

Modeling carcass removal time and estimation of a scavenging correction factor for avian mortality assessment in wind farms using parametric survival analysis.

REGINA BISPO, JOANA BERNARDINO, TIAGO A. MARQUES
and DINIS PESTANA

In monitoring studies at wind farms, the estimation of avian mortality caused by collision must take into account carcass removal by scavengers. To analyze the time of carcass removal from trials conducted at ten Portuguese wind farms we used parametric survival models, assuming four main competing lifetime distributions (exponential, Weibull, log-logistic and log-normal). The fitted models enabled the parametric estimation of carcass persistence rates and the calculation of a scavenging removal correction factor.

In eight wind farms, log-normal and log-logistic models fitted better. The Weibull model was the best model in the two remaining sites. In four out of the ten studied sites, season and/or bird body size significantly affected removal times. Furthermore, the data analysis showed that the carcass size effect can be stronger than the season effect.

The results showed that the estimated values for the carcass removal correction factors can vary considerably, depending on the fitted model. The effect of model choice on the mortality estimation is examined.

The proposed methodology avoids performing several univariate analysis and reduce bias estimation of scavenging rates. Additionally, it establishes a standardized statistical procedure for the analysis of carcass removal times in subsequent studies.

Key words: Accelerated failure time model, bias correction factor, lifetime distribution, removal rate, scavenging rate, wind energy.

R. Bispo is Assistant Professor, Departamento de Estatística, ISPA - Instituto Universitário, Lisboa, Portugal and researcher at CEAUL - Centro de Estatística e Aplicações da Universidade de Lisboa, Portugal (E-mail: rbispo@ispa.pt). J. Bernardino is Team Leader, Field Supervisor and Field Biologist, Bio3 - Estudos e Projectos em Biologia e Valorização de Recursos Naturais, Portugal (E-mail: joana.bernardino@bio3.pt). T. A. Marques is Researcher Fellow, Centre for Research into Ecological and Environmental Modeling, The Observatory, Buchanan Gardens, St Andrews, Scotland UK and researcher at CEAUL - Centro de Estatística e Aplicações da Universidade de Lisboa, Portugal (E-mail: tiago@mcs.st-and.ac.uk). D. Pestana is Professor in Probability and Statistics, Departamento de Estatística e Investigação Operacional, Faculdade de Ciências, Universidade de Lisboa, Portugal and senior researcher at CEAUL - Centro de Estatística e Aplicações da Universidade de Lisboa, Portugal (E-mail: ddpestanda@fc.ul.pt).

1 INTRODUCTION

Bird and bat collision with man-made structures such as wind turbines, communication masts, power lines, buildings and fences is a well known phenomena, extensively described in the literature (e.g. Newton 1998; Barrios and Rodriguez 2004; Smallwood and Thelander 2004; Hass, Nipkow, Fielder, Schneider, Haas, and Schürenberg 2005; Gelb and Delacretaz 2006; Thelander and Smallwood 2007). Considered as a potential cause of significant avian mortality, it is pointed out, by some authors, to be the greatest unintended human cause of avian fatalities (Kelm, Keck, Marty, Ball, Niciu, and Plat 2004).

Currently, fatality of flying vertebrates through collision with rotating turbine rotor blades and other structures in wind farms receives most attention as consequence of the growing risk posed by the rapid increase in the number of wind turbines worldwide (Drewitt and Langston 2008). Recent monitoring studies indicate wind farms as responsible for the decrease or the occurrence of demographic changes in some species populations (e.g. Hunt 2002; Stewart, Pullin, and Coles 2005; Hunt and Hunt 2006; Everaert and Stienen 2007; Carrete, Sánchez-Zapata, Benítez, Lobón, and Donázar 2009), although many other studies reveal that these impacts are not important when compared to those originated by other infrastructures (e.g. Erickson, Johnson, Strickland, Young, Sernka, and Good 2001; Erickson, Johnson, and Young 2005; Drewitt and Langston 2008).

Understanding the real impact posed by wind farms projects, regarding avian and bat populations, implies mortality estimation. Despite the existence of numerous technical reports on the monitoring of bird and bat collisions with wind turbines (e.g. Orloff and Flannery 1992; Kerlinger 2002; Morrison 2002; Johnson, Erickson, White, and McKinney 2003; Schmidt, Piaggio, Bock, and Armstrong 2003; Anderson, Neumann, Tom, Erickson, Strickland, Bourassa, Bay, and Sernka 2004; Smallwood and Thelander 2004; Arnett 2005; Erickson et al. 2005; Stewart et al. 2005; Jain, Kerlinger, and Slobodnik 2007), there are still few studies published in the peer-reviewed literature (Musters, Noordervliet, and Terkeus 1996; Osborn, Higgins, Usgaard, Dieter, and Neiger 2000; Johnson, Erickson, Strickland, Shepherd, Shepherd, and Sarappo 2003; Barrios and Rodriguez 2004; Lucas, Janss, and Ferrer 2004; Chamberlain, Rehfish, Fox, Desholm, and Anthony 2006; Kunz, Arnett, Cooper, Erickson, Larkin, Mabee, Morrison, Strickland, and Szewczac 2007; Arnett, Brown, Erickson, J, Hamilton, Henry, Jain, Johnson, Kerns, Koford, Nicholson, O'Connell, Piorkowski, and Tankersley 2008; Drewitt and Langston 2008; Carrete et al. 2009).

Throughout the literature, estimation of mortality, caused by collision, is recommended to be adjusted for scavenger removal. This adjustment accounts for the fact that carcasses can be removed, either by predators or decomposition, prior to the time that the searchers arrive the location where the collision occurred.

Currently available methods to accommodate mortality estimates for scavenger removal vary greatly and are frequently poorly described. Several authors (e.g. Kunz et al. 2007; Ar-

nett et al. 2008) mentioned the lack of a reliable scavenging correction factor as an important source of unreliability in the bird and bat mortality estimation. Next, we describe the current applied methods for the estimation of scavenger removal rates. The described methodological heterogeneity illustrates the need for a unified estimation solution in order to ensure a correct evaluation of carcass removal and to contribute to find reliable and comparable mortality estimates between wind farms worldwide.

We start describing one of the most popular procedures that estimates the scavenger removal by the mean length of time that a carcass remains on the study area before removal (\bar{t}) (e.g. Johnson et al. 2003; Erickson, Jeffrey, Kronner, and Bay 2004; Fiedler 2004). This method is based on the assumption that removal times follow an exponential distribution (Johnson et al. 2003; Erickson et al. 2004). Therefore, \bar{t} is estimated by $\bar{t} = \sum_{i=1}^S t_i / (S - S_c)$, where t is the time since placement, S is the total number of carcasses planted for the trial and S_c is the number of censored observations, which gives the maximum likelihood estimator for the mean value under an exponential distribution, assuming S_c right-censored observations. Barrios and Rodriguez (2004) estimated the number of birds carcasses that were removed by fitting an exponential function to the time of disappearance, $f(t)$. These authors interpret this function as giving the rate of disappearance, and thus the removal probability, although the presented equations are neither probability density functions or probability distribution functions. They calculate the scavenging correction factor by $\sum f(t)/T$ with T being the number of days elapsed between searches. Other authors adjust the mortality estimates for scavenger removal by dividing the number of carcasses remaining at the end of a time period by the number of carcasses at the beginning of the period (e.g. Kerlinger 2002; Schmidt et al. 2003; Anderson et al. 2004; Brown and Hamilton 2006). Some authors (e.g. Schmidt et al. 2003; Brown and Hamilton 2006) calculate this proportion in the end of several week periods and adopt the correction factor as being the average of weekly values. Instead of finding the proportion of unscavenged carcasses at the end of a search cycle, Jain et al. (2007) calculated the proportion of removed carcasses after approximately half the actual search cycle, based on the assumption that the probability of a collision event is equally distributed over all days between searches. Kerns, Erickson, and Arnett (2005) conducted trials for 21 days and estimated carcass persistence rate based on the empirical cumulative probability distribution by averaging the daily proportions of unscavenged carcasses for seven days periods, $\frac{1}{7} \sum_{t=t_0}^{t_1} (1 - P(T \leq t))$, with (t_0, t_1) being (1, 7), (8, 14) and (15, 21) days. Linz, Davis, Engeman, Otis, and Avery (1991) estimated carcass removal by scavengers in cattail marshes using the product-limit life table method (Kaplan and Meier 1958). In their study, these authors compare removal curves under different conditions, but do not present an estimator to the overall scavenging rate. Based on Linz et al. (1991) work, Osborn et al. (2000) explicitly mention the use of nonparametric survival analysis methods (Kaplan-Meier) to analyze scavenging data at a wind farm site. These authors also estimate the percentage of unscavenged carcasses by dividing the number of carcasses

remaining at the end of a time period by the number of carcasses at the beginning of the period. Rivera-Milan, Zaccagnini, and Canavelli (2004) and Kostecke, Linz, and Bleier (2001) used survival analysis to estimate removal rates of bird carcasses in other contexts rather than wind turbine mortality estimation. These authors used parametric survival analysis methods, modeling data through an exponential regression. Tobin and Dolbeer (1990), also working in a different theoretical context, estimate bird carcass persistence rates using an accelerated failure time model, by fitting a Weibull distribution to the time that carcasses remained in place until removal.

The present study aims to solve the problem of modeling carcass removal time data and estimation of scavenging rates by (1) establishing a statistical methodology for analyzing data from removal trials, (2) formally defining a scavenger removal correction factor and (3) investigating the impact that different modeling assumptions can have on estimating the parameters of interest.

In the subsequent sections we describe carcass removal trials (section 2), detail statistical development (sections 3 and 4), define the proposed scavenger removal correction factor (section 5) and comment on the statistical findings of our research (section 6). In the last section, we discuss the addressed problem, highlighting the practical value and the importance of the developed work.

2 CARCASS REMOVAL TRIALS

The motivating data comes from carcass removal trials conducted in ten wind farms located in the north and center of Portugal (for confidentiality reasons sites names are coded from WF1 to WF10). Trials were spread over two seasons (May/June and September/October or January/February and July/August) to incorporate the potential effects of weather conditions. Complete and fresh carcasses of parakeets (*Melopsittacus undulates*), quails (*Coturnix coturnix*) and partridges (*Alectoris rufa*) were used to represent three bird size classes — small (length under 15 cm), medium (length between 15 and 25 cm) and large (length above 25 cm) — aiming to reflect the potential effect of carcass size in scavenging rates. Bird carcasses were obtained in avian breeding facilities. The carcasses were placed in the area of influence of the wind farm at a minimum distance of 500 m from each other. The size class was chosen randomly. After its placing, all carcasses were monitored daily, every morning, for a maximum period of 20 days.

3 STATISTICAL ANALYSIS OF REMOVAL TIMES

Data from scavenger removal trials refer to time until removal and are classical examples of survival times. Their underlying distribution is typically positively skewed and often includes right censored observations, because carcass monitoring, in most cases, is planned to end at a predetermined time.

These type of data is not amenable to standard statistical procedures (Collet 2003). Proper survival analysis includes both nonparametric and parametric methodologies. Modeling survival data by using nonparametric procedures has the advantage to be unrestricted to a particular probability distribution resulting in a more flexible and of a wider applicability model, but limits inference and prediction. In particular, nonparametric methods are useful in connection with graphical assessments of goodness of fit for complex models (Cox and Oakes 1998). Parametric methods, by assuming a specific form to the underlying data distribution, allow more precise inferences (Collet 2003), although, in this case, estimates and their correspondent variances depend heavily on the validity on the assumptions.

In order to specify a time failure (T) distribution it is useful to define the survivor function, $S(t) = P(T > t) = 1 - F_T(t)$, where $F_T(t)$ is the distribution function of T . This function represents the probability that a subject survives from the time origin to some time beyond t . In this context, hazard function — $h(t) = \lim_{\delta t \rightarrow 0} [P(t \leq T < t + \delta t | T \geq t / \delta t)]$ — is also of interest because it expresses the risk of the event at some time t .

In the next two sections we detail the proposed statistical methodology for the analysis of data from scavenger removal trials.

4 EMPIRICAL REMOVAL TIME DISTRIBUTION

Assuming that carcass removals occur independently of one another, the empirical probability of being removed beyond the time t can be determined using the Kaplan-Meier estimator (Kaplan and Meier 1958) given by

$$\hat{S}(t) = \prod_{j=1}^k \frac{n_j - d_j}{n_j} \quad (4.1)$$

where n_j ($j = 1, \dots, r$) denote the number of carcasses not removed and d_j denote the number of removed carcasses at time t_j , for $t_{(k)} \leq t < t_{(k+1)}$ ($k = 1, 2, \dots, r$) with r being the number of not censored observations. Note that in the absence of censoring the Kaplan-Meier estimate is simply the ratio between the number of carcasses not removed until time t and the total number of carcasses placed in the beginning of the trial. This means that, if no censoring occurs, the empirical probability a carcass remains at least t days prior to removal can be estimated nonparametrically as Kerns et al. (2005) recommended (see introduction). Nevertheless, when censored observations occur, this estimator can be biased.

The approximate estimated standard error of the Kaplan-Meier estimator is given by

$$se\{\hat{S}(t)\} \approx \hat{S}(t) \left\{ \sum_{j=1}^k \frac{d_j}{n_j(n_j - d_j)} \right\} \quad (4.2)$$

5 PARAMETRIC MODELING OF SCAVENGER REMOVAL DATA

Parametric survival procedures are based on a distributional assumption. There are several probability distributions described in the literature as suitable for survival data. The exponential, Weibull, log-logistic and log-normal distributions are among the most frequently used (e.g. Kalbfleisch and Prentice 2002; Lawless 2003).

5.1 MODELING HOMOGENEOUS POPULATIONS

In this section, we introduce the four mentioned distributions for modeling the removal process in a homogeneous population.

The exponential distribution with parameter ρ ($\rho > 0$) and mean $1/\rho$ has probability density function $f(t) = \rho \exp\{-\rho t\}$ ($t > 0$). The survivor function is therefore given by

$$S(t) = \exp\{-\rho t\} \quad (5.1)$$

Under this distribution, the hazard is constant, $h(t) = \rho$. Although an exponential distribution of scavenger removal times did not seem an appropriate choice, because a constant risk of removal appears to be unlikely, this distribution was included in the present study for comparison purposes because several authors used it to model data (e.g. Johnson et al. 2003; Erickson et al. 2004; Fiedler 2004).

The Weibull distribution with parameters ρ ($\rho > 0$) (scale parameter) and γ ($\gamma > 0$) (shape parameter) has density $f(t) = \gamma \rho (\rho t)^{\gamma-1} \exp\{-(\rho t)^\gamma\}$ ($t > 0$). The survivor function is defined by

$$S(t) = \exp\{-(\rho t)^\gamma\} \quad (5.2)$$

and the hazard function is given by $h(t) = \gamma \rho (\rho t)^{\gamma-1}$. Hence, for this distribution the hazard is monotone decreasing for $\gamma < 1$, which seemed to be a plausible situation in scavenger removal trials, as the risk of removal is likely to be decreasing. Furthermore, this distribution seemed attractive to model data due to the fact it is an heavy tail distribution and removal is known to be potentially a rather rapid process. However, in modeling carcass removal time it is possible to admit situations in which removal risk first increases (because of smell, for instance) and then decreases. In these situations, log-logistic and log-normal models, whose hazard functions have a positive mode, may be more adequate than the Weibull model.

The log-logistic distribution, with parameters κ e ρ , has density $f(t) = [\kappa \rho^\kappa t^{\kappa-1}] / [(1 + (\rho t)^\kappa)^2]$ ($t > 0$) and has survivor function

$$S(t) = \frac{1}{1 + (\rho t)^\kappa} \quad (5.3)$$

The hazard function $h(t) = [\kappa \rho^\kappa t^{\kappa-1}] / [1 + (\rho t)^\kappa]$ decreases monotonically if $\kappa \leq 1$. With $\kappa > 1$, the hazard has a single mode.

Despite having more complicated algebraic expressions than the log-logistic distribution, the log-normal distribution also has a central role in lifetime data analysis (Lawless 2003). The density function for survival time can be written as $f(t) = 1/(\sqrt{2\pi}\sigma) \exp[-0.5((\log t - \mu)/\sigma)^2]$. The survivor and hazard function involve the normal cumulative function $\Phi(z) = \int_{-\infty}^z \phi(u)du$, being defined as

$$S(t) = 1 - \Phi\left(\frac{\log t - \mu}{\sigma}\right) \quad (5.4)$$

and $h(t) = f(t)/S(t)$, respectively.

5.2 MODELING DEPENDENCY ON EXPLANATORY VARIABLES

The previously mentioned probability models can be generalized to account for covariates effect. A general family of regression models that encompasses all the above mentioned survival distributions is called the *accelerated failure time model* (e.g. Kalbfleisch and Prentice 2002). Here we describe how removal time was modeled, using this class of regression models, to allow the study of season and body size factors effect.

Considering the random variable T_i that represents the removal time for the i -th carcass, $Y_i = \log T_i$ can be related to the vector of p covariates $\mathbf{x}'_i = (x_{1i}, \dots, x_{pi})$ via a linear model

$$\log T_i = \mu + \alpha \mathbf{x}'_i + \sigma \varepsilon_i \quad (5.5)$$

where $\alpha = (\alpha_1, \dots, \alpha_p)'$ is the vector of the unknown coefficients of the p covariates. μ and σ are, respectively, intercept and scale parameter and ε_i is the error variable. Accordingly,

$$S_i(t|\mathbf{x}_i) = P(T_i \geq t) = P\left(\varepsilon_i \geq \frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma}\right) \quad (5.6)$$

Denoting the survivor function of the random variable ε_i by S_{ε_i} we obtain

$$S_i(t) = S_{\varepsilon_i}\left(\frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma}\right) \quad (5.7)$$

which represents the the survivor function for the i -th carcass in an accelerated failure time model.

The corresponding density function can be found by differentiation with respect to t , giving

$$f_i(t) = \frac{1}{\sigma t} f_{\varepsilon_i}\left(\frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma}\right) \quad (5.8)$$

where $f_{\varepsilon_i}(\varepsilon)$ is the density function of random variable ε_i .

For an exponential or a Weibull distribution of the survival times, then ε_i in the log-linear representation of the model (equation 5.5) follows the extreme value Gumbel distribution (Cox and Oakes 1998; Collet 2003)) with survivor function given by $S_{\varepsilon_i}(\varepsilon) = \exp(-\exp(\varepsilon))$

and density function $f_{\varepsilon_i}(\varepsilon) = \exp(\varepsilon - \exp(-\varepsilon))$ ($-\infty < \varepsilon < \infty$). Thus, the survivor function of T_i is given by

$$S_{\varepsilon_i}(t) = \exp \left[- \exp \left(\frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma} \right) \right] \quad (5.9)$$

and the density function is

$$f_{\varepsilon_i}(t) = \frac{1}{\sigma t} \exp \left\{ \frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma} - \exp \left[- \left(\frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma} \right) \right] \right\} \quad (5.10)$$

For the special case of an exponential distribution of T_i , $\sigma = 1$, thus survivor and hazard functions become simply

$$S_i(t) = \exp[-\exp(\log t - \mu - \alpha \mathbf{x}'_i)] \quad (5.11)$$

$$f_{\varepsilon_i}(t) = \frac{1}{t} \exp\{\log t - \mu - \alpha \mathbf{x}'_i - \exp[-(\log t - \mu - \alpha \mathbf{x}'_i)]\} \quad (5.12)$$

When T_i has a log-logistic distribution, then ε_i has a logistic distribution, with survivor function $S_{\varepsilon_i}(\varepsilon) = (1 + \exp \varepsilon)^{-1}$ and density function $f_{\varepsilon_i}(\varepsilon) = [\exp(-\varepsilon)]/[1 + \exp(-\varepsilon)]^2$.

In this case, T_i has survivor function given by

$$S_i(t) = \left[1 + \exp \left(\frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma} \right) \right]^{-1} \quad (5.13)$$

and the density for the i -th subject is

$$f_{\varepsilon_i}(t) = \frac{1}{\sigma t} \frac{\exp\left(-\frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma}\right)}{\left[1 + \exp\left(-\frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma}\right)\right]^2} \quad (5.14)$$

Last, assuming a log-normal distribution for T_i , ε_i has normal distribution with survivor function $S_{\varepsilon_i}(\varepsilon) = 1 - \Phi(\varepsilon)$ and density $f_{\varepsilon_i}(\varepsilon) = (1/\sqrt{2\pi}) \exp(-\varepsilon^2/2)$. Therefore, the survivor function of T_i is given by

$$S_i(t) = 1 - \Phi \left[\frac{\log t - \mu - \alpha \mathbf{x}'_i}{\sigma} \right] \quad (5.15)$$

and the density function of T_i is

$$f_i(t) = \frac{1}{\sqrt{2\pi}\sigma t} \exp \left(- \frac{(\log t - \mu - \alpha \mathbf{x}'_i)^2}{2\sigma^2} \right) \quad (5.16)$$

5.3 PARAMETER ESTIMATION

The parametric models were fitted using maximum likelihood estimation. In the presence of censored observations, the likelihood of n survival times is given by

$$\mathcal{L} = \prod_{i=1}^n \{f_i(t_i)\}^{\delta_i} \{S_i(t_i)\}^{1-\delta_i} \quad (5.17)$$

where $f_i(t_i)$ and $S_i(t_i)$ are the density and the survivor functions, and δ_i is an indicator variable, which takes the value one for noncensored observations and zero for censored observations (Collet 2003).

In homogeneous populations, the likelihood function for the exponential model is given by

$$\mathcal{L}(\rho|\tilde{t}) = \prod_{i=1}^n \rho^{\delta_i} \exp\{-\rho t\} \quad (5.18)$$

with $\tilde{t} = (t_1, \dots, t_n)$.

The maximum likelihood estimator of ρ can then be found easily, differentiating the corresponding log-likelihood function with respect to ρ , which gives

$$\hat{\rho} = \frac{r}{\sum_{i=1}^n t_i} \quad (5.19)$$

Under the Weibull model, the likelihood function is

$$\mathcal{L}(\rho, \gamma|\tilde{t}) = \prod_{i=1}^n [\gamma \rho (\rho t_i)^{\gamma-1}]^{\delta_i} \exp\{-(\rho t_i)^\gamma\} \quad (5.20)$$

and the maximum likelihood estimates of ρ and γ for Weibull model can be found from

$$\begin{cases} \hat{\rho} = \left(\frac{r}{\sum_{i=1}^n t_i^\gamma} \right)^{1/\gamma} \\ \frac{r}{\hat{\gamma}} - r \frac{\sum_{i=1}^n t_i^{\hat{\gamma}} \log t_i}{\sum_{i=1}^n t_i^{\hat{\gamma}}} + \sum_{i=1}^n \delta_i \log t_i = 0 \end{cases} \quad (5.21)$$

using the an iterative numerical procedure.

Considering the log-logistic model, the likelihood function is expressed by

$$\mathcal{L}(\rho, \kappa|\tilde{t}) = \prod_{i=1}^n \frac{[\kappa \rho^\kappa t_i^{\kappa-1}]^{\delta_i}}{[1 + (\rho t_i)^\kappa]^{\delta_i+1}} \quad (5.22)$$

and the parameter estimates can be found solving

$$\begin{cases} \frac{r\kappa}{\rho} - \sum_{i=1}^n [\delta_i + 1] \left[\frac{\kappa \rho^{\kappa-1} t_i^\kappa}{1 + (\rho t_i)^\kappa} \right] = 0 \\ \frac{r}{\kappa} - r \log \rho + \sum_{i=1}^n \delta_i \log t_i - \sum_{i=1}^n [\delta_i + 1] \left[\frac{(\rho t_i)^\kappa \log(\rho t_i)}{1 + (\rho t_i)^\kappa} \right] = 0 \end{cases} \quad (5.23)$$

For the log-normal model, no explicit equations are found and the maximum likelihood estimates of the unknown parameters were calculated using an iterative numerical procedure.

The accelerated failure time models were also fitted using maximum likelihood estimation. From equation 5.17 and the described $f_i(t_i)$ and $S_i(t_i)$ functions, the likelihood

functions for the exponential, Weibull, log-logistic and log-normal regression models are, respectively, given by

$$\mathcal{L}(\alpha, \mu) = \prod_{i=1}^n (t_i)^{-\delta_i} \{\exp[z_i - \exp(z_i)]\}^{\delta_i} \{\exp[-\exp(z_i)]\}^{1-\delta_i} \quad (5.24)$$

$$\mathcal{L}(\alpha, \mu, \sigma) = \prod_{i=1}^n (\sigma t_i)^{-\delta_i} \{\exp[z_i - \exp(z_i)]\}^{\delta_i} \{\exp[-\exp(z_i)]\}^{1-\delta_i} \quad (5.25)$$

$$\mathcal{L}(\alpha, \mu, \sigma) = \prod_{i=1}^n (\sigma t_i)^{-\delta_i} \left\{ \frac{\exp(-z_i)}{[1 + \exp(-z_i)]^2} \right\}^{\delta_i} \{1 + \exp(z_i)\}^{\delta_i - 1} \quad (5.26)$$

$$\mathcal{L}(\alpha, \mu, \sigma) = \prod_{i=1}^n (\sigma t_i)^{-\delta_i} \{(1/\sqrt{2\pi}) \exp(-z_i^2/2)\}^{\delta_i} \{1 - \phi(z_i)\}^{\delta_i - 1} \quad (5.27)$$

where $z_i \equiv (y_i - \mu - \mathbf{x}_i' \alpha) / \sigma$ (recall that for the exponential model $\sigma = 1$).

The maximum likelihood estimates of the unknown parameters were found using the Newton-Raphson procedure, implemented in `survreg` function of R survival package (R Development Core Team 2009). The significance of the explanatory variables in regression models was tested using the Wald statistic.

5.4 MODELS GOODNESS-OF-FIT

After fitting several models it is important to compare their relative fit. As, in this context, the final goal of inference is to use fitted parametric models to estimate carcass persistence probabilities, and these can depend heavily on the model selected, procedures used to check model adequacy are particularly important.

Both goodness of fit measures and plotting procedures were used to discriminate between the four mentioned competing parametric models. In previous work, **** (2010) concluded that although plotting procedures are interesting to illustrate model adjustment, they do not discriminate sufficiently enough the fitted models. It was also concluded that the Akaike's Information Criterion (AIC) and the Bayesian's Information Criterion (BIC) allow to select the best model consistently pointing to the same choice. Hence, in this work we present only values for the AIC criterium.

6 SCAVENGING CORRECTION AND ACCELERATION FACTORS

Assuming that the number of collision-caused deaths is uniformly distributed over time, the scavenging correction factor (R_{ij}) can be defined, based on parametrically estimated risk scores, by

$$R_{ij}(t) = \frac{1}{t_i - t_{(i-1)}} \sum_{t=1}^{t_i - t_{(i-1)}} \hat{S}_j(t) \quad (6.1)$$

where t_i is the time (number of days) at the i -th search. R_{ij} expresses the average carcass persistence rate at the i -th search for the j -th condition defined by the covariates levels (or combination of levels). This estimator assumes that the fatalities caused by collision occur with the same probability at any time t in the interval $t_{i-1} < t \leq t_i$, i.e., at any time t between two consecutive searches.

Equation 6.1 represents essentially the same estimator used by Kerns et al. (2005). For calculations, these authors used the empirically estimated survivor function (i.e., one minus the estimated empirical probability that a carcass remains at least t days prior to removal). Here, we propose a estimation of $S(t)$ based on the best fitted parametric survival model to simultaneous allow inference and prediction.

The acceleration failure time model is a general model in which explanatory variables are assumed to act multiplicatively on the time-scale. Hence, this type of model specifies that $S_1(t) = S_2(t/\phi)$ ($t > 0$), where $S_1(t)$ and $S_2(t)$ represent the survivor functions for subjects under the conditions 1 and 2. The parameter ϕ reflect the impact that a certain condition has on the baseline time scale. The quantity ϕ^{-1} , termed *acceleration factor*, indicates the acceleration (if > 1) or the deceleration (if < 1) on the time of removal of a carcass under a specific condition, relatively to a reference situation. Thereby, it is particularly useful, since it provides direct assessment of the fitted models in terms of the speed of removal.

7 RESULTS

The Wald test results showed homogeneous removal times regarding season and body size factors in 6 (WF1 to WF6 wind farms) out of the 10 wind farms (at WF5 wind farm, the experimental design did not include body size effect). In WF7 and WF8 wind farms, season proved to have a significant effect ($p < 0.001$) and in WF9 and WF10 wind farms, both covariates had a significant effect on the removal times ($p < 0.001$). Sections 7.1 and 7.2 detail results in each of the 10 wind farms, according to the type of fitted model. In section 7.3, we illustrate the importance of considering modeling using different plausible models, giving examples of the effect of model choice on the estimation of the parameters of interest.

7.1 HOMOGENEOUS PARAMETRIC MODELS

Table 1 presents AIC values for the fitted models. In the first six mentioned sites removal time data were modeled using homogeneous parametric survival models. Considering these sites, we found that for WF1, WF3, WF4 and WF6 wind farms, Akaike's information measure was lowest for the log-normal model. At WF2 and WF5 wind farms, log-logistic models presented lower values. However, differences between AIC values regarding log-logistic and log-normal models were in every case minimal, suggesting similar goodness of

Table 1. Akaike's information criterion for the fitted parametric survival models.

Wind farms	Exponential	Weibull	Log-logistic	Log-normal
WF1	243.09	244.70	234.99	234.52
WF2	305.82	307.82	286.97	288.42
WF3	100.09	101.61	99.54	98.84
WF4	265.27	255.01	251.87	247.14
WF5	91.70	93.57	85.06	85.85
WF6	321.68	323.11	314.37	312.53
WF7	408.37	409.75	401.94	399.22
WF8	186.13	175.52	179.17	178.53
WF9	278.59	262.22	263.87	262.40
WF10	152.07	147.58	146.88	147.01

fit.

Figure 1 shows the empirical survivor distributions (step functions) of carcass persistence and the best fitted parametric models for the six wind farms in which carcass size and season did not significantly affected the removal times (WF1 to WF6 wind farms).

The analysis of the empirical distributions shows that the removal processes at WF4 (plot 4, Figure 1) and WF5 (plot 5, Figure 1) were the fastest among these six sites, with only 3% and 15%, respectively, of the carcasses remaining after seven days of placement. In these two wind farms, complete removal occurred shortly after 13 and 15 days of placement, respectively. In the remaining four sites the removal process was slower and censored observations were registered. The slowest removal process was recorded at WF3 (plot 3, Figure 1). For this wind farm, the observed percentage of carcasses that remained unscavenged was always higher than the recorded at the other sites, never below 35%. From these plots, we see that the removal processes can be very distinct between sites which reinforces the need for separate modeling. Overall, plots in Figure 1 show a very good agreement between the observed and the fitted survivor functions.

The values of the scavenger removal correction factors calculated for a time interval of seven days (from equation 6.1) varied according to the fitted parametric survival model, within each study site (table 2). If in some sites the parametric estimates of the correction factors are quite homogeneous (e.g., WF1 and WF6 wind farms), there are others sites (such as the WF5 wind farm), in which the correction factor value clearly depends on the model distributional assumption, suggesting that the use of an incorrect model can severely bias mortality estimation, as we will discuss in section 7.3.

Additionally, the scavenging correction factor values clearly differ between the six farms (table 2). Values from best fitted models range from 36 to 75%. At WF4 and WF5 wind farms, where the removal process was faster, only 36 to 37% of the carcasses are expected to remain unscavenged during a period of time of seven days. By contrast, at WF3 wind farm, for the same time interval, 75% of the carcasses persist due to the slow process

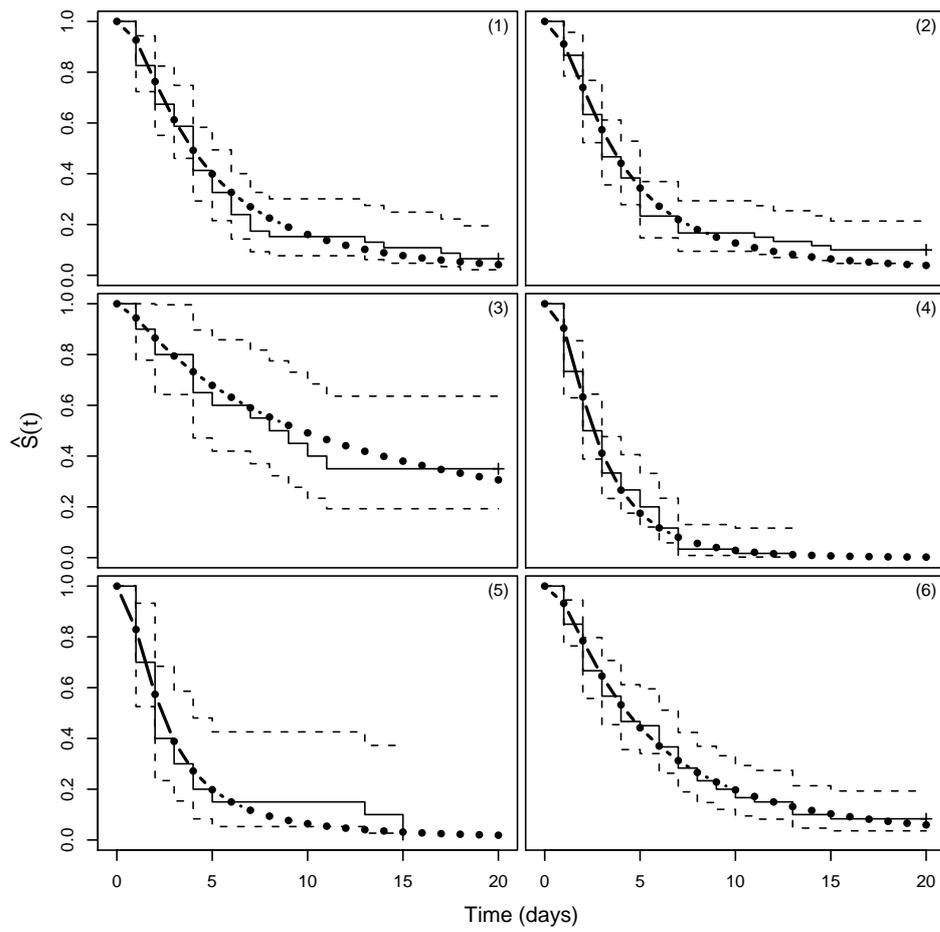


Figure 1. Empiric survivor function (step functions) for homogeneous populations. Superimposed on the step functions are the best fitted models (points connected by lines). Plots represent estimated functions at (1) WF1, (2) WF2, (3) WF3, (4) WF4, (5) WF5 and (6) WF6 wind farms. The character (+) at the end of the step functions indicates the existence of right censored observations. Dashed lines represent the confidence interval bands for the empiric survival functions.

Table 2. Scavenger removal correction factors calculated for a time interval of seven days from fitted homogeneous parametric survival models. Bolded figures indicate the correction factors values from the best fitted model.

Wind farms	Exponential	Weibull	Log-logistic	Log-normal
WF1	0.55	0.56	0.53	0.54
WF2	0.55	0.55	0.50	0.53
WF3	0.78	0.75	0.74	0.75
WF4	0.37	0.39	0.37	0.37
WF5	0.45	0.44	0.36	0.41
WF6	0.58	0.60	0.57	0.57

of removal in this site.

7.2 ACCELERATION FAILURE TIME MODELS

7.2.1 One-factor acceleration time failure models — Models accounting for season effect

The regression models based on log-normal and Weibull distributions fitted better to data in WF7 and WF8 wind farms, respectively, as indicated by the decrease of AIC values (table 1).

At WF7 and WF8 sites, persistence rates were significantly affected by season. In Figure 2 (plots 7 and 8), the persistence carcass decay at these two wind farms is plotted by season. In these sites a similar scenario holds, in the sense that in both wind farms a rapid removal process was observed during the hot season and a slower process of removal prevailed during the cold season. At WF7 site, the removal process was faster during Jul/Aug than during Jan/Feb, but censored times were observed in both trials. The season effect was even more notorious in WF8 wind farm, where five days since placement were enough to observe complete removal of avian carcasses during spring. At this same site, the removal was slower during fall. During this season complete removal was observed after 15-days of placement and no censored observations were registered.

Table 3 show the correction factors for a time interval of seven days for WF7 and WF8 wind farms. Like for homogeneous populations, the estimated correction factors at these sites depend on the distributional assumption. In particular, the differences were more evident for the WF8 wind farm, during Sep/Oct, where parametric estimated values ranged from 0.62 (under the exponential model) to 0.74 (under the Weibull model).

The heterogeneity across sites regarding the correction factors values calculated from the best fitted models was even higher than the recorded for homogeneous populations. At these wind farms, the weekly values ranged from 16% to 74%. For WF7 site, the weekly average persistence rates were 30% during summer and 58% during winter seasons. At WF8 site, the average rates were of 16% for spring and 74% for fall seasons, showing a more evident season effect than the one found in WF7, as expected from the graphical

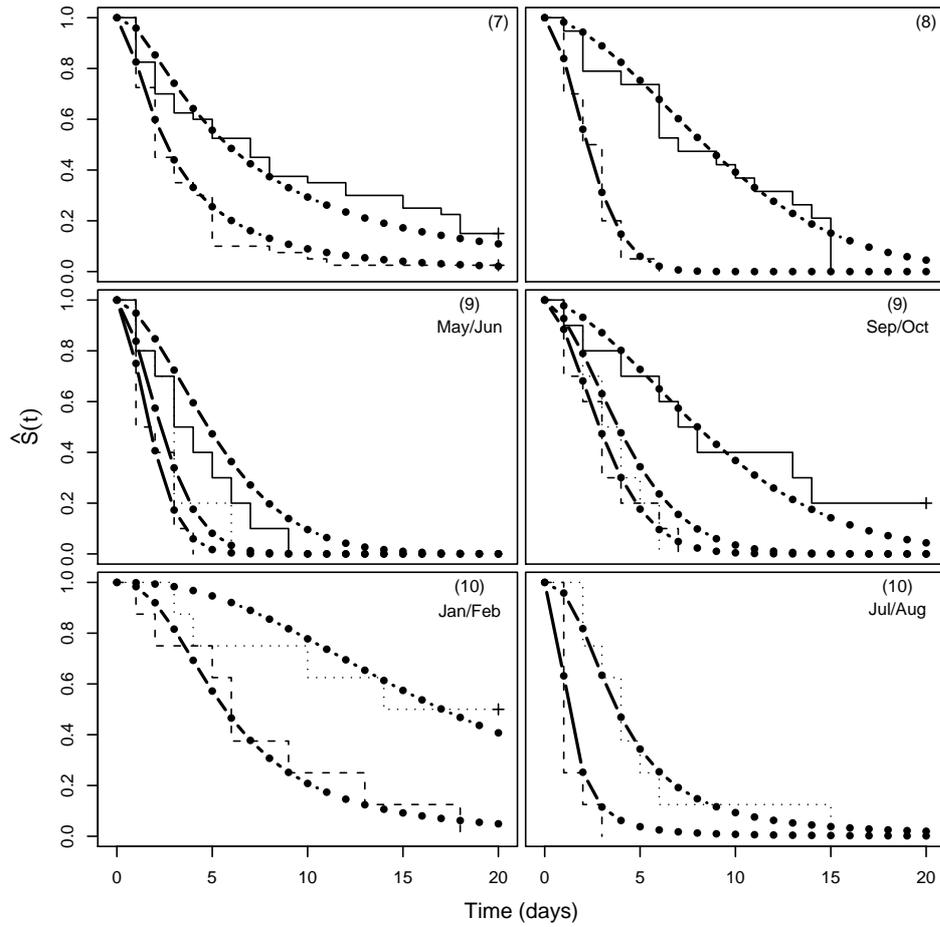


Figure 2. Empiric survivor function (step functions) for nonhomogeneous populations. Superimposed on the step functions are the best fitted models (points connected by lines). Plots represent estimated functions at (7) WF7 (solid line: Jan/Feb and dashed line: Jul/Aug), (8) WF8 (solid line: Sep/Oct and dashed line: May/Jun), (9) WF9 (solid lines: small size carcasses, dashed lines: medium size carcasses and dotted lines: large size carcasses) and (10) WF10 (dashed lines: medium size carcasses and dotted lines: large size carcasses) wind farms. The character (+) at the end of the step functions indicates the existence of right censored observations. Confidence interval bands for the empiric survival functions were omitted for clarity.

representation of the survival functions (plots 7 and 8, Figure 2).

The acceleration factors by covariate levels, that allow the interpretation of the models in terms of speed of removal, are also presented in table 3. At WF8 site, where the best model is the Weibull model, the time of removal of a avian carcass during Sep/Oct was found to be about 4 ($1/0.26 = 3.85$) times lower than the recorded during May/Jun. At WF7 wind farm, where the best model is the log-normal model, the acceleration factor value indicates a removal process about 2 times faster during Jul/Aug than during Jan/Feb.

Globally, these results show that the removal rates can depend heavily on season.

7.2.2 Two-factors acceleration time failure models — Models accounting for season and bird size effects

At WF9 and WF10 wind farms, both covariates affected significantly time until removal. The AIC values point to Weibull and log-logistic based models as the more suitable for the WF9 and WF10 wind farms data, respectively (table 1). Note, however, that this measure has very close values for Weibull, log-logistic and log-normal regression models.

Figure 2 presents the observed and the best fitted survivor functions at WF9 (plots 9) and WF10 (plots 10) sites. Globally, these plots show that during the colder seasons, persistence rates tend to be higher depending, however, on the size of the carcass. In fact, at WF9 wind farm (plot 9, Figure 2), during the May/Jun trial, carcasses of medium and large sizes were completely removed by the fourth and sixth days, respectively, and small size carcasses persisted in place until nine days of placement. By contrast, during Sep/Oct, carcasses of medium and large sizes were completely removed after seven and six days, respectively, and small size carcasses still remained unremoved after the end of the trial, originating censored observations. At WF10 wind farm (plot 10, Figure 2), a similar scenario was found. For the trial conducted in Jul/Aug, carcasses of medium size were completely removed shortly after three days of placement and the large size carcasses remained unscavenged until 15 days of placement, when completed removal occurred. During the Jan/Feb trial, medium size carcasses were completely removed after 18 days of placement and large size carcasses observations were censored at the end of the trial.

As for the homogeneous populations, plots in Figure 2 show a general good agreement between the observed and the fitted survivor functions.

At WF9 and WF10 wind farms, the weekly correction removal factors (table 4) also vary depending on the assumed lifetime distribution. The differences between estimates are more notorious for the WF9 wind farm. At this wind farm, the differences between models were higher during Sep/Oct, for large size carcasses, with estimates ranging from 0.32 (under the Weibull model) to 0.52 (under the log-logistic model).

Considering values from the best fitted models, the smallest weekly scavenging correction factors (table 4) were found at WF9 wind farm for medium size carcasses (weekly

Table 3. Scavenger removal correction factors calculated for a time interval of seven days from fitted one-factor parametric survival models and acceleration factors under the conditions defined by covariates levels (acceleration factors are one for reference categories). Bolded figures indicate the correction factors values from the best fitted model.

Wind farms	Season	Parameter	Exponential	Weibull	Log-logistic	Log-normal
WF7	Jan/Feb	Correction factor	0.62	0.64	0.59	0.58
		Acceleration factor	1.00	1.00	1.00	1.00
	Jul/Aug	Correction factor	0.29	0.30	0.29	0.30
		Acceleration factor	2.77	2.76	2.38	2.24
WF8	May/Jun	Correction factor	0.18	0.16	0.20	0.20
		Acceleration factor	1.00	1.00	1.00	1.00
	Sep/Oct	Correction factor	0.62	0.74	0.71	0.68
		Acceleration factor	0.25	0.26	0.29	0.31

average rates of 12% and 23% for May/Jun and Sep/Oct, respectively). At this wind farm, the large size carcasses (weekly average rates of 18% and 32% for May/Jun and Sep/Oct, respectively) were removed after medium size carcasses and small size carcasses were the last to be removed (weekly average rates of 38% and 55% for May/Jun and Sep/Oct, respectively). Within each carcass size category, removal process was always faster during summer than during fall. At WF10 wind farm, the correction factors were much higher for larger size carcasses (weekly average rates of 96% and 52% for Jan/Feb and Jul/Aug, respectively) than for medium size carcasses (weekly average rates of 69% and 16% for Jan-Feb and Jul/Aug, respectively). In both sites, medium size carcasses were removed prior to large size carcasses.

The values of the acceleration factors for the fitted models at these wind farms (table 4) show that, at WF9 wind farm, the removal process of avian carcasses occurred following the decreasing order: medium size-May/Jun, large-May/Jun, medium-Sep/Oct, large-Sep/Oct, small-May/Jun and small-Sep/Oct. At WF10 site, the removal process was clearly faster for carcasses of medium size during Jul/Aug, which registered a five times more rapid removal than carcasses of medium size during Jan/Feb. At this wind farm, the removal followed the decreasing order: medium-Jul/Aug, medium-Jan/Feb, large-Jul/Aug and large-Jan/Feb. Hence, it seems that the size carcass effect can be stronger than the season effect.

7.3 IMPACT OF THE REMOVAL TIME MODEL DISTRIBUTIONAL ASSUMPTION ON THE ESTIMATION OF MORTALITY

The scavenging correction factors were found to clearly depend on the model distributional assumption. In this section we illustrate the importance of considering different plausible models by giving examples of the effect of model choice on the estimation of the parameters of interest.

First, consider a carcass search protocol where weekly spaced searches are used. Further, consider that mortality rate (number of corpses per period of time) at the i -th search for the j -condition (M_{ij}), can be simply estimated by (Jain et al. 2007)

$$M_{ij} = \sum_{i=1}^n C_{ij} / (p \times R_{ij}) \quad (7.1)$$

where C_{ij} and R_{ij} denote, respectively, the observed mortality (number of carcasses found by turbine) and the scavenging correction factor (here defined by equation 6.1) for the i -th search and the j -condition. Suppose p , the detection probability, fixed at 0.25.

Assume that WF1 wind farm is being monitored and that after a period of one week, two bird carcasses per turbine were found. Recall that in this wind farm, estimated correction removal factors for a time interval of seven days are 0.55, 0.56, 0.53 and 0.54, under exponential, Weibull, log-logistic and log-normal regression models, respectively (see table 2). Then, in this case, the estimated mortality (equation 7.1) would be, respectively, of 15

Table 4. Scavenger removal correction factors calculated for a time interval of seven days from fitted two-factors parametric survival models and acceleration factors under the conditions defined by covariates levels (acceleration factors are one for reference categories). Bolded figures indicate the correction factors values from the best fitted model.

Wind farms	Season	Carcass Size	Parameter	Exponential	Weibull	Log-logistic	Log-normal
WF9	May/June	Small	Correction factor	0.51	0.38	0.55	0.53
			Acceleration factor	1.00	1.00	1.00	1.00
		Medium	Correction factor	0.20	0.12	0.23	0.23
			Acceleration factor	2.82	2.80	2.45	2.34
		Large	Correction factor	0.28	0.18	0.34	0.33
			Acceleration factor	2.06	2.08	1.69	1.66
	Sep/Oct	Small	Correction factor	0.66	0.55	0.74	0.72
			Acceleration factor	0.59	0.60	0.64	0.64
		Medium	Correction factor	0.35	0.23	0.37	0.37
			Acceleration factor	1.65	1.67	1.57	1.50
		Large	Correction factor	0.45	0.32	0.52	0.51
			Acceleration factor	1.21	1.24	1.09	1.06
WF10	Jan/Fev	Medium	Correction factor	0.61	0.69	0.69	0.65
			Acceleration factor	1.00	1.00	1.00	1.00
		Large	Correction factor	0.87	0.94	0.96	0.95
			Acceleration factor	0.27	0.29	0.33	0.33
		Medium	Correction factor	0.13	0.13	0.16	0.17
			Acceleration factor	5.42	5.05	4.50	3.92
	Large	Correction factor	0.49	0.55	0.52	0.54	
		Acceleration factor	1.46	1.45	1.50	1.31	

(i.e., $2/(0.25 \times 0.55)$), 14, 15 and 15 birds. In this case, differences in mortality estimates, due to the different distributional assumption of the removal process, are minor.

Consider the same observed number of carcasses in wind farm WF5. In this case, the estimated mortality would be, respectively, of 17 (i.e., $2/(0.25 \times 0.45)$), 18, 22 and 20 birds, for the exponential, Weibull, log-logistic and log-normal regression models (see weekly removal correction factors in table 2). In this case, by assuming the exponential model as the correct model instead of the log-logistic model as it should be (recall that log-logistic was the best fitted model for the WF5 site data), mortality would be underestimated by five birds. Furthermore, admitting this week as representative, we would underestimate mortality by 260 birds per turbine in a year, i.e, by a total of 1040 birds in a year, considering the four existing turbines in the WF5 wind farm.

Last, admit that WF9 wind farm is being monitored and that after a period of one week, during September, five carcasses of large size were found. In this wind farm, estimated scavenging correction factors for a time interval of seven days, during Sep/Oct, for large size carcasses are 0.45, 0.32, 0.52 and 0.51, under exponential, Weibull, log-logistic and log-normal regression models, respectively (see table 4). In this case, the estimated mortality would then be, respectively, of 44 (i.e., $5/(0.25 \times 0.45)$), 62, 38 and 39 birds, reflecting major differences in mortality estimation. For WF9 wind farm, results showed that the best model was the Weibull model. Hence, if working, for instance, with the exponential model, in a single week, the mortality would be underestimated in 18 birds (or 252 birds across all turbines, considering the 14 turbines in WF9).

8 DISCUSSION

Nowadays, wind generated energy is considered as one of the most lowest-priced renewable energy sources available in nature and is recognized to be a viable option for supplying current and future energy needs. As a consequence, the number of wind turbine farms has been increasing considerably worldwide. Despite being considered a clean energy, the existence of potential environmental impacts, namely on flying vertebrates, is broadly recognized. To assess the impact on avian and bat populations, strict monitoring studies have to be conducted. The ultimate goal of these studies is to provide the authorities and stakeholders with the best possible information upon which decisions about turbine placement, impact assessment, mitigation measures development and monitoring strategies are to be made. This work intends to be a contribution to improve the quality of these monitoring studies, having an immediate and importante practical value.

Previous studies estimate scavenger persistence rates either (1) empirically (e.g. Kerlinger 2002; Anderson et al. 2004; Kerns et al. 2005; Jain et al. 2007), which limits and may compromise inference; (2) based on *a priori* distribution (exponential distribution) (e.g. Johnson et al. 2003; Erickson et al. 2004; Fiedler 2004) that fits acceptably on hand (in the

published literature, goodness of fit procedures were not found), or (3) using estimators not accounting for censored observations, even when scavenging was stated to be minimal (e.g. Kerlinger 2002; Schmidt et al. 2003; Brown and Hamilton 2006). Additionally, the comparison of the results from the previous studies is limited and of arguable value as, in many studies, different methods of scavenger persistence rates estimation were used.

Here, we propose a method for the analysis of scavenger removal data aiming to standardize procedures and overcome the above mentioned limitations. The described parametric survival analysis method enables, simultaneously, to model carcass removal times accounting for covariates effects and to estimate persistence probabilities for all covariates levels. With this methodology, estimation is based on the most suitable probability distribution and accounts for censored observations, diminishing bias. Also, the integration of the estimation problem with the analysis of covariates effects, avoids performing several univariate analysis controlling the overall probability of making any incorrect decision, regarding covariates effect. We formally define a scavenging correction factor, as the average of parametrical estimated persistence probabilities for a considered time interval (equation 6.1), applicable to any time interval between searches used in carcass search protocols in wind farms monitoring projects or any other projects that imply carcass removal evaluation.

In six out of the ten wind farms no significant effects of body size and/or season were found, but in the remaining wind farms covariates were found to be highly significant, affecting substantially removal process and persistence rates. This underlines the need for accounting these covariates in scavenger removal trials, but also motivates the study of other explanatory variates that might influence estimation (e.g., type of vegetation cover, scavenger densities). Note that the proposed method for the analysis of carcass removal trials data is straightforward expandable to account for any other factors effects, by simply including other covariates in regression models.

Typically, persistence rates were found to be higher during colder seasons and lower for hotter seasons. Medium and large carcasses were removed prior to small carcasses. Data analysis showed, additionally, that carcass size effect can be stronger than season effect making carcasses of bigger sizes to be removed at a higher speed during cold seasons than smaller size carcasses during hot seasons. Thus, we concur with other authors indications (e.g. Morrison 2002) that a separate trials by season and size carcass design is needed when measuring scavenging removal field bias.

In most wind farms, the log-normal and the log-logistic regression models fitted better the removal time data. In the presence of factors that, under certain conditions, accelerated substantially the removal process, the Weibull model adjusted better. The exponential model was never the best option. The removal correction factors clearly differ between wind farms, showing that adjusting mortality based on scavenger removal rates determined elsewhere is not useful, and that, instead, the time of removal must be determined within each site as recommended previously by other authors (e.g. Arnett et al. 2008)

The persistence rates estimated parametrically clearly depended on the model distributional assumptions. If, in some wind farms, estimated removal correction factors differed only slightly depending on the model (as, e.g., in WF1 wind farm), other estimates differed substantially (as, e.g., in WF9 wind farm). Hence, the study of different plausible models regarding its adequacy is crucial to reduce bias estimation of scavenging rates and increase confidence in inference results.

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