

Wind energy development: methods to assess bird and bat fatality rates post-construction

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Abstract: Monitoring fatalities at wind energy facilities after they have been constructed can provide valuable information regarding impacts of wind power development on wildlife. The objective of this monitoring is to estimate abundance of a super-population of carcasses that entered the area within a designated period of time. By definition, the population is not closed and carcasses can enter as they are killed through collision with turbines, and leave as they are removed by scavengers or decompose to a point where they are not recognizable. In addition, the population is not inherently mobile, but can only change location through some external force. A focus on number of animal carcasses comprising the super-population, combined with peculiar traits that resist classic assumptions, distinguish fatality estimation at wind-power facilities from more classic abundance estimates that can be addressed through mark-recapture techniques or other well-known abundance estimators. We review the available methods to estimate the super-population of carcasses at wind power facilities. We discuss the role of these estimates in determining appropriate levels of minimization and mitigation of impacts to individual species of concern. We discuss the potential to extrapolate these measurements to reflect the cumulative effect of the industry on individual species. Finally, we suggest avenues of research needed to strengthen our understanding of the effect wind power development has, and might have in the future, on wildlife on this continent and worldwide.

Key words: Bayes' theorem, credible intervals, detection probability, fatality estimator

AN UNINTENDED CONSEQUENCE of wind power development is bird and bat fatality caused by collisions with the turbines. When affected species are already threatened or endangered, this new source of mortality may further inhibit their ability to recover. Unbiased estimates of the fatality caused by wind power facilities (WPF) are critical to understanding the effect of wind power on birds and bats.

Accurate estimation will allow evaluation of impacts relative to species population numbers and effective methods of mitigation or minimization (Baerwald et al. 2009, Arnett et al. 2010, Arnett et al. 2013), and comparison of impacts among different WPFs, across regions, over time, and across experimental treatments (Arnett et al. 2008).

Accurate estimation is complicated because many animals killed at a facility may go undetected. When conducting post-construction surveys of animal carcasses, researchers collect a time series of the number of unique carcasses detected

during each search, where detected carcasses are removed, marked, or otherwise restricted from being counted twice. It has long been recognized that these counts do not represent all individuals entering the population of carcasses, as some may 1) fall outside the searched area; 2) be removed by scavengers or deteriorate beyond recognition prior to detection; or 3) remain undiscovered by searchers even when present (Rogers et al. 1977). Models of spatial distribution of carcasses can be used to estimate the fraction of carcasses landing outside the searched area (Huso and Dalthorp 2014a). Independent trials are conducted parallel to the search process to estimate the probability that a carcass persists until the next search and to estimate the probability that it is then discovered by a searcher. In persistence trials, marked carcasses are placed in the field and monitored periodically (e.g., once per day on days 1, 2, 3, 4, 7, 10, 14, 21, and 28 after carcass placement) until they are no longer present or the study period ends. Parametric or non-parametric persistence models

are fit to the trial data to give the probability of persistence as a function of time since carcass placement. In searcher efficiency trials, marked carcasses are placed in the field for discovery by search teams in the normal course of monitoring. All estimators of wind turbine-caused bird and bat fatality must account for these primary sources of imperfect detection, each of which will lead to an underestimate of fatality if ignored, or a biased estimator if incorrectly modeled.

If detection probability were constant, there would be no need to develop an estimator that adjusts observed counts for imperfect detectability; observed counts could be used as a simple index of fatality (Huso 2011). But detectability varies with time, location, species characteristics, and other factors, so direct comparison is no longer possible, and differences in detectability must be incorporated into estimates to allow meaningful comparisons.

Estimators of bird and bat fatality

Since the late 1990s, several estimators of fatality at WPFs have been proposed, each suggesting an improvement over previous estimators (Bernardino et al. 2013, Warren-Hicks et al. 2013). All are elaborations of a simple model of number of observed carcasses (X) as a binomial random variable dependent on actual number of fatalities (F) and probability of detection (g), or $X \sim \text{binomial}(F, g)$, and F is estimated as $\hat{F} = X/g$. When g is a known constant, this estimator is unbiased. However, in practice, g is not known and must be estimated by \hat{g} . The estimator $\hat{F} = X/\hat{g}$ is not unbiased, although it might be approximately so (Thompson 1992) and is inherently more variable than X/g . Furthermore, detection probability varies in space and time. Even within a search plot at a single turbine, the detection probability may vary greatly due to vegetation patterns, ground texture, scavenging rates, time of year, and search schedule; effects of each of these may vary with size, age, and other characteristics of the carcass. In addition, search conditions, including search personnel, at different turbines within a site, different sites within a region, and different times of year or different years may also vary. To account for the variation, the entire area and period of interest is typically divided into i classes or subunits, reflecting combinations of location, time, and carcass characteristics, each with a (potentially)

different probability of detection g_i . Data for the separate classes (X_i and \hat{g}_i) are then combined to estimate the total number of fatalities at a site. Two methods of doing so are: (1) estimate the fraction of carcasses that arrive in each class as \hat{a}_i (including the unsearched area with detection probability 0) and the total fatality as $\hat{F} = \sum X_i / \sum \hat{a}_i \hat{g}_i$, or (2) $\hat{F} = (\sum X_i / \hat{g}_i) / \hat{a}$ where \hat{a} is the estimated fraction of carcasses that arrive in the searched area and summation is over all i such that $\hat{g}_i > 0$.

The estimators differ primarily in their assumptions about carcass removal and search processes, which can lead to substantial differences in estimates of g_i and ultimately of F . We briefly summarize these differences below with parameters defined in Table 1.

Erickson et al. (2000a) formulated the simple and intuitively attractive estimator:

$$\hat{g}_i^E = \frac{\hat{t}_i}{I} \hat{p}_i$$

where \hat{t}_i is the estimated average carcass persistence time (from time of death to removal by scavengers) and \hat{p}_i is estimated searcher efficiency in the i th subunit. Although it was used in many early fatality studies, the estimator relies on an implicit assumption that the carcass population is in a steady state, with carcass arrivals and removals in balance (Shoenfeld 2004). That balance is routinely disrupted by removal of carcasses upon discovery by search teams. As a result, the estimator tends to have a negative bias and underestimates fatality rates unless the search interval is much longer than average persistence time (Wolpert 2013).

Shoenfeld (2004) proposed an alternative, "periodic" estimator that circumvents the steady-state assumption of \hat{g}_i^E by introducing an adjustment factor to account for removal of carcasses after observation:

$$\hat{g}_i^S = \frac{\hat{t}_i}{I} \hat{p}_i \left(\frac{e^{I/\hat{t}_i} - 1}{e^{I/\hat{t}_i} - 1 + \hat{p}_i} \right)$$

The estimator is an important improvement over \hat{g}_i^E but still suffers from 2 implicit assumptions that appear unrealistic in common situations. First, \hat{g}_i^S assumes that scavenging rate is constant and does not depend on carcass age; however, fresh and aged carcasses may not be equally attractive to scavengers and may be removed at different rates (Bispo et al. 2013,

Péron et al. 2013, Warren-Hicks et al. 2013). Second, \hat{g}_i^S relies on the assumption that searcher efficiency is the same for all searches and that carcasses that have been missed in ≥ 1 searches are no more difficult to find than carcasses that are found on the first search after arrival (i.e., $k = 1$). However, carcasses tend to become more difficult to observe as they age (Wolpert 2013), and carcasses that search teams find and remove tend to be those that are relatively easy to find, leaving behind carcasses that are more difficult to observe (Huso 2011, Korner-Nievergelt et al. 2011). In practice, these mistaken assumptions systematically lead to underestimates of fatality. The degree of bias depends on how closely the assumptions are met, which varies by site and year.

Huso (2011) proposed the estimator $\hat{g}_i^H = \hat{p}_i \hat{r}_i$, where \hat{r}_i is the probability that a carcass persists unscavenged until a search. This relaxes the assumption that carcass persistence follows an exponential distribution and allows any form of persistence distribution, such as Weibull, log-normal, or log-logistic. For a given survival function S (where $S = 1 -$ cumulative distribution function of persistence times), \hat{r}_i can be calculated:

$$\hat{r}_i = \int_0^{I_i} \hat{S}_i(t) dt / I_i$$

where I_i is the length of the search interval for subunit i . An explicit assumption is that carcasses that are missed in one search are not discoverable in later searches (i.e., $k = 0$). In practice, that assumption can be met by including in X only those carcasses believed to have been killed in the interval preceding their discovery. Huso (2011) further introduced the concept that p may not be constant (i.e., $0 \leq k \leq 1$) and tested robustness of the estimator under this condition.

Korner-Nievergelt et al. (2011; note erratum in Formula 2) incorporated $0 \leq k \leq 1$ into their estimator, noting that with removal of many easily detectable carcasses in the first search, "searcher efficiency for a cohort of carcasses will... decrease in repeated searches." Korner-Nievergelt et al. (2011) modeled the decrease in searcher efficiency as $p_j = p \cdot k^{j-1}$, where j is the number of searches that have been conducted after arrival of a carcass and $0^0 \equiv 1$. Accommodating $0 \leq k \leq 1$ (instead of requiring $k = 0$ or $k = 1$) results in a more complicated estimator:

$$\hat{g}_i^K = \frac{A \hat{p}_i \left(n + \sum_{h=2}^n \sum_{j=1}^{h-1} (\hat{k}^{h-j} \hat{r}_{1i}^{(h-j)I_i} \prod_{s=0}^{h-j-1} (1 - \hat{p}_i \hat{k}^s)) \right)}{n I_i}$$

where $A = \hat{r}_{1i} \left(\frac{1 - \hat{r}_{1i}^{I_i}}{1 - \hat{r}_{1i}} \right)$

and \hat{r}_{1i} is the estimated daily persistence probability for a carcass in class i . With this formulation, the estimator assumes carcasses arrive only at the beginning of search intervals and persistence distribution is exponential, but an updated model (Korner-Nievergelt et al. 2015) offers options for other persistence distributions and for carcasses to arrive uniformly within search intervals.

Wolpert (2013) introduces a generalized, partially periodic fatality estimator that can accommodate non-constant scavenging rates, $k \in [0,1]$, and searcher efficiency that varies continuously with season and/or carcass age:

$$\hat{g}_i^W = \sum_{j=0}^{\infty} \theta^j \int_{jI_i}^{(j+1)I_i} S(t) p(t) \prod_{1 \leq n \leq j} [1 - p(t - nI_i)] dt / I_i$$

where θ is the proportion of carcasses that are not discovered in one search but remain discoverable in the next search (bleed-through), and searcher efficiency is expressed as a function of time to account for decreases in detectability due to carcass aging. Wolpert's (2013) estimator essentially includes the Erickson et al. (2000b), Shoenfeld (2004), Huso (2011), and Korner-Nievergelt et al. (2015) estimators as special cases, although some minor features of Huso (2011) and Korner-Nievergelt et al. (2015) are not incorporated.

Dalthorp et al. (2014) offered an estimator

$$\hat{g}_i^D = \sum_j \sum_h \prod_{i=0}^{j-h-1} (1 - k^i p) k^{j-h} p \int_{t_{h-1}}^{t_h} S(t_j - t) v(t) dt$$

where v is the relative arrival rate of carcasses through the monitoring season (so $\int v(t) dt = 1$). The estimator is similar to Wolpert's (2013) but allows for non-constant carcass arrival functions and, following Korner-Nievergelt et al. (2011), combines effects of bleed-through and carcass aging on searcher efficiency into a single factor, k .

In addition to these estimators, two others based on mark-recapture methods have been proposed. Péron et al. (2013) acknowledge that p and r may vary with time since death because of intrinsic changes in carcass properties with age

and environmental heterogeneity (preferential removal of easy-to-detect carcasses). They propose a 2-class age structure that ultimately requires estimating a large number of parameters ($6n$). However, when applying their model to a case study, identifiability problems as well as data collection methods inconsistent with model needs, forced them to abandon the time-varying parameter approach and return to the restrictive assumptions that within age class, persistence time is exponential and p remains constant among searches (i.e., $k = 1$; Péron et al. 2013).

Etterson (2013) also developed a mark-recapture-based approach, showing the similarities and differences with Shoenfeld's (2004) and Huso's (2011) approaches. Both Etterson's (2013) and Péron et al.'s (2013) mark-recapture-based approaches are appealing in that their foundation in the mark-recapture literature is well established, but both require significant changes to typical post-construction survey protocol, mainly that each search must be conducted by 2 independent observers searching (almost) simultaneously and without alerting the other to discovery of any carcass. Both approaches take advantage of observed carcasses and the double sampling process to obviate the need for searcher efficiency and carcass persistence trials to estimate detection parameters and allow searcher efficiency to decline with search (i.e., $k < 1$). However, Etterson (2013) points out that to do this in practice, a large number of animals killed is required to obtain a sufficient number of carcasses detected by both observers to allow precise estimation of p and r without additional experimental trial data.

Combining probability of detection within search classes to estimate overall probability of detection

After monitoring is complete, carcass counts (X_i) have been compiled, and detection probabilities (\hat{g}_i) have been estimated for search classes $i = 0, 1, \dots, N$, data from the N search classes (with $i = 0$ designating the unsearched area, so $g_0 = 0$) can be combined into an estimate of the overall detection probability for carcasses at the site (including those falling in searched and unsearched areas) during the monitoring period. If the proportion of carcasses (a_i with $\sum_{i=0}^N a_i = 1$) in each search class i is known, then the overall detection probability can be estimated as the

weighted average of the \hat{g}_i 's, or $\hat{g} = \sum a_i \hat{g}_i$ and total number of fatalities estimated as

$$\hat{F}^{EA} = \frac{\sum X_i}{\sum a_i \hat{g}_i}$$

(Dalthorp et al. 2014). In practice, the a_i 's are not known, and accurate estimation may be difficult. When $\sum X_i$ is not small (≥ 10), the search classes can be empirically self-weighted by the data, and the total estimated as $\hat{F}^{HT} = \sum (X_i / \hat{g}_i)$ (Horvitz and Thompson 1952) where summation is over all i such that $\hat{g}_i > 0$, which is the approach taken by Huso (2011) and Wolpert (2013). However, when few carcasses are found (< 5), the variance of \hat{F}^{HT} can be quite large compared to the mean, and mean squared error of \hat{F}^{EA} will be $< \hat{F}^{HT}$ even with a moderate to high degree of misspecification in the a_i 's. We address this situation in the next section.

Endangered species and evidence of absence

A problem arises in estimating fatality when few or no carcasses are actually observed. Counts of 0 can be observed either because few or no animals were actually killed, or because detection probabilities were low and some, perhaps many animals were killed, but missed in the search process. Distinguishing these 2 cases is critical when the focal species is protected under legislation and few or no fatalities are permitted. If $X = 0$, Horvitz-Thompson-based estimators can only return estimates of 0 with no variance and no confidence interval. However, if detection probability is low, $X = 0$ provides little assurance that there were not large numbers of fatalities (Huso et al. 2015).

Dalthorp et al. (2014) provide an approach to estimation that is specially tailored for use with rare events or when observed carcass counts are low, such as take of endangered species. It uses a generalized estimator to calculate \hat{g} from the search parameters and then uses Bayes' theorem to calculate a posterior distribution for total number of fatalities:

$$P(F = f | \hat{g}, X) = \frac{P(X|F = f, \hat{g})P(F=f)}{\sum_j P(X|F = j, \hat{g})P(F=j)}$$

The posterior distribution is a representation of what is known about the total number of fatalities that occurred during the monitoring period. It is

Table 1. Definitions of parameters used in estimator equations.

Parameter	Definition
I	length of the search interval (days); may be irregular
a	proportion of wind turbine-caused fatalities landing in the searched area
$S(t)$	probability that carcass persists at least t days after arrival
r	proportion of carcasses expected to persist through the search interval
\bar{t}	average persistence time for a carcass (days)
p	proportion of carcasses in searched area that are discovered by searcher
k	factor by which p changes with each search
n	number of searches conducted during study ($n\bar{I}$ = total study period)
g	probability of observing a carcass that arrives during the study period

especially useful for defining credible intervals for fatality levels that are consistent with monitoring data and providing a quantitative assessment of strength of evidence that take did not exceed a specified threshold, and in the context of a regulatory program, degree of certainty that compliance is achieved.

The approach works well in the regulatory context of the U.S. Endangered Species Act and the Bald and Golden Eagle Protection Act, under which the U.S. Fish and Wildlife Service (USFWS) can issue a permit for “incidental take” (ITP) of a protected species. The application for an incidental take permit for an endangered species requires a Habitat Conservation Plan (HCP) that identifies anticipated impact of the take and outlines steps the applicant will implement to minimize and mitigate the impact of the taking. The HCP uses information from the species’ Recovery Plan, which outlines threats to the species throughout its range and any known methods to reduce or ameliorate these threats to achieve clearly defined biological goals and objectives to manage and recover the species. Before issuing an ITP, the USFWS must conclude that the anticipated conservation provided by the measures proposed is sufficient to ensure that the project will not jeopardize the continued existence of the species. States may add further requirements; for example, Hawai’i requires that the HCPs provide assurance of a net benefit of

the conservation measures proposed to minimize and mitigate the impact of the taking.

Post-construction fatality monitoring provides a measure of compliance with permitted take limits and effectiveness of required minimization measures. If monitoring demonstrates that take is less than anticipated, then the required mitigation may provide additional net benefit to the covered species than originally projected. If monitoring demonstrates that take is occurring at a faster rate than anticipated, then adaptive management may

be required to reduce take so that the authorized take level is not exceeded and additional mitigation may be necessary to offset impact of the take. Alternatively, the wwwHCP may be amended and resubmitted with an application requesting an increase in permitted incidental take.

In a simplistic example, suppose a company is required to provide 90% assurance that take did not exceed the permitted limit of 5 individuals. Carcass persistence and searcher efficiency trials were conducted and a search schedule was designed; g was determined to be 0.3. Although no carcasses were found in searches, with $g = 0.3$ we would expect to miss 70% of the carcasses that were generated. If there were 2 or 3 fatalities, it would not be a surprise to find 0 carcasses, so strength of the monitoring protocol was not sufficient for ruling out 2 or 3 fatalities. But if there were 20 or 30 fatalities, we would be almost certain to find at least a few carcasses; after finding 0, we could effectively rule out 20 or 30 fatalities. But could we rule out the permitted take limit of 5 fatalities? The posterior distribution (Dalthorp et al. 2014) can be used to quantify the level of credibility for asserting that take did not exceed the limit of 5. In this example, $P(M \leq 5 | \hat{g} = 0.3, X = 0) = 0.883$, which falls short of the required 90% credibility level, suggesting that a more rigorous monitoring protocol that achieves a greater detection probability may be needed.

System-wide monitoring

If all estimators were unbiased and had similar variance, then comparing fatality rates between facilities, or estimates of cumulative fatality within regions, could be made without concern for which estimator was used at each facility. However, accuracy of an estimator depends on how well its implicit assumptions match conditions in the field, which can vary among sites, years, seasons, different areas within a single facility (e.g., vary by vegetation cover, scavenging rates, search schedule, quality of observers, and configuration and size of searchable areas). Simple estimators (e.g., Erickson et al. 2000b, Shoenfeld 2004) that implicitly assume constant searcher efficiency and scavenging rates may be reasonably accurate under certain conditions but highly biased (typically underestimating) under other conditions. If an estimator does not adequately model conditions in the field, then differences in estimated fatalities among sites or years may reflect differences in scavenging and search conditions more than differences in actual fatalities. Therefore, it is essential to use estimators that are accurate under a broad range of conditions. Generalized estimators (e.g., Wolpert 2013, Dalthorp et al. 2014) allow for non-constant searcher efficiency and scavenging rates and are accurate under a much wider array of conditions than are simple estimators. By assuming $k = 0$, Huso's (2011) estimator exchanges the problem of accurately estimating k for the problem of accurately determining carcass age (i.e., whether an observed carcass arrived before or after the previous search) and allows for non-constant scavenging rates. In practice, although Huso's (2011) estimator resembles the simple estimators in form, it is probably more akin to the general estimators in consistency and accuracy.

Current approaches for take and impact assessment are based on concern for species that are currently protected under federal legislation. As environmental pressures mount, the list of protected species may change, and accurate numbers of turbine-caused fatality estimates will be needed to assess population-level impacts. For example, white-nose syndrome has devastated populations of cave-roosting bats in the northeastern United States (Frick et al. 2010) in only a few years. Although *Myotis* spp. populations might have been capable of absorbing turbine-caused fatality 10 years ago,

these impacts need to be reconsidered in today's context.

Future directions

Piorkowski et al. (2012) reported development of standardized fatality estimators as the number one research priority to measure potential impact of wind energy development on bird and bat populations. Clearly, an all-encompassing, generalized estimator of fatality that is flexible with respect to assumptions regarding carcass arrival patterns, persistence distributions, and searcher efficiency would be welcome. In addition to possessing desirable statistical qualities of unbiasedness, consistency, and minimum variance, it would need to be accessible to non-statisticians, perhaps through specialized software (e.g., Huso et al. 2012, Korner-Nievergelt et al. 2015). Included in the software could be modules to calculate necessary parameters from ancillary trial data such as searcher efficiency trials, carcass persistence trials, or from carcass location data (to estimate the fraction of carcasses likely to land in the search area).

While the Land-based Wind Energy Guidelines (U.S. Fish and Wildlife Service 2012) provide an overarching voluntary context for post-construction fatality monitoring, specific recommendations and example protocols to conduct post-construction monitoring are lacking and would be very useful in removing some of the unnecessary ambiguity or imprecision of current estimates of fatality. Dalthorp et al. (2014) developed a design tool to calculate Bayesian credible intervals (CIs) for fatality when 0 or few carcasses are observed. A similar tool could be developed for general fatality monitoring with an objective of achieving a stated level of precision for the estimated fatality.

A well-designed assessment of current and projected cumulative level of impact of wind development on bird and bat populations would provide important information to scientists as well as policymakers and managers who rely on science to provide the best information possible on which to base their decisions. An evaluation of national and regional impacts of wind power could be based on a selection of sites that accurately reflect wind power development in the United States and unbiased fatality estimates at each site (Huso and Dalthorp 2014b), which may not be achievable with current publicly

available data. Site-specific estimates have been based on different methodologies, and methodologies differ so widely among sites that estimates from individual sites cannot be compared or combined (Huso 2011). States and regions differ greatly in their requirements to monitor and make results publicly available, so that even a random sample of available data may not be representative of the industry as a whole (Warren-Hicks et al. 2013). Currently, accuracy of regional or national cumulative-fatality estimates is hampered by these shortcomings in unpredictable ways so that an accurate estimate of cumulative impact is not possible at this time.

But this is not to say it is impossible. A coordinated program to estimate fatality rates of birds and bats in North America could begin with a statistically-based selection of sites to be monitored. At each of these, consistent and appropriate monitoring protocols could be applied to ensure that quality of data collected would be adequate. Finally, data should be processed using an unbiased estimator of fatality. Costs of such a program would not be trivial, but it could be achieved with relatively little additional cost over what is currently required by state and federal agencies, through a coordinated effort, collaboration, and pooled resources among all stakeholders (i.e., industry, government, conservation groups). The resulting estimates would provide valuable insight into impact of wind power on birds and bats in the United States, information that developers, managers, and policymakers use to inform decisions affecting the future of power generation as well as wildlife on this continent. Such a program could serve as an example to other countries or regions of the world interested in understanding regional impacts of wind power development on wildlife.

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Literature cited

Arnett, E. B., W. K. Brown, W. P. Erickson, J. K.

- Fiedler, B. L. Hamilton, T. H. Henry, A. Jain, G. D. Johnson, J. Kerns, R. R. Koford, C. P. Nicholson, T. J. O'Connell, M. D. Piorkowski, and R. D. Tankersley, Jr. 2008. Patterns of bat fatalities at wind energy facilities in North America. *Journal of Wildlife Management* 72:61–78.
- Arnett, E. B., C. D. 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(6): 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.
- Baerwald, E. F., J. Edworthy, M. Holder, and R. M. R. Barclay. 2009. A large-scale mitigation experiment to reduce bat fatalities at wind energy facilities. *Journal of Wildlife Management* 73:1077–1081.
- 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. A. 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.
- Dalthorp, D. H., M. M. P. Huso, D. Dail, and J. Kenyon. 2014. Evidence of Absence Software. Corvallis, OR: USGS. ISBN. Available online at <http://pubs.usgs.gov/ds/0881/>.
- Erickson, W. P., G. D. Johnson, M. D. Strickland, and K. Kronner. 2000a. Avian and bat mortality associated with the Vansycle Wind Project, Umatilla County, Oregon 1999 study year. Umatilla County Department of Resource Services and Development, Pendleton, Oregon, and Cheyenne, Wyoming, USA.
- Erickson, W. P., M. D. Strickland, G. D. Johnson, and J. W. Kern. 2000b. Examples of statistical methods to assess risk of impacts to birds from wind plants. Pages 172–181 *in* Proceedings of the National Avian–Wind Power Planning Meeting III. Avian Subcommittee of the National Wind Coordinating Committee, Washington, D.C., USA.
- Etterson, M. A. 2013. Hidden Markov models for estimating animal mortality from anthropogenic

- hazards. *Ecological Applications* 23:1915–1925.
- Frick, W. F., J. F. Pollock, A. C. Hicks, K. E. Langwig, D. S. Reynolds, G. G. Turner, C. M. Butchkoski, and T. H. Kunz. 2010. An emerging disease causes regional population collapse of a common North American bat species. *Science* 329:679–682.
- Horvitz, D. G., and D. J. Thompson. 1952. A generalization of sampling without replacement from a finite universe. *Journal of the American Statistical Association* 47:663–685.
- Huso, M. M. P. 2011. An estimator of wildlife fatality from observed carcasses. *Environmetrics* 22:318–329.
- Huso, M. M. P., D. Dalthorp, D. Dail, and L. Madsen. 2015. Estimating wind-turbine-caused bird and bat fatality when zero carcasses are observed. *Ecological Applications* 25:1213–1225.
- Huso, M. M. P., and D. H. Dalthorp. 2014a. Accounting for unsearched areas in estimating wind turbine-caused fatality. *Journal of Wildlife Management* 78:347–358.
- Huso, M. M. P., and D. H. Dalthorp. 2014b. A comment on "Bats killed in large numbers at United States wind energy facilities." *Bioscience* 64:546–547.
- Huso, M. M. P., N. Som, and L. Ladd. 2012. Fatality estimator user's guide. U.S. Geological Survey Data Series 729.
- Korner-Nievergelt, F., O. Behr, R. Brinkmann, M. A. Etterson, M. Huso, D. H. Dalthorp, P. Korner-Nievergelt, T. Roth, and I. Niermann. 2015. Mortality estimation from carcass searches using the R-package carcass – a tutorial. *Wildlife Biology* 21:30–43.
- 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.
- Péron, G., J. E. 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.
- Piorkowski, M. D., A. J. Farnsworth, M. Fry, R. W. Rohrbaugh, J. W. Fitzpatrick, and K. V. Rosenberg. 2012. Research priorities for wind energy and migratory wildlife. *Journal of Wildlife Management* 76:451–456.
- 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 Technical Report COO-0092-77/2, Columbus, Ohio, USA.
- Shoenfeld, P. 2004. Suggestions regarding avian mortality extrapolation. Report for the West Virginia Highlands Conservancy, Hillsboro, West Virginia, USA.
- Thompson, S. K. 1992. Sampling. First edition. John Wiley and Sons, New York, New York, USA.
- U.S. Fish and Wildlife Service. 2012. U.S. Fish and Wildlife Service land-based wind energy guidelines. U.S. Fish and Wildlife Service, <<http://www.fws.gov/windenergy/guidance.html>>. Accessed January 15, 2015.
- 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.
- Wolpert, R. 2013. Appendix B: A partially periodic equation for estimating avian mortality rates. Pages B1–B3 in W. Warren-Hicks, editor. Improving methods for estimating fatality of birds and bats at wind energy facilities. California Wind Energy Association, Berkeley, California, USA.

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