

Estimating occupancy and abundance using aerial images with imperfect detection

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Abstract

1. Species distribution and abundance are critical population characteristics for efficient management, conservation, and ecological insight. Point process models are a powerful tool for modelling distribution and abundance, and can incorporate many data types, including count data, presence-absence data, and presence-only data. Aerial photographic images are a natural tool for collecting data to fit point process models, but aerial images do not always capture all animals that are present at a site. Methods for estimating detection probability for aerial surveys usually include collecting auxiliary data to estimate the proportion of time animals are available to be detected.
2. We developed an approach for fitting point process models using an N -mixture model framework to estimate detection probability for aerial occupancy and abundance surveys. Our method uses multiple aerial images taken of animals at the same spatial location to provide temporal replication of sample sites. The intersection of the images provide multiple counts of individuals at different times. We examined this approach using both simulated and real data of sea otters (*Enhydra lutris kenyoni*) in Glacier Bay National Park, southeastern Alaska.
3. Using our proposed methods, we estimated detection probability of sea otters to be 0.76, the same as visual aerial surveys that have been used in the past. Further, simulations demonstrated that our approach is a promising tool for estimating occupancy, abundance, and detection probability from aerial photographic surveys.
4. Our methods can be readily extended to data collected using unmanned aerial vehicles, as technology and regulations permit. The generality of our methods for other aerial surveys depends on how well surveys can be designed to meet the assumptions of N -mixture models.

KEYWORDS

abundance estimation, aerial photographic surveys, availability bias, detection bias, detection probability, occupancy estimation, perception bias, point process models, sea otters

1 | INTRODUCTION

Aerial surveys are an important tool for estimating abundance and distribution of vertebrate populations. Methods for design and data analysis of aerial surveys have been developed to accommodate

visual observations where observers count animals from aircraft (Caughley, 1974; Caughley & Goddard, 1972; Certain & Bretagnolle, 2008; Goddard, 1967, 1969; Jolly, 1969a, 1969b; Pennycuik & Western, 1972; Siniff & Skoog, 1964; Watson, Parker, & Allan, 1969), and for photographic survey methods (Bechet, Reed, Plante, Giroux,

& Gauthier, 2004; Boyd, 2000; Buckland et al., 2012; Conn et al., 2015; Leedy, 1948; Leonard & Fish, 1974; Ver Hoef & Jansen, 2014). Undercounting animals from aircraft presents a major estimation problem with both visual and photographic aerial surveys (Caughley, 1974; Graham & Bell, 1969). Animals are undercounted because they are not available to be counted (e.g. underwater as in Lukacs, Kissling, Reid, Gende, & Lewis, 2010, termed availability bias), or observers miss animals that are available to be counted (termed perception bias; Marsh & Sinclair, 1989). Aerial images improve perception bias, but not necessarily availability bias (Bayliss & Yeomans, 1990; Frederick, Hylton, Heath, & Ruane, 2003; Gibbs, Woodward, Hunter, & Hutchinson, 1988; Leonard & Fish, 1974). For example, many seabirds and marine mammals are virtually certain to be detected in images if they are at the surface of the water, but animals may be diving beneath the surface of the water and unavailable to be photographed (Buckland et al., 2012; Conn et al., 2014). Aerial images alone typically do not provide sufficient information for estimating availability, and auxiliary information is usually required to estimate absolute abundance. For example, activity budgets or time spent diving underwater can be estimated from telemetry devices including VHF transmitters, satellite-linked transmitters, or time-depth recorders (Bechet et al., 2004; Conn et al., 2014; Heide-Jørgensen, Laidre, Borchers, Samarra, & Stern, 2007). Often, aerial image data are easily obtainable, but auxiliary data may be more challenging to acquire due to financial, logistical, or regulatory constraints, precluding estimation of availability. Even when auxiliary information can be collected, there is often a disparate scale of inference between auxiliary data and aerial image data, potentially introducing a variety of statistical challenges for modelling and inference (Gotway & Young, 2002). Further, it is difficult to determine whether correction factors based on behavioural data (e.g. dive times) are appropriate because corrections may not apply to animals engaged in different activities such as feeding or resting; activities that might be difficult to characterize from an aircraft (Hiby & Lovell, 1998).

Another method for estimating availability is to use multiple aircraft in tandem, where observers in each aircraft count animals independently (Hiby & Lovell, 1998). Using aircraft in tandem is twice as expensive as using one aircraft, and transects of each aircraft might not overlap due to error in GPS locations and misaligned flight paths. Further, methods for using aircraft in tandem have relied on identifying individual animals (i.e. duplicates seen by each aircraft) which is often problematic (Hiby & Lovell, 1998).

In light of these constraints, we describe a point process model that leverages an N -mixture framework for simultaneously estimating detection probability, occupancy, and abundance from aerial images (Royle, 2004). The N -mixture model fits naturally within the framework of a point process model. The N -mixture model is advantageous in that it does not rely on data auxiliary to aerial images. Data required to fit N -mixture models can be collected from a single aircraft, and individual animals need not be uniquely identified. In addition, aerial photographic images provide a permanent record that is available for independent verification, may be used for automated detection, and allows for quantification of habitat covariates (Martin et al., 2012; McNabb, Womble, Prakash, Gens, & Haselwimmer, 2016).

Photographic sampling methods can also be extended to unmanned aerial vehicles, which are relatively new low-cost platforms that can be used to quantify wildlife and their habitats (Hodgson, Kelly, & Peel, 2013; Sweeney et al., 2015).

An ecological application motivating the methods we present involves the use of aerial photographic survey methods for estimating the distribution and abundance of sea otters (*Enhydra lutris kenyoni*) in Glacier Bay National Park (GBNP), southeastern Alaska. Sea otters were recently identified as a vital sign for long-term monitoring in GBNP because of their role as a keystone species and their influence in structuring nearshore marine communities (Estes & Palmisano, 1974). Data on sea otter abundance in GBNP were formerly collected using design-based, visual aerial surveys, where observers counted sea otters along randomly selected transects (Bodkin & Udevitz, 1999; Williams et al., 2017). Detection probability for the design-based survey was estimated by conducting intensive searches at 469 randomly-selected locations from the design-based survey that contained sea otters. At these random sites, observers first conducted the design-based survey along the transect and counted individuals along the strip. The plane then deviated off the transect to conduct intensive searches which entailed circling a group of otters five times at a given speed and altitude (Bodkin & Udevitz, 1999). The number of circles was based on the estimated dive duration or aerobic dive limit of sea otters. The additional survey effort allowed observers to obtain more precise counts of sea otters, including individuals that were underwater and not available for detection during the original design-based phase. The National Park Service is developing an aerial survey method that extends previous survey methods with the specific objectives of (1) improving safety and reducing risk associated with aerial surveys, (2) decreasing cost and optimizing efficiency, (3) increasing the number of pilots capable of conducting the surveys, (4) creating a permanent record that can be independently verified, (5) reducing observer bias, (6) quantifying associated habitat covariates from imagery, (7) developing a platform and survey design that is capable of being extended to unmanned aerial vehicles, and (8) improving precision of occupancy and abundance estimates. The use of aerial images improves objectives 1–7, relative to the original surveys. However, objective 8 relies on accurate and precise estimation of detection probability. Thus, we developed field-based methods and an associated statistical framework for simultaneously estimating occupancy, abundance, and detection probability of animals using only aerial images, where a subset of images overlap in space. We demonstrate our approach by first applying our framework to simulated data of sea otters in GBNP. We conducted a pilot study in which we assessed our ability to collect temporally replicated images of spatially referenced sites containing sea otters. Finally, we estimated abundance and detection probability of our sampled sites.

2 | MATERIALS AND METHODS

Individuals in a population exist as points in space and time and therefore can be modelled as a spatio-temporal point process (Figure 1; Hefley & Hooten, 2016). A point process is a stochastic process that

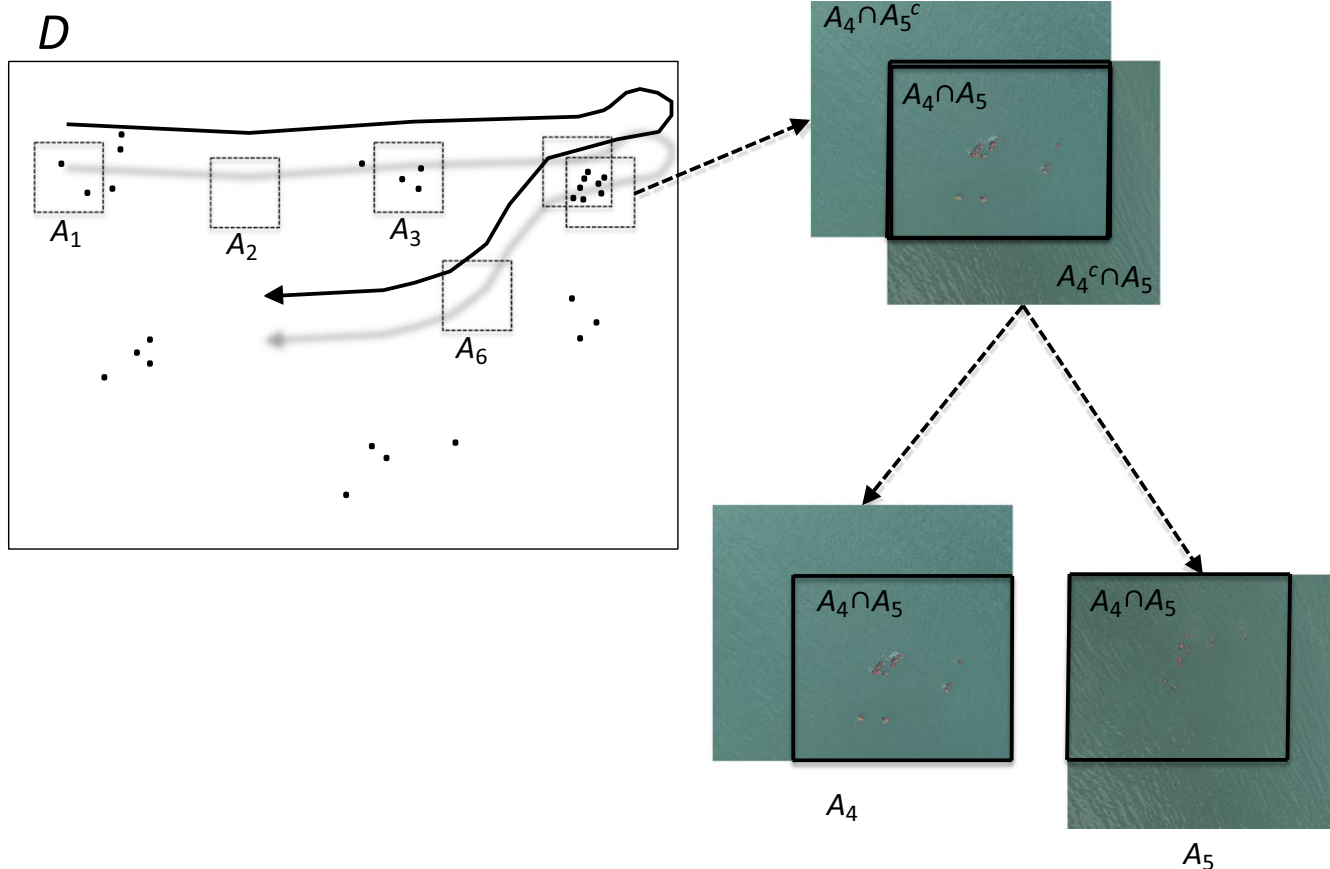


FIGURE 1 Depiction of aerial survey of domain D , with image locations A_1, \dots, A_n . Overlapping images provide temporal replication at sites where the images intersect

governs the location of a set of points $\{s_i\}$ in some set $D \subset \mathbb{R}^d$ (Cressie & Wikle, 2011; Diggle, 2013; Moller & Waagepetersen, 2003). We consider the two-dimensional space $D \subset \mathbb{R}^2$ that describes a study area of interest during time interval $[0, T]$. We let $s = (\text{latitude}, \text{longitude})'$ represent any 2×1 vector of coordinates in D , and the set of coordinates $\{s_i, \forall i\}$ represents the locations of animals in D . A point process $N(\cdot)$ is characterized by counting the number of points (e.g. animals) that belong to various measurable subsets $A \subset D \subset \mathbb{R}^2$ (e.g. A represents the subset of area in D captured by aerial images). Let $N(A, t)$ represent a count of the true number of animals in A during time t . A fundamental quantity of interest of a point process is the expected abundance in A . The expected abundance can be calculated in terms of a locally integrable intensity function $\lambda(s, t)$. The intensity function describes the expected abundance of an infinitely small area ds centred at point s . The expected abundance of the bounded subset A from time t to $t + \Delta t$ can be obtained by integrating the intensity function over A from time t to $t + \Delta t$,

$$\lambda(A, t) = E(N(A, t)) = \int_A \int_t^{t+\Delta t} \lambda(s, t) dt ds < \infty.$$

If $\lambda(s, t)$ varies in space and/or time, and is deterministic, and we assume $N(A_1, t)$ and $N(A_2, t)$ are independent whenever $A_1 \cap A_2 = \emptyset$, where \cap represents the intersection, then $N(A, t)$ is an inhomogeneous Poisson point process and

$$N(A, t) \sim \text{Poisson}(\lambda(A, t)) \tag{1}$$

(Cressie & Wikle, 2011; Moller & Waagepetersen, 2003). Similarly, if $\lambda(s, t)$ is a stochastic process, then $N(A, t)$ is known as a Cox process (Cox, 1955). We consider inhomogeneous Poisson processes for the remainder of the paper; a number of authors provide details on more general point processes that could be used in our framework (e.g. Baddeley, Rubak, & Turner, 2015; Banerjee, Carlin, & Gelfand, 2014; Cressie & Wikle, 2011; Illian, Penttinen, Stoyan, & Stoyan, 2008; Moller & Waagepetersen, 2003). An important derived quantity of Equation 1 is the probability that $N(A, t) > 0$ (i.e. the occupancy probability, $\phi(A, t)$). Useful distribution models predict both occupancy and abundance (Oppel et al., 2012). The spatio-temporal occupancy probability is

$$\phi(A, t) = P(N(A, t) > 0) = 1 - e^{-\lambda(A, t)} \tag{2}$$

(see Hefley & Hooten, 2016; Williams et al., 2017).

A set of n aerial images taken at locations $\{c_i\}_{i=1}^n$ capture information on bounded subregions A_i , and therefore can be used to characterize the point process (Cressie & Wikle, 2011). We denote counts of animals on an image of site A_i taken during time t as $y(A_i, t)$, where the area captured by the aerial image is denoted as $|A_i|$, and in practice $\sum_{i=1}^n |A_i| \ll |D|$. Counts of individuals are usually obtained by examining images post-flight, and summing the number of individuals within

the image (see *Field and lab methods*, below). Counts often contain false negatives; some proportion of animals within A_i will not appear on images or are missed when investigators count the animals. Therefore, we adopt the most commonly used model for false negatives,

$$y(A_i, t) \sim \text{Binomial}(N(A_i, t), p(A_i, t)), \quad (3)$$

where $p(A_i, t)$ is the detection probability, potentially varying in space and time. If occupancy is a state variable of interest, Equation 3 reduces to $I_{\{y(A_i, t) > 0\}} \sim \text{Bernoulli}(\phi(A_i, t))$, where $I_{\{y(A_i, t) > 0\}}$ is an indicator function that equals one when $y(A_i, t) > 0$, and zero otherwise (Hefley & Hooten, 2016). Note that $p(A_i, t)$ is a composite parameter of both the probability of an observer counting an individual on the image, conditional on it being available to be counted ($p_1(A_i, t)$), and the probability an individual is available to be counted ($p_2(A_i, t)$). That is, $p(A_i, t) = p_1(A_i, t)p_2(A_i, t)$. If aerial images have sufficient resolution such that the observer detection probability $p_1(A_i, t) = 1$, then $p(A_i, t) = p_2(A_i, t)$. For our application, we assume $p(A_i, t) = p_2(A_i, t)$. When this assumption is not valid, other techniques could be used to estimate $p_1(A_i, t)$ when individuals are counted on images (e.g. double observer methods as used in Buckland et al., 2012). Following the terminology of Berliner (1996), Equation 3 is a data model and Equation 1 is a process model (e.g. an inhomogeneous Poisson process model), and the hierarchical formulation of the model is

$$\begin{aligned} y(A_i, t) &\sim \text{Binomial}(N(A_i, t), p(A_i, t)), \\ N(A_i, t) &\sim \text{Poisson}(\lambda(A_i, t)), \\ \lambda(A_i, t) &= \int_{A_i} \int_t^{t+\Delta t} \lambda(\mathbf{c}, t) dt d\mathbf{c}, \\ \log(\lambda(\mathbf{c}, t)) &= \mathbf{x}(\mathbf{c}, t)' \boldsymbol{\beta} \end{aligned} \quad (4)$$

where $\mathbf{x}(\mathbf{c}, t)$ is a vector of covariates for locations \mathbf{c} , time t , and $\boldsymbol{\beta}$ is a vector of parameters to be estimated.

To estimate detection probability, p , we assume a subset of A_i and A_k ($k \in \mathcal{I}; i \neq k$) intersect (Figure 1). That is, an aerial image of subregion A_i taken at time $j = j_1$ overlaps an image of subregion A_k taken at time $j = j_1 + \Delta j$, where Δj is sufficiently small so it can be assumed that the point pattern realization is static, and in practice, $\Delta j \ll \Delta t$ (cf., *primary* and *secondary* sampling periods *sensu* Kendall & Nichols, 1995, for t and j , respectively). We can view the union of A_i and A_k as 3 distinct bounded sites; $A_i \cap A_k^c$, $A_i \cap A_k$, and $A_i \cap A_k^c$ (Figure 1), where “ c ” represents the complement. Counts of individuals (or alternatively, occupancy status) in the subregion $A_i \cap A_k$ can be obtained from each image (Figure 1). Counting individuals from each image in the intersection $A_i \cap A_k$ provides temporal replication, $y(A_i \cap A_k, j, t)$, $j = 1, \dots, J$, and can be used to estimate p in an N -mixture model framework (Royle, 2004). That is, assuming Δj is sufficiently small to ensure the population being sampled is closed with respect to movement, mortality, and recruitment, and conditional on $N(A_i \cap A_k, t)$, $y(A_i \cap A_k, j, t)$ may be viewed as independent and identically distributed binomial random variables

$$y(A_i \cap A_k, j, t) \sim \text{Binomial}(N(A_i \cap A_k, t), p(A_i \cap A_k, t))$$

(Royle, 2004). Thus, the Poisson process assumes that when $A_1 \cap A_2 = \emptyset$, $N(A_1)$, and $N(A_2)$ are independent and Poisson, conditional

on $\lambda(A_1)$ and $\lambda(A_2)$, respectively. The N -mixture model assumes that when $A_1 \cap A_2 \neq \emptyset$, counts of individuals in the intersection are independent and binomial, conditional on $N(A_1 \cap A_2)$ and $p(A_1 \cap A_2)$.

It is not necessary to collect intersecting images at all spatial locations, but collecting intersecting images in a variety of environmental conditions provides sufficient information to estimate how detection probability may vary in response to spatial or temporal covariates. For example, heterogeneity in detection probability could be modeled as

$$\text{logit}(p(A_i \cap A_k, t)) = \mathbf{w}(A_i \cap A_k, t)' \boldsymbol{\alpha}, \quad (5)$$

where $\mathbf{w}(A_i \cap A_k, t)$ are covariates associated with detection probability collected at $A_i \cap A_k$ at time t , and $\boldsymbol{\alpha}$ are parameters to be estimated. To simplify notation in what follows, we assume that all sites (i.e. A_i , A_k , $A_i \cap A_k$, $A_i^c \cap A_k$, $A_i \cap A_k^c$) are represented with i .

The parameters of our model ($\boldsymbol{\beta}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$) can be estimated using either Bayesian methods (Royle & Dorazio, 2008), or maximum likelihood methods (Royle, 2004). Assuming a Bayesian hierarchical specification of the model, the full Bayesian posterior distribution of Equations 4 and 5 is

$$[\mathbf{N}, \boldsymbol{\alpha}, \boldsymbol{\beta} | \mathbf{Y}] \propto \prod_{i=1}^n \prod_{t=1}^T \left\{ \prod_{j=1}^{J_i} \{ [y(A_i, j, t) | N(A_i, t), \boldsymbol{\alpha}] [N(A_i, t) | \boldsymbol{\beta}] \} \right\} [\boldsymbol{\alpha}, \boldsymbol{\beta}], \quad (6)$$

where we use the square-bracket notation $[a|b]$ to represent the probability density or mass function of variable a given variable b (Gelfand & Smith, 1990).

3 | APPLICATION: SEA OTTERS IN GLACIER BAY NATIONAL PARK

We conducted a simulation study to evaluate our model (Appendix S1). After our simulation study, we developed and implemented field methods to assess the logistics of collecting the necessary data required to fit our model (Appendix S2). Although Equations 4 and 6 are described in sufficient generality to incorporate relevant spatio-temporal processes for time $t = 1, \dots, T$, to simplify demonstration, our example assumes $t = 1$.

3.1 | Simulated data

We simulated sea otter abundance data across GBNP (Appendix S1) using the model described in Equation 6, and included an intercept and four covariates to associate abundance to local conditions in GBNP. The covariates were ocean depth, distance to shore, slope of the ocean floor, and shoreline complexity. We based the relationship (positive or negative) between abundance intensity and parameter values on Williams et al. (2017). We also allowed detection probability to vary in space. We simulated values of $w(\mathbf{s}_i)$ using a Bernoulli distribution with success probability equal to 0.5. Specifically,

$$\begin{aligned} \log(\lambda(\mathbf{s}_i)) &= -2.4 + 0.75 \text{depth}(\mathbf{s}_i) - 0.75 \text{distance}(\mathbf{s}_i) + 0.4 \text{slope}(\mathbf{s}_i) \\ &\quad - 0.4 \text{complexity}(\mathbf{s}_i), \\ \text{logit}(p(\mathbf{s}_i)) &= 1 + 0.5 w(\mathbf{s}_i). \end{aligned}$$

We simulated 8,895 images from 50 transects placed randomly across GBNP, and selected 100 random locations containing sea otters where one additional replicate image was taken (Appendix S1). We then fit a Bayesian hierarchical N -mixture model to the simulated data. We assumed vague prior distributions for all parameters. After fitting the model, we compared the estimated posterior distributions to the parameter values that were used to simulate the data. We also plotted the true expected abundance ($\lambda(s)$) and occupancy ($\phi(s)$) and the estimated expected abundance and occupancy (Figure 3). All posterior distributions had good coverage of true parameter values (Figure 2), and the estimated expected abundance and occupancy probability represented the truth well (Figure 3).

3.2 | Field and lab methods

We developed a pilot study to assess the ability of obtaining intersecting aerial images of groups of sea otters in GBNP. We obtained aerial digital imagery to estimate abundance and detection of sea otters. Three separate aerial photographic surveys were conducted during July and September 2016 in Glacier Bay from a de Havilland Canada DHC-2 Beaver single-engine high-winged aircraft (Ward Air Inc., Juneau, AK, USA). The aircraft was flown at c. 213–250 m at 157–166 km/hr. Overlapping digital photographic images of sea otter groups were taken directly under the plane using a vertically-aimed digital camera (Nikon D810, 36.3 megapixel; Shinagawa, Tokyo, Japan) with an 85 mm focal length lens (Zeiss F/1.4 ZF.2).

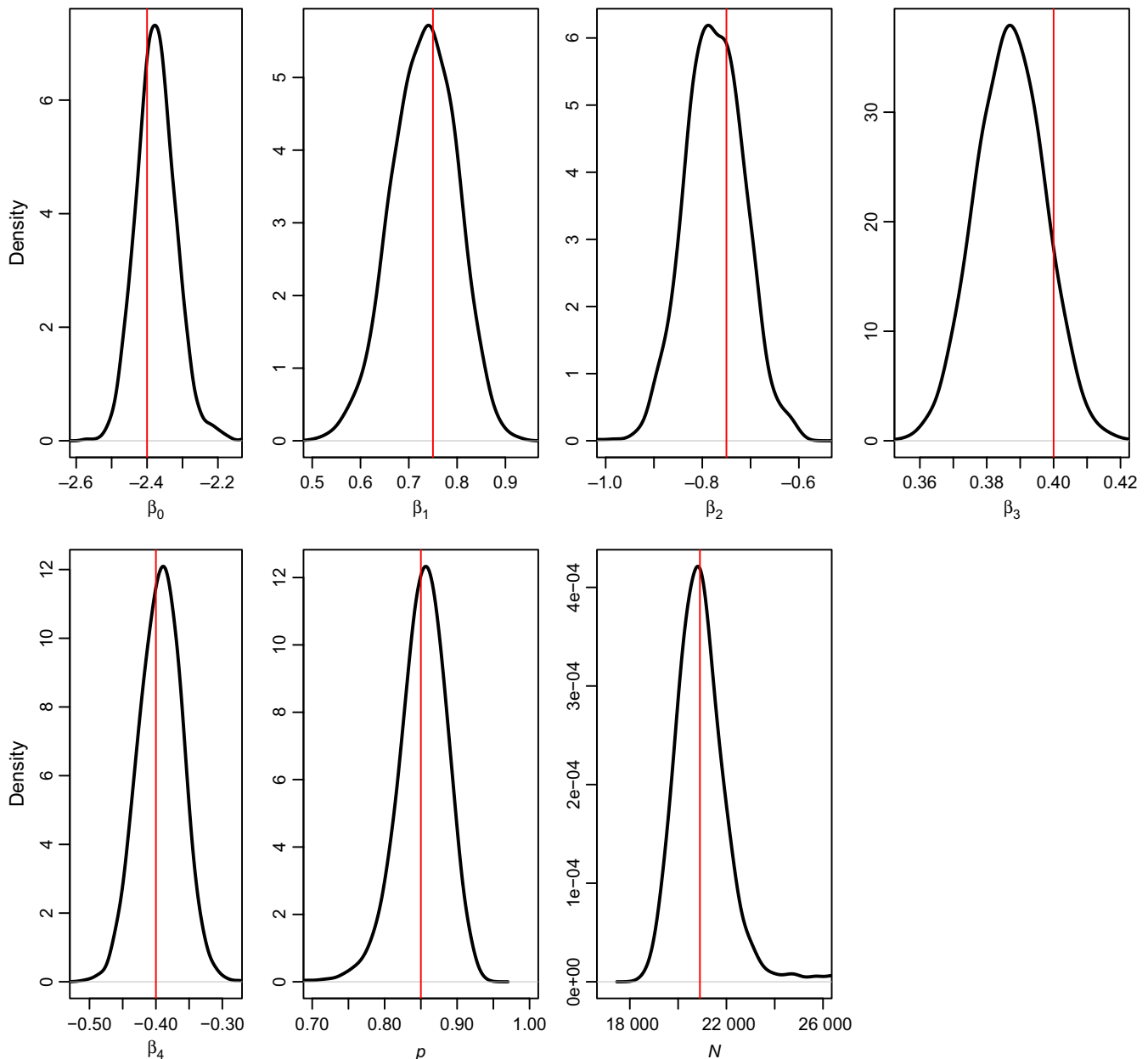


FIGURE 2 Marginal estimated posterior distributions (black lines) of parameters in aerial sea otter abundance model fit to simulated data. Red lines indicate values used to simulate data (see Appendix S1)

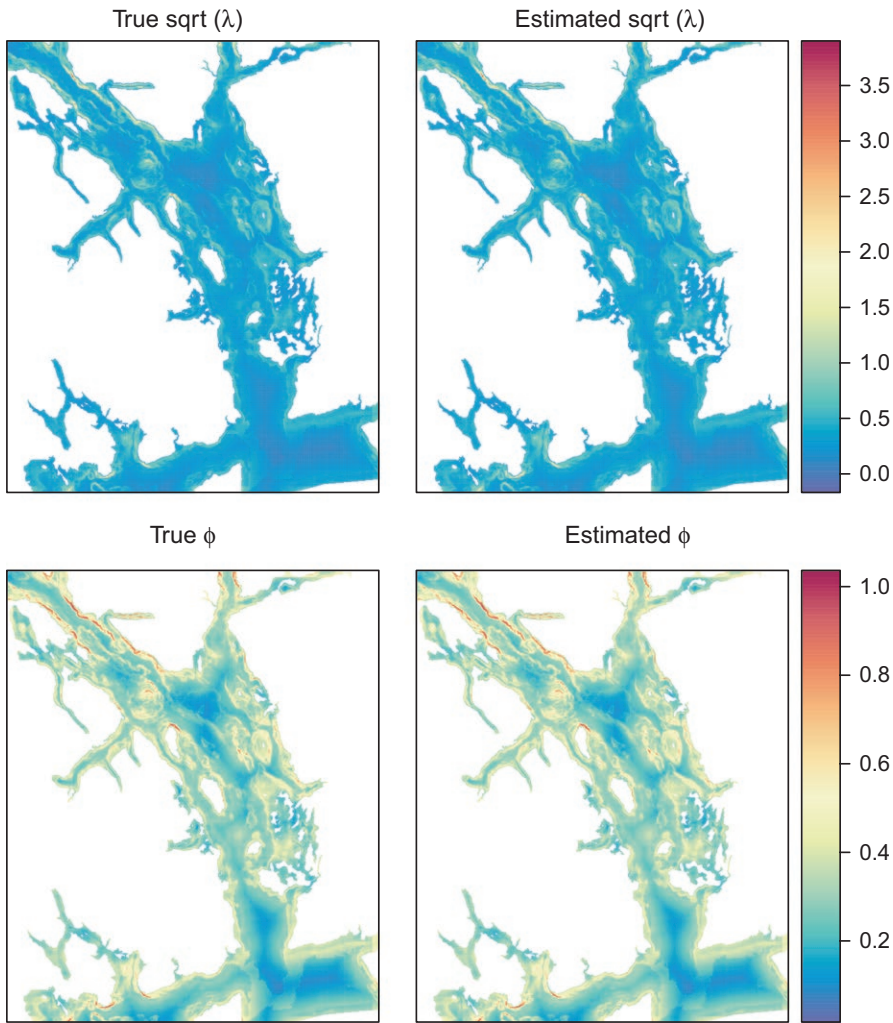


FIGURE 3 Left: True expected abundance ($\lambda(s)$; top) and occupancy probability ($\phi(s)$; bottom) used to simulate abundance data for sea otters in Glacier Bay National Park, southeastern Alaska, USA. Right: The estimated expected abundance and occupancy probability using simulated aerial photographs. The square-root of $\lambda(s)$ was used to highlight spatial variation

The camera was attached to a tripod head and mounted to a plywood platform that was secured in the belly porthole of the aircraft. The camera captured an image every second, using a digital timer (Nikon MC36) that was attached to the camera and operated by the primary observer. A second observer monitored movement of individual sea otters to determine if any sea otters were dispersing or moving in or out of the photograph footprint. After one transect was complete (i.e. one survey occasion), the pilot attempted to fly the same transect (using a combination of a GPS and visual cues) to obtain replicate images. At one site, otters dispersed in varying directions after the initial photograph, and therefore, we removed it from analysis because it would potentially violate the closure assumption. The speed–altitude combination did not appear to have an observable influence on sea otter behaviour.

An onboard global positioning system (GPS; Garmin 76 CSX; Olathe, KS, USA), with an external antenna, was used to record the track line and position of the plane (latitude, longitude, altitude) at 1-s intervals. Each digital image ($7,360 \times 4,912$ pixel JPG) covered c. $90 \text{ m} \times 60 \text{ m}$ at the surface of the water with a 1.64 cm pixel resolution. The rate of image capture and dimensions of the photographed area provided a linear mosaic of overlapping images with c. 30 m of overlap between adjacent images.

The latitude, longitude, and altitude from the track line were downloaded and written to the EXIF headers of each digital image to permanently embed the location data into each image using RoboGeo v6.3 (Pretek, Incorporated, Christiana, TN, USA). All images were reviewed using ACDSee Pro 9 (ACD Systems International, Incorporated, Seattle, WA, USA). From each survey occasion at each site, one image was selected based on its clarity and location of sea otters with respect to the boundary of the photographed area. Although images within one survey occasion created a linear mosaic of intersecting images and could be used as temporal replicates, we selected one image from each survey occasion to use in our analysis. Selecting one image from each survey occasion increased Δj between temporal replicates, increasing the probability that individual sea otters would make state transitions from available to unavailable (or *vice versa*; i.e. so subsequent images were more likely to be independent). Images where a raft of sea otters was in the centre of the image were preferred to help ensure closure assumptions were reasonably met. The best image for each group of sea otters and sampling occasion was selected and imported into Count Clusters (Dynamic Ventures, Incorporated, Cupertino, CA, USA), a custom software program that can be used for counting objects in digital images. An experienced observer marked each sea otter in the image. The total number of individuals per image as well as attribute data from each digital image including date,

time, latitude, longitude, and altitude were exported to a file for analysis. All analyses were conducted in R version 3.2.3 (R Core Team, 2013).

Our field-based methods were associated with a pilot study with limited spatial coverage, thus, we did not attempt to estimate abundance for all of GBNP. We collected 60 images from 20 locations containing sea otters (Table 1). We focused our estimates of detection probability and abundance in the sites we surveyed. We visited each site multiple times. However, visiting each site multiple times is not required, and monitoring designs can be made more efficient by coupling the information from sites with multiple visits and sites that are visited once, provided the same standards that are used to collect and analyse overlapping photographs are used in all photographs.

The estimated posterior distributions for detection probability and abundance for these data are provided in Figure 4. The mean of the posterior distribution, optimal for squared-error loss (e.g. Williams & Hooten, 2016), for detection probability from the aerial image data from 20 sites equaled 0.76, the same as the mean of the posterior distribution from the original design-based survey of sea otters estimated from 469 intensively searched sites (Williams et al., 2017). We assessed model fit using Bayesian p -values (Hobbs & Hooten, 2015). We used the χ^2 goodness-of-fit discrepancy function for calculating Bayesian p -values (Gelman, Carlin, Stern, & Rubin, 2014). The Bayesian p -value was .52, suggesting no lack of model fit.

TABLE 1 Counts of sea otters from aerial images taken at 20 sites in Glacier Bay National Park, Alaska. Sampling occasion refers to the number of times a site was flown over in an aircraft and a picture was taken of the same group of sea otters

	Sampling occasion				
	1	2	3	4	5
Site 1	20	17	15	15	
Site 2	60	62	58	55	
Site 3	15	16	15	15	
Site 4	8	12			
Site 5	9	10			
Site 6	19	20	19	19	
Site 7	17	17	17	13	
Site 8	52	53			
Site 9	162	171			
Site 10	37	40			
Site 11	144	138			
Site 12	21	25	17		
Site 13	20	19	18	18	
Site 14	86	83	87	91	
Site 15	47	46			
Site 16	21	20			
Site 17	19	12			
Site 18	2	1	1		
Site 19	83	85	83	85	83
Site 20	55	48	52		

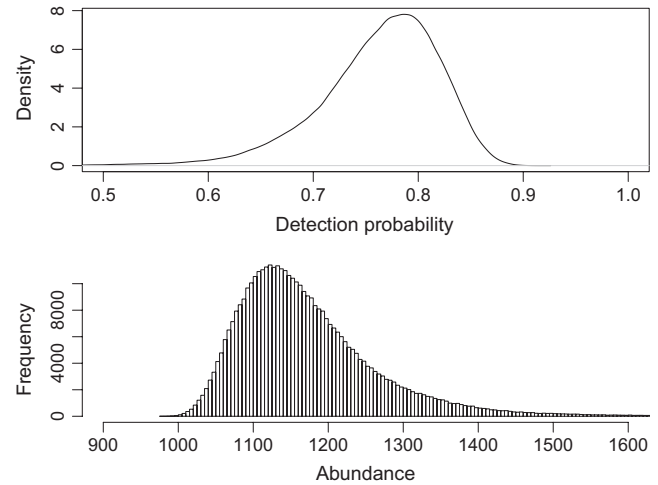


FIGURE 4 Marginal estimated posterior distributions of detection probability and abundance from aerial image data collected at 20 sites containing sea otters in Glacier Bay National Park, AK, USA (see Appendix S2)

4 | DISCUSSION

We presented a spatio-temporal point process model, in combination with a novel application of N -mixture models fitted to digital aerial survey data when detection probability is <1 due to animals being unavailable for detection. We used this framework to simultaneously estimate detection probability, occupancy probability, and total abundance based on an intensity surface that is a realization of a continuous spatio-temporal inhomogeneous Poisson process. Applying our model to both simulated data and real data on sea otters collected during a pilot study demonstrated that this framework is a promising tool for estimating occupancy, abundance, and detection probability from aerial image surveys. Additionally, the spatio-temporal point process model is sufficiently flexible to accommodate count data, presence-absence data, presence only data (Dorazio, 2014; Fithian, Elith, Hastie, & Keith, 2015; Hefley & Hooten, 2016), and spatio-temporal dependence in ecological processes (Cressie & Wikle, 2011).

Model estimates based on simulated data recovered true parameters well. This was not surprising, as previous simulation studies have shown that N -mixture models usually perform well for estimating abundance and detection probability for a variety of conditions with varying level of detection probability, few replicate temporal counts, and few sites (Couturier, Cheylan, Bertolero, Astruc, & Besnard, 2013; Dennis, Morgan, & Ridout, 2015; Hunt, Weckerly, & Ott, 2012; Kéry, Royle, & Schmid, 2005; McCaffery, Nowak, & Lukacs, 2016; Yamaura, 2013). The novel application in our simulation was the use of the intersection of two overlapping spatial sites as temporal replication. Although the formulation of the model has been used for other purposes, our application extends it to new situations involving survey design. For example, if known-radius point counts (e.g. Henry, Haddad, Wilson, Hughes, & Gardner, 2015) are conducted to collect data to estimate abundance, sites could be chosen such that neighbouring sites

intersect to make temporal replication more efficient than replicating visits to sites over multiple days.

The general applicability of these methods for aerial images depends on whether sample sites are closed with respect to movement, mortality, and recruitment. Mortality and recruitment are unlikely during the course of an aerial survey for most populations. However, the movement assumption may not be valid for highly mobile animals. In temporally replicated counts, we assume that the set of animals that occupy a site (but not necessarily observed in the site), is unchanged. Thus, if animals move in or out of the area in the time difference Δj between images, the closure assumption will be violated and estimates of detection probability could be biased depending on how animals disperse in and out of sites. If dispersal is random, bias will likely be small. If animals systematically disperse away from a site after an initial survey, perhaps in response to the aircraft, then bias may be large, unless this dispersal can be modelled. For example, if it is possible to uniquely identify some individuals in repeated images, movement models could be used to explicitly account for animal movement among photographs (e.g. Hooten, Johnson, McClintock, & Morales, 2017; Royle & Young, 2008).

Another assumption of the N -mixture model is that organisms are detected independently of each other (Dorazio, Martin, & Edwards, 2013; Martin et al., 2011; Royle & Dorazio, 2008). This assumption may be violated if behaviour among organisms is correlated, and affects their probability of being detected (e.g. manatees surfacing for air in groups; Martin et al., 2011). Martin et al. (2011) developed an extension to the N -mixture model for accounting for correlated behaviour and non-independent detection of individuals. Our goodness-of-fit evaluation for the sea otter data suggested no lack of model fit, and therefore, there was no evidence that this assumption was violated. However, alternative models (e.g. negative binomial; Ver Hoef & Boveng, 2007) can be implemented when violations, or lack of model fit occur.

There are at least two design considerations that can help prevent violations in the closure assumption. The first consideration applies mainly to populations that congregate in groups (e.g. rafts of sea otters, flocks of birds, pods of whales, rafts of pinipeds), or are relatively immobile among replicate surveys, and is to use a camera, lens, and altitude combination that produces images that have a larger footprint (cf., plot size; Efford & Dawson, 2012). A larger footprint may provide a buffer around a group of animals, requiring more time for individuals to move out of the footprint (or move from outside the footprint into the footprint). In our application, sea otter movement between subsequent photographs was small, relative to the footprint of the photographs we used. Further, we selectively chose photographs with groups of sea otters located in the centre of photographs, reducing the opportunity sea otters had to leave the area captured by photographs. Thus, although it is possible that there was some movement into or out of areas captured by replicate photographs, our survey design minimized this possibility, (which was corroborated by observations from the secondary observer), and any violation of this assumption was small (the secondary observer never witnessed it), and likely negligible for estimating abundance and detection probability

of sea otters in GBNP. The second consideration is to reduce time between survey occasions (i.e. decrease Δj) limiting the time animals have to move out of the footprint. During our pilot survey, it required c. 2–3 min to fly over a group of sea otters twice. However, because we acquired several images each time we flew over sea otters, and neighbouring images contained overlap, we could have used these intersecting regions to provide temporal replication, minimizing the probability that any otter moved out of the area captured by the intersecting images. However, using multiple images within a transect may result in neighbouring images that are not independent, and therefore we selected one image from each transect. Additionally, multiple cameras can be mounted on an aircraft such that one faces forward and one faces backward, programmed on a timer such that they capture an image of the same area at different times in the same flight pass. Similarly, cameras could be placed side-to-side to increase horizontal size of footprints (see Conn et al., 2016, fig. 2, for a picture of this setup). Extensions that use this framework for video surveys are also possible.

Another design consideration for the application of N -mixture models to aerial survey data is the time it requires for animals to switch between the states of unavailable to available. That is, whether Δj is sufficiently large so that intersecting photographs are independent, conditional on $N(A_j)$. Sea otters are good candidates for these models because they are relatively shallow divers with short dive durations (mean dive duration was 85 s; Bodkin, Esslinger, & Monson, 2004). Further, the calculated aerobic dive limit (cADL) for sea otters is <5 min (cADL for juveniles = 3.62 min; cADL for adults = 4.82 min; Thometz, Murray, & Williams, 2015). Gibbs et al. (1988) used aerial images to estimate the number of great blue heron (*Ardea herodias*) nests. Many nests were unavailable for detection due to vegetation obstructing nests from the line-of-sight of the camera. Because it is unlikely that vegetation would change within the course of a survey, allowing additional nests to be identified in subsequent images, the estimate of availability for these data might be biased high, and therefore, nest counts biased low.

Aerial images are often taken along irregular flight paths that do not necessarily form a rectangular grid that partitions a domain of interest, making traditional design-based estimates of abundance difficult (Figure 1; Ver Hoef & Jansen, 2014). Our proposed methods used a model-based approach for estimating abundance based on a spatial point process that can be integrated, resulting in a Poisson regression model that matches the scale of the data, and subsequently, could be incorporated in an N -mixture model. In our application, the abundance intensity was determined by the parameters (β) using generalized linear regression. The model-based approach provides additional flexibility, compared to design-based estimates, that allows incorporation of spatial, temporal, or spatio-temporal autocorrelation (Cressie, 1993; Cressie & Wikle, 2011; Diggle, 2013), and computationally efficient methods for fitting them (Hefley et al., 2017; Hooten, Garlick, & Powell, 2013; Ver Hoef & Jansen, 2014).

In our study, we achieved temporal replication by identifying a group of sea otters at a location, and then conducting multiple flights over the group and taking images. We used this method to reduce the

possibility of spatial displacement by sea otters. Any flight plan could be selected to obtain temporal replication of sites, provided it reasonably meets the assumptions of the model. Additionally, the precision and robustness of parameter estimates, with respect to the number of replicate sites conducted, and the amount of overlap obtained in photographs, can be evaluated using a simulation that is specific to individual study systems.

Finally, if detection probability is likely to change between survey periods (e.g. each year), temporal replication of images can be incorporated into each survey using randomization, or model-based optimization (e.g. Hooten, Wikle, Sheriff, & Rushin, 2009; Wikle & Royle, 1999, 2005). Alternatively, if detection probability is not likely to change through time, a pilot study could be conducted to examine availability bias, and then used as an informative prior distribution for future aerial surveys, precluding the necessity to conduct replicate surveys during each sampling period.

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AUTHORS' CONTRIBUTIONS

P.J.W., M.B.H., J.N.W., and M.R.B. designed the research. J.N.W. and M.R.B. organized field studies. J.N.W. and P.J.W. collected data. P.J.W. and M.B.H. contributed new analytic tools. P.J.W. developed simulations and analysed data. P.J.W., M.B.H., J.N.W., and M.R.B. wrote the paper.

DATA ACCESSIBILITY

All data used in the manuscript are reported in Table 1.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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