Title: A fine-grained behavior-based approach to estimating the probability of collision between moving vehicles and birds

Authors:

1) Ryan B. Lunn[1]
2) Bradley F. Blackwell[2]
3) Esteban Fernández-Juricic[1]

[1] Department of Biological Sciences, Purdue University, 915 Mitch Daniels Blvd, West Lafayette, IN, 47907, United States of America

[2] United States Department of Agriculture, Animal and Plant Health and Inspection Services, National Wildlife Research Center, Sandusky, 610 Columbus Ave, OH, 44870, United States of America

Corresponding Author: Ryan B. Lunn, email: rlunn@purdue.edu

Keywords: Road Ecology, Animal Behavior, Animal & Vehicle Collisions, Escape Behavior, Bird & Aircraft Collisions, Canada geese, Modeling, Drones

Open Research Statement

All code, files, supplementary material and data generated from this study are available at https://osf.io/9rh47/overview?view_only=1750d6840d3a4478bec0432b2fec2424

Conflict of Interest:

No conflict of interest declared

Abstract

1. Collisions between animals and vehicles contribute to biodiversity loss, threaten human safety, and have economic consequences. Escape responses of wildlife to vehicles are a critical factor in determining whether a collision occurs. However, presently species-

specific vulnerability estimates do not consider the species escape behavior, potentially resulting in inaccurate mortality estimates.

2. Recently, a mathematical model was proposed to estimate whether a collision occurs considering fine-grained properties of both an approaching vehicle and the species escape response. Herein, we expanded upon an existing model and applied it for the first time to estimate the probability of collision in a behavioral experiment where a UAS directly approached Canada geese with different light (light-off, light-on steady, light-on pulsing) and approach type (level, descending) treatments.
3. The probability of collision for the light-on steady and light-on pulsing treatment increased by 9.92% and 25.47%, respectively, during level approaches but decreased during descending approach treatments by 34.38% and 37.24%, respectively, relative to the light-off treatment. We attribute this interaction effect to differences in the ratio of UAS to LED light surface area.
4. We examined the role of the different parameters in the model and found that flight-initiation distance had the largest effect size, followed by escape trajectory, and UAS altitude. Specifically, longer flight-initiation distances, an increase in an away escape trajectory, and higher UAS altitude all contributed to reducing the probability of collision.
5. *Synthesis and applications*. Using a fine-grained behavioral approach, our model can provide estimates of the probability of an animal-vehicle collision when observing a collision is either logistically challenging or unethical. We also demonstrate that our model can provide quantitative guidance on UAS based hazing strategies to improve animal welfare. Lastly, our model can be used to quantitatively estimate how many animal-vehicle interactions were avoided due to the escape response of the animal, thus

enabling conservation strategies to not just focus on reducing collisions but also promoting successful avoidance.

Introduction

Collisions between animals and vehicles regularly have lethal consequences for wildlife, contributing to biodiversity loss (Loss et al., 2015, Lima et al., 2015, Grilo et al., 2021, Moore et al., 2024), in addition to threatening human safety, and economic cost (Huijser et al., 2008, Conover, 2019). A common practice to prevent animal-vehicle collisions is to exclude animals from areas near transportation routes or infrastructure to reduce collisions by reducing the probability of an animal and vehicle interaction (Glista et al., 2009, DeVault et al., 2013, van der Ree et al., 2015, Rytwinski et al., 2016). However, such a drastic strategy is often not logistically possible (Ascensão, et al., 2013, Huijser, et al., 2016, Spanowicz et al., 2020). Consequently, other strategies have been used, such as hazing (Harris et al., 1998, Belant, 2011, Seiler & Olsson, 2017), deterring wildlife from moving vehicles (Blackwell et al, 2012, Schoeman, et al., 2020, Pakula et al., 2025) or adjusting vehicle trajectory (Mammeri et al., 2016, Silva & Calabrese, 2024). One of the challenges of assessing different strategies has been the limited theoretical frameworks to estimate the probability of collision between the vehicle and the animal (Lunn et al., 2022).

The escape response of wildlife near an approaching vehicle is commonly invoked as a critical factor in determining whether a collision does or does not occur (DeVault et al., 2015, Blackwell et al., 2019, Brieger et al., 2022). Escape responses of prey animals to approaching *predators* form a sequence of dynamic behaviors (Lima & Dill, 1990, Cooper & Blumstein, 2015, Evans et al., 2019, Branco & Redgrave, 2020), where multiple components (e.g., flight-initiation distance, escape trajectory, escape speed, etc.) may vary depending on perceived

predation risk (Domenici & Blake, 1991, Domenici et al. 2011, Kawabata et al. 2023). Escape responses of wildlife to approaching *vehicles* also appear to be dynamic and multifaceted (Lima et al., 2015, Lunn et al., 2022). However, previous empirical studies (DeVault et al. 2015, Guenin et al. 2024) have been limited to estimating whether a collision occurs based on only a single escape response component, the distance between the animal and the vehicle the moment the animal initiates escape (i.e., flight-initiation distance).

Recently, a mathematical framework was proposed (Lunn et al. 2026) to estimate whether an animal-vehicle collision occurs by considering simultaneously multiple components of both the escape response of an animal and the approaching vehicle. However, this mathematical framework has yet to be applied to estimate the probability of collision with empirical data. Specifically, estimates for the probability of collision have three direct applications. First, estimates for the probability of collision can be used to readily translate how a given management strategy might reduce economic costs (Huijser, et al., 2009, Bissonette et al., 2009, Altringer, et al., 2021). Second, species-specific estimates for the probability of collision can be used to improve forecasts of a species vulnerability to roadway mortality (Grilo et al., 2020, Jacobson et al., 2016, Bénard et al., 2024), which is a key component in transportation development infrastructure projects. Third, estimates for the probability of collision can be used to identify the approach speeds for different vehicles at which a species behavioral response is insufficient to prevent an impending collision and whether additional infrastructure is needed to mitigate collisions.

Our study has two goals. First, we further develop Lunn et al.'s (2026) model to generalize its applicability to estimate the probability of collision regardless of the shape of the frontal surface area of the vehicle. Second, we applied this model to quantify the probability of

collision for the first time using parameters measured within a single empirical study and analyzed how different components of a species' escape response contribute to the probability of collision. More specifically, we estimated the probability of collision in a study assessing the behavioral responses of Canada geese (*Branta canadensis*) to an unoccupied aerial system (hereafter, UAS) approaching from different altitudes and with different light treatments (Lunn et al. 2025). We selected this study because it was the only experiment for which six of the seven variables needed to estimate the probability of collision with Lunn et al.'s (2026) model were empirically measured (Lunn et al. 2025).

Methods

Model overview and improvements

The model proposed in *Lunn et al. (*2026*),* is composed of two phases. Phase one estimates whether the animal and vehicle overlap at the same location and time. Phase two estimates whether the animal and the vehicle overlap in altitude, given a collision is possible. Collisions occur only when the animal and vehicle share the same location at the same time (phase one) and share a common altitude (phase two). Explicitly, the formulation of the model is built on several assumptions (Supporting Information 1) including that the animal is within or near the trajectory of the vehicle and that the trajectory of the vehicle and animal is linear and fixed after escape is initiated.

We built upon the existing model (Lunn et al. 2026*)* to facilitate application to a variety of different vehicles (i.e., variation in frontal surface area) and improve upon the accuracy of model predictions. We made three distinct changes. First, in phase one the animal must travel beyond the width of the vehicle and its own body length/width to completely clear the trajectory

of the vehicle, where the additional distance the animal must travel due to body length/width varies depending on the escape trajectory of the animal. Herein, we include an equation to estimate the additional distance the animal must travel for its body to completely clear the trajectory of the vehicle based on its escape trajectory. Second, in phase one we now account for the sensory motor-delay period in the estimates of the time remaining until the vehicle reaches the animal, because the animal does not functionally begin to change its position within the trajectory of the vehicle until after the sensory motor-delay period (Provini et al., 2012, Guenin et al., 2024). Third, we adjusted phase two of the model to explicitly consider the altitude of the animal to estimate whether the frontal surface of the animal and vehicle overlap as opposed to inferring a probability of collision based on the frontal surface area of the vehicle alone (Lunn et al. 2026).

Phases one and two

Phase one of the model in Lunn et al., 2026 estimates whether a collision is possible by comparing the time the animal needs to escape the trajectory of the approaching vehicle (T_a) relative to the time remaining before the vehicle reaches the animal after escape is initiated (T_v). The time the animal needs to escape the trajectory of the vehicle (T_a) is calculated using equation 1 with the following variables: the minimum distance to safety determined by the width of the vehicle (U_w), the trajectory adjusted length of the animal (l_{adj}), escape speed (S_a), escape angle (θ), and sensory-motor delay as the animal reorients and begins to accelerate (δ).

$$T_a = \left(\frac{\frac{U_w + l_{adj}}{\sin(\theta)}}{S_a} \right) + \delta \qquad \text{(Eq.1)}$$

The total distance the animal needs to travel to clear the trajectory of the vehicle varies slightly depending on the escape trajectory of the animal. Equation 2 estimates the trajectory adjusted length (l_{adj}) the animal must travel to clear the trajectory of the vehicle,

$$l_{adj} = |(G_l * \sin(\theta)) + (G_w * \cos(\theta))| \quad \text{(Eq. 2)}$$

where the variables of G_l and G_w respectively correspond to the body length, here defined as the length from beak tip to tail feathers, and width, here defined as wingspan, of the animal.

The time remaining until the vehicle reaches the location of the animal after the animal begins to move (T_v) is calculated using equation 3 with the following variables: flight-initiation distance (D_{FID}), sensory motor-delay period (δ), escape speed (S_a), and escape angle (θ) of the animal, and the approach speed of the vehicle (S_v).

$$T_v = \frac{D_{FID} - (S_v * \delta)}{S_v + (\cos(\theta) * S_a)} \quad \text{(Eq.3)}$$

Escape speed (S_a) and trajectory (θ) of the animal affect the time the vehicle reaches the location of the animal; however, only when the animal begins moving. The animal does not functionally begin to change its position within the trajectory of the vehicle until after the sensory motor-delay period (δ). During that period, the UAS continues to approach and as a result the distance between the animal and vehicle decreases, where the decrease is distance is determined by the UAS approach speed (i.e., $S_v * \delta$). If T_a (i.e., time needed to escape) is greater than or equal to T_v (i.e., time remaining to successfully escape) a collision is possible, where if $T_a < T_v$ a collision is entirely avoided. Phase two of the model is only applicable if $T_a \geq T_v$.

Phase two of Lunn et al., 2026 estimates whether the animal and vehicle overlap in altitude, given the location of the animal within the trajectory of the vehicle. The location of the

146 animal ($D_{collision}$) within the trajectory of the vehicle the moment the vehicle reaches the animal
147 is calculated using equation 4 with the following variables: the animals initial location in the
148 trajectory of the vehicle ($D_{initial}$), escape speed (S_a), escape angle (θ), and the time remaining
149 until the vehicle reaches the location of the animal after escape initiation (T_v).

150 $$D_{collision} = D_{initial} + (\cos(\theta) * S_a * (T_v)) \quad \text{(Eq. 4)}$$

151 Based on the location of the animal within the trajectory of the vehicle we explicitly
152 estimate whether the animal and vehicle overlap in altitude. To facilitate model application, we
153 elected to estimate whether two uniform rectangular shapes overlap in a 2D plane as opposed to
154 considering the specific shape of the vehicle. The x and y coordinates of both shapes within the
155 2D plane correspond to the position and altitude of the vehicle and animal (Eq. 5a-5f, Fig.1).
156 Equation 5a and 5b respectively estimate the length of overlap in vehicle height and
157 width with the animal. Equation 5a considers vehicle altitude (U_{alt}) and height (U_h) and animal
158 altitude (G_{alt}) and height (G_h).

159 $$h_{\cap} = min\left(U_{alt} + \frac{U_h}{2}, G_{alt}\right) - max(\, U_{alt} - \frac{U_h}{2}, G_{alt} - G_h) \quad \text{(Eq. 5a)}$$

160 Goose altitude (G_{alt}) is defined as the part of the bird with the highest altitude (e.g., the head of
161 the animal), where the altitude of the vehicle is defined as the midpoint point of vehicle height
162 (U_{alt}). Equation 5b considers the width of the vehicle (U_w) and animal (G_w).

163 $$w_{\cap} = min\left(U_x + \frac{U_w}{2}, D_{collision} + \frac{U_w}{2}\right) - max(U_x - \frac{U_w}{2}, -l_{adj} + (D_{collision} + \frac{U_w}{2}) \quad \text{(Eq. 5b)}$$

164 Equation 5b assumes that the furthest and tallest edge of the animal (i.e., the head) was aligned
165 with the center of the vehicle at the moment of escape initiation (Fig. 1, t_1). The overlap in width
166 is determined by the trajectory adjusted length (l_{adj}) and how far the animal moved after escape
167 initiation ($D_{collision}$), given that the animal's initial position started in alignment with the center of

the vehicle ($\frac{U_w}{2}$) (Fig. 1, t_2). We only considered positive values of $h_\cap$ and $w_\cap$ (i.e., when overlap between the vehicle and animal occurred) (Eq. 5c & 5d).

$$H(h_\cap) = \begin{cases} 0, & h_\cap \leq 0 \\ h_\cap, & h_\cap > 0 \end{cases} \quad \text{(Eq.5c)}$$

$$W(w_\cap) = \begin{cases} 0, & w_\cap \leq 0 \\ w_\cap, & w_\cap > 0 \end{cases} \quad \text{(Eq.5d)}$$

Equation 5e estimates the surface area of the vehicle overlapping with the animal and then equation 5f converts that metric of overlap into a binary variable. All model estimates were made in R programing (version 4.3.2, R Core Team).

$$A_U = H(h_\cap) * W(w_\cap) \quad \text{(Eq. 5e)}$$

$$P(A_u) = \begin{cases} 0, & A_u \leq 0 \\ 1, & A_u > 0 \end{cases} \quad \text{(Eq. 5f)}$$

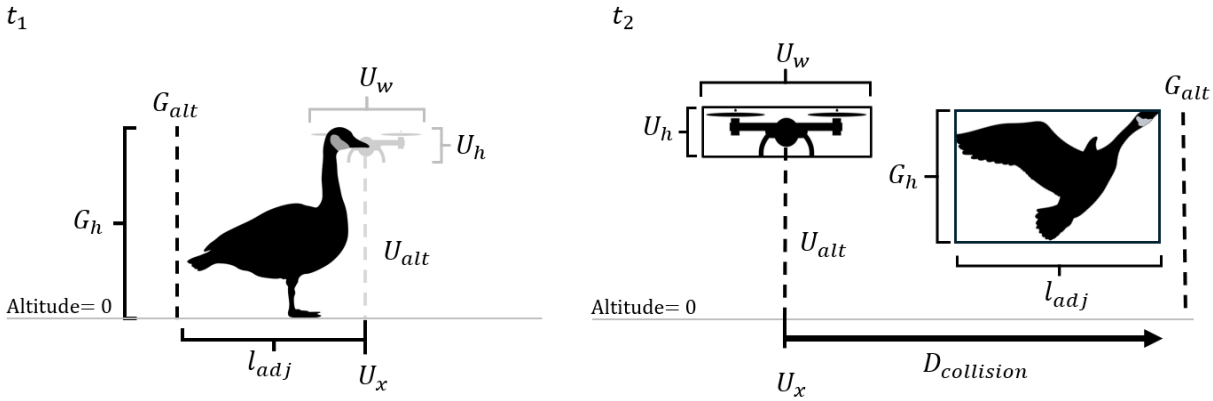

Figure 1. Graphical description of the variables featured in equations 5a-5f. At t_1 prior to escape initiation it was assumed the head of the animal was aligned with the center point of the UAS and the goose was at an altitude of 0 m (i.e., a collision course). At t_2 the UAS reaches the location of the animal (i.e., the minimum bypass distance), where if a collision is possible whether the two shapes overlap is estimated.

Model application and parameter selection

We applied the model to empirical data from a behavioral experiment (Lunn et al. 2025) that featured an experiment where Canada geese were approached directly with an unoccupied-aerial system (hereafter, UAS) to assess how different approach types (i.e., low-altitude vs. high altitude) and light treatments (i.e., light-off, light-on steady, and light-on pulsing) affected their escape responses (Lunn et al. 2025). Onboard light technology tuned to the avian eye has been shown to elicit early avian alert responses (Blackwell & Fernandez-Juricic et al. 2013, Blackwell et al. 2012, Doppler et al. 2015), thus enabling the animal to escape earlier (i.e., longer T_v) potentially reducing the probability of collision (Blackwell & Fernández-Juricic, 2013). In this field study, Canada geese increased flight initiation distance and tended to move away from the vehicle when the UAS approached from a higher altitude during the light-on steady & light-on pulsing treatments (Lunn et al. 2025), which potentially could reduce the probability of collision.

For this study, we used goose flight-initiation distance (D_{FID}), escape trajectory (θ), escape speed (S_a), and the sensory-motor delay (δ) for every trial measured in Lunn et al. (2025). All "NA" values for flight-initiation distance (D_{FID}), escape trajectory (θ), escape speed (S_a), and sensory-motor delay (δ) were assigned a value of zero. These circumstances were typically due to geese hiding or ducking in response to the approaching UAS. Additionally, UAS altitude (U_{alt}) at flight initiation and the mean UAS approach speed for the entire trial (S_v) were recorded from the UAS flight log data (Lunn et al. 2025). UAS altitude values at flight-initiation listed as "NA" due to an flight-initiation distance value of zero were imputed with the mean UAS altitude values. Further, UAS altitude values at flight initiation that exceeded the maximum height of the arena (1.82 m) were subsequently limited to a value of 1.82 m.

The small quadcopter UAS used in Lunn et al. 2025 was a DJI Mavic 3 classic. Specifically, the dimensions were 0.347 m in length x 0.527 m in width x 0.107 m in height

(https://www.dji.com/mavic-3-classic/specs, Dia-Jiang Innovations, Shenzhen, China), where the vehicle width also included the additional width attributable to propeller length (https://store.dji.com/product/dji-mavic-3-low-noise-propellers, Dia-Jiang Innovations, Shenzhen, China). The dimensions of the light onboard the UAS (Lume Cube RGB Panel Pro 2.0, https://lumecube.com/products/panel-pro , Toledo, OH, U.S.A) were 0.152 m in width and 0.08 m in height. The height used in equations 5a-5f was a combination of both the UAS and the light (i.e., 0.27 m, the height of two lights stacked and the UAS), but the width of the light did not extend beyond the UAS. For the Canada goose dimensions, we selected a single value for the length and width based on empirical data of goose anatomical measurements: 1.025 m length (Bellrose, 1976, Mowbray et al. 2020), 1.485 m width (Hanson, 1951, Sibley, 2014) (i.e., the wingspan), 0.513 m in height (i.e., half the length).

Lunn et al. 2025 did not measure the altitude of the goose during the escape phase. Consequently, to estimate $P(A_u)$ in phase two of the model, we simulated goose altitude (G_{alt}) values. For each empirical trial, we simulated 1,000,000 altitude values from a uniform distribution ranging from 0.256 to 1.82 m. A minimum value of 0.256 m was selected because it was half the height of the goose (i.e., attempting to crouch) and a maximum value of 1.82 was selected because of the maximum height of the experimental arena (1.82 m) (i.e., attempting to take flight). We estimated the probability of altitudinal overlap for each trial as the total number of altitudes wherein the animal overlapped with the vehicle divided by the number of simulated altitude values (i.e., 1,000,000).

We estimated whether the vehicle and the animal did or did not share a common altitude (i.e., a binary variable) based on a threshold value (see below) for the probability of altitudinal overlap, where values greater than or equal to threshold were labelled as overlapping in altitude

while values less than threshold were considered to not overlap in altitude. We selected a threshold value for the probability of altitudinal overlap based on a value of 28% based on the results of a sensitivity analysis examining how different threshold values from 0% to 100% affected the estimated total number of trials with altitudinal overlap (Supporting Information 2). No trial had a probability of altitudinal overlap greater than or equal to 68% but 131 trials had a probability of altitudinal overlap for a threshold greater than 0%. Consequently, we selected the median value of 34% (i.e., 118 trials) as the threshold for the probability of altitudinal overlap as a compromise between high sensitivity (i.e., a threshold of greater than 0%) and higher specificity at the cost of lower sensitivity (i.e., a threshold of greater than 68%).

Experimental treatments and the probability of collision

We demonstrated the utility of the model by assessing how the experimental treatments from Lunn et al. (2025) affected the model estimates of the probability of collision. We used a generalized linear model with the same statistical model structure in the analysis of the probability of collision estimates as Lunn et al. (2025), so the assessments of approach type and light treatment were comparable to the assessments for each element of the behavioral response measured. Specifically, each model included three categorical variables (light treatment, approach type treatment, approach speed (i.e., slow: 0.27 m/s to 5.52 m/s, vs. fast: 5.52 m/s to 8.09 m/s), three continuous variables (wind speed, goose weight, irradiance) and three different interaction effects (light treatment and approach type treatment, light treatment and approach speed, and approach type treatment and approach speed).

We used the *stats* package to run our generalized linear model (R Core Team). We determined significance for each independent variable with type 3 sum of squares analysis from

the *car* package (Fox et al., 2012). For each treatment condition and the corresponding interaction between treatments we present the model estimated means with the *emmeans* package (Lenth et al., 2019). Additionally, we used the *binom* package to estimate the confidence intervals using the Agresti-Coull method (Aho & Bowyer, 2014, Dorai-Raj, 2022). Whenever a treatment with more than two levels was significant, we utilized the tukey method to test for significance among the different levels via the *emmeans* package (Lenth, 2017).

Effect sizes of model parameters

The mathematical model included several parameters (see section *Model application and parameter selection*) to estimate the probability of collision. We investigated the relative contribution of each parameter on the estimated probability of collision using a generalized linear model that considered all model inputs as independent variables using the *stats* R package (R Core Team). Specifically, the statistical model included goose flight-initiation distance, escape speed, escape trajectory, sensory-motor delay period, UAS altitude, and UAS speed. We estimated the model predicted effect size using the *emmeans* package (Lenth, 2017). Herein we estimated both Tjur's R^2 for the entire model (Tjur, 2009) and the partial omega-squared for each independent variable (i.e., ω_p^2) with the *effectsize* package (Ben-Shachar et al., 2020). We categorized ω_p^2 as either being either a "very small", "small", "medium", or "large" effect based on Cohen 1992.

We conducted all statistical analyses and developed all figures in R version 4.3.2 (R Core Team. 2024). All code, datasets and metadata necessary to reproduce this study are available at OSF [https://osf.io/9rh47/overview?view_only=1750d6840d3a4478bec0432b2fec2424].

Throughout the results, we present the model estimated means and 95% confidence intervals within brackets.

Results

Experimental treatments and the probability of collision

The probability of collision for the light-on steady treatment (59.44%, [48.10%, 71.95%]) and light-on pulsing treatment (66.20, [49.92%, 73.94%]) was respectively, 12.38% and 5.62% lower relative to the light-off treatment (71.82, [57.58%, 79.82%]), with light treatment significantly affecting the probability of collision (Table 1), but no significant differences between different light treatment levels. The probability of collision for the descending approach treatment (61.21%, [50.28%, 70.19%]) was 9.28% lower compared to the level approach treatment (70.49, [58.09%, 76.66%]), without a significant effect of approach treatment (Table 1). However, light treatment and approach treatment interacted significantly (Table 1, Figure 1). More specifically, for level approach treatments, the probability of collision for both the light-on steady (68.34%, [50.03%, 81.54%]) and light-on pulsing (82.59%, [60.96%, 89.27%]) treatments increased by 9.92% and 25.47% respectively relative to the light-off treatment (57.09%, [40.74%,73.61%]). However, for descending approach treatments, the probability of collision for both the light-on steady (49.88%, [36.14%, 69.77%]) and light-on pulsing (44.71%, [27.57%, 62.70%]) treatments decreased by 34.38% and 37.24%, respectively, relative to the light-off treatment (83.00%, [64.32%, 91.48%]). Within the interaction both the light-on steady ($z = 2.487$, $p = 0.035$) and light-on pulsing treatments ($z = 2.844$ $p = 0.012$) were significantly different than the light-off treatment but only during descending approaches.

Table 1. Generalized linear model results for probability of collision and independent variables and covariates used in the analysis of Lunn et al., 2025.

Generalized Linear Model	X^2	***d.f***	***P***
Probability of Collision:			
Altitudinal Overlap Threshold > 34%			
Light treatment	7.300	2	**0.026***
Approach type treatment	0.939	1	0.333
Goose Weight	2.536	1	0.111
Speed	0.794	1	0.373
Irradiance	0.004	1	0.952
Wind Speed	0.071	1	0.790
Light Treatment X Approach type treatment	12.202	2	**0.002****
Light Treatment: X Speed	0.689	2	0.708
Approach type treatment X Speed	3.696	1	0.055

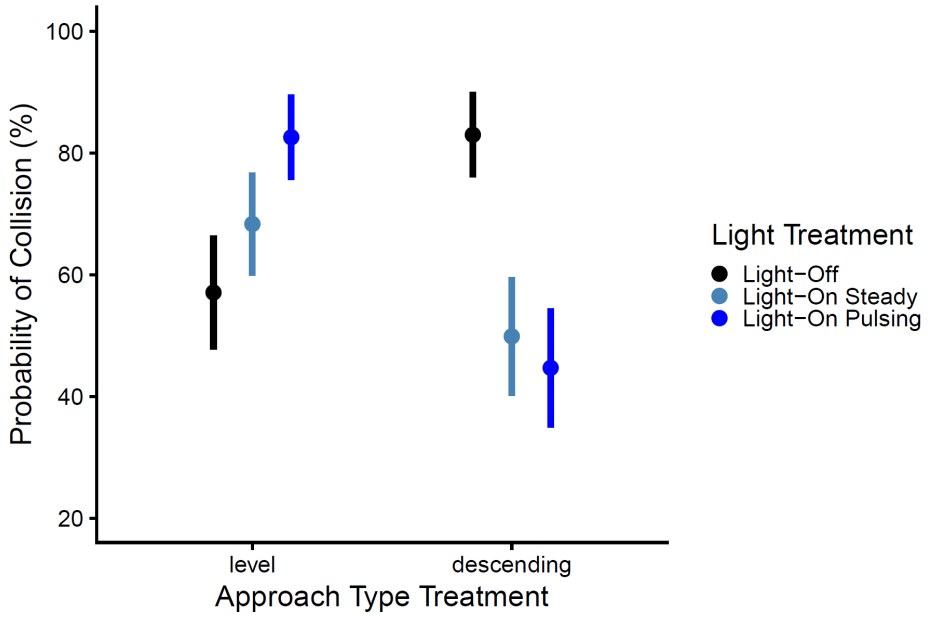

Figure 2. The estimated marginal means and S.E for the significant interaction effect between light and approach type treatment reported from the generalized linear model for the probability of collision estimates

Effect sizes of model parameters

After including the mathematical model inputs in a generalized linear model on the probability of collision, the variable with the largest effect size was flight-initiation distance (ω_p^2 of 0.26, large effect), where a change in flight-initiation distance from 0 to 198.17 m resulted in a decrease in the probability of collision from 78.54% to 0.51% with an inflection point of 38.84 m (Fig.3a). The variable with the second largest effect size was escape trajectory (ω_p^2 of 0.20, medium effect), where a change in escape trajectory from 0 to 178.84° resulted in a decrease in the probability of collision from 84.10% to 16.57% with an inflection point of 90.33 deg (Fig.3b). The variable with the third largest effect size was UAS altitude (ω_p^2 of 0.14, medium effect), where a change in UAS altitude from 0.7 to 1.82 m resulted in a decrease in the probability of collision from 92.74% to 12.15% with an inflection point of 1.32 m (Fig.3c). The variable with

the fourth largest effect size was sensory-motor delay (ω_p^2 of 0.03, small effect), where a change in a sensory-motor delay from 0 to 3.77 seconds resulted in a decrease in the probability of collision from 76.87% to 5.94%, with an inflection point of 1.14 seconds (Fig.3d). The variable with the fifth largest effect size was UAS approach speed (ω_p^2 of <0.01, very small effect), where a change in UAS approach speed from 0.27 to 8.09 m/s resulted in an increase in the probability of collision from 50.12% to 73.05% with no inflection point (Fig.3e). Lastly, the variable with the smallest effect size was escape speed (ω_p^2 of <0.01, very small effect), where a change in escape speed from 0 to 7.74 m/s resulted in a decrease in the probability of collision from 75.84% to 44.56% with an inflection point of 6.48 m/s (Fig.3f). The overall model had a Tjur's R^2 value = 0.497, which is deemed as a large effect size.

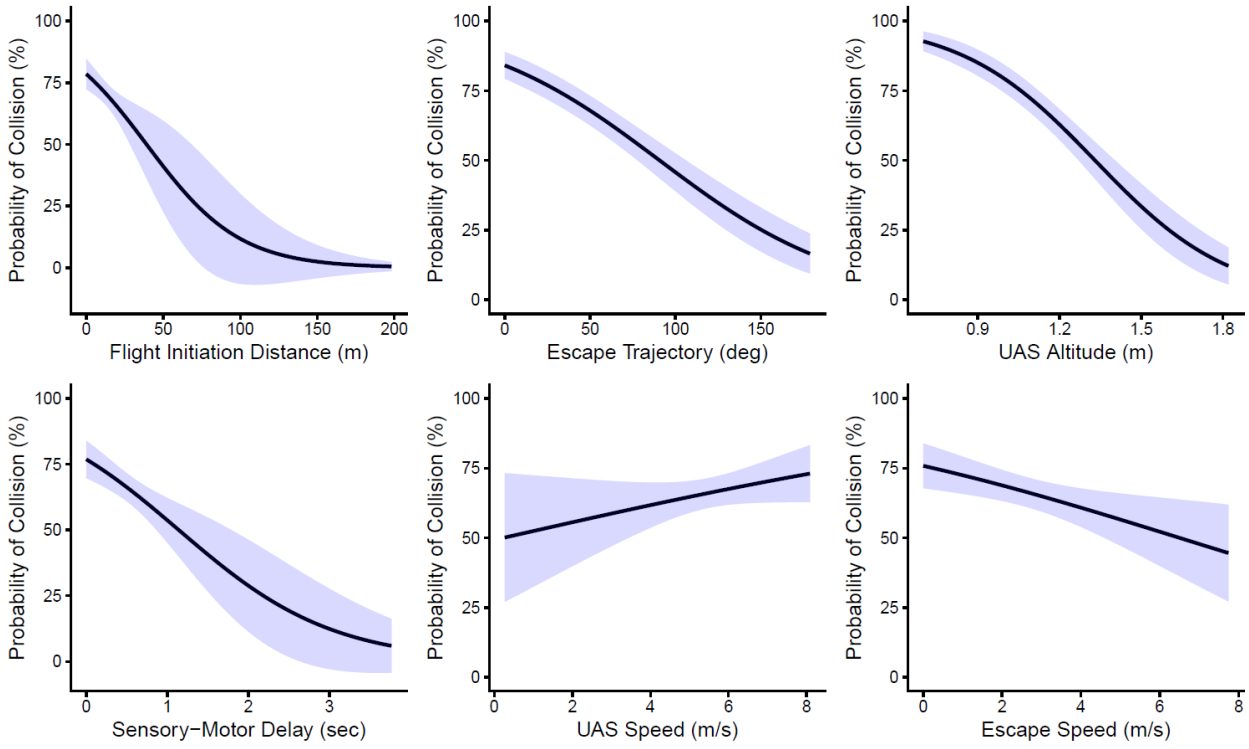

Figure 3. The black curve is the predicted probability of collision from the generalized linear model for a given value of each mathematical model input based on empirical data from Lunn et

al. (2025). The blue shading represents the standard error estimates form the generalized linear model.

Discussion

We propose a more generalized version of an existing mathematical model to estimate the probability of collision between a bird and an approaching vehicle. We applied this model to estimate the probability of collision for an empirical experiment where a UAS approached a Canada goose testing the effects of different onboard-lights and approach types. Overall, the effect of light tuned to the visual system of Canada geese on the probability of collision heavily depended on how the UAS approached the animal. Generally, for level UAS approach treatments the light-on treatments tended to increase the probability of collision by 12 to 25 percentage points, but for the descending approach treatments the light-on treatments tended to decrease the probability of collision by 27 to 30 percentage points. The variable with the largest effect on determining whether an estimated collision occurred was flight-initiation distance, followed by UAS altitude, and escape trajectory.

One possible explanation for the increase in the probability of collision during level flight approaches and, alternatively, a decrease in the probability of collision for descending approaches is that the light masked the presence of the UAS for level flights but facilitated detection of the UAS for descending flights. Animals have limited attention that is selectively allocated (Dukas & Kamil, 2000, & Blumstein et al., 2010). For onboard lighting to be effective it should draw the animal's attention towards the approaching vehicle, but not mask the presence of the vehicle, such that an animal can distinguish the vehicle from the light because mortality risk stems from vehicle size and speed (Bernhardt et al., 2010, DeVault et al., 2015). Differences

in the ratio of UAS to LED light surface area may have resulted in the light masking the approaching vehicle during level approaches but drawing the animal's attention towards the vehicle during descending approaches. For level approaches, we estimated that the ratio of UAS to LED light surface area was 1.39 to 1 based on the frontal surface of the UAS (Fig. 4); however, for descending approaches, the ratio was 4.51 to 1, potentially allowing greater visual access to the bottom of the UAS and making it relatively easier to differentiate the UAS from the LED light (Fig. 4). This masking phenomenon might explain why during low ambient light conditions we observe that light stimuli hinder the escape response of some species (Erritzoe et al., 2003, Guenin et al.,2024) because the increased sensitivity to light in the visual system in low light conditions (Lind et al., 2014) might prevent the animal from detecting the vehicle (Blackwell et al., 2014, DeVault et al., 2020). Consequently, lights aimed at mitigating animal-vehicle collisions should maintain a higher ratio of vehicle to LED light surface area. Practically, this could be achieved by using narrower beam angles (i.e., reducing the dispersion of light) to reduce the probability of masking the vehicle.

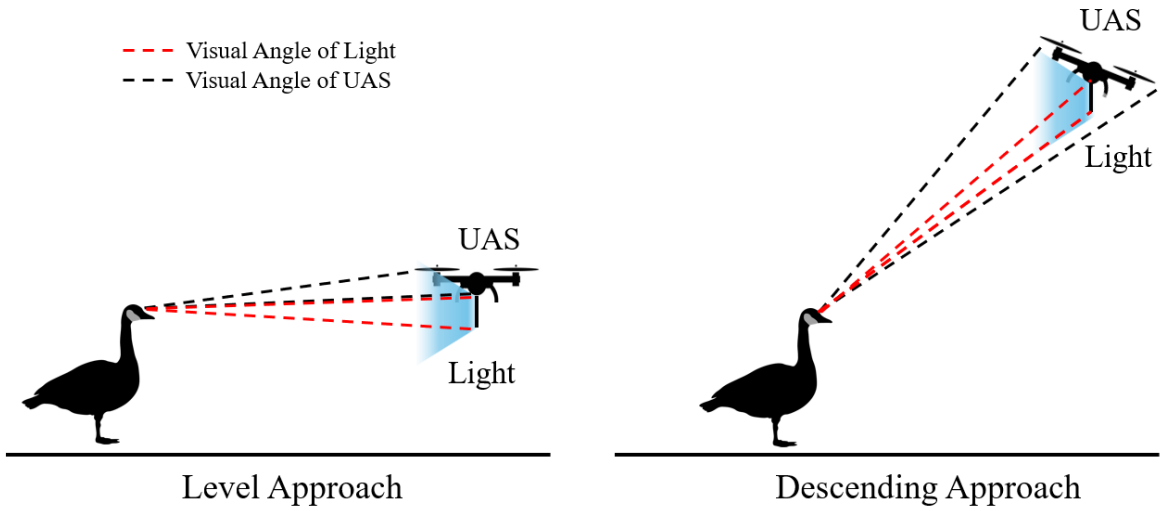

Figure 4. Visual illustration of the difference in surface area ratio geese had visual access to between the two different approach type treatments. Red lines indicate the visual angle of the light where black lines indicate the visual angle of the UAS.

Studies of animal vehicle collisions have focused overwhelmingly on differences in flight-initiation distance, where longer flight-initiation distances have been assumed to translate to a lower probability of collision (DeVault et al., 2015, Blackwell et al., 2019). However, escape responses are a dynamic and interdependent sequence of behaviors (Lima & Dill, 1990, Cooper & Blumstein, 2015, Evans et al., 2019, Branco & Redgrave, 2020). While flight-initiation distance has a large effect on the probability of collision (Lunn et al. 2026), and herein was the variable with the largest effect size, our results suggest that the assumption that a long enough flight-initiation distances will completely reduce the probability of collision is incorrect because the effectiveness of flight-initiation distance simultaneously depends on other components of an escape response. Figure 5 illustrates how escape trajectory, another component of an escape response, modulates the effect of flight-initiation distance on the probability of collision for different treatment combinations, where the probability of collision is based on the estimates from the generalized linear model built with model inputs. If the probability of collision was completely dependent on flight-initiation distance the contour lines, which represent a 5% change in the probability of collision, would be completely vertical. However, the contour lines have a decreasing slope indicating that the probability of collision is regulated by both flight initiation distance and escape trajectory. Figure 5 shows that even the longest flight-initiation distance observed (i.e., 198 m) had a probability of collision > 0% for an escape trajectory directly towards the UAS. This finding suggests that a threshold flight-initiation distance long enough to make all other components of the escape response irrelevant either does not exist or is extremely rare. The empirically observed values of flight-initiation distance and escape trajectory suggests that Canada geese, while at times did change flight-initiation distance to reduce the

probability of collision, more readily adjusted escape trajectory to manage the perceived mortality risk especially for shorter flight-initiation distances.

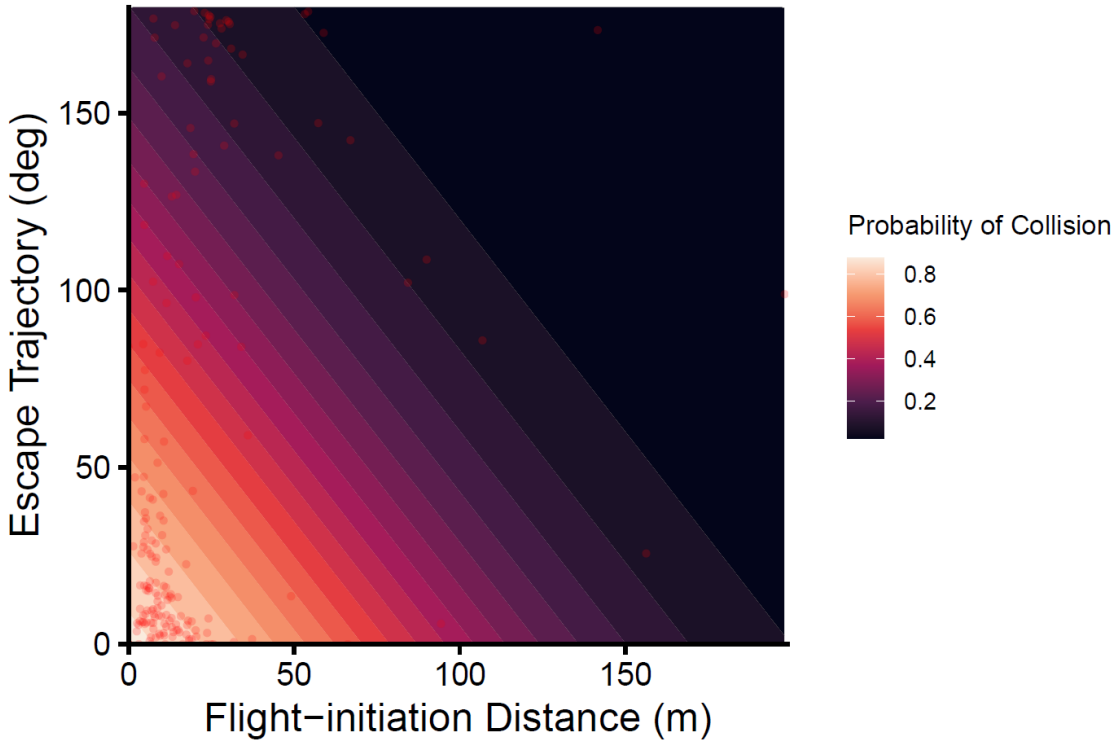

Figure 5. Flight-initiation distance plotted against escape trajectory where the shading represents differences in the predicted probability of collision from the generalized linear built with model inputs. Different shades represent bins of 5% probability of collision. Red dots are the empirical values observed in Lunn et al., 2025 for flight-initiation distance and escape trajectory.

In the predator-prey literature, a common assumption is that a flight-initiation distance of zero is associated with prey mortality because predators actively target prey (Ydenberg & Dill, 1986, Broom & Ruxton,2005). However, in the context of animal-vehicle collisions, our findings challenge this assumption. The intercept of our generalized linear model estimated the probability of collision for a flight-initiation distance of zero to actually be 69.41%, providing evidence that a flight-initiation distance of zero can result in successful collision avoidance with a vehicle. This is likely due to the interplay between vehicle size and shape, animal size and shape, and whether the vehicle approaches directly or indirectly (i.e., the animal is near but

outside of the trajectory of the vehicle). For example, a bird within the path trajectory of an aircraft can pass underneath its wing and still avoid a collision (Lunn et al., 2026). Consequently, a flight-initiation distance of zero in some bird species might be a feature of their vehicle collision avoidance behavior and might in part explain why in previous studies birds did not flee when approached by a vehicle (Blackwell et al. 2019, Guenin et al. 2024) or fled only after the vehicle has passed (Pfeiffer et al. 2025).

UAS have been proposed as a potential solution to haze birds from areas of anthropogenic activity, such as landfills, airports, and buildings (Pfieffer et al., 2021, Pfieffer et al., 2023, White et al., 2025). Generally, the literature suggests that lower altitude flights directly targeting individuals tend to be more effective at dispersing birds (Vas et al., 2015, Egan et al., 2020, Pfieffer et al., 2025). However, low altitude flights, especially near wildlife can result in a collision damaging both the bird and UAS (Lunn et al., 2025), which can negatively affect animal welfare. We applied the model to a hazing scenario to demonstrate its utility at providing general recommendations about how UAS flight altitude and speed might be safely flown to minimize the probability of harming birds while hazing. Using the generalized linear model built with the model inputs, we predicted the probability of collision as UAS approach speed increased from 1 to 20 m/s and UAS altitude increased from 0.5 to 2.6 m for every trial, assuming all other components of the escape response of the animal remained the same. Generally, an altitude of 2.4 m or higher regardless of UAS speed had a 0% probability of colliding with Canada geese (Fig. 6). Alternatively, the absolute minimum altitude a UAS can still maintain a 0% probability of collision is 1.51 m at the slowest possible approach speed (i.e., 1 m/s) (Fig. 6). Based on the slope of the contour line (i.e., the threshold between a 0 and 5% probability of collision), the model suggests that UAS operators hazing Canada geese should

increase altitude by 4.6 cm for every 1 m/s increase in UAS approach speed to maintain a 0% probability of collision (Fig. 6).

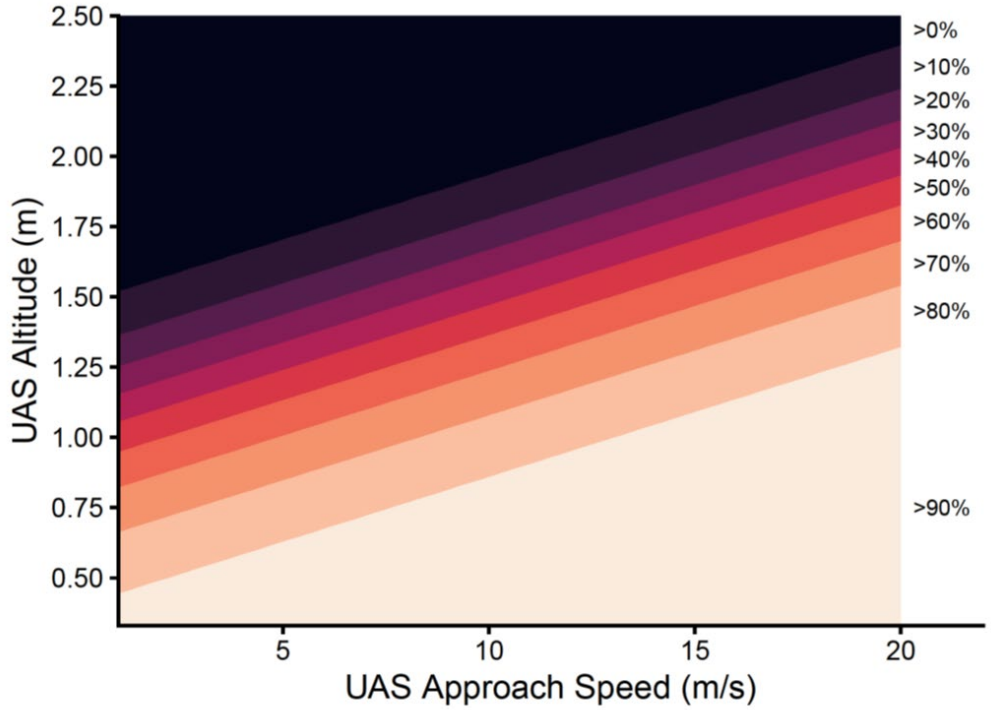

Figure 6. The relationship between UAS approach speed (x-axis), altitude (y-axis) and the predicted probability of collision (color shading) based on the generalized linear model built with model inputs. Each contour line denotes the separation of the probability of collision in 10% bins.

We presented the first application to empirical data of a mathematical framework directly connecting multiple components of an animal escape response to estimate the probability of collision with an approaching vehicle. The results of our approach yield two key insights that can be incorporated into future research on animal-vehicle collisions: (1) while longer flight-initiation generally decrease the probability of collision, importantly they also depend on other components of the animals escape response; and (2) a flight-initiation distance of zero does not necessarily result in a collision occurring. Further, the model provides a step forward in improving the accuracy of transportations infrastructures mortality effect on wildlife. Animal-

vehicle collision and wildlife-road mortality research is often severely limited by "survivor" bias, where often we only observe the consequences of collisions, assuming a wildlife-vehicle interaction occurred. Yet there is limited to no understanding of 1) how many total wildlife-vehicle interactions occurred, 2) how many collisions occurred but were not detected, and 3) how many of those interactions did not result in a collision. Failing to account for any of these unknowns could consequently result in either over or underestimates of the mortality impact of transportation infrastructure on wildlife and subsequently result in misguided and ineffective management strategies. Our model can quantitatively provide answers to how many interactions did not result in a collision by pairing the estimated probability of collision based on the escape response of the animal with the frequency of collisions observed (i.e., carcasses/reported collisions) to provide more accurate estimates for the mortality risk caused by transportation infrastructure.

References

Ascensão, F., Clevenger, A., Santos-Reis, M., Urbano, P. and Jackson, N., 2013. Wildlife–vehicle collision mitigation: Is partial fencing the answer? An agent-based model approach. *Ecological Modelling*, *257*, pp.36-43. https://doi.org/10.1016/j.ecolmodel.2013.02.026

Aho, K. and Bowyer, R.T., 2015. Confidence intervals for ratios of proportions: implications for selection ratios. *Methods in Ecology and Evolution*, *6*(2), pp.121-132. https://doi.org/10.1111/2041-210X.12304

Altringer, L., Navin, J., Begier, M.J., Shwiff, S.A. and Anderson, A., 2021. Estimating wildlife strike costs at US airports: A machine learning approach. *Transportation Research Part D: Transport and Environment*, *97*, p.102907. https://doi.org/10.1016/j.trd.2021.102907

Ben-Shachar, M.S., Makowski, D., Lüdecke, D., Patil, I., Wiernik, B.M., Kelley, K., Stanley, D., Burnett, J. and Karreth, J., 2021. Package 'effectsize'. *R Package*.

Bernhardt, G.E., Blackwell, B.F., DeVault, T.L. and Kutschbach-Brohl L., 2010. Fatal injuries to birds from collisions with aircraft reveal anti-predator behaviours. Ibis, 152(4), pp.830-834. https://doi.org/10.1111/j.1474-919X.2010.01043.x

Blackwell, B. F., & Bernhardt, G. E. (2004). Efficacy of aircraft landing lights in stimulating avoidance behavior in birds. *The Journal of wildlife management*, *68*(3), 725-732. https://doi.org/10.2193/2008-014

Blackwell, B.F., DeVault, T.L., Seamans, T.W., Lima, S.L., Baumhardt, P. and Fernández-Juricic, E., 2012. Exploiting avian vision with aircraft lighting to reduce bird strikes. *Journal of Applied Ecology*, *49*(4), pp.758-766. https://doi.org/10.1111/j.1365-2664.2012.02165.x

Blackwell, B.F., Fernández-Juricic, E., 2013. Behavior and Physiology in the Development and. *Wildlife in airport environments: preventing animal–aircraft collisions through science-based management*, p.11–22, 1st edn. Baltimore, MD: Johns Hopkins University Press

Blackwell, B.F. and Seamans, T.W., 2009. Enhancing the perceived threat of vehicle approach to deer. *The Journal of Wildlife Management*, *73*(1), pp.128-135.

Blackwell, B.F., Seamans, T.W., DeVault, T.L., Lima, S.L., Pfeiffer, M.B. and Fernández-Juricic, E., 2019. Social information affects Canada goose alert and escape responses to vehicle approach: implications for animal–vehicle collisions. *PeerJ*, *7*, p.e8164.. https://doi.org/10.7717/peerj.8164.

Belant, J. L. (2011). *Bird harassment, repellent, and deterrent techniques for use on and near airports* (Vol. 23). Transportation Research Board.

Bellrose, F.C., 1976. *Ducks, geese and swans of North America* (pp. 541-pp).

Bénard, A., Lengagne, T. and Bonenfant, C., 2024. Integration of animal movement into wildlife-vehicle collision models. *Ecological Modelling*, *492*, p.110690. https://doi.org/10.1016/j.ecolmodel.2024.110690

Bissonette, J.A., Kassar, C.A. and Cook, L.J., 2008. Assessment of costs associated with deer–vehicle collisions: human death and injury, vehicle damage, and deer loss. *Human-Wildlife Conflicts*, *2*(1), pp.17-27. https://www.jstor.org/stable/24875102

Blumstein, D.T., 2010. Flush early and avoid the rush: a general rule of antipredator behavior?. *Behavioral Ecology*, *21*(3), pp.440-442. https://doi.org/10.1093/beheco/arq030

Branco, T. and Redgrave, P., 2020. The neural basis of escape behavior in vertebrates. *Annual review of neuroscience*, *43*(1), pp.417-439. https://doi.org/10.1146/annurev-neuro-100219-122527

Brieger, F., Kämmerle, J.L., Hagen, R. and Suchant, R., 2022. Behavioural reactions to oncoming vehicles as a crucial aspect of wildlife-vehicle collision risk in three common wildlife species. *Accident Analysis & Prevention*, *168*, p.106564. https://doi.org/10.1016/j.aap.2021.106564

Broom, M. and Ruxton, G.D., 2005. You can run—or you can hide: optimal strategies for cryptic prey against pursuit predators. *Behavioral Ecology*, *16*(3), pp.534-540. https://doi.org/10.1093/beheco/ari024

Cohen, J., 1992. Statistical power analysis. *Current directions in psychological science*, *1*(3), pp.98-101. https://doi.org/10.1111/1467-8721.ep10768783

Conover, M.R., 2019. Numbers of human fatalities, injuries, and illnesses in the United States due to wildlife. *Human-Wildlife Interactions*, *13*(2), pp.264-276. https://www.jstor.org/stable/27316125

Cooper, W.E. and Blumstein, D.T. eds., 2015. *Escaping from predators: an integrative view of escape decisions*. Cambridge University Press.

Domenici, P., Blagburn, J.M. and Bacon, J.P., 2011. Animal escapology I: theoretical issues and emerging trends in escape trajectories. Journal of Experimental Biology, 214(15), pp.2463-2473. https://doi.org/10.1242/jeb.029652.

Domenici, P. and Blake, R.W., 1991. The kinematics and performance of the escape response in the angelfish (*Pterophyllum eimekei).* Journal of Experimental Biology, 156(1), pp.187-205. https://doi.org/10.1242/jeb.156.1.187

Doppler, M.S., Blackwell, B.F., DeVault, T.L. and Fernández-Juricic, E., 2015. Cowbird responses to aircraft with lights tuned to their eyes: Implications for bird–aircraft collisions. *The Condor: Ornithological Applications*, *117*(2), pp.165-177. https://doi.org/10.1650/CONDOR-14-157.1

DeVault, T.L., Blackwell, B.F. and Belant, J.L. eds., 2013. *Wildlife in airport environments: preventing animal–aircraft collisions through science-based management*. JHU Press.

DeVault, T.L., Blackwell, B.F., Seamans, T.W., Lima, S.L. and Fernández-Juricic, E., 2015. Speed kills: ineffective avian escape responses to oncoming vehicles. *Proceedings of the Royal Society B: Biological Sciences*, *282*(1801). https://doi.org/10.1098/rspb.2014.2188.

DeVault, T. L., Seamans, T. W., & Blackwell, B. F. (2020). Frontal vehicle illumination via rear-facing lighting reduces potential for collisions with white-tailed deer. *Ecosphere*, *11*(7), e03187. https://doi.org/10.1002/ecs2.3187

Dorai-Raj S., 2022. Package 'binom': Binomial Confidence Intervals for Several Parameterizations. *R package version* 1(1.1).

Dukas, R. and Kamil, A.C., 2000. The cost of limited attention in blue jays. *Behavioral Ecology*, *11*(5), pp.502-506. https://doi.org/10.1093/beheco/11.5.502

Egan, C.C., Blackwell, B.F., Fernández-Juricic, E. and Klug, P.E., 2020. Testing a key assumption of using drones as frightening devices: Do birds perceive drones as risky?. *The Condor*, *122*(3), p.duaa014. https://doi.org/10.1093/condor/duaa014

Erritzoe, J., Mazgajski, T.D. and Rejt, Ł., 2003. Bird casualties on European roads—a review. *Acta Ornithologica*, *38*(2), pp.77-93. https://doi.org/10.3161/068.038.0204

Evans, D.A., Stempel, A.V., Vale, R. and Branco, T., 2019. Cognitive control of escape behaviour. *Trends in cognitive sciences*, *23*(4), pp.334-348. https://doi.org/10.1016/j.tics.2019.01.012

Fox, J., Weisberg, S., Adler, D., Bates, D., Baud-Bovy, G., Ellison, S., Firth, D., Friendly, M., Gorjanc, G., Graves, S. and Heiberger, R., 2012. Package 'car'. Vienna: R Foundation for Statistical Computing, 16(332), p.333.

Hanson, H.C., 1951. A morphometrical study of the Canada goose, Branta canadensis interior Todd. *The Auk*, *68*(2), pp.164-173.

Harris, R.E. and Davis, R.A., 1998. Evaluation of the efficacy of products and techniques for airport bird control. *LGL Limited for Aerodrome Safety Branch, Transport Canada*, *1*, pp.425-31.

Huijser, M.P., Fairbank, E.R., Camel-Means, W., Graham, J., Watson, V., Basting, P. and Becker, D., 2016. Effectiveness of short sections of wildlife fencing and crossing structures along highways in reducing wildlife–vehicle collisions and providing safe crossing opportunities for large mammals. *Biological conservation*, *197*, pp.61-68. https://doi.org/10.1016/j.biocon.2016.02.002

Huijser, M. P., Duffield, J. W., Clevenger, A. P., Ament, R. J., & McGowen, P. T. (2009). Cost–benefit analyses of mitigation measures aimed at reducing collisions with large ungulates in the United States and Canada: a decision support tool. *Ecology and society*, *14*(2). https://www.jstor.org/stable/26268301

Huijser, M.P., McGowan, P., Fuller, J., Hardy, A.,Kociolek, A.V., Clevenger, A. P., Smith, D., Ament, R., 2008. Wildlife-vehicle collision reduction study: report to congress. No. FHWA-HRT-08-034. https://rosap.ntl.bts.gov/view/dot/88021

Glista, D.J., DeVault, T.L. and DeWoody, J.A., 2009. A review of mitigation measures for reducing wildlife mortality on roadways. *Landscape and urban planning*, *91*(1), pp.1-7. https://doi.org/10.1016/j.landurbplan.2008.11.001

Grilo, C., Borda-de-Água, L., Beja, P., Goolsby, E., Soanes, K., le Roux, A., Koroleva, E., Ferreira, F.Z., Gagné, S.A., Wang, Y. and González-Suárez, M., 2021. Conservation threats from roadkill in the global road network. *Global Ecology and Biogeography*, *30*(11), pp.2200-2210. https://doi.org/10.1111/geb.13375

Grilo, C., Koroleva, E., Andrášik, R., Bíl, M. and González-Suárez, M., 2020. Roadkill risk and population vulnerability in European birds and mammals. *Frontiers in Ecology and the Environment*, *18*(6), pp.323-328. https://doi.org/10.1002/fee.2216

Guenin, S., Pakula, C.J., Skaggs, J., Fernández-Juricic, E. and DeVault, T.L., 2024. Inefficacy of mallard flight responses to approaching vehicles. *PeerJ*, *12*, p.e18124. https://doi.org/10.7717/peerj.18124

Lenth, R., Singmann, H., Love, J., Buerkner, P. and Herve, M., 2019. Package 'emmeans'. *R package version*, *1*(3.2).

Lima, S.L. and Dill, L.M., 1990. Behavioral decisions made under the risk of predation: a review and prospectus. *Canadian journal of zoology*, *68*(4), pp.619-640. https://doi.org/10.1139/z90-092

Lima, S.L., Blackwell, B.F., DeVault, T.L. and Fernández-Juricic, E., 2015. Animal reactions to oncoming vehicles: a conceptual review. *Biological Reviews*, *90*(1), pp.60-76. https://doi.org/10.1111/brv.12093

Loss, S.R., Will, T. and Marra, P.P., 2015. Direct mortality of birds from anthropogenic causes. *Annual Review of Ecology, Evolution, and Systematics*, *46*(1), pp.99-120. https://doi.org/10.1146/annurev-ecolsys-112414-054133

Lunn, R.B., Blackwell, B., Baumhardt, P., Talbot, A., Di Domenico, I. and Fernández-Juricic, E., 2025. Light tuned to the avian eye elicits early detection and escape from an approaching aircraft. *Royal Society Open Science*, *12*(6). https://doi.org/10.1098/rsos.250047

Lunn, R.B., Blackwell, B.F., DeVault, T.L. and Fernández-Juricic, E., 2022. Can we use antipredator behavior theory to predict wildlife responses to high-speed vehicles?. *PLoS One*, *17*(5), p.e0267774. https://doi.org/10.1371/journal.pone.0267774

Lunn, R.B., Blackwell, B.F. and Fernández-Juricic, E., 2026. A model to quantify the probability of collision between birds and aircraft: Applications for onboard lighting. *Ecological Applications*, *36*(3), p.e70227. https://doi.org/10.1002/eap.70227

Mammeri, A., Zhou, D. and Boukerche, A., 2016. Animal-vehicle collision mitigation system for automated vehicles. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *46*(9), pp.1287-1299. doi: 10.1109/TSMC.2015.2497235

Moore, L.J., Petrovan, S.O., Bates, A.J., Hicks, H.L., Baker, P.J., Perkins, S.E. and Yarnell, R.W., 2023. Demographic effects of road mortality on mammalian populations: a systematic review. *Biological Reviews*, *98*(4), pp.1033-1050. https://doi.org/10.1111/brv.12942

Mowbray, T. B., C. R. Ely, J. S. Sedinger, and R. E. Trost (2020). Canada Goose (*Branta canadensis*), version 1.0. In Birds of the World (P. G. Rodewald, Editor). Cornell Lab of Ornithology, Ithaca, NY, USA. https://doi.org/10.2173/bow.cangoo.01

Kawabata, Y., Akada, H., Shimatani, K.I., Nishihara, G.N., Kimura, H., Nishiumi, N. and Domenici, P., 2023. Multiple preferred escape trajectories are explained by a geometric model incorporating prey's turn and predator attack endpoint. *Elife*, *12*, p.e77699. https://doi.org/10.7554/eLife.77699

Jacobson, S.L., Bliss-Ketchum, L.L., de Rivera, C.E. and Smith, W.P., 2016. A behavior-based framework for assessing barrier effects to wildlife from vehicle traffic volume. *Ecosphere*, *7*(4), p.e01345. https://doi.org/10.1002/ecs2.1345

Pakula, C.J., D'Angelo, G.J., Mowrer, A., Rhodes Jr, O.E. and DeVault, T.L., 2025. Caught in headlights: captive white-tailed deer responses to variations in vehicle lighting during imminent collision scenarios. *Applied Animal Behaviour Science*, *287*, p.106652. https://doi.org/10.1016/j.applanim.2025.106652

Provini, P., Tobalske, B.W., Crandell, K.E. and Abourachid, A., 2012. Transition from leg to wing forces during take-off in birds. *Journal of Experimental Biology*, *215*(23), pp.4115-4124. https://doi.org/10.1242/jeb.074484

Pfeiffer, M.B., Blackwell, B.F., Seamans, T.W., Buckingham, B.N., Hoblet, J.L., Baumhardt, P.E., DeVault, T.L. and Fernández-Juricic, E., 2021. Responses of turkey vultures to unmanned aircraft systems vary by platform. *Scientific Reports*, *11*(1), p.21655. https://doi.org/10.1038/s41598-021-01098-5

Pfeiffer, M.B., Pullins, C.K., Beckerman, S.F., Hoblet, J.L. and Blackwell, B.F., 2023. Investigating nocturnal UAS treatments in an applied context to prevent gulls from nesting on rooftops. *Wildlife Society Bulletin*, *47*(2), p.e1423. https://doi.org/10.1002/wsb.1423

Pfeiffer, M.B., Hoblet, J.L., Blackwell, B.F. and Fernández-Juricic, E., 2025. Preliminary effects of UAS angle of approach on escape responses of a large-bodied raptor. *Drone Systems and Applications*, *13*, pp.1-9. https://doi.org/10.1139/dsa-2024-0047

R Core Team. 2024. R: A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.R-project.org/.

Rytwinski, T., Soanes, K., Jaeger, J.A., Fahrig, L., Findlay, C.S., Houlahan, J., Van Der Ree, R. and van der Grift, E.A., 2016. How effective is road mitigation at reducing road-kill? A meta-analysis. *PLoS one*, *11*(11), p.e0166941. https://doi.org/10.1371/journal.pone.0166941

Schoeman, R.P., Patterson-Abrolat, C. and Plön, S., 2020. A global review of vessel collisions with marine animals. *Frontiers in Marine Science*, *7*, p.292. |https://doi.org/10.3389/fmars.2020.00292

Seiler, A. and Olsson, M., 2017. Wildlife deterrent methods for railways—an experimental study. In *Railway ecology* (pp. 277-291). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-57496-7_17

Sibley, A., 2014. The Sibley guide to birds.

Silva, I. and Calabrese, J.M., 2024. Emerging opportunities for wildlife conservation with sustainable autonomous transportation. *Frontiers in Ecology and the Environment*, *22*(2), p.e2697. https://doi.org/10.1002/fee.2697

Spanowicz, A.G., Teixeira, F.Z. and Jaeger, J.A., 2020. An adaptive plan for prioritizing road sections for fencing to reduce animal mortality. *Conservation Biology*, *34*(5), pp.1210-1220. https://doi.org/10.1111/cobi.13502

Tjur, T., 2009. Coefficients of determination in logistic regression models—A new proposal: The coefficient of discrimination. *The American Statistician*, *63*(4), pp.366-372. https://doi.org/10.1198/tast.2009.08210

Van der Ree, R., Gagnon, J.W. and Smith, D.J., 2015. Fencing: a valuable tool for reducing wildlife-vehicle collisions and funnelling fauna to crossing structures. *Handbook of road ecology*, pp.159-171. https://doi.org/10.1002/9781118568170.ch20

Vas, E., Lescroël, A., Duriez, O., Boguszewski, G. and Grémillet, D., 2015. Approaching birds with drones: first experiments and ethical guidelines. Biology letters, 11(2). https://doi.org/10.1098/rsbl.2014.0754

White, M.G., Duttenhefner, J.L. and Klug, P.E., 2025. Establishing protocols to apply repellents while hazing crop pests: importance of habitat, flock size, and time on blackbird (*Icteridae*) responses to a drone capable of spraying. *Wildlife Research*, *52*(3), p.WR24066. https://doi.org/10.1071/WR24066

Ydenberg, R.C. and Dill, L.M., 1986. The economics of fleeing from predators. In *Advances in the Study of Behavior* (Vol. 16, pp. 229-249). Academic Press. https://doi.org/10.1016/S0065-3454(08)60192-8