INTEGRATING WILDLIFE BEHAVIOR, DRIVER BEHAVIOR, AND VEHICLE LIGHTING DURING NIGHTTIME ENCOUNTERS: IMPLICATIONS FOR REDUCING WILDLIFE–VEHICLE COLLISIONS

by

Carson Jacob Pakula

(Under the Direction of Travis L. DeVault and Olin E. Rhodes Jr.)

ABSTRACT

Wildlife-vehicle collisions are a pervasive global issue, posing a threat to both animals and humans. These collisions result from a complex interplay of driver behavior, animal behavior, and environmental factors. Despite contributing to nearly every collision, little is known about the factors that influence driver behavior during wildlife encounters. Furthermore, most mitigation methods are ineffective or impractical to implement widely. This dissertation addressed these gaps by investigating both driver and animal behavior during wildlife-vehicle encounters and evaluating altered vehicle lighting as a potential mitigation method. A literature review revealed that relatively little is known about the factors that influence driver behavior during wildlife-vehicle interactions, with few papers conducting controlled, manipulative studies. Using volunteer drivers and infrared videography, I demonstrated that drivers struggle to detect wild white-tailed deer (*Odocoileus virginianus*) and wild pigs (*Sus scrofa*) at safe distances at night. Detection ability improved with increased illumination from high-beam headlights but suffered from fast vehicle speeds and driver fatigue. Focusing on wildlife behavior, I found that altered vehicle lighting can influence captive white-tailed deer behavior during imminent collision scenarios. Specifically, high-beam, halogen headlights without increased frontal vehicle illumination from a rear-facing lightbar had the greatest probability of eliciting an alert response. However, there were large variations in responses among deer, highlighting the difficulty in developing a universally effective mitigation method. Vehicle approaches towards free-ranging deer and wild pigs revealed that vehicle lighting can increase the likelihood of favorable animal responses. Compared to older, halogen headlights, LED headlights largely did not affect deer responses but resulted in earlier avoidance behaviors by wild pigs. Additionally, increased frontal vehicle illumination via a rear-facing lightbar improved responses for both species. Beyond vehicle lighting effects, we also observed large variations in responses among free-ranging deer and wild pigs. Collectively, this dissertation shows that wildlife-vehicle collisions are the result of both maladaptive wildlife behavior and ineffective driver detection ability. Despite this, altered vehicle lighting represents a promising method to reduce collisions by increasing favorable wildlife responses. Overall, this dissertation provides critical insights into a major global concern and offers practical strategies to help improve animal and driver safety.

INDEX WORDS: Wildlife-vehicle collisions, White-tailed deer (*Odocoileus virginianus*), Road ecology, Driver behavior, Vehicle lighting, Wildlife damage management

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DEDICATION

I dedicate this dissertation to my family: Karen, Norbert, Parker, and Lindsey Pakula.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Wildlife-vehicle collisions (WVCs) are ubiquitous in developed regions of the world (Hill et al., 2019; Seiler and Helldin, 2006) and are an increasing concern as human population and infrastructure grow (Dulac, 2013). In the United States alone, vehicle collisions with deer (*Odocoileus* spp.) cause US$8.4 billion in damage annually (in 2008 USD; Huijser et al., 2008a), with an estimated 58,622 people injured and 440 human deaths from deer-vehicle collisions (Conover, 2019). Despite these major impacts, WVCs are difficult to manage due to the combination of many human, animal, and environmental factors that contribute to collisions.

Understanding how visual and situational factors impact driver behavior and hazard perception is crucial to reduce WVCs. Although influences on driver behavior have been studied extensively in the transportation and pedestrian safety literature (Tyrrell et al., 2016; Wood, 2020), less research has been conducted with respect to driver behavior and WVCs. Most of the literature on the causes of WVCs has focused on environmental conditions or landscape configuration with more emphasis on animal behavior (e.g., Beasley et al., 2013; Pagany, 2020) than on factors influencing driver behavior per se. Of the research that has addressed driver behavior and WVCs, most studies have explored coarse scale, large collision datasets rather than variation in driver behavior across encounters (e.g., Colino-Rabanal et al., 2018; Tanner et al., 2017). Only three studies have directly addressed the ability of drivers to detect wildlife, but they used decoys or taxidermized animals and were conducted at relatively slow speeds (10–48 km/h) along a short course (<1 km; Hobday, 2010; Mastro et al., 2010; Rodgers and Robins, 2006). A driver's ability to detect free-ranging wild animals and the factors that influence that ability have not been investigated.

Although the causes of WVCs are complex, it is generally accepted that wildlife are ill-equipped to process and react effectively to approaching vehicles (Lima et al., 2015). Motor vehicles are evolutionarily novel, only existing on the landscape for a little over a century, forcing wildlife to rely on antipredator behaviors to assess and react to vehicle approach (Blackwell et al., 2016; Lima et al., 2015). These antipredator behaviors are often ineffective for avoiding modern vehicles traveling at high speeds (e.g., DeVault et al., 2015). Many antipredator models have been developed that predict prey behavior in response to predators (e.g., escape distance), including economic escape models (Blumstein, 2003; Ydenberg and Dill, 1986), the perceptual limit hypothesis (Quinn and Cresswell, 2005), the flush early and avoid the rush hypothesis (Blumstein, 2010), visual stimulus hypotheses (Javůrková et al., 2012; Schiff et al., 1962; Sun and Frost, 1998), and the Bayesian optimal escape model (Sutton and O'dwyer, 2018). However, many of these models cannot generate quantitative predictions relative to speed, suggesting they may be ineffective at predicting animal behavior in response to approaching vehicles (Lunn et al., 2022). A better understanding of how wildlife species respond to approaching vehicles and identifying the factors that influence escape distance is a crucial first step to reducing WVCs.

Due in part to their large economic and safety concerns, many mitigation methods have been implemented with varying degrees of success (Huijser et al., 2008b). Many commonly implemented mitigation methods are largely ineffective, including standard road crossing signs (Glista et al., 2009; Huijser et al., 2008a; Mastro et al., 2008), “deer whistles” (Romin and Dalton, 1992; Valitzski et al., 2009), and roadside reflectors (Benten et al., 2019; Benten et al., 2018; D'Angelo et al., 2006). Wildlife over and underpasses are the most effective mitigation methods currently available, especially when paired with roadside fencing (Donaldson and Elliott, 2021; Huijser et al., 2008b; Mastro et al., 2008); however, these methods are relatively expensive ($5-15 million per installation; Brennan et al., 2022) and widespread implementation across the road network is impractical. Recent work on modified vehicle lighting has shown promise in eliciting earlier avoidance responses from wildlife (Blackwell and Seamans, 2009; DeVault et al., 2020). Specifically, DeVault et al. (2020) found that increased frontal vehicle illumination via a rear-facing lightbar reduced “freezing” behavior and reduced dangerous encounters with deer in Ohio, USA. The authors suggested that increased vehicle illumination by the lightbar may have resulted in a more reliable looming object for deer, resulting in greater perceived risk. Although DeVault et al. (2020) found promising results, the effectiveness of increased frontal vehicle illumination at multiple field sites and with other species remains unexplored.

Despite recent advances, few studies have investigated how popular, commercially available lighting systems influence wildlife behavior. The two most common types of headlights currently in use are tungsten-halogen headlights (hereafter, halogen) and light emitting diode (LED) headlights, with LEDs now installed on 86% of new vehicles (Consumer Reports 2019). LEDs generally emit higher photometric illumination levels (Edmonds, 2015; Lee et al., 2014), which could enhance a driver's ability to detect wildlife, but direct evidence of this advantage is limited. Additionally, it remains unclear whether LED headlights result in more favorable or more negative responses by wildlife. One main difference between the headlight types is their spectral properties: LED headlights produce more blue light (380–500 nm), which more closely matches the peak sensitivities of deer and wild pig photoreceptors (Cohen et al., 2014; Neitz and Jacobs, 1989), while halogens emit more long wavelength light (620–750 nm). Despite their increasing popularity, no study has investigated how LED headlights influence wild pig or deer behavior. It currently remains unknown whether headlights that more closely match the peak sensitivities of deer photoreceptors (i.e. LEDs) will result in more favorable reactions to vehicles, as suggested by Blackwell and Seamans (2009), or if those headlights might overwhelm deer vision at night and result in more negative reactions, as suggested by Cohen et al. (2014).

The wide-ranging impacts of wildlife-vehicle collisions on wildlife and humans have been well documented, yet substantial gaps remain in the literature regarding their causes and effective mitigation methods. In Chapter 2, I conduct a comprehensive literature review of the factors influencing driver behavior during wildlife-vehicle encounters. Specifically, I categorize these factors and highlight key gaps in the literature. Building on these knowledge gaps, Chapter 3 investigates factors influencing driver detection of free-ranging wildlife at night. By using volunteer drivers and a 75-km route, I specifically quantify detection probability, detection distance, and probability of a dangerous encounter under realistic conditions. Chapter 4 uses captive deer to investigate the role of vehicle lighting on deer responses during imminent collision scenarios. In a confined experimental arena and a modified electric golf cart, I explore the effects of headlight type (LED vs. halogen) and its potential interaction with increased frontal vehicle illumination via a rear-facing lightbar on deer behavior. Chapter 5 extends these findings to free-ranging wildlife encountered opportunistically at night. Again, I test the effects of headlight type and a rear-facing lightbar as well as vehicle speed on wildlife responses, with a focus on deer and wild pigs. Finally, Chapter 6 synthesizes the proceeding chapters, summarizes key findings and discusses their implications. I provide practical recommendations for mitigating wildlife-vehicle collision through both driver and animal behavior and highlight potential avenues for future research to further advance the field of applied animal behavior and wildlife-vehicle collision mitigation.

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CHAPTER 2

EVALUATING CAUSES OF WILDLIFE-VEHICLE COLLISIONS THROUGH THE LENS OF DRIVER BEHAVIOR[1]

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Abstract

Animal-vehicle collisions (AVCs) are ubiquitous in developed regions of the world and pose risks to both wildlife and humans. In the United States, collisions with deer (*Odocoileus spp*.) cause billions of dollars in economic losses and thousands of human injuries annually. The current AVC literature has largely focused on factors unrelated to driver behavior including AVC hotspots, wildlife movement, and damages caused by AVCs. However, despite being a component in every AVC, few studies have investigated driver behavior during animal-vehicle interactions. Here, we systematically reviewed literature databases to identify factors influencing driver behavior during these interactions and to highlight apparent gaps in the literature. We found that vehicle speed, road attributes, environmental conditions, and vehicle types show inconsistent associations with AVCs and the mechanisms by which they influence driver behavior is not well understood. Many studies focused on mitigation methods to influence driver behavior, including various warning signs; however, the effectiveness of these systems varies considerably. Other topics including wildlife attributes, roadway illumination, and inherent driver attributes directly influence driver behavior, but are understudied. Most studies relied on seemingly logical explanations for results or associations between variables to identify these influences, but few studies directly tested how specific variables influenced driver behavior and detection ability of wildlife. Given that driver behavior influences every potential AVC, future research should directly investigate the behavioral and perceptual mechanisms behind driver detection of wildlife and other factors influencing overall driver behavior during wildlife-vehicle interactions.

1. Introduction

Animal-vehicle collisions (AVCs) are ubiquitous in developed regions of the world (Hill et al., 2019) and cause significant damage to wildlife and humans annually. As the human population and road infrastructure continue to grow (Dulac, 2013), the number of AVCs will likely increase (Hill et al., 2020), as will direct mortality of wildlife resulting in billions of vertebrate deaths each year (Seiler and Helldin, 2006). Increasing road infrastructure can cause habitat fragmentation leading to additional negative consequences for wildlife, such as reduced gene flow (Epps et al., 2005) and reduced animal movements during dispersal, migration, and breeding seasons (Clark et al., 2010; Jochimsen et al., 2004; Shepard et al., 2008). The direct effects of AVCs also pose a substantial risk to species, especially those of conservation concern. For example, Florida panthers (*Puma concolor coryi*) and red wolves (*Canis rufus*) are large-bodied mammals that are intensively managed to increase population size, but AVCs are responsible for 20% of all Florida panther deaths and 34% of red wolf deaths are attributed to anthropogenic causes (Hinton et al., 2017; Schwab and Zandbergen, 2011). Not only are AVCs a concern for wildlife, but also for humans. In the United States, most damaging AVCs occur with deer (*Odocoileus spp.*), resulting in >$8 billion (2008 USD) in economic losses every year (Huijser et al., 2008). Furthermore deer-vehicle collisions result in >56,000 people being injured, and the deaths of >440 in the United States annually (Conover, 2019).

The historical and recent AVC literature has largely focused on factors related to collision hotspots and animal movements. Using large collision datasets, studies have identified many environmental and road attributes associated with AVCs, including time of day, time of year, nearby habitat, traffic level, and traffic speed (Beasley et al., 2013; Cunningham et al., 2022; Kusta et al., 2017; Sullivan, 2011). These associations have been used to map AVC hotspots and high-risk locations (e.g., Barthelmess, 2014; Snow et al., 2014). Other studies have used onboard or roadside cameras to document wildlife behavior prior to and during wildlife-vehicle interactions (Blackwell et al., 2014; Brieger et al., 2022). These videos have shed light on how specific animal behaviors can influence the risk of an AVC (Brieger et al., 2022) and have been instrumental in evaluating the effectiveness, or lack thereof, of AVC mitigation methods, including deer whistles and modified vehicle lighting (Blackwell and Seamans, 2009; DeVault et al., 2020; Valitzski et al., 2009).

Although AVCs are inherently a product of both animal and driver behavior, a paucity of research has focused on the role of driver behavior during animal-vehicle interactions. In contrast, there has been extensive research evaluating factors that influence driver behavior in the context of driver and pedestrian safety (e.g., May, 2011; Sayer and Mefford, 2004; Wood, 2020). Driver behavior and ability to detect non-animal road hazards are influenced by distractions, blood alcohol levels, and age (Choudhary and Velaga, 2017; Christoforou et al., 2013; Tyrrell et al., 2016; Wood et al., 2014). However, it is unclear whether factors that influence driver detection of road hazards will affect drivers similarly during animal-vehicle interactions. Few studies have quantified the ability of drivers to detect animals directly (Hobday, 2010; Mastro et al., 2010; Rodgers and Robins, 2006), and only one has used free-ranging wildlife (Pakula et al., 2023). A better understanding of driver behavior during animal-vehicle interactions could shed light on a pervasive issue in today’s society.

In this review, our objective was to evaluate the scientific literature to identify factors influencing driver behavior during animal-vehicle interactions, to summarize how those factors could affect the risk of animal-vehicle collisions, and to highlight apparent gaps in the literature. At the end of each section, we provide recommendations for future research.

2. Methods

In December 2023, we conducted a systematic literature search of Web of Science's Core Collection and Google Scholar for English language peer-reviewed articles with publication dates through the date of the search. We used the following search terms in a single search for both databases:

("animal*" OR "wildlife*" OR "ungulate*" OR "deer" OR "moose" OR "elk*" OR "bird*" OR "reptile*" OR "amphibian*" OR "mammal*") AND ("driver*" OR "motorist*") AND ("wildlife vehicle collision*" OR "animal vehicle collision*")

Given the extensive number of results returned by Google Scholar, we limited our search results to the first 300 articles (Haddaway et al., 2015; Patterson et al., 2022). Additionally, we included relevant articles that were found through the citations and references of articles returned by our searches. Our review emphasized articles that conducted primary research to highlight the current state of the literature, though we also referenced review papers when they provided relevant summations of broad topics.

For inclusion in our review, a study must have investigated a factor that influenced driver behavior during animal-vehicle interactions either directly (manipulation of a variable) or indirectly (authors suggested an impact on driver behavior could explain their observed results) based on the author's interpretation. Many factors can influence both animal and driver behavior, but we only included studies that directly stated that there was an effect on driver behavior. One exception to this inclusion rule was when a variable was found to impact vehicle speed. In those cases, regardless of the author's interpretation, we included those articles because a vehicle's speed is inherently a result of driver behavior. For all relevant articles, we recorded the effect observed and the type of investigation (direct or indirect) to highlight any discrepancy in research effort.

To illustrate the key behavioral steps drivers must take during vehicle-wildlife interactions to avoid a collision, we adapted the Lima et al. (2015) framework for critical steps an animal must take to avoid a collision to pertain to drivers. Those steps include (1) detecting the animal, (2) identifying the animal as a threat, and (3) initiating braking with sufficient time to stop before reaching the animal (Figure 2.1). We then organized this review paper by grouping the articles we selected from our literature search into eight broad topic areas that influence one or more of these key behavioral steps (see below). At the end of each topic area, we provide 2-4 major takeaways highlighting gaps in the current literature.

3. Results Overview

Our searches returned 120 studies from Web of Science and 1,172 studies through Google Scholar. After screening all the results from Web of Science, the first 300 studies returned by Google Scholar, and relevant studies cited in their references, we identified 118 unique research articles relating to driver behavior. Those studies covered eight broad topic areas: vehicle speed (n=27), wildlife warning systems (n=33), wildlife attributes (n=10), road attributes (n=37), roadway illumination (n=14), environmental attributes (n=10), vehicle attributes (n=6), and driver attributes (n=31; Figure 2.1). Studies addressing multiple topics were included in all relevant sections. Additionally, the vehicle speed category refers only to studies attributing an effect to vehicle speed by itself and does not include studies that aimed to influence driver speed through some other method (e.g., wildlife warning system).

3.1. Vehicle Speed

One of the most common associations with AVC risk is vehicle speed, as it inherently limits the amount of time a driver has to react to a hazardous animal, and braking distance increases exponentially as speed increases. For example, drivers traveling at 60 and 90 km/h need 82.5 and 154.4 m, respectively, to identify and brake to avoid an object in the road (Fambro et al., 1997). Due to this decrease in afforded reaction time, it is no surprise that many studies have found an increase in AVCs or the risk of an AVC with increasing vehicle speeds (Ahmed and Ahmed, 2022; Collinson et al., 2019; Green Vision Services, 2022; Gurumurthy et al., 2022; Hobday and Minstrell, 2008; Hurley et al., 2007; Lao et al., 2011a; Lao et al., 2011b; Meisingset et al., 2014; Neumann et al., 2012; Pakula et al., 2023; Rahman et al., 2023; Rea, 2012; Roy and Ksaibati, 2021, 2022; Sullivan, 2009; Sullivan, 2011; Tayade et al., 2019; Valero et al., 2016; Yang et al., 2019). One proposed mechanism for this effect is that at night headlights provide a fixed visibility distance and thus higher speeds cause drivers to cover that distance more quickly, reducing the time available to identify and react to an animal (Riginos et al., 2022; Sullivan, 2009; Sullivan, 2011). This phenomenon is often referred to as “outrunning the headlights”. Further supporting this concept, Pakula et al. (2023) found that drivers’ detection distance of deer at night does not increase as their speed increases (range: 72-89 km/h), likely due to the fixed illumination distance of the headlights. However, a standardized method for measuring effective illumination distance for detecting wildlife across headlight types has yet to be established (see Roadway Illumination, below).

Although logical, the mechanism underlying the association between faster speeds and more AVCs is often not directly investigated, which could explain why the data supporting this association are conflicting. Even though faster vehicle speeds unavoidably reduce available driver reaction time, this explanation fails to account for animal behavior. Inherently, AVCs cannot occur if there are no animals entering the roadways. To this point, high speed roadways can act as a barrier to animal crossings, leading to more AVCs occurring along roadways with intermediate speeds (Rendall et al., 2021; Seiler, 2005). Similarly, animals often avoid crossing high trafficked roads (Gagnon et al., 2007; Kusta et al., 2017; Zeller et al., 2020). This barrier effect highlights the difficulty in interpreting AVC data due to the interaction of driver behavior and animal behavior.

Other studies have found no effect of vehicle speed on AVCs (Bénard et al., 2024; Bissonette and Kassar, 2008; Rea et al., 2014; Riginos et al., 2022). Specifically, Bissonette and Kassar (2008) examined >24,000 deer-vehicle collisions in Utah and found no effect of posted speed limits on rates of deer-vehicle collisions, and provided multiple potential explanations for their findings. One explanation was that posted speed limits might explain little variation in actual driving speeds and that other variables (e.g., road curvature, traffic volume, topography) may have a greater effect on AVC rates. Furthermore, they suggested that large collision datasets might suffer from a data scale issue. Vehicle speed is often reported by mile markers but posted speed limits often change within a given stretch of road. Bissonette and Kassar (2008) suggested that for AVC hotspot identification, current data on mile markers is acceptable, but for predicting AVC risk, more fine-scale data are needed.

Overall, there are mixed results on the direct effect of vehicle speed on AVCs. Clearly, travelling at faster speeds is riskier, because there is an unavoidable reduction in available driver reaction time and an increase in braking distance. This risk is compounded by animals often not increasing their flight initiation distance (how far they are from the vehicle when they flee) with increasing vehicle speeds (Blackwell et al., 2014; DeVault et al., 2014, 2015). Studies suggest decreasing speed limits during periods of peak animal activity could be effective for reducing AVCs (Rodgers and Robins, 2006), but there is very little research that has investigated whether drivers will decrease their speed as posted speed limits change, or whether reduction in speed will translate to fewer AVCs. In the only peer-reviewed study of its kind, Riginos et al. (2022) experimentally reduced speed limits from 113 to 89 km/h at night on interstate highways at six sites in Wyoming using a static speed limit sign with flashing beacons. The new speed limits reduced vehicle speeds by 6.5-8 km/h, but speeds still routinely exceeded the new 89 km/h speed limit, on average traveling 96-105 km/h. Ultimately, the reduction in speed limits did not result in a reduction in deer-vehicle collisions (Riginos et al., 2022). The authors concluded that the lack of driver adherence to the new posted speed limits confounded their ability to interpret the effect of vehicle speed on AVC rate directly. Increasing speed enforcement through patrols or cameras could be one way to ensure new speed limits are obeyed (Soole et al., 2013; Vaa, 1997; Wasson et al., 2011).

3.1.1. Vehicle Speed Summary

- Faster vehicle speeds inherently increase the risk of an AVC by increasing the minimum braking distance.
- Although there is support for the phenomenon of "outrunning the headlights", it is currently unknown at what speeds this occurs and how it differs by headlight type or brightness.
- Associations between higher vehicle speeds and AVC rates lack fine scale data leading to conflicting results in the literature. A better understanding of how speed directly impacts drivers' ability to detect wildlife and subsequent evasive maneuvers (e.g., braking, swerving) is needed.
- Posted speed limits could be poor proxies of actual vehicle speeds contributing to conflicting associations of speed and AVC rates.

3.2. Wildlife Warning Systems

Wildlife warning systems is a broad category encompassing any method employed to increase driver awareness of the potential for roadside wildlife. The most common of these systems is the use of wildlife warning signs. The effectiveness of these methods is often measured with crash data in a before-and-after study design or by evaluating vehicle speed, a proxy for increased driver alertness. As mentioned above, decreased driver speed is often assumed to result in fewer AVCs and is often the goal of these systems. Wildlife warnings signs come in many forms including standard warnings signs (e.g., deer jumping sign, "Wildlife Crossing" sign), enhanced road crossing signs (e.g., standard warning signs with blinking lights), dynamic message signs (also known as variable message signs; signs that display words but no flashing lights), temporary wildlife warning signs (any type of sign that is not permanent), and animal detection systems.

3.2.1. Standard warning signs

Standard animal crossing signs are the most common AVC mitigation method used by state agencies but their effectiveness rarely has been scientifically evaluated (Romin and Bissonette, 1996). We identified multiple studies that claim that wildlife warning signs are effective, but their results may not be generalized easily. One study in Utah found that the number of AVCs per mile decreased with the number of warning signs used, but they provided no statistical tests to support their claims (Khalilikhah and Heaslip, 2017). Another study in South Africa found that a snake warning sign resulted in more drivers swerving to avoid a collision with a dummy snake (Collinson et al., 2019). However, the drivers were only travelling 40 km/h and swerving is not recommended to avoid AVCs because the driver could lose control and crash (Ramp et al., 2016; Smoot et al., 2010), especially when travelling at faster speeds. When paired with other mitigation methods (e.g., rumble strips, vegetation removal, public awareness campaigns), standard crossing signs reduce AVCs (Lester, 2015; Poot and Clevenger, 2018; Rea, 2012). However, given their implementation with other mitigation methods, the effectiveness of the signs, specifically, is unknown.

Alternatively, multiple studies have found that standard road crossing signs are ineffective at reducing AVCs (Ahmed and Ahmed, 2022; Green Vision Services, 2022), potentially because they rarely reduce driver speeds (Al-Ghamdi and AlGadhi, 2004; Jägerbrand and Antonson, 2016; Jägerbrand et al., 2018). Furthermore, review papers on AVC mitigation methods routinely conclude that standard warning signs are ineffective for affecting driver behavior and reducing AVCs or that the topic is data deficient (Hedlund et al., 2004; Huijser et al., 2008; Mastro et al., 2008).

Due to their ubiquitous usage, standard warning signs are subject to driver habituation (Khalilikhah and Heaslip, 2017). If drivers see them regularly, but rarely, if ever, encounter an animal shortly afterwards, drivers may begin to ignore the warning signs. Habituation could explain why standard signs are often considered ineffective at reducing vehicle speeds. Furthermore, caution should be applied when evaluating the effectiveness of recently installed standard warning signs because driver habituation to the signs could occur months or years later.

3.2.2. Enhanced Road Crossing Signs

To counteract habitation to standard warnings signs, enhanced road crossing signs attempt to capture drivers' attention with blinking lights. Unlike animal detection systems (see below), enhanced road crossing signs only attempt to increase driver awareness of the possibility of an encounter with wildlife or to reduce driver speeds; they do not provide real-time information about animals near the roadway. Studies have found that these signs decrease driver speeds by 3-10 km/h (Riginos et al., 2022; Stanley et al., 2006). Despite the reduction in vehicle speeds, Riginos et al. (2022) argued that the reduction was insufficient to reduce the number of collisions with mule deer (*Odocoileus hemionus*) in their study. However, seasonal usage of enhanced road crossing signs during mule deer migrations led to reductions in speeding vehicles and a 50% reduction in collisions (Sullivan et al., 2004), suggesting that temporary usage of signs could be effective by reducing driver habituation when the threat of animal collision is more apparent due to increased animal abundance during migrations.

3.2.3. Dynamic Message Signs

Similar to enhanced road crossing signs, dynamic message signs aim to reduce driver habituation and increase driver alertness by displaying a given message less frequently. These signs can be altered to display any message, like those used to detour drivers around construction sites. For example, a dynamic message sign that reads, "Animal crossing next 20 miles, be alert" reduced driver speeds by 7.4 km/h and increased braking distances by 9.6 m compared to a standard road crossing sign in a driving simulator study (Stanley et al., 2006). The increase in braking distance was even more pronounced when the dynamic message sign was paired with an enhanced road crossing sign (deer crossing sign with a flashing beacon; Stanley et al., 2006). Another study using actual drivers found that dynamic message signs reduced driver speed and were most effective at night (Hardy et al., 2006). However, this study lasted only 16 days, and it is unknown whether drivers would have eventually habituated to the signs. Surveys suggest that dynamic message signs that display updated counts of AVCs in the area or dates of high risk could increase their effectiveness (Bond and Jones, 2013), but no study has empirically tested whether drivers will decrease their driving speeds.

In an attempt to increase driver alertness but avoid driver habituation, Donaldson and Kweon (2019) evaluated seasonal dynamic message signs. They employed dynamic message signs that were in effect every other day from 5 pm to 9 am from October to November (during the deer breeding season). They found that the signs reduced driver speed by 1.9 km/h on average and led to a 51% reduction in deer-vehicle collisions. The authors estimated that the signs could save hundreds of thousands of dollars over the 15-year lifespan of the signs (Donaldson and Kweon, 2019).

Contrary to Donaldson and Kweon (2019), Riginos et al. (2022) observed a 5-10 km/h reduction in vehicle speeds but no decrease in collisions when using dynamic message signs. Although speed reductions provide drivers with more time to react to a hazard, the mechanism impacting AVCs could be increased driver alertness more so than vehicle speed, suggesting that driver speed could be a poor predictor of mitigation potential. However, the reported effectiveness of speed reduction and its ultimate effect on AVCs is uncertain, suggesting these results are location dependent or could be influenced by untested variables.

3.2.4. Road Based Animal Detection and Warning Systems

Road based animal detection systems use sensors to detect wildlife entering the roadway and notify the driver through a flashing animal crossing sign. These systems are designed to maximize driver engagement and minimize driver habituation by only illuminating animal crossing signs when an animal is on or near the roadway. They often rank as the type of sign most likely to affect driver behavior on driver preference surveys (Bond and Jones, 2013). They also provide an alternative to road crossing structures, which are generally effective at reducing AVCs, but expensive (Huijser et al., 2016; McCollister and Van Manen, 2010; Sugiarto, 2022). There is a relatively large diversity in the design and installation of these systems, as managers and researchers balance effectiveness, reliability, and cost. The different types of animal detection systems include infrared cameras (Bhardwaj et al., 2022; Gagnon et al., 2010; Gagnon et al., 2019; Grace et al., 2015; Sielecki, 2017), break-the-beam systems (Grace et al., 2017; Sharafsaleh et al., 2012), radar (Huijser et al., 2017; Mukherjee et al., 2015; Sielecki, 2017), buried cable systems that produce an invisible electromagnetic detection field

(Druta and Alden, 2020; Huijser et al., 2012), and geophones that detect ground vibration caused by animals (Gordon et al., 2001).

Most of these systems are effective in reducing driver speeds, but the relative amount of speed reduction varies among studies (Gagnon et al., 2010; Gagnon et al., 2019; Gordon et al., 2001; Grace et al., 2015, 2017; Huijser et al., 2017; Mukherjee et al., 2015; Nowakowski et al., 2013; Sharafsaleh et al., 2012; Sielecki, 2017). Speed reductions due to animal detection systems ranged from 1.11 km/h (Huijser et al., 2017) up to 16.1 km/h (Gagnon et al., 2010), but the effect size is often impacted by other factors like season, time of day, and inclement weather. Animal detection systems are also effective in increasing driver alertness, which is often measured by observing drivers engaging in a braking maneuver when the warning sign was illuminated (Druta and Alden, 2020; Gagnon et al., 2010; Gagnon et al., 2019; Grace et al., 2015). When working properly, there appears to be no difference in the effectiveness of these systems based on the animal detection mechanism employed, which is unsurprising given that all animal detection systems include a flashing or illuminated wildlife crossing sign to influence driver behavior. Therefore, the main differences between systems are their cost and reliability to effectively detect wildlife and relay that message to drivers. Due to their relative complexity (animal detection, software, relay to signs, energy demands), some systems struggle to reliably detect animals accurately, especially under adverse conditions (Huijser et al., 2012; Huijser et al., 2006).

Although animal detection systems are effective in reducing vehicle speeds and increasing driver alertness, less is known about their ultimate impact on AVCs. The few studies that have addressed this issue directly have found that animal detection systems can reduce AVCs by 60-75% one year after installation (Bhardwaj et al., 2022; Druta and Alden, 2020). Although promising, caution should be applied when contextualizing these results. The 75% reduction in AVCs reported by Druta and Alden (2020) was a decline from four to one collision based on police records of AVCs near the experimental area and was not supported by a formal statistical analysis. Furthermore, the relatively high reduction in AVCs observed by Bhardwaj et al. (2022) could have been affected by their animal detection system being paired with a 5.2 km fence that included a 30 m wide opening for animals to cross the road. Well maintained fencing is regarded as one of the best AVC mitigation methods (Clevenger et al., 2001; Huijser et al., 2016); therefore, it is unknown to what extent the animal detection system studied by Bhardwaj et al. (2022) directly influenced driver behavior in a manner that reduced AVCs beyond the benefits provided by fencing.

The effectiveness of animal detections systems might be increased by using picture-based warning signs instead of word-based signs. Using a driving simulator, picture-based warning signs resulted in reduced driver speeds at twilight, increased braking distances at night, and overall fewer hypothetical AVCs than word-based signs compared to the control of no sign (Grace et al., 2015). Again, caution should be applied to interpretation of these results, as the word-based and picture-based signs differed in their flashing light design (eight LED lights vs. 2 large lights, respectively), which could have contributed to the observed results.

There are no long-term data available concerning the effectiveness of road-based detection systems or their lifespan, and it currently is unknown whether these systems are immune to driver habituation over the long term. However, habituation seems unlikely, given that the signs only activate when an animal is entering the road, informing the driver of a dangerous situation. Additionally, like all signs, these systems are location dependent and thus careful consideration is needed when determining where one should be installed. The reliability and cost of these systems should be considered before widespread installation.

3.2.5. Vehicle Based Animal Detection and Warning Systems

With recent technological and data processing advancements, there has been an increase in efforts to train models to process videos from vehicle mounted cameras in real time to detect and alert the driver of a potential threat. Numerous technical papers have been published on image processing speed and accuracy (e.g., Munian et al., 2022; Munian et al., 2021; Parkavi et al., 2025), but few have directly implemented their systems to capture real world animal-vehicle encounters. Currently, the studies that have directly addressed real-world feasibility have been successful only for daytime driving at slow speeds (<35 km/h; Sharma and Shah, 2016). Also, most systems lack a training dataset robust enough to identify all hazardous wildlife at far enough distances to allow drivers enough time to brake to avoid a collision, especially at faster speeds (e.g., 89 km/h on a rural road). Additional obstacles to implement these technologies remain, including reliable detection of small and medium sized animals, detection and alarm speed, accuracy under adverse conditions, limited datasets, and cost (Nandutu et al., 2022).

Despite the technical and logistical challenges, multiple vehicle-based infrared camera systems are available on the market. For example, some automobile manufacturers, including Jeep and Cadillac, offer a “night vision” technology option that reportedly can detect pedestrians and animals up to 100 m ahead (Cadillac, n.d.; Jeep, n.d.). Third-party cameras that drivers can install on vehicle dashes are also available with claims of large object detections from 300 m (Thermal Master, n.d.) to 1600 m (Texas Fowlers, n.d.). Additionally, Teledyne FLIR offers an artificial intelligence software package that can be used with thermal cameras to detect, classify, and track objects including animals, but the details of this system are not readily available (FLIR, n.d.). All these are passive hazard detection systems that could highlight potential animals using pattern recognition systems, but do not actively alert the driver. Despite these advancements and claims, it is unclear whether these systems, at this time, can reliably detect and notify drivers with enough time to safely brake to avoid a collision. To this point, we found no empirical research evaluating the effectiveness of these systems. The widespread use of infrared cameras is a promising but relatively young field that could reduce AVCs as technology advances and barriers to implementation (e.g., cost, reliability) decrease. Aside from signs and cameras, one unique form of increasing driver alertness using existing technology within the vehicle is to use radio messages to communicate to a driver the threat of an animal on the road. Using a driving simulator, both Jägerbrand and Antonson (2016) and Jägerbrand et al. (2018) demonstrated that a radio message stating, “Traffic announcement aimed at motorists on Highway 34 between Linköping and Vimmerby at Törnevik: we have received several calls about a moose on the roadside of the wildlife fence” was effective at reducing driver speeds. However, in both studies, the radio was only active during the message and the message was accompanied by a road sign informing the driver where they were located to ensure the drivers knew the message pertained to them. It is unclear if similar effects would be seen under real-world conditions.

3.2.6. Wildlife Warning Systems Summary

- Enhanced, dynamic, and temporary warning signs provide potential alternatives to standard road crossing signs, but the long-term risk of driver habituation to these signs remains unknown.
- Although numerous studies have evaluated the effects of wildlife warning signs, particularly road-based detection systems, on driving speeds, few have directly evaluated their effect on AVC rates. Even then, many studies do not fully incorporate data on driver speeds or alertness to identify the mechanism influencing AVC rates.
- Vehicle based detection and warning systems are growing in popularity, but the effectiveness of these systems has not been empirically studied. Additionally, no studies have investigated the driver warning component of vehicle-based systems.

3.3. Wildlife Attributes

3.3.1. Intrinsic Attributes

Wildlife attributes can impact a driver's ability to detect animals at safe distances and thus strongly influence the risk of a collision. A driver's ability to detect an animal varies from species to species, likely due to several factors (Hobday, 2010; Mastro et al., 2010; Pakula et al., 2023; Papadimitriou and Psarianos, 2015; Rodgers and Robins, 2006). Unsurprisingly, larger bodied animals are often detected at farther distances than smaller animals. For example, moose (*Alces alces*) are typically detected at farther distances than white-tailed deer (*Odocoileus virginianus*) and Tasmanian mammals

(Hobday, 2010; Mastro et al., 2010; Pakula et al., 2023; Rodgers and Robins, 2006). With respect to animal-vehicle collisions specifically, Medrano-Vizcaíno et al. (2022) observed higher roadkill rates with intermediate sized mammals (~3 kg), and suggested that larger animals could be more easily detected by drivers. However, they acknowledged that lower population density or local abundance of larger animals also could have contributed to their findings. In contrast, Hobday (2010) found that decoy height did not impact driver detection distances, although all their decoys were <1 m tall. This suggests that wildlife size might not matter for wildlife detection among similarly sized animals.

Other intrinsic wildlife attributes that are thought to influence driver detection of wildlife on roadways include coat color and the presence of eyeshine (tapetum lucidum). Humans have difficulty distinguishing similarly colored objects at night; Joyce and Mahoney (2001) suggested that this concept could apply to wildlife like moose and a background of trees at night. Empirically, Hobday (2010) demonstrated that Tasmanian mammal species with brighter coats were detected at farther distances, but it is unclear whether similar results would be found with species in other regions of the world. Although not directly tested, Pakula et al. (2023) suggested that the presence of eyeshine in wild white-tailed deer could explain why they found longer detection distances compared to Mastro et al. (2010), who used deer decoys lacking eyeshine. In contrast, wild pigs (*Sus scrofa*) lack eyeshine which could explain, in part, why they are very rarely detected at safe distances (Pakula et al., 2023). Future research should further investigate the effect of eyeshine, or lack thereof, on driver detection ability for various wildlife species.

3.3.2. Movement Behavior

Outside of intrinsic attributes, behavioral characteristics of wildlife can also impact a driver's detection ability, specifically an animal's location and movement behavior. Drivers typically detect animal decoys at longer distances when the decoys are in the road (Hobday, 2010; Mastro et al., 2010; Rodgers and Robins, 2006) with deer decoys 10 m off the driving side of the road being detected farther than deer decoys located off the far side of the road (right for left hand traffic and left for right hand traffic; Mastro et al., 2010). Although drivers did not detect a deer decoy manually moved by a researcher more readily than a stationary decoy (Mastro et al., 2010), Pakula et al. (2023) found that moving wild deer were detected on average 23 m farther than stationary deer.

3.3.3. Group Size

To our knowledge, only one study directly tested the effect of animal group size on driver detection ability. Pakula et al. (2023) observed no effect of group size on driver detection probability or detection distance of free-ranging white-tailed deer. Although that study found no effect, more research is needed on other species. Identifying how animal group size impacts driver detection ability could have major implications for better understanding risks of collisions with gregarious species compared to nongregarious species or sexes.

3.3.4. Human Altered Wildlife Attributes

Managers have attempted to make wildlife more visible to drivers by painting antlers with reflective paint and outfitting animals with reflective collars (Memmott, 2014; Thiessen, 2010). Despite these attempts, the use of reflective paint on reindeer (*Rangifer tarandus*) antlers in Finland was ineffective at reducing collisions for multiple reasons. Drivers often mistook the nighttime reflection as a person and assumed they would not run into the road, and reindeer actively removed their reflector collars and paint (Huuhtanen, 2016). The effectiveness of these methods has not been systematically tested and modifying wildlife visibility is not generally a reasonable solution for widespread and abundant species like white-tailed deer.

3.3.5. Wildlife Attributes Summary

- Despite the large differences in wildlife attributes across species, we know relatively little about how these impact driver detection ability. Specifically, the role of eyeshine in driver detection of wildlife is understudied.
- The lack of information on the influence of wildlife attributes on driver detection ability likely stems from the difficulty of conducting manipulative studies with wildlife. Animal decoys have often been used, but their generalizability is limited.
- Little is known about how drivers detect animal groups differently than individuals. Such information could help identify risks among species and sexes.

3.4. Road Attributes and Management

3.4.1. Road Geometry

Road geometry can impact the rate of AVCs, but the effect is context dependent. Roads that are more sinuous and have elevation changes often have higher rates of AVCs due to reduced visibility of wildlife and limited driver reaction time (Ahmed and Ahmed, 2022; Ahmed et al., 2021; Bakaloudis et al., 2023; Huchton, 2022; Jensen et al., 2014; Laube et al., 2023; Psaralexi et al., 2022; Rodriguez, 2015; Snow et al., 2011). For example, deer-vehicle collisions were more common on curved roads, likely due to a reduction in driver visibility (Ahmed et al., 2021). However, other studies have documented more AVCs on flatter, straighter roads (Blackwell, 2017; Laliberté and St-Laurent, 2020; Lao et al., 2011a; Tanner et al., 2017; Valero et al., 2016). These studies often attributed their findings to drivers travelling at faster speeds on straighter roads and reduced roadside vigilance. Supporting this, the transportation literature has documented that at higher speeds, drivers tend to focus farther down the road and have a narrower field of view (Capaldo et al., 2020; Rogers et al., 2005; van Leeuwen et al., 2015), potentially inhibiting drivers' ability to detect roadside wildlife at safe distances. In contrast, several studies found no clear association between curved roads and AVCs, likely to due to drivers naturally reducing their speeds along curves (Gunson et al., 2005; Sevigny et al., 2021), which could offset the reduced visibility associated with sinuous roads. Highlighting the tradeoff between speed and visibility, Canal et al. (2019) observed fewer collisions near curves due to slower driver speeds, an increase at moderate distances from curves, where speeds increased but visibility remained limited, and then a decrease again at farther distances as driver visibility improved. There is no clear consensus on how road geometry impacts AVCs, partly because most studies use some metric of sinuosity or available sight distance as a predictor in statistical models. As such, the results might provide a correlation between collisions and road sinuosity but lack clear evidence of the underlying mechanism, allowing for wide ranging interpretations. For example, more AVCs on straight roads could result from drivers travelling at faster speeds, but more collisions on curved roads could be attributed to limited visibility. We acknowledge that data on vehicle speed when a collision takes place is typically not available; however, we recommend that future research should employ more directed attempts to identify how the available sight distance afforded by road geometry impacts vehicle speed and subsequent driver detection ability of wildlife.

Although receiving less attention, other road features can influence driver behavior during wildlife-vehicle interactions, including roadside elevation, roadside fencing, and the presence of road shoulders. For example, white-tailed deer located at elevations lower and higher relative to the surface of the road were detected less often by drivers (Pakula et al., 2023). One simulator study found that roadside fencing did not affect driver speed but resulted in drivers braking later and less hard, likely due to the fence providing a sense of security (Antonson et al., 2015). Another study found that drivers tended to drive faster when roads had shoulders, resulting in more AVCs (Lao et al., 2011a). Rumble strips, designed to increase driver alertness when entering a high risk collision zone, resulted in fewer collisions; however, they were paired with wildlife warning signs and roadside vegetation clearance making it difficult to determine the effect of any single mitigation method (Lester, 2015).

3.4.2. Roadside Vegetation

Roadside vegetation can influence AVCs through three main mechanisms: impacting drivers' ability to detect wildlife, impacting driver vigilance, and altering wildlife behavior near roadways. Many studies have found that more AVCs occur in locations with obstructive roadside vegetation, likely due to reduced driver visibility (Espinoza, 2022; Fedorca et al., 2021; Green-Barber and Old, 2019; Grilo et al., 2009; Kazemi et al., 2016; Keken et al., 2019; Lala et al., 2021; Lester, 2015; Lograsso, 2013; Meisingset et al., 2014; Rea et al., 2014; Rodriguez, 2015; Seidel et al., 2018; Tajchman et al., 2020). Most studies rely on this logical association between roadside vegetation and driver detection ability, but few have directly removed vegetation to allow for a manipulative study. When studies directly cleared roadside vegetation as part of the experiment, deer and moose-vehicle collisions decreased by 20-53% but were found to be seasonally dependent (Lavsund and Sandegren, 1991; Meisingset et al., 2014). However, roadside vegetation removal does not always lead to fewer AVCs and can, in some cases, increase them. Open roadways provided by roadside vegetation removal have been suggested to increase AVCs by giving drivers a false sense of security, leading to reduced scanning of roadsides for wildlife (Tanner et al., 2017). Additionally, vegetation removal can increase wildlife browsing of emerging vegetation, bringing vehicles and wildlife in closer proximity and potentially increasing the risk of AVCs (Child et al., 1991; Rea, 2003). Alternatively, some studies found that recently cut roadside vegetation is unattractive foraging habitat for moose (Tanner and Leroux, 2015), highlighting that animal response to vegetation clearance can vary. Further highlighting vegetation's influence on more than just driver behavior, during moose-train interactions (a scenario in which driver detection ability is irrelevant), vegetation clearing reduced collisions, likely due to a reduction in moose usage of areas near railways (Andreassen et al., 2005; Jaren et al., 1991). Roadside vegetation can also impact road crossing behavior of animals. DeVault et al. (2020) observed that when deer within 3 m of the road were approached by a vehicle, deer only crossed the road in front of the vehicle when the nearest vegetative cover was on the far side of the road. The influence of roadside vegetation on both driver and wildlife behavior could explain why other studies have found no effect of vegetation on AVCs (Normandeau Associates Inc., 2012; Rea et al., 2018; Sevigny et al., 2021), or mixed effects dependent on species (Denneboom et al., 2024; Rendall et al., 2021) or vegetation height (Canal et al., 2019).

One approach to untangle the interaction of vegetation on driver and animal behavior is to directly measure the effect of vegetation on driver behavior rather than identifying associations between collision data and vegetation. In driving simulator studies, drivers braked later when a moose was in dense vegetation compared to sparse vegetation, likely due to limited driver visibility (Antonson et al., 2015; Jägerbrand and Antonson, 2016), although vegetation did not impact vehicle speed (Antonson et al., 2015). Similar results were found with free ranging white-tailed deer, as detection probability decreased when roadside deer were partially obstructed by vegetation (Pakula et al., 2023). From the limited controlled studies on driver behavior, it is likely that roadside vegetation impacts a driver's ability to detect roadside wildlife, but caution should be applied when discussing crash data because vegetation can influence both driver and animal behavior.

3.4.3. Road Attributes and Management Summary

- When interpreting road geometry and AVC data, researchers should incorporate afforded visibility data and vehicle speed during those interactions to better identify the underlying mechanisms.
- Roadside vegetation removal impacts both driver detection ability and wildlife behavior. Untangling this interaction would be useful for managers.
- Few studies have directly evaluated the before-and-after effect of roadside vegetation removal.

3.5. Roadway Illumination

3.5.1. Vehicle Headlights

Because most damaging AVCs occur under low-light conditions (Cunningham et al., 2022; Sullivan, 2011), it is logical to assume that the type and configuration of a vehicles headlights influence a driver's ability to detect wildlife at night. One common explanation for the increase in collisions at night, especially at high speeds, is that headlights provide a fixed preview distance of the road, inherently limiting the distance and time a driver has to detect an animal (Riginos et al., 2022; Sullivan, 2009; Sullivan, 2011). Drivers can increase this fixed preview distance by using high beam headlights, which increases detection distance of wildlife (Hobday, 2010; Mastro et al., 2010; Pakula et al., 2023; Rodgers and Robins, 2006). The type of vehicle headlights also can impact a driver's available sight distance and concomitantly a driver's ability to detect wildlife at night (e.g. High Intensity Discharge-Xenon vs. Tungsten-Halogen, Papadimitriou and Psarianos, 2015). A vehicle's headlight height is dependent on the vehicle type and also can influence roadway illumination and driver detection ability. Hobday (2010) found that detection distance of Tasmanian mammals was greater in four-wheel drive (4WD) vehicles than standard vehicles for high-beam headlights, but the opposite when using low-beam headlights. They suggested that the greater headlight height of a 4WD vehicle allowed for a greater illumination distance compared to standard vehicles when using high beam headlights. However, this finding is contrary to Rodgers and Robins (2006) findings that headlight height had no effect on detection distances of a moose decoy. More research is needed to identify the relationship between vehicle headlight height and angle of road illumination and driver detection distances of wildlife. We found no studies that directly investigated the effect of headlight type on the rate of AVCs. However, Brumbelow (2022) found that vehicles with headlights that received a “good” rating by the Insurance Institute of Highway Safety (IIHS), which grades headlights on illumination distance (IIHS, 2018), had a lower risk of nighttime animal-vehicle collisions, seemingly due to increased visibility afforded to the driver.

Although headlights are an inherently integral component of a driver’s ability to see at night, it is still not well understood how far ahead headlights allow drivers to detect wildlife. One of the most relevant studies to date was conducted by Papadimitriou and Psarianos (2015), in which they modelled the effect of two different headlights on the afforded available sight distance of domestic goat (*Capra hircus*) and white-tailed deer across three driver age classes. Although Papadimitriou and Psarianos (2015) did not specify whether their results were based on a specific vehicle, their modeled available sight distances for halogen headlights were similar to the field results Pakula et al. (2023) found with wild white-tailed deer and a 2018 Ford F-150 with halogen headlights. Available sight distances are not currently available for a wide range of vehicles, but other organizations like the IIHS have developed their own metrics (e.g., “useful illumination distance”) and these data are readily available for many common vehicles (https://www.iihs.org/ratings). However, the IIHS’s metric has no empirical basis for detection ability of wildlife at night. To this point, Pakula et al. (2023) demonstrated that driver detection distances of wild white-tailed deer were greater than IIHS’s evaluation of “useful illumination distance” for the tested vehicle when using low beams (66.1 m vs. 45.5 m), but lower than IIHS’s listed value for high beams (90.5 m vs. 125.6 m). In contrast, detection distances of wild pigs were less than half of IIHS’s listed values for both low beams (23.0 m vs. 45.5 m) and high beams (36.6 m vs. 125.6 m). The authors suggested that the presence of eyeshine in white-tailed deer compared to the lack thereof in wild pigs could have been responsible for the discrepancy (see the Wildlife Attributes, above).

3.5.2. Street Lighting

Because headlights provide a fixed preview distance at night, roadway illumination via streetlamps might help reduce collisions by increasing the driver's illuminated field of view, but the limited number of studies on the topic provide conflicting results. One study found that roadway lighting did not affect vehicle speed and that any increase in awareness afforded by the increased lighting did not translate to a reduction in deer-vehicle collisions (Reed and Woodard, 1981). On the other hand, Denneboom et al. (2024) found that there was less roadkill in areas with roadway lighting, potentially due to the increased lighting allowing drivers to identify smaller species from a greater distance. Even so, the authors acknowledged that the effect could be due to the lighting acting as a deterrent for nocturnal species. Another study found that most grey kangaroo (*Macropus giganteus*) collisions occurred on roads without road illumination but within 200 m of a streetlight, potentially due to increased road crossings in dark stretches of the road or an effect of lighting on driver behavior (Green-Barber and Old, 2019). The authors suggested that AVCs could be more common immediately following illuminated sections of roads because the photoreceptors in a driver's eyes take time to adjust from bright to low-light conditions (i.e., transition from cone to rod dominated vision). A similar phenomenon was suggested by Joyce and Mahoney (2001) who speculated that other vehicle headlights can bleach the drivers' visual receptors, potentially leading to AVCs as drivers' vision adjusts back to low-light conditions.

3.5.3. Wildlife Reflectors

Wildlife reflectors were designed to reflect vehicle headlights to the sides of the road, thereby deterring wildlife from entering the road. In addition to their original purpose, they have also been suggested to influence driver behavior by alerting drivers to the presence of roadside animals that obscure the light reflected from regularly spaced reflectors (Mastro et al., 2010; Rowden et al., 2008). Only two studies have directly addressed driver behavior with respect to wildlife reflectors and they found that the reflectors had no effect on deer-vehicle collisions (Benten et al., 2018) and even resulted in shorter detection distances of a deer decoy (Mastro et al., 2010). Although the present paper is focused on driver behavior, we note that wildlife reflectors are also ineffective at reducing AVCs from an animal behavior perspective (Benten et al., 2019; Brieger et al., 2016; D'Angelo et al., 2006).

3.5.4. Roadway Illumination Summary

- The distance at which headlights allow drivers to detect wildlife under low-light conditions remains unclear. Furthermore, there is a lack of information on how headlight characteristics (e.g., type, height, angle) impact drivers' detection ability of wildlife.
- Street lighting can impact both driver detection ability and wildlife behavior. However, few studies have investigated this topic.
- Understanding how human vision is temporarily impacted by oncoming vehicle headlights or street lighting could elucidate how these factors contribute to AVCs.

3.6. Environmental Conditions

3.6.1. Adverse Weather

Many environmental conditions have been suggested to affect a driver's ability to avoid AVCs, although we found no studies that directly simulated different weather conditions in controlled settings. Instead, most studies identified associations in their analyses. Among potential environmental conditions, it is well accepted that most AVCs occur under the low-light conditions of twilight or nighttime (Borowik et al., 2021; Chyn et al., 2019; Espinoza, 2022; Joyce and Mahoney, 2001; Niemi et al., 2017; Psaralexi et al., 2022). In contrast, many other conditions have shown less consistent trends or are difficult to interpret. For example, studies have found increased rates of AVCs under foggy (Borowik et al., 2021) and rainy (Myers et al., 2008) conditions, with the authors attributing their results to the environmental conditions limiting driver visibility. Alternatively, other studies found that rain and adverse weather resulted in no effect (Borowik et al., 2021) or fewer AVCs (Green-Barber and Old, 2019; Roy and Ksaibati, 2021), with the explanation that adverse weather conditions cause drivers to be more cautious, resulting in slower vehicle speeds which give drivers more time to avoid AVCs. Although these explanations are logical, they often rely on untested assumptions, particularly regarding vehicle speed, which could obscure the underlying mechanism. Future research should attempt to collect vehicle speed data or other related variables to help support their conclusions.

3.6.2 Road Surface Conditions

Adverse weather conditions can impact road surface conditions, which could potentially impact driver behavior. Joyce and Mahoney (2001) attributed the high occurrence of moose-vehicle collisions under dry road conditions to drivers being less attentive to road hazards under favorable driving circumstances. On the other hand, Rea et al. (2018) examined YouTube videos of moose-vehicle encounters and found no effect of road conditions on the likelihood of a driver hitting a moose. The effect of road conditions on driver behavior is not well understood and is likely influenced by confounding factors including vehicle speed and driver awareness.

3.6.3 Environmental Conditions Summary

- Most AVCs occur under lowlight conditions likely due, in part, to reduced driver visibility.
- The effect of environmental conditions on driver behavior is confounded by other variables including inferred impacts on vehicle speeds.

3.7. Vehicle Attributes

3.7.1. Vehicle Type

Vehicle attributes, other than headlights (see *3.5.1.* Roadway Illumination), such as vehicle type, can influence a driver's behavior during wildlife-vehicle interactions. For example, as the percentage of trucks (i.e., tractor trailers) on the road increases, the number of AVCs tends to decrease, potentially due to trucks having a higher vantage point and wider field of view or because other drivers are more cautious in their presence (Lao et al., 2011a; Lao et al., 2011b; Yang et al., 2019). However, the underlying cause of these results should be considered carefully, given that the studies also noted that trucks often produce more noise than other vehicles, thereby potentially deterring wildlife from roadways. Additionally, Gunson et al. (2003) found more AVCs with large vehicles (e.g., semi-trucks, recreational vehicles, and buses), potentially due to larger vehicles inherently having a longer stopping distance. The authors note that they found an effect despite a collision reporting bias, as collisions with passenger vehicles are more likely to be reported due to a greater likelihood of damage. As some of these studies noted, the association between vehicle type and AVCs can be due to multiple factors, and it is difficult to identify an underlying mechanism without manipulative studies.

3.7.2. Vehicle Age

Using 2018 deer-vehicle collision data from the Pennsylvania Department of Transportation's crash database, Ahmed et al. (2021) found that vehicles manufactured in 2012 or later had a higher likelihood of being involved in a deer-vehicle collision compared to vehicles manufactured before 2012. The authors suggested that this finding was likely an example of driver risk compensation in which drivers become less vigilant and alert as vehicles have more safety features, a finding that has been documented outside the AVC context (Winston et al., 2006). Although more evidence is needed, this study suggested that as manufacturers add more safety features to vehicles, especially in the context of AVC mitigation, there might not be an overall reduction in AVCs.

3.7.3. Vehicle Attributes Summary

- Despite the diversity of vehicles in use, few studies have directly investigated how vehicle type influences driver detection ability of wildlife or their response to detecting an animal.
- Associations between vehicle type and AVCs can be due to multiple factors, and it is difficult to identify an underlying mechanism without manipulative studies.

3.8. Driver Attributes

3.8.1. Human Vision

Human vision is adapted for well-lit rather than low-light conditions. Under bright conditions, human vision is dominated by cone photoreceptors which increase color vision and visual acuity. At night, under dark conditions, human vision is dominated by rod photoreceptors which increase low-light sensitivity but decrease spatial acuity, contrast sensitivity, and motion perception (Gegenfurtner et al., 2000; Lamb, 2016; Stockman and Sharpe, 2006). Due to these inherent physiologically changes, the ability for humans to identify objects (e.g., pedestrians) at night is hindered (Tyrrell et al., 2016), which can lead to increased AVCs during low-light conditions (Cunningham et al., 2022; Sullivan, 2011). Drawing from human vision literature, one study suggested that a human's inability to differentiate similar colored objects at night could make it difficult to distinguish moose against a background of trees (Joyce and Mahoney, 2001). Furthermore, as a vehicle's speed increases, a driver's visibility angle narrows with drivers fixating farther down the road (Capaldo et al., 2020; Rogers et al., 2005; van Leeuwen et al., 2015), which can be complicated by headlights limiting visibility down the road at night (Riginos et al., 2022; Sullivan, 2009; Sullivan, 2011). Compounding this issue, drivers at night spend more time looking at the center of the road than scanning the road edges (Olson et al., 1989). This reduced peripheral attention at night, especially as speed increases, has been suggested to be an important factor contributing to AVCs at night (Özcan and Özkazanç, 2017).

Despite the obvious impact of driver vision on wildlife detection ability, we found no studies that directly investigated driver contrast sensitivity or visual acuity and only one that considered the use of corrective lenses on drivers' ability to detect wildlife. Pakula et al. (2023) observed no difference in detection ability or detection distance of white-tailed deer between drivers that wore corrective lenses and those who did not during the study. Despite this study, this literature gap is concerning given research indicating that vision attributes strongly influence driver detection of pedestrians at night. Specifically, even when drivers meet the visual requirements (visual acuity) for licensing, drivers with normal vision responded to a roadside pedestrian at night at distances 3.6 to 5.5 times longer than those with moderately blurred vision from incorrect lens strength and simulated cataracts, respectively (Wood et al., 2012), suggesting that even common visual impairments can greatly hinder hazard detection at night. This has major safety implications, especially for older drivers, as an estimated 20.5 million (17.2%) Americans older than 40 years have a cataract in at least one eye (Congdon et al., 2004). Driver vision remains an underappreciated field of study that can have substantial impacts on a driver's ability to avoid AVCs.

3.8.2. Age, Experience, and Knowledge

A driver's previous experience and knowledge can influence their behavior during wildlife-vehicle interactions. Age can be an indicator of driver experience and can thus influence driver behavior. One study suggested that younger drivers (age 25-34) were more likely to be involved in AVCs because they are less experienced and more likely to engage in risky driving habits (Roy and Ksaibati, 2021), a well-documented phenomenon in the transportation safety literature (Jonah, 1990; Voogt et al., 2014). Despite this finding other studies found that middle aged (Bramati et al., 2012; Roy and Ksaibati, 2022) and older drivers (Ahmed et al., 2021; Papadimitriou and Psarianos, 2015) are more likely to be involved in AVCs, suggesting driver age alone might not be a strong predictor of AVCs. There is likely some interaction between age-related risk-taking behavior while driving and age-related vision impairment that contributes to these conflicting results.

Many drivers do not know the safest response to an animal in the road (i.e., controlled braking) and often report that they engage in swerving as their main evasive maneuver (Vanlaar et al., 2019). In an effort to increase driver knowledge of the hazards of AVCs and how best to react during wildlife-vehicle interactions, many institutions engage in public awareness campaigns. Although 22 U.S. states participate in efforts to inform the public of the dangers of deer-vehicle collisions (Romin and Bissonette, 1996), the effectiveness of public education on driver behavior is largely unknown (Mastro et al., 2008). However, anecdotal evidence suggests these campaigns can increase driver awareness (Del Frate and Spraker, 1991), and when combined with other mitigation methods, like increased wildlife warning signs, have resulted in measurable reductions in AVCs (Poot and Clevenger, 2018; Rea, 2012). However, as most public awareness campaigns occur alongside other mitigation methods, the effectiveness of these campaigns alone is not well understood.

It seems logical that drivers that have previously been in a large animal-vehicle collision would have increased knowledge of how to avoid future collisions, but this is not necessarily the case. Drivers report braking and steering straight as the safest reaction at similar rates, regardless of prior collision experience, and 39.1% of drivers who have been in a collision are unaware of the safest response (Vanlaar et al., 2019). Similarly, despite drivers reporting that they drive slower at high-risk times, data on vehicle speed suggests otherwise (Ramp et al., 2016). Overall, driving experience does not necessarily result in a reduced chance of an AVC. In fact, the risk of an AVC increases with more years driven and longer distances driven per year, suggesting that the experience gained each year may not sufficiently offset the increased exposure risk, especially given the stochastic nature of many AVCs (Borza et al., 2023).

3.8.3. Attitudes

A driver's experience and general attitudes towards wildlife can influence their behavior during a wildlife-vehicle encounter. Surveys show that there are large taxonomic biases in driver perception and attitudes towards hitting certain species (Crawford and Andrews, 2016; Kioko et al., 2015; Norshaqinah et al., 2023). Most drivers are more apprehensive about hitting large mammals, likely due to safety concerns, and are more upset about hitting mammals and domestic animals (e.g, canids and felids), while showing the least concern for hitting herpetofauna like snakes (Crawford and Andrews, 2016; Norshaqinah et al., 2023). Similarly, Kioko et al. (2015) found that drivers intentionally hit species that would cause less damage to the vehicle (frogs and birds), as well as dogs which are considered "nuisances" in Tanzania, where the study took place. How this taxonomic bias in attitudes translates to roadkill, specifically, has mixed results in the literature. Despite many studies documenting intentional collisions with snakes and other herpetofauna (Langley et al., 1989; Paul Ashley et al., 2007) likely due to their negative attitudes towards the taxa (e.g., Crawford and Andrews, 2016), other studies have found the opposite. For example, two studies from Brazil found that drivers will swerve to hit anything in the road and that snakes were not targeted more than control objects (bottles; de Resende Assis et al., 2022; Secco et al., 2014). These contrasting results could reflect the influence of other factors impacting drivers' propensity to intentionally hit animals such as education and cultural differences. Similar studies on swerving behaviors with regard to small and meso-mammals and birds have not been explored.

3.8.4. Evasive Maneuvers

How drivers respond to an animal in the roadway can influence their risk of a collision, and these reactions can be shaped by their knowledge and attitudes as outlined above. Controlled braking is often regarded as the safest response to a hazardous animal because a driver can potentially stop before reaching the animal, while simultaneously giving the animal additional time to leave the path of the vehicle. However, studying evasive maneuvers by drivers can be difficult given the type of data required and the need for data on many wildlife-vehicle interactions. Most of the current literature is based on simulator studies or the use of dummy animals. For example, when confronted with a dummy snake, 37% of drivers changed their behavior (slowed down, stopped, or swerved), which increased to 61% when there was a wildlife warning sign present (Collinson et al., 2019). Furthermore, Collinson et al. (2019) found that swerving was the most effective response to avoid a collision with a dummy snake. However, swerving to avoid an animal, although common, is not recommended because it can lead to drivers colliding with other roadside objects (Ramp et al., 2016; Smoot et al., 2010). Unsurprisingly, simulator studies have shown that earlier braking often results in fewer AVCs (Grace et al., 2015), but the timing of braking can be influenced by roadside objects (e.g., fencing, vegetation; Antonson et al., 2015).

How hard a driver applies the brakes can impact safety, because harsh braking can lead to a loss of control. Counterintuitively, Gupta and Velaga (2024) found that riders of a two-wheeler braked less harshly when engaged in conversation, which was attributed to some drivers not reacting at all or driving slower due to the distraction. Additionally, they found that delivery drivers were more likely to engage in harsher braking than adventurous drivers. They attributed their findings to the delivery drivers being rushed and not paying as much attention to sudden hazards, suggesting driver occupation can influence reaction types. One unique study used YouTube dash cam videos of moose-vehicle encounters and found that braking was the only variable that increased the probability of a near miss compared to a collision (Rea et al., 2018). Despite the straightforward benefits of braking and the dangers of swerving, many drivers still report that they should swerve to avoid an animal (Vanlaar et al., 2019).

3.8.5. Fatigue

Nighttime driving is often associated with drivers being fatigued and this has been extensively studied in the transportation literature (May, 2011; Thiffault and Bergeron, 2003; Ting et al., 2008). For example, the inherent decrease in driver awareness at night could potentially cause higher rates of moose-vehicle collisions (Joyce and Mahoney, 2001). Furthermore, fatigue was suggested as a reason why driver detection distance decreased and the probability of a dangerous encounter with white-tailed deer increased as driving duration increased (Pakula et al., 2023). Given the relatively few studies that have explored fatigue with respect to AVCs, future research should further investigate how fatigue directly impacts a driver’s ability to detect and avoid wildlife, especially at night.

3.8.6. Alcohol Use

Despite the known impact of alcohol on cognitive functions and driver performance (Dong et al., 2024; Ogden and Moskowitz, 2004), we identified only a few studies that considered alcohol consumption and AVCs, all of which were retroactive analyses based on collision or medical records. When driving a two-wheeler (e.g., motorcycle), drivers were under the influence of alcohol in 14% (Mohanty et al., 2021) and 16% (9 out of 55; Nelson et al., 2006) of AVCs. Bramati et al. (2012) found only 4% of AVCs involved alcohol, but found that for 92% of the collisions, alcohol use was not tested for, highlighting a potential underreporting bias in collision databases. We found no studies describing alcohol-related AVC rates for standard, four-wheeled vehicles. However, using a national database on fatal collisions, Langley et al. (2006) found that 17.3% of fatal AVCs involved intoxicated drivers (>0.08 mg/dL) and only 27.5% of the dataset involved motorcycles.

Beyond its influence on AVC rates, alcohol has also been linked to more severe injuries during AVCs. Alcohol use often results in more severe injuries during two-wheeler accidents (Mohanty et al., 2021; Nelson et al., 2006), which can be attributed to delayed driver responses (Mohanty et al., 2021) or reduced use of safety measures like failing to wear a helmet (Nelson et al., 2006). Contrary to the earlier studies, Moghaddam et al. (2020) found no association of alcohol use on crash severity, but their data seemingly involved four-wheeled vehicles which suggests, unsurprisingly, the severity risk of an AVC differs between two- and four-wheel vehicles. These conflicting results highlight a need to better understand the mechanism underlying how alcohol contributes to AVCs. We identified no study that has investigated alcohol use with respect to driver detection ability or responses during wildlife-vehicle interactions, providing a potential avenue for future research.

3.8.7. Driver Attributes Summary

- Despite previous research on human vision, few studies have investigated how driver vision at night impacts detection ability of wildlife specifically. How well a driver can see and the factors that influence this aspect of wildlife-vehicle interactions is an underappreciated topic within AVC research.
- Experience, age, and attitudes can all impact how drivers respond during a wildlife-vehicle interaction, however there are often conflicting results. There appears to be a disconnect between what drivers say they should or will do and what action they perform.
- Fatigue appears to greatly influence driver behavior but the research into its influence during animal-vehicle interactions is understudied
- Alcohol can negatively impact driver behavior and increase the risk and severity of collisions, but its direct impact on driver's ability to detect wildlife is unknown.

4. Conclusions

Wildlife-vehicle collisions are a major issue throughout the developed world, posing risks to animals and drivers (Conover, 2019; Seiler and Helldin, 2006). Although previous AVC research has largely focused on collision hotspots or animal behavior, this review focused on driver behavior, a largely underappreciated aspect of AVCs even though it is inherently a factor in nearly every AVC.

We identified eight broad categories affecting at least one of three aspects of driver behavior during wildlife-vehicle interactions. These factors influenced either (1) driver detection ability of hazardous wildlife, (2) whether a driver identifies the animal as a threat, or (3) whether the driver brakes with sufficient time to stop before reaching the animal (Figure 2.1).

Several frequently studied topics such as vehicle speed, road attributes, and environmental conditions have all been linked to AVCs through altered driver behavior. However, these studies often inferred an impact on driver behavior post-hoc rather than investigating the influence directly. These studies often attributed their findings to a change in driver speed. However, failure to directly measure vehicle speed can lead to an oversimplification of variables involved or misattribution of the results to speed instead of other variables. Relying on logical explanations and broad associations without mechanistic data contributes to conflicting results among studies. Although these studies can be informative about large scale patterns, to further advance the field more directed research on how these variables directly impact driver behavior is needed.

In contrast, there are several other factors that directly influence driver behavior but remain understudied, including roadway illumination, wildlife attributes, and driver attributes. Although headlights provide drivers with vital illumination at night, little is known about how they impact driver detection ability of wildlife. This is an important avenue for research, given that most vehicles are transitioning to LED headlights (Linkov, 2019), which are reported to increase roadway illumination. Similarly, driver attributes, including vision impairments, have been well studied in the context of pedestrian safety but have yet to be explored with respect to widllife. Beyond drivers, how wildlife attributes impact driver behavior is one of the most understudied topics we identified, despite its likely strong influence. Understanding the risk of AVC across species requires a taxa specific investigation into the possible causes.

Ultimately, identifying the causes of AVCs requires an integrated approach. Combining existing research on broad scale patterns with directed studies on how individual factors specifically impact driver detection ability of wildlife is needed to better understand drivers of AVCs. Although this review has demonstrated that driver behavior is important when evaluating causes of AVCs, it represents only one side of the AVC equation. A failure to consider both driver and animal behavior when interpreting results can lead to misattributed findings and conflicting trends, as is the case with roadside vegetation removal. When possible, future research should incorporate both driver and animal behavior when researching AVCs.

Animal-vehicle collisions are the result of a complex interaction of environment, animal, and driver related factors. A deeper understanding of factors influencing driver behavior during wildlife-vehicle interactions is essential for moving beyond broad associations and to develop more effective mitigation methods.

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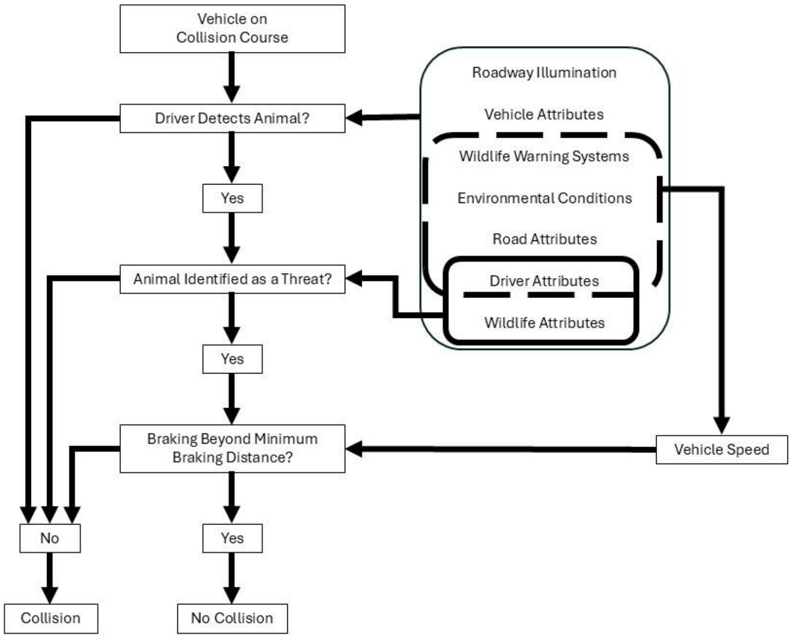

Figure 2.1 Key behavioral steps drivers must complete to avoid striking an animal on a collision course with the vehicle (left). A failure at any step will result in a collision. Also shown are eight categories of factors identified in the literature that influence these behavioral steps (right).

CHAPTER 3

DRIVING IN THE DARK: DECIPHERING NIGHTTIME DRIVER DETECTION OF FREE-RANGING ROADSIDE WILDLIFE[1]

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[1] Pakula, C. J., Guenin, S., Skaggs, J., Rhodes Jr, O. E., & DeVault, T. L. (2023). Transportation Research Part D: Transport and Environment, 122, 103873. https://doi.org/10.1016/j.trd.2023.103873. Reprinted here with permission of the publisher.

Abstract

Wildlife-vehicle collisions are dangerous for motorists; however, few studies have addressed driver detection of roadside animals, and none have evaluated detection of free-ranging wildlife. We used 24 volunteer drivers, infrared videography, a 75-km route, and free-ranging wildlife to quantify factors influencing (1) probability of wildlife detection, (2) detection distance, and (3) probability of dangerous encounters (i.e., detection distance < distance required for braking) for multiple species at night in South Carolina, USA. Detection probability of white-tailed deer (*Odocoileus virginianus*) was impacted by multiple driver, animal, and roadside factors. Deer detection distances increased by 20.99 m when drivers used high-beam headlights and 23.36 m when deer were moving but decreased by 0.71 m for every minute into a drive. Every encounter with wild pigs (*Sus scrofa*) and most encounters with small mammals were considered dangerous. Our findings suggest most drivers cannot safely detect deer, wild pigs, and small mammals at night.

1. Introduction

Wildlife-vehicle collisions (WVCs) are common throughout the world and cause substantial harm to wildlife and humans. Billions of vertebrates across various taxa are killed by cars, boats, and airplanes each year (Hill et al., 2019, Seiler and Helldin, 2006) and these deaths can negatively impact populations (Fahrig and Rytwinski, 2009, Moore et al., 2023). In the United States alone, WVCs with deer (*Odocoileus* spp.), elk (*Cervus canadensis*), and moose (*Alces alces*) cause US$8.4 billion in damages annually (Huijser et al., 2008), with an estimated 58,622 people injured and 440 human deaths from deer-vehicle collisions (Conover, 2019). Although most WVCs in the United States that cause damage to vehicles involve deer (Conover, 2019, Huijser et al., 2008), wild pigs (*Sus scrofa*) pose an emerging threat (Beasley et al., 2013), as their population has increased 44% from 2004 to 6.9 million animals in 2016 (Lewis et al., 2019). Wild pig-vehicle collisions are estimated to cause >US$181 million in damages each year in the United States (Strickland et al., 2020) and will likely increase as wild pig populations continue to expand (Lewis et al., 2019).

There has been extensive research on WVC mitigation methods, which often focused on increasing driver awareness or modifying wildlife behavior. However, most mitigation methods aimed at increasing driver awareness have been shown to be ineffective, including standard road crossing signs (Glista et al., 2009, Huijser et al., 2008, Mastro et al., 2008), reduced posted speed limits (Mastro et al., 2008, Riginos et al., 2022), and highway lighting (Huijser et al., 2008, Reed and Woodard, 1981). Similarly, many mitigation methods designed to modify wildlife behavior, including “deer whistles” and roadside reflectors, are also largely ineffective (Huijser et al., 2008, Mastro et al., 2008, Valitzski et al., 2009). Wildlife road crossing structures combined with roadside fencing are considered to be the most effective mitigation methods but are expensive and often impractical to implement widely (Glista et al., 2009, Huijser et al., 2008).

Wildlife-vehicle collisions are complex events influenced by many factors including driver behavior (Mastro et al., 2010), animal behavior (Lima et al., 2015, Pfeiffer et al., 2020), and environmental characteristics (Beasley et al., 2013, Pagany, 2020). Most WVCs occur under low-light conditions (Cunningham et al., 2022, Huijser et al., 2008) when driver detection of wildlife is most difficult. To our knowledge, no studies have quantified how collision probability is influenced by driver awareness at various distances from the animal. Even so, it is logical to assume that an early detection by the driver will reduce the likelihood of a collision compared to a late detection (Rumar, 1990). As such, an increased understanding of the factors that improve or hinder driver detection of wildlife on and near roadways at night could lead to improved mitigation strategies.

Previous research on driver behavior examined driver gaze (Green, 2002, Olson et al., 1989), reaction time (Green, 2000, Guo et al., 2019), detection distance of pedestrians (Kandil et al., 2009), and the effects of distractions (Lipovac et al., 2017), but these studies were typically conducted outside of the context of WVCs. We found only three studies that quantified driver detection distance of wildlife at night. These studies investigated driver detection of white-tailed deer (*Odocoileus virginianus*; Mastro et al., 2010), moose (Rodgers and Robins, 2006), and Tasmanian fauna (Hobday, 2010) using decoys or taxidermies (hereafter, decoys). These studies suggest that distance to the road

(Mastro et al., 2010), the side of the road on which the animal is located (Mastro et al., 2010, Rodgers and Robins, 2006), and headlight intensity (Hobday, 2010, Mastro et al., 2010, Rodgers and Robins, 2006) influence detection distance. Even so, all three studies found that at current speed limits, most drivers generally do not detect animals with enough time to avoid a collision if the animal enters the path of the vehicle (Hobday, 2010, Mastro et al., 2010, Rodgers and Robins, 2006).

The aforementioned studies provide a foundation for understanding factors that influence driver detection of roadside animals at night. However, all three studies used decoys, which are unlikely to be representative of free-ranging wildlife (Hobday, 2010, Mastro et al., 2010, Rodgers and Robins, 2006). For example, decoys lack eyeshine (i.e., tapetum lucidum), which is present in many wild animals including deer. Reflected light from eyeshine could increase driver detection distances in the same way pedestrians wearing reflective clothing are detected at farther distances by drivers (Sayer and Mefford, 2004, Tyrrell et al., 2016). Additionally, decoys inherently do not move or otherwise react to an approaching vehicle. Although Mastro et al. (2010) simulated deer movement by manually moving decoys, it is difficult to mimic or reliably predict behaviors exhibited by wild animals. Furthermore, the drivers in these studies drove at relatively slow speeds (10-48 km/h) along a short course (<1 km) and were aware that they would encounter a decoy at some point during the drive, which may have increased driver awareness. Lastly, these studies tested a limited suite of variables that may influence driver detection and a small proportion of the species that a driver may encounter in a given area.

In the present study, we built upon previous decoy-based research (Hobday, 2010, Mastro et al., 2010, Rodgers and Robins, 2006) to better understand driver detection of wildlife along roads at night. We evaluated the influence of multiple driver, encounter, and environmental characteristics on driver detection of several species of free-ranging wildlife along a 75-km route composed of secondary roads with standard posted speeds ranging from 72 to 89 km/h. Given that this study evaluated driver detection of free-ranging, wild animals while driving at realistic speeds, many of the limitations inherent to previous studies regarding lack of eyeshine, lack of natural animal movements, and potentially heightened awareness of drivers were avoided. Our specific objectives were to quantify factors influencing (1) the probability a driver detected an animal during an encounter, (2) detection distance, and (3) the probability of an encounter with wildlife being dangerous (i.e., detection distance < distance required for braking; see below) for multiple species.

2. Methods

2.1 Study site

We conducted our study at the Savannah River Site (SRS), which is operated by the U.S. Department of Energy (DOE) in west-central South Carolina, USA. The 803-km^2 site has an extensive road system of 225 km of maintained primary roads and 2,253 km of secondary roads or jeep trails (Blake et al., 2005) with speed limits not exceeding 89 km/h (Mayer and Johns, 2007). Over recent decades the SRS has averaged 11-15,000 on-site workers (Blake et al., 2005; Savannah River Site, n.d.) but has restricted public access and a perimeter fence that is permeable to wildlife including deer and wild pigs. SRS is home to 4,000-5,000 white-tailed deer (Johns and Kilgo, 2005) and several thousand wild pigs (Keiter et al., 2017). Approximately 100 deer collisions (Johns and Kilgo, 2005) and 40 wild pig collisions occur annually at the SRS (Beasley et al., 2013).

The topography of the SRS is largely flat, with elevation ranging from 20 to 130 m above sea level (Kolka et al., 2005). Most road surfaces are bordered by ~4 m of mowed grass adjacent to an un-mowed strip of vegetation that varies from short grass to 2 m tall thick grass or woody vegetation. Beyond this intermediary vegetation, for most of the site's roadways, is a tree line on both sides of the road that varies in distance to the road surface. Exceptions include larger mowed and deforested areas around intersections, railroad crossings, and recent areas of timber harvest.

2.2 *Research Participants*

Due to security restrictions, all potential research participants were required to possess a permanent SRS site access badge and be a U.S. citizen. To meet these requirements, we recruited individuals employed by the University of Georgia's Savannah River Ecology Laboratory through bimonthly emails and in-person communication. Individuals were required to possess a valid U.S. driver's license, be over the age of 18, have no physical disabilities that might impair their driving ability, and be comfortable driving at night. If individuals participated more than once, they were assigned the same driver identification (hereafter, driver ID) for statistical analyses. Before each trial, we collected participant data including birthdate and use of corrective lenses.

2.3 Vehicle Characteristics

All research participants drove the same 2018 Ford F-150 pickup truck. The Ford F-series has been the top selling vehicle in the USA for the past 41 years (Ford Media

Center 2023) and thus is a representative vehicle for testing. The truck was equipped with a forward-looking infrared (FLIR) camera (FLIR M625S, FLIR Systems, Goleta, California, USA) and a MobileMule 4 Channel Mobile DVR (RVS-6202, Rear View Safety, Brooklyn, New York, USA) to allow for recording of each trial. A live feed video from the FLIR was displayed on a monitor mounted to the passenger seat’s dashboard, which allowed the researcher to view wildlife near the road up to 800 m away in real time (Blackwell et al., 2014, DeVault et al., 2020). The monitor was not visible to the driver and was manually dimmed resulting in a negligible distraction to the driver. The study vehicle was outfitted with stock halogen reflector headlights (IIHS, n.d.). Before each nightly trial, the windshield and headlights were washed with soap and water.

2.4 Field Methods

Each trial began ~30 min after sunset under dry, fogless conditions when there was no ambient light detectable with a LI-COR LI-250A Light Meter and LI-190R Quantum Sensor (0.00-0.01 μmol·m^{-2}·s^{-}1; LI-COR Biosciences, Lincoln, Nebraska, USA). The driver was instructed to drive a pre-determined 75-km route of paved roads at SRS travelling up to the posted speed limit, but not exceeding the comfort level of the driver (i.e., drivers typically drove within ~16 km/h of the speed limit). The nearly circular route did not repeat the same stretch of road within each night except for a 4.0-km stretch where encountered animals were only included as data points either at the start or end of the route, which was randomly determined before the trial. An additional 0.5-km section was repeated during the trial but animals in this section were only included as data points during the first pass. The driving direction (clockwise or counterclockwise) was randomized before each trial. The seven trials that occurred outside of daylight saving time (11/2021-03/2022) began 1.5 h after sunset to avoid rush-hour traffic and to more closely match traffic levels of the trials conducted during daylight saving time. To limit the confounding influence of other vehicles (e.g., increased road illumination), we refrained from recording encounters in the presence of other vehicles (<5 encounters).

To quantify the influence of low- and high-beam headlights on driver detection of wildlife, the starting treatment was randomized and then alternated at the halfway point of the route, except for the first eight drives of the study where the headlight intensity alternated after every encounter in which the driver detected an animal. We simulated real-world driving conditions as much as possible by allowing drivers to play low-volume music and engage in casual conversation with the researcher but not enough to result in excessive distraction. The driver was instructed to notify the researcher the moment they first detected any animal. Although drivers were aware of the purpose of the study (i.e., identifying factors influencing detection of wildlife), the presence of free-ranging animals along the test route was unknown. During the trial, the researcher in the passenger seat of the vehicle continuously viewed the FLIR monitor for wildlife near the roadway. The researcher notified the driver of the presence of an undetected animal only if the vehicle was within ~50 m of the animal and was deemed at risk of collision. When the driver notified the researcher that they detected an animal, the researcher immediately recorded a GPS point with a handheld GPS unit (Figure 3.1; Garmin GPSMap 66st, Olathe, Kansas). The Garmin GPSMap 66st is accurate to within roughly 3 m, 95% of the time (Garmin, n.d.). The GPS point was taken at the first sign of a notification from the driver, including a verbal cue, pointing, or braking. Regardless of whether the encountered animal was detected by the driver, a GPS point was taken when the vehicle reached the point perpendicular to the initial location of all animals observed by the researcher on the FLIR (Figure 3.1). Even under minimal roadside illumination provided by the vehicle's headlights, the researcher was able to visually identify the initial location of the animals by monitoring their location (distance to road, location to roadside objects, movement) throughout the entire approach on the FLIR monitor. In cases for which the researcher was unable to visually locate the animal, the researcher estimated the location of the animal based on the relative location of the animal on the monitor and speed at which the animal was approaching the edge of the screen during the approach. After the encounter, the researcher recorded the number of individual animals the driver detected and their location. This study received human subjects approval from University of Georgia's Institutional Review Board (no. 00004146) and animal subjects approval from the University of Georgia's Institutional Animal Care and Use Committee (no. A2021 06-013-Y1-A0).

2.5 Data Extraction

Several environmental variables were collected and calculated for each encounter with an animal regardless of whether the animal was detected by the driver (hereafter, encounter; Table 3.1). We recorded the proportion of the moon illuminated at the time of each encounter using the U.S. Naval Observatory website (U.S. Naval Observatory) from a coordinate at the center of the SRS (439232.26 E, 3680769.03 N; Table 3.1). We calculated time variables associated with each encounter including minutes from the start of the trial and trial start time (hours from previous midnight; Table 3.1).

To ensure we extracted predictor variables from the FLIR recordings at the correct time, we accounted for any differences in the Mobile Mule DVR GPS time and the Garmin GPS time every night. Using video playback of each trial, we documented species, group size, the side of the path of the vehicle of each individual (location, i.e., left or right), and if the animal was moving when the driver detected the animal (hereafter, detection; Table 3.1). The vehicle's speed was extracted from the Garmin GPS (Table 3.1). Because drivers inherently perceived animals before they notified the researcher, we extracted predictor variable values 1 s before the detection waypoint time (if the animal was detected) to ensure that our predictor variables reflected the stimulus that led to a driver perceiving an animal. The 1 s delay was based on the perception-brake time, i.e., the elapsed time between driver perception of a hazard and initiation of braking (Olson and Sivak, 1986, Summala, 2000). We assumed that perception-brake time was similar to the time it took a driver to notify the researcher after perception of an animal.

The animals' distances to the road edge were estimated to the nearest m from the FLIR recordings using known distances to objects on the landscape (e.g., width of the road, telephone poles, guardrails, and drainage ditches) and using Google Earth (Mountain View, California), when applicable. We applied a correction to each encounter's distance to the road edge to obtain each animal's distance to the path of the vehicle under the assumption that each lane was 3 m wide (Table 3.1). The animal's elevation relative to the surface of the road was also estimated (to the nearest m) from the videos (Table 3.1). These two variables were estimated 1 s before the detection waypoint to capture the animal's position at driver perception, as described above. We validated the accuracy of our distance and elevation relative to the road estimations by measuring those values in the field for a subset of our data. Specifically, we randomly chose ~20%

of the encounters, across all species, during which a driver saw at least one animal. Of those selected encounters, we randomly chose one individual from the encountered group to avoid pseudo-replication. Using the GPS points from the animals' locations, we returned to the location of the selected animals. Using video playback, two researchers identified the animal's location at driver detection and measured its distance to the path of the vehicle to the nearest m with a measuring tape. The ground-truth measurements were conducted by the researcher that estimated the animals' distances during playback but was blind to those values. The mean absolute difference in an animal's distance to the path of the vehicle between video and field scoring was 0.97 m (SE = 0.15, range = 0-3 m, n=38). The range of video-scored animals' distance to the road was 0-20.5 m. The mean absolute difference in an animal's elevation relative to the road between video and field scoring was 0.16 m (SE = 0.06, range = 0-1m, n= 38). The range of the animals' elevation relative to the road was -2-1 m. From these comparisons we concluded that video scoring provided a reasonable degree of accuracy for our objectives and all future analyses used the video-scored distances.

Because vegetation can potentially impact a driver's detection ability, we categorized whether each animal was unobstructed or obstructed by the vegetation at the time the driver detected the animal (if applicable; Table 3.1). The "unobstructed" vegetation class was characterized by no vegetation obscuring the animal. If grasses or shrubs concealed a portion of the animal ranging from legs to full torso concealment (but still visible to the FLIR), the vegetation class was scored as "obstructed." If an animal was detected, the animal's vegetation class was estimated 1 s before the detection waypoint to capture the animal's position at driver perception, as described above.

We validated categorization of vegetation classes from FLIR videos by scoring the vegetation category during the day at each encounter that occurred between late July 2022 and mid-September 2022. We scored vegetation classes in the field within the same week of the data collection trial except for one trial in late July that was field validated two weeks later under the assumption that the vegetation had not changed substantially. Additionally, for validation, we only compared video and field scoring for encounters with animals for which at least one individual in the group was not in the road and did not enter the tree line. Across all species, scoring vegetation by video was identical to field scoring 82.5%, 92.5%, and 80.0% of the time at FLIR detection, driver detection/notification by the researcher, and when the animal left the FLIR's field of view, respectively (n=40 for all three). From these comparisons we concluded that video scoring provided a reasonable degree of accuracy for our objectives and all future analyses used the video scored vegetation classes.

Although GPS points taken by the Garmin GPS unit and the Mule Mobile DVR are relatively precise, they are not always accurate on the landscape due to the interaction of the unit's refresh rate (i.e., how often the unit updated its position) and vehicle speed. In other words, GPS points would be projected onto a map some distance before the point was actually recorded. We accounted for the Mobile Mule DVR and the Garmin GPS's "lag" based on the speed of the vehicle for every distance calculation.

All GPS coordinates were snapped to a GIS road layer for our study site (mean snapping distance: 5.46±0.11 m). All points were visually inspected for erroneous snapping to the wrong road. An encounter's approach distance was calculated by taking the Euclidian distance between the coordinates of the animal's initial location and the coordinates displayed on the FLIR for the frame the FLIR first detected an animal (Figure 3.1). Because the Mobile Mule DVR's GPS displays the same coordinates for 1 s due to its refresh rate, we interpolated the frame's position between two GPS points. A driver's detection distance was calculated by taking the Euclidean distance between the coordinates of the animal's initial location and the coordinates of the driver detection waypoint (Figure 3.1). Although drivers would have perceived the animal before the driver notified the researcher resulting in the detection waypoint, we report detection distance at the moment of detection notification, following Mastro et al. (2010). Both distance values were calculated by taking the Euclidean distance between two Universal Transverse Mercator (UTM) zone 17S projected coordinates. The driver detection distance received an additional correction based on the reaction time between the driver signaling that they saw an animal and the researcher pressing the GPS waypoint button. The researcher's reaction time to an auditory tone was tested using Inquisit software V6.6 by Millisecond Software (Seattle, Washington) and was found to be 0.2349±0.004 s (n=20).

For all analyses we excluded any animals that entered the tree line during the approach without being detected because the driver was not allowed the full approach to detect them. Groups of animals were scored based on the closest individual to the path of travel, as this was likely the first individual detected by the driver. Due to our inability to distinguish coyotes (*Canis latrans*) from foxes (*Vulpes vulpes* and *Urocyon cinereoargenteus*) on FLIR videos, we analyzed them together as a single canid group. Additionally, any species shorter than a fox and all unidentifiable small individuals that were not a canid, or a wild pig were grouped as small mammals.

Given that the goal of our study was to investigate a driver's ability to detect wildlife rather than to investigate every encounter, we truncated artificially short approaches with wildlife. For example, some encounters occurred immediately after drivers turned onto a road or as the animal emerged from the tree line when the vehicle was passing. In those scenarios, the driver's detection ability and detection distance were constrained and might not be represented fairly because drivers were allowed a relatively short approach distance to detect the animal. Therefore, for all analyses we excluded short approaches that might have limited a driver's detection distance artificially. To do so, we used the pooled data for all drivers and visually inspected driver detection distance histograms for each animal group. We then identified each animal group-specific threshold for which there was an obvious reduction in detections greater than that distance and ≥90% of the detection distances were below those values. Those thresholds were considered the minimum approach distances for each animal group. We censored any trial's approach that was shorter than the animal group-specific minimum approach distance, which was 174 m, 172 m, 84 m, and 81 m for deer, canids, wild pigs, and small mammals, respectively. This resulted in >85% of encounters for deer and 83-100% of those for all other animal groups being retained for analyses.

For approaches that resulted in non-detections by the driver, animal associated variables were scored both at the animal group-specific minimum approach distance and at the moment the animal left the FLIR's field of view. Variables collected for non-detections, including the animal's distance to the path of travel and elevation relative to the road, were then scored as the average between those two points (Table 3.1). Animal movement was scored as a binary; if the animal moved at any point within the minimum approach distance and vegetation class was scored as the most concealing class within which the animal was located within the minimum braking distance (Table 3.1). The animal's location was scored at the moment the animal left the FLIR's field of view (Table 3.1). The vehicle's speed was extracted from the Garmin GPS at the moment the vehicle passed the initial location of the animal, as that was the last moment the driver could have detected the animal (Table 3.1).

2.6 Data Analysis

We sought to understand the role of driver, encounter, and environmental characteristics on driver detection of wildlife using three separate analyses to determine (1) the probability a driver detected an animal at any point during the encounter, (2) the detection distance of a detected animal, and (3) the probability that an encounter was dangerous (see below). However, due to inadequate sample sizes of non-deer animal groups, the following analyses were conducted only for deer. For the first analysis investigating the factors influencing detection probability, we excluded deer below the deer-specific minimum approach distance as well as those >21.5 m from the path of the vehicle to eliminate deer that presented very little hazard of collision and that the driver had little chance of detecting (Mastro et al., 2010). Additionally, we excluded approaches during which the researcher notified the driver to brake due to safety concerns because in those cases the driver was not allowed the full approach distance to detect the animal. For this first analysis, we used a logistic regression model to examine the probability of driver detection with driver ID as a random intercept.

For the second analysis investigating the factors influencing detection distance, we again excluded deer below the deer-specific minimum approach distance and those

>21.5 m from the path of the vehicle as well as approaches during which the researcher notified the driver. We also excluded encounters during which the driver did not detect a deer. For this second analysis, we used a linear regression model with driver ID as a random intercept and maximum likelihood estimation (ML).

For the third analysis investigating the factors influencing the probability of a dangerous encounter, we used only deer within 6.5 m of the path of the vehicle to limit the analysis to deer that posed a substantial threat to drivers (Brieger et al., 2022). An approach was deemed dangerous (DeVault et al., 2020) if the driver did not detect the deer, the researcher had to notify the driver to brake for safety concerns, or the driver's detection distance was less than the minimum braking distance. The minimum braking distance was calculated using the American Association of State Highway and Transportation Officials' formula (AASHTO, 2018) for calculating braking distance under level conditions:

$$d_B = 0.039V^2/a$$

where d_B is the braking distance in m, V is the vehicle's velocity in km/h at driver detection, and a is the vehicle's deceleration rate (3.4 m/s^2 is recommended). At the two most common speed limits in our study (72 and 89 km/h), the minimum braking distances were 59.5 and 90.9 m, respectively. For this analysis, we used a logistic regression with driver ID as a random intercept.

All three analyses were conducted in R version 4.1.1 (R Core Team 2021). To evaluate the most influential variables we fit all three models using the package lme4 (Bates et al., 2015) using every combination of predictor variables (Table 3.1) and ranked them using AICc (Burnham and Anderson, 2002) with the package MuMin (Barton, 2020). We also included elevation relative to the road as a quadratic term (Table 3.1) to account for potentially similar effects at low and high elevations relative to the roads. We only considered models that had either the linear term only, or the linear and quadratic term (elevation^2) together. (Nelder, 2000, Peixoto, 1987). We present all models within ΔAICc <2 but limit interpretation to the top-ranking model for each analysis. For each variable in the top model, we calculated its 85% confidence interval (Arnold, 2010). For the driver detection distance analysis, we identified the top model and then re-estimated parameters using restricted maximum likelihood estimation (REML; Zuur et al., 2009) for interpretation. Estimated marginal means were calculated using the package ggeffects (Lüdecke, 2018) to show model predictions over a range of conditions and to compare mean values with previously published values when other model parameters were held constant.

For canids, wild pigs, and small mammals, we repeated the same data processing as described above; however, due to low sample sizes we were unable to fit models for these groups. Instead, we calculated descriptive statistics including proportions for detection probability and dangerous encounter probability. For detection distance, we calculated means and standard errors for each animal group.

3. Results

3.1 Driving Participants

We conducted 33 drives from September 2021-Sepetember 2022. We had 24 unique driver participants (11 females, 13 males) whose ages ranged from 22.3-60.8 y (mean: 31.4 y). No driver participated in more than two trials. One-half of the participants used some form of corrective lenses (glasses: 8, contact lenses: 3, laser vision correction surgery: 1).

3.2 Wildlife Encountered

Across all encounters, drivers detected 105 of the 180 encountered deer groups, 7 of the 11 encountered canid groups, 11 of the 45 encountered wild pig groups, and 11 of the 31 encountered small mammal groups (Table 3.3). The encountered groups averaged (±SE) 11.33 ± 0.38 m, 7.82 ± 1.38 m, 9.17 ± 0.54 m, 6.35 ± 0.58 m to the path of the vehicle for deer, canids, wild pigs, and small mammals, respectively. The detected animal groups averaged 9.12 ±0.41 m, 5.64 ± 1.14 m, 6.23 ± 0.90 m, 4.68 ± 0.86 m to the path of the vehicle for deer, canids, wild pigs, and small mammals, respectively.

3.3 Detection Probability

Our dataset used for analyses consisted of 180 unique encounters with deer (i.e., groups or individuals). Four of the five variables within our top-ranking model (distance to path of vehicle, vegetative cover, elevation relative to the road, and elevation^2) were present in all models ΔAICc <2, whereas headlight intensity was present in 11 of the 14 top models (Table 3.2). We found that detection probability decreased as a deer's distance to the path of the vehicle increased (β = -0.25, 85% CI= -0.33, -0.18; Table 3.2; Figure 3.2), when deer were at lower and higher elevations relative to the road ($\beta_{Elevation^{\wedge}2}$= -0.54, 85% $CI_{Elevation^{\wedge}2}$= -0.81, -0.30; Table 3.2), and when deer were in vegetative cover (β = -1.97, 85% CI= -2.72, -1.26; Table 3.2; Figure 3.2). Detection probability increased with the use of high-beam headlights (β = 0.79, 85% CI= 0.18, 1.44; Table 3.2; Figure 3.2). When holding a deer's distance to the path of the vehicle at its mean (11.33 m), vegetation class at "unobstructed", and elevation relative to the road at 0 m, the probability of detecting a deer at some point during an encounter was 0.77 (85% CI= 0.67, 0.84) for low-beam headlights and 0.88 (95% CI= 0.81, 0.93) for high-beam headlights.

Regardless of headlight intensity, the proportion of encountered deer and canids that were detected were similar, but the proportion of encountered wild pigs and small mammals that were detected appeared lower than deer and canids (Table 3.3). For non-deer animal groups, we found no clear trend of detection probability across headlight intensity (Table 3.3).

3.4 Detection Distance

Our dataset used for analyses consisted of 105 unique driver detections of deer. The three variables within our top-ranking model (headlight intensity, deer movement, time into trial) were present in all models ΔAICc <2 (Table 3.4). According to the top model fitted with REML, detection distances of deer increased by 20.99 m when drivers used high-beam headlights (85% CI = 8.04, 34.16; Figure 3.3) and by 23.36 m when the deer was moving at detection (85% CI= 9.45, 36.69; Figure 3.3). Over the course of a trial, detection distances decreased by 0.71 m for every minute the trial progressed (85% CI= -1.04, -0.39; Figure 3.3).

Detection distances of canids were similar to deer, but detection distances of wild pigs and small mammals were approximately 50% of that for deer (Table 3.3; Figure 3.4). Across all non-deer groups, there was a trend of increased detection distances when using high-beam headlights (Table 3.3), although sample sizes were too low to conduct robust statistical tests.

3.5 Dangerous Encounter Probability

Our dataset used for analyses consisted of 40 unique encounters with deer within 6.5 m from the path of the vehicle. Two of the three variables within our top-ranking model (vehicle speed and time into the trial) were present in all models ΔAICc <2, whereas distance to the path of the vehicle was present in three of the five top models (Table 3.5). The probability of an encounter with a deer being dangerous increased with vehicle speed (β = 0.11, 85% CI= 0.05, 0.20; Table 3.5; Figure 3.5), time into trial (β = 0.06, 85% CI= 0.02, 0.09; Table 3.5; Figure 3.5), and as a deer's distance to the path of the vehicle increased (β=0.46, 85% CI= 0.05, 0.93; Table 3.5). When holding time into the trial and a deer's distance to the path of the vehicle at their means (30.67 min and 4.67 m, respectively), the probability of an encountered deer within 6.5 m of the path of the vehicle being dangerous was 0.26 (85% CI= 0.14, 0.44) when driving at 72 km/h and 0.72 (85% CI= 0.51, 0.86) when driving at 89 km/h (Figure 3.5).

We had no encounters with canids within 6.5 m of the path of the vehicle when drivers used high-beam headlights. When driving with low-beam headlights, three of five encounters with canids were dangerous (Table 3.3). Regardless of headlight intensity, all 19 encounters with wild pigs were dangerous (Table 3.3). Similarly, 20 of 21 encounters with small mammals were dangerous (Table 3.3).

4. Discussion

4.1 Detection Probability

Nighttime driver detection of wildlife is a complex process that is impacted by multiple driver, animal, and environmental related factors. We found that detection probability decreased as a deer's distance to the path of the vehicle increased, when deer were at lower and higher elevations relative to the road, when deer were obstructed by vegetation, and when using low-beam headlights as opposed to high-beam headlights. Mastro et al. (2010) similarly found that white-tailed deer decoys located 20 m from the road were detected less often than decoys at 0 and 10 m from the road, an effect likely explained by the driver's gaze generally being aligned with the vehicle's path of travel. Directionality of the driver's gaze also likely contributed to our finding of higher detectability of deer at road level, as opposed to lower and higher elevations relative to the road (Green, 2002, Olson et al., 1989). Likewise, the effect of obstruction by vegetation decreasing detection probability was unsurprising, given that partially concealed deer also were less likely to be detected during roadside deer counts (Sage et al., 1983).

Although the location of deer relative to the path of the vehicle, elevation relative to the road, and obstruction by vegetation are beyond the control of the driver, drivers can easily switch between low- and high-beam headlights. We found that use of high-beam headlights increased the probability of a driver detecting deer, an effect similar to that observed for driver detection of pedestrians at night (Wood et al., 2005).

As for driver detection of animals other than deer, canids were detected at similar frequencies during encounters above the animal group-specific minimum approach thresholds (deer: 58.3%; canids: 63.6%; Table 3.3), whereas wild pigs and small mammals were detected less than half as often as deer (wild pigs: 24.4%; small mammals: 35.5%; Table 3.3). Although the reasons some animal groups were detected more readily than others are not completely understood, we suspect eyeshine, stature, and pelage color likely influenced the ability of drivers to detect various species in our study (Hobday, 2010, Mastro et al., 2010, Rodgers and Robins, 2006).

4.2 Detection Distance

Under conditions similar to the decoy studies (animal movement = “no”; time into trial = 5 min), our top ranking model predicted that drivers would detect free-ranging wild deer at 71.73 m (85% CI= 57.30, 86.16) when using low-beam headlights, which was greater than that reported for low-beam detection of deer decoys (41 m; Mastro et al., 2010) and Tasmanian fauna decoys (24.9-46.4 m; Hobday, 2010) and similar to what was observed for moose decoys (74 m; Rodgers and Robins, 2006). Under the same conditions, our top ranking model predicted that when using high-beam headlights, drivers would detect free-ranging deer at 92.72 m (85% CI = 78.21, 107.23), which was greater than high-beam detection of deer decoys (73 m; Mastro et al., 2010), similar to Tasmanian fauna (60.8-115.9; Hobday, 2010), and less than that reported for moose decoys (137 m; Rodgers and Robins, 2006). Drivers possibly detected free-ranging deer in our study more readily than previously found with deer decoys (Mastro et al., 2010) due to wild deer possessing eyeshine. To this point, drivers in our study occasionally commented that eyeshine first alerted them to the presence of deer, but this aspect of detection did not appear to offset the larger size of moose decoys.

Contrary to Mastro et al. (2010), who manually moved deer decoys, we found that moving wild deer were detected at longer distances than stationary deer. Although this difference could be attributed to artificial movement of decoys not perfectly mimicking wild deer movement, the presence of eyeshine in wild deer could also play a role. As mentioned earlier, drivers in this study often reported that they detected eyeshine before they saw the body of the deer. The movement of a reflective object (i.e., eyeshine) might be the first indication to the driver that there is an animal near the road rather than a benign roadside object like a reflector post.

We found a substantial decrease in detection distances with time into the trial, which we attribute to increasing driver fatigue as the trials progressed (Ting et al., 2008). Driver fatigue can occur with increased time spent on a single task, along with passive fatigue of monotonous driving which often occurs with little vehicular traffic (May, 2011). Additionally, Thiffault and Bergeron (2003) found that driving fatigue peaked 20-25 min into a simulated drive. Our trials took place with few other vehicles on the road and took ~60 min to complete. Alternatively, given that drivers in our study were aware of the study goals, the decreasing detection distances we observed as our trials progressed could have resulted from drivers being artificially alert to the presence of roadside animals earlier in the trial, which likely waned as the drivers became more relaxed later in the drives. This potential explanation for the decrease in detection distance of 0.71 m for every min the trial progressed (Figure 3.3) is concerning because it suggests that under normal conditions, real-world driver detection distances of deer are closer to the lower values we observed (i.e., the right side of Figure 3.3) and thus more dangerous than the mean values would indicate.

Deer and canids were detected at similar distances, whereas small mammals and wild pigs were detected at much shorter distances (Table 3.3; Figure 3.4). Like our findings for detection probability, the short detection distances of wild pigs likely reflected their lack of eyeshine (Ollivier et al., 2004), short stature (shoulder height <0.8m; Mayer et al., 2020), and the generally brown to black pelage color of the local wild pig population (pers. obs.). Detection distances of small mammals in our study were much shorter than detection distances of similarly sized Tasmanian fauna (Hobday, 2010), which is likely due to drivers in the Tasmanian study being more aware due to driving a shorter route (0.6 km) at slower speeds (10-15 km/h) compared to our study (75 km at generally 72-89 km/h).

4.3 Dangerous Encounter Probability

The probability of a dangerous encounter increased with vehicle speed, time into the trial, and with a deer's distance to the path of the vehicle. At faster speeds the minimum braking distance increases, which generally means detection distances must also increase for an encounter to be safe. However, we did not find a major effect of vehicle speed on detection distance (see above), suggesting that at higher speeds, drivers likely cannot compensate for the longer detection distances needed to avoid a dangerous encounter. Surprisingly, the use of high-beam headlights did not decrease the probability of a dangerous encounter. Thus, while high-beam headlights did increase detection distances by 20.99 m (Figure 3.3), this increase likely did not suffice to offset the influence of the minimum braking distance required to avoid dangerous encounters at the speeds traveled by our drivers. Our observed increase in dangerous encounter probability as time into the trial increased was, again, likely due to driver fatigue or drivers being overly alert to the potential of encountering roadside animals at the start of each trial. As discussed previously, detection distances decreased as time into the trial increased (Figure 3.3), and thus as the trial progressed, more detections occurred after the minimum braking distance was passed. Perhaps counterintuitively, we found that the probability of a dangerous encounter with a deer within 6.5 m of the path of the vehicle increased as a deer’s distance to the path of the vehicle increased. This was likely due to a decrease in detection probability as a deer’s distance to the path of the vehicle increased (Table 3.2, Figure 3.2).

Most encounters with canids while using low-beam headlights were dangerous. Additionally, every encounter with wild pigs and all but one encounter with small mammals was dangerous. The high rate of dangerous encounters for wild pigs and small mammals was likely due to the relatively short detection distances observed for those groups (Table 3.3; Figure 3.4). As such, our results suggest that drivers generally do not have enough time to brake to avoid a collision when wild pigs and small mammals move into the roadway at the speeds driven during our study.

4.4 Implications of Ineffective Driver Detection

The results of this study have broad implications, as it is the first study to characterize factors that impact driver detection of free-ranging wildlife, building upon previous decoy-detection studies to encompass more realistic driving scenarios. As such, we provide an explanation of why WVCs are so common. For example, the 2.6 million deer-vehicle collisions that are estimated to occur annually in the USA (Conover, 2019) is unsurprising when viewed in light of our finding of a relatively high probability of a dangerous encounter with deer located near the roadway (Figure 3.5). Vehicle collisions with deer are an increasing concern for motorists (Hill et al., 2020, Sullivan, 2011), causing \$6,617 (2007 US\$) in damage per collision on average (Huijser et al., 2009). Our study suggests that maladaptive behavior of deer in response to approaching vehicles (Blackwell et al., 2014, DeVault et al., 2020, Lima et al., 2015) is not the only cause of collisions; ineffective driver detection also likely plays a major role (Regan and Hallett, 2011, Rumar, 1990).

Our finding of 100% dangerous encounter probability for wild pigs was due to the inability of drivers to detect pigs with enough time to brake to avoid a collision. Wild pigs continue to increase in both population size and range (Lewis et al., 2019, Mayer and Beasley, 2018), which will likely lead to increased human injury, fatalities, and overall economic impacts due to collisions with this species (Strickland et al., 2020). We likewise found that drivers cannot detect most small mammals at safe distances. Although collisions with small mammals pose a relatively minor risk to drivers directly, late detections of these animals could lead to drivers swerving and subsequent injury, as Conn et al. (2004) observed for large mammals. Additionally, small mammals can comprise the majority of mammalian mortality on some roads (Smith-Patten and Patten, 2008) but are often undercounted in surveys due to their short persistence times (Santos et al., 2011, Teixeira et al., 2013). Our study suggests that ineffective driver detection likely contributes greatly to the large number of small mammals killed by vehicle collisions, which can create additional hazards for drivers by attracting larger scavengers to roads (DeVault et al., 2014).

The effect of roadside vegetation on driver detection of deer has implications for roadside habitat management. We found that deer located within roadside vegetation were detected less often than unobstructed deer. Although previous research has found that vegetation clearing can lead to a reduction in large ungulate collisions (Lavsund and Sandegren, 1991, Meisingset et al., 2014), some studies highlight that increased vegetation removal may lead to increased roadside usage by wildlife, potentially counteracting any benefits of increased driver visibility (Milton et al., 2015, Rea, 2003). Further research is needed to fully address how roadside vegetation impacts a driver's ability to detect wildlife and the effect of mowing on the likelihood of a collision.

4.5 Headlights and Future Research

According to the Insurance Institute for Highway Safety (IIHS), only one in three headlight systems tested for 2022 vehicles received a "good" rating (IIHS, 2022). Furthermore, vehicles with headlights rated as "good" by the IIHS had 14.5% fewer nighttime animal-vehicle collisions than vehicles with headlights rated as "poor" (Brumbelow, 2022). Given that most new vehicles are equipped with poorly rated headlights, it is especially critical for future research to investigate how headlight characteristics influence driver detection of wildlife at night to help guide development of headlight technology. For example, the IIHS listed our study vehicle's average useful illumination distance for low-beam headlights at 45.5 m to the right edge of the roadway. However, drivers in our study generally detected deer and canids at distances greater than this value (Table 3.3), suggesting that the IIHS's definition of minimum useful illumination may not directly translate to wildlife detection distances, potentially due to the presence of eyeshine in some species. Furthermore, wild pigs lack eyeshine and were detected at an average distance of 22.98 m when drivers used low-beam headlights (Table 3.3), which is half the IIHS's listed useful illumination distance. Additional research is needed to tease apart the interaction between increased road illumination by headlights and the role of eyeshine and other animal characteristics on driver detection distance.

5. Conclusion

Understanding the most influential factors that impact driver detection of wildlife at night can direct management of roadside habitat, inform recommendations for headlight usage, influence posting of speed limits, and provide valuable information for assessing future wildlife-vehicle collision mitigation methods. We identified several factors that influence driver detection of wildlife at night including driver behavior (vehicle speed, time into the trial, and headlight intensity), animal behavior (movement), and roadside habitat (vegetation, elevation relative to the road).

Results of this study indicate that drivers can increase their chances of detecting wildlife at safe distances by using high-beam headlights, limiting the amount of time driving at night, and reducing their speed. Additionally, drivers should be aware that their attention to potential road hazards like wildlife will likely decrease with driving duration. Future research should further investigate the role of driver fatigue and headlight characteristics on driver detection of wildlife. Furthermore, combining our findings with studies investigating wildlife responses to vehicles (e.g., Blackwell et al., 2014, Lima et al., 2015, Pfeiffer et al., 2020) could provide a more comprehensive understanding of the risk of WVCs and aid in the development of onboard mitigation methods designed to elicit movement of wildlife away from the road at safe distances (DeVault et al., 2020).

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Table 3.1. Variables evaluated for driver detection of white-tailed deer (*Odocoileus virginianus*). All variables were included in global models for detection probability, detection distance, and dangerous encounter probability except Elevation and Vegetation Class, which were included in the first two analyses only.

Variable	Definition
Headlight	The headlight intensity (low-beam or high-beam) used during the encounter.
Speed (km/h)	The vehicle's speed at the moment of detection or when the researcher notified the driver of the presence of an animal. For non-detections, the vehicle's speed when the animal left the field of view of the forward-looking infrared camera (FLIR).
Location	The side of the path of the vehicle (left or right) where the animal was located at the moment of detection or when the researcher notified the driver of the presence of an animal. For non-detections, the side of the path of the vehicle when the animal left the FLIR's field of view.
Dist. to Path (m)	The animal's distance to the path of the vehicle at the moment of detection or when the researcher notified the driver of the presence of an animal. For non-detections, the average of the animal's distance to the path of the vehicle at the animal group-specific minimum approach distance and when the animal left the FLIR's field of view.
Elevation (m)*	The animal's elevation relative to the to the road's surface at the moment of detection or when the researcher notified the driver of the presence of an animal. For non-detections, the average of the animal's elevation relative to the road at the animal group-specific minimum approach distance and when the animal left the FLIR's field of view. * The quadratic term (Elevation^2) was also considered for the first two analyses.
Moon Illumination	The percentage of the moon that was illuminated at the time of the encounter.
Age (y)	The driver's age on the night of the drive.
Time into Trial (min)	The number of minutes from the start of the trial when the encounter occurred.

Trial Start Time (h)	The number of hours from the previous midnight when the trial started.
Movement	A binary of whether the animal was moving at the moment of detection or when the researcher notified the driver of the presence of an animal. For non-detections, a binary of whether the animal moved within the animal group-specific minimum approach distance. Movement was defined as locomotion or full body turning.
Group Size	The number of individuals within a group of animals. The maximum inter-individual distance defining a group was approximately the vehicle's minimum approach distance. Individuals that entered cover during the approach were excluded from this value. This variable was scored into three categories: 1, 2, or ≥3 individuals. This value includes all individuals on the landscape regardless of distance to the path of the vehicle cutoff values.
Corrective Lenses	A binary of whether the driver wore some form of corrective lenses during the drive or previously had laser vision correction surgery.
Vegetation Class	A binary of whether the animal was unobstructed or obstructed by the vegetation at the moment of detection or when the researcher notified the driver of the presence of an animal. For non-detections, a binary of whether the animal was unobstructed or obstructed by the vegetation at the animal group-specific minimum approach distance. For non-detections, if the animal moved between vegetation classes within the minimum approach distance, the most concealing vegetation class was used.

Table 3.2. The top models (ΔAICc <2) for the probability of driver detection of an encountered deer within 21.5 m of the path of the vehicle. df= degrees of freedom; loglik= log-likelihood; AICc= Akaike information criterion corrected for small sample sizes; weight = model's Akaike weight recalculated among top models. Elevation was defined as the deer's elevation relative to the road. Variables not included in any top model and not shown below: Moon Illumination, Speed, Group Size, Distance to the Path of the Vehicle:Location, Headlight:Speed, and Trial Start Time:Time into Trial.

Intercept	Age (y)	Corrective Lenses (Yes)	Dist to Path (m)	Headlight (High)	Location (Right)	Movement (Yes)	Elevation (m)	Elevation^2	Trial Start Time (h)	Time into Trial (min)	Veg Class (Obstructed)	df	logLik	AICc	delta	weight
4.02			-0.25	0.79			0.41	-0.54			-1.97	7	-71.26	157.18	0.00	0.14
4.55			-0.27	0.80	-0.58		0.43	-0.54			-1.85	8	-70.48	157.81	0.63	0.10
4.44			-0.25	0.76			0.46	-0.57		-0.01	-2.01	8	-70.69	158.22	1.04	0.08
4.26		-0.41	-0.25	0.79			0.41	-0.54			-2.02	8	-70.79	158.43	1.25	0.07
4.21			-0.24				0.40	-0.56			-1.93	6	-72.99	158.46	1.28	0.07
-1.33			-0.26	0.90			0.44	-0.54	0.27		-2.20	8	-70.83	158.50	1.32	0.07
4.67	-0.02		-0.25	0.79			0.40	-0.56			-2.06	8	-70.84	158.52	1.34	0.07
4.89		-0.54	-0.26	0.75			0.48	-0.59		-0.01	-2.10	9	-69.92	158.90	1.72	0.06
4.73			-0.26		-0.58		0.42	-0.57			-1.81	7	-72.18	159.02	1.84	0.06
4.80		-0.43	-0.27	0.79	-0.59		0.44	-0.55			-1.90	9	-69.98	159.02	1.84	0.06
5.28	-0.02		-0.27	0.79	-0.61		0.42	-0.56			-1.95	9	-69.99	159.03	1.85	0.06
3.86			-0.24	0.79		0.26	0.41	-0.53			-1.98	8	-71.11	159.05	1.87	0.05
4.67			-0.24				0.45	-0.60		-0.01	-1.96	7	-72.25	159.16	1.97	0.05
-0.82			-0.28	0.90	-0.58		0.46	-0.54	0.27		-2.08	9	-70.05	159.16	1.98	0.05

Table 3.3. Proportions of encounters that were detected, mean (± SE) detection distance (m) of detected encounters, and the proportion of encounters with an animal within 6.5 m of the path of the vehicle that were dangerous. Note that the deer group represents summary data and is not from model outputs.

Animal Group	Headlight Intensity	Detected Encounters	Detection Distance (m)	Dangerous Encounters
Deer				
	Low Beam	54/101 (53.47%)	66.10 ± 6.41	13/27 (48.15%)
	High Beam	51/79 (64.56%)	90.50 ± 7.69	5/13 (38.46%)
	Total	105/180 (58.33%)	77.95 ± 5.10	18/40 (45.00%)
Canid				
	Low Beam	5/6 (83.33%)	66.67 ± 15.05	3/5 (60.00%)
	High Beam	2/5 (40.00%)	86.42 ± 61.99	0/0 (0.00%)
	Total	7/11 (63.63%)	72.32 ± 17.44	3/5 (60.00%)
Wild Pig				
	Low Beam	5/25 (20.00%)	22.98 ± 5.50	11/11 (100%)
	High Beam	6/20 (30.00%)	36.63 ± 9.25	8/8 (100%)
	Total	11/45 (24.44%)	30.42 ± 5.78	19/19 (100%)
Small Mammal				
	Low Beam	6/14 (42.86%)	34.89 ± 6.15	10/10 (100%)
	High Beam	5/17 (29.41%)	47.44 ± 14.00	10/11 (90.90%)
	Total	11/31 (35.48%)	40.59 ± 7.06	20/21 (95.24%)

Table 3.4. The top models (ΔAICc <2) for driver detection distance of detected deer within 21.5 m of the path of the vehicle. df= degrees of freedom; loglik= log-likelihood; AICc= Akaike Information Criterion corrected for small sample sizes; weight = model's Akaike weight recalculated among top models. Elevation was defined as the deer's elevation relative to the road. Variables not included in any top model and not shown below: Location, Moon Illumination, Group Size, Vegetation Class, Distance to the Path of the Vehicle:Location.

Intercept	Age (y)	Corrective Lenses (Yes)	Dist to Path (m)	Headlight (High)	Movement (Yes)	Elevation (m)	Elevation^2	Speed (km/h)	Trial Start Time (h)	Time into Trial (min)	Headlight: Speed	Trial Start Time : Time into Trial	df	logLik	AICc	delta	weight
75.42				21.07	23.16					-0.71			6	-553.52	1119.90	0.00	0.16
82.07				20.27	22.45	1.74	-11.55			-0.80			8	-551.39	1120.28	0.38	0.13
125.44				21.19	23.22			-0.62		-0.72			7	-552.67	1120.49	0.58	0.12
72.81				127.67	24.63			0.04		-0.74	-1.34		8	-551.64	1120.79	0.88	0.10
82.40		-12.00		20.73	22.70					-0.74			7	-553.03	1121.21	1.31	0.08
83.95			-0.91	21.83	21.98					-0.71			7	-553.18	1121.51	1.61	0.07
403.01				16.27	22.34	-1.08	-13.71		-15.84	-11.23		0.52	10	-549.61	1121.55	1.65	0.07
63.82				134.31	24.07	2.70	-10.96	0.23		-0.82	-1.43		10	-549.63	1121.60	1.69	0.07
90.68	-0.50			20.69	23.46					-0.70			7	-553.22	1121.60	1.70	0.07
120.51				20.44	22.51	1.64	-10.68	-0.49		-0.80			9	-550.86	1121.61	1.71	0.07
89.59		-12.98		19.90	22.03	2.55	-11.41			-0.82			9	-550.86	1121.62	1.72	0.07

Table 3.5. The top models (ΔAICc <2) for the probability that an encounter with a deer within 6.5 m of the path of the vehicle was dangerous. An encounter was deemed dangerous if (1) the driver did not detect the deer, (2) the driver was notified to brake by the researcher, or (3) the detection distance was less than the minimum braking distance. df= degrees of freedom; loglik= log-likelihood; AICc= Akaike Information Criterion corrected for small sample sizes; weight = model's Akaike weight recalculated among top models. Elevation, Elevation^2, and Vegetation Class were not evaluated due to minimal variation. Variables not included in any top model and not shown below: Age, Headlight, Moon Illumination, Movement, Group Size, Distance to the Path of the Vehicle:Location, Headlight:Speed, and Trial Start Time:Time into Trial.

Intercept	Corrective Lenses (Yes)	Dist to Path (m)	Location (Right)	Speed (km/h)	Trial Start Time (h)	Time into Trial (min)	df	logLik	AICc	delta	weight
-13.15		0.46		0.11		0.06	5	-18.49	48.75	0.00	0.28
-9.78				0.10		0.05	4	-19.81	48.76	0.01	0.28
-13.86		0.66	-1.58	0.12		0.07	6	-17.58	49.70	0.95	0.18
-15.63	-1.08	0.63		0.14		0.07	6	-17.88	50.31	1.56	0.13
-19.79				0.10	0.51	0.05	5	-19.30	50.36	1.61	0.13

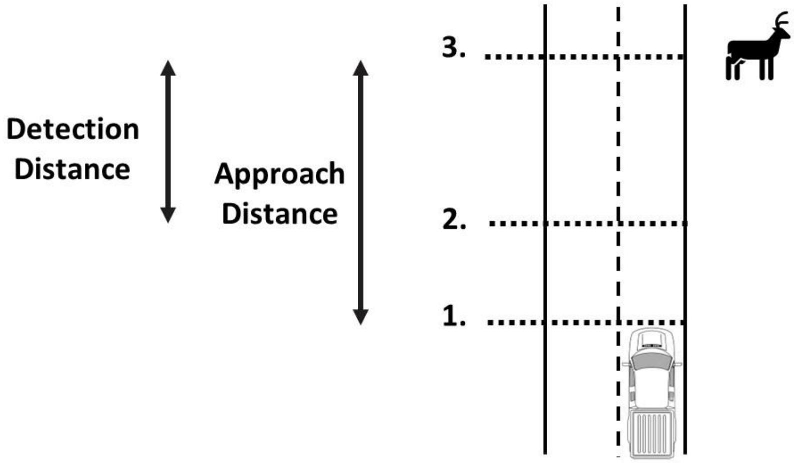

Figure 3.1. Schematic of field methods. A GPS point was taken at the following locations: (1) forward-looking infrared camera detection of an animal (Approach Distance), (2) driver detection of animal (Detection Distance), and (3) point on the road perpendicular to the initial location of the animal.

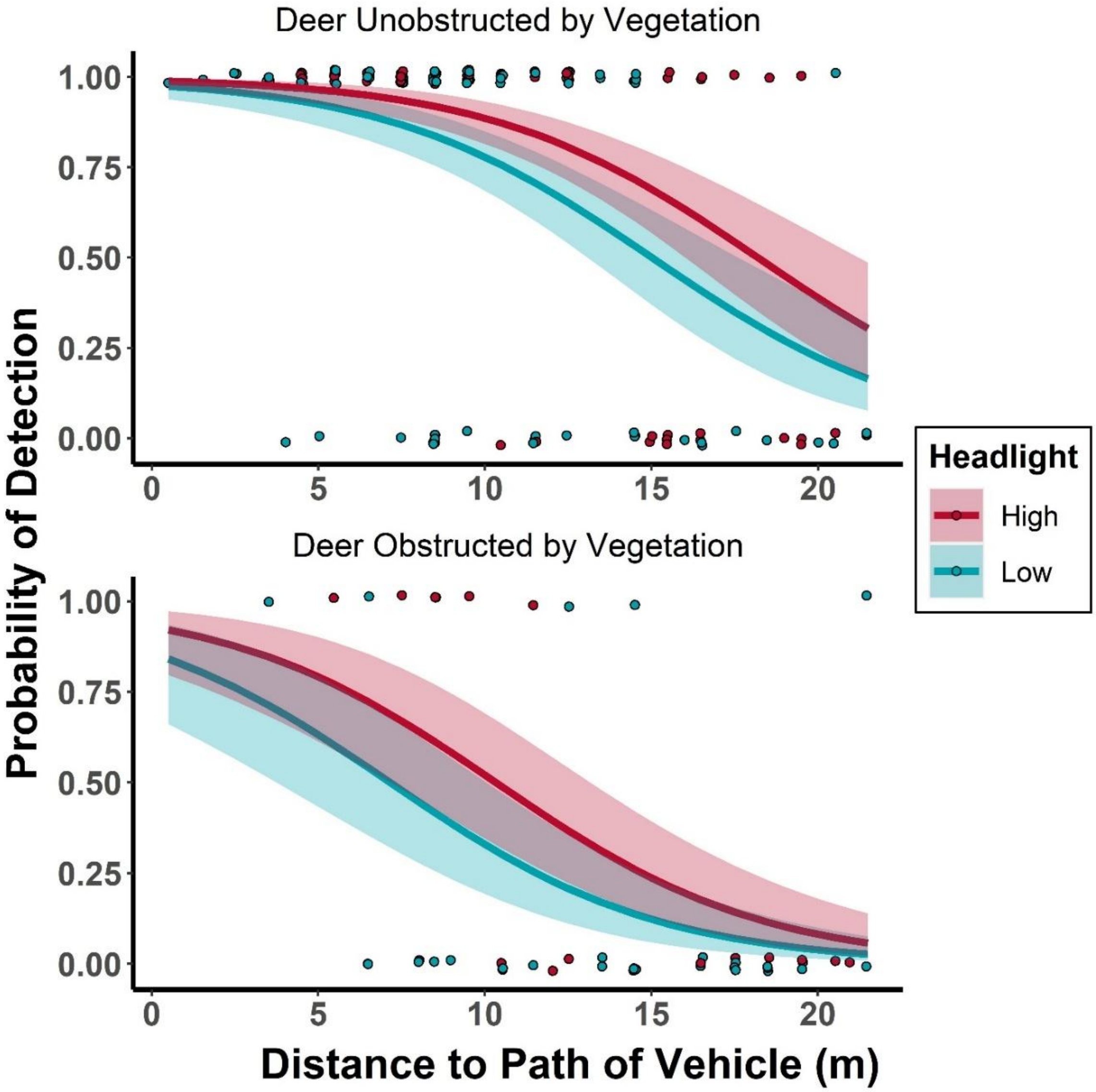

Figure 3.2. Probability that a driver detected a deer within 21.5 m of the path of the vehicle by the vegetation within which the deer was located, the deer's perpendicular distance to the path of the vehicle (m), and headlight intensity (high-beam and low-beam). Data points are raw data. The trendlines and 85% confidence intervals are from the top model when deer elevation relative to the road was held constant at 0 m.

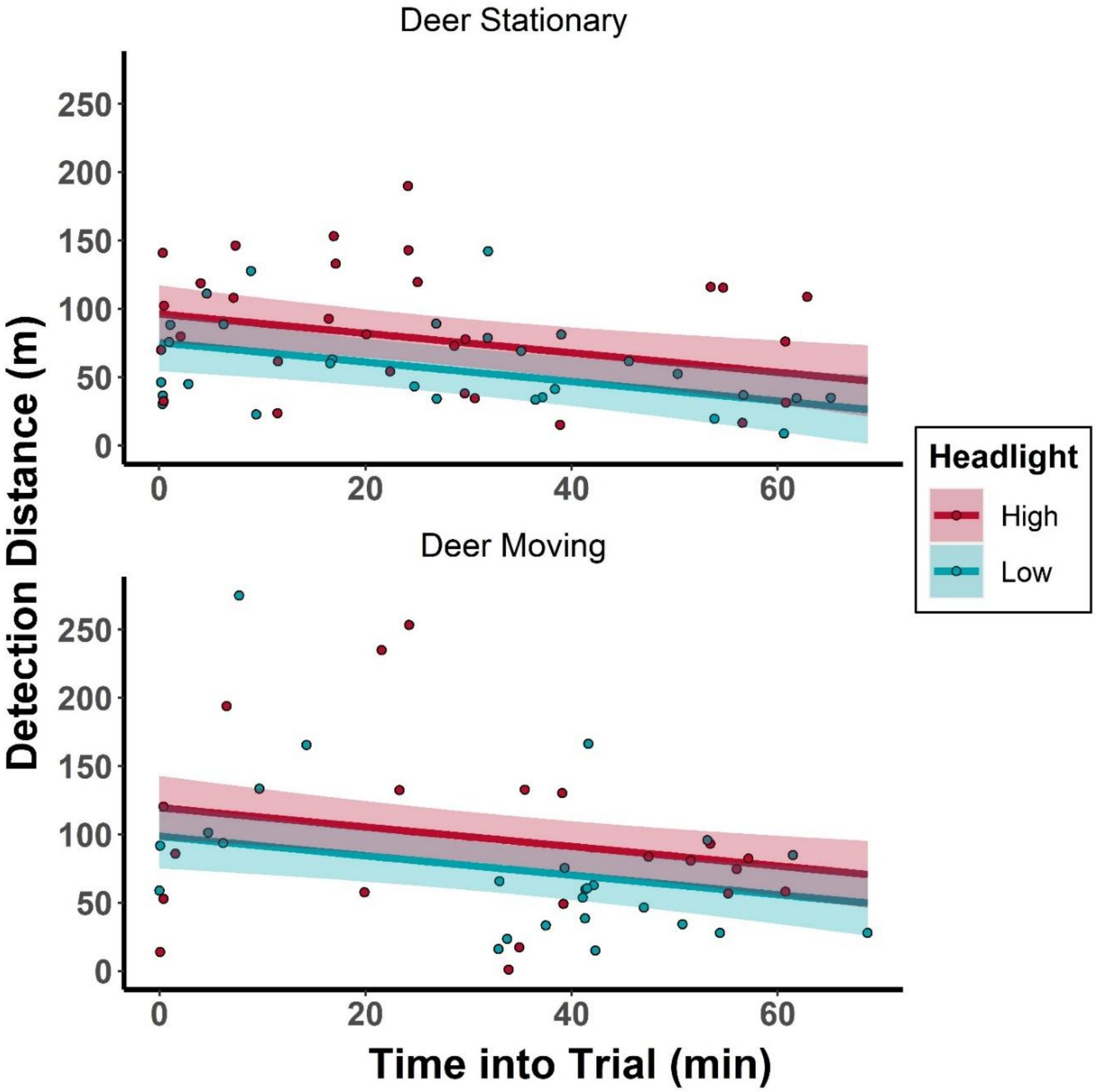

Figure 3.3. Driver detection distance of deer within 21.5 m of the path of the vehicle by deer movement, time into the trial (min) and headlight intensity (high-beam and low-beam). Data points are raw data. Trendlines and 85% confidence intervals are from the top model.

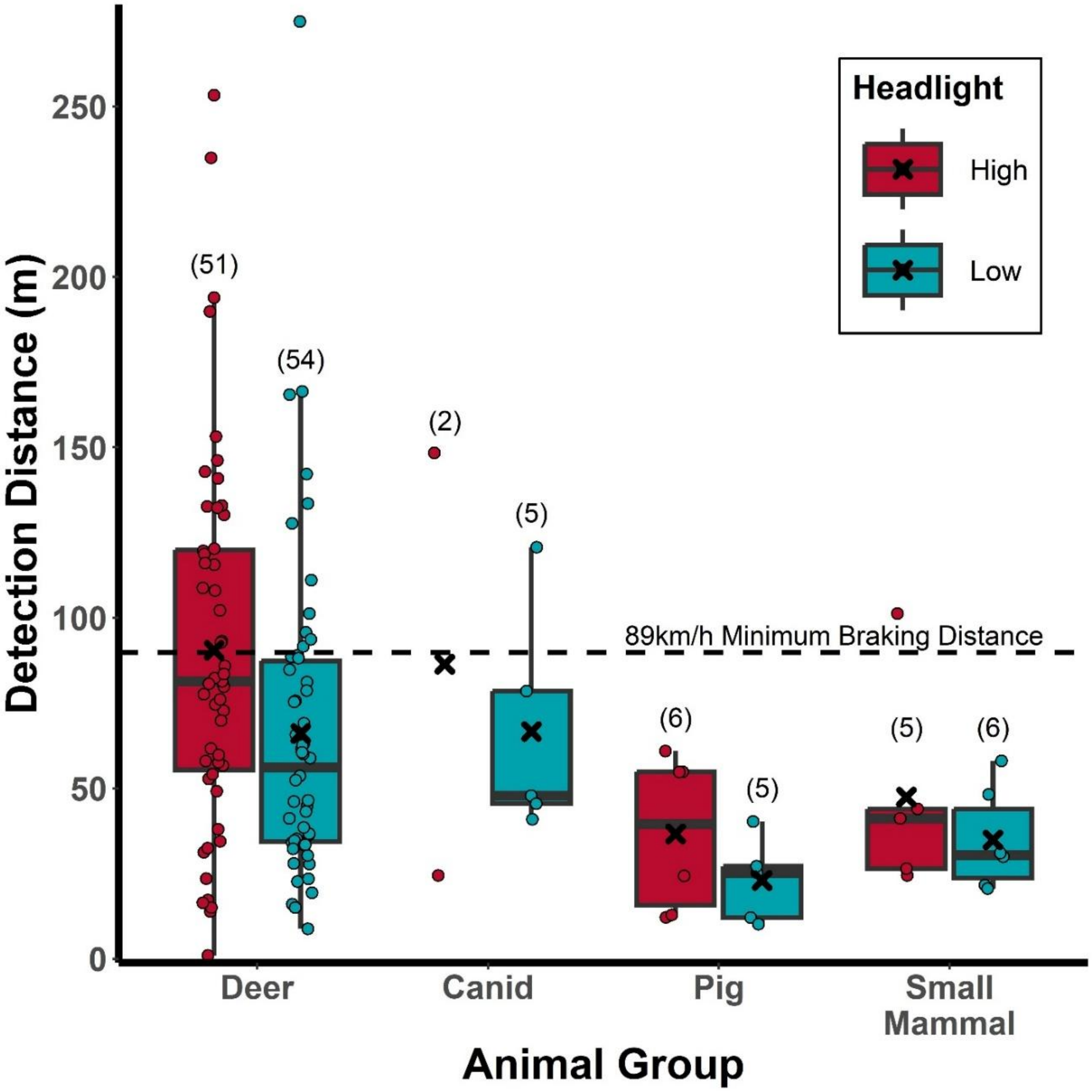

Figure 3.4. Detection distance (m) by animal group and headlight intensity. Boxplots show the median detection distance (bar), quartiles (0.25, 0.75), and whiskers show the furthest point from the median not exceeding 1.5 times the interquartile range. An "X" denotes the mean value. The number in parentheses denotes sample size. Note that the 89 km/h minimum braking distance line is shown for reference; not all encounters occurred at that speed.

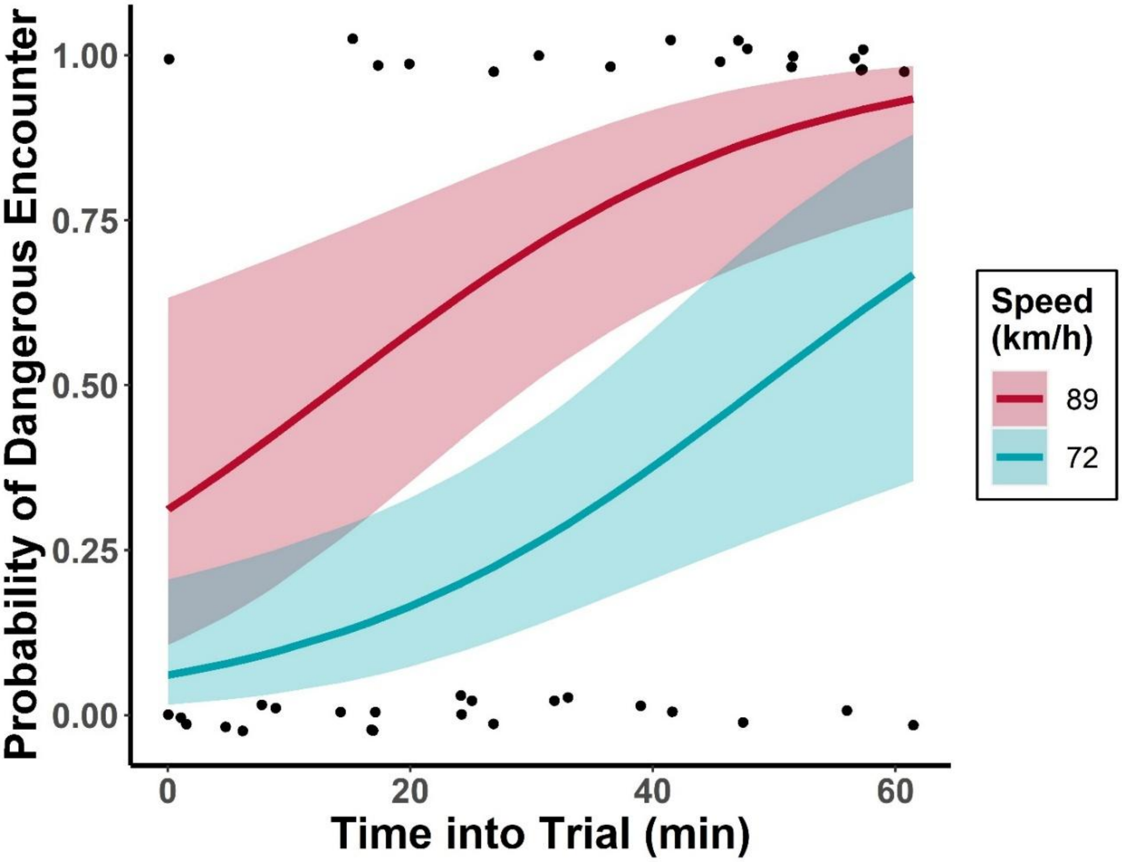

Figure 3.5. Probability that an encounter with a deer within 6.5m of the path of the vehicle was dangerous by vehicle speed (km/h) and time into the trial (min). Speeds of 72 and 89 km/h (45 and 55 mph, respectively) represent the speed limits throughout the study's driving route. An encounter was deemed dangerous if (1) the driver did not detect the deer, (2) the driver was notified to brake by the researcher, or (3) the detection distance was less than the minimum braking distance. Data points are raw data. Trendlines and 85% confidence intervals are from the top model when deer distance to the path of the vehicle was held at its mean value (4.67 m).

CHAPTER 4

CAUGHT IN HEADLIGHTS: CAPTIVE WHITE-TAILED DEER RESPONSES TO VARIATIONS IN VEHICLE LIGHTING DURING IMMINENT COLLISION SCENARIOS[1]

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[1] Pakula, C. J., D'Angelo, G. J., Mowrer, A., Rhodes Jr, O. E., & DeVault, T. L. (2025). *Applied Animal Behaviour Science*, 106652. https://doi.org/10.1016/j.applanim.2025.106652. Reprinted here with permission of the publisher.

Abstract

Vehicle collisions with deer (*Odocoileus* spp.) cause billions of dollars in damages and injure thousands of drivers every year in the United States, and few mitigation methods have proven effective. However, recent research suggests that vehicle lighting might influence white-tailed deer (*Odocoileus virginianus*; hereafter, deer) responses to oncoming vehicles. Most new vehicles are manufactured with light emitting diode (LED) headlights which differ in total radiance and wavelength of light emitted compared to the previous industry standard of tungsten-halogen (halogen) headlights. Also, frontal vehicle illumination through rear-facing lighting has shown promise in enhancing deer responses to vehicles, but its effectiveness has not been tested under various headlight conditions (headlight type or intensity). As such, it remains unclear how these aspects of vehicle lighting affect deer responses to an approaching vehicle. We used 23 captive, wild-type deer to investigate how variations in vehicle lighting affect deer responses to an approaching vehicle at night, when most collisions occur. We released deer into a 95m long, 3m wide chute and approached them from the opposite end with an electric golf cart outfitted with two versions of stock 2017-2020 Ford Fusion headlights (LED and halogen) and a 51cm rear-facing lightbar to test how vehicle lighting affected deer avoidance behaviors in an imminent, head-on collision scenario. Each deer received eight lighting treatments consisting of unique combinations of headlight type (LED vs. halogen), light intensity (low vs. high beam), and rear-facing lighting (lightbar off vs. on). We measured deer alert and flight behavior using infrared videography. We found that the halogen, high beam, lightbar off treatment had the greatest probability of evoking an alert response. Furthermore, when the lightbar was off, high beams appeared to

increase alert probability for halogen headlights. Also, we found evidence that high beam, halogen headlights tend to increase alert probability over high beam, LED headlights. We found no effect of our lighting treatments on deer alert distance, flight probability, or flight initiation distance. Across all behavioral responses, the random effect deer ID explained 0.86-9.19× more variation than our lighting treatments, reflecting large differences in responses among deer. Overall, we found that vehicle lighting can impact deer behavior during an imminent, head-on collision scenario, although lighting was ineffective at increasing favorable flight behaviors. Future research should investigate how vehicle lighting treatments affect free-ranging, wild deer in a variety of real-world scenarios and at longer approach distances.

1. Introduction

Wildlife-vehicle collisions are common throughout the world and cause significant damage to wildlife populations and injuries to humans annually (Seiler and Helldin, 2006). In the United States, deer within the *Odocoileus* genus (henceforth, deer) cause most collisions that result in property damage and human injury (Huijser et al., 2009) and the number of collisions has increased over recent decades (Sullivan, 2011). Further, deer-vehicle collisions (DVCs) cause $8.4 billion (in 2008 USD) in economic losses (Huijser et al., 2008) and are responsible for >58,000 human injuries and 440 human deaths annually in the U.S. (Conover, 2019). Most DVCs occur under low-light conditions due to multiple factors including poor nighttime driver detection ability (Pakula et al., 2023), the crepuscular nature of deer activity and peak traffic levels (Cunningham et al., 2022), and maladaptive deer responses to approaching vehicles (Blackwell et al., 2014; DeVault et al., 2020; Pfeiffer et al., 2020).

Due to the ubiquity of deer-vehicle collisions and their impacts, many studies have investigated the effectiveness of commercially available mitigation methods (e.g., Romin and Dalton, 1992) and experimental mitigation methods (e.g., Blackwell and Seamans, 2009; DeVault et al., 2020). Although many commercial methods like roadside reflectors and deer whistles are ineffective at reducing the risk of DVCs (Benten et al., 2019; Benten et al., 2018; D'Angelo et al., 2006; Romin and Dalton, 1992; Valitzski et al., 2009), modified onboard lighting methods have shown promising results (Blackwell and Seamans, 2009; DeVault et al., 2020). Specifically, DeVault et al. (2020) found that increased frontal vehicle illumination via a rear-facing lightbar reduced deer freezing behavior and decreased dangerous encounters. They suggested that this effect was potentially due to more complete vehicle illumination resulting in a more reliable looming stimulus under dark conditions. However, DeVault et al. (2020) conducted their study at one site using only one headlight type; therefore, the effectiveness of rear-facing vehicle illumination at multiple independent field sites and in conjunction with other headlight characteristics (e.g., headlight type and intensity) remains unexplored.

Despite many studies focusing on deer behavior and DVC mitigation methods, no investigators have directly tested the effect of different commercially available types of headlights on deer behavior (but see Blackwell and Seamans, 2009 for the effects of an auxiliary Xenarc high intensity discharge lamp on deer behavior). The two most common types of headlights today are tungsten-halogen (hereafter, halogen) headlights and light emitting diode (LED) headlights, with 86% of new vehicles equipped with LED headlights (Linkov, 2019). A primary difference between halogen headlights and LED headlights is their spectral properties. Specifically, halogen lights produce more long wavelength light (orange-red; 620-750 nm) compared to LED lights which produce more short wavelength light (blue; 380-500 nm). This difference could affect the likelihood of deer-vehicle collisions, as the peak sensitivities of deer photoreceptors more closely match the emission spectrum of LED headlights (Cohen et al., 2014). Deer are well adapted for low light conditions and have two cone photoreceptors with peak sensitivities at 450-460 nm and 537 nm and one rod photoreceptor with a peak sensitivity at 497 nm (Cohen et al., 2014; Jacobs et al., 1994). Due to the peak cone sensitivity occurring in the blue range of the visible light spectrum, deer could be more visually overwhelmed by the increased blue light produced by LED headlights. Cohen et al. (2014) specifically suggested that longer wavelength headlights (i.e., halogen) could potentially reduce

DVCs by producing wavelengths to which deer are less sensitive compared to headlights that produce more blue light (i.e., LED).

Furthermore, no studies have explored how headlight intensity affects deer behavior. Although high-beam headlights clearly increase driver detection of wildlife (Hobday, 2010; Mastro et al., 2010; Pakula et al., 2023; Rodgers and Robins, 2006), drivers do not consistently use high beam headlights under low-light conditions (Reagan et al., 2017; Sullivan et al., 2004). A better understanding of the effects of high beam headlights during deer-vehicle encounters would elucidate mechanisms of DVCs by accounting for both deer and driver behavior. More specifically, it is currently unknown whether the positive effects of high-beam headlights (increased driver detection distances; Pakula et al., 2023) are compounded by an increase in favorable movements by deer (earlier avoidance responses) or are offset by reduced favorable movements by deer (delayed avoidance responses). Understanding this relationship could improve public awareness campaigns aimed at reducing DVCs and inform future research on mitigation methods.

Notwithstanding previous research quantifying deer behavior during deer-vehicle interactions (e.g., Blackwell et al., 2014; DeVault et al., 2020), no study has directly tested how deer react to vehicles during one of the most dangerous situations: an imminent head-on collision. According to antipredator theory, animals tend to perceive a more direct approach as a greater threat (Frid and Dill, 2002; Stankowich and Blumstein, 2005; Stankowich and Coss, 2006) and during deer-vehicle interactions, deer increase their flight initiation distance (i.e., distance between the deer and vehicle at the onset of the avoidance response) when they are closer to the path of a vehicle (Pfeiffer et al., 2020). However, very little information is available quantifying deer behavior during those last few seconds before a potential collision, nor how vehicle lighting could influence those behaviors. This absence of information likely stems from the difficulty of collecting such data. In the wild, deer are free to move about the landscape making it difficult to study head-on collision scenarios, and video playback experiments (e.g., DeVault et al., 2015; Guenin et al., 2024) are impractical for wild large ungulates. Gaining insight into how deer react in the final moments before an imminent collision is crucial to understanding deer behavior and to develop mitigation methods to increase driver safety.

In this study we experimentally quantified how commercially available vehicle lighting affected white-tailed deer (*Odocoileus virginianus*) behavior in a controlled setting using penned deer running towards an approaching vehicle in an imminent collision scenario. Specifically, we tested the individual and combined effects of rear-facing vehicle illumination (off vs. on), headlight types (halogen vs. LED), and headlight intensity (low beam vs. high beam) on deer behavior in a controlled environment with experimental trials conducted on individual deer.

2. Methods

2.1 Study Site and Animal Care

Our study took place at the Whitehall Deer Research Facility on the University of Georgia's campus in Athens, Georgia, U.S. We used a total of 23 female white-tailed deer for our study. Each deer had an ear tag which allowed for individual identification. The deer in our study were housed in 2.5×5.9 m individual indoor stalls prior to experimental trials. We provided deer with pelleted feed (Purina® Deer Antler Advantage Deer 20

ARS), perennial peanut hay (*Arachis glabrata*), and water ad libitum. When not participating in trials for this study, the deer were housed in a 0.45 ha outdoor pen.

Of the 23 deer used for this experiment, eight were 1-3 years old, six were 4-5 years old, and nine were 6+ years old. All deer were raised and cared for with limited human intervention resulting in the retention of flight responses around humans reflecting wild deer behaviors. This study received animal subjects approval from the University of Georgia's Institutional Animal Care and Use Committee (no. A2023 07-017-Y1-A0).

2.2 Vehicle Characteristics and Treatments

To evaluate how different lighting treatments affect deer behavior, a 2021 electric Yamaha golf cart (Model DR2E21 AC-L) was outfitted with two sets of stock 2017-2020 Ford Fusion headlights (Figure 4.1). These headlights were chosen because they represented a common vehicle that, depending on the trim level, had either halogen or LED projector headlights (IIHS, n.d.). Additionally, the relatively smaller sized headlights (compared to large pickup trucks' headlights) allowed for more realistic experimental configuration on the golf cart. The headlights were separated by 1.3 m and were located 0.6-1 m above ground level to replicate the visual stimulus of a standard vehicle's headlights. We also attached a 51cm rear-facing LED lightbar that consisted of 20, 5-watt white LED lights producing 7,200 lumens (Model 70720, Rough Country, Dyersburg, Tennessee, USA) to the front of the golf cart. The light bar illuminated the front of the vehicle without being visible to the driver. Our study consisted of eight treatments in a randomized complete block design: (1) low-beam halogen headlights and lightbar off, (2) low-beam halogen headlights and lightbar on, (3) high-beam halogen headlights and lightbar off, (4) high-beam halogen headlights and lightbar on, (5) low-beam LED headlights and lightbar off, (6) low-beam LED headlights and lightbar on, (7) high-beam LED headlights and lightbar off, and (8) high-beam LED headlights and lightbar on (Figure 4.1). The headlight beams were adjusted according to the 2020 Ford Fusion operating manual (Ford Motor Company, 2019) and their alignment was checked before every trial night.

The vehicle was equipped with a forward-looking infrared (FLIR) camera (FLIR M625S, FLIR Systems, Goleta, California, USA) connected to a monitor to allow for real-time monitoring of the deer's position and behavior during vehicle approaches (Figure 4.1). The FLIR was connected to a digital video recorder (RVS-5500, Rear View Safety, Brooklyn, New York, USA) for recording each trial. An additional FLIR camera (FLIR E60, FLIR Systems, Goleta, California, USA) was located outside of the experimental arena and positioned to record both the vehicle and the deer simultaneously (Figure 4.2). The golf cart's electronics and lighting treatments were powered by two, external 12V direct current car batteries that were fully charged prior to each night of trials.

Each treatment's spectral profile and total radiance (W/sr/m^2) was measured using a spectrometer (PR-650 SpectraScan SpectraColorimter) positioned 95 m away from the vehicle and 1.1 m above the ground (DeVault et al., 2020). We took five measurements of each treatment before and after an evening of trials to test for any reduction in headlight radiance due to the use of batteries as the power source and the absence of an alternator.

All 23 deer received each of the eight unique treatments for a total of 184 total trials. The 23 deer were divided into two separate groups, with the first group containing 11 deer and the second group containing 12 deer, due to housing limitations of the barn.

Trials for each group consisted of eight sessions which occurred on separate days. During each session, each of the deer used in that session participated in only one trial and each unique deer received a different treatment in each of the eight sessions, resulting in each deer participating in eight total trials throughout the study. The treatment each deer received in each session, the order of treatments, and order of deer usage within each night was randomized.

2.3 Experimental Arena and Trial Procedure

We conducted our trials in a modified movement chute (hereafter, runway; Figure 4.2). The runway was 175 m long, 3.4 m wide and bordered by a 2.4-3 m tall metal fence. The substrate in the runway was intermixed grass and gravel. The fencing was covered in shade cloth for deer safety and to create an opaque barrier to the surrounding environment. Deer entered the runway from the attached barn (Figure 4.2). Near where the deer entered the runway was a 3 m wide gate that led to a temporary holding pen and a 0.45 ha long term pen (Figure 4.2). Preliminary trials revealed that when the gate was left open, the deer would immediately leave the runway resulting in invalid trials. To avoid this, the gate was initially closed when deer entered the runway but was opened after the deer passed the gate and subsequently initiated a flight response, or the golf cart driver initiated braking. For each trial, the golf cart was positioned 95 m up the runway (longest level stretch of the runway) from the gate and continuously displayed the lighting treatment during the deer release process. To encourage the deer's familiarity with the runway, deer were given access to the runway for two weeks prior to the start of trials by leaving the gate separating the runway and the adjoining pen open to allow deer to freely move about the runway without pressure from humans or vehicles.

We conducted trials from 02/20/2024- 05/02/2024 beginning one hour after sunset, when there was no remaining sunlight. One at a time, deer were directed from their stalls and into the runway by a researcher. During this time the barn was illuminated only by dim red lights to minimize the chance of deer acclimating to a bright environment before starting the trial. To ensure the deer did not stop at the closed gate in the runway, the trial did not start until the deer was 5 m past the gate (95 m away from the golf cart) and was consistently moving up the runway (Figure 4.2). When deer did not immediately run up the runway, the researcher who released the deer gave the deer more pressure by walking towards the deer. During this time the golf cart, located 95 m up the runway, had one of the eight lighting treatments enabled for the trial. Once the deer crossed the 95 m mark, the researcher releasing the deer notified the driver to begin their approach via radio. The driver then quickly accelerated the vehicle to its top speed of 28.3 km/h (17.6 mph) while approaching the deer. The driver initiated braking once the deer exhibited a distinct flight behavior or the vehicle was 15 m away from the deer (i.e., safe braking distance). After each trial, the deer was either released into a 0.45 ha permanent pen or placed back within the barn depending on the trial schedule. For cases during which the deer was placed back in the barn after the trial, the runway gate to the outdoor pen was closed for the entire trial.

2.4 Data Extraction

Using recordings from the stationary FLIR camera, we scored the video frame at which a deer first demonstrated alert and flight behavior (if applicable). We defined alert behavior as a distinct departure from the previous behavior (running up the runway) that resulted in a change in orientation of the neck and head. This often was accompanied by an abrupt stop in their movement up the runway. We defined flight behavior as the moment a deer initiated a movement that resulted in distinct locomotion away from its initial position or current running path. Because deer were confined within a runway, we suspected their flight behaviors might not be as pronounced as those exhibited by deer in field conditions, similar to concerns raised by Blackwell et al. (2019) regarding penned Canada geese (*Branta canadensis maxima*). Therefore, any deer movement that resulted in deer taking steps towards the fence was scored as a flight behavior. However, we did not score small steps in place as flight (e.g., turning to the side).

To score alert and flight initiation distance (FID), we estimated the position of the deer and the golf cart within the runway at the moment each behavior occurred (identified video frames) using recordings from both FLIR cameras, which were synchronized before every trial. Wooden fence posts along the runway served as distance markers. Specifically, we calculated the golf cart's position at the moment of each behavior using its FLIR camera's known field of view (25˚) and the known distances of the wooden fence posts relative to the 95 m starting location. Alert distance and FID were then calculated as the difference between the deer and golf cart's position at the time of the respective behaviors. For a more detailed description of how alert distance and FID were calculated, see Supplemental Methods 1.

Alert and flight behaviors were only scored prior to braking, because such responses exhibited during braking could have been caused by the braking process and not the lighting treatment per se. If a deer failed to initiate a response by the time the vehicle reached the mandatory braking distance (15 m), the deer was considered to have exhibited a no alert or no flight response (DeVault et al., 2020; Pfeiffer et al., 2020).

2.5 Statistical Analysis

All analyses were conducted in R version 4.3.1 (R Core Team, 2023). To compare the differences in headlight radiance values across treatments, we fit a multiple linear regression using the base R package: stats (R Core Team, 2023). The fixed effects of the model were headlight treatment, light intensity treatment, light bar treatment, and battery depletion (pre vs. post-trial readings). We calculated estimated marginal means using the emmeans R package and performed consecutive pairwise comparisons using the mvt method for p-value adjustments (Lenth, 2023). These comparisons tested estimated marginal means that differed in only one condition at a time, while holding the two other factors constant.

We used generalized mixed effects models to evaluate the effects of our lighting treatments on deer alert and flight probability and linear mixed effects models to evaluate the effects on deer alert and flight initiation distance. Within each model, the fixed effects included the headlight treatment, light intensity treatment, light bar treatment, the trial's time from sunset (min), how long the deer was in the runway before the trial started (settle sec), deer group number (1 or 2), deer age groups (1-3y, 4-5y, 6+y), and trial number for each deer (1^{st}-8^{th}). To account for any systematic sensitization or habituation in deer responses throughout the eight trials (sensu DeVault et al., 2018), we treated trial number as a continuous variable to reduce model complexity and promote model convergence (Lazic, 2008). The random effects structure of each model contained deer ID. Given the sensitivity of deer photoreceptors and the differences in vehicle lighting options, we included all two-way and three-way interactions among our lighting treatments to assess whether and how their effects depend on each other. To reduce model complexity we initially fit a model with all variables listed above, assessed covariate significance and removed any non-significant covariates. We then proceeded to fit a model that included only our lighting treatments, their interactions, any significant covariates, and deer ID as a random effect. All models retained the lighting treatments, as these variables represented the specific lighting conditions that we expected could influence deer behavior and reflected the treatments each deer received. We confirmed that the reduced model's fit did not differ from the original model with a likelihood ratio test from the base R package: stats (R Core Team, 2023). For the likelihood ratio test of our mixed effects linear models we used maximum likelihood estimation, then re-estimated parameters using restricted maximum likelihood estimation for interpretation (Zuur et al., 2009). When significant lighting treatment effects were observed, we calculated estimated marginal means and performed consecutive pairwise comparisons using the same method as described above. We present both uncorrected and corrected p-values from multiple comparisons to highlight trends that may be obscured due to the conservative nature of the corrections (Lattin and Romero, 2014; Rothman, 1990). All mixed effects models were fitted using the R package glmmTMB (Brooks et al., 2017). For each model we assessed collinearity among predictors. However, models with interaction terms inherently have elevated variance inflation factor (VIF) values, so we refit each model without interaction terms to assess collinearity among fixed effects (Lüdecke et al., 2021). All variance inflation factors values for every model without interactions terms were low (VIF < 5; Lüdecke et al., 2021) unless otherwise noted.

To focus on the relative contribution of the lighting treatments compared to the variation among deer in behavioral responses, we fit reduced models that only contained the fixed effects (and their interactions) of our lighting treatments and deer ID as a random intercept for models that had non-significant variables other than the lighting treatments. We calculated the marginal and conditional R-squared values using the method described by Nakagawa et al. (2017) with the Performance package (Lüdecke et al., 2021) in R. The marginal R-squared represents the variance explained by the fixed effects, whereas the conditional R-squared represents the variance explained by both fixed and random effects. The relative contribution of the random effects structure (i.e., deer ID) was calculated by subtracting the marginal R-squared from the conditional R-squared value (Lüdecke et al., 2021).

3. Results

3.1 Headlight Readings

Before an evening of trials, headlight readings when the lightbar was off showed high beams increased halogen and LED headlight radiance by 58% and 76%, respectively. Similarly, the radiance of halogen headlights was 60% and 44% greater than LEDs for low beams and high beams, respectively. Overall, the light produced by the halogen headlights was concentrated at longer, red (620-750) wavelengths, whereas the light emitted by LED headlights was concentrated near the blue (430-450nm) and green light wavelengths (520-600nm; Figure 4.3). After one night of trials, we found no systematic decrease in headlight radiance values due to battery depletion (Table 4.S1).

3.2 Trial Overview

Due to camera malfunctions, one deer had valid data for only six of eight treatments, and two deer had usable data for only seven of eight treatments. Additionally, one deer was removed from the study due to safety concerns after only two trials because it was uncooperative when being moved after each trial. We retained the data from this individual in all analyses. Two individuals received two treatments within one night due to camera malfunctions identified before the end of the study. These individuals had ~1 hour of rest between trials. Overall, the 23 deer participated in 174 of the 184 possible trials.

3.3 Alert Probability

Across all trials, deer alerted to the vehicle during 127 of the 174 trials (73.0%). Individual deer alerted between 2 and 8 times across their eight unique treatment trials (Figure 4.4). From our full model, group number was the only non-lighting variable to have a significant effect (β=-1.08, p=0.04; 4.S2) and was retained in our lighting treatment reduced model, which had a similar fit to the full model (X^2=5.1, df=5, p=0.40). From our reduced model, we found a significant effect of high-beams (β=2.46, p=0.03; Table 4.1), significant two-way interactions for LED headlights and high-beams (β=-2.76, p=0.04; Table 4.1) and high-beams and lightbar on (β=-3.04, p=0.03; Table 4.1), as well as a significant three-way interaction of LED headlights, high-beams, and lightbar on (β=3.44, p=0.04; Table 4.1). When comparing estimated marginal means, we found that that when the lightbar was off, halogen high beams headlights showed a trend of increased alert probability compared to LED high beam headlights (z-ratio = -2.18, p=0.03; Table 4.2; Figure 4.5). Also, we found evidence that halogen high beams showed a trend of increased alert probability over halogen low beams when the lightbar was off (z-ratio = 2.14, p=0.03; Table 4.2; Figure 4.5). However, these differences were not significant when accounting for multiple comparisons (p=0.24, p=0.26, respectively).

The variance explained by our lighting treatments for alert probability was 0.154, whereas the variance explained by the random effect of deer ID was 0.132 (Figure 4.6).

3.4 Alert Distance

From our full model, no covariate had a significant effect (all $p>0.11$; Table 4.S3) and our reduced model of only lighting treatments had a similar fit to the full model ($X^2=7.8$, df=6, $p=0.25$). From our reduced model, we found no significant effect of any variables or interaction on deer alert distance (all $p>0.19$; Table 4.S4). The variance explained by our lighting treatments for alert distance was 0.040, whereas the variance explained by the random effect of deer ID was 5.83× greater at 0.233 (Figure 4.6).

3.5 Flight Probability

Across all trials, deer initiated flight during 90 of the 174 trials (51.7%). Individual deer initiated flight between 1 and 7 times across their eight unique treatment trials (Figure 4.4). From our full model, no covariate had a significant effect (all $p>0.13$; Table 4.S5) and our reduced model of only lighting treatments had a similar fit to the full model ($X^2=5.1$, df=6, $p=0.53$). In our reduced model, we found no significant effect of any variable or interaction on deer flight probability (all $p>0.19$; Table 4.S6). The variance explained by our lighting treatments for flight probability was 0.026, whereas the variance explained by the random effect of deer ID was 9.19× greater at 0.265 (Figure 4.6).

3.6 Flight Initiation Distance

From our full model, no covariate had a significant effect (all $p>0.45$; Table 4.S7) and our reduced model of only lighting treatments had a similar fit to the full model

(X^2=2.8, df=6, p=0.83). We found no significant effect of any variable or interaction on deer FID (all p >0.17; Table 4.S8). The variance explained by our lighting treatments and the random effect of deer ID were equal, both accounting for 0.097 (Figure 4.6).

4. Discussion

4.1 Headlight Characteristics

Overall, halogen headlights produced higher radiance values than LED headlights and their light was concentrated at longer wavelengths (i.e., red light), which is inherently due to halogen headlights using a burning filament to produce light. However, understanding how deer perceive light requires a detailed knowledge of visual physiology, which, while well studied in other taxa like birds (e.g., Doppler et al., 2015; Goller et al., 2018), has received relatively little attention in deer and Cervidae in general. Although studies have investigated various aspects of visual physiology (photoreceptor density, color discrimination, visual acuity) in deer (D'Angelo et al., 2008; Newman and D’Angelo, 2024; Smith et al., 1989; Watson et al., 2022), no studies have developed perceptual models for light spectra in deer. Our readings showed that the emission spectrum of LED headlights better matched the peak sensitivity of deer photoreceptors than halogen headlights (Cohen et al., 2014; Jacobs et al., 1994); however, it remains unclear whether LED headlights produce a more salient looming image or a more visually overwhelming stimulus for this dark-adapted species. Additional research into deer perceptual modeling is needed.

4.2 Alert Probability

Deer appeared to alert to the vehicle more reliably when exposed to the halogen, high beam, lightbar off treatment compared to the LED, high beam, lightbar off treatment, suggesting that the differences in wavelength emitted by each headlight type influenced deer behavior. However, we did not identify the mechanism underlying this behavior. It is possible that halogen headlights might have increased alerting behavior because long wavelength light does not closely match the peak sensitivity of deer photoreceptors (Cohen et al., 2014; Jacobs et al., 1994) and thus deer could more readily identify the vehicle with halogen headlights as a threat without being visually overwhelmed. Similarly, deer may have alerted less often to LED headlights because the increased blue light emitted by the LED headlights overwhelmed the deer's dark-adapted vision, especially at the relatively short approach distances used in this study, resulting in the deer being unable to identify the vehicle as a threat.

We also found that when the lightbar was off, high beam halogen headlights tended to increase alert probability over low beam halogen headlights. Given that we only saw this effect with halogen headlights, alert probability did not increase with overall radiance of headlights, but rather was a result of the increased radiance of long wavelengths produced by the halogen headlights. Furthermore, we observed no effects of light wavelength or intensity on deer alert behavior when the lightbar was on, suggesting that the increased frontal illumination offset the effects of the halogen and high beam treatments.

Although we were unable to identify the mechanisms for the observed results, we found that headlight type (halogen vs. LED) and headlight intensity (low beam vs. high beam) appear to influence deer alert behavior. To our knowledge, this is the first study to document an effect of vehicle lighting on deer alert behavior, although other studies have found effects of vehicle lighting on other deer behaviors (Blackwell and Seamans, 2009; DeVault et al., 2020).

4.3 Alert Distance

We found no effect of our lighting treatments on deer alert distance, which could be a byproduct of our study design. Our experimental arena was relatively short (95 m) and involved deer running towards an oncoming vehicle. The relatively short start distance might not have allowed enough variation in deer alert distances to observe an effect. For example, Stankowich and Coss (2006) found that Columbian black-tailed deer (*Odocoileus hemionus columbianus*) alert distance was positively correlated with start distance for approaches by humans on foot (range: 75-275m), suggesting we might have observed greater variations in alert distance if deer had been afforded longer start distances, as is often the case with real world deer-vehicle interactions. However, it is difficult to accurately measure deer alert distance to an approaching vehicle in the field; studies have noted that they were unable to quantify alert distance accurately with vehicle mounted infrared cameras (Blackwell and Seamans, 2009; Blackwell et al., 2014). Regardless, this was the first study to assess the effects of vehicle lighting on deer alert distance and more research is needed to further evaluate whether the lack of an effect due to vehicle lighting is consistent in other settings.

4.4 Flight Probability

We found no effect of our lighting treatments on deer flight probability. Although this lack of effect could reflect the importance of untested predictors or variation in behavior across individual deer (see below), it also could have resulted from the short start distance used in our study. More specifically, our finding of no effect of the lightbar on deer flight probability contrasts with the findings of DeVault et al. (2020), who found that the lightbar reduced immobility (freezing) behavior in deer. However, deer in the DeVault et al. (2020) study had a mean flight initiation distance of 134m and 173m for lightbar off and on, respectively. Those FID values were unattainable in our study due to our 95 m runway, thus we cannot rule out that the lightbar might increase deer flight probability when approached at sufficiently long distances.

Additionally, our 3.4 m wide runway could have affected deer flight behavior. Because deer were unable to move laterally to avoid the path of the vehicle, deer might have spent more time assessing the vehicle and their surroundings to identify an escape route rather than engaging in an early flight behavior. Although we were interested in observing deer behavior during an imminent head-on collision scenario and thus were compelled to confine deer in a runway, we likely would have observed different results in the field with free-ranging deer. In our study, deer initiated flight during only 51.7% of the trials, whereas studies with free-ranging deer observed flight for 68-90% of the deer encountered within 3-5 m of the road surface (Blackwell et al., 2014; DeVault et al., 2020).

4.5 Flight Initiation Distance

In contrast to previous studies, we observed no effect of our lighting treatments on deer flight initiation distance, suggesting vehicle lighting could be ineffective at reducing the danger inherent to a sudden encounter with deer. Previously, Blackwell and Seamans (2009) found that an auxiliary high intensity discharge lamp paired with standard halogen increased deer FIDs over the halogen headlights alone. However, the mean start distance in the Blackwell and Seamans (2009) study was 420 m, and they observed an increase in FID from 116-136 m, distances that were unattainable in our study.

Additionally, the lack of an effect of our lighting treatment on deer FID could be due to low statistical power. As mentioned above, our methods focusing on imminent collision scenarios resulted in lower flight probabilities (51.7%) compared to other studies (68-90%; Blackwell et al., 2014; DeVault et al., 2020). As a result, our trials resulted in only 90 useable deer flight responses (out of 174 trials) across 23 deer to estimate the effect of lighting treatments on deer FID. Field studies focusing on other aspects of deer-vehicle encounters and thus using longer approach distances might find higher rates of flight and thus higher power for FID analyses.

4.6 Response Variability

Although we observed that vehicle lighting can impact deer behavior during an imminent head-on collision, deer responses appeared to be influenced greatly by factors other than our lighting treatments, as evident from our pseudo R-squared values. For example, lighting treatment explained only 2.6% of the variation for deer flight probability, whereas the random effect of deer ID explained 23.9% of the variation. Large variations in deer responses to vehicles across individuals have been reported repeatedly, especially for flight probability and FID (Blackwell and Seamans, 2009; Blackwell et al., 2014; DeVault et al., 2020; Pfeiffer et al., 2020). Variability in flight responses among deer could be attributed to untested variables, including differences in deer experience and personality (Pettorelli et al., 2011). Alternatively, inconsistency in deer behavior when reacting to approaching threats could have developed as an adaptive response to approaching predators (Humphries and Driver, 1970). Regardless, large variations in behaviors among deer reduce the predictability of deer behaviors during vehicle encounters. To date, no mitigation methods for imminent collision scenarios have been developed that can overcome the large interindividual variation in deer responses, likely contributing to the lack of effectiveness of many mitigation methods and devices (D'Angelo et al., 2006; Huijser et al., 2008; Valitzski et al., 2009). Despite this, mitigation methods outside of those intended to influence deer behavior during animal-vehicle interactions have been shown to be effective at reducing collisions, including targeted deer population control (Delisle et al., 2024; DeNicola and Williams, 2008; Kilgo et al., 2020) and roadside fencing (Clevenger et al., 2001), especially when paired with wildlife over- and underpasses (Huijser et al., 2016; McCollister and Van Manen, 2010).

4.7 Implication and Future Research

The use of vehicle lighting to impact behavior of roadside wildlife has wide ranging implications for driver safety and wildlife conservation. However, research to date has focused specifically on responses of stationary roadside deer (Blackwell and Seamans, 2009; Blackwell et al., 2014; DeVault et al., 2020; Pfeiffer et al., 2020). This was the first study to quantify how vehicle lighting impacts deer behavior during an imminent head-on collision scenario, simulating a last second deer-vehicle interaction akin to a vehicle turning onto a road and immediately interacting with a moving deer. We found that variations in vehicle lighting can influence deer alert behavior, but were ineffective in altering deer flight behaviors, suggesting that vehicle lighting could be ineffective at reducing the danger of sudden encounters with moving deer.

More specifically, we found that the high-beam, halogen, lightbar off treatment resulted in the highest probability of deer alerting to the vehicle and differences in headlight type (wavelengths emitted) and intensity (overall radiance) can affect deer alert behavior. However, additional research is needed on deer perceptual modeling of vehicle lighting. Although deer photoreceptor sensitivity is already described (Cohen et al., 2014; Jacobs et al., 1994), it remains unclear how deer perceive different wavelengths (and amount) of light produced by halogen and LED headlights. A better understanding of how deer perceive these fundamental aspects of light would help tailor more beneficial headlight designs and other mitigation methods.

Although we found support for headlight type and intensity affecting deer behavior, certain untested factors warrant further exploration. For example, our study involved only two types of headlights. It remains unclear whether similar results would be seen with other headlight brands given the potential differences in emission spectrum or if other aspects of headlights have an effect in practice (e.g., headlight alignment, headlight height). Given the logistical limitations of our study, we were only able to use adult females; different results could be seen with bucks, especially during the rut, and fawns. Additionally, our study specifically tested how moving deer reacted during imminent collision scenarios, which warranted testing of individual deer given our experimental setup. Even so, deer are a gregarious species, which could affect individual responses to an approaching threat (Blackwell et al., 2019; Lagory, 1987). Although one study found that vehicle approaches with roadside deer often involve solitary individuals (59.6%; DeVault et al 2020), we acknowledge that deer within groups could respond differently, presenting an opportunity for future research.

5. Conclusion

Deer-vehicle collisions clearly pose a substantial risk to drivers in the United States and around the world and are, in part, the result of maladaptive deer responses to vehicles. Better understanding how visual stimuli impact deer behavior is crucial in the development of effective onboard mitigation methods. In this study we found that headlight type and intensity appeared to impact deer alert behavior in a captive setting, but we did not observe an effect of vehicle lighting on deer alert distance or flight behavior. The absence of observed effects suggests that vehicle lighting might be ineffective at influencing these aspects of deer behavior during short distance vehicle approaches, but it remains unclear how the lighting variations tested here would affect deer under different experimental settings (e.g., longer approach distances, free-ranging deer). Overall, this was the first study to evaluate how vehicle lighting impacts a moving deer's behavior during a head-on collision scenario. The results of this study provide a foundation for further investigation of vehicle lighting on deer responses to vehicles in real world settings as the transportation industry transitions to an LED dominated driving landscape.

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Table 4.1. Reduced model results examining the factors affecting deer alert probability. p<0.05 are bolded.

Fixed Effects	Term	Estimate	Std. Error	z-value	p-value
	(Intercept)	1.193	0.577	2.067	**0.039**
	HeadlightLED	0.245	0.701	0.349	0.727
	BrightnessHigh	2.459	1.152	2.136	**0.033**
	LightbarOn	0.821	0.756	1.087	0.277
	Group.Num2	-0.637	0.484	-1.318	0.187
	HeadlightLED:BrightnessHigh	-2.764	1.352	-2.044	**0.041**
	HeadlightLED:LightbarOn	-1.361	1.031	-1.320	0.187
	BrightnessHigh:LightbarOn	-3.036	1.387	-2.189	**0.029**
	HeadlightLED:BrightnessHigh:LightbarOn	3.444	1.699	2.027	**0.043**
Random Effects	**Group**	**Std. Dev**			
	Deer.ID	7.03e-01			

Table 4.2. Pairwise comparisons of the estimated marginal means of the effects of lighting treatments on deer alert probability. Halogen and LED represent tungsten-halogen and light emitting diode headlights, respectively. Contrasts indicate the first treatment level compared to the second treatment level. Both unadjusted p-values and adjusted p-values for multiple comparisons are reported. p<0.05 are bolded.

Brightness	**Lightbar**	**Headlight**	**Contrast**	**Odds Ratio**	**SE**	**z-ratio**	**p-value unadjusted**	**p-value adjusted**
Low	Off	.	LED / Halogen	1.278	0.896	0.349	0.727	1.000
High	Off	.	LED / Halogen	0.081	0.093	-2.182	**0.029**	0.235
Low	On	.	LED / Halogen	0.328	0.247	-1.480	0.139	0.701
High	On	.	LED / Halogen	0.647	0.448	-0.629	0.530	0.996
.	Off	Halogen	High / Low	11.698	13.472	2.136	**0.033**	0.260
.	Off	LED	High / Low	0.738	0.521	-0.431	0.667	1.000
.	On	Halogen	High / Low	0.562	0.431	-0.751	0.453	0.988
.	On	LED	High / Low	1.110	0.747	0.154	0.877	1.000
Low	.	Halogen	On / Off	2.274	1.719	1.087	0.277	0.916
Low	.	LED	On / Off	0.583	0.407	-0.773	0.440	0.986
High	.	Halogen	On / Off	0.109	0.127	-1.911	0.056	0.394
High	.	LED	On / Off	0.877	0.598	-0.192	0.848	1.000

Figure 4.1. The electric golf cart used for our trials was outfitted with two sets of stock 2017-2020 Ford Fusion headlights (tungsten-halogen and light emitting diode), a rear-facing lightbar, and a forward-looking infrared camera for behavioral recording. Images display tungsten-halogen, low-beam, lightbar off (left) and light emitting diode, high-beam, lightbar on (right) treatments.

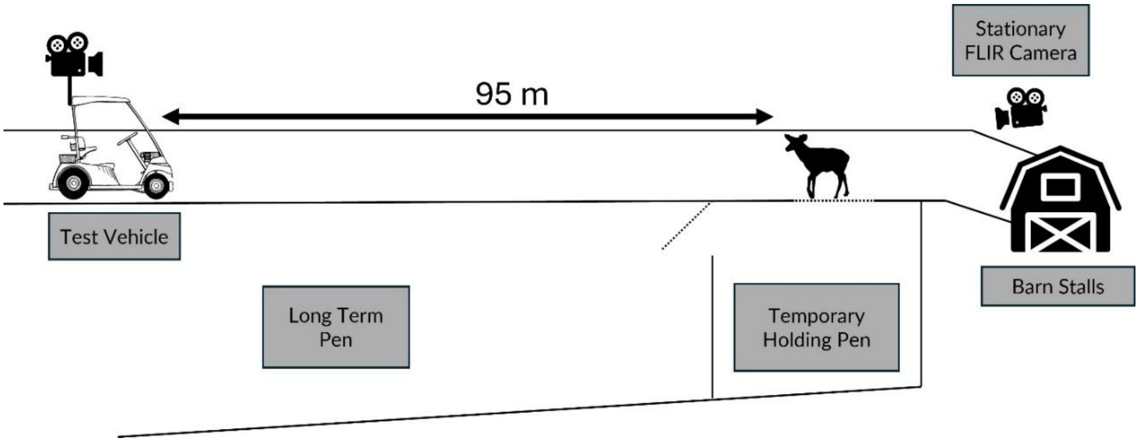

Figure 4.2. A schematic of the experimental design showing a deer being released from the barn into the runway while the golf cart was parked 95 m down the runway with the appropriate lighting treatment already displayed. Dashed lines depict gates. Note that the runway gate was held shut until after the trial was completed.

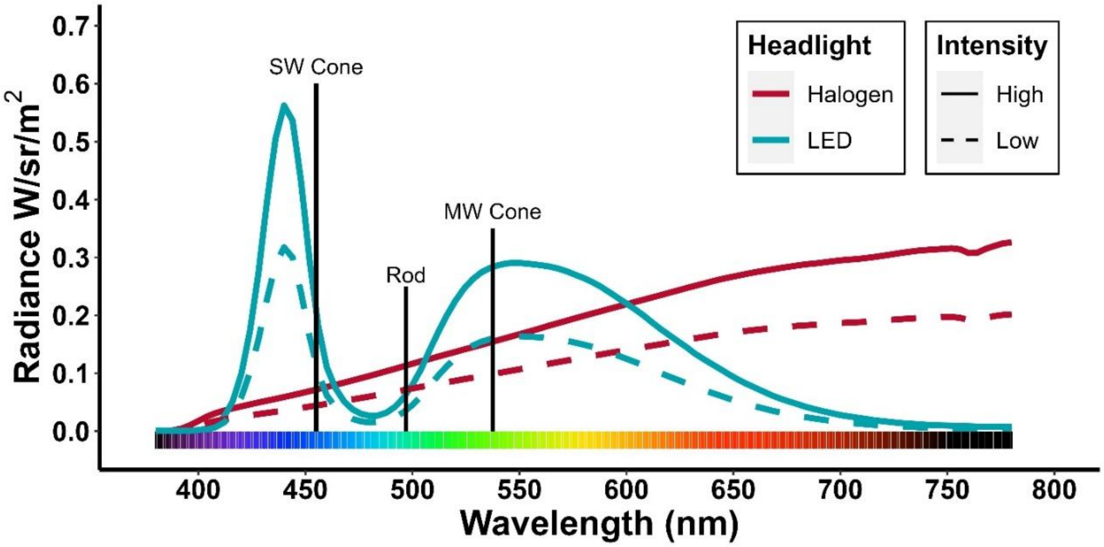

Figure 4.3. The radiance (W/sr/m^2) of the lighting treatments by wavelength measured at 95m when the lightbar was off. Halogen and LED represent tungsten-halogen and light emitting diode headlights, respectively. The lightbar provided a negligible change in radiance values and is not shown for clarity. The SW Cone, Rod, and MW Cone depict the peaks of deer sensitivity curves for their short-wavelength cone, rod, and middle-wavelength cone, respectively (Cohen et al. 2014; Jacobs et al., 1994).

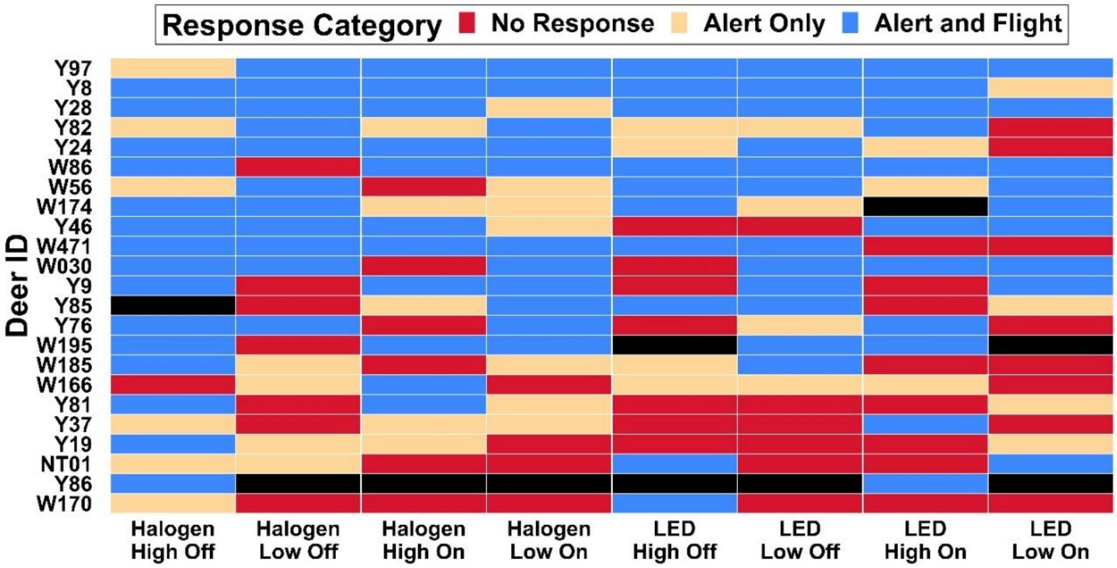

Figure 4.4. Each deer's response type (no response, alert only, and alert and flight) to each unique lighting treatment. Halogen and LED represent tungsten-halogen and light emitting diode headlights, respectively. Rows indicate each deer's response across treatments. Columns indicate variability in responses among deer for each unique lighting treatment. Deer are ordered by most responses (alert only or alert and flight) to least responses (no response). For example, Y97 alerted and fled to seven of the eight treatments while W170 exhibited no response to six of the eight treatments. Black cells are missing data.

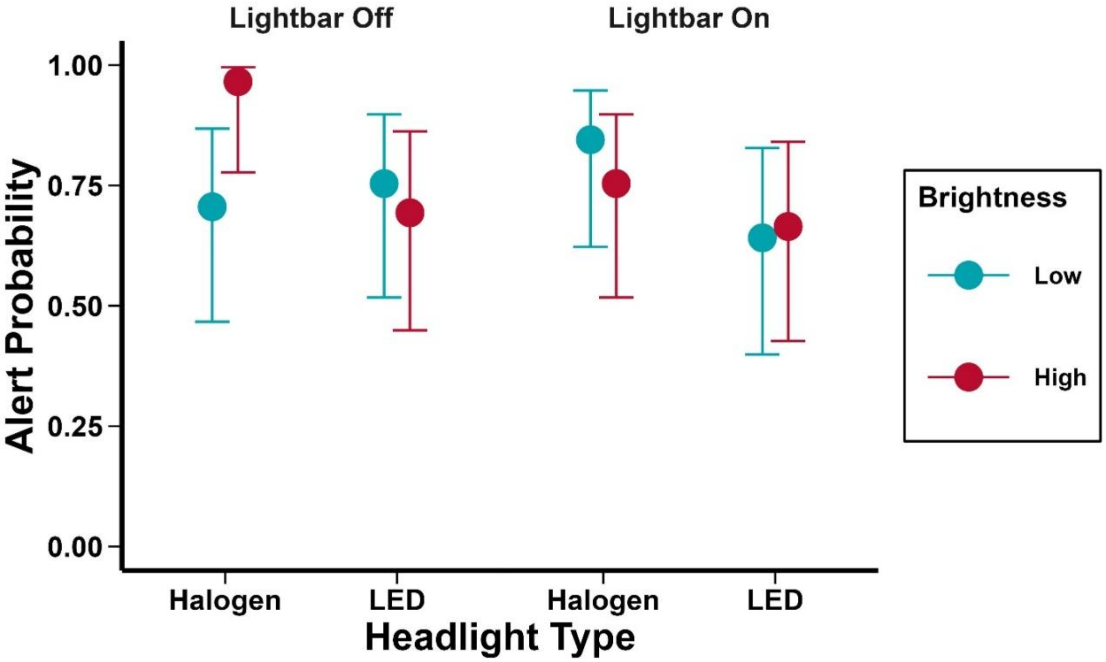

Figure 4.5. The estimated marginal means of a deer's probability of alerting to the vehicle for all eight unique treatments.

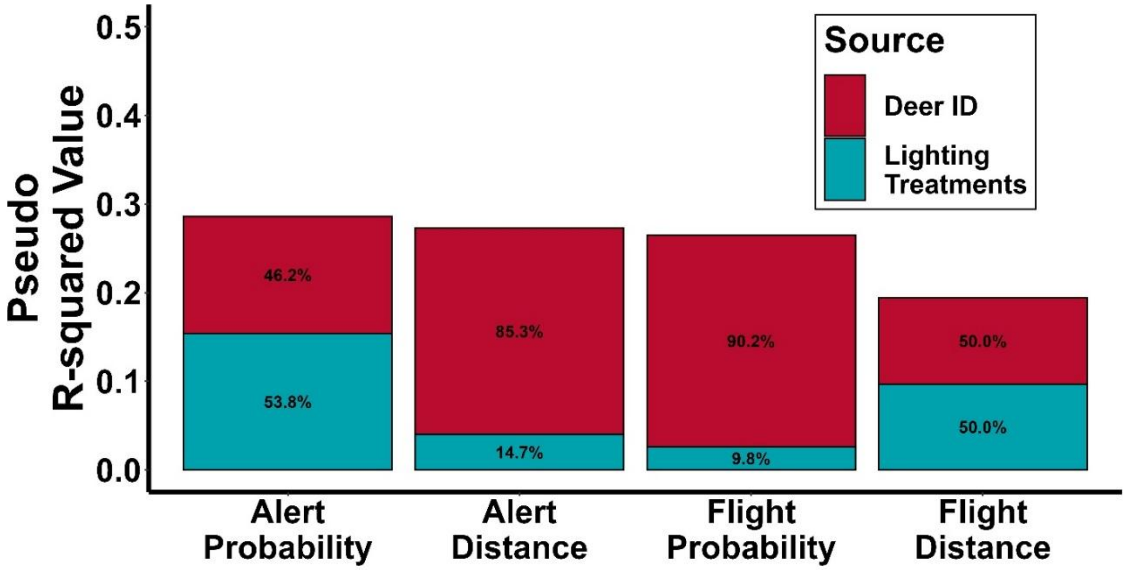

Figure 4.6. The pseudo R-squared values of our four behavioral models with relative contributions of our lighting treatments (marginal) and the random effect of Deer ID (conditional-marginal). These models only included the fixed effects and the interactions of our lighting treatments and Deer ID as a random intercept after no other variables tested were found to be significant.

Supplemental Methods 1. Detailed description of how alert and flight initiation distances were calculated from the two infrared cameras used during the study.

After identifying the alert and flight behaviors (if applicable) using the stationary FLIR camera, we estimated the deer's position within the runway (to the nearest meter) at each behavior by using the two FLIR videos, which were synchronized before each trial, and referencing large wooden fence posts that lined the outside of the runway. To calculate the golf cart's position at each behavior, we first translated the stationary FLIR camera's alert and flight frames to the corresponding golf cart's frame numbers. We calculated the golf cart's position at each behavior by using its FLIR's known field of view (25°) and the known distances of the wooden fence posts relative to the 95 m starting location. We calculated how far the vehicle was from the deer's 95 m away starting location for each wooden pole it passed using the following formula:

$$Vehicle\ Distance = Pole\ Dist + \frac{Pole\ Dist\ to\ FLIR}{\left[\tan\left(\left(\frac{FLIR\ FOV}{2}\right) * \left(\frac{\pi}{180}\right)\right)\right]} - Vehicle\ Length$$

Where Vehicle Distance was the distance from the golf cart to the 95 m away starting location of the deer (m), the Pole Dist was the distance from the fence pole to the starting location of the deer (m), Pole Dist to FLIR was the horizontal distance from the fence pole to the FLIR (m), FLIR FOV was the field of view of the FLIR in degrees (25°), and Vehicle Length was the distance from the headlights to the mounted FLIR (2.56 m).

If an alert or flight behavior occurred at the same frame that a wooden fence post left the golf cart FLIR's frame of view, then that calculated distance was used as the golf cart's position from the deer's initial location. However, most behaviors occurred when the edge of the golf cart’s field of view was between two wooden fence posts. In those cases, we determined the frame of the behavior relative to the frames when the previous and next wooden posts exited the golf cart FLIR’s field of view. Using the known positions of the golf cart at those frames, we interpolated its position at the moment of the behavior. Finally, alert distance and flight initiation distance were calculated by subtracting the deer’s distance from its 95m starting location from the golf cart’s distance from the deer’s 95 m starting location.

Table 4.S1. Estimated marginal means of the lighting treatments radiance (in W/sr/m^2). Halogen and LED represent tungsten-halogen and light emitting diode headlights, respectively. Battery Depletion refers to measurements taken before or after an evening of trials. For every treatment, n=5 and df=64.

Headlight	**Intensity**	**Lightbar**	**Battery Depletion**	**Mean**	**Lower CI**	**Upper CI**
Halogen	Low	Off	Before	47.7	47.14	48.25
LED	Low	Off	Before	29.7	29.19	30.30
Halogen	High	Off	Before	75.5	74.93	76.03
LED	High	Off	Before	52.5	51.91	53.02
Halogen	Low	On	Before	45.0	44.46	45.57
LED	Low	On	Before	30.3	29.76	30.86
Halogen	High	On	Before	69.1	68.50	69.61
LED	High	On	Before	51.6	51.05	52.15
Halogen	Low	Off	After	51.8	51.25	52.35
LED	Low	Off	After	31.2	30.63	31.73
Halogen	High	Off	After	85.2	84.60	85.70
LED	High	Off	After	50.3	49.73	50.84
Halogen	Low	On	After	48.0	47.46	48.56
LED	Low	On	After	31.4	30.82	31.93
Halogen	High	On	After	80.7	80.19	81.29
LED	High	On	After	51.8	51.24	52.34

Table 4.S2. Full model results examining the factors affecting deer alert probability. p<0.05 are bolded.

Fixed Effects	Term	Estimate	Std. Error	z-value	p-value
	(Intercept)	2.344	1.202	1.951	0.051
	HeadlightLED	0.213	0.713	0.299	0.765
	BrightnessHigh	2.580	1.167	2.211	**0.027**
	LightbarOn	0.698	0.764	0.913	0.361
	Time.From.Sunset	-0.008	0.007	-1.176	0.240
	Settle.Sec	0.025	0.024	1.027	0.304
	Group.Num.2	-1.075	0.532	-2.020	**0.043**
	Age.Group.4-5y	-0.578	0.597	-0.967	0.333
	Age.Group.6+y	0.450	0.584	0.770	0.441
	Trial.Num	-0.063	0.084	-0.747	0.455
	HeadlightLED:BrightnessHigh	-2.878	1.369	-2.102	**0.036**
	HeadlightLED:LightbarOn	-1.316	1.038	-1.267	0.205
	BrightnessHigh:LightbarOn	-3.155	1.400	-2.253	**0.024**
	HeadlightLED:BrightnessHigh:LightbarOn	3.660	1.720	2.128	**0.033**
Random Effects	**Group**	**Std. Dev**			
	Deer.ID	5.75e-01			

Table 4.S3. Full model results examining factors affecting deer alert distance (m). p<0.05 are bolded.

Fixed Effects	Term	Estimate	Std. Error	z-value	p-value
	(Intercept)	44.038	8.489	5.188	**0.000**
	HeadlightLED	2.601	5.271	0.494	0.622
	BrightnessHigh	-3.807	5.004	-0.761	0.447
	LightbarOn	3.071	5.160	0.595	0.552
	Time.From.Sunset	0.058	0.051	1.141	0.254
	Settle.Sec	-0.032	0.133	-0.244	0.807
	Group.Num.2	0.706	5.087	0.139	0.890
	Age.Group.4-5y	9.701	6.007	1.615	0.106
	Age.Group.6+y	0.767	5.649	0.136	0.892
	Trial.Num	-0.754	0.586	-1.287	0.198
	HeadlightLED:BrightnessHigh	-6.673	7.347	-0.908	0.364
	HeadlightLED:LightbarOn	-8.479	7.611	-1.114	0.265
	BrightnessHigh:LightbarOn	3.260	7.177	0.454	0.650
	HeadlightLED:BrightnessHigh:LightbarOn	10.479	10.624	0.986	0.324
Random Effects	**Group**	**Std. Dev**			
	Deer.ID	8.66e+00			
	Residual	1.43e+01			

Table 4.S4. Reduced model results examining factors affecting deer alert distance (m). $p<0.05$ are bolded.

Fixed Effects	Term	Estimate	Std. Error	z-value	p-value
	(Intercept)	49.637	4.194	11.836	**0.000**
	HeadlightLED	2.892	5.284	0.547	0.584
	BrightnessHigh	-3.658	4.972	-0.736	0.462
	LightbarOn	3.304	5.154	0.641	0.521
	HeadlightLED:BrightnessHigh	-5.601	7.336	-0.764	0.445
	HeadlightLED:LightbarOn	-9.887	7.599	-1.301	0.193
	BrightnessHigh:LightbarOn	3.004	7.074	0.425	0.671
	HeadlightLED:BrightnessHigh:LightbarOn	10.073	10.650	0.946	0.344
Random Effects	**Group**	**Std. Dev**			
	Deer.ID	8.21e+00			
	Residual	1.45e+01			

Table 4.S5. Full model results examining factors affecting deer flight probability. $p<0.05$ are bolded.

Fixed Effects	**Term**	**Estimate**	**Std. Error**	**z-value**	**p-value**
	(Intercept)	1.024	1.120	0.915	0.360
	HeadlightLED	0.223	0.683	0.327	0.744
	BrightnessHigh	0.956	0.714	1.340	0.180
	LightbarOn	-0.001	0.680	-0.001	0.999
	Time.From.Sunset	-0.006	0.006	-0.958	0.338
	Settle.Sec	-0.007	0.021	-0.351	0.726
	Group.Num.2	-0.945	0.620	-1.525	0.127
	Age.Group.4-5y	-0.679	0.716	-0.947	0.343
	Age.Group.6+y	0.233	0.688	0.339	0.735
	Trial.Num	0.065	0.078	0.834	0.404
	HeadlightLED:BrightnessHigh	-1.197	0.991	-1.208	0.227
	HeadlightLED:LightbarOn	-0.543	0.972	-0.559	0.576
	BrightnessHigh:LightbarOn	-0.960	0.985	-0.975	0.330
	HeadlightLED:BrightnessHigh:LightbarOn	1.531	1.391	1.101	0.271
Random Effects	**Group**	**Std. Dev**			
	Deer.ID	9.73E-01			

Table 4.S6. Reduced model results examining factors affecting deer flight probability.

Fixed Effects	Term	Estimate	Std. Error	z-value	p-value
	(Intercept)	0.025	0.524	0.048	0.962
	HeadlightLED	0.227	0.674	0.336	0.737
	BrightnessHigh	0.908	0.699	1.299	0.194
	LightbarOn	0.000	0.672	0.000	1.000
	HeadlightLED:BrightnessHigh	-1.211	0.978	-1.238	0.216
	HeadlightLED:LightbarOn	-0.541	0.960	-0.564	0.573
	BrightnessHigh:LightbarOn	-0.908	0.970	-0.936	0.349
	HeadlightLED:BrightnessHigh:LightbarOn	1.504	1.374	1.095	0.274
Random Effects	**Group**	**Std. Dev**			
	Deer.ID	1.04E+00			

Table 4.S7. Full model results examining factors affecting deer flight initiation distance (m). $p<0.05$ are bolded.

Fixed Effects	**Term**	**Estimate**	**Std. Error**	**z-value**	**p-value**
	(Intercept)	41.246	10.672	3.865	**0.000**
	HeadlightLED	-3.112	6.724	-0.463	0.644
	BrightnessHigh	-4.519	6.523	-0.693	0.488
	LightbarOn	9.738	6.969	1.397	0.162
	Time.From.Sunset	-0.009	0.067	-0.135	0.893
	Settle.Sec	0.053	0.281	0.188	0.851
	Group.Num.2	3.168	5.069	0.625	0.532
	Age.Group.4-5y	2.067	5.862	0.353	0.724
	Age.Group.6+y	-1.815	5.262	-0.345	0.730
	Trial.Num	-0.610	0.800	-0.763	0.446
	HeadlightLED:BrightnessHigh	4.818	9.557	0.504	0.614
	HeadlightLED:LightbarOn	-10.133	9.975	-1.016	0.310
	BrightnessHigh:LightbarOn	-1.637	9.782	-0.167	0.867
	HeadlightLED:BrightnessHigh:LightbarOn	13.215	13.843	0.955	0.340
Random Effects	**Group**	**Std. Dev**			
	Deer.ID	5.81e+00			
	Residual	1.56e+01			

Table 4.S8. Reduced model results examining factors affecting deer flight initiation distance (m). $p<0.05$ are bolded.

Fixed Effects	Term	Estimate	Std. Error	z-value	p-value
	(Intercept)	39.166	4.841	8.090	**0.000**
	HeadlightLED	-3.099	6.484	-0.478	0.633
	BrightnessHigh	-4.895	6.163	-0.794	0.427
	LightbarOn	9.171	6.605	1.388	0.165
	HeadlightLED:BrightnessHigh	5.935	9.117	0.651	0.515
	HeadlightLED:LightbarOn	-9.603	9.607	-1.000	0.318
	BrightnessHigh:LightbarOn	-0.527	9.013	-0.059	0.953
	HeadlightLED:BrightnessHigh:LightbarOn	11.857	13.345	0.888	0.374
Random Effects	**Group**	**Std. Dev**			
	Deer.ID	5.29e+00			
	Residual	1.53e+01			

CHAPTER 5

WILDLIFE RESPONSES TO VEHICLE LIGHTING DURING NIGHTTIME ENCOUNTERS AND IMPLICATIONS FOR VEHICLE-BASED COLLISION MITIGATION STRATEGIES[1]

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[1] Pakula, C. J., Guenin, S., Skaggs, J., Rhodes Jr, O. E., & DeVault, T. L. To be submitted to *Journal of Applied Ecology*.

Abstract

Every year in the United States, vehicle collisions with deer (*Odocoileus* spp.) and wild pigs (*Sus scrofa*) cause billions of dollars in damages and injure thousands of drivers, with most collisions occurring during low-light conditions. Recent research evaluating increased frontal vehicle illumination with a rear-facing lightbar has shown promise, but its effectiveness with different headlight types remains unexplored. Furthermore, light-emitting diode (LED) headlights have grown in popularity compared to tungsten-halogen (halogen), yet no study has investigated their effects on free-ranging wildlife behavior. Compared to halogen headlights, LED headlights produce more blue light, which more closely matches the peak sensitivities of deer and wild pig photoreceptors, potentially affecting their responses. In this study, we investigated how headlight type, increased frontal vehicle illumination, and vehicle speed influenced white-tailed deer (*O. virginianus*) and wild pig responses to an approaching vehicle using infrared videography and GPS data. Specifically, we evaluated flight probability, flight initiation distance (FID), road entering behavior, and the danger level of an encounter. We also recorded responses of other wildlife species including canids (*Canidae spp*.), rabbits (*Sylvilagus spp*), armadillos (*Dasypus novemcinctus*), and bobcats (*Lynx rufus*), although sample sizes were low. Over two years, we conducted 95 weekly nighttime drives along a 75-km paved route in South Carolina, USA. For deer, LED headlights increased road entry but generally at safe distances from the vehicle, whereas for wild pigs, LED headlights increased FIDs by 114.8m. The lightbar mitigated the effects of increased freezing and dangerously close FIDs by deer at faster vehicle speeds, when crash severity is usually highest. For wild pigs, the lightbar increased FIDs at faster

vehicle speeds, providing drivers with more time to respond. Generally, LED headlights had neutral or beneficial effects on wildlife responses, suggesting they could reduce collisions given the increased illumination levels they provide drivers. Additionally, our results support previous research indicating increased frontal vehicle illumination can reduce dangerous encounters with wildlife. Our findings suggest that relatively simple modifications to vehicles can result in potentially large economic and driver and safety benefits when scaled to the millions of wildlife-vehicle collisions that occur yearly.

1. Introduction

Wildlife-vehicle collisions (WVCs) are common throughout the world and significantly impact both wildlife and humans. Seiler and Helldin (2006) estimated that billions of vertebrates across various taxa are killed by cars, boats, and airplanes each year and these numbers will likely increase with expanding infrastructure and transportation networks. Not only do vehicle collisions impact wildlife populations (Forman and Alexander, 1998; Schwab and Zandbergen, 2011), but they are also dangerous and costly to humans. In the United States, deer (*Odocoileus* spp.) represent the majority of wildlife-vehicle collisions that result in monetary damage and human injury (Huijser et al., 2009; Huijser et al., 2008). Every year, deer-vehicle collisions (DVCs) in the U.S. alone result in an average of $8.4 billion in damages (in 2008 USD; Huijser et al., 2008), 440 human deaths, and >58,000 human injuries (Conover, 2019). Although most damaging WVCs occur with deer, collisions with wild pigs (*Sus scrofa*) pose an increasing risk to humans and vehicles in North America and Europe, and the factors influencing these collisions have not been thoroughly evaluated. In 2022, an estimated 16,714 wild pig-vehicle collisions occurred in the U.S. resulting in $110.3 million (USD) in repair costs alone, not including medical expenses (McKee et al., 2025; McKee et al., 2024). As the population of wild pigs continues to increase (Lewis et al., 2019), there will likely be an increase in the number of collisions and overall monetary impact of wild pigs.

Multiple studies have quantified deer behavior to approaching road-based vehicles to better understand the causes of DVCs (Blackwell et al., 2014; Pfeiffer et al., 2020). White-tailed deer (*Odocoileus virginianus*) do not modify their flight initiation distance with increasing vehicle speed, suggesting collisions are more likely at higher vehicle speeds (Blackwell et al., 2014; Pfeiffer et al., 2020). However, Pfeiffer et al. (2020) found that white-tailed deer flight initiation distance (FID) and road crossing behavior increased with a deer's proximity to the road, likely due to the directionality and thus increased perceived risk of the threat. When an escape response is initiated, road crossing, one of the most dangerous behaviors exhibited by white-tailed deer, was found to only occur when the nearest concealing cover was across the road from the deer (DeVault et al., 2020) and this behavior was not correlated with group size (Blackwell et al., 2014). On the other hand, much less is known about WPVCs. To date, WPVC studies have largely focused on characteristics of the collisions themselves and surrounding habitats, rather than the behavior that preceded the collisions (e.g., Beasley et al., 2013; Kusta et al., 2017; Mayer and Beasley, 2018; Psiropoulos et al., 2024). However, Brieger et al. (2022) found that compared to roe deer (*Capreolus capreolus*) and red fox (*Vulpes vulpes*), wild boar (*Sus scrofa*) were least affected by approaching vehicles and had the lowest probability of reacting in a way that minimized the risk of a collision.

Many of the most commonly implemented mitigation methods aimed at influencing animal behavior are largely ineffective, including roadside reflectors (Benten et al., 2019; Benten et al., 2018; D'Angelo et al., 2006) and “deer whistles” (Romin and Dalton, 1992; Valitzski et al., 2009). Roadside fencing and wildlife over- and underpasses are considered the most effective mitigation methods, especially when combined (Donaldson and Elliott, 2021; Huijser et al., 2008; Mastro et al., 2008). However, these methods are costly ($5-15 million per installation; Brennan et al., 2022) and widespread implementation across the road network is impractical. An effective, onboard mitigation method would be a major advancement, because it would be present during all wildlife-vehicle encounters. However, there are currently no commercially available, effective, onboard mitigation technologies (Huijser et al., 2008).

Recent research has focused on onboard vehicle lighting as a method to influence wildlife behavior and invoke movement away from the road, with similar approaches explored for aircraft lighting and birds (Blackwell et al., 2012; Doppler et al., 2015; Lunn et al., 2025). With regard to road-based vehicles, Blackwell and Seamans (2009) found that adding a constantly illuminated Xenarc high-intensity discharge lamp to the roof of a vehicle equipped with standard tungsten-halogen headlamps resulted in deer fleeing at farther distances and suggested that headlamps with emission spectrum more aligned with deer visual capabilities could reduce DVCs. More recently, DeVault et al. (2020) found that increased frontal vehicle illumination via a rear-facing lightbar reduced "freezing" behavior and dangerous encounters with deer in Ohio, USA. The authors suggested that increased vehicle illumination by the lightbar might have provided a more reliable looming object for deer, resulting in greater perceived risk. Although DeVault et al. (2020) found promising results, the effectiveness of the rear-facing lightbar at multiple field sites and with other species remains unexplored.

Despite the advances outlined above, very little research has investigated how popular, commercially available lighting systems influence wildlife behavior. The two most common types of headlights used today are tungsten-halogen headlights (hereafter, halogen) and light emitting diode (LED) headlights, with 86% of new vehicles equipped with LED headlights (Consumer Reports 2019). Compared to halogens, LEDs likely improve driver detection of wildlife at night due to higher photometric illumination levels

(Lee et al., 2014), but direct evidence evaluating this potential benefit is lacking. It remains unclear, however, whether LED headlights lead to more or less favorable reactions by wildlife. One key difference between LED and halogen headlights is that the former produces more blue light (380–500 nm), which more closely matches the peak sensitivities of deer and wild pig photoreceptors (Cohen et al., 2014; Neitz and Jacobs, 1989). Despite their growing popularity, no study has investigated how LED headlights influence wild pig behavior and only one examined their effect on deer. Pakula et al. (2023) found that, for approaches with wild-type captive deer, both headlight type and headlight intensity (low vs. high beam) can influence deer behavior in imminent collision scenarios. Specifically, high-beam halogen headlights increased deer alert probability. Although this study was the first to demonstrate that headlight type and its interaction with increased frontal vehicle illumination can impact deer behavior, the effect of vehicle lighting on free-ranging wild populations under realistic conditions (e.g., longer approach distances, faster vehicle speeds) remains virtually unexplored. Furthermore, it is currently unknown whether headlights that more closely match the peak sensitivities of deer photoreceptors (i.e., LEDs) will result in more positive reactions to vehicles (e.g., longer flight distances), as suggested by Blackwell and Seamans (2009), or if those headlights might overwhelm deer vision at night and result in more negative reactions (e.g., freezing behavior, late flight responses), as suggested by Cohen et al. (2014).

In this study we build upon DeVault et al. (2020) and Pakula et al. (2023) by comparing the effects of halogen versus LED headlights, as well as their potential interaction with increased frontal vehicle illumination, on free-ranging wildlife responses to an approaching vehicle traveling at common road speeds. Specifically, we quantified multiple behavioral responses of roadside wildlife: probability of flight, flight initiation distance, probability of entering the road, and the danger level of each encounter. As more vehicles are produced with LED headlights, understanding their impact on widllife response is necessary. Furthermore, evaluating the interaction of the rear-facing lightbar and headlights provides a more comprehensive understanding of the benefits of a potential mitigation method.

2. Methods

2.1 Study site

We conducted our study at the Savannah River Site (SRS), a U.S. Department of Energy (DOE) facility located in west-central South Carolina, USA. The 803-km^2 site has a large road system of 225 km of maintained primary roads (Blake et al., 2005) with speed limits ranging from 56-89 km/h (Mayer and Johns, 2007). Recently, the SRS has averaged 11-15,000 on-site workers annually (Blake et al., 2005; Savannah River Site, n.d.), but otherwise the SRS has restricted public access and a perimeter fence that is permeable to wildlife including deer and wild pigs. The SRS is estimated to support 4,000-5,000 white-tailed deer (Johns and Kilgo, 2005) and several thousand wild pigs (Keiter et al., 2017). Every year, approximately 100 deer collisions (Johns and Kilgo, 2005) and 40 wild pig collisions occur at the SRS (Beasley et al., 2013).

The SRS is characterized by largely flat terrain with elevation ranging from 20 to 130 m above sea level (Kolka et al., 2005). Most paved roads are bordered by 4 m of regularly mowed grass that transition to an un-mowed strip of vegetation that varies from short grass to 2 m tall, thick grass or woody vegetation. In most areas, a tree line is located beyond this grassy vegetation on both sides of the road, but its distance to the road surface varies. Exceptions to this pattern include larger areas around intersections, railroad crossings, and recent areas of timber harvest, where there are larger patches of maintained grass or open fields (Pakula et al., 2023).

2.2 Vehicle Characteristics

All trials were conducted with the same 2018 Ford F-150 pickup truck. The Ford F-series has been the top selling vehicle in the USA for the past 41 years (Ford Media Center 2023) and thus is a representative vehicle for testing. The truck was equipped with an LED light bar that consisted of 30, 5-watt white LED lights and produced 12,000 lumens (Rough Country Model 70730, Rough Country, Dyersburg, Tennessee, USA). The lightbar was attached to the truck's brush guard, 9 cm from its surface, and was angled downward toward the grille to ensure light from the lightbar was not visible to the driver (DeVault et al., 2020). We equipped the truck with a forward-looking infrared (FLIR) camera (FLIR M625S, FLIR Systems, Goleta, California, USA) that displayed a live feed video on a monitor mounted to the passenger seat's dashboard, which allowed the researcher to view wildlife near the road up to 800 m away in real time (Blackwell et al., 2014, DeVault et al., 2020). The FLIR was connected to a GPS-enabled MobileMule 4 Channel Mobile Digital Video Recorder (RVS-6202, Rear View Safety, Brooklyn, New York, USA), which recorded each wildlife encounter and overlaid the vehicle's current location on the video.

2.3 Trial Phases

Our study vehicle was manufactured with either halogen reflector or LED reflector headlights, depending on the trim level (IIHS, n.d.), allowing us the opportunity to evaluate differences in wildlife responses between headlight types. The trials conducted from August 2021-August 2022 used the factory-installed halogen headlights, whereas the trials conducted from July 2024-June 2025 were conducted with stock 2018-2020 Ford F-150 LED headlight assemblies obtained from an authorized Ford dealer.

To characterize each headlight assembly's spectral profile and total radiance (W/sr/m^2), we measured the light emitted from both headlights using a spectrometer (PR-650 SpectraScan SpectraColorimeter), on a level road during a moonless night. We recorded five readings for each headlight type with the spectrometer positioned 1.1 m off the ground (DeVault et al., 2020) and at distances of 105, 150, 200, 250, 300, 400, 500, and 600 m away. Readings from shorter distances were omitted because the spectrometer's measurement windows did not fully encompass both headlights, resulting in potentially misleading values.

2.4 Field Methods

Each trial began ~30 min after sunset under dry, fogless conditions when there was no ambient light detectable with a LI-COR LI-250A Light Meter and LI-190R Quantum Sensor (0.00-0.01 μmol·m^{-2}·s^{-}1; LI-COR Biosciences, Lincoln, Nebraska, USA). The starting location of each trial was randomized among four locations that corresponded to four entrances to the SRS. For each trial, we drove a 75-km route of paved roads throughout the SRS, approximately one night per week for two full calendar years. Exceptions occurred when adverse weather conditions (e.g., rain) prevented a trial for a given week. The weekly trials were spaced at least four days apart to minimize autocorrelation among datapoints. We conducted the first 16 halogen headlight trials at the posted speed limit (mostly 89 km/h). To evaluate the effectiveness of our lighting treatments at different vehicle speeds, the remaining halogen headlight drives were conducted, randomly, at 60, 75, and 89 km/h at a relative proportion of 0.4, 0.4, and 0.2, respectively. During our second trial phase (LED headlights), our trials were conducted, randomly, at 60, 75, and 89 km/h in equal proportions. During both phases we drove segments of roads at the posted speed when it was slower than the trial speed and recorded the vehicle speed after each encounter. Although vehicle speed was predetermined before each trial, we drove and recorded lower speeds when the posted speed limit was below the trial speed or when we encountered an animal shortly after turning onto a different road.

Each trial followed a nearly circular route that did not repeat the same stretch of road within each night. The driving direction (clockwise or counterclockwise) was randomized before each trial. The trials that occurred outside of daylight saving time (11/2021-03/2022 and 11/2024-03/2025) began 1.5 h after sunset to avoid rush-hour traffic and to more closely match traffic levels of the trials conducted during daylight saving time. To limit the confounding influence of other vehicles (e.g., increased road illumination), we refrained from recording encounters in the presence of other vehicles. For all trials, we drove with the high-beam headlights enabled for all vehicle approaches, but the lightbar treatment (on vs. off) was alternated after each encounter with an animal (DeVault et al., 2020).

During the trials, a researcher in the passenger seat of the vehicle continuously viewed the FLIR monitor for wildlife near the roadway. The passenger notified the driver when an animal was detected on the FLIR monitor. Using the vehicle’s cruise control, the driver maintained a constant speed and initiated braking once all individuals fled the area or the vehicle was ~40 m away from an animal that did not exhibit a flight response. The driver then stopped the vehicle perpendicular to the initial location of the animal. After the vehicle was stopped and the animals fled the area, the driver measured the animals' distance to the road (to the nearest meter) using a tape measure. The initial location of the animals was determined by discussion between the driver and the passenger that was monitoring the FLIR video. The animal's distance to concealing cover (vegetation tall and dense enough to conceal a standing animal) was measured to the nearest meter on each side of the road using a tape measure or a laser rangefinder (Ranger 1800, Vortex Optics, Bareneveld, Wisconsin, USA). This study received animal subjects approval from the University of Georgia's Institutional Animal Care and Use Committee (no. A2021 06-013-Y1-A0 and A2024 04-004-Y1-A0).

2.5 Data Extraction

Several variables were collected and calculated for each encounter with an animal (hereafter, encounter) including group size, time from sunset (in minutes), and season (Table 1). We categorized seasons around deer peak breeding dates (Oct. 15-Nov.15) within our study area (SC DNR, n.d.): fall (Sep. 16- Dec. 15), winter (Dec.16-Mar. 15), spring (Mar.16-Jun.15), and summer (Jun.16-Sep. 15).

During video review, we confirmed that the animals' distance to the road measurements from the night trials were reasonable. In cases for which the animal's initial location was determined not to be accurate from the inspection of the FLIR video, the animals' distances to the road edge were estimated to the nearest m from the FLIR recordings using known distances to objects on the landscape (e.g., width of the road, utility poles, guardrails, and drainage ditches) and Google Earth (Mountain View, California), when applicable. This method is comparable to field scoring with an absolute error of 0.97 m (SE =0.15; Pakula et al., 2023). We applied a correction to each encounter’s distance to the road edge to obtain each animal’s distance to the path of the vehicle under the assumption that each driving lane was 3-m wide and the vehicle was driving in the middle of the lane (Table 1).

Although GPS points taken by the MobileMule DVR were relatively precise, they were not always accurate on the landscape due to the interaction of the unit’s refresh rate (i.e., how often the unit updated its position) and vehicle speed. As a result, GPS points displayed on the video represented locations some short but unknown distance before the behavior being measured actually occurred. We accounted for the MobileMule “lag” based on the speed of the vehicle for every distance calculation (Pakula et al., 2023).

We projected all GPS coordinates to Universal Transverse Mercator (UTM) zone 17S and then snapped them to a GIS road layer for our study site. All points were visually inspected to ensure they were snapped to the correct road. We calculated each encounter’s approach distance by calculating the Euclidean distance between the coordinates of the animal’s initial location and the coordinates displayed on the FLIR for the frame corresponding to when the first individual within a group was detected (Fig. 1). To correct for the Mobile Mule DVR’s GPS displaying the same coordinates for 1 s due to its refresh rate, we interpolated the detection frame’s relative position between successive GPS points. An animal’s flight initiation distance (FID) was calculated by calculating the Euclidean distance between the coordinates of the animal’s initial location and the coordinates displayed on the FLIR video when the animal initiated a movement that resulted in locomotion away from their initial location (Fig. 1). Again, we adjusted the FID value based on the flight frame’s relative position between the current and subsequently displayed GPS points. If an animal only moved its head or turned without locomotion, we did not consider that behavior a flight response. Furthermore, if an animal was initially browsing while slowly moving, we defined a flight response as a distinct change in movement speed which usually followed a change in behavior (e.g., a deer raising its head from browsing before walking faster). We excluded encounters during which an animal was initially moving when the animal was first detected by the FLIR (e.g., sustained movement not associated with browsing), because we were unable to determine whether the animal's movement was caused by the vehicle. If an animal displayed multiple flight responses during the same approach, we scored only the first flight response. For all analyses, we excluded any animals that were initially in the tree line when detected by the FLIR as their responses could not be reliably measured.

Because approach distance inherently limits FID (Dumont et al., 2012), we excluded encounters with short approach distances. Minimum approach distance cutoffs were set to values greater than the raw median FID for each species group to ensure that approach distance did not systematically limit FID for more than half of the samples. Those distances were 250m, 200m, 200m, 100m, 100m, 150m, for deer, wild pigs, canids, raccoons (*Procyon lotor*), rabbits (*Sylvilagus spp.*), armadillos (*Dasypus novemcinctus*), and bobcats (*Lynx rufus*), respectively. Due to our inability to distinguish coyotes (*Canis latrans*) from foxes (*Vulpes vulpes* and *Urocyon cinereoargenteus*) on the FLIR videos, we analyzed them together as a single canid group. These thresholds were chosen because most raw FID values were below them, suggesting that they did not limit FIDs. Additionally, we excluded any individual with an FID value greater than 600m, 500m, 400m, and 200m for deer, wild pigs, canids, and rabbits, respectively, because the resolution of the video at those distances prohibited us from accurately assessing flight behavior. To standardize our encounters to the individuals that posed the greatest threat to the driver, we excluded any individual located on hilltops or in depressions when their elevation differed by more than 2m above or below the road surface.

2.6 Data Analysis

We evaluated the influence of headlight type (halogen vs. LED), lightbar usage (off vs. on), vehicle speed (treated as a continuous variable), and other covariates on the following response variables: (1) the probability that all animals within a group initiated flight, (2) the average flight initiation distance of groups that fled, (3) the probability that an individual entered the road, (4) the distance from the vehicle when an individual entered the road, and (5) the danger level of each encounter. Table 2 provides additional information on each analysis. Because each analysis used a different subset of data based on specific inclusion and data-cleaning criteria, the reported sample sizes differ among analyses.

Due to inadequate sample sizes of animal groups other than deer and wild pigs (i.e., canids and small mammals), we were unable to fit robust models for these groups. Thus, for animal groups other than deer and wild pigs, we calculated only descriptive statistics including proportions for flight probability and the mean FIDs and standard errors (SE) for each animal group. We use the term *group* to denote a single encounter, regardless of whether it involved one or more individuals. Below we describe the analyses conducted for each of the four response variables recorded for deer and wild pigs.

For all analyses other than road entering probability and distance, we restricted our analyses to groups located entirely within 10m of the path of the vehicle, because those individuals posed the greatest hazard to drivers (see Road Entering Probability below), and could be reliably observed. Flight probability was then defined as whether all individuals within a group initiated flight beyond 45m from the vehicle. Individuals located farther from the road inherently left our FLIR's field of view at farther distances away from the vehicle (e.g., an individual located 10m from the path of the vehicle left the camera's field of view when the vehicle was 45m away). To reduce this observation bias, we only evaluated individuals located within 10m of the vehicle path and defined flight probability based on a 45m FID threshold. We analyzed flight probability at the group level, as that provided the greatest indication of driver safety. For example, if one individual within a group initiated flight, but others remained, we classified the group as non-flight as the remaining individuals posing a danger to the driver. Similarly, the flight initiation distance analysis only included groups in which all individuals initiated flight as reporting the FID of only the individuals that fled within a group would fail to represent non-responding individuals. Conversely, reporting FID = 0m for individuals that did not flee within mixed-response groups would lower group FID mischaracterizing the group's flight behavior.

For our analysis investigating the factors influencing the encounter's danger level, we classified behavioral responses into three ordered danger levels: low, medium, and high. Low danger was attributed to individuals that initiated flight (i.e., had an FID) greater than the minimum braking distance; in other words, individuals began leaving the road area beyond the distance needed to stop a vehicle safely. The second danger level (medium) was defined as individuals that exhibited no flight. Although stationary individuals did not enter the road, they can cause drivers to swerve (Conn et al., 2004; Rowden et al., 2008; Smoot et al., 2010) and have a higher risk of being startled by sudden vehicle movements (braking) which could evoke flight into the road given their close proximity. The high danger level was attributed to animals that were in the road when the vehicle reached its minimum braking distance, or an animal was within 10m of the path of the vehicle and exhibited a flight response at a distance less than the vehicle's minimum braking distance (see below). These flights near the road can lead to drivers swerving and potentially crashing their vehicle (Conn et al., 2004; Smoot et al., 2010).

A vehicle's minimum braking distance was calculated using the American Association of State Highway and Transportation Officials' formula (AASHTO, 2018) for calculating braking distance under level conditions:

$$SSD = 0.278Vt + 0.039V^2/a$$

where SSD is the stopping sight distance, V is the vehicle's velocity in km/h at driver detection, t is brake reaction time (2.5s is recommended), and a is the vehicle's deceleration rate (3.4 m/s^2 is recommended). This formula incorporates both a driver's reaction time to a sudden hazard in the road and a vehicle's inherent stopping distance, providing a relevant measure how much distance a driver needs to safely observe an animal, identify it has a hazard, and slow the vehicle to a stop. At the three speed treatments in our study (60, 75, and 89 km/h), the minimum braking distances were 83.0, 116.6, and 152.7 m, respectively. For this analysis we investigated the odds an encounter was at a higher danger level (Table 2).

All analyses were conducted in R version 4.3.1 (R Core Team, 2023). To evaluate the most influential variables for each analysis we developed 10-20 *a priori* candidate models based on previous study results, knowledge of the system, and raw data plots (Bolker, 2008; Burnham and Anderson, 2002; Johnson and Omland, 2004). We ranked these models using AICc (Burnham and Anderson, 2002) with the package MuMin (Barton, 2023). We report the coefficients and 85% confidence interval (CI; Arnold, 2010; Sutherland et al., 2023) for the variables in the competing model ΔAICc <2 but focus our interpretation on the most parameterized model within the nested set for which all coefficients' 85% CI did not cross zero, following Sutherland et al. (2023). We refer to this model as the *best performing model* and all figures are based on this model. We report r-squared values for the best performing model for each analysis using the performance package (Lüdecke et al., 2021). For logistic regressions, we report the variables' effect as odds ratio (OR). For all reporting within the text, we report the back transformed estimates. Estimated marginal means were calculated using the package ggeffects (Lüdecke, 2018) to visualize model predictions over a range of conditions and to compare mean values. All continuous variables (except group size) were standardized (mean = 0, SD =1) using the scale() function in R.

3. Results

3.1 Vehicle Headlights

Across all distances from the vehicle, halogen headlights radiated more light (380-780nm) than LED headlights, with the greatest differences at closer distances to the vehicle (Fig. 2). Compared to halogens, the LED headlights produced more light in the blue (420-468nm), and the green spectrum range (508-604 nm), whereas halogen headlights produced more long-wavelength, red light (608-780nm; Fig. 3). The rear-facing lightbar increased the area of illumination on the front of the vehicle and provided a slight increase in the vehicle's overall radiance (0.05-0.08%; Fig. 4; Fig. 5).

3.2 Trial Overview

We conducted 47 drives with halogen and 48 with LED headlights totaling 95 drives and 7,125 km travelled throughout the study. Overall, we had the most encounters with deer followed by wild pigs, rabbits, armadillos, canids, raccoons, bobcats, striped skunks and opossums (Fig. 6). We were unable to identify the species for 2.8% of the encounters.

3.3 Flight Probability

We encountered 156 groups of deer for which all individuals were within 10m of the path of the vehicle. The mean group size was 1.45 ± 0.80 SD (range: 1-5) and median group distance to the path of the vehicle was 6.5m ± 1.99 SD. All individuals initiated a flight response in 112 of the 156 groups (71.8%). Out of the full candidate set of models, six were considered competing (Table 3, Table 4). Our best performing model suggested deer approached from longer distances had a higher probability of initiating flight (OR per 50m = 1.13, 85% CI: 1.01, 1.27). Vehicle speed had contrasting effects depending on the usage of the lightbar. When the lightbar was off, the probability of flight significantly decreased with increasing speeds (OR per km/h = 0.94, 85% CI: 0.92, 0.97; Fig. 7), whereas when the lightbar was on, the negative effect of speed was mitigated, resulting in a slight increase in flight probability as speed increased (OR per km/h = 1.03, 85% CI: 1.01, 1.06; Fig. 7). At 60 km/h, the probability of flight was lower with the lightbar off (0.66, 85% CI: 0.54, 0.76) than with the lightbar on (0.86, 85% CI: 0.76, 0.93). At

90 km/h, the pattern reversed; flight probability was higher with the lightbar on (0.83, 85% CI: 0.72, 0.90) compared to off (0.55, 85% CI: 0.42, 0.67; Fig. 7). Our best performing model had a pseudo r-squared value of 0.09.

We encountered 57 groups of wild pigs in which all individuals were within 10m of the path of the vehicle. The mean group size was 2.14 ± 1.82 (range: 1-9) and median group distance to the path of the vehicle was 6.5 ± 2.02. All individuals initiated a flight response in 24 of the 57 groups (42.1%). Out of the full candidate set of models, three were considered competing (Table 5, Table 6). Our best performing model included only the variable group size, which had a negative effect on the probability that all individuals within a group fled (OR: 0.76, CI: 0.58, 0.99; Fig. 8). The null model was a competing model (Table 6); however, our top performing model's confidence intervals did not overlap zero, suggesting that there was weak effect of group size on wild pig flight probability. Our best performing model had a pseudo r-squared value of 0.05.

When evaluating the other animal groups, we observed that all canid and bobcat groups initiated flight during every encounter, regardless of lighting treatment (Fig. 9). There was a trend of fewer flight responses when raccoons were approached with LED headlights, but we only observed 3 encounters with halogen headlights (Fig. 9). Rabbits fled at similar rates across treatments, except for the halogen and lightbar on treatment which resulted in 100% flight (n= 9; Fig. 8). Armadillos rarely initiated flight regardless of lighting treatment (Fig. 9).

3.4 Flight Initiation Distance

Of the 112 groups in which all deer initiated flight, four models were considered competing (Table 7, Table 8). From the best performing model, median group FID increased with increasing approach distance (β_{Original}= 0.36, 85% CI: 0.26, 0.47), distance from nearest cover (β_{Original}= 3.53, 85% CI: 1.64, 5.41), time from sunset (β_{Original}= 0.29, 85% CI: 0.03-0.55), and group size (β_{Original}= 17.1, 85% CI: 0.22, 33.88; Fig. 10). Median FID values decreased as distance to the path of the vehicle increased (β_{Original}= -13.08, 85% CI: -19.98, -6.19; Fig. 10). Neither of our lighting treatments nor vehicle speed were present in the competing models and thus those variables showed no evidence of influencing deer FID. Overall, when all predictors were held at their median values (approach distance: 375.8m, distance to path of vehicle: 6.5m, distance to nearest cover: 6.75m, time from sunset: 111.7min, group size: 1 individual), the median group FID was 217.7m (CI: 202.1, 233.16; Fig. 10). Our best performing model had an r-squared value of 0.39.

Of the 24 wild pig groups in which all individuals initiated flight, two models were considered competing (Table 9, Table 10). Our best performing model suggested that median group FIDs increased with increasing approach distance (β_{Original}= 0.22, 85% CI: 0.10, 0.35) and increased by 114.8m when the wild pigs were approached with LED headlights compared to halogen headlights (CI: -66.8, 162.8; Fig. 11). When the lightbar was off, FIDs decreased with increasing vehicle speed (β_{Original}= -3.26, CI: -5.95, -0.57; Fig. 11); however, when the lightbar was on, FIDs increased as speed increased (β_{Original}= 3.20, CI: 1.35, 5.06; Fig. 11). Our best performing model had an r-squared value of 0.65. Compared to deer and wild pigs, canids had similar FIDs (Fig. 12). There was a potential trend of lightbar increasing FID when using LED headlights, but the sample size was small (n= 6 and 3, respectively). Rabbits had relatively shorter FIDs compared to the other species. Low sample sizes of bobcats, raccoons, and armadillos limit any meaningful interpretation.

3.5 Road Entering Probability

Of the 258 groups of deer we encountered, 28 (10.9%) groups had at least one individual enter the road in front of the vehicle during the approach. Of the full candidate set of models, six were considered competing (Table 11, Table 12). From the best performing model, the odds of a deer entering the road increased with approach distance (OR per 50m = 1.04, 85% CI: 1.01–1.07) and with LED headlights (OR: 2.14, CI: 1.12-4.27; Fig. 13). A deer's distance to the road had a negative effect on road entering probability, but the magnitude of this effect differed by side of the road (Fig. 13). There was a stronger negative effect for deer on the left side of the road (OR: 0.57, CI: 0.42-0.77) compared to deer on the right side of the road (OR: 0.86, CI: 0.76-0.96; Fig. 13). However, the confidence intervals of the predicted road entry probabilities overlapped for all distances to the road, indicating a relatively weak effect. Our best performing model had a pseudo r-squared value of 0.11.

Of the full candidate set of models for deer road entering distance, no model had ΔAIC <2 relative to the top model (Table 13, Table 14). From this best performing model, the distance from the vehicle at which deer entered the road increased with approach distance (β_{Original}= 0.26, 85% CI: 0.22, 0.32) and deer farther from the road entered the road at shorter distances away (β_{Original}= -9.85, 85% CI: -16.5, -3.22; Fig. 14). Additionally, when the nearest cover was on the same side of the road as the deer, deer entered the road at closer distances to the vehicle (β = -78.3, CI: -129.2, -27.5; Fig. 14). When all predictors were held at their median values (approach distance: 406.7m, distance to road: 3m), road entering distance was 365.1m (CI: 315.9, 414.2) when nearest cover was across the road and 286.7m (CI: 265.6, 307.8) when the nearest cover was on the same side of the road as the deer (Fig. 14). Our best performing model had an r-squared value of 0.84.

Of the 91 groups of wild pigs we encountered, 7 (7.7%) groups had at least one individual enter the road in front of the vehicle during the approach. Due to the low number of road entries, we were unable to evaluate the influence of predictor variables in a formal analysis.

3.6 Dangerous Encounters

We encountered 193 groups of deer with at least one individual within 10m of the path of the vehicle. Of those encounters, 114 (59.1%) were low danger (FID > minimum braking distance), 39 (20.2%) were medium danger (no flight), and 40 (20.7%) were high danger (FID < minimum braking distance). Of the full candidate set of models, three were considered competing (Table 15, Table 16). The odds of being at a higher danger level decreased with increasing approach distances (OR per 50m: 0.87, CI: 0.80, 0.96) and with increasing distance to the path of the vehicle (OR: 1.14, CI: 1.02, 1.26; Fig. 15). When the lightbar was off, faster vehicle speeds resulted in higher odds of an encountered deer being at a higher danger level (OR: 1.06, CI: 1.04, 1.09), but this effect was mitigated when the lightbar was on (OR: 1.00, CI: 0.98, 1.02; Fig. 15). Specifically, the probability of a high danger encounter (FID < minimum braking distance) when the lightbar was off increased from 0.09 (CI: 0.05, 0.15) to 0.37 (CI: 0.28, 0.47) at 60 and 90 km/h, respectively (Fig. 15). However, when the lightbar was on, the probability of a high danger encounter was 0.19 (CI: 0.13, 0.27) at 60 km/h and remained similar at 90 km/h at 0.19 (CI: 0.12, 0.28; Fig. 15). Our best performing model had a pseudo r-squared value of 0.14.

We encountered 74 groups of wild pigs with at least one individual within 10m of the path of the vehicle. Of those encounters, 23 (31.1%) were low danger (FID > minimum braking distance), 33 (44.6%) were medium danger (no flight), and 18 (24.3%) were high danger (FID < minimum braking distance). Out of the full candidate set of models, three were considered competing (Table 17, Table 18). The odds of an encounter being at a higher danger level decreased with increasing approaching distances (OR per 50m: 0.89, CI: 0.80, 0.99) but increased with increasing vehicle speed (OR: 1.03, CI: 1.01, 1.06) and group size (OR: 1.30, CI: 1.12, 1.51; Fig. 16). Group size had the greatest effect, as the probability of a high danger encounter when travelling 90 km/h with a mean approach distance (417.6m) was 0.25 (CI: 0.15, 0.40), 0.49 (0.33, 0.65) and 0.78 (CI: 0.52, 0.92) for group sizes of 1,5, and 10, respectively (Fig.16). Neither of the lighting treatments affected the probability of a dangerous encounter with wild pigs. Our best performing model had a pseudo r-squared value of 0.17.

4. Discussion

Overall, our results demonstrate that vehicle lighting influences the behavior of roadside wildlife, with the potential to help reduce wildlife-vehicle collisions. Deer and wild pigs responded differently to the approaching vehicle, but broadly we observed neutral to positive effects of LED headlights and the rear-facing lightbar on their behavior. These results highlight the potential for vehicle-based lighting configurations to serve as potential collision mitigation methods.

4.1 Headlights

For the stock headlights of a 2018 Ford F-150 pickup truck, halogen headlights produced higher radiance values than LEDs. However, the LEDs produced higher radiance values in the ranges to which deer are most sensitive (blue and green light; Cohen et al., 2014; Jacobs et al., 1994). The rear-facing lightbar increased frontal illumination of the vehicle, but had a small effect on the overall radiance values measured (DeVault et al., 2020). Despite LED headlights producing lower radiance values overall, it remains unknown whether deer perceive LED headlights as "brighter" compared to halogen headlights, which would require perceptual modeling (e.g., Goller et al., 2018). Because the radiance values of the headlights in this study decreased exponentially with distance, future research should examine how vehicle headlights affect wildlife visual systems at varying distances.

4.2 Flight Probability

For deer groups within 10m of the vehicle's path, all individuals fled during 66-83% of the encounters, but these rates were impacted by vehicle speed and lightbar usage. When the lightbar was off, fewer groups initiated flight as vehicle speed increased. In other words, faster vehicle speeds resulted in higher rates of freezing behavior in deer when the lightbar was off. This likely reflects the difficulty in processing and assessing a vehicle as a threat at the evolutionarily novel speeds they travel (Blackwell et al., 2016), a pattern also observed in other species including birds (DeVault et al., 2015). However, the use of the lightbar mitigated the reduction in flight initiation at faster speeds. Interestingly, at the 60 km/h speed tested in DeVault et al. (2020), we found that the lightbar reduced flight probability, contrary to their findings. Although we found strong evidence that the lightbar increased flight at faster vehicle speeds, the discrepancy at 60 km/h may reflect study methodological or site differences such as habitat or deer experiences with vehicles (Blackwell and Seamans, 2009; Stankowich, 2008). Increased frontal illumination of the vehicle might have provided deer with more information about the approach threat (DeVault et al., 2020), counteracting the overwhelming effect of faster vehicle speeds.

Wild pig flight probability was primarily influenced by group size. As the number of wild pigs within a group increased, the probability that all of them fled decreased. This likely reflects group dynamics, as the likelihood of all individuals responding similarly decreases with larger group sizes. Consequently, encountering larger groups increases the probability that at least one individual will remain next to the road, potentially increasing the chances of a multiple-individual collision (Beasley et al., 2013; Psiropoulos et al., 2024). Contrary to our findings with deer, we found no effect of the lightbar or vehicle speed on wild pig flight probability. Previous work with wild boar found that flight behavior was more likely when the boar were attentive before the vehicle approach and that groups often focused on intra-specific interactions rather than vehicle traffic (Brieger et al., 2022), potentially explaining the relatively lower rate of flights we observed for wild pigs compared to deer (42.1% vs. 71.8%).

4.3 Flight Initiation Distance

For deer groups in which all individuals initiated flight, FID values were most influenced by variables that affected deer's threat perception of the vehicle. As observed previously, deer closer to the path of the vehicle initiated flight at longer distances (Pfeiffer et al., 2020), highlighting increased perceived risk for direct vs. tangential approaches (Stankowich, 2008; Stankowich and Blumstein, 2005). Similarly, deer FID increased when they were located farther from cover, likely highlighting their vulnerability and higher perceived risk of their location away from safety (Stankowich and Blumstein, 2005). Both of these findings were consistent with antipredator behavior (Frid and Dill, 2002). As deer group sizes increased, FIDs also increased, likely due to more individuals identifying the threat leading to longer flights (Stankowich and Coss, 2007). Deer fled at the same distance regardless of vehicle speed (Blackwell et al., 2014; Pfeiffer et al., 2020), suggesting deer might have used a spatial margin of safety, rather than adjusting their FID based on vehicle speed (temporal margin of safety ; Cárdenas et al., 2005; Lunn et al., 2022). Similar to previous studies, we observed no effect of vehicle lighting on deer FID (DeVault et al., 2020; Pakula et al., 2025).

Contrary to deer, for the groups of wild pigs that initiated flight, we found that vehicle lighting influenced their FIDs. When the lightbar was off, wild pig FIDs decreased as vehicle speeds increased, reflecting a delayed margin of safety (Guenin et al., 2024). This type of escape response is generally attributed to animals delaying their flight response due to limited attention being allocated to vigilance compared to other activities (e.g., foraging), and thus faster speeds result in the vehicle approaching closer before the animal initiates flight (Lunn et al., 2022). However, the lightbar on treatment resulted in a different escape behavior being employed, as FIDs increased with increasing speed, reflecting a temporal margin of safety (Guenin et al., 2024; Lunn et al., 2022). It is possible that increased vehicle illumination increased wild pig threat assessment of the vehicle, resulting in a more beneficial flight response in the form of longer FIDs. Fleeing at greater distances as speed increases is advantageous because this strategy gives the animal more time to remove itself from the path of the vehicle, but these responses are relatively uncommon at the relatively fast speeds travelled by modern vehicles (e.g., DeVault et al., 2015). Additionally, we found that LED headlights increased wild pig FID regardless of speed or lightbar usage. Wild pigs are sensitive to blue and green light (Neitz and Jacobs, 1989), and thus LED headlights might produce a more salient looming image to them. Although deer and wild pig vision is similar in cone photoreceptor sensitivity (Jacobs et al., 1994; Neitz and Jacobs, 1989) and have comparable rod and cone densities (Blackwell and Seamans, 2009; D'Angelo et al., 2008; Gerke et al., 1995; Hendrickson and Hicks, 2002; Miller and Snyder, 1977), an important difference is that wild pigs lack a tapetum lucidum (Ollivier et al., 2004). This reflective layer increases an animal's sensitivity to low-light conditions which might make deer vision more easily overwhelmed by LED headlights compared to wild pigs, potentially explaining the differences we observed in the effect of headlights on FID values. Although our sample size was low (n = 24), to our knowledge, this was the first study to document wild pig FIDs to approaching vehicles and the influence of vehicle lighting.

4.4 Road Entering Probability

We found that road entering was largely influenced by a deer's location relative to the road. Deer closer to the road were more likely to enter, likely due to increased risk perception during more direct approaches (Stankowich, 2008; Stankowich and Blumstein, 2005) and because deer farther from the path of the vehicle were less likely to initiate a flight (see Flight Probability above). However, the model suggested that the decline in road entry probability with increasing distance from the road was steeper for deer on the left side. Because deer on the left were inherently 3m farther from the vehicle's path compared to those on the right, they may have perceived a more rapid decrease in risk (Pfeiffer et al., 2020; Stankowich, 2008; Stankowich and Blumstein, 2005). We observed a weak effect of LED headlights increasing deer road entry probability. It remains unclear why LED headlights affected road entries but not other behavioral responses; however, one potential explanation is that deer are more sensitive to the wavelengths of light produced by LEDs, which may partially overwhelm or confuse them (Cohen et al., 2014; Pakula et al., 2025), increasing their likelihood of fleeing in any direction, including into the road. Overall, deer in our study entered the road in front of the vehicle only 10.9% of the time, a substantially smaller value than the 36.5% and 41.7% reported by Blackwell et al. (2014) and DeVault et al. (2020), respectively. Notably, the latter two studies were conducted at the same location, suggesting that site-level factors could be more influential than headlights on road entering behavior. DeVault et al. (2020) also reported that deer only crossed the road in front of the vehicle when the nearest cover was across the road; however, our models did not support this finding. These differences could reflect differences in roadside habitats. The DeVault et al. (2020) study site contained 31% open fields and mowed grass up to 30m from the road, whereas our study was more forested, had smaller rights of way, and often had concealing cover on both sides of the road, potentially explaining the lack of an effect of cover on road crossing probability.

Only 7.69% of the wild pig groups we encountered had an individual enter the road. Although we were unable to formally evaluate variables influencing road entry, this value was similar to our findings for deer. At the SRS, there is roughly 1 deer collision per 45 deer in the population, and similarly, 1 wild pig collision per 50-100 wild pigs

(Beasley et al., 2013; Johns and Kilgo, 2005; Keiter et al., 2017). Given their similar rates of road crossing and collisions, it is likely that as wild pig populations continue to increase, especially in the southeastern USA (Lewis et al., 2019), wild pig collisions will continue to grow and potentially lead to prominent management concerns akin to deer (Beasley et al., 2013; Mayer and Johns, 2007; McKee et al., 2024).

4.5 Road Entering Distance

We found that neither headlight type nor lightbar usage affected the distance at which deer entered the road. Although LEDs increased the probability that a deer would enter the road, they often did so at distances beyond the minimum braking distance and beyond a driver's ability to detect the deer (Pakula et al., 2023), limiting the overall negative effect of LED headlights. In contrast, a deer's proximity to cover strongly influenced its road entering distance. When the nearest cover was on the same side of the road as the deer, they entered the road, on average, 78m closer to the vehicle. Although drivers may assume that deer positioned near a tree line are less likely to enter the road, our results indicate that when those individuals do enter the road, they tend to do so at much shorter distances, potentially increasing the risk of a collision. Our data cleaning methods removed deer from analyses with approach distances > 250m, and on average, those that entered the road did so at 365.1m, suggesting that most deer enter the road at safe distances. However, it remains unclear how often deer enter the road when approached from shorter distances, when they have less time to react favorably, increasing the likelihood of a collision.

4.6 Dangerous Encounter Probability

The odds of an encounter with a deer being at a higher danger level increased with increasing vehicle speed. Because deer did not adjust their FID as speed increased (see Flight Initiation Distance above; Blackwell et al., 2014) and a faster vehicle requires a longer distance to stop (AASHTO, 2018), deer were more likely to initiate flight within the minimum braking distance as vehicle speed increased, resulting in a higher probability of high-danger encounters. However, we found that the lightbar mitigated this effect, as the odds of being at each danger level remained constant across speeds. Specifically, when driving with the lightbar on, the probability of deer freezing (medium danger) and the probability of a deer's FID < minimum braking distance (high danger) remained constant across speeds. Our findings generally support those from DeVault et al. (2020) in that the lightbar reduced dangerous encounters with deer. Even so, we found no effect of the lightbar at the speeds travelled in DeVault et al. (2020) study (60 km/h), but instead the effect of the lightbar emerged as speed increased. This difference could potentially be attributed to DeVault et al. (2020) defining a dangerous encounter as those during which a deer's FID was <50m (proxy for driver detection distance; Mastro et al., 2010), whereas we evaluated danger on an ordinal response scale that incorporated minimum braking distances (AASHTO, 2018). Despite LED headlights increasing deer road entering probability, we found no effect of headlight type on dangerous encounter probability.

Similar to deer, the odds of an encounter with a wild pig being at a higher danger level increased with vehicle speed; however, unlike deer we found no effect of the lightbar for wild pigs. Specifically, the probability of a high danger encounter increased with vehicle speed, suggesting wild pigs were more likely to initiate flight within the minimum braking distance at faster speeds. Additionally, encountering a large group of wild pigs increased the probability of a high danger encounter, as there was a greater likelihood that at least one individual would flee within the minimum braking distance. Even though collisions with wild pigs typically occur with one individual (76-89%), it is not uncommon for them to involve multiple individuals (Beasley et al., 2013; Mayer and Johns, 2007; Psiropoulos et al., 2024). Although LED headlights increased FID for groups in which all individuals initiated flight, they had no effect on the odds of a dangerous encounter. One potential explanation is that our FID analysis only considered groups of wild pigs for which all individuals initiated flight, whereas our dangerous encounter analysis accounted for the most dangerous individual within a group, including groups comprising individuals that did not flee. Compared to deer, wild pigs had higher rates of individuals not exhibiting a flight response (medium danger) or initiating flight within the minimum braking distance (high danger), especially at larger group sizes. Our results align with previous research that found wild boar were the species least affected by vehicles from a behavioral perspective, especially compared to roe deer (Brieger et al., 2022). The higher rates of immobile and short FID responses compared to deer is concerning, because drivers usually fail to detect wild pigs at safe distances (Pakula et al., 2023).

4.7 Implications for Driver Safety

Every year, an estimated 2.6 million deer-vehicle collisions occur in the USA (Conover, 2019), and one million ungulate-vehicle collisions occur in Europe (Langbein et al., 2010). These collisions result from not only ineffective driver detection (Mastro et al., 2010; Pakula et al., 2023), but also from maladaptive wildlife responses (Blackwell et al., 2014; Lima et al., 2015). Our findings demonstrate that vehicle lighting can influence these behaviors in a way that can increase driver safety. At faster vehicle speeds, deer were more likely to freeze and wild pigs tended to initiate flight at shorter distances; however, these responses were influenced by vehicle lighting. Specifically, LED headlights increased road entry for deer but generally at safe distances from the vehicle, whereas for wild pigs, LED headlights increased FIDs regardless of vehicle speed. Taken together, our results suggest that LEDs have neutral or beneficial effects on wildlife response compared to halogen headlights. Given that LED headlights increase photometric illumination distances (Edmonds, 2015; Lee et al., 2014), likely increasing drivers' ability to detect wildlife at night, it is probable that LEDs will have a net benefit in reducing wildlife-vehicle collisions. However, more research is needed on the effects of other headlight types and the role of specific headlight properties (e.g., height, alignment, intensity, spectral profile) on wildlife responses.

Our findings generally support those from DeVault et al. (2020) indicating that increased frontal vehicle illumination increases deer flight behavior at safe distances from the vehicle, reducing the probability of a dangerous encounter. More specifically, we found that the lightbar mitigated the effects of increased freezing and dangerously close FIDs by deer at faster vehicle speeds, when crash severity is usually highest (Savolainen and Ghosh, 2008). For wild pigs, the lightbar increased FIDs at faster vehicle speeds, providing drivers with more time to respond. Collectively, our results suggest that increased frontal vehicle illumination via rear-facing lighting represents a relatively low-cost modification that can help reduce WVCs, although data from species other than white-tailed deer and wild pigs are needed.

Although our findings are limited by including one location, using one vehicle, and restricting our analyses to only initially stationary individuals, our study represents one of the most comprehensive investigations into the effects of vehicle lighting on wildlife reactions to approaching vehicles under realistic conditions. Overall, we found large variations in deer behavior (Pakula et al., 2025), highlighting the challenge of developing universally effective mitigation methods. To further understand the causes of WVCs, more research is needed on individual variation in responses to vehicles and how these are shaped by experience (e.g., habituation or sensitization; DeVault et al., 2018; DeVault et al., 2017; Stankowich, 2008). Even so, we observed measurable effects of increased frontal vehicle illumination via the lightbar and headlight type on deer and wild pig behaviors. As WVCs remain a major threat to drivers and wildlife, even modest improvement in wildlife responses can have profound safety benefits when scaled to the millions of annual encounters between wildlife and vehicles.

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Table 5.1. The variables used in our deer and wild pig analyses.

Variable	Definition
Headlight	The headlight type (halogen or LED) used during the encounter.
Lightbar	The rear-facing lightbar treatment (off or on) used during the encounter.
Vehicle Speed	The vehicle's speed (km/h) during the encounter.
Approach Dist	The animal's distance from the vehicle when it was first detected with the FLIR camera.
Dist Path Vehicle	The animal's distance (m) to the path of the vehicle when it initiated a flight behavior or when it left the camera's field of view. For group level responses, the group's median distance was used.
Group Size	The number of individuals within close proximity (~100m). Individuals within concealing cover were not considered.
Dist Nearest Cover	The individual's distance (m) to vegetation that was tall and dense enough to conceal it. For group level responses, the group's median distance was used.
Nearest Cover	A binary of whether the nearest concealing cover was across the road or on the same side of the road as the individual.
Season	The time of year of the encounter. Fall: Sep. 16- Dec. 15, Winter: Dec.16-Mar. 15, Spring: Mar.16-Jun.15, Summer: (Jun.16-Sep. 15).
Time From Sunset	The time of the encounter from sunset (in minutes).

Table 5.2. The details of the five analyses conducted. FID: flight initiation distance. MBD: minimum braking distance.

Response Variable	Definition	Inclusion Criteria	Additional Info	Model Type
Group Flight Probability	Probability that all individuals within a group initiated flight	Only groups for which all individuals were <10m from vehicle's path; flight defined as FID >45m	"No Flight" if flight occurred after vehicle braking; median covariates used for groups >1 individual	Logistic regression
Group Flight Initiation Distance (m)	Individual's FID or median FID for groups	Only groups for which all individuals were <10m from vehicle's path; Only groups for which all individuals fled were considered	Approach distance included in all candidate models[1]; median covariates used for groups >1 individual	Linear regression
Road Entering Probability	Probability at least one individual within a group entered the road	All individuals regardless of distance to vehicle's path. Focal individual was the first one to enter the road within a group or closest individual to vehicle's path for no road entering	Focal individual was the first individual within a group to enter the road	Logistic regression
Road Entering Distance (m)	The distance from the vehicle when the individual entered the road	Only individuals that enter the road were considered. Focal individual was the first one to enter the road within a group	Approach distance included in all candidate models[1]; Focal individual was the first individual within a group to enter the road	Linear regression
Encounter Danger Level	The odds an individual was at one of three danger levels	Only groups for which all individuals were <10m from vehicle's path; Focal individual was the closest animal to the vehicle's path with the highest danger level within the group	Ordered categories: low (FID > MBD), medium (no flight), high (in road at MBD or FID < MBD)	Ordinal logistic regression. clmm function ordinal package

[1] Approach distance inherently limits flight initiation distance and road entering distance (Dumont et al., 2012); therefore, it was included as a covariate in all models to account for this constraint.

Table 5.3. Candidate model results for deer flight probability.

Model	Intercept	Headlight LED	Lightbar On	Vehicle Speed	Approach Dist	Dist Path Vehicle	Dist Path Vehicle^2	Group Size	Dist Nearest Cover	Season Spring	Season Summer	Season Winter	Time From Sunset
m12	1.07		0.02	-0.80	0.31								
m11	1.03		0.06	-0.85									
m16	1.08		0.04	-0.82	0.30	-0.23							
m13	1.03		0.10	-0.85		-0.24							
m15	1.36		0.02	-0.87				-0.21					
m14	0.82		0.16	-0.85		-0.20	0.19						
m17	1.04		0.07	-0.90		-0.24			-0.14				
m18	1.35		0.04	-0.92		-0.23		-0.19	-0.13				
m3	1.59	-0.63	-0.44	-1.97									
m5	1.51	-0.52	-0.28	-1.92		-0.24							
m4	1.53	-0.55	-0.39	-1.76	0.25								
m1	0.93												
m19	0.93		0.09	-0.79						0.24	0.57	-0.46	0.11
m7	1.48	-0.46	-0.26	-1.74	0.24	-0.23							
m6	1.25	-0.45	-0.16	-1.86		-0.21	0.19						
m8	1.52	-0.51	-0.31	-1.98		-0.24			-0.13				
m9	1.84	-0.48	-0.35	-2.01		-0.24		-0.21	-0.12				
m20	0.87		0.15	-0.17									
m10	1.46	-0.52	-0.45	-1.87						0.13	0.56	-0.58	0.12
m2	1.44	-0.25	-0.21	-1.64	0.31	-0.29		-0.16	-0.15	0.28	0.71	-0.34	0.02

Model	Headlight LED: Lightbar On	Headlight LED: Vehicle Speed	Lightbar On: Vehicle Speed	Headlight LED: Lightbar On: Vehicle Speed	K	AICc	Delta AICc	ModelLik	AICcWt	LL	Cum.Wt
m12			1.25		5	181.26	0.00	1.00	0.21	-85.43	0.21
m11			1.28		4	181.61	0.34	0.84	0.18	-86.67	0.39
m16			1.29		6	182.07	0.81	0.67	0.14	-84.75	0.53
m13			1.31		5	182.15	0.88	0.64	0.14	-85.87	0.67
m15			1.27		5	182.92	1.66	0.44	0.09	-86.26	0.76
m14			1.31		6	183.26	2.00	0.37	0.08	-85.35	0.84
m17			1.34		6	183.80	2.53	0.28	0.06	-85.62	0.90
m18			1.33		7	185.31	4.04	0.13	0.03	-85.27	0.93
m3	0.54	1.50	2.43	-1.55	8	186.44	5.18	0.08	0.02	-84.73	0.94
m5	0.33	1.44	2.43	-1.54	9	187.19	5.93	0.05	0.01	-83.98	0.95
m4	0.45	1.28	2.24	-1.37	9	187.22	5.96	0.05	0.01	-83.99	0.96
m1					1	187.63	6.36	0.04	0.01	-92.80	0.97
m19			1.19		8	188.03	6.77	0.03	0.01	-85.53	0.98
m7	0.27	1.24	2.28	-1.38	10	188.16	6.89	0.03	0.01	-83.32	0.99
m6	0.27	1.39	2.37	-1.47	10	188.54	7.27	0.03	0.01	-83.51	0.99
m8	0.34	1.45	2.45	-1.50	10	189.05	7.79	0.02	0.00	-83.77	1.00
m9	0.33	1.47	2.43	-1.46	11	190.59	9.33	0.01	0.00	-83.38	1.00
m20					3	190.71	9.44	0.01	0.00	-92.27	1.00
m10	0.61	1.46	2.27	-1.49	12	193.25	11.99	0.00	0.00	-83.54	1.00
m2	0.22	1.13	2.09	-1.16	16	198.39	17.12	0.00	0.00	-81.24	1.00

Table 5.4. Competing models (ΔAIC <2) for deer flight probability. Estimates with 85% CI that do not cross zero are bolded.

Model	Term	Estimate	Lower	Upper
m12	(Intercept)	**1.07**	0.68	1.49
	LightbarOn	0.02	-0.56	0.59
	Vehicle.Speed	**-0.80**	-1.26	-0.39
	Approach.Dist	**0.31**	0.03	0.62
	LightbarOn:Vehicle.Speed	**1.25**	0.69	1.84
m11	(Intercept)	**1.03**	0.65	1.45
	LightbarOn	0.06	-0.51	0.63
	Vehicle.Speed	**-0.85**	-1.31	-0.43
	LightbarOn:Vehicle.Speed	**1.28**	0.72	1.87
m16	(Intercept)	**1.08**	0.69	1.50
	LightbarOn	0.04	-0.54	0.61
	Vehicle.Speed	**-0.82**	-1.29	-0.41
	Approach.Dist	**0.30**	0.01	0.61
	Dist.Path.Vehicle	-0.23	-0.52	0.05
	LightbarOn:Vehicle.Speed	**1.29**	0.73	1.89
m13	(Intercept)	**1.03**	0.65	1.44
	LightbarOn	0.10	-0.48	0.67
	Vehicle.Speed	**-0.85**	-1.32	-0.43
	Dist.Path.Vehicle	-0.24	-0.52	0.03
	LightbarOn:Vehicle.Speed	**1.31**	0.74	1.91
m15	(Intercept)	**1.36**	0.71	2.04
	LightbarOn	0.02	-0.55	0.59
	Vehicle.Speed	**-0.87**	-1.33	-0.45
	Group.Size	-0.21	-0.54	0.13
	LightbarOn:Vehicle.Speed	**1.27**	0.71	1.87
m14	(Intercept)	**0.82**	0.35	1.32
	LightbarOn	0.16	-0.42	0.74
	Vehicle.Speed	**-0.85**	-1.31	-0.44
	Dist.Path.Vehicle	-0.20	-0.50	0.10
	Dist.Path.Vehicle^2	0.19	-0.07	0.48
	LightbarOn:Vehicle.Speed	**1.31**	0.74	1.90

Table 5.5. Candidate model results for wild pig flight probability.

Model	**Intercept**	**Headlight LED**	**Lightbar On**	**Vehicle Speed**	**Approach Dist**	**Dist Path Vehicle**	**Group Size**	**Dist Nearest Cover**	**Season Spring**	**Season Summer**	**Season Winter**	**Time from Sunset**
m15	0.23						-0.27					
m1	-0.32											
m16	0.36				0.38		-0.33					
m14	-0.32				0.22							
m13	-0.32			-0.21								
m20	0.23						-0.27					-0.08
m18	0.23					-0.06	-0.27					
m11	-0.46	0.31										
m12	-0.46		0.31									
m17	-0.32					-0.05						
m19	0.25					-0.05	-0.28	0.25				
m10	0.22	0.35		-0.50			-0.33					
m8	-0.43	0.27		-0.35								
m9	-0.44	0.29		-0.40		0.09						
m7	0.02	0.47	0.42	-0.63			-0.31					
m3	-0.63	0.64	0.47	-0.46								
m4	-0.60	0.60	0.44	-0.43	0.11							
m5	-0.63	0.64	0.47	-0.46		0.00						
m6	-0.60	0.60	0.44	-0.43	0.11	0.00						
m2	0.28	0.26	0.47	-0.54	0.34	0.18	-0.36	0.33	-0.40	-0.97	0.28	-0.35

Model	HeadlightLED: LightbarOn	HeadlightLED: Vehicle Speed	LightbarOn: Vehicle Speed	HeadlightLED: LightbarOn: Vehicle Speed	K	AICc	Delta_AICc	ModelLik	AICcWt	LL	Cum.Wt
m15					2	79.20	0.00	1.00	0.19	-37.49	0.19
m1					1	79.66	0.47	0.79	0.15	-38.80	0.34
m16					3	79.74	0.55	0.76	0.15	-36.65	0.49
m14					2	81.17	1.98	0.37	0.07	-38.48	0.56
m13					2	81.20	2.00	0.37	0.07	-38.49	0.63
m20					3	81.35	2.16	0.34	0.07	-37.45	0.70
m18					3	81.37	2.18	0.34	0.06	-37.46	0.76
m11					2	81.49	2.30	0.32	0.06	-38.64	0.82
m12					2	81.49	2.30	0.32	0.06	-38.64	0.89
m17					2	81.78	2.59	0.27	0.05	-38.78	0.94
m19					4	82.85	3.65	0.16	0.03	-37.04	0.97
m10		0.61			5	84.10	4.91	0.09	0.02	-36.46	0.99
m8		0.31			4	85.20	6.00	0.05	0.01	-38.21	1.00
m9		0.34			5	87.52	8.33	0.02	0.00	-38.17	1.00
m7	-0.24	1.64	0.37	-1.78	9	91.56	12.36	0.00	0.00	-34.87	1.00
m3	-0.69	1.43	0.31	-1.88	8	91.63	12.43	0.00	0.00	-36.31	1.00
m4	-0.69	1.37	0.31	-1.85	9	94.32	15.12	0.00	0.00	-36.25	1.00
m5	-0.69	1.43	0.31	-1.88	9	94.46	15.26	0.00	0.00	-36.31	1.00
m6	-0.69	1.37	0.31	-1.85	10	97.27	18.08	0.00	0.00	-36.25	1.00
m2	-0.24	1.32	0.19	-1.44	16	112.05	32.86	0.00	0.00	-33.23	1.00

Table 5.6. Competing models (ΔAIC <2) for wild pig flight probability. Estimates with 85% CI that do not cross zero are bolded.

Model	Term	Estimate	Lower	Upper
m15	(Intercept)	0.23	-0.40	0.89
	Group.Size	**-0.27**	-0.57	-0.03
m16	(Intercept)	0.36	-0.29	1.05
	Group.Size	**-0.33**	-0.64	-0.08
	Approach.Dist	0.38	-0.04	0.85
m14	(Intercept)	-0.32	-0.72	0.06
	Approach.Dist	0.22	-0.17	0.62

Table 5.7. Candidate model results for deer flight initiation distance (m). Continuous variables other than Group Size were standardized.

Model	Intercept	Headlight LED	Lightbar On	Vehicle Speed	Approach Dist	Dist Path Vehicle	Group Size	Dist Nearest Cover	Season Spring	Season Summer	Season Winter	Time from Sunset
m10	248.8				48.4	-24.4		25.7				16.6
m12	224.6				47.7	-25.7	17.1	25.3				15.1
m13	221.6				49.3	-28.3	19.2	27.4				
m7	248.8				50.3	-27.1		28.2				
m9	234.0				47.7	-27.7		23.7	8.3	48.3	7.3	23.6
m11	213.9				47.3	-29.1	18.0	23.8	-1.5	43.7	-2.4	22.3
m8	237.3				49.4	-28.3		25.2	-1.1	28.6	31.8	
m6	248.8				57.2	-26.9						
m14	231.7				57.7				10.4	42.3	26.4	26.8
m5	248.8				63.3							
m15	240.5	14.3			63.5							
m16	254.3		-11.7		63.4							
m17	248.8			2.5	63.4							
m2	219.5	-20.6	-34.1	-4.3	46.2	-28.3	19.9	26.7	8.5	57.7	-2.5	27.4
m4	246.4	13.9	-12.0	3.2	63.7							
m3	255.9	-3.7	-33.7	-6.0	63.1							
m1	248.8											

Model	Headlight LED: Lightbar On	Headlight LED: Vehicle Speed	Lightbar On: Vehicle Speed	Headlight LED: Lightbar On: Vehicle Speed	K	AICc	Delta AICc	ModelLik	AICcWt	LL	Cum.Wt
m10					6	1346.1	0.0	1.0	0.3	-666.6	0.3
m12					7	1346.1	0.1	1.0	0.3	-665.5	0.5
m13					6	1346.5	0.4	0.8	0.2	-666.9	0.7
m7					5	1347.1	1.0	0.6	0.2	-668.2	0.9
m9					9	1349.3	3.2	0.2	0.1	-664.8	0.9
m11					10	1349.4	3.3	0.2	0.0	-663.6	1.0
m8					8	1351.2	5.1	0.1	0.0	-666.9	1.0
m6					4	1353.8	7.7	0.0	0.0	-672.7	1.0
m14					7	1358.9	12.8	0.0	0.0	-671.9	1.0
m5					3	1359.3	13.2	0.0	0.0	-676.5	1.0
m15					4	1360.9	14.8	0.0	0.0	-676.3	1.0
m16					4	1361.1	15.0	0.0	0.0	-676.3	1.0
m17					4	1361.3	15.3	0.0	0.0	-676.5	1.0
m2	50.0	21.9	30.2	-48.1	17	1362.7	16.6	0.0	0.0	-661.1	1.0
m4					6	1364.9	18.8	0.0	0.0	-676.0	1.0
m3	37.6	0.8	18.8	-4.1	10	1372.5	26.4	0.0	0.0	-675.2	1.0
m1					2	1393.5	47.5	0.0	0.0	-694.7	1.0

Table 5.8. Competing models (ΔAIC <2) for deer flight initiation distance (m). Estimates with 85% CI that do not cross zero are bolded. Continuous variables other than Group Size were standardized.

Model	Term	Estimate	Lower	Upper
m10	(Intercept)	**248.8**	235.7	261.8
	Approach.Dist	**48.4**	34.4	62.3
	Dist.Path.Vehicle	**-24.4**	-38.0	-10.7
	Dist.Nearest.Cover	**25.7**	12.1	39.4
	Time.from.Sunset	**16.6**	2.9	30.3
m12	(Intercept)	**224.6**	197.2	251.9
	Approach.Dist	**47.7**	33.8	61.6
	Dist.Path.Vehicle	**-25.7**	-39.3	-12.0
	Dist.Nearest.Cover	**25.3**	11.7	38.9
	Time.from.Sunset	**15.1**	1.4	28.7
	Group.Size	**17.1**	0.1	34.0
m13	(Intercept)	**221.6**	194.2	249.0
	Approach.Dist	**49.3**	35.4	63.2
	Dist.Path.Vehicle	**-28.3**	-41.8	-14.7
	Dist.Nearest.Cover	**27.4**	13.9	41.0
	Group.Size	**19.2**	2.2	36.1
m7	(Intercept)	**248.8**	235.6	261.9
	Approach.Dist	**50.3**	36.3	64.3
	Dist.Path.Vehicle	**-27.1**	-40.7	-13.5
	Dist.Nearest.Cover	**28.2**	14.6	41.8

Table 5.9. Candidate model results for wild pig flight initiation distance (m). Continuous variables other than Group Size were standardized.

Model	Intercept	Headlight LED	Lightbar On	Vehicle Speed	Approach Dist	Dist Path Vehicle	Group Size	Dist Nearest Cover	Season Spring	Season Summer	Season Winter	Time from Sunset
m14	158.2	100.3			43.2							
m5	146.1	114.8	25.9	-50.2	42.8							
m6	164.4	103.2	35.5	-52.2	50.2		-10.0					
m17	208.4				59.3							
m4	142.1	100.9	31.6	17.1	43.8							
m15	194.6		27.5		59.9							
m16	208.4			12.9	59.3							
m18	208.4				59.5	-4.4						
m11	123.4	139.3	69.0	14.1	43.5							
m1	208.4											
m7	162.8	104.3	37.5	-54.6	49.9	3.6	-10.0					
m8	142.0	101.0	31.8	15.8	43.7							
m19	208.4				59.8	-4.7		-4.4				
m3	125.7	167.5	67.1	-19.2	46.1							
m12	137.1	131.5	78.7	14.1	49.4		-8.0					
m20	231.2				66.7	-6.2	-13.3	-2.3				
m9	155.4	92.2	39.8	12.4	48.8		-7.5					
m13	139.4	130.8	76.4	17.7	50.0	-6.6	-8.1					
m10	155.8	91.9	39.0	13.5	48.9	-1.2	-7.5					
m2	172.9	136.0	121.3	-42.4	71.1	37.6	-19.1	20.2	-78.9	-19.7	-12.0	-21.5

Model	Headlight LED: Lightbar On	Headlight LED: Vehicle Speed	Lightbar On: Vehicle Speed	Headlight LED: Lightbar On: Vehicle Speed	K	AICc	Delta AICc	ModelLik	AICcWt	LL	Cum.Wt
m14					4	290.1	0.0	1.0	0.4	-140.0	0.4
m5			99.4		7	290.5	0.4	0.8	0.3	-134.8	0.8
m6			102.6		8	294.0	3.9	0.1	0.1	-134.2	0.8
m17					3	294.0	4.0	0.1	0.1	-143.4	0.9
m4					6	295.3	5.2	0.1	0.0	-139.2	0.9
m15					4	296.4	6.4	0.0	0.0	-143.2	0.9
m16					4	296.5	6.5	0.0	0.0	-143.2	1.0
m18					4	296.9	6.8	0.0	0.0	-143.4	1.0
m11	-76.8				7	298.0	7.9	0.0	0.0	-138.5	1.0
m1					2	299.0	8.9	0.0	0.0	-147.2	1.0
m7			103.2		9	299.2	9.1	0.0	0.0	-134.2	1.0
m8		2.1			7	299.4	9.3	0.0	0.0	-139.2	1.0
m19					5	300.1	10.0	0.0	0.0	-143.4	1.0
m3	-95.5	-81.0	67.9	77.7	10	301.2	11.1	0.0	0.0	-132.1	1.0
m12	-80.5				8	302.0	12.0	0.0	0.0	-138.2	1.0
m20					6	302.4	12.4	0.0	0.0	-142.8	1.0
m9		7.8			8	303.5	13.5	0.0	0.0	-139.0	1.0
m13	-82.9				9	307.2	17.1	0.0	0.0	-138.2	1.0
m10		7.0			9	308.8	18.7	0.0	0.0	-139.0	1.0
m2	-99.5	-126.4	71.5	149.1	17	394.4	104.4	0.0	0.0	-129.2	1.0

Table 5.10. Competing models (ΔAIC <2) for wild pig flight initiation distance (m). Estimates with 85% CI that do not cross zero are bolded. Continuous variables were standardized.

Model	Term	Estimate	Lower	Upper
m14	(Intercept)	**158.2**	119.1	197.3
	Approach.Dist	**43.2**	14.2	72.1
	HeadlightLED	**100.3**	43.6	157.0
m5	(Intercept)	**146.1**	104.5	187.7
	HeadlightLED	**114.8**	64.6	164.9
	LightbarOn	25.9	-22.0	73.7
	Vehicle.Speed	**-50.2**	-93.4	-6.9
	Approach.Dist	**42.8**	17.4	68.2
	LightbarOn:Vehicle.Speed	**99.4**	46.7	152.2

Table 5.11. Candidate model results for deer road entering probability. Continuous variables other than Group Size were standardized.

Model	(Intercept)	Headlight LED	Lightbar On	Vehicle Speed	Approach Dist	Dist Road	Location Right	Group Size	Season Spring	Season Summer	Season Winter	Dist Nearest Cover	Nearest Cover Same
m22	-4.1	0.8			0.3	-2.7	1.3						
m8	-2.6				0.3	-1.2							
m20	-4.1	0.8				-2.8	1.3						
m9	-3.6				0.3	-2.6	1.2						
m6	-2.5					-1.3							
m7	-3.6					-2.7	1.3						
m17	-3.4		-0.4		0.3	-2.6	1.2						
m15	-3.4		-0.4			-2.7	1.3						
m12	-2.5					-1.2							-0.1
m11	-2.5					-1.3						0.0	
m10	-4.3					-2.9	1.5		0.3	1.2	0.4		
m21	-4.1	0.8		0.0		-2.8	1.3						
m16	-3.4		-0.3	-0.3		-2.7	1.3						
m5	-3.0	0.9	-0.3	-0.5		-1.3							
m18	-2.5	0.6											
m1	-2.1												
m13	-1.9		-0.4										
m14	-1.9		-0.4	-0.4									
m19	-2.5	0.6		-0.1									
m4	-2.5	0.7	-0.7	-0.5	0.4								
m2	-5.9	1.0	-0.5	-0.4	0.4	-3.0	1.6	-0.1	0.6	1.7	0.5	0.5	0.9
m3	-2.4	0.7	-0.6	-0.5									

Model	Time from Sunset	Headlight LED: Lightbar On	Headlight LED: Vehicle Speed	Lightbar On: Vehicle Speed	Dist Road: Location Right	Dist Nearest Cover: Nearest Cover Same	Headlight LED: Lightbar On: Vehicle Speed	K	AICc	Delta AICc	ModelLik	AICcWt	LL	Cum.Wt
m22					2.0			6	162.7	0.0	1.0	0.2	-75.2	0.2
m8								3	163.1	0.4	0.8	0.2	-78.5	0.3
m20					2.0			5	163.4	0.6	0.7	0.1	-76.6	0.5
m9					1.8			5	163.5	0.8	0.7	0.1	-76.6	0.6
m6								2	164.1	1.4	0.5	0.1	-80.0	0.7
m7					1.9			4	164.4	1.7	0.4	0.1	-78.1	0.8
m17					1.9			6	164.9	2.1	0.3	0.1	-76.3	0.8
m15					1.9			5	165.8	3.1	0.2	0.0	-77.8	0.9
m12								3	166.1	3.4	0.2	0.0	-80.0	0.9
m11								3	166.1	3.4	0.2	0.0	-80.0	0.9
m10					2.0			7	166.4	3.7	0.2	0.0	-76.0	1.0
m21			-0.1		2.0			7	167.5	4.7	0.1	0.0	-76.5	1.0
m16				0.6	1.9			7	168.2	5.4	0.1	0.0	-76.9	1.0
m5		0.0	0.3	1.2			-0.8	9	172.6	9.9	0.0	0.0	-77.0	1.0
m18								2	179.0	16.3	0.0	0.0	-87.5	1.0
m1								1	179.2	16.5	0.0	0.0	-88.6	1.0
m13								2	180.2	17.5	0.0	0.0	-88.1	1.0
m14				0.6				4	181.7	18.9	0.0	0.0	-86.7	1.0
m19			0.0					4	182.8	20.1	0.0	0.0	-87.3	1.0
m4		0.3	0.1	1.3			-0.8	9	183.3	20.6	0.0	0.0	-82.3	1.0
m2	0.0	0.2	0.3	1.4	2.1	-0.7	-1.0	20	183.9	21.1	0.0	0.0	-70.2	1.0
m3		0.3	0.2	1.2			-0.7	8	186.9	24.2	0.0	0.0	-85.2	1.0

Table 5.12. Competing models (ΔAIC <2) for deer road entering probability. Estimates with 85% CI that do not cross zero are bolded. Continuous variables were standardized.

Model	Term	Estimate	Lower	Upper
m22	(Intercept)	**-4.1**	-5.7	-2.9
	HeadlightLED	**0.8**	0.1	1.5
	Approach.Dist	**0.3**	0.0	0.6
	Dist.Road	**-2.7**	-4.3	-1.4
	LocationRight	**1.3**	0.1	2.8
	Dist.Road:LocationRight	**2.0**	0.5	3.7
m8	(Intercept)	**-2.6**	-3.0	-2.2
	Dist.Road	**-1.2**	-1.8	-0.7
	Approach.Dist	**0.3**	0.1	0.6
m20	(Intercept)	**-4.1**	-5.7	-3.0
	HeadlightLED	**0.8**	0.1	1.5
	Dist.Road	**-2.8**	-4.5	-1.5
	LocationRight	**1.3**	0.1	2.8
	Dist.Road:LocationRight	**2.0**	0.6	3.7
m9	(Intercept)	**-3.6**	-5.1	-2.5
	Dist.Road	**-2.6**	-4.2	-1.3
	LocationRight	**1.2**	0.1	2.8
	Approach.Dist	**0.3**	0.1	0.6
	Dist.Road:LocationRight	**1.8**	0.4	3.6
m6	(Intercept)	**-2.5**	-3.0	-2.1
	Dist.Road	**-1.3**	-1.8	-0.7
m7	(Intercept)	**-3.6**	-5.1	-2.5
	Dist.Road	**-2.7**	-4.4	-1.4
	LocationRight	**1.3**	0.1	2.8
	Dist.Road:LocationRight	**1.9**	0.4	3.6

Table 5.13. Candidate model results for deer road entering distance (m). Continuous variables other than Group Size were standardized.

Model	(Intercept)	Headlight LED	Lightbar On	Vehicle Speed	Approach Dist	Dist Road	Location Right	Group Size	Season Spring	Season Summer	Season Winter	Dist Nearest Cover	Nearest Cover Same
m10	369.7				119.7	-30.0							-78.3
m6	303.0				120.9	-29.5							
m9	255.6				106.2	-31.7		26.1				13.0	
m8	303.0				119.6	-29.6						16.0	
m14	309.3		-17.2		121.6	-28.8							
m19	293.3	13.8			122.2	-28.2							
m16	286.3	23.7			134.3								
m11	310.7		-21.0		133.6								
m7	271.2				117.2	-78.6	41.6						
m15	308.7		-15.5		120.3	-29.0						15.6	
m20	296.1	9.8			120.6	-28.7						15.5	
m12	312.1		-13.0	10.0	136.0								
m13	277.2		-21.1		117.8	-78.0	44.8						
m18	257.0	19.3			119.3	-83.9	40.4						
m17	286.4	23.7		-6.2	133.0								
m4	336.9	-24.4	-32.9	71.9	134.4								
m5	338.1	-34.2	-14.2	38.6	118.1	-29.9							
m1	303.0												
m3	366.7	-79.3	28.0	45.9									
m2	273.0	-15.3	39.9	68.0	107.8	-74.5	3.9	13.6	15.8	-15.7	17.5	65.4	2.0

Model	Time from Sunset	Headlight LED: Lightbar On	Headlight LED: Vehicle Speed	Lightbar On: Vehicle Speed	Dist Road: Location Right	Dist Nearest Cover: Nearest Cover Same	Headlight LED: Lightbar On: Vehicle Speed	K	AICc	Delta AICc	ModelLik	AICcWt	LL	Cum Wt
m10								5.0	310.7	0.0	1.0	0.5	-148.9	0.5
m6								4.0	312.9	2.2	0.3	0.2	-151.5	0.6
m9								6.0	313.6	2.9	0.2	0.1	-148.7	0.7
m8								5.0	314.4	3.7	0.2	0.1	-150.8	0.8
m14								5.0	315.5	4.8	0.1	0.0	-151.3	0.8
m19								5.0	315.7	5.0	0.1	0.0	-151.4	0.9
m16								4.0	316.2	5.5	0.1	0.0	-153.2	0.9
m11								4.0	316.3	5.6	0.1	0.0	-153.2	0.9
m7					48.5			6.0	317.1	6.4	0.0	0.0	-150.5	0.9
m15								6.0	317.4	6.7	0.0	0.0	-150.6	1.0
m20								6.0	317.6	6.9	0.0	0.0	-150.7	1.0
m12				-55.0				6.0	317.8	7.1	0.0	0.0	-150.8	1.0
m13					48.0			7.0	320.1	9.4	0.0	0.0	-150.1	1.0
m18					57.2			7.0	320.4	9.7	0.0	0.0	-150.2	1.0
m17			-9.9					6.0	321.4	10.7	0.0	0.0	-152.6	1.0
m4		26.7	-71.8	-150.4			111.7	10.0	332.7	21.9	0.0	0.0	-149.5	1.0
m5		22.2	-41.7	-153.8			127.1	11.0	334.6	23.9	0.0	0.0	-147.5	1.0
m1								2.0	351.2	40.5	0.0	0.0	-173.4	1.0
m3		5.1	-76.2	-264.4			276.6	9.0	371.8	61.1	0.0	0.0	-171.6	1.0
m2	-17.2	-47.9	-81.2	-228.7	47.4	-73.5	202.1	21.0	494.9	184.2	0.0	0.0	-134.1	1.0

Table 5.14. Competing models (ΔAIC <2) for deer road entering distance (m). Estimates with 85% CI that do not cross zero are bolded. Continuous variables were standardized.

Model	Term	Estimate	Lower	Upper
m10	(Intercept)	**369.7**	321.1	418.2
	Approach.Dist	**119.7**	98.8	140.5
	Dist.Road	**-30.0**	-50.9	-9.1
	Nearest.Cover.Same	**-78.3**	-130.9	-25.7

Table 5.15. Candidate model results for the odds an encounter with a deer was at a higher danger level. Continuous variables other than Group Size were standardized.

Model	Danger1| Danger2	Danger2| Danger3	Headlight LED	Lightbar On	Vehicle Speed	Approach Dist	Dist Path Vehicle	Group Size	Dist Nearest Cover	Season Spring	Season Summer	Season Winter	Time from Sunset
m17	0.52	1.59		0.07	0.83	-0.36	0.27						
m18	0.84	1.92		0.10	0.85	-0.39	0.28	0.17					
m16	0.52	1.58		0.12	0.82	-0.38							
m13	0.42	1.47			0.38	-0.41	0.22						
m12	0.41	1.45			0.40	-0.42							
m14	0.42	1.47			0.38	-0.40	0.22		-0.03				
m6	0.65	1.69	0.37	0.05	0.40	-0.43							
m4	0.67	1.75	0.25	0.06	0.52	-0.43							
m8	0.41	1.42				-0.41	0.25						
m20	0.62	1.63	0.35			-0.42	0.25						
m7	0.39	1.40				-0.43							
m19	0.60	1.61	0.35			-0.44							
m11	0.03	1.07				-0.41				-0.35	-1.17	-0.23	-0.29
m9	0.41	1.42				-0.40	0.25		-0.07				
m10	0.70	1.72				-0.42	0.27	0.16	-0.11				
m15	0.37	1.38		-0.05		-0.43							
m5	0.57	1.58	0.31	0.01	0.41								
m3	0.65	1.70	0.27	0.09	0.72								
m1	0.37	1.34											
m2	0.69	1.80	0.22	0.01	0.50	-0.43	0.29	0.17	-0.06	-0.23	-0.80	-0.34	-0.11

Model	Headlight LED: Lightbar On	Headlight LED: Vehicle Speed	Lightbar On: Vehicle Speed	Headlight LED: Lightbar On: Vehicle Speed	K	AICc	Delta AICc	ModelLik	AICcWt	LL	Cum.Wt
m17			-0.84		7	361.21	0.00	1.00	0.32	-173.3	0.32
m18			-0.84		8	361.86	0.65	0.72	0.23	-172.5	0.55
m16			-0.77		6	362.12	0.91	0.64	0.20	-174.8	0.75
m13					5	364.01	2.80	0.25	0.08	-176.8	0.83
m12					4	364.12	2.91	0.23	0.07	-178.0	0.90
m14					6	366.08	4.87	0.09	0.03	-176.8	0.93
m6					6	366.78	5.57	0.06	0.02	-177.2	0.95
m4	0.12	0.49	-0.53	-0.38	10	368.14	6.93	0.03	0.01	-173.5	0.96
m8					4	368.45	7.24	0.03	0.01	-180.1	0.97
m20					5	369.10	7.89	0.02	0.01	-179.4	0.98
m7					3	369.22	8.00	0.02	0.01	-181.5	0.98
m19					4	369.83	8.62	0.01	0.00	-180.8	0.99
m11					7	370.27	9.06	0.01	0.00	-177.8	0.99
m9					5	370.32	9.11	0.01	0.00	-180.0	0.99
m10					6	370.97	9.76	0.01	0.00	-179.3	1.00
m15					4	371.27	10.06	0.01	0.00	-181.5	1.00
m5					5	372.16	10.95	0.00	0.00	-180.9	1.00
m3	0.03	0.26	-0.72	-0.24	9	372.59	11.38	0.00	0.00	-176.8	1.00
m1					2	374.74	13.53	0.00	0.00	-185.3	1.00
m2	0.20	0.37	-0.62	-0.16	17	377.33	16.12	0.00	0.00	-169.9	1.00

Table 5.16. Competing models (ΔAIC <2) for the odds an encounter with a deer was at a higher danger level. Estimates with 85% CI that do not cross zero are bolded. Continuous variables were standardized.

Model	Term	Estimate	Lower	Upper
m17	LightbarOn	0.07	-0.38	0.51
	Vehicle.Speed	**0.83**	0.49	1.19
	Approach.Dist	**-0.36**	-0.61	-0.13
	Dist.Path.Vehicle	**0.27**	0.05	0.50
	LightbarOn:Vehicle.Speed	**-0.84**	-1.30	-0.38
m18	LightbarOn	0.10	-0.34	0.55
	Vehicle.Speed	**0.85**	0.51	1.21
	Approach.Dist	**-0.39**	-0.64	-0.15
	Dist.Path.Vehicle	**0.28**	0.06	0.51
	Group.Size	0.17	-0.03	0.36
	LightbarOn:Vehicle.Speed	**-0.84**	-1.31	-0.38
m16	LightbarOn	0.12	-0.31	0.56
	Vehicle.Speed	**0.82**	0.48	1.17
	Approach.Dist	**-0.38**	-0.62	-0.14
	LightbarOn:Vehicle.Speed	**-0.77**	-1.23	-0.32

Table 5.17. Candidate model results for the odds an encounter with a wild pig was at a higher danger level. Continuous variables other than Group Size were standardized.

Model	Danger1|Danger2	Danger2|Danger3	Headlight LED	Lightbar On	Vehicle Speed	Approach Dist	Dist Path Vehicle	Group Size	Dist Nearest Cover	Season Spring	Season Summer	Season Winter	Time from Sunset
m14	-0.17	2.03			0.44	-0.36		0.26					
m15	-0.15	2.09			0.34	-0.40	0.33	0.27					
m10	-0.09	2.12				-0.46	0.40	0.29	-0.20				
m12	-0.21	1.84						0.23					
m16	-0.17	1.89		0.13				0.22					
m13	-0.83	1.21			0.42	-0.26							
m17	-0.21	1.94		0.09	0.39			0.22					
m18	-0.11	2.13		0.19	0.21	-0.42	0.34	0.26					
m8	-0.83	1.19				-0.31	0.37						
m1	-0.80	1.13											
m7	-0.81	1.16				-0.30							
m9	-0.83	1.20				-0.32	0.35		-0.08				
m5	-0.74	1.29	-0.12	0.31	0.44								
m20	-0.85	1.18	-0.02			-0.31	0.36						
m19	-0.86	1.11	-0.10			-0.29							
m6	-0.70	1.36	-0.04	0.33	0.41	-0.27							
m11	-0.59	1.48				-0.23				0.85	1.09	-0.22	0.08
m3	-1.11	1.02	-0.99	-0.39	0.27								
m4	-1.07	1.08	-0.87	-0.36	0.16	-0.29							
m2	-0.24	2.21	-0.71	-0.45	0.07	-0.37	0.27	0.24	-0.42	1.19	1.39	-0.26	0.17

Model	Headlight LED: Lightbar On	Headlight LED: Vehicle Speed	Lightbar On: Vehicle Speed	Headlight LED: Lightbar On: Vehicle Speed	K	AICc	Delta AICc	ModelLik	AICcWt	LL	Cum.Wt
m14					5	156.53	0.00	1.00	0.32	-72.83	0.32
m15					6	157.07	0.54	0.76	0.24	-71.91	0.56
m10					6	158.43	1.90	0.39	0.12	-72.59	0.69
m12					3	158.81	2.28	0.32	0.10	-76.24	0.79
m16					4	160.97	4.43	0.11	0.03	-76.19	0.82
m13					4	161.13	4.59	0.10	0.03	-76.27	0.85
m17			0.15		6	161.21	4.67	0.10	0.03	-73.98	0.89
m18			0.24		8	161.61	5.07	0.08	0.03	-71.70	0.91
m8					4	162.01	5.48	0.06	0.02	-76.72	0.93
m1					2	162.12	5.58	0.06	0.02	-78.97	0.95
m7					3	162.44	5.91	0.05	0.02	-78.05	0.97
m9					5	164.18	7.65	0.02	0.01	-76.65	0.97
m5					5	164.24	7.71	0.02	0.01	-76.68	0.98
m20					5	164.31	7.78	0.02	0.01	-76.71	0.99
m19					4	164.63	8.09	0.02	0.01	-78.02	0.99
m6					6	165.23	8.69	0.01	0.00	-75.99	1.00
m11					7	167.21	10.67	0.00	0.00	-75.75	1.00
m3	1.50	-0.46	-0.02	1.05	9	169.66	13.12	0.00	0.00	-74.42	1.00
m4	1.43	-0.32	0.05	0.98	10	170.85	14.32	0.00	0.00	-73.68	1.00
m2	1.21	0.06	0.16	0.28	17	180.36	23.83	0.00	0.00	-67.72	1.00

Table 5.18. Competing models (ΔAIC <2) for the odds an encounter with a wild pig was at a higher danger level. Estimates with 85% CI that do not cross zero are bolded. Continuous variables were standardized.

Model	Term	Estimate	Lower	Upper
m14	Vehicle.Speed	**0.44**	0.11	0.77
	Approach.Dist	**-0.36**	-0.72	-0.03
	Group.Size	**0.26**	0.11	0.42
m15	Vehicle.Speed	0.34	0.00	0.69
	Approach.Dist	**-0.40**	-0.76	-0.06
	Dist.Path.Vehicle	0.33	-0.02	0.68
	Group.Size	**0.27**	0.13	0.43
m10	Approach.Dist	**-0.46**	-0.82	-0.12
	Dist.Path.Vehicle	**0.40**	0.06	0.75
	Dist.Nearest.Cover	-0.20	-0.54	0.14
	Group.Size	**0.29**	0.14	0.46

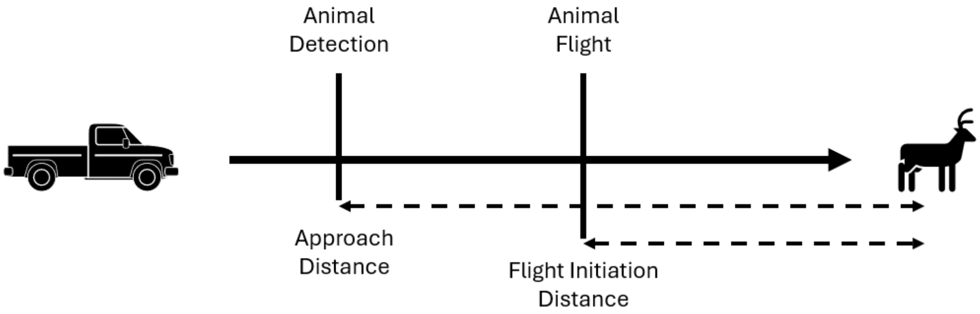

Figure 5.1. Schematic of field methods. The displayed GPS point on the video was recorded when the animal was detected and when the animal initiated flight (if applicable). Distances were calculated from the GPS point at the animal's location. Not shown is road entering distance, although the methods were the same.

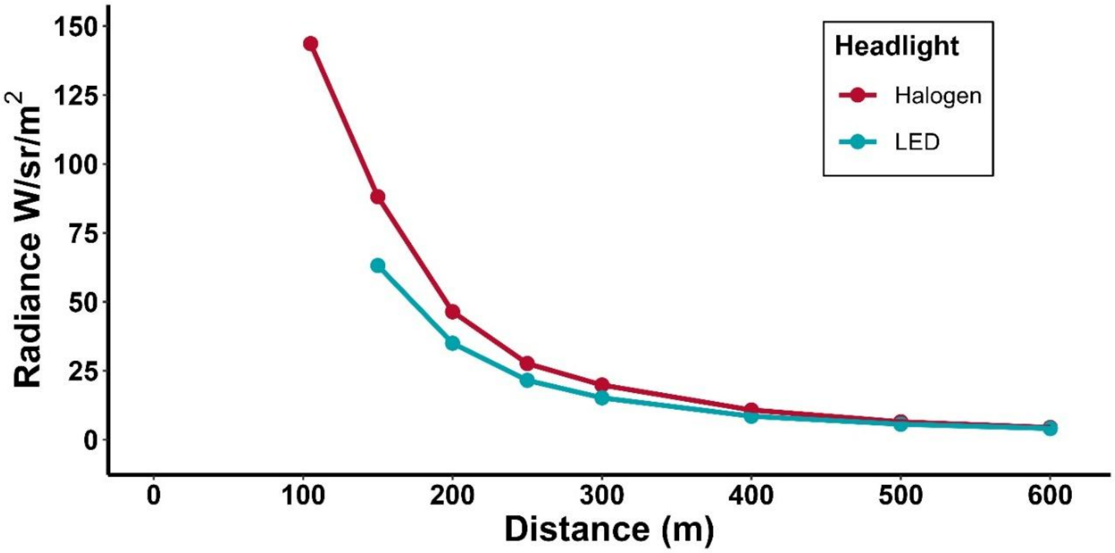

Figure 5.2. The overall radiance (W/sr/m^2; 380nm-780nm) of the study vehicle's halogen and LED high-beam headlights by distance. The 105m LED headlight value is missing due to equipment failure.

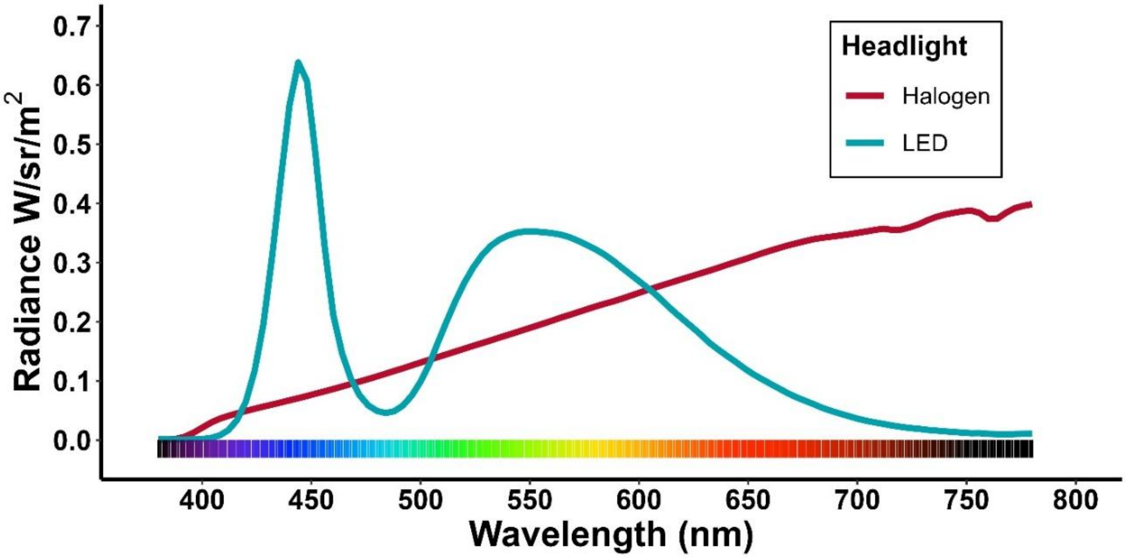

Figure 5.3. The radiance (W/sr/m^2) of the study vehicle's halogen and LED high-beam headlights by wavelength, measured at 150m. The lightbar treatment emitted a relatively small amount of light and is not shown for clarity.

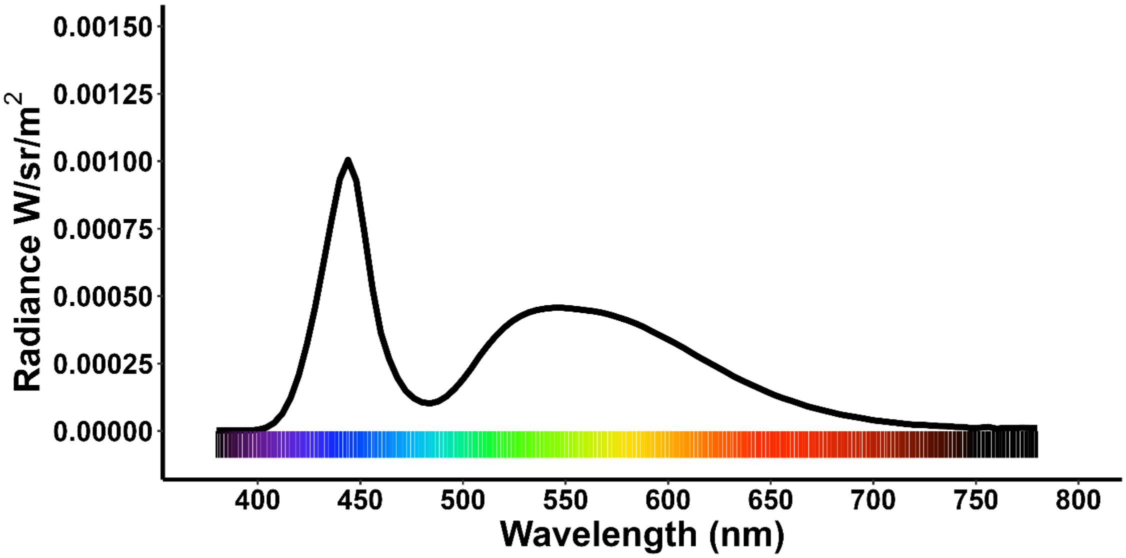

Figure 5.4. The radiance (W/sr/m^2) of the study vehicle's rear-facing lightbar when recorded at 105m with the headlights off.

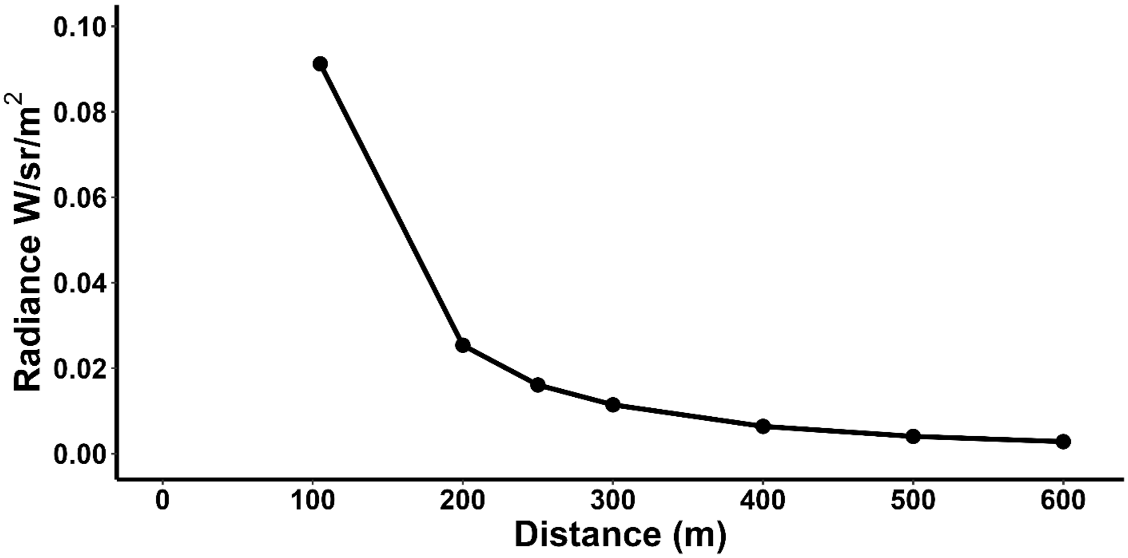

Figure 5.5. The overall radiance (W/sr/m^2; 380nm-780nm) of the study vehicle's rear-facing lightbar by distance with the headlights off.

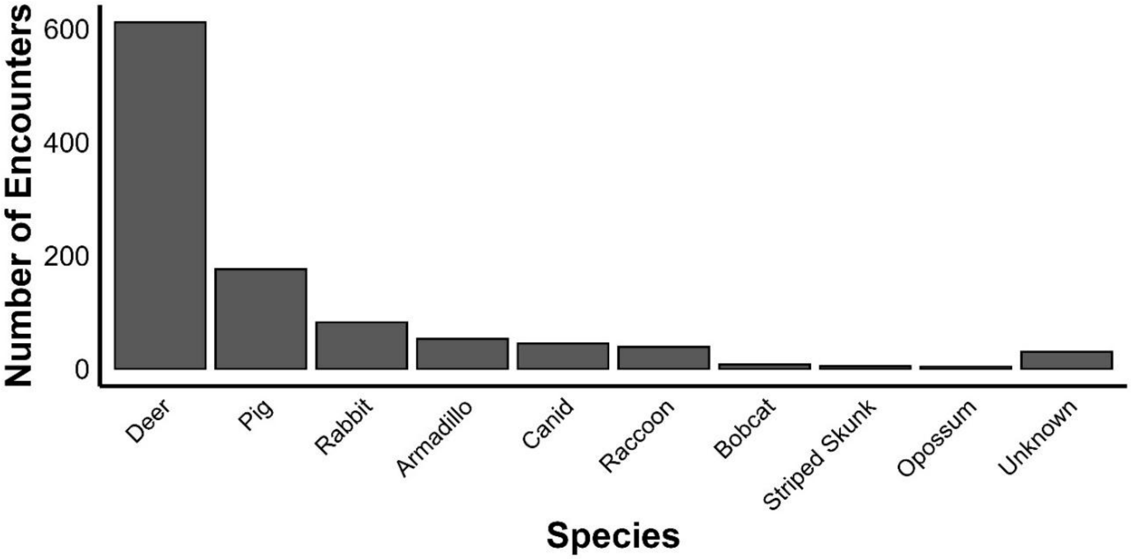

Figure 5.6. Total number of encounters with each animal group across all trials. Values show raw data before data cleaning as described in the Methods.

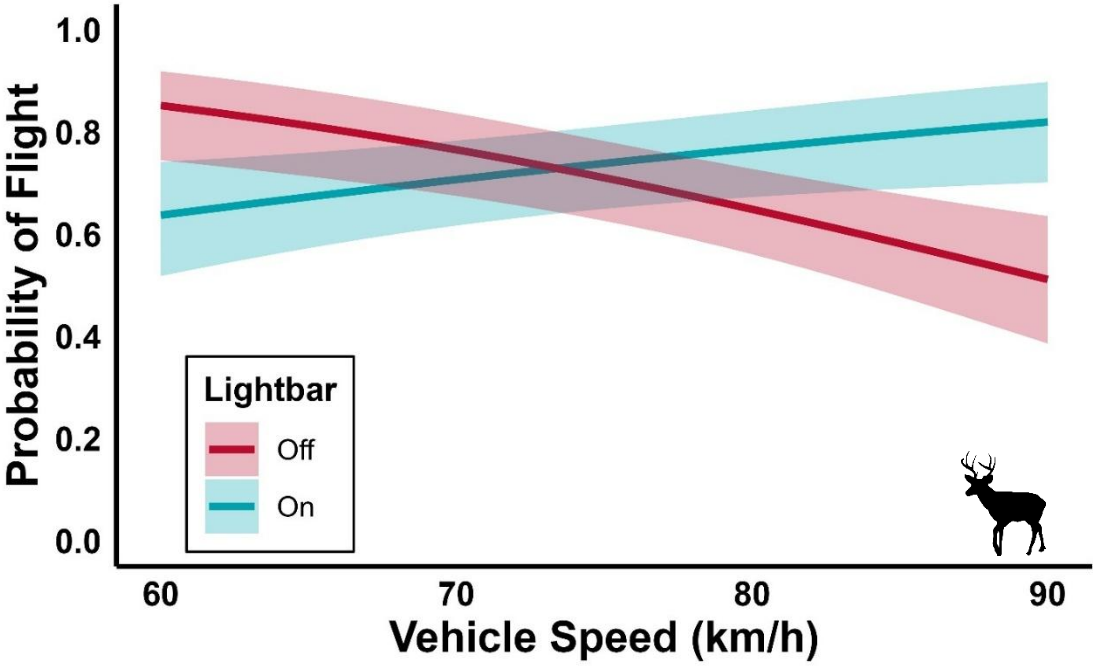

Figure 5.7. The probability that all deer within a group initiated a flight response by vehicle speed and lightbar treatment. Only groups located within 10m of the path of the vehicle were considered. Predictions are from the best-performing model, holding approach distance at its median value (368.0m). Deer flight initiation distance by the deer’s distance to the path of the vehicle and distance to nearest cover.

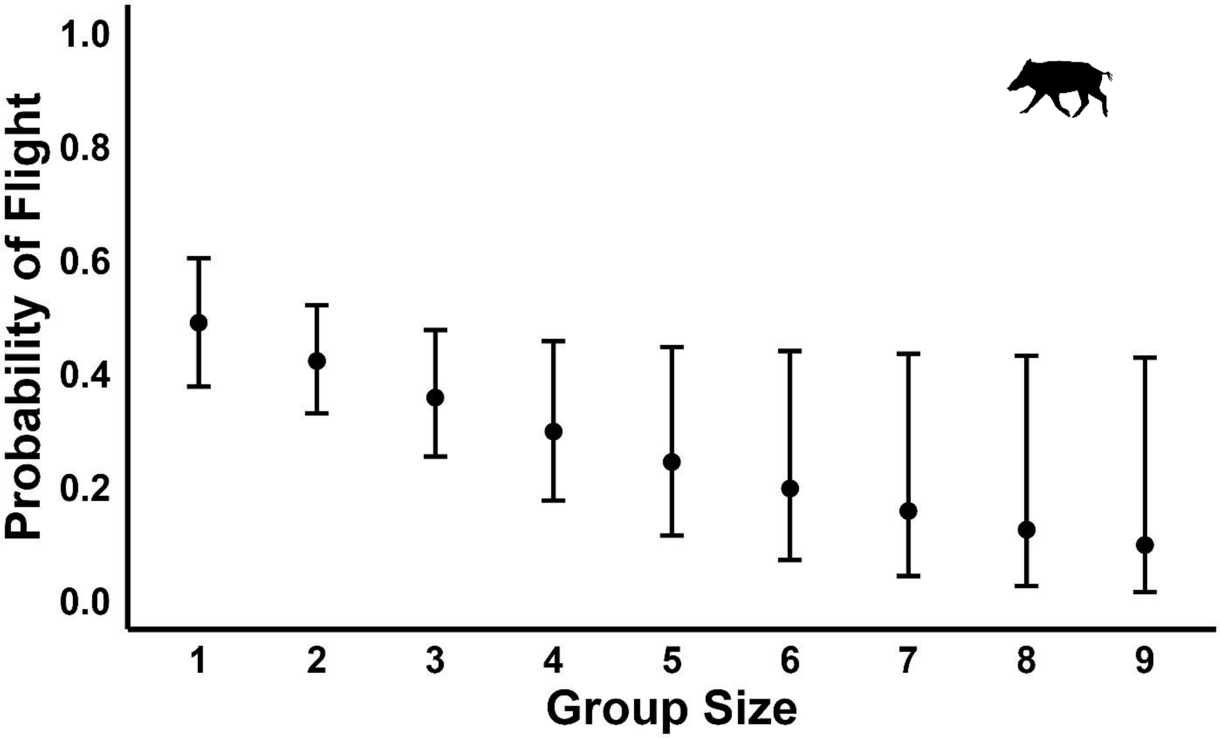

Figure 5.8. The probability that all wild pigs within a group initiated a flight response by group size. Only groups located within 10m of the path of the vehicle were considered. Predictions are from the best-performing model.

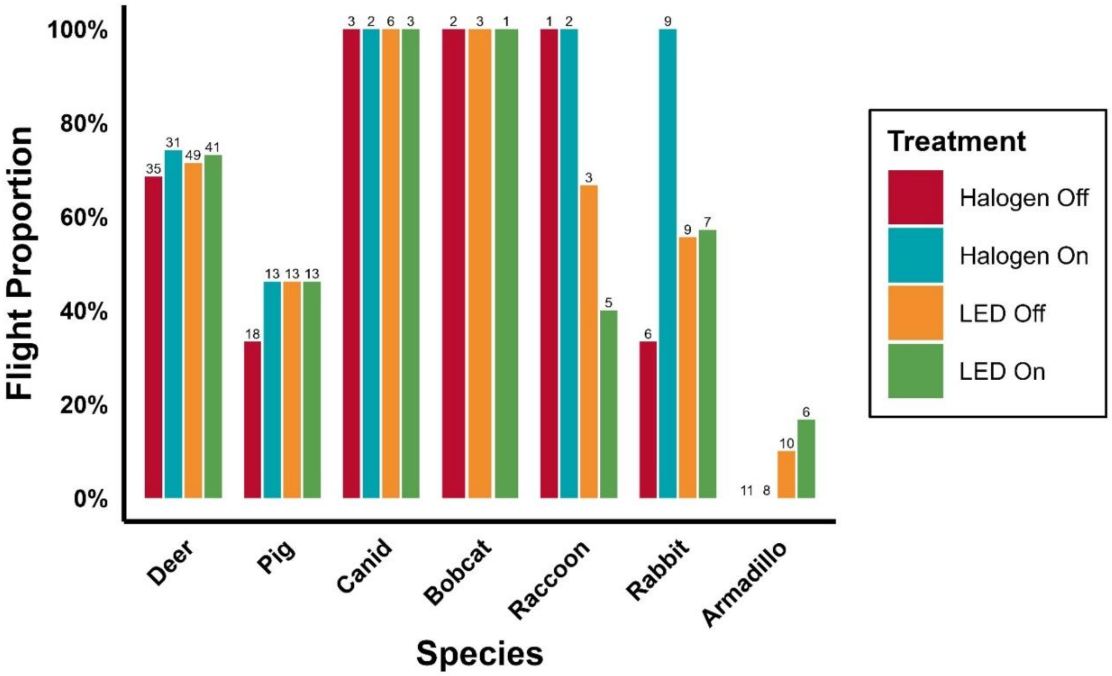

Figure 5.9. The proportion of encounters in which all individuals within a group initiated flight by vehicle lighting treatment. Only groups located within 10m of the path of the vehicle were considered. Figure shows raw data rather than model predictions.

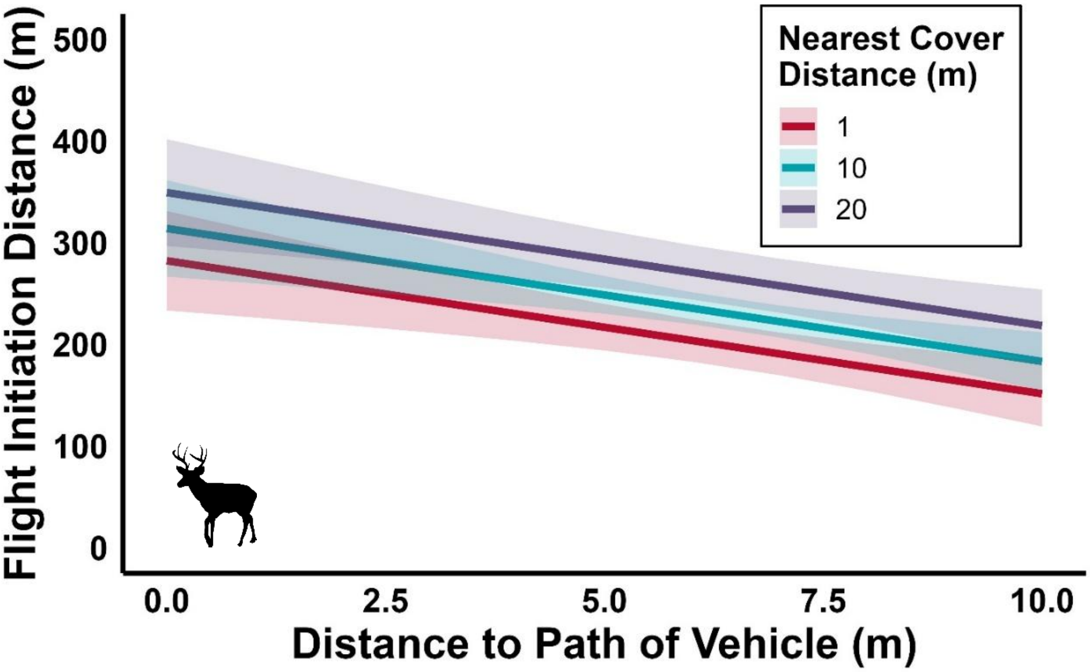

Figure 5.10. Deer flight initiation distance by the deer's distance to the path of the vehicle and distance to nearest concealing cover. Only deer groups located within 10m of the path of the vehicle in which all individuals initiated flight were considered. For groups with >1 individual, we report the group's median response and predictor values. Predictions are from the best-performing model, holding approach distance and time from sunset at their median values (375.8m and 111.65min, respectively).

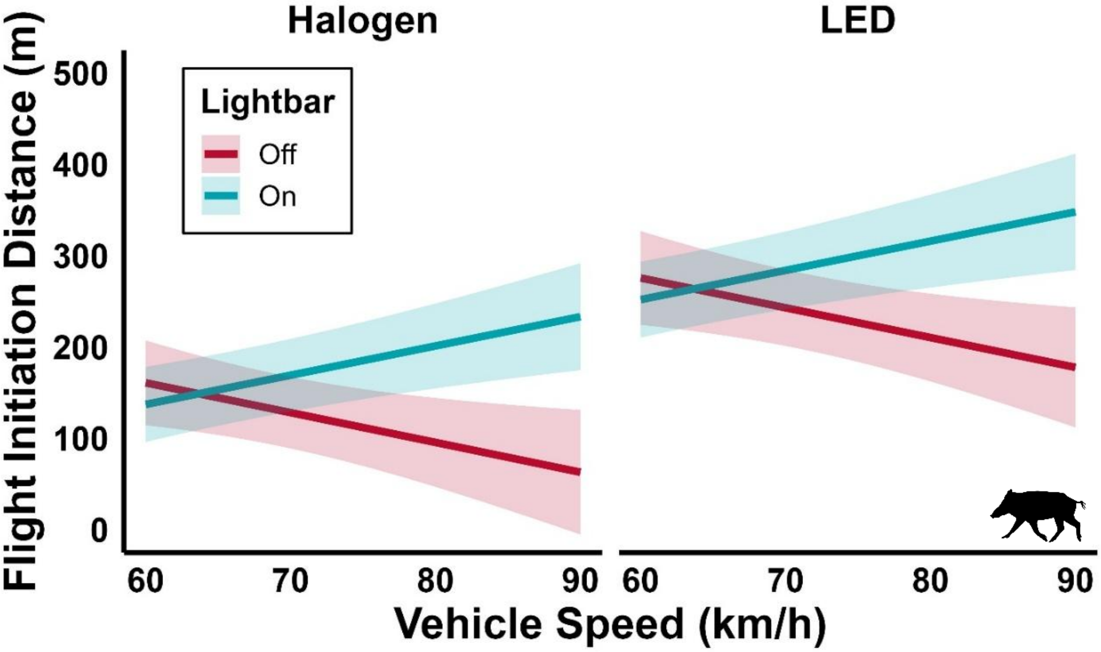

Figure 5.11. Wild pig flight initiation distance by vehicle speed, headlight and lightbar treatment. Only wild pig groups located within 10m of the path of the vehicle in which all individuals initiated flight were considered. For groups with >1 individual, we report the group's median response value. Predictions are from the best-performing model, holding approach distance at its median value (391.1m).

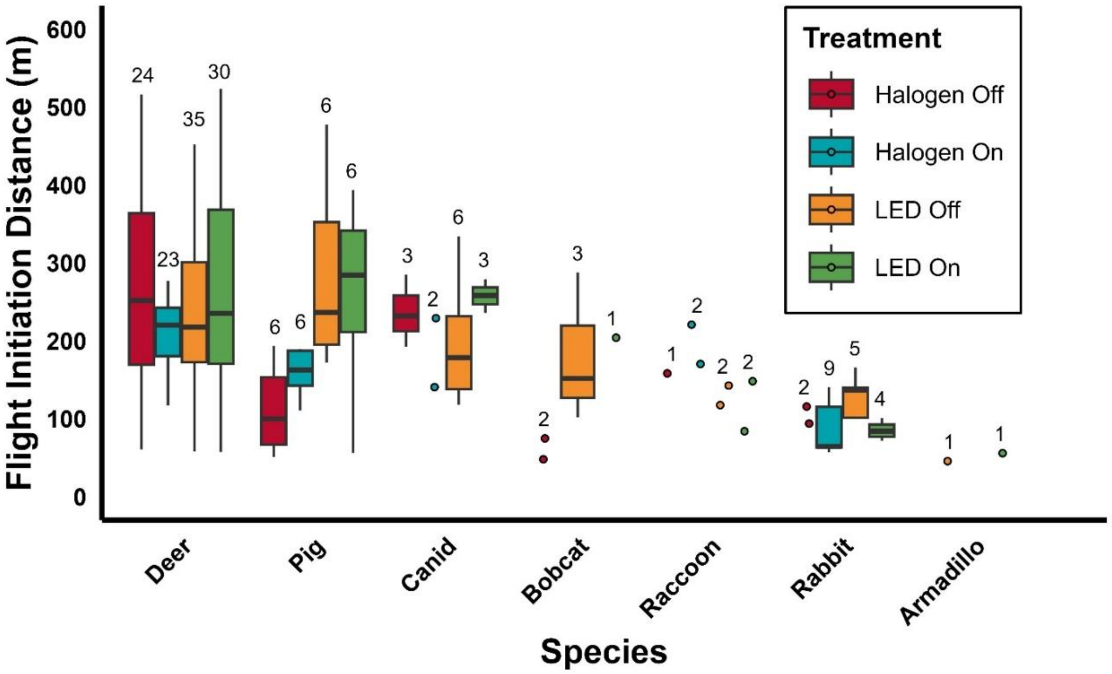

Figure 5.12. Each animal group's flight initiation distance by headlight and lightbar treatments. Only groups located within 10m of the path of the vehicle in which all individuals initiated flight were considered. For groups with >1 individual, we report the group's median response value. Figure shows raw data rather than model predictions. Values above each box represent sample size.

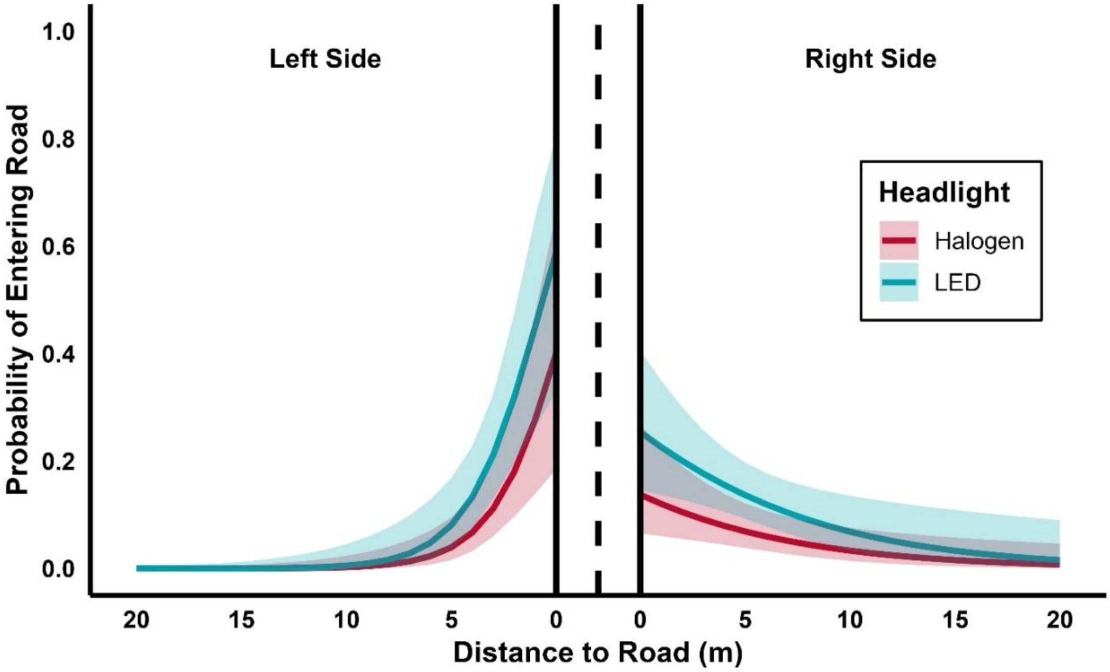

Figure 5.13. The probability a deer entered the road by distance to the road, side of road, and headlight treatment. Predictions are from the best-performing model, holding approach distance at its median value (361.6m).

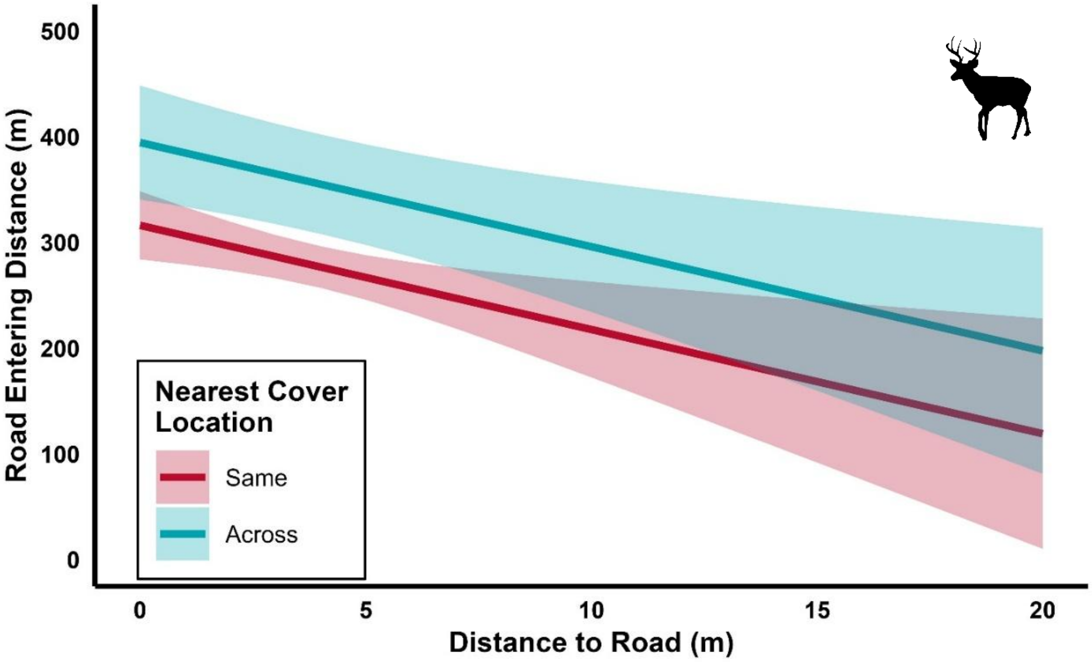

Figure 5.14. The road entering distance of deer that entered the road by their distance to the road and location of nearest cover relative to the deer. Predictions are from the best-performing model, holding approach distance at its median value (406.7m).

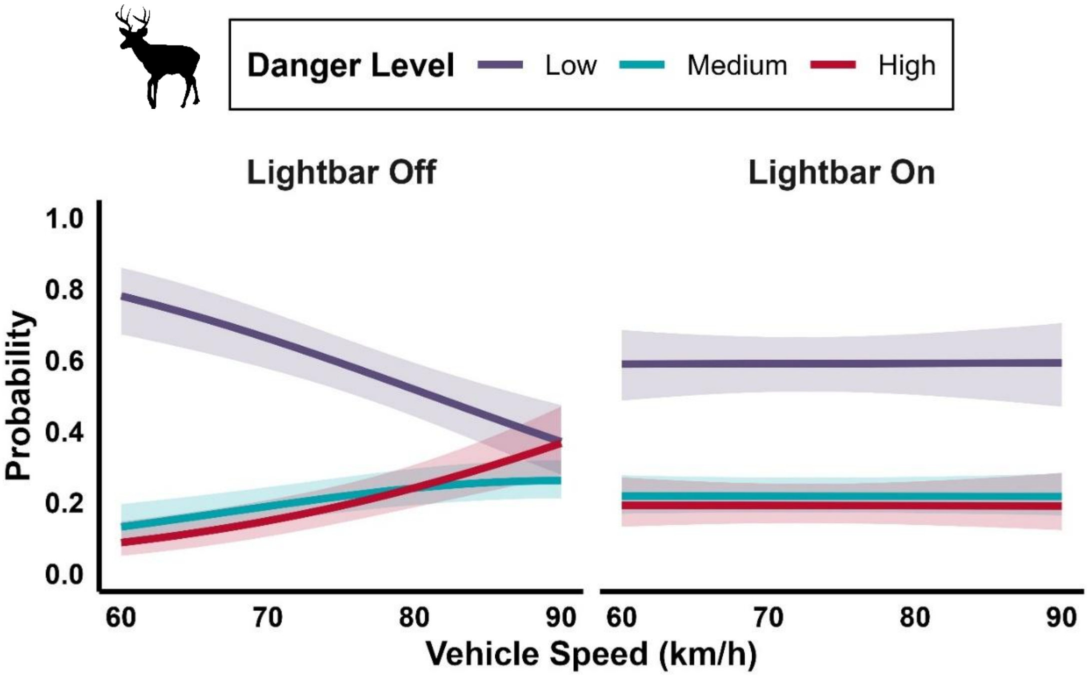

Figure 5.15. The probability an encounter with a deer group was classified as low, medium, or high danger by vehicle speed and lightbar treatment. For groups with >1 individual, we selected the closest individual to the vehicle's path exhibiting the highest danger response. Only deer located within 10m of the path of the vehicle were considered. Danger levels were defined as follows: low danger- flight initiation distance > minimum braking distance; medium danger- no flight response; high danger- deer was in the roadway when the vehicle was at its minimum braking distance or the deer's flight initiation distance was < minimum braking distance. Predictions are from the best-performing model, holding approach distance at its median value (381.4 m).

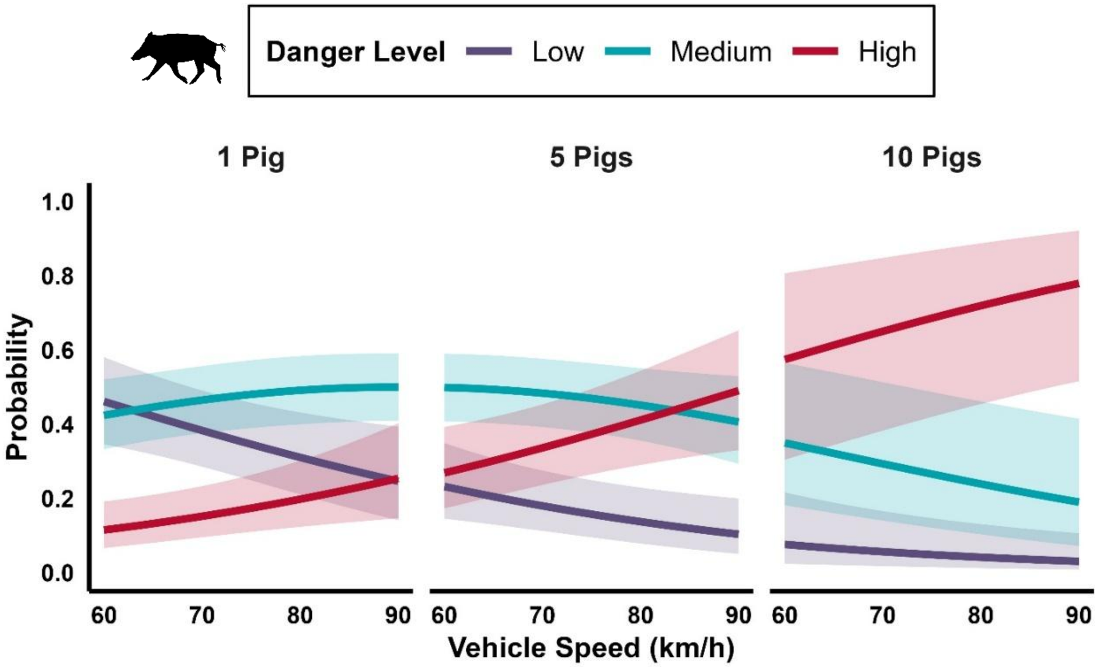

Figure 5.16. The probability an encounter with a wild pig group was classified as low, medium, or high danger by vehicle speed and group size. For groups with >1 individual, we selected the closest individual to the vehicle's path exhibiting the highest danger response. Only wild pigs located within 10m of the path of the vehicle were considered. Danger levels were defined as: low danger- flight initiation distance > minimum braking distance; medium danger- no flight response; high danger- deer was in the roadway when the vehicle was at its minimum braking distance or the wild pig's flight initiation distance was < minimum braking distance. Predictions are from the best-performing model, holding approach distance at its median value (417.6m).

CHAPTER 6

CONCLUSIONS

Animal-vehicle collisions (AVCs) are ubiquitous in developed regions of the world (Hill et al., 2019) and cause significant damage to wildlife and humans annually (Conover, 2019; Huijser et al., 2008; Langbein et al., 2010). As the human population and road infrastructure continue to grow (Dulac, 2013), the number of AVCs will likely increase (Hill et al., 2020), as will direct mortality of wildlife resulting in billions of vertebrate deaths each year (Seiler and Helldin, 2006). Understanding the factors that cause WVCs is necessary to develop effective mitigation methods, but WVCs are complex with influences from driver behavior, animal behavior, and environmental conditions. In this dissertation, I quantified factors affecting both driver and animal behavior during nighttime encounters to better uncover their role in causing WVCs. Specifically, I categorized factors influencing driver behavior during wildlife-vehicle encounters and highlighted gaps in the literature. With respect to driver behavior, I quantified driver detection ability of free-ranging wildlife at night. Pivoting to animal behavior, I investigated how headlight type, headlight intensity, and increased frontal illumination via a rear-facing lightbar impacted deer behavior during an imminent collision scenario using captive deer. Finally, I applied those findings to the real world and tested how vehicle lighting impacted free-ranging wildlife encountered opportunistically at night. Collectively, these chapters provide insight into the causes of wildlife-vehicle collisions with implications for developing methods to mitigate them.

In Chapter 2, I conducted a comprehensive literature review of the factors influencing driver behavior during wildlife-vehicle collisions. My literature search revealed that many studies focused on mitigation methods, likely due to the economic and safety impacts of WVCs, but their effectiveness varied considerably. The topics of wildlife attributes, roadway illumination, and inherent driver attributes remain understudied. Most studies relied on seemingly logical explanations for results or associations between variables, but few studies directly tested how specific variables influenced a driver's ability to detect wildlife or their behavior during wildlife-vehicle encounters. Overall, this chapter synthesized the current knowledge and identified key gaps in the literature for future research to further explore.

Given the gaps previously identified, Chapter 3 investigated how well drivers can detect free-ranging wildlife at night. Volunteer drivers drove a predetermined paved route and notified a researcher when they detected an animal. Results from the chapter showed that high-beam headlights increased detection distance of deer, but detection distances decreased with increasing time into the drive. Dangerous encounters with deer increased with vehicle speed and time into the drive. Additionally, every encounter with wild pigs was dangerous, likely due to their short stature, dark pelage, and lack of eyeshine limiting driver detection distances. Overall, this chapter built upon previous research with animal decoys (Hobday, 2010; Mastro et al., 2010; Rodgers and Robins, 2006) to quantify driver detection ability of free-ranging wildlife. This study highlighted the benefits of using high-beam headlights and the danger of travelling at fast vehicle speeds and for prolonged duration at night.

Chapter 4 investigated how vehicle lighting impacted deer behavior at night. I used captive deer and a confined experimental arena to evaluate the effects of headlight type (halogen vs. LED), headlight laneintensity (low vs. high beam), and increased frontal vehicle illumination via a rear-facing lightbar (lightbar off vs. on) on deer behavior during an imminent collision scenario. I found that headlight type, headlight intensity and lightbar usage all had an effect on deer responses. Specifically, the halogen, high beam, lightbar off treatment had the greatest probability of evoking an alert response. However, I found that no vehicle lighting treatment affected alert probability, flight probability, or flight distance. My results also showed large variations in behavioral responses among deer, underscoring the difficulty in developing a universally effective mitigation method.

In Chapter 5, I further examined how vehicle lighting impacted animal responses to an approaching vehicle at night using free-ranging wildlife encountered opportunistically. I specifically tested the effects of headlight type (halogen vs. LED), increased frontal vehicle illumination (lightbar off vs. on) and vehicle speed. I found that compared to halogen headlights, LED headlights largely did not impact deer responses but resulted in more favorable responses in wild pigs in the form of increased flight initiation distance. The lightbar reduced higher danger encounters with deer at faster vehicle speeds and increased wild pig flight initiation distance at faster speeds, providing drivers with more time to respond. Overall, the results of this chapter suggested that altering vehicle lighting can impact wildlife behavior, potentially reducing wildlife-vehicle collisions.

By investigating both driver and animal behavior, this dissertation provides novel insight into the causes of wildlife-vehicle collisions. My findings indicate that these collisions result from not only maladaptive animal behavior in response to approaching vehicles, but also from ineffective driver detection of animals. In light of this, my dissertation provides further evidence that vehicle lighting has the potential to increase favorable responses by wildlife, which could reduce wildlife-vehicle collisions when scaled to the millions of annual collisions. Although wildlife-vehicle collisions will remain a global issue, this dissertation advances our understanding of their underlying causes and identifies an avenue for future mitigation methods to help improve both animal and driver safety.

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