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LARGE-SCALE MONITORING OF SHOREBIRD POPULATIONS USING COUNT DATA AND *N*-MIXTURE MODELS: BLACK OYSTERCATCHER *(HAEMATOPUS BACHMANI)* SURVEYS BY LAND AND SEA

James E. Lyons,[1,8] J. Andrew Royle,[2] Susan M. Thomas,[3] Elise Elliott-Smith,[4] Joseph R. Evenson,[5] Elizabeth G. Kelly,[6] Ruth L. Milner,[5] David R. Nysewander,[5] and Brad A. Andres[7]

[1]*U.S. Fish and Wildlife Service, Division of Migratory Bird Management, Patuxent Wildlife Research Center, 11510 American Holly Drive, Laurel, Maryland 20708, USA;*
[2]*U.S. Geological Survey, Patuxent Wildlife Research Center, 12100 Beech Forest Road, Laurel, Maryland 20708, USA;*
[3]*U.S. Fish and Wildlife Service, Washington Maritime NWRC and Migratory Birds and Habitat Programs, 715 Holgerson Road, Sequim, Washington 98382, USA;*
[4]*U.S. Geological Survey, Forest and Rangeland Ecosystem Science Center, 3200 SW Jefferson Way, Corvallis, Oregon 97331, USA;*
[5]*Washington Department of Fish and Wildlife, 600 Capitol Way N, Olympia, Washington 98501, USA;*
[6]*U.S. Fish and Wildlife Service, 2127 SE Marine Science Drive, Newport, Oregon 97365, USA; and*
[7]*U.S. Fish and Wildlife Service, Division of Migratory Bird Management, 755 Parfet, Suite 496B, Lakewood, Colorado 80215, USA*

Abstract.—Large-scale monitoring of bird populations is often based on count data collected across spatial scales that may include multiple physiographic regions and habitat types. Monitoring at large spatial scales may require multiple survey platforms (e.g., from boats and land when monitoring coastal species) and multiple survey methods. It becomes especially important to explicitly account for detection probability when analyzing count data that have been collected using multiple survey platforms or methods. We evaluated a new analytical framework, *N*-mixture models, to estimate actual abundance while accounting for multiple detection biases. During May 2006, we made repeated counts of Black Oystercatchers (*Haematopus bachmani*) from boats in the Puget Sound area of Washington ($n = 55$ sites) and from land along the coast of Oregon ($n = 56$ sites). We used a Bayesian analysis of *N*-mixture models to (1) assess detection probability as a function of environmental and survey covariates and (2) estimate total Black Oystercatcher abundance during the breeding season in the two regions. Probability of detecting individuals during boat-based surveys was 0.75 (95% credible interval: 0.42–0.91) and was not influenced by tidal stage. Detection probability from surveys conducted on foot was 0.68 (0.39–0.90); the latter was not influenced by fog, wind, or number of observers but was ~35% lower during rain. The estimated population size was 321 birds (262–511) in Washington and 311 (276–382) in Oregon. *N*-mixture models provide a flexible framework for modeling count data and covariates in large-scale bird monitoring programs designed to understand population change. *Received 9 November 2011, accepted 24 May 2012.*

Key words: Bayesian analysis, Black Oystercatcher, detection probability, *Haematopus bachmani*, hierarchical model, monitoring, sampling frame, survey.

Monitoreo a Gran Escala de Poblaciones de Aves Playeras mediante Datos de Conteo y Modelos de Mixturas*:* Censos de *Haematopus bachmani* en Tierra y Mar

Resumen.—El monitoreo a gran escala de poblaciones de aves frecuentemente se basa en datos de conteo recolectados a través de escalas espaciales que pueden incluir múltiples regiones fisiográficas y tipos de hábitat. El monitoreo en grandes escalas espaciales puede requerir de múltiples plataformas de muestreo (e.g., desde botes y desde tierra en especies costeras) y múltiples métodos de censado, por lo que es especialmente importante tener en cuenta explícitamente la probabilidad de detección de individuos cuando se analizan los datos de conteo que han sido obtenidos usando múltiples plataformas o métodos de muestreo. Evaluamos un nuevo método analítico, los modelos de *N* mixturas, para estimar la abundancia real teniendo en cuenta múltiples sesgos en los métodos de detección. Durante mayo de 2006, hicimos conteos repetidos de *Haematopus bachmani* desde botes en el área de Puget Sound, Washington ($n = 55$ sitios), y desde tierra a lo largo de la costa de Oregon ($n = 56$ sitios). Usamos un análisis bayesiano de modelos de *N* mixturas para (1) determinar la probabilidad de detección como función de covariables del ambiente y del método de censo y (2) estimar la abundancia total de *H. bachmani* durante la

[8]E-mail: james_lyons@fws.gov

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temporada reproductiva en las dos regiones. La probabilidad de detectar individuos durante los censos desde botes fue 0.75 (intervalo de confianza del 95%: 0.42-0.91) y no se vio influenciada por el estado de la marea. La probabilidad de detección de los censos hechos desde tierra fue 0.68 (0.39-0.90); esta última no fue influenciada por la niebla, el viento o el número de observadores, pero fue cerca del 35% menor cuando llovía. El tamaño poblacional estimado fue de 321 (262-511) aves en Washington y 311 (276-382) en Oregon. Los modelos de *N* mixturas proveen un marco flexible para el modelamiento de los datos de conteos y sus covariables en los programas de monitoreo de aves a gran escala diseñados para entender cambios en las poblaciones.

Large-scale bird monitoring programs can provide managers and conservation decision-makers with reliable information on changes in population size in relation to environmental variation and conservation actions. Monitoring programs permit stronger inference about population dynamics if the design of the program results in adequate spatial coverage for the population of interest, and if field methods account for imperfect detection during surveys (Pollock et al. 2002, Nichols and Williams 2006). The geographic extent of monitored populations often includes multiple physiographic regions and habitat types. For most large-scale monitoring programs, it is not possible to monitor entire populations and detect all individuals during surveys. Usually, some type of spatial sampling and accounting for detection probability during surveys are necessary (Pollock et al. 2002). Furthermore, it may not be possible to identify one survey method or survey platform (e.g., from boats and from land) that is suitable at all survey locations given, for example, variation in habitat structure, density of local target population, logistical constraints, and other factors. It thus becomes especially important when using multiple survey methods or platforms to use estimates of actual abundance, rather than simple counts or indices of abundance, to facilitate comparisons of count data collected across space and time. Successful monitoring thus requires that the sampled population is representative of the population of interest, and that auxiliary data are collected to understand the portion of the population actually counted during surveys (Pollock et al. 2002).

The observation or detection process during bird surveys has received considerable attention recently, and several methods have been developed to correct for bias caused by imperfect detection (Nichols et al. 2000, Buckland 2006, Alldredge et al. 2007). Nichols et al. (2009) identified four components of detection operating in the process that generates count data. The first component, related to spatial sampling and study design, is the probability that a portion of an individual's home range or territory overlaps a sampling unit (e.g., area of point count, line-transect, etc.; P_s in the notation of Nichols et al. 2009). Second, at the time of the survey, the individual must be present on the portion of its territory or home range that is included in the sampling unit (P_p); that is, the individual must not have temporarily emigrated from the sampled area. For example, breeding birds that commute from a nest to distant foraging areas may not be present during a survey of the nesting location. Third, the individual must also be available for detection (P_a); for example, birds that do not call or sing during auditory surveys are not available for detection. Fourth, the observer conducting the survey must be able to perceive and identify the individual (P_d). The perception component (P_d) is often a function of habitat structure, distance from observer, observer skill, survey conditions, and other factors (Nichols et al. 2009). Survey techniques that account for imperfect detection (e.g., capture–recapture, distance sampling, and removal methods) address different components of the entire detection process. Therefore, the interpretation of detection probability is not the same with all methods (Riddle et al. 2010). Our approach, repeated counts and *N*-mixture models, accounts for temporary emigration, availability, and perception.

The Black Oystercatcher (*Haematopus bachmani*; hereafter "oystercatcher") has been designated a species of high concern in both the U.S. and Canadian Shorebird Conservation Plans (Donaldson et al. 2000, Brown et al. 2001) and a Focal Species of the U.S. Fish and Wildlife Service (U.S. Fish and Wildlife Service 2012). The species is of conservation concern for several reasons, including limited nesting habitat, vulnerability to oil spills, and introduction of invasive species and disturbance at coastal sites and offshore islands used for nesting (Andres and Falxa 1995). Tessler et al. (2007) outlined a conservation strategy for the species, including the initiation of a coordinated range-wide monitoring effort to determine population status and detect trends. The conservation strategy recommends breeding-ground surveys in the northern range (Alaska) and southern range (Washington to California) of the species, which would require both land- and boat-based surveys because suitable habitat is found both on and off shore. Given the differences between searching for birds from a boat and on foot, it is unlikely that detection probability for these two survey methods would be equal. Therefore, it is necessary to understand oystercatcher detectability during both land- and boat-based surveys before a range-wide monitoring program using multiple field methods can be initiated.

In addition to survey platform (land or boat), there are a number of factors that may affect the probability of detecting oystercatchers. One factor may be movements associated with foraging, especially at low tide when some oystercatchers make extra-territorial movements to forage in intertidal areas (Hartwick 1978), which is a form of temporary emigration from the surveyed area. Another factor is visibility of, and access to, oystercatcher habitat. Because of their cryptic coloration, oystercatchers are difficult to detect on steep, rocky cliffs or offshore islands (when surveyed from shore). Finally, detection probability may vary among observers, depending on their experience with oystercatcher surveys.

Our analysis of count data uses *N*-mixture models, as described by Royle (2004), which derive estimates of abundance and detection probability from a set of spatially and temporally replicated counts. This method has advantages over other methods for estimating detection probability (e.g., capture–recapture, double-observer) because it does not require individual encounter history data or multiple observers (Kéry and Royle 2010; for a review of abundance and detection estimation procedures, see Williams et al. 2002). Because *N*-mixture models rely on simple counts of individuals, the repeated-counts method may reduce the time and effort required to effectively monitor population size, and may be more feasible than alternative approaches to large-scale monitoring. We conducted a large-scale study of the abundance and distribution of oystercatchers on breeding areas in Washington and Oregon in 2006. The goals of our study were to (1) assess probability of detection during both land- and boat-based surveys in relation to several covariates; (2) revise existing standardized survey methods and develop an analytical framework for a range-wide, long-term monitoring plan; and (3) collect baseline information on oystercatcher abundance from defined sampling frames in Washington and Oregon.

Methods

Number of sites and timing of repeated surveys.—Our study was conducted at 55 island sites in the San Juan Archipelago and nearby inner marine waters of northern Puget Sound, Washington (Fig. 1), which were surveyed by boat, and at 56 mainland sites in Oregon, which were surveyed on foot (Fig. 2). In each region of the study area, we first identified the extent of oystercatcher breeding habitat on the basis of our collective experience with the study area, gained during prior survey efforts, and then delineated sampling units ("sites") to include in a sampling frame. Sites were defined as geologically discrete islands, sections of shoreline on larger islands, or clusters of small islands that afforded some protection from predators and human disturbance and contained potential nesting habitat (exposed rocky headlands, rocky islets, or beaches with mixed sand, gravel, and cobble; Andres and Falxa 1995). In Washington, the sampling frame for the San Juan Archipelago included 81 sites from which we randomly selected 55 sites to be surveyed by boat. Length of shoreline that was surveyed at Washington sites ranged from 0.12 to 6.7 km (mean = 1.6 km, SD = 1.4). In Oregon, our sampling frame included 56 sites (discrete stretches of rocky shoreline) and we surveyed all of them (i.e., in this case, our set of surveyed sites and sampling frame were the same). The Oregon sampling frame included most available mainland habitat and near-shore islands but did not include a small number of distant offshore islands that could be surveyed only by boat. Length of shoreline at Oregon sites ranged from 0.2 to 8.0 km (mean ± SD = 1.7 ± 1.3). Shoreline length is useful for comparing variability in size of sites in Washington and Oregon but may not be a reasonable measure of available habitat because of the complex nature of the rocky coast and associated intertidal habitats. Therefore, we did not include shoreline length in our models of oystercatcher abundance. A permanent archive of our sampling frames and site boundaries will be maintained by E.E.S. (Oregon) and R.L.M. (Washington).

Boat-based surveys were conducted during 17–26 May; every boat-based site was surveyed twice. Land-based surveys were conducted during 13–28 May, and the number of sites surveyed once, twice, three, and four times was 11, 39, 5, and 1, respectively. Oystercatchers breeding in the study area actively defend territories at this time of year, and we expected detection probability to be high compared with other times of the breeding season. We also expected this to be a time of minimal permanent ingress and egress from local populations, an important consideration for the analytical approach (see below). Once nesting territories have been established, breeding birds are likely to remain associated with their territory while an active nest is present and will often renest (Andres and Falxa 1995).

Field methods.—Protocols for oystercatcher surveys at mainland sites and coastal islands in Washington, Oregon, and California were available from prior survey efforts (E. Elliott-Smith and

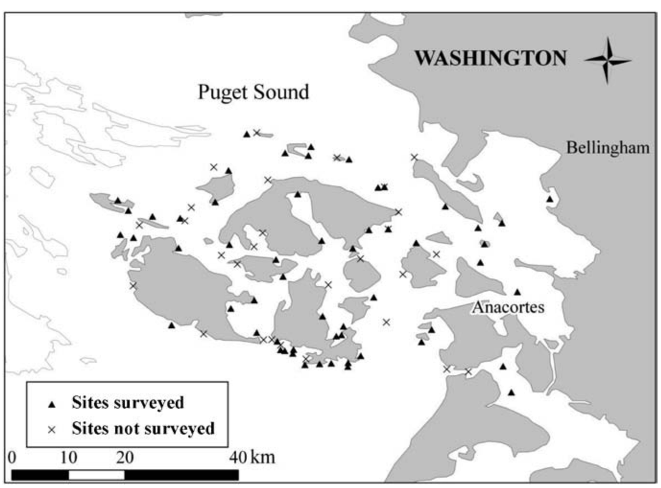

Fig. 1. Locations of 81 sites in the sampling frame for the protected waters of northern Puget Sound, Washington. Sites that were surveyed in May 2006 for Black Oystercatchers are indicated by filled triangles (n = 55); sites that were not surveyed are indicated by an "×" (n = 26).

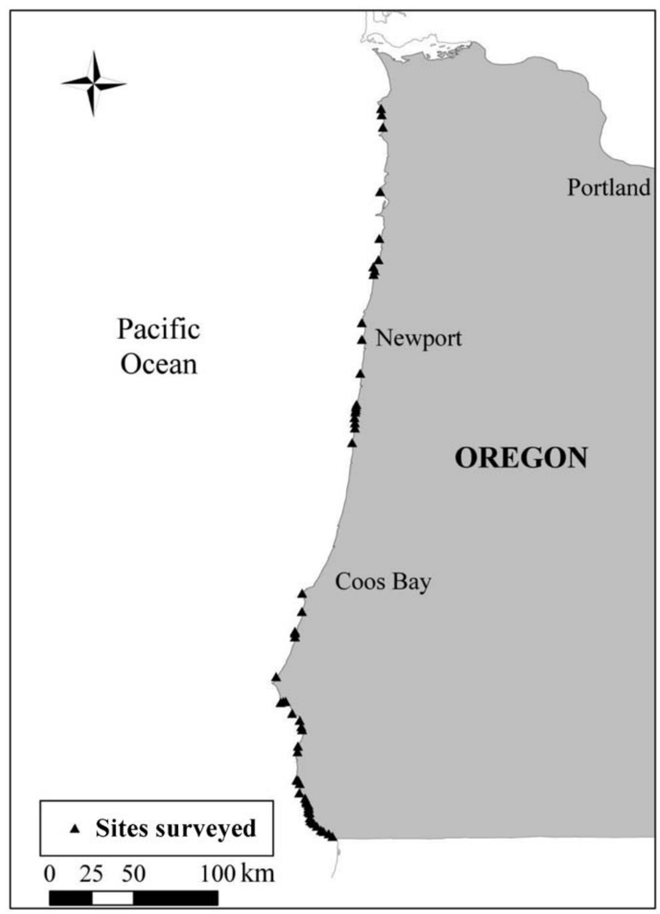

Fig. 2. Locations of 56 sites in coastal Oregon where Black Oystercatchers were surveyed from land in May 2006.

S. M. Haig unpubl. data). We followed these protocols during our surveys, with minor modifications to facilitate standardized, repeated counts. Our field protocols emphasized the importance of at least two replicate visits to each site under conditions as similar as possible (e.g., similar survey duration, area coverage). Site boundaries were drawn on large-scale maps before surveys began, and observers were made familiar with the boundaries so that the same area would be surveyed on every visit to the site. Observers conducted an area search of all suitable nesting habitat within site boundaries and recorded the total number of oystercatchers detected. In Washington, (boat-based) surveys were conducted by the same two experienced professional biologists (S.M.T. and R.L.M.). Boats were piloted by a third participant. Observers were thus free to focus on bird detection and communicate all detections to minimize double counting. In Oregon (land-based) surveys, number of observers was not the same at all sites, but for a given site we attempted to have the same number of observers during each visit. Oregon surveys were conducted by both experienced professional biologists and volunteers. Through the use of volunteers, we were able to increase the number of sites visited and reduce time between the first and subsequent counts at each site. Like all observers, volunteers were given guidance on conducting repeated surveys and were asked to review a written protocol. To the extent possible, observers followed standardized protocols (E. Elliott-Smith and S. M. Haig unpubl. data) regarding suitable survey conditions (e.g., no rain, low wind), field equipment, observer qualifications, and suggestions to minimize double counting.

Statistical models.—*N*-mixture models are a class of hierarchical models for estimating animal abundance and probability of detection from count data (Royle 2004). The models require a set of temporally replicated counts at a number of sample locations or sites. Royle's (2004) *N*-mixture models assume that the number of birds exposed to sampling does not change during the survey season (i.e., no permanent immigration or births when young cannot be distinguished from adults and no permanent emigration or deaths). We consider this assumption met when all counts are conducted in a narrow time window. Repeated counts at site i may then be viewed as independent realizations of a binomial random variable with index parameter N_i (local abundance) and outcome probability p (probability of detection; Royle 2004). The analytic framework is extremely flexible: it is possible to model both abundance and detection as a function of spatially and temporally varying covariates (e.g., habitat variables, survey effort), and even to model simultaneous effects of a single covariate on both abundance and detection (Kéry 2008).

Count data from the oystercatcher surveys were summarized in a site-by-survey matrix of counts (**c**), with rows (i) representing different sites and columns (t) representing temporally replicated surveys. Ideally, every site is surveyed t times, but for sites without full replication, we use missing values in **c**. Element $c_{i,t}$ is the number of birds counted at site i during survey t or a missing value. That is, let $c_{i,t}$; $t = 1, 2,\ldots, T$ be the independent counts made at sites $i = 1, 2, \ldots, R$ so that $c_{i,t} \sim \text{Bin}(N_i, p_{i,t})$. Under this binomial sampling model, the joint likelihood of the data from all sites is the product binomial

$$L(N_i, p_{i,t} \mid c_{i,t}) = \prod_{i=1}^{R} \left\{ \prod_{t=1}^{T} \text{Bin}(c_{i,t} \mid N_i, p_{i,t}) \right\}$$

which is a function of unknown abundance parameters $\{N_i\} = (N_1, N_2, \ldots, N_R)$ and time- and site-specific detection probability $p_{i,t}$. The *N*-mixture model is a hierarchical (or multilevel) model because it combines the joint likelihood above (level 1) with a prior distribution for the unobservable abundance parameters (level 2), yielding estimates of both detection probability and average local abundance. The second level of the model in our analysis was a Poisson prior distribution for average local abundance, a distribution commonly used to model counts of animals (Kéry et al. 2005).

Given the prior distribution $N_i \sim \text{Poisson}(\lambda)$, and the joint likelihood of the data above, estimation of λ and parameters of the model describing the detection process p is based on the marginal likelihood of the data:

$$L(\lambda, p_{i,t} \mid c_{i,t}) = \prod_{i=1}^{R} \left\{ \sum_{N_i=\max(c_i)}^{\infty} \left(\prod_{t=1}^{T} \text{Bin}\left(c_{i,t} \mid N_i, p_{i,t}\right) \right) \text{Poisson}(N_i \mid \lambda) \right\}$$

We carried out a Bayesian analysis of *N*-mixture models using WinBUGS software (Spiegelhalter et al. 2003). We used non-informative priors for all parameters and ran three Markov chain Monte Carlo (MCMC) simulations. We monitored chain convergence on posterior distributions with the $\hat{R}$ statistic (Gelman and Hill 2007). Each Markov chain contained 20,000 iterations, and we discarded the first 10,000 as "burn-in." We evaluated model fit using posterior predictive checks and summarized posterior distributions of abundance and detection parameters using medians and 95% Bayesian credible intervals (BCI; Gelman and Hill 2007).

Covariates of abundance and detection.—Two of our primary goals were to (1) evaluate detection probability during boat- and land-based surveys and (2) identify both field and analytical methods useful for long-term monitoring. With *N*-mixture models, covariates are evaluated using log-linear (for abundance) and logistic-linear (for detection) models. Our model of site-specific abundance for both Oregon and Washington sites was an overdispersed Poisson (Kéry and Schaub 2012):

$$N_i \sim \text{Poisson}(\lambda)$$
$$\log(\lambda_i) = \alpha + \delta_i$$
$$\delta \sim \text{Normal}(0, \sigma^2_\lambda)$$

where α is mean bird density and δ_i is a random error term for each site; no additional covariates for abundance were used. Similar to the negative binomial, this Poisson log-normal allows for more variability in abundance than a Poisson. One of the useful features of a Bayesian analysis of this model is the ease with which we can estimate abundance for all sites in our sampling frame, not just the surveyed sites. We simply added a row to our data set for each unsurveyed site (with missing values for count data), and population size at unsurveyed sites was estimated as part of the updating of the MCMC algorithm with full propagation of the combined estimation uncertainty.

We used overdispersed logistic regression models to evaluate effects of environmental and survey covariates thought to influence the probability of detecting oystercatchers:

$$\text{logit}(p_{i,t}) = \beta_0 + \beta_1 \times X_{i,t} + \varepsilon_{i,t}$$
$$\varepsilon \sim \text{Normal}(0, \sigma^2_p)$$

where β_0 is the logit-scale estimate of detection probability when covariate $X = 0$, $X_{i,t}$ is the covariate value at site i at survey time t, β_1 is the logit-scale estimate of change in detection probability for each unit change in X, and $\varepsilon_{i,t}$ is a random error term for extra-binomial variation associated with each site visit (Kéry and Schaub 2012). For boat-based surveys, tidal stage was expected to influence detection probability via reduced ability to approach and see elevated nesting habitat from the boat at low tide. Therefore, observers recorded the tidal stage using a six-point scale based on time since last high tide: high-falling (0–2 h after high tide), mid-falling (2–4 h), low-falling (4–6 h), low-rising (6–8 h), mid-rising (8–10 h), and high-rising (10–12 h). Tidal stages were converted to circular data using the midpoint (θ) of the tidal stage arc on a 360° scale. For example, "high-falling" occurs from 0 to 2 h after high tide; the midpoint of this period is 1 h after high tide, which corresponds to θ = 30°. For analysis, we used cosine θ as the tidal stage covariate for detection during boat-based surveys; cosine θ reaches a maximum at high tide and a minimum at low tide. Note that the cosine-transformation combines equivalent tidal stages into three categories for analysis (low-falling is equivalent to low-rising, mid-rising is equivalent to mid-falling, and high-rising is equivalent to high-falling). For land-based surveys, detection probability was modeled as a function of precipitation, wind speed, and number of observers. During each visit, observers recorded amount of precipitation on an ordinal scale: (0) none, (1) fog or drizzle, (2) light rain, or (3) rain. Precipitation categories 2 and 3 were combined in one category ("rain"), and precipitation was treated as a categorical variable with three levels for analysis. Wind speed was recorded using the Beaufort scale (0–7) and treated as a continuous variable; wind data were standardized to have mean 0 and variance 1 by subtracting the mean and dividing by the sample standard deviation before analysis. Boat-based surveys were generally conducted only during favorable conditions, so environmental covariates other than tidal stage were not recorded and were not included in the analysis. Number of observers was evaluated only for land-based surveys because number of observers was held constant for boat-based surveys (two observers on every survey).

Results

In Washington, observers detected 133 and 145 oystercatchers during the first and second replicate surveys, respectively, at 55 randomly selected sites. Using the *N*-mixture model to account for detection probability, we estimated the population size at these 55 surveyed sites to be 219 (95% BCI: 194–279). The sum of maximum counts at each site, a conventional population estimate uncorrected for detection probability, was 179 birds, which was only 82% of our estimated population total for surveyed sites. For all 81 sites in the Washington sampling frame, our estimated total population size was 321 birds (95% BCI: 262–511). In Oregon, observers detected 223 birds during the first survey (n = 56 sites). Using the *N*-mixture model to account for detection probability, we estimated the total population size at all 56 sites in Oregon to be 311 birds (95% BCI: 276–382). The sum of maximum counts at each site was 252, which was only 80% of our estimated population total. There was more unexplained variation in abundance (random site effects) at Washington sites (σ_λ = 0.82; 95% BCI: 0.56–1.17) than at Oregon sites (σ_λ = 0.49; 95% BCI: 0.29–0.73).

For boat-based surveys, which were always conducted by two observers, probability of detection was 0.75 (95% BCI: 0.42–0.91). The standard deviation of normally distributed random survey effects associated with boat-based surveys (σ_p) was 2.07 (Table 1). We conducted boat surveys during all tidal stages: 49 (43%) during low tides, 29 (25%) during mid-tides, and 36 (32%) during high tides. Most sites (89%) were surveyed at different tidal stages during the first and second surveys, but we found that tidal stage did not influence detection probability (Table 1). For land-based surveys, probability of detecting an oystercatcher was 0.68 (95% BCI: 0.39–0.90).

Table 1. Detection probability and covariate effects for boat- and land-based surveys. Tide, Rain, Fog, Wind, and Observers, respectively, are logit-scale parameter estimates for effects of tidal stage, rain, fog, wind speed, and number of observers (single vs. multiple). β_0 is logit-scale mean detection probability under reference conditions for each model (mid-tide for boat-based surveys; one observer, no rain, no fog, and average wind for land-based surveys), σ_p^2 is standard deviation of random survey effects, and BCI is Bayesian credible interval.

	Median	95% BCI
Boat-based surveys		
β_0(boat)	1.08	–0.33 to 2.36
Tide	0.33	–0.48 to 1.33
σ_p^2 (boat)	2.07	0.69 to 3.52
Land-based surveys		
β_0(land)	0.74	–0.44 to 2.18
Rain	-1.43	–3.27 to 0.17
Fog	-0.88	–2.92 to 0.85
Wind	0.24	–0.21 to 0.82
Observers	0.16	–1.42 to 1.62
σ_p^2 (land)	2.17	1.16 to 3.46

This estimate is average detection probability under reference conditions: one observer and favorable weather conditions (no fog or rain, and average wind speed). For multiple observers under favorable conditions, detection probability increased to 0.71 (95% BCI: 0.32–0.94; Fig. 3). Although not influenced by fog or wind, detection probability during land-based surveys was ~35% lower during rain than under conditions without rain (Table 1 and Fig. 3). The effects of rain and number of observers were marginal compared with random unexplained variation in detection probability, however; standard deviation of random effects associated with land-based surveys (σ_p) was 2.17 (Table 1). Thus, detection probability was more variable during land-based surveys than during boat-based surveys. Confidence intervals for effects of fog, rain, wind, and number of observers included zero (Table 1).

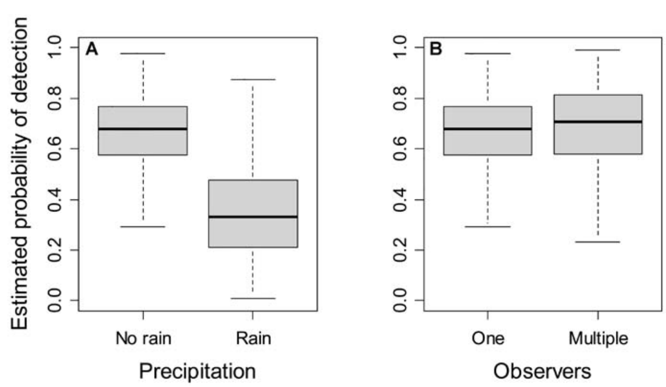

Fig. 3. Estimated probability of detecting Black Oystercatchers during land-based surveys in Oregon as a function of (A) precipitation conditions and (B) number of observers conducting the survey. Each boxplot shows the posterior distribution for estimated detection probability using an *N*-mixture model for repeated counts. Heavy line is the median of posterior distribution, and box width indicates 25% and 75% quantiles.

Discussion

Large-scale wildlife monitoring plans should consider methods to account for imperfect detection of animals during field surveys (Pollock et al. 2002, Kéry and Schmid 2004). In most field situations it is not reasonable to assume that there is no space- or time-trend in detection of birds, especially when monitoring at large temporal and spatial scales or when using multiple survey platforms or observers. Our study demonstrates a reasonable approach to correcting bird count data for multiple sources of bias. Repeated counts and *N*-mixture models are a flexible framework for analysis of count data from spatially and temporally replicated surveys (Royle 2004, Kéry 2008). Repeated counts worked especially well in our study because the Royle (2004) model accounts for bias not only from perception by observers, but also from temporary emigration (e.g., foraging away from the nesting territory during low tide) and availability for detection (Nichols et al. 2009). *N*-mixture models also were effective in our study because the structure of oystercatcher habitat made it possible to delineate discrete sites (sample units) that were large in relation to the size of individual nesting territories and that circumscribed a local population. A similar approach to delineating sites and local populations would probably work well for many wetland-dependent shorebirds because it is often possible to clearly describe wetland boundaries.

We collected baseline information on oystercatcher abundance from defined sampling frames in the San Juan Archipelago and Oregon that complement prior surveys of these areas and serve as a firm basis for future monitoring. Robust comparisons with prior survey data are confounded by differences in methodology, but our population estimates are generally higher than previous estimates. In a 2003 single-count survey of the San Juan Archipelago and adjacent areas, 193 birds were detected (D. R. Nysewander unpubl. data), which is substantially lower than our estimate for the region. A 2005 statewide survey in Oregon, which unlike our 2006 survey included boat-based surveys for distant islands, detected 320 birds, including 247 at land-based sites (Tessler et al. 2007, E. Elliott-Smith and E. G. Kelly unpubl. data). We detected a similar number at land-based sites in 2006, but after accounting for detection probability our population estimate for land-based sites is somewhat greater. For future statewide surveys in Oregon, our sampling frame would need to be expanded to include distant offshore islands because it appears that a substantial number of oystercatchers breed on these islands. Given the different methods and sampling frames, it is not possible to determine whether discrepancies among available abundance estimates are real population change. For future efforts, the present study not only establishes a repeatable sampling frame and standardized protocols to account for detection probability, but also provides baseline information. Additional work is needed to develop procedures to quantify oystercatcher habitat so that more complex models of abundance can be assessed, which will increase our understanding of habitat relationships and increase the precision of population estimates.

Understanding detection probability.—We are not aware of any previous effort to formally estimate detection probability of oystercatchers during land- or boat-based surveys. Our results indicate that ~70% of oystercatchers associated with a particular site are detected during one-time, standardized surveys. Several factors may influence the probability of detecting oystercatchers during the breeding season, some independent of survey platform and others applicable only to land-based surveys. Detection probability can be low, regardless of survey platform, wherever observers have difficulty accessing or completely viewing steep, rocky cliffs. In areas of complex topography, there are many places where incubating or resting birds may not be entirely visible to observers, or where detection probability is low as a result of the species' cryptic coloration. This may be particularly true for offshore rocks being surveyed from land because an oystercatcher resting or foraging on the ocean side of such rocks at the time of the survey will not be available for detection unless it vocalizes. Boat-based surveys may be able to minimize this problem because the observer can circle the island and view a greater proportion of available habitat. Land-based surveys had more unexplained variation in detection probability than boat-based surveys, some of which may have arisen from differences in accessibility. Some unexplained variation may also have been due to unmodeled observer effects (e.g., skill and experience) and inconsistent survey effort across repeated visits at particular sites; there was some indication that coverage of available habitat by volunteer observers was <100% during some surveys.

It is important to evaluate assumptions and potential bias of any survey method and assess implications of bias for long-term monitoring plans. We assumed that no births, deaths, permanent immigration, or permanent emigration occurred during the survey window (15 days in Oregon and 9 days in Washington). We do not believe that these are strong assumptions given the short duration of the study. For long-lived birds, probability of death during 9–15 days early in the breeding season is negligible. We also assumed that birds are associated with only one of our sites. During our surveys, we simply recorded number of birds because it is difficult to distinguish between breeding adults and nonbreeding subadults. Subadult oystercatchers generally do not defend territories, and they may wander (move among multiple sites) more than adults. If subadults regularly use more than one of the sites in our sampling frame, individual birds could be double counted and our population size estimates would be biased high. Furthermore, movements of subadults could be a source of heterogeneity in detection probability. Studies using individually marked birds and telemetry (cf. Johnson et al. 2010), implemented at an intensive, local scale, would help us understand the implications of local movements for detection probability during surveys, and potential for bias in our population estimates. To improve monitoring designs, we must understand daily movements, the number of sites that birds use on a regular basis, and the probability that an individual is present and available for detection during a survey. In addition, we must understand how these factors differ between breeding adults and subadults and what proportion of the population is in each age class.

The possibility of time trends in detection probability undermining long-term monitoring programs for shorebirds and other bird groups may not be fully appreciated. When initiating long-term bird monitoring programs, investigators identify sampling designs, draft protocols, and begin data collection. Over time, protocols are often refined, observers become more skilled in conducting standardized surveys, and unforeseen logistical constraints may be removed. In our experience, institutions and observer corps, especially volunteers, became more adept at conducting oystercatcher surveys over time. This suggests that detection probabilities may increase over time, which could be incorporated into methods like *N*-mixture models that explicitly account for the observation process to adjust raw counts (Nichols et al. 2009). Climate change may also produce time trends in environmental factors, such as precipitation, that can affect detection probability. Analyses based on raw counts and index methods, rather than methods such as *N*-mixture models that can explicitly account for possible time trends in detection, may result in spurious conclusions about population change if a trend in detection probability exists (Kéry and Royle 2010).

Management, monitoring, and conservation planning.—Our results can be used to plan future monitoring efforts for oystercatchers and other shorebird populations. Federal and state land management agencies have recommended a comprehensive range-wide survey of oystercatchers (Tessler et al. 2007), and our results can be used to improve sampling designs and protocols. The final sampling design for a range-wide survey will depend on the specific objectives of the monitoring plan, but we can suggest design elements to consider on the basis of our results. It will be important to (1) ensure adequate spatial coverage of the target population, which may include the entire breeding range of the species; (2) divide the target population into discrete sampling units, which constitute the sampling frame (Cochran 1977:6); and (3) select sampling units in a probabilistic manner such that the sampled population represents the target population. Prior surveys for oystercatchers in our study area have often used disparate sampling frames over time, variously including or excluding offshore islands, for example. We found it difficult to make comparisons with available historical data because sampling frames were generally not well defined.

Our results provide strong evidence that detection probability is lower when it is raining. If logistically feasible, observers could postpone surveys scheduled for rainy days or make an additional survey of the site on a clear day. At the very least, we hope that data collection and analyses would employ analytical methods, such as *N*-mixture models, that explicitly account for detection probability as a function of important covariates. We found no evidence that detection probability is affected by tidal stage during boat surveys; thus, managers could increase efficiency and reduce costs by conducting surveys throughout the tidal cycle. The influence of tidal stage on land-based surveys, which we did not investigate, is unknown and may require further study.

Other considerations when designing a range-wide survey include duration of sampling each year, especially when using repeated counts and *N*-mixture models. In general, the timing of the surveys in our study area (late May) seemed to coincide with a period of minimal ingress and egress from local populations and one of relatively high detection probability because breeding birds were actively defending territories. Timing of surveys in other parts of the range could be designed to match local breeding phenology (i.e., match timing of territory establishment and defense and of nest initiation). In our study, we were able to survey most sites two or three times. It is not necessary to visit every site more than once, but most sites should be visited multiple times. If resources allow, increasing the number of visits will increase the precision of detection probability estimates. Incorporating additional explanatory covariates for detection probability and abundance in the *N*-mixture models may reduce heterogeneity among sites and improve the precision of estimates for both parameters. Finally, managers and other decision-makers may wish to estimate population trends over time. Extending our single-season analysis to multiple seasons (years) as part of a long-term, large-scale monitoring effort for individual sites or all sites in a sampling frame is a straightforward procedure with *N*-mixture models (Kéry and Royle 2010).

In coastal areas, shorebird populations face a plethora of threats: changes in carrying capacity of intertidal habitat as a result of sea-level rise, changes in prey resources as a result of warming sea-surface temperatures, and increased disturbance resulting from coastal development and urbanization (Galbraith et al. 2002, Piersma and Lindström 2004). In a time of limited resources for conservation and management, but no shortage of uncertainty about underlying causes of population declines, monitoring based on consistent sampling frames and proper accounting of detection probability is an effective way to increase our understanding of shorebird population dynamics.

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Literature Cited

Alldredge, M. W., K. H. Pollock, T. R. Simons, J. A. Collazo, and S. A. Shriner. 2007. Time of detection method for estimating abundance from point-count surveys. Auk 124:653–664.

Andres, B. A., and G. A. Falxa. 1995. Black Oystercatcher (*Haematopus bachmani*). *In* The Birds of North America, no. 155 (A. Poole and F. Gill, Eds.). Academy of Natural Sciences, Philadelphia, and American Ornithologists' Union, Washington, D.C.

Brown, S., C. Hickey, B. Harrington, and R. Gill, Eds. 2001. United States Shorebird Conservation Plan, 2nd ed. Manomet Center for Conservation Sciences, Manomet, Massachusetts.

Buckland, S. T. 2006. Point transect surveys for songbirds: Robust methodologies. Auk 123:345–357.

Cochran, W. G. 1977. Sampling Techniques, 3rd ed. Wiley, New York.

Donaldson, G., C. Hyslop, G. Morrison, L. Dickson, and I. Davidson, Eds. 2000. Canadian Shorebird Conservation Plan. Canadian Wildlife Service, Ottawa, Ontario.

Galbraith, H., R. Jones, R. Park, J. Clough, S. Herrod-Julius, B. Harrington, and G. Page. 2002. Global climate change and sea level rise: Potential losses of intertidal habitat for shorebirds. Waterbirds 25:173–183.

Gelman, A., and J. Hill. 2007. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press, New York.

Hartwick, E. B. 1978. The use of feeding areas outside of the territory of breeding Black Oystercatchers. Wilson Bulletin 90: 650–652.

Johnson, M., P. Clarkson, M. I. Goldstein, S. M. Haig, R. B. Lanctot, D. F. Tessler, and D. Zwiefelhofer. 2010. Seasonal movements, winter range use, and migratory connectivity of the Black Oystercatcher. Condor 112:731–743.

Kéry, M. 2008. Estimating abundance from bird counts: Binomial mixture models uncover complex covariate relationships. Auk 125:336–345.

Kéry, M., and J. A. Royle. 2010. Hierarchical modelling and estimation of abundance and population trends in metapopulation designs. Journal of Animal Ecology 79:453–461.

Kéry, M., J. A. Royle, and H. Schmid. 2005. Modeling avian abundance from replicated counts using binomial mixture models. Ecological Applications 15:1450–1461.

Kéry, M., and M. Schaub. 2012. Bayesian Population Analysis Using WinBUGS: A Hierarchical Perspective. Academic Press, Waltham, Massachusetts.

Kéry, M., and H. Schmid. 2004. Monitoring programs need to take into account imperfect species detectability. Basic and Applied Ecology 5:65–73.

Nichols, J. D., J. E. Hines, J. R. Sauer, F. W. Fallon, J. E. Fallon, and P. J. Heglund. 2000. A double-observer approach for estimating detection probability and abundance from point counts. Auk 117:393–408.

Nichols, J. D., L. Thomas, and P. B. Conn. 2009. Inferences about landbird abundance from count data: Recent advances and future directions. Pages 201–235 *in* Modeling Demographic Processes in Marked Populations (D. L. Thomson, E. G. Cooch, and M. J. Conroy, Eds.). Springer, New York.

Nichols, J. D., and B. K. Williams. 2006. Monitoring for conservation. Trends in Ecology & Evolution 21:668–673.

Piersma, T., and Å. Lindström. 2004. Migrating shorebirds as integrative sentinels of global environmental change. Ibis 146:61–69.

Pollock, K. H., J. D. Nichols, T. R. Simons, G. L. Farnsworth, L. L. Bailey, and J. R. Sauer. 2002. Large scale wildlife monitoring studies: Statistical methods for design and analysis. Environmetrics 13:105–119.

Riddle, J. D., S. J. Stanislav, K. H. Pollock, C. E. Moorman, and F. S. Perkins. 2010. Separating components of the detection process with combined methods: An example with Northern Bobwhite. Journal of Wildlife Management 74:1319–1325.

Royle, J. A. 2004. *N*-mixture models for estimating population size from spatially replicated counts. Biometrics 60:108–115.

Spiegelhalter, D. J., A. Thomas, N. G. Best, and D. Lunn. 2003. WinBUGS version 1.4 User Manual. MRC Biostatistics Unit, Cambridge, United Kingdom.

Tessler, D. F., J. A. Johnson, B. A. Andres, S. Thomas, and R. B. Lanctot. 2007. Black Oystercatcher (*Haematopus bachmani*) Conservation Action Plan, version 1.0. International Black Oystercatcher Working Group; Alaska Department of Fish and Game, Anchorage; U.S. Fish and Wildlife Service, Anchorage; and Manomet Center for Conservation Sciences, Manomet, Massachusetts.

U.S. Fish and Wildlife Service. 2012. Focal species strategy. [Online.] Available at www.fws.gov/migratorybirds/CurrentBirdIssues/Management/FocalSpecies.html.

Williams, B. K., J. D. Nichols, and M. J. Conroy. 2002. Analysis and Management of Animal Populations. Academic Press, San Diego, California.

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