Do the presence of culverts and their attributes influence the spatial distribution of roadkill along Autoroute 10 and Route 112 in Southern Québec?

Michael Jairus Rolheiser

A

Thesis

In

The Department

of

Geography, Planning, & Environment

Presented in Partial Fulfillment of the Requirement

For the Degree of Master of Science (Geography, Urban and Environmental Studies) at

Concordia University

Montréal, Québec, Canada

CONCORDIA UNIVERSITY

School of Graduate Studies

This is to certify that the thesis prepared

By: Michael Jairus Rolheiser

Entitled: Do the presence of culverts and their attributes influence the spatial distribution of roadkill along Autoroute 10 and Route 112 in Southern Québec?

and submitted in partial fulfillment of the requirements for the degree of

Master of Science (Geography, Urban and Environmental Studies)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final Examining Committee:

____ Chair

Dr. Angela Kross

____ Examiner

Dr. Angela Kross

____ External Examiner

Dr. Tom Langen

____ Supervisor

Dr. Jochen Jaeger

Approved by ____

Dr. Craig Townsend

Chair of Department of Geography Planning and Environment

____

Dr. Pascale Sicotte

Dean of Faculty of Arts and Science Date: July 31, 2025

ABSTRACT

Do the presence of culverts and their attributes influence the spatial distribution of roadkill along Autoroute 10 and Route 112 in Southern Québec?

Michael Jairus Rolheiser

Roads impact wildlife by fragmenting habitats, impeding movement, and though wildlife-vehicle collisions (WVCs). Proven mitigation strategies include wildlife crossing structures, but wildlife also utilize existing water culverts and underpasses to cross roadways. They offer opportunities for retrofitting when budget constraints limit the feasibility of wildlife passages. This study investigates the spatial relationship between roadkill distribution and culvert presence along a four-lane divided freeway (A10) and a two-lane regional highway (R112) in Québec, Canada. I evaluate how culvert structural characteristics (e.g., materials, shapes, functions, and dimensions) and surrounding environmental features influence roadkill frequencies separately for amphibians, mammals, and reptiles. I address three research questions: (1) Does the presence of culverts influence the spatial distribution of roadkill? (2) Which structural and environmental attributes are associated with higher or lower roadkill frequencies for different animal groups? (3) What are the similarities and differences between R112 and A10? The findings provide strong evidence for culvert influence on roadkill patterns. Mammal and reptile fatalities were more frequently associated with dry passages, amphibians with wet passages, and all groups showed a preference for using concrete structures over metal or plastic and for larger culvert openings. The results support the installation of wildlife exclusion fencing to reduce roadkill and improve driver safety. Moving forward, this study may serve as the first phase of a Before-After-Control-Impact (BACI) study, the second phase should evaluate the effectiveness of retrofitted culverts with

added wildlife fencing to produce high-inference results for evidence-based WVC mitigation strategies.

ACKNOWLEDGEMENTS

I first must thank my supervisor Dr. Jochen Jaeger for his guidance and patience throughout this process, and to my committee, Dr. Angela Kross and Dr. Sarah Turner, for their care and critically helpful suggestions. Thank you to Dr. Guillaume Larocque (QCBS) for his immense help in all manner statistics and to Victor Grivegnée-Dumoulin (Corridor appalachien) for sharing your ecological expertise. I thank the Ministère des Transports et de la Mobilité durable and Dr. Richard Pither (Environment and Climate Change Canada) for funding this project. Thank you, Jenn Srey, for always looking out for me, Marco Burelli for your consistent computer wizardry, Emory Shaw for the bikes, and my research assistants Ryan Collins, Jaynina Deku, and Avital Moalem for their extraordinarily hard work and for taking this project as seriously as I did. Many thanks to past and present labmates: Dr. Jonathan Cole, Clara-Freeman Cole, Steffy Velosa, my sister-wives Sabrina Mruczek, Sepideh Mosharafiandehkordi, Mehrdokht Pourali, Parnian Pourtaherian, and to Zahra Najmi, Navid Forouhar, Dalia Assi, and Valérie Bolduc, as well as to non-labmates but still mates: Leila Vaziri and Dr. Stephanie Eccles – thank you all for your support, conversation, friendship, and for contributing to my MSc experience.

To my mom Janice MacDougall, and to my two brothers Kyle MacDougall and Mark MacDougall, thank you for your love and support. To Dr. Julián Velez, Chantal Peredery, Natasha Peredery, Jeffrey Sadler, and Cameron Shirt – I am eternally grateful for our shared insanity. To my Montréal family: Dr. Kevin Guo, Sheila Dobie and Abbot, Panda, Mystie and Georgia, Sonny, Daisy, Florian, Oliver, Eleanor, Klaus, Pierre, Pinto, Merlot, Natas, Leo, Piper, Juni, Riley, Tuuli, Jack and Louie, Artemis, and Lily Quarantina – all contributors to my life's meaning in immeasurable ways. And finally, to my best friend, my little constant companion and raison d'être, the best boy, my Marty.

CONTRIBUTION OF AUTHORS

As first author, I was responsible for the data analysis and writing of the manuscript related to this thesis. The manuscript was co-authored by Dr. Jochen Jaeger, who obtained the necessary government permits and funding to conduct this study and advised on study design, statistics, editing and revisions. Additionally, the road mortality survey data collection protocol (Appendix A: Driving Protocol) was co-authored by Steffy Velosa and Dr. Jochen Jaeger.

TABLE OF CONTENTS

ABSTRACT....III
ACKNOWLEDGEMENTS....IV
CONTRIBUTION OF AUTHORS....V
LIST OF FIGURES....VIII
LIST OF TABLES....VIII
INTRODUCTION....1
LITERATURE REVIEW....4
2.1. Effects of Roads....4
    2.1.1. The Road Effect Zone and Habitat Fragmentation....5
    2.1.2. Habitat Loss....6
    2.1.3. Habitat Degradation and Edge Effects....6
    2.1.4. Barrier Effect and Road Avoidance....7
    2.1.5. Attraction to the Road....8
    2.1.6. Road Mortality....9
2.2 Road Mortality Survey Protocols....11
2.3 Mitigation Measures....12
    2.3.1 Before Mitigation: Initial Considerations....12
    2.3.2 Wildlife Exclusion Fences....14
    2.3.3. Wildlife Crossing Structures....16
    2.3.4. Water Culverts as De Facto Wildlife Crossing Structures....18
MANUSCRIPT....20
    ABSTRACT....20
    INTRODUCTION....22
    METHODS....24
    3.1 Study Area....24
    3.2 Fieldwork Protocols for Road Mortality Surveys....28
    3.3 Data Preparation....32
    3.4 GIS Bins....34
    3.5 Predictor Variables....38
        3.5.1 Environmental Predictor Variables....38
        3.5.2 Structural Predictor Variables....43
        3.5.3 Iterative Predictor Variable Selection Process....49
            3.5.3.1 Step 1: Landscape Predictor Variables....49
            3.5.3.2 Step 2: Structural Predictor Variables....51
    3.6 Statistical Analysis....53
    RESULTS....58
    4.1 The influence of 'HALF'....58
    4.2 Scenario A....58
        4.2.1. Scenario A, Amphibians....59
        4.2.2. Scenario A, Mammals....62
        4.2.3. Scenario A, Reptiles....64
    4.3 Scenario B....66
        4.3.1. Scenario B, Amphibians....76
        4.3.2. Scenario B, Mammals....79

4.3.3. Scenario B, Reptiles....81
4.4 Scenario C....83
4.4.1. Scenario C, Amphibians....83
4.4.2. Scenario C, Mammals....85
4.4.3. Scenario C, Reptiles....87
4.5 Scenario D....89
4.5.1. Scenario D, Amphibians....90
4.5.2. Scenario D, Mammals....92
4.5.3. Scenario D, Reptiles....94
DISCUSSION....97
5.1.1 Influence of Crossing Structures....97
5.1.2 Influence of Wildlife Corridors....100
5.1.3 Influence of Guardrails....101
5.2. Influence of Materials....102
5.3. Influence of Shapes....103
5.4. Influence of Functions....104
5.5. Influence of Dimensions and Dimension+....106
5.6. Comparing Autoroute 10 and Route 112....107
5.7. Fences....110
5.8. Limitations....111
CONCLUSION AND RECOMMENDATIONS....112
THESIS CONCLUSION....113
REFERENCES....116
APPENDIX A. FIELDWORK PROTOCOLS & FIELDWORK SCHEDULE....138
A.1 Driving Survey Protocol....138
A.2 Cycling Survey Protocol....148
A.3 Fieldwork Survey Schedule....152
A.4 Analyzed Roadkill....153
A.5 Roadkill Heatmap....154
APPENDIX B. STEP 1 & STEP 2 TEMPLATES....155
APPENDIX C. Variance Inflation Factors (VIF) value tables....158
C.1 Scenario A....158
C.2 Scenario B....159
C.3 Scenario C....160
C.4 Scenario D....161
APPENDIX D. Photographs....162

LIST OF FIGURES

Figure 1. Three categories of wildlife crossing structures....................17
Figure 2. Autoroute 10 and Route 112....................26
Figure 3. The study area sections of Autoroute 10....................27
Figure 4. Bin exclusions....................30
Figure 5. Fieldwork data collection....................32
Figure 6. Section AF [A10]....................36
Figure 7. Section BE [A10] and Route 112 west, included and excluded bins....................37
Figure 8. Section CD [A10] and Route 112 east, included and excluded bins....................37
Figure 9. The number of bins and roadkill proportions, by scenario....................38
Figure 10. The landcover files: LC_10m, LC_30m, and LC_FINAL....................39
Figure 11. Bins and buffer creation....................40
Figure 12. Full and half crossing structure distributions by highway and their attributes....................43
Figure 13. The present/absent assignment of 'corridor', 'guardrail', 'full', and 'half'....................44
Figure 14. Photographs of crossing structure Material, Shape, and Function predictors....................45
Figure 15. Structural predictor variables, by scenario....................47
Figure 16. Landcover predictor Step 1 model format....................49
Figure 17. Boxplots depicting Wilcoxon rank-sum results....................58
Figure 18. Boxplots of Scenario A roadkill count by crossing structure type....................59
Figure 19. Boxplots of Scenario B roadkill count by crossing structure type....................66
Figure 20. Boxplots of Scenario C roadkill count by crossing structure type....................83
Figure 21. Boxplots of Scenario D roadkill count by crossing structure type....................89
Figure 22. Heat map visual depicting roadkill levels on A10 by animal type....................154
Figure 23. Photographs of deceased amphibians with visible signs of barotrauma....................162
Figure 24. Fieldwork photographs demonstrating body size and physical state....................163
Figure 25. Photographs of turtle roadkill....................164

LIST OF TABLES

Table 1. Data by scenario....................34
Table 2. Landcover predictor variables....................42
Table 3. Structural predictor variables....................48
Table 4. Step 1 iteration template depicting the Forest landcover class models. 49
Table 5. Scenario A results, amphibians....................59
Table 6. Scenario A results, mammals....................62
Table 7. Scenario A results, reptiles....................64
Table 8. Scenario B results, amphibians....................76
Table 9. Scenario B results, mammals....................79
Table 10. Scenario B results, reptiles....................81
Table 11. Scenario C results, amphibians....................84
Table 12. Scenario C results, mammals....................85
Table 13. Scenario C results, reptiles....................87
Table 14. Scenario D results, amphibians....................90
Table 15. Scenario D results, mammals....................92
Table 16. Scenario D results, reptiles....................94

Table 17. Crossing structure sample size, mean, and median..97
Table 18. Crossing structure influence on roadkill, by animal type and scenario.........................98
Table 19. 'SAME' and 'OPPOSITE’ roadkill totals, by wildlife group analyzed...........................99
Table 20. Survey schedule for all three fieldwork seasons...152
Table 21. Species of roadkill used in the analyses, by year and highway...................................153
Table 22. The Step 1 Template..155
Table 23. The Step 2 Template used in Scenarios A, B, and C...156
Table 24. The Step 2 Template for Scenario D...157
Table 25. The VIF values for the global and final models of Scenario A...................................158
Table 26. The VIF values for the global and final models of Scenario B...................................159
Table 27. The VIF values for the global and final models of Scenario C...................................160
Table 28. The VIF values for the global and final models of Scenario D...................................161

For my uncle James Rudolph Rolheiser, whose love of wildlife was a gift that I did not appreciate when we still had time together, but it is one that I understand, appreciate, and gratefully accept now.

INTRODUCTION

Global road construction continues unabated with a projected 3 million to 4.7 million kilometres of roadway expected to be added to existing road networks by mid-century compared to 2017 (Meijer et al., 2018). In Canada, 43,316 km of two-lane equivalent roadway were added to the national network in 2019 and 2020 (Statistics Canada, 2022). Roads reduce areas of suitable wildlife habitat by land occupation, facilitate the spread of chemicals, noise, light, and other forms of pollutants creating inhospitable habitat conditions that degrade adjacent habitat and threaten the persistence of some wildlife populations, and act as barriers for wildlife movement between the fragments of remaining habitat patches (Ascensão et al., 2018; Barrientos et al., 2021; Bennett, 2017; Boyes et al., 2021; Jaeger, 2012). Each time wildlife attempt to cross, there is a chance that the attempt will result in a wildlife-vehicle collision (WVC) causing injury and often death to wildlife (Bennett, 2017). Globally, WVCs resulting in vertebrate wildlife death are estimated to number in the billions per year (Seiler & Helldin, 2006). Humans are often Injured or killed as well; an average of four to eight WVCs involving large mammals occur hourly in Canada with 570 WVCs resulting in human fatality between the years of 2000 and 2020 (Barrett et al., 2023; Haddock et al., 2013). Monetarily, WVC-related property damage in Canada is estimated to cost $200 million annually (Elton & Drescher, 2018). Transport ministries are tasked with reducing these impacts, typically beginning mitigation efforts by identifying road sections with high wildlife mortality, followed by constructing barriers to prevent wildlife from accessing the road and/or installing crossing structures that allow animals to cross safely (Soanes et al., 2024; van der Ree et al., 2015). Water culverts are common road network infrastructure and are the subject of research interest to determine if, and to what degree, they may offer a viable option for wildlife to cross (Brunen et al., 2020; Delgado et al., 2018; Warnock-Juteau et al., 2022). With variation in culvert materials and design, the diversity of wildlife, and the differences in data collection and analytical methods, it is perhaps unsurprising that available studies reached differing conclusions. For example, Delgado et al. (2018) found no significant correlation between the spatial patterns of roadkill and culvert locations, whereas both Brunen et al. (2020) and Warnock-Juteau et al. (2022) observed mammals making use of culverts to cross, with the latter observing a higher frequency of crossing in culverts without human presence.

Efforts to improve environmental health through the restoration of landscape connectivity was a primary goal of the signatory provinces (Quebec, New Brunswick, Prince Edward Island, Nova Scotia, and Newfoundland and Labrador) and states (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont) first in Resolution 40-3 and reaffirmed in Resolution 45-2, which asserted their commitment to ecological connectivity, climate change adaptation, and biodiversity conservation (NEG-ECP, 2024). In our study area in southern Quebec, Autoroute 10 (A10), a four-lane, divided, controlled-access highway, represents a significant barrier to the goal of ecological connectivity. Through its Highway 10 – Ecological Connectivity Plan, the non-governmental organization Corridor appalachien advocated for improving A10's permeability; proposed measures included retrofitting existing culverts with dry shelves for wildlife use (Corridor Appalachien, 2022). This study aims to assess the potential use of culverts by wildlife type (amphibians, mammals, and reptiles) in their current, unimproved state by analyzing the spatial relationship between the locations of culverts and other potential crossing structures and roadkill distribution patterns along A10. Additionally, Route 112 (R112), a two-lane secondary highway located north of and parallel to A10, was included in the study to provide comparative insight, as it differs from A10 in road class and speed limits but lies within the same ecological region with the same wildlife species composition. If wildlife near a potential crossing structure (within 100 meters) are using it to cross the road, then a measurable difference in roadkill frequency would be expected between areas with these structures and areas without. Delgado et al. (2018) found no significant relationship between the locations of potential crossing structures and roadkill distribution patterns. However, their study included relatively few roadkill observations (n = 238) with long roadway segments (1 km) as the units of analysis, which may not have achieved the resolution needed to detect such relationships. In contrast, our study analyzes 4,370 roadkill observations and employs 100 meter road segments as the unit of analysis. This segment length better aligns with the mobility range of the dominant wildlife group observed (amphibians) and provides a sufficiently large number of segments (n = 560) for meaningful statistical analysis.

There is an urgent need to install wildlife mitigation along roads as rapidly intensifying climate change will accelerate the poleward migration of wildlife, placing countless species at heightened risk as they try to adapt by seeking more favourable habitat across roads (Corridor Appalachien, 2022; McGuire et al., 2016; Pecl et al., 2017). This thesis investigates relationships between the locations of unfenced culverts and roadkill patterns, seeking to evaluate whether existing culverts already serve as informal wildlife passageways, even in their unimproved state. If a relationship between culvert locations and roadkill is established, it may support culvert usage as crossing pathways, and a strong argument in favour of relatively inexpensive culvert retrofits with dry paths or dry shelves, funnel fencing, and other measures to make culvert use more attractive to be used by wildlife.

This thesis addresses the following research questions:

- Does the presence of culverts influence the spatial distribution of roadkill along Autoroute 10 and Route 112 in Southern Québec?

- Which structural and environmental attributes are associated with higher or lower levels of roadkill?
- What are the similarities and differences between Route 112 and Autoroute 10?

LITERATURE REVIEW

2.1. Effects of Roads

The advent of combustion-engine vehicles and their associated infrastructure is a relatively recent development in global landscapes. In just over a century, the introduction of personalized mechanized transportation has necessitated a fundamental transformation of urban and rural thoroughfares—from cobblestone streets and dirt paths to the straightened, widened, and paved roadways that now define modern mobility. Roads are ubiquitous and indispensable components of modern life. As a result, the study of their environmental impacts—known as Road Ecology (from the German Straßenökologie, meaning "street (or road) ecology")—has emerged as a distinct scientific discipline. This field is dedicated to understanding, evaluating, and mitigating the multifaceted effects of roads on ecosystems, particularly in the context of wildlife-vehicle collisions (WVCs), which pose serious risks to both human safety and biodiversity (van der Ree et al., 2011).

The expansion of the global road network in recent decades has been both rapid and extensive. It has fragmented Earth's terrestrial surface into an estimated 600,000 discrete landscape patches, of which only 7% exceed 100 km^2, and nearly half measure just 1 km^2 or less (Ibisch et al., 2016). Projections indicate that road development will continue at a vigorous pace. Meijer et al. (2018) forecast a 14%–23% increase in total road length by 2050 (from 2017), amounting to an additional 3.0 to 4.7 million kilometres. In a related study, Dulac (2013) estimated that global paved lane length could expand by 35%–60% over 2010 levels, adding 14.8

to 25.3 million kilometres by mid-century. Although these estimates differ due to the methods employed and underlying data used in their respective studies, large-scale road expansion continues with much of it concentrated within developing regions that is home to much of the planet's richest and most biodiverse wilderness (Meijer et al., 2018).

2.1.1. The Road Effect Zone and Habitat Fragmentation

Roads exert a measurable influence on the surrounding environment, forming what is termed the road-effect zone (REZ). This zone represents the geographic extent to which the presence of a road and the traffic it facilitates affects adjacent landscape (Forman & Deblinger, 2000). The REZ is not a fixed distance but varies depending on multiple environmental and infrastructural factors, including wind direction, topography, soil composition, drainage, vegetation type, and road classification (van der Ree et al., 2011). As road density increases, the proportion of land unaffected by road influence diminishes, intensifying overall ecological disruption (Fahrig & Rytwinski, 2009; Torres et al., 2016).

A direct effect of roads is habitat fragmentation, whereby roadways divide landscapes into isolated patches, effectively severing the connectivity of wildlife and plants within the patch from areas beyond the patch (Coffin, 2007; Fahrig & Rytwinski, 2009). In addition to direct effects, indirect road effects arise from the construction, operation, and maintenance of roads, such as pollutants introduced into downstream ecosystems (Coffin, 2007; Schwartz, 2020). In practice, the following effects are seldom isolated; they interact and consolidate, cumulatively amplifying the strength of each effect (van der Ree et al., 2015).

2.1.2. Habitat Loss

The presence of a road always results in habitat loss, by both the physical footprint of the road but adjacent land alterations, such as vegetation clearance for visibility and the excavation of stormwater retention basins. Moreover, the construction of new roads can lead to a process of induced demand, whereby expanded road capacity attracts additional traffic, which in turn encourages further road development in part because of the increased traffic (Duranton & Turner, 2011; Hymel, 2019). These land-use transitions are recognized as major drivers of biodiversity loss, and modern infrastructure development continues to penetrate increasingly remote and ecologically valuable areas (WWF, 2022).

2.1.3. Habitat Degradation and Edge Effects

Roads degrade adjacent habitats through a range of physical and ecological disturbances. Physical degradation can include the removal of vegetation, soil erosion, and the creation of drainage ditches. The elevation or depression of the roadway in relation to the surrounding environment alters natural drainage patterns (Coffin et al., 2021). Traffic noise interferes with the calls of birds and other animals (Parris & Schneider, 2009). Pollutants and chemicals from vehicle exhaust and de-icing agents, tire fibres, oil, fuel, antifreeze, and other spilled vehicle liquids, paint and tar from the road surface, and trash from passing vehicles eventually enter waterways to expand the road effect zone (Collins & Russell, 2009; ECCC, 2012; Mayer et al., 2024; Pocock & Lawrence, 2005).

Roads also create sharp and abrupt artificial habitat edges. These artificial edges alter microclimates and expose previously sheltered interior habitats to increased sunlight, wind, and temperature fluctuations (Azevedo, 2023). Invasive species can exploit such locations, outcompeting native flora unable to adapt to edge environments. The resulting shift in vegetation composition can lead to cascading effects on wildlife reliant on interior habitat conditions. Many wildlife species require essential resources provided by habitat interiors, such as shelter from predators and protection from the elements (Sun, wind, precipitation, wide temperature fluctuations), access to food and water, and opportunities for reproduction (van der Ree et al., 2015).

2.1.4. Barrier Effect and Road Avoidance

Roads can significantly hinder the movement of wildlife, either as a physical barrier or by wildlife avoidance behaviour, together known as the barrier effect (Jaeger et al., 2005). For many species, roads are wide spaces lacking cover or protection; structural features such as fencing, guardrails, steep embankments, flooded ditches, and a lack of continuous vegetation all contribute to reduced habitat connectivity (Grilo et al., 2012; Pagany, 2020). Additionally, street and vehicle lighting, vehicle emissions and other pollutants, noise, and road-related microclimates can amplify the barrier effect (Boyes et al., 2021; Jaeger & Fahrig, 2004).
A meta-analysis by Benítez-López et al. (2010) found that the decline in mammal and bird abundance was spatially more extensive in open habitats compared to forested areas, implying greater sensitivity and road avoidance in less sheltered environments. Furthermore, Fahrig and Rytwinski (2009) observed lower wildlife density correlates with higher road density, suggesting heightened degrees of wildlife avoidance in areas of higher road density; alternatively, local populations may have already been reduced by road mortality (Fahrig et al., 1995).

Ecological consequences of restricted movement include limited access to resources, breeding partners, and dispersal opportunities, and ultimately reduced population abundance, skewed sex ratios, and altered demographic dynamics (Beckmann et al., 2010; Jaeger & Fahrig, 2004). Over time, reduced movement and dispersal can decrease species' genetic variation and consequently, reduce their resiliency to environmental change and disease (Daigle, 2010; Jaeger, 2012). Crooks et al. (2017) showed a significant correlation between the degree to which species' habitats are fragmented and a higher risk of species extinction. If mitigation measures are not put in place to counter barrier effects, decreasing range mobility with increasing isolation may result in reduced population persistence, and species become more vulnerable to extinction (Ascensão et al., 2016; Jaeger et al., 2005; van der Ree et al., 2015).

2.1.5. Attraction to the Road

In contrast to avoidance behaviours, certain features of roads and their surrounding environments can attract opportunistic plants and wildlife because of reduced competition (plants) and food or habitat resources (wildlife) (van der Ree et al., 2015). Birds are known to scavenge for roadkill along roads (Bishop & Brogan, 2013). Reptiles are drawn to warm asphalt for thermoregulation and sandy verges are an attractive spot for turtles to lay eggs, while adjacent ponds and wetlands offer amphibians suitable habitat (Anđelković, M., & Bogdanović, 2022; Ascensao et al., 2019; Barrientos et al., 2021). Spilled grains and other agricultural products attract many types of wildlife onto the road, while herbaceous wildlife are attracted to grassy verges (Rees 2016; Seiler & Helldin, 2006). In colder climates, pooled de-icing salt accumulated along rumble strips attracts moose (Grosman et al., 2009). Nocturnal insects are drawn to the light of streetlights and passing vehicles (Boyes et al., 2021; Eisenbeis & Hänel, 2009). These attractions can have dire consequences; for example, the nocturnal insect attraction to artificial light can be so strong that they circle the light until dropping dead of exhaustion (Eisenbeis & Hänel, 2009). Streetlights impair the insects' ability to disperse and maintain a robust gene pool (Boyes et al., 2021).

2.1.6. Road Mortality

Wildlife-vehicle collisions (WVCs) are one of the most visible and violent impacts of roads on wildlife, frequently resulting in injury or death. It is estimated that approximately one million vertebrates are killed daily on roads in the United States, and up to 1.3 million in Brazil (BBC Brazil, 2015; Forman & Alexander, 1998). Annually, an estimated 194 million birds and 29 million mammals are killed on European roads (Grilo et al., 2020). These figures highlight the pervasive nature of road mortality, which is a leading cause of death for many species (Hill et al., 2019). The consequences extend beyond individual deaths; they reduce a population's abundance, affect the number of potential mates, and decrease the chances of locating a potential mate (Fahrig & Rytwinski, 2009).

Not all species are equally threatened by road mortality. Particularly vulnerable species are those with slow reactivity and mobility, wildlife with large habitat ranges required to meet lifecycle needs, and wildlife attracted to roads for reasons explored above (thermoregulation, nesting, and scavenging) (Fahrig & Rytwinski, 2009). Additionally, high WVC rates of some species can be linked to other anthropogenic activities; for example, the targeted killing of deer predators (cougars and wolves) to protect livestock has inadvertently caused rapidly increasing deer populations, allowing for more WVCs involving deer (Gilbert et al., 2017; Raynor et al. 2021).

High road mortality rates can still occur in areas with low traffic volumes and on short and narrow roads (Magioli et al., 2019). While lower traffic reduces associated noise, dust, and emissions, some species still experience significant mortality regardless of volume (Coffin et al., 2021; Grilo et al., 2015). Rather, all roads should have mitigation measures implemented; traffic volumes as low as 300 vehicles per day could result in high mortality rates for some species

(Hels & Buchwald, 2001). Roads with higher traffic volumes adjacent to good quality habitat increase the probability of WVCs (Lin, 2016). A decline in road mortality in the presence of high traffic volumes suggests an already-reduced wildlife population (Ascensão et al., 2019; Eberhardt et al., 2013; Fahrig et al., 1995). Conversely, low observed mortality on high-traffic roads may indicate depleted local wildlife populations, particularly in proximity to good quality habitat (Ascensão et al., 2019; Fahrig et al., 1995).

Mortality can also occur without physical impact from a vehicle. Hummel (2001) proposed that the changes in pressure caused by passing vehicles would be enough to cause lethal internal damage in amphibians without direct vehicle-wildlife contact. Hummel argued that a vehicle moving at a speed of only 30 km/h could induce fatal lung collapse (barotrauma). While this theory remains contested (Hels and Buchwald, 2001; Mayer et al., 2018; Schmidt & Zumbach, 2008), our experience during fieldwork support Hummel. Drawing on two summers of road mortality surveys, numerous amphibians were found freshly dead with externally unmarked and intact bodies but having had their entrails pulled out through their mouths (for photos, see Appendix D). Dornas et al. (2019) documented similar injuries in amphibians along railway tracks, reinforcing the plausibility of Hummel's hypothesis. Many newts and salamanders were found entirely intact though desiccated, possibly killed by the process posited by Hummel; alternatively, small body size and slow mobility may also account for some of these fatalities, desiccating before a completed crossing (Dornas et al., 2019; McGuire et al., 2020).

Importantly, locations with high mortality rates reflect where crossing attempts have most frequently failed—not necessarily where crossing attempts are most common (Neumann et al., 2011). Other road segments may experience more frequent, but more successful, crossings due to favourable habitat features or lower risk conditions.

Habitat fragmentation by roads is a multifaceted challenge to ecological resilience. These effects are not static; they fluctuate in intensity and often interact in complex ways with difficult to predict consequences (van der Ree et al., 2015). In Canada, the Environmental Impact Assessment (EIA) process is designed to evaluate such risks in the planning stages of infrastructure development (van der Ree et al., 2015). Increasingly, researchers advocate for the adoption of the precautionary principle in EIAs, emphasizing the need for proponents to demonstrate the absence of environmental harm rather than placing the burden of proof on conservation advocates (Jaeger, 2015; Jaeger & Torres, 2021; Rohwer & Marris, 2021). Accordingly, an EIA should not only assess mitigation strategies but also consider whether the proposed road should be built at all (Jaeger & Torres, 2021).

2.2 Road Mortality Survey Protocols

With growing awareness of the ecological impacts of roads, an increasing number of jurisdictions now rely on ecologists to guide mitigation strategies aimed at reducing WVCs (Denneboom et al., 2021; Garrah et al., 2015). The ability of ecologists to fulfill this role effectively depends on the collection of robust and reliable data. Central to this effort is a rigorous road mortality survey protocol, which is critical for identifying high-risk locations and informing the design of effective mitigation infrastructure.

Roadkill surveys can be conducted through various modes of travel, including driving, cycling, or walking. Each method presents trade-offs between spatial coverage and detection accuracy (Langen et al., 2007; Winton et al., 2018). Vehicle-based surveys are efficient for covering long distances but often yield lower detection probabilities, particularly for small-bodied species, due to limited visibility and faster speeds (Collinson et al., 2014). Walking surveys offer the highest detection probability but are limited in coverage, while cycling provides a balanced approach between the two. Survey methodology should be tailored to the target species and environmental conditions. Factors such as body size, rates of scavenger removal, and speed of carcass decomposition all influence the optimal survey frequency and mode (Langen et al., 2007; Pagany, 2020; Winton et al., 2018). In addition to recording GPS coordinates and attempting species-level identification of each carcass, researchers should also collect contextual data, including road characteristics (speed limit, traffic volume, number of lanes), physical obstructions (fencing and barriers or guardrails that may prevent wildlife from accessing the road), adjacent land use and cover types, and temporal variables such as time of day and weather conditions (Pagany, 2020). Although researchers have called for a standardized global protocol for roadkill surveys, no universal data collection protocol has been adopted (Collinson et al., 2014; Pagany, 2020). For this study, the survey protocol developed by the Jaeger Lab was adopted, providing consistent data collection methods tailored to study area conditions (see Methods and Appendix A.1 for the Driving Protocol and Appendix A.2 for the Cycling Protocol).

2.3 Mitigation Measures

2.3.1 Before Mitigation: Initial Considerations

The most effective action decision-makers can take to prevent ecological effects from roads is to not build them at all. Drawing on Jaeger and Torres (2021), a sound EIA should ask if the road is truly necessary. This question is seldom considered because of the narrow range of effects studied, a lagging application of recent ecological findings, and a lacking use of analytical technological advancements in the EIA process. If a road is to be built, mitigation measures should already be incorporated in the planning stages, where they can be designed to be the most effective at preventing wildlife mortality and preserving some level of landscape connectivity while being comparatively cost-effective relative to wildlife mortality mitigation methods applied to existing roads (Jaeger & Torres, 2021, Rytwinski et al., 2016).

Before any mitigation measure is implemented, researchers should identify the mechanisms driving the road effects that are to be addressed. Correctly identifying these mechanisms supports an efficient allocation of resources (Denneboom et al., 2021; Lima Santos et al., 2017; Spanowicz et al., 2020; Teixeira et al., 2020; Valerio et al., 2021). Three common road effects and their underlying mechanisms include wildlife-vehicle collisions (WVCs), reduced habitat quality due to road-related disturbances such as noise, light, and chemical pollution, and decreased habitat connectivity from road construction or expansion (Coffin, 2007; Forman & Alexander, 1998; Teixeira et al., 2020). While researchers often aim to mitigate all three effects simultaneously, some studies suggest that increasing habitat connectivity is over-recommended to decision-makers, whereas direct mitigation of road mortality remains underemphasized (Teixeira et al., 2020). Importantly, mitigation must be evidence-based to demonstrate that public expenditures result in perceptible ecological and safety benefits. Poorly conceived or ineffective measures risk public skepticism and resistance to future mitigation efforts (Bíl & Andrasik, 2020).

Helldin et al. (2016), in their report for the Conference of European Directors of Roads (CEDR), offer a concise list of road effects and corresponding mitigation strategies. For reducing road mortality, the report recommends wildlife exclusion fencing (with escape devices) and wildlife crossing structures, either purpose-built or retrofitted, to reduce WVCs with terrestrial animals. Other recommendations include tree planting to force birds and bats to higher flight paths and adjusting construction schedules to accommodate wildlife migratory timing. Additional methods include static wildlife crossing signage, reflectors fixed to roadside poles, and auditory deterrents attached to vehicles to discourage wildlife from approaching the road and traffic; however, their effectiveness remains in question (Rytwinski et al., 2016; van der Ree et al., 2015; WCPP, 2022).

Dynamic wildlife crossing signage, also known as animal detection systems (ADS), feature flashing warning signs that are triggered by wildlife, which alert motorists of a potential wildlife road crossing attempt, has been shown to be effective in reducing WVCs with ungulates when paired with effective wildlife fencing flanking either side of the highway (Gagnon et al., 2019).

2.3.2 Wildlife Exclusion Fences

Wildlife exclusion fencing is effective in reducing WVCs by physically preventing animals from accessing the road surface. Meta-analyses suggest an inter-species average reduction of 54% and an average of 80% for ungulates in WVCs (Rytwinski et al., 2016), particularly for species that do not naturally avoid roads (Jaeger & Fahrig, 2004). Fence material (e.g., wood, metal, plastic, concrete) and design features (e.g., mesh size, height, length) should be tailored to the target species or species groups (Clevenger & Huijser, 2011; Glista et al., 2009; McCollister & van Manen, 2010). Herpetofauna, for example, require fencing that is climb-resistant, at least 50 cm high, partially buried to prevent burrowing, and ideally including a lip or overhang to prevent jumping over the fence and accessing the road. The highway side may also be backfilled to allow animals that are on the road to escape (Boyle et al., 2019; Ovaska et al., 2014). Such targeted designs can reduce amphibian and reptile road mortality by up to 85% (Helldin & Petrovan, 2019). Hybrid fencing approaches can be used to serve multiple taxa; for instance, combining herpetofauna fencing with tall wire mesh fencing for large mammals where both groups coexist (Clevenger & Huijser, 2011).

Fence length should at minimum match the home range of the target species, with fence ends strategically placed in hard to access areas, e.g., a rock cliff or culvert entrance (Clevenger & Huijser, 2011). A fence length less than the home range of the target species may easily result in a fence-end effect, in which a new location of high mortality is created by wildlife following the fence to its end and attempt to cross the road there (Huijser et al., 2016). To successfully avoid the fence-end effect, fences need to be longer than the distance the target animal is willing to travel to circumvent it (Huijser et al., 2016; Wilansky & Jaeger, 2024). Crucially, fencing must be routinely inspected and properly maintained. Clevenger and Huijser (2011) recommend thorough, on-foot inspections every six months. Without regular maintenance, structural deficiencies may allow wildlife to access the road surface, potentially increasing the risk of collisions in areas where such incidents were previously rare or absent (Sedoník et al., 2023).

While fences reduce WVCs, they can contribute to reduced population persistence (Jaeger & Fahrig, 2004). Fences can fragment populations and reduce gene flow, leading to increased vulnerability to disease and environmental change (Jackson & Fahrig, 2011; Lesbarrères & Fahrig, 2012). Therefore, it is recommended that fencing be a first step in road mitigation to preserve the lives of individual wildlife or help to restore depleted populations until crossing structures can be constructed to restore landscape connectivity, species mobility, and genetic exchange (Jaeger & Fahrig, 2004; Spanowicz et al., 2020; Teixiera et al., 2017). Species with high mobility and low road avoidance should be prioritized for mitigation over species with lower mobility and higher road avoidance, unless the species is endangered (Fahrig & Rytwinski, 2009; Rytwinski & Fahrig, 2012; Rytwinski & Fahrig, 2013).

2.3.3. Wildlife Crossing Structures

Wildlife crossing structures —structures designed specifically for wildlife movement across roads—facilitate landscape connectivity and allow animals access to resources, mates, and alternate habitats (Barrientos et al., 2021). While fencing reduces road mortality, a paring of fencing and wildlife crossing structures is essential to minimize habitat fragmentation (Rytwinski et al., 2016). The following discussion of wildlife crossing structures the follows implies a pairing with wildlife exclusion fencing.

Wildlife crossing structures can be broadly categorized into three types: wildlife underpasses, viaducts, and wildlife overpasses (Figure 1) (Denneboom et al., 2021). Some wildlife species or species groups favour one type over the other, e.g., amphibians and small mammals prefer small soil-lined underpasses that maintain a close proximity to water (amphibians) or mimic a burrow with a dry path (small mammals) (Brunen et al., 2020; Denneboom et al., 2021; Helldin & Petrovan, 2019; Lesbarrères et al., 2004). Large mammals prefer overpasses or very large and open viaducts (Denneboom et al., 2021). Structural enhancements such as natural "furniture" (e.g., rocks, logs, and vegetation) increase usage by minimizing transitions between the habitat and crossing structure while offering cover from potential predators (van der Ree et al., 2007). The pairing of properly designed crossing structures and wildlife exclusion fencing can reduce WVCs by 85% to 100% for amphibians and 80% to 97% for large mammals (Coelho et al., 2012; Helldin & Petrovan, 2019; Huijser et al., 2016). Wildlife-only structures tend to be used more frequently than co-use structures (human and wildlife); however, crossing structures are much more likely to be funded and constructed if a human crossing component is incorporated (Denneboom et al., 2021; Newell et al., 2022).

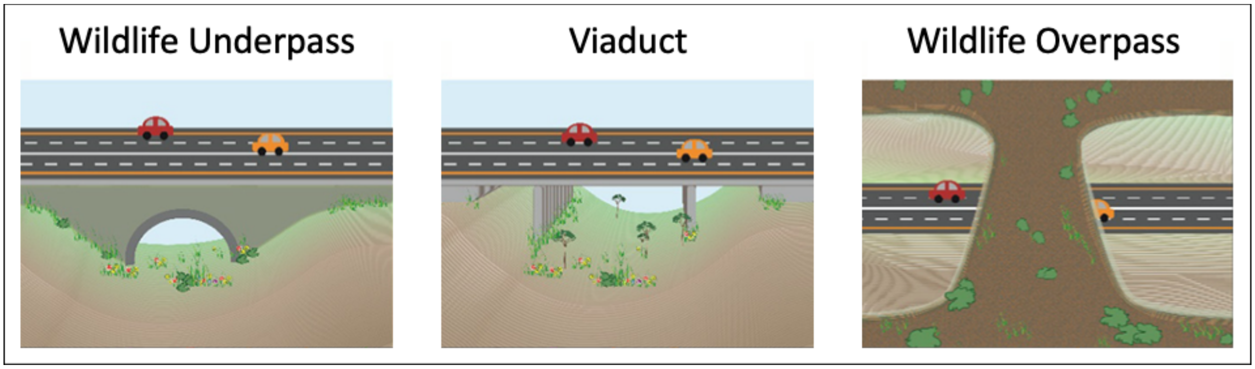


Figure 1. The three categories of wildlife crossing structures (source: Denneboom et al., 2021)

In their meta-analysis of factors affecting the usage of crossing structures by wildlife, Denneboom et al. (2021) noted that studies often focused on large mammals with a lack of focus on reptiles, birds, and small mammals. This research imbalance reflects transportation agencies prioritization of human safety in efforts to reduce WVCs involving large mammals that result in human injury, death, and property damage, with little concern for wildlife themselves (Newell et al., 2022).

A notable North American example of effective mitigation is the Trans-Canada Highway (TCH) in Banff National Park, Canada. The phased construction of multiple crossing structures (both wildlife underpasses and wildlife overpasses) paired with exclusion fencing coincided with the TCH's twinning (two lanes in either direction, separated by a central median) (Clevenger & Barrueto, 2014). Despite increased traffic volume as each phase was completed, WVCs among large mammals was reduced by an average of 80% (Clevenger & Barrueto, 2014). Additionally, genetic testing on wildlife during site monitoring in the 2010s confirmed genetic mixing, demonstrating that the mitigation infrastructure successfully supported both wildlife mortality reduction and population persistence. This case study reinforces the critical importance of pairing fencing with wildlife passages to achieve effective mortality mitigation while minimizing the barrier effect (Beckmann et al., 2010; Clevenger & Barrueto, 2014; Glista et al., 2009; Jaeger & Fahrig, 2004; Rytwinski et al., 2016).

2.3.4. Water Culverts as De Facto Wildlife Crossing Structures

In their meta-analysis, Denneboom et al. (2021) identified several structural and environmental variables that influence wildlife use of potential crossing structures including water culvert length, opening height, width, and general shape, composite materials, usage type (single- or multi-species, human-wildlife co-use), and the presence of retrofitted elements such as dry shelves. Their findings, consistent with Brunen et al. (2020), suggest that water culverts constructed from plastic composites are less frequently used by wildlife as crossing structures compared to those made of concrete. Importantly, water culverts with natural flooring materials —such as stone, rock, or soil with vegetation cover—were found to facilitate higher levels of use (Denneboom et al. (2021). Both studies recommended retrofitting pre-existing water culverts with dry shelves as a cost-effective way to encourage highway permeability. Brunen et al. (2020) found that structures without a dry path are unlikely to be used by species other than raccoons (*Procyon lotor*), river otters (*Lontra canadensis*), and American mink (*Neovison vison*). Water culverts used by large carnivores might discourage usage by prey species (Gagnon et al., 2011). Large carnivores exhibit a strong aversion to using crossing structures that are shared with humans, highlighting the importance of wildlife-exclusive passages to ensure more successful crossings (LaPoint et al., 2003; Warnock-Juteau et al., 2022). Interestingly, fencing intended to guide wildlife toward water culverts has been shown to discourage use by large carnivores. Denneboom et al. (2021) propose that this may be due to an association between fencing and human infrastructure, suggesting large carnivore avoidance of areas with perceived human presence.

Longer water culvert length was shown to discourage usage by all wildlife except for small non-carnivorous mammals, amphibians, and reptiles; wider openings and greater ceiling height encourage usage for many species among these wildlife groups (Denneboom et al., 2021). Small mammal water culvert use is increased if the entrance to the culvert is within 100 meters from the highway (Ford & Clevenger, 2011). Gagnon et al. (2011) recommend avoiding long water culverts in mitigation strategies targeting large herbivores such as elk (*Cervus canadensis*) and white-tailed deer (*Odocoileus virginianus*), as these species are less likely to enter structures of extended length.

In Clevenger et al. (2001), traffic volume had the highest relative importance for coyote (*Canis latrans*), marten (*Martes americana*), and red squirrel (*Tamiasciurus hudsonicus*) culvert crossings, with higher traffic volume discouraging culvert crossings for coyotes while increasing culvert crossing use for marten and red squirrel. Noise level was the predictor with the highest relative importance for snowshoe hare (*Lepus americanus*), where increased noise levels discouraged culvert crossings; for weasels (*Mustela erminea*) and (*Mustela frenata*), culverts of larger heights had the highest relative importance and had a positive influence on culvert crossings.

Unfortunately, studies about water culverts as wildlife crossing structures seldom state explicitly if wildlife exclusion fencing is present. A reasonable assumption is that fencing to guide wildlife must be present for water culverts to be effective crossing structures much in the same way that fencing is required for wildlife crossing structures to be effective (Rytwinski et al., 2016), but this interpretation of the literature remains speculation.

MANUSCRIPT

Do the presence of culverts and their attributes influence the spatial distribution of roadkill along Autoroute 10 and Route 112 in Southern Québec?

Michael J. Rolheiser[1] and Jochen J. A. Jaeger[1]

[1] Concordia University Montreal, Department of Geography, Planning and Environment, 1455 De Maisonneuve Blvd. West, Suite H1255, Montreal, QC, H3G 1M8

ABSTRACT

Roads impact wildlife by fragmenting habitats, impeding movement, and though wildlife-vehicle collisions (WVCs). Proven mitigation strategies include wildlife crossing structures, but wildlife may also utilize existing water culverts and underpasses to cross roadways. They offer opportunities for retrofitting when budget constraints limit the feasibility of wildlife passages. This study investigates the spatial relationship between roadkill distribution and culvert presence along a four-lane divided freeway (A10) and a two-lane regional highway (R112) in Québec, Canada. We evaluate how culvert structural characteristics (e.g., materials, shapes, functions, and dimensions) and surrounding environmental features influence roadkill frequencies separately for amphibians, mammals, and reptiles. We address three research questions: (1) Does the presence of culverts influence the spatial distribution of roadkill? (2) Which structural and environmental attributes are associated with higher or lower roadkill frequencies for different animal groups? (3) What are the similarities and differences between R112 and A10? The findings provide strong evidence for culvert influence on roadkill patterns. Mammal and reptile fatalities were more frequently associated with dry passages, amphibians with wet passages, and all groups showed a preference for using concrete structures over metal or plastic and for larger culvert openings. The results support the installation of wildlife exclusion fencing to reduce roadkill while improving driver safety. Moving forward, this study may serve as the first phase

of a Before-After-Control-Impact (BACI) study; the second phase should evaluate the effectiveness of retrofitted culverts with added wildlife fencing to produce high-inference results for evidence-based WVC mitigation strategies.

INTRODUCTION

The numerous and significant environmental impacts of roads are well documented. Roads contribute to habitat fragmentation, habitat degradation, and habitat loss (Glista et al., 2009; Jaeger et al., 2005; van der Ree et al., 2011). For many dispersing wildlife species, roads and related traffic act as behavioural and physical barriers (Jaeger et al., 2005; Lima et al., 2015; Shepard et al., 2008). The traffic facilitated by roads introduce a wide range of pollutants into the environment, including road salt, tire particulate, vehicle exhaust and leaked fluids, as well as noise and light pollution (Collins & Russell, 2009; ECCC, 2012; Eisenbeis & Hanel, 2009; Mayer et al., 2024; Pocock & Lawrence, 2005). The presence of roads and traffic can repel some wildlife species, resulting in potentially reduced gene mixing and diminished population persistence, while simultaneously attracting others to roadside vegetation, thermoregulation, or carrion, increasing the odds of wildlife-vehicle collisions (WVC) (Ascensao et al., 2019; Barrientos et al., 2021). WVCs are recognized as a leading cause of wildlife mortality (Moore et al., 2023), contributing to local population declines, and potentially, to local species extinction (Torres et al., 2016). Globally, estimates for the number of wildlife deaths caused by WVCs exceed billions per year (Seiler & Helldin, 2006), including one million per day in the continental U.S. (Lalo, 1987), 1.3 million per day in Brazil (CBEE, 2015), 17.5 million birds and mammals in Latin America (Medrano-Vizcaíno et al., 2022), and 194 million birds and 29 million mammals per year in Europe (Grilo et al., 2025). Accordingly, interest in mitigating the ecological impacts of roads, often aided by road ecologists, has grown among decision-makers in parallel with increasing public concern over the environmental consequences of road networks (Schilthuizen, 2022). Road ecologists can advise on a strategic implementation of infrastructure aimed at reducing WVCs by first identifying road segments with high wildlife mortality of the target species, assessments that are often based on data collected using a rigorous and standardized data collection protocol. However, prioritizing areas of high wildlife mortality for WVC mitigation is contested; selecting areas of favourable habitat but with lower observed mortality for mitigation may be more appropriate when already diminished local populations is suspected or if the target species is rare or endangered and mortality data are consequently limited (van der Ree et al., 2015).

In Québec, 7,684 km were added to the provincial road network between 2000 and 2022, including a 473 km increase in primary roads (Cole et al., 2022). Expansion of road networks contributes to habitat fragmentation, reducing landscape connectivity and limiting the ability of wildlife to move freely across the environment. Greater road density is associated with greater restrictions on wildlife movement and elevated WVC risk (Bennett, 2017). Climate change-driven shifts in specie'' ranges increase the frequency of WVCs as wildlife migrate into new areas in search of suitable environmental conditions to replace those rendered increasingly inhospitable (Urban, 2020). Recognizing the need for coordinated responses, the New England Governors and Eastern Canadian Premiers adopted Resolution 40-3 in 2016, reaffirmed in Resolution 45-2, committing to biodiversity conservation, climate adaptation, and the maintenance of ecological connectivity across this transboundary region (NEG-ECP, 2024). An attractive component in the work of protecting landscape connectivity while mitigating WVCs involves the strategic use and retrofitting of pre-existing drainage infrastructure as a cost-effective measure for improving wildlife movement across roads and throughout landscapes. Recent studies have evaluated the potential of water culverts—though not originally designed as wildlife crossing structures—as functional crossing structures for fauna (Brunen et al., 2020; Koju et al., 2025; Warnock-Juteau et al., 2022). Brunen et al. (2020) and Warnock-Juteau et al.

(2022) observed mammals making use of culverts to cross, with the latter observing a higher frequency of crossing in culverts without human presence. Koju et al. (2025) reported the median WVC counts were lowest in the vicinity of culverts when compared with WVC count medians in the vicinity of roadside wildlife warning signage and bridges. Furthermore, Koju et al. noted that the average distance between culverts and WVCs was relatively consistent at 150 meters, a greater distance than for wildlife warning signage (50-100 meters) and similar to that of bridges (200 meters but with much greater variability compared to culverts) (2025).

This study examines whether the locations of unfenced culverts along southern Québec's Autoroute 10 (a four-lane, divided, unrestricted access highway) and Route 112 (a two-lane secondary highway/collector road) are influential on roadkill distribution patterns. Our goal is to evaluate if existing potential crossing structures in their current, unimproved state, already act as informal wildlife crossing structures. Providing evidence to such an effect strengthens the argument to provide relatively inexpensive modifications to existing potential crossing structures, such as dry shelves, rocks and other 'furniture', and funnel fencing, in order to increase existing potential crossing structure use by wildlife as a means to cross highways. Specifically, we ask (1) do the presence of culverts and their attributes influence the spatial distribution of roadkill along Autoroute 10 and Route 112 in Southern Québec? (2) Which structural and environmental attributes are associated with higher or lower levels of roadkill? And (3) what are the similarities and the differences between Route 112 and Autoroute 10?

METHODS

3.1 Study Area

The study area lies within the Northern Green Mountains located in Southern Québec, an area noted for its extensive forest cover (75% of the land cover) and considerable human population

(5.4 million). The geology of the region is a mix of volcanic rock and sedimentary deposits, a lush green rolling hill landscape formed over a 150-million-year process (450 to 290 million years B.P.) (Li & Ducruc 1999). Agricultural use occupies much of the valley land situated between the slopes, an estimated 15% within ‘The Appalachians,’ a region defined by Québec’s Environment Ministry, that overlaps with the project area and extends northeast to include the Gaspé peninsula (Li & Ducruc 1999).

The region’s elevation from sea level to over 1200 m allows for many different habitat types where an array of flora, fauna, and other organisms have adapted to their local conditions (Corridor appalachien, n.d.; Li & Ducruc, 1999). The predominant forest cover is mixed deciduous with some coniferous cover at higher elevations, and among forested areas are several types of forest ecosystems: old growth (no human disturbance), refuge (habitat for species at risk), and rare forests, the components of which are uncommon (Corridor appalachien, n.d.; Li & Ducruc 1999). Fauna in the project area is varied and includes 472 vertebrate species including moose (*Alces alces*), raccoon (*Procyon lotor*), snapping turtle (*Chelydra serpentina*), bobcat (*Lynx rufus*), Golden-winged warbler (*Vermivora chrysoptera*), pickerel frog (*Lithobates palustris*), and fisher (*Martes pennanti*) (Anderson et al. 2006; Corridor appalachien, n.d.), among many others. This diverse landscape has encouraged extensive cross-discipline conservation efforts, including: “Two Countries, One Forest” and Resolution 40-3 (St-Pierre et al., 2019; endorsed in 2024 by Resolution 45-2) among others, to maintain and/or re-establish connectivity (2C1Forest, 2021; Corridor appalachien, 2022). The roadways of study, Autoroute 10 (A10) and Route 112 (R112), slice through the Northern Green Mountains eco-corridor region, hazards in the landscape where wildlife wishing to access habitat on the opposite sides must attempt a crossing.

The study area is between kilometre markers 78.5 and 118 along Autoroute 10, a four-lane divided highway running from Sherbrooke in the east to Montréal in the west (Figure 2). Designed for uninterrupted traffic flow, A10 is a controlled-access highway with a posted speed maximum of 100 km/hr and a speed minimum of 60 km/hour. Traffic volumes are estimated at around 25,000 vehicles per day (Government of Québec, 2022).

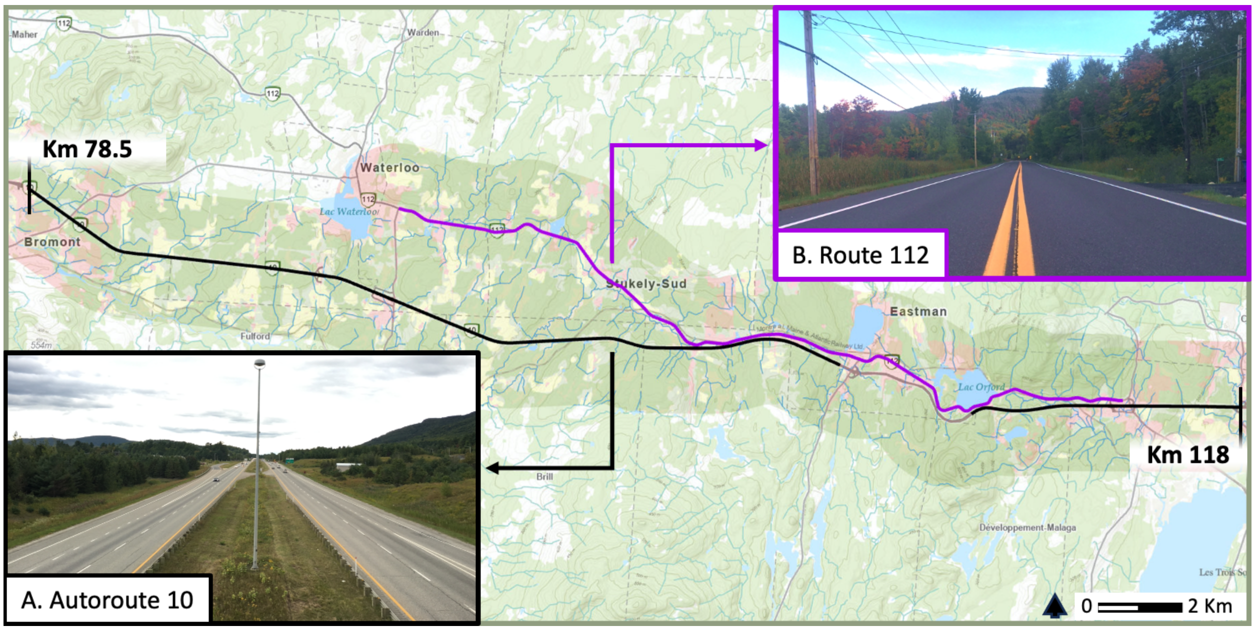


Figure 2. A. Autoroute 10, surveyed between kilometre markers 78.5 and 118, between May and August, 2019; May and September, 2020; and in August and September, 2021. B. Route 112, surveyed between the municipality of Waterloo, QC., in the west, and kilometre marker 115 on Autoroute 10 in the east. Photo credit: Michael Rolheiser.

Route 112 is a two-lane secondary roadway north of and nearly parallel to A10. Here, the study area included 25.1 km of roadway between the towns of Waterloo in the west and Magog in the east, passing through the townships of Frost Village, Stukely-Sud, and Eastman, and abutting the southern side of Parc national du Mont-Orford. Posted speed limits vary between 30 km/hour for school zones to 50 km/hour within the townships, and 90 km/hour between them. The shoulders of R112 are used by residents and tourists alike as de facto sidewalks and cycling paths. Traffic volumes are estimated at around 2,700 vehicles per day (Government of Québec, 2022).

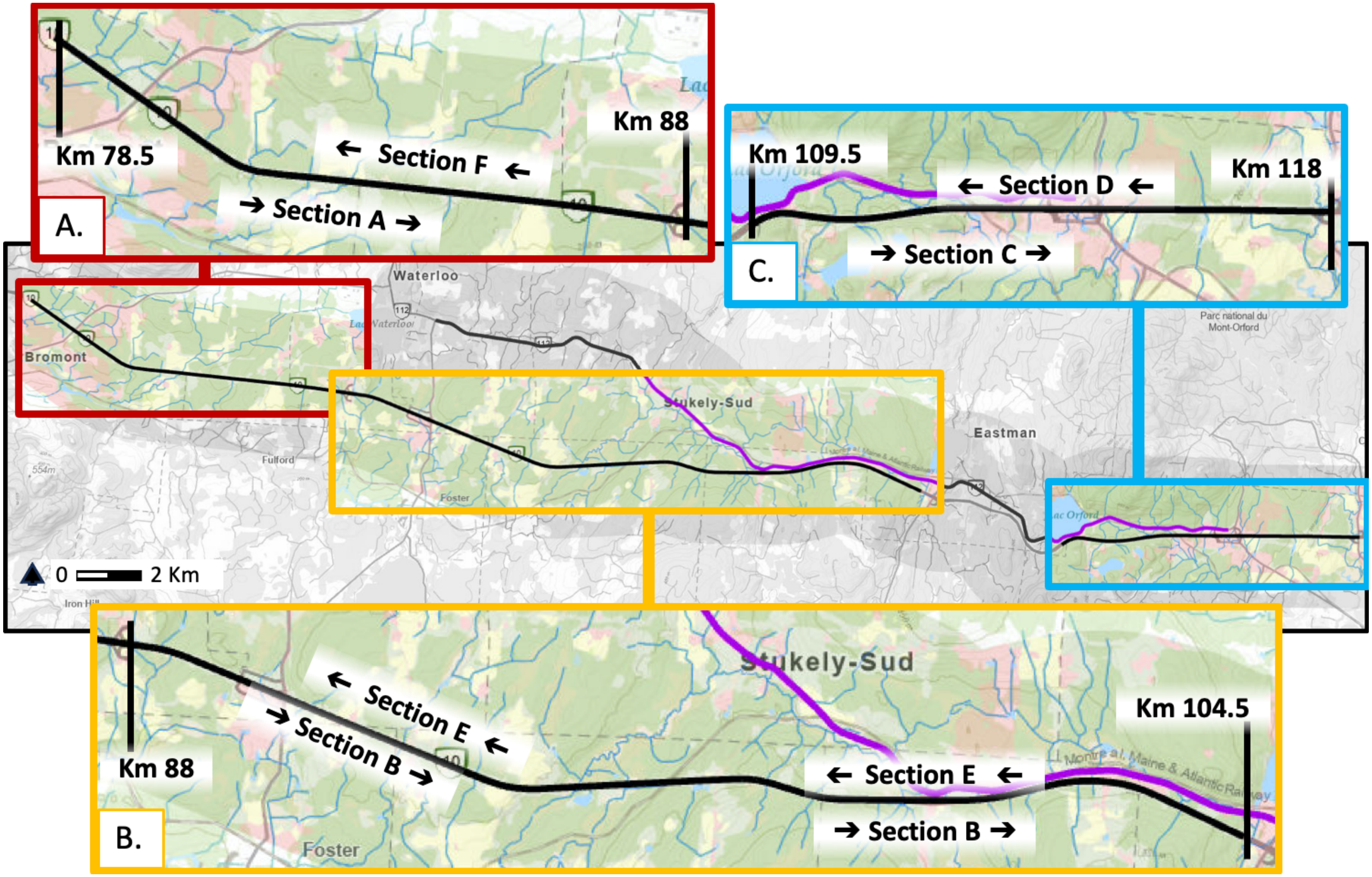


Figure 3. The study area sections of Autoroute 10. A. Section AF (A = easterly direction; F = westerly direction), between kilometre markers 78.5 and 88. B. Section BE (B = easterly direction; E westerly direction), between kilometre markers 88 and 104.5. C. Section CD (C = easterly direction; D = westerly direction), between kilometre markers 109.5 and 118.

3.2 Fieldwork Protocols for Road Mortality Surveys

Road mortality surveys on A10 were conducted over three summer seasons from 2019 to 2021 while R112 was surveyed in 2021 only. Two road mortality survey protocols were developed; the first, designed for automobile surveys, was created by Steffy Velosa in 2019 under the supervision of Dr. Jochen Jaeger at Concordia University, while the second was a 2021 adaptation for bicycle-based surveys (Velosa, 2020). The Driving protocol directed mortality survey procedures, including vehicle speed (30km/h) and the three researcher positions (Driver, Passenger, and Backseat) and their duties. The Driver operates the vehicle while the Passenger scans the road in front of the vehicle and to the right including the ditch. The Backseat researcher scans the road to the left of the vehicle. Recorded attributes per roadkill detected included: GPS coordinates, species-level identification (if not possible, determine animal type: Amphibian, Reptile, Mammal, Bird, or Unknown), the lane in which the animal was found, and the decomposition level. Beginning in summer 2020, an effort was made to photograph as many detected carcasses as possible where safety requirements permitted, as well as the screen of the GPS device with coordinates displayed. The photos were shared with partnered biologists in the event of uncertain species identifications and device photos served as backups in the event of a device glitch and memory loss.

The stretch of A10 studied was subdivided into six segments (A, B, C, D, E, and F). Segment A began at kilometre marker 78.5 and continued east, followed by segments B and C. Segments D, E, and F doubled back in a westbound direction, with the end of Segment F aligned with the beginning of Segment A at kilometre marker 78.5, effectively creating a loop where Segment F ends across the median from the beginning of Segment A (Figure 3.1). The starting point of each survey would alternate equally among the six segments so as to reduce potential bias relating to the specific time any particular area of road was surveyed (Plante et al, 2019). The six segments were initially created following a Before-After-Control-Impact (BACI) study design, i.e., the study area would be surveyed both before and after mitigation. Sections B/E would be the most likely site of mitigation as tentatively indicated by the Ministère des Transports et de la Mobilité durable (MTMD), and sections A/F and C/D would serve as controls.

Initially three of the six segments were surveyed in the morning with the remaining three segments surveyed in the evening. The first 17 surveys in summer 2019 were conducted in this manner, resulting in the detection of 37 carcasses along 49 km of A10. This split was done to allay concerns regarding assumed traffic disturbances relating to the presence of the team during morning and evening rush hours. Experience during these initial surveys determined that traffic disturbances were minimal, and the survey protocol was modified so that all six segments would be surveyed either in the morning or in the evening, depending on the survey schedule (see Appendix A.3 for full fieldwork schedule of all three years). Additionally, 11.5 km of roadway were added to the study permit issued by the MTMD, extending the survey length to 60.5 km. Following these modifications, 49 surveys were completed where 171 animal carcasses were detected (Velosa, 2020). A total of 208 carcasses were detected in summer 2019.

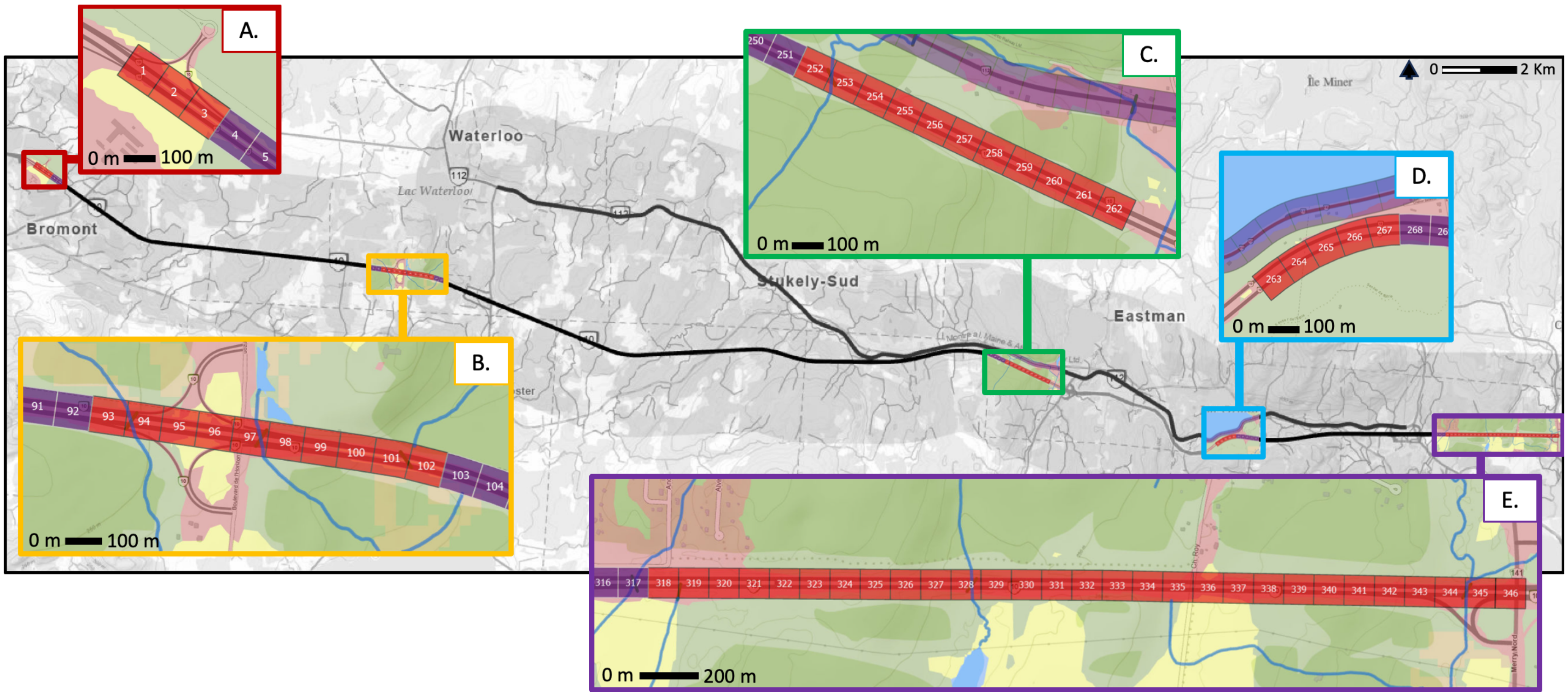


Figure 4. Excluded bins from analysis on Autoroute 10. A. Bins 1-3 were dropped as it was often difficult to perform surveys at acceptable standards (i.e., on both sides of A10) given the off ramp at the end of Section F. B. In 2019, bins 93-102 were not surveyed according to the work permit (permit extensions were added in 2020 and maintained in 2021). C. Surveys ended after bin 251 in 2019 but continued until bin 262 in 2020 and 2021, for similar aforementioned permitting reasons. D. The survey starting point for this section was in bin 268 (kilometre marker 110), but in 2020 and 2021, the survey start point was moved to kilometre marker 109.5 (changes in permitting). E. Throughout all survey years it was possible to survey A10 eastbound only up until kilometre marker 115 (bin 318) as the emergency lane on which we drove our survey vehicle narrows to a width less than that of the vehicle; however, it was possible to survey A10 westbound, beginning immediately upon merging onto A10 from the merge lane (kilometre marker 118). Bins 318-346 were excluded as only A10 westbound was surveyed.

In summer 2020, additional roadway sections of a combined 4.5 km in length were added to the work permit, increasing the total survey length to 65 km. Eighty surveys were completed detecting 1229 carcasses. The 65 km survey length was repeated in summer 2021, completing 37 surveys and detecting 1237 carcasses. Surveys began on Route 112 in collaboration with Environment and Climate Change Canada (ECCC) using our adapted cycling protocol. Each survey day, one A10 driving survey and one R112 cycling survey were completed, one survey in the morning and the other in the evening. By comparison, R112 is narrower than A10 and conducting surveys by bicycle allowed for full access to the roadway surface beyond the shoulder, crossing to the other side to record carcass detections. It was decided that one pass through, cycling either eastward or westward, would constitute one completed cycling survey (as opposed to also cycling back to the starting position). The following survey the next day would reverse direction, beginning where the previous survey ended, i.e., two surveys on R112 completed a loop. With minor adaptations, the same attributes recorded as for A10 were recorded for each carcass on R112. On R112, 37 surveys were completed with 1696 carcasses detected.

In total, 183 surveys were conducted on A10 with 2674 carcasses detected. Including R112 data, a total of 220 surveys from all years were completed, yielding 4370 carcasses (Table 1). All data were recorded in an Excel spreadsheet.

Figure 5. Fieldwork data collection. Photo A: Common garter snake removal on R112. Photo B: Identifying an osprey next to the central median on A10. Photo C: recording a striped skunk on A10. Photo D: Raccoon removal on A10. Photo E: Porcupine removal on A10. Photo credits: Jaynina Deku, Avital Moalem, and Michael Rolheiser.

3.3 Data Preparation

Of the 4370 recorded carcasses, 399 were excluded due to GPS error (56) or the following study design considerations (344) (see Table 1 for a full summary). Every effort was made to reduce the number of GPS error rejections, including cross-referencing questionable GPS device coordinates with the coordinates recorded in the metadata of photos taken of the carcass in question. However, 56 datapoints were unsalvageable due to a GPS device malfunction. For example, during one survey in 2020, the GPS device recorded the same GPS coordinates for each of the 17 carcasses detected during that survey, a malfunction only realized when entering data post-survey.

My analysis explores the relationship between the presence of potential crossing structures and wildlife roadkill locations by animal type therefore, all Unknowns (39) were removed as these animals could not be assigned to one of the four main animal groups. Furthermore, while it is possible for birds to use crossing structures to cross a highway, the differences in avian mobility when compared with terrestrial wildlife is too great to assume an equal cause-and-effect relationship between the predictor variables and roadkill locations; all Birds (269) were excluded from the analysis. A total of 37 carcasses recorded in 2019 before the Fieldwork Protocol [Driving] revision and survey extensions were excluded. To increase the inferential strength of the findings of this study, a consistent survey method and length common to all three years is required–- the 2019 post-extensions study area was selected as the standard. By removing the detections from the first 17 surveys, all portions of the standard study area were surveyed the same number of times.

In total, 3,970 carcasses are included for analysis (2,354 on A10 and 1,616 on R112). See Table 1 for a review of data point rejections.

Table *1*. A summary of wildlife detected, excluded, or accepted for analysis, by highway, survey year, and animal type. Scenario A used data from all three survey years that were recorded within the bounds of the 2019 standard survey area. Data used in Scenarios B and C are based on the 2021 survey area and include data from 2021 only. Scenario D included data from bins with crossing structures and from 2021 only.

Highway & Year	Animal Type	Detected	Pre-protocol (Excluded)	Bird & Unknown (Excluded)	GPS Error (Excluded)	Accepted	Scenario A [290 bins]	Scenario B [308 & 252 bins]	Scenario C [560 bins]	Scenario D [190 bins]
A10 [2019]	Amphibian	22	4	-	6	12	12			
	Bird	59	1	59	-	-	-			
	Mammal	111	31	-	8	72	69			
	Reptile	16	1	-	1	14	14			
	Unknown	-	-	-	-	-	-			
	Total	**208**	**37**	**59**	**15**	**98**	**95**			
A10 [2020]	Amphibian	762	-	-	17	745	722			
	Bird	114	-	114	-	-	-			
	Mammal	296	-	-	18	278	248			
	Reptile	57	-	-	1	56	50			
	Unknown	-	-	-	-	-	-			
	Total	**1229**	**-**	**114**	**36**	**1079**	**1020**			
A10 [2021]	Amphibian	937	-	-	1	936	874	925	925	376
	Bird	39	-	39	-	-	-	-	-	-
	Mammal	153	-	-	1	152	136	142	142	34
	Reptile	89	-	-	-	89	80	88	88	25
	Unknown	19	-	19	-	-	-	-	-	-
	Total	**1237**	**-**	**58**	**2**	**1177**	**1090**	**1155**	**1155**	**435**
R112 [2021]	Amphibian	1395	-	-	2	1393		1393	1393	605
	Bird	57	-	57	-	-		-	-	-
	Mammal	85	-	-	1	84		84	84	38
	Reptile	139	-	-	-	139		139	139	49
	Unknown	20	-	20	-	-		-	-	-
	Total	**1696**	**-**	**77**	**3**	**1616**		**1616**	**1616**	**692**
A10 & R112	Grand Total	**4370**	**37**	**308**	**56**	**3970**	**2205**	**2771**	**2771**	**1127**

3.4 GIS Bins

Infrastructure shapefiles (the Québec road network (QRN), kilometre markers, guardrails, bridge and crossing structures) and landscape shapefiles (watercourses, proposed wildlife corridors, and land cover use) were obtained from governmental, academic, or NGO sources. To reduce rendering time, the specific study area within the QRN shapefile was isolated and the rest of the polylines removed. The Buffers tool was used to create a 2 km area centred on the surveyed areas of A10 and R112; this buffer was used multiple times with the Clip tool to trim all of the infrastructure and environment shapefiles saving only the region within the study area.

In ArcMAP, A10 and R112 shapefiles were divided into 100 m segments using the Split tool, resulting in 598 segments. Using the Buffer tool, square-ended buffers were created around each segment forming bins; bins were numbered 1 to 346 on A10 from west to east, and 347 to 598 on R112 from west to east. Within these bins, the sum of roadkill was calculated by animal type. Garrah et al. (2015) tested 100 m, 200 m, 500 m, and 1000 m segments, suggesting that 200 m segments are the most practical for road management considerations (i.e., installing effective fencing), while Langen et al. (2009) suggest 100 m divisions when considering amphibians, reptiles, and potentially other wildlife types with lower mobility ranges. Bins of 100 m in length resulted in 346 bins on A10 and 252 bins on R112 – a fair balance between the types of wildlife considered in the analysis, an adequate sample size, and reducing the number of bins with zero roadkill detections. Particular attention was paid to locations along A10 where conditions allowed for only one direction of the divided highway to be surveyed. Excluding these one-sided bins removes a potential bias introduced by equating bins with both traffic directions surveyed and bins with only one traffic direction surveyed (Figures 6, 7, and 8). 56 bins of single-side surveys with 150 carcasses were removed to align with the 2019 standard survey area, while 38 bins containing 55 carcasses were removed from the analysis according to 2020/2021 survey-area specifications.

All 3,971 accepted roadkill datapoints were plotted using the GPS coordinates recorded for each carcass detected. Each datapoint was examined to ensure that its mapped location agreed with several location-related variables recorded during fieldwork.

Databases for four scenarios were created: (A) A10 data from all three years detected in the 2019 standard survey area (2,205 carcasses / 290 bins), (B) compared A10 and R112 by using carcasses from 2021 only (A10: 1,155 carcasses / 308 bins; and R112: 1,616 carcasses / 252 bins), (C) combined A10 and R112 2021 data (2771 carcasses / 560 bins), and (D) considered only bins that include crossing structures to test for influence of crossing structure dimensions, i.e., height, width, length, and opening area (height multiplied by width) (1127 carcasses / 190 bins). Scenario A considered roadkill variability over the longest time period (three summers) and Scenario B allowed for a direct comparison of results between A10 and R112 as both highways were surveyed the same number of times and on the same dates (to our knowledge the first study of its kind). Refer to Appendix A.4 for a summary table of roadkill used in analysis, by species, year, and highway, and Appendix A.5 for a heatmap depicting roadkill count per bin, by animal type.

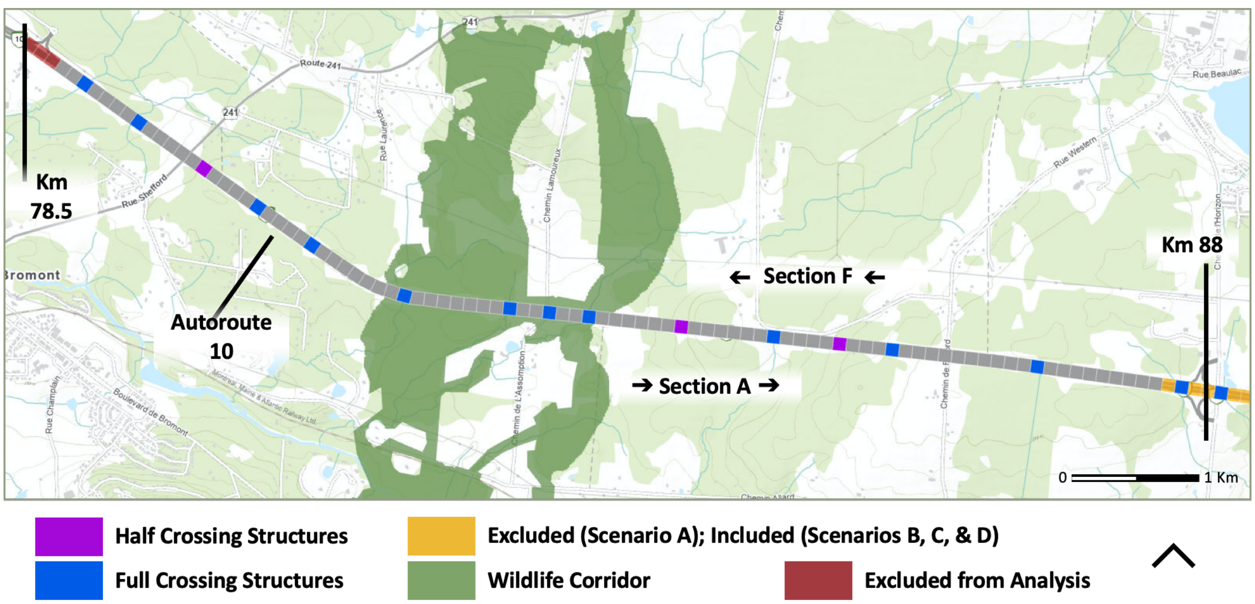


Figure 6. Section AF depicting bins with crossing structures, by type, bins that were excluded from Scenario A but retained in Scenarios B, C, and D, and bins that were excluded from all analysis.

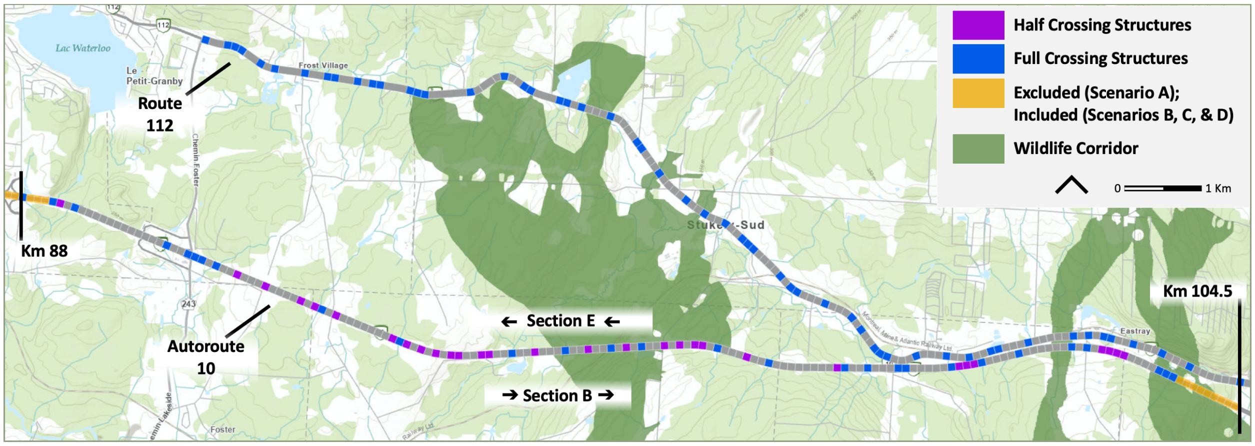


Figure 7. Section BE on Autoroute 10 and the western portion of Route 112. Depicted are bins with crossing structures, by type, bins that were excluded from Scenario A but retained in Scenarios B, C, and D, and bins that were excluded from all analysis.

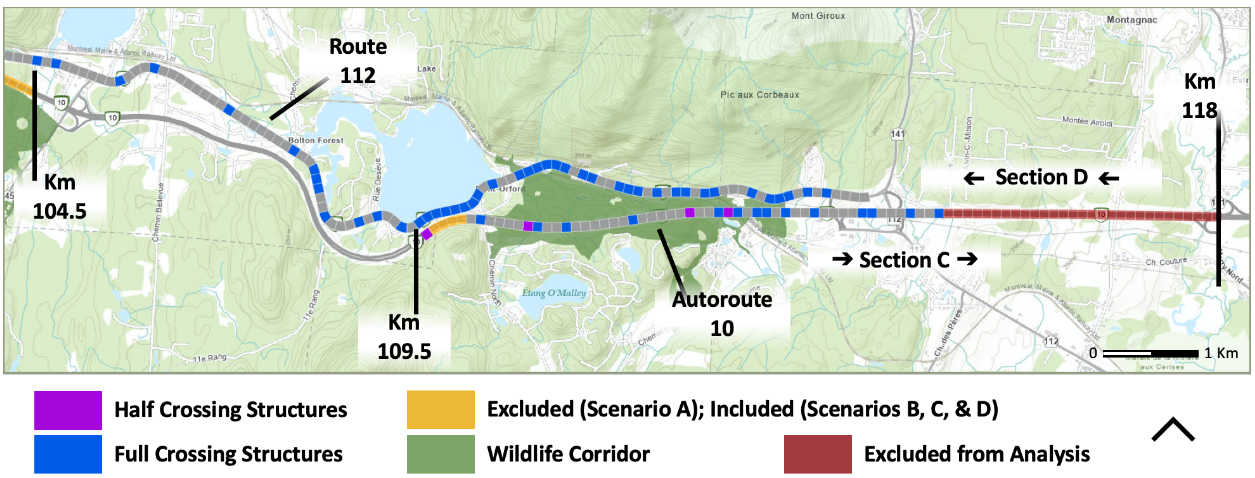


Figure 8. Section CD on Autoroute 10 and the eastern portion of Route 112. Depicted are bins with crossing structures, by type, bins that were excluded from Scenario A but retained in Scenarios B, C, and D, and bins that were excluded from all analysis.

Scenario C considered the highest number of bins possible by combining both highways, and Scenario D focused on the possible influence of crossing structure dimensions by isolating only those bins with crossing structures (Figures 6, 7, and 8). Moreover, the unique parameters of Scenario D afforded a further step of analysis, 'Dimension+'. Because Scenario D data involved only bins with crossing structures, a coded value of '0' (not present) implied that a '1' was present in another structural predictor group, i.e., a '0' coded for concrete implied a '1' coded in one of the other two Material predictors, either metal or plastic. Structural predictors were fit to test models in combinations beyond structural predictor groups, i.e., predictors from Material, Shape, and Function were combined in the same test model and tested with the Dimension values. Figure 5 provides a visual comparison of the number of bins and the proportion of carcasses, by Scenario.

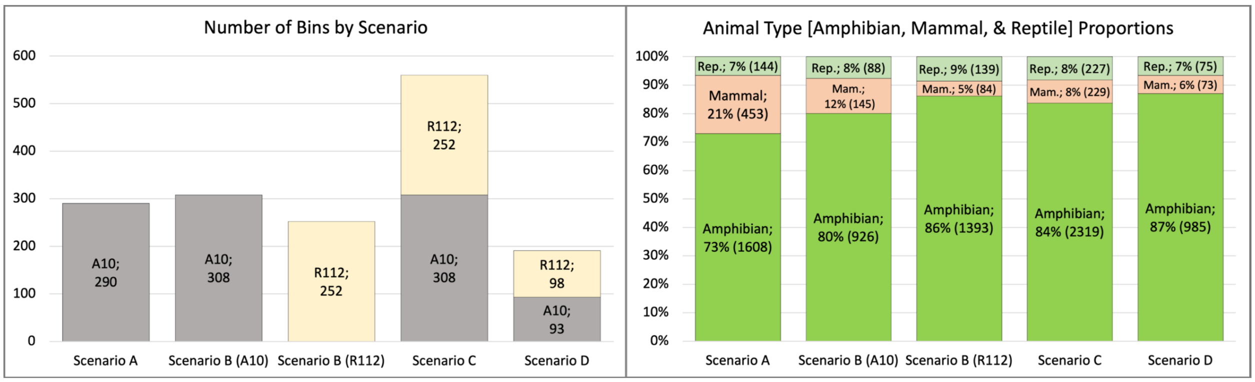


Figure 9. The number of bins and the proportion of carcasses included for analysis, by scenario.

3.5 Predictor Variables

3.5.1 Environmental Predictor Variables

To investigate the influence of crossing structures on roadkill, I first needed to identify other predictor variables which may also influence roadkill distribution such as landcover (environmental predictor variables). While the interest of my study is not focused on landcover variables per se, my aim was to first create base models of best fit using only environmental predictor variables (Step 1) and then add crossing structure variables (Step 2) to isolate their effects otherwise obscured if combined in a single step. To assess the influence of land cover on roadkill, two landcover raster files were sourced and combined (LC_10M and LC_30M, see Figure 10). While LC_10M had the advantage of a finer resolution (10 m), LC_30M had primary and secondary landcover class descriptors. Specifically, LC_30M had marshland secondary descriptors for land classified as forest in LC_10M; marshland presence is assumed to be crucial for amphibians and reptiles. Additionally, I wanted to limit the number of landcover classes to reduce the number of environmental predictor variables in my models. A combination of reassigning overlapping landcover classes from LC_10M to a LC_30M secondary descriptor and eliminating some landcover classes altogether, LC_FINAL was created and used in landcover base models (Figure 10).

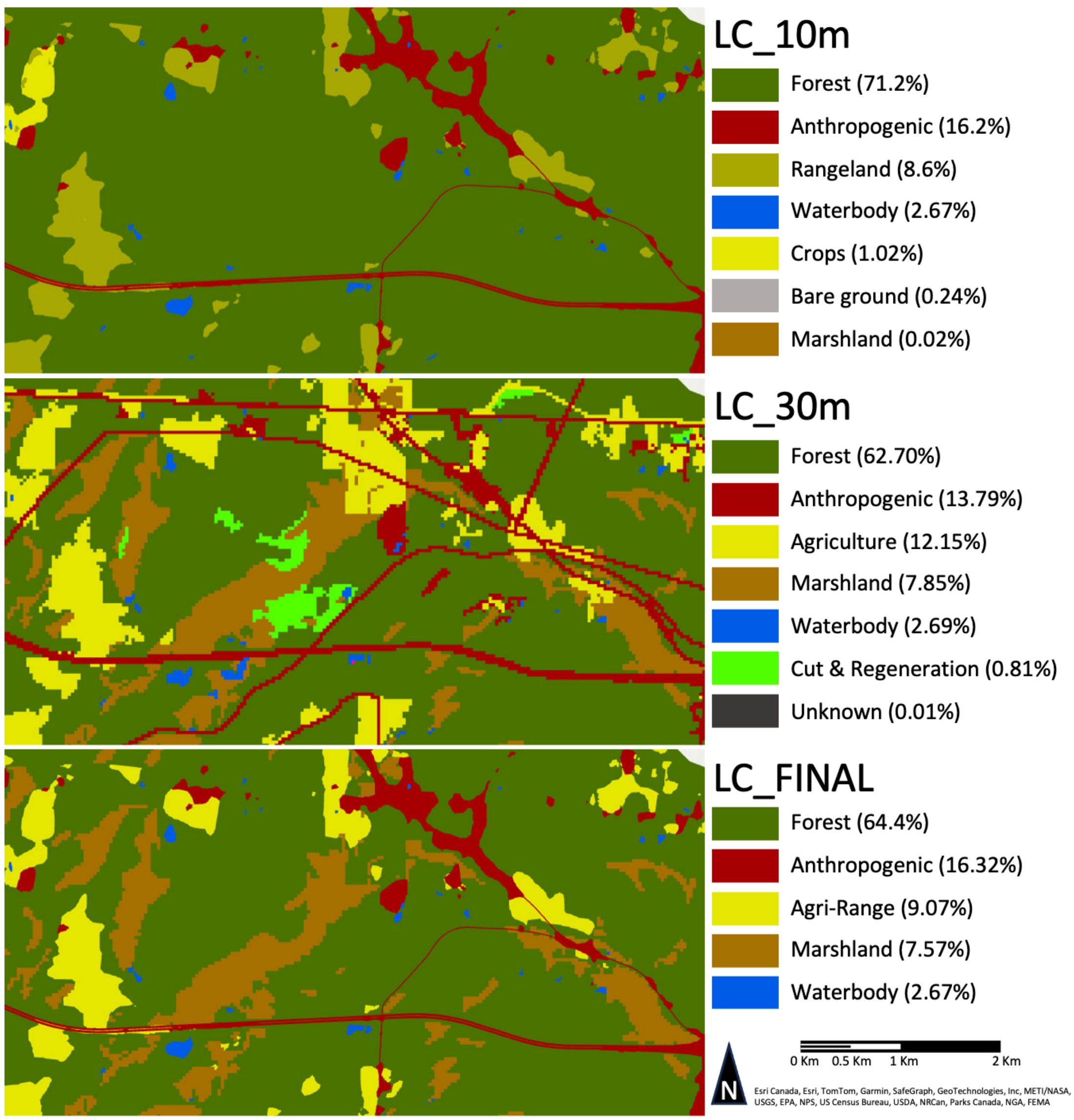


Figure 10. Two landcover files, LC_10m and LC_30m, were combined to produce LC_FINAL, the landcover file that was used in the analysis. The listed landcover classes for each file are ordered by overall percent coverage per class.

The proportion of each land cover class (forest, anthro, marsh, agri, and water) was measured within circular buffers of five sizes (100 m, 200 m, 500 m, 1 km, and 2 km radius), centred on the centroid of each bin (Figure 11). The linear density of watercourses ('wc') was calculated within each buffer in meters per hectare. The range of buffer sizes reflects the differences in animal mobility capacity among the animal types considered, e.g., 100 m and 200 m for amphibians, 200 m and 500 m for reptiles, and the full range of buffers for mammals.

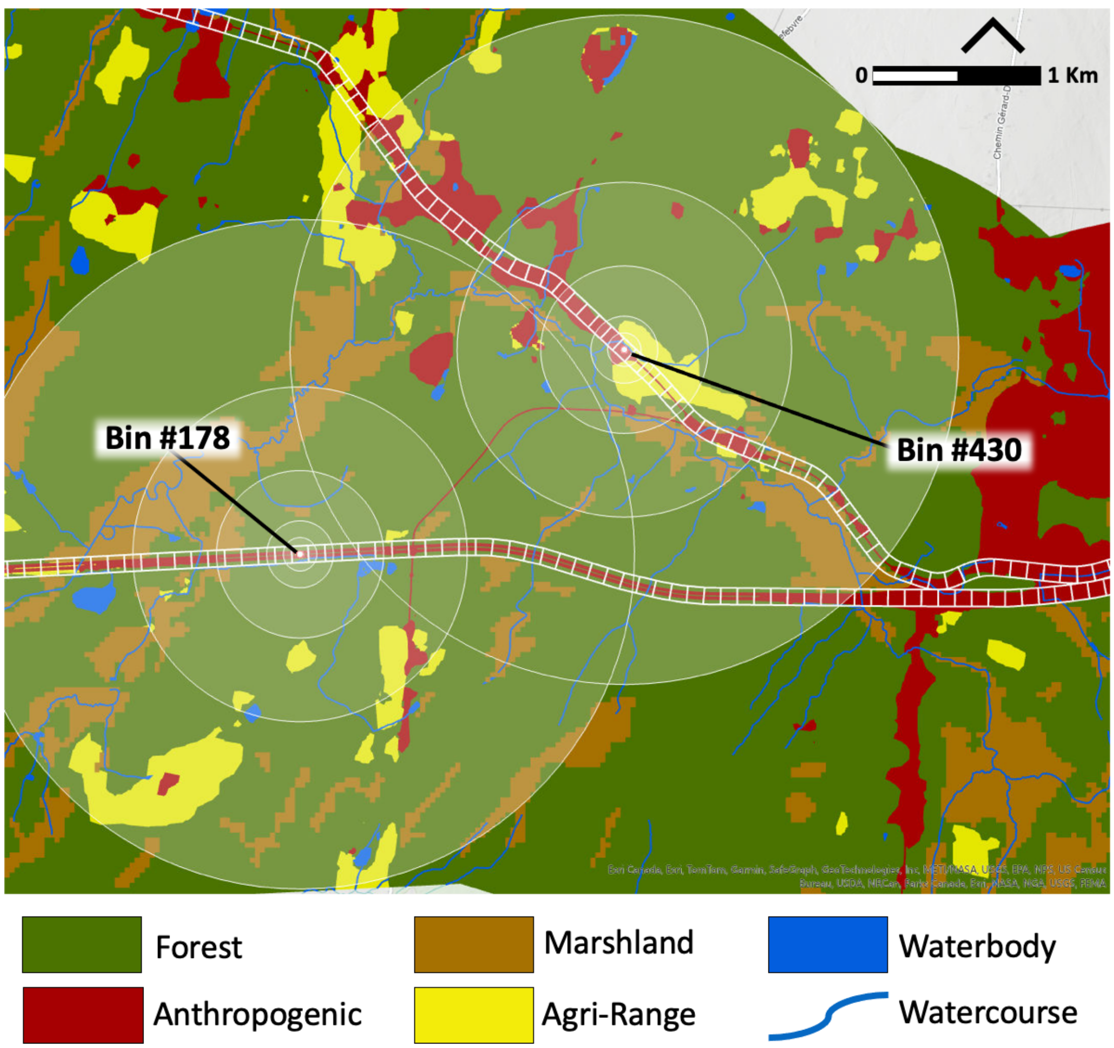


Figure 11. Bins were created by splitting the combined lengths of Autoroute 10 and Route 112 into 100 meter segments. Centroids were created for each bin and from this point five buffers of different radii were created. The proportion of landcover by class was calculated for each buffer. 'Distance-to' predictor variables were also calculated from the centroid of each bin. See Figure 10 for an example of structural predictor assignments for bin 178 (A10) and bin 430 (R112).

The naming of these variables uses the land cover class and the radius size, i.e., forest_500 and agri_2k are the proportion of forest cover within a buffer of 500 m in radius and the proportion of agriculture-range land within a buffer of 2 km in radius, respectively. Additionally, the distance to each land cover class (forest, marshland, waterbody, and agriculture-range) and the distance to the nearest watercourse were calculated from the centroid of each bin (note: roadways are classed as anthropogenic and therefore the value would always be zero meters). The naming of 'distance to' variables used the land cover class with '_m' for meters, i.e., forest_m and wc_m are the distances in meters to the nearest forest cover and watercourse, respectively (see Table 2 for a summary of landcover class predictor variables). Following examples in Zuur et al. (2009), the proportion and distance-to data were logarithmically transformed and added to the dataset as alternate predictor variables to be tested (outlined below in section 3.5.3.1). Lastly, proposed wildlife corridors were considered ('corridor'). Defined by Salvant (2017) and revised by Daguet & Lelièvre (2019) for medium and large mammal usage, these corridors represent prime wildlife habitat where an increased number of wildlife may be present. 'Corridor' was recorded binarily, i.e., if the 100 m bin did or did not intersect 'corridor,' it was recorded '1' (present) and '0' (absent), respectively. Although 'corridor' is functionally an environmental predictor since its boundaries reflect habitat favourability, it was included in models only at Step 2 (see Section 3.5.3.2), in combination with structural predictors.

Table 2. A Summary of landcover predictor variables. Only one predictor variable per landcover class and one predictor variable per distance-to was included in the global models.

Land Cover Class	Variable Short name	Buffer Size [m]	Proportion	Logarithm [log.]	Environmental or Structural
Agri-Range (%)	agri_	100	agri_100	log.agri_100	Environmental
		200	agri_200	log.agri_200	
		500	agri_500	log.agri_500	
		1000	agri_1k	log.agri_1k	
		2000	agri_2k	log.agri_2k	
Anthropogenic (%)	anthro_	100	anthro_100	log.anthro_100	Environmental
		200	anthro_200	log.anthro_200	
		500	anthro_500	log.anthro_500	
		1000	anthro_1k	log.anthro_1k	
		2000	anthro_2k	log.anthro_2k	
Forest (%)	forest_	100	forest_100	log.forest_100	Environmental
		200	forest_200	log.forest_200	
		500	forest_500	log.forest_500	
		1000	forest_1k	log.forest_1k	
		2000	forest_2k	log.forest_2k	
Marshland (%)	marsh_	100	marsh_100	log.marsh_100	Environmental
		200	marsh_200	log.marsh_200	
		500	marsh_500	log.marsh_500	
		1000	marsh_1k	log.marsh_1k	
		2000	marsh_2k	log.marsh_2k	
Waterbody (%)	water_	100	water_100	log.water_100	Environmental
		200	water_200	log.water_200	
		500	water_500	log.water_500	
		1000	water_1k	log.water_1k	
		2000	water_2k	log.water_2k	
Watercourse (m/ha)	wc_	100	wc_100	log.wc_100	Environmental
		200	wc_200	log.wc_200	
		500	wc_500	log.wc_500	
		1000	wc_1k	log.wc_1k	
		2000	wc_2k	log.wc_2k	

Land Cover Class	Variable Short name	Units	Linear Distance	Logarithm [log.]	Environmental or Structural
Agri-Range (m)	agri_m	Meters	agri_m	log.agri_m	Environmental
Forest (m)	forest_m	Meters	forest_m	log.forest_m	Environmental
Marshland (m)	marsh_m	Meters	marsh_m	log.marsh_m	Environmental
Waterbody (m)	water_m	Meters	water_m	log.water_m	Environmental
Watercourse (m)	wc_m	Meters	wc_m	log.wc_m	Environmental

3.5.2 Structural Predictor Variables

'Guardrail' was considered as a predictor variable for its potential ability to restrict wildlife movement onto the road. Additionally, guardrails may be a proxy for relatively sharp roadway turns, changes in surface elevation, and gravel or sandy embankments used to anchor guardrail supports, and may attract reptiles for nesting or temperature regulation (basking) (Shine et al., 2004). Crossing structures were divided into two groups, 'crossing structure (full)' and 'crossing structure (half)'. Applicable only to crossing structures on A10, a total of 38 out of 92 bins contained 'crossing structure (half)' crossing structures, crossing under only one direction of traffic (i.e., two of A10's four lanes of traffic, or *half* of the highway; there were 54 bins with 'crossing structure (full)' crossing structures on A10) (Figure 12).

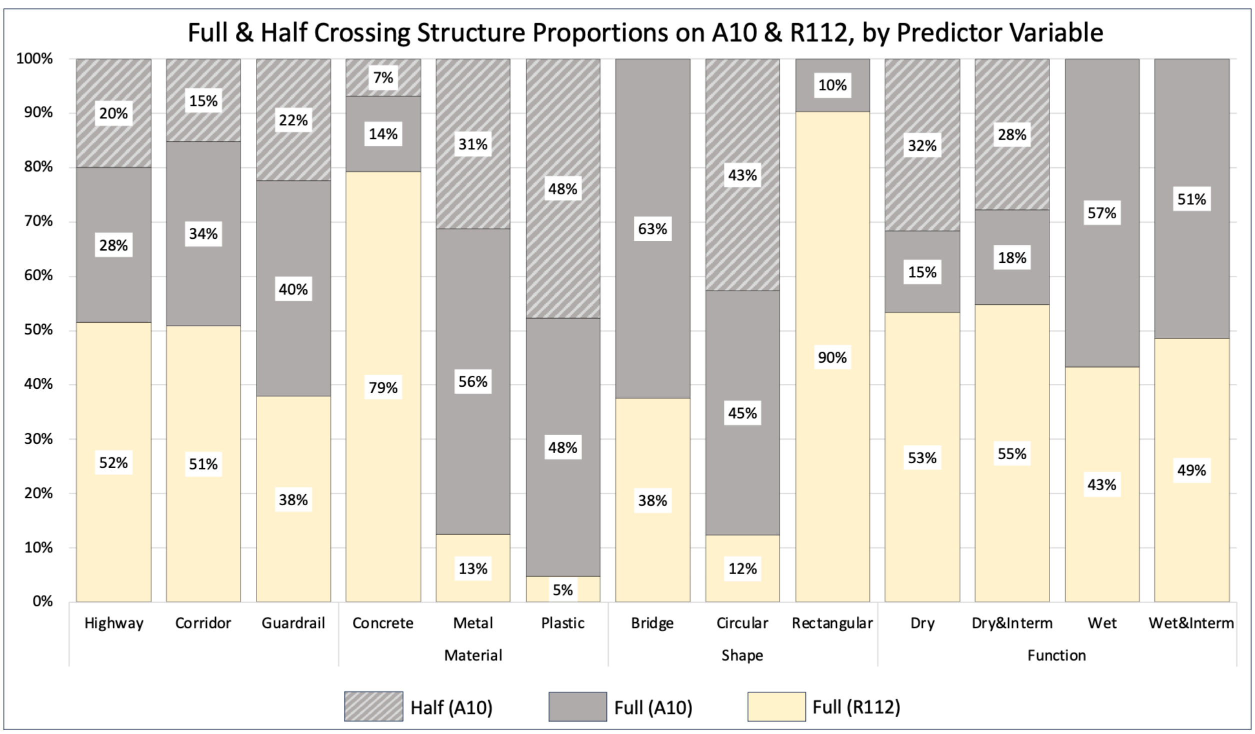


Figure 12. Existing crossing structure types (full, half) by highway and by the proportion of material, shape, and function predictors. Half existing crossing structures are recorded on A10 only, and all of these structures were dry and circular.

It is important to distinguish between ‘crossing structure (full)’ and ‘crossing structure (half)’, because of the possibility that wildlife are using ‘crossing structure (half)’ to cross safely under one set of traffic lanes but are killed while attempting to cross the remaining set of lanes at grade. R112 is not a divided highway; all of R112’s crossing structures are ‘crossing structure (full)’. These four predictors (‘guardrail’, ‘crossing structure (full)’, ‘crossing structure (half)’, and ‘corridor’) were coded as present = 1 if they fall within the bin (Figure 13). Other crossing structure attributes were expanded within four predictor variable groups: Material, Shape, Function, and Dimension (Table 3).

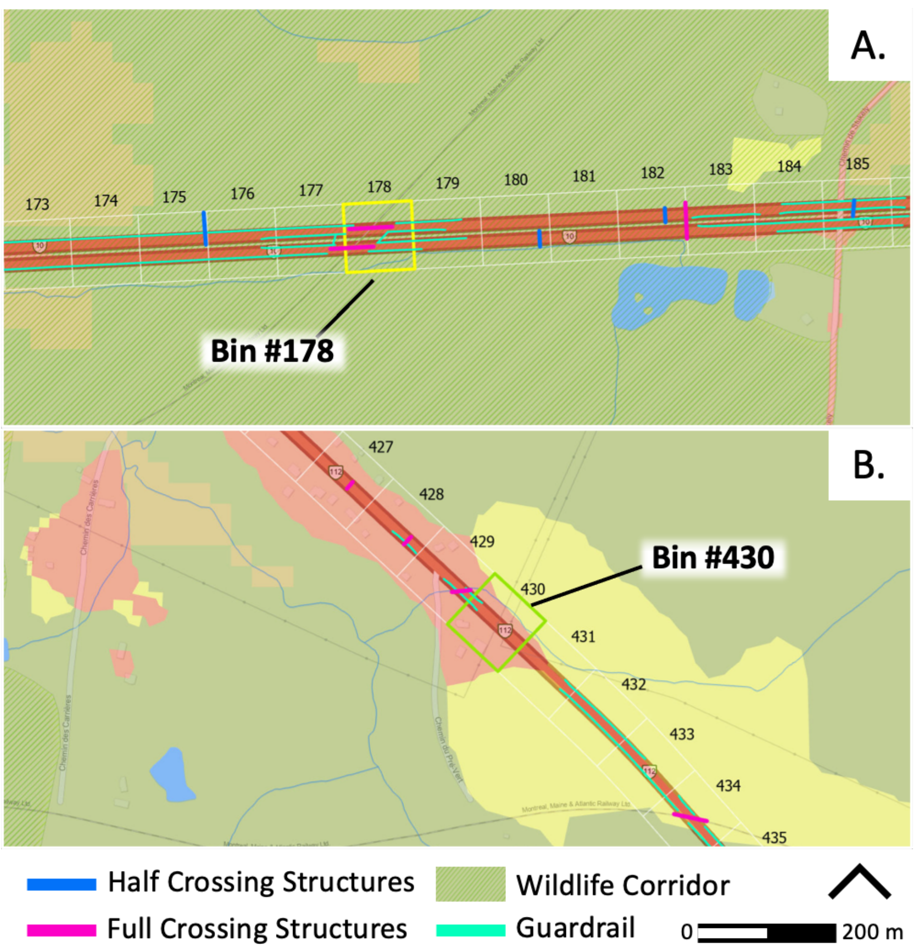


Figure 13. The present/absent assignment of the predictors ‘corridor’, ‘guardrail’, ‘crossing structure (full)’, and ‘crossing structure (half)’. A. Bin 178 (A10) has a ‘crossing structure (full)’ (‘concrete’, 'bridge’, ‘dry’), presence of ‘guardrail’, and ‘corridor’. B. Bin 430 (R112) has ‘guardrail’ presence but does not have a crossing structure, nor does it intersect with ‘corridor’.

The Material group considered the dominant material of the crossing structures, ‘concrete’, ‘metal’, and ‘plastic’. The Shape group included ‘bridge’, ‘circular’, or ‘rectangular’ crossing structure shapes. ‘Bridge’ included underpasses (roads and train tracks running below the highways) and natural bottom crossing structures. Refer to Figure 14 for Material, Shape, and Function examples.

Figure 14. Photo examples of crossing structure Material, Shape, and Function predictors. Photos A and B are alternate views of the same existing crossing structure (concrete, circular, and wet (permanent watercourse)). Photo C of is a rail crossing structure (concrete, bridge, and dry). Photo D is of a metal, circular, and wet existing structure. Photo credit: Michael Rolheiser.

The Function group included ‘dry’ for non-aquatic related uses (e.g., an underpass with a road; stormwater management infrastructure), and ‘wet’ for crossing structures that enable the flow of permanent watercourses. The watercourse shapefile further separated watercourses into permanent and intermittent. Intermittent watercourses may be seasonal (runoff) or active during or immediately following precipitation events, but may be dry absent of these events, i.e., the state of an intermittent watercourse on a specific date is unknown. Therefore, two additional predictors were created to include all watercourses available within the study area, ‘dry & interm’ (combined ‘dry’ and intermittent watercourses that may be absent), and ‘wet & interm’ (combined ‘wet’ and intermittent watercourses that may be present). In the dataframe, each predictor from the Material, Shape, and Function groups received an individual column and were binarily coded as ‘1’ (present) or ‘0’ (absent). See Figure 15 for the proportion of structural predictor variables included for analysis, by scenario.

The dimension group predictors included ‘height’, ‘width’, and ‘length’, all recorded in meters, and ‘opening’ recorded in meters squared. ‘Height’ was measured from the ground upwards; ‘width’ was the largest measurement of width parallel to the roadway, and ‘length’ was measured perpendicular to the roadway. ‘Opening’ was the product of ‘height’ and ‘width’ when the crossing structure is ‘rectangular’ and $\pi(\text{‘width’}/2)^2$ when the crossing structure is ‘circular’. While the precise shape of ‘bridge’ crossing structures is unknown, i.e., inverse-triangular, arched, or semi-circular (personal observation), ‘opening’ was calculated as the product of ‘height’ and ‘width’. While this may overestimate the true opening of structures with irregularly shaped openings, ‘bridge’ crossing structures had large heights and especially large widths. Eight of the nine ‘bridge’ crossing structures have the largest ‘width’ and ‘opening’ values of any crossing structure; ‘bridge’ crossing structures were consistently the largest and most open of all crossing structures analyzed, and their dimensions defined the upper limits for all crossing structure dimensions.

Lastly, 'highway' was included as a random variable, coded as '1' (A10) and '0' (R112); coded '0,' R112 was used as the default category. 'Highway' was fit to Scenario C and D models only, as only these two scenarios combined data from both highways.

Figure 15. The proportions of structural predictor variables included for analysis, by scenario.

Table 3. A Summary of structural predictor variables.

Variable or Variable Group Name	Variable Short Name	Definition / Explanation	Units	Environmental or Structural
Wildlife Corridor	corridor_	Intersection of a bin with a proposed wildlife corridor	1 = Present; 0 = Absent	Environmental
Guardrail	guardrail_	A bin with a minimum of one guardrail present	1 = Present; 0 = Absent	Structural
Crossing Structure (Full)	xfull_	A bin with at least one full (crossing all lanes of the highway) structure present	1 = Present; 0 = Absent	Structural
Crossing Structure (Half)	xhalf_	A bin with at least one half (not crossing all lanes of the highway) structure present	1 = Present; 0 = Absent	Structural
Highway	hwy_	Autoroute 10 or Route 112 (Scenarios C & D only)	1 = A10; 0 = R112	Structural
Materials of Crossing Structures	con_	A bin with a predominantly concrete crossing structure	1 = Present; 0 = Absent	Structural
	met_	A bin with a predominantly metal crossing structure	1 = Present; 0 = Absent	Structural
	plas_	A bin with a predominantly plastic crossing structure	1 = Present; 0 = Absent	Structural
Shapes of Crossing Structures	bri_	A bin with an underpass or natural bottom crossing structure	1 = Present; 0 = Absent	Structural
	cir_	A bin with a circular crossing structure	1 = Present; 0 = Absent	Structural
	rec_	A bin with a rectangular crossing structure	1 = Present; 0 = Absent	Structural
Functions of Crossing Structures	dry_	A bin with a crossing structure without a watercourse	1 = Present; 0 = Absent	Structural
	wet_	A bin with a crossing structure with a permanent watercourse	1 = Present; 0 = Absent	Structural
	dry_interm_	A bin with a crossing structure without a permanent watercourse	1 = Present; 0 = Absent	Structural
	wet_interm_	A bin with a crossing structure with a permanent or temporal watercourse	1 = Present; 0 = Absent	Structural
Dimensions of Crossing Structures	height_m_	The height of the crossing structure	Meters	Structural
	length_m_	The length of the crossing structure [Perpendicular to the highway]	Meters	Structural
	width_m_	The width of the crossing structure [Parallel to the highway]	Meters	Structural
	opening_m2_	The area of the crossing structure opening [Height X Width]	Meters squared	Structural

3.5.3 Iterative Predictor Variable Selection Process

3.5.3.1 Step 1: Landscape Predictor Variables

The following is the base model format used for all models in Step 1 and each landcover predictor variables' ordered position within the model (Figure 16).

Model	<- glm(	y	~ Forest (Proportion)	+ Anthropogenic (Proportion)	+ Marshland (Proportion)	+ Agriculture (Proportion)	+ Waterbody (Proportion)	+ Watercourse (Linear density)	
			+ Forest (Distance-to)	+ Marshland (Distance-to)	+ Agriculture (Distance-to)	+ Waterbody (Distance-to)	+ Watercourse (Distance-to)	, family = family, data = data)	

Figure 16. The Step 1 model format used in all models.

Each Scenario included three animal-type response variables (amphibian, mammal, and reptile). Each of the five proportional landcover class predictors and the watercourse linear density predictor had 10 versions reflecting the radial measurement, in meters, of the buffer, i.e., forest_100, forest_200, forest_500, forest_1k, forest_2k, and the logarithm of each of them. Each of the five distance-to predictors contains two versions, i.e., forest_m and the logarithm of forest_m. With billions of variable combinations possible for each final model, an iterative template was created and used as a guide for Step 1 (Appendix B, Table 20). The distribution family of the model was dependant on the mean/variance ratio (section 3.6) but was subject to revision after Step 2 was completed.

Table 4. A section of the Step 1 iteration template depicting the Forest landcover class models.

Mod.animal_step1	<- glm(animal	~ Forest (Proportion)	+ Anthropogenic (Proportion)	+ Marsh (Proportion)	+ Agriculture (Proportion)	+ Waterbody (Proportion)	+ Watercourse (Linear Density)	+ Forest (Distance-to)	+ Marshland (Distance-to)	+ Agriculture (Distance-to)	+ Waterbody (Distance-to)	+ Watercourse (Distance-to)	, family = poisson(), data = data)
#### FOREST													
mod.animal_forest100	<- glm(animal	~ forest_100	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_forest200	<- glm(animal	~ forest_200	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_forest500	<- glm(animal	~ forest_500	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_forest1k	<- glm(animal	~ forest_1k	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_forest2k	<- glm(animal	~ forest_2k	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest100	<- glm(animal	~ log.forest_100	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest200	<- glm(animal	~ log.forest_200	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest500	<- glm(animal	~ log.forest_500	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest1k	<- glm(animal	~ log.forest_1k	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest2k	<- glm(animal	~ log.forest_2k	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_forest100, mod.animal_forest200, mod.animal_forest500, mod.animal_forest1k, mod.animal_forest2k)													
AIC(mod.animal_logforest100, mod.animal_logforest200, mod.animal_logforest500, mod.animal_logforest1k, mod.animal_logforest2k)													

Forest landcover was evaluated by fitting 10 models, each differing only in the version of the forest landcover variable used in the ‘forest’ proportion position depicted in Table 4. Specifically, these versions included proportion values for each of the five buffer sizes and logarithmically transformed proportion values for the same five buffer sizes. All other aspects of the models were held constant (for ease of consistency, proportional variables were set to 100 meters and distance-to variables were set to linear distance for the initial trial). The Akaike information criterion (AIC) value was calculated for each model using the ‘AIC’ function (R Core Team, 2021), to compare models based on their goodness of fit. A trade-off between model complexity and model fit, assuming all else is equal, simpler models yield lower AIC values compared to more complex models. A comparatively lower AIC indicates the better-fitting model (Zuur, 2009). Burnham and Anderson (1998) suggest that two or more models are considered competitive, i.e., similarly supported by the data, when the difference in AIC < 2 units, a conventional standard I adopted for my analyses. Conversely, a difference AIC > 4 units indicates substantially less support for the model with the higher AIC, suggesting it is unlikely to fit the data as well as the lower-AIC model. Since the only difference among the 10 models was the version of the ‘forest’ proportion variable, the version associated with the model that had the lowest AIC value was selected for the ‘forest’ proportion variable in all subsequent models within this scenario and animal type. One ‘iteration’ consisted of 70 models (10 for each landcover class and watercourse density and two for each distance-to predictor variable). The process was repeated until a full iteration produced no new lower AIC value. These lowest-AIC landscape models (Step 1 models) were used as the base model in Step 2 where crossing structure variables were added and then evaluated. In order to suggest any influence of crossing structures on roadkill numbers, AIC values calculated in Step 2 must be lower than the AIC value of the Step 1 model. Without a comparative reduction in AIC values, it can be determined that no added crossing structure predictor yields a better model fit.

3.5.3.2 Step 2: Structural Predictor Variables

A template was created to fit all possible combinations of structural predictor variables: ‘corridor’, ‘guardrail’, ‘crossing structure (full)’, ‘crossing structure (half)’, ‘highway’, and the predictors of each Material, Shape, Function, and Dimension group with Step 1 models. A predictor was retained only if its inclusion yielded a model with a lower AIC than the Step 1 model. If no structural predictors reduced the AIC, the interpretation is that no structural predictor provides an additional benefit to data-model fit; in these instances, the original Step 1 land-cover model was kept as the global model for that animal type and scenario. The sole limitation on predictor combinations involved ‘crossing structure (full)’ and ‘crossing structure (half)’, as the coding of these two predictors directly correlates to values for Material, Shape, Function, and Dimension predictors. The presence of these crossing structure predictors obliged the presence of a Material predictor, a Shape predictor, a Function predictor, and Dimension values. Conversely, the absence of ‘crossing structure (full)’ and ‘crossing structure (half)’ must result in all Material, Shape, and Function predictors to be coded as ‘0’ (Dimension values were only included in Scenario D analysis, i.e., when used, Dimension predictors always contained arithmetic non-zero measurements). However, for Scenarios A, B, and C, the inverse is not true; for example, a coding of ‘0’ for ‘concrete’ might signify that there is no crossing structure present (requiring zeros coded for all Material, Shape, and Function groups), or a coding of ‘0’ for ‘concrete’ might signify that a present crossing structure is constructed from an alternate material (requiring a coded ‘1’ among at least one predictor per predictor group). ‘Crossing structure (full)’ and ‘crossing structure (half)’ were included to assess potential influence of crossing structures regardless of material, shape, function, or dimensions, but because of the double meaning of a coded ‘0’ for these groups, models that include ‘crossing structure (full)’ and ‘crossing structure (half)’ do not include Material, Shape, Functional or Dimension predictors.

In the analysis for Scenarios A, B, and C, the template was organized into four sections: CGX (‘corridor_’, ‘guardrail_’, ‘xfull_’, and ‘xhalf_’), Material, Shape, and Function (Appendix B, Table 21). For each animal type and each scenario, seven CGX models were fit, reflecting all possible combinations of ‘corridor’, ‘guardrail’, and ‘crossing structure (full)’ and ‘crossing structure (half)’ (‘crossing structure (full)’ and ‘crossing structure (half)’ were always fit as a pair). Twenty-eight models each for Material, Shape, and Function predictors were fit, reflecting all possible combinations of ‘corridor’, ‘guardrail’, ‘concrete’, ‘metal’, and ‘plastic’ for Material models, ‘corridor’, ‘guardrail’, ‘bridge, ‘circular, and ‘rectangular for Shape models, and ‘corridor’, ‘guardrail’, ‘dry, ‘wet, ‘dry & interm’, and ‘wet & interm’ for Function models (‘dry & interm’ and ‘wet & interm’ were not fit to the same model as bins with intermittent watercourses would be in the same model twice). Ninety-one models were fit for each animal type for Scenarios A, B, and C, with a possible four models selected as global models; three models with the lowest AIC values within each Material, Shape, and Function group, and the model with the lowest AIC value within the CGX group, but only if that model contained ‘crossing structure (full)’ and ‘crossing structure (half)’. If ‘crossing structure (full)’ and ‘crossing structure (half)’ were absent from the lowest AIC CGX model, analysis within the CGX group was not pursued further (i.e., recorded as global and final models in Results), as this thesis’ focus is on the potential influence of crossing structures and not that of ‘corridor’ or ‘guardrail’.

The template used for Scenario D analysis added a fifth section, Dimension (Appendix B, Table 22). Additionally, 'xhalf' was excluded as a predictor because an absence of 'xfull' implies a presence of 'xhalf'. Sixty models were fit to reflect all possible combinations of 'corridor', 'guardrail', 'height', 'length', 'width', and 'opening'. 151 models were fit for each animal type for Scenario D, with up to four models selected as global models; the lowest AIC model from each of the Material, Shape, and Function groups, and the lowest AIC CGX model if 'crossing structure (full)' and 'crossing structure (half)' are included. Because Scenario D data involved only bins with crossing structures, the model with the lowest AIC value overall, regardless of CGX, Material, Shape, Function, or Dimension group, was fit and iteratively tested with all remaining structural predictors in combination until a lower AIC value could not be produced. The model with the lowest AIC value overall was recorded as 'Dimension+' in the Results section.

Final models were derived from global (Step 2) models using the 'step' function in R Studio, stats base package (R Core Team, 2021), a stepwise reduction process where each predictor was excluded from global models one at a time until no lower AIC value could be produced. This process of predictor reduction was performed on final models only, following the inclusion of structural predictors to those of environmental predictors.

3.6 Statistical Analysis

All statistical analyses were performed in R version 4.1.2 (R Core Team, 2021). Histograms were produced to visualize the distribution shape of the data. Kruskal–Wallis tests ('kruskal.test' function, stats package) were performed for each scenario to assess whether roadkill counts differed significantly ($p < 0.05$) by crossing structure form and absence, coded: 'FULL', ‘HALF’, or ‘NONE’ for each animal group (R Core Team, 2021). There were only two categories for Scenario B (R112) (‘FULL’ and ‘NONE’) and Scenario D (‘FULL’ and ‘HALF’); therefore, Wilcoxon rank-sum tests were performed using the ‘wilcox.test’ function, stats package, to compare roadkill medians between bins with ‘FULL’ and ‘NONE’ for Scenario B, and between bins with ‘FULL’ and ‘HALF’ for Scenario D (R Core Team, 2021). For these series of tests, H0: no difference in roadkill between ‘FULL’, ‘HALF’, and ‘NONE’; Ha: a difference in roadkill exists, in order from lowest to highest levels of roadkill: ‘FULL’, ‘HALF’, and ‘NONE’. In the event of a significant Kruskal–Wallis test, Dunn’s test for multiple comparisons would be performed using the ‘dunnTest’ function, FSA package, to identify which pairwise group differences were statistically significant (Ogle et al., 2025).

To assess the hypothesis that wildlife may be using ‘HALF' to cross safely under one side of A10 only to be killed while attempting a crossing of the other side of A10 at grade (H_0: no difference in roadkill between ‘SAME’ and ‘OPPOSITE’; H_a: ‘SAME’ had less roadkill than ‘OPPOSITE’), a series of Wilcoxon rank-sum tests were performed using data from bins with ‘HALF’ roadkill only. The first column (‘SAME’) included roadkill values from the side of A10 shared with ‘HALF’, while the second column (‘OPPOSITE’) included roadkill values from the side of A10 without ‘HALF’. These tests were performed for six categories of wildlife, amphibians, medium-sized mammals, small mammals, medium-sized and small mammals combined, reptiles, and snakes. These categories considered wildlife body size, i.e., if the animal could physically fit through ‘HALF’; therefore, no large mammals were included, and separated by animal type to reflect potential differences in wildlife behaviour.

Mean-variance ratios were calculated and used to determine the distribution family for each Generalized Linear Model (GLM). An assumption of the Poisson distribution is that the variance equals the mean. If the variance exceeds the mean, the data is overdispersed and a negative binomial distribution may be better suited as it is adapted to handle overdispersion (Zuur et al., 2009). Poisson models were fit using the ‘glm’ function in the base package (R Core Team, 2021), and negative binomial models were fit using the ‘glm.nb’ function from the MASS package (Venables & Ripley, 2002). The comparison of AIC values aided in selecting a distribution family by fitting two otherwise identical models, one with a Poisson distribution and one with a negative binomial distribution, with the model that produced a lower AIC preferred (Zuur et al., 2009). An additional check on an assumed distribution family is the value of theta from a negative binomial model; high theta values (>5) indicate the model is approaching a Poisson distribution; therefore, choosing a Poisson distribution is more appropriate.

Predictors with particularly wide value ranges resulting in very large coefficients (>5) were standardized using the ‘scale’ function included in the base package (R Core Team, 2021). This function subtracts the mean of the predictor variable from each original data value and divides by the standard deviation. This results in a predictor mean of zero and a standard deviation of 1.

Variance inflation factor (VIF) values were calculated for global models following Step 2 and for the final models to check that problematic collinearity (VIF >10) was not a concern (O’Brien, 2007). Relationships between two or more (collinear) predictor variables can lead to uncertainty with respect to identifying the amount of influence on the response variable from a specific predictor variable (Dormann et al., 2013). VIFs were calculated using the ‘vif’ function of the car package (Fox & Weisberg, 2019). Instances of problematic collinearity necessitated a revision of the model by adopting a stepwise reduction process whereby one variable is excluded at a time, calculating the new VIF and AIC values, and choosing the model that produces VIFs all under 10 with the lowest AIC value. VIFs change as predictors are added to or dropped from models, therefore my focus was on final model VIFs (see Appendix C for predictor variable VIF values from all global and final models).

To address the possibility of zero-inflation, a comparison of the AIC values of the proposed final model and its corresponding zero-inflated version, fit with the ‘zeroinfl’ function of the pscl package, was performed (Zeileis et al., 2008). If the AIC value of the zero-inflated model is more than 2 units lower than that of the proposed final model, this provides evidence that the zero-inflated version improves model fit despite the added complexity. Within the ‘zeroinfl’ function, users can specify which predictor variables directly contribute to zero-inflation, or it can be assumed that each observation has an equal probability of being zero-inflated by including only an intercept (‘| 1’). In practice, it is not known with certainty if observed zeros are true zeros or false zeros and which predictor variables may be responsible for producing false zeros; therefore, the zero-inflated component of all zero-inflated models were fit with an intercept only (Zeileis et al., 2008).

McFadden’s pseudo-R^2 was calculated for each final model and its zero-inflated counterpart by using the formula ‘pseudo $R^2 = 1 - (logLik\_mod / logLik\_null)$’, where ‘logLik_mod’ is the log likelihood of the model and ‘logLik_null’ is an intercept-only version of the model. While pseudo-R^2 values were not used to guide model selection, they were calculated to provide a descriptive measure of how well the selected predictors included in each model explain variation in the response variable when compared to an intercept-only model.

Relative importance values (RIV) were calculated for all predictor variables in both global and final models by multiplying the absolute value of each coefficient by the difference between the predictor’s maximum and minimum values. These values rank each model’s predictor variables by their relative importance in influencing the response variable. In addition, average relative importance values (aRIV) were calculated (within each Scenario) by the sum of RIV for each instance the predictor appeared in a model, divided by the number of models in which the predictor appeared. The resulting averages were ranked from highest to lowest and assigned a sequential integer. These values rank each predictor's relative importance for each Scenario, by animal type.

Average significance levels (aSL) of each predictor were calculated by assigning a numerical value based on the symbol value given in each R Studio 'summary()' function output; '***' ($p \leq 0.001$) received a 3, '**' ($0.001 < p \leq 0.01$) received a 2, '*' ($0.01 < p \leq 0.05$) received a 1, '.' ($0.05 < p \leq 0.1$) received 0.5, and $p > 0.1$ received a 0. The aSL was calculated as the sum of the assigned numerical value divided by the number of models in which the predictor appeared in a model. RIV and aSL together offer a measure of how strongly each predictor contributes to the explanatory power of the model; these values appear in the Results chapter.

RESULTS

4.1 The influence of ‘HALF’

The six Wilcoxon rank-sum tests performed to assess the influence of ‘HALF’ produced significant results for medium-sized mammals (p = 0.0236) and marginally significant results for amphibians (p = 0.0829) (Figure 17).

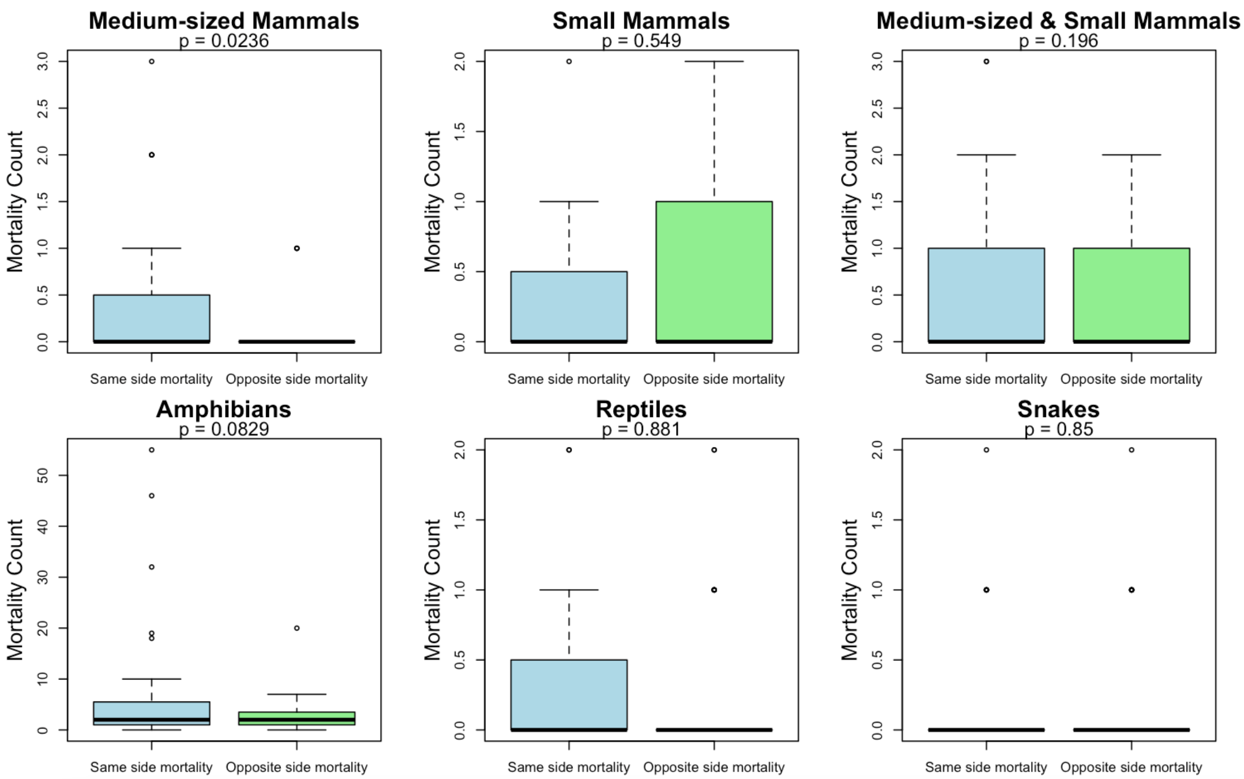


Figure 17. Boxplots depicting Wilcoxon rank-sum results for the six roadkill categories analyzed. Medium-sized mammals produced a significant result (p = 0.0236), while amphibians produced a marginally significant result (p = 0.0829).

4.2 Scenario A

A total of 1608 amphibians, 453 mammals, and 144 reptiles detected during the 166 surveys completed in 2019, 2020, and 2021 were considered for analysis. Amphibians, mammals, and reptiles had roadkill-per- kilometre rates of 55.4/km, 15.6/km, and 4.97/km, respectively.

The Kruskal–Wallis tests revealed a significant difference in Scenario A amphibian roadkill counts among crossing structure forms and absence (*p* = 0.0169) (Figure 18). The Dunn's post hoc comparisons indicated that bins with 'HALF' structures differed significantly from those with 'NONE' (adj. *p* = 0.014), and marginally from those with 'FULL' (adj. *p* = 0.050). Kruskal-Wallis tests involving mammal (*p* = 0.0841) and reptile (*p* = 0.406) roadkill were not significant.

Amphibians were fit with a negative binomial model given a variance/mean ratio of nearly 13:1. Both mammals (1.11:1) and reptiles (1.47:1) were fit with Poisson models.

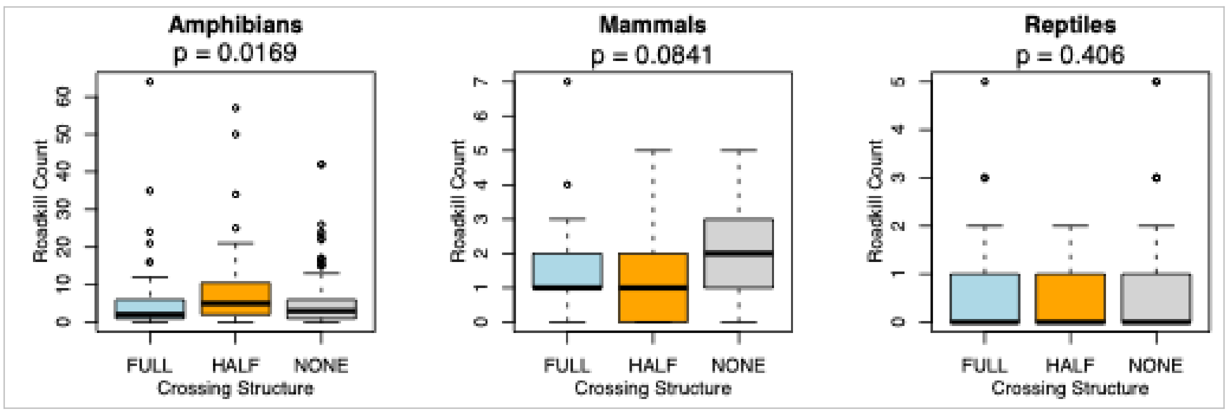


Figure 18. Boxplots illustrating roadkill counts across crossing structure forms and absence ('FULL', 'HALF', 'NONE') for each animal type.

4.2.1. Scenario A, Amphibians

The model producing the lowest AIC value was the global/final Material model including 'plastic' (+) and 'corridor' (-).

Table 5. The predictor variables included in the global and final models for amphibians. The relative importance values (RIV), direction of influence (I.), and significance level (SL) are provided for each predictor variable included in a model. The average RIV (aRIV) and average significance level (aSL) are given for each predictor under the 'Averages' columns. The AIC values and the minimum - maximum variance inflation factor (VIF) ranges are given for each model, in addition to the AIC values for the zero-inflated version of the Final model and the pseudo-R^2 values of the Final model compared with that of its zero-inflated version. The Material models (global = final) with 'plastic' (+) produced the lowest AIC values.

SCENARIO A		AMPHIBIANS								AVERAGES	
		CGX		Material		Shape		Function		Global	Final
		Global	Final	Global	**Final**	Global	Final	Global	Final		
Predictor Variables		RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	aRIV I. aSL	aRIV I. aSL
CGX	Corridor	11 [-] ***	11 [-] ***	11 [-] ***	**11 [-] ***	12 [-] ***	12 [-] ***	12 [-] ***	12 [-] ***	11 [-] 3.0	11 [-] 3.0
	Guardrail										
	Full Structure	14 [+]	- - -							17 [+] 0.0	- - -
	Half Structure	13 [+] *	13 [+] *							13 [+] 1.0	13 [+] 1.0
	Highway										
Material	Concrete										
	Metal										
	Plastic			13 [+] *	**13 [+] ***					13 [+] 1.0	13 [+] 1.0
Shape	Bridge										
	Circular					13 [+] *	13 [+] *			13 [+] 1.0	13 [+] 1.0
	Rectangular										
Function	Dry							14 [+] *	14 [+] *	17 [+] 1.0	17 [+] 1.0
	Wet							13 [+] .	13 [+] .	13 [+] 0.5	13 [+] 0.5
	Dry & Intermittent										
	Wet & Intermittent										
Landcover	Forest (%)	10 [+] .	10 [+] .	10 [+] .	**10 [+] .**	10 [+] .	10 [+] .	10 [+] *	10 [+] *	10 [+] 0.6	10 [+] 0.6
	Anthropogenic (%)	3 [-] ***	4 [-] ***	3 [-] ***	**3 [-] ***	3 [-] ***	3 [-] ***	3 [-] ***	3 [-] ***	3 [-] 3.0	3 [-] 3.0
	Marshland (%)	2 [+] ***	2 [+] ***	2 [+] ***	**2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] 3.0	2 [+] 3.0
	Agri-Range (%)	9 [+] **	8 [+] **	8 [+] **	**8 [+] ****	8 [+] **	8 [+] **	9 [+] **	9 [+] **	9 [+] 2.0	9 [+] 2.0
	Waterbody (%)	1 [+] ***	1 [+] ***	1 [+] ***	**1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] 3.0	1 [+] 3.0
	Watercourse (m/ha)	12 [+] .	12 [+] .	12 [+] .	**12 [+] .**	11 [+] *	11 [+] *	11 [+] *	11 [+] *	11 [+] 0.8	11 [+] 0.8
Distance-to	Forest (m)	8 [+] *	9 [+] *	7 [+] *	**7 [+] ***	9 [+] *	9 [+] *	7 [+] *	7 [+] *	7 [+] 1.0	8 [+] 1.0
	Marshland (m)	7 [-] **	7 [-] **	9 [-] **	**9 [-] ****	7 [-] **	7 [-] **	8 [-] **	8 [-] **	7 [-] 2.0	7 [-] 2.0
	Agri-Range (m)	5 [+] ***	5 [+] ***	5 [+] ***	**5 [+] ***	4 [+] ***	4 [+] ***	4 [+] ***	4 [+] ***	4 [+] 3.0	5 [+] 3.0
	Waterbody (m)	6 [+] **	6 [+] **	6 [+] **	**6 [+] ****	6 [+] **	6 [+] **	6 [+] **	6 [+] **	6 [+] 2.0	6 [+] 2.0
	Watercourse (m)	4 [-] **	3 [-] ***	4 [-] ***	**4 [-] ***	5 [-] **	5 [-] **	5 [-] **	5 [-] **	4 [-] 2.3	4 [-] 2.5
	AIC	1450.28	1449.47	1448.83	**1448.83**	1448.96	1448.96	1450.54	1450.54		
	VIF Range	1.20 - 3.28	1.11 - 3.28	1.15 - 3.28	**1.15 - 3.28**	1.12 - 3.29	1.12 - 3.29	1.15 - 3.28	1.15 - 3.28		
	AIC Zero Infl. Fin. Mod.		1450.41		**1448.92**		1449.35		1450.49		
	Pseudo R^2 [Final v Z.I. Final]		12.3 v 12.4		**12.3 v 12.4**		12.3 v 12.4		12.3 v 12.5		

A CGX model fit with the ‘crossing structure (full)’ (+) and ‘crossing structure (half)’ (+), and ‘corridor’ (-), produced a lower AIC value compared to the Step 1 model. The final CGX model excluded ‘crossing structure (full)’ but retained ‘crossing structure (half)’ and ‘corridor’. In the global model, ‘crossing structure (half)’ exhibited more than twice the level of influence (coef: 0.392) on amphibian roadkill compared with ‘crossing structure (full)’ (coef: 0.169).

Present in the Materials model were ‘plastic’ and ‘corridor’. In the Shape model, ‘circular’ (+) and ‘corridor’ (-) were present. In the Function model, ‘dry’ (+), ‘wet’ (+), and ‘corridor’ (-) were present. No structural or environmental predictors were excluded from the global models to produce lower AIC values, i.e., the global models equal the final models, except for ‘crossing structure (full)’ from the final CGX model. Across all four models, the VIF values indicate low collinearity (<4), and the small difference between the AIC values of the final models and their zero-inflated equivalents (<1 unit) do not suggest zero-inflation.

The predictors with the highest average relative importance values (aRIVs) were ‘waterbody (%)’ (+), ‘marshland (%)’ (+), and ‘anthropogenic (%)’ (-). All three predictors had the highest average significance levels (aSLs) possible (3.0). The predictors with the lowest aRIVs were ‘crossing structure (full)’ (+), and ‘dry’ (+), with aSLs between 0 and 1.0.

4.2.2. Scenario A, Mammals

The model producing the lowest AIC value was the final Material model including ‘concrete’ (-).

Table 6. The predictor variables included in the global and final models for mammals. Relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor included in a model (righthand side). The AIC values for each model, the minimum - maximum variance inflation factor (VIF) range for each model, the AIC values for the zero-inflated version of the Final model, and the pseudo-R^2 values of the Final model compared with that of its zero-inflated version are provided. The Material Final model produced the lowest AIC value where ‘concrete’ had a negative influence on roadkill.

SCENARIO A		MAMMALS																		AVERAGES					
		Material						Shape						Function						Global			Final		
		Global			Final			Global			Final			Global			Final								
Predictor Variables		RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	aRIV	I.	aSL	aRIV	I.	aSL
CGX	Corridor							9	[-]		6	[-]	.	9	[-]		6	[-]	*	7	[-]	0.0	6	[-]	0.5
	Guardrail																								
	Full Structure																								
	Half Structure																								
	Highway																								
Material	Concrete	6	[-]	*	5	[-]	*													7	[-]	1.0	8	[-]	1.0
	Metal																								
	Plastic																								
Shape	Bridge																								
	Circular																								
	Rectangular							7	[-]		-	-	-							9	[-]	0.0	-	-	-
Function	Dry													10	[-]		7	[-]		12	[-]	0.0	10	[-]	0.0
	Wet																								
	Dry & Intermittent																								
	Wet & Intermittent																								
Landcover	Forest (%)	1	[-]	**	1	[-]	***	1	[-]	**	1	[-]	**	1	[-]	**	1	[-]	**	1	[-]	2.0	2	[-]	2.3
	Anthropogenic (%)	2	[-]	*	4	[-]	*	2	[-]	*	2	[-]	***	2	[-]	*	2	[-]	**	2	[-]	1.0	5	[-]	2.0
	Marshland (%)	5	[-]		7	[-]	*	6	[-]		4	[-]	*	6	[-]		5	[-]	.	5	[-]	0.0	9	[-]	0.8
	Agri-Range (%)	7	[-]		-	-	-	5	[-]		3	[-]	.	5	[-]		-	-	-	5	[-]	0.0	2	[-]	0.2
	Waterbody (%)	4	[+]	.	3	[+]	*	4	[+]	*	-	-	-	4	[+]	.	4	[+]	.	4	[+]	0.7	4	[+]	0.5
	Watercourse (m/ha)	11	[+]		-	-	-	10	[+]		-	-	-	8	[+]		-	-	-	11	[+]	0.0	-	-	-
Distance-to	Forest (m)	10	[+]		-	-	-	11	[+]		-	-	-	12	[+]		-	-	-	13	[+]	0.0	-	-	-
	Marshland (m)	9	[-]		-	-	-	12	[-]		-	-	-	13	[-]		-	-	-	14	[-]	0.0	-	-	-
	Agri-Range (m)	8	[+]		6	[+]	**	8	[+]		5	[+]		7	[+]	.	3	[+]	**	10	[+]	0.2	7	[+]	1.3
	Waterbody (m)	3	[+]	.	2	[+]	.	3	[+]		-	-	-	3	[+]		-	-	-	3	[+]	0.2	1	[+]	0.2
	Watercourse (m)	12	[+]		-	-	-	13	[+]		-	-	-	11	[+]		-	-	-	15	[+]	0.0	-	-	-
	AIC	926.36			918.77			930.11			921.36			928.86			921.09								
	VIF Range	1.05 - 5.85			1.01 - 1.92			1.14 - 6.59			1.22 - 2.00			1.06 - 6.62			1.03 - 1.97								
	AIC Zero Infl. Fin. Mod.				918.59						921.49						920.95								
	Pseudo R^2 [Final v Z.I. Final]				3.1 v 2.8						2.6 v 2.3						7.7 v 2.5								

‘Concrete’ was the only crossing structure-related predictor included in the Materials model. In the Shape model, ‘rectangular’ (-) and ‘corridor_’ (-) were present in the global model; ‘rectangular’ was dropped from the final model. For the Function model, ‘dry’ (-) and ‘corridor’ (-) were present. Across these models, the VIF values indicate no problematic collinearity. While the Material and Function final models have AICs that are slightly higher than zero-inflated equivalents, the difference is minimal (<0.18), suggesting the zero-inflation component does not add a marked benefit to overall model-data fit.

The global model predictors with the highest aRIVs were ‘forest (%)’ (-), ‘anthropogenic (%)’ (-), and ‘waterbody (m)’ (+). The aSLs ranged between 0.2 and 2.0. The final model predictors with the highest aRIVs were ‘waterbody (m)’ (+), ‘forest (%)’ (-), and ‘agri-range (%)’ (-); the aSLs ranged from 0.2 to 2.3. ‘watercourse (m)’ (+), ‘forest (m)’ (+), and ‘marshland (m)’ (-) had the lowest global model aRIVs; the lowest aRIVs all had aSLs of zero. The final model predictors with the lowest aRIVs were ‘dry’ (-), ‘corridor’ (-), and ‘marshland (%)’ (-), as ‘watercourse (m)’, ‘forest (m)’, and ‘marshland (m)’ were all excluded from the final models. Two of the three highest aRIV predictors also had the highest aSL, ‘forest (%)’ (2.3) and ‘anthropogenic (%)’ (2.0), while ‘waterbody (m)’ had an aSL of 0.5. The lowest aRIV predictors also shared some of the lowest aSLs: ‘dry’ (0.0), ‘corridor’ (0.8), and ‘marshland (%)’ (0.8).

4.2.3. Scenario A, Reptiles

The model producing the lowest AIC value was the final Shape model including ‘rectangular’ (-).

Table 7. The global and final model predictor variables for reptile models in Scenario A. The relative importance value (RIV), direction of influence (I.), and significance (SL) are provided for each predictor variable included in a model. An average RIV (aRIV) and average significance (SL) are given for each predictor (righthand side). The AIC values and the minimum - maximum variance inflation factor (VIF) range are given for each model. Also included are the AIC values for the zero-inflated version of the Final model and the pseudo-R^2 values of the Final model compared with its zero-inflated version. The Shape final model had the lowest AIC, with Rectangular (-) and Wildlife Corridor (+).

SCENARIO A		REPTILES																		AVERAGES					
		Material						Shape						Function						Global			Final		
		Global			Final			Global			**Final**			Global			Final								
Predictor Variables		RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	**RIV**	**I.**	**SL**	RIV	I.	SL	RIV	I.	SL	aRIV	I.	aSL	aRIV	I.	aSL
CGX	Corridor							12	[+]		**11**	**[+]**								4	[+]	0.0	4	[+]	0.0
	Guardrail																								
	Full Structure																								
	Half Structure																								
	Highway																								
Material	Concrete	11	[+]		10	[+]														13	[+]	0.0	12	[+]	0.0
	Metal																								
	Plastic																								
Shape	Bridge																								
	Circular																								
	Rectangular							4	[-]		**5**	**[-]**								4	[-]	0.0	6	[-]	0.0
Function	Dry																								
	Wet																								
	Dry & Intermittent																								
	Wet & Intermittent													11	[+]		-	-	-	13	[+]	0.0	-	-	-
Landcover	Forest (%)	4	[-]	***	3	[-]	***	5	[-]	***	**4**	**[-]**	*******	4	[-]	***	3	[-]	***	6	[-]	3.0	3	[-]	3.0
	Anthropogenic (%)	1	[-]	***	1	[-]	***	1	[-]	***	**1**	**[-]**	*******	1	[-]	***	1	[-]	***	1	[-]	3.0	1	[-]	3.0
	Marshland (%)	7	[-]	*	9	[-]	*	9	[-]	*	**10**	**[-]**	*****	7	[-]	*	9	[-]	*	9	[-]	1.0	11	[-]	1.0
	Agri-Range (%)	5	[-]	***	5	[-]	***	7	[-]	***	**6**	**[-]**	*******	5	[-]	***	5	[-]	***	7	[-]	3.0	7	[-]	3.0
	Waterbody (%)	2	[-]	***	2	[-]	***	2	[-]	***	**2**	**[-]**	*******	2	[-]	***	2	[-]	***	2	[-]	3.0	2	[-]	3.0
	Watercourse (m/ha)	8	[+]	**	7	[+]	**	8	[+]	**	**8**	**[+]**	******	8	[+]	*	7	[+]	**	10	[+]	1.7	9	[+]	2.0
Distance-to	Forest (m)	6	[+]	***	6	[+]	***	6	[+]	***	**7**	**[+]**	*******	6	[+]	***	6	[+]	***	8	[+]	3.0	8	[+]	3.0
	Marshland (m)	10	[-]		-	-	-	11	[-]		-	-	-	10	[-]		-	-	-	12	[-]	0.0	-	-	-
	Agri-Range (m)	12	[+]		-	-	-	13	[-]		-	-	-	12	[+]		-	-	-	15	[+/-]	0.0	-	-	-
	Waterbody (m)	9	[-]	*	8	[-]	*	10	[-]		**9**	**[-]**	**.**	9	[-]	*	8	[-]	*	11	[-]	0.7	10	[-]	0.8
	Watercourse (m)	3	[+]	***	4	[+]	***	3	[+]	***	**3**	**[+]**	*******	3	[+]	***	4	[+]	***	3	[+]	3.0	4	[+]	3.0
	AIC	496.84			493.60			495.56			**492.42**			498.36			493.65								
	VIF Range	1.14 - 3.70			1.13 - 3.21			1.00 - 3.91			**1.00 - 3.43**			1.26 - 3.73			1.21 - 3.21								
	AIC Zero Infl. Fin. Mod.				493.86						**490.99**						493.42								
	Pseudo R^2 [Final v Z.I. Final]				17.1 v 15.5						**17.7 v 16.4**						16.8 v 15.2								

‘Concrete’ (+), (Material model), ‘rectangular’ and ‘corridor’ (+) (Shape model), and ‘wet & interm’ (+) (Function model) were included in their respective global models. Of these, ‘wet & interm’ was the only predictor excluded from the otherwise identical final models. Due to wide value ranges among included predictors, the predictors for the Shape model were standardized using the scale function in R Studio, and ridge regression was applied to reduce the magnitude of coefficients; ridge regression was performed using the glmnet package (Friedman et al., 2010). No predictor had a VIF value above 4, well below the problematic collinearity threshold of 10. There is some support that the Shape final model is zero-inflated as the AIC value for the zero-inflated model is 1.437 units less than the same model without the zero-inflation component; however, because this difference is less than the standard 2-unit difference, the simpler model without zero-inflation remains competitive and is retained.

The global predictors with the highest aRIVs were 'anthropogenic (%)' (-), 'waterbody (%)' (-), and 'watercourse (m)' (+); all three predictors were highly significant (aSLs = 3.0). The lowest aRIV predictors were 'agri-range (m) (+/-); 'agri-range (m)' is the only environmental predictor in this study to switch its direction of influence within the same scenario (for Material and Function global models, 'agri-range (m)' is positively associated with roadkill, while negatively associated with roadkill in the Shape global model). It's aSL was zero and the predictor was excluded from any final model. The remaining lowest aRIVs were for 'corridor' (+), 'concrete' (+), and 'wet & interm' (+), each having an aSL value of zero. The Final model predictors with the highest aRIVs were 'anthropogenic (%)' (-), 'waterbody (%)' (-), and 'forest (%)' (-); again, all three predictors were highly significant (aSLs = 3.0). 'Corridor' and 'concrete' remained the lowest aRIV, each with an aSL value of zero, while 'wet & interm' was excluded from the final models.

4.3 Scenario B

A total of 2771 roadkill were detected, 2318 amphibians (925 on A10, 1393 on R112), 226 mammals (142 on A10, 84 on R112), and 227 reptiles (88 on A10, 139 on R112) during 74 surveys (37 surveys each on A10 and R112) were considered for analysis. The roadkill-per-kilometre rates varied widely between A10 and R112 for amphibians (30.0/km on A10, 54.6/km on R112) and reptiles (2.9/km on A10, 5.5/km on R112), but were relatively similar for mammals (4.6/km on A10, 3.3/km on R112). The Kruskal–Wallis tests revealed no significant difference in Scenario B roadkill counts by crossing structure forms and absence (Figure 19).

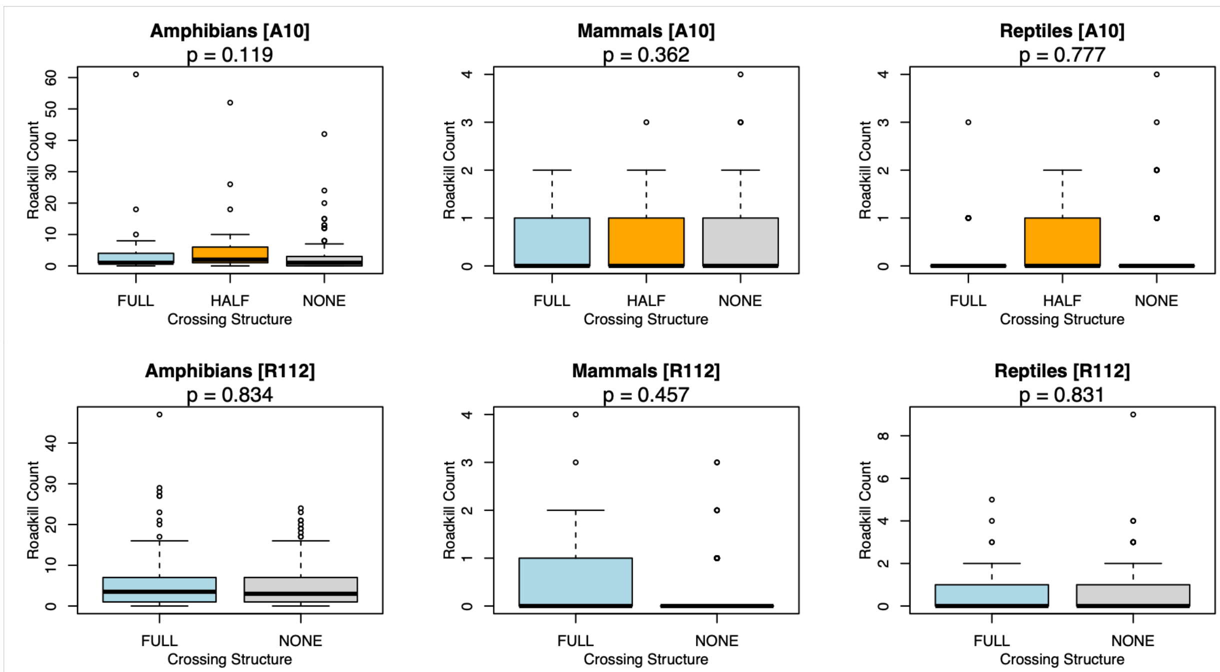


Figure 19. Boxplots depicting roadkill counts by crossing structure forms and absence, by animal type. Top row: A10 (‘FULL’, ‘HALF’, ‘NONE’). Bottom row: R112 (‘FULL’, ‘NONE’).

Amphibians were fit with negative binomial models given a 12:1 and a nearly 8:1 variance/mean ratio on A10 and R112, respectively. Mammals were fit with Poisson models for both A10 (1.1:1) and R112 (1.3:1). For reptiles, a Poisson model was chosen for A10 (1.2:1), while a negative binomial model was chosen for R112 as the variance was twice that of the mean (2.0:1). All continuous predictors were standardized due to large value ranges.

4.3.1. Scenario B, Amphibians

Table 8. The predictor variables included in the global and final models for amphibians in Scenario B. The relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each included predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor. Included are the AIC values for each model, the minimum - maximum variance inflation factor (VIF) range, the AIC values for the zero-inflated version of the final model, and the pseudo-R^2 values of the final model compared with its zero-inflated version. To compare A10 with R112, the Material models (global = final) produced the lowest AIC values for A10 where 'corridor' (-), 'concrete' (-), and 'plastic' (+), while the R112 final models produced the lowest AIC values, where all structural predictor variables were excluded and only landcover predictor variables remained.

SCENARIO B		AMPHIBIANS (A10)						AMPHIBIANS (R112)						A10 AVERAGES		R112 AVERAGES	
		Material		Shape		Function		Material		Shape		Function		Global	Final	Global	Final
		Global	**Final**	Global	Final	Global	Final	Global	**Final**	Global	**Final**	Global	**Final**				
	Predictor Variables	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	aRIV I. aSL	aRIV I. aSL	aRIV I. aSL	aRIV I. aSL
CGX	Corridor	13 [-] **	**13 [-] ****	13 [-] **	13 [-] **	12 [-] **	12 [-] **							14 [-] 2.0	14 [-] 2.0		
	Guardrail																
	Full Structure																
	Half Structure																
	Highway																
Material	Concrete	10 [-] **	**10 [-] ****					12 [+]	- - -					11 [-] 2.0	11 [-] 2.0	12 [+] 0.0	- - -
	Metal																
	Plastic	14 [+] .	**14 [+] .**											16 [+] 0.5	16 [+] 0.5		
Shape	Bridge			3 [-] *	3 [-] *									3 [-] 1.0	3 [-] 1.0		
	Circular																
	Rectangular									12 [+]	- - -					12 [+] 0.0	- - -
Function	Dry					13 [+]	13 [+]							15 [+] 0.0	15 [+] 0.0		
	Wet																
	Dry & Intermittent											12 [+]	- - -			12 [+] 0.0	- - -
	Wet & Intermittent																
Landcover	Forest (%)	1 [+] ***	**1 [+] *****	2 [+] ***	2 [+] ***	1 [+] **	1 [+] **	1 [-] ***	**1 [-] *****	1 [-] ***	**1 [-] *****	1 [-] ***	**1 [-] 3**	1 [+] 2.7	1 [+] 2.7	1 [-] 3.0	1 [-] 3.0
	Anthropogenic (%)	7 [+] **	**7 [+] ****	6 [+] **	6 [+] **	7 [+] **	7 [+] **	6 [-] ***	**6 [-] *****	6 [-] ***	**6 [-] *****	6 [-] ***	**6 [-] 3**	8 [+] 2.0	8 [+] 2.0	6 [-] 3.0	6 [-] 3.0
	Marshland (%)	4 [+] ***	**4 [+] *****	4 [+] ***	4 [+] ***	3 [+] ***	3 [+] ***	10 [+] ***	**10 [+] *****	11 [+] ***	**11 [+] *****	9 [+] ***	**9 [+] 3**	4 [+] 3.0	4 [+] 3.0	11 [+] 3.0	11 [+] 3.0
	Agri-Range (%)	8 [+] ***	**8 [+] *****	9 [+] ***	9 [+] ***	8 [+] ***	8 [+] ***	5 [+] *	**5 [+] ***	5 [+] *	**5 [+] ***	5 [+] *	**5 [+] 1**	9 [+] 3.0	9 [+] 3.0	5 [+] 1.0	5 [+] 1.0
	Waterbody (%)	2 [+] ***	**2 [+] *****	1 [+] ***	1 [+] ***	2 [+] ***	2 [+] ***	2 [-] ***	**2 [-] *****	2 [-] ***	**2 [-] *****	2 [-] ***	**2 [-] 3**	2 [+] 3.0	2 [+] 3.0	2 [-] 3.0	2 [-] 3.0
	Watercourse (m/ha)	11 [+] .	**11 [+] .**	12 [+] .	12 [+] .	10 [+] .	10 [+] .	4 [-] ***	**4 [-] *****	4 [-] ***	**4 [-] *****	4 [-] ***	**4 [-] 3**	12 [+] 0.5	12 [+] 0.5	4 [-] 3.0	4 [-] 3.0
Distance-to	Forest (m)	12 [-]	**12 [-]**	11 [-] .	11 [-] .	11 [-]	11 [-]	7 [-] **	**7 [-] ****	8 [-] **	**8 [-] ****	8 [-] **	**8 [-] 2**	13 [-] 0.2	13 [-] 0.2	7 [-] 2.0	7 [-] 2.0
	Marshland (m)	9 [-] **	**9 [-] ****	10 [-] **	10 [-] **	9 [-] **	9 [-] **	9 [-] *	**9 [-] ***	7 [-] *	**7 [-] ***	11 [-] *	**11 [-] 1**	10 [-] 2.0	10 [-] 2.0	8 [-] 1.0	8 [-] 1.0
	Agri-Range (m)	3 [+] ***	**3 [+] *****	5 [+] ***	5 [+] ***	4 [+] ***	4 [+] ***	8 [+] **	**8 [+] ****	9 [+] **	**9 [+] ****	10 [+] **	**10 [+] 2**	5 [+] 3.0	5 [+] 3.0	8 [+] 2.0	8 [+] 2.0
	Waterbody (m)	6 [+] ***	**6 [+] *****	8 [+] ***	8 [+] ***	5 [+] ***	5 [+] ***	3 [-] ***	**3 [-] *****	3 [-] ***	**3 [-] *****	3 [-] ***	**3 [-] 3**	7 [+] 3.0	7 [+] 3.0	3 [-] 3.0	3 [-] 3.0
	Watercourse (m)	5 [-] **	**5 [-] ****	7 [-] **	7 [-] **	6 [-] **	6 [-] **	11 [-] **	**11 [-] ****	10 [-] **	**10 [-] ****	7 [-] ***	**7 [-] 3**	6 [-] 2.0	6 [-] 2.0	10 [-] 2.3	10 [-] 2.3
	AIC	1248.09	**1248.09**	1251.85	1251.85	1257.08	1255.19	1233.75	**1233.30**	1234.58	**1233.30**	1233.79	**1233.30**				
	VIF Range	1.12 - 4.69	**1.12 - 4.69**	1.02 - 4.71	1.02 - 4.71	1.10 - 4.70	1.50 - 4.67	1.13 - 2.98	**1.29 - 2.95**	1.11 - 2.97	**1.29 - 2.95**	1.09 - 2.98	**1.29 - 2.95**				
	AIC Zero Infl. Fin. Mod.		**1249.54**		1253.85		1257.18		**1232.64**		**1232.64**		**1232.64**				
	Pseudo R^2 [Final v Z.I. Final]		**11.1 v 11.2**		10.7 v 10.7		10.3 v 10.3		**14.3 v 14.5**		**14.3 v 14.5**		**14.3 v 14.5**				

The model producing the lowest AIC value for A10 was the global/final Material model including ‘corridor’ (-), ‘concrete’ (-), and ‘plastic’ (+), while the models producing the lowest AIC value for R112 was the Step 1 land cover only model as all structural predictors were excluded from final R112 models.

‘Concrete’ was the lone Material predictor included in both A10 and R112 global models; however, ‘concrete’ was negatively associated with amphibian roadkill on A10 while on R112 ‘concrete’ was positively associated with amphibian roadkill (Figure 21). For final models on A10, ‘dry’ was the only predictor included in a global model but excluded in a final model; all other final models were identical to global model counterparts. All structural predictors were excluded for final models on R112. The highest VIF value overall of ~4.8 indicated no problematic collinearity among the predictors, and on A10 none of the zero-inflated models have lower AICs over their standard counterparts. The AIC value for the Step 1 landcover model on R112 (1233.30) is higher than the zero-inflated negative binomial (ZINB) version (1232.64), but the difference is not a large enough (> 2) to support the ZINB model over the final negative binomial model.

The highest two aRIV predictors for global models were the same for both A10 and R112: ‘forest (%)’ and ‘waterbody (%)’; however, ‘forest (%)’ and ‘waterbody (%)’ were both positively associated with amphibian roadkill on A10 while negatively associated with amphibian roadkill on R112. The third aRIV on A10 was ‘bridge’ (-) and on R112 the third aRIV was ‘waterbody (m)’ (-). The top three A10 aRIV predictors had aSLs ranging from 1.0 (‘bridge’) to 3.0 (‘waterbody (%)’). All three of the top R112 aRIV predictors were highly significant (aSL = 3.0). The lowest aRIV predictors for A10 were all structural predictors, ‘plastic’ (+), ‘dry’ (+), and ‘corridor’ (-), with aSLs ranging from 0 (‘dry’) to 2.0 (‘corridor’).

Similarly, for R112, the lowest aRIV predictors were structural predictors, ‘rectangular’ (+), ‘dry & interm’ (+), and ‘concrete’ (+), with aSLs of 0.0 for each.

For final models, the lone predictor excluded among all A10 models was ‘dry’. There was no change in the top three aRIVs from those of global models, while the bottom three aRIV predictors were ‘plastic’ (+), ‘corridor’ (-), and ‘watercourse (m/ha)’ (+). The aSLs for these predictors ranged between 0.5 (‘plastic’ and ‘watercourse (m/ha)’) and 2.0 (‘corridor’). For R112, the top three aRIV predictors were ‘forest (%)’ (-), ‘waterbody (%)’ (-), and ‘waterbody (m)’ (-), with high significance (aSL = 3.0). All structural predictors were excluded from R112 Final models, leaving ‘marshland (%)’ (+) and ‘watercourse (m)’ (-) with the lowest aRIV. The range in aSLs were 2.3 (‘watercourse (m)’) to 3.0 (‘marshland (%)’).

4.3.2. Scenario B, Mammals

Table 9. The predictor variables included in the global and final models for mammals in Scenario B. The relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each included predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor. Included are the AIC values for each model, the minimum - maximum variance inflation factor (VIF) range, the AIC values for the zero-inflated version of the final model, and the pseudo-R^2 values of the final model compared with its zero-inflated version. To compare A10 with R112, the Function final model produced the lowest AIC value for A10 with 'wet' (-), while all the structural predictors were excluded from R112 final models with the Step 1 model producing the lowest AIC value.

SCENARIO B		MAMMALS (A10)						MAMMALS (R112)						A10 AVERAGES		R112 AVERAGES	
		Material		Shape		Function		Material		Shape		Function		Global	Final	Global	Final
		Global	Final	Global	Final	Global	Final	Global	Final	Global	Final	Global	Final				
Predictor Variables		RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	aRIV I. aSL	aRIV I. aSL	aRIV I. aSL	aRIV I. aSL
CGX	Corridor																
	Guardrail																
	Full Structure																
	Half Structure																
	Highway																
Material	Concrete																
	Metal	12 [-]	- - -					10 [+]	- - -					13 [-] 0.0	- - -	10 [+] 0.0	- - -
	Plastic																
Shape	Bridge																
	Circular			12 [-]	- - -					10 [+]	- - -			13 [-] 0.0	- - -	10 [+] 0.0	- - -
	Rectangular																
Function	Dry																
	Wet					8 [-]	8 [-]							8 [-] 0.0	9 [-] 0.0		
	Dry & Intermittent																
	Wet & Intermittent											10 [+]	- - -			10 [+] 0.0	- - -
Landcover	Forest (%)	2 [-]	2 [-]	2 [-]	2 [-]	2 [-] .	2 [-] .	4 [-] *	3 [-] *	4 [-] .	3 [-] *	4 [-] *	3 [-] *	2 [-] 0.2	2 [-] 0.2	4 [-] 0.8	3 [-] 1.0
	Anthropogenic (%)	5 [+] *	5 [+] .	5 [+] *	5 [+] .	4 [+] *	5 [+] *	7 [-]	8 [-]	7 [-]	8 [-]	7 [-]	8 [-]	5 [+] 1.0	7 [+] 0.7	7 [-] 0.0	8 [-] 0.0
	Marshland (%)	7 [-]	6 [-] .	7 [-]	6 [-] .	9 [-]	6 [-] .	1 [-] ***	2 [-] ***	1 [-] ***	2 [-] ***	2 [-] ***	2 [-] ***	7 [-] 0.0	8 [-] 0.5	1 [-] 3.0	2 [-] 3.0
	Agri-Range (%)	8 [+]	- - -	8 [+]	- - -	10 [+]	- - -	3 [-] **	4 [-] *	3 [-] *	4 [-] *	3 [-] *	4 [-] *	10 [+] 0.0	- - -	3 [-] 1.3	4 [-] 1.0
	Waterbody (%)	3 [-]	3 [-]	3 [-]	3 [-]	5 [-]	3 [-]	5 [-] **	6 [-] **	5 [-] **	6 [-] **	5 [-] **	6 [-] **	3 [-] 0.0	4 [-] 0.0	5 [-] 2.0	6 [-] 2.0
	Watercourse (m/ha)	4 [-] *	4 [-] *	4 [-] .	4 [-] *	3 [-] .	4 [-] *	6 [-] *	5 [-] *	6 [-] .	5 [-] *	6 [-] .	5 [-] *	3 [-] 0.7	5 [-] 1.0	6 [-] 0.7	5 [-] 1.0
Distance-to	Forest (m)	1 [-] .	1 [-] .	1 [-] .	1 [-] .	1 [-] .	1 [-] .	11 [+]	- - -	11 [+]	- - -	11 [+]	- - -	1 [-] 0.5	1 [-] 0.5	13 [+] 0.0	- - -
	Marshland (m)	10 [+]	- - -	11 [+]	- - -	12 [+]	- - -	2 [-] ***	1 [-] ***	2 [-] **	1 [-] ***	1 [-] ***	1 [-] ***	12 [+] 0.0	- - -	2 [-] 2.7	1 [-] 3.0
	Agri-Range (m)	6 [+] *	- - -	6 [+] .	7 [+] .	6 [+] .	7 [+] .	9 [-]	- - -	9 [-]	- - -	8 [-]	- - -	6 [+] 0.7	6 [+] 0.3	9 [-] 0.0	- - -
	Waterbody (m)	11 [+]	- - -	10 [+]	- - -	11 [+]	- - -	12 [-]	- - -	12 [-]	- - -	12 [-]	- - -	11 [+] 0.0	- - -	14 [-] 0.0	- - -
	Watercourse (m)	9 [-]	7 [+] .	9 [-]	- - -	7 [-]	- - -	8 [-]	7 [-] .	8 [-]	7 [-] .	9 [-]	7 [-] .	9 [-] 0.0	3 [+] 0.2	8 [-] 0.0	7 [-] 0.5
	AIC	558.41	551.52	558.11	551.52	556.43	551.36	374.16	368.04	374.16	368.04	373.79	368.04				
	VIF Range	1.05 - 7.49	1.00 - 7.16	1.06 - 7.35	1.00 - 7.16	1.10 - 7.32	1.01 - 7.10	1.14 - 4.47	1.10 - 2.95	1.06 - 4.30	1.10 - 2.95	1.40 - 4.33	1.10 - 2.95				
	AIC Zero Infl. Fin. Mod.		553.20		553.20		553.04		369.39		369.39		369.39				
	Pseudo R^2 [Final v Z.I. Final]		3.8 v 3.5		3.8 v 3.5		4.2 v 3.8		9.1 v 7.7		9.1 v 7.7		9.1 v 7.7				

‘Metal’ and ‘circular’ appeared in global Material and Shape models for both A10 and R112 but with opposing directions of influence; ‘metal’ (-) and ‘circular’ (-) for A10 and ‘metal’ (+) and ‘circular’ (+) for R112 (Figure 22). These two predictors were excluded from A10 and R112 final models. ‘Wet’ for A10 was included in both global and final Function models, the only structural predictor to be included in any final model for either highway, while ‘wet & interm’ was included in the global Function model on R112 but was excluded from the final model.

The top aRIV predictors included ‘forest (m)’ (-), ‘forest (%)’ (-), and ‘watercourse (m/ha)’ (-) for A10 and ‘marshland (%)’ (-), ‘marshland (m)’ (-), and ‘agri-range (%)’ (-) for R112. The top A10 aRIV predictors aSL values ranged from 0.0 to 0.7, and 1.3 to 3.0 for the top aRIV R112 aSL predictors. The lowest aRIV predictors included the two predictors excluded from final A10 models, ‘metal’ (-) and ‘circular’ (-), while for R112 the lowest aRIVs included ‘forest (m)’ (+) and ‘waterbody (m)’ (-); all four of these predictors had aSLs of 0.0.

Across all models the range of VIF values (~1 to 7.5) suggest some collinearity. All models have lower AIC values than their zero-inflated versions.

4.3.3. Scenario B, Reptiles

Table 10. The predictor variables included in the global and final models for Scenario B: reptiles. The relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each included predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor. Included are the AIC values for each model, the minimum - maximum variance inflation factor (VIF) range, the AIC values for the zero-inflated version of the final model, and the pseudo-R^2 values of the final model compared with its zero-inflated version. To compare A10 with R112, the Shape Final model including 'rectangular' (-) and 'corridor' (-) produced the lowest AIC value for A10, and the final Function model including 'guardrail' (-) and 'wet & interm' (+) produced the lowest AIC value for R112.

SCENARIO B		REPTILES (A10)						REPTILES (R112)						A10 AVERAGES		R112 AVERAGES	
		Material		Shape		Function		Material		Shape		Function		Global	Final	Global	Final
		Global	Final	Global	Final	Global	Final	Global	Final	Global	Final	Global	Final				
Predictor Variables		RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	aRIV I. aSL	aRIV I. aSL	aRIV I. aSL	aRIV I. aSL
CGX	Corridor	11 [-]	9 [-] *	12 [-]	10 [-] *	11 [-]	9 [-] *							12 [-] 0.0	10 [-] 1.0		
	Guardrail							13 [-] *	12 [-] *	13 [-] *	12 [-] *	11 [-] **	11 [-] **			15 [-] 1.3	13 [-] 1.3
	Full Structure																
	Half Structure																
	Highway																
Material	Concrete																
	Metal							12 [-]	- - -							14 [-] 0.0	- - -
	Plastic	13 [-]	- - -											14 [-] 0.0	- - -		
Shape	Bridge									9 [+]	- - -					9 [+] 0.0	- - -
	Circular																
	Rectangular			2 [-]	2 [-]									2 [-] 0.0	2 [-] 0.0		
Function	Dry																
	Wet																
	Dry & Intermittent					13 [+]	- - -							14 [+] 0.0	- - -		
	Wet & Intermittent											10 [+] .	10 [+] **			11 [+] 0.5	12 [+] 2.0
Landcover	Forest (%)	1 [+] *	1 [+] **	1 [+] *	1 [+] **	1 [+] *	1 [+] **	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] 1.0	1 [+] 2.0	1 [+] 3.0	1 [+] 3.0
	Anthropogenic (%)	3 [+] *	3 [+] **	6 [+] **	6 [+] **	3 [+] *	3 [+] **	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	4 [+] 1.3	4 [+] 2.0	2 [+] 3.0	2 [+] 3.0
	Marshland (%)	4 [+] ***	2 [+] ***	4 [+] ***	3 [+] ***	4 [+] ***	2 [+] ***	6 [+] *	5 [+] *	4 [+] *	5 [+] *	3 [+] **	3 [+] **	4 [+] 3.0	3 [+] 3.0	4 [+] 1.3	5 [+] 1.3
	Agri-Range (%)	6 [+] **	5 [+] **	8 [+] **	8 [+] **	6 [+] **	5 [+] **	4 [+] ***	3 [+] ***	5 [+] ***	3 [+] ***	4 [+] ***	4 [+] ***	7 [+] 2.0	6 [+] 2.0	4 [+] 3.0	3 [+] 3.0
	Waterbody (%)	10 [-]	- - -	11 [-]	- - -	10 [-]	- - -	10 [+]	11 [+]	11 [+]	11 [+]	8 [+]	7 [+] .	11 [-] 0.0	- - -	10 [+] 0.0	10 [+] 0.2
	Watercourse (m/ha)	7 [+] .	6 [+] .	10 [+] .	9 [+] .	7 [+] .	6 [+] .	9 [-]	9 [-]	10 [-]	9 [-]	12 [-]	- - -	8 [+] 0.5	7 [+] 0.5	12 [-] 0.0	7 [-] 0.0
Distance-to	Forest (m)	2 [-]	- - -	3 [-]	- - -	2 [-]	- - -	3 [-] *	4 [-] *	3 [-] *	4 [-] *	5 [-] .	5 [-] *	3 [-] 0.0	- - -	3 [-] 0.8	5 [-] 1.0
	Marshland (m)	12 [-]	- - -	13 [-]	- - -	12 [-]	- - -	7 [+] .	7 [+] .	7 [+] .	7 [+] .	6 [+] *	6 [+] *	13 [-] 0.0	- - -	6 [+] 0.7	8 [+] 0.7
	Agri-Range (m)	8 [+] *	7 [+] *	9 [+] *	7 [+] *	8 [+] *	7 [+] *	8 [+] .	8 [+] .	8 [+] .	8 [+] .	7 [+] .	8 [+] .	9 [+] 1.0	7 [+] 1.0	7 [+] 0.5	9 [+] 0.5
	Waterbody (m)	9 [-]	8 [-]	7 [-] .	5 [-] .	9 [-]	8 [-]	11 [-]	10 [-]	12 [-]	10 [-]	9 [-]	9 [-]	9 [-] 0.2	7 [-] 0.2	13 [-] 0.0	10 [-] 0.0
	Watercourse (m)	5 [+] *	4 [+] *	5 [+] *	4 [+] *	5 [+] *	4 [+] *	5 [-] *	6 [-] *	6 [-] *	6 [-] *	13 [-]	- - -	6 [+] 1.0	4 [+] 1.0	8 [-] 0.7	4 [-] 0.7
	AIC	417.62	412.13	412.95	409.69	417.89	412.13	489.18	487.73	489.18	487.73	486.37	483.84				
	VIF Range	1.07 - 9.53	1.35 - 5.60	1.00 - 9.83	1.00 - 5.58	1.11 - 9.85	1.35 - 5.60	1.04 - 3.99	1.16 - 3.99	1.10 - 4.01	1.16 - 3.99	1.22 - 4.02	1.14 - 3.80				
	AIC Zero Infl. Fin. Mod.		412.89		410.67		412.89		489.08		489.08		484.75				
	Pseudo R^2 [Final v Z.I. Final]		7.8 v 7.0		8.8 v 8.0		7.8 v 7.0		9.1 v 9.2		9.1 v 9.2		9.5 v 9.7				

'Corridor' (-) on A10 and 'guardrail' (-) on R112 were included in every global and final model. Three additional structural predictors were included in A10 global models, 'plastic' (-), 'rectangular' (-), and 'dry & interm' (+), with only 'rectangular' included in an A10 final model. Likewise, three additional structural predictors were included in R112 global models, 'metal' (-), 'bridge' (+), and 'wet & interm' (+), with 'wet & interm' the sole predictor of the three to be included in a final R112 model. The top A10 aRIV predictors included 'forest (%)' (+), 'rectangular', and 'marshland (%)' (-), with aSLs ranging from 0.0 to 3.0. The top R112 aRIV predictors also included 'forest (%)' (+), as well as 'anthropogenic (%)' (+) and 'agri-range (%)' (+); all three of these predictors were highly significant (aSL = 3.0).

VIF values among A10 global models were on the threshold of indicating problematic collinearity (<9.9) however these values lowered (<5.6) for final models. All VIF values remained below five for all R112 models. All six final models had lower AIC values than their zero-inflated versions.

4.4 Scenario C

A total of 2771 roadkill were detected, 2318 amphibians, 226 mammals, and 227 reptiles during 74 surveys (37 surveys each on A10 and R112) completed in 2021. The roadkill-per- kilometre rates for amphibians was 41.4/km, while the values for mammals and reptiles were nearly identical at 4.04/km and 4.05/km, respectively. The Kruskal–Wallis tests revealed no significant difference in Scenario C roadkill counts by crossing structure forms and absence (Figure 20).

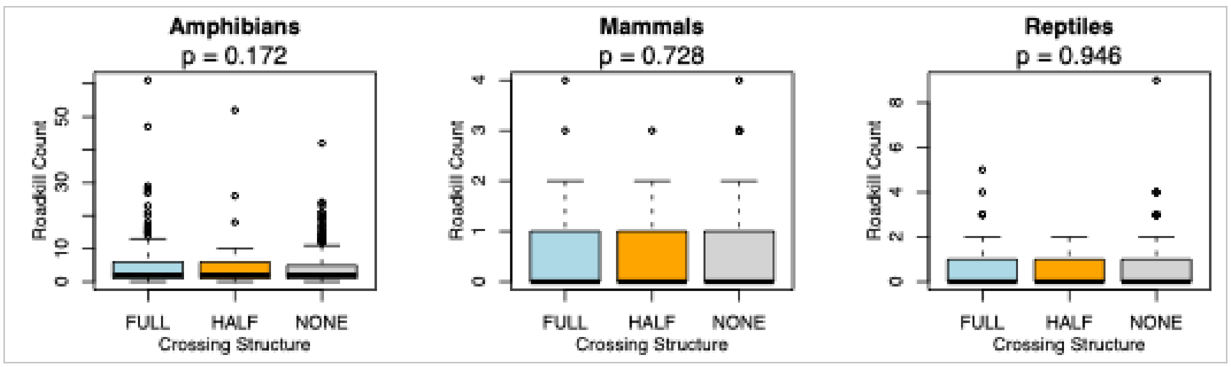


Figure 20. Boxplots illustrating Scenario C roadkill counts across crossing structure forms and absence (‘FULL’, ‘HALF’, ‘NONE’), by animal type.

Amphibians were fit with negative binomial models given a ~10:1 variance/mean ratio. Mammals were fit with Poisson models (1.2:1). The Step 1 model for reptiles (1.8:1) was fit to both a Poisson and a negative binomial model and AIC values were calculated for both, with the negative binomial model chosen as it produced an AIC value (905.05) more than 50 units less than that of the Poisson model’s AIC value (956.08). All predictors were standardized. ‘Highway’ was included as data from both highways were combined. All continuous predictors were standardized due to large value ranges.

4.4.1. Scenario C, Amphibians

The model producing the lowest AIC value was the global/final Material model, including ‘corridor’ (-), ‘guardrail’ (+), ‘plastic’ (+), and ‘highway’ (-). The difference in AIC between the Material models (AIC = 2558.65) and the model with the second-lowest AIC (Shape models, AIC = 2565.03) is high (6.38 units); following Burnham and Anderson (1998), a difference in AIC > 4 units indicates that the Material models provide a considerably better fit to the data than models from any other group.

Table 11. The predictor variables included in the global and final models for Scenario C: amphibians. The relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each included predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor. Included are the AIC values for each model, the minimum - maximum variance inflation factor (VIF) range, the AIC values for the zero-inflated version of the final model, and the pseudo-R^2 values of the final model compared with its zero-inflated version. The final Material model produced the lowest AIC value, including the predictors 'corridor' (-), 'guardrail' (+), 'highway' (-), and 'plastic' (+).

SCENARIO C		AMPHIBIANS								AVERAGES	
		CGX		Material		Shape		Function			
		Global	Final	Global	**Final**	Global	Final	Global	Final	Global	Final
Predictor Variables		RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	aRIV I. aSL	aRIV I. aSL
CGX	Corridor	14 [-] **	14 [-] **	14 [-] **	**14 [-] ****	14 [-] *	14 [-] *	13 [-] **	13 [-] **	17 [-] 1.8	17 [-] 1.8
	Guardrail			15 [+]	**15 [+]**	16 [+]	16 [+]			8 [+] 0.0	8 [+] 0.0
	Full Structure	15 [+]	15 [+]							19 [+] 0.0	19 [+] 0.0
	Half Structure	13 [+] .	13 [+] .							16 [+] 0.5	16 [+] 0.5
	Highway	11 [-] ***	11 [-] ***	10 [-] ***	**10 [-] *****	11 [-] ***	11 [-] ***	11 [-] ***	11 [-] ***	12 [-] 3.0	12 [-] 3.0
Material	Concrete										
	Metal										
	Plastic			11 [+] ***	**11 [+] *****					13 [+] 3.0	13 [+] 3.0
Shape	Bridge					10 [-] .	10 [-] .			11 [-] 0.5	11 [-] 0.5
	Circular					15 [+] *	15 [+] *			19 [+] 1.0	19 [+] 1.0
	Rectangular										
Function	Dry										
	Wet										
	Dry & Intermittent										
	Wet & Intermittent							14 [+] *	14 [+] *	18 [+] 1.0	18 [+] 1.0
Landcover	Forest (%)	10 [-]	10 [-]	13 [-]	**13 [-]**	12 [-] .	12 [-] .	10 [-] *	10 [-] *	14 [-] 0.4	14 [-] 0.4
	Anthropogenic (%)	9 [+] **	9 [+] **	9 [+] **	**9 [+] ****	9 [+] **	9 [+] **	9 [+] **	9 [+] **	10 [+] 2.0	10 [+] 2.0
	Marshland (%)	2 [+] ***	2 [+] ***	2 [+] ***	**2 [+] *****	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] 3.0	2 [+] 3.0
	Agri-Range (%)	12 [+] .	12 [+] .	12 [+] *	**12 [+] ***	13 [+] *	13 [+] *	12 [+] .	12 [+] .	15 [+] 0.8	15 [+] 0.8
	Waterbody (%)	1 [-] ***	1 [-] ***	1 [-] ***	**1 [-] *****	1 [-] ***	1 [-] ***	1 [-] ***	1 [-] ***	1 [-] 3.0	1 [-] 3.0
	Watercourse (m/ha)	5 [-] ***	5 [-] ***	5 [-] ***	**5 [-] *****	5 [-] ***	5 [-] ***	6 [-] ***	6 [-] ***	5 [-] 3.0	5 [-] 3.0
Distance-to	Forest (m)	7 [-] *	7 [-] *	7 [-] *	**7 [-] ***	7 [-] *	7 [-] *	5 [-] *	5 [-] *	7 [-] 1.0	7 [-] 1.0
	Marshland (m)	8 [-] ***	8 [-] ***	8 [-] ***	**8 [-] *****	8 [-] ***	8 [-] ***	8 [-] ***	8 [-] ***	9 [-] 3.0	9 [-] 3.0
	Agri-Range (m)	6 [+] ***	6 [+] ***	6 [+] ***	**6 [+] *****	6 [+] ***	6 [+] ***	4 [+] ***	4 [+] ***	6 [+] 3.0	6 [+] 3.0
	Waterbody (m)	3 [-] ***	3 [-] ***	3 [-] ***	**3 [-] *****	3 [-] ***	3 [-] ***	3 [-] ***	3 [-] ***	3 [-] 3.0	3 [-] 3.0
	Watercourse (m)	4 [-] ***	4 [-] ***	4 [-] ***	**4 [-] *****	4 [-] ***	4 [-] ***	7 [-] **	7 [-] **	4 [-] 2.8	4 [-] 2.8
	AIC	2569.23	2569.23	2558.65	**2558.65**	2565.03	2565.03	2567.24	2567.24		
	VIF Range	1.15 - 3.77	1.15 - 3.77	1.13 - 3.78	**1.13 - 3.78**	1.04 - 3.81	1.04 - 3.81	1.21 - 3.72	1.21 - 3.72		
	AIC Zero Infl. Fin. Mod.		2571.23		**2560.65**		2567.03		2569.24		
	Pseudo R^2 [Final v Z.I. Final]		10.0 v 10.0		**10.3 v 10.3**		10.2 v 10.2		10.0 v 10.0		

Global models were identical to final models for CGX, Material, Shape, and Function groups. 'Corridor' (-) and 'Highway' (-) were present in all models; the negative influence of Highway attributed to A10 having less amphibian roadkill compared with R112.

The CGX models included 'crossing structure (full)' (+) and 'crossing structure (half) (+) in addition to 'corridor' and 'highway'. The Shape models included 'bridge' (-) and 'circular'

(+), in addition to 'guardrail' (+), 'corridor' and 'highway'. The Function models included 'wet & interm' (+), in addition to 'corridor' and 'highway'. All eleven landscape predictors were included in final models.

The predictors with the highest aRIVs included 'waterbody (%)' (-), 'marshland (%)' (+), and 'waterbody (m)' (-), with high significance (aSL = 3.0) among these predictors. The lowest aRIV predictors included 'corridor (-), 'crossing structure (full)' (+), and 'wet & interm' (+), with aSLs ranging from 0.0 to 1.8. Interestingly, the coefficients for 'crossing structure (full)' and crossing structure (half)' were 0.166 and 0.326, respectively, suggesting that 'crossing structure (half)' had twice the influence on amphibian roadkill as 'crossing structure (full)', similar to the 2:1 difference in influence produced by crossing structure predictors for amphibians in Scenario A.

Collinearity was minimal (<4), and the final models were all exactly two AIC units less than their zero-inflated versions, support that zero-inflation was not present.

4.4.2. Scenario C, Mammals

The model with the lowest AIC value is the Step 1 land cover model.

Table 12. The predictor variables included in the global and final models for Scenario C: mammals. The relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each included predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor. Included are the AIC values for each model, the minimum - maximum variance inflation factor (VIF) range, the AIC values for the zero-inflated version of the final model, and the pseudo-R^2 values of the final model compared with its zero-inflated version. The models that produced the lowest AIC values contained no structural predictor variables.

SCENARIO C		MAMMALS																		AVERAGES					
		Material						Shape						Function						Global			Final		
		Global			Final			Global			Final			Global			Final								
Predictor Variables		RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	aRIV	I.	aSL	aRIV	I.	aSL
CGX	Corridor																								
	Guardrail																								
	Full Structure																								
	Half Structure																								
	Highway	12	[+]		-	-	-	11	[+]		-	-	-	12	[+]		-	-	-	12	[+]	0.0	-	-	-
Material	Concrete																								
	Metal	13	[-]		-	-	-													13	[-]	0.0	-	-	-
	Plastic																								
Shape	Bridge																								
	Circular							13	[-]		-	-	-							13	[-]	0.0	-	-	-
	Rectangular																								
Function	Dry													13	[-]		-	-	-	13	[-]	0.0	-	-	-
	Wet																								
	Dry & Intermittent																								
	Wet & Intermittent																								
Landcover	Forest (%)	1	[+]	*	**1**	**[+]**	***	1	[+]	*	**1**	**[+]**	***	1	[+]	*	**1**	**[+]**	***	1	[+]	1.0	1	[+]	3.0
	Anthropogenic (%)	2	[+]	***	**2**	**[+]**	***	2	[+]	***	**2**	**[+]**	***	2	[+]	***	**2**	**[+]**	***	2	[+]	3.0	2	[+]	3.0
	Marshland (%)	10	[-]		-	-	-	10	[-]		-	-	-	11	[-]		-	-	-	10	[-]	0.0	-	-	-
	Agri-Range (%)	4	[+]	**	**4**	**[+]**	***	4	[+]	**	**4**	**[+]**	***	4	[+]	**	**4**	**[+]**	***	4	[+]	2.0	4	[+]	3.0
	Waterbody (%)	3	[+]	***	**3**	**[+]**	***	3	[+]	***	**3**	**[+]**	***	3	[+]	***	**3**	**[+]**	***	3	[+]	3.0	3	[+]	3.0
	Watercourse (m/ha)	9	[+]		-	-	-	9	[+]		-	-	-	9	[+]		-	-	-	9	[+]	0.0	-	-	-
Distance-to	Forest (m)	8	[-]		-	-	-	8	[-]		-	-	-	8	[-]		-	-	-	8	[-]	0.0	-	-	-
	Marshland (m)	6	[-]		-	-	-	6	[-]		-	-	-	6	[-]		-	-	-	6	[-]	0.0	-	-	-
	Agri-Range (m)	7	[+]	.	**6**	**[+]**	.	7	[+]	.	**6**	**[+]**	.	7	[+]	.	**6**	**[+]**	.	7	[+]	0.5	6	[+]	0.5
	Waterbody (m)	5	[+]	.	**5**	**[+]**	.	5	[+]	.	**5**	**[+]**	.	5	[+]	.	**5**	**[+]**	.	5	[+]	0.5	5	[+]	0.5
	Watercourse (m)	11	[+]		-	-	-	12	[+]		-	-	-	10	[+]		-	-	-	11	[+]	0.0	-	-	-
AIC		937.34			**927.26**			936.73			**927.26**			937.41			**927.26**								
VIF Range		1.07 - 4.45			**1.45 - 2.51**			1.13 - 4.49			**1.45 - 2.51**			1.07 - 4.47			**1.45 - 2.51**								
AIC Zero Infl. Fin. Mod.					**926.83**						**926.83**						**926.83**								
Pseudo R^2 [Final v Z.I. Final]					**3.6 v 3.0**						**3.6 v 3.0**						**3.6 v 3.0**								

All predictors included in global models, ‘metal’ (-) for the Material group, ‘circular’ (-) for the Shape group, and ‘dry’ (-) were excluded from final models. These structural predictors had the lowest aRIVs and had aSL of zero. ‘Highway’ (+) was likewise excluded from any final model. The predictors with the highest aRIVs included ‘forest (%)’ (+), ‘anthropogenic (%)’ (+), and ‘waterbody (%)’ (+) with aSLs ranging from 1.0 to 3.0. VIF values remained below 5.0 throughout all models, and the AIC values for the zero-inflated final models were lower (0.43 units), however the difference is well below the 2-unit threshold, not large enough to support the presence of zero-inflation is present.

4.4.3. Scenario C, Reptiles

The model with the lowest AIC value was the final Function model, including the predictors 'dry' (-) and 'highway' (-).

Table 13. The predictor variables included in the global and final models for Scenario C: reptiles. The relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each included predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor. Included are the AIC values for each model, the minimum - maximum variance inflation factor (VIF) range, the AIC values for the zero-inflated version of the final model, and the pseudo-R^2 values of the final model compared with its zero-inflated version. The final Function model including 'dry' (-) and 'highway' (-) produced the lowest AIC.

SCENARIO C		REPTILES																		AVERAGES					
		Material						Shape						Function											
		Global			Final			Global			Final			Global			**Final**			Global			Final		
Predictor Variables		RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	RIV	I.	SL	aRIV	I.	aSL	aRIV	I.	aSL
CGX	Corridor																								
	Guardrail																								
	Full Structure																								
	Half Structure																								
	Highway	9	[-]	***	7	[-]	***	9	[-]	***	7	[-]	***	9	[-]	***	**7**	**[-]**	*******	9	[-]	3.0	7	[-]	3.0
Material	Concrete	13	[-]		-	-	-													15	[-]	0.0	-	-	-
	Metal																								
	Plastic																								
Shape	Bridge																								
	Circular																								
	Rectangular							12	[-]	.	-	-	-							13	[-]	0.5	-	-	-
Function	Dry													11	[-]		**8**	**[-]**	**.**	12	[-]	0.0	8	[-]	0.5
	Wet																								
	Dry & Intermittent																								
	Wet & Intermittent																								
Landcover	Forest (%)	1	[+]	***	1	[+]	***	1	[+]	***	1	[+]	***	1	[+]	***	**1**	**[+]**	*******	1	[+]	3.0	1	[+]	3.0
	Anthropogenic (%)	2	[+]	**	2	[+]	***	2	[+]	**	2	[+]	***	2	[+]	**	**2**	**[+]**	*******	2	[+]	2.0	2	[+]	3.0
	Marshland (%)	3	[+]	***	3	[+]	***	3	[+]	***	3	[+]	***	3	[+]	***	**3**	**[+]**	*******	3	[+]	3.0	3	[+]	3.0
	Agri-Range (%)	6	[+]	*	5	[+]	*	6	[+]	*	5	[+]	*	6	[+]	*	**5**	**[+]**	*****	6	[+]	1.0	5	[+]	1.0
	Waterbody (%)	4	[+]	***	4	[+]	***	4	[+]	***	4	[+]	***	4	[+]	**	**4**	**[+]**	*******	4	[+]	2.7	4	[+]	3.0
	Watercourse (m/ha)	10	[+]		-	-	-	10	[+]		-	-	-	12	[+]		-	-	-	10	[+]	0.0	-	-	-
Distance-to	Forest (m)	5	[+]		-	-	-	5	[+]		-	-	-	5	[+]		-	-	-	5	[+]	0.0	-	-	-
	Marshland (m)	12	[+]		-	-	-	13	[+]		-	-	-	13	[+]		-	-	-	14	[+]	0.0	-	-	-
	Agri-Range (m)	8	[+]	*	6	[+]	*	8	[+]	*	6	[+]	*	8	[+]	*	**6**	**[+]**	*****	8	[+]	1.0	6	[+]	1.0
	Waterbody (m)	7	[+]		-	-	-	7	[+]		-	-	-	7	[+]		-	-	-	7	[+]	0.0	-	-	-
	Watercourse (m)	11	[+]		-	-	-	11	[+]		-	-	-	10	[+]		-	-	-	10	[+]	0.0	-	-	-
	AIC	905.97			899.62			903.99			899.62			904.25			**898.40**								
	VIF Range	1.21 - 6.99			1.21 - 5.02			1.27 - 7.13			1.21 - 5.02			1.07 - 7.00			**1.02 - 5.06**								
	AIC Zero Infl. Fin. Mod.				901.62						901.62						**900.40**								
	Pseudo R^2 [Final v Z.I. Final]				6.4 v 6.4						6.4 v 6.4						**6.8 v 6.8**								

'Highway' remained in all final models. The global Material model included 'concrete' (-) and the global Shape model included 'rectangular' (-); both predictors were excluded from final models. The predictors with the highest aRIVs included 'forest (%)' (+), 'anthropogenic (%)' (+), and 'marshland (%)' (+), with aSLs ranging from 2.0 to 3.0. The predictors with the lowest global aRIVs were of the excluded structural predictors, ‘concrete’ (-) and ‘rectangular’ (-), as well as ‘marshland (m)’ (+); aSLs ranged from zero to 0.5. The lowest final model aRIVs included ‘dry’ ‘highway’ and ‘agri-range (m)’ (+); aSL values ranged from 0.5 to 3.0. Global model VIF values ranged from ~1 to 7 but were reduced for final models (~1 to 5). The AIC values among the zero-inflated final models all exceeded those of the final models; zero-inflation is not supported.

4.5 Scenario D

A total of 1127 roadkill were detected, 981 amphibians, 72 mammals, and 74 reptiles during 74 surveys (37 surveys each on A10 and R112) completed in 2021. Scenario D considers only bins with crossing structures; 190 bins, or 19 km of road. The roadkill-per- kilometre rates for amphibians was 51.6/km while the values for mammals and reptiles were 3.8/km and 3.9/km, respectively. The Kruskal–Wallis tests revealed no significant difference in Scenario D roadkill counts by crossing structure forms (Figure 21).

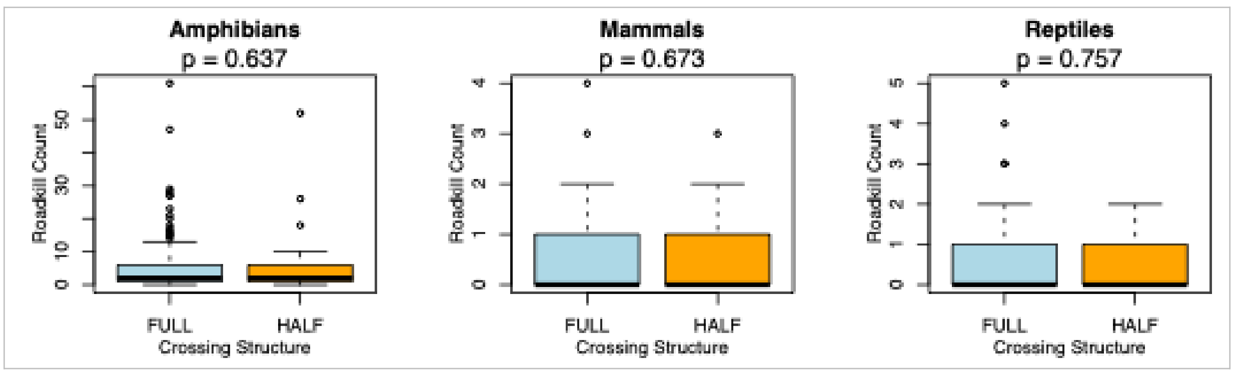


Figure 21. Boxplots illustrating roadkill counts across crossing structure forms (‘FULL’, ‘HALF’) by animal type.

Amphibians were fit with negative binomial models given a ~13.7:1 variance/mean ratio. Mammals were fit with Poisson models (1.2:1). Reptiles best fit a Poisson model (1.5:1). In addition to the Material, Shape, and Function models, models were fit with predictors from the Dimension group. Furthermore, predictors across Material, Shape, and Function groups were fit in combination with Dimension group predictors. These models are referred to as ‘Dimension+’ models, presented below. All continuous predictors were standardized due to large value ranges.

4.5.1. Scenario D, Amphibians

Table 14. The predictor variables included in the global and final models for Scenario D: amphibians. The relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each included predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor. Included are the AIC values for each model, the minimum - maximum variance inflation factor (VIF) range, the AIC values for the zero-inflated version of the final model, and the pseudo-R^2 values of the final model compared with its zero-inflated version. The final Dimension+ model produced the lowest AIC value, including the predictors ‘plastic’ (+), ‘opening’ (-), ‘highway’ (-), and ‘corridor’ (-).

SCENARIO D		AMPHIBIANS										AVERAGES	
		Material		Shape		Function		Dimension		Dimension+			
		Global	Final	Global	Final	Global	Final	Global	Final	Global	**Final**	Global	Final
Predictor Variables		RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	aRIV I. aSL	aRIV I. aSL
CGX	Corridor	14 [-] *	13 [-] *	13 [-] .	13 [-]	12 [-] *	12 [-] *	14 [-] .	13 [-] .	15 [-] .	**14 [-] .**	17 [-] 0.7	15 [-] 0.6
	Guardrail												
	Full Structure												
	Half Structure												
	Highway	10 [-] ***	11 [-] ***	10 [-] ***	11 [-] ***	11 [-] ***	11 [-] ***	12 [-] ***	12 [-] ***	11 [-] ***	**12 [-] *** **	13 [-] 3.0	13 [-] 3.0
Material	Concrete												
	Metal												
	Plastic	12 [+] ***	12 [+] **							13 [+] **	**13 [+] ** **	15 [+] 2.5	14 [+] 2.0
Shape	Bridge												
	Circular			12 [+] *	12 [+] *							7 [+] 0.5	7 [+] 0.5
	Rectangular												
Function	Dry					14 [-]	- - -					9 [-] 0.0	- - -
	Wet												
	Dry & Intermittent												
	Wet & Intermittent												
Dimension	Height												
	Length												
	Opening							1 [-] .	1 [-] .	1 [-]	**1 [-]**	1 [-] 0.3	1 [-] 0.3
	Width												
Landcover	Forest (%)	8 [-] **	8 [-] **	9 [-] **	9 [-] **	9 [-] *	10 [-] **	10 [-] **	10 [-] **	10 [-] **	**10 [-] ** **	12 [-] 1.8	11 [-] 2.0
	Anthropogenic (%)	3 [+] ***	3 [+] ***	3 [+] ***	3 [+] ***	3 [+] ***	3 [+] ***	4 [+] ***	4 [+] ***	4 [+] ***	**4 [+] *** **	4 [+] 3.0	4 [+] 3.0
	Marshland (%)	1 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	1 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	**2 [+] *** **	2 [+] 3.0	3 [+] 3.0
	Agri-Range (%)	6 [+] **	5 [+] **	4 [+] ***	4 [+] ***	4 [+] **	5 [+] **	5 [+] ***	5 [+] ***	6 [+] **	**6 [+] ** **	5 [+] 2.4	6 [+] 2.4
	Waterbody (%)	11 [-] .	10 [-] *	11 [-]	10 [-] *	10 [-] .	9 [-] *	11 [-]	11 [-] *	12 [-]	**11 [-] ***	14 [-] 0.2	12 [-] 1.0
	Watercourse (m/ha)	4 [-] ***	4 [-] ***	5 [-] ***	5 [-] ***	5 [-] ***	4 [-] ***	6 [-] ***	6 [-] ***	5 [-] ***	**5 [-] *** **	5 [-] 3.0	5 [-] 3.0
Distance-to	Forest (m)	9 [-] *	9 [-] *	8 [-] **	8 [-] **	7 [-] **	8 [-] **	8 [-] **	7 [-] **	9 [-] *	**9 [-] ***	11 [-] 1.6	10 [-] 1.6
	Marshland (m)	7 [-] ***	7 [-] ***	7 [-] ***	7 [-] ***	6 [-] ***	7 [-] ***	9 [-] **	9 [-] **	8 [-] **	**8 [-] ** **	10 [-] 2.6	9 [-] 2.6
	Agri-Range (m)	2 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	2 [+] ***	1 [+] ***	3 [+] ***	3 [+] ***	3 [+] ***	**3 [+] *** **	3 [+] 3.0	2 [+] 3.0
	Waterbody (m)	13 [+]	- - -	14 [+]	- - -	13 [+]	- - -	13 [+]	- - -	14 [+]	**- - -**	16 [+] 0.0	- - -
	Watercourse (m)	5 [-] **	6 [-] **	6 [-] **	6 [-] *	8 [-]	6 [-] *	7 [-] *	8 [-] *	7 [-] **	**7 [-] ** **	8 [-] 1.4	8 [-] 1.4
	AIC	920.28	918.94	927.22	925.48	929.49	927.47	925.25	923.77	919.01	**917.67**		
	VIF Range	1.53 - 3.63	1.46 - 3.58	1.53 - 3.60	1.45 - 3.53	1.35 - 3.62	1.34 - 3.53	1.07 - 3.63	1.07 - 3.57	1.08 - 3.67	**1.08 - 3.61**		
	AIC Zero Infl. Fin. Mod.		920.94		927.48		929.47		925.77		**919.67**		
	Pseudo R^2 [Final v Z.I. Final]		13.4 v 13.4		12.8 v 12.6		12.4 v 12.4		13.0 v 13.0		**13.7 v 13.7**		

The model with the lowest AIC value was the Dimension+ final model, including the predictors ‘corridor’ (-), ‘plastic’ (+), ‘opening’ (-), and ‘highway’ (-).

The predictors ‘corridor’ (-) and ‘highway’ (-) were included in all models. In addition to these two predictors, the Material models included ‘plastic’ (+), the Shape models included ‘circular’ (+), the global Function model included ‘dry’ (-) but was excluded from the final Function model, and the Dimension model included ‘opening’ (-). ‘Opening’ was the predictor with the highest aRIV, along with ‘marshland (%)’ (+) and ‘agri-range (m)’ (+); their aSLs ranged from 0.3 to 3.0. For global models, the predictors with the lowest aRIVs included ‘plastic’, ‘corridor’ and ‘waterbody (m)’ (+), while for final models the lowest aRIVs included ‘corridor’, ‘plastic’, and ‘highway’, as both ‘dry’ and ‘waterbody (m)’ were excluded from final models. The aSLs for these predictors ranged from 0.6 to 3.0. VIF remained low across all models (< 4) and the AIC values for the final models were exactly 2 units lower than those of their zero-inflated versions, supporting the absence of zero-inflation.

4.5.2. Scenario D, Mammals

Table 15. The predictor variables included in the global and final models for Scenario D: mammals. The relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each included predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor. Included are the AIC values for each model, the minimum - maximum variance inflation factor (VIF) range, the AIC values for the zero-inflated version of the final model, and the pseudo-R^2 values of the final model compared with its zero-inflated version. The lowest AIC final model included 'length' (-).

SCENARIO D		MAMMALS										AVERAGES	
		Material		Shape		Function		Dimension		Dimension+		Global	Final
		Global	Final	Global	Final	Global	Final	Global	**Final**	Global	**Final**		
Predictor Variables		RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	aRIV I. aSL	aRIV I. aSL
CGX	Corridor												
	Guardrail												
	Full Structure												
	Half Structure												
	Highway	13 [+]	- - -	13 [-]	- - -	13 [-]	- - -	13 [+]	- - -	13 [+]	- - -	16 [+/-] 0.0	- - -
Material	Concrete												
	Metal	12 [-]	- - -									6 [-] 0.0	- - -
	Plastic												
Shape	Bridge			12 [+]	- - -							6 [+] 0.0	- - -
	Circular												
	Rectangular												
Function	Dry												
	Wet					12 [-]	- - -					6 [-] 0.0	- - -
	Dry & Intermittent												
	Wet & Intermittent												
Dimension	Height												
	Length							7 [-] .	**9 [-]**	7 [-] 0.5	**9 [-]**	10 [-] 0.5	9 [-] 0.0
	Opening												
	Width												
Landcover	Forest (%)	1 [-] **	1 [-] **	1 [-] **	1 [-] **	1 [-] **	1 [-] **	1 [-] **	**1 [-] ** **	1 [-] ###	**1 [-] ** **	1 [-] 2.0	1 [-] 2.0
	Anthropogenic (%)	3 [-] *	3 [-] .	3 [-] *	3 [-] .	3 [-] *	3 [-] .	4 [-] .	**3 [-] .**	4 [-] 0.5	**3 [-] .**	3 [-] 0.8	3 [-] 0.5
	Marshland (%)	4 [-] *	6 [-] *	4 [-] *	6 [-] *	4 [-] *	6 [-] *	3 [-] *	**5 [-] ***	3 [-] 1	**5 [-] ***	4 [-] 1.0	6 [-] 1.0
	Agri-Range (%)	5 [-] *	5 [-] *	5 [-] *	5 [-] *	5 [-] *	5 [-] *	5 [-] *	**6 [-] ***	5 [-] 1	**6 [-] ***	5 [-] 1.0	5 [-] 1.0
	Waterbody (%)	2 [-] **	2 [-] **	2 [-] **	2 [-] **	2 [-] **	2 [-] **	2 [-] **	**2 [-] ** **	2 [-] 2	**2 [-] ** **	2 [-] 2.0	2 [-] 2.0
	Watercourse (m/ha)	7 [-] *	7 [-] *	7 [-] *	7 [-] *	7 [-] *	7 [-] *	8 [-] *	**7 [-] ***	8 [-] 1	**7 [-] ***	11 [-] 1.0	7 [-] 1.0
Distance-to	Forest (m)	6 [-]	4 [-] .	6 [-]	4 [-] .	6 [-]	4 [-] .	6 [-]	**4 [-] .**	6 [-] 0	**4 [-] .**	6 [-] 0.0	4 [-] 0.5
	Marshland (m)	10 [-]	- - -	10 [-]	- - -	10 [-]	- - -	11 [-]	- - -	11 [-] 0	- - -	14 [-] 0.0	- - -
	Agri-Range (m)	8 [+] .	8 [+] .	8 [+] .	8 [+] .	8 [+] .	8 [+] .	10 [+]	**8 [+]**	10 [+] 0	**8 [+]**	12 [+] 0.3	8 [+] 0.3
	Waterbody (m)	9 [+]	- - -	9 [+]	- - -	11 [+]	- - -	12 [+]	- - -	12 [+] 0	- - -	15 [+] 0.0	- - -
	Watercourse (m)	11 [-]	- - -	11 [-]	- - -	9 [-]	- - -	9 [-]	- - -	9 [-] 0	- - -	13 [-] 0.0	- - -
AIC		314.64	309.00	314.76	309.00	315.78	309.00	312.23	**308.83**	312.23	**308.83**		
VIF Range		1.91 - 9.98	1.44 - 9.22	1.07 - 9.99	1.44 - 9.22	1.31 - 9.77	1.44 - 9.22	1.42 - 9.54	**1.10 - 9.44**	1.42 - 9.54	**1.10 - 9.44**		
AIC Zero Infl. Fin. Mod.			308.32		308.32		308.32		**308.16**		**308.16**		
Pseudo R^2 [Final v Z.I. Final]			6.5 v 6.4		6.5 v 6.4		6.5 v 6.4		**7.2 v 7.1**		**7.2 v 7.1**		

The models (Dimension = Dimension+) producing the lowest AIC included the predictor ‘length’ (-). ‘Length’ was the only structural variable included in both global and final models. Predictors that were included in global models but absent from final models included ‘metal’ (-), ‘bridge’ (+), ‘wet’ (-), and ‘highway’ (+/-). ‘Highway’ is the only structural predictor in this study to have both positive and negative influence on roadkill within the same scenario (Scenario D: mammals and again for Scenario D: reptiles, see section 4.4.3).

The predictors with the highest aRIVs were ‘forest (%)’ (-), ‘waterbody (%)’ (-), and ‘anthropogenic (%)’ (-), with aSLs that ranged between 0.5 and 2.0. The global model predictors with the lowest aRIVs included ‘highway’, ‘marshland (m)’ (-), and ‘waterbody (m)’ (+); the aSLs for these predictors were all zero. Lowest final model aRIVs included 'watercourse (m)’ (-), ‘agri-range (m)’ (+), and ‘length’ (-), with aSLs ranging from 0 to 1.0.

Global model VIFs approached the problematic threshold of 10 (the highest VIF was for ‘forest (%)’ at 9.994), with a slight reduction in the highest VIF in the final models (the VIF for ‘forest (%)’ was reduced to a maximum of 9.44; see Appendix C for all predictor VIFs). The zero inflated models all yielded lower AIC values compared with the final models, suggesting some level of zero-inflation; however, the difference between the AIC of a final model and that of its zero-inflated equivalent remained below 1 unit.

4.5.3. Scenario D, Reptiles

Table 16. The predictor variables included in the global and final models for Scenario D: reptiles. The relative importance values (RIV), direction of influence (I.), and significance (SL) are provided for each included predictor variable. An average RIV (aRIV) and average significance (aSL) are given for each predictor. Included are the AIC values for each model, the minimum – maximum variance inflation factor (VIF) range, the AIC values for the zero-inflated version of the final model, and the pseudo-R^2 values of the final model compared with its zero-inflated version. The final model including 'crossing structure (full)' produced the lowest AIC.

SCENARIO D		REPTILES												AVERAGES	
		CGX		Material		Shape		Function		Dimension		Dimension+		Global	Final
		Global	**Final**	Global	Final	Global	Final	Global	Final	Global	Final	Global	Final		
	Predictor Variables	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	RIV I. SL	aRIV I. aSL	aRIV I. aSL
CGX	**Corridor**														
	Guardrail														
	Full Structure	11 [-]	**10 [-] .**											17 [-] 0.0	14 [-] 0.5
	Half Structure	11 [+]	- - -											17 [+] 0.0	- - -
	Highway	13 [-] .	**11 [-] ***	12 [-]	10 [-]	11 [-]	10 [-]	12 [-]	10 [-]	15 [+]	- - -	15 [+]	- - -	21 [+/-] 0.1	11 [-] 0.2
Material	**Concrete**														
	Metal			13 [+]	- - -									9 [+] 0.0	- - -
	Plastic														
Shape	**Bridge**														
	Circular														
	Rectangular					13 [-]	- - -							9 [-] 0.0	- - -
Function	**Dry**														
	Wet							13 [-]	- - -					9 [-] 0.0	- - -
	Dry & Intermittent							13 [+]	- - -					9 [+] 0.0	- - -
	Wet & Intermittent														
Dimension	**Height**									6 [+] **	6 [+] **	6 [+] **	6 [+] **	6 [+] 2.0	8 [+] 2.0
	Length									9 [-]	11 [-] *	9 [-]	11 [-] *	15 [-] 0.0	15 [-] 1.0
	Opening									4 [-]	4 [-] .	4 [-]	4 [-] .	4 [-] 0.0	4 [-] 0.5
	Width														
Landcover	**Forest (%)**	1 [+] ***	**1 [+] *****	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] ***	1 [+] 3.0	1 [+] 3.0
	Anthropogenic (%)	3 [+] **	**2 [+] ****	3 [+] **	3 [+] **	3 [+] **	3 [+] **	3 [+] **	3 [+] **	3 [+] **	2 [+] **	3 [+] **	2 [+] **	3 [+] 2.0	2 [+] 2.0
	Marshland (%)	2 [+] ***	**3 [+] *****	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	2 [+] ***	3 [+] ***	2 [+] ***	3 [+] ***	2 [+] 3.0	2 [+] 3.0
	Agri-Range (%)	8 [+] *	**8 [+] ***	7 [+] **	8 [+] *	7 [+] **	8 [+] *	7 [+] **	8 [+] *	10 [+] *	9 [+] *	10 [+] *	9 [+] *	13 [+] 1.5	13 [+] 1.0
	Waterbody (%)	4 [+] ***	**4 [+] *****	4 [+] ***	4 [+] ***	4 [+] ***	4 [+] ***	4 [+] ***	4 [+] ***	5 [+] ***	5 [+] ***	5 [+] ***	5 [+] ***	5 [+] 3.0	6 [+] 3.0
	Watercourse (m/ha)	7 [+] .	**7 [+] ***	8 [+] .	7 [+] *	8 [+] .	7 [+] *	8 [+] .	7 [+] *	11 [+] .	10 [+] .	11 [+] .	10 [+] .	14 [+] 0.5	12 [+] 0.8
Distance-to	**Forest (m)**	9 [+]	- - -	9 [+]	- - -	9 [+]	- - -	10 [+]	- - -	12 [+]	- - -	12 [+]	- - -	16 [+] 0.0	- - -
	Marshland (m)	5 [+] *	**6 [+] ***	5 [+] *	5 [+] *	5 [+] *	5 [+] *	5 [+] *	5 [+] *	8 [+] *	7 [+] *	8 [+] *	7 [+] *	6 [+] 1.0	7 [+] 1.0
	Agri-Range (m)	14 [+]	- - -	11 [+]	- - -	12 [+]	- - -	11 [+]	- - -	13 [+]	12 [+]	13 [+]	12 [+]	20 [+] 0.0	4 +][+ 0.0
	Waterbody (m)	6 [+]	**5 [+]**	6 [+]	6 [+]	6 [+]	6 [+]	6 [+]	6 [+]	7 [+] .	8 [+]	7 [+] .	8 [+]	8 [+] 0.2	10 [+] 0.0
	Watercourse (m)	10 [-] .	**9 [-] ***	10 [-]	9 [-] .	10 [-]	9 [-] .	9 [-]	9 [-] .	14 [-]	- - -	14 [-]	- - -	19 [-] 0.1	8 [-] 0.4
	AIC	301.93	**299.90**	303.99	300.62	303.12	300.62	303.87	300.62	301.07	298.26	301.07	298.26		
	VIF Range	1.41 - 8.42	**1.24 - 7.25**	1.20 - 8.05	1.05 - 6.86	1.24 - 8.21	1.05 - 6.86	1.22 - 8.18	1.05 - 6.86	1.42 - 8.23	1.14 - 4.48	1.42 - 8.23	1.14 - 4.48		
	AIC Zero Infl. Fin. Mod.		**297.80**		298.28		298.28		298.28		298.40		298.40		
	Pseudo R^2 [Final v Z.I. Final]		**15.2 v 14.2**		14.4 v 13.5		14.4 v 13.5		14.4 v 13.5		16.3 v 14.7		16.3 v 14.7		

The model producing the lowest AIC was the final CGX model that included ‘crossing structure (full)’ (-) and ‘highway’ (-).

The global Material model included ‘metal’ (+), ‘rectangular’ (-) was included in the global Shape model, and both ‘wet’ (-) and ‘dry & interm’ (+) were included in the global Function model. None of these predictors were included in the final models. The global Dimension model was identical to the global Dimension+ model; they included ‘height’ (+), ‘length’ (-), ‘opening’ (-), and ‘highway’ (+). The final models for Dimension and Dimension+ were identical as well, with only ‘highway’ excluded from their global model counterpart. Note that ‘highway’ was positively correlated with reptile roadkill for Dimension and Dimension+ models while its association to reptile roadkill was negative in the CGX, Material, Shape, and Function model. ‘Highway’ switched its direction of influence for in both the mammal and reptile analysis in Scenario D. The lowest AIC final model for Dimension and Dimension+ originally included ‘width’ as well, however its inclusion produced VIF values exceeding 10. ‘Opening’ is direct directly influenced by the value of ‘width’ as ‘opening’ is the product of ‘height’ and ‘width’ (if ‘bridge’ or ‘rectangular’) and π(‘width’/2)^2 if ‘circular’. A series of test models were fit with all of the predictors from the lowest AIC model, including ‘width’, with each test model excluding one predictor in turn. AIC values were calculated and the model that produced the lowest AIC while also producing VIF values below 10 was selected, i.e., ‘width’ was excluded. VIF values across global models ranged from 1.20 to 8.42; however, for final models, VIF values were reduced, with a range from 1.05 to 7.25.

The predictors with the highest aRIVs were ‘forest (%)’ (+), ‘marshland (%)’ (+), and ‘anthropogenic (%)’ (+); aSLs ranged from 2.0 to 3.0. The lowest global aRIVs included ‘watercourse (m)’ (-), ‘agri-range (m)’ (+), and ‘highway’ (+/-); these predictors had aSLs ranging between 0.1 and 1.0. The lowest aRIVs for the final models included ‘agri-range (%)’ (+), ‘length’, and ‘crossing structure (full)’ (-); aSLs ranged between 0.5 and 1.0. Zero-inflation may be present as indicated by the difference in AIC between the final CGX model and its zero-inflated counterpart (2.1 units). The differences between all other final models and their zero-inflated counterparts are less than 2 units.

DISCUSSION

5.1.1 Influence of Crossing Structures

The results of the Kruskal–Wallis tests regarding the differences in roadkill count and crossing structure forms and absence, by animal type were significant among Scenario A amphibians ($p = 0.0169$), specifically between half crossing structures and bins without crossing structures (adj. $p = 0.014$), and marginally significant between half crossing structures and full crossing structures (adj. $p = 0.050$). Furthermore, there was no significant difference between full crossing structures and bins without crossing structures (adj. $p = 0.894$). Half crossing structures have the greatest mean ($\bar{x} = 9.92$) and median (5) compared with both full crossing structures ($\bar{x} = 6.2$; median = 2) and bins without crossing structures ($\bar{x} = 4.62$; median = 3). Correspondingly, in Scenario A amphibian models, both forms of crossing structures were positively associated with amphibian roadkill, where half crossing structures (Coeff. = 0.392) had twice the influence over full crossing structures (Coeff. = 0.169). In Scenario C amphibian models, similar differences between the coefficients for full crossing structures (Coeff. = 0.166) and half crossing structures (Coeff. = 0.326) were observed. Taken together, these findings suggest that amphibians may have used half crossing structures to cross under one set of lanes on A10 but were killed while attempting to cross the remaining set of lanes at grade.

Table 17. A summary of crossing structure form and absence bins with sample size (*n*), mean, and median given for each category.

	n	Mean ($\bar{x}$)	Median
'Crossing structure (full)'	49	6.20	2
'Crossing structure (half)'	36	9.92	5
No crossing structure	305	4.62	3

The higher mean and median of amphibian roadkill counts in bins with full crossing structures compared to those without may reflect a greater abundance of amphibians in the surrounding habitat. Among these full structures, 17 are ‘dry’ while 32 support either permanent ($n = 27$) or intermittent ($n = 5$) water flow. Elevated roadkill counts at these locations could be attributed to higher local amphibian densities supported by adjacent water sources, increasing the likelihood of road mortality. However, it is also possible that a correspondingly greater number of amphibians in these areas are successfully using full crossing structures to cross under A10.

For reptiles, the global model coefficient for full crossing structures was -0.662. In Scenario D ‘xfull’ was dummy coded where 1 = presence and 0 = absence, with an absence of ‘xfull’ requiring a presence of ‘xhalf’; the negative influence of ‘xfull’ is in relation to that of the reference level, ‘xhalf’. In the final model, ‘crossing structure (full)’ was included and its negative influence increased to –0.729. A stronger negative influence for full crossing structures in reptile models may support the above hypothesis for amphibians, that wildlife are using half crossing structures to safely cross one side of the divided highway only to be killed while trying to cross the other side of the highway at grade.

Table 18. Crossing structure influence on roadkill, by animal type and scenario.

Animal Type	Scenario & Model	Full Structure [Influence]	Half Structure [Influence]	Comments
Amphibians	A [Global]	Present [+]	Present [+]	$Coeff_{Full}$: 0.169; $Coeff_{Half}$: 0.392
	A [Final]	Absent	Present [+]	Global $Coeff_{Half}$: 0.392; Final $Coeff_{Half}$: 0.364
	C [Global]	Present [+]	Present [+]	$Coeff_{Full}$: 0.166; $Coeff_{Half}$: 0.326
	C [Final]	Present [+]	Present [+]	Global = Final model; no change
Reptiles	D [Global]	Present [-]	Present [+]	$Coeff_{Full}$: -0.662
	D [Final]	Present [-]	Absent	Final $Coeff_{Full}$: -0.729

Interestingly, an earlier analysis of crossing structure influence relied on a sole crossing structure presence/absence predictor variable, 'xstruc'. This variable appeared in a global mammal model for A10 in Scenario B, with a negative direction of influence (Global $Coeff_{xstruc}$: -0.196). Additionally, 'xstruc' was included in amphibian models in Scenario A and C; however, there was no CGX model for reptiles. Taken together, crossing structures maintain a positive influence on roadkill for amphibians, suggesting more amphibian abundances in the vicinity of crossing structures available to be killed by passing traffic because crossing structures are often located along watercourses, providing habitat for amphibians. If the mammal example from the previous analysis is included, crossing structures have a negative influence on roadkill for mammals and full crossing structures have a negative influence on reptile roadkill, suggesting crossing structure use by these wildlife types to cross under the highways. However, it is important to note that the relatively small dimensions of 'HALF' (diameters from 0.2 m to 1.5 m, mean = 0.41 m) limit usage to wildlife with small body sizes and to wildlife not adverse to entering small, enclosed spaces.

The results of the Wilcoxon rank-sum tests performed to assess the influence of 'HALF' on roadkill amounts between the north and south sides of A10 produced a significant result for medium-sized mammals (p = 0.0236) and a marginally significant result for amphibians (p = 0.0829). Interestingly, while these tests produced significant results which aligned with the alternate hypothesis that there would be a difference in roadkill totals between 'SAME' (the side with 'HALF') and 'OPPOSITE' (the side without 'HALF'), we assumed more roadkill on 'OPPOSITE' and less roadkill on 'SAME', but for most analyzed groups of wildlife there were more roadkill on 'SAME' and less roadkill on 'OPPOSITE' (Table 19).

Table 19. A summary of 'SAME' and 'OPPOSITE' roadkill totals, by wildlife group analyzed.

	'SAME' Roadkill Total	'OPPOSITE' Roadkill Total

Amphibians	72% [252]	28% [97]
Medium-sized mammals	82% [14]	18% [3]
Small mammals	43% [10]	57% [13]
Medium & small mammals	60% [24]	40% [16]
Reptiles	52% [11]	48% [10]
Snakes	47% [7]	53% [8]

It is possible that wildlife were not using 'HALF' as crossing structures, or that wildlife used 'HALF' crossing structures but there were more individuals in the vicinity of 'HALF' to increase roadkill. We do not know which direction wildlife travelled (crossing A10 south to north or north to south) and if crossing directions were predominantly in one direction, relatively equal, or if seasonality had an influence (e.g., south to north crossing in June and July, north to south crossing in August and September). In addition to the aforementioned size restrictions of 'HALF', all of these structures were 'circular' and 'dry'; all three materials were represented (8 concrete, 10 metal, and 20 plastic), and analysis shows a correlation between materials and roadkill levels (discussed below). Future studies should incorporate temperature, precipitation, and seasonality predictors in effort to account for the potential influence of these factors on roadkill.

5.1.2 Influence of Wildlife Corridors

Curiously, Wildlife Corridor – designed for use by large and medium-size mammals, with the assumption that more mammals would be moving in these areas – was included (negatively) in two final models for Scenario A; this may suggest a lower number of mammals within the wildlife corridor, a result at odds with its design and presumed functionality. Reduced mammal roadkill in wildlife corridors overall is also supported by the remaining predictors included in Scenario A models: 'concrete', 'rectangular', and 'dry'; it is possible that nearby mammals are making use of concrete, rectangular, and dry structures to cross under the roadway rather than at grade. Moreover, the data used for Scenario A had the largest sample size of mammal roadkill ($n_A = 453$) compared to the other scenarios ($n_{B(A10)} = 142$; $n_{B[R112]} = 84$; $n_C = 226$; $n_D = 72$) and had the highest number of surveys (165) over the longest period of time (three years; for direct comparability, data for Scenarios B, C, and D included 2021 survey results only from 37 surveys). These characteristics of Scenario A suggest a greater inferential strength for the predictors included in the scenario's models. This contrast in results underscores the need for surveys to be performed as consistently as possible and spanning the greatest duration of time possible.

5.1.3 Influence of Guardrails

'Guardrail' was present in all global and final reptile models for Scenario B on R112, where it had a negative influence on roadkill; 'guardrail' was not included in any reptile Scenario C model. In contrast, 'guardrail' was included in two global and final amphibian models for Scenario C (but in no Scenario B models), where it was positively associated with roadkill (see Section 5.6. Comparing Autoroute 10 and Route 112, for more). It is unlikely that the guardrails themselves act directly as barriers to road surface access for amphibians or that they attract reptiles onto the road surface. A more plausible explanation for the influence of 'guardrail' might involve the gravel or rocky substrate commonly present around guardrail installations, attracting reptiles for basking or nesting (Shine et al., 2004). Conversely, amphibians may be deterred by heated gravel and rocky substrate, or perhaps steep embankments are an additional deterrent; steep embankments are common in locations where guardrails are often installed for driver safety. Bi et al. (2023) found that amphibians are capable of climbing concrete slopes up to 45° but not beyond 65°. While it is likely that most roadside embankments have a slope less than 65°, it may be true that moderate slopes are enough of a deterrent to discourage amphibians from making a full ascent up to the road surface. 'Guardrail' was not included in any mammal model, suggesting no effect or that their potential proxy effects may be more relevant to amphibians or thermoregulating animals.

5.2. Influence of Materials

'Plastic' was consistently associated with higher levels of amphibian roadkill across all four scenarios. Brunen et al. (2020) observed reduced crossing rates through plastic culverts when compared to those made of concrete and metal; however, their study focused on mammals only. While 'plastic' was not included in any mammal model, 'concrete' was, and it was negatively associated with mammal roadkill. 'Concrete' was included in one final amphibian model in Scenario B [A10] with a negative influence (and in one global model, also in Scenario B but on R112; however, it was excluded from the final R112 model). For reptiles, 'concrete' had a positive influence in Scenario A but a negative influence in Scenario C. In comparing the textures of concrete, metal, and plastic crossing structures, concrete structures exhibit a similar traction to that of natural substrates (Brunen et al., 2020), a characteristic which may make concrete crossing structures more favourable to mammals and explain the negative influence of 'concrete' . Brunen et al. (2020) also noted a reduced echo in concrete structures when compared to metal or plastic structures, perhaps an advantage of 'concrete' over the other two materials for mammals. 'Concrete' was one of only five structural predictors to be included in a final mammal model, along with 'corridor', 'dry', 'wet', and 'length' —all of which were negatively associated with roadkill. For reptiles, 'plastic' was negatively associated with roadkill in the global model for Scenario B (A10), but its influence was weak; the coefficient was small, and the variable was excluded from the final model. 'Metal' was included in four global mammal models with a negative influence on roadkill (except for R112 in Scenario B, where 'metal' was positive).

‘Metal was included in two global reptile models, Scenario B (R112) where the direction of influence was positive and Scenario D where it was negative. ‘Metal’ did not appear in any final model, and the predictor’s significance was always zero in models where ‘metal’ was included. From these results, mammals appear to have preferred ‘concrete’ crossing structures, for amphibians’ ‘plastic’ is associated with increased roadkill, and for reptiles, results were mixed, however, ‘plastic; was never included in any model, indicating ‘concrete’ and ‘metal’ are more influential.

5.3. Influence of Shapes

The shape of a crossing structure can influence how water flows through it and whether a dry, walkable surface remains accessible for wildlife use. As water level increases in a circular structure, the portion of walkable area decreases and the angle of the remaining dry portion increases. If levelled properly, rectangular crossing structures would not have any dry area for wildlife passage (although, it is possible that the structure is not perfectly level, and that one side of the structure has deeper water flow than that of the opposite side, which may remain dry). For ‘bridge’, both flowing water and a dry pathway may be present, but the size of the opening and volume of the structure would be greater than that of both ‘circular’ and ‘rectangular’ structures. In general, Shape predictors had a weak association with roadkill in global models and were often excluded from final models. ‘Bridge’ was included in two amphibian final models, both with a negative influence on roadkill. ‘Bridge’ was included in only one global model for mammals and for reptiles, with a positive influence on roadkill. The influence of ‘bridge’ was weak for both mammal and reptile global models and the predictor was excluded from both of the two final models. ‘Bridge’ (or viaduct) crossing structure shapes are known to be attractive crossing structure forms, in part because ample height, width, natural substrate bottoms, and the likelihood of a dry pathway (Denneboom et al., 2021). While some ‘bridge’ structures in this study had natural bottoms, others were roadway underpasses. It is possible that there were not enough ‘bridge’ crossing structures included to produce strong results for mammals or reptiles.

‘Circular’ was included in four amphibian models with a consistent positive relation to roadkill. For global mammal models, ‘circular’ was twice negative for Scenario B (A10) and Scenario C, and once positive for Scenario B (R112); it was not included in any final mammal model. For Reptiles, ‘circular’ did not appear in any model. ‘Rectangular’ structures were positively correlated with roadkill for amphibians (one global model) but negatively correlated for mammals (one global model) and reptiles (three global models). ‘Rectangular’ was dropped from all final models except for Scenario B (A10), reptiles.

Taken together, it is possible that of the Material, Shape, or Function predictors, those of Material and Function are more influential on potential wildlife usage. Importantly, the proportions of ‘bridge’, ‘circular’, and ‘rectangular’ were highly uneven within and between highways. In all scenarios, ‘bridge’ structures comprised no more than 6% of the total. On A10, the dominant shape was ‘circular’ (85%), whereas on R112, it was ‘rectangular’ (86%). Unbalanced categorical predictor levels can lead to estimates with high variability; the variability of estimates tend to increase when the proportion of zeros or ones in the dataset is extreme (Salas-Eljatib et al., 2018). A higher amount of mammal and reptile data would aid in stabilizing predictor coefficients, especially for Scenarios B, C, and D.

5.4. Influence of Functions

The importance of a dry pathway for wildlife movement is supported by the negative association between ‘dry’ and roadkill in all mammal and reptile models. In contrast, ‘wet & interm’ was positively associated with roadkill for both mammals and reptiles, indicating that these animal types favour a passage with dry paths. ‘Dry & interm’ was positively associated with reptile roadkill in one global model; however, its influence was weak, and the variable was excluded from the final model. For mammals, these findings align with Brunen et al. (2020), who reported that mammals generally avoid culverts without a dry path, with the exception of raccoons, which were less deterred.

For amphibians, results were more variable. Across all scenarios, every Function predictor was included in a model, with a positive influence on roadkill, i.e., ‘wet’, ‘dry & interm’, and ‘wet & interm’ were included in one model each, while ‘dry’ was included in three models, with a positive influence on roadkill in two of those three models. The only occurrence of any Function predictor with a negative influence on roadkill was in Scenario D where ‘dry’ was included in a global model but excluded in the final model. Amphibians typically prefer soil-lined culverts that are nearby to water with pooled water near the entrance to encourage entry, but without deep water within the structure itself should a dry path be absent, so as not to hinder successful passage (Helldin & Petrovan, 2019; Lesbarrères et al., 2004). As such, conditions favourable for amphibian mobility may have not been captured using the ‘wet’, ‘dry’, ‘dry & interm’, or ‘wet & interm’ categorical assignments; perhaps these assignments were too coarse or generalized to meaningfully capture the environmental conditions relevant to amphibians. Additionally, Pagany (2020) suggested including a ‘weather’ predictor to account for the influence of temperature or precipitation on wildlife movement and thus serve as a possible roadkill predictor. From personal observation, large numbers of amphibian roadkill were recorded during or immediately following precipitation events, or during periods of high atmospheric humidity; rainfall and high humidity levels were positively correlated with emergence and increased distances travelled (Roe & Grayson, 2008). While temperature and general weather conditions were recorded, we did not include temperature and precipitation data in the analysis, and we acknowledge that doing so would require a major revision to our data aggregation and statistical methods. Moreover, considering the relatively small movement profiles for amphibians, weather conditions may have to be recorded every few hundred meters rather than a regional average for this data to be a meaningful predictor for amphibian roadkill.

5.5. Influence of Dimensions and Dimension+

According to Denneboom et al. (2021), longer culverts were associated with reduced crossing rates across all animal groups (except small mammals), whereas greater width and height were shown to encourage usage among amphibians, mammals, and reptiles. In Scenario D, the Dimension model for amphibians included Wildlife Corridor and Opening, both negatively associated with roadkill. The Dimension+ model introduced Plastic, which was positively associated with roadkill, and produced the lowest AIC value among all amphibian models in Scenario D. There was no change between the Dimension and Dimension+ models for both mammals and reptiles, indicating that no additional predictor or combination of additional predictors absent from the Dimension model produced a lower AIC than the Dimension model itself, i.e., given the predictors available, the Dimension model provided the best model fit. For mammals, only ‘length’ (-) was included in the global model and retained in the final model. For reptiles, ‘height’, ‘length’, ‘width’, and ‘opening’ were all initially included. However, due to high VIF values indicating collinearity, ‘width’ was excluded, while ‘height’ (+), ‘length’ (-), and ‘opening’ (-) were retained. These findings across all animal types align with Denneboom et al. (2021) for ‘height’ and ‘opening’ but not for ‘length’. However, because the lengths of ‘crossing structure (half)’ (average length = 28.6m; median = 25.1m) are less than the lengths of ‘crossing structure (full)’ (on A10, average length = 64.6m, median = 63.3m), the results regarding the negative influence of ‘length’ on roadkill may support the hypothesis posited in Section 5.1, that as wildlife use crossing structures spanning only one direction or two lanes, e.g., ‘crossing structure (half)’, they are killed while attempting to cross the other side of the highway at grade. As the value of ‘length’ increases, roadkill decreases, i.e., higher roadkill in areas of smaller ‘length’ values and lower roadkill in areas with greater values of ‘length’ will be observed.

Perhaps just as interesting as the predictors included in Dimension+ models are the predictors that were not included. Despite the flexibility of the Dimension+ framework to test all possible combinations of structural variables, only one model included an additional variable to the Dimension model, for amphibians, ‘plastic’ (+), and ‘corridor’ (-) were included. This may simply reflect insufficient data, especially considering the number of amphibians included (n = 981) when compared to those of mammals (n = 72) and reptiles (n = 74) and given the high percentage of bins with zero roadkill for mammals (71%) and reptiles (72%), compared to amphibians (17%). Furthermore, the reduction in AIC of 2.1 units from the CGX reptile final model to its zero-inflated equivalent supports the possibility of zero-inflation, the only occurrence in this study where the difference in AIC between a final model and its zero-inflated counterpart exceeded 2 units.

5.6. Comparing Autoroute 10 and Route 112

For amphibians and mammals, final models for Route 112 excluded all structural predictors that were included in the global models; the final models for both amphibians and mammals on R112 included only landcover predictors. In contrast, final A10 amphibian models included ‘corridor’ (-), ‘plastic’ (+), ‘concrete’ (-), ‘bridge’ (-), and ‘dry’ (+), while final A10 mammal models included ‘wet’ (-).

For amphibians, ‘concrete’ was included in both A10 and R112 models, while for mammals, ‘metal’ and ‘circular’ were included in both A10 and R112 global models. For reptiles, there was no overlap in predictor selection between A10 and R112 models. On A10, Corridor (–) appeared in all reptile models, while it was entirely absent from R112, whereas Guardrail (–) was consistently included on R112 but absent on A10. Other predictors in A10 models included ‘rectangular’ (–), ‘plastic’ (–), and ‘dry & interm’ (+), with ‘plastic’, and ‘dry & interm’ excluded from the final models. R112 models included ‘wet & interm’ (+), 'bridge’ (+), and ‘metal’ (–), with only ‘wet & interm’ remaining in the final model.

Contrasting the predictors included in Scenario B models (A10 and R112 separate) with those in Scenario C models (A10 and R112 combined) revealed an interesting dynamic, where some predictors were included in models in both scenarios, some predictors were present in Scenario B models but excluded in Scenario C models, and some predictors were absent in Scenario B but included in Scenario C models (aside from ‘highway’, which was not tested in Scenario B). For amphibians, ‘corridor’ (-), ‘plastic’ (+), and ‘bridge’ (-) were included in Scenario B and Scenario C and maintained their direction of influence. ‘Guardrail’ (+), ‘crossing structure (full)’ (+), ‘crossing structure (half)’ (+), ‘circular’ (+), and ‘wet & interm’ (+) were not included in any Scenario B amphibian model but were included in Scenario C amphibian models. ‘Concrete’ (-), ‘rectangular’ (+), ‘dry’ (+), and ‘dry & interm’ (+), present in Scenario B models were absent in Scenario C models. For mammals, both ‘metal’ and ‘circular’ were included in Scenario B models for A10 and for R112. Notably, both predictors had a negative influence on roadkill on A10, but a positive influence on R112. In Scenario C models, ‘metal’ and ‘circular’ were again included and both had a negative influence on roadkill, aligned with the direction of influence observed on A10. To contrast the distribution of Material and Shape predictors between the two highways offers an explanation. On A10, the proportions of 'concrete' (27%), 'metal' (30%), and 'plastic' (43%) crossing structures are relatively balanced. In contrast, crossing structures on R112 are dominated by 'concrete' structures (94%), with only 4% 'metal' and 2% 'plastic'. When the data are combined in Scenario C, the resulting proportions shift to 61% 'concrete', 17% 'metal', and 22% 'plastic' (Figure 15). Similarly, the proportion of 'circular' structures in Scenario B, 85% (A10) and 11% (R112), balances out to 47% in Scenario C. These patterns suggest that when data are pooled (Scenario C), predictors influential at the highway-specific level (Scenario B) may diminish in effect or reverse direction due to shifts in their relative representation. This underscores the importance and utility of evaluating predictor effects at multiple spatial or categorical scales, as amalgamated data may obscure possible fine-scale influence of predictors.

For reptiles, Scenario B models included the following predictors: 'plastic' (-), 'rectangular' (-), 'dry & interm' (+), 'metal' (-), 'bridge' (+), and 'wet & interm' (+). Only 'rectangular' was included in a Scenario C model, with the same negative direction of influence as observed in Scenario B. Two additional predictors were included in Scenario C models, 'concrete' (-) and 'dry' (-). Interestingly, 'dry & interm' and 'wet & interm' both had a positive influence on roadkill in Scenario B, while 'dry' had a negative influence on roadkill for Scenario C. These three predictors are indeed different as they reflect differing environmental conditions and incorporate different data, yet contrasting their effects across scenarios may point to subtle, unmeasured differences between A10 and R112 individually, and A10 and R112 combined. This again underscores the importance of considering highway-specific contexts when interpreting predictor effects (Gunson et al., 2011), and suggests the use of caution when applying the results from one highway to another, even if in very close proximity, as fine-scale variation in environmental or infrastructure exhibit influence on roadkill patterns. This analysis suggests that conclusions drawn from one highway cannot be applied to another with total confidence, especially when data collection methods differ (e.g., cycling versus driving surveys). Furthermore, these findings are based on data from only 37 surveys performed over two months. Long-term, multi-year monitoring is vital in producing results that better reflect the ecological conditions of the study area.

Although A10 and R112 are in close proximity and are subject to broadly similar environmental conditions, key differences between the two roadways might have contributed to observed differences in model results. A10 is bordered by wide, clear-cut verges designed to improve driver visibility and safety. In contrast, R112 is characterized by tall vegetation immediately adjacent to the road surface, often forming a tree-cover canopy over some sections of R112. Clevenger and Waltho (2005) identified distance to vegetative cover as the most influential landscape variable affecting wildlife use of crossing structures. Many species rely on cover for protection, and areas with higher vegetative cover are attractive to wildlife species seeking protection. Additionally, R112 is more curvilinear than A10, and when combined with dense roadside vegetation, blind spots around bends are common, features largely absent along A10. Blind spots would necessitate caution from attentive drivers as both response time and breaking distance may be increased. These differences in road design and surrounding landscape are likely to influence driver behaviour, wildlife movement patterns, and the spatial distribution of roadkill.

5.7. Fences

Although the model results are notable, they must be interpreted cautiously due to the absence of wildlife fencing in the study area. The presence of wildlife fencing of adequate lengths has been shown to be crucial for both reducing roadkill by restricting wildlife from accessing the road and to guide wildlife to crossing structures (Clevenger et al., 2001; Huijser et al., 2016; Rytwinski et al., 2016). The aim of this study was to determine whether wildlife usage could be detected in the absence of fencing; if so, it would strengthen the argument for adapting a selection of the existing crossing structures analyzed as suitable for wildlife passages, to be paired with wildlife fencing. This study does provide indirect evidence of wildlife using existing crossing structures even along unfenced roads. Ideally, this study should serve as the Before part of a two-part BACI design where road mortality surveys would continue After modifications will have been made, then analyzed together with unmodified Control sections, whereby the Impact of the modifications can be assessed to a high inferential degree (Rytwinski et al., 2015).

5.8. Limitations

A distance-based analytical approach might have been more appropriate for modelling amphibian roadkill. Rather than aggregating roadkill counts in bins set at a width of 100 m, distances to all environmental and structural predictors might have been measured from each roadkill data point, i.e., each roadkill point would serve as a data point. This method might yield results more reflective of the scale of amphibian mobility. In addition, different species among the three wildlife types analyzed behave differently and require differing resources to fulfill their lifecycles, e.g., although reptiles might be attracted to roads to regulate their body temperatures through basking, turtle habitat is generally associated with wetlands whereas snakes favour dryness by comparison. It would be advantageous to group wildlife by resource necessity and behaviour, not stratified solely along amphibian, mammal, or reptile wildlife classifications.

We acknowledge the limitation posed by sample size. While Scenarios B through D provided a unique opportunity to compare roadkill patterns between two adjacent highways from data collected over the same time period and by the same research team, the limited number of mammal and reptile observations may have limited the statistical power of the models.

CONCLUSION AND RECOMMENDATIONS

We recommend conducting surveys over a time span long enough to capture likely wildlife migrations throughout the landscape and across the roads, ideally extending across multiple seasons or years. Wildlife movement is directly influenced by seasonal migrations, which can significantly affect roadkill survey results (D'Amico et al., 2015). Additional data may uncover the seemingly contradictory finding that more roadkill are located on the side of the highway with half crossing structures than the side of the highway without crossing structures. There is an untested dynamic playing out involving predictor variables not included, and perhaps more data would augment patterns not fully apparent or tamper down any data anomalies (if there are any).

A refinement to the predictors included for analysis and the scales at which they are measured may produce results that are more reflective of the ecological dynamics within the study area. Notably, the consistently high number of structural and environmental predictors present in global mammal models that were excluded from final mammal models was a key difference among the three animal groups. With consistently low mammal model pseudo-R^2 values (2.6 to 9.1%) when compared with amphibians (10 to 14.3%) and reptiles (6.4 to 17.7%), the inference is that unknown additional structural or environmental factors with influence on mammal roadkill have not been included in the mammal models. In addition, refinements to response variables may yield more meaningful results insofar as running analyses for small mammals, medium mammals, and large mammals, or separate analyses for turtles and snakes, as wildlife among the mammal and reptile groupings exhibit different behavioural traits and seek out or require different resources or habitat conditions.

Future studies of this nature should also consider potential interaction effects among two or more predictors (Gunson et al., 2011; Pagany, 2020). For instance, contrasting the interaction affects between 'concrete', a material negatively associated with roadkill in this study, and 'wet' structures, given known wildlife movement patterns along watercourses and adjacent riparian zones, with 'concrete' and 'dry' structures, given established wildlife preferences for dry paths, especially among mammals (Brunen et al, 2020; Denneboom et al., 2021; Jensen et al., 2022; O'Connell et al., 1993). While VIF analysis was useful in identifying multicollinearity and identifying predictors with questionable influence by themselves, a more robust approach would involve incorporating interaction terms (using the '*' operator) in the GLM models. This would allow for more systematic testing and identification of interaction effects that may otherwise be unknown.

Wildlife exclusion fencing must be installed and properly maintained along roadways to reduce roadkill while potentially increasing the effectiveness of existing structures as wildlife crossing infrastructure. Crucially, different species and taxonomic groups require different types of exclusion fencing; therefore, in areas where roadkill mitigation targets multiple wildlife types, fencing designs should reflect the structural requirements proven to mitigate roadkill for each target species. Furthermore, in efforts to increase landscape connectivity, a selection of existing crossing structures adjacent to suitable habitat should be retrofitted with dry shelves and wildlife exclusion fencing to encourage wildlife use. If encouraging wildlife usage of existing crossing structures is an objective, areas with several small and wet existing crossing structures should be replaced by wider structures that can facilitate both a watercourse and a permanently present dry path (Brunen et al., 2020).

THESIS CONCLUSION

In this thesis I have assessed the influence of existing crossing structures on the spatial distribution of roadkill. I considered full and half crossing structures in addition to their material, shape, functional, and dimensional attributes individually, in combination, and with additional predictor variables (Wildlife Corridor, Guardrail, Watercourse Density (ha/m^2), landcover class proportional cover, and distance to the nearest land cover class).

The research questions were answered by using a data collection protocol we adapted (driving) and then modified (cycling) to collect roadkill data over three research seasons in a rigorous and consistent manner. I found for research question 1 that crossing structures and their various attributes had influence to varying degrees and directions on roadkill by animal type and highway. While the previous study by Delgado et al. (2016) found no influence of crossing structures on roadkill distributions, my thesis refined the bin size (100 meters) to better reflect the movement abilities of the vast majority of wildlife detected (amphibians), a notable improvement on the 1-km bin size used in Delgado et al. Additionally, the roadkill database amassed for use in this thesis is considerable, with 4,370 detections made and using 3,971 data in the analysis. In comparison, Delgado et al. (2016) based their results on only 238 roadkill events detected along four low-traffic volume highways. My thesis incorporates and contrasts the results from two road mortality survey methods and from two highways of differing size, speed limits, and traffic volumes. In 2021, I had the privilege of performing two road mortality surveys per fieldwork day (driving and cycling), acquiring firsthand experience with the advantages and limitations of each delivery method (additional publication to follow), to then contrast the results from surveys performed on the same day (to our knowledge, the first study of this kind).

Regarding research question 2, while crossing structure predictors involving materials, shapes, and functions were shown to influence roadkill, they were frequently among the lowest in relative influence and were often excluded from final models, depending on animal type. However, crossing structure attributes from the Dimensions group were among the strongest in predictor influence and were retained in final models. Regarding research question 3, the model predictors from A10 and those from R112 (Scenario B) often differed, perhaps due to the differing methods of data collection used on each highway. Additionally, the differences in model predictors between those identified for A10 and R112 (Scenario B) and those identified for Scenario C (A10 and R112) were notable. I found that predictor results from one highway could not be reliably applied to a neighbouring highway, nor can combining data from both highways produce results which closely resemble those from either highway individually. While it may be tempting to generalize the findings of this study to other highways, I advise that mitigation measures in efforts to reduce roadkill be implemented at the local scale. In the interim, the MTMD should install wildlife exclusion fencing along roadways to restrict wildlife movement onto the road surface in efforts to reduce roadkill, in particular when adjacent to suitable habitat or where animals are often killed, with structural designs tailored to the needs of target species. To maintain a level of habitat connectivity, the ministry should retrofit existing crossing structures to improve their suitability for and attractiveness to wildlife, to encourage the usage of existing structures for wildlife to safely cross the roadways.

REFERENCES

Anđelković, M., & Bogdanović, N. (2022). Amphibian and reptile road mortality in special nature reserve Obedska Bara, Serbia. *Animals, 12*(5), Article 561 https://doi.org/10.3390/ani12050561

Anderson, M. G., Vickery, B., Gorman, M., Gratton, L., Morrison, M., Maillet, J., Olivero, A., Ferree, C., Morse, D., Kehm, G., Rosalska, K., Khanna, S., & Bernstein, S. (2006). *The Northern Appalachian/Acadian Ecoregion: Conservation assessment status and trends: 2006*. The Nature Conservancy Eastern Regional Science in collaboration with The Nature Conservancy of Canada: Atlantic and Quebec Regions. Retrieved from http://support.natureconservancy.ca/pdf/blueprints/Northern_Appalachians_Acadia.pdf

Ascensão, F., Mata, C., Malo, J. E., Ruiz-Capillas, P., Silva, C., Silva, A. P., Santos-Reis, M., & Fernandes, C. (2016). Disentangle the causes of the road barrier effect in small mammals through genetic patterns. *PLOS ONE, 11*(3), Article e0151500. https://doi.org/10.1371/journal.pone.0151500

Ascensão, F., Fahrig, L., Clevenger, A. P., Corlett, R. T., Jaeger, J. A., Laurance, W. F., & Pereira, H. M. (2018). Environmental challenges for the belt and road initiative. *Nature Sustainability, 1*(5), 206–209. https://doi.org/10.1038/s41893-018-0059-3

Ascensão, F., Kindel, A., Teixeira, F. Z., Barrientos, R., D'Amico, M., Borda-de-Água, L., & Pereira, H. M. (2019). Beware that the lack of wildlife mortality records can mask a serious impact of linear infrastructures. *Global Ecology and Conservation, 19,* Article e00661. https://doi.org/10.1016/j.gecco.2019.e00661

Azevedo, F. J. de. (2023). Environmental impacts on wild fauna caused by roads and the effectiveness of mitigation measures. *Scientific Journal of Applied Social and Clinical Science, 3*(1), Article e216312301019. https://doi.org/10.22533/at.ed.216312301019

Barrett, H., Vanlaar, W. G. M., & Robertson, R. D. (2023). Wildlife-vehicle collisions in Canada 2000–2020 [Fact sheet]. https://tirf.ca/news/wildlife-vehicle-fatal-crash-data-guide-prevention-strategies/

Barrientos, R., Ascensão, F., D'Amico, M., Grilo, C., & Pereira, H. M. (2021). The lost road: Do transportation networks imperil wildlife population persistence? *Perspectives in Ecology and Conservation, 19*(4), 411–416. https://doi.org/10.1016/j.pecon.2021.07.004

Beckmann, C., & Shine, R. (2011). Do drivers intentionally target wildlife on roads? *Austral Ecology, 37*(5), 629–632. https://doi.org/10.1111/j.1442-9993.2011.02329.x

Benítez-López, A., Alkemade, R., & Verweij, P. A. (2010). The impacts of roads and other infrastructure on mammal and bird populations: A meta-analysis. *Biological Conservation, 143*(6), 1307–1316. https://doi.org/10.1016/j.biocon.2010.02.009

Bennett, V. J. (2017). Effects of road density and pattern on the conservation of species and biodiversity. *Current Landscape Ecology Reports, 2*(1), 1–11. https://doi.org/10.1007/s40823-017-0020-6

Bi, B., Tong, J., Lei, S., Chen, D., Jin, Q., Hong, D., Wang, X., Chen, J., & Zhao, S. (2023). Using behavioural characteristics to design amphibian ladders for concrete-lined irrigation channels. *Sustainability, 15*(7), Article 6029. https://doi.org/10.3390/su15076029

Bíl, M., & Andrášik, R. (2020). The effect of wildlife carcass underreporting on KDE+ hotspots identification and importance. *Journal of Environmental Management, 275*, Article 111254. https://doi.org/10.1016/j.jenvman.2020.111254

Bishop, C. A., & Brogan, J. M. (2013). Estimates of avian mortality attributed to vehicle collisions in Canada. *Avian Conservation and Ecology, 8*(2), Article 2. https://doi.org/10.5751/ace-00604-080202

Boyes, D. H., Evans, D. M., Fox, R., Parsons, M. S., & Pocock, M. J. (2021). Is light pollution driving moth population declines? A review of causal mechanisms across the life cycle. *Insect Conservation and Diversity, 14*(2), 167–187. https://doi.org/10.1111/icad.12447

Boyle, S. P., Dillon, R., Litzgus, J. D., & Lesbarrères, D. (2019). Desiccation of herpetofauna on roadway exclusion fencing. *The Canadian Field-Naturalist, 133*(1), 43–48. https://doi.org/10.22621/cfn.v133i1.2076

Brunen, B., Daguet, C., & Jaeger, J. A. G. (2020). What attributes are relevant for drainage culverts to serve as efficient road crossing structures for mammals? *Journal of Environmental Management, 268*, Article 110423. https://doi.org/10.1016/j.jenvman.2020.110423

Burnham, K. P., & Anderson, D. R. (1998). Model-selection uncertainty and rules of thumb in assessing ΔAIC values. In *Model selection and inference: A practical information theoretic approach* (pp. 118–158). Springer-Verlag.

Centro Brasileiro de Estudos em Ecologia [CBEE] (2015). Atropelômetro. Centro Brasileiro de Estudos em Ecologia de Estradas, Brasil. Retrieved October 2022, from http://cbee.ufla.br/portal/atropelometro/

Clevenger, A. P., Chruszcz, B., & Gunson, K. (2001). Drainage culverts as habitat linkages and factors affecting passage by mammals. *Journal of Applied Ecology, 38*(6), 1340–1349.

Clevenger, A. P., & Waltho, N. (2005). Performance indices to identify attributes of highway crossing structures facilitating movement of large mammals. *Biological Conservation, 121*(3), 453–464. https://doi.org/10.1016/j.biocon.2004.04.025

Clevenger, T., & Huijser, M. P. (2011). *Wildlife crossing structure handbook: Design and evaluation in North America*. U.S. Department of Transportation.

Clevenger, A. P., & Barrueto, M. (Eds.). (2014). *Trans‒Canada highway wildlife and monitoring research, final report. Part B: Research*. Parks Canada Agency.

Coelho, I. P., Teixeira, F. Z., Colombo, P., Coelho, A. V., & Kindel, A. (2012). Anuran road-kills neighbouring a peri-urban reserve in the Atlantic Forest, Brazil. *Journal of Environmental Management, 112*, 17–26. https://doi.org/10.1016/j.jenvman.2012.07.004

Coffin, A. W. (2007). From roadkill to road ecology: A review of the ecological effects of roads. *Journal of Transport Geography, 15*(5), 396–406. https://doi.org/10.1016/j.jtrangeo.2006.11.006

Coffin, A. W., Ouren, D. S., Bettez, N. D., Borda-de-Água, L., Daniels, A. E., Grilo, C., Jaeger, J. A. G., Navarro, L. M., Preisler, H. K., & Rauschert, E. S. J. (2021). *The ecology of rural roads: Effects, management, and research* (Issues in Ecology, Report No. 23). The Ecological Society of America.

Cole, J. R., Kross, A., & Jaeger, J. A. G. (2022). Monitoring changes in landscape structure in the Adirondack-to-Laurentians (A2L) transboundary wildlife linkage between 1992 and 2018: Identifying priority areas for conservation and restoration. *Landscape Ecology, 38*(2), 383–408. https://doi.org/10.1007/s10980-022-01561-2

Collins, S. J., & Russell, R. W. (2009). Toxicity of road salt to Nova Scotia amphibians. *Environmental Pollution, 157*(1), 320–324. https://doi.org/10.1016/j.envpol.2008.06.032

Collinson, W. J., Parker, D. M., Bernard, R. T. F., Reilly, B. K., & Davies-Mostert, H. T. (2014). Wildlife road traffic accidents: A standardized protocol for counting flattened fauna. *Ecology and Evolution, 4*(15), 3060–3071. https://doi.org/10.1002/ece3.1097

Corridor appalachien. (n.d.). Geographical portrait. Retrieved October 2022, from http://www.corridorappalachien.ca/en/geographical-portrait/

Corridor appalachien. (2022). A dozen mayors support the Highway 10 – ecological connectivity plan [Press release]. Retrieved October 2022, from https://www.corridorappalachien.ca/en/highway-10-eco-connectivity-plan/

Crooks, K. R., Burdett, C. L., Theobald, D. M., King, S. R., Di Marco, M., Rondinini, C., & Boitani, L. (2017). Quantification of habitat fragmentation reveals extinction risk in terrestrial mammals. *Proceedings of the National Academy of Sciences, 114*(29), 7635–7640. https://doi.org/10.1073/pnas.1705769114

Daguet, C., & Lelièvre, M. (2019). Identification et protection des corridors naturels de part et d'autre de l'autoroute 10 (Estrie et Montérégie Est) et amélioration de sa perméabilité faunique : premiers résultats. *Le Naturaliste canadien, 143*(1), 32–39. https://doi.org/10.7202/1054115ar

Daigle, P. (2010). A summary of the environmental impact of roads, management responses, and research gaps: A literature review. *BC Journal of Ecosystems and Management, 10*(3), 65–89. http://www.forrex.org/publications/jem/ISS52/vol10_no3_art8.pdf

D'Amico, M., Román, J., de los Reyes, L., & Revilla, E. (2015). Vertebrate road-kill patterns in Mediterranean habitats: Who, when and where. *Biological Conservation*, *191*, 234–242. https://doi.org/10.1016/j.biocon.2015.06.010

Delgado, J. D., Morelli, F., Arroyo, N. L., Durán, J., Rodríguez, A., Rosal, A., Palenzuela, M. del, & Rodríguez, J. D. G. P. (2018). Is vertebrate mortality correlated to potential permeability by underpasses along low-traffic roads? *Journal of Environmental Management, 221*, 53–62. https://doi.org/10.1016/j.jenvman.2018.05.043

Denneboom, D., Bar-Massada, A., & Shwartz, A. (2021). Factors affecting usage of crossing structures by wildlife – a systematic review and meta-analysis. *Science of The Total Environment, 777*, Article 146061. https://doi.org/10.1016/j.scitotenv.2021.146061

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J. R., Gruber, B., Lafourcade, B., Leitão, P. J., Münkemüller, T., McClean, C., Osborne, P. E., Reineking, B., Schröder, B., Skidmore, A. K., Zurell, D., & Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography, 36*(1), 27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x

Dornas, R. A. P., Teixeira, F. Z., Gonsioroski, G., & Nóbrega, R. A. A. (2019). Strain by the train: Patterns of toad fatalities on a Brazilian Amazonian railroad. *Science of The Total Environment, 660*, 493–500. https://doi.org/10.1016/j.scitotenv.2018.12.371

Dulac, J. (2013). *Global land transport infrastructure requirements: Estimating road and railway infrastructure capacity and costs to 2050*. International Energy Agency. Retrieved from https://www.researchgate.net/profile/Juan-Munoz-42/publication/272015722_A_review_of_technological_improvements_in_bus_rapid_transit_BRT_and_buses_with_high_level _of_service_BHLS/links/55f229ba08aef559dc49348c/A-review-of-technological-improvements-in-bus-rapid-transit-BRT-and-buses-with-high-level-of-service-BHLS.pdf

Duranton, G., & Turner, M. A. (2011). The fundamental law of road congestion: Evidence from US cities. *American Economic Review, 101*(6), 2616–2652. https://doi.org/10.1257/aer.101.6.2616

Eberhardt, E., Mitchell, S., & Fahrig, L. (2013). Road kill hotspots do not effectively indicate mitigation locations when past road kill has depressed populations. *The Journal of Wildlife Management, 77*(7), 1353–1359. https://doi.org/10.1002/jwmg.592

Eisenbeis, G., & Hänel, A. (2009). Light pollution and the impact of artificial night lighting on insects. In *Ecology of cities and towns* (pp. 243–263). Cambridge University Press. https://doi.org/10.1017/cbo9780511609763.016

Elton, K., & Drescher, M. (2018). Implementing wildlife-management strategies into road infrastructure in Southern Ontario: A critical success factors approach. *Journal of Environmental Planning and Management, 62*(5), 862–880. https://doi.org/10.1080/09640568.2018.1447445

Environment and Climate Change Canada [ECCC]. (2012). Air pollution: Effects on wild animals. Government of Canada. https://www.canada.ca/en/environment-climate-change/services/air-pollution/quality-environment-economy/ecosystem/wild-animals.html

Fahrig, L., Pedlar, J. H., Pope, S. E., Taylor, P. D., & Wegner, J. F. (1995). Effect of road traffic on amphibian density. *Biological Conservation, 73*(3), 177–182. https://doi.org/10.1016/0006-3207(94)00102-v

Fahrig, L., & Rytwinski, T. (2009). Effects of roads on animal abundance: An empirical review and synthesis. *Ecology and Society,14*(1), Article 21. Retrieved May 20, 2022, from http://www.ecologyandsociety.org/vol14/iss1/art21/

Ford, A. T., Clevenger, A. P., Huijser, M. P., & Dibb, A. (2011). Planning and prioritization strategies for phased highway mitigation using wildlife-vehicle collision data. *Wildlife Biology, 17*(3), 253–265. https://doi.org/10.2981/09-051

Forman, R. T., & Alexander, L. E. (1998). Roads and their major ecological effects. *Annual Review of Ecology and Systematics, 29*(1), 207–231. https://doi.org/10.1146/annurev.ecolsys.29.1.207

Forman, R. T. T., & Deblinger, R. D. (2000). The ecological road-effect zone of a Massachusetts (USA) suburban highway. *Conservation Biology, 14*, 36–46.

Fox, J., & Weisberg, S. (2019). *An R Companion to Applied Regression* (3rd ed.). Sage, Thousand Oaks CA. https://socialsciences.mcmaster.ca/jfox/Books/Companion/

Friedman, J., Tibshirani, R., & Hastie, T. (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software, 33*(1), 1–22. https://doi.org/10.18637/jss.v033.i01

Gagnon, J. W., Dodd, N. L., Ogren, K. S., & Schweinsburg, R. E. (2011). Factors associated with use of wildlife underpasses and importance of long-term monitoring. *The Journal of Wildlife Management, 75*(6), 1477–1487. https://doi.org/10.1002/jwmg.160

Gagnon, J. W., Dodd, N. L., Sprague, S. C., Ogren, K. S., Loberger, C. D., & Schweinsburg, R. E. (2019). Animal-activated highway crosswalk: Long-term impact on elk-vehicle collisions, vehicle speeds, and motorist braking response. *Human Dimensions of Wildlife, 24*(2), 132–147. https://doi.org/10.1080/10871209.2019.1551586

Garrah, E., Danby, R. K., Eberhardt, E., Cunnington, G. M., & Mitchell, S. (2015). Hot spots and hot times: Wildlife road mortality in a regional conservation corridor. *Environmental Management, 56*(4), 874–889. https://doi.org/10.1007/s00267-015-0566-1

Gilbert, S. L., Sivy, K. J., Pozzanghera, C. B., DuBour, A., Overduijn, K., Smith, M. M., Zhou, J., Little, J. M., & Prugh, L. R. (2017). Socioeconomic benefits of large carnivore recolonization through reduced wildlife-vehicle collisions. *Conservation Letters, 10*(4), 431–439. https://doi.org/10.1111/conl.12280

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

Government of Québec. (2022). *Débit de circulation* [Dataset]. Données Québec. Retrieved October 2022 from https://www.donneesquebec.ca/recherche/dataset/debit-de-circulation/resource/2bd6ea5d-ba7f-44d5-afcd-4ca968897c1d

Grilo, C., Sousa, J., Ascensão, F., Matos, H., Leitão, I., Pinheiro, P., Costa, M., Bernardo, J., Reto, D., Lourenço, R., Santos-Reis, M., & Revilla, E. (2012). Individual spatial responses towards roads: Implications for mortality risk. *PLOS ONE, 7*(9), Article e43811. https://doi.org/10.1371/journal.pone.0043811

Grilo, C., Ferreira, F. Z., & Revilla, E. (2015). No evidence of a threshold in traffic volume affecting road-kill mortality at a large spatio-temporal scale. *Environmental Impact Assessment Review, 55*, 54–58. https://doi.org/10.1016/j.eiar.2015.07.003

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

Grilo, C., Neves, T., Bates, J., le Roux, A., Medrano-Vizcaíno, P., Quaranta, M., Silva, I., Soanes, K., Wang, Y., & Data Collection Consortium. (2025). Global roadkill data: A dataset on terrestrial vertebrate mortality caused by collision with vehicles. *Scientific Data, 12*, Article 505. https://doi.org/10.1038/s41597-024-04207-x

Grosman, P. D., Jaeger, J. A. G., Biron, P. M., Dussault, C., & Ouellet, J.-P. (2009). Reducing moose–vehicle collisions through salt pool removal and displacement: An agent-based modelling approach. *Ecology and Society, 14*(2), Article 17. http://www.ecologyandsociety.org/vol14/iss2/art17/

Gunson, K. E., Mountrakis, G., & Quackenbush, L. J. (2011). Spatial wildlife-vehicle collision models: A review of current work and its application to transportation mitigation projects. *Journal of Environmental Management, 92*(4), 1074–1082. https://doi.org/10.1016/j.jenvman.2010.11.027

Haddock, R. L., Lee, T., Knapik, M., & Clevenger, A. P. (2013). *Highways and wildlife: An infographic*. In *Proceedings of the 2013 International Conference on Road Ecology and Transportation (ICOET 2013)*. https://www.rockies.ca/files/HW_InfographicScreenVersion.pdf

Helldin, J. O., Broekmeyer, M., Campeny, R., & Kistenkas, F. (2016). *Roads and wildlife: Legal requirements and policy targets* (Technical Report 1). Conference of European Directors of Roads.

Helldin, J. O., & Petrovan, S. O. (2019). Effectiveness of small road tunnels and fences in reducing amphibian roadkill and barrier effects at retrofitted roads in Sweden. *PeerJ, 7*, Article e7518. https://doi.org/10.7717/peerj.7518

Hels, T., & Buchwald, E. (2001). The effect of road kills on amphibian populations. *Biological Conservation, 99*(3), 331–340. https://doi.org/10.1016/S0006-3207(00)00215-9

Hill, J. E., DeVault, T. L., & Belant, J. L. (2019). Cause-specific mortality of the world's terrestrial vertebrates. *Global Ecology and Biogeography, 28*(5), 680–689. https://doi.org/10.1111/geb.12881

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

Hummel, D. (2001). Amphibienschutz durch Geschwindigkeitsbegrenzung: Eine aerodynamische Studie. *Natur und Landschaft, 76*(12), 530–533. Retrieved April 20, 2022 from https://trid.trb.org/view/956118

Hymel, K. M. (2019). If you build it, they will drive: Measuring induced demand for vehicle travel in urban areas. *Transport Policy, 76*, 57–66. https://doi.org/10.1016/j.tranpol.2018.12.006

Ibisch, P. L., Hoffmann, M. T., Kreft, S., Pe'er, G., Kati, V., Biber-Freudenberger, L., DellaSala, D., Vale, M. M., Hobson, P. R., & Selva, N. (2016). A global map of roadless areas and their conservation status. *Science, 354*, 1423–1427. https://doi.org/10.1126/science.aaf7166

Jackson, N. D., & Fahrig, L. (2011). Relative effects of road mortality and decreased connectivity on population genetic diversity. *Biological Conservation, 144*(12), 3143–3148. https://doi.org/10.1016/j.biocon.2011.09.010

Jaeger, J. A., & Fahrig, L. (2004). Effects of road fencing on population persistence. *Conservation Biology, 18*(6), 1651–1657. https://doi.org/10.1111/j.1523-1739.2004.00304.x

Jaeger, J. A. G., Bowman, J., Brennan, J., Fahrig, L., Bert, D., Bouchard, J., Charbonneau, N., Frank, K., Gruber, B., & von Toschanowitz, K. T. (2005). Predicting when animal populations are at risk from roads: An interactive model of road avoidance behaviour. *Ecological Modelling, 185*(2–4), 329–348. https://doi.org/10.1016/j.ecolmodel.2004.12.015

Jaeger, J. A. G. (2012). Road ecology. In R. K. Craig, J. C. Nagle, B. Pardy, O. J. Schmitz, & W. K. Smith (Eds.), *Berkshire encyclopedia of sustainability: Ecosystem management and sustainability* (Vol. 5, pp. 344–350). Berkshire Publishing Group.

Jaeger, J. A. G. (2015). Improving environmental impact assessment and road planning at the landscape scale. In R. van der Ree, D. J. Smith, & C. Grilo (Eds.), *Handbook of road ecology* (pp. 32–42). John Wiley & Sons. https://doi.org/10.1002/9781118568170.ch5

Jaeger, J. A. G., & Torres, A. (2021). Fourteen lessons from road ecology for cumulative effect assessments. In J. A. E. Blakley & D. M. Franks (Eds.), *Handbook of cumulative impact assessment* (pp. 250–273). Edward Elgar.

Jensen, A. J., Perrine, J. D., Schaffner, A., Brewster, R., Giordano, A. J., Robertson, M., & Siepel, N. (2022). Mammal use of undercrossings is influenced by openness and proximity to riparian corridors. *Wildlife Research, 50*(7), 495–506. https://doi.org/10.1071/WR21183

Koju, N. P., Anish, K. C., Dodhari, K., Giri, P., Lee, M., Pokhrel, S., Ghimire, A., Nyaichyai, L., Onditi, K. O., Jiang, X., & Kyes, R. C. (2025). Spatiotemporal patterns and environmental determinants of wildlife vehicle collisions in Banke National Park, Nepal. *Scientific Reports, 15*(1), Article 19478. https://doi.org/10.1038/s41598-025-04609-w

Lalo, J. (1987). The problem of roadkill. *American Forests*, *93*(9–10), 50–52.

Langen, T. A., Machniak, A., Crowe, E. K., Mangan, C., Marker, D. F., Liddle, N., & Roden, B. (2007). Methodologies for surveying herpetofauna mortality on rural highways. *Journal of Wildlife Management, 71*(4), 1361–1368. https://doi.org/10.2193/2006-385

Langen, T. A., Ogden, K. M., & Schwarting, L. L. (2009). Predicting hot spots of herpetofauna road mortality along highway networks. *Journal of Wildlife Management, 73*(1), 104–114. https://doi.org/10.2193/2008-017

LaPoint, S. D., Kays, R. W., & Ray, J. C. (2003). Animals crossing the Northway: Are existing culverts useful? *Union College Adirondack Journal of Environmental Studies, 10*(1), 11–17. https://digitalworks.union.edu/ajes/vol10/iss1/5

Lesbarrères, D., Lodé, T., & Merilä, J. (2004). What type of amphibian tunnel could reduce road kills? *Oryx, 38*(2), 220–223. https://doi.org/10.1017/S0030605304000389

Lesbarrères, D., & Fahrig, L. (2012). Measures to reduce population fragmentation by roads: What has worked and how do we know? *Trends in Ecology & Evolution, 27*(7), 374–380. https://doi.org/10.1016/j.tree.2012.01.015

Li, T., & Ducruc, J. P. (1999). *Les provinces naturelles: Niveau I du cadre écologique de référence du Québec*. Ministère de l'Environnement, Direction de la conservation et du patrimoine écologique. http://www.mddep.gouv.qc.ca/biodiversite/aires_protegees/provinces/index.htm

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

Lima Santos, R. A., Ascensão, F., Ribeiro, M. L., Bager, A., Santos-Reis, M., & Aguiar, L. M. S. (2017). Assessing the consistency of hotspot and hot-moment patterns of wildlife road mortality over time. *Perspectives in Ecology and Conservation, 15*(1), 56–60. https://doi.org/10.1016/j.pecon.2017.03.003

Lin, S. C. (2016). Landscape and traffic factors affecting animal road mortality. *Journal of Environmental Engineering and Landscape Management, 24*(1), 10–20. https://doi.org/10.3846/16486897.2015.1098652

Magioli, M., Bovo, A. A. A., Huijser, M. P., Abra, F. D., Miotto, R. A., Andrade, V. H. V. P., Nascimento, A. M., Martins, M. Z. A., & Ferraz, K. M. P. M. de B. (2019). Short and narrow roads cause substantial impacts on wildlife. *Oecologia Australis, 23*(1), 99–111. https://doi.org/10.4257/oeco.2019.2301.09

Mayer, M., Lyons, J., Shine, R., & Natusch, D. (2018). Air-pressure waves generated by vehicles do not imperil road-crossing amphibians. *Salamandra, 54*(1), 80–82.

Mayer, P. M., Moran, K. D., Miller, E. L., Brander, S. M., Harper, S., Garcia-Jaramillo, M., Carrasco-Navarro, K. T., … Fender, C. L. (2024). Where the rubber meets the road: Emerging environmental impacts of tire wear particles and their chemical cocktails. *Science of the Total Environment, 927*, Article 171153. https://doi.org/10.1016/j.scitotenv.2024.171153

McCollister, M. F., & van Manen, F. T. (2010). Effectiveness of wildlife underpasses and fencing to reduce wildlife–vehicle collisions. *Journal of Wildlife Management, 74*(8), 1722–1731. https://doi.org/10.2193/2009-535

McGuire, J. L., Lawler, J. J., McRae, B. H., Nuñez, T. A., & Theobald, D. M. (2016). Achieving climate connectivity in a fragmented landscape. *Proceedings of the National Academy of Sciences, 113*(26), 7195–7200. https://doi.org/10.1073/pnas.1602817113

McGuire, T. M., Clevenger, A. P., Ament, R., Callahan, R., & Jacobson, S. (Eds.). (2020). *Innovative strategies to reduce the costs of effective wildlife overpasses* (Gen. Tech. Rep. PSW-GTR-267). U.S. Department of Agriculture Forest Service, Pacific Southwest Research Station.

Medrano-Vizcaíno, P., Grilo, C., Brito-Zapata, D., & González-Suárez, M. (2022). Roadkill patterns in Latin American birds and mammals. *Global Ecology and Biogeography, 31*(9), 1756–1783. https://doi.org/10.1111/geb.13557

Meijer, J. R., Huijbregts, M. A. J., Schotten, K. C., & Schipper, A. M. (2018). Global patterns of current and future road infrastructure. *Environmental Research Letters, 13*(6), Article 064006. https://doi.org/10.1088/1748-9326/aabd42

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

Neumann, W., Ericsson, G., Dettki, H., Bunnefeld, N., Keuler, N. S., Helmers, D. P., & Radeloff, V. C. (2011). Difference in spatiotemporal patterns of wildlife road-crossings and wildlife–vehicle collisions. *Biological Conservation, 145*(1), 70–78. https://doi.org/10.1016/j.biocon.2011.10.011

Newell, R., Dale, A., & Lister, N.-M. (2022). An integrated climate-biodiversity framework to improve planning and policy: An application to wildlife crossings and landscape connectivity. *Ecology and Society, 27*(1), Article 23. https://doi.org/10.5751/es-12999-270123

Northeastern Governors and Eastern Canadian Premiers [NEG-ECP]. (2024). *Resolution 45-2: Ecological connectivity, climate adaptation, and biodiversity conservation*. Conference of the New England Governors and Eastern Canadian Premiers. https://cap-cpma.ca/wp-content/uploads/2024/09/NEG-ECP-Resolution-45-2-Ecology-Climate-EN.pdf

O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity, 41*(5), 673–690. https://doi.org/10.1007/s11135-006-9018-6

O'Connell, M. A., Hallett, J. G., & West, S. D. (1993). *Wildlife use of riparian habitats: A literature review* (TFW WLi 93-001). Washington State Department of Natural Resources. https://www.dnr.wa.gov/Publications/fp_tfw_wl1_93_001.pdf

Ogle, D. H., Doll, J. C., Wheeler, A. P., and Dinno, A. (2025). FSA: Simple Fisheries Stock Assessment Methods. R package version 0.10.0. https://CRAN.R-project.org/package=FSA

Ovaska, K., Sopuck, L., Engelstoft, C., Matthias, L., Wind, E., & MacGarvie, J. (2014). *Guidelines for amphibian and reptile conservation during urban and rural land development in British Columbia*. B.C. Ministry of Forests, Lands and Natural Resource Operations. Retrieved October 2022 from https://www.env.gov.bc.ca/wld/documents/bmp/HerptileBMP_complete.pdf

Pagany, R. (2020). Wildlife-vehicle collisions – influencing factors, data collection and research methods. *Biological Conservation, 251*, Article 108758. https://doi.org/10.1016/j.biocon.2020.108758

Parris, K., & Schneider, A. (2009). Impacts of traffic noise and traffic volume on birds of roadside habitats. *Ecology and Society, 14*(1), Article 29. Retrieved May 25, 2022 from http://www.ecologyandsociety.org/vol14/iss1/art29/

Pecl, G. T., Araújo, M. B., Bell, J. D., Blanchard, J., Bonebrake, T. C., Chen, I.-C., Clark, T. D., Colwell, R. K., Danielsen, F., Evengård, B., Falconi, L., Ferrier, S., Frusher, S., Garcia, R. A., Griffis, R. B., Hobday, A. J., Janion-Scheepers, C., Jarzyna, M. A., Jennings, S., … Williams, S. E. (2017). Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science, 355*(6332), Article eaai9214. https://doi.org/10.1126/science.aai9214

Plante, J., Jaeger, J. A. G., & Desrochers, A. (2019). How do landscape context and fences influence roadkill locations of small and medium-sized mammals? *Journal of Environmental Management, 235*, 511–520. https://doi.org/10.1016/j.jenvman.2018.10.093

Pocock, Z., & Lawrence, R. E. (2005). How far into a forest does the effect of a road extend? Defining road-edge effect in eucalypt forests of south-eastern Australia. IN: Proceedings of the 2005 International Conference on Ecology and Transportation, Eds. Irwin CL, Garrett P, McDermott KP. Center for Transportation and the Environment, North Carolina State University, Raleigh, NC: pp. 397-405. https://escholarship.org/uc/item/4q576877

R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Raynor, J. L., Grainger, C. A., & Parker, D. P. (2021). Wolves make roadways safer, generating large economic returns to predator conservation. *Proceedings of the National Academy of Sciences, 118*(22), Article e2023251118. https://doi.org/10.1073/pnas.2023251118

Rees, J. D. (2016). Observation of mass road-kill of superb parrots feeding on split grain. *Corella, 40*(4), 99–100. Retrieved November 2022 from https://absa.asn.au/wp-content/uploads/2016/11/Corella_Vol40No4_NOV16_FINALPROOF_2016.pdf

Roe, A. W., & Grayson, K. L. (2008). Terrestrial movements and habitat use of juvenile and emigrating adult eastern red-spotted newts, *Notophthalmus viridescens*. *Journal of Herpetology, 42*(1), 22–30. http://www.jstor.org/stable/40060478

Rohwer, Y., & Marris, E. (2021). Ecosystem integrity is neither real nor valuable. *Conservation Science and Practice, 3*(4), Article e411. https://doi.org/10.1111/csp2.411

Rytwinski, T., & Fahrig, L. (2012). Do species life history traits explain population responses to roads? A meta-analysis. *Biological Conservation, 147*(1), 87–98. https://doi.org/10.1016/j.biocon.2011.11.023

Rytwinski, T., & Fahrig, L. (2013). Why are some animal populations unaffected or positively affected by roads? *Oecologia, 173*(3), 1143–1156. https://doi.org/10.1007/s00442-013-2684-x

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

Salas-Eljatib, C., Fuentes, R., Yáñez, A., & Vásquez, R. A. (2018). A study on the effects of unbalanced data on ecological modelling: A simulation approach. *Ecological Modelling, 385*, 1–9. https://doi.org/10.1016/j.ecolmodel.2018.06.001

Schilthuizen, M. (2022). Roadkill literally 'drives' some species to extinction. *Scientific American*. https://www.scientificamerican.com/article/roadkill-literally-drives-some-species-to-extinction/

Schmidt, B. R., & Zumbach, S. (2008). Amphibian road mortality and how to prevent it: A review. In J. C. Mitchell, R. E. Jung Brown, & B. Bartolomew (Eds.), *Urban herpetology* (pp. 157–167). St. Louis, MO. https://doi.org/10.5167/uzh-10142

Schwartz, A. L., Shilling, F. M., & Perkins, S. E. (2020). The value of monitoring wildlife roadkill. *European Journal of Wildlife Research, 66,* Article 18. https://doi.org/10.1007/s10344-019-1357-4

Sedoník, J., Andrášik, R., & Bíl, M. (2023). STKDE+ approach reveals wildlife-vehicle collision hotspots at broken fence locations. *European Journal of Wildlife Research, 69*, Article 104. https://doi.org/10.1007/s10344-023-01735-6

Seiler, A., & Helldin, J. O. (2006). Mortality in wildlife due to transportation. In J. Davenport & J. L. Davenport (Eds.), *The ecology of transportation: Managing mobility for the environment* (pp. 165–189). Springer.

Shepard, D. B., Kuhns, A. R., Dreslik, M. J., & Phillips, C. A. (2008). Roads as barriers to animal movement in fragmented landscapes. *Animal Conservation, 11*(4), 288–296. https://doi.org/10.1111/j.1469-1795.2008.00183.x

Shine, R., LeMaster, M., Wall, M., Langkilde, T., & Mason, R. (2004). Why did the snake cross the road? Effects of roads on movement and location of mates by garter snakes

(*Thamnophis sirtalis parietalis*). *Ecology and Society, 9*(1), Article 9. http://www.ecologyandsociety.org/vol9/iss1/art9

Soanes, K., Rytwinski, T., Fahrig, L., Huijser, M. P., Jaeger, J. A. G., Teixeira, F. Z., van der Ree, R., & van der Grift, E. A. (2024). Do wildlife crossing structures mitigate the barrier effect of roads on animal movement? A global assessment. *Journal of Applied Ecology, 61*(3), 417–430. https://doi.org/10.1111/1365-2664.14582

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

St-Pierre, D., Nappi, A., de Bellefeuille, S., Lévesque Aubé, A.-A., & Martin, S. (2019). La connectivité au-delà des frontières : Résolution 40-3 concernant la connectivité écologique, l'adaptation aux changements climatiques et la conservation de la biodiversité. *Le Naturaliste canadien, 143*(1), 8–11. https://doi.org/10.7202/1054111ar

Statistics Canada. (2022). *Canada's core public infrastructure survey: Roads, bridges, and tunnels, 2020*. Government of Canada. Retrieved October 2022 from https://www150.statcan.gc.ca/n1/daily-quotidien/220524/dq220524a-eng.htm

Teixeira, F., Kindel, A., Hartz, S. M., Mitchell, S., & Fahrig, L. (2017). When road-kill hotspots do not indicate the best sites for road-kill mitigation. *Journal of Applied Ecology, 54*(5), 1544–1551. https://doi.org/10.1111/1365-2664.12870

Teixeira, F. Z., Rytwinski, T., & Fahrig, L. (2020). Inference in road ecology research: What we know versus what we think we know. *Biology Letters, 16*(7), Article 20200140. https://doi.org/10.1098/rsbl.2020.0140

Torres, A., Jaeger, J. A. G., & Alonso, J. C. (2016). Assessing large-scale wildlife responses to human infrastructure development. *Proceedings of the National Academy of Sciences, 113*(30), 8472–8477. https://doi.org/10.1073/pnas.1522488113

Two Countries One Forest [2C1Forest]. (2021). *Northern Appalachian/Acadian Ecoregion Conservation Atlas*. Retrieved October 21, 2022, from https://2c1forest.databasin.org/

Urban, M. C. (2020). Climate tracking species are not invasive. *Nature Climate Change, 10*(5), 382–384. https://doi.org/10.1038/s41558-020-0770-8

Valerio, F., Basile, M., & Balestrieri, R. (2021). The identification of wildlife–vehicle collision hotspots: Citizen science reveals spatial and temporal patterns. *Ecological Processes, 10,* Article 6. https://doi.org/10.1186/s13717-020-00271-4

van der Ree, R., Gulle, N., Holland, K., van der Grift, E., Mata, C., & Suárez, F. (2007). Overcoming the barrier effect of roads—How effective are mitigation strategies? In Proceedings of the 2007 International Conference on Ecology and Transportation, edited by C. Leroy Irwin, Debra Nelson, and K.P. McDermott. Raleigh, NC: Center for Transportation and the Environment, North Carolina State University, 2007. pp. 423-431. https://escholarship.org/uc/item/66j8095x

van der Ree, R., Jaeger, J. A. G., van der Grift, E., & Clevenger, A. P. (2011). Effects of roads and traffic on wildlife populations and landscape function: Road ecology is moving toward larger scales. *Ecology and Society, 16*(1), Article 48. http://www.ecologyandsociety.org/vol16/iss1/art48/

van der Ree, R., Smith, D. J., & Grilo, C. (Eds.). (2015). *Handbook of road ecology*. John Wiley & Sons.

Velosa, S. (2020). *Death by a thousand cars: Road mortality and the need for road mitigation measures along Autoroute 10 in Southern Quebec* (Undergraduate honours thesis, Concordia University).

Venables, W. N., & Ripley, B. D. (2002). *Modern applied statistics with S* (4th ed.). Springer.

Warnock-Juteau, K., Bolduc, V., LoScerbo, D., Anderson, M., Daguet, C., & Jaeger, J. A. G. (2022). Co-use of existing crossing structures along roads by wildlife and humans: Wishful thinking? In: Santos S, Grilo C, Shilling F, Bhardwaj M, Papp CR (Eds) Linear Infrastructure Networks with Ecological Solutions. Nature Conservation 47, 235-270. https://doi.org/10.3897/natureconservation.47.73060

Wilansky, J., & Jaeger, J. A. G. (2024). Predicting the effectiveness of wildlife fencing along roads using an individual-based model: How do fence-following distances influence the fence-end effect? *Ecological Modelling, 495*, Article 110784. https://doi.org/10.1016/j.ecolmodel.2024.110784

Wildlife Collision Prevention Program [WCPP]. (2022). *Making BC's roads safer for people and wildlife*. British Columbia Conservation Foundation. Retrieved October 2022 from https://www.wildlifecollisions.ca/

World Wildlife Fund [WWF]. (2022). *Living planet report 2022 – Building a nature-positive society* (R. E. A. Almond, M. Grooten, D. Juffe Bignoli, & T. Petersen, Eds.). WWF.

Zeileis, A., Kleiber, C., Jackman, S. (2008). Regression Models for Count Data in R. *Journal of Statistical Software 27*(8), 1–25. http://www.jstatsoft.org/v27/i08/

Zuur, A. F., Ieno, E. N., Walker, N., Saveliev, A. A., & Smith, G. M. (2009). *Mixed effects models and extensions in ecology with R*. Springer.

Appendix A. Fieldwork Protocols & Fieldwork Schedule
A.1 Driving Survey Protocol

Data collection protocol for highways with an emergency lane (A10)

This protocol was designed to monitor road mortality along highway A10 in Quebec during the summer months. It needs to fit the restrictions imposed by the work permit issued by the Quebec Ministry of Transport, allowing us to conduct our research along highway A10. The initial protocol was designed, tested, and modified to maximize the efficiency of the surveys, as well as to ensure that it may be replicated precisely in the future.

Survey days: Surveys are conducted over the span of 10-day sessions from Tuesday of the first week to Thursday of the following week, followed by a break of 4 days. From Tuesday to Saturday, surveys are done in the morning starting at 30 minutes after sunrise. From Sunday to Thursday surveys are done in the evenings. The evening survey's start time varies depending on the sunset time. (Evening surveys began around 5:30 pm from May 14th to August 8th. From August 12th to August 15th surveys began around 5:00 pm, and from August 26th to August 29th surveys began around 4:30 pm. There was a total of 8 sessions completed in 2019 during a 4-month period.)

Table: Survey schedule followed for each 2-week survey session.

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Week 1	No survey	No survey	Morning survey	Morning survey	Morning survey	Morning survey	Morning survey
Week 2	Evening survey	Evening survey	Evening survey	Evening survey	Evening survey	No survey	No survey

The highway has two lanes in each direction and an emergency lane. Parts of the highway have guardrails. In this protocol, two cases need to be distinguished depending on the presence of guardrails next to the emergency lane, because we are not allowed to stop the vehicle in front of a guardrail. However, we are allowed to drive in the emergency lane along a guardrail.

Case 1: Where there is no guardrail:
The vehicle drives in the emergency lane of the road at 30 km/h with the directional traffic arrow and orange revolving lights on the roof of the car turned on. All three members of the research team are in the car: one driver and two observers. One observer sits in the front passenger seat looking at the shoulder, emergency lane, and right lane. The other observer sits in the left backseat, looking out the left side window to scan the left lane and left shoulder.
When an observer spots an object that might be a potential animal carcass, the vehicle stops as far to the right as possible. The front passenger and back passenger exit the vehicle using the

right vehicle doors. They put up three orange cones behind the vehicle. Once the cones are places, they refrain from going behind the car as much as possible for safety reasons.

Depending on where the object is:

A. On the shoulder or on the emergency lane: The observers determine if the object is roadkill, identify the species, and record a GPS point. The driver stays in the car and takes notes on any useful information (e.g., closest km marker, location of the carcass) while waiting for the return of the observers. Additional information is added as soon as the observers return with their notes. The observers remove the roadkill from the road if possible (and also if it is a different object, to not get confused by it again). They add a line of yellow spray paint on the emergency lane asphalt in line with the carcass that was found in the shoulder, if it is still visible from the road. The team then continues the search.
B. On the right lane: No person is allowed to walk onto the right lane. Binoculars are used to identify as best as possible the object on the right lane. If it is suspected to be roadkill, GPS coordinates are recorded from the shoulder, the species identified as best as possible, and information is included about how certain or uncertain the species information is. Since we cannot remove the carcass from the road, and we cannot paint the carcass directly, the observers paint a red line on the asphalt of the emergency lane in line with the carcass and write the day and session number below the line. If the carcass is a large mammal (e.g., a deer), the team calls 511 and informs the receptionist while providing them with information about the nearest km marker. Road patrol will then come and remove the carcass at a later time. The road patrol should also take note of this and tell the research team what species it is (to their best ability) and in what lane is was found. We do not need to call 511 about small and medium-sized mammals because these do not pose a substantial risk to drivers and because the road is regularly patrolled and carcasses in the lanes will then be removed promptly.
C. On the left lane: No person is allowed to walk onto the left lane at any time. Binoculars are used to identify the object on the left lane as best as possible. If it is suspected to be roadkill, GPS coordinates are recorded from the shoulder, a best guess is made about the species and information included about how certain or uncertain the species information is. Since we cannot remove the carcass, and we cannot paint the carcass directly, the observers paint a blue line on the asphalt of the emergency lane in line with the carcass and write the day and session number below the line. If the carcass is a large mammal (e.g., a deer), the team calls 511 and informs the receptionist (providing them with information about the nearest km). Road patrol will then come and remove the carcass at a later time. They should take note of this and tell the research team what species it is (to the best of their ability) and in what lane is was found. We do not need to call about small and medium-sized mammals because these do not pose a substantial risk to drivers and because the road is regularly patrolled and carcasses in the lanes will then be removed promptly.

Case 2: Where there is a guardrail:

The vehicle drives on the emergency lane of the road at 30 km/h with the directional traffic arrow and orange revolving lights on the roof of the car turned on. All three members of the research team are in the car: one driver, two observers. One observer sits in the front passenger seat looking at the shoulder, emergency lane, and right lane. The other observer sits in the left backseat, looking out the left side window at the left lane and left shoulder.
When an observer spots an object that might be potential animal carcass, the km-maker is taken note of. The team continues to drive to the closest gap in the guardrail while continuing with the search. At the gap in the guardrail, the vehicle stops and the two observers get out (on the right side of the vehicle) and walk outside of the guardrail back to all the carcasses that were spotted from the car. They investigate and identify the species from behind the guardrail using binoculars. The driver stays in the car and takes notes on any useful information (e.g., closest km marker, location of the carcass) while waiting for the return of the observers. Additional information is added as soon as the observers return with their notes.

Depending on where the object is:

A. The object is on the shoulder and can be reached with a fork or shovel from behind the guardrail. The researchers identify the species, take a more precise GPS point, and remove the carcass from the road. At no time are we allowed to be on the inside of the guardrail. Yellow paint is added to the outside of the guardrail and on the reachable part of the emergency lane asphalt in line with the carcass' new position on the shoulder if still visible.
B. The object is in the emergency lane, right lane, or left lane or on the shoulder and cannot be reached with a fork or shovel from behind the guardrail. The researchers use binoculars to identify the species and take a more precise GPS point. The guardrail and reachable asphalt are marked with a line of spray paint in line with the carcass, as well as session day and session number. Yellow spray paint is used to refer to the emergency lane, red for the right lane, and blue for the left lane.

Naming waypoints on GPS for carcasses found:
When a carcass is found and identified, a waypoint must be taken on GPS to record its coordinates. The following procedure is used in order to standardize the naming of waypoints.

1st: The unique species identifier. This is made of 4 letters based on the scientific name of the species. For example, the scientific name of a porcupine is *Erethizon dorsatum*. Its unique species identifier would therefore be the first 2 letters of the first name (ER), followed by the first 2 letters of the second name (DO). The unique species identifier in this case is ERDO. Similarly, the scientific name for a red fox is *Vulpes vulpes*. Therefore, its unique species identifier would be VUVU.
Note: If the species cannot be identified, the code UNK will be used instead of the unique species identifier. If the animal can be identified as a bird, frog, or turtle, but the specific species cannot be identified, the code UNKBIRD, UNKFROG, UNKTURT should be used as the unique species identifier. Similarly, the code UNKSM is used for small mammals, UNKROD for rodents, UNKMM for medium-sized mammals and UNKSNA for snakes. If

possible, take a photo of any unidentifiable carcasses and send the photo for the species to be identified by experts.

2nd: The number of times individuals of the species has been observed on that particular day. For example, if it is the first porcupine observed during this survey, the number will be 1. If it is the second, the number will be 2 and so on. Following the previous porcupine example, and assuming this is the first time a porcupine has been observed this day, the waypoint marker should now read ERDO1.

3rd: The session day number (1-10). For example, if it is the 1st day of surveys in the session the number will be 1. If it is the second day of surveys the number will be 2, the third will be 3, and so on. A dash is to be placed between numbers to make them easier to read and ensure there is no confusion as to what they represent. Following the same example, if it were the 6th day of surveys the waypoint marker should now read ERDO1-6.

4th: The session number. For example, if this is the first 10-day survey session of the year, the number will read 1. If it is the 3rd 10-day survey session of the year, the number will be 3. Following the example, if it were the 8th survey session, the waypoint should read ERDO1-6-8.

Spray Paint system for Lane Information:
If the carcass cannot be removed entirely from the road (anytime the carcass can still be seen from the road, including in the road shoulder), a line of colour is spray painted on the asphalt in line with the carcass. The paint colour used signifies which lane the carcass is in.

Blue paint – Left Lane, Left shoulder, Left Asphalt Strip

Red paint – Right Lane

Yellow paint – Emergency lane (in the presence of a guardrail) or the shoulder (where there is no guard rail, because the animal has been moved to the shoulder of the road but is still visible).

In the same colour as the line, the session day and session number is added below the line with a dash in between the numbers. It must be big enough and oriented in a way that can be read from the survey vehicle.

When a carcass is spotted within 10 meters on either side of a painted line on a subsequent day, the information from the colour of the paint and the session day number should be used to identify the corresponding entry in the notebook. If the species of the new carcass matches the species in the notebook entry for that location, GPS coordinates should not be taken to avoid double counting. The carcass has likely already been accounted for. If the species is different from the entry, GPS coordinates should be taken as it is a new data point.

Notes for the driver:
If the carcass is located closer to the beginning of a long stretch of guardrail than to the end of the guardrail, the driver lets out the 2 observers at the end of the guardrail (not at the beginning because it is not yet known if there will be carcasses found and because the search needs to be done consistently), then takes the nearest exit to drive back around and pick up the observers at the start of the guardrail. No additional points are taken for the stretch of this guardrail to avoid double counting.
The driver should take notes about the weather, road conditions (wet/dry), start time, and starting temperature before beginning the survey when the vehicle is stopped safely at the start of the first survey section. The end time and end temperature should also be noted once the survey is complete.
The driver should also be taking notes when waiting in the car for the observers to return. Write down as much information as possible without the observers and add additional details once the observers have returned with their analysis notes. Notes should be complete before continuing the survey.

Information that should be written:
- Nearest km marker to the carcass.
- Lane in which the carcass was found.
- Species of the animal and how it was identified.
- Code that was entered into the GPS.
- Level of decomposition.
- Level of confidence in species identification.
- Whether the animal is an adult or a juvenile (best guess).
- Animal size (if the animal can be measured by an observer).
- The action taken by the observers (i.e.: paint, removed from road, etc.).

Conditions which may affect the protocol:
(1) Heavy rain: Drive to a location that is near the starting point of the survey that day to assess the weather conditions at that point (since weather varies greatly from Magog to Bromont). Wait for the rain to subside or calm then begin the survey and complete as much as possible. If the rain persists, cancel the survey. If there is thunder and lightning, wait until it stops before going to the starting point and beginning the survey.
(2) Not enough space: Stretches where the vehicle cannot drive to the right of the rumble strip (i.e., emergency lane is not wide enough between the rumble strip and the guardrail) are excluded from the survey area.
(3) Can’t walk: Areas where we cannot walk behind the guardrail (i.e., if the terrain is too steep, the passage behind the guardrail is blocked, or there is an underpass) are excluded from the survey area.
(4) Sun: On very sunny days, plan to drive towards Montreal in the morning around sunrise, and towards Sherbrook around sunset to avoid sun blindness. If experiencing intense sun blindness on the road, exclude areas where visibility is severely affected from the survey that day. The reason is safety, i.e., visibility of our vehicle by passing traffic.

(5) Traffic: In the morning start survey 30 minutes after sunrise. Plan to avoid driving in section F (section going west towards Montreal near Bromont) after 7:30 am during morning surveys. In the evenings, start surveys when peak traffic has subsided and finish before it becomes difficult to see objects on the road. The start and end time of evening surveys should vary as daylight hour's change throughout the summer. Do not do evening surveys on Fridays since there is consistently too much traffic due to vacationers. Monitor traffic on Sundays and Mondays during long weekends. Start survey later if there is too much traffic from vacationers returning to Montreal.

Note taking:
Take note of any deviations from standard protocol, i.e., excluding a section due to sun blindness, stopping due to bad weather, waiting due to traffic, etc.

Confidence level between 0-3:
0 – The species cannot be identified.
1 – It is possible that the species has been identified correctly. However, due to the state or positioning (visibility) of the carcass, at least one observer feels it could also possibly be a different species.
2 – The species has most likely been identified correctly, although at least one observer is not fully convinced the species is correct. Alternatively, both observers feel that the species is most likely identified, but they cannot be certain due to the decomposition level or positioning (visibility).
3 – Confident the species is correctly identified. Both observers must agree fully.

Decomposition level:
Freshly killed – The animal has been killed within 12 hours of the survey. Blood may be present. The body has not begun to decompose. It is usually easiest to identify species in this state unless the body has been severely mutilated from a collision.
Moderately decomposed – The body is still more or less in tact but has begun to decompose. Bugs may be present.
Highly decomposed – the body is in the process of disintegrating; bugs may also be present. Observers must identify the species based on only some intact features.

Traffic volume:
None – 30 seconds or more may go by without another vehicle passing by. Cars are always able to switch into the left lane.
Light – Cars pass by in intervals of 15 seconds or more. Cars are always able to switch into the left lane before passing the research vehicle.
Moderate – Cars pass by in intervals of less than 15 seconds. Cars can usually switch into the left lane but there may be bursts of traffic where cars in the right lane cannot switch lanes before passing the research vehicle.

Heavy – Cars cannot drive at 100 km/hour due to the volume of cars on the road. Cars are unable to switch lanes because there is too much traffic. The survey cannot be done in these traffic conditions.

Starting points: Starting points are chosen every day. Count of each time a starting point is used is taken to ensure all starting points are used equally. The starting point is chosen at random as much as possible but sometimes must be chosen specifically to plan for certain conditions such as traffic, or sunny weather. The reason is to avoid potential bias among the road sections surveyed (Plante et al. 2019).

Modifications made to the protocol:
Initially (in April 2019), traffic was thought to have been heavy in both the east and west directions along all sections of the highway between 7:30 and 9 am. For this reason, the survey sections were done in 2 rounds of surveys on the same day. Three sections were surveyed in the morning, and the remaining three were surveyed at night, so that all six sections were done in the same day.
After the first session (in May 2019), it was noted that traffic was only heavy between these times in one section, going west closest towards Montreal. It was also noted that the amount of time between surveys varied between 12, 24 and 36 hours depending on the section and the starting points (since the starting point would vary). It was also observed that sun blindness was only an issue for an hour after sunrise and an hour before sunset on very sunny days. For these reasons, the protocol was modified for all six sections to be driven in one survey. Surveys would take place in the morning for the first 5 days (Tuesday-Saturday), and in the evening for the remaining 5 days (Sunday-Thursday). Four of the six survey sections were also extended to include a greater survey area. The new, finalized protocol was implemented on June 12th, 2019.

Data entry form for road morality surveys.

Column header	Explanation
Year	Year of survey
Date (DD – Month)	Day – Month
Day of the week	(Mon/Tues/Wed etc.)
Car	Model of car used for surveys
Morning/Evening	When was the survey conducted (in the morning or evening)
Time start	Start time of survey
Time end	End time of survey
Session day	1 to 10 (because we surveyed for 10 consecutive days)
Session number	1 to 8 for summer 2019 (because we had 8 survey sessions)
Weather	Describe (e.g., sunny, cloudy, raining, overcast etc.)
Road condition	Wet/Dry

Temp start (˚C)	Temperature at the start of the survey
Temp end (˚C)	Temperature at the end of the survey
Wind speed (km/hr)	Speed of the wind during the survey
Wind direction	Direction of the wind during the survey
Sunrise	Time of sunrise
Sunset	Time of sunset
Visibility	Describe the ability to see carcasses on the road (high, moderate, low; clear, dark, foggy etc.)
Starting section	The section surveyed first
Starting section tally	The number of times the survey started from that section throughout the summer. (e.g., F14 = the 14th time we started in section F during the study period)
Order of surveyed sections	Order of survey sections on our route (e.g., A-B-C-D-E-F)
Traffic level Section 1	Letter corresponding to the section followed by the traffic density: none, light, moderate, heavy. (e.g., F-Moderate)
Traffic level Section 2	Letter corresponding to the section followed by the traffic density: none, light, moderate, heavy. (e.g., A-Light)
Traffic level Section 3	Letter corresponding to the section followed by the traffic density: none, light, moderate, heavy. (e.g., B-Moderate)
Traffic level Section 4	Letter corresponding to the section followed by the traffic density: none, light, moderate, heavy. (e.g., C-Moderate)
Traffic level Section 5	Letter corresponding to the section followed by the traffic density: none, light, moderate, heavy. (e.g., D-light)
Traffic level Section 6	Letter corresponding to the section followed by the traffic density: none, light, moderate, heavy. (e.g., E-None)
Time since last survey	Amount of time passed since last survey (24 hours, 36 hours (when switching from morning to evening surveys), 4 days (after CRT weekend))
Average speed (km/hr)	Average speed the vehicle was driven at (always 30 km/hr)
Driver	Name of the driver
Observers (Passengers)	Names of the observers/passengers
Number of animals	The total number of animals found during the survey
Moon phase	Moon phase that night

Animals found outside of permit zone + km markers	If there were carcasses spotted outside of the study area (travelling at normal speeds), they are marked here with the nearest km marker.
Notes	Any relevant information or deviations from the protocol.

Data entry form for animals observed during surveys.

Column header	Explanation
Date (dd-mm-yy)	Day – Month – Year
Month	5 = May; 6 = June; 7 = July; 8 = August; 9 = September
Session day	1 to 10 (because we surveyed for 10 consecutive days)
Session number	1 to 8 for summer 2019 (because we had 8 survey sessions)
AM/PM	AM = Found during morning survey; PM = Found during evening survey
Lane	RS = Right Shoulder/ditch, EL = Emergency Lane, RL = Right Lane, LL = Left Lane, LS = Left Shoulder/ditch
Guardrail	Y = Yes, N = No
Km marker	Deemed closest to carcass
Driving direction	EAST = to Sherbrooke, WEST = to Montreal
Section	A, B, C = eastward; D, E, F = westward
Starting section	A, B, D, C, D, E, or F
Start time of section	These are important when comparing our data with HPP data
Animal	Common name
Pic (picture)	Picture taken of animal: Y = Yes, N = No
GPS code	GEnus + SPecies = GESP + Species Count + Day Number + Session Number = GESP-X-D#-S#
Latitude	Coordinate
Longitude	Coordinate
Animal group	Small mammal, medium-sized mammal, large mammal, bird, amphibian, reptile
State	Fresh, Moderately Decomposed, Decomposed
Confidence	0 = Unknown, 1 = Somewhat confident but researchers disagree, 2 = Confident; one researcher has doubts, 3 = Confident in correct identification.

Action	Remove (if located on RS or EL), Paint : Yellow = RS & EL, Red = RL, Blue = LL & LS.
GPS mark number	Sequential number from GPS device
Pic GPS	Picture taken of GPS (to safeguard against GPS data loss): Y = Yes, N = No
Notes	Relevant information & clarifications (e.g., if comments/help were received from others)

A.2 Cycling Survey Protocol

Data collection protocol for highways without an emergency lane (R112)

This protocol was designed to monitor road mortality by bicycle along Route 112 in Quebec during the summer months. The initial protocol was designed, tested, and modified in July-August 2021 to maximize the efficiency of the surveys, as well as to ensure that it can be precisely replicated in the future.

Surveys performed on bicycle facilitate increased detection probability compared to those performed by vehicle while increasing the length of road sections surveyed when compared to walking surveys. Cycling surveys expose the research team to a variety of weather conditions and potential traffic dangers; therefore, caution must be taken to ensure researcher and public safety. On many two-lane roads, surveys by vehicle driving slowly are not feasible without resulting in considerable traffic disruption and the creation of potential traffic hazards. The shoulder of R112, at one meter in width, is not wide enough to accommodate the breadth of most passenger vehicles, i.e., the survey vehicle driving on the shoulder would overlap with the driving lane, resulting in motorists needing to switch to the other lane (and potentially into oncoming traffic) in order to pass. Therefore, the data collection protocol developed for highways with an emergency lane (such as A10) cannot be used for R112. Public perception of the research team also needs to be considered; the research team does not want to disrupt community traffic flow.

Route 112, as an example of a highway without an emergency lane, is a two-lane secondary highway. It includes one eastbound and one westbound lane with narrow shoulders of about one meter in width flanking both driving lanes. Much of the surveyed section of 25 km in length bisects forested and agricultural land. The eastern terminus borders Lac Orford and Parc national du Mont-Orford while the western end connects the communities of Frost Village and Stukely, where homes and businesses immediately abut Route 112. Guardrails are present spanning bridge lengths over streams and several other waterbodies, and in some areas of tight curves or sharp verge angles. Guardrails do not impede passage along the highway's shoulder. Cyclists travelling along the shoulder are common. Each survey, on average, is completed in two hours and thirty-five minutes (corresponding to slightly less than 6.5 minutes per kilometre on average); however, completion times are highly variable and range from an hour and a half to over three and a half hours.

Survey days: Surveys are conducted over the span of 10-day sessions from Tuesday for the first week to Thursday of the following week. From Tuesday to Saturday, surveys are done in the evenings and are timed to be completed one half hour before sunset. From Sunday to Thursday surveys are done in the mornings starting one half hour after sunrise. Conducting both evening and morning surveys considers both differences in the time of animal mortality to occur over a 24-hour period, and variation in carcass persistence (i.e., how long a carcass remains in situ on the road and is detectable). The end point of the survey on the first day serves as the starting point for the survey on the second day but travelling in the opposite direction. Every two days a full circuit of the survey area is completed; 25 km westbound followed by 25 km eastbound.

Equipment

The equipment includes:

- Three road bikes, helmets for cyclists, reflective safety vests, headlights, taillights, a portable air pump, sunglasses, sunscreen, insect repellent, two wire brushes, sidewalk chalk, and baskets or waterproof bags for transporting fieldwork tools. Two bikes are needed for each survey, while the third bike acts as a spare should the need arise, e.g., in case of need for repair of one of the other two.
- A field vehicle.
- One retractable rake, ecofriendly cleanser, and gloves to remove roadkill.
- A portable battery pack to charge cellphones.
- Two Garmin eTrex 20 units, one for each Cyclist. They are small and convenient handheld GPS devices, used to record carcass GPS coordinates.
- We used our personal smartphones to communicate among the two Cyclists while in the field and between the Cyclists and the Driver to coordinate pick-up times. Additionally, we used portable battery packs to maintain adequate charge on our cellphones, ensuring open communication between team members and allowing for many photos of carcasses to be taken.

Research team

- At the beginning and at the end of each survey, the time, temperature, humidex, visibility, and weather conditions are noted. Weather forecasts spanning the hours of the survey are consulted, including radar imagery, informing the team of expected weather conditions and appropriate clothing.
- Three researchers rotate through two designated positions: one Driver and two Cyclists (surveyors). The Driver transports the two cyclists by field vehicle to each day's survey starting point and collects them from the survey end point after each survey. The Driver remains in the field vehicle monitoring the weather and alert to respond to a call for aid from the Cyclists. The position of Driver conveniently serves also as a break for the researcher, a period of rest after two days of participation in the cycling surveys.
- Both Cyclists are equipped with their own Garmin eTrex 20 GPS, stopping to mark waypoints as required. The cyclists work in tandem, each passing the other until spotting a new carcass to be recorded. This is an efficient method, developed in the wake of discovering up to 200 animals per survey, a response for the need to use field time most effectively.
- When a Cyclist encounters roadkill, (s)he will pin a waypoint on the Garmin eTrex GPS to mark its location. Next, a name is entered for each point, an acronym derived from the variables to be measured (species of the animal, traffic lane of carcass location, whether a guardrail is present, and the degree of decomposition).
- After entering the variables in the GPS, the Cyclists remove the carcass from the roadway using a gloved hand, rake, or a combination of the two. The carcass is tossed into the ditch, obscured by tall plant growth. If traces of the carcass remain, and should safety permit, a wire brush is used in an attempt to remove all trace of the carcass. Often, not all of the carcass can be removed, in which case a Cyclist uses chalk to mark an 'X' overtop of what

remains. Doing so avoids double counting during subsequent surveys. The chalk ought to wash away during precipitation events at the same rate of time as that of the animal carcass remains underneath.

Encountering roadkill on the traffic lanes or on the shoulder in the opposite direction of travel: With great caution, the Cyclist proceeds onto the roadway after scanning for traffic in both directions. Crossing Route 112 is achievable but to do so may require a small wait time of several seconds for a safe clearing in traffic. Cyclists move onto and/or cross the roadway in order to identify, to remove, or to mark unremovable carcasses with chalk – all other survey time is spent within the relative safety of the shoulder.

Weather events:
For safety purposes, it is good practice to research the study area well before fieldwork begins to prepare maps marked with locations of relevant businesses or shelter points. Camping sites, restaurants, gas stations, and rest stops can serve as shelter points. The hourly weather forecast is consulted before each survey. If it is currently raining or begins to rain in a way that the rain considerably reduces visibility, the team waits for the rain to subside or calm, then begin (or continue) the survey and complete as much as possible.
Surveys in the rain continue until visibility is compromised (rain in researchers' eyes) or if the Driver radioed that the bike survey should stop. Cyclist safety is paramount; clear and honest communication between the Cyclists should determine when the survey will pause or be cancelled. In other words, if the cyclists do no longer feel safe, the work needs to stop.
If heavy rain persists, the survey is cancelled. If there is thunder and lightning, the researchers wait until it stops before going to the starting point and beginning the survey. If the rain reduces visibility significantly, the cyclists will discuss and pause the survey to see if conditions improve, and if they do not improve within a reasonable time limit, the cyclists stop the survey for the day (due to reduced detection probability and safety concerns).

GPS:
A Garmin eTrex 20x GPS device was used by each Cyclist to record carcass' location, lane and direction, the presence of a guardrail, decomposition level, and action taken by the Cyclist. Each waypoint code is a simple acronym where the first character entered was the first letter of the species common name:
B for American Bullfrog, T for American Toad, N for Eastern Newt, R for Ranidae sp. (unknown frog species), and L for Leopard frog. Less common animals followed naming methods employed during previous surveys where a four-letter code is created from combining the first two letters from both the carcass' genus and of the species, e.g., a raccoon (Procyon lotor) is entered as PRLO, and a striped skunk (Mephitis mephitis) is entered as MEME.
The subsequent characters entered follow the logic below:

- Lane: eastbound shoulder (EE), eastbound traffic lane (E), westbound traffic lane (W), and westbound shoulder (WW)
- Presence of guardrail: yes (Y) or no (N)
- Decomposition level: decomposed (D), moderately decomposed (M), or Fresh (F)

- Action: removed (R), marked with chalk (C), or not removed (NR). Often a removed carcass will still leave noticeable traces, so to avoid double counting the site, our most common action was to remove as much of the carcass as was possible, and with chalk we marked the asphalt with an 'X.'

The variables entered into the Garmin eTrex GPS always followed the same order. For example, the code of 'BWNDRC' indicates an American Bullfrog (B) found in the westbound traffic lane (W) with no guardrail (N), decomposed (D), removed (R) and the location was marked with chalk (C). For another example, 'REEYFR' indicates Ranidae sp. (R), found on the eastbound shoulder (EE) with a guardrail present (Y), the decomposition level is fresh (F), we removed it completely from the roadway (R) leaving no trace. While this system may seem confusing at first, a standardized use of single-letters for variable representation saved hours of time when recording data. When faced with hundreds of dead animals and limited time in which to record them, employing such a coding system maximizes efficiency while limiting surveyor fatigue.

Information that should be recorded:

Column Header	Explanation
Date	Day – Month – Year
Time (start/end)	The time the survey started and the time it ends
Temperatures	The temperature at the start and at the end of the survey
Session Number	1 to 4, as we had four sessions during summer 2021
Session Day	1 to 10, as each session consists of ten days
AM/PM	AM = found during the morning survey, or PM = found during the evening survey
Cycling Direction	EAST = towards Magog, or WEST = towards Montreal
Lane	EE = Eastbound shoulder; E = Eastbound lane; W = Westbound lane; or WW = Westbound shoulder
Guardrail (Y/N)	Y = Yes, or N = No
GPS #1	The waypoint number from our main GPS used
GPS #2	The waypoint number from our secondary GPS used
Animal	Common name
Animal Type	Amphibian; Bird; Mammal; Reptile; or Unknown
Latitude	Coordinate
Longitude	Coordinate
Photo Name	GPS waypoint number + Species + [Highway; Survey number] E.g., 101. Raccoon [R112; 2-1]
Carcass State	Fresh; Moderately decomposed; or Decomposed
Action	Removed and/or an 'X' marked with chalk on the asphalt
Notes	Landmarks noted

Decomposition level:

Freshly killed – The animal has been killed within about 12 hours of the survey. Blood may be present. The body has not begun to decompose. It is usually easiest to identify species in this state unless the body has been severely mutilated from a collision.

Moderately decomposed – The body is still more or less intact but has begun to decompose. Swelling of the carcass is evident; bugs may be present.

Highly decomposed – the body is in the process of disintegrating; bugs may also be present. Flesh, if remaining, is often dehydrated. Observers must identify the species based on only some intact features.

Notes:

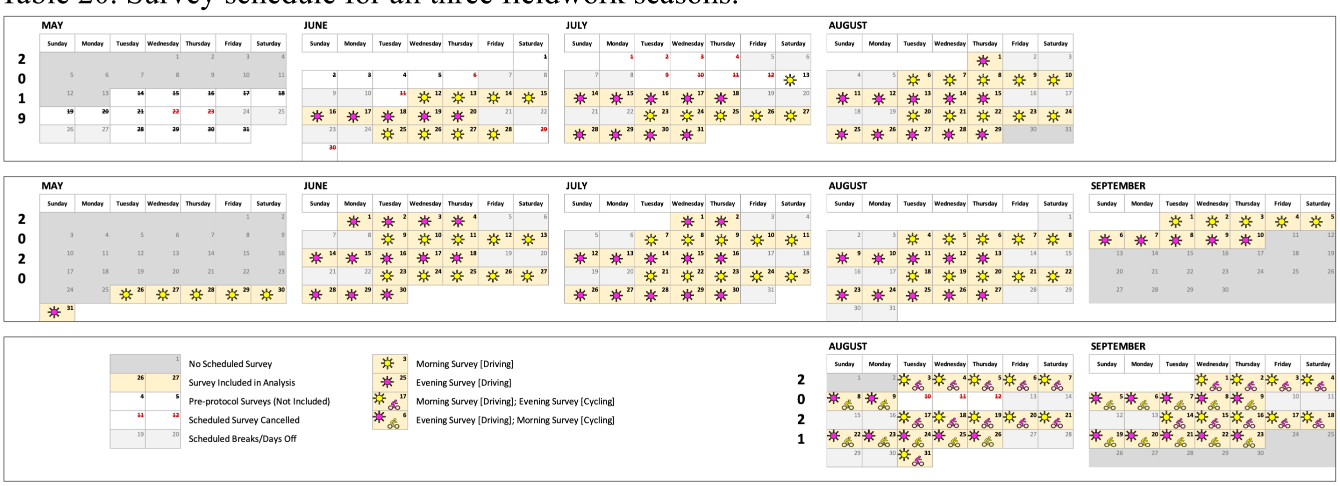
- In an effort to be more expedient during data collection in the field, carcasses not immediately identified at the level of species (e.g., due to the state of the carcass), photos of the carcass are taken, using a ruler for scale [front, back, paws or feet, face and/or beak] and to be identified later in the fieldhouse. Advantages include a paced and thorough review of animal identification books (e.g., Oiseaux du Québec et du Canada (2019), edited by Bird & Denault).
- Animals recorded as 'removed' have been removed out of view from the road. If the carcass occurs to be still visible from the road, a marking of chalk with the session and survey day is written parallel to the carcass on the shoulder. From experience, an adult raccoon or other animal of similar size can completely decompose to bones and tufts of fur in a few days. Larger animals, namely deer, are tagged with an orange flag and removed by the Ministère des Transports et de la Mobilité durable. The research team records these carcasses but does not move them.
- The research area along R112 is 25.1 km in length.

Reference

Plante, J., Jaeger, J.A.G., Desrochers, A. (2019): How do landscape context and fences influence roadkill locations of small and medium-sized mammals? Journal of Environmental Management 235: 511-520.

A.3 Fieldwork Survey Schedule

Table 20. Survey schedule for all three fieldwork seasons.



A.4 Analyzed Roadkill

Table 21. A complete list of all roadkill used in the analyses, by year and highway.

Latin	Species	A10_2019	A10_2020	A10_2021	R112_2021	Total
Lithobates catesbeianus	American Bullfrog	4	10	42	54	110
Anaxyrus americanus americanus	American Toad	1	114	58	29	202
Hyla (Dryophytes) versicolor	Eastern Gray Tree Frog	0	1	0	0	1
Notophthalmus viridescens viridescens	Eastern Newt	0	121	109	67	297
Lithobates clamitans	Green Frog	1	241	4	5	251
Lithobates pipiens	Leopard Frog	1	8	9	8	26
Lithobates septentrionalis	Mink Frog	1	1	0	0	2
Pseudacris crucifer crucifer	Northern Spring Peeper	0	4	8	5	17
Ranidae sp.	Ranidae sp.	4	189	617	1221	2031
Ambystoma maculatum	Spotted Salamander	0	4	2	3	9
Lithobates sylvaticus	Wood Frog	0	52	87	1	140
	Total:	**12**	**745**	**936**	**1393**	**3086**
Castor canadensis	American Beaver	0	1	0		1
Martes americana	American Marten	2	1	0		3
Mustela vison	American Mink	2	7	3	2	14
Tamias striatus	Chipmunk	1	11	2	7	21
Canis latrans	Coyote	1	0	0		1
Felis catas domesticus	Domestic Cat	0	0	1	1	2
Mustela erminea	Ermine	4	12	7	2	25
Sciurus carolinensis	Grey Squirrel	7	19	3		29
Lasiurus cinereus	Hoary Bat	0	1	0		1
Marmota monax	Marmot	5	18	3	2	28
Muroidea sp.	Muroidea sp.	3	42	44	16	105
Ondatra zibethicus	Muskrat	0	3	2	2	7
Rattus norvegicus	Norway Rat	0	2	0		2
Erethizon Dorsatum	North American Porcupine	7	26	11	3	47
Procyon lotor	North American Raccoon	14	54	16	5	89
Vulpes Vulpes	Red Fox	0	5	3		8
Tamiasciurus hudsonicus	Red Squirrel	6	21	2	8	37
Lutra canadensis	River Otter	1	3	0		4
Lepus americanus	Snowshoe Hare	2	4	0	1	7
Soricidae sp.	Soricidae sp.	1	0	6	10	17
Condylura cristata	Star-nosed Mole	0	0	1	1	2
Mephitis mephitis	Striped Skunk	9	19	28	9	65
	Unknown Mammal	1	13	13	14	41
Didelphis virginiana	Virginia Opossum	0	1	0		1
Odocoileus virginianus	White-tailed Deer	6	15	7	1	29
	Total:	**72**	**278**	**152**	**84**	**586**
Thamnophis sirtalis	Common Garter Snake	0	12	20	73	105
Chrysemys picta picta	Painted Turtle	6	4	2		12
Storeria occipitomaculata occipitomaculata	Redbelly Snake	0	32	26	30	88
Diadophis punctatus edwardsii	Ring-necked Snake	0	0	11	11	22
Chelydra serpentina	Snapping Turtle	6	5	4	5	20
Squamata sp.	Squamata Sp.	0	2	23	20	45
	Unknown Reptile	0	0	1		1
	Unknown Turtle	1	1	0		2
Glyptemys insculpta	Wood Turtle	1	0	2		3
	Total:	**14**	**56**	**89**	**139**	**298**
	Overall Total:	**98**	**1079**	**1177**	**1616**	**3970**

A.5 Roadkill Heatmap

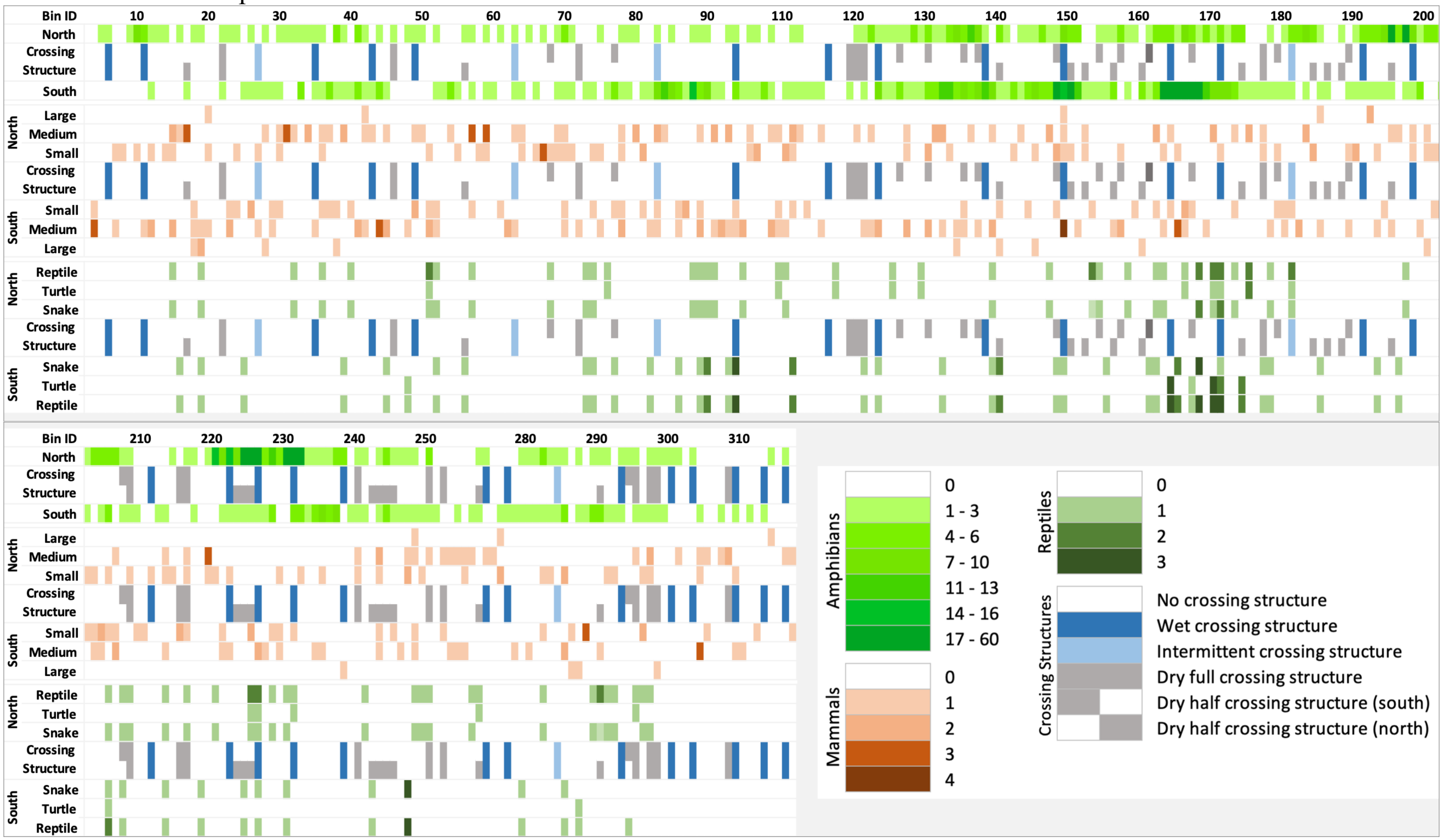


Figure 22. Heat map visual depicting roadkill levels on A10. To show the differences in roadkill levels between the north and south sides of the divided highway, each bin has been divided into north and south with roadkill levels reflecting the number of roadkill detected within each bin, by side of highway. Rows depicting full and half crossing structures are colour-coded to show dry (grey), wet (dark blue), or intermittent (light blue) crossing structures, and appear between the north and south side roadkill levels for amphibians, mammals of large, medium, and small body size, and reptiles, turtles, and snakes.

Appendix B. Step 1 & Step 2 Templates

Table 22. The Step 1 Template. The variable selection process was repeated as many times as required (~ 2 to 4 times) until a full iteration produced no lower AIC value.

Mod.animal_step1	<- glm(animal ~	Forest (Proportion)	Anthropogenic (Proportion)	Marsh (Proportion)	Agriculture (Proportion)	Waterbody (Proportion)	Watercourse (Linear km/ha)	Forest (Distance-to)	Marshland (Distance-to)	Agriculture (Distance-to)	Waterbody (Distance-to)	Watercourse (Distance-to)	, family = poisson(), data = data)
#### FOREST													
mod.animal_forest100	<- glm(animal ~	forest_100	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_forest200	<- glm(animal ~	forest_200	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_forest500	<- glm(animal ~	forest_500	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_forest1k	<- glm(animal ~	forest_1k	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_forest2k	<- glm(animal ~	forest_2k	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest100	<- glm(animal ~	log.forest_100	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest200	<- glm(animal ~	log.forest_200	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest500	<- glm(animal ~	log.forest_500	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest1k	<- glm(animal ~	log.forest_1k	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logforest2k	<- glm(animal ~	log.forest_2k	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_forest100, mod.animal_forest200, mod.animal_forest500, mod.animal_forest1k, mod.animal_forest2k)													
AIC(mod.animal_logforest100, mod.animal_logforest200, mod.animal_logforest500, mod.animal_logforest1k, mod.animal_logforest2k)													
# Model with the lowest AIC =	log.forest_200												
#### ANTHROPOGENIC													
mod.animal_anthro100	<- glm(animal ~	log.forest_200	+ anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_anthro200	<- glm(animal ~	log.forest_200	+ anthro_200	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_anthro500	<- glm(animal ~	log.forest_200	+ anthro_500	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_anthro1k	<- glm(animal ~	log.forest_200	+ anthro_1k	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_anthro2k	<- glm(animal ~	log.forest_200	+ anthro_2k	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_loganthro100	<- glm(animal ~	log.forest_200	+ log.anthro_100	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_loganthro200	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_loganthro500	<- glm(animal ~	log.forest_200	+ log.anthro_500	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_loganthro1k	<- glm(animal ~	log.forest_200	+ log.anthro_1k	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_loganthro2k	<- glm(animal ~	log.forest_200	+ log.anthro_2k	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_anthro100, mod.animal_anthro200, mod.animal_anthro500, mod.animal_anthro1k, mod.animal_anthro2k)													
AIC(mod.animal_loganthro100, mod.animal_loganthro200, mod.animal_loganthro500, mod.animal_loganthro1k, mod.animal_loganthro2k)													
# Model with the lowest AIC =	log.anthro_200												
#### MARSH													
mod.animal_marsh100	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_marsh200	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ marsh_200	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_marsh500	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ marsh_500	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_marsh1k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ marsh_1k	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_marsh2k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ marsh_2k	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logmarsh100	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_100	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logmarsh200	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_200	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logmarsh500	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logmarsh1k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_1k	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logmarsh2k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_2k	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_marsh100, mod.animal_marsh200, mod.animal_marsh500, mod.animal_marsh1k, mod.animal_marsh2k)													
AIC(mod.animal_logmarsh100, mod.animal_logmarsh200, mod.animal_logmarsh500, mod.animal_logmarsh1k, mod.animal_logmarsh2k)													
# Model with the lowest AIC =	log.marsh_500												
#### AGRICULTURE													
mod.animal_agri100	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_agri200	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ agri_200	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_agri500	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ agri_500	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_agri1k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ agri_1k	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_agri2k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ agri_2k	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logagri100	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logagri200	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_200	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logagri500	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_500	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logagri1k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_1k	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logagri2k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_2k	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_agri100, mod.animal_agri200, mod.animal_agri500, mod.animal_agri1k, mod.animal_agri2k)													
AIC(mod.animal_logagri100, mod.animal_logagri200, mod.animal_logagri500, mod.animal_logagri1k, mod.animal_logagri2k)													
# Model with the lowest AIC =	log.agri_100												
#### WATERBODY													
mod.animal_water100	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_water200	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ water_200	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_water500	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ water_500	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_water1k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ water_1k	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_water2k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ water_2k	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwater100	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_100	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwater200	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwater500	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_500	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwater1k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_1k	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwater2k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_2k	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_water100, mod.animal_water200, mod.animal_water500, mod.animal_water1k, mod.animal_water2k)													
AIC(mod.animal_logwater100, mod.animal_logwater200, mod.animal_logwater500, mod.animal_logwater1k, mod.animal_logwater2k)													
# Model with the lowest AIC =	log.water_200												
#### WATERCOURSE													
mod.animal_wc100	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_wc200	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_200	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_wc500	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_500	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_wc1k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_1k	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_wc2k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_2k	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwc100	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ log.wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwc200	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ log.wc_200	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwc500	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ log.wc_500	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwc1k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ log.wc_1k	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_logwc2k	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ log.wc_2k	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_wc100, mod.animal_wc200, mod.animal_wc500, mod.animal_wc1k, mod.animal_wc2k)													
AIC(mod.animal_logwc100, mod.animal_logwc200, mod.animal_logwc500, mod.animal_logwc1k, mod.animal_logwc2k)													
# Model with the lowest AIC =	wc_100												
####DistancetoForest####													
mod.animal_forest_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_log_forest_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ log.forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_forest_m, mod.animal_log_forest_m)													
# Model with the lowest AIC =	forest_m												
####DistancetoMarsh####													
mod.animal_marsh_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_log_marsh_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ forest_m	+ log.marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_marsh_m, mod.animal_log_marsh_m)													
# Model with the lowest AIC =	marsh_m												
####DistancetoAgriculture													
mod.animal_agri_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_log_agri_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ forest_m	+ marsh_m	+ log.agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_agri_m, mod.animal_log_agri_m)													
# Model with the lowest AIC =	agri_m												
####DistancetoWaterbody####													
mod.animal_water_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_log_water_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ x1_wc_100	+ x2_forest_m	+ marsh_m	+ agri_m	+ log.water_m	+ wc_m	, family = poisson(), data = data)
AIC(mod.animal_water_m, mod.animal_log_water_m)													
# Model with the lowest AIC =	log.water_m												
####DistancetoWatercourse													
mod.animal_wc_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ wc_100	+ forest_m	+ marsh_m	+ agri_m	+ log.water_m	+ wc_m	, family = poisson(), data = data)
mod.animal_log_wc_m	<- glm(animal ~	log.forest_200	+ log.anthro_200	+ log.marsh_500	+ log.agri_100	+ log.water_200	+ x1_wc_100	+ x2_forest_m	+ marsh_m	+ agri_m	+ log.water_m	+ log.wc_m	, family = poisson(), data = data)
AIC(mod.animal_wc_m, mod.animal_log_wc_m)													
# Model with the lowest AIC =	wc_m												

Table 23. The Step 2 Template used in Scenarios A, B, and C. Global model fitting was completed by adding structural predictors in combination, by Material, Shape, and Function group, to Step 1 models. The lowest AIC value per group was chosen as a global model.

	cs.mod.ani.scenario.grp	<- glm(animal ~	CGX				MATERIAL			SHAPE			FUNCTION		+ STEP1 MODEL	
CGX	cs.mod.animal.D.cgx	<- glm(animal ~	corridor_	+ guardrail_	+ xfull_	+ xhalf_									+ STEP1 MODEL	LOWEST AIC = GLOBAL MODEL (must incl. xstrucs.)
	cs.mod.animal.D.cgx	<- glm(animal ~	corridor_	+ guardrail_											+ STEP1 MODEL	
	cs.mod.animal.D.g	<- glm(animal ~		guardrail_											+ STEP1 MODEL	
	cs.mod.animal.D.gx	<- glm(animal ~		guardrail_	+ xfull_	+ xhalf_									+ STEP1 MODEL	
	cs.mod.animal.D.cx	<- glm(animal ~	corridor_		+ xfull_	+ xhalf_									+ STEP1 MODEL	
	cs.mod.animal.D.c	<- glm(animal ~	corridor_												+ STEP1 MODEL	
	cs.mod.animal.D.x	<- glm(animal ~			xfull_	+ xhalf_									+ STEP1 MODEL	
MATERIAL	cs.mod.animal.D.cg_mat1	<- glm(animal ~	corridor_	+ guardrail_			+ met_	+ plas_	+ con_						+ STEP1 MODEL	LOWEST AIC = GLOBAL MODEL (MATERIAL)
	cs.mod.animal.D.cg_mat2	<- glm(animal ~	corridor_	+ guardrail_			+ met_	+ plas_							+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat3	<- glm(animal ~	corridor_	+ guardrail_			+ met_		+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat4	<- glm(animal ~	corridor_	+ guardrail_			+ met_								+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat5	<- glm(animal ~	corridor_	+ guardrail_				+ plas_	+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat6	<- glm(animal ~	corridor_	+ guardrail_				+ plas_							+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat7	<- glm(animal ~	corridor_	+ guardrail_					+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.g_mat1	<- glm(animal ~		guardrail_			+ met_	+ plas_	+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.g_mat2	<- glm(animal ~		guardrail_			+ met_	+ plas_							+ STEP1 MODEL	
	cs.mod.animal.D.g_mat3	<- glm(animal ~		guardrail_			+ met_		+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.g_mat4	<- glm(animal ~		guardrail_			+ met_								+ STEP1 MODEL	
	cs.mod.animal.D.g_mat5	<- glm(animal ~		guardrail_				+ plas_	+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.g_mat6	<- glm(animal ~		guardrail_				+ plas_							+ STEP1 MODEL	
	cs.mod.animal.D.g_mat7	<- glm(animal ~		guardrail_					+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.c_mat1	<- glm(animal ~	corridor_				+ met_	+ plas_	+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.c_mat2	<- glm(animal ~	corridor_				+ met_	+ plas_							+ STEP1 MODEL	
	cs.mod.animal.D.c_mat3	<- glm(animal ~	corridor_				+ met_		+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.c_mat4	<- glm(animal ~	corridor_				+ met_								+ STEP1 MODEL	
	cs.mod.animal.D.c_mat5	<- glm(animal ~	corridor_					+ plas_	+ con_						+ STEP1 MODEL	
	cs.mod.animal.D.c_mat6	<- glm(animal ~	corridor_					+ plas_							+ STEP1 MODEL	
	cs.mod.animal.D.c_mat7	<- glm(animal ~	corridor_						+ con_						+ STEP1 MODEL	
	cs.mod.animal.D._mat1	<- glm(animal ~					met_	+ plas_	+ con_						+ STEP1 MODEL	
	cs.mod.animal.D._mat2	<- glm(animal ~					met_	+ plas_							+ STEP1 MODEL	
	cs.mod.animal.D._mat3	<- glm(animal ~					met_		+ con_						+ STEP1 MODEL	
	cs.mod.animal.D._mat4	<- glm(animal ~					met_								+ STEP1 MODEL	
	cs.mod.animal.D._mat5	<- glm(animal ~						plas_	+ con_						+ STEP1 MODEL	
	cs.mod.animal.D._mat6	<- glm(animal ~						plas_							+ STEP1 MODEL	
	cs.mod.animal.D._mat7	<- glm(animal ~							con_						+ STEP1 MODEL	
SHAPE	cs.mod.animal.D.cg_shp1	<- glm(animal ~	corridor_	+ guardrail_						+ cir_	+ rec_	+ bri_			+ STEP1 MODEL	LOWEST AIC = GLOBAL MODEL (SHAPE)
	cs.mod.animal.D.cg_shp2	<- glm(animal ~	corridor_	+ guardrail_						+ cir_	+ rec_				+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp3	<- glm(animal ~	corridor_	+ guardrail_						+ cir_		+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp4	<- glm(animal ~	corridor_	+ guardrail_						+ cir_					+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp5	<- glm(animal ~	corridor_	+ guardrail_							+ rec_	+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp6	<- glm(animal ~	corridor_	+ guardrail_							+ rec_				+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp7	<- glm(animal ~	corridor_	+ guardrail_								+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.g_shp1	<- glm(animal ~		guardrail_						+ cir_	+ rec_	+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.g_shp2	<- glm(animal ~		guardrail_						+ cir_	+ rec_				+ STEP1 MODEL	
	cs.mod.animal.D.g_shp3	<- glm(animal ~		guardrail_						+ cir_		+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.g_shp4	<- glm(animal ~		guardrail_						+ cir_					+ STEP1 MODEL	
	cs.mod.animal.D.g_shp5	<- glm(animal ~		guardrail_							+ rec_	+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.g_shp6	<- glm(animal ~		guardrail_							+ rec_				+ STEP1 MODEL	
	cs.mod.animal.D.g_shp7	<- glm(animal ~		guardrail_								+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.c_shp1	<- glm(animal ~	corridor_							+ cir_	+ rec_	+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.c_shp2	<- glm(animal ~	corridor_							+ cir_	+ rec_				+ STEP1 MODEL	
	cs.mod.animal.D.c_shp3	<- glm(animal ~	corridor_							+ cir_		+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.c_shp4	<- glm(animal ~	corridor_							+ cir_					+ STEP1 MODEL	
	cs.mod.animal.D.c_shp5	<- glm(animal ~	corridor_								+ rec_	+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D.c_shp6	<- glm(animal ~	corridor_								+ rec_				+ STEP1 MODEL	
	cs.mod.animal.D.c_shp7	<- glm(animal ~	corridor_									+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D._shp1	<- glm(animal ~								cir_	+ rec_	+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D._shp2	<- glm(animal ~								cir_	+ rec_				+ STEP1 MODEL	
	cs.mod.animal.D._shp3	<- glm(animal ~								cir_		+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D._shp4	<- glm(animal ~								cir_					+ STEP1 MODEL	
	cs.mod.animal.D._shp5	<- glm(animal ~									rec_	+ bri_			+ STEP1 MODEL	
	cs.mod.animal.D._shp6	<- glm(animal ~									rec_				+ STEP1 MODEL	
	cs.mod.animal.D._shp7	<- glm(animal ~										bri_			+ STEP1 MODEL	
FUNCTION	cs.mod.animal.D.cg_typ1	<- glm(animal ~	corridor_	+ guardrail_									+ dry_	+ wet_	+ STEP1 MODEL	LOWEST AIC = GLOBAL MODEL (FUNCTION)
	cs.mod.animal.D.cg_typ2	<- glm(animal ~	corridor_	+ guardrail_									+ dry_		+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ3	<- glm(animal ~	corridor_	+ guardrail_										+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ4	<- glm(animal ~	corridor_	+ guardrail_									+ dry_interm_	+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ5	<- glm(animal ~	corridor_	+ guardrail_									+ dry_interm_		+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ6	<- glm(animal ~	corridor_	+ guardrail_									+ dry_	+ wet_interm_	+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ7	<- glm(animal ~	corridor_	+ guardrail_										+ wet_interm_	+ STEP1 MODEL	
	cs.mod.animal.D.g_typ1	<- glm(animal ~		guardrail_									+ dry_	+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D.g_typ2	<- glm(animal ~		guardrail_									+ dry_		+ STEP1 MODEL	
	cs.mod.animal.D.g_typ3	<- glm(animal ~		guardrail_										+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D.g_typ4	<- glm(animal ~		guardrail_									+ dry_interm_	+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D.g_typ5	<- glm(animal ~		guardrail_									+ dry_interm_		+ STEP1 MODEL	
	cs.mod.animal.D.g_typ6	<- glm(animal ~		guardrail_									+ dry_	+ wet_interm_	+ STEP1 MODEL	
	cs.mod.animal.D.g_typ7	<- glm(animal ~		guardrail_										+ wet_interm_	+ STEP1 MODEL	
	cs.mod.animal.D.c_typ1	<- glm(animal ~	corridor_										+ dry_	+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D.c_typ2	<- glm(animal ~	corridor_										+ dry_		+ STEP1 MODEL	
	cs.mod.animal.D.c_typ3	<- glm(animal ~	corridor_											+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D.c_typ4	<- glm(animal ~	corridor_										+ dry_interm_	+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D.c_typ5	<- glm(animal ~	corridor_										+ dry_interm_		+ STEP1 MODEL	
	cs.mod.animal.D.c_typ6	<- glm(animal ~	corridor_										+ dry_	+ wet_interm_	+ STEP1 MODEL	
	cs.mod.animal.D.c_typ7	<- glm(animal ~	corridor_											+ wet_interm_	+ STEP1 MODEL	
	cs.mod.animal.D._typ1	<- glm(animal ~											dry_	+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D._typ2	<- glm(animal ~											dry_		+ STEP1 MODEL	
	cs.mod.animal.D._typ3	<- glm(animal ~												wet_	+ STEP1 MODEL	
	cs.mod.animal.D._typ4	<- glm(animal ~											dry_interm_	+ wet_	+ STEP1 MODEL	
	cs.mod.animal.D._typ5	<- glm(animal ~											dry_interm_		+ STEP1 MODEL	
	cs.mod.animal.D._typ6	<- glm(animal ~											dry_	+ wet_interm_	+ STEP1 MODEL	
	cs.mod.animal.D._typ7	<- glm(animal ~												wet_interm_	+ STEP1 MODEL	

Table 24. The Step 2 Template for Scenario D with the added Dimension predictor variables.

	cs.mod.ani.scenario.grp	<- glm(animal ~	CGX			MATERIAL			SHAPE			FUNCTION		DIMENSIONS				+ STEP1 MODEL	
CGX	cs.mod.animal.D.cgx	<- glm(animal ~	corridor_	+ guardrail_	+ xfull_													+ STEP1 MODEL	LOWEST AIC = GLOBAL MODEL (must incl. xstrucs.)
	cs.mod.animal.D.cg	<- glm(animal ~	corridor_	+ guardrail_														+ STEP1 MODEL	
	cs.mod.animal.D.g	<- glm(animal ~		guardrail_														+ STEP1 MODEL	
	cs.mod.animal.D.gx	<- glm(animal ~		guardrail_	+ xfull_													+ STEP1 MODEL	
	cs.mod.animal.D.cx	<- glm(animal ~	corridor_		+ xfull_													+ STEP1 MODEL	
	cs.mod.animal.D.c	<- glm(animal ~	corridor_															+ STEP1 MODEL	
	cs.mod.animal.D.x	<- glm(animal ~			xfull_													+ STEP1 MODEL	
MATERIAL	cs.mod.animal.D.cg_mat1	<- glm(animal ~	corridor_	+ guardrail_		+ met_	+ plas_	+ con_										+ STEP1 MODEL	LOWEST AIC = GLOBAL MODEL (MATERIAL)
	cs.mod.animal.D.cg_mat2	<- glm(animal ~	corridor_	+ guardrail_		+ met_	+ plas_											+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat3	<- glm(animal ~	corridor_	+ guardrail_		+ met_		+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat4	<- glm(animal ~	corridor_	+ guardrail_		+ met_												+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat5	<- glm(animal ~	corridor_	+ guardrail_			+ plas_	+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat6	<- glm(animal ~	corridor_	+ guardrail_			+ plas_											+ STEP1 MODEL	
	cs.mod.animal.D.cg_mat7	<- glm(animal ~	corridor_	+ guardrail_				+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.g_mat1	<- glm(animal ~		guardrail_		+ met_	+ plas_	+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.g_mat2	<- glm(animal ~		guardrail_		+ met_	+ plas_											+ STEP1 MODEL	
	cs.mod.animal.D.g_mat3	<- glm(animal ~		guardrail_		+ met_		+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.g_mat4	<- glm(animal ~		guardrail_		+ met_												+ STEP1 MODEL	
	cs.mod.animal.D.g_mat5	<- glm(animal ~		guardrail_			+ plas_	+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.g_mat6	<- glm(animal ~		guardrail_			+ plas_											+ STEP1 MODEL	
	cs.mod.animal.D.g_mat7	<- glm(animal ~		guardrail_				+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.c_mat1	<- glm(animal ~	corridor_			+ met_	+ plas_	+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.c_mat2	<- glm(animal ~	corridor_			+ met_	+ plas_											+ STEP1 MODEL	
	cs.mod.animal.D.c_mat3	<- glm(animal ~	corridor_			+ met_		+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.c_mat4	<- glm(animal ~	corridor_			+ met_												+ STEP1 MODEL	
	cs.mod.animal.D.c_mat5	<- glm(animal ~	corridor_				+ plas_	+ con_										+ STEP1 MODEL	
	cs.mod.animal.D.c_mat6	<- glm(animal ~	corridor_				+ plas_											+ STEP1 MODEL	
	cs.mod.animal.D.c_mat7	<- glm(animal ~	corridor_					+ con_										+ STEP1 MODEL	
	cs.mod.animal.D._mat1	<- glm(animal ~				+ met_	+ plas_	+ con_										+ STEP1 MODEL	
	cs.mod.animal.D._mat2	<- glm(animal ~				+ met_	+ plas_											+ STEP1 MODEL	
	cs.mod.animal.D._mat3	<- glm(animal ~				+ met_		+ con_										+ STEP1 MODEL	
	cs.mod.animal.D._mat4	<- glm(animal ~				+ met_												+ STEP1 MODEL	
	cs.mod.animal.D._mat5	<- glm(animal ~					+ plas_	+ con_										+ STEP1 MODEL	
	cs.mod.animal.D._mat6	<- glm(animal ~					+ plas_											+ STEP1 MODEL	
	cs.mod.animal.D._mat7	<- glm(animal ~						+ con_										+ STEP1 MODEL	
SHAPE	cs.mod.animal.D.cg_shp1	<- glm(animal ~	corridor_	+ guardrail_					+ cir_	+ rec_	+ bri_							+ STEP1 MODEL	LOWEST AIC = GLOBAL MODEL (SHAPE)
	cs.mod.animal.D.cg_shp2	<- glm(animal ~	corridor_	+ guardrail_					+ cir_	+ rec_								+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp3	<- glm(animal ~	corridor_	+ guardrail_					+ cir_		+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp4	<- glm(animal ~	corridor_	+ guardrail_					+ cir_									+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp5	<- glm(animal ~	corridor_	+ guardrail_						+ rec_	+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp6	<- glm(animal ~	corridor_	+ guardrail_						+ rec_								+ STEP1 MODEL	
	cs.mod.animal.D.cg_shp7	<- glm(animal ~	corridor_	+ guardrail_							+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.g_shp1	<- glm(animal ~		guardrail_					+ cir_	+ rec_	+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.g_shp2	<- glm(animal ~		guardrail_					+ cir_	+ rec_								+ STEP1 MODEL	
	cs.mod.animal.D.g_shp3	<- glm(animal ~		guardrail_					+ cir_		+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.g_shp4	<- glm(animal ~		guardrail_					+ cir_									+ STEP1 MODEL	
	cs.mod.animal.D.g_shp5	<- glm(animal ~		guardrail_						+ rec_	+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.g_shp6	<- glm(animal ~		guardrail_						+ rec_								+ STEP1 MODEL	
	cs.mod.animal.D.g_shp7	<- glm(animal ~		guardrail_							+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.c_shp1	<- glm(animal ~	corridor_						+ cir_	+ rec_	+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.c_shp2	<- glm(animal ~	corridor_						+ cir_	+ rec_								+ STEP1 MODEL	
	cs.mod.animal.D.c_shp3	<- glm(animal ~	corridor_						+ cir_		+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.c_shp4	<- glm(animal ~	corridor_						+ cir_									+ STEP1 MODEL	
	cs.mod.animal.D.c_shp5	<- glm(animal ~	corridor_							+ rec_	+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D.c_shp6	<- glm(animal ~	corridor_							+ rec_								+ STEP1 MODEL	
	cs.mod.animal.D.c_shp7	<- glm(animal ~	corridor_								+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D._shp1	<- glm(animal ~							+ cir_	+ rec_	+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D._shp2	<- glm(animal ~							+ cir_	+ rec_								+ STEP1 MODEL	
	cs.mod.animal.D._shp3	<- glm(animal ~							+ cir_		+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D._shp4	<- glm(animal ~							+ cir_									+ STEP1 MODEL	
	cs.mod.animal.D._shp5	<- glm(animal ~								+ rec_	+ bri_							+ STEP1 MODEL	
	cs.mod.animal.D._shp6	<- glm(animal ~								+ rec_								+ STEP1 MODEL	
	cs.mod.animal.D._shp7	<- glm(animal ~									+ bri_							+ STEP1 MODEL	
FUNCTION	cs.mod.animal.D.cg_typ1	<- glm(animal ~	corridor_	+ guardrail_								+ dry_	+ wet_					+ STEP1 MODEL	LOWEST AIC = GLOBAL MODEL (FUNCTION)
	cs.mod.animal.D.cg_typ2	<- glm(animal ~	corridor_	+ guardrail_								+ dry_						+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ3	<- glm(animal ~	corridor_	+ guardrail_									+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ4	<- glm(animal ~	corridor_	+ guardrail_								+ dry_interm_	+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ5	<- glm(animal ~	corridor_	+ guardrail_								+ dry_interm_						+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ6	<- glm(animal ~	corridor_	+ guardrail_								+ dry_	+ wet_interm_					+ STEP1 MODEL	
	cs.mod.animal.D.cg_typ7	<- glm(animal ~	corridor_	+ guardrail_									+ wet_interm_					+ STEP1 MODEL	
	cs.mod.animal.D.g_typ1	<- glm(animal ~		guardrail_								+ dry_	+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D.g_typ2	<- glm(animal ~		guardrail_								+ dry_						+ STEP1 MODEL	
	cs.mod.animal.D.g_typ3	<- glm(animal ~		guardrail_									+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D.g_typ4	<- glm(animal ~		guardrail_								+ dry_interm_	+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D.g_typ5	<- glm(animal ~		guardrail_								+ dry_interm_						+ STEP1 MODEL	
	cs.mod.animal.D.g_typ6	<- glm(animal ~		guardrail_								+ dry_	+ wet_interm_					+ STEP1 MODEL	
	cs.mod.animal.D.g_typ7	<- glm(animal ~		guardrail_									+ wet_interm_					+ STEP1 MODEL	
	cs.mod.animal.D.c_typ1	<- glm(animal ~	corridor_									+ dry_	+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D.c_typ2	<- glm(animal ~	corridor_									+ dry_						+ STEP1 MODEL	
	cs.mod.animal.D.c_typ3	<- glm(animal ~	corridor_										+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D.c_typ4	<- glm(animal ~	corridor_									+ dry_interm_	+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D.c_typ5	<- glm(animal ~	corridor_									+ dry_interm_						+ STEP1 MODEL	
	cs.mod.animal.D.c_typ6	<- glm(animal ~	corridor_									+ dry_	+ wet_interm_					+ STEP1 MODEL	
	cs.mod.animal.D.c_typ7	<- glm(animal ~	corridor_										+ wet_interm_					+ STEP1 MODEL	
	cs.mod.animal.D._typ1	<- glm(animal ~										dry_	+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D._typ2	<- glm(animal ~										dry_						+ STEP1 MODEL	
	cs.mod.animal.D._typ3	<- glm(animal ~											wet_					+ STEP1 MODEL	
	cs.mod.animal.D._typ4	<- glm(animal ~										dry_interm_	+ wet_					+ STEP1 MODEL	
	cs.mod.animal.D._typ5	<- glm(animal ~										dry_interm_						+ STEP1 MODEL	
	cs.mod.animal.D._typ6	<- glm(animal ~										dry_	+ wet_interm_					+ STEP1 MODEL	
	cs.mod.animal.D._typ7	<- glm(animal ~											wet_interm_					+ STEP1 MODEL	
DIMENSIONS	cs.mod.animal.D.cg_dim1	<- glm(animal ~	corridor_	+ guardrail_										+ height_m_	+ width_m_	+ length_m_	+ opening_m_2_	+ STEP1 MODEL	LOWEST AIC = GLOBAL MODEL (DIMENSIONS)
	cs.mod.animal.D.cg_dim2	<- glm(animal ~	corridor_	+ guardrail_										+ height_m_	+ width_m_	+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim3	<- glm(animal ~	corridor_	+ guardrail_										+ height_m_	+ width_m_		+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim4	<- glm(animal ~	corridor_	+ guardrail_										+ height_m_		+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim5	<- glm(animal ~	corridor_	+ guardrail_											+ width_m_	+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim6	<- glm(animal ~	corridor_	+ guardrail_										+ height_m_	+ width_m_			+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim7	<- glm(animal ~	corridor_	+ guardrail_										+ height_m_		+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim8	<- glm(animal ~	corridor_	+ guardrail_										+ height_m_			+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim9	<- glm(animal ~	corridor_	+ guardrail_											+ width_m_	+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim10	<- glm(animal ~	corridor_	+ guardrail_											+ width_m_		+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim11	<- glm(animal ~	corridor_	+ guardrail_												+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim12	<- glm(animal ~	corridor_	+ guardrail_										+ height_m_				+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim13	<- glm(animal ~	corridor_	+ guardrail_											+ width_m_			+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim14	<- glm(animal ~	corridor_	+ guardrail_												+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.cg_dim15	<- glm(animal ~	corridor_	+ guardrail_													+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.g_dim1	<- glm(animal ~		guardrail_										+ height_m_	+ width_m_	+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.g_dim2	<- glm(animal ~		guardrail_										+ height_m_	+ width_m_	+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.g_dim3	<- glm(animal ~		guardrail_										+ height_m_	+ width_m_		+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.g_dim4	<- glm(animal ~		guardrail_										+ height_m_		+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.g_dim5	<- glm(animal ~		guardrail_											+ width_m_	+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.g_dim6	<- glm(animal ~		guardrail_										+ height_m_	+ width_m_			+ STEP1 MODEL	
	cs.mod.animal.D.g_dim7	<- glm(animal ~		guardrail_										+ height_m_		+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.g_dim8	<- glm(animal ~		guardrail_										+ height_m_			+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.g_dim9	<- glm(animal ~		guardrail_											+ width_m_	+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.g_dim10	<- glm(animal ~		guardrail_											+ width_m_		+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.g_dim11	<- glm(animal ~		guardrail_												+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.g_dim12	<- glm(animal ~		guardrail_										+ height_m_				+ STEP1 MODEL	
	cs.mod.animal.D.g_dim13	<- glm(animal ~		guardrail_											+ width_m_			+ STEP1 MODEL	
	cs.mod.animal.D.g_dim14	<- glm(animal ~		guardrail_												+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.g_dim15	<- glm(animal ~		guardrail_													+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.c_dim1	<- glm(animal ~	corridor_											+ height_m_	+ width_m_	+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.c_dim2	<- glm(animal ~	corridor_											+ height_m_	+ width_m_	+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.c_dim3	<- glm(animal ~	corridor_											+ height_m_	+ width_m_		+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.c_dim4	<- glm(animal ~	corridor_											+ height_m_		+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.c_dim5	<- glm(animal ~	corridor_												+ width_m_	+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.c_dim6	<- glm(animal ~	corridor_											+ height_m_	+ width_m_			+ STEP1 MODEL	
	cs.mod.animal.D.c_dim7	<- glm(animal ~	corridor_											+ height_m_		+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.c_dim8	<- glm(animal ~	corridor_											+ height_m_			+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.c_dim9	<- glm(animal ~	corridor_												+ width_m_	+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.c_dim10	<- glm(animal ~	corridor_												+ width_m_		+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.c_dim11	<- glm(animal ~	corridor_													+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D.c_dim12	<- glm(animal ~	corridor_											+ height_m_				+ STEP1 MODEL	
	cs.mod.animal.D.c_dim13	<- glm(animal ~	corridor_												+ width_m_			+ STEP1 MODEL	
	cs.mod.animal.D.c_dim14	<- glm(animal ~	corridor_													+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D.c_dim15	<- glm(animal ~	corridor_														+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D._dim1	<- glm(animal ~												+ height_m_	+ width_m_	+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D._dim2	<- glm(animal ~												+ height_m_	+ width_m_	+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D._dim3	<- glm(animal ~												+ height_m_	+ width_m_		+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D._dim4	<- glm(animal ~												+ height_m_		+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D._dim5	<- glm(animal ~													+ width_m_	+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D._dim6	<- glm(animal ~												+ height_m_	+ width_m_			+ STEP1 MODEL	
	cs.mod.animal.D._dim7	<- glm(animal ~												+ height_m_		+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D._dim8	<- glm(animal ~												+ height_m_			+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D._dim9	<- glm(animal ~													+ width_m_	+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D._dim10	<- glm(animal ~													+ width_m_		+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D._dim11	<- glm(animal ~														+ length_m_	+ opening_m_2_	+ STEP1 MODEL	
	cs.mod.animal.D._dim12	<- glm(animal ~												+ height_m_				+ STEP1 MODEL	
	cs.mod.animal.D._dim13	<- glm(animal ~													+ width_m_			+ STEP1 MODEL	
	cs.mod.animal.D._dim14	<- glm(animal ~														+ length_m_		+ STEP1 MODEL	
	cs.mod.animal.D._dim15	<- glm(animal ~															+ opening_m_2_	+ STEP1 MODEL	

APPENDIX C. Variance Inflation Factors (VIF) value tables

C.1 Scenario A

Table 25. The VIF values for the global and final models of Scenario A.

SCENARIO A											Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
AMPHIBIANS			Corridor	XFull	XHalf	Plastic	Circular	Dry	Wet												
	Crossing Structure	Global	1.856	1.200	1.141						2.000	2.912	1.478	2.048	2.021	1.661	3.283	1.346	2.014	2.538	1.594
		Final	1.837		1.108						1.996	2.858	1.477	2.040	2.020	1.657	3.279	1.340	2.012	2.530	1.467
	Material	Global	1.844			1.151					2.002	2.919	1.482	2.057	2.022	1.697	3.282	1.353	2.006	2.531	1.450
		Final	1.844			1.151					2.002	2.919	1.482	2.057	2.022	1.697	3.282	1.353	2.006	2.531	1.450
	Shape	Global	1.839				1.116				2.004	2.862	1.466	2.046	2.020	1.641	3.291	1.344	2.016	2.542	1.473
		Final	1.839				1.116				2.004	2.862	1.466	2.046	2.020	1.641	3.291	1.344	2.016	2.542	1.473
	Function	Global	1.855					1.153	1.203		2.000	2.937	1.481	2.051	2.029	1.646	3.278	1.346	2.010	2.542	1.643
		Final	1.855					1.153	1.203		2.000	2.937	1.481	2.051	2.029	1.646	3.278	1.346	2.010	2.542	1.643
MAMMALS			Corridor	Concrete	Rectangular	Dry					Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
	Material	Global		1.051							2.967	5.027	5.851	2.088	1.897	1.924	2.611	6.398	1.861	2.376	1.285
		Final		1.012							1.742	1.737	1.101		1.813				1.232	1.918	
	Shape	Global	1.582		1.137						3.151	5.105	6.041	2.113	1.879	1.969	2.758	6.596	1.881	2.531	1.373
		Final	1.264								2.002	1.701	1.223	1.639					1.691		
	Function	Global	1.552			1.058					3.178	5.013	6.060	2.083	1.879	2.018	2.675	6.619	1.862	2.539	1.300
		Final	1.334			1.014					1.968	1.578	1.127		1.080				1.256		
REPTILES			Corridor	Concrete	Rectangular	Wet+Intermittent					Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
	Material	Global		1.135							3.695	3.673	2.831	3.331	1.295	1.844	2.235	3.095	2.177	1.811	2.620
		Final		1.128							3.212	3.132	1.801	2.723	1.257	1.819	1.992			1.761	2.518
	Shape	Global	1.831		1.000						3.914	3.643	2.790	3.234	1.381	1.868	2.262	3.063	2.215	2.073	2.552
		Final	1.808		1.000						3.430	3.035	1.738	2.654	1.338	1.836	1.990			2.012	2.453
	Function	Global				1.788					3.734	3.646	2.845	3.257	1.258	2.667	2.188	3.080	2.149	1.775	2.562
		Final									3.209	3.096	1.778	2.684	1.214	1.809	1.944			1.720	2.446

C.2 Scenario B

Table 26. The VIF values for the global and final models of Scenario B.

SCENARIO B																		
AMPHIBIANS [A10]			Corridor	Plastic	Concrete	Bridge	Dry	Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
	Material	Global	1.521	1.123	1.120			3.245	4.693	1.591	2.748	1.999	1.774	3.311	1.494	1.913	2.226	2.030
		Final	1.521	1.123	1.120			3.245	4.693	1.591	2.748	1.999	1.774	3.311	1.494	1.913	2.226	2.030
	Shape	Global	1.505			1.022		3.241	4.707	1.520	2.707	1.990	1.710	3.289	1.505	1.905	2.234	2.058
		Final	1.505			1.022		3.241	4.707	1.520	2.707	1.990	1.710	3.289	1.505	1.905	2.234	2.058
	Function	Global	1.522				1.096	3.241	4.698	1.571	2.709	1.994	1.754	3.276	1.498	1.919	2.234	2.062
		Final	1.508					3.234	4.667	1.521	2.700	1.992	1.711	3.274	1.498	1.913	2.231	2.059
AMPHIBIANS [R112]			Concrete	Rectangular	Dry+Intermittent			Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
	Material	Global	1.129					2.980	2.874	2.086	2.732	1.789	1.678	1.614	2.734	2.591	1.963	1.391
		Final						2.953	2.870	2.078	2.726	1.729	1.657	1.612	2.708	2.574	1.929	1.292
	Shape	Global		1.112				2.969	2.872	2.081	2.729	1.780	1.669	1.625	2.728	2.592	1.950	1.362
		Final						2.953	2.870	2.078	2.726	1.729	1.657	1.612	2.708	2.574	1.929	1.292
	Function	Global			1.087			2.977	2.876	2.078	2.729	1.764	1.669	1.611	2.746	2.592	1.983	1.305
		Final						2.953	2.870	2.078	2.726	1.729	1.657	1.612	2.708	2.574	1.929	1.292
MAMMALS [A10]			Metal	Circular	Wet			Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
	Material	Global	1.051					6.611	1.705	1.522	1.911	1.200	2.336	7.483	1.348	1.995	1.629	1.445
		Final						6.478	1.479	1.276		1.004	1.968	7.164		1.516		
	Shape	Global		1.062				6.519	1.723	1.506	1.915	1.199	2.322	7.348	1.335	1.998	1.617	1.428
		Final						6.478	1.479	1.276		1.004	1.968	7.164		1.516		
	Function	Global			1.100			6.469	1.694	1.493	1.900	1.193	2.278	7.321	1.332	1.975	1.604	1.503
		Final			1.017			6.418	1.480	1.276		1.006	1.969	7.100		1.522		
MAMMALS [R112]			Metal	Circular	Wet+Intermittent			Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
	Material	Global	1.137					2.440	4.384	3.230	1.672	3.043	1.846	4.466	2.116	2.147	1.420	1.427
		Final						2.457	1.554	2.886	1.097	2.861	1.792		1.645			1.348
	Shape	Global		1.063				2.451	4.293	3.181	1.643	2.950	1.909	4.302	2.096	2.138	1.431	1.426
		Final						2.457	1.554	2.886	1.097	2.861	1.792		1.645			1.348
	Function	Global			1.891			2.447	4.328	3.165	1.639	2.969	1.959	4.298	2.094	2.159	1.401	2.470
		Final						2.457	1.554	2.886	1.097	2.861	1.792		1.645			1.348
REPTILES [A10]			Corridor	Plastic	Rectangular	Dry+Intermittent		Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
	Material	Global	1.530	1.066				6.599	9.535	2.235	2.805	1.336	2.298	5.440	2.090	1.837	1.545	2.353
		Final	1.348					5.599	5.091	1.755	2.265		2.258			1.815	1.372	1.955
	Shape	Global	1.495		1.000			6.483	9.832	2.235	2.860	1.340	2.305	5.465	2.062	1.851	1.505	2.312
		Final	1.341		1.000			5.580	5.062	1.751	2.284		2.287			1.831	1.359	1.938
	Function	Global	1.512			1.105		6.638	9.852	2.245	2.826	1.326	2.386	5.564	2.093	1.838	1.532	2.381
		Final	1.348					5.599	5.091	1.755	2.265		2.258			1.815	1.372	1.955
REPTILES [R112]			Guardrail	Metal	Bridge	Wet+Intermittent		Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
	Material	Global	1.169	1.041				3.899	3.993	2.998	2.574	2.416	1.939	1.720	2.210	1.265	2.005	1.801
		Final	1.159					3.924	3.985	2.979	2.572	2.392	1.915	1.718	2.178	1.263	2.006	1.761
	Shape	Global	1.208		1.101			3.910	4.011	2.985	2.582	2.412	1.914	1.772	2.190	1.280	2.017	1.766
		Final	1.159					3.924	3.985	2.979	2.572	2.392	1.915	1.718	2.178	1.263	2.006	1.761
	Function	Global	1.224			2.098		3.997	4.021	3.017	2.604	2.435	2.077	1.706	2.295	1.274	2.039	3.104
		Final	1.218			1.145		3.594	3.799	3.010	2.554	2.343		1.618	2.124	1.260	2.036	

C.3 Scenario C

Table 27. The VIF values for the global and final models of Scenario C.

SCENARIO C												Highway
AMPHIBIANS			Corridor	XFull	XHalf	Guardrail	Plastic	Circular	Bridge	Wet+Intermittent	Highway
AMPHIBIANS	Crossing Structure	Global	1.436	1.152	1.169						1.523
AMPHIBIANS	Crossing Structure	Final	1.436	1.152	1.169						1.523
AMPHIBIANS	Material	Global	1.463			1.411	1.131				1.928
AMPHIBIANS	Material	Final	1.463			1.411	1.131				1.928
AMPHIBIANS	Shape	Global	1.467			1.434		1.192	1.038		1.924
AMPHIBIANS	Shape	Final	1.467			1.434		1.192	1.038		1.924
AMPHIBIANS	Function	Global	1.428							1.208	1.437
AMPHIBIANS	Function	Final	1.428							1.208	1.437
MAMMALS			Metal	Circular	Dry						Highway
MAMMALS	Material	Global	1.070								1.379
MAMMALS	Material	Final									
MAMMALS	Shape	Global		1.130							1.472
MAMMALS	Shape	Final									
MAMMALS	Function	Global			1.067						1.372
MAMMALS	Function	Final									
REPTILES			Concrete	Rectangular	Dry						Highway
REPTILES	Material	Global	1.214								1.402
REPTILES	Material	Final									1.213
REPTILES	Shape	Global		1.267							1.456
REPTILES	Shape	Final									1.213
REPTILES	Function	Global			1.068						1.313
REPTILES	Function	Final			1.019						1.218

SCENARIO C			Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
AMPHIBIANS	Crossing Structure	Global	3.769	1.803	1.689	1.902	2.081	1.848	3.411	1.650	1.687	2.291	1.814
AMPHIBIANS	Crossing Structure	Final	3.769	1.803	1.689	1.902	2.081	1.848	3.411	1.650	1.687	2.291	1.814
AMPHIBIANS	Material	Global	3.783	1.792	1.698	1.920	2.120	1.879	3.413	1.638	1.690	2.308	1.797
AMPHIBIANS	Material	Final	3.783	1.792	1.698	1.920	2.120	1.879	3.413	1.638	1.690	2.308	1.797
AMPHIBIANS	Shape	Global	3.811	1.783	1.688	1.923	2.125	1.909	3.404	1.640	1.693	2.311	1.823
AMPHIBIANS	Shape	Final	3.811	1.783	1.688	1.923	2.125	1.909	3.404	1.640	1.693	2.311	1.823
AMPHIBIANS	Function	Global	3.721	1.767	1.674	1.913	2.046	1.855	3.396	1.641	1.681	2.280	2.047
AMPHIBIANS	Function	Final	3.721	1.767	1.674	1.913	2.046	1.855	3.396	1.641	1.681	2.280	2.047
MAMMALS			Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
MAMMALS	Material	Global	4.446	2.587	2.859	2.294	2.368	2.982	2.649	2.882	1.510	2.151	3.307
MAMMALS	Material	Final	2.514	2.500		2.030	2.205				1.448	1.828	
MAMMALS	Shape	Global	4.487	2.599	2.861	2.285	2.364	2.964	2.637	2.889	1.512	2.144	3.282
MAMMALS	Shape	Final	2.514	2.500		2.030	2.205				1.448	1.828	
MAMMALS	Function	Global	4.466	2.616	2.860	2.290	2.360	2.972	2.634	2.887	1.511	2.159	3.232
MAMMALS	Function	Final	2.514	2.500		2.030	2.205				1.448	1.828	
REPTILES			Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
REPTILES	Material	Global	6.994	4.757	2.072	2.000	3.989	1.638	4.158	2.243	1.646	4.012	1.845
REPTILES	Material	Final	5.020	4.250	1.289	1.972	1.410				1.575		
REPTILES	Shape	Global	7.134	4.787	2.074	2.001	3.965	1.643	4.201	2.244	1.637	3.989	1.840
REPTILES	Shape	Final	5.020	4.250	1.289	1.972	1.410				1.575		
REPTILES	Function	Global	6.999	4.776	2.065	1.997	3.892	1.598	4.116	2.251	1.640	3.956	1.859
REPTILES	Function	Final	5.055	4.306	1.290	1.974	1.379				1.585		

C.4 Scenario D

Table 28. The VIF values for the global and final models of Scenario D. Predictors for the lowest-AIC Function model exhibited perfect multicollinearity. One categorical predictor was created, FUNCTION, with two levels (‘wet’ and ‘dry & interm’). As a test, models with FUNCTION, and models with ‘wet’, and ‘dry & interm’ were tested and all produced identical VIF values (and all were excluded from the final Function model).

SCENARIO D

AMPHIBIANS		Corridor	Plastic	Circular	Dry	Opening	Highway	Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
Material	Global	1.527	1.531				1.873	1.532	3.573	1.659	1.689	2.254	2.427	3.632	1.733	1.796	1.976	1.852
	Final	1.535	1.529				1.863	1.462	3.536	1.608	1.676	1.618	2.420	3.575	1.669	1.793		1.864
Shape	Global	1.553		2.661	1.598		2.642	1.527	3.506	1.667	1.699	2.229	2.485	3.599	1.730	1.784	2.012	1.834
	Final	1.552		2.601			2.638	1.453	3.473	1.605	1.681	1.616	2.470	3.531	1.674	1.778		1.839
Function	Global	1.505			1.598		1.345	1.511	3.553	1.622	1.671	2.251	2.426	3.624	1.737	1.826	1.985	2.597
	Final	1.512					1.336	1.426	3.471	1.566	1.656	1.595	2.392	3.528	1.661	1.787		1.847
Dimension	Global	1.536				1.072	1.365	1.490	3.577	1.690	1.677	2.337	2.430	3.627	1.765	1.788	2.020	1.862
	Final	1.543				1.071	1.360	1.425	3.533	1.642	1.666	1.646	2.427	3.572	1.693	1.786		1.874
Dimension +	Global	1.555	1.591			1.083	1.947	1.527	3.632	1.711	1.700	2.348	2.461	3.667	1.760	1.795	2.023	1.877
	Final	1.564	1.589			1.083	1.938	1.457	3.588	1.660	1.688	1.663	2.455	3.610	1.690	1.793		1.891

MAMMALS		Metal	Bridge	Wet	Length	Highway	Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
Material	Global	1.246				1.543	9.975	7.418	2.901	6.052	5.333	1.937	1.697	2.684	1.408	1.911	1.419
	Final						9.221	7.000	1.533	5.246	5.106	1.529	1.454		1.436		
Shape	Global		1.074			1.435	9.994	7.557	2.898	5.917	5.058	1.732	1.710	2.692	1.406	1.912	1.405
	Final						9.221	7.000	1.533	5.246	5.106	1.529	1.454		1.436		
Function	Global			1.314		1.463	9.771	7.469	2.837	5.806	4.927	1.745	1.681	2.640	1.411	1.843	1.714
	Final						9.221	7.000	1.533	5.246	5.106	1.529	1.454		1.436		
Dimension	Global				2.018	2.602	9.539	7.494	2.812	5.713	4.788	1.718	1.674	2.599	1.423	1.793	1.437
	Final				1.098		9.438	7.033	1.531	5.188	4.917	1.506	1.413		1.455		
Dimension +	Global				2.018	2.602	9.539	7.494	2.812	5.713	4.788	1.718	1.674	2.599	1.423	1.793	1.437
	Final				1.098		9.438	7.033	1.531	5.188	4.917	1.506	1.413		1.455		

REPTILES		XSTRUC[A]	Metal	Rectangular	FUNCTION[B]	Height	Length	Opening	Highway	Forest [%]	Anthro. [%]	Marsh [%]	Agri. [%]	Water [%]	W.C. [m/ha]	Forest [m]	Marsh [m]	Agri. [m]	Water [m]	W.C. [m]
Crossing Structure	Global	1.928							1.809	8.423	5.855	5.355	1.552	3.335	1.607	1.977	2.194	1.507	2.465	1.414
	Final	1.935							1.761	7.251	5.705	5.407	1.497	3.192	1.505		2.122		2.372	1.241
Material	Global		1.353						1.383	8.045	5.579	5.225	1.529	3.300	1.631	1.926	2.204	1.493	2.453	1.195
	Final								1.164	6.860	5.348	5.243	1.469	3.155	1.491		1.491	2.145	2.355	
Shape	Global			2.928					2.954	8.206	5.735	5.203	1.588	3.237	1.609	2.236	2.189	1.478	2.453	1.235
	Final								1.164	6.860	5.348	5.243	1.469	3.155	1.491		1.491	2.145	2.355	
Function	Global				2.262				1.223	8.183	5.572	5.247	1.539	3.287	1.617	2.177	2.201	1.490	2.518	2.427
	Final								1.164	6.860	5.348	5.243	1.469	3.155	1.491		2.145	2.355	1.051	
Dimension	Global					3.238	3.891	1.884	3.298	8.232	6.004	5.422	1.603	3.592	1.600	1.999	2.286	1.691	2.624	1.419
	Final					2.846	1.551	1.704		7.078	5.316	5.156	1.582	3.441	1.576		2.199	1.720	2.604	
Dimension +	Global					3.238	3.891	1.884	3.298	8.232	6.004	5.422	1.603	3.592	1.600	1.999	2.286	1.691	2.624	1.419
	Final					2.846	1.551	1.704		7.078	5.316	5.156	1.582	3.441	1.576		2.199	1.720	2.604	

APPENDIX D. Photographs

Figure 23. Photographs of deceased amphibians with visible signs of barotrauma (photos A and B), freshly deceased amphibians with no obvious injuries (photos D and E), and two desiccated amphibians (photos C and F). (Photo credits: Jaynina Deku, Avital Moalem, and Michael Rolheiser).

Figure 24. Fieldwork photographs. Photo A. In efforts to provide species-level identification, we discovered that we could take very clear photos by holding our bird-watching monocle to the lens of our cell phone cameras. This photo of a mammal laying in the rumble strip of the left hand shoulder was taken from the emergency lane. Photos B and C. The differences in body size of detected roadkill. Photo E. An idealized data point – clearly identifiable. Photos D and F. Less idealized data points. Perhaps pulverized by passing vehicles or scavenged, many of the amphibians detected where nothing more than a pair of desiccated legs or a section of skin pressed and dried onto the road surface. The pairs of legs were removable; the skin had to be scoured off the road surface with a BBQ cleaning brush (Photo credits: Ryan Collins, Jaynina Deku, Avital Moalem, and Michael Rolheiser).

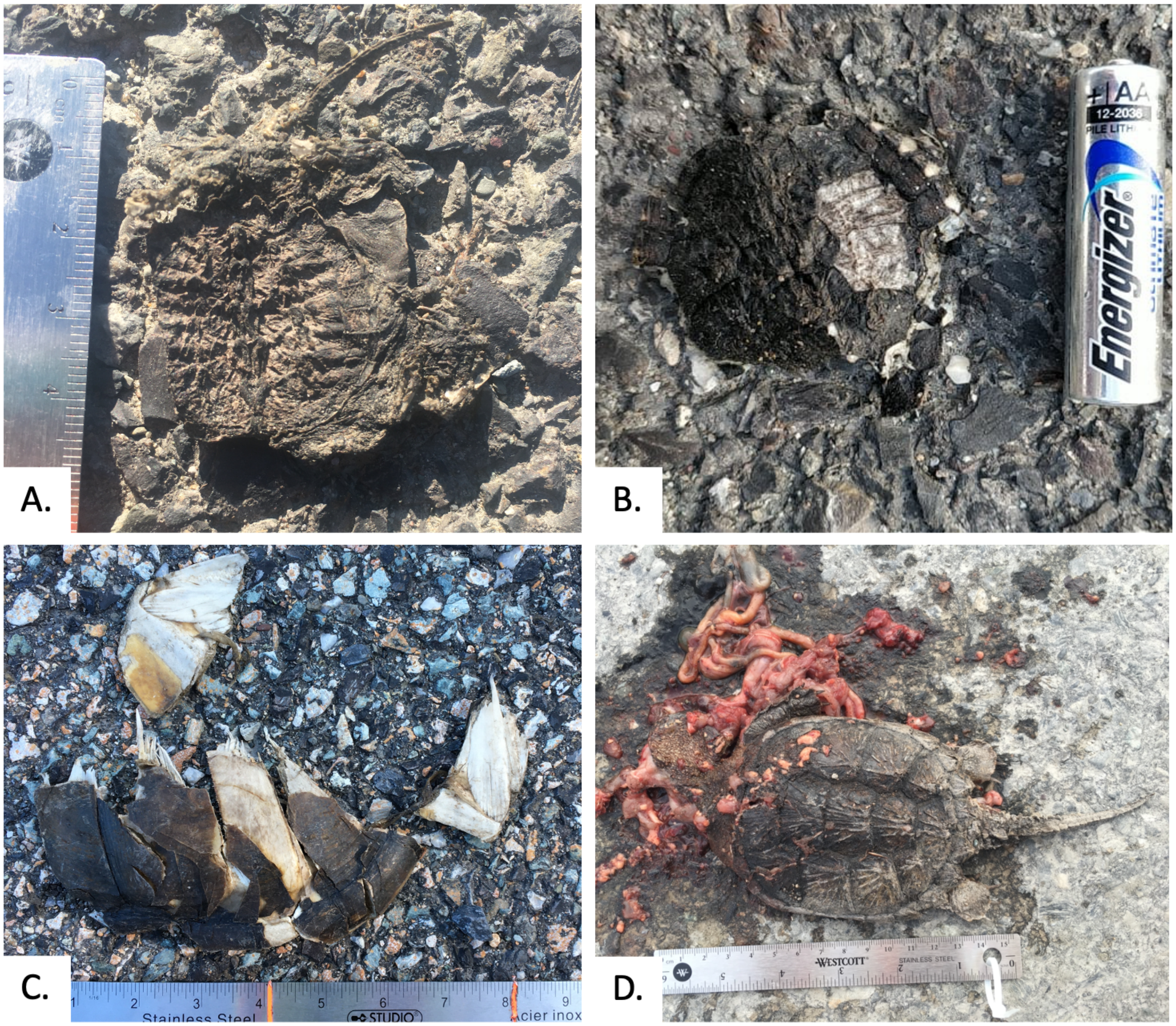


Figure 25. Photos showing turtle roadkill. Photos A and B. Turtle roadkill was highly temporal; these two photos are of the same snapping turtle, but no less than five similarly sized snapping turtles were found within the same few surveys. Photo C. Shards of carapace. Photo D. A freshly killed snapping turtle. It was identified (alive) the previous survey but when approached for relocation it scurried into the brush. The following day it was found dead in the same vicinity. (Photo credit: Michael Rolheiser).