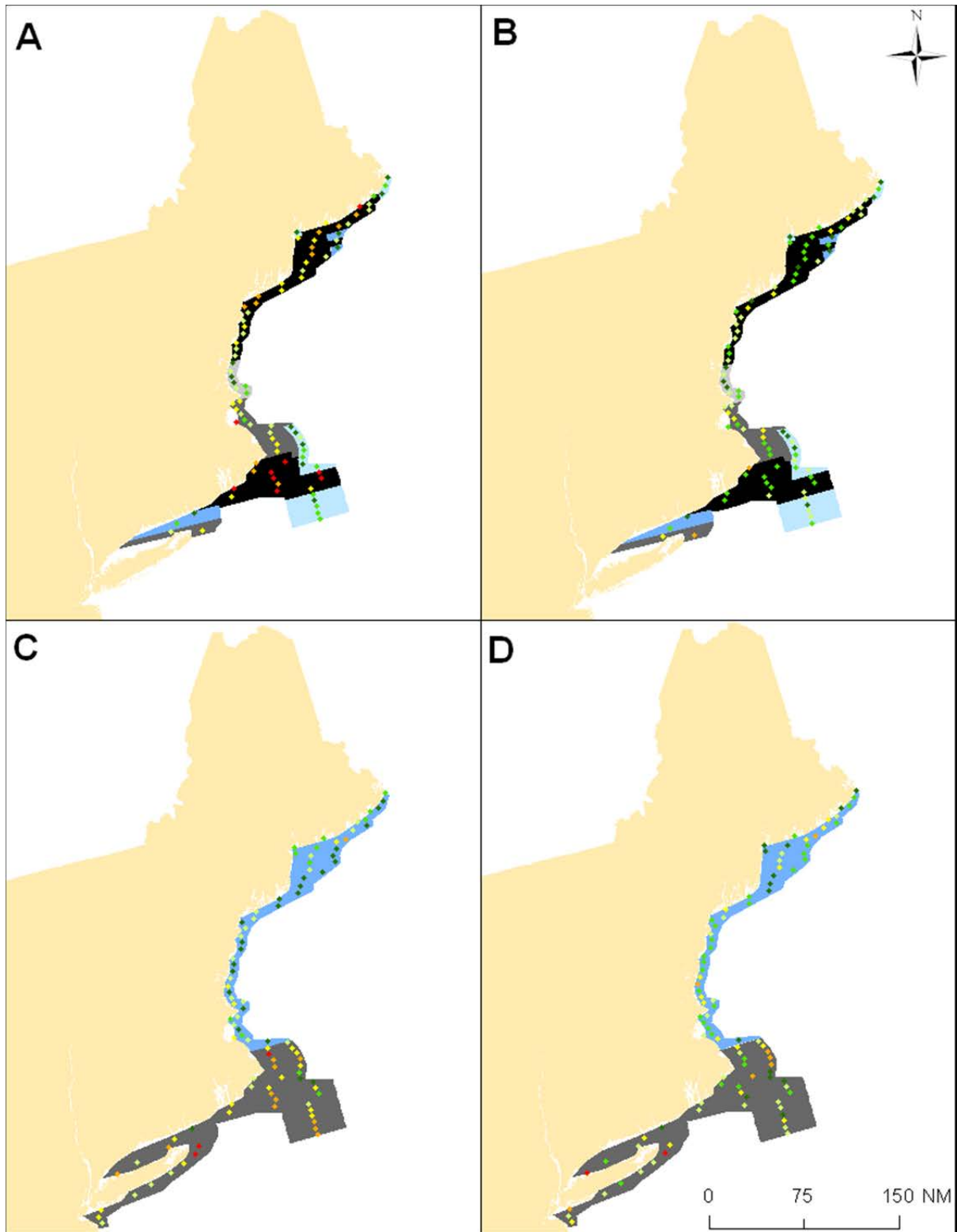
Figure A1.4. Density regions for common eider (A-B, 12 regions) and white-winged scoter (C-D, 2 regions) with transect densities. Regions are illustrated by the polygons, which are color coded from high to low density: black, dark grey, light grey, blue, light blue. In (A) and (C) the transect midpoints, indicated by colored dots, are coded by the six three-year average density categories from high to low: red, orange, yellow, bright green, green, dark green. In (B) and (D), the dots indicate the maximum change between 2009-11 in annual density category: from red for transects in both the highest and lowest density category to dark green for transects where the density category did not change. Thus, red and orange indicate large shifts in density and green indicates little to no change.

Figure A1.5. Density regions for long-tailed duck (A-B, 4 regions) and surf scoter (C-D, 3 regions) with transect densities. Regions are illustrated by the polygons, which are color coded from high to low density: black, dark grey, light grey, blue, light blue. In (A) and (C) the transect midpoints, indicated by colored dots, are coded by the six three-year average density categories from high to low: red, orange, yellow, bright green, green, dark green. In (B) and (D), the dots indicate the maximum change between 2009-11 in annual density category: from red for transects in both the highest and lowest density category to dark green for transects where the density category did not change. Thus, red and orange indicate large shifts in density and green indicates little to no change.
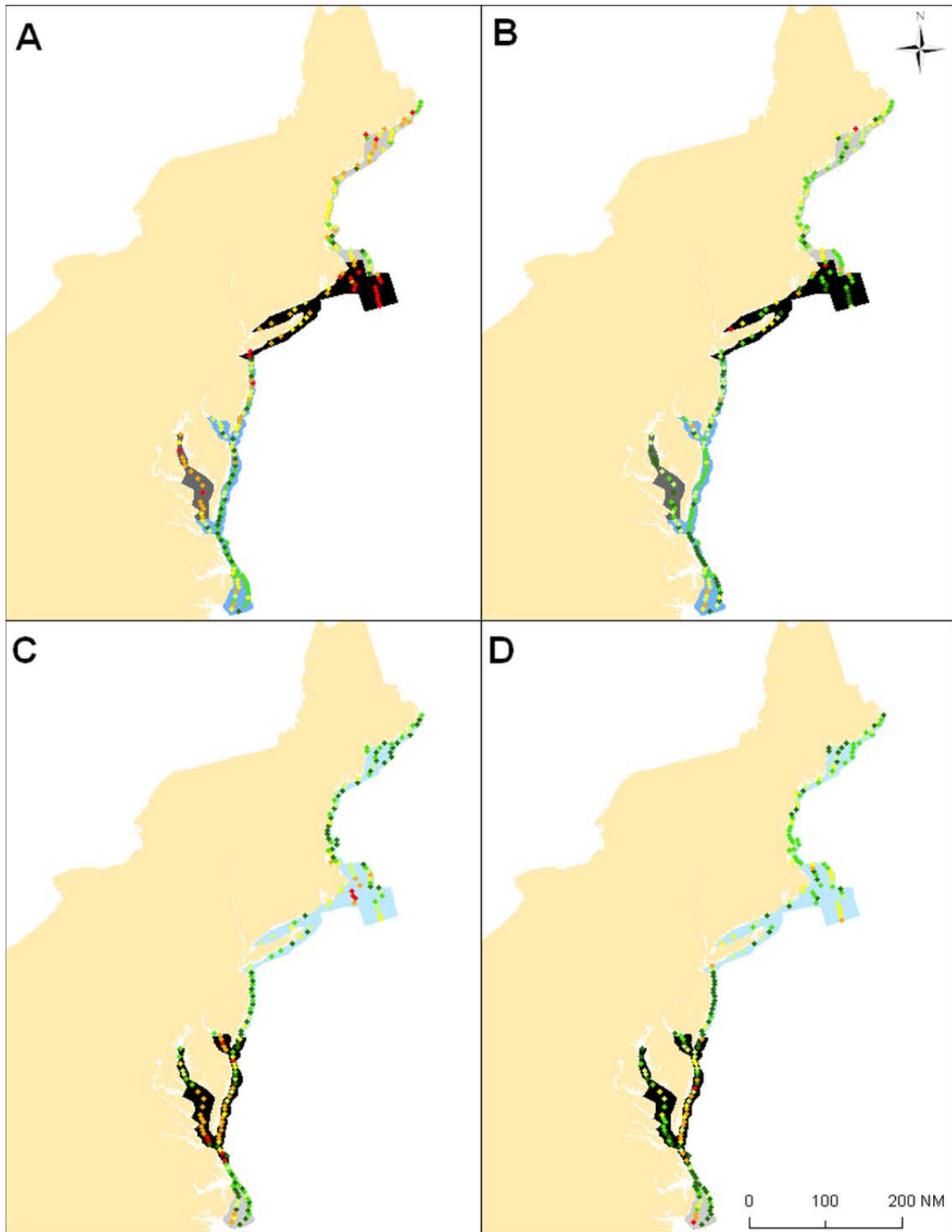
A1-25

Figure A1.6. Density regions for black scoter with annual transect densities. The density regions are illustrated by the polygons, coded from high to low density: black, dark grey, light grey, blue, light blue. Dots in (A), (B), and (C), illustrate the six annual transect density categories by year, for 2009-11, respectively, and are coded from high to low: red, orange, yellow, bright green, green, dark green. In (D), the dots indicate the maximum change between 2009-11 in annual density category: from red for transects in both the highest and lowest density category to dark green for transects where the density category did not change. Thus, red and orange indicate large shifts in density and green indicates little to no change.
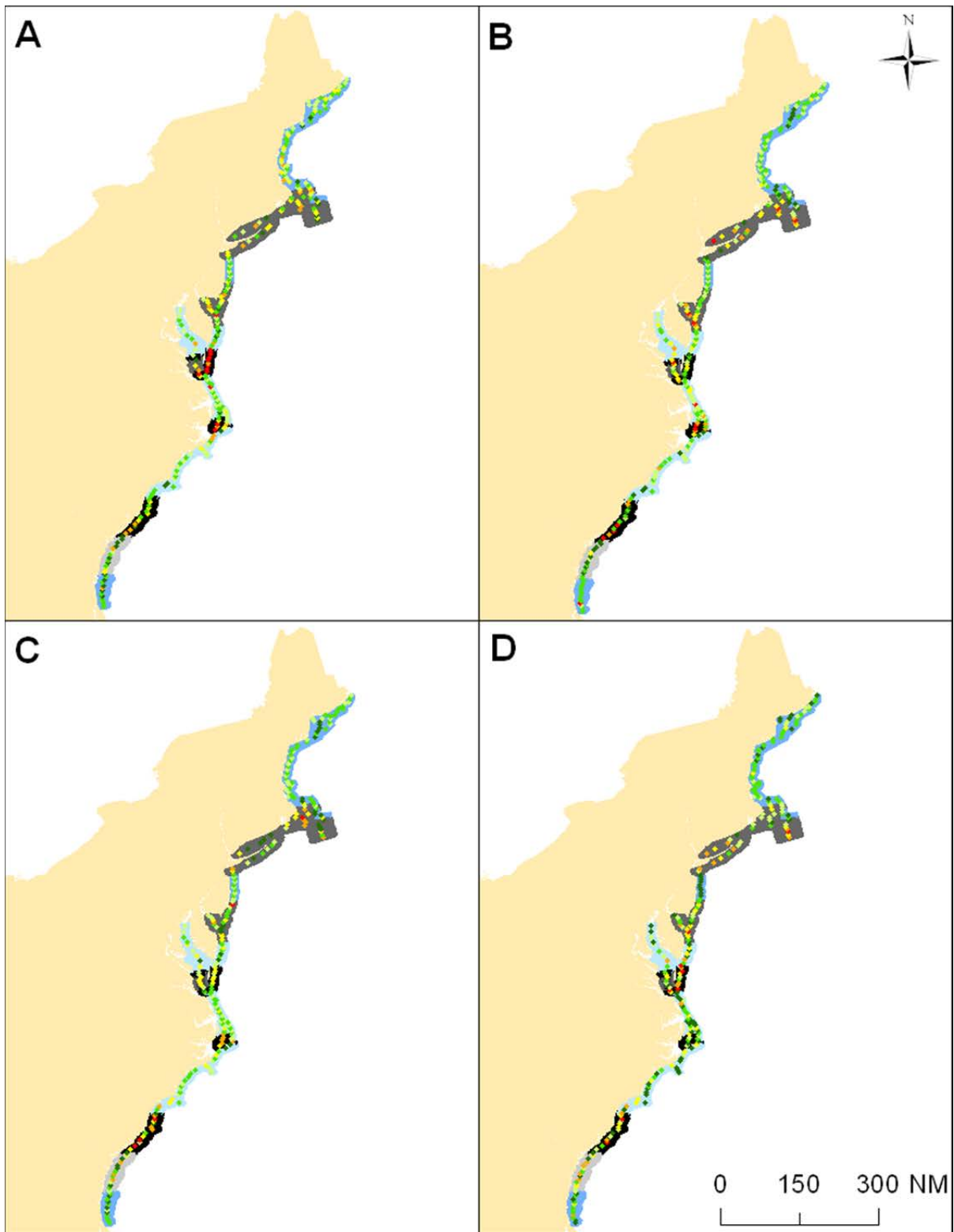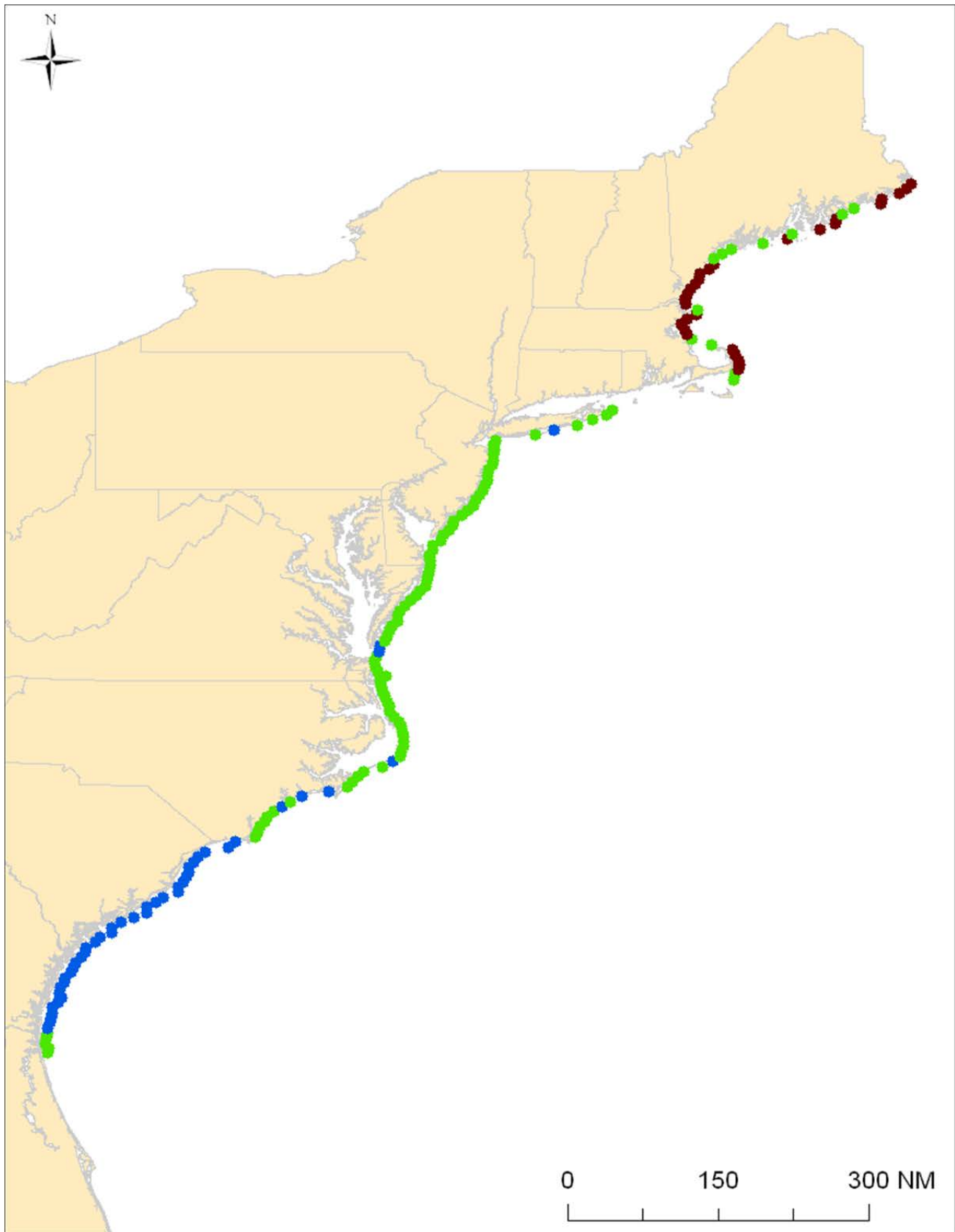
Figure A1.7. Transects coded by bathymetry classification identified by *k*-means clustering analysis. Maroon: Steep profile; Green: Moderate profile; Blue: Flat profile.
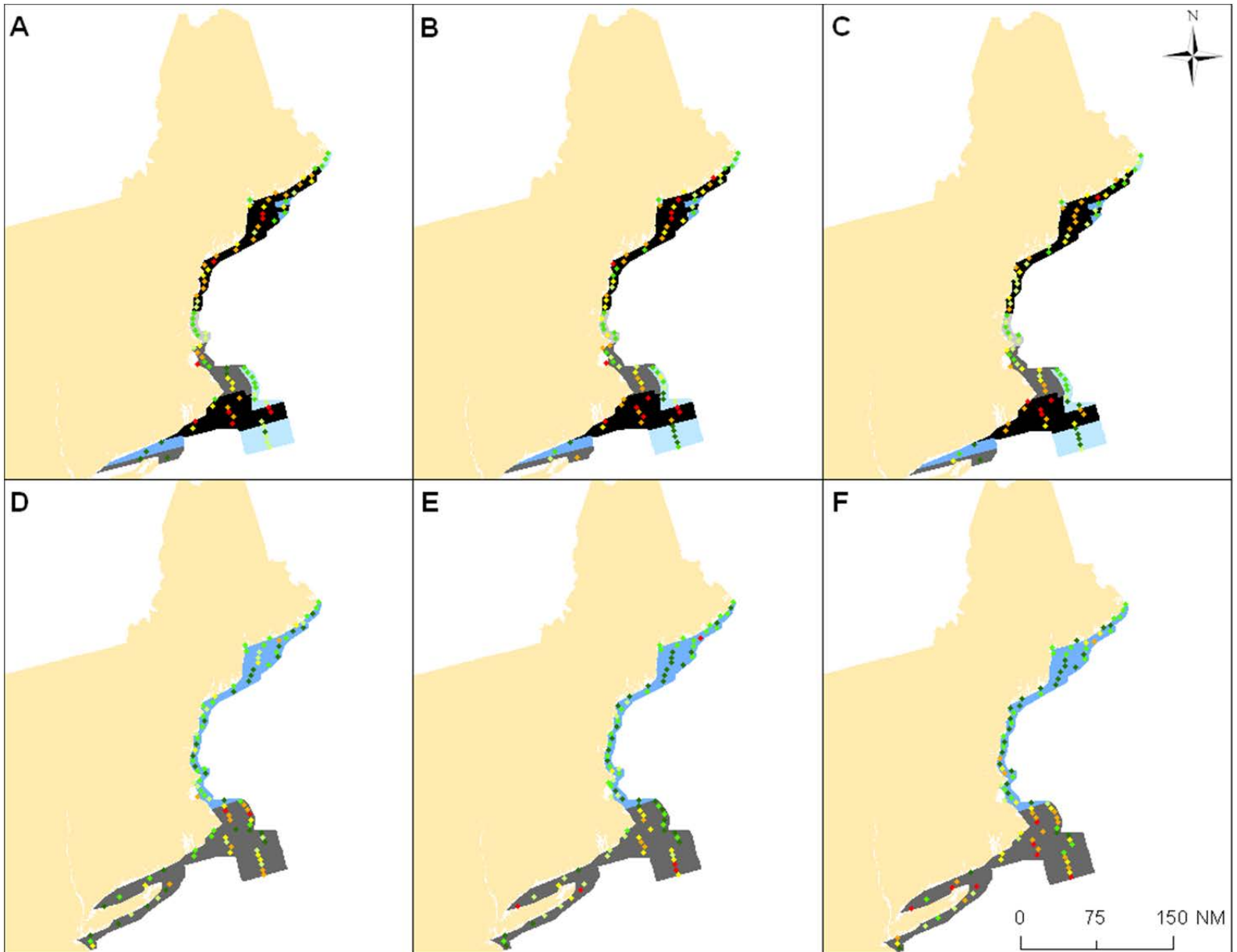
Figure A1.8. Density regions for common eider (top row) and white-winged scoter (bottom row) with annual transect densities. Regions are color coded based on density: black (high), dark grey, light grey, light blue, blue (low). Points illustrate the transect density categories by year and are coded into density categories, from high to low: red, orange, yellow, bright green, green, dark green. (A, D = 2009; B, E = 2010; C, F = 2011.).

Figure A1.9. Density regions for long-tailed duck (top row) and surf scoter (bottom row) with annual transect densities. Regions are color coded based on density: black (high), dark grey, light grey, light blue, blue (low). Points illustrate the transect density categories by year and are coded into density categories, from high to low: red, orange, yellow, bright green, green, dark green. (A, D = 2009; B, E = 2010; C, F = 2011.).
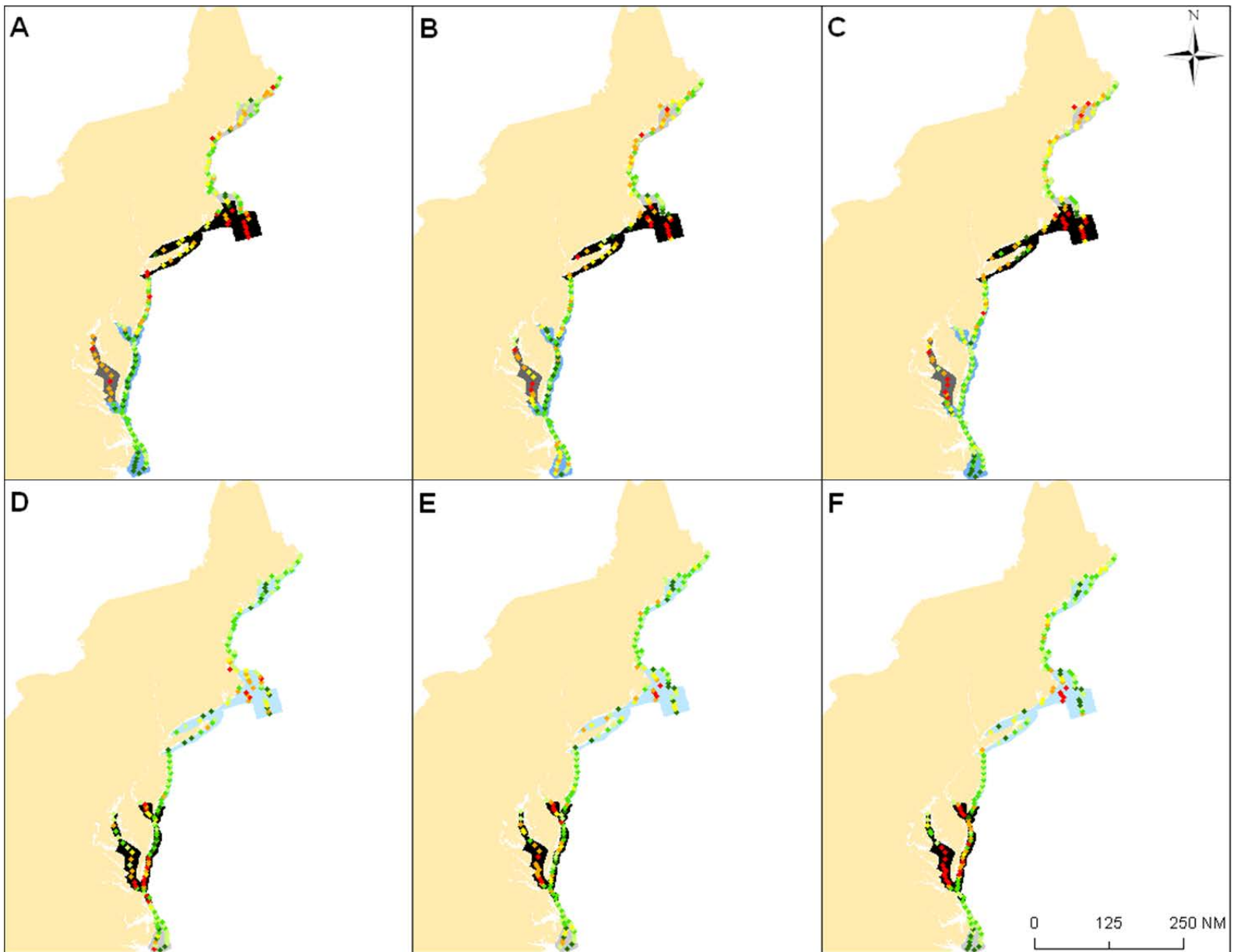
Appendix 2

FITTING STATISTICAL DISTRIBUTIONS TO SEA DUCK COUNT DATA:
IMPLICATIONS FOR SURVEY DESIGN AND ABUNDANCE ESTIMATION

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1. Abstract

Determining appropriate statistical distributions for modeling animal count data is important for accurate estimation of abundance, distribution, and trends. In the case of sea ducks along the U.S. Atlantic coast, managers want to estimate local and regional abundance to detect and track population declines, to define areas of high and low use, and to predict the impact of future habitat change on populations. In this paper, we used a modified marked point process to model survey data that recorded flock sizes of common eider, long-tailed duck, and black, surf, and white-winged scoters. The data come from an experimental aerial survey, conducted by the United States Fish & Wildlife Service (USFWS) Division of Migratory Bird Management, during which east-west transects were flown along the Atlantic Coast from Maine to Florida during the winters of 2009-11. To model the number of flocks per transect (the points), we compared the fit of four statistical distributions (zero-inflated Poisson, zero-inflated geometric, zero-inflated negative binomial and negative binomial) to data on the number of species-specific sea duck flocks that were recorded for each transect flown. To model the flock sizes (the marks), we compared the fit of flock size data for each species to seven statistical distributions: positive Poisson, positive negative binomial, positive geometric, logarithmic, discretized lognormal, zeta and Yule-Simon. Akaike's Information Criterion and Vuong's closeness tests indicated that the negative binomial and discretized lognormal were the best distributions for all species for the points and marks, respectively. These findings have important implications for estimating sea duck abundances as the discretized lognormal is a more skewed distribution than the Poisson and negative binomial, which are frequently used to model avian counts; the lognormal is also less heavy-tailed than the power law distributions (e.g., zeta and Yule-Simon), which are becoming increasing popular for group size modeling. Choosing appropriate statistical distributions for modeling flock size data is fundamental to accurately estimating population summaries, determining required survey effort, and assessing and propagating uncertainty through decision-making processes.

2. Introduction

Effective management of wildlife populations requires high quality estimates of population abundance and distribution with associated measures of uncertainty. Managers use abundance estimates to determine population status, for comparison to environmental carrying capacities, and to monitor population trends (Silvy 2012). Understanding patterns of abundance and aggregation is necessary at both regional and local scales to evaluate the impacts of conservation actions and human disturbance. Obtaining accurate population indices is difficult, however, because animals are often unevenly and unpredictably distributed (Caraco 1980, Certain et al. 2007, Silverman et al. 2001); for example, counts often include many zeros

(Hall 2000, Martin et al. 2005) and distributions of count data can be extremely right skewed (Bonabeau et al. 1999, Griesser et al. 2011). The problem is compounded by a need for consistent repeated estimates over time; yet, sufficient data to characterize highly aggregated species distributions are expensive to collect and maintain. The choice of appropriate statistical models for wildlife count distributions is fundamental for consistency and efficiency of abundance and distribution estimation and to facilitate more reliable uncertainty assessments (Williams et al. 2002).

Waterfowl managers are especially interested in population estimates for five species of North American sea ducks (Tribe Mergini) that winter in large numbers off the Atlantic coast of the United States (Sea Duck Joint Venture 2003). Data from a variety of sources suggest that common eider (*Somateria mollissima*), long-tailed duck (*Clangula hyemalis*), and black, surf, and white-winged scoters (*Melanitta nigra*, *M. perspicillata*, and *M. fusca*) may be declining (Perry and Deller 1995, Sea Duck Joint Venture 2003), and proposed offshore energy development has the potential to significantly alter their wintering habitat (Drewitt 2006, Garthe and Huppop 2004, Larsen and Guillemette 2007). Waterfowl managers need accurate and precise coast-wide winter abundance indices to assess trends and set annual harvest regulations, while energy regulators need predictions of spatial variation in abundance to inform responsible site placement of offshore structures and to guide future development activities.

During winter, sea ducks form large foraging flocks, but can also be found alone or in small groups (Caithamer et al. 2000). Their distributions can shift within and between years, due to changes in habitat, weather, and prey availability (Guillemette et al. 1993, Kirk et al. 2008, Lewis et al. 2008, Zipkin et al. 2010), and they can be found up to 40 miles from land (Appendix 1). As a result, effective monitoring surveys are expensive, dangerous, and fraught with logistical challenges. If the resulting data are to be worth collecting, then appropriate statistical models to interpret the data need to be available and accessible.

The United States Fish & Wildlife Service (USFWS) Division of Migratory Bird Management initiated an experimental aerial survey, conducted from Maine to Florida in the winters of 2009-11, to assess the feasibility and effectiveness of a long-term winter sea duck monitoring program along the Atlantic coast. Determining whether precise estimates of regional annual abundance are possible for the five target species is necessary to evaluate the effectiveness of the survey. To meet these objectives, we explore the fit of a set of statistical models to data from the Atlantic coast wintering sea duck survey. Our goals are: 1) to identify a model, or models, that accurately describes the distribution of counts, characterized by an unusually heavy right tail and an excessive number of zeros; 2) to determine if the best model choice varies by species; and 3) to compare parameter estimates among species and assess whether more refined models (e.g., that stratify regions by high and low density or include habitat covariates) and/or data collection efforts are necessary. Identifying a parsimonious model is of primary

importance because monitoring programs require repeated, timely estimates that are easy to explain and robust to unexpected data reduction or other survey changes. Thus, analytically complex and data-hungry approaches are ill-advised for management-oriented monitoring programs.

The most challenging problem we face is characterizing a count distribution with an extreme variance to mean ratio, as is often observed in sea duck data (Zipkin et al. 2010). Identifying appropriate statistical distributions for analyzing count data of animal populations is an ongoing area of investigation in ecology. For reasons based on first principles and for convenience, the Poisson distribution has frequently been used (Caraco 1980) and is popular in modeling avian species (e.g., Fujisaki et al. 2008, Link and Sauer 2007). Yet the assumption that the variance equals the mean often does not hold for many seabird species, which are known to form large flocks. The negative binomial distribution, which allows the variance to exceed the mean, is used as an alternative to the Poisson to characterize the count distributions for species where spatial aggregation is known to occur (e.g., Beauchamp 2011, Cohen 1972, Wood 1985). The negative binomial distribution is the result of a Poisson-Gamma mixture and converges to the Poisson distribution as the shape parameter, k, approaches infinity (Table A2.4). Okubo (1986) recommended the geometric distribution – a discrete analog to the exponential distribution and also a special case of the negative binomial where the shape parameter equals one – to handle extremely large group sizes and demonstrated its applicability for a number of taxa including birds. Empirical evidence suggests, however, that the negative binomial and geometric models do not adequately capture observed distributions of counts for some populations, especially those that are found in very large group sizes, such as some fish and bird species. Ma et al. (2011) derived a logarithmic distribution from first principles based on rules for when individuals should join and leave groups; this model has outperformed the Poisson and negative binomial distributions in studies of house sparrows (Griesser et al. 2011) and seabirds (Jovani et al. 2008b). Ma et al. (2011) additionally pointed out that the logarithmic can be derived as a limiting case of the negative binomial distribution as the shape parameter (k, Table A2.4) approaches zero (see also Quenouille 1949), placing it in the context of other distributions used to model ecological count data.

More recently, the power law distribution has been proposed for modeling group sizes when the variance to mean ratio is much larger than can be accommodated by the aforementioned models (Bonabeau and Dagorn 1995, 1999). Several studies have demonstrated that the power law distribution fits well to a number of empirical examples including populations of fish, seabirds, and mammals (Clauset et al. 2009, Beauchamp 2011, Jovani et al. 2008b, Kiett and Stanley 1998, Sjoberg et al. 2000). However, the power law distribution (using ecologically relevant parameter ranges) is capable of producing extremely large counts (e.g., in the millions; Clauset et al. 2009), which are not realistic for most sea duck species. The power law can be truncated or combined with an exponentially decaying

function (Niwa 2003) to address this problem. In fact, Ma et al. (2011) pointed out that the logarithmic distribution itself is a discrete form of a power law distribution with an exponential cutoff, where the power law exponent is -1 and the upper tail decays exponentially above a cutoff that is directly related to the average group size experienced by an individual. Bonabeau et al. (1999) also presents mechanistic models of group size that lead to power law distributions with exponential decay.

Other heavy-tailed distributions exist and should be considered in a model selection context before concluding that "power law-like" behavior observed in empirical data necessarily indicates a power law distribution (Clauset et al. 2009).   These include the Yule-Simon and the discretized lognormal distributions, which themselves can be viewed, respectively, as limiting distributions of stochastic preferential attachment or multiplicative growth processes (Clauset et al. 2009, Mitzenmacher 2003). Given the diversity of possibilities, a model selection framework would be useful to guide choices of appropriate distributions to model highly skewed ecological count data (Beauchamp 2011).

In this paper, we test the fit of a series of over-dispersed statistical distributions, from the negative binomial to the power law, to counts of sea duck flock sizes; we also assess the fit of a series of over-dispersed models to the distribution of flock frequencies. Our assessment is a critical first step in the applied statistical work needed for the development of rigorous survey designs, power analysis, risk and impact assessments, and optimal management strategies for sea ducks. Appropriate modeling of the basic underlying distributional characteristics of avian count data is critical for making strong inferences about the distribution of target populations, particularly in the marine environment where logistics are inherently more difficult than in terrestrial systems and reliance upon statistical models is correspondently greater.

3. Methods

3.1 Data Collection

The USFWS aerial survey was conducted along the Atlantic coast from the U.S.-Canadian border ($44^o46'$ N) to Jacksonville, FL ($30^o21'$ N) between January and March, 2009-11. Four fixed-wing aircraft were flown along east-west transects spaced systematically at intervals of five minutes of latitude (approximately 5 nm apart). These transects extended east from the coastline to the longer of two distances: 8 nm or the distance to 16 m depth. Transects ranged in length from 1-80 nm (with 95% of transects between 4.8-46.4 nm). The mean transect length was 17.9 nm (standard deviation: 12.8 nm) with transects less than 8 nm in areas that span bays and longer transects paralleling the shoreline in complicated coastal areas (e.g., Long Island Sound).

The survey crews, which consisted of an observer and pilot-observer, flew at 110 knots and 70 m altitude, while counting sea ducks and other aquatic birds within 400 m-width strip transects (the observer

counts a 200 m strip on one side of the plane while the pilot does the same on the opposite side). After completing their entire set of transect lines, each crew flew north to their first east-west transect line and replicated every other transect from north to south. The replicate surveys were conducted approximately one week after the first surveys and do not duplicate the original track exactly, making the possibility of recounting the same individuals remote. The three scoter species are difficult to distinguish reliably in the field, leading to a large number of scoters identified only to genus (*Melanitta* spp.). As such, we focused our analyses on generic scoter species (records for all three species combined with unidentified scoters), along with the common eider and Long-tailed duck. We refer to these two species and one genus as the "species groups" of interest.

Surveys were conducted 1-18 February in 2009, 23 January to 2 March in 2010, and 31 January to 17 February in 2011. Due to the vagaries of field operations, transects and replicates varied somewhat between years. We use data from the 236 transects, and 76 replicates that were successfully surveyed in all three years. Common eider and long-tailed duck do not winter in the southern portions of the survey area, and so models fit for them are based on fewer transects (88 for common eider, of which 21 were replicated; 173 for long-tailed duck, of which 54 were replicated).

The data consist of observations along survey transects recording the (1) location, (2) species, and (3) number of birds seen at the location. We refer to the group of birds recorded at one location (including single birds) as a "flock", and the number of birds seen as the "flock size." Note that birds are counted only within the transect boundaries, while the actual flock might have extended well beyond.

3.2 Analysis

To estimate the abundance of sea ducks by species, we represent the data as a modified marked point process (Daley and Vere-Jones 2003, Jacobsen 2006) where the flocks are the points and the size of the flocks, discrete and independent of the points, are the marks. The point process is summarized by transect: we first model the flock counts (i.e., number of flocks) on each transect, and then model the flock sizes, conditional on the number of flocks observed. Preliminary analyses indicated large variations and only small correlations in the number of species-specific flocks (points) among neighboring transects (0.23 for common eider, 0.41 for long-tailed duck, and 0.24 for scoters), due in part to zero-zero neighbors in areas of low density. This suggests that the number of flocks on one transect is not predictive of the flock count on neighboring transects. We additionally found no significant relationships between the number/density of flocks per transect and the sizes of those flocks, which fits our assumption of independence in marks and points.

To determine the appropriate model to describe the observed number of flocks per transect (the point process), we tested the fit of four distributions to the transect-level flock counts: zero-inflated

Poisson, zero-inflated geometric, and zero-inflated negative binomial, as well as the standard negative binomial (Table A2.4). The data were fit separately for common eider, long-tailed duck, and scoter species and we included an offset for transect area (to account for variable transect lengths), which was standardized by dividing the area of each transect by the mean of all transect areas. We fit each model using maximum likelihood estimation (MLE) in the program R (version 2.13.2; R development Core 2011) with the VGAM package (Yee 2010).

For the flock size data (the marks), we fit seven discrete distributions with positive integer support (because there are no flocks of size zero): positive Poisson, positive negative binomial, positive geometric, logarithmic, discretized lognormal (a discretized version of the continuous lognormal, truncated to a minimum of one), zeta (discrete power law), and Yule-Simon (which we refer to as the Yule) distributions (Table A2.5). We modeled the data for species groups separately using each statistical distribution (R development Core 2011). We again estimated the parameters for distributions using MLE in the program R (version 2.13.2; R development Core 2011). We used the VGAM package (Yee 2010) to estimate parameters for the positive Poisson, positive negative binomial, positive geometric, and logarithmic distributions. We used the methods and code provided in Clauset et al. (2009) to estimate the parameters for the discretized lognormal, the zeta, and the Yule distributions. In applying the zeta distribution, both a shape parameter as well as a threshold (sometimes referred to as x_{min}) can be estimated, below which data are excluded from the analysis. This is sometimes done because it is hypothesized that power law distributions may occur only above some minimum value for a given data set (Clauset et al. 2009). Because we were interested in fitting each of these distributions to the complete dataset, we set the threshold equal to one for the zeta distribution (and other distributions, where applicable).

For both the points and marks, we calculated the log-likelihood of each model. We used the likelihoods to calculate Akaike's Information Criterion corrected for finite sample sizes (AICc), which we then used to rank the models (Burnham and Anderson 2002). We further assessed model fit using the Vuong closeness test (Vuong 1989) for pair-wise comparisons of the best fitting models to the flock size data (marks). The Vuong is a likelihood-ratio test that measures whether one model is closer than the other to the unknown true model using the Kullback-Leibler information criterion (Vuong 1989) and can be derived for both nested and non-nested models. The benefit of using the Vuong test is that it allowed us to evaluate the hypothesis that models ranked higher based on AICc were significantly closer to the true data-generating model than lower-ranked models through estimation of a p-value. We implemented the Vuong test by generalizing the "vuong" function for non-nested models (because all top models turned out to be non-nested) in the pscl package in program R (Zeileis et. al. 2008). We then compared parameter estimates for the top models for each species group.

4. Results

There were 1742, 2709, and 4047 flocks observed from 2009-11 for common eider, long-tailed duck, and scoters, respectively, with the total number of individuals being 28,968 common eider, 30,677 long-tailed duck, and 55,859 scoters. The number of flocks per transect ranged from 0-95 for common eider, 0-130 for long-tailed duck, and 0-104 for scoters. Even after accounting for species ranges, there were a large number of transects in which no flocks were observed: 166 out of 327 for common eider, 413 out of 681 for long-tailed duck, 525 out of 936 for scoters.

Flock size ranged from 1-2000 for common eider, 1-750 for long-tailed duck, and 1-5000 for scoters with the median flock size equal to three for common eider and long-tailed duck and four for scoters. However, the standard deviation of flock size was quite high: 94 for common eider, 39 for long-tailed duck, and 112 for scoters. These statistics and plots of log-frequency versus log-abundance (Figure A2.1) demonstrate the right skew of the flock size distributions.

4.1 Distribution of number of flocks per transect

The negative binomial distributions (zero-inflated and standard) were the best fitting distributions for the data on the number of flocks per transect for all species groups (Table A2.1; this was also true for the three scoter species identified to species – results not shown). For the common eider, the zero-inflated negative binomial distribution had a slightly higher log-likelihood (and hence lower AICc value) than the standard negative binomial. In the case of the long-tailed duck and scoters, the zero inflation parameter was estimated to be zero, collapsing to the standard negative binomial distribution. The zero-inflated geometric and Poisson distributions had considerably lower log-likelihoods and comparably poorer fits to the data (Table A2.1).

4.2. Distribution of flock sizes

The discretized lognormal distribution produced the best fit to the data for flock sizes of all three species groups (Table A2.2; Figure A2.1). This was a consistent result applying to all species together (Figure A2.2), each species separately (including the three scoter species when identified to species; results not shown) and each species separately by year (2009-11; results not shown). In all cases, the discretized lognormal had the lowest AICc value when compared to the other six candidate distributions and had a significantly better fit compared to the other top models as inferred from Vuong pair-wise closeness tests (Table A2.2). The next best models varied by species group with the logarithmic, Yule, zeta, and positive negative binomial distributions all producing reasonable (although inferior) fits to the data (Table A2.2; Figure A2.1). For all three species, the positive negative binomial had a very similar, although slightly inferior fit as compared to the logarithmic distribution using AICc and Voung tests (e.g., the positive

negative binomial model is obscured by the logarithmic in Figure A2.1). This is consistent with the fact that the logarithmic distribution is a limiting case of the negative binomial (Quenouille 1949, Ma et al. 2011) and that the shape parameter in the negative binomial for all species was close to zero (Table A2.3). This was also true for the Yule and zeta distributions, whose fits were qualitatively very similar, although the Yule outperformed the zeta for all species by AICc and Vuong tests (Table A2.2). The geometric and positive Poisson models were the worst fitting models in all cases with likelihoods much lower than the other models (see caption for Table A2.2) and were thus excluded from further consideration.

In all comparisons, the direction of the Vuong test statistic supported the ranking of model fits by their AICc values (and by their log-likelihoods). The discretized lognormal had a significantly better fit as compared to the other six distributions for all three species groups (p<0.001; Table A2.2). In all other pair-wise comparisons, the distribution with the highest likelihood value was judged closer to the true model than the inferior model, although in some situations the difference between models was not significant.

Figure A2.2 shows log-probability versus log-abundance plots for each distribution for simulated data using parameter values as estimated by maximum likelihood fitting to combined flock size data from all species (Figure A2.2 column 1) as compared to the actual data of all species groups combined (Figure A2.2 column 2). The figure demonstrates that the positive Poisson, positive geometric, logarithmic, and positive negative binomial distributions are unable to account for the large flocks sizes that are observed in the data while the zeta and Yule are capable of producing flock sizes that are much larger than observed in the data. Figure A2.2 highlights the superior fit of the discretized lognormal distribution – which best captures the range of variation observed in the right tail – to the sea duck data as compared to the other six distributions.

The parameter estimates for the top models were comparable among species groups with estimates generally being more similar between common eider and long-tailed duck as compared to scoters (Table A2.3). In the parameterization of the zeta and Yule distributions that we present (Table A2.5), the mean is not finite for values of $a < 1$ (Clauset et al. 2009, Yee 2010), yet for all three species groups the maximum likelihood estimates for these parameters were less than one. Thus, in order to compare the output from the fit of each statistical distribution, we simulated count data for each species group that was the size of the sample data ($n_{all} = 8498$; $n_{common\ eider} = 1742$; $n_{long-tailed\ ducks} = 2709$; $n_{scoters} = 4047$) 10,000 times and report the mean values for the summary statistics (Table A2.3). These results demonstrate the relationship between sample moments and moments of MLE fitted distributions. Note that the mean of the fitted logarithmic and negative binomial distributions match the observed sample mean (as expected given that the sample mean is the maximum likelihood estimator of the negative binomial and logarithmic means), but result in too many moderately large groups (3rd

quartile), too few very large groups (maximum), and an underestimation of the variance observed in the data. Thus, although the fitted negative binomial and logarithmic distributions describe the mean of the data well, they mischaracterize other aspects of the data distribution and underestimate uncertainty about the mean. On the other end of the spectrum, the Yule and zeta distributions have unrealistically heavy tails and overestimate the variance in the counts. For example, the average standard deviation of flock size for all species combined (as estimated from simulations) was 1.15E+09 for the zeta distribution as compared to 25.8 for the discretized lognormal and 23.6 for the negative binomial (and 91.1 in the observed data). Although the standard deviation of flock size is only slightly higher with the discretized lognormal as compared to the logarithmic and negative binomial distributions, the latter two distributions are more likely to underestimate maximum flock size (last column, Table A2.3). The discretized lognormal distribution best matches the range of the observed data (Figure A2.2, Table A2.3) but it also consistently underestimates the mean flock size, in part because it produces too few very large counts. Thus, while the discretized lognormal captures the variance and the upper tail probability of the data somewhat better than the other distributions (negative binomial and logarithmic underestimate upper tail probability and variance; zeta and Yule overestimate upper tail probability and variance), this comes at a cost to efficient estimation of the mean (negative bias of 20-30% in our simulations). Given this result, Poisson mixture distributions may currently be preferable for abundance estimation, assuming reasonable variance corrections could be incorporated.

5. Discussion

We described a marked point process framework for modeling flock numbers and flock sizes to characterize sea duck distribution and abundance in the Atlantic. We employed model selection techniques to choose appropriate models for skewed and zero-inflated distributions of flock numbers and highly right-skewed distributions of flock sizes. Our process-oriented approach should be useful in modeling other highly aggregated, patchily distributed species. The distributions that best fit the "points," i.e., the number of flocks per transect, (negative binomial and zero inflated negative binomial) and "marks," i.e., the flock sizes, (discretized lognormal) were surprisingly consistent across sea duck species and did not vary among years.

Our results have important implications for estimating annual abundances of wintering sea ducks and for designing future surveys that will be able to generate information on population statuses and trends. Inappropriate choice of the distribution family in a modeling framework can lead not only to bias in parameter estimates, but to inaccurate assessments of uncertainty and statistical power. Appropriate characterization of uncertainty and estimation of statistical power are of particular importance in a management context because uncertainty will be propagated through decision-making processes and will

affect our understanding of population dynamics, as well as the design and implementation of future monitoring programs. For example, national harvest regulations for many species of ducks are set annually by the U.S. Fish and Wildlife Service using population estimates derived from aerial surveys of breeding areas (e.g., USFWS 2012, Williams et al. 2002); these regulatory decisions are informed by predictions from models of population dynamics that are also derived from survey estimates. Because the sea ducks considered here breed in remote areas that are not covered by current surveys, estimates from winter areas may provide our best means of monitoring responses to exploitation and environmental change, but only if estimates from winter surveys can correctly and precisely estimate abundance. Our results are also particularly relevant to applications that require proper modeling of the extreme values of abundance observed for many species and where surveying presents logistical challenges, thereby limiting the number of samples collected. This includes risk and impact assessments, as well as detection of high-use areas. As marine environments along the eastern United States are currently being considered for development of wind energy production (Bowes and Allegro 2012), sufficient survey methods and accurate maps are critically needed to assess the potential impacts of the proposed development on sea ducks and seabirds.

The best-fitting distributions for flock size in our study (discretized lognormal, logarithmic, negative binomial, Yule, and zeta) differ from each other primarily in the shape of the upper tail. The probability mass of the zeta distribution declines log-linearly in the tail (that is, linearly on doubly logarithmic axes), and the Yule distribution nearly so, making them the heaviest tailed distributions in our candidate set. This is evident in the relatively common occurrence of very large counts in these distributions (column one in Figure A2.2, Table A2.3). The probability mass of the upper tail of the discretized lognormal distribution declines in a log-quadratic fashion, whereas the logarithmic and negative binomial display an exponential decay in the upper tail. Thus, the heaviness of tails in these distributions is ranked as follows: zeta ≈ Yule > discretized lognormal > logarithmic ≈ negative binomial. That the discretized lognormal distribution was consistently selected for our three sea duck species groups suggests that the upper tails of flock size distributions for these species are not exponentially bounded (logarithmic and negative binomial), but not as extreme as would be predicted under power law-type distributions (e.g., zeta, Yule). This is fortunate for abundance estimation, because power law behavior implies that the variance (for $a < 2$) and mean (for $a < 1$) are not finite; that is, that sample moments would increase with the area and time spent sampling rather than providing estimates of meaningful characteristic properties of the abundance distribution.

The lognormal distribution has a long history in ecology (e.g., Preston 1948) and a diversity of other fields (Limpert et al. 2001) where it often arises as a plausible alternative to other heavy-tailed distributions like power laws (e.g., in birds; Allen et al. 2001). One classical generative process for a

lognormal distribution is the multiplicative stochastic growth process first proposed by Gibrat (1931), in which the size of an entity changes by successive multiplicative random effects; if the multiplicative random effects are independent and lognormally distributed, then the size distribution will be lognormal. The lognormal distribution arises even more generally as a direct consequence of the Central Limit Theorem for products of random variables; any process that involves the product of a sufficiently large number of independent and identically distributed random variables having any distribution with finite mean and variance has a limiting lognormal distribution. Thus, a discretized lognormal distribution of counts could arise from a variety of plausible ecological mechanisms. However, the lognormal distribution is known to produce biased estimates of the mean and variance when it is "contaminated" with even small amounts of data from other distributions (Myers and Pepin 1990). In our dataset of flock sizes, the discretized lognormal underestimated the sample mean for all three species (Table A2.3), which suggests that our data may not conform perfectly to a lognormal distribution. One possible reason for small deviations from lognormality might be nonstationarity in the underlying process. It may be possible to control for this problem by stratifying areas of high/low abundance or adding covariates that account for changes in group sizes, such that the conditional distribution is closer to lognormal. The lack-of-fit of the lognormal may also reflect the manner in which observers count birds in aerial surveys: singles and pairs have a higher probability of being undetected (Pollock and Kendall 1987), whereas flocks with more birds are typically undercounted (Pearse et al. 2008). Further exploration of the counting process and the relationship of the observed counts to actual sea duck flock sizes might help explain the disparity between the observed and lognormal tails. The ultimate choice of which distribution is the most appropriate depends on the modeling purpose. In our case, the discretized lognormal was identified as the best fitting distribution overall, and therefore might be the best choice for simulation modeling that requires a compact representation of the whole distribution. Yet, given the sensitivity of moment estimators to slight deviations from the lognormal distribution (Myers and Pepin 1990), one might be justified in choosing a statistical distribution with a lower total log-likelihood that can provide more robust mean abundance estimates, such as the logarithmic or negative binomial distributions. Simulation studies could help to choose the optimal distribution for particular applications.

Bonabeau et al. (1999) suggested that an exponentially decaying power law may be a useful distribution for dealing with heavy-tailed data that is bounded. To determine the appropriateness of the exponentially decaying zeta distribution compared to our top performing models, we additionally fit this distribution to flock size data for the three species groups. While the exponentially decaying zeta distribution had greater log-likelihood values (-5324.3 for common eider, -7854.3 for long-tailed duck, and -12713.0 for scoters) than either the zeta or Yule (suggesting a comparatively better fit; Table A2.2), it was still outperformed by the discretized lognormal (p<0.001 in Vuong pair-wise comparison tests and

lower AICc) for all three species groups, supporting the hypothesis that our data, while skewed, are less heavy-tailed than distributions in the power law family. Although the exponentially decaying power law may not produce a better fit to our data than the discretized lognormal, it may provide a useful alternative because of the above mentioned problems associated with estimating the moments of lognormal distributions when the lognormal is not a perfect fit. By no means did we present an exhaustive list of possible statistical distributions for modeling skewed count data. We suggest further exploration of the exponentially decaying zeta distribution, as well as other distributions as possible alternatives to the discretized lognormal, when abundance estimation is the objective.

It is important to note that selection among statistical distribution models that differ primarily in their tails is notoriously difficult with small sample sizes and noisy data (Beauchamp 2011, Clauset et al. 2009). We have used data from a very large survey, but many ecological datasets are substantially smaller and would not allow discrimination among the more similar of the models studied here (Myer and Pepin 1990). This suggests a useful role for meta-analysis, synthetic analysis of large databases, and validation of mechanistic models of processes determining group size distributions, so that recommendations for appropriate choices of distributions can be made for selection of distributions on the basis of taxonomy, life history, environment, etc. The similarity in model fits among species, species groups, and years is encouraging, as it suggests that model power and estimator precision for individual species groups can be gained by borrowing information both over time and across species (Williams et al. 2002).

Many mechanistic models of group size formation and aggregation have been proposed to give rise to several of the distributions studied here. For example, Caraco (1980), Niwa (2003) and Ma et al. (2011) have each demonstrated how differing rules related to the decision on when to join or leave groups can lead to negative binomial, decaying power law, and logarithmic distributions of group size, respectively. However, in our sea duck example, flock detection and flock size counts are likely the result not only of the biological processes associated with flocks coalescing, but also the specific fixed-width sampling protocol used during the surveys (i.e., the observation process). In this case, the negative binomial distribution combined with the discretized lognormal produced the best fit to our marked point process for observed number of flocks and flocks sizes, but it is possible that other sampling approaches could yield different combinations. Counting large flocks on the ocean within a 200 meter strip while in a fast moving airplane is a difficult task, but one that can be improved through training and revised protocols. Beauchamp (2011) noted that rough conditions at sea could bias counts and possibly alter which statistical distribution fits best to observed flock sizes. Further exploration of how to minimize and account for the effects of the observation process, such as including covariates, detection functions, and upper limits imposed by the size of the observation unit, may lead to more accurate and precise counts

and better estimates of uncertainty, allowing for better understanding of the biological mechanisms that produce variation in sea duck flock sizes.

Statistical models of ecological count data can be far more complex than those presented here. It is common to include spatial, temporal, and habitat strata, environmental and biological covariates influencing ecological processes leading to the presence or absence of a species, and sampling covariates, which can affect the detection process of individuals during surveying. We intentionally focused our study on simple distributional models for avian count data, neglecting additional complexity that may in some cases improve model explanatory power. It is fundamental to first determine what form of the underlying statistical distribution is appropriate before real world complexities can be incorporated into models. Our marked point process approach matches the observational process (e.g., seeing a flock, then determining its size) and readily allows for inclusion of covariates for both flock detection and flock size estimation.

A parsimonious approach is recommended for a second reason: large scale monitoring programs often do not have the capacity to collect, maintain, and utilize extensive ancillary data sets, and long-term changes in distribution, abundance, or phenology may make models calibrated to fixed strata (e.g., the study area; areas of high density) inappropriate or inefficient at large scales. Thus, simple descriptions that generalize across species and years are extremely valuable, when possible. Our results suggest that the sea duck counts based on our survey methodology have similar statistical properties, and comparable models can be used over time and across species. These models will form the basis for continued exploration aimed at identifying the covariates affecting wintering sea duck populations, and providing decision makers with the best possible description of sea duck distributional patterns and trends.

6. References

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Table A2.1. Log-likelihood and parameter estimates for distributions fit to data on the number of flocks per transect for common eider, long-tailed duck, and all scoters combined. Likelihoods are presented because likelihood rankings were identical to AICc rankings (sample sizes were relatively large and the number of parameters for all fitted models ranged from 2-3). Specifications for each distribution are given in Table A2.4. The parameter Ø is the zero inflation parameter (ranging from 0-1) and is the probability of a structural zero. The second to last column shows the observed sample mean number of flocks per transect for each species (bold) and estimates of the mean under each distributional assumption. Note that the MLE of the negative binomial distribution is the sample mean by definition. The last column shows the observed proportion of transects without flocks (bold) and the proportion estimated under each distributional assumption. The zero inflated negative binomial is excluded from this table for the long-tailed duck and scoter species because the zero-inflated parameter was estimated to be zero, collapsing the distribution to a standard negative binomial.

	Log-likelihood	Ø	Parameter estimates		Mean flocks per transect	Transects with no flocks
Common eider					**5.33**	**0.51**
Zero inflated negative binomial	-727.72	0.19	$\mu=7.20$	$k=0.43$	5.81	0.43
Negative binomial	-743.24		$\mu=5.33$	$k=0.24$	5.33	0.48
Zero inflated geometric	-885.62	0.07	$p=0.55$		1.12	0.57
Zero inflated Poisson	-1444.37	0.56	$\lambda=9.57$		4.18	0.49
Long-tailed duck					**3.98**	**0.61**
Negative binomial	-1162.43		$\mu=3.98$	$k=0.21$	3.98	0.54
Zero inflated geometric	-1644.99	0.05	$p=0.66$		1.86	0.68
Zero inflated Poisson	-2270.05	0.45	$\lambda=6.82$		3.73	0.45
Scoters					**4.32**	**0.56**
Negative binomial	-1782.63		$\mu=4.32$	$k=0.20$	4.32	0.53
Zero inflated geometric	-2286.72	0.07	$p=0.59$		1.33	0.61
Zero inflated Poisson	-4280.94	0.49	$\lambda=7.80$		4.00	0.49

Table A2.2. Model selection results for each model fit to non-zero flock size data for common eider, long-tailed duck, all scoter species combined. Log-likelihood values are shown in the diagonals. Likelihoods are presented because likelihood rankings were identical to AICc rankings (sample sizes were relatively large and the number of parameters ranged from 1-2 for all fitted models). The off-diagonals report the results from pair-wise Vuong closeness tests. In all pair-wise comparisons, the distribution with the lower log-likelihood value was also identified as the best (closest to unknown true model) by the Vuong test statistic. However, the values in grey show when the difference was not significant. The positive Poisson and geometric models are excluded from our comparison because their likelihoods indicated very poor fits to our data (common eider: -6585.6 geom, -61,046.0 pois; long-tailed duck: -9160.3 geom, -48,029.6 pois; scoters: -14519.5 geom, -111268.9 pois).

	Discretized lognormal	Yule	Zeta	Logarithmic	Positive negative binomial
Common eider					
Discretized lognormal	-5227.0				
Yule	<0.001	-5347.9			
Zeta	<0.001	<0.001	-5404.8		
Logarithmic	<0.001	0.049	0.333	-5425.5	
Positive negative binomial	<0.001	0.041	0.304	<0.001	-5429.3
Long-tailed duck					
Discretized lognormal	-7718.0				
Yule	<0.001	-7922.1			
Logarithmic	<0.001	0.394	-7931.6		
Positive negative binomial	<0.001	0.352	<0.001	-7935.9	
Zeta	<0.001	<0.001	0.007	0.007	-8022.5
Scoters					
Discretized lognormal	-12312.9				
Logarithmic	<0.001	-12764.7			
Positive negative binomial	<0.001	<0.001	-12774.4		
Yule	<0.001	0.126	0.149	-12901.7	
Zeta	<0.001	0.005	0.008	<0.001	-13069.6

Table A2.3. Parameter estimates for the top five models to the flock size data for: all species combined, common eider, long-tailed duck, and scoters (listed in order by AICc). The values shown are the parameters for each distribution as described in Table A2.5. The six right-most columns of the table give summary statistics of the observed flock size data for each species (bold) as well as summary statistics of simulations of flock size under each fitted distribution. The summaries for each distribution are the mean values based on 10,000 simulations using each species parameter estimates and size of the sample data. The last column is the standard deviation of the maximum count over the 10,000 simulations. Note that the MLE parameters for the negative binomial and logarithmic distributions are such that the estimated mean of the distribution is the sample mean by definition.

	Parameter estimates		1st quartile	Median	Mean	3rd quartile	Max	SD (max)
All species			**2**	**3**	**13.59**	**9**	**5000**	
Discretized lognormal	$\mu=1.093$	$\sigma=1.478$	2.00	4.00	10.03	9.11	993.72	634.77
Logarithmic	$p=0.982$		1.89	4.45	13.59	14.50	343.81	58.40
Positive negative binomial	$\mu=0.438$	$k=0.008$	1.96	4.63	13.54	14.57	338.26	59.22
Yule	$a=0.610$		1.00	2.00	4.6E+06	7.88	3.9E+10	3.3E+12
Zeta	$a=0.518$		2.00	4.00	2.0E+07	14.56	1.7E+11	9.6E+12
Common eider			**2**	**3**	**16.63**	**9**	**2000**	
Discretized lognormal	$\mu=0.866$	$\sigma=1.680$	1.14	3.40	11.83	9.45	959.22	843.11
Yule	$a=0.609$		**1.00**	2.03	3.6E+04	7.84	6.2E+07	1.7E+09
Zeta	$a=0.521$		**2.00**	3.96	1.4E+08	14.37	2.4E+11	2.2E+13
Logarithmic	$p=0.986$		1.97	5.05	16.63	17.34	347.07	75.37
Positive negative binomial	$\mu=0.419$	$k=0.006$	1.99	5.13	16.89	17.69	350.89	76.29
Long-tailed duck			**2**	**3**	**11.32**	**7**	**750**	
Discretized lognormal	$\mu=0.886$	$\sigma=1.526$	1.03	3.01	9.13	8.16	649.26	459.21
Yule	$a=0.652$		1.00	2.00	1.5E+04	6.84	4.1E+07	1.5E+09
Logarithmic	$p=0.977$		1.16	4.00	11.33	12.33	231.47	47.87
Positive negative binomial	$\mu=0.314$	$k=0.008$	1.23	4.00	11.29	12.35	227.77	46.70
Zeta	$a=0.548$		2.00	3.64	8.2E+05	12.56	2.2E+09	1.0E+11
Scoters			**2**	**4**	**13.80**	**10**	**5000**	
Discretized lognormal	$\mu=1.286$	$\sigma=1.369$	2.00	4.00	9.97	9.94	589.93	359.30
Logarithmic	$p=0.982$		1.85	4.57	13.80	14.71	315.93	60.20
Positive negative binomial	$\mu=0.919$	$k=0.017$	1.98	4.90	14.04	15.15	313.52	61.90
Yule	$a=0.586$		2.00	2.06	1.2E+05	8.48	4.9E+08	1.3E+10
Zeta	$a=0.498$		2.00	4.00	9.0E+07	16.20	3.6E+11	2.4E+13

Table A2.4. Parameters and probability mass functions for the four distributions that we compare using the data on the number of sea duck flocks per transect. In all cases, the support is $x \in \{0,1,2,3,...\}$. Specifications of all distributions are as in the VGAM R package (Yee 2010).

Distribution	Parameters	Probability mass function	
		$P[X = 0]$	$P[X = x]$
Zero-inflated Poisson	$0 \leq \emptyset \leq 1$ $\lambda > 0$	$\emptyset + (1 - \emptyset)e^{-\lambda}$	$(1 - \emptyset)\dfrac{\lambda^x e^{-\lambda}}{x!}$
Zero-inflated geometric	$0 \leq \emptyset \leq 1$ $0 < p \leq 1$	$\emptyset + (1 - \emptyset)p$	$(1 - \emptyset)p(1 - p)^x$
Zero-inflated negative binomial	$0 \leq \emptyset \leq 1$ $\mu > 0$ $k > 0$	$\emptyset + (1 - \emptyset)\left(\dfrac{k}{\mu + k}\right)^k$	$(1 - \emptyset)dnbinom(x, \mu, k)$
Negative binomial	$\mu > 0$ $k > 0$	$dnbinom = \binom{x + k - 1}{x}\left(\dfrac{\mu}{\mu + k}\right)^x\left(\dfrac{k}{\mu + k}\right)^k$	

Table A2.5. Parameters and probability mass functions for the seven distributions that we compare using the sea duck flock size data. In all cases, the support is $x \in \{1,2,3, ...\}$. Specifications of all distributions are as in the VGAM R package (Yee 2010) except for the discretized lognormal which is specified as in Clauset et al. (2009).

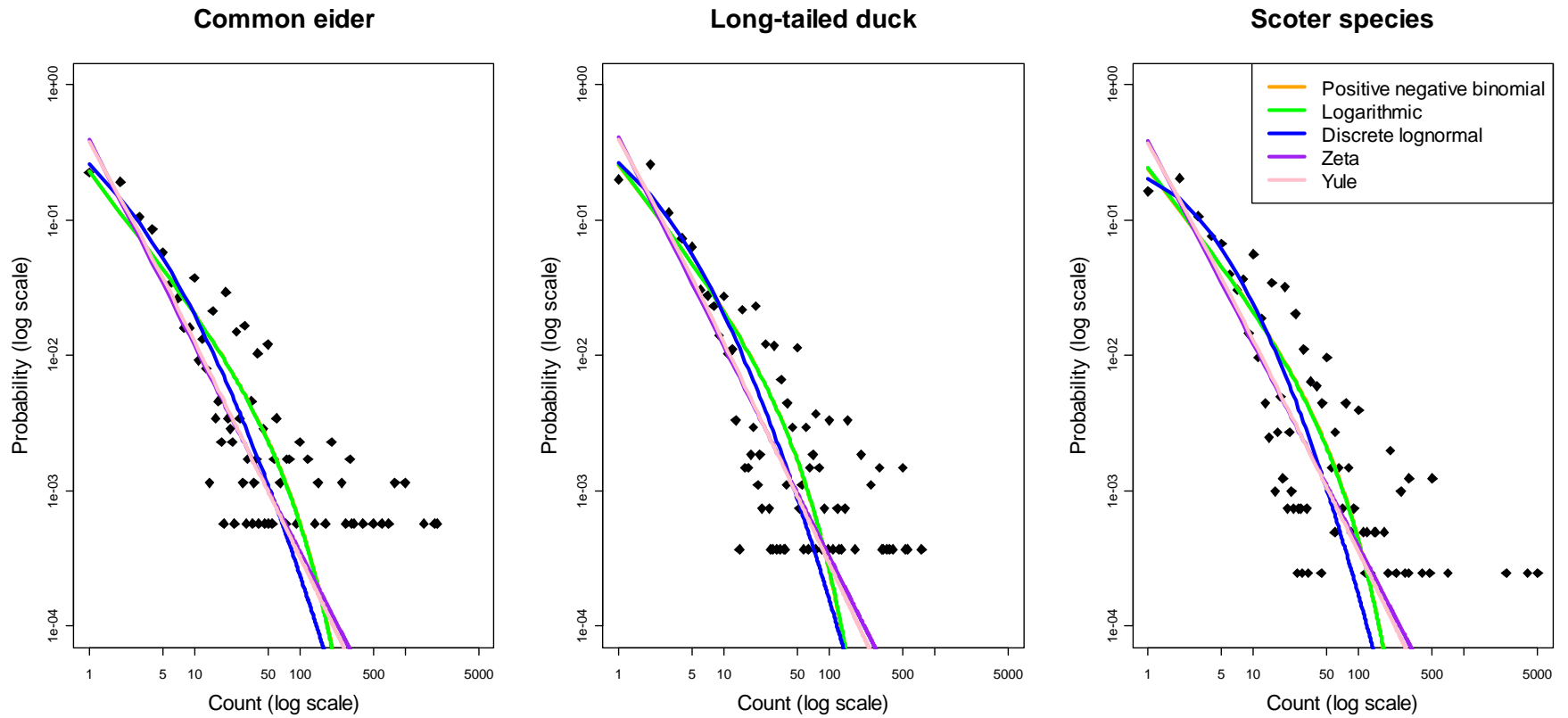| Distribution	Parameters	Probability mass function
Positive Poisson	$\lambda > 0$	$\dfrac{\frac{\lambda^x}{x!} e^{-\lambda}}{1 - P[X = 0]}$
Positive negative binomial	$\mu > 0$ $k > 0$	$\dfrac{\binom{x + k - 1}{x} \left(\frac{\mu}{\mu + k}\right)^x \left(\frac{k}{\mu + k}\right)^k}{1 - P[X = 0]}$
Geometric	$0 < p \leq 1$	$p(1 - p)^{x-1}$
Logarithmic	$0 < p < 1$	$\dfrac{-1}{\ln(1 - p)} \dfrac{p^x}{x}$
Discretized lognormal	$\mu > 0$ $\sigma > 0$	$\dfrac{\sqrt{\frac{2}{\pi\sigma^2}} \, exp\left(-\frac{\left(\ln\left(round(\text{x})\right) - \mu\right)^2}{2\sigma^2}\right)}{round(x)\left[erfc\left(\frac{\ln 1 - \mu}{\sqrt{2}\sigma}\right)\right]}$
Zeta	$a > 0$	$\dfrac{1}{x^{a+1}} \Big/ \sum_{n=1}^{\infty} \dfrac{1}{n^{a+1}}$
Yule	$a > 0$	$\dfrac{a\,\Gamma(x)\Gamma(a+1)}{\Gamma(x+a+1)}$

Figure A2.1. Model fits (lines) and observed probabilities (black dots) for count data for the three species groups: common eider, long-tailed duck, and scoters. Fits are shown for the top 5 models: logarithmic, discretized lognormal, zeta, Yule, and positive negative binomial. The positive negative binomial fit is not visible because it is obscured by the logarithmic fit.
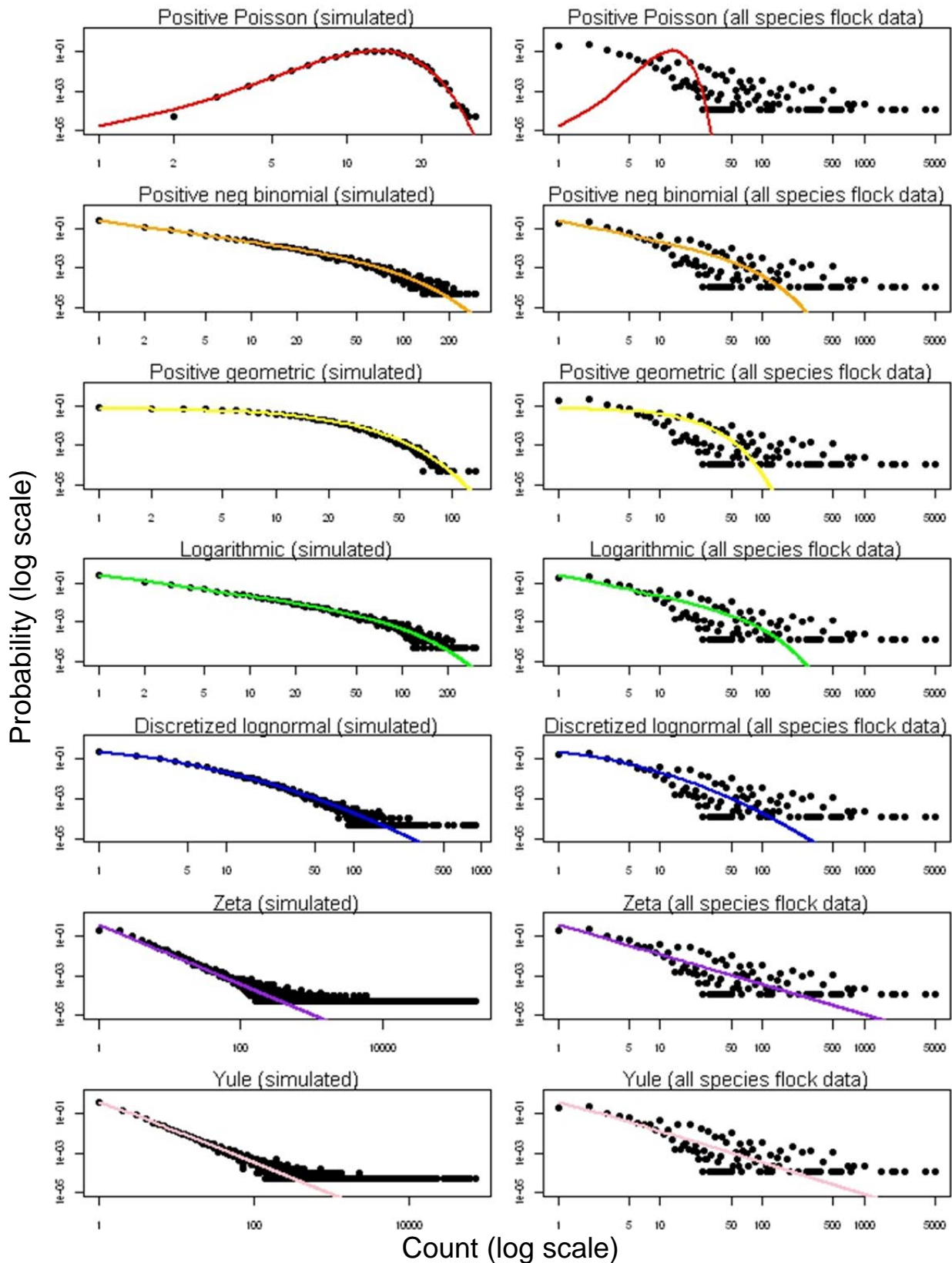
Figure A2.2. Simulated (left column) and observed (right column) data for all species fitted using the seven distributions that we compared. Note the variable x-axes for the simulated data.