Supplementary Material

Bird collisions with an Unmarked Extra-high Voltage Transmission Line in an Average Landscape - an Appeal to Take a Closer Look

Arno Reinhardt[1#], Moritz Mercker[2,3], Maike Sabel[1,4], Kristina Henningsen[1,5], Frank Bernshausen[1,6]

[1] TNL Energie GmbH, Raiffeisenstrasse 7, 35410 Hungen, Hesse, Germany

[2] Bionum GmbH, Finkenwerder Norderdeich 15A, 21129 Hamburg, Hamburg, Germany

corresponding author: arno.reinhardt@tnl-umwelt.de

[3] mmercker@bionum.de; orcid.org/0000-0002-7685-6193

[4] maike.sabel@tnl-umwelt.de; orcid.org/0000-0003-4784-5505

[5] kristina.henningsen@tnl-umwelt.de

[6] frank.bernshausen@tnl-umwelt.de

This supplementary material contains:

1. Study Site
1.1. Characterization of Avifauna
1.2. Powerline Features

2. Field Experiments
2.1. Decomposition Experiments
2.2. Searcher Efficiency Rate Experiments
2.3. Removal Experiments
2.4. Cadaver Procurement

3. Statistical Analysis
3.1 Carcass Correction Factors
3.2 Searcher Efficiency Analysis
3.3 Removal Analysis
3.4 Field Tests and Decomposition Process

4. Results
4.1 Field Experiments
4.2 Additional Figures

1. Study Site

1.1. Characterization of Avifauna

No specific studies of the local avifauna (breeding/resting birds) were commissioned, but observations of breeding and resting birds noted during the fieldwork provided a rough characterization of the area's avifauna. Typical small resting species included: Skylark (*Alauda arvensis*), Woodlark (*Lullula arborea*), Meadow Pipit (*Anthus pratensis*), Whinchat (*Saxicola rubetra*), Stonechat (*Saxicola rubicola*), Linnet (*Linaria cannabina*), and Barn Swallow (*Hirundo rustica*). The area also included resting and wintering pigeon species (especially Wood Pigeons, *Columba palumbus*) due to favourable climatic (part of the Atlantic region within North Rhine-Westphalia) and feeding (e.g., acorns, beechnuts) conditions. Roosting aggregations of the Wood pigeon with approx. 50-100 individuals were regularly observed in trees near the powerline between pylons 46 and 47, especially outside the breeding season (especially on a single oak tree located north of the powerline). Due to the lack of wetlands, larger gatherings of resting waterfowl in the winter tended to be dominated by ubiquitous species such as Greylag Geese (*Anser anser*) and Canada Geese (*Branta canadensis*), as well as Black-headed Gulls (*Chroicocephalus ridibundus*), regularly accompanied by smaller groups of White-fronted Geese (*Anser albifrons*) and Bean Geese (*Anser fabalis*) in the intensive grassland areas. Large communal resting birds including White Storks (*Ciconia ciconia*), and Great Egrets (*Ardea alba*) were also observed. The study site lays outside the area frequented by wintering Arctic geese in the Lower Rhine, so no relevant occurrences were expected in this regard. The Lippe and the Wesel-Datteln Canal were the only bodies of water in the vicinity, of these the Lippe is largely lined by woodland and waterfowl would only be expected to occur in small numbers (as confirmed), and local movements of waterfowl were more likely along the canal. There were no known specific resting areas in the immediate vicinity.

Overall, the study area was surrounded by copse islands and a larger forested area north of the study site, some of which may be of conservation value due to their structure and age. Accordingly, several species of woodpeckers (especially Middle-spotted Woodpecker (*Leiopicus medius)* and Black Woodpecker (*Dryocopus martius*) were assumed to breed in the extended surroundings. Raptors breeding in the vicinity of the study area included Eurasian Hobby (*Falco subbuteo*), Peregrine Falcon (*Falco peregrinus*), Goshawk (*Accipiter gentilis*), Buzzard (*Buteo buteo*), and Red Kite (*Milvus milvus*), and Eurasian Hobby and Peregrine Falcon repeatedly used the pylons as perching sites. Common Ravens (*Corvus corax*) also bree in the area. Small birds of high conservation value in the immediate vicinity of the study area included Red-backed Shrike (*Lanius collurio*), Stonechat and Redstart (*Phoenicurus phoenicurus*) (the latter two with approximately five territories/breeding pairs each), as well as Common Kingfisher (*Alcedo atthis*) at the River Lippe. According to the habitat around the River Lippe, rarer wet-grassland species (e.g., waterfowl) were absent during the breeding season.

1.2. Powerline Features

The powerline under investigation was a 380 kV overhead line (number Bl. 4569) in the form of a 'fir pylon' with three crossbeams and one earth cable tip (Figure S1). One 4-bundle conductor cable (380 kV) per side was placed on the upper crossbeam and two 4-bundle conductor cables (380 kV) were located on each side of the middle crossbeam. There were three 2-bundle conductor cables (220 kV) on the northern side of the lower crossbeam and two 2-bundle conductor cables and two 1-bundle cables (the latter two from Deutsche Bahn) on the southern side of the lower crossbeam. The powerline was operated by Amprion GmbH – one of the four operators of extra-high voltage powerlines (> 110 kV) in Germany. These powerlines represent the transmission grid.

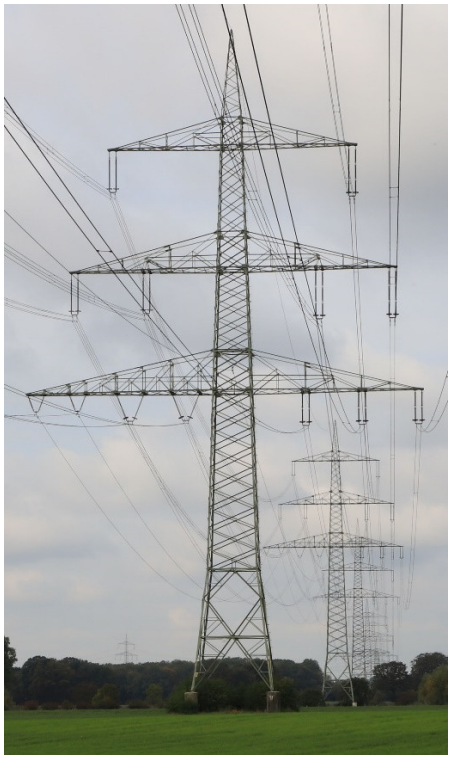


Figure S1: photo of a 380 kV pylon in the study area.

Table S1: powerline features

pylon number	pylon height (m)	max. crossbeam width (m) (distance between outer conductors)	distance between top (earth cable) and bottom wires (m)	span length (m)
0046	59,61	35,50	ca. 35	350,00
0047	77,17	35,50	ca. 35	365,00
0048	74,35	35,50	ca. 35	385,00
0050	61,23	35,50	ca. 35	400,00
0051	66,23	35,50	ca. 35	

2. Field Experiments

2.1. Decomposition Experiments

We estimated the decomposition time of carcasses experimentally by laying out and regularly monitoring carcasses. In addition, some carcasses from the removal experiments (see section 1.3) had very long retention times (longest documented retention time was a Buzzard (*Buteo buteo*) laid out on 03/12/2020, which had not been removed by 11/01/2021), and could thus be used to evaluate decomposition time. In summary, we concluded that the decomposition process could be considered negligible regarding its effect on the correction factors and was thus excluded from subsequent calculations.

2.2. Searcher Efficiency Rate Experiments

The searcher efficiency rate describes the proportion of birds found during the checks along a defined transect route in relation to the total number of bird carcasses actually present. The searcher efficiency rate depended on the vegetation structure (cover, height), the size and coloration of the collided birds, and the width of the transect (distance to the transect line), as well as individual surveyor errors (see for example [1]).

All four searchers/observers participated int the two experiments during the study, both in the summer period (08/06/2021 and 17/08/2021), and each experiment also included an experimental transect with low vegetation cover, to represent the search conditions within periods with lower vegetation cover.

During the experiments, well-preserved carcasses of different sizes (maximum 20 individuals, exact number unknown to the searcher) were distributed along a transect line on plots with different vegetation structures [2, 3]. The species used were intended to be representative of the range-specific species spectrum, within the limits of carcass availability. The distribution was random with respect to the number and size of carcasses, the distance between carcasses, and the distance of carcasses from the transect line (0-10 m, reduced to < 5 m transect with dense reygrass as beyond this the probability of detection tended towards zero from the outset). The test searches were carried out as for real searches (speed, etc.).

2.3. Removal Experiments

To take account of the influence of scavengers and predators on the number of collision victims found, the removal rate was determined as the length of time that bird carcasses remained in the study area (persistence time). The removal rate, and searcher efficiency rate represent the most important variables for calculating correction factors.

The removal rate may depend on several factors, including the size of the carcass (bird size), vegetation structure (density, height), and time of year, which should be given priority in determining persistence time.

Different seasons and vegetation conditions were considered. A total of 12 experiments were conducted in the study year, with up to 10 carcasses of different sizes (small, medium, large) laid out in each experiment. To investigate the influence of vegetation on persistence time, the birds were laid out in areas with different vegetation heights and structures. To avoid conditioning resident scavengers to a food supply, only a few carcasses were deliberately scattered. The carcasses were laid out within the study area (60 m to the right and left in the surveyed span fields).

To obtain accurate information about the removal time and predators, and to minimize the effort of daily monitoring, carcasses were observed using infrared cameras installed 2-4 m in front of each carcass. and mounted on short (60 cm) or long poles (150 cm), depending on the vegetation height. The camera data were read based on the estimated search interval in each case. Photographs were evaluated with respect to the timing of carcass clearance and the type of predator. To minimize any possible influence of the cameras on predators ('attraction effects'), some cameras (5 each) were deployed without carcasses ('blank tests').

2.4. Carcass Procurement

Bird carcasses were needed for the above experiments. For reasons of comparability, wild birds covering the species spectrum present in the study area were preferable to other options (e.g., laying hens or day-old chicks), and dead wild birds were obtained from the Clinic for Birds, Reptiles, Amphibians, and Fish, Justus Liebig University, Giessen, Germany. This clinic accepts injured wild birds with the aim of rehabilitating them and releasing them back into the wild, however, some individuals die or are euthanized, and the clinic made these carcasses (from as wide range of species as possible) available to TNL for an expense allowance. The necessary permit for both the clinic and TNL was obtained from the responsible regional authority (Regierungspräsidium Giessen, reference: RPGI-53.2-25a020078-2019/2 of 03.09.2020).

The following size classes were defined for the carcasses in all further analyses:

- small: birds up to and including Blackbirds (*Turdus merula*)/Great Spotted Woodpecker (*Dendrocopos major*)
- medium: birds larger than Blackbird/Great Spotted Woodpecker up to ducks/Long-eared Owls (*Asio otus*) (e.g., Sparrowhawk (*Accipiter nisus*), doves, Green/Black Woodpeckers (*Picus viridis*/*Dryocopus martius*), Kestrel (*Falco tinnunculus*), Carrion Crow (*Corvus corone*), Jackdaw (*Corvus monedula*), Magpie (*Pica pica*))
- large: birds larger than ducks/Long-eared Owls (e.g., Buzzard (*Buteo buteo*), Goshawk (*Accipiter gentilis*), Peregrine Falcon (*Falco peregrinus*), Eagle Owl (*Bubo bubo*), Egyptian Goose (*Alopochen aegyptiaca*), Mute Swan (Cygnus olor), Great Egret/Grey Heron (*Ardea alba/cinerea*), White Stork (*Ciconia ciconia*), Great Cormorant (*Phalacrocorax carbo*)).

3. Statistical Analysis

3.1 Carcass Correction Factors

The collision victim count survey was based on regular searches conducted in a defined area ('search area') around the structure of interest, i.e., the 380-kV overhead transmission line. A fundamental problem with carcass counts is that they usually underestimate the actual collision victim count N, because not all collided individuals die within the search area, not all carcasses remain in the area until the next search sweep due to removal by scavengers or decomposition processes, and not all remaining carcasses are located by the searchers [4, 5].

In addition these processes result in a non-random subsample of actual carcass quantity and are sometimes highly selective, e.g., the detection probability is usually skewed in favour of large carcasses [6].

Scientific studies dealing with collision casualty estimation should generally meet the following criteria:

1. An appropriate estimator $\widehat{N}$ should be used that approximates the true carcass number N based on the found number of carcass N^R while correcting for the above biases. In particular, the estimation method should be expectation-true, i.e., unbiased, in the context of the experimental and data structure.
2. Confidence intervals should be calculated that contain the true value N with given probability, to indicate the quality of the estimate.
3. Statistical tests involving carcass counts should use an appropriate method that considers both the scatter among the estimates and the quality of the estimates, using only field data or point-by-point estimates will generally result in inadequate significance values.

Despite recent advances in the statistical estimation of N (e.g., reviews in Bernardino et al. [7] and Korner-Nievergelt et al. [5]) previous methods imply different assumptions that are not necessarily met. Typical limitations relate to the regularity of search intervals, the underlying distribution function of carcasses (e.g., in Bayesian approaches [8]), or specific functional structures for removal or searcher efficiency rates. In addition, the fact that carcasses can be missed during a search pass and found at a later search pass ('bleed-through') is often neglected. These limitations mean that, each of the previous estimation methods produces biased results under certain conditions [8], and no universal flexible estimation method existed until recently [7, 9].

The present study thus, used the new flexible statistical method as presented in Mercker [14], which is based on regular carcass searches and additional field experiments to determine removal and searcher efficiency rates. This method allows both bias-free estimation of N under a variety of conditions/ data structures, as well as estimation of appropriate confidence intervals. The presented approach is based

on correction factors comparable to the method of 'sampling weights' [10] as used in the context of 'sightability models' [11–13]. In particular Mercker [14] and Jödicke et al. [3] used simulation methods to demonstrate that this method worked without bias under diverse even complex/ heterogeneous data situations.

General notation

M represents the actual number of birds that collided with an anthropogenic structure within a study period, and $N = sum(M)$ represents its sum, approximated by the statistical estimator $\widehat{N}$ (derived below). As described above, only a subset of the carcasses, $M^F \subset M$, is found during J searches, where M^F represents the individual carcass finds M_i associated with covariate vectors $\vec{X}_i$, where i is a continuous index. This covariate vector $\vec{X}_i = (x_1, x_2, ...)$ contains various information about the time, number of search passes, and local vegetation, etc., and contains all parameters that were also recorded during the additional experiments performed (e.g., probability of detection and clearance) (cf. following sections). These experiments are necessary to estimate the retention rate $s()$,detection probability $f()$,decomposition time $t_d()$, and the proportion of carcasses dying outside the search area, $A_{in}()$. These approximations are given below in terms of statistical models $\hat{s}()$, $\hat{f}()$, $\hat{t}_d()$ and $\hat{A}_{in}()$. In the following subsections, we define these models and develop the estimator $\widehat{N}$ for the actual number of collided birds based on the models, where $\widehat{N}$ represents the sum of the set of pointwise estimates $\{\hat{\theta}(\sim\vec{X}_1), \hat{\theta}(\sim\vec{X}_2), ...\} = \widehat{M}$. A detailed overview of the mathematical notation used in developing the correction factors can be found in the supporting information for Mercker [14].

Removal rate by scavengers

The removal or retention rate is commonly estimated by distributing carcasses in a search area (e.g., a subplot of the study area) and recording their whereabouts over time. In this way, it is possible to narrow down the appropriate time in case of removal. Checks can be carried out e.g. every 24 h by inspection, or at shorter time intervals using camera trap [15]. The frequency of inspections is described below by the scaling factor α_t relative to the number of days, e.g., $\alpha_t = 24$ indicate hourly inspections. All time windows (e.g., $D_{(k,l)}$) are given in units of $\alpha_t \cdot days$. To ensure the most general form of regression models for removal, we referred to recent studies of carcass removal by scavengers and modelled this time-dependent process in the context of 'survival analysis' using appropriate survival regression models that allow for inspection of many different possible random distributions and any number of covariates [5, 16, 17]. Based on Akaike's Information Criterion (AIC) [18], the most appropriate random distribution as well as an appropriate set of covariates can then be selected, resulting in the statistical model $\hat{s}()$. $\hat{s}()$ then depends on the time a (measured from the time the carcass was laid out) and another set of covariates $\vec{X}^s$. In this way, $\hat{s}(a, \vec{X}^s)$ approximates the retention rate s of carcasses (with a given set of covariate values $\vec{X}^s$) in the time interval $[0, a]$, which is

equivalent to the proportion of carcasses remaining compared to with starting time. We were also interested in relative retention rates at 'later' time intervals $[a, b]$ with $a > 0$ (i.e., to address fraction of carcasses remaining after time interval $[0, a]$ that remained after interval $[a, b]$). Many previous studies approximated this rate by $\hat{s}([a, b]) \approx \hat{s}([0, b - a])$ [7, 8], however, this relation only holds if $\hat{s}([a, b])$ falls exponentially with time, and this condition is easily violated, e.g., when the removal rate is linked to the age of the carcasses. Temporally non-constant retention rates thus produce corresponding biases in existing estimators [8].

In the present study, we avoided biases in this regard by calculating $\hat{s}([a, b])$ explicitly over

$$([a, b], \vec{X}^s) = 1 - \frac{\hat{s}(a, \vec{X}^s) - \hat{s}(b, \vec{X}^s)}{\hat{s}(a, \vec{X}^s)} = \frac{\hat{s}(b, \vec{X}^s)}{\hat{s}(a, \vec{X}^s)} \quad (1)$$

because $\frac{\hat{s}(a,\vec{X}^s)-\hat{s}(b,\vec{X}^s)}{\hat{s}(a,\vec{X}^s)}$ describes the relative change in the fraction of carcasses detected by us between time points a and b. Further, $\hat{s}(0, \vec{X}^s) := 1$ was set because a carcass was never cleared at the time of the bird strike.

Probability of detection

The detection probability $f()$ can be determined experimentally by conducting 'artificial carcass searches' where the true number of carcasses laid out is known (but not to the searcher). Here, we used a (logistic) Generalized Linear Mixed Model (GLMM) to describe the experimental data, because the outcome variable was binary in nature ('found' vs. 'overlooked') and the data were 'nested' in searchers. The use of mixed models prevents bias due to stochasticity in the experimental data [5]. As in the case of the removal regression, it is possible to consider any number of covariates X^f; the best set of covariates was again determined by AIC analyses [18], leading to the final estimator of the detection probability, $\hat{f}(\vec{X}^f)$.

Decomposition time

The decay time $t_d()$ describes the average number of days until a carcass is no longer detectable due to decay/decomposition. Under certain circumstances, $t_d()$ can be estimated jointly with $s()$, leading to a generalized form of the retention rate, $\tilde{s}(a, \vec{X}^s)$, however, given that both the time scales and the underlying processes are fundamentally different, it is recommended to estimate both processes separately. $t_d()$ can be estimated, for example, by laying out carcasses for extended periods and using cages to protect them from removal by scavengers.

Due to the large differences in the time scale between removal and decay, decay often has little effect on the effective detection probability/ correction factors. The experimental effort to determine $t_d()$ should thus be adjusted accordingly, and determination of the empirical mean value $\hat{t}_d() := \overline{t_d()}$ is

often sufficient as a simple statistical model. As stated above, our decay experiments suggested that decay could be neglected as a factor in the present study.

Proportion of birds that died within the search area

It is important to estimate the proportion of birds that die outside the search area, to avoid underestimating the total number of bird-strike victims [19]. Because visual methods or the use of marked individuals only allow the examination of very small samples [19, 20], we used a method similar to distance correction [21, 22]: if detected carcass quantities were sufficiently large, a truncated half-normal distribution of the distance of each carcass to the anthropogenic structure can be fitted via maximum likelihood. Here it is important to use a truncated half-normal distribution coincident with the boundaries of the search area, to avoid over- or underestimation of $A_{in}()$. The variance/ standard deviation derived from this fit (which determines the 'width' of the curve) can then in turn be fitted to a non-truncated half-normal distribution to calculate the proportion of $A_{in}()$ that is within the above limits. The variance/confidence intervals for $A_{in}()$ can then be determined, e.g., by bootstrapping the carcass data. Here, moving block bootstrap procedures should be used, if necessary, to account for temporal (and possibly local) dependencies [23, 24], however, using a (truncated) half-normal distribution is only legitimate for static structures, and additional ballistic effects (as in the context of wind turbines) require more complex models [25]. Notably, the data should already be corrected with respect to the retrieval and removal rates before the fitting process, to avoid biases in this respect.

We estimated the proportion of collision victims that died outside the search area by fitting a truncated half-normal distribution to all carcass data with respect to their respective distance from the centre-line (Figure S12). The boundaries of the distribution were 60 m, the same as the search area. The maximum likelihood fit (using the function dtruncnorm()) of the R package truncnorm as well as the function fitdist()) was based on the R package fitdistrplus [18]. Moving block bootstrap procedures were used to calculate the variance to adequately account for temporal (and possibly local) dependencies [19, 20].

Derivation and calculation of the estimator $\widehat{N}$

$\vec{X}_i$ represents the vector associated with the carcass i found in search pass $j \in \{1,2,\dots,J\}$, containing all covariates of the "best" regression models $\hat{s}()$, $\hat{f}()$, $\hat{t}_d()$ and $\hat{A}_{in}()$ (cf. previous sections) And $D_{(j,k)}$ represents the number of days between search pass j and search pass k, scaled by the factor α_t (cf. section 'Removal rate by scavengers'). Below, we develop correction factors $\hat{\theta}(\vec{X}_i)$ that correct each carcass i for the number of birds (with equal covariates) that died outside the search area, were cleared by scavengers, were missed by searchers, or decayed. The formula for $\widehat{N}$ to estimate the true collision number N is based on a simultaneous application/reweighting of the raw data by the regression models

$\hat{s}()$, $\hat{f}()$, $\hat{t}_d()$ and $\hat{A}_{in}()$ developed in the previous sections. In particular, $\widehat{N}$ is given as the sum of the corrected individual carcasses $\hat{\theta}_{(j)}(\vec{X}_i)$ and possible imputed missing data $\hat{\theta}_k^{imput}$ over

$$\widehat{N} = \sum_{i=1}^{I} \hat{\theta}(\vec{X}_i) + \sum_{k=1}^{K} \hat{\theta}_k^{imput} \tag{2}$$

Each value $\hat{\theta}_{(j)}(\vec{X}_i)$ is in turn given by

$$\hat{\theta}_{(j)}(\vec{X}_i) = \frac{1}{\hat{s}_M(D_{(j,j-1)}, \vec{X}_i) \cdot \hat{f}(\vec{X}_i) \cdot \hat{A}_{in}(\vec{X}_i)} - \frac{(1 - \hat{f}(\vec{X}_i))}{\hat{f}(\vec{X}_i) \cdot \sum_{n=j+1}^{J} \hat{\theta}_{(n)}(\vec{X}_i) L_j^{(n)}(X_i) \hat{A}_{in}(\vec{X}_i)} \tag{3}$$

This equation must be solved iteratively to obtain $\hat{\theta}_{(j)}(\vec{X}_i)$: by starting with $\hat{\theta}_{(J)}(\vec{X}_i)$ (which is uniquely defined, cf. Mercker [14]), $\hat{\theta}_{(J-1)}(\vec{X}_i)$ is uniquely given in the following, to give $\hat{\theta}_{(J-2)}(\vec{X}_i)$,..., up to $\hat{\theta}_{(j)}(\vec{X}_i)$. Furthermore, to solve equation 3, we need the following two definitions, viz.

$$\hat{s}_M\left(D_{(j,j-1)}, \vec{X}_i\right) = \overline{\left\{\hat{s}(t, \vec{X}_i) \middle| t = 1, \dots, D_{(j,j-1)}\right\}}$$

and

$$L_j^{(j+m)}(\vec{X}_i) = \left(1 - \hat{f}(\vec{X}_i)\right)^{m-1} \cdot \hat{f}(\vec{X}_i) \cdot \hat{s}_M([D_{(j,j-1)}, D_{j,j+m}], \vec{X}_i),$$

which are based on equation 1. For further details concerning the successive derivation of these formulas are given in Mercker [14].

Estimation of the variance

The variance is influenced by numerous factors, and calculating the variance or the confidence interval of the estimated value $\widehat{N}$ is thus not trivial, and analytical methods for calculating the variance often reach their limits, especially when the estimation method shows a high degree of complexity [26]. Available analytical variance estimators (e.g., Steinhorst & Samuel [13]) refer to much simpler models than that presented here, but the analytical estimators led to several different problems, even in these simpler models. For example, some of the analytical estimators were not bias-free, and errors in the numerical implementation of the rather complex formulas led to additional biases [11]. Bootstrap methods represent a possible attractive alternative to analytical variance estimation methods [10, 26, 27]. Here, all events affecting the variance were replicated using appropriate resampling algorithms applied to the original data, and all stochastic processes were reproduced based on Monte Carlo simulations [23, 28, 29]. While calculating $\widehat{N}$, various underlying random processes were approximated by empirical means. These random processes, shown below, increased the variance and must therefore be accounted for (and replaced by Monte Carlo simulations) in the context of the resampling procedure:

1. a collided bird may die inside or outside the search area

2. a carcass may or may not be cleared by scavengers
3. the time of collision (e.g., between two search passes) is variable and affects the probability of removal until the following search pass
4. a non-cleared carcass may or may not be detected by the searcher on one and all subsequent search passes
5. all statistical models used for correction factors are biased (due to sampling error)
6. imputation of missing values is associated with corresponding uncertainties

A detailed description of the resampling algorithm developed and used, including the methods for calculating confidence intervals for $\widehat{N}$, can be found in Mercker [14].

3.2 Searcher Efficiency Trials Analysis

Field method and implementation

A total of two different searcher efficiency trials were conducted (in June and August 2021), in which a total of 21 carcasses were laid out. These were then recorded by the four searchers involved in the study, resulting in a total of 84 observations.

Covariates

Regarding possible covariates influencing the searcher efficiency rate, we restricted our investigations to the following variables [3, 6]:

- bird class: categorical variable with three levels; differentiated by three different bird sizes
- local vegetation height: continuous variable measured in classes of 5 cm
- local vegetation density: continuous variable measured in cover classes of 10%
- large-scale vegetation type: categorical variable with two levels (‘grassland’ and ‘cropland’)
- surveyor ID: categorical variable
- distance: continuous variable, distance to transect line

Other possible covariates (e.g., belly/dorsal position of the bird, or sun position, Grünkorn et al. [6]) were not considered in this study due to added complexity. In addition, Grünkorn et al. [6] showed that for 10 m wide transects in any direction, the distance to the observer has a negligible influence on the searcher efficiency rate. Using the above variables, we developed and compared 19 apparently biologically meaningful different regression models (‘hierarchical predictor selection’ Field et al. [30]). The examination of interaction terms was omitted with the aim of obtaining robust results.

Table S2: Fixed predictors of the four best logistic regression models for searcher efficiency rate. ΔAIC denotes the difference in AIC value compared to with best regression model.

Fixed predictors	**ΔAIC**
veg. height + bird class	0.00
veg. height + veg. cover + bird class	0.72
veg. height + bird class + distance transect line	1.79
veg. height + veg. cover + bird class + distance transect line	2.61

Data structure and exploratory data analysis

The data set consists of 84 observations with no missing values. Overall, the design was sufficiently balanced with respect to the different predictor values, and sufficient observations were available for each predictor value. The continuous variables 'vegetation cover' and 'vegetation height' correlated with each other (Pearson's correlation coefficient r = 0, 69). For the following analysis (logistic regression, cf. following sections), a sufficiently high case density required for all combinations and levels of predictors, otherwise individual regression coefficients may be subject to very large standard errors [30]. Analysis of the cross-tabulations showed that this condition was fulfilled in all cases, according to the criteria mentioned in Field et al. [30]. The only exceptions were for variables that were naturally highly correlated with each other, such as vegetation cover and height or vegetation category and height. An increase in regression standard errors caused by this collinearity was prevented by the (AIC-based) predictor/model selection following the regression.

Model structure and selection and software

*S*tatistical modelling of the retrieval process was carried out using *R* statistical software [31]. Because the dependent variable of the regression model was binary ('overlooked' vs. 'found') and the covariates were both continuous and factorial, statistical modelling of the finding process was based on a logistic regression model. Using the *R* package lme4, all the above-mentioned predictors were initially used here as fixed effects, with observer ID as a random effect (because all observations were 'nested' in the observers, where the latter can be conceived as a random sample of the set of all possible observers). In addition, all continuous predictors were rescaled to improve convergence properties in the regression, Thus, we used a GLMM with logit-link function and binomial-distributed outcome. Model/ predictor selection was based on the procedures described in Zuur et al. [32] and Field et al. [30]. We thus created a set of biologically meaningful models (with different predictors and interactions) and compared them using AIC, and then selected the favoured model based on the minimum AIC.

Results of model selection

The best four of the 19 regression models (evaluated according to AIC [18]) are listed in Table S2. Bird class and local vegetation height played important roles (analogous to Jödicke et al. [3]) and were thus classified as the most important predictors. The individual searcher was also tested as an additional ('random intercept') predictor. AIC-based selection showed that systematic differences between individual searchers did not play an important role and this factor could therefore be ignored. The predictor 'large-scale vegetation type' caused instabilities in model fit (presumably due to collinearities with vegetation height) and, could thus not be considered. In the following, the 'best' regression model for the finding process, i.e., the model with minimum AIC, is referred to as the 'finding regression model' and is used in the context of the correction factors. The predictors/covariates used in this model represent a significant improvement in the fit of the model over a constant mean searcher efficiency rate ('null model') (likelihood ratio test: $p < 0.001$).

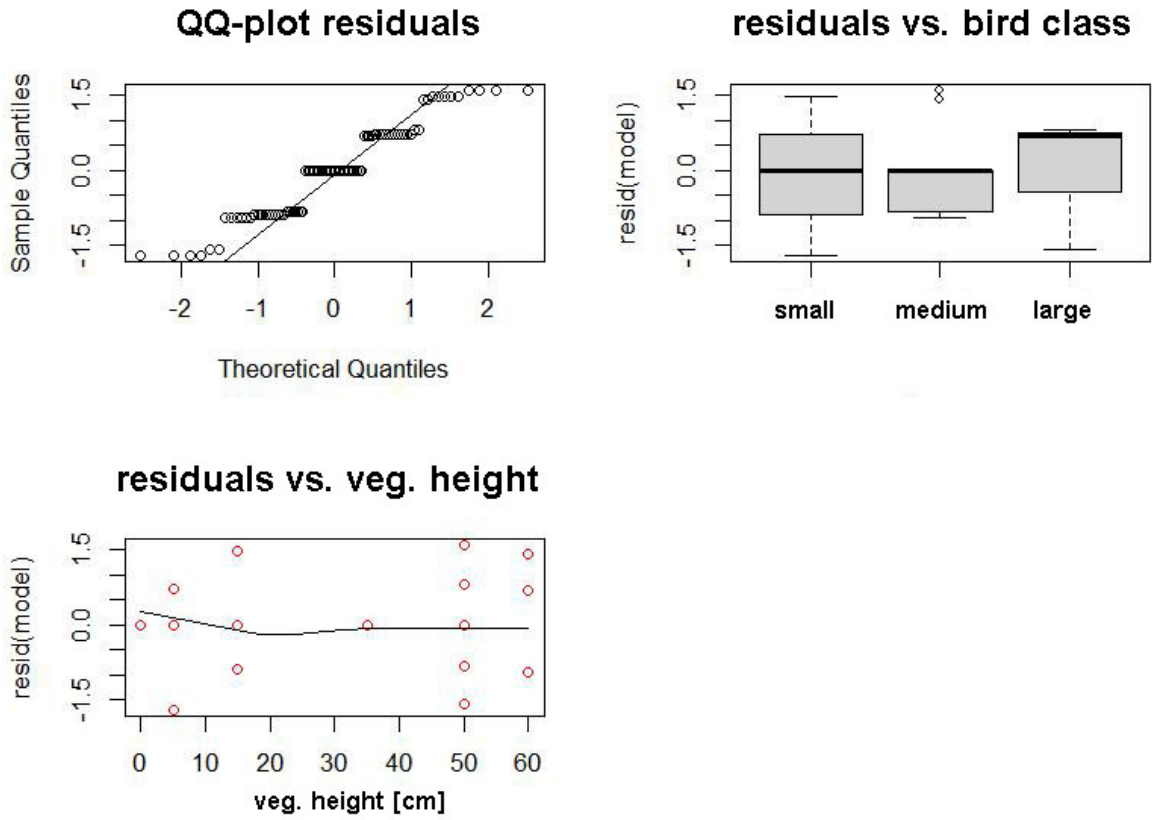


Figure S2: Validation plots to check the (asymptotic) normality of the residuals, linearity, and homogeneity of variances with respect to the detection regression model.

Model validation

The detection regression model needed to be validated to ensure its generalization to other samples (e.g., in the context of use as a correction factor). In particular, the (asymptotic) normality of the

residuals, homogeneity of variances, and linearity should be checked, and when using the *glmer*-function, it should also be checked if the mean of the random effects is close to zero [30, 32, 33].
Corresponding validation plots are shown in Figure S2. The QQ plot shows sufficient normality of the residuals. Scatterplots of the residuals as a function of the different predictors do not indicate any violation of homogeneity of variances. Furthermore, we validated that the mean of the random effects was close to zero. The conditions for a generalization of the model to other samples were thus largely fulfilled, i.e., the best regression model for the searcher efficiency rate can be used as a correction factor.

3.3 Removal Experiments

Field method and implementation

A total of 114 carcasses were deployed on 12 different days over different seasons. The locations of the carcasses were monitored using camera trap [15].

Covariates

Regarding possible covariates influencing the removal of carcasses by scavengers, we limited our investigations to the following variables:

- carcass size: categorical variable with three levels; differentiated by bird size
- local vegetation height: continuous variable measured in classes of 5 cm
- local vegetation density: continuous variable measured in cover classes of 10%
- large-scale vegetation type: categorical variable with two levels ('grassland' and 'cropland')
- coordinates: geographic section of the line
- month: continuous variable, nonlinear (polynomial) dependencies allowed

Using the above variables, we developed 34 different regression models deemed to be biologically meaningful (‘hierarchical predictor selection’, Field et al. [30]). Again, interaction terms were omitted in favour of the robustness of the models.

Data structure and exploratory data analysis

The data set consisted of 109 observations with no unexpected missing values. For all predictors, the design was sufficiently balanced, and sufficient observations were available for each predictor value. The continuous variables ‘vegetation cover’ and ‘vegetation height’ were correlated with each other (Pearson’s correlation coefficient: $r = 0.745$). For the following analysis (regression with survival models), a sufficiently high case density should be present for all combinations and levels of the predictors, otherwise individual regression coefficients may be subject to very large standard errors [30]. An analysis of the cross-tabulations showed that this condition was sufficiently fulfilled in all cases. The only exceptions were for variables that were naturally highly correlated, such as vegetation

cover and height or vegetation category and height. An increase in regression standard errors caused by this collinearity was prevented by the (AIC-based) predictor/ model selection following the regression.

Problem of missing removal photos

In the camera-based experiments some carcass removal events were not photographically recorded. To use these data without causing corresponding biases, the first photo without a carcass was taken as the end of the experiment for these cases. Because in our survival regression methods time points with data loss could be explicitly specified and considered, these data could be integrated into the analysis without any problems.

Model structure and selection and software

Statistical modeling of the removal process was accrued out using *R* statistical software [31]. Consistent with recent studies on carcass removal by scavengers, we modelled this time-dependent process context of survival analysis with appropriate survival regression models [5, 17, 30]. Using the R package *survival,* all the above predictors were first used ('maximum-complex model') to determine the most appropriate distribution between Exponential, Weibull, Log-Logistic, and Log-Normal using AIC analysis. Subsequently, the best of the 34 biologically meaningful models was selected by AIC analysis ('Hierarchical Predictor Selection' Field et al. [30]) to verify the most suitable probability distribution again with the final model via AIC analysis.

Table S3: Predictors of four best survival regression models for removal. ΔAIC denotes difference in AIC value compared with best regression model, p(.) is a second-degree polynomial.

predictors	**ΔAIC**
p(month) + bait size	0.00
bait size	0.97
p(month)	1.52
NULL	2.85

Results of model selection

With both the maximum-complex model and after predictor selection, the log-normal distribution provided the minimum AIC value, and was therefore used in the following (Figure S8). The best four of the 34 regression models examined (evaluated according to AIC [18]) are listed in Table S3. Carcass size, as well as a nonlinear (polynomial second degree) dependence on month were the most important predictors. In the following, the 'best' regression model for the removal process, i.e., the model with minimum AIC, is referred to as the 'removal regression model' and is used in the context of the correction factors. The predictors/covariates used in this model represent small significant

improvements in model fit compared with a model with only time as a predictor ('null model') (likelihood ratio test: p = 0.23). Nevertheless, we decided to use the model selected by AIC value over the null model because, despite the lack of significance, the p-value mean that the difference between the null and AIC-preferred models was not due to chance with a probability of about 4:1.

Model validation

The regression model first had to be validated to ensure its applicability to other samples (as in the context of use as a correction factor). In particular, we checked the homogeneity of variances and linearity [30, 32, 33], but did not check the normality of the residuals because a non-normal (in this case namely a log-normal;, Bispo et al. [16]) random distribution was explicitly assumed. Boxplots and scatter plots of the residuals as a function of the different predictors did not indicate a strong violation of homogeneity of variances or linearity (data not shown). The conditions for generalizing the model to other samples were thus largely met, i.e., the best regression model for removal can be further used as a correction factor.

3.4 Field Tests and Decomposition Process

We investigated the decomposition period in more detail by laying out carcasses at different times of the year. In all cases, there was no massive decay within 14 days that would have impaired detectability. We therefore assumed that the decay process was negligible with respect to its effect on the correction factors.

4. Results

4.1 Field Experiments

Searcher efficiency trials

The overall mean searcher efficiency rate was 59% which was similar to the values in previous studies (e.g., Grünkorn et al. [6] and Jödicke et al. [3] - in Jödicke et al. (just under 57%) [3]).

Table S4: Logistic regression results - best model for searcher efficiency rate. 'ns' = not significant ($p > 0.05$), '*' = $p < 0.05$, '**' = $p < 0.01$, '***' = $p < 0.001$.

	Regression coefficient	**Standard error**	**z-value**	**p-value**
(Intercept)	1.654	0.55	3.01	0.002
veg. height	-0.14	0.04	-3.38	<0.001***
bird class (medium)	4.96	1.80	2.75	<0.01*
bird class (large)	7,12	2.10	3.38	<0.001**

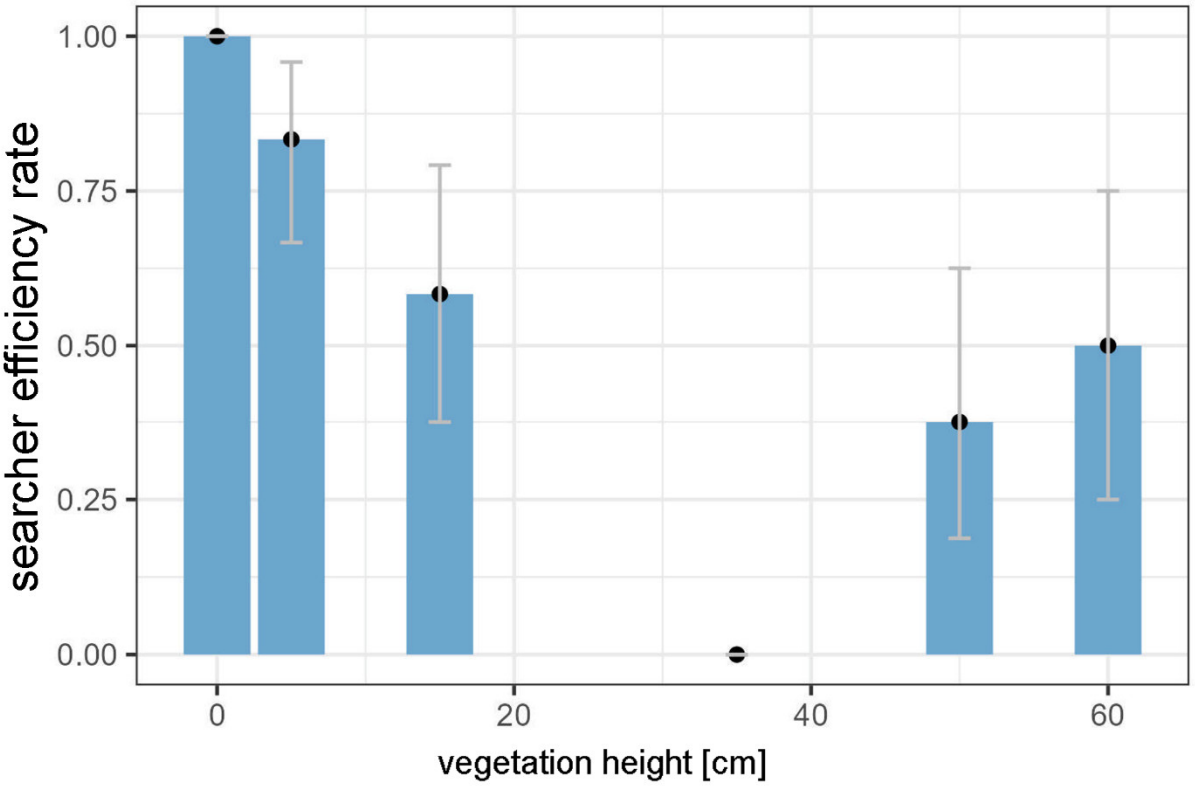


Figure S3: Mean searcher efficiency rate as a function of vegetation height (cm). Rate (y-axis) x 100 gives the percentage of individuals found.

The regression parameters of the detection regression model (cf. Table S4) showed that vegetation height had a highly significant effect on the searcher efficiency rate: the higher the vegetation, the less likely the bird was to be found (Figure S3), with a particular impact between 0 and 10 cm, and saturation thereafter. The bird size also significantly affected detectability: the larger more likely it was to be found (Figure S4).

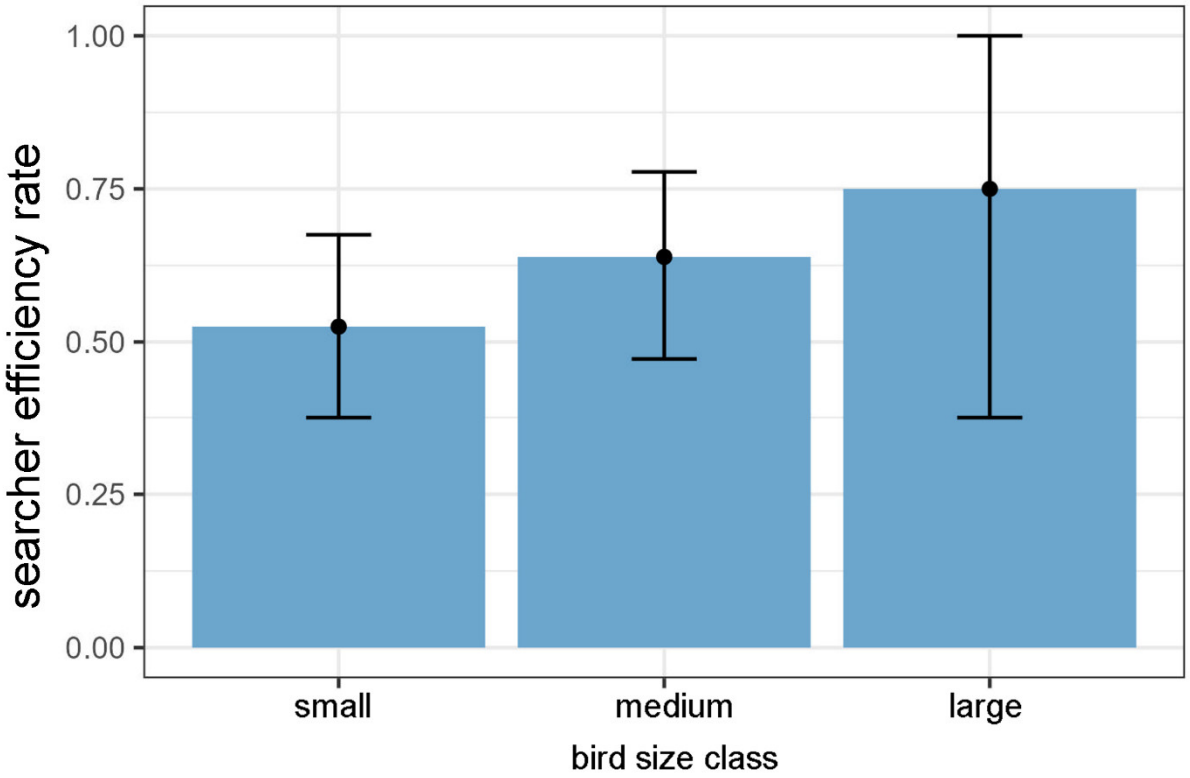


Figure S4: Mean searcher efficiency rate as a function of bird size (small, medium, and large). Rate (y-axis) x100 gives the percentage of individuals found.

Removal experiments

During the removal experiments, removals of carcasses could be documented by camera trap. Of a total of 113 carcasses laid out, 60 were removed during the experiment, 45 were not removed, and there were no records for eight individuals. Most carcasses were removed by Foxes (Figure S5), and three Kestrels were removed by a dog (Figure S6). Some carcasses were taken apart by other birds (e.g., crows or birds of prey) but were not completely removed (Figure S7). Occasional photographs recorded other animals (Badger, Wild Boar, Coypu) approaching the laid-out carcasses (Figure S8).



Figure S5: Removal of a Wood Pigeon (*Columba palumbus*) by a Fox (*Vulpes vulpes* 06/25/2021, 07:45) (left) and removal of a Jackdaw (*Corvus monedula*) by a Fox (06/29/2021, 00:14) (right).



Figure S6: Removal of two Kestrels (*Falco tinnunculus*) by a dog on 12/03/2020, 16:03 (left) and 12/04/2020, 15:40 (right).



Figure S7: A Kestrel (*Falco tinnunculus*) was dispersed by Buzzards (*Buteo buteo*) (2:29 p.m. 12/16/2020) but not removed (left), and a Buzzard was dispersed by Carrion Crows (*Corvus corone*) (12:16 p.m., 5/1/2021) but not removed (right).





Figure S8: Badger (*Meles meles*) at of Buzzard (*Buteo buteo*) carcass (04/16/2021, 12:03 am and 08/05/2021, 4:02 am), Wild Boar (*Sus scrofa*) at Carrion Crow carcass (*Corvus corone*) (08/15/2021, 12:40 am), Coypu (*Myocastor coypus*) near Kestrel carcass (*Falco tinnunculus*) (12/14/2020, 21:22 pm).

The mean clearance/removal rate was only about 10% after 5 days (Figure S9), which was lower than in most other studies (cf. e.g., Jödicke et al. [3] and Bispo et al. [16]). The reasons for this can only be speculated but may be because many studies were conducted in areas of high nature conservation value, which may have higher scavenger abundances than the current area.

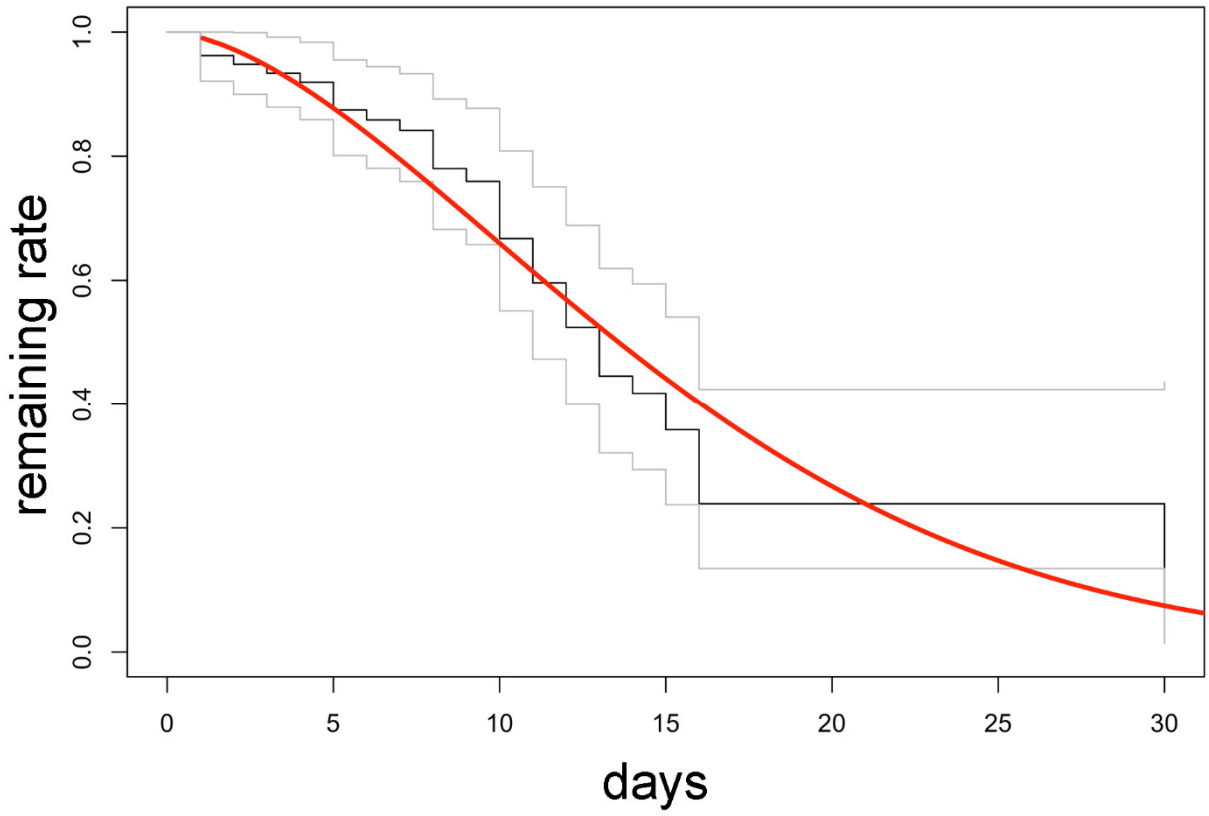


Figure S9: Partial effect plot of regression model for removal by scavengers. Black line, data (Kaplan-Meier curve) with 95% confidence intervals; red line, fitted log-normal survival regression model.

Curve indicates proportion of remaining carcasses (y-axis) with number of days after deposition (or until removal) (x-axis). Rate (y-axis) x 100 gives percentage of individuals remaining.

Table S5: Logistic regression results; best model for removal rate. ns = not significant ($p > 0.05$), * = $p < 0.05$, ** = $p < 0.01$, *** = $p < .0001$.

	Value	**Standard error**	**z-value**	**p-value**
(Intercept)	2.58	0.19	13.29	0.00**
poly(month, 2)1	1.00	1.30	0.77	0.44^{ns}
poly(month, 2)2	0.68	1.25	0.55	0.58^{ns}
bird class (small)	0.13	0.36	0.37	0.71^{ns}
bird class (medium)	-0.11	0.28	-0.38	0.70^{ns}

The regression parameters of the removal regression model (Table S5) show that small birds were removed slightly faster than large and medium birds (though the difference was not significant), which were removed at similar rates (see also Figure S10, but note that the binary variable 'removed' vs. 'not removed' after the end of the respective test was considered rather than the removal rare, and these results are therefore simplified and may differ from the results of the regression model). In addition, the removal rate was lowest in the middle of the year (Figure S11). Other parameters (e.g., vegetation height) were not selected in the model, indicating that they had no significantly measurable influence in each case.

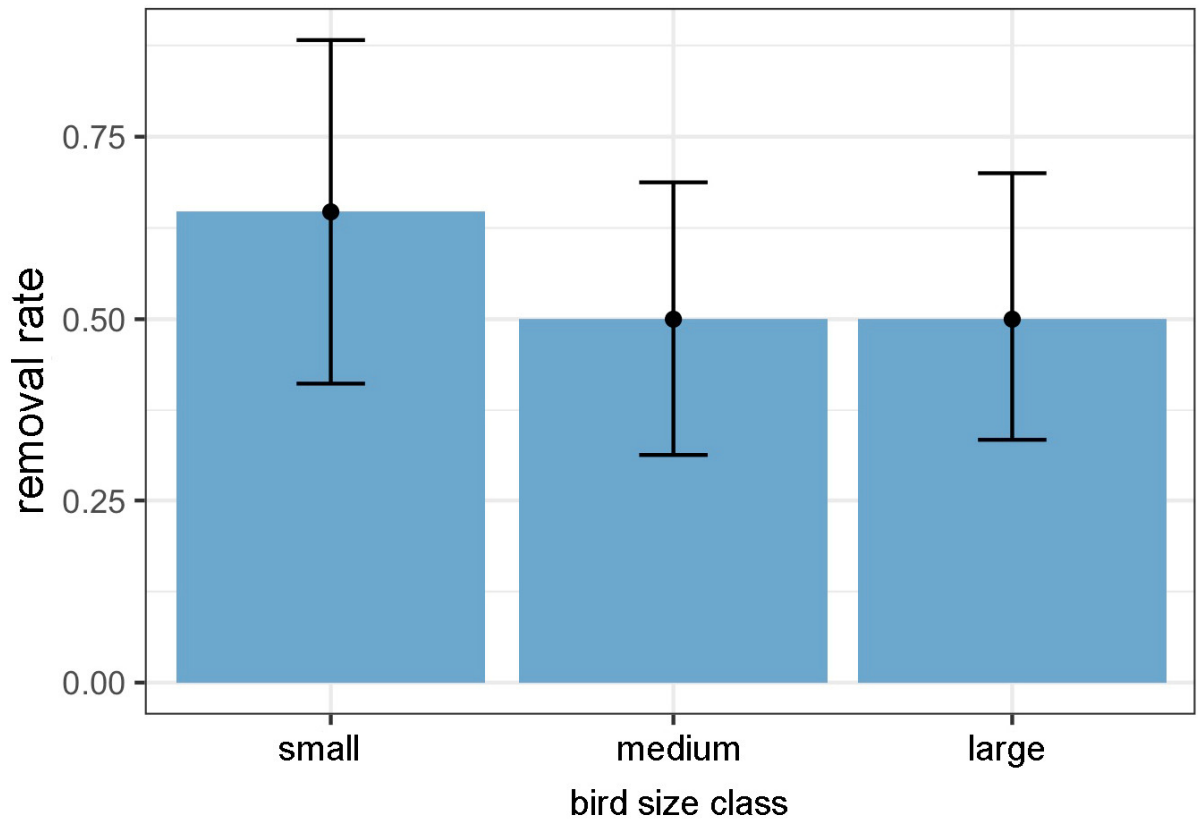


Figure S10: Removal rate after end of the experiment as a function of bird size (small, medium, and large). Rate (y-axis) x 100 gives the percentage of individuals removed after the end of the experiment (maximum 16 days).

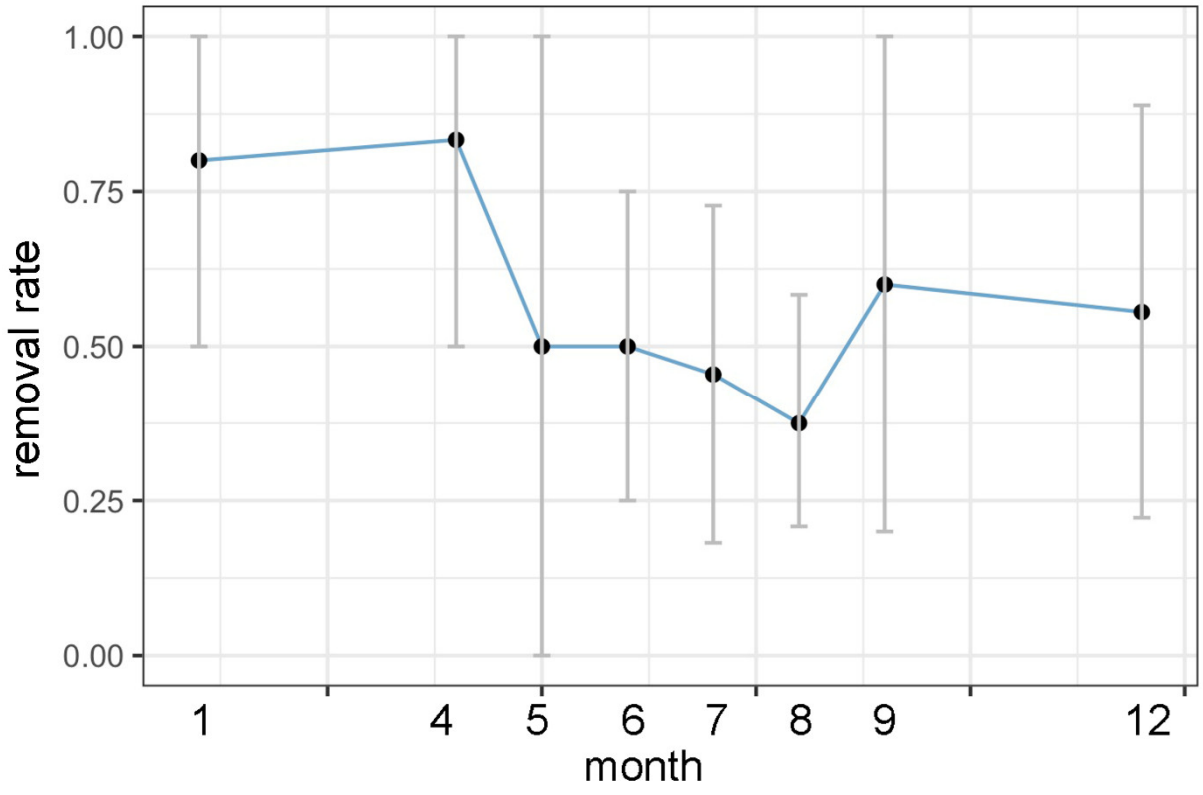


Figure S11: Removal rate after end of the experiment as a function of month. Rate (y-axis) x 100 gives the percentage of individuals removed after the end of the experiment (maximum 16 days).

Proportion of birds dying outside the search area

An average of 94% of bird-strike victims died within the search area (Figure S12). Analysis of variance using random-moving block bootstrap yielded a 95% confidence interval of 0.87 - 0.99. The proportion of birds that died outside the search area could thus be determined relatively precisely, and this factor therefore made only a small contribution to the variance/ estimation uncertainties of the true carcass numbers.

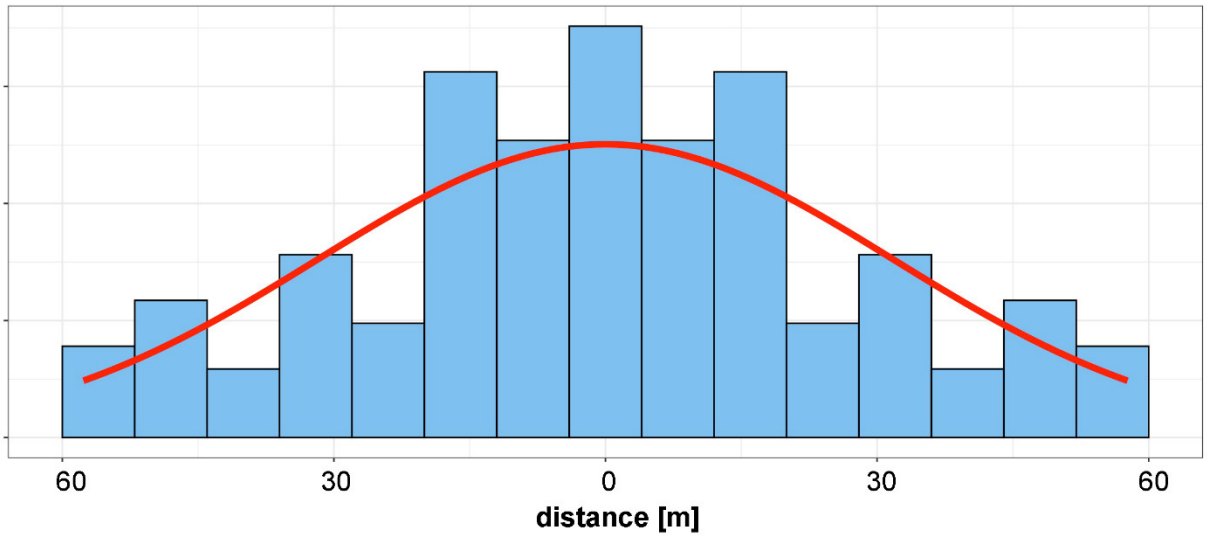


Figure S12: Histogram of carcass counts as a function of distance (m) from the overhead line (blue bars) and fitted truncated normal distribution (red line). Assuming a symmetric distribution, the data were mirrored on the y-axis. The y-axis shows the relative frequency rather than absolute values.

4.2 Additional Figures

Reactions to the lines

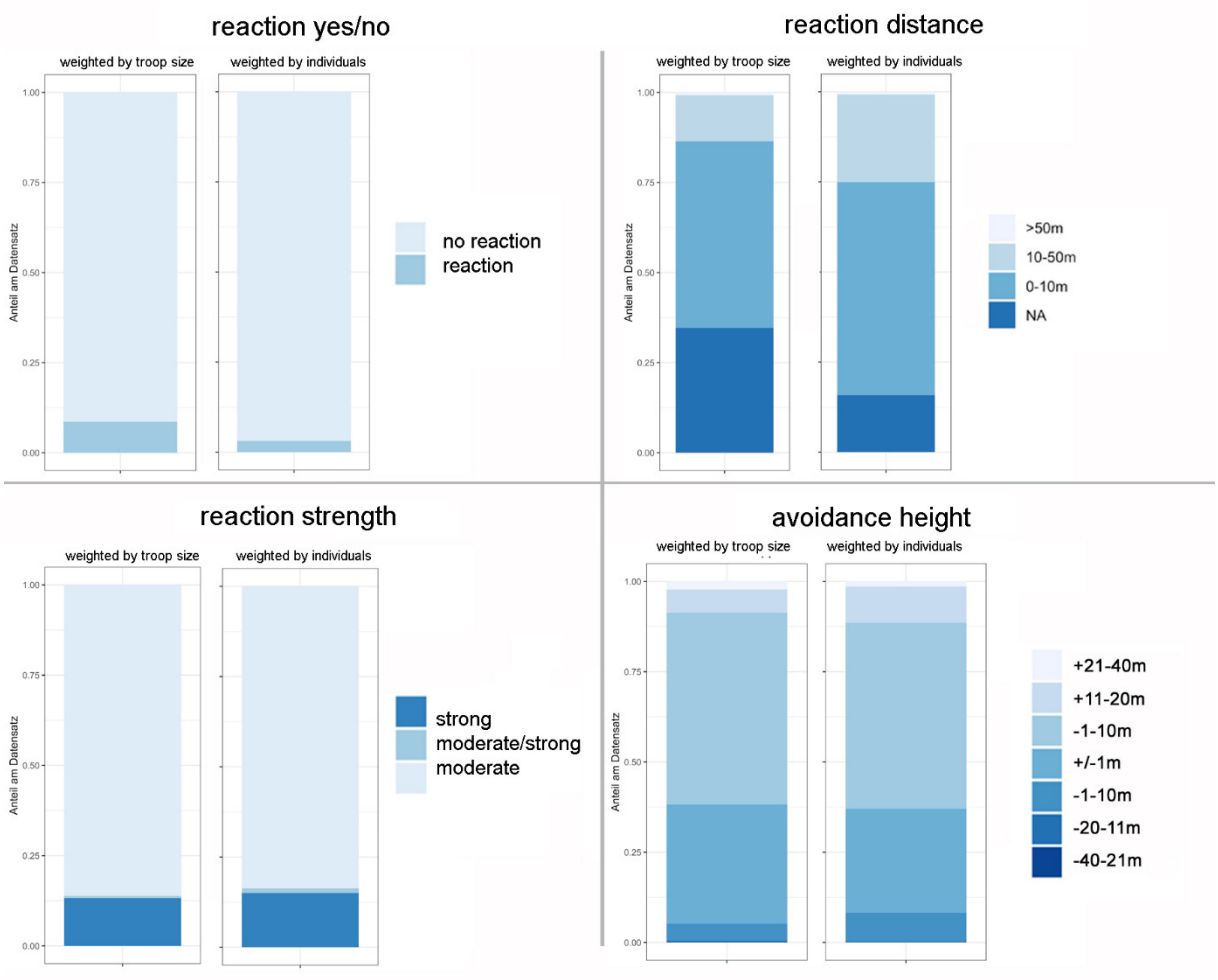


Figure S13: Proportion of individuals and flocks reacting to the lines (top left) More detailed analyses of the reaction distance (top right), reaction strength (bottom left) and evasion height (bottom right) in relation to the reacting birds or flocks.

Relative proportion of different crossing heights

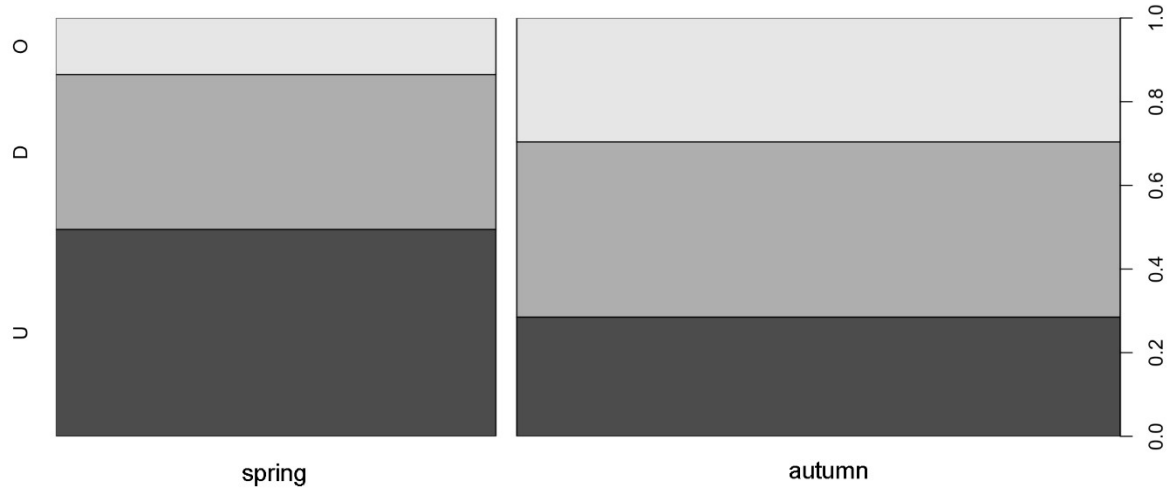


Figure S14: Relative proportion of different crossing heights. U= under the lines (black); D= through the lines (dark grey); O= above the lines (light grey) depending on the half of the year (spring jday < 200; autumn jday >= 200).

Proportion of different species complexes in bird-flight data vs. bird-strike victims

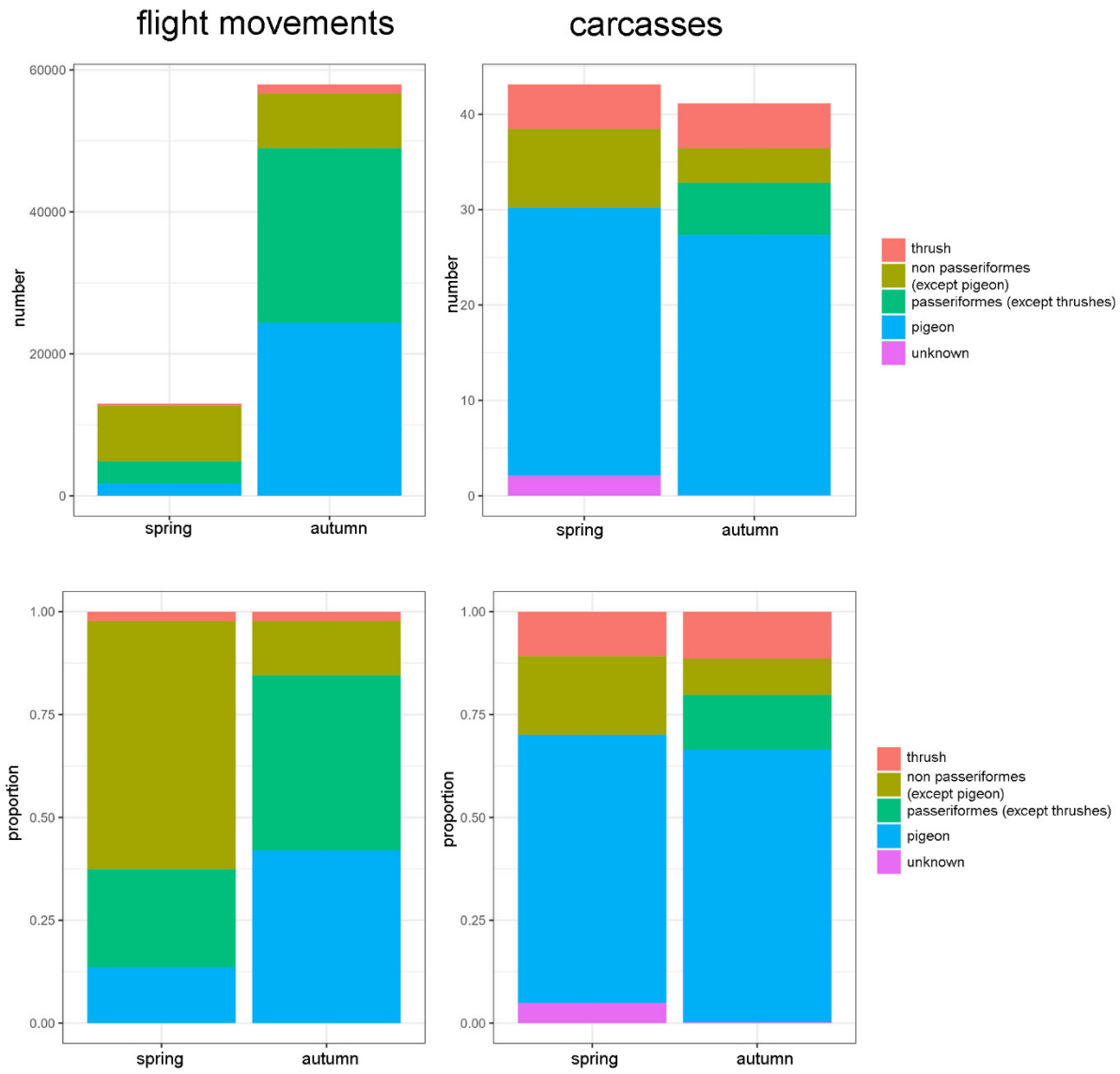


Figure S15: Proportion of different species complexes in bird-flight data (left) vs. (corrected) bird-strike victims (right). Above, absolute numbers; below, relative differences. Spring jday < 200; autumn jday >= 200.

Proportion of different species complexes in bird-flight data

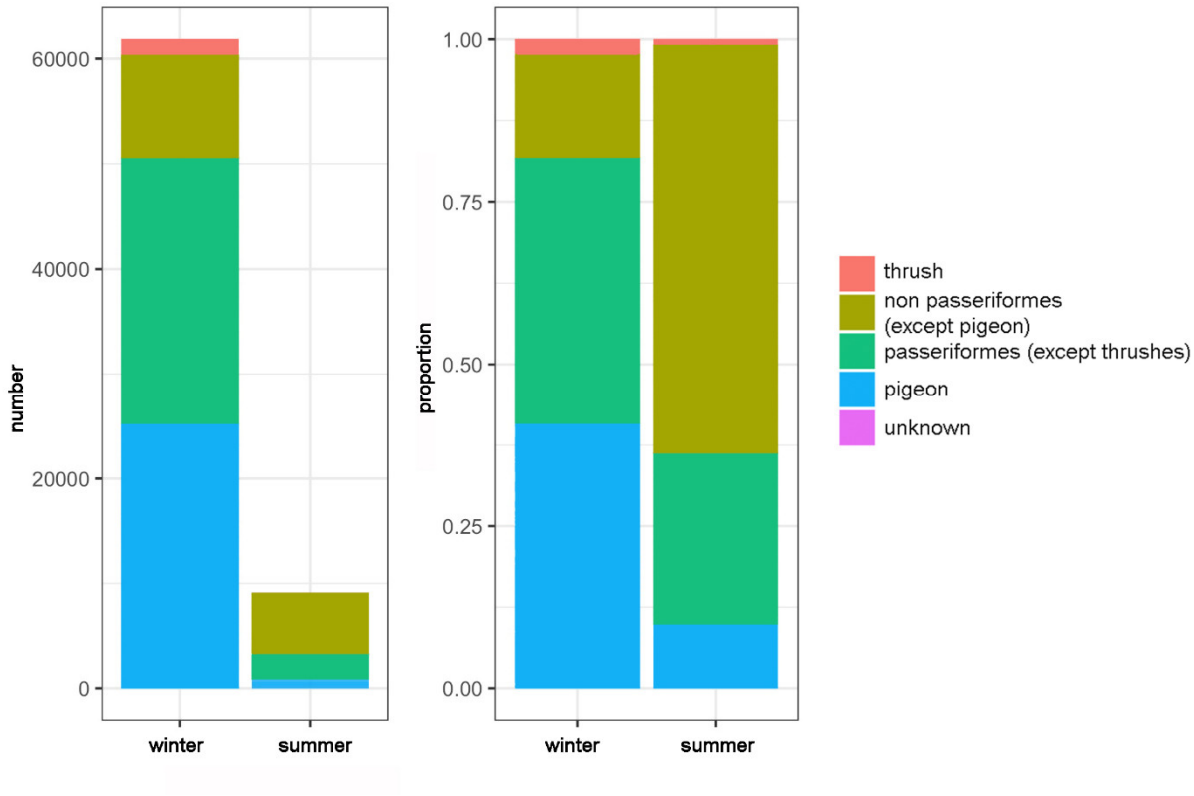


Figure S16: Proportion of different species complexes in bird-flight data. Left, absolute numbers; right, relative differences. Winter jday 220 - 80; Summer, rest of year.

Relative proportion of different species complexes in the bird-flight data vs. carcass data averaged over whole year

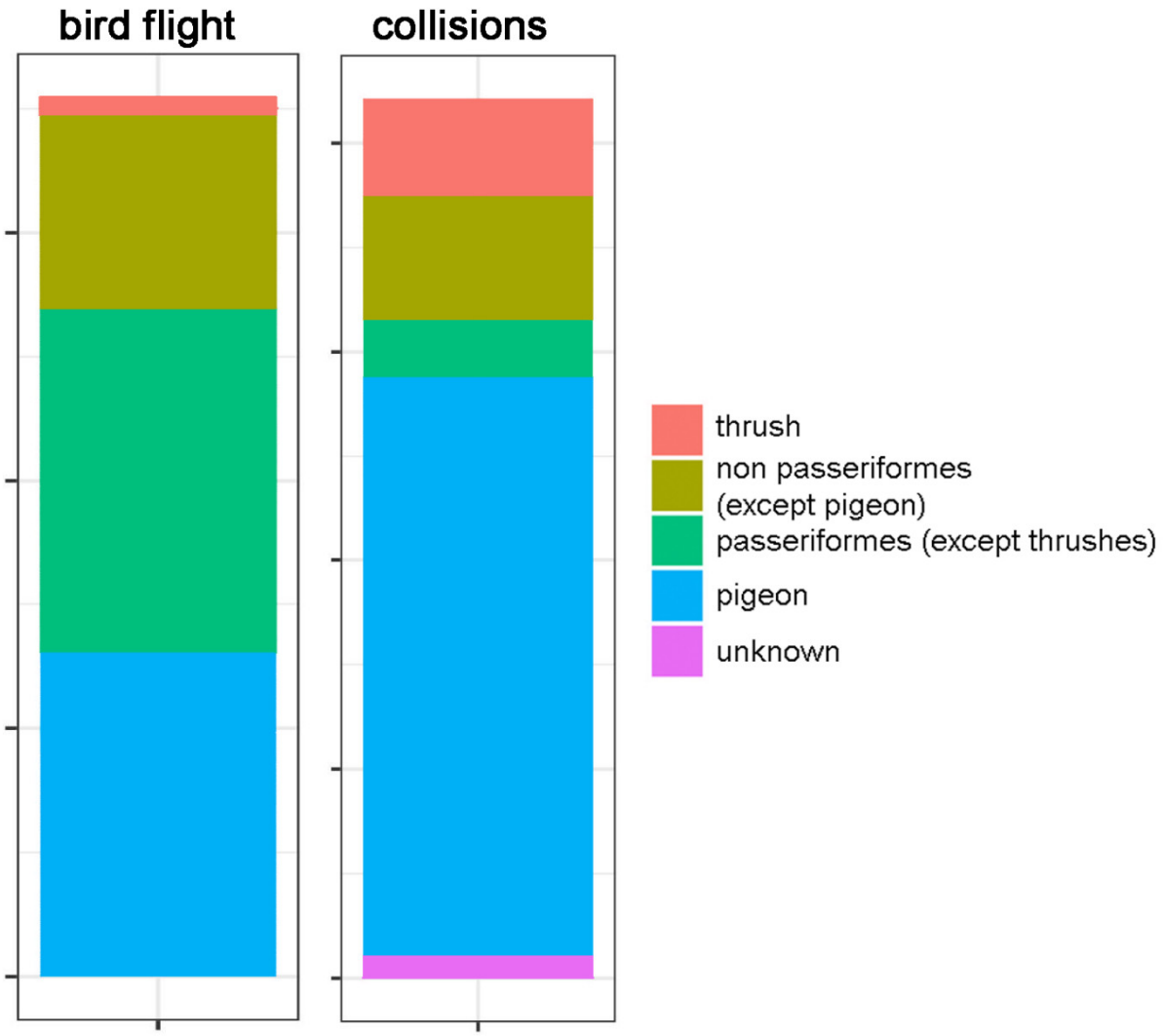


Figure S17: Relative proportion of the different species complexes in bird-flight data vs. carcass data averaged over whole year.

Partial effect of hourly recorded bird crossings as a function of time after sunrise

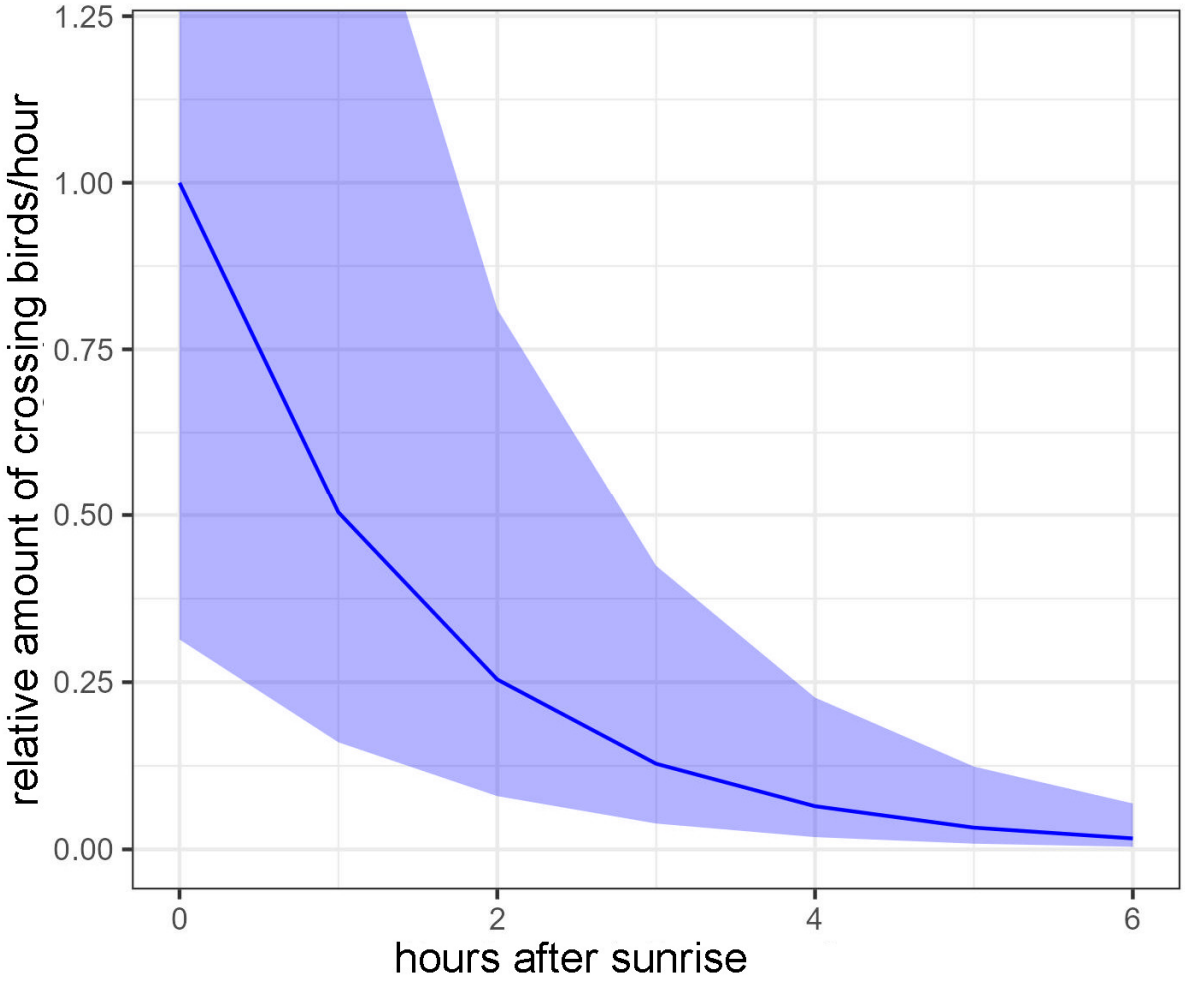


Figure S18: Partial effect (i.e., relative changes) in hourly recorded bird crossings as a function of time after sunrise based on a generalized additive model analysis.

REFERENCES

[1] Bernardino, J.; Martins, R.C.; Bispo, R.; Marques, A.T.; Mascarenhas, M.; Silva, R.; Moreira, F. Ecological and methodological drivers of persistence and detection of bird fatalities at power lines: Insights from multi-project monitoring data. *Environmental Impact Assessment Review*, **2022**, *93,* 106707.

[2] Hartmann, J.C.; Gyimesi, A.; Prinsen, H.A.M. *Zijn vogelflappen effectief als draadmarkering in een hoogspanningslijn?: Veldonderzoek naar draadslachtoffers en vliegbewegingen bij een gemarkeerde 150 kV verbinding:* Culemborg (NL), **November 08, 2010**.

[3] Jödicke, K.; Lemke, H.; Mercker, M. Wirksamkeit von Vogelschutzmarkierungen an Erdseilen von Höchstspannungsfreileitungen: Ermittlung von artspezifischen Kollisionsraten und Reduktionswerten in Schleswig-Holstein. *Naturschutz und Landschaftsplanung (NuL)*, **2018**, *50,* 286–294.

[4] Jödicke, K.; van de Fliert, M.; Reinhardt, A.; Bernshausen, F.; Beste, C.; Göbel, B.; Herden, C.; Jechow, B.; Mercker, M.; Spannagel, J.; Strobach, T. Artenschutzprüfung mit dem Rechenschieber?: Kritische Anmerkungen zur Arbeitshilfe "Arten- und gebietsschutzrechtliche Prüfung bei Freileitungsvorhaben" des BfN. *Naturschutz und Landschaftsplanung (NuL)*, **2021**, *53,* 18–27.

[5] Korner-Nievergelt, F.; Behr, O.; Brinkmann, R.; Etterson, M.A.; Huso, M.M.P.; Dalthorp, D.; Korner-Nievergelt, P.; Roth, T.; Niermann, I. Mortality estimation from carcass searches using the R-package carcass — a tutorial. *Wildlife Biology*, **2015**, *21,* 30–43.

[6] Grünkorn, T.; Diederichs, A.; Stahl, B.; Poszig, D.; Nehls, G. *Entwicklung einer Methode zur Abschätzung des Kollisionsrisikos von Vögeln an Windenergieanlagen;* BioConsult SH: Hockensbühl, **2005**.

[7] Bernardino, J.; Bispo, R.; Costa, H.; Mascarenhas, M. Estimating bird and bat fatality at wind farms: A practical overview of estimators, their assumptions and limitations. *New Zealand Journal of Zoology*, **2013**, *40,* 63–74.

[8] Korner-Nievergelt, F.; Korner-Nievergelt, P.; Behr, O.; Niermann, I.; Brinkmann, R.; Hellriegel, B. A new method to determine bird and bat fatality at wind energy turbines from carcass searches. *Wildlife Biology*, **2011**, *17,* 350–363.

[9] Bernardino, J.; Bispo, R.; Mascarenhas, M.; Costa, H. Are we properly assessing bird and bat mortality at onshore wind farms? *Proceedings of the 32nd Annual Meeting of International Association for Impact Assessment*, **2012,** 1–4.

[10] Lohr, S. *Sampling: Design and analysis. Second edition;* Brooks/Cole, Pacific Grove, California, USA, **2010**.

[11] Fieberg, J.R. Estimating Population Abundance Using Sightability Models: R SightabilityModel Package. *Journal of statistical software*, **2012**, *51,* 1–20.

[12] Manning, J.A.; Garton, E.O. A sightability model for correcting visibility and availability biases in standardized surveys of breeding burrowing owls in southwest agroecosystem environments. *Management and Conservation*, **2012**, *76,* 65–74.

[13] Steinhorst, R.K.; Samuel, M.D. Sightability Adjustment Methods for Aerial Surveys of Wildlife Populations. *Biometrics*, **1989**, *45,* 415–425.

[14] Mercker, M. *A flexible point and variance estimator to assess bird/bat fatality from carcass searches*; Preprint, **2021**.

[15] Paula, J.J.S.; Bispo, R.M.B.; Leite, A.H.; Pereira, P.G.S.; Costa, H.M.R.G.; Fonseca, C.M.M.S.; Mascarenhas, M.R.T.; Bernardino, J.L.V. Camera-trapping as a methodology to assess the persistence of wildlife carcasses resulting from collisions with human-made structures. *Wildlife Research*, **2014**, *41*.

[16] Bispo, R.; Bernardino, J.; Marques, T.A.; Pestana, D. Modeling Carcass removal time for avian mortality assessment in wind farms using survival analysis. *Environ Ecol Stat.*, **2012**.

[17] Bispo, R.; Bernardino, J.; MArques, T.:A.; Pestana, D. Discrimination Between Parametric Survival Models for Removal Times of Bird Carcasses in Scavenger Removal Trials at Wind Turbines Sites. *Studies in Theoretical and Applied Statistics*, **2013,** 65–72.

[18] Akaike, H. Information theory and an extension of the maximum likelihood principle. *International Sympossium on Information Theroy*, **1973**, *Second Edition,* 267–281.

[19] Bech, N.; Beltran, S.; Boissier, J.; Allienne, J.F.; Resseguier, J.; Novoa, C. Bird mortality related to collisions with ski-lift cables: Do we estimate just the tip of the iceberg? *Animal Biodiversity and Conservation*, **2012**, *35 (1),* 95–98.

[20] Bevanger, K. Estimates and population consequences of tetraonid mortality caused by collisions with high tension power lines in Norway. *Journal of Applied Ecology*, **1995,** 745–753.

[21] Buckland, S.T.; Anderson, D.R.; Burnham, K.P.; Laake, J.L.; Borchers, D.L.; Thomas, L. *Introduction to Distance Sampling: Estimating Abundance of Biological Populations;* Oxford University Press, New York, **2001**.

[22] Thomas, L.; Buckland, S.T.; Burnham, K.P.; Anderson, D.R.; Laake, J.L.; Borchers, D.L.; Strindberg, S. *Distance Sampling;* John Wiley & Sons, Ltd, Chichester, **2002**.

[23] Davison, A.C.; Hinkley, D.V. *Bootstrap Methods and Their Application;* Cambridge University Press, **1997**.

[24] Ju, H. Moving Block Bootstrap for Analyzing Longitudinal Data. *Commun Stat Theory Methods*, **2015**, *44,* 1130–1142.

[25] Huso, M.M.P.; Dalthorp, D. Accounting for unsearched areas in estimating wind turbine-caused fatality. *The Journal of Wildlife Management*, **2014**, *78,* 347–358.

[26] Pearse, A.T.; Gerard, P.D.; Dinsmore, S.J.; Kaminski, R.M.; Reinecke, K.J. Estimation and correction of visibility bias in aerial surveys of wintering ducks. *The Journal of Wildlife Management*, **2008**, *72,* 808–813.

[27] Fieberg, J.R. Written communication, **2015**.

[28] Efron, B.; Tibshirani, R.J. *An introduction to the bootstrap;* New York: Chapmann & Hall, **1993**.

[29] Canty, A.J.; Davidson, A.C.; Hinkley, D.V.; Ventura, V. Bootstrap diagnostics and remedies. *The Canadian Journal of Statistics*, **2006**, *34,* 5–27.

[30] Field, A.; Miles, J.; Field, Z. *Discovering statistics using R;* SAGE Publications Ltd, **2012**.

[31] R Core Team. *R: A language and environment for statistical computing.*, **2022**.

[32] Zuur, A.F.; Ieno, E.N.; Walker, N.J.; Saveliev, A.A.; Smith, G.M. *Mixed Effect Models and Extensions in Ecology with R;* Springer Science+Business Media, LLC, New York, **2009**.

[33] Korner-Nievergelt, F.; Roth, T.; Felten, S. von; Guelat, J.; Almasi, B.; Korner-Nievergelt, P. *Bayesian Data Analysis in Ecology Using Linear Models with R, BUGS, and Stan;* Elsevier, London, **2015**.