# Title: A new model to quantify the probability of collision between birds and aircraft: applications for onboard lighting

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**Open Research Statement**

All code, files, and data generated from this study are available at https://osf.io/zh68x/

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## Abstract

Globally, bird and aircraft collisions are a major safety hazard and monetary expense for the aviation industry. Empirical evidence suggests that the behavioral response of the animal just prior to a collision is a critical factor in determining whether a collision occurs. However, no theoretical framework exists to predict the probability of a collision based on the escape response of the animal to an approaching vehicle. We adapted concepts from existing predator-prey theoretical frameworks to develop a novel model to quantify the outcome of an animal-vehicle interaction. Specifically, our model consists of two distinct phases. Phase one determines if a collision is even possible based on the amount of time the animal has available to clear the trajectory of the approaching vehicle. If the animal does not have enough time, then phase two of the model estimates the probability of collision based on the surface area of the vehicle given the location of the animal within the trajectory. We demonstrate the utility of the model by estimating the probability of collision between a Canada goose and an approaching Boeing-737 aircraft with the absence and presence of onboard lights of different wavelength, a technological intervention aimed at minimizing bird strikes. Our model predicts that when a Canada goose is within the trajectory of a Boeing-737, the average probability of collision is approximately 0.43; however, onboard lights with wavelengths tuned to the visual system of the species can reduce that probability on average by either 19% (red-light onboard) or 32% (blue-light onboard). The highest probability of collision occurred when the animal was in the center of the trajectory of the vehicle. The behaviors with the largest effect on reducing the probability of collision were an increase in flight-initiation distance and an increase in escape speed. Our approach provides a framework to quantitatively predict how the probability of collision might change across different species, vehicles, and situations, which could be used in forecasting the impacts of present and future transportation projects on wildlife populations.

## Introduction

Globally, collisions between birds and aircraft pose a major safety hazard and monetary expense for the aviation industry (Allan, 2000, Altringer et al., 2021, Dolbeer et al., 2023). As air traffic is slated to increase with the proliferation of unoccupied aerial systems (i.e., UAS) (Mulero-Pázmany et al., 2017, Federal Aviation Administration Aerospace Forecasts Fiscal Years 2024–2044, 2024, Davies et al., 2021), the frequency of bird and aircraft collisions, hereafter bird strikes, is expected to increase. At a time when bird populations are globally declining (Rosenberg et al. 2017, Burns et al. 2021, Lees et al. 2022), mitigating bird-strikes has the potential to reduce both avian and human mortality as well as economic damage.

We know from the empirical literature that animal behavioral responses to an imminent collision with an approaching vehicle are critical in determining whether a collision does (i.e., the two come into contact) or does not occur (i.e., near miss), hereafter referred to as the probability of collision (DeVault et al., 2015, Blackwell et al., 2019, Brieger et al., 2022). Mathematical models exist to predict whether a prey animal can escape an approaching predator based on properties of their escape response (Dill 1974, Domenici, 2002, Broom & Ruxton, 2005, Corcoran & Conner, 2016, Ruxton et al., 2018, Kawabata, et al., 2023, Bartashevich et al., 2024). However, these models have yet to be applied to quantify how changes in the behavioral response of an animal affect the probability of colliding with an approaching vehicle (DeVault et al. 2015, Guenin et al. 2024). Herein, we build upon existing models of predator-prey interactions to propose a novel model to estimate the probability of collision when an animal is exposed to an approaching vehicle.

Our study has three aims. First, we introduce a model that can be used to quantify the probability of collision considering variables such as escape trajectory, escape speed, vehicle size

and vehicle speed. The model also incorporates new elements such as the location of the animal within the trajectory of the vehicle, and a stochastic component based on estimates of the relative sizes of the vehicle and the animal. Second, we demonstrate the application of the probability of collision model to a scenario involving an approaching Boeing-737 aircraft and a Canada goose (*Branta canadensis*), a large bodied, abundant, flocking species that can cause substantial damage upon collision (Dolbeer et al. 2014, DeVault et al., 2018). We parameterized our model with empirical data found in the peer-reviewed literature of Canada goose escape responses to an approaching vehicle. Third, we then applied the model to a scenario where a Canada goose is approached by an aircraft but with onboard lights to investigate how different properties might affect the behavioral responses of Canada geese (Blackwell et al., 2012) and consequently the probability of collision.

Aircraft lighting of high chromatic contrast relative to the visual system of a target species has been proposed as a method to mitigate bird and aircraft collisions, especially beyond the airport boundary where mitigation methods are difficult to implement (Dolbeer et al., 2011, Blackwell & Fernández-Juricic, 2013). Specifically, experimental evidence has shown that these onboard lights tuned to the avian visual system increase the distance a bird first detects an approaching aircraft, ultimately allowing more time for the animal to execute an escape response (Blackwell et al., 2009, Blackwell et al., 2012, Doppler et al., 2015). Additional evidence suggests that lights might also facilitate a more effective escape response by promoting avoidance responses (Goller et al., 2018, Lunn et al., 2023). However, to date no quantitative estimates have been made for how changes in behavior caused by lights might reduce the probability of collision between a bird and an aircraft.

*Probability of collision model overview*

Our model for the probability of collision has two distinct phases. Phase one calculates whether the animal has enough time to escape the trajectory of the approaching vehicle (Table 1). If the animal has enough time to escape the trajectory of the vehicle, then a collision is avoided. However, if the animal does not have enough time, then the vehicle overtakes the animal and therefore a collision is possible. Phase one assumes that the animal is within or near the trajectory of the vehicle and therefore a collision is possible, and that the trajectory of the vehicle is fixed (Table 2, Assumptions 1 & 2). Phase two assigns the animal some probability of collision depending on the location of the animal within the trajectory of the vehicle.

*Phase one*

Phase one rearranges the classic formula for speed (i.e., $Speed = \frac{Distance}{Time}$) and incorporates additional parameters to determine whether a collision is possible. Functionally, in phase one we estimate the time that the animal needs to escape the trajectory of the vehicle ($T_a$) and the remaining amount of time until the vehicle reaches the location of the animal after escape is initiated ($T_v$)(Table 1). If the time the animal needs to escape ($T_a$) is great than or equal to the amount of time remaining prior to the vehicle reaching the animal ($T_v$), then the situation results in a potential collision ($T_a \geq T_v$). Alternatively, if the time the animal needs to escape ($T_a$) is less than the time remaining prior to the arrival of the vehicle ($T_v$), then a collision is avoided ($T_a < T_v$). The time needed to escape the trajectory of the vehicle ($T_a$) depends on the distance the animal needs to travel to safety ($D_{\min}$), the body length of the animal ($l$), escape speed ($S_a$), escape angle ($\theta$), and sensory-motor delays as the animal reorients and begins to accelerate ($\delta$) (Table 1, Fig.1). After initiating escape, the animal needs time to travel some minimum distance

to safety ($D_{min}$) and additionally travel beyond its own body length ($l$) to completely avoid a collision, where the maximum possible value of $D_{min}$ is the entire width of the vehicle (Eq. 1).

$$D_{safe} = D_{min} + l \quad \text{(Eq.1)}$$

$D_{safe}$ is the total distance the animal needs to travel to clear the trajectory of the vehicle.

Animals often combine a mixture of protean and optimal escape trajectories, alternatively escape angle ($\theta$), to successfully escape or avoid an approaching threat, such as a natural predator (Domenici, 2002, Walker et al., 2005, Kimura & Kawabata, 2018, Kawabata et al., 2023). Escape angles ($\theta$) are typically defined relative to the approach angle of the threat. Herein we define $0^{o}$ as flight directly towards the approaching vehicle and $180^{o}$ as flight directly away from the vehicle, where escape angles are limited between a range of $0^{o}$ to $180^{o}$. Escape angles that differ from a perpendicular escape angle (i.e., $90^{o}$) extend the time needed for the animal to completely cross $D_{safe}$. Additionally, $T_a$ is dependent upon the escape speed of the animal ($S_a$) and the additional time required to reorient and accelerate as it enacts its escape response (δ) (Eq. 2; Figure 1).

$$T_a = \frac{\frac{D_{safe}}{\sin(\theta)}}{S_a} + \delta \quad \text{(Eq.2)}$$

Equation 2 assumes a constant escape speed by the animal (Table 2, Assumption 3).

The time remaining until the vehicle reaches the location of the animal after escape initiation ($T_v$) depends on the flight-initiation distance ($D_{FID}$), escape speed ($S_a$), and escape angle ($\theta$) of the animal, and the approach speed of the vehicle ($S_v$) (Table 1, Fig.1). After the animal initiates its escape response ($D_{FID}$), it has a limited amount before the vehicle reaches the location of the animal depending on the approach speed of the vehicle ($S_v$). However, depending on the escape speed ($S_a$) and angle ($\theta$) of the animal, the vehicle will reach the position of the

118 animal either relatively sooner or later as the animal moves either farther away or closer to the
119 approaching vehicle (Eq. 3).

120 $$T_v = \frac{D_{FID}}{S_v + (\cos(\theta) * S_a)} \quad \text{(Eq.3)}$$

121 Equation 3 assumes a constant vehicle approach speed ($S_v$) and animal escape speed ($S_a$).

122 Consequently, if $T_a$ (i.e., time needed to escape) is greater than or equal to $T_v$ (i.e.,
123 time remaining to successfully escape), a collision is possible. If a collision is possible then
124 phase two of the model estimates some probability of collision based on the location of the
125 animal within the trajectory of the vehicle. However, phase two is not applicable to situations
126 where $T_a < T_v$ because a collision is entirely avoided, assuming the animal does not change
127 directions or stop (Table 2, Assumption 3).
128
129 *Phase two*
130 Phase two has two distinct components: 1) an estimate of the location of the animal within the
131 trajectory of the vehicle at the moment of collision ($D_{\text{collision}}$); and 2) the assignment of the
132 probability of collision based on that location (i.e., $P(Collision)$).
133 We estimated $D_{\text{collision}}$ based on the absolute minimum distance to safety ($D_{\text{min}}$), the
134 entirety of the vehicles width ($D_{\text{width}}$), the escape speed ($S_a$) and angle ($\theta$) of the animal, and
135 the duration of time that elapsed since the animal initiated escape ($T_v$). First, the minimum
136 distance to safety ($D_{\text{min}}$) and the trajectory width of the vehicle ($D_{\text{width}}$) are used to estimate the
137 initial position of the animal in the trajectory of the vehicle at the time when escape is initiated
138 ($D_{initial}$) (Table 1, Fig.1, Eq. 4).

139 $$D_{initial} = D_{\text{min}} - D_{\text{width}} \quad \text{(Eq.4)}$$

140 From the initial location of the animal $D_{initial}$ the model estimates how much further the animal

travels within the trajectory of the vehicle while the vehicle continues to approach by multiplying escape speed ($S_a$), angle ($\theta$), and the time remaining since escape initiation ($T_v$, see Eq.3), which yields equation 5.

$$D_{collision} = D_{initial} + (\cos(\theta) * S_a * T_v) \quad \text{(Eq. 5)}$$

$D_{collision}$ is the location, specifically the midpoint, of the animal in the trajectory of the vehicle at the moment the vehicle reaches the animal.

Estimates of $P(Collision)$ are based on the frontal surface area of the vehicle ($A_{front}$) and width of the animal the point of contact based on the location of the animal in the trajectory of the vehicle ($D_{\text{collision}}$) and body length of the animal($l$) (Table 1). We defined the trajectory of the vehicle as a 2-D planar space bound by vehicle width ($D_{\text{width}}$) and height ($D_{\text{height}}$), which, respectively, can be thought of as the x and y axes (Fig. 2). We estimated the probability of collision as the ratio between all the space occupied by the frontal surface area of the vehicle ($A_{front}$) and the entire surface area at that location on the x-axis where the animal could be (i.e., product of $l$ and $D_{\text{height}}$), assuming the animal (i.e., a bird) could be at any random altitude (i.e., y-axis) within the collision window (Table 2, Assumption 4, Eq.6a-6c).

$$coord_1 = D_{collision} - (\tfrac{l}{2}) \quad \text{(Eq. 6a)}$$

$$coord_2 = D_{collision} + (\tfrac{l}{2}) \quad \text{(Eq. 6b)}$$

$$P(Collision) = \frac{1}{D_{height} * l} \int_{coord_1}^{coord_2} A_{front} \quad \text{(Eq. 6c)}$$

# Methods

*Parameter selection & simulation approach*

We applied our model to estimate the probability of collision for a scenario where a high-speed aircraft (i.e., a Boeing737) approaches a Canada goose. We investigated how the probability of

collision changes by systematically iterating through a range of realistic values for four different parameters: goose escape speed ($S_a$), sensory-motor delay ($\delta$), the minimum distance to safety ($D_{\min}$), and aircraft approach speed ($S_v$). (Table 1). Herein, we used only a single value for body length ($l$), where we defined body length as the linear distance from the tip of the beak to the outer edges of the tail feathers (115 cm, Bellrose, 1976).

We varied escape speed ($S_a$) between 1 m/s to 17 m/s, in increments of 2 m/s, based on the recorded flight speed of Canada geese (Wege & Raveling, 1984). The sensory-motor delay values ($\delta$) varied between 0 to 1 second in increments of 0.1 secs based on the observed response delays of different bird species (Provini et al., 2012, Guenin et al., 2024). A sensory-motor delay of 0 seconds represents a scenario where the animal is actively moving when it crosses into the trajectory of the vehicle, whereas 1 second means the animal took an entire second before it actually began to move. The minimum distance to safety ($D_{\min}$) varied from 1 to 14.35 m by increments of 1.48 m for a total of 10 different intervals. We chose 14.35 m as the maximum distance to safety based on the width between the edges of the horizontal stabilizers of a 737commercial aircraft (Fig. 2). We elected not to use the entire width of the aircraft wingspan because the collisions with the highest probability of damage, once a collision occurs, are impacts to the fuselage or engine ingestion (Liu et al., 2018, Dolbeer et al., 2023) (Fig. 2). Lastly, we varied aircraft approach speed ($S_v$) between 70.47 (i.e., 150 knots) to 270.97 m/s by increments of 14.32 m/s for a total of 15 different approach speeds based on the range of Federal Aviation Administration recommended approach speeds that occur at different flight phases (e.g., take-off run, climb, cruise, approach, landing) (Instrument Procedures Handbook: FAA-H-8083-16A, 2017).

For each run of the model, we simulated a single flight-initiation distance ($D_{FID}$) and

187 escape angle ($\theta$). We simulated flight-initiation distance values ($D_{FID}$) from a normal
188 distribution with a mean of 56.2 m and a standard deviation of 16.5 m, based on Canada goose
189 escape responses to direct approaches by an automobile (i.e., a truck) (Blackwell et al. 2019).
190 Escape angle values ($\theta$) were simulated from one of two different uniform distributions. Birds
191 either received an escape angle ($\theta$) from a uniform distribution with escape angles ($\theta$) ranging
192 from 0.01 to 89.99°, hereafter referred to as the "toward" distribution, or from a uniform
193 distribution with escape angles ($\theta$) ranging from 90.01 to 179.99°, hereafter the "away"
194 distribution. In our parametrization of the model, geese had a different probability of receiving
195 either an escape angle from the "toward" (0.58) or "away" (0.42) distribution based on the
196 frequency of different Canada goose behavioral responses reported by pilots obtained from the
197 "Remarks" section of the Federal Aviation Administration wildlife collision database (Appendix
198 S1).
199 To account for variation in model predictions attributable to differences in simulated
200 flight-initiation distance ($D_{FID}$) and escape angle ($\theta$) values, we ran the model with 500 iterations
201 for each unique combination of parameter values.
202
203 *Estimating the probability of collision*
204 We quantified the probability of collision by digitizing a to-scale-schematic of a Boeing-737
205 (Fig. 2). We estimated the frontal surface area of the vehicle ($A_{front}$) by summing all the pixels
206 occupied by the aircraft (Fig. 2), divided by the total number of pixels within a specific
207 subsection along the x-axis defined by the length of the goose and height of the aircraft, hereafter
208 referred to as the "collision window". We converted the length of the goose to pixels by first
209 dividing the width of the trajectory (i.e., 14.35 m) by the width of the aircraft schematic image

(i.e., 1031 pixels) (Fig. 2) to estimate the m/pixels conversion factor (0.0139 m/pixels), then divided goose length ($l$) (i.e., 115 cm) by the conversion factor to estimate the length of a goose in nearest whole pixels (83 pixels).

*Model application*

We applied our model to quantify how lights of different wavelengths onboard an approaching aircraft might affect the probability of collision through altering the behavior of Canada geese. Lights have been shown to lead to earlier alert responses to approaching vehicles (Blackwell et al., 2012). Specifically, Canada geese alerted 4.1 seconds earlier to an approaching aircraft with a light turned on (11.4 ± 4.4 sec) relative to an aircraft with a light turned off (7.3 ± 4.4) (Blackwell et al., 2012). This early alert provides an opportunity for the animal to escape sooner, thus expanding the range of potential flight-initiation distances ($D_{FID}$) (Blackwell & Fernández-Juricic, 2013). Consequently, for an aircraft approaching with lights on we simulated flight-initiation distance ($D_{FID}$) values from a uniform distribution with a minimum of 0 m and maximum flight-initiation distance ($D_{FID}$) based on the maximum possible alert distance. We estimated the maximum possible alert distance by multiplying the temporal benefit provided by the light source, hereafter $\beta$, by the aircrafts approach speed. We systematically varied the temporal benefit of the light source ($\beta$) from 0 to 8.5 seconds by increments of 0.88 seconds for 10 different intervals, based on the mean observed temporal benefit (4.1 sec) and SD in alert time (4.4 sec) observed in Blackwell et al. (2012).

Light wavelengths of high chromatic contrast have also been shown to affect the avoidance responses in Canada geese in a single choice experiment (i.e., a T-maze test), where differences in the probability of avoidance could potentially translate to differences in the escape

angle of the animal (Lunn et al., 2023). Lunn et al., 2023 found that after repeated exposures geese tended to avoid a 483 nm light (i.e., blue) (probability of avoidance 0.65) and were attracted to 631 nm light (i.e., red) (probability of avoidance 0.11). Consequently, we explored how the probability of collision changes for different wavelengths of high chromatic contrast (i.e., a blue- and red-light) assuming an avoidance response translates to an escape trajectory away from the approaching aircraft (i.e., an escape angle ($\theta$) > 90 deg). Specifically, in a blue-light scenario geese had a 65% chance of receiving an escape angle from the "away" distribution, where in a red-light scenario geese had a 11% chance of receiving an escape angle from the "away" distribution according to the difference in the probability of avoidance reported in the final trials of Lunn et al. 2023.

No study that we are aware of has examined how different wavelengths of light simultaneously affect different combinations of flight-initiation distance ($D_{FID}$) and escape angles ($\theta$). Lunn's et al. (2023) findings indicate that geese developed an attraction response to the red-light but showed a mild avoidance response to the blue-light after repeated exposures. We assumed for both the blue- and red-light scenarios that "toward" escape angles are indicative of a potential attraction response to the lights (not necessarily to the approaching aircraft) and thus paired them with shorter flight-initiation distances ($D_{FID}$); whereas "away" escape angles were indicative of avoidance and paired with longer flight-initiation distances ($D_{FID}$). Specifically, the presence of attractants such as a food source, potential mate, or flock members results in shorter flight-initiation distances, where the presences of an aversive stimuli or repellent associated with greater perceived risk, such as faster and more direct predator approaches, results in longer flight-initiation distances (Ydenberg & Dill 1986, Cooper et al., 2009, Blackwell et al. 2019, Ventura et al., 2021, Hammer et al., 2025). Additionally, birds can

either be attracted or repelled by different light stimuli (Poot et al., 2008, Rodríguez et al., 2017, Adams et al., 2021, Van Doren et al., 2021), potentially leading either to shorter or longer flight-initiation distances, respectively.

For both the blue- and red-light scenarios if the simulated escape angle ($\theta$) was received from the "toward" distribution then consequently the flight-initiation distance ($D_{FID}$) was simulated from the same distribution as a no-light scenario (i.e., normal distribution, mean= 56.2 m, SD=16.5, and not affected by $\beta$). However, if an escape angle ($\theta$) was received from the "away" distribution, then consequently flight-initiation distance values were simulated from the distribution affected by $\beta$ (i.e., a uniform distribution ranging from 0, to $S_a \times \beta$).

*Reporting results*

We generated a total of 222,750,000 predictions of whether a collision would or would not occur with our model for all combinations of goose escape speed ($S_a$), sensory-motor delays ($\delta$), the minimum distance to safety ($D_{\min}$), aircraft approach speed ($S_v$),and the three different light scenarios (i.e., no-light, blue-light, red-light) which included the temporal benefit ($\beta$) afforded by a light onboard. For each combination of parameters, we generated 500 predictions with different simulated values for flight-initiation distance ($D_{FID}$) and escape angle ($\theta$).

We present the model predictions for the probability of collision in Figures 3 and 4, where both figures show the relationship between the probability of collision and a single variable. In Figure 3, the x-axes were variables that we systematically manipulated, whereas in Figure 4 the x-axes are simulated variables (see above). We estimated the predicted probability of collision in Figure 3 by first summing the number of collisions that occurred for each unique combination of parameters and then divided the total by 500, representing the number of

different runs of the model with simulated flight-initiation distance ($D_{FID}$) and escape angle ($\theta$) values. We estimated the predicted probability of collision in Figure 4 by first binning both flight-initiation distance ($D_{FID}$) and escape angle ($\theta$) to within 0.1 of either a meter or degree and then added the total number of collisions that occurred within that bin divided by the total number of predictions within that bin. To describe the relationship between our continuous variables and the probability of collision regarding the three different light scenarios, we fitted a curve from a general additive model using the *geom_smooth* in the *ggplot2* package (Wickham & Chang, 2016). The results of each figure can be interpreted as the average effect of that single parameter value on the probability of collision across all other possible parameter values.

## Results

*Overview*

First, the mean probability of collision among all combinations of parameters was the lowest for the blue-light scenario (mean ± SD, 0.292 ± 0.167), with an increase for the red-light scenario (0.347 ± 0.161), and with the highest probability of collision occurring for the no-light scenario (0.429 ± 0.189) (Fig. 3a). Second, an increase in escape speed of the animal ($S_a$) generally resulted in a non-linear asymptotic decrease in the probability of collision (Fig. 3b.). For the blue- and red-light scenarios, probability of collision decreased at a decreasing rate with escape speed. In contrast, the no-light scenario yielded a probability of collision that decreased but at an increasing rate with increasing escape speed (Fig. 3b). As sensory-motor delays increased, the probability of collision increased linearly and slightly, with a similar pattern across all three light scenarios (Fig. 3c). An increase in aircraft approach speed resulted in the probability of collision increasing to an asymptote for each light scenario (no-light > red-light > blue-light; Fig. 3d). The

relationship between the minimum distance to safety and the probability of collision was multimodal with three different inflection points (Fig. 3e). Generally, as the minimum distance to safety increased, so did the probability of collision. However, the shape of the curve strongly reflected the difference in the probability of collision based on the shape of the aircraft and the location of the animal within the trajectory. Specifically, the probability of collision was highest when the location of the animal within the trajectory of the aircraft coincided with either the fuselage or the engines, where this pattern was similar for all three light scenarios (Fig. 3e). Also, as the temporal benefit afforded by a light source increased, the probability of collision decreased to an asymptote and was only relevant for the blue- and red-light scenarios (Fig. 3f).

Larger flight-initiation distances ($D_{FID}$) resulted in dramatically lower probabilities of collision for both the blue- and red-light scenarios (Fig 4a). Additionally, escape angles ($\theta$) closer to 90º (i.e., escaping perpendicularly to the approaching vehicle) had a lower probability of collision relative to escape angles ($\theta$) closer to either 0º or 180 (Fig. 4b). The "away" escape angles for both the blue- and red-light scenarios (i.e., paired with longer flight-initiation distance ($D_{FID}$) yielded a dramatically lower probability of collision, in contrast to a perpendicular escape angle (Fig. 4b).

## Discussion

To summarize, we built upon an existing theoretical foundation (Domenici, 2002, Kawabata, et al., 2023) to propose a new mathematical model to estimate the probability of collision an animal faces given it is within the trajectory of vehicle, where herein applied to an approaching aircraft. Our model quantifies how differences in specific aspects of an escape response in the final seconds prior to the arrival of a high-speed approaching vehicle affects the probability of

collision. We then applied the model to quantify how a given technological intervention (i.e., onboard light stimuli) aimed at altering the escape response of the animal subsequently affects the probability of collision. Our model demonstrates the importance of considering how animals simultaneously alter multiple properties of an escape response to reduce the probability of collision, how the probability of collision varies depending on the location of the animal within the trajectory of the vehicle, and that the presence of onboard lighting tuned to eyes of the target species has the potential to reduce the probability of collision.

Animals often rely on a combination of several different sequential behaviors to reduce the mortality risk associated with an approaching predator (Evans et al., 2019, Branco & Redgrave, 2020). Evidence suggests that animals rely on similar behaviors when attempting to avoid approaching vehicles (Lima et al., 2015, DeVault et al., 2015, Lunn et al., 2022). Specifically, individuals can adjust their flight-initiation distance (Ydenberg & Dill 1986, Stankowich & Blumstein, 2005, Cooper & Blumstein, 2015), escape speed (Domenici & Blake, 1991, Lind et al., 2002), escape angle (Domenici & Blake, 1993, Domenici et al., 2011a, Domenici et al., 2011b), or opt to not escape at all (Broom & Ruxton, 2005, Cooper 2009b), Blackwell et al., 2020), to reduce mortality risk from an approaching threat (Caro et al., 2005).

The model can be used to identify the components of an escape response that have the largest effect on the probability of collision. Technological interventions or management can then target these specific behaviors of relatively larger effect size to enact the larger reductions in the probability of collision. For instance, in the case of Canada geese and an approaching 737 with no-light onboard, flight-initiation distance had the largest effect, where an increase from 0 m (0.460) to greater than 120 m (0.361) resulted in a 21.6 % decrease in the probability of collision (Fig. 4a). Differences in escape speed had the second largest effect, where an increase

348 from 0 (0.467) to 17 m/s (0.377) resulted in a 19.3% decrease in the probability of collision (Fig.
349 3b). Lastly, difference in escape angle from 0º (0.467) or 180º (0.464) to 90º (0.397) (Fig. 4b)
350 respectively resulted in a 14.9% and 14.4% decrease in the probability of collision, respectively
351 (Fig. 3c). Thus, we would expect that a strategy aimed at increasing Canada goose flight-
352 initiation distance or escape speed would yield the largest reduction in the probability of collision
353 relative to an approaching 737.

354 Our model also enables us to quantify how different vehicle approach scenarios affect the
355 probability of collision, which can aid in developing collision mitigation strategies. For example,
356 in the case of a 737 approaching a Canada goose, the location of the animal in the trajectory of
357 the vehicle had the largest effect, where the difference between a minimum distance to safety of
358 1 m (0.102) versus 8.42 m (0.673) resulted in a 570% increase in the probability of collision.
359 Specifically, the three inflection points (i.e., peaks) in Figure 3e correspond to the aircraft
360 engines and fuselage, where the probability of collision increases due to their larger frontal
361 surface areas. The predictions of our model align with the Federal Aviation Administration's
362 wildlife strike database, where the most frequently struck locations of Canada geese on a 737 are
363 the engines and the fuselage (n=193, Federal Aviation Administration Wildlife Strike Database)
364 (Fig.5a & b). A potential mitigation strategy therefore might focus on deterring birds away from
365 sections of the aircraft with the largest frontal surface area.

366 Our model also provides a quantitative framework to make predictions about high-speed
367 vehicle approach scenarios that are difficult to test empirically. Previously the fastest simulated
368 approach speed empirically tested was 100 m/s by DeVault et al., 2015 (Fig. 5c). In our example
369 with a Canada goose and a Boeing-737, we were able to estimate that the probability of collision
370 increased by 27% from 70 (0.359) to 271 (0.457) m/s, extremely fast approach speeds.

Additionally, previous empirical studies have been limited to estimating whether a collision occurs based on only a few properties of an escape response (i.e., flight-initiation distance) and approaching vehicle (i.e., approach speed, vehicle width) (DeVault et al. 2015, Guenin et al., 2024). Our model proposes a framework for the additional variables that need to be collected to more accurately predict the outcome of an animal-vehicle interaction. While the predictions of our model align qualitatively with the empirical data (i.e., an increase in approach is associated with an increase in the probability of collision; DeVault et al., 2015, Guenin et al., 2024), the disparity in the probability of collision estimates between empirical and theoretical approaches (Fig. 5c) is likely due to our model considering how animals might alter many different components of their escape response simultaneously.

Both the probability of capture in the context of predator-prey interactions and the probability of collision in the context of animal-vehicle interactions rely on similar variables to quantify the outcome of an interaction with either a predator or a vehicle; however, additional assumptions and parameters are needed to estimate the probability of collision (Table 2). We argue that three major differences need to be considered. First, the probability of collision, especially for larger vehicles, is often not homogenous throughout trajectory of the vehicle (i.e., portions with larger frontal surface area increase the probability of collision). As a result, the specific location of the animal within that trajectory should be considered, because a collision still might be avoided despite the vehicle reaching the location of the animal (e.g., a goose passing over the fuselage of the aircraft, see Phase two above).

Second, vehicles generally remain on a fixed and linear trajectory when approaching an animal as opposed to the dynamic trajectories of predators (Peterson et al., 2021). Models of predator-prey capture vary in whether they assume a predator approaches linearly or non-linearly

394 (Corcoran & Conner, 2016, Domenici, 2002, Kawabata et al., 2023). Vehicles are commonly
395 limited to travelling on a designated substrate (i.e., road) or predetermined course (i.e., flight
396 path), especially at faster speeds; therefore, when modeling animal vehicle collisions generally a
397 linear approach can be assumed. Yet, a fixed and linear trajectory does not necessarily mean that
398 the behavior of the vehicle does not change (e.g., pilots alter flight paths, speeds, etc.). An
399 important component for future research is to assess the effects of driver behavior seconds prior
400 to a collision (e.g., Pakula et al., 2023).

401 Third, the probability of collision is dependent on the approach angle of the vehicle. In
402 empirical studies, approach angles are often categorized as either direct or indirect, defined by
403 whether the trajectory of the predator intersects or simply bypasses the prey animal (e.g.,
404 Domenici, 2002, Stankowich & Blumstein 2005). However, the threshold approach angle that
405 distinguishes between direct versus indirect angles is generally not explicitly defined, primarily
406 because predators can dynamically alter their approach angle based on prey escape trajectories as
407 they get closer (Howland, 1974, Corcoran & Conner, 2016, Peterson et al., 2021).

408 However, because vehicles are often limited to fixed trajectories (see above), we propose
409 that the critical angle of a direct or indirect approach can be quantitatively defined as:

410 $$\theta_{threshold} = sin^{-1}\left(\frac{D_{half+l}}{D_{mid}}\right); \quad \text{(Eq. 7)}$$

411 where $\theta_{threshold}$ is the critical approach angle differentiating between an indirect and direct
412 approach, $D_{mid}$ is the distance between the center of the vehicle and the animal, and $D_{half}$ is half
413 the maximum width of the vehicle, and $l$ is the length of the animal. Specifically, vehicle
414 approach angles greater than $\theta_{threshold}$ will equate to an indirect approach where if the animal
415 does not enact an escape response a collision can be avoided, where approach angles less than or
416 equal $\theta_{threshold}$ will result in a potential collision if no response is enacted. The probability of

collision with a vehicle being completely dependent on approach angle might explain in part why some animals appear to adopt relatively shorter flight-initiation distances (Holmes et al., 1993, Blackwell et al., 2020), not flee at all (Guenin et al., 2024), or flee after the vehicle has passed (Pfieffer et al., 2025) because the probability of collision is 0 for an indirect approach.

Importantly, equation 7 does not explicitly affect the predictions of our model because assumption 1 (Table 2) states the vehicle is approaching directly and therefore the approach angle is below $\theta_{threshold}$ and a collision is possible, if no response is enacted. As computer vision technology becomes further integrated into automated vehicle navigation (i.e., advanced air mobility) estimating the vehicles approach angle ($\theta_{threshold}$) relative to a detected wildlife hazard could be important in monitoring the prevailing probability of collision and whether collision avoidance measures are necessary by the vehicle (Huijser et al., 2015, Corcoran et al., 2021, Nandutu et al., 2022).

The Federal Aviation Administration's wildlife strike database reports that interactions with Canada geese and aircraft over a 23-year period have cost the airline industry approximately 183 million dollars, a 7.95-million-dollar annual cost (Dolbeer et al., 2023). Our model suggests that blue and red onboard lighting tuned to the eyes of Canada geese would reduce the probability of collision by about 14 % and 8%, respectively, which potentially could have saved 25 and 15 million US dollars, respectively, over a 23-year period for just one species. However, a more structured analysis is necessary to truly estimate the potential financial savings and variation in savings afforded by light stimuli following the approaches put forth by Altringer et al. (2021, 2024). Additionally, these estimates are based on assumptions about how animals change multiple aspects of their escape behavior simultaneously in response to a light stimulus, and future research needs to evaluate these assumptions.

Future efforts to quantify the probability of collision for an approaching vehicle can build upon this existing model in several concrete ways. First, our modelling approach can be applied to other vehicle types (e.g., rotorcraft, automobiles, boats, etc.) and other taxa of management or conservation concerns. Second, in our modelling approach we did not incorporate any parameter or make any assumption about how animals delay escape after detection and continue to assess an approaching threat before initiating escape (Blumstein 2010, Chan et al., 2010, DeVault et al., 2015, Lunn et al., 2022, Guenin et al., 2024). As such, the absolute value for the probability of collision estimates are most likely conservative (i.e., smaller), especially given the extremely fast range of speeds we used to model an approaching aircraft. Future studies quantifying the probability of collision should explicitly incorporate a delay in time for risk assessment after detection and before flight-initiation distance into estimates of the time needed for the animal to clear the path trajectory of the vehicle. Third, our model implicitly assumes that the altitude of the animal in the path trajectory of the vehicle is random because the animal could be at potentially at any height (Fig. 2). In reality, the aircraft could be ascending or descending, and the bird as well could be attempting to gain or lose altitude to escape the trajectory of the vehicle. We did not assume any specific height within the trajectory of the vehicle because of the scarcity of empirical data to support a given range. However, if we had data on both take-off velocity and take-off or dive angle for Canada geese, we could improve the accuracy of the probability of collision estimates.

We envision that our model be applied to quantitatively estimate the probability of collision for various species and different vehicle approach scenarios, which could ultimately aid in forecasting the impacts of present and future transportation projects on wildlife populations. Additionally, our model allows us to estimate the probability of specific components of the

aircraft (fuselage, engines, wings, etc.) being struck, helping in the estimation of economic damage and safety hazards (Dolbeer et al., 2023). Overall, our framework can be used to develop targeted and preventative animal vehicle collision mitigation strategies, especially as air-traffic volume is forecasted to increase.

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**Author Contributions:**

- Ryan B. Lunn: Conceptualization, Methodology, Data processing & analysis, Visualization, Writing-original draft, writing-review and editing, project administration
- Bradley F. Blackwell: Funding acquisition, Conceptualization, Writing-original draft, Writing-review and editing, Project Administration
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**Conflict of Interest:**

No conflict of interest declared

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Figure legends

Figure 1. A top-down (a) and front-view (b) illustration of the variables considered in both phase 1 and 2 of the model. All definitions are provided in table 1.

Figure 2. a) The schematic of a Boeing 737 aircraft used to estimate the frontal surface area. The red, dotted line represents the x-axis intercepts of both $coord_1$ and $coord_2$ that define the location of the collision window on the x-axis. b) The sum of all pixels per the entirety of the goose body length and relative to each potential location of the goose along the x-axis of the aircraft's trajectory. Here, the right side shows the decrease in the probability of collision as the gooses body length exits the trajectory.

Figure 3. The relationship between each variable manipulated in our modeling and the probability of collision, where grey bars represent the standard deviation. a) The mean and standard deviation in the probability of collision for each of the three light scenarios, where each point represents the average probability of collision for over 500 runs of the model and with the same combination of manipulated variables. b) The relation between escape speed (m/s) and probability of collision for the three light scenarios. c) The relation between sensory-motor delay (sec) and probability of collision for the three light scenarios. d) The relation between aircraft approach speed (m/s) and probability of collision for the three light scenarios. e) The relation between the minimum distance to safety (m) and probability of collision for the three light scenarios. f) The relation between the minimum distance to safety (m) and probability of collision for the three light scenarios.

Figure 4. a) Plot of the average probability of collision for all model predictions made with aspecific flight-initiation distance (m) separated by the three light scenarios. b) Plot of the average probability of collision for all model predictions made with a specific escape angle (degree), separated by the three light scenarios.

Figure 5. a) The relationship between approach speed and the model-predicted probability of collision compared to the empirical relationship between observed probability of collision and vehicle approach speed reported in DeVault et al., (2015) & Guenin et al. (2024. b & c). A density map of the collision locations reported in the FAA wildlife strike database between

Canada geese and a 737 aircraft, where b) is the frontal view of an aircraft & c) a top-down view of the aircraft.

822 Table 1. A list of all variables, their corresponding symbols, definitions and units used for
823 equations 1 to 6 in the main text.
824

| Symbol | Definition | Units |
|---|---|---|
| $T_a$ | Time needed for the animal to escape the vehicles trajectory | sec |
| $T_v$ | Time until the vehicle reaches the location of the animal within its trajectory | sec |
| $D_{min}$ | Distance needed to clear the trajectory of the approaching vehicle | m |
| $l$ | Body length or wingspan of the animal | m |
| $D_{safe}$ | The total distance the animal needs to travel to reach safety (Eq.1) | m |
| $S_a$ | Escape speed of the animal | m/s |
| $\theta$ | Escape angle ranging from 0 to 180 degrees, where 0 is directly towards the approaching vehicle and 180 degrees is directly away | deg |
| $\delta$ | The time needed for the animal to re-orient and initiate escape | sec |
| $D_{FID}$ | Flight-initiation distance or distance between the animal and the aircraft when the animal initiates escape | m |
| $S_v$ | Approach speed of vehicle | m/s |
| $D_{height}$ | The maximum height of the approaching vehicle | m |

| | | |
|---|---|---|
| $D_{width}$ | The maximum width of the approaching vehicle | m |
| $D_{initial}$ | The animal's initial position within the vehicle's trajectory relative vehicle width (Eq. 4) | m |
| $D_{collision}$ | The animal's position within the vehicle's trajectory relative to vehicle width when the vehicle reaches the location of the animal (Eq. 5) | m |
| $A_{front}$ | The frontal surface area of the approaching aircraft | $m^2$ |

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840 Table 2. A list of the model assumptions
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| | Assumptions |
|---|---|
| 1 | The vehicle is approaching directly, alternatively the animal is within the path trajectory of the vehicle. |
| 2a | The trajectory of the vehicle is linear and constant |
| 2b | Vehicle approach speed ($S_v$) is constant |
| 3a | The trajectory of the animal is linear and constant after it initiates escape |
| 3b | Animal escape speed is constant ($S_a$) after it initiates escape |
| 4 | The animal can be located at any altitude within the trajectory of the vehicle |
| 5 | Per the light application exercise, towards escape angles are paired with shorter flight-initiation distances as part of a larger attraction response to the light stimuli |

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844 Figure 1.

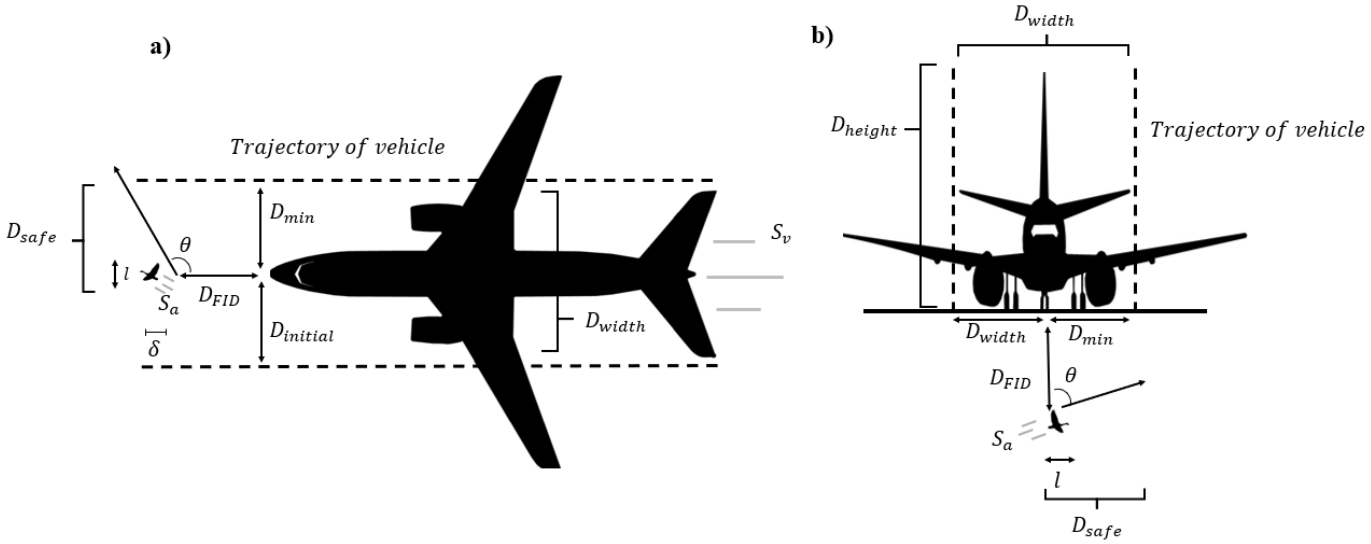


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Figure. 2

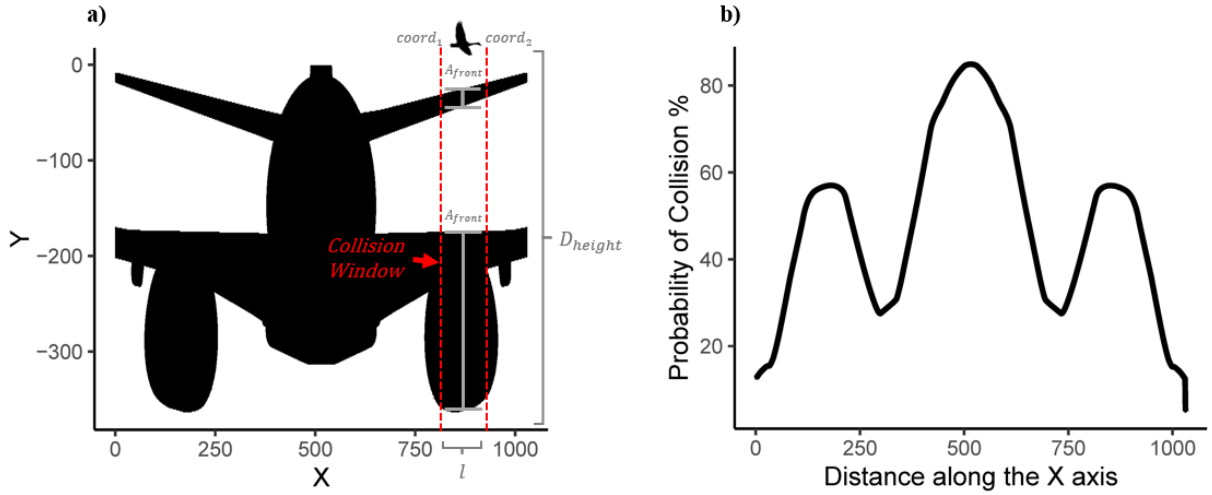

a)
b)
$coord_1$
$coord_2$
$A_{front}$
$A_{front}$
$D_{height}$
Collision Window
Y
X
$l$
0
−100
−200
−300
0
250
500
750
1000
Probability of Collision %
Distance along the X axis
20
40
60
80

Figure 3.

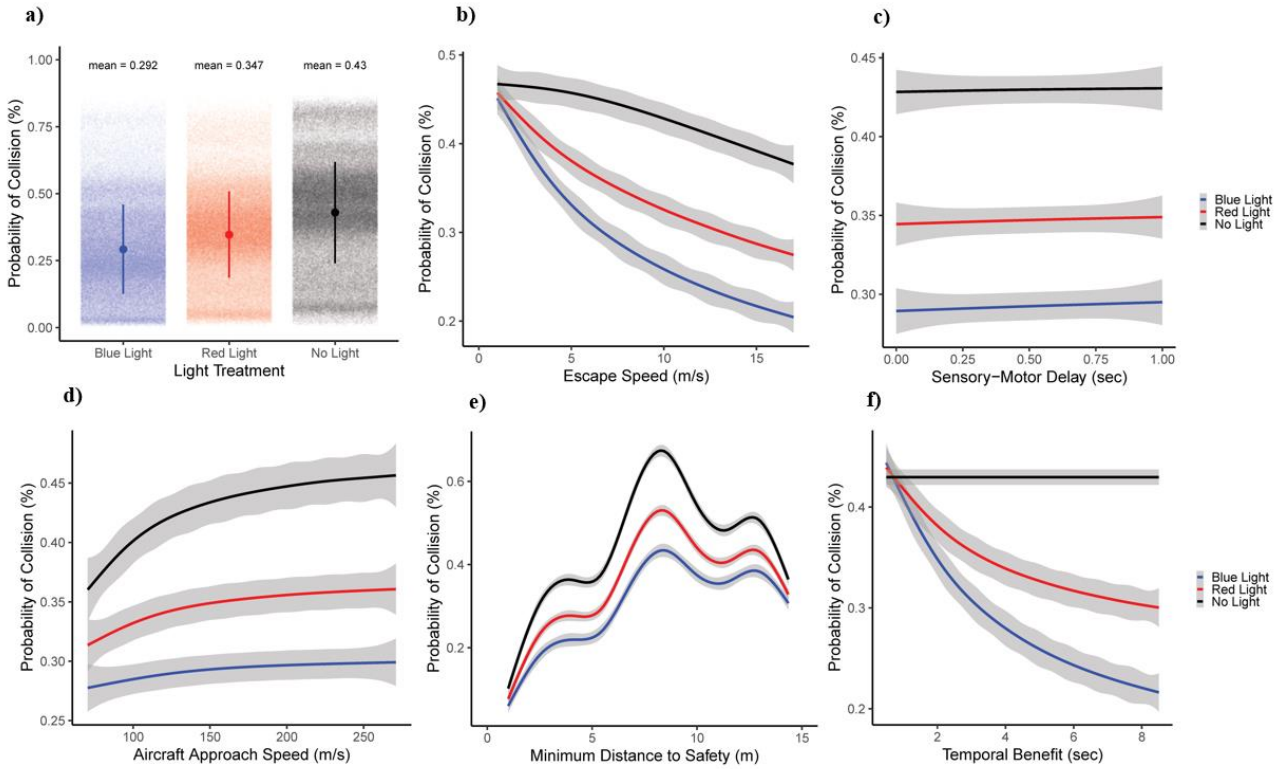

a)
b)
c)
d)
e)
f)
mean = 0.292
mean = 0.347
mean = 0.43
Probability of Collision (%)
Blue Light
Red Light
No Light
Light Treatment
Escape Speed (m/s)
Sensory−Motor Delay (sec)
Aircraft Approach Speed (m/s)
Minimum Distance to Safety (m)
Temporal Benefit (sec)

Figure 4.

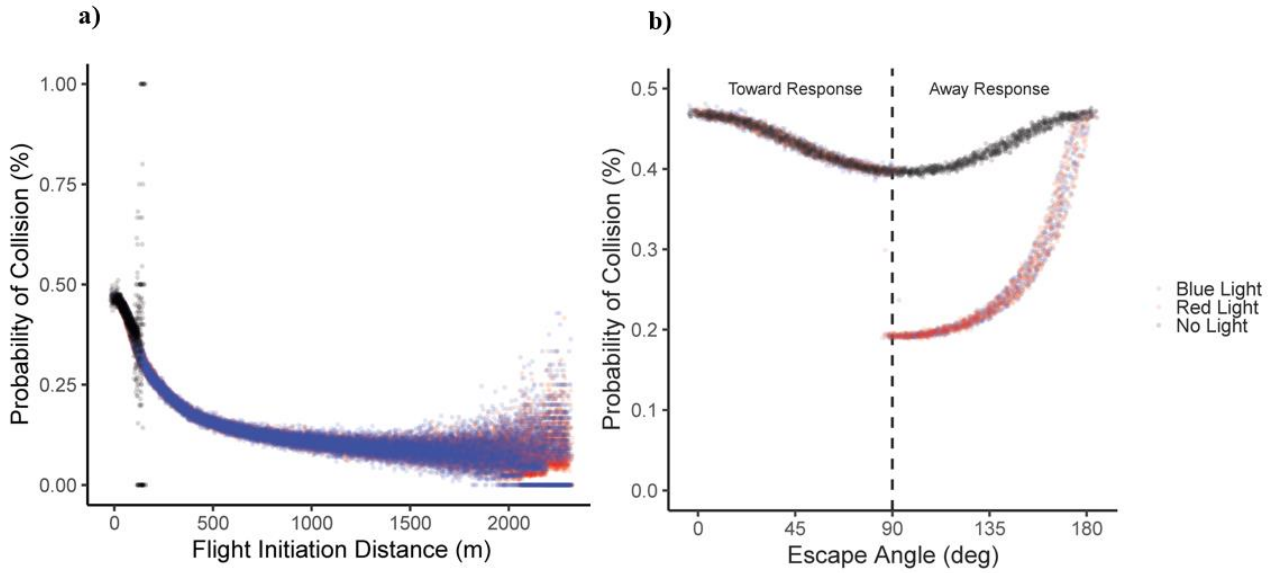
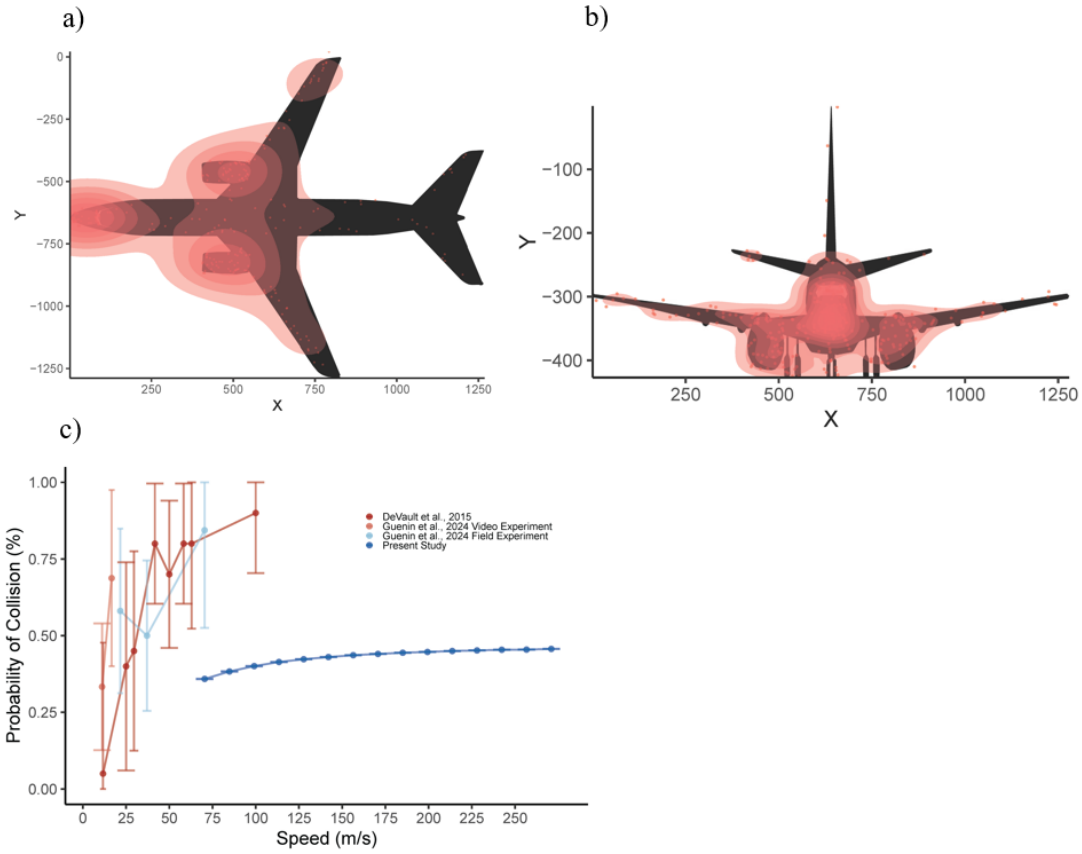



Figure 5.


a)
b)
c)
Y
X
Probability of Collision (%)
Speed (m/s)
DeVault et al., 2015
Guenin et al., 2024 Video Experiment
Guenin et al., 2024 Field Experiment
Present Study

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