

## ***Estimating wind-turbine-caused bird and bat fatality when zero carcasses are observed***

The Faculty of Oregon State University has made this article openly available.  
Please share how this access benefits you. Your story matters.

<b>Citation</b>	Huso, M. M., Dalthorp, D. H., Dail, D. A., & Madsen, L. J. (2015). Estimating wind-turbine caused bird and bat fatality when zero carcasses are observed. <i>Ecological Applications</i> , 25(5), 1213-1225. doi:10.1890/14-0764.1
<b>DOI</b>	10.1890/14-0764.1
<b>Publisher</b>	Ecological Society of America
<b>Version</b>	Version of Record
<b>Terms of Use</b>	<a href="http://cdss.library.oregonstate.edu/sa-termsfuse">http://cdss.library.oregonstate.edu/sa-termsfuse</a>

# Estimating wind-turbine-caused bird and bat fatality when zero carcasses are observed

MANUELA M. P. HUSO,<sup>1,3</sup> DAN DALTHORP,<sup>1</sup> DAVID DAIL,<sup>2,4</sup> AND LISA MADSEN<sup>2</sup>

<sup>1</sup>U.S. Geological Survey, Forest and Rangeland Ecosystem Science Center, 777 NW 9th Street, Suite 400, Corvallis, Oregon 97330 USA

<sup>2</sup>Department of Statistics, Oregon State University, Kidder Hall, Corvallis, Oregon 97331 USA

**Abstract.** Many wind-power facilities in the United States have established effective monitoring programs to determine turbine-caused fatality rates of birds and bats, but estimating the number of fatalities of rare species poses special difficulties. The loss of even small numbers of individuals may adversely affect fragile populations, but typically, few (if any) carcasses are observed during monitoring. If monitoring design results in only a small proportion of carcasses detected, then finding zero carcasses may give little assurance that the number of actual fatalities is small. Fatality monitoring at wind-power facilities commonly involves conducting experiments to estimate the probability ( $g$ ) an individual will be observed, accounting for the possibilities that it falls in an unsearched area, is scavenged prior to detection, or remains undetected even when present. When  $g < 1$ , the total carcass count ( $X$ ) underestimates the total number of fatalities ( $M$ ). Total counts can be 0 when  $M$  is small or when  $M$  is large and  $g \ll 1$ . Distinguishing these two cases is critical when estimating fatality of a rare species. Observing no individuals during searches may erroneously be interpreted as evidence of absence. We present an approach that uses Bayes' theorem to construct a posterior distribution for  $M$ , i.e.,  $P(M|X, \hat{g})$ , reflecting the observed carcass count and previously estimated  $g$ . From this distribution, we calculate two values important to conservation: the probability that  $M$  is below a predetermined limit and the upper bound ( $M^*$ ) of the  $100(1 - \alpha)\%$  credible interval for  $M$ . We investigate the dependence of  $M^*$  on  $\alpha$ ,  $g$ , and the prior distribution of  $M$ , asking what value of  $g$  is required to attain a desired  $M^*$  for a given  $\alpha$ . We found that when  $g < \sim 0.15$ ,  $M^*$  was clearly influenced by the mean and variance of  $\hat{g}$  and the choice of prior distribution for  $M$ , but the influence of these factors is minimal when  $g > \sim 0.45$ . Further, we develop extensions for temporal replication that can inform prior distributions of  $M$  and methods for combining information across several areas or time periods. We apply the method to data collected at a wind-power facility where scheduled searches yielded  $X = 0$  raptor carcasses.

**Key words:** Bayes' theorem; endangered species; imperfect detection; posterior; prior; rare species; superpopulation; wind power.

## INTRODUCTION

Wind turbines have long been known to pose a threat to passing bats and birds (Hall and Richards 1972, Rogers et al. 1977). They have been implicated in lethal takes of several species protected under the U.S. Endangered Species Act (ESA), including the Hawaiian Petrel (*Pterodroma sandwichensis*), Hawaiian Goose (*Branta sandvicensis*), Hawaiian hoary bat (*Lasiurus cinereus semotus*; U.S. Fish and Wildlife Service 2011b), and the Indiana bat (*Myotis sodalists*; U.S. Fish and Wildlife Service 2014b). There is also concern about endangered species that live near wind-power facilities but have not been reported as casualties, including the

California Condor (*Gymnogyps californianus*; Barringer 2013, U.S. Bureau of Land Management 2013), Whooping Crane (*Grus Americana*; U.S. Fish and Wildlife Service 2011a), and several lesser-known species, such as the Virginia big-eared bat (*Corynorhinus townsendii virginianus*), gray bat (*Myotis grisescens*), Piping Plover (*Charadrius melodus*), Interior Least Tern (*Sterna antillarum athalassos*), and Kirtland's Warbler (*Setophaga kirtlandii*; U.S. Fish and Wildlife Service 2012c).

Understanding that there may be some unintended fatalities of endangered species at wind power facilities, the U.S. Fish and Wildlife Service (USFWS) has begun issuing incidental take permits (ITPs), permitting certain levels of take at wind-power facilities. In 2006, Kaheawa Wind Project in Hawaii became the first wind-power project in the United States to receive a take permit for species protected by the ESA (Hawaiian hoary bat, Hawaiian Petrel, Hawaiian Goose, and Newell Shearwater; U.S. Fish and Wildlife Service 2007), and recently

Manuscript received 5 July 2014; revised 16 October 2014; accepted 10 November 2014. Corresponding Editor (ad hoc): E. M. Hanks.

<sup>3</sup> E-mail: mhuso@usgs.gov

<sup>4</sup> Present address: 1111 Polaris Parkway, Columbus, Ohio 43240 USA.

USFWS issued its first ITP to a wind-energy company to kill endangered species (Indiana bat and Virginia big-eared bat) on the United States mainland (U.S. Fish and Wildlife Service 2013c). Incidental take permits for Indiana bats are under consideration by USFWS at sites in Indiana (U.S. Fish and Wildlife Service 2013a), Ohio (U.S. Fish and Wildlife Service 2012a), Maryland (U.S. Fish and Wildlife Service 2012b), and Missouri (U.S. Fish and Wildlife Service 2010, 2012c). In 2014, an ITP was issued to allow a wind-power company to kill up to five Golden Eagles over a five-year period (U.S. Fish and Wildlife Service 2014a), and USFWS is actively considering ITPs for Golden Eagles at many other sites in the United States (Clarke 2013).

Permitting take leads naturally to the question of estimating take. Take permits often include mitigation requirements to compensate for estimated take. The level of mitigation is determined by the predicted take calculated using collision-risk models or extrapolation from take levels at similar sites, and these models require field-based estimates of fatality to confirm the accuracy of their predictions. Because overestimating potential take could result in costly and unjustified mitigation, and underestimating could result in unanticipated declines in species populations already at risk, predictions and estimates of take need to be precise and accurate. Confirming the accuracy of predicted take can be problematic. Often no carcasses are observed, leading to the potentially misguided inference that no (or few) individuals have actually been killed. This inference is justified only when the probability of observing an individual is close to 1. As the probability of observing an individual decreases, the probability of missing carcasses increases, making it unclear how to interpret having observed 0 carcasses.

A typical approach to estimating the number of birds or bats killed at a wind power facility is for a field crew to search the ground beneath a subset of turbines at specified time intervals and count the carcasses that show signs of having been killed by a turbine (U.S. Fish and Wildlife Service 2012d). Carcass counts are adjusted for imperfect detection due to scavengers, searcher error, and unsearched areas (Huso 2011, Korner-Nievergelt et al. 2011, Bispo et al. 2013, Warren-Hicks et al. 2013, Huso and Dalthorp 2014). The most common estimators of the total abundance of carcasses ( $M$ ) at a site over an extended but fixed period of time are variations or elaborations of  $X/\hat{g}$ , where  $X$  is the total number of carcasses observed within a sampled area during the time period and  $\hat{g}$  is the estimated overall detection probability, i.e., the probability of observing a carcass that was killed by any turbine at the site during the time period of interest. Methods for determining  $\hat{g}$  vary widely (MacKenzie et al. 2005, Bernardino et al. 2013, Warren-Hicks et al. 2013, Etersson 2014). A critical limitation of these common approaches is that they necessarily yield  $\hat{M}=0$  with no variance when  $X=0$  (e.g., Erickson et al. 2000, Schoenfeld 2004, Huso 2011,

Korner-Nievergelt et al. 2011, Peron et al. 2013, Warren-Hicks et al. 2013). A zero count can indicate that either no animals were killed or that some (perhaps many) were killed but all the carcasses were missed in the searches. With greater values of  $g$ , we can more credibly make a case that not a large number of carcasses went undetected. But when  $g \ll 1$ , there is little assurance that the number killed was 0 even if no carcasses were observed, i.e.,  $X=0$ . If the objective is to estimate take, observing no carcasses when  $g$  is small offers little more than absence of evidence, rather than evidence of absence.

Although we define our problem in terms of estimating take at a wind turbine facility, our approach has application in many other situations where interest is in estimating a credible upper bound of a superpopulation, where the population is open (individuals can leave the area), the population may be small (perhaps even 0), and the probability of detection  $< 1$  (sometimes  $\ll 1$ ) resulting in observed counts of 0. These include estimating the number of manatees that arrived in, and hence were exposed to, an area contaminated by an oil spill (Martin et al. 2014), the number of raptors killed by electrocution from transmission lines during a year (Lehman et al. 2007, 2010), or the number of Indiana bats killed during a migratory season at a wind-power facility (U.S. Fish and Wildlife Service 2012b).

There is a rich literature for estimating abundance of a superpopulation (Williams et al. 2011, Peron et al. 2013) or of an open population (Seber 1982, Schwarz and Seber 1999, White 2008, Dail and Madsen 2011), but the literature addressing estimating abundance when observed count is 0 is limited. Royle et al. (2005) have shown that concluding absence when detection probability  $< 1$  and observed count is 0 introduces bias into the estimation of abundance. Dupuis et al. (2011) propose a conditional approach to estimating occupancy rate of a rare or hard to detect species, but it is conditioned on the true presence of the target species, a condition that may not necessarily be met in our context. Recently, models that use simple presence/absence have been developed to estimate abundance (MacKenzie et al. 2002, 2003, Royle and Nichols 2003), but these models depend on actually observing at least some members of the population. Fieberg et al. (2013) develop a Bayesian model-based approach to overcome the inefficiencies of modified Horvitz-Thompson estimator when detection probabilities are low, but their approach was not focused on estimation of abundance when no animals were observed. Martin et al. (2014) derived estimates of both occupancy rate and upper bounds of the number of manatees present at the time of sampling, even when no manatees were observed. However, their approach restricts estimates to the time of sampling and does not seek to estimate the total number of individuals arriving over an extended period.

*Research questions*

The goal of our study is to develop an approach to estimate the  $100(1 - \alpha)\%$  credible upper bound ( $M^*$ ) of the abundance of a superpopulation when the observed count is 0, the probability of detection is  $<1$ , and there is some potential that the species of interest is in fact absent. We use an approach similar to that of Bayley and Peterson (2001) but extend the approach to estimating abundance rather than simple presence/absence when all samples are 0. This analysis was motivated by discussions with the U.S. Fish and Wildlife Service managers concerned with assuring that a permitted level of take of Indiana bats is not exceeded at a wind-power facility. Much of our focus in the methods and discussion is on wind power, but the approach should be relevant to a number of situations.

When issuing an ITP, the objective shifts from estimating fatality to providing assurance that the number of individuals killed has not exceeded the (often very small) allowed limit,  $\tau$ . To address this, we propose an approach that, through application of Bayes' formula, results in a posterior probability distribution of the total abundance of carcasses ( $M$ ) arriving at a site over an extended but fixed period of time. From this distribution, we can calculate two values important to conservation: an estimated probability that the population abundance did not exceed a predetermined limit,  $\tau$ , and a critical value,  $M^*$ , which is the  $100(1 - \alpha)\%$  credible maximum, i.e., the minimum value such that  $P(M > M^* | g, X) \leq \alpha$ . We investigate the sensitivity of results on  $\alpha$ ,  $g$ , and the prior distribution of  $M$ , asking what value of  $g$  is required to attain a desired  $M^*$  for a given  $\alpha$ . Further, we develop extensions for incorporating previous years' data to inform prior distributions, as well as methods for combining information across  $n$  sites to calculate  $P(M > M^* | X = (x_1, x_2, \dots, x_n), g = (g_1, g_2, \dots, g_n))$ . We apply the method to calculate  $M^*$  for raptors killed at a wind-power facility where no raptor carcasses were observed during scheduled searches.

METHODS

Let  $X$  denote the total count of individuals detected, and let  $M$  denote the total number of individuals that arrived in an area over an extended but fixed period of time, which we refer to as a season, although it can comprise any period of time. Within a season, several searches may be conducted. We assume that individuals that are detected in a search are marked, removed from the study area, or are otherwise prevented from being counted more than once. Furthermore, we also assume that an estimate of  $g$ , the overall probability of detecting an individual in the population, is available, whether through sampling protocol, historical data, or experimental trials. The value of  $g$  may depend on a number of factors, such as season, vegetation structure, observer, etc. Assuming that all individuals have the same probability  $g$  of being observed and that individuals arrive, persist, and are detected independently,  $X$  is then

distributed as a binomial random variable with parameters  $M$  and  $g$  (MacKenzie et al. 2005). Given prior probabilities  $P(M = m)$ , we can calculate a posterior distribution of  $M$  using Bayes' formula

$$p(M = m | X; g) = \frac{P(X | M = m; g)P(M = m)}{\sum_i P(X = i; g)P(M = i)}. \quad (1)$$

For a given overall detection probability  $g$ , observed count  $X$ , prior distribution of  $M$ , and desired  $\alpha$ , the  $100(1 - \alpha)\%$  credible interval  $[X, M^*]$  defines the range where  $M$  is most likely be. We note that the most informative prior for the total number of arrivals  $M$  in a season would be full knowledge of the temporal distribution of  $M$  among seasons. We seek to estimate the number of arrivals in a particular season, i.e., a single random draw from the temporal distribution of  $M$ .

*Sensitivity of  $M^*$  on  $\alpha$ ,  $g$ , and the prior distribution of  $M$*

We investigate the dependence of  $M^*$  on  $\alpha$ ,  $g$ , and the assumed prior distribution of  $M$ , asking what value of  $g$  is required to attain a desired  $M^*$  for a given  $\alpha$  if  $X=0$ . All calculations were carried out using the software package R (R Development Core Team 2013; see Supplement).  $M^*$  is calculated for  $\alpha = 0.01, 0.05, 0.10$ , and  $0.20$ , detection probabilities  $g = E[\hat{g}]$  ranging from  $0.05$  to  $0.99$ , and for three different prior distributions for  $M$ , which we will refer to as uninformative (uniform), moderately informative, and highly informative.

In practice,  $g$  is not known with certainty but estimated by  $\hat{g}$ , which we assume to be distributed as a beta random variable and incorporated into the analysis by replacing the  $g$ 's in Eq. 1 with  $\hat{g}$ 's and calculating  $P(X | M = m; \hat{g})$  as a binomial when  $\hat{g} = g$  is fixed and known and as a beta-binomial probability when  $g$  is estimated by  $\hat{g}$ . The effects of uncertainty about  $g$  are assessed by comparing graphs of  $M^*$  vs.  $g$  for three different levels of uncertainty:  $\hat{g} = g$  (fixed and known), moderate uncertainty in  $\hat{g}$ , and great uncertainty in  $\hat{g}$  (Fig. 1) and by calculating the relative increase in  $M^*$  with increasing uncertainty in  $\hat{g}$ . We incorporate uncertainty about  $g$  into the model by taking  $\hat{g}$  as a beta-distributed random variable with  $E[\hat{g}] = g$ , support in  $[g_{\min}, g_{\max}] = [g/[g + 0.5\psi(1 - g)], 2\psi g/[2\psi g + (1 - g)]]$ , and the central 95% of the distribution defined by  $[g_{0.025}, g_{0.975}] = [g/[g + \psi(1 - g)], \psi g/[\psi g + (1 - g)]]$ . With this formulation,  $\psi$  is a measure of the spread of the distribution of  $\hat{g}$  around  $g$ , with  $\psi = 1$  representing the case where  $g$  is fixed and known and with greater values of  $\psi$  corresponding to greater uncertainty about  $g$ . Values of  $\psi = 1, \sqrt{3}$ , and  $3$  were used to represent three degrees of uncertainty about  $g$ , i.e., fixed and known, moderate uncertainty in  $g$ , and great uncertainty in  $g$ , respectively (Fig. 1). For a given value of  $\psi > 1$ , the variance of  $\hat{g}$  is greatest at  $g=0.5$  and the distribution of  $\hat{g}$  is symmetric. As  $g$  approaches 0 or 1, the variance decreases and the distribution of  $\hat{g}$  becomes increasingly skewed (Fig. 2).

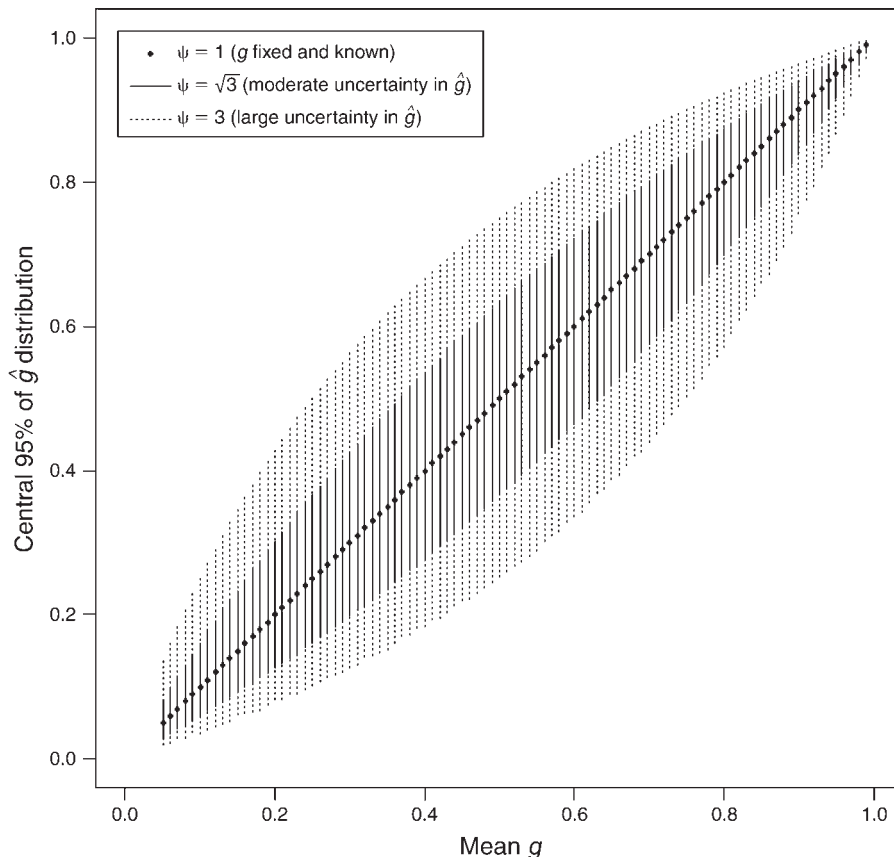


FIG. 1. Central 95% of distribution of the probability of detection ( $g$ ), for  $g$  fixed and known ( $\psi = 1$ ), moderate uncertainty about  $g$  ( $\psi = \sqrt{3}$ ), and great uncertainty about  $g$  ( $\psi = 3$ ), presented over all possible values of  $g$ .

We compared  $M^*$  values derived from three different priors (Fig. 3) representing different degrees of knowledge about the random process generating  $M$  in any given year.

1) The uniform prior for integer  $m$  is defined as

$$P(M = m) = \begin{cases} \frac{1}{201} & \text{for } m \leq 200 \\ 0 & \text{otherwise} \end{cases}$$

and represents the uninformative case where  $M$  could be anything. The value of  $m = 200$  was chosen as the maximum of the uniform prior because it is small enough to allow for rapid calculations yet large enough that larger maxima would yield virtually identical results.

2) The moderately informative prior is taken as a negative binomial  $P(M = m) = [\Gamma(m + \alpha)] / [m! \Gamma(\alpha)] p^\alpha (1 - p)^m$  with parameters  $\alpha = 1.25$  and  $p = 0.1$ , which has a mean of 11.25 and a 95th percentile of 34 and represents the case where we have enough prior information to assume that  $P(M = m)$  generally decreases with  $m$  and is unlikely to exceed 34. This is comparable to a prior constructed

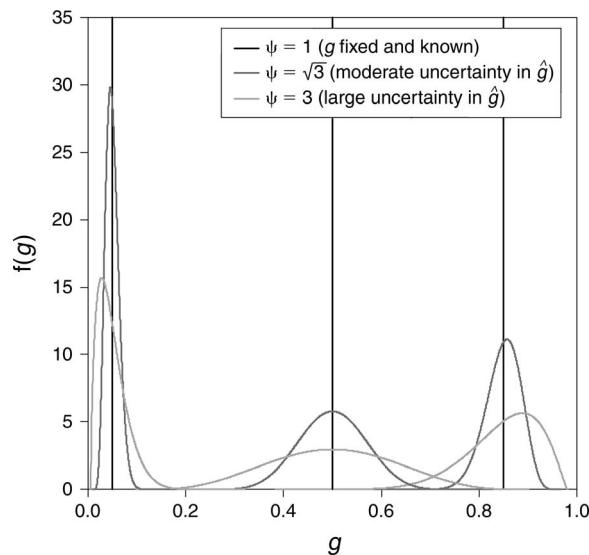


FIG. 2. Distribution of the probability of detection ( $g$ ) for three scenarios:  $g$  fixed and known ( $\psi = 1$ ), moderate uncertainty about  $g$  ( $\psi = \sqrt{3}$ ), and great uncertainty about ( $\psi = 3$ ), presented for three arbitrary values of  $g$ : 0.05, 0.5, and 0.85;  $\psi$  is a measure of the spread of the distribution of  $\hat{g}$  around  $g$ . In practice,  $g$  is not known with certainty but estimated by  $\hat{g}$ .



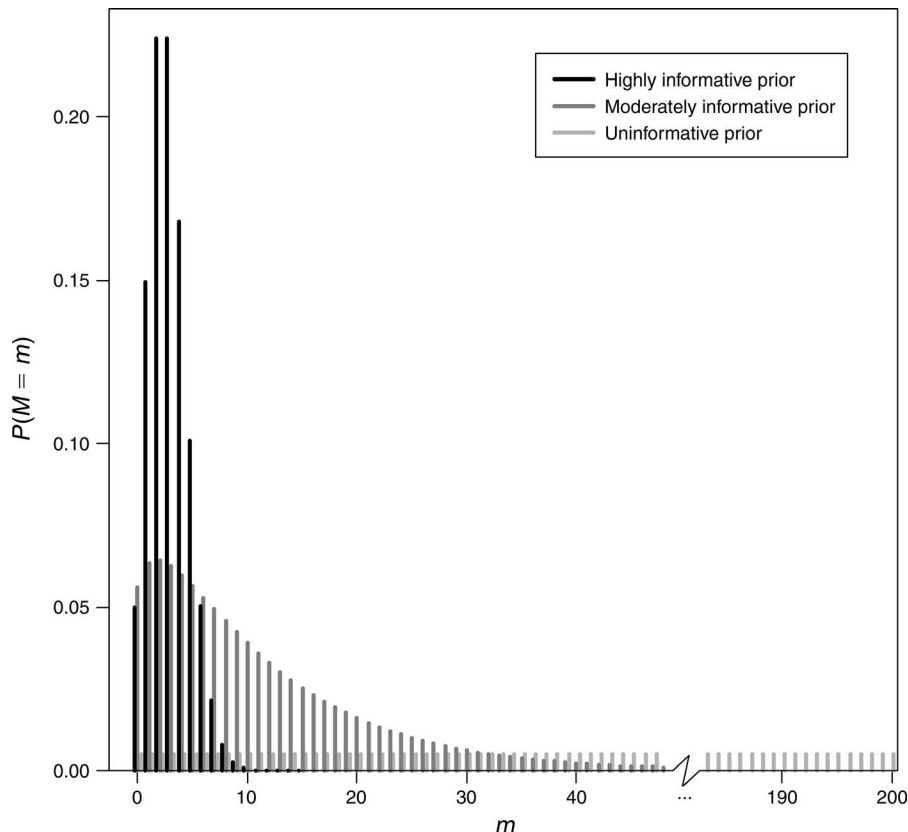


FIG. 3. Prior distributions of the number of fatalities generated at a site in a year ( $M$ ): highly informative prior (Poisson[ $\lambda=3$ ]), moderately informative prior (negative binomial with parameters  $\alpha = 1.25$  and  $\beta = 0.10$ ), and uninformative prior (uniform with parameters  $X$  and 200).

from a previous season’s search data with  $X = 0$ ,  $g = 0.15$  with a 95% confidence interval for  $\hat{g}$  equal to  $[0.05, 0.29]$  using the procedure discussed in *Methods: Incorporating previous years’ observations into prior distribution of  $M$  for current year*.

- 3) The maximally informative prior assumes that the number of fatalities varies from year to year as a Poisson random variable with mean known to be  $\lambda = 3$ . The maximally informative prior represents a best-case scenario that might not be attainable in practice, because the true mean will never be known and the variation in the number of fatalities from year to year will most likely exceed Poisson variation in real-world situations.

*Incorporating previous years’ observations into prior distribution of  $M$  for current year*

The annual number of fatalities is a random variable ( $M$ ) with unknown distribution. The search data from one year gives information about the random process generating carcasses. For example, if there is perfect overall detection probability  $g = 1$  in a given year but no carcasses are found ( $X = 0$ ), then we conclude there were  $m = 0$  fatalities in that year. It does not mean there will

necessarily be zero the following year, but it does give some indication that a very high number of fatalities will be unlikely unless the random process that generates carcasses is extremely variable or changes substantially. We formalize that notion as follows. We start with an assumption that the number of fatalities generated at a site in a year is a random variable  $\mathcal{M} \sim \text{Poisson}(\lambda)$  and later relax that assumption. The previous year’s search data are then used to calculate a posterior distribution of  $\lambda$  as  $P(\lambda | X) = P(X | \lambda)P(\lambda) / \int P(X | \lambda)P(\lambda)d\lambda$ . We assume a uniform prior distribution for  $\lambda$  on the interval  $[0, \lambda_{\max}]$  (where  $\lambda_{\max}$  is small enough to be computationally efficient yet large enough that a larger value would not yield appreciably different results), so  $P(\lambda | X) = P(X | \lambda) / \int_0^{\lambda_{\max}} P(X | \lambda)d\lambda$ . For a given  $\lambda$ ,  $P(X | \lambda) = \sum_m P(X | \mathcal{M}_\lambda = m)P(\mathcal{M}_\lambda = m)$ , where  $\mathcal{M}_\lambda$  signifies the conditional distribution  $\mathcal{M} | \lambda$ . The terms  $P(X | \mathcal{M}_\lambda = m)$  are beta-binomial probabilities, i.e.,  $X | (\mathcal{M}_\lambda = m) \sim \text{binomial}(m, \hat{g})$ , where  $\hat{g} \sim \text{beta}(\alpha, \beta)$ . In practice,  $\alpha$  and  $\beta$  can be estimated from searcher proficiency trials, carcass persistence trials, and the search schedule parameters (e.g., time between searches, fraction of turbines searched, density-weighted proportion of area searched, etc.) and  $\hat{\alpha}$  and  $\hat{\beta}$  used in lieu of  $\alpha$  and  $\beta$ . The terms  $P(\mathcal{M}_\lambda = m)$  are Poisson probabilities

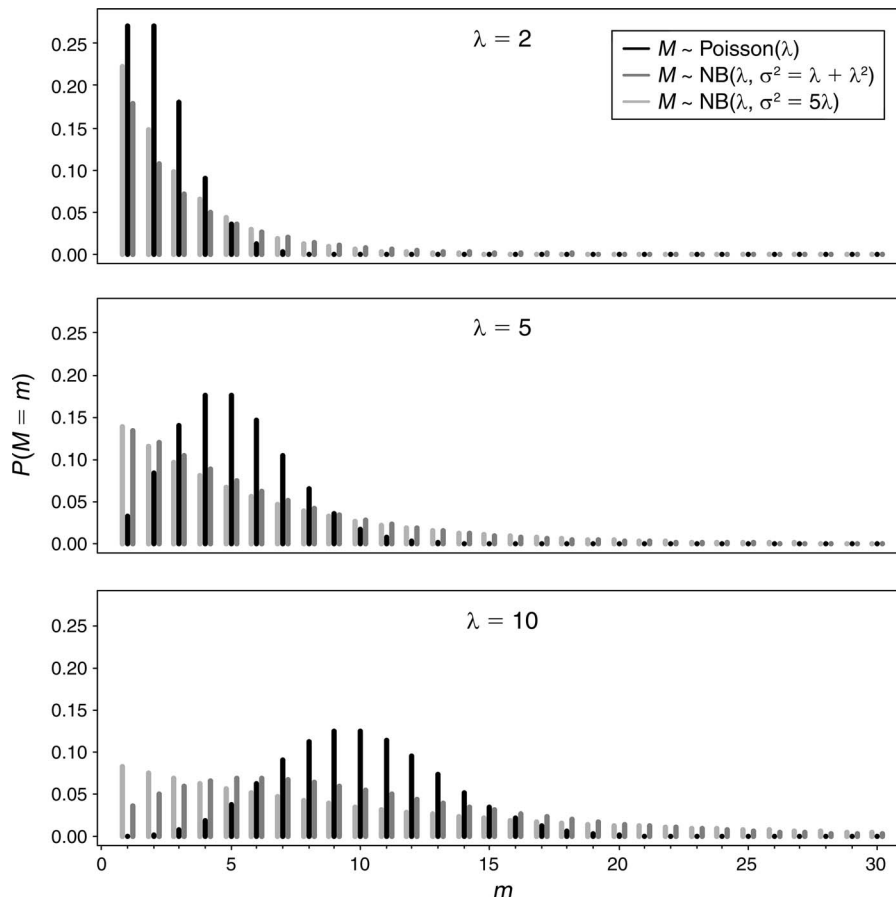


FIG. 4. Assumed distributions of the number of fatalities generated at a site ( $M$ ) across years: Poisson( $\lambda$ ), NB( $\lambda, \lambda + \lambda^2$ ), and NB( $\lambda, 5\lambda$ ) for  $\lambda = 2, 5$ , and  $10$ . NB is negative binomial.

$\lambda^m e^{-\lambda} / m!$ , from which we calculate  $P(\lambda | X)$ . The prior distribution for  $M$  for the following year is then given as  $P(M = m) = \int_0^{\lambda_{\max}} P(\mathcal{M}_\lambda = m) P(\lambda) d\lambda$ .

In practice, the distribution of  $\mathcal{M}$  from year to year is likely to have greater variability than a Poisson random variable, so we assess the effects on  $M^*$  of assuming  $\mathcal{M}$  is distributed as a negative binomial. Letting  $\lambda$  and  $\sigma^2$  signify the mean and variance of  $\mathcal{M}$ , we compare  $M^*$  for three different assumptions about the variance: (1)  $\sigma^2 = \lambda$  (Poisson), (2)  $\sigma^2 = \lambda + \lambda^2$ , and (3)  $\sigma^2 = 5\lambda$ . The calculations for the latter two cases are similar to those for the Poisson but with negative binomial probabilities,

$$P(M_\lambda = m) = \frac{\Gamma(m + a)}{m! \Gamma(a)} p^a (1 - p)^m,$$

where  $p = \lambda / \sigma^2$  and  $a = \lambda^2 / (\sigma^2 - \lambda)$  (Fig. 4).

*Estimation of  $M_T$  = the total number of fatalities across  $n$  detection classes*

An overall detection probability ( $g$ ) applies to carcasses that arrive in a given area during a specified time, and the scope of inference of the posterior distribution  $P(M = m | X; \hat{g})$  is limited to the area and

time to which  $g$  applies. However, detection probabilities may vary from site to site, from year to year, or season to season at a single site, or among different areas within a site due to differences in search protocol, scavenging rates, landscape and vegetation patterns, or other causes. We refer to the area and specified time to which a given detection probability applies as a detection class (or simply class) and provide a method for combining classes for estimating the total number of carcasses across all the classes. For example, if the search protocol at a site changes between year one and year two, each year represents a different detection class with distinct detection probabilities that can be combined into an overall  $g$  for estimation of total number of fatalities at the site over the two years. Similarly, total fatality at  $n$  sites can be estimated by first combining the site-wise detection probabilities ( $\hat{g}_1, \dots, \hat{g}_n$ ) into an overall detection probability ( $\hat{g}$ ) and then calculating a posterior distribution for the total  $P(M = m | X; \hat{g})$ , where  $X$  is the total carcass count at all the sites combined. Estimating the combined overall detection probability ( $\hat{g}$ ) among  $n$  detection classes requires estimates of the detection probabilities ( $\hat{g}_k$ ) and relative arrival rates ( $a_k$ ) for each class  $k = 1, \dots, n$ ,

where the relative arrival rate for class  $k$  represents the proportion of carcasses arriving in the class. Calculation of the combined  $\hat{g}$  relies on some further definitions and a simplifying assumption. First, define the total number of fatalities in the  $n$  classes combined as  $M_T = \sum M_k$ , where  $M_k$  is the number of carcasses arriving at site  $k$ . Then, assuming the  $M_i$ 's are independent Poisson random variables with rates  $\lambda_i$  and the detection probabilities  $\hat{g}_k$  are independent with means  $E[\hat{g}_k] = g_k$  and variances  $V[\hat{g}_k] = \sigma^2$ , the estimated overall detection probability  $\hat{g}$  for carcasses arriving in one of the classes has expected value  $g = E[\hat{g}] \cong \sum g_k a_k$  with variance  $\sigma^2 = V[\hat{g}] \cong \sum a_k^2 \sigma_k^2 + (\sum a_k (g_k^2 + \sigma_k^2) - g^2) / \lambda$ , where  $\lambda = \sum \lambda_k$  and  $a_k = (\lambda_k / \lambda)$  (see Appendix A). We then estimate  $g$  by  $\hat{g} = \sum \hat{g}_k a_k$  and  $\sigma^2$  by

$$\hat{\sigma}^2 = \sum a_k^2 \hat{\sigma}_k^2 + \frac{\sum a_k (\hat{g}_k^2 + \hat{\sigma}_k^2) - \hat{g}^2}{\hat{\lambda}}$$

Thus, the overall detection probability  $g$  is estimated as the weighted average of  $\hat{g}_k$ 's, with weights  $a_k$  equal to the expected proportion of total carcasses landing in class  $k$ . For example, in the absence of any other information (often the case with rare or endangered species) an assumption of constant per-turbine arrival rate throughout the region is not unreasonable. Each  $a_k$  would then be proportional to the number of turbines at the site with  $\sum a_k = 1$ . Likewise, suppose we are estimating the total number of fatalities at a single site over two years. Then after the first year, an intensified search protocol is implemented so that  $\hat{g}_2 > \hat{g}_1$ , and the number of turbines doubles, so it is assumed that  $a_2 = 2a_1$ . Because  $\sum a_k$  must equal 1,  $a_2 = 2/3$  and  $a_1 = 1/3$ . The estimated variance of  $\hat{g}$  depends on the total arrival rate  $\lambda = E[M_T]$ , which is unknown but can be estimated as  $\hat{\lambda} = X_T / \hat{g}$  where  $X_T$  is the total carcass count in the  $n$  classes when at least one carcass is observed. If no carcasses are observed at any site, then estimate total arrival rate as  $\hat{\lambda} = 0.5 / \hat{g}$ .

The same procedure can be applied to estimate the total number of fatalities over several years. Detection probabilities ( $g_i$ ) at a site may vary from year to year with changes in search protocol, scavenging rates, and landscape and vegetation patterns. The relative arrival rates of carcasses ( $a_i$ ) may change with site expansion, risk reduction measures, e.g., by curtailment of turbines during high-risk periods (Arnett et al. 2010) or by deterrents to reduce collision risk (Arnett et al. 2013), changes in animal activity (e.g., population numbers, local flight patterns, migration routes), or other factors.

*Estimation of M when detection probabilities vary within a site*

Within a site, detection probabilities  $\mathbf{g} = (g_1, \dots, g_n)$  may vary with vegetation, ground texture and coloration, landscape characteristics, search protocol, and other factors, and the site may be divided into blocks or

classes with differing detection probabilities. Carcass allocation among classes can be modeled as a multinomial random variable  $\mathbf{M} = (M_1, \dots, M_n)$  with probabilities  $\mathbf{a} = (a_1, \dots, a_n)$ , where  $a_i$  is the relative arrival rate (or the expected proportion of total carcasses landing in class  $i$ ) and  $M_i$  is the number of carcasses arriving in class  $i$ . Carcass arrival rates vary with distance from turbine, and relative arrival rates can be estimated as a density-weighted proportions (Huso and Dalthorp 2014). Other factors, such as turbine size (Barclay et al. 2007, Georgiakakis et al. 2012), direction from turbine (Hull and Muir 2010), habitat (Cryan and Barclay 2009), and activity (Barrios and Rodriguez 2004) also influence arrival rates and may be incorporated into estimates of  $a_i$ . Given detection probabilities ( $\mathbf{g}$ ), relative arrival rates ( $\mathbf{a}$ ), and a prior distribution on the total number of fatalities at a site ( $P[M = m \text{ for } m = 0, 1, 2, \dots]$ ), a posterior distribution for  $M$  given  $\mathbf{g}$ ,  $\mathbf{a}$ , and the observed counts in each class ( $\mathbf{X} = (X_1, \dots, X_n)$ ) can be calculated as

$$P(M = m | \mathbf{X}, \mathbf{g}, \mathbf{a}) = \frac{P(\mathbf{X} | M = m; \mathbf{g}, \mathbf{a}) P(M = m)}{\sum_m P(\mathbf{X} | M = m; \mathbf{g}, \mathbf{a}) P(M = m)}$$

The prior probabilities  $P(M = m)$  are supplied as before, with the remaining term calculated as

$$P(\mathbf{X} | M = m; \mathbf{g}, \mathbf{a}) = \sum_m \sum_{\{\mathbf{M}: M=m\}} P(\mathbf{X} | \mathbf{M} = \mathbf{m}, M = m; \mathbf{g}) \times P(\mathbf{M} = \mathbf{m} | M = m; \mathbf{a}).$$

The first probability in the right side is the product of independent binomials over the set  $S$ , defined as all classes  $k \in 1, \dots, n$  such that  $X_k$  is observed

$$P(\mathbf{X} | \mathbf{M} = \mathbf{m}, M = m; \mathbf{g}) = \prod_{k \in S} \binom{m_k}{X_k} g_k^{X_k} (1 - g_k)^{m_k - X_k}$$

and the second probability is a multinomial

$$P(\mathbf{M} = \mathbf{m} | M = m; \mathbf{a}) = \frac{m!}{\prod_{k=1}^n m_k!} \prod_{k=1}^n g_k^{m_k}$$

RESULTS

*Sensitivity of  $M^*$  on  $\alpha$ ,  $g$ , and the prior distribution of  $M$*

In general, the value of  $M^*$  depends on the desired credibility level  $100(1 - \alpha)\%$ , the overall detection probability  $g$ , and the assumed prior distribution of  $M$ .  $M^*$  is larger if we require a greater assurance (small  $\alpha$ ) that the population size does not exceed  $M^*$  (Fig. 5). If  $g$  is small, then it is difficult to rule out high fatality rates, so  $M^*$  will be large, but small improvements in detection probability can result in large decreases in  $M^*$  (Fig. 5). When  $g$  is greater than about 0.45,  $M^*$  is less than 5 for all credibility levels  $\leq 0.95$  (Fig. 5). Also, when  $g$  is small ( $< \sim 0.4$ ), decreasing  $\alpha$  from 0.2 to 0.1, 0.5, and 0.01 leads to an increase in  $M^*$  by a factor of about 1.4, 1.8, and 2.8, respectively (Fig. 6). As  $g$



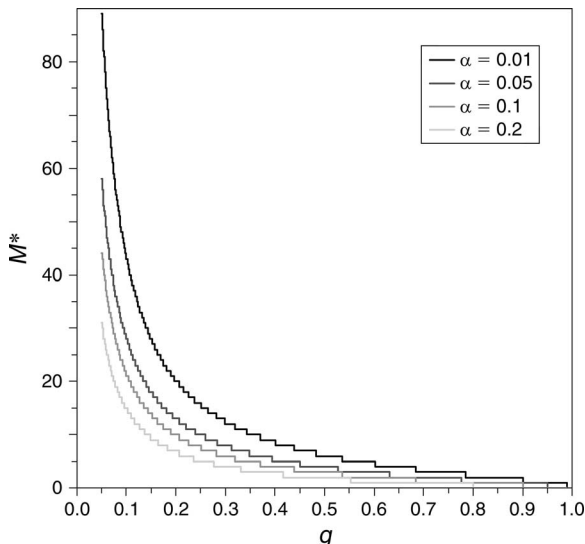


FIG. 5. Dependence of the 100(1- $\alpha$ )% credible maximum fatality at a site ( $M^*$ ) on the probability of detection ( $g$ ) and  $\alpha$  for a uniform prior. The lack of smoothness in the lines is a result of the discrete nature of  $M^*$ .

increases,  $M^*$  decreases and the discrete nature of the  $M^*$  estimates causes the ratios to vary widely (Fig. 6).

The degree of uncertainty in  $g$  appears to have little impact on  $M^*$  when  $g > \sim 0.45$ , but when  $g < 0.3$ ,  $M^*$  increases dramatically as uncertainty about  $g$  increases (Fig. 7). When  $g < 0.1$ , the degree of uncertainty about  $g$  has a profound effect. For example, for a given  $g < 0.1$ , increasing the uncertainty in  $g$  from fixed and known ( $\psi = 1$ ) to highly uncertain ( $\psi = 3$ ) leads to an increase in  $M^*$  by more than a factor of 2 (Fig. 8). As  $g$  increases,

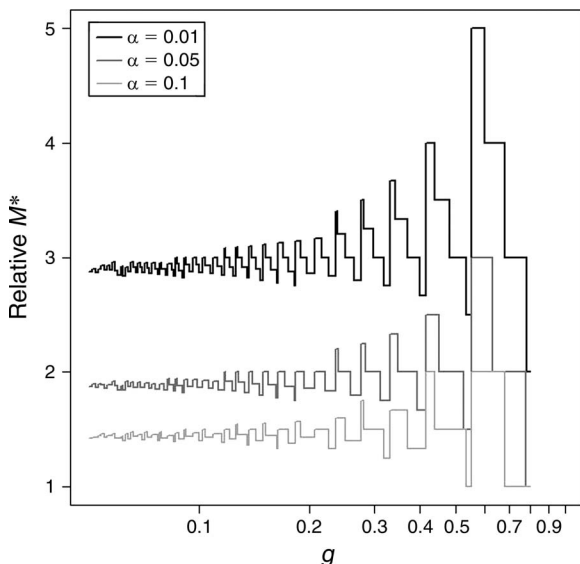


FIG. 6. Fractional increase in the 100(1 -  $\alpha$ )% credible maximum fatality at a site ( $M^*$ ) for  $\alpha = 0.10, 0.05, 0.01$  relative to  $M^*$  for  $\alpha = 0.20$ . The lack of smoothness in the lines is a result of the discrete nature of  $M^*$ .

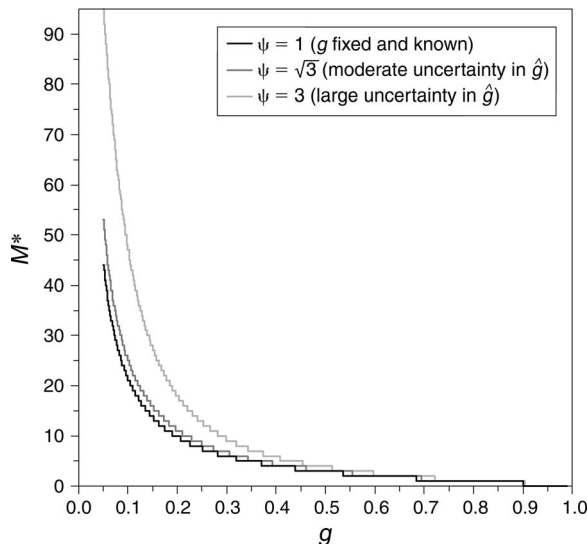


FIG. 7. Dependence of the 90% credible maximum fatality at a site ( $M^*$ ) on the probability of detection ( $g$ ) and the level of uncertainty about  $g$  ( $\psi$ );  $\psi = 1$  for  $g$  fixed and known;  $\psi = \sqrt{3}$  for moderate uncertainty;  $\psi = 3$  for great uncertainty. See Fig. 1 for definition of  $\psi$ .

the influence of uncertainty declines to the point where if  $g > \sim 0.45$ , then  $M^*$  values for highly uncertain  $g$  are identical to  $M^*$  values for fixed  $g$  over 75% of the time and the difference never exceeds 1. For moderate uncertainty ( $\psi = \sqrt{3}$ ), the  $M^*$  values are less than 1.4 times the  $M^*$ s for fixed  $g$  when  $g < 0.1$ , and the ratio decreases gradually until  $g > 0.3$ , where the  $M^*$  values for moderately uncertain  $g$  and fixed  $g$  agree over 90% of the time and never differ by more than 1. Again, as  $g$  increases,  $M^*$  decreases and the discrete nature of the  $M^*$  estimates causes the ratios to vary widely (Fig. 8).

When  $g$  is small, informed prior distributions can markedly decrease  $M^*$  values in comparison with  $M^*$  values derived from a uniform prior (Fig. 9). However, with  $g > \sim 0.35$ , choice of prior distribution had little effect on the resulting  $M^*$  values and the difference never exceeds 1 (Fig. 9).

*Incorporating previous year's observations into prior distribution of  $M$  for current year*

When using a previous year's study to inform the current year's prior at a site, the assumption of more highly variable temporal distribution of  $M$  generally led to greater  $M^*$  values when  $\alpha = 0.01$  and  $g$  was small, but the reverse was true as  $\alpha$  and  $g$  increased (Fig. 10). When  $\alpha > 0.01$ , the difference in  $M^*$  from these assumed temporal distributions of  $M$  was never greater than a single animal (see Fig. 10).

DISCUSSION

Unless detection probability is 1, finding no carcasses does not provide assurance that no animals have been killed. If even small numbers of fatalities are a concern,

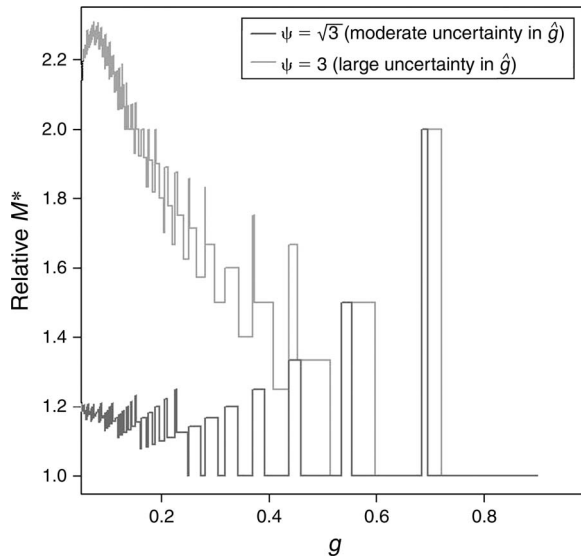


FIG. 8. Ratio of the 90% credible maximum fatality at a site ( $M^*$ ) when the probability of detection,  $g$ , is estimated with moderate uncertainty ( $\psi = \sqrt{3}$ ) and great uncertainty ( $\psi = 3$ ), relative to when  $g$  is fixed and known ( $\psi = 1$ ). See Fig. 1 for definition of  $\psi$ . The lack of smoothness in the lines is a result of the discrete nature of  $M^*$ . The ratio is inestimable beyond  $g = 0.9$  because  $M^* = 0$  for  $\psi = 1$ , hence the ratio is undefined.

then Bayes' theorem can be used to calculate a  $100(1 - \alpha)\%$  credible upper bound  $M^*$  on the number of fatalities that have occurred, even when no carcasses are observed during searches. The value of  $M^*$  depends strongly on both the detection probability  $g$  and on the uncertainty in the estimate of  $g$ . However, the influence of these factors is greatly diminished as  $g$  increases. When  $g > \sim 0.45$ , the difference in  $M^*$  was never greater than a single animal.

Overall, detection probability can often be increased by increasing the number of turbines searched, increasing the area searched under each turbine, improving searcher efficiency (e.g., by clearing vegetation, intensifying searches by narrowing search transect widths, using well-trained dogs; see Mathews et al. 2013), or searching more frequently. Searcher efficiency and carcass persistence are key components of overall detection probability and are typically estimated by means of placing and tracking trial carcasses throughout the sampling season. Increasing the number of carcasses used in the trials increases the precision in estimates of  $g$ , which in turn decreases  $M^*$  values.

Search data from previous years can be used to inform a subsequent year's prior to improve the estimation of  $M$ . This involves assumptions about how  $M$  varies from year to year. Normally, the number of fatalities cannot be assumed to be the same each year, so assumptions about how  $M$  varies through time must be made. With a constant population and a constant probability of an individual being killed,  $M$  would be approximately distributed as a Poisson random variable with variance

equal to the mean. In practice, the fatality rate and the size of the susceptible population would be expected to vary, so  $M$  would likely be more variable than a Poisson. However, if  $M$  is assumed to follow a negative binomial distribution with large variance ( $\sigma^2 = 5\lambda$  or  $\sigma^2 = \lambda + \lambda^2$ ) instead of a Poisson distribution ( $\sigma^2 = \lambda$ ), the effect on  $M^*$  does not appear to be large and the difference in  $M^*$  from these assumed temporal distributions of  $M$  was never greater than a single animal when  $g > 0.3$ .

Adjacent sites with similar landscape characteristics can have substantially differing fatality rates (Arnett et al. 2008, deLucas et al. 2008, Drake et al. 2012, Arnett and Baerwald 2013), so using search data from one site or group of sites to inform the prior at a different site may be difficult to justify.

Setting the credibility level ( $1 - \alpha$ ) involves a compromise between maximizing assurance that a specified level of take has not been exceeded when no carcasses are observed and the implementation costs of achieving the detection probability to satisfy this level of credibility. For example, for  $\tau = 3$ ,  $P(M > \tau | X = 0) \leq 0.2$  can be achieved with  $g \geq 0.33$ , whereas  $P(M > \tau | X = 0) \leq 0.01$  requires  $g \geq 0.68$  (Fig. 5).

*Example case*

Concerns about potential impacts of wind-power development on populations of rare and protected species have been growing since the late 1980s, when reports of possibly hundreds of raptors being killed by turbines in California were published (Orloff and Flannery 1992). Of particular concern have been the large numbers of Golden Eagles (*Aquila chrysaetos*) and

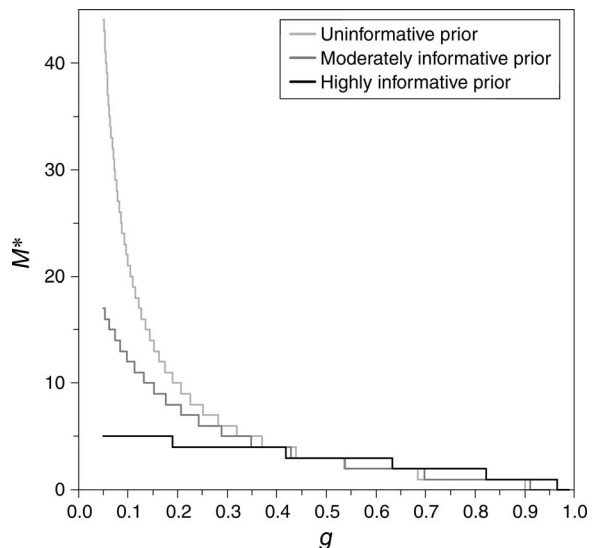


FIG. 9. Dependence of the 90% credible maximum fatality at a site ( $M^*$ ) estimated with uninformative (uniform), moderately informative, and highly informative prior distributions on the actual fatality at a site ( $M$ ) on the probability of detection ( $g$ ). The lack of smoothness in the lines is a result of the discrete nature of  $M^*$ .

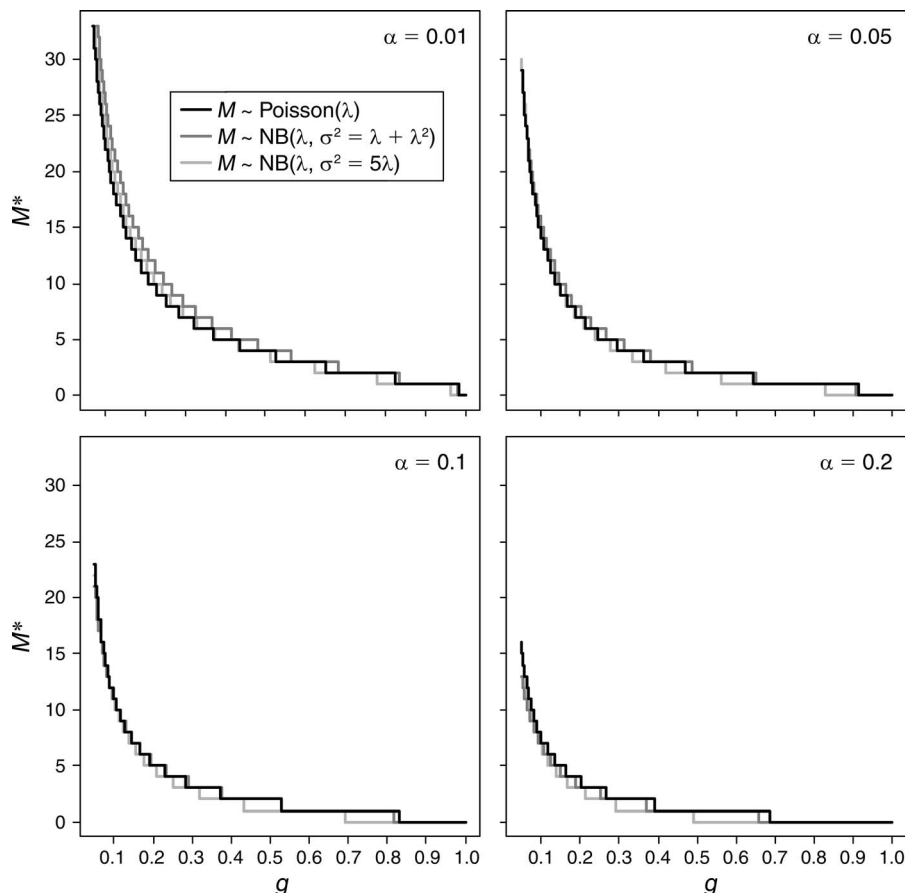


FIG. 10. Dependence of the  $100(1 - \alpha)\%$  credible maximum fatality at a site ( $M^*$ ) estimated with three assumed distributions of the actual fatality of a rare species at a site ( $M$ ) through time on the probability of detection ( $g$ ). The lack of smoothness in the lines is a result of the discrete nature of  $M^*$ . NB is negative binomial.

smaller numbers of Bald Eagles (*Haliaeetus leucocephalus*) estimated to have been killed at sites across the United States (Smallwood and Thelander 2008, Leslie et al. 2013, Pagel et al. 2013). A U.S. wind-power company was recently convicted of violating the Migratory Bird Treaty Act (MBTA) for killing 14 Golden Eagles and dozens of other birds at two wind-power sites in Wyoming (U.S. Department of Justice 2013). In 2009, the U. S. Fish and Wildlife Service (USFWS) was granted the authority to issue incidental take permits (ITPs) for Golden Eagles and Bald Eagles (U.S. Fish and Wildlife Service 2009) that would allow power companies to kill limited numbers of eagles as an unintended consequence of normal operations. Golden Eagle ITPs have been requested for at least 14 sites (Clarke 2013), but USFWS did not issue its first ITP for eagles until June 2014, allowing the Shiloh IV Wind Project to kill up to five Golden Eagles over a five-year period (U.S. Fish and Wildlife Service 2014a). In 2013, USFWS changed its permitting rules to allow issuance of 30-year take permits for eagles (U.S. Fish and Wildlife Service 2013b).

We illustrate the application of our approach at a site in south-central Wyoming where potential turbine-caused fatality of Golden Eagles was of concern (Young et al. 2003). Despite high levels of use of the area by Golden Eagles, no carcasses were observed. However, five carcasses of other raptor species were found during scheduled searches of the facility from November 1998 through June 2002. The authors concluded that “due to low scavenger removal rate and high searcher efficiency for medium and large carcasses it is likely that the [five raptors] found were the only raptors killed . . . during the study period” suggesting that no Golden Eagles were killed.

Using data presented in the report, we reconstruct  $g$  and calculate  $M^*$  such that  $P(M > M^* | \hat{g}, X = 0) \leq 0.1$ . Because sampling protocol changed during the course of the study, we restrict our evaluation to only the final year of monitoring, June 2001–June 2002. The facility is composed of 69 0.6-MW turbines, approximately 40 m at hub-height with a rotor-swept diameter of 42 m and spaced approximately 84 m apart. Every 28 days, trained biologists searched for carcasses within 8–10 m wide linear transects covering all areas within 63 m of a

sample of half the turbines. Searchers removed each detected carcass after recording the species, size, condition, and location of discovery. Auxiliary to the search effort from 1998–2001, researchers conducted experimental trials to estimate both searcher efficiency and the distribution of carcass persistence times. At randomly selected times, carcasses of adult female mallards (representing larger raptors) were placed within the study area and tested either for their detection or persistence. No searcher efficiency or carcass persistence trials were conducted June 2001–June 2002, so estimates from previous years were assumed to apply to this period.

Given the information provided by Young et al. (2003), we estimated  $g$ , the overall probability of detection for large carcasses, to be 0.335 (95% CI: 0.309, 0.355; see Appendix B for details) and assumed an uninformative uniform prior for  $M$ . From this and the fact that no Golden Eagles were found, we find that we can assert with only 34% credibility that no Golden Eagles were killed, but we can assert with 90% credibility that no more than five Golden Eagles were killed during this period. With this level of detection probability, the lack of evidence does not support the suggestion that eagle take was indeed zero.

#### *Limitations*

An uninformative prior is likely the most reasonable option in the first year, but can result in large differences in  $M^*$  relative to an informative prior, particularly when  $g$  is low. However, conflict over choice of an appropriate initial prior can be deflated by assuring  $g$  is at least 0.45, because the effect of the prior on  $M^*$  is minimal when  $g$  is at this level.

We do not address methods for estimating  $g$ . The factors affecting  $g$  include searcher efficiency, carcass persistence times, search intervals, the proportion of carcasses expected to fall in the searched area, the sampling fraction of the turbines, and spatial and temporal variation in all these factors. The point of this exercise is not to address methods of estimating  $g$ , but to provide insight into the effects of detection probability on credible intervals of total take. Our finding that  $g > \sim 0.45$  can result in relatively precise estimates of  $M^*$ , even when  $X = 0$ , supports the idea that with careful design, precise estimates are attainable.

#### *Conservation implications*

When considering take in the context of the Endangered Species Act, we are often concerned with assuring that loss of a species either arising from a consistent source (e.g., power lines, light houses, wind-power facilities) or following a single lethal event (e.g., oil spill, blasting project) does not exceed some limit within a certain area and time period. The credibility with which we can assert that the limit has not been exceeded is dependent on the probability of observing an individual in the population during monitoring to detect

take. Monitoring programs for which the probability of detection of an individual is low cannot provide precise information with which to evaluate the actual effect of the lethal source. Furthermore, if observing no carcasses is interpreted as evidence of no effect, or if there are negative consequences to finding carcasses (e.g., expensive mitigation or prosecution), then there is a perverse incentive to design and implement the most ineffective search protocol possible, i.e., low overall detection probability. If, on the other hand, there are negative consequences to large values of  $M^*$  (e.g., expensive mitigation) due to low probability of detection, then there will be strong incentive to design monitoring protocol to achieve the highest overall detection probability possible.

When a monitoring protocol is designed to achieve a relatively high probability of detection, results can also inform models of risk, providing feedback to refine models to improve their predictive capacity. Increasing the probability of detection will increase credibility, and high levels of credibility are needed when exceeding the set limit could result in further, perhaps irreversible declines in a species at risk, or could result in expensive but perhaps unnecessary mitigation efforts to offset the loss.

Without 100% probability of detection, it will be impossible to assert that no take has occurred, even when no carcasses are observed. When probability of detection is high, observing no carcasses can be construed as evidence that no or few animals have been killed, i.e., evidence of absence. When probability of detection is low, however, finding zero carcasses does not credibly rule out the possibility of a large take. We are left with only absence of evidence. While many factors influence  $M^*$ , our work indicates that their influence is minimal when  $g > \sim 0.45$ .

The actual target level of  $g$  will depend on the set take limit ( $\tau$ ) and the  $100(1 - \alpha)\%$  credible level, but not on species, in a general sense. Of course, achieving a given target level of  $g$  will be much more difficult for a small cryptic species at a site with dense vegetation or steep terrain (e.g., a bat at a wind facility in the Adirondack Mountains) than for a large, easily observed species in flat, open terrain with little vegetation (e.g., an eagle in the Mojave desert). But given the same  $\tau$  and  $\alpha$ , the target level of  $g$  will be the same.

This analysis was motivated by discussions with the U.S. Fish and Wildlife Service managers concerned with assuring that a set level of take of Indiana bats was not exceeded at wind-power facilities, but our approach applies to any species for which detection probability can be estimated and any situation in which the sampling fraction is known or estimable, e.g., oil spills, power line, or fence line searches, etc.

#### ACKNOWLEDGMENTS

We thank T. J. Miller and Dawn Bruns of the U.S. Fish and Wildlife Service (USFWS) for their tireless support of this project. We thank Jessica Kenyon for her rigorous evaluation



of our statistical approach. We thank Ephraim Hanks, Dawn Bruns, and two anonymous reviewers for suggestions that strengthened this manuscript. Funding for this research was provided by the Ecosystems Mission Area Wildlife Program of the U.S. Geological Survey (USGS) and the USFWS. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

## LITERATURE CITED

- Arnett, E. B., and E. F. Baerwald. 2013. Impacts of wind energy development on bats: implications for conservation. Pages 435–456 in R. A. Adams and S. C. Pedersen, editors. *Bat evolution, ecology, and conservation*. Springer Science+Business Media, New York, New York, USA.
- Arnett, E. B., et al. 2008. Patterns of bat fatalities at wind energy facilities in North America. *Journal of Wildlife Management* 72:61–78.
- Arnett, E. B., C. Hein, M. Schirmacher, M. M. P. Huso, and J. M. Szewczak. 2013. Evaluating the effectiveness of an ultrasonic acoustic deterrent for reducing bat fatalities at wind turbines. *PLoS ONE* 8:e65794.
- Arnett, E. B., M. M. P. Huso, M. R. Schirmacher, and J. P. Hayes. 2010. Altering turbine speed reduces bat mortality at wind-energy facilities. *Frontiers in Ecology and the Environment* 9:209–214.
- Barclay, R. M. R., E. F. Baerwald, and J. M. Gruver. 2007. Variation of bird and bat fatalities at wind energy facilities: assessing the effects of rotor size and tower height. *Canadian Journal of Zoology* 85:381–387.
- Barringer, F. 2013. Turbine plans unnerve fans of condors in California. *New York Times*. 25 May 2013.
- Barrios, L., and A. Rodriguez. 2004. Behavioural and environmental correlates of soaring-bird mortality at on-shore wind turbines. *Journal of Applied Ecology* 41:72–81.
- Bayley, P. R., and J. T. Peterson. 2001. An approach to estimate probability of presence and richness of fish species. *Transactions of the American Fisheries Society* 130:620–633.
- Bernardino, J., R. Bispo, H. Costa, and M. Mascarenhas. 2013. Estimating bird and bat fatality at wind farms: a practical overview of estimators, their assumptions and limitations. *New Zealand Journal of Zoology* 40:63–74.
- Bispo, R., J. Bernardino, T. Marques, and D. Pestana. 2013. Modeling carcass removal time for avian mortality assessment in wind farms using survival analysis. *Environmental and Ecological Statistics* 20:147–165.
- Clarke, C. 2013. CA wind facilities want permits that will allow them to harm eagles. *ReWire*, 13 June 2013.
- Cryan, P. M., and R. M. R. Barclay. 2009. Causes of bat fatalities at wind turbines: hypotheses and predictions. *Journal of Mammalogy* 90:1330–1340.
- Dail, D., and L. Madsen. 2011. Models for estimating abundance from repeated counts of an open metapopulation. *Biometrics* 67:577–587.
- deLucas, M., G. Janss, D. P. Whitfield, and M. Ferrer. 2008. Collision fatality of raptors in wind farms does not depend on raptor abundance. *Journal of Applied Ecology* 45:1695–1703.
- Drake, D., S. Schumacher, and M. Sponsler. 2012. Regional analysis of wind turbine-caused bat and bird fatality. *Environmental and Economic Research and Development Program of Wisconsin's Focus on Energy*, Madison, Wisconsin, USA.
- Dupuis, J. A., F. Bled, and J. Joachim. 2011. Estimating the occupancy rate of spatially rare or hard to detect species: a conditional approach. *Biometrics* 67:290–298.
- Erickson, W. P., M. D. Strickland, G. D. Johnson, and J. W. Kern. 2000. Examples of statistical methods to assess risk of impacts to birds from wind plants. Pages 172–181 in LGL Ltd., editor. *National Avian-Wind Power Planning Meeting III*, San Diego, California, USA.
- Etterson, M. A. 2014. Hidden Markov models for estimating animal mortality from anthropogenic hazards. *Ecological Applications* 23:1915–1925.
- Fieberg, J., M. Alexander, S. Tse, and K. St. Clair. 2013. Abundance estimation with sightability data: a Bayesian data augmentation approach. *Methods in Ecology and Evolution* 4:854–864.
- Georgiakakis, P., E. Kret, B. Cárcamo, B. Doutau, A. Kafkaletou-Diez, D. Vasilakis, and E. Papdatou. 2012. Bat fatalities at wind farms in North-Eastern Greece. *Acta Chiropterologica* 14:459–468.
- Hall, L. S., and G. C. Richards. 1972. Notes on *Tadarida australis* (Chiroptera: Molossidae). *Australian Mammalogy* 1:46.
- Hull, C., and S. Muir. 2010. Search areas for monitoring bird and bat carcasses at wind farms using a Monte Carlo model. *Australian Journal of Environmental Management* 17:77–87.
- Huso, M. M. P. 2011. An estimator of wildlife fatality from observed carcasses. *Environmetrics* 22:318–329.
- Huso, M. M. P., and D. H. Dalthorp. 2014. Accounting for unsearched areas in estimating wind turbine-caused fatality. *Journal of Wildlife Management* 78:347–358.
- Korner-Nievergelt, F., P. Korner-Nievergelt, O. Behr, I. Niermann, R. Brinkmann, and B. Hellriegel. 2011. A new method to determine bird and bat fatality at wind energy turbines from carcass searches. *Wildlife Biology* 17:350–363.
- Lehman, R. N., P. Kennedy, and J. Savidge. 2007. The state of the art in raptor electrocution research: a global review. *Biological Conservation* 136:159–174.
- Lehman, R. N., J. A. Savidge, P. L. Kennedy, and R. E. Harness. 2010. Raptor electrocution rates for a utility in the intermountain western United States. *Journal of Wildlife Management* 74:459–470.
- Leslie, D., J. Schwartz, and B. Karas. 2013. Altamont Pass Wind Resource Area bird fatality study, bird years 2005–2011. ICF International, Sacramento, California, USA.
- MacKenzie, D., J. D. Nichols, G. B. Lachman, S. Droege, J. A. Royle, and C. A. Langtimm. 2002. Estimating site occupancy rates when detection probabilities are less than one. *Ecology* 83:2248–2255.
- MacKenzie, D., J. D. Nichols, G. B. Lachman, S. Droege, J. A. Royle, and C. A. Langtimm. 2003. Estimating site occupancy, colonization and local extinction probabilities when a species is not detected with certainty. *Ecology* 84:2200–2207.
- MacKenzie, D., J. D. Nichols, N. Sutton, K. Kawanishi, and L. Bailey. 2005. Improving inferences in population studies of rare species that are detected imperfectly. *Ecology* 86:1101.
- Martin, J., et al. 2014. Estimating upper bounds for occupancy and number of manatees in areas potentially affected by oil from the Deepwater Horizon oil spill. *PLoS ONE* 9:e91683.
- Mathews, F., M. Swindells, R. Goodhead, T. A. August, P. Hardman, D. M. Linton, and D. J. Hosken. 2013. Effectiveness of search dogs compared with human observers in locating bat carcasses at wind-turbine sites: a blinded randomized trial. *Wildlife Society Bulletin* 37:34–40.
- Orloff, S., and A. Flannery. 1992. Wind turbine effects on avian activity, habitat use, and mortality in Altamont Pass and Solano County Wind Resource Areas: 1989–1991. Report to California Energy Commission, Sacramento, California. BioSystems Analysis, Santa Cruz, California, USA.
- Pagel, J. E., K. J. Kritz, B. A. Millsap, R. K. Murphy, E. L. Kershner, and S. Covington. 2013. Bald eagle and golden eagle mortalities at wind energy facilities in the contiguous United States. *Journal of Raptor Research* 47:311–315.
- Peron, G., J. Hines, J. D. Nichols, W. L. Kendall, K. A. Peters, and D. S. Mizrahi. 2013. Estimation of bird and bat mortality at wind-power farms with superpopulation models. *Journal of Applied Ecology* 50:902–911.
- R Development Core Team. 2013. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. [www.r-project.org](http://www.r-project.org)



- Rogers, S. E., B. W. Cornaby, C. W. Rodman, P. R. Sticksel, and D. A. Tolle. 1977. Environmental studies related to the operation of wind energy conversion systems. U.S. Department of Energy, Columbus, Ohio, USA.
- Royle, J. A., and J. D. Nichols. 2003. Estimating abundance from repeated presence-absence data or point counts. *Ecology* 84:777–790.
- Royle, J. A., J. D. Nichols, and M. Kéry. 2005. Modelling occurrence and abundance of species when detection is imperfect. *Oikos* 110:353–359.
- Shoenfeld, P. 2004. Suggestions regarding avian mortality extrapolation. Report for the West Virginia Highlands Conservancy. West Virginia Highlands Conservancy, Charleston, West Virginia, USA.
- Schwarz, C. J., and G. A. Seber. 1999. Estimating animal abundance: review III. *Statistical Science* 14:427–456.
- Seber, C. A. F. 1982. Estimation of animal abundance and related parameters. Hafner Press, New York, New York, USA.
- Smallwood, K. S., and C. Thelander. 2008. Bird mortality in the Altamont Pass Wind Resource Area, California. *Journal of Wildlife Management* 72:215–223.
- U.S. Bureau of Land Management. 2013. Final environmental impact statement, Alta East Wind Project, (CACA 52537). Volume 2A. U.S. Department of the Interior, Bureau of Land Management, California, Ridgecrest, California, USA.
- U.S. Department of Justice. 2013. Utility company sentenced in Wyoming for killing protected birds at wind projects. *Justice News* 13-1253.
- U.S. Fish and Wildlife Service. 2007. Endangered and threatened wildlife and plants; permits. *Federal Register* 72(239):70885–70887.
- U.S. Fish and Wildlife Service. 2009. Eagle permits; take necessary to protect interests in particular localities. *Federal Register* 74:46836–46879.
- U.S. Fish and Wildlife Service. 2010. Endangered and threatened wildlife and plants; Indiana bat; notice of intent to prepare an environmental impact statement on a proposed habitat conservation plan and incidental take permit. *Federal Register* 75:48359–48360.
- U.S. Fish and Wildlife Service. 2011a. Draft environmental impact statement and habitat conservation plan for commercial wind energy developments within nine states. *Federal Register* 76:41510–41513.
- U.S. Fish and Wildlife Service. 2011b. Kaheawa wind power I—proposed permit amendment to reduce the take of federally protected species available for public comment. PIFWO-11-08 RO-11-177, 30 November 2011. Pacific Island Fish and Wildlife Office, Honolulu, Hawaii, USA. [http://www.fws.gov/pacificislands/news%20releases/News%20Release%20Kaheawa%20I%20Amendment\\_NR\\_final\\_113011.pdf](http://www.fws.gov/pacificislands/news%20releases/News%20Release%20Kaheawa%20I%20Amendment_NR_final_113011.pdf)
- U.S. Fish and Wildlife Service. 2012a. Availability of a draft environmental impact statement and habitat conservation plan; receipt of an application for an incidental take permit, Buckeye Wind Power Project, Champaign County, OH. *Federal Register* 77:38819–38821.
- U.S. Fish and Wildlife Service. 2012b. Draft environmental assessment, habitat conservation plan, and application for an incidental take permit for Indiana bat, Criterion Power Partners, LLC. *Federal Register* 77:45368–45369.
- U.S. Fish and Wildlife Service. 2012c. Draft Midwest wind energy multi-species habitat conservation plan within eight-state planning area. *Federal Register* 77:52754–52755.
- U.S. Fish and Wildlife Service. 2012d. U.S. Fish and Wildlife Service Land-based wind energy guidelines. U.S. Fish and Wildlife Service, Arlington, Virginia, USA. <http://www.fws.gov/windenergy/guidance.html>
- U.S. Fish and Wildlife Service. 2013a. Draft environmental impact statement, draft habitat conservation plan, draft programmatic agreement, and draft implementing agreement; application for an incidental take permit, Fowler Ridge Wind Farm, Benton County, Indiana. *Federal Register* 78:20690–20692.
- U.S. Fish and Wildlife Service. 2013b. Eagle permits; changes in the regulations governing permitting. *Federal Register* 78:73704–73725.
- U.S. Fish and Wildlife Service. 2013c. Record of decision. Proposed issuance of a section 10(a)(1)(B) incidental take permit to Beech Ridge Energy LLC and Beech Ridge Energy II LLC for the Beech Ridge Wind Energy Project, December 2013. U.S. Department of the Interior, Fish and Wildlife Service, Hadley, Massachusetts, USA.
- U.S. Fish and Wildlife Service. 2014a. Golden eagles; programmatic take permit decision; finding of no significant impact of final environmental assessment; Shiloh IV Wind Project, Solano County, California. *Federal Register* 79:36552–36553.
- U.S. Fish and Wildlife Service. 2014b. U.S. Fish and Wildlife Service announces final habitat conservation plan for Indiana wind farm. 16 January 2014. Midwest Region Fish and Wildlife Office, Bloomington, Minnesota, USA. <http://www.fws.gov/midwest/news/706.html>
- Warren-Hicks, W., J. Newman, R. Wolpert, B. Karas, and L. Tran. 2013. Improving methods for estimating fatality of birds and bats at wind energy facilities. California Wind Energy Association, Berkeley, California, USA.
- White, G. 2008. Closed population estimation models and their extensions in Program MARK. *Environmental and Ecological Statistics* 15:89–99.
- Williams, K. A., P. C. Frederick, and J. D. Nichols. 2011. Use of the superpopulation approach to estimate breeding populations size: an example in asynchronously breeding birds. *Ecology* 92:821–828.
- Young, D. P., Jr., W. P. Erickson, R. E. Good, M. D. Strickland, and G. D. Johnson. 2003. Avian and bat mortality associated with the initial phase of the Foote Creek Rim windpower project, Carbon County, Wyoming. Pacificorp, Portland, Oregon, USA.

#### SUPPLEMENTAL MATERIAL

##### Ecological Archives

Appendices A and B and the Supplement are available online: <http://dx.doi.org/10.1890/14-0764.1.sm>