THE RELATIONSHIP BETWEEN WILDLIFE-VEHICLE COLLISIONS, TRAFFIC VOLUME, AND HABITAT SUITABILITY-BASED WILDLIFE CROSSING AREAS IN VERMONT, USA

by

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of
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The Relationship between Wildlife-Vehicle Collisions, Traffic Volume, and Habitat Suitability-Based Wildlife Crossing Areas in Vermont, USA

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DEDICATION

This is dedicated to my good friend, Alex Knoppel, who passed away on April 2nd, 2016.

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Words are never enough, thank you everyone!

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LIST OF ABBREVIATIONS

kilometers	km
United States	US
hectares	ha
Geographic Information Systems	GIS
Vermont	VT
meter	m
Average Annual Daily Traffic	AADT
Vermont Center for Geographic Information	VCGI
Wildlife-Vehicle Collisions Density	WVCD
Land Use/Land Cover	LULC
Wildlife Crossing Index	WCI
Ordinary Linear Squares	OLS
Interstate 91	I-91
U.S. Route 2	US-2
Vermont Route 114	VR-144
Functional 7	F7
Functional 6	F6
Functional 2	F2
Functional 1	F1
Variance Inflation Factor	VIF
Studentized Breusch-Pagan	BP
Lagrange Multiplier	LM

ABSTRACT

THE RELATIONSHIP BETWEEN WILDLIFE-VEHICLE COLLISIONS, TRAFFIC VOLUME, AND HABITAT SUITABILITY-BASED WILDLIFE CROSSING AREAS IN VERMONT, USA

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Of the many negative effects roads can have on wildlife, wildlife-vehicle collisions are the most devastating. Efforts to predict where wildlife cross roads are vital for mitigation and prevention efforts. In this study, a Geographic Information Systems (GIS)-based approach was used to evaluate the relationship between wildlife-vehicle collisions, road traffic volume, and wildlife habitat suitability near roads. Road characteristics that potentially affect driver visibility and travel speeds, including the slope and curviness of the roads, were also considered. The robustness of the results was evaluated by varying the maximum length of the road segments in the spatial data and the distance from the roads used to estimate a wildlife crossing index based on habitat suitability. The case study evaluated moose (*Alces alces*) and black bear (*Ursus americanus*) collisions in VT from 1990 to 2006 for all roads in the state, three major roadways, and four functional classes of roadways. Habitat suitability had the most

consistent results across models, as road segments with better suitability had a higher collision density. The robustness analysis showed that as the buffer distance used to estimate the wildlife crossing index increased, the explained variation of wildlife-vehicle collision density increased as well. Road traffic volume demonstrated mixed results across models, as higher volume was associated with more collisions in the models with all roads, but was associated with fewer collisions in the roadway-specific and functional classification models. The length of the road segments in the spatial data layer affected the predictive power of the models, suggesting that scale may be an important factor in characterizing these relationships. The results offer an improved understanding of wildlife-vehicle collisions, which can potentially be used to develop mitigation and prevention efforts aimed at reducing the negative effects of roads on wildlife.

INTRODUCTION

In 2014, there were approximately 6,759,000 kilometers (km) of road in the United States (US), increasing from roughly 6,276,000 km in 1980 (U.S. Department of Transportation 2014). Due to increased road construction, the U.S. Department of Transportation (1996) estimated that 4,784,351 hectares (ha) of land and water bodies have been lost, which is most likely an underestimate of the actual value (Trombulak and Frissell 2000). The effects from increasing transportation infrastructure have become one of the greatest threats to wildlife populations. One of the most devastating effects roads can have on wildlife is wildlife-vehicle collisions. Huijser et al. (2008) estimated that 1-2 million collisions occur annually in the US at a cost of $8.3 billion, and the number of collisions has significantly increased since the 1990s (Austin et al. 2006; Slesar et al. 2003; Synder et al. 2015).

Roads fragment continuous blocks of habitat and become barriers that limit the movement of wildlife (Fahrig 2003; Forman et al. 2003). While wildlife generally avoids roads, crossings still occur as wildlife attempt to avoid surrounding development, follow established migration patterns, find food, or pursue mates, all of which may lead to wildlife-vehicle collisions (Alexander et al. 2005; Trombulak and Frissell 2000). Maintaining and improving habitat connectivity via road crossing structures can counteract the effects of an increasing transportation infrastructure, primarily by preventing wildlife collisions (Mata et al. 2008). As more crossing structures are built, access to segmented areas of habitat increases and wildlife are able to resume their normal, if slightly altered, ranges of movement (Bissonette and Adair 2008; Mata et al. 2008).

Building crossing structures requires detailed knowledge of wildlife crossing sites (Eberhardt et al. 2013). As such, tracking wildlife movement to identify these sites can be time and cost intensive (Clevenger et al. 2002; Mata et al. 2008). The use of Geographic Information Systems (GIS) to conduct a suitability analysis in an effort to identify likely wildlife crossings along roadways provides a low-cost solution and has proven to be an adept approach (Clevenger et al. 2002; Malo et al. 2004). For example, Clevenger et al. (2002) successfully leveraged GIS capabilities to develop two habitat models to identify crossing sites for black bear (*Ursus americanus*) based on information collected from experts and a literature review. By integrating GIS-based approaches, mitigation planning to counteract the negative effects of roads has improved in capability and feasibility.

Habitat based-crossing locations should not be the only criterion that guides mitigation efforts. If wildlife already successfully cross roads at a predicted crossing location, mitigation efforts at those sites would be wasted (Austin et al. 2006; Mata et al. 2008). Instead, predicted locations should be used in conjunction with collision records (Austin et al. 2006). However, habitat-based crossing locations may not completely explain areas with high collision counts (Neumann et al. 2012). Most wildlife-vehicle collisions probably involve a combination of conditions that contribute to high animal abundance near roads, high road traffic volume, and reduced driver awareness (Farmer and Brooks 2012; Seiler 2005). The complex relationships among these conditions and their effect on wildlife-vehicle collisions remains far from being settled in the academic literature. Clevenger et al. (2015) noted that the inconsistencies in findings may arise because the relationships are specific to a study site or species. As the understanding of relationships between the conditions that contribute to wildlife-vehicle collisions improves, mitigation efforts can be targeted on specific areas.

This research leveraged GIS capabilities to determine whether variation in observed wildlife-vehicle collisions could be explained by road traffic volume, wildlife crossing areas based on habitat suitability, and road characteristics that affect travel speed. I hypothesized that roads located in better habitat suitability regions and having a greater traffic volume, reduced sinuosity (curviness), and lower slope would have a greater number of wildlife-vehicle collisions. The empirical evidence regarding the relationship among wildlife-vehicle collisions and each of the independent variables has been mixed, which may have been due to the geographic extent of the study region (Clevenger et al. 2015; Malo et al 2004). Thus, this research examined the effects of extent by conducting the analysis at both a state-scale and on individual roads within the state. Additionally, certain road types have also been observed to affect wildlife-vehicle collisions (Clevenger et al. 2003; Myers et al. 2008). Accordingly, this research examined the effects of road type by conducting the analysis on different types of road based on the federal highway classification system (FHWA 1989). Finally, previous research has not considered that the observed relationships among wildlife-vehicle collisions and the previously listed factors may be sensitive to 1) the distance from roads used to define habitat suitability and 2) the maximum length of the road features used in the analysis. I included a robustness analysis to evaluate how changes in these parameters influenced the statistical outcomes. The research was performed using data from the state of Vermont (VT), where state agencies have been focusing efforts to address the effects of roads on wildlife (Austin et al. 2010; Kart et al. 2005).

LITERATURE REVIEW

Increased development of road infrastructure threatens to fragment and destroy large, continuous areas of habitats. Fragmented habitat occurs when previously continuous areas of habitat become segmented into small, isolated patches; however, wildlife populations require a certain amount of habitat, which varies by species, to survive and reproduce (Fahrig 2003). Due to habitat loss and fragmentation from development, individuals within a population or populations within a species can become isolated, causing a considerable decline in reproductive ability and genetic diversity that eventually increases extinction rates (Fahrig 2003; Lode 2000). Roads exacerbate these issues by acting as semi-barriers that limit wildlife movement; further isolate populations; and limit access to food resources, water, mates, and suitable habitat (Coffin 2007; Mata et al. 2008).

Wildlife may avoid roads due to their high density within a region, increased traffic volume, noise, or the physical qualities of the road (Coffin 2007). Brody and Pelton (1989) observed that black bears (*U. americanus)* in North Carolina moved their home ranges to be further away from high road density areas. Many species' home ranges are bound by roads, with animals rarely crossing them unless food becomes scarce within the home range (Hammond 2002). Despite a general pattern of avoidance, wildlife has been observed to cross roads at specific locations based on surrounding development, suitable habitat, and road conditions (Alexander et al. 2005; Gunson et al. 2011). For example, Lewis et al. (2011) observed that black bears (*U. americanus)* in Idaho only crossed highways at locations within forested areas with moderate to high amounts of forest and shrub cover, close to streams, and no human-made structures. However, the conditions that affect wildlife crossing occurrence may vary by species or location (Lewis et al. 2011). In contrast to Lewis et al. (2011), McCoy (2005) observed black bears (*U. americanus)* in Montana did not avoid crossing roads based on the presence of human development, likely because the bears scavenged for food close to human residences. Understanding the conditions that cause wildlife to cross or avoid crossing roads remains an area of ongoing study.

When an animal males an attempt to cross a road, there is a risk of a wildlife-vehicle collision. The risk of collision increases in areas that have many crossing attempts, greater traffic volume, or higher speed limits (Alexander et al. 2005; Trombulak and Frissell 2000). While species with large populations may not be significantly affected by a high rate of collision mortality, threatened species and those with low fecundity are at greater risk (Alexander et al. 2005; Coffin 2007). For example, the endangered Florida panther (*Felis concolor coryir*) lost 10% of its population due to collisions (Forman and Alexander 1998). Efforts to limit or eliminate the risk of collisions are necessary to allow threatened species to recover and prevent others from becoming threatened.

Collision mitigation and prevention efforts attempt to direct and prevent wildlife movement across specific sections of road with the goal of reducing collisions (Forman et al. 2003; Malo et al. 2004; Mata et al. 2008). These efforts take various forms, such as passages above roads, fences, and modified culverts (Malo et al. 2004; Mata et al. 2008). For example, in response to swarming Northern Leopard frogs (*Lithobates pipiens),* VT officials launched one of the state's first projects to mitigate wildlife-vehicle collisions by building a temporary fence along the roadway to keep the frogs from crossing (Hoffman 2003). Based on their efforts, collision numbers were reduced by 80%. In another example, Bissonette and Rosa (2012) observed a 98.5% decline in deer-vehicle collisions and increased habitat connectivity after mitigation efforts were taken along roads in Utah. After the first year, deer began to increasingly use the passages put in place to cross the roads during migration movements in the fall and spring. Mitigation that directs movement across roads reestablishes wildlife movement, reconnecting landscapes and counteracting some of the negative effects from roads (Alexander et al. 2005; Clevenger 2005; Mata et al. 2007).

Mitigation measures are costly, however, and cannot be implemented along every section of road (Clevenger et al. 2002; Mata et al. 2008). Researchers and policy makers have sought to identify key areas where such efforts should be focused, which requires knowing where wildlife crossings are occurring (Lewis et al. 2011; Mata et al. 2008). To identify these areas, wildlife movement has been tracked using various approaches, including radio-tracking, capture-mark-recapture, remote cameras, genetic sampling, and tracking surveys (Clevenger et al. 2002; Kaminski et al. 2013). For example, McCoy (2005) tracked black bear (*U. americanus*) movement with GPS collars. These tracking methods are time intensive, costly, and not necessarily well-suited for analysis at the landscape scale (Clevenger 2005). Landscape scale has been defined as the interactions between spatial patterns and ecological processes at a state, regional, national, or ecosystem scale (Turner et al. 2005). Henschel and Ray (2003) noted that studies using camera traps have high start-up costs and require long personnel hours both to set up the cameras and sort through thousands of hours of footage. Also, setting up cameras throughout a study area may not be possible due to cost or accessibility constraints. Silveira et al. (2003) collected 24,480 hours of data from camera traps over 44 days that required more months of analysis, whereas Clevenger et al. (2002) successfully used GIS-based models to develop habitat models for black bears (*U. americanus)* in two months. While tracking methods should not be discounted because they provide essential baseline information on wildlife at small scales, GIS-based models have been increasingly used to target initial mitigation efforts to reduce wildlife-vehicle collisions because of their applicability at landscape scales and speed of implementation (Clevenger et al. 2002).

GIS-based models have been used at the landscape scale to identify sections of highway most likely crossed by wildlife (Hoctor et al. 2000). Many of the models rely on expert-based opinion to identify the conditions used to predict wildlife crossings when actual data is not available (Clevenger et al. 2002; Kaminski et al. 2013; Kilgo et al. 2002). Some models employ a habitat suitability index, which ranks and evaluates habitat variables that factor into the location of possible crossing sites (Kaminski et al. 2013; Kilgo et al. 2002; Tirpak et al. 2009). The conditions determining the identification of crossing areas are often based on wildlife habitat and human activities; however, these conditions may vary by species (Kaminski et al. 2013; Lewis et al. 2011). At the landscape scale, analyses often focus on wildlife groupings, rather than specific species, because it better supports policymakers and state conservation efforts (Clevenger et al. 2002; Kaminski et al. 2013). The landscape scale also favors wildlife that range or are present over large spatial scales (Kaminski et al. 2013). No matter the findings of these analyses, some form of verification is required to test their validity (Clevenger et al. 2002; Kaminski et al. 2013; Tirpak et al. 2009).

Where wildlife cross roads, collisions can be expected to occur and therefore may act as validation of predicted crossing areas (Lewis et al. 2011; Neumann et al. 2012). While some studies have attempted to direct mitigation efforts solely based on collision sites, this does not account for all possible areas of conflict (Malo et al. 2004; Neumann et al. 2012; Ramp et al. 2005). Collision data is often collected based on opportunity rather than by designed surveys and thus does not present a true account of areas used by wildlife along roads (Alexander et al. 2005; Malo et al. 2004). For example, Austin et al. (2006) obtained collision records from wildlife-vehicle collisions reported to the police and Department of Transportation. Another issue with only considering collision data arises when crossings occur at locations resulting in few, if any, collisions (Alexander et al. 2005). There could be only a few or no collisions at a section of road because the conditions contributing to collisions have been addressed. Another possibility is that wildlife populations have declined to the extent that crossing attempts either rarely or no longer occur (Clevenger et al. 2003). Crossing locations and collision records should both be used when directing mitigation efforts (Alexander et al. 2005; Eberhardt et al. 2013; Neumann et al. 2012).

Factors Affecting Wildlife-Vehicle Collisions

As previously established, GIS-based models have employed habitat suitability to predict wildlife crossing areas (Kaminski et al. 2013; Lewis et al. 2011). For example, Clevenger et al. (2002), Kaminski et al. (2013), and Lewis et al. (2011) successfully predicted wildlife crossing areas based on habitat suitability for black bear (*U. americanus*). Only Lewis et al. (2011) recommended that its predicted crossing areas be used to mitigate bear-vehicle collisions; Clevenger et al. (2002) and Kaminski et al. (2013) did not broach the subject. In another study, Neumann et al. (2012) indirectly compared predicted crossing locations of moose (*A. alces*) based on habitat suitability data and observed collisions by using both to predict collision risk zones, but concluded the predicted crossings insufficiently explained the risk zones while observed collisions overestimated the risk. Studies rarely affirm the relationship between wildlife-vehicle collisions and the predicted crossing areas.

Conditions such as housing density, forest coverage, and the location of water have been used to predict wildlife crossing areas, which are then used to predict wildlife-vehicle collisions (Grilo et al. 2009; Malo et al. 2004). Yet, these efforts to determine the relationships among habitat conditions and wildlife-vehicle collisions have demonstrated mixed results (Clevenger et al. 2015). For example, a relationship was not found between deer (*Odocoileus* spp.) vehicle collisions and the amount of forest cover in Minnesota (Nielsen et al. 2003), but was found in Illinois and Iowa (Finder et al. 1999; Hubbard et al. 2000). While the mixed results have been attributed to regional, or even local, idiosyncrasies, investigation into the issue has been limited (Clevenger et al. 2015; Malo et al 2004).

Habitat conditions used to predict wildlife crossing areas or the sites of wildlife-vehicle collisions have been examined at a variety of distances away from the roads used in the analysis. Clevenger et al. (2015) described habitat conditions within 100 m of a road, while Grilo et al. (2009) and Barthelmess (2014) used 500 m and 1,000 m, respectively. Only a few studies provided an explanation for how or why the distances were chosen or evaluated whether the distance chosen influenced the results of the analysis (Danks and Porter 2010; Finder et al. 1999). This is an issue because habitat conditions may significantly change as distance from a road is increased. For example, if a grassy meadow gives way to forest at 225 meters away from a road, but the distance is set at 200 meters, the change in habitat conditions would not be included in the analysis and could possibly alter the predicted crossing areas. The extent to which changes in the distance from a road alter estimated habitat conditions (and therefore habitat suitability) remains sufficiently unexplored.

Road traffic volume has also been utilized by many studies to predict wildlife-vehicle collisions (Framer and Brooks 2012; Lewis et al. 2011; Mountrakis and Gunson 2009). Previous studies were inconsistent about the relationship between road traffic volume and wildlife-vehicle collisions: no relationship (Shepard et al. 2008), a mixed relationship (Seiler 2005), or a positive relationship (Farmer and Brooks 2012). Road avoidance behavior by wildlife has been postulated as an explanation for the inconsistent results (Brockie et al. 2009; Seiler 2005). Species may cross roads until a certain threshold of road traffic volume has been reached, which has been estimated to be 1,200 vehicles a night for carnivores (Grilo et al. 2009) and 3,000 vehicles a day for mammals

(Brockie et al. 2009). Alexander et al. (2005) estimated a range of 500-5,000 vehicles a day for ungulates. Further, the threshold may vary by species and possibly not even apply if the crossing area is part of a long-established migration route (Bruggeman et al. 2007). Variation at individual sites or along individual roads may also cause mixed results within a study if it uses a landscape scale without examination of individual parts of the road network under consderaion (Bissonette and Adair 2008; Clevenger et al. 2015). A comparison of the relationship between road traffic volume and wildlife-vehicle collisions at the landscape and local scales may provide a better understanding of the role of scale and extent.

A relationship between vehicle speed and wildlife-vehicle collisions has been postulated by researchers, but the empirical evidence has also been mixed (Bissonette and Adair 2008). For example, Barthelmess (2014) observed no significant relationship between the pair, while Seiler (2005) observed a quadratic relationship with more mammal-vehicle collisions occurring on roads where vehicles traveled at intermediate vehicle speeds. An improved understanding of the relationship between vehicle speed and wildlife-vehicle collisions would be beneficial to researchers; however, observed vehicle speeds have proven difficult to obtain as spatial data.

There are road characteristics widely available as spatial data that have the potential to affect vehicle speeds and, subsequently, wildlife-vehicle collisions. Two such road characteristics are the sinuosity and topography of a road. Sinuosity, or the curviness of a road, has been positively associated with mammal-vehicle collisions (Klocker et al. 2006). However, Barthelmess (2014) did not observe a statistically significant relationship, possibly because of issues with the length of the road features. When a road is curved, there is reduced driver visibility (Barthelmess 2014; Farmer and Brooks 2012), but also may lead to slower vehicle speeds. Topographic variation along the roads may affect travel speed and visibility (Clevenger et al. 2003). The relationship between road topography and wildlife-vehicle collisions has shown mixed results in the literature. Clevenger et al. (2003) observed raised and partially-raised roads had a high, negative relationship with wildlife-vehicles collisions, with more collisions occurring along level roads. In contrast, Barthelmess (2014) observed mammal-vehicle collisions were less likely to occur on buried and partially-buried roads than level roads. Road sinuosity and topography require further evaluation, with attention to road length, to determine each condition's relationship with wildlife-vehicle collisions.

Wildlife-Vehicle Collisions in VT, US

The case study is conducted within the state of VT, which has a land area of approximately 24,800 km^2 (U.S. Census Bureau 2012). Forestland encompasses 75% of the state, with coverage increasing from west to east due to extensive agricultural and developed land along the western border (Synder et al. 2015). VT forests face an increasing risking risk of fragmentation. Between 1982 and 1992, approximately 2,630 ha of open space and 202 ha of significant wildlife habitat were lost each year; a loss that has only increased since 1992 (Austin et al. 2010; Austin et al. 2013). The rising risk of forest fragmentation is due to an expansion of the transportation infrastructure, which includes roads, to accommodate an increasing population (Austin et al. 2013; Synder et al. 2015). In VT, the human population has increased by 10% during the past three decades, matched by a 20% increase in automobile registration (Austin et al. 2013; Shilling et al. 2012). As of 2015, there are approximately 46,990 km of roads in VT; however, this number is projected to increase in the upcoming years, stemming from the need to connect dispersed residential and commercial communities and a rapidly increasing population (Austin et al. 2010; U.S. Department of Transportation 2014).

While residents are aware of the significant occurrence of vehicle-wildlife collisions, there are few actual reports containing reported collision numbers and damage costs in VT (Austin et al. 2006; Slesar et al. 2003; Synder et al. 2015). Hoffman (2003) reported 10,200 Northern Leopard frogs (*L. pipiens)* killed by vehicles daily along VT Route 2 during the summer months. Austin et al. (2013) reported approximately 2,500 White-tailed deer (*Odocoileus virginanus*) and moose (*Alces alces)* were struck by vehicles each year. Romin and Bisoonette (1996) estimated $31,141,777 as the cost in damages from vehicle-deer collisions in VT between 1981 and 1991. Austin et al. (2006) initiated the creation and maintenance of a collision database by the VT Fish and Wildlife Department, but so far records past 2006 have not been made public. From the database, deer (*O. virginanus*), moose (*Alces alces*), and black bear (*U. americanus*) are the most commonly reported species involved in collisions (Austin et al. 2006). Wildlife-vehicle collisions have increased nationwide and cost more in damages each year; VT has not been an exception to this trend (Huijser et al. 2008; Malo et al. 2004).

Due to the rising concern of the potential effects roads have on local wildlife, VT initiated a series of studies to determine the extent of wildlife connectivity within its borders and to identify mitigation and prevention strategies in areas where it was lacking

(Austin et al. 2010; Slesar et al. 2003). These issues were acknowledged by VT in the state's Wildlife Action Plan, which called for an examination of the effects of roads on wildlife (Kart et al. 2005). Austin et al. (2006) and Sorensen and Osborne (2014) successfully developed a model to identify potential wildlife linkage habitats associated with VT roads, which are areas where wildlife was most likely to cross based on suitable conditions. The two studies observed that habitat connectivity declined near urban areas, which coincided with higher numbers of wildlife-vehicle collisions. The findings from these and other studies caused VT state agencies to create and maintain management plans to restore wildlife habitat connectivity and make informed choices about transportation design (Shilling et al. 2012). VT state agencies have continued to address the effects of roads on wildlife by identifying wildlife-highway crossings and collecting data on wildlife-vehicle collisions to determine where mitigation and preventions efforts are required (Shilling et al. 2012; Sorensen and Osborne 2014).

MATERIALS AND METHODS

Traffic Data

A roads spatial data layer with average annual daily traffic (AADT), measured in vehicles/day for VT's interstates, highways, and other major roads from 1990-2006, was acquired from the VT Center for Geographic Information (VCGI, http://vcgi.vermont.gov/opendata). The total length of roads represented in the data layer is approximately 6,200 km with an average road segment length of 1.8 km (range of approximately 8 m to 25.5 km). Following the methods in Austin et al. (2006), the road features in the AADT layer were split into segments having a maximum length of 800 m. Preliminary analysis suggested that the road segment length affected the analysis; therefore, two additional data layers were created with road features having a maximum segment length of 400 m and 1,600 m. After the roads layers were split, the feature lengths were recalculated and all road features with a length less than 200 m were removed from each layer, as the presence of extremely short road features led to processing errors and extreme values in later calculations. Removal of the short road features did not substantially affect the amount of data represented in the original roads layer; after removing road features with a length less than 200m, the spatial features used in the analysis represented 96.7% (400 m), 98% (800 m), and 98.6% (1,600 m) of the road features, by road length, in the original dataset. Following the spatial processing to implement the maximum segment length, the mean AADT was calculated over 1990-2006 to mirror the wildlife-vehicle collision data.

Wildlife-Vehicle Collision Data

A spatial data layer containing wildlife-vehicle collision records for VT during 1990-2006 was acquired from the VCGI. This database was created and quality checked as described in Austin et al. (2006). For each wildlife-vehicle collision, the database includes the animal type and date reported. Records for moose (*A. alces*; n=1,333) and black bear (*U. americanus*; n=273) were subset from the data and used in the analysis, as these species were wide-ranging mammals upon which the habitat characteristics of the wildlife crossing index were based.

A visual inspection of the collisions data revealed that it included events that occurred on roads not represented in the AADT roads layer. Because the two layers did not share attribute information that would allow them to be linked via a table join, the distance from each collision location to the nearest road feature in the AADT layer was measured. Of the 1,606 moose and black bear collisions, 1,562 collisions (97.26%) were within 200 m of a road feature represented in the AADT layer, while 15 (0.93%) were located 200-400 m, 6 (0.37%) were located 400-600 m, 7 (0.44%) were located 600-800 m, 7 (0.44%) were located 800-1,000 m, and 7 (0.44%) were located more than 1,000 m from a road feature; thus the 44 collisions (2.74%) that were located outside of 200 m from the final roads layer were removed from the analysis, as this appeared to be an appropriate threshold to ensure the collisions occurred on a road represented in the AADT layer.

The final analytic dataset included 1,562 wildlife-vehicle collisions (267 bear and 1,295 moose). The collision point features were spatially joined to the three road data layers, which resulted in a count of collisions per road feature. As the wildlife-vehicle collisions were opportunistically reported, any road features containing no reported collisions were removed from further analysis (Austin et al. 2006; Bissonette and Kassar 2008). To standardize the values for variations in road feature length, the collision count for each road feature was divided by that road feature's measured length to calculate a wildlife-vehicle collisions density (WVCD) value, measured in collisions/m.

Habitat Suitability and Wildlife Crossing Index

The wildlife crossing index is a road-level metric that captures the propensity of wildlife to cross at a given road segment, and is based on the wildlife habitat in the region near the segment; thus, a habitat suitability layer was first created. Austin et al. (2006) and Sorensen and Osborne (2014) detail the approach to model large mammal habitat suitability and calculate the wildlife crossing index, which was implemented in this research and is summarized in the following paragraphs.

The three landscape characteristics used to create the large mammal habitat suitability layer were land use / land cover (LULC), structure density, and core habitat areas. The 2006 data layer from the National Land Cover Dataset (30m^2 cell resolution, https://www.mrlc.gov/nlcd2006.php) was used for the LULC layer. A point layer containing the locations of manmade structures was acquired from the VCGI. The points were converted to a structure density raster layer (30 m^2 cell resolution) by counting the number of structures within a 500 m radius of every cell location and dividing by the area of the circle (values were returned in structures/mi^2). A core habitat polygon layer was acquired from the VCGI and used to create a core habitat raster layer. The approach implemented a variable distance buffer to create a set of five concentric rings surrounding each core habitat polygon. The specific buffer distance for each habitat polygon is based on the area of the habitat polygon, such that larger polygons have larger buffer distances. The five buffer layers were overlain with the original core area polygon layer to create a final layer containing core area habitat patches and concentric distance “bands” surrounding each. This layer was converted to a raster layer (30m^2 cell resolution) for further processing.

The three layers representing habitat suitability characteristics were each rescaled from 1-10 with one indicating low suitability and ten indicating high suitability (see Figure 1 and Supplementary Tables A.1-3). The layers were then combined (summed) using the following weighting scheme, LULC (27.5%), structure density (45%), and core habitat (27.5%), to create a final habitat suitability layer. Because the three weights used in this operation summed to one, the final habitat suitability layer had the same numeric scale and interpretation as the component layers.

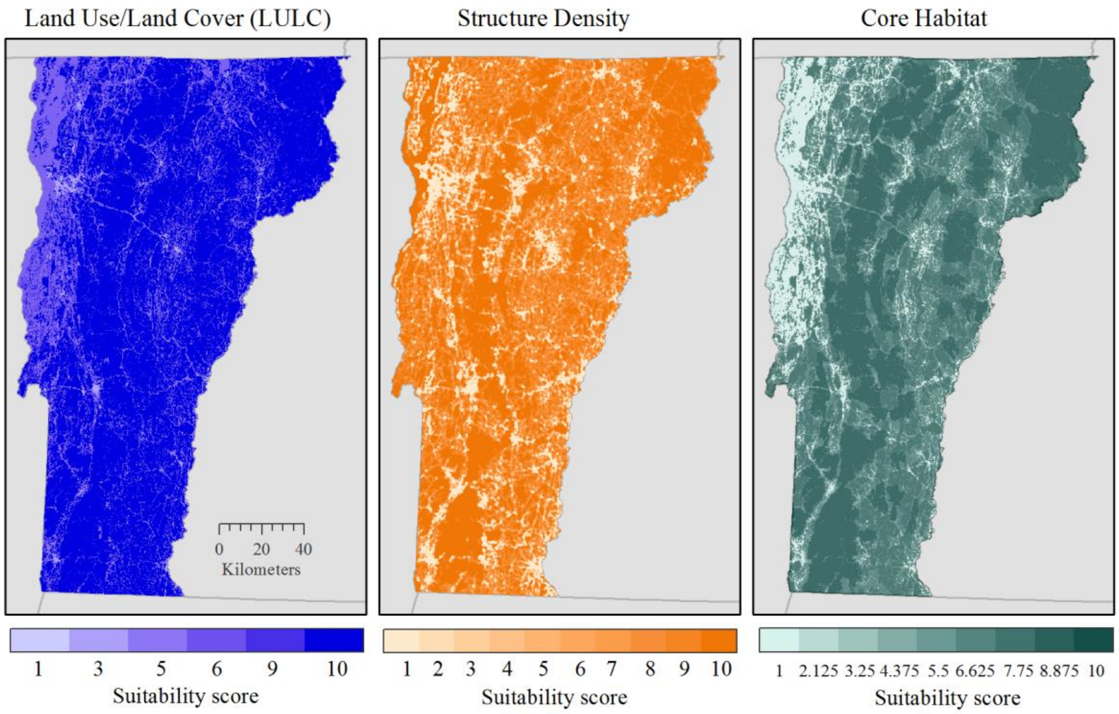

Figure 1. Habitat suitability scores for the Land use/land cover (LULC), structure density, and core habitat layers used to create the wildlife crossing index (WCI).

The wildlife crossing index (WCI) score was calculated for each road feature by creating a buffer around the feature and calculating the mean habitat suitability of all cells located within the buffered region. This process was completed individually for all road features in the 400 m, 800 m, and 1600 m maximum segment length road layers. In the operation, the buffers were capped such that they did not extend past the endpoints of the road features in an effort to only consider habitat along the side of each road. Per Austin et al. (2006), the buffers extended 800 m from each side of the road (i.e., a buffer 1,600 m wide, centered on the road feature). However, to evaluate the robustness of the specific buffer distance used to calculate the WCI value, the index scores were also calculated based on 400 m and 1,200 m (per side) buffers for each road feature. There was a lack of research to guide what distance from the road should be considered to evaluate for robustness, thus 400 m was subtracted and added to the 800 m buffer offered by Austin et al. (2006). Figure 2 shows the final WVCD, AADT, and habitat suitability layers used in the analysis.

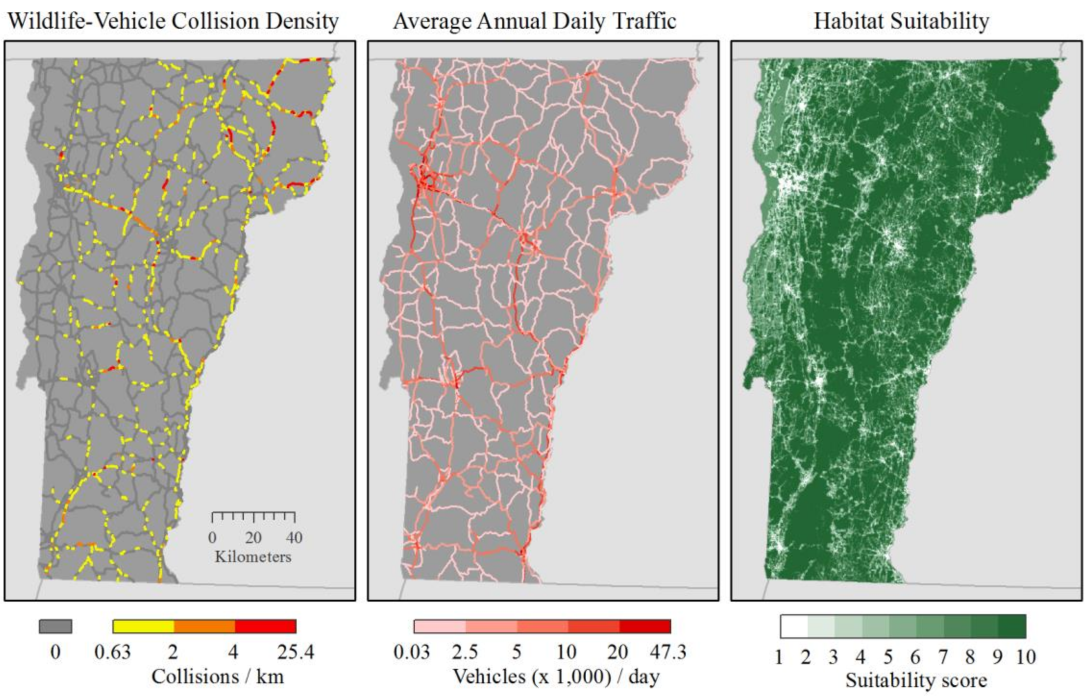

Figure 2. Wildlife-vehicle collision density (WVCD), average annual daily traffic (AADT) for 1990-2006, and habitat suitability for VT.

Road Characteristics

Speed limit data for the roads containing AADT information were not available. Therefore, two characteristics of the roads that had the potential to affect vehicle speeds were calculated for this study. Road sinuosity was calculated for each road feature by dividing the feature's length by the straight-line distance connecting the endpoints of the feature (Barthelmess 2014). Using this formula, roads that are meandering or curved have a higher sinuosity value than straight roads. Topographic variation along the roads may also affect travel speed and visibility; hence, the mean slope (Slope) was calculated for each road feature. While Barthelmess (2014) used a field observation approach to collect topographic information at collision locations, this was not possible given the scope of this research. Therefore, slope was used as a proxy for topographic change over a segment of a road. A slope (%) data layer (10m^2 cell resolution) was downloaded from VCGI. A 5 m buffer was created around each road feature (10 m total width) in an effort to capture a continuous set of slope values along each feature. The mean slope was then calculated using the slope of all cells located within each road feature's buffer.

Data Analysis

The relationships between wildlife-vehicle collision density (WVCD), average annual daily traffic (AADT), and wildlife crossing index (WCI) were evaluated using multiple ordinary linear squares (OLS) regression. In the model, WVCD was the dependent variable, and AADT and WCI were independent variables. Sinuosity, Slope, and (road segment) Length were also included as independent variables in the regression model an effort to control for road characteristics. The individual road features with WVCD greater than zero functioned as the observation units in the model.

Separate regression models were constructed for the three maximum road segment lengths used to partition the roads data (400 m, 800 m, and 1,600 m). Further, for each maximum segment length model, separate models were also constructed for the three different buffer distances used to calculate the WCI values (400 m, 800 m, and 1,200 m), which resulted in a total of nine models. Basic descriptive statistics for the input data in the all roads models are presented in Table 1.

Table 1. Descriptive statistics for variables used in the all roads multiple regression models.

Model variables	Minimum	Maximum	Mean	Std. Devation
All Roads, 400 m (n=1,037)				
WVCD	0.003	0.028	0.004	0.003
AADT	122.941	47,313.529	5,410.565	6,312.081
WCI (400 m)	1.017	9.880	6.917	1.840
WCI (800 m)	1.192	10.000	7.460	1.735
WCI (1200 m)	1.240	10.000	7.739	1.681
Sinuosity	1.000	2.142	1.012	0.043
Slope	2.000	101.158	11.407	7.298
Segment length	203.094	400.000	392.853	30.356
All Roads, 800 m (n=919)				
WVCD	0.001	0.025	0.002	0.002
AADT	122.941	47,313.529	5,475.550	6,311.519
WCI (400 m)	1.032	9.902	6.783	1.809
WCI (800 m)	1.028	10.000	7.345	1.718
WCI (1200 m)	1.049	10.000	7.613	1.680
Sinuosity	1.000	1.809	1.025	0.048
Slope	2.000	62.416	10.813	5.641
Segment length	203.094	800.000	760.314	120.019
All Roads, 1600 m (n=758)				
WVCD	0.001	0.025	0.002	0.002
AADT	122.941	47,313.529	5,459.665	6,259.832
WCI (400 m)	1.057	9.881	6.605	1.745
WCI (800 m)	1.061	10.000	7.190	1.677
WCI (1200 m)	1.500	10.000	7.483	1.638
Sinuosity	1.000	1.562	1.040	0.062
Slope	2.000	54.075	10.890	5.028
Segment length	205.097	1,600.000	1,422.851	352.919

To examine the effects of local and regional characteristics of roadways, the nine regression models were also constructed separately using data from three main roadways in VT: Interstate 91 (I-91), U.S. Route 2 (US-2), and VT Route 114 (VR-114). These three roadways were selected because of their differing directional orientation and relative location within the state. The roadways are mapped in Figure 3. Descriptive statistics for the roadway-specific data are presented in Supplementary Tables A.4-6. To illustrate how WVCD, AADT, WCI, and Slope vary along a specific roadway, the values are graphed along the extent of I-91 (from north to south) in Figure 4.

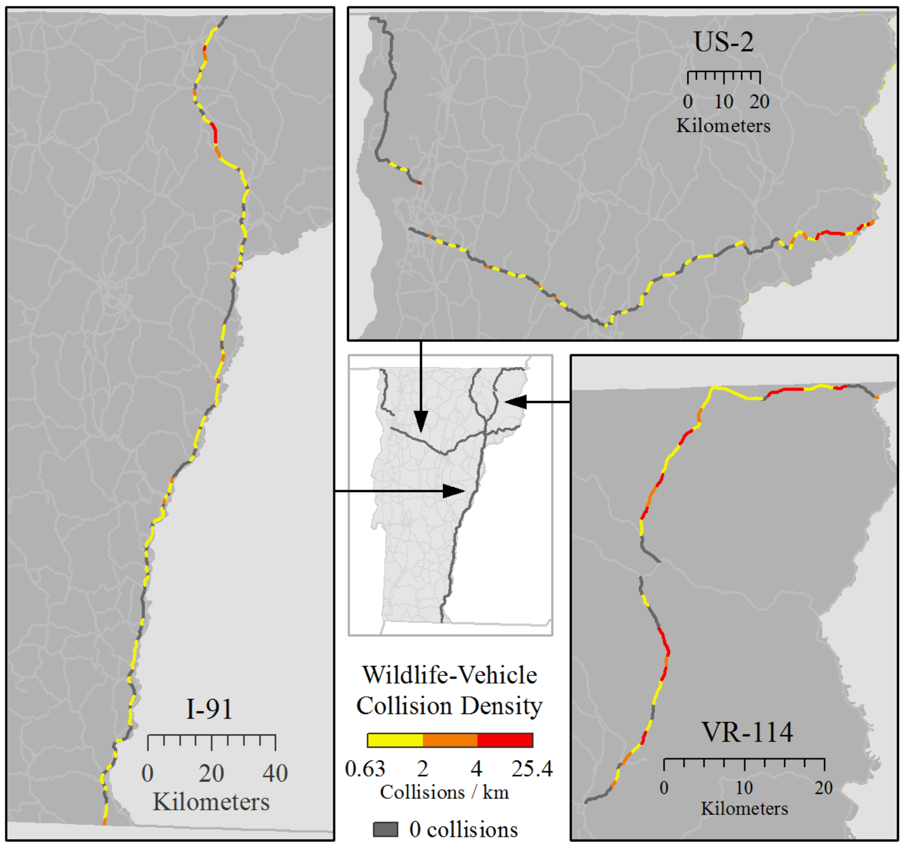

Figure 3. Map of Interstate 91 (I-91), U.S. Route 2 (US-2), and VT Route 114 (VR-114).

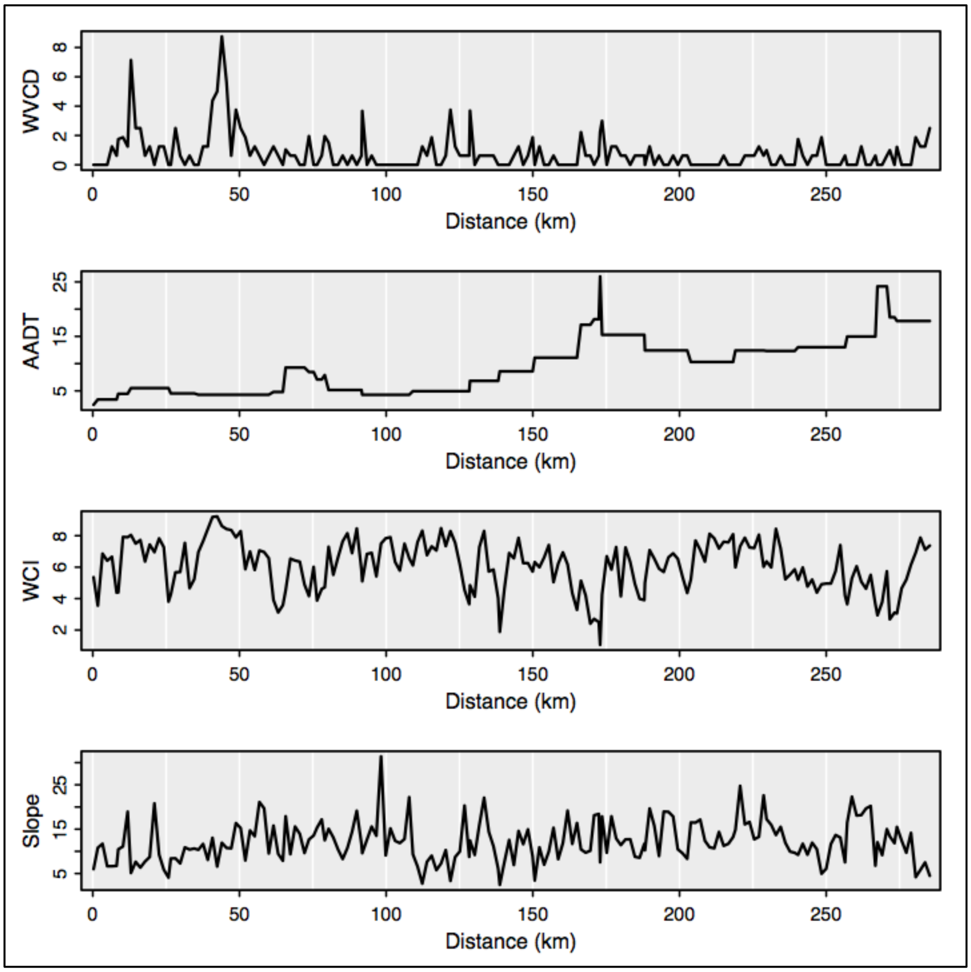

Figure 4. Graph of WVCD (collisions per km), AADT (average over 1990-2006, average number of vehicles per day / 1,000), WCI (800 m), and Slope (%) along I-91. Distance on the x-axis is distance along the roadway, measured from the northern-most endpoint.

The nine regression models were also constructed separately using data from four functional classes of roadway in VT: Functional 7 (F7), Functional 6 (F2), Functional 2 (F2), and Functional 1 (F1). These groups were selected because the other functional classes (not listed) contained less than 20 total road features. The functional classification system for the four groups is presented in Table 2 (FHWA 1989; VGIS 2005), and the four functional roadway classes are mapped in Figure 5 (descriptive statistics of the functional-specific models can be found in Supplementary Tables A.7-10).

Table 2. Descriptions of the four functional roadway classes.

Functional	Functional Class	Class Description
7 (F7)	Rural Major Collector	Serve intra-regional travel corridors. Link large towns to major traffic generators (schools and employment centers), larger towns, and cities.
6 (F6)	Rural Minor Arterial	Provide interstate and regional service to large towns and traffic generators that attract travelers. Spaced at intervals based on population density to ensure developed areas are near a principal arterial highway.
2 (F2)	Rural Principal Arterial	Acts as an integrated network in urban areas totaling more than 25,000-50,000 people.
1 (F1)	Rural Principal Arterial - Interstate	Acts as an integrated network in urban areas totaling more than 25,000-50,000 people. Official interstate highway number has been assigned.

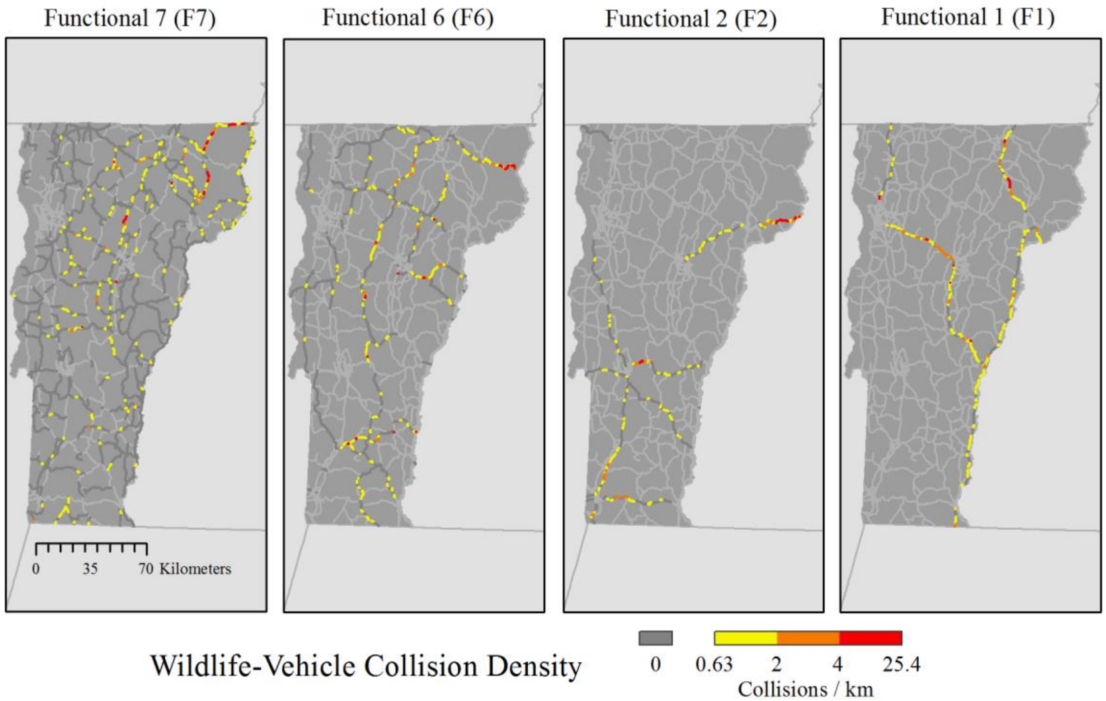

Figure 5. Map of Functional 7 (F7), Functional 6 (F6), Functional 2 (F2), and Functional 1 (F1).

Prior to performing the regressions, the values for WVCD and AADT were log transformed, as the distributions of these variables were positively skewed. All regression models were evaluated for multicollinearity among the independent variables using Variance Inflation Factor (VIF). For the all roads models, the I-91 models, the US-2 models, the F7 models, the F6 models, the F2 models, and the F1 models, all independent variables had a VIF < 2 (Tables 3-10), which indicates strong independence within the independent variable set (Graham 2003). In the VR-114 models, the VIF values for WCI were slightly larger than 2 in the models using a maximum road feature length of 1,600 m, indicating slight, but non-problematic multicollinearity. The same finding occurred in the F6 models using a maximum road feature length of 1,600 m and buffer distances of 400 m and 800 m. All regression models were evaluated for heteroskedasticity among the regression residuals using the Studentized Breusch-Pagan (BP) test (Tables 3-10). Some of the preliminary regression results demonstrated heteroskedastic regression residuals, so a White adjustment was employed to account for heteroskedasticity by adjusting the standard errors of the regression coefficients and their resulting *p*-values (White 1980; Zeileis 2004). The resulting coefficients for the independent variables were standardized, thus allowing for the relative magnitude of the variables to be evaluated within each model.

Table 3. Results of the Studentized Breusch-Pagan (BP) and Variance Inflation Factor (VIF) tests for the all roads regression models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
BP	49.577	***	47.596	***	47.257	***	68.108	***	61.036	***	64.231	***	71.309	***	65.043	***	60.070	***
VIF																		
AADT	1.338		1.404		1.374		1.415		1.502		1.427		1.430		1.529		1.492	
WCI	1.357		1.419		1.392		1.456		1.540		1.482		1.531		1.610		1.550	
Sinuosity	1.029		1.029		1.029		1.069		1.069		1.069		1.102		1.102		1.103	
Slope	1.032		1.024		1.022		1.054		1.043		1.045		1.084		1.068		1.062	
Length	1.014		1.018		1.019		1.056		1.058		1.065		1.102		1.096		1.073	

Table 4. Results of the Studentized Breusch-Pagan (BP) and Variance Inflation Factor (VIF) tests for I-91 regression models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
BP	15.856	**	16.239	**	17.324	**	11.9676	*	12.826	*	13.647	*	12.940	*	13.616	*	12.761	*
VIF																		
AADT	1.284		1.300		1.272		1.245		1.264		1.194		1.196		1.246		1.201	
WCI	1.322		1.319		1.278		1.319		1.339		1.281		1.390		1.465		1.283	
Sinuosity	1.137		1.130		1.122		1.072		1.074		1.068		1.161		1.130		1.098	
Slope	1.058		1.053		1.052		1.026		1.019		1.020		1.055		1.039		1.037	
Length	1.037		1.025		1.022		1.072		1.066		1.083		1.204		1.246		1.147	

Table 5. Results of the Studentized Breusch-Pagan (BP) and Variance Inflation Factor (VIF) tests for US-2 regression models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
BP	16.562	**	14.802	*	12.442	*	17.001	**	16.049	**	13.559	*	13.062	*	11.796	*	10.535	
VIF																		
AADT	1.229		1.303		1.374		1.248		1.390		1.523		1.305		1.534		1.485	
WCI	1.217		1.269		1.337		1.310		1.412		1.526		1.365		1.515		1.409	
Sinuosity	1.097		1.091		1.089		1.195		1.179		1.173		1.076		1.066		1.070	
Slope	1.056		1.058		1.071		1.144		1.166		1.167		1.092		1.063		1.074	
Length	1.072		1.072		1.073		1.064		1.046		1.039		1.100		1.088		1.079	

Table 6. Results of the Studentized Breusch-Pagan (BP) and Variance Inflation Factor (VIF) tests for VR-114 regression models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
BP	4.524	4.021	4.989	2.087	2.201	1.769	4.828	2.645	4.574
VIF									
AADT	1.345	1.355	1.463	1.553	1.679	1.488	1.463	1.545	1.663
WCI	1.331	1.338	1.445	1.605	1.741	1.459	2.071	2.342	2.118
Sinuosity	1.008	1.004	1.004	1.066	1.065	1.063	1.066	1.084	1.088
Slope	1.039	1.036	1.038	1.119	1.116	1.090	1.301	1.320	1.304
Length	1.045	1.048	1.045	1.194	1.187	1.189	1.531	1.618	1.300

Table 7. Results of the Studentized Breusch-Pagan (BP) and Variance Inflation Factor (VIF) tests for Functional 7 regression models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
BP	16.473 **	14.690 *	17.065 **	24.421 ***	16.012 **	22.727 ***	32.345 ***	23.961 ***	14.778 *
VIF									
AADT	1.256	1.202	1.245	1.310	1.265	1.338	1.397	1.331	1.335
WCI	1.320	1.247	1.294	1.415	1.339	1.423	1.514	1.384	1.380
Sinuosity	1.015	1.015	1.015	1.035	1.034	1.034	1.085	1.085	1.085
Slope	1.065	1.047	1.048	1.091	1.064	1.058	1.094	1.076	1.074
Length	1.026	1.032	1.030	1.046	1.050	1.059	1.084	1.063	1.057

Table 8. Results of the Studentized Breusch-Pagan (BP) and Variance Inflation Factor (VIF) tests for Functional 6 regression models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
BP	21.656 ***	18.247 **	17.061 **	25.267 ***	20.947 **	21.013 ***	34.880 ***	29.200 ***	25.441 ***
VIF									
AADT	1.659	1.622	1.426	1.807	1.784	1.773	1.977	1.963	1.693
WCI	1.722	1.696	1.528	1.899	1.902	1.961	2.135	2.090	1.799
Sinuosity	1.020	1.020	1.016	1.046	1.048	1.045	1.102	1.103	1.102
Slope	1.058	1.053	1.058	1.064	1.069	1.083	1.092	1.078	1.057
Length	1.035	1.044	1.064	1.072	1.089	1.120	1.128	1.131	1.135

Table 9. Results of the Studentized Breusch-Pagan (BP) and Variance Inflation Factor (VIF) tests for Functional 2 regression models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
BP	12.257 *	11.839 *	10.785	15.314 **	13.908 *	14.117 *	12.200 *	11.167 *	12.774 *
VIF									
AADT	1.139	1.133	1.126	1.228	1.235	1.216	1.201	1.211	1.212
WCI	1.155	1.158	1.154	1.278	1.280	1.246	1.279	1.305	1.293
Sinuosity	1.033	1.037	1.037	1.108	1.112	1.107	1.260	1.267	1.264
Slope	1.045	1.047	1.050	1.115	1.111	1.115	1.242	1.243	1.246
Length	1.016	1.016	1.016	1.046	1.038	1.026	1.091	1.094	1.082

Table 10. Results of the Studentized Breusch-Pagan (BP) and Variance Inflation Factor (VIF) tests for Functional 1 regression models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
BP	8.150	14.108 *	17.293 **	8.994	12.421 *	14.288 *	4.997	7.503	9.827
VIF									
AADT	1.159	1.106	1.064	1.162	1.106	1.055	1.135	1.089	1.051
WCI	1.228	1.152	1.081	1.216	1.151	1.078	1.336	1.322	1.193
Sinuosity	1.100	1.089	1.075	1.061	1.056	1.045	1.043	1.034	1.025
Slope	1.028	1.024	1.023	1.025	1.021	1.024	1.033	1.022	1.019
Length	1.024	1.021	1.013	1.050	1.053	1.044	1.184	1.237	1.163

Only a few studies that examined wildlife-vehicle collisions using regression-based approaches have assessed and corrected for spatial autocorrelation in the regression residuals (Clevenger et al. 2015; Farmer and Brooks 2102; Grilo et al 2009; Neumann et al. 2012). However, none of these studies used line features in the models, so they provided no guidance on how address spatially autocorrelated residuals. Specifically, the definition of neighborhood features for line data was of concern because distance-based neighbors would not enforce road connectivity, but methods to establish connectivity-based neighbors were not available for line features. Further review of the literature did not uncover a method that was developed specifically for line features. Therefore, in this study, the OLS regression residuals were assessed for spatial autocorrelation using Moran's I with neighborhoods defined using an inverse distance squared relationship with no enforced maximum distance. Inverse distance squared was selected because the closer road features were in space, the more they influenced each other. Neighborhoods were row standardized to account for features having an unequal set of neighboring features (Aneslin 2004). Of the 72 OLS regression models, 49 (68%) demonstrated significant spatial autocorrelation in the residuals (Tables 11-18).

Table 11. Moran's I results for the all roads models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Moran's I	0.174	***	0.179	***	0.176	***	0.185	***	0.187	***	0.192	***	0.179	***	0.184	***	0.184	***
Expected Value	-0.001		-0.001		-0.001		-0.001		-0.001		-0.001		-0.001		-0.001		-0.001	
Variance	0.001		0.001		0.001		0.001		0.001		0.001		0.001		0.001		0.001	
Z-score	7.110		7.292		7.152		7.442		7.504		7.709		6.923		7.098		7.094	

Table 12. Moran's I results for I-91 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Moran's I	0.206	**	0.204	**	0.200	**	0.043		0.037		0.053		0.163	*	0.167	*	0.147	
Expected Value	-0.007		-0.007		-0.007		-0.008		-0.008		-0.008		-0.010		-0.010		-0.010	
Variance	0.005		0.005		0.005		0.006		0.006		0.006		0.007		0.007		0.007	
Z-score	2.897		2.866		2.805		0.655		0.586		0.790		2.013		2.059		1.825	

Table 13. Moran's I results for US-2 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
Moran's I	0.083	0.131	0.147	0.143	0.151	0.158	0.052	0.076	0.084
Expected Value	-0.012	-0.012	-0.012	-0.015	-0.015	-0.015	-0.020	-0.020	-0.020
Variance	0.009	0.009	0.009	0.013	0.013	0.013	0.023	0.023	0.023
Z-score	0.993	1.500	1.666	1.386	1.455	1.518	0.478	0.637	0.690

Table 14. Moran's I results for VR-114 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
Moran's I	0.193 *	0.206 *	0.221 *	0.098	0.073	0.143	0.001	0.020	-0.043
Expected Value	-0.012	-0.012	-0.012	-0.017	-0.017	-0.017	-0.025	-0.025	-0.025
Variance	0.008	0.008	0.008	0.010	0.010	0.010	0.018	0.018	0.017
Z-score	2.266	2.413	2.571	1.124	0.876	1.557	0.195	0.340	-0.139

Table 15. Moran's I results for Functional 7 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
Moran's I	0.282 ***	0.293 ***	0.293 ***	0.274 ***	0.278 ***	0.267 ***	0.265 ***	0.275 ***	0.275 ***
Expected Value	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.004	-0.004	-0.004
Variance	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Z-score	6.324	6.569	6.559	5.934	6.025	5.795	5.414	5.598	5.618

Table 16. Moran's I results for Functional 6 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
Moran's I	0.088	0.096	0.097	0.118 *	0.136 *	0.136 *	0.129 *	0.139 *	0.147 *
Expected Value	-0.004	-0.004	-0.004	-0.005	-0.005	-0.005	-0.006	-0.006	-0.006
Variance	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Z-score	1.683	1.829	1.849	2.097	2.398	2.399	2.285	2.445	2.585

Table 17. Moran's I results for Functional 2 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
Moran's I	0.185 **	0.201 **	0.196 **	0.322 ***	0.335 ***	0.338 ***	0.277 **	0.287 **	0.284 **
Expected Value	-0.006	-0.006	-0.006	-0.007	-0.007	-0.007	-0.009	-0.009	-0.009
Variance	0.005	0.005	0.005	0.005	0.005	0.005	0.007	0.007	0.007
Z-score	2.805	3.030	2.963	4.481	4.671	4.702	3.321	3.436	3.402

Based on the method described by Aneslin (2004), each of OLS regression models with spatially autocorrelated residuals was assessed for spatial dependence using the Lagrange Multiplier (LM) test. The results of the test determined whether a spatial error or spatial lag regression model was the most appropriate. A spatial lag model was selected because 33 of the 48 (69%) tested models were significant for 1) Lag; or 2) both Error and Lag, of which Lag had the higher test value (Supplementary Tables A.11-17). As with the Moran's I tests, neighborhoods were conceptualized as inverse distance squared for all spatial lag regression models. The model residuals were evaluated for heteroskedasticity using the BP test. Some of the models demonstrated heteroskedastic regression residuals, so a White adjustment was employed for these specific models (Table 19). As with the OLS regression models, the resulting coefficients for the independent variables of the spatial regression models were standardized.

Table 18. Moran's I results for Functional 1 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
Moran's I	0.131 *	0.116 *	0.101	0.151 **	0.116 *	0.105	0.201 **	0.168 **	0.147 *
Expected Value	-0.004	-0.004	-0.004	-0.005	-0.005	-0.005	-0.006	-0.006	-0.006
Variance	0.003	0.003	0.003	0.003	0.003	0.003	0.004	0.004	0.004
Z-score	2.424	2.156	1.875	2.671	2.074	1.888	3.159	2.652	2.333

Table 19. Results of the Studentized Breusch-Pagan (BP) test for all spatial regression models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
Roads Models									
All Roads	48.969 ***	46.785 ***	46.690 ***	67.335 ***	59.639 ***	63.097 ***	75.808 ***	67.713 ***	61.843 ***
I-91	16.600 **	17.121 **	18.217 **	-	-	-	13.859 *	13.280 *	-
VR-114	7.007	6.624	7.723	-	-	-	-	-	-
F7	16.256 **	14.462 *	17.261 **	23.487 ***	15.242 **	23.075 ***	32.888 ***	24.307 ***	13.941 *
F6	-	-	-	25.143 ***	20.513 **	20.663 ***	34.265 ***	27.884 ***	23.380 ***
F2	12.433 *	12.115 *	11.244 *	16.431 **	15.295 **	15.574 **	12.564 *	11.463 *	13.241 *
F1	8.911	14.615 *	-	10.379	14.002 *	-	4.970	0.258	0.164

Software

The GIS processing and analysis steps were completed using ArcGIS v10.3 (ESRI 2012) and QGIS v2.4 (Quantum GIS Development Team 2017). All statistical analysis was performed using R v3.2.3 (R Core Team 2015).

RESULTS

All Roads Models

The results for the regression models with all roads are presented in Tables 20 (OLS) and 21 (Spatial Regression). Spatial regression models were only presented when the residuals of the OLS regression models demonstrated significant spatial autocorrelation. Since the residuals of all nine of the all roads OLS regression models demonstrated significant spatial autocorrelation, there was a total of nine spatial regression models. Therefore, the following description of the results are drawn from the spatial regression models, except where noted.

Table 20. Original regression results for the all roads models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Observations	1037		1037		1037		919		919		919		758		758		758	
F	20.59	***	19.89	***	20.14	***	41.44	***	38.45	***	42.56	***	56.32	***	50.57	***	47.95	***
Adjusted R2	0.086		0.084		0.085		0.181		0.169		0.185		0.268		0.247		0.237	
Coefficients																		
AADT	0.071	*	0.082	*	0.077	*	0.107	**	0.111	**	0.114	***	0.172	***	0.175	***	0.156	***
WCI	0.283	***	0.283	***	0.283	***	0.328	***	0.311	***	0.339	***	0.422	***	0.392	***	0.364	***
Sinuosity	-0.035	*	-0.033		-0.038	*	-0.070	**	-0.074	**	-0.079	**	-0.047		-0.051	*	0.057	*
Slope	-0.106	***	-0.098	***	-0.097	***	-0.130	***	-0.117	***	-0.123	***	-0.129	***	-0.108	***	-0.099	**
Length	-0.175	***	-0.178	***	-0.180	***	-0.362	***	-0.359	***	-0.369	***	-0.475	***	-0.462	***	-0.445	***

Table 21. Spatial regression results for the all roads models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Rho	0.360	***	0.366	***	0.362	***	0.378	***	0.378	***	0.370	***	0.433	***	0.433	***	0.431	***
LR	32.857	***	33.951	***	33.098	***	41.29	***	40.851	***	39.35	***	60.077	***	58.803	***	57.591	***
AIC	2,826.2		2,828.1		2,827.7		2,393.6		2406.1		2,390.5		1,865.0		1,887.6		1,898.6	
AIC for LM	2,857.0		2,860.1		2,858.8		2,432.9		2445.0		2,427.9		1,923.1		1,944.4		1,954.2	
Coefficients																		
AADT	0.101	**	0.112	**	0.106	**	0.134	***	0.136	***	0.139	***	0.205	***	0.206	***	0.185	***
WCI	0.258	***	0.259	***	0.257	***	0.300	***	0.280	***	0.309	***	0.391	***	0.358	***	0.329	***
Sinuosity	0.030		0.030		0.036		0.063	*	0.068	*	0.074	**	0.041		0.045		0.052	
Slope	-0.100	***	-0.093	***	-0.092	***	-0.117	***	-0.104	***	-0.110	***	-0.110	***	-0.090	***	-0.081	**
Length	-0.178	***	-0.181	***	-0.182	***	-0.358	***	-0.354	***	-0.364	***	-0.466	***	-0.453	***	-0.436	***

All spatial regression models had highly positive, significant spatial dependence parameter ($p < 0.001$), and were improved by the inclusion of the spatially-lagged values as the Likelihood Ratio (LR) tests were highly significant ($p < 0.001$). For all spatial regression models, AIC was lower than the AIC for the OLS models, indicating an improved model fit from the original regression models, which were statistically significant ($p < 0.001$). The explanatory power of the OLS models increased concurrently with the maximum road segment in the data, i.e., roughly 0.08 (400 m), 0.18 (800 m), and 0.25 (1,600 m). The spatial regression models were an improved fit from the OLS models, so the explanatory power of the spatial regression models was slightly improved.

The standardized coefficients presented in Table 21 show that the effects of each independent variable were quite consistent across changes in the maximum road feature length and buffer distance for the WCI variable. Specifically, AADT and WCI had positive, statistically significant relationships with WVCD across all spatial regression models. The influence of WCI on WVCD was much stronger than AADT, varying from roughly 2x to 3x more influence across models. The statistical strength of the relationship between WVCD and AADT was variable across the models. Specifically, AADT was weakly significant in the 400 m road length models ($p < 0.01$), but increased as the maximum segment length increased to 1,600 m ($p < 0.001$). WCI did not demonstrate variation across models ($p < 0.001$ in all models).

Of the control variables, Sinuosity had the weakest relationship with WVCD, as this variable was insignificant in six models ($p > 0.05$) and weakly significant in two models ($p < 0.05$), and slightly more significant in one model ($p < 0.01$). When significant, Sinuosity had a weak positive relationship with WVCD. The Slope variable was highly significant in eight models ($p < 0.001$) and slightly less significant in one model ($p < 0.01$), while having a consistently negative relationship with WVCD. In this case, WVCD was higher on roads that had a lower Slope (were flatter), which may also reflect higher average vehicle speeds due to the flat terrain. The relationship between WVCD and Slope was similar in magnitude to WVCD and AADT for the 400 m and 800 m maximum road length models, but was lesser in magnitude for the 1,600 m models.

In all spatial regression models, the control variable for Length was statistically significant ($p < 0.001$) and negatively related to WVCD. Since a single WVC event can result in varying WVCD values based on the road feature's length (e.g., a single WVC produces higher a WVCD for shorter road features), the negative relationship was not surprising. Importantly, while not tied to a specific physical process, these results confirmed the importance of controlling for variations in road feature length, even when many of the features are of a similar length (i.e., normalized via the process of splitting the original roads layer into segments having a specific maximum length).

Models of Specific Roads

Results of the I-91, US-2, VR-114 regression models are presented in Tables 22, 24, and 25 (OLS) and Tables 23 and 26 (spatial lag). As previously stated, spatial regression model results were only presented when the residuals of the OLS regression models demonstrated significant spatial autocorrelation of the residuals. For I-91, five of the OLS models were replaced by spatial regression models. None of the US-2 OLS models demonstrated significant spatial autocorrelation. Three of the VR-114 OLS regression models were replaced by spatial regression models. Spatial regression models took the place of their OLS counterparts when appropriate. Therefore, the results below describe a mixture of the OLS and spatial regression models.

Table 22. Original regression results for I-91 models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Observations	147		147		147		127		127		127		104		104		104	
F	5.915	***	5.957	***	5.801	***	12.320	***	12.950	***	12.800	***	14.27	***	13.24	***	11.85	***
Adjusted R2	0.144		0.145		0.141		0.310		0.322		0.319		0.3918		0.3727		0.345	
Coefficients																		
AADT	-0.184	*	-0.180	*	-0.190	**	-0.143		-0.127		-0.150	*	-0.092		-0.079		-0.114	
WCI	0.212	**	0.215	**	0.200	**	0.287	***	0.315	***	0.302	***	0.464	***	0.448	***	0.377	***
Sinuosity	-0.060		-0.063		-0.070		-0.135	***	-0.130	***	-0.135	***	-0.001		-0.031		-0.072	
Slope	-0.126	*	-0.117	*	-0.109	*	-0.194	**	-0.177	**	-0.163	**	-0.256	***	-0.221	**	-0.203	**
Length	-0.193	***	-0.186	***	-0.182	***	-0.394	***	-0.396	***	-0.404	***	-0.530	***	-0.540	***	-0.479	***

Table 23. Spatial regression results for I-91 models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400			1600	
Buffer distance (WCI)	400	800	1200	400	800
Rho	0.257	0.255	0.258	0.295 *	0.321 *
LR	2.673	2.621	2.687	4.376 *	5.205 *
AIC	401.5	401.4	402.0	248.9	251.3
AIC for LM	402.2	402.0	402.7	251.2	254.5
Coefficients					
AADT	-0.114	-0.111	-0.120	-0.033	-0.013
WCI	0.191 **	0.193 **	0.178 *	0.439 ***	0.427 ***
Sinuosity	0.058	0.061	0.067	-0.025	-0.001
Slope	-0.132 **	-0.123 **	-0.117 *	-0.227 ***	-0.191 **
Length	-0.203 ***	-0.197 ***	-0.193 ***	-0.543 ***	-0.556 ***

Table 24. Original regression results for US-2 models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
Observations	84	84	84	69	69	69	52	52	52
F	4.852 ***	4.061 **	3.654 **	4.612 **	3.903 **	4.058 **	5.058 ***	3.906 **	3.932 **
Adjusted R2	0.188	0.156	0.138	0.210	0.176	0.184	0.285	0.222	0.223
Coefficients									
AADT	-0.175	-0.173	-0.171	-0.314 **	-0.334 ***	-0.303 **	-0.287 **	-0.329 **	-0.330 *
WCI	0.378 ***	0.332 ***	0.307 **	0.254 **	0.158	0.194	0.315 **	0.156	0.157
Sinuosity	0.030	0.045	0.052	-0.047	-0.022	-0.024	-0.147	-0.123	-0.127
Slope	-0.107	-0.077	-0.062	-0.227 *	-0.219 *	-0.213 *	-0.284 **	-0.241 *	-0.221
Length	-0.078	-0.082	-0.082	-0.261 ***	-0.238 ***	-0.235 ***	-0.372 ***	-0.345 ***	-0.332 *

Table 25. Original regression results for VR-114 models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400			800			1600		
Buffer distance (WCI)	400	800	1200	400	800	1200	400	800	1200
Observations	83	83	83	61	61	61	41	41	41
F	3.527 **	3.169 *	3.318 **	4.129 **	2.753 *	3.054 *	3.896 **	3.070 *	1.785
Adjusted R2	0.134	0.117	0.124	0.207	0.127	0.146	0.266	0.206	0.089
Coefficients									
AADT	-0.068	-0.081	-0.048	0.070	0.043	0.007	-0.013	-0.010	0.064
WCI	0.336 **	0.304 *	0.331 **	0.522 ***	0.411 *	0.408 **	0.715 ***	0.674 **	0.442
Sinuosity	0.159	0.178	0.182	0.121	0.127	0.146	-0.051	-0.057	-0.027
Slope	-0.103	-0.096	-0.099	-0.326 **	-0.301 *	-0.284 *	-0.408 *	-0.395 *	-0.329
Length	-0.186	-0.190	-0.186	-0.260 *	-0.230	-0.238	-0.579 **	-0.575 **	-0.390 *

Table 26. Spatial regression results for VR-114 models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400		
Buffer distance (WCI)	400	800	1200
Rho	-0.860	-0.910	-0.927
LR	3.297	3.643	3.840
AIC	230.3	231.6	230.7
AIC for LM	231.6	233.2	232.5
Coefficients			
AADT	-0.208	-0.227	-0.198
WCI	0.281 *	0.250 *	0.280 *
Sinuosity	-0.161	-0.177	-0.181
Slope	-0.068	-0.061	-0.063
Length	-0.206 *	-0.211 *	-0.208 *

Roadway-specific OLS regression models using roads with a larger maximum feature length best explained the variation in WVCD density. Of the OLS regression models, variation in WVCD was best explained on the I-91 roadway. The resulting R^2 values were generally similar to the other roadway models for the 400 m maximum road length models, but appreciably higher in the 800 m and 1,600 m maximum road length models.

The I-91 and VR-114 OLS models were not improved by the inclusion of the lagged values in the spatial lag models. Spatial dependence was insignificant ($p > 0.05$), which was not unexpected because the LR tests were not significant ($p > 0.05$). An exception to this trend were the 1,600 m maximum road length spatial regression models of I-91. For these models, spatial dependence was significant ($p < 0.05$) and the model fit was improved by the inclusion of the lagged values. Overall, AIC was lower than the AIC for the OLS models for all spatial regression models, indicating an improved model fit from the OLS regression models.

Results were variable across the three different roadways in VT, but had some similarity with the results of the all roads models. For WCI, the results were semi-consistent across the roadway-specific models and congruent with the results of the all roads models. Specifically, WCI had a positive, significant relationship with WVCD in 22 of 27 models. The results for AADT were not as strong in the roadway-specific models, showing a significant relationship with WVCD in only 7 of 27 models. Surprisingly, the direction of the relationship between AADT and WVCD was negative when significant, meaning that an increase in traffic volume was associated with a decrease in collision density.

The results for Sinuosity were largely insignificant across the roadway-specific models, with an exception in the negative results of the three 800 m max road feature length models for I-91. As Sinuosity captures the “curviness” of a road segment, this relationship can be interpreted inversely; WVCD is slightly higher on straighter roads, which may be due to higher average vehicle speeds on these roads. Slope was significant in 19 of 27 models. Interestingly, in this set of models, while the directionality of the relationship between Slope and WVCD was consistent with the all roads models (negative), the magnitude of the relationship with was much higher, meaning changes in the Slope along these main roadways had a much more pronounced effect on WVCD than in the all roads models.

The control variable for Length was statistically significant ($p < 0.05$) and negatively related to WVCD in 22 out of 27 regression models. Exceptions in significance were all three 400 m max road feature length models for US-2 and two of the 800 m max road feature length models for VR-114. In all significant regression models, Length had the highest or second highest impact on WVCD. As stated previously, the negative relationship was not surprising. As with the all roads models, these results confirmed the importance of controlling for variations in road feature length.

Models of Functional Roadway Classes

Results of the F7, F6, F2, and F1 regression models are presented in Tables 27, 29, 31, and 33 (OLS) and Tables 28, 30, 32, and 34 (Spatial Regression). Similar to the previous results, spatial regression models were only presented when the residuals of the OLS regression models demonstrated significant spatial autocorrelation. For F7, all nine of the OLS models were replaced by spatial regression models. Six of the F6 models demonstrated significant spatial autocorrelation and were replaced by spatial regression models. All nine of the F2 OLS models were replaced by spatial regression models.

Seven of the F1 OLS regression models demonstrated significant spatial autocorrelation and were replaced by spatial regression models. As stated previously, spatial regression models took the place of their OLS counterparts. Therefore, OLS and spatial regression models were used in the following description of the results as appropriate.

Table 27. Original regression results for Functional 7 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Observations	340		340		340		299		299		299		256		256		256	
F	7.651	***	6.643	***	7.512	***	12.880	***	10.680	***	13.500	***	20.950	***	18.320	***	16.610	***
Adjusted R2	0.089		0.077		0.088		0.166		0.140		0.173		0.281		0.254		0.234	
Coefficients																		
AADT	0.043		0.017		0.039		0.052		0.016		0.066		0.034		-0.008		-0.024	
WCI	0.313	***	0.277	***	0.306	***	0.353	***	0.288	***	0.368	***	0.421	***	0.353	***	0.314	***
Sinuosity	-0.059	*	-0.051		-0.054	*	-0.100	*	-0.104	*	-0.106	**	-0.152	***	-0.145	***	-0.146	***
Slope	-0.074		-0.058		-0.063		-0.103		-0.076		-0.082		-0.094		-0.071		-0.064	
Length	-0.172	**	-0.176	**	-0.177	**	-0.333	***	-0.326	***	-0.345	***	-0.460	***	-0.435	***	-0.425	***

Table 28. Spatial regression results for Functional 7 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Rho	0.383	***	0.397	***	0.388	***	0.383	***	0.391	***	0.373	***	0.417	***	0.420	***	0.417	***
LR	20.991	***	22.846	***	21.73	***	22.627	***	23.298	***	21.302	***	29.739	***	29.584	***	28.582	***
AIC	921.6		924.42		921.6		780.8		789.4		779.5		621.7		631.5		639.0	
AIC for LM	940.6		945.3		941.3		801.4		810.7		798.8		649.4		659.1		665.58	
Coefficients																		
AADT	0.041		0.021		0.038		0.062		0.029		0.072		0.059		0.020		0.001	
WCI	0.273	***	0.248	***	0.270	***	0.317	***	0.257	***	0.326	***	0.388	***	0.323	***	0.281	***
Sinuosity	0.044		0.036		0.039		0.067		0.070		0.073	*	0.100	**	0.093	**	0.094	*
Slope	-0.066		-0.053		-0.057		-0.095		-0.071		-0.076		-0.084		-0.062		-0.055	
Length	-0.175	***	-0.177	***	-0.177	***	-0.334	***	-0.328	***	-0.344	***	-0.468	***	-0.446	***	-0.435	***

Table 29. Original regression results for Functional 6 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Observations	231		231		231		210		210		210		181		181		181	
F	7.805	***	7.316	***	7.359	***	17.030	***	15.610	***	15.690	***	22.310	***	20.940	***	19.930	***
Adjusted R2	0.129		0.121		0.122		0.277		0.259		0.260		0.372		0.357		0.345	
Coefficients																		
AADT	-0.181	*	-0.207	**	-0.223	***	-0.077		-0.123		-0.121		-0.088		-0.126		-0.182	*
WCI	0.202	*	0.164	*	0.159	**	0.282	***	0.214	**	0.223	**	0.319	***	0.261	**	0.195	**
Sinuosity	0.017		0.015		0.010		-0.009		-0.008		-0.017		0.024		0.030		0.025	
Slope	-0.084		-0.076		-0.078		-0.110	*	-0.102	*	-0.108	*	-0.142	**	-0.128	*	-0.112	*
Length	-0.229	***	-0.230	***	-0.238	***	-0.491	***	-0.487	***	-0.496	***	-0.596	***	-0.588	***	-0.582	***

Table 30. Spatial regression results for Functional 6 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	800						1,600					
Buffer distance (WCI)	400		800		1200		400		800		1200	
Rho	0.222	*	0.220	*	0.213	*	0.279	**	0.278	**	0.278	**
LR	4.665	*	4.523	*	4.239	*	8.547	**	8.345	**	8.074	**
AIC	533.1		538.4		538.5		430.7		435.3		438.9	
AIC for LM	535.7		541.0		540.7		437.3		441.6		445.0	
Coefficients												
AADT	-0.036		-0.082		-0.085		-0.036		-0.072		-0.129	
WCI	0.282	***	0.214	***	0.217	**	0.322	***	0.267	***	0.200	*
Sinuosity	0.002		0.002		0.012		-0.022		-0.029		-0.023	
Slope	-0.105	*	-0.097	*	-0.102		-0.122	*	-0.108	*	-0.092	
Length	-0.495	***	-0.491	***	-0.499	***	-0.589	***	-0.583	***	0.576	***

Table 31. Original regression results for Functional 2 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Observations	168		168		168		145		145		145		108		108		108	
F	4.820	***	5.094	***	4.895	***	6.526	***	6.216	***	6.598	***	7.172	***	6.503	***	6.506	***
Adjusted R2	0.103		0.109		0.104		0.161		0.153		0.163		0.224		0.205		0.205	
Coefficients																		
AADT	-0.174		-0.171		-0.177	*	-0.189		-0.198		-0.189		-0.234	*	0.251	*	-0.250	*
WCI	0.226	**	0.242	***	0.231	**	0.208	**	0.184	**	0.211	**	0.262	***	0.214	**	0.214	**
Sinuosity	-0.038		-0.045		-0.044		-0.069		-0.072		-0.069		0.034		0.035		0.037	
Slope	-0.149	**	-0.152	**	-0.154	*	-0.199	**	-0.194	**	-0.200	**	-0.189	**	-0.188	**	-0.190	*
Length	-0.067		-0.066		-0.059		-0.195	***	-0.187	***	-0.180	***	-0.284	***	-0.275	**	-0.270	**

Table 32. Spatial regression results for Functional 2 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Rho	0.360	**	0.365	**	0.360	**	0.424	***	0.428	***	0.430	***	0.372	***	0.375	***	0.372	***
LR	9.139	**	9.476	**	9.134	**	16.178	***	16.437	***	16.802	***	12.25	***	12.246	***	12.008	***
AIC	459.4		457.8		459.1		379.9		380.9		379.0		276.5		279.2		279.42	
AIC for LM	466.5		465.3		466.2		394.1		395.4		393.8		286.8		289.5		289.43	
Coefficients																		
AADT	-0.095		-0.090		-0.098		-0.081		-0.086		-0.076		-0.132		-0.145		-0.147	
WCI	0.221	**	0.240	**	0.225	**	0.199	**	0.182	**	0.210	**	0.262	***	0.222	***	0.217	**
Sinuosity	0.008		0.015		0.014		0.040		0.043		0.039		-0.015		-0.014		-0.017	
Slope	-0.148	**	-0.152	**	-0.154	**	-0.185	**	-0.180	**	-0.187	**	-0.178	**	-0.177	**	-0.180	*
Length	-0.042		-0.041		-0.035		-0.157	***	-0.149	***	-0.143	***	-0.251	***	-0.244	***	-0.238	**

Table 33. Original regression results for Functional 1 models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
Observations	252		252		252		216		216		216		171		171		171	
F	4.084	**	5.104	***	5.616	***	8.328	***	10.170	***	11.950	***	13.650	***	15.600	***	15.410	***
Adjusted R2	0.058		0.076		0.084		0.146		0.176		0.203		0.271		0.300		0.298	
Coefficients																		
AADT	0.047		0.045		0.029		0.081		0.076		0.049		0.153	*	0.134	*	0.099	
WCI	0.190	**	0.232	***	0.245	***	0.250	***	0.305	***	0.340	***	0.430	***	0.469	***	0.442	***
Sinuosity	0.044		0.049		0.044		-0.003		0.002		-0.008		0.040		0.030		0.005	
Slope	-0.149	*	-0.147	**	-0.144	**	-0.173	**	-0.173	**	-0.182	**	-0.189	**	-0.179	**	-0.173	**
Length	-0.191	**	-0.195	***	-0.190	***	-0.339	***	-0.353	***	-0.355	***	-0.519	***	-0.558	***	-0.521	***

Table 34. Spatial regression results for Functional 1 models. The *p*-values are represented as follows: *p* < 0.001 (***), *p* < 0.01 (**), and *p* < 0.05 (*).

Max Road Feature Length	400				800				1600					
Buffer distance (WCI)	400		800		400		800		400		800		1200	
Rho	0.369	***	0.347	**	0.391	***	0.361	***	0.354	***	0.331	***	0.319	**
LR	11.421	***	9.967	**	14.493	***	12.154	***	14.186	***	12.395	***	11.163	**
AIC	698.6		695.3		574.4		569.0		426.5		421.4		423.5	
AIC for LM	708.0		703.3		586.9		579.1		438.7		431.8		432.7	
Coefficients														
AADT	0.045		0.043		0.074		0.072		0.119		0.104		0.074	
WCI	0.159	*	0.194	**	0.190	**	0.241	**	0.363	***	0.398	***	0.369	***
Sinuosity	-0.034		-0.038		0.032		0.026		-0.053		-0.043		-0.019	
Slope	-0.144	*	-0.142	**	-0.164	**	-0.165	**	-0.168	**	-0.161	**	-0.155	*
Length	-0.203	***	-0.206	***	-0.333	***	-0.345	***	-0.511	***	-0.544	***	-0.509	***

Like the all roads and roadway-specific models, explanation for the variation in WVCD in the OLS regression models improved when using roads with a larger maximum feature length. Of all the functional roadway class models, variation in WVCD was best explained in the F6 models. For all the spatial regression functional class regression models, spatial dependence was significant and the inclusion of the lagged values improved model fit since the LR tests were significant. All spatial regression models had a lower AIC than the AIC for the OLS models, indicating an improved model fit from the OLS regression.

The results for each of the independent variables were somewhat consistent across the functional roadway class models, similar to the results of the all roads and roadway-specific regression models. As with previous models, WCI had a positive, significant relationship with WVCD in all models. Surprisingly, AADT was only significant in 3 of the 36 functional class regression models, specifically the three 400 m max road feature length F6 models. In these three models, AADT had a negative relationship with WVCD, which was also observed for 7 of the I-91 and US-2 OLS regression models.

The results for Sinuosity were insignificant in of 32 the 36 functional roadway class models. Exceptions in significance were the 1,200 m buffer distance of the 800 m max road feature length model and three 1,600 m max road feature length models for F7. Slope had a negative, significant relationship with WVCD in 22 of the 36 functional roadway class models. It was not significant in the spatial regression F7 models, the 400 m max road feature length original regression models for F6, and the 1,200 m buffer distance of the 800 m and 1,600 max road feature length spatial regression models. The negative relationship between Slope and WVCD was consistent with the all roads and road-specific models, but the magnitude of the relationship in the F2 and F1 spatial regression models was much higher than in the all roads spatial regression models.

In 33 out of 36 regression models, the control variable for Length was statistically significant ($p < 0.05$) and negatively related to WVCD. Exceptions in significance were all three 400 m max road feature length regression models for F2. As with the all roads and roadway-specific regression models, Length had the highest or second highest impact on WVCD compared to the other coefficients and the negative relationship was not surprising. These results conclusively confirmed the importance of controlling for variations in road feature length.

Summary

Each of the independent variables affected the probability of a wildlife-vehicle collision in the multiple regression models as summarized in Table 35. AADT generally did not demonstrate a significant relationship with WVCD; when the results did show significance, the relationship was nearly perfectly balanced between positive and negative. WCI had the most consistent relationship with WVCD, demonstrating a strong, positive relationship in 67 of 72 models. Sinuosity largely had little effect on WVCD, as it was only significant in 10 of 72 models. In contrast, Slope and Length had consistently negative relationships with WVCD; each demonstrated significant results in more than 50 of the 72 models.

Table 35. Summary of multiple regression models. The *p*-values considered to be significant were $p < 0.05$.

Coefficients	Total	Significant Positive	Significant Negative	Insignificant
AADT	72	9	10	53
WCI	72	67	0	5
Sinuosity	72	7	3	62
Slope	72	0	51	21
Length	72	0	61	11

DISCUSSION

The regression models explained a relatively low, but significant portion of the variability of the observed rate of wildlife-vehicle collisions. Generally, the predictive power of the models was greater for the models using roads data with a longer maximum segment length. The models for I-91 had the highest predictive power, with the 1,600 m maximum road length models accounting for 35-40% of the variation in collision density. The directionality and magnitude of each relationship between AADT, WCI, Sinuosity, Slope, and Length and WVCD was dependent on the location and functional classification of the road.

The models may have been affected by the nature of the dataset used in the analysis. As the collision data in VT were collected based on opportunity, it does not represent a complete data set (Austin et al. 2006). Some studies caution that WVCs are underreported and therefore any reports should be considered minimum estimates pf the true number of collisions (Bissonette and Kassar 2008; Brockie et al. 2009; Mountrakis and Gunson 2009). However, Snow et al. (2015) observed that predicted relationships between conditions and moose-vehicle collisions remained robust until underreporting of collisions exceeded 70%. For this research, the percent of unreported collisions was unknown, but underreporting in some areas of VT was acknowledged by Austin et al. (2006).

The use of wildlife crossing areas based on predicted habitat suitability may have also affected the models. However, Clevenger et al. (2002), compared field empirical models to those based on expert-opinion and literature review and concluded expert-opinion and literature-based models were suitable replacements for empirical models. While models using field-collected data would be preferable, time or financial constraints on collecting such data may prevent that from being possible (Barthelmess 2014; Clevenger et al. 2002; Mata et al. 2008). The significant portion of the WVCD variability explained by the predicted WCI affirms that prediction-based data may be successfully used to explain variation in wildlife-vehicle collisions.

Collisions will occur where wildlife gather to cross roads as predicted by suitable habitat (Farmer and Brooks 2012). The findings of this study confirm this expectation as the wildlife-crossing index was found to be a significant, positive predictor of the rate of wildlife-vehicle collisions in 67 of the 72 models that were constructed for this analysis. Based on the standardized coefficients from the models, WCI had a strong effect compared with the other factors in the models. Interestingly, the results of the regression models did vary across the 400, 800, and 1,200 m buffer distances from the roads to calculate WCI. The models using the 1,600 m buffer distance WCI appear to be the strongest (highest coefficient in 15 of 16 model sets), which suggests that habitat suitability outside of the immediate vicinity of the road does potentially affect where wildlife will cross roads; hence, only considering habitat suitability near to the roadway (e.g., within 400 m) may not be prudent for predicting where collisions will occur. The extent of habitat suitability that should be considered may rely on the range of movement specific to a species (Danks and Porter 2010; Finder et al. 1999). It may also depend on the presence of pre-established migration routes, which may only be detectible using a larger buffer distance (Austin et al. 2006; Clevenger et al. 2015). Future research is warranted to better understand the how relationship between distance (from the road) and habitat suitability affects the ability to accurately predict wildlife-vehicle collisions. Specifically, this provides an opportunity that is well suited for GIS-based analysis, such that numerous distance measurements can be examined with relatively low costs.

While collision data may be used to identify wildlife crossing areas, some would be missing because of the opportunistic nature of many collision data sources. In this study, a GIS-based method was implemented to determine a wildlife-crossing index value based on habitat suitability near roads. As the results demonstrate that changes in the wildlife-crossing index are strongly related with wildlife-vehicle collision density, it behooves those working on collision mitigation efforts to make use of both pieces of information. Validation is a consistent issue across studies predicting wildlife crossing areas or wildlife-vehicle collisions (Clevenger et al. 2002; Kaminski et al. 2013; Lewis et al. 2011). Given the nature of the data available, this research struggled with the same issue. One way to extend the findings of this research would be to use the model results to predict the locations of wildlife-vehicle collisions along sections of roads in VT and conduct field surveys to validate the predicted sites.

Interestingly, traffic volume was not a consistently strong predictor of wildlife-vehicle collision density. This result contradicted previous research that has shown traffic volume to have the greatest impact on wildlife of all road-based threats (Eberhardt et al.

2013; Gunson et al. 2011; Jaarsma et al. 2006; Jaeger et al. 2005). While traffic volume was a significant, positive predictor in the all roads models, the magnitude of its effect on collision density was much smaller than the wildlife crossing index. The results of the major roadway-specific models demonstrated highly mixed results. For the I-91 and VR-114 models, traffic volume was either insignificant or not strongly significant in the models. In the US-2 models, traffic volume was a significant predictor, but demonstrated a negative relationship with collision density. In the functional classification models, traffic volume was not a significant predictor at all, except for the 400 m maximum road length F6 models. While somewhat confusing, these results do provide evidence that the relationship between wildlife-vehicle collisions and traffic density may be more complex and nuanced than a simple positive relationship (i.e., more vehicles on a road increases the chance of a collision). Specifically, increased traffic volume has been observed to increase road avoidance for some species, preventing any road-crossing attempts (Danks and Porter 2010; Jaarsma et al. 2006). Further, Danks and Porter (2010) observed that high volumes of traffic increased the probability of wildlife-vehicle collisions on roads having lower speed limits and decreased the probability on roads having higher limits. Importantly, while traffic volume may indeed affect the probability of a wildlife-vehicle collision, the directionality and importance of this relationship will likely be variable depending on location, animal behavior, and road characteristics. This research showed highly mixed results across models, thus further examination of how traffic volume affects collisions across may help to disentangle this complex relationship.

As spatial data on vehicle speed proved difficult to obtain, two road characteristics that affect a driver's speed and visibility were used instead in this research (Clevenger et al. 2003; Klocker et al. 2006). Previous research has found the sinuosity of a road to be both a significant and insignificant predictor of wildlife-vehicle collisions (Barthelmess 2014; Klocker et al. 2006). Barthelmess (2014) had noted the maximum length of a road segment might affect the significance of sinuosity as a predictor variable. Specifically, this is because the sinuosity calculation uses the road segment length in the calculation and is potentially influenced by scale. Different maximum lengths of the road segments were evaluated in this research and 7 of the 10 (70%) models where sinuosity was a significant predictor had maximum road segment lengths of 800 m. Despite the evaluation of different maximum road segment lengths, sinuosity was largely an insignificant predictor of wildlife-vehicle collisions though and may not be capturing the nature of the driving conditions along each road feature. In contrast, the slope of a road was a consistently significant predictor of wildlife-vehicle collisions, whereby collisions increased as the slope decreased. This observation agreed with the results of Barthelmess (2014) and Clevenger et al. (2003). Slope was a significant predictor across the models, but the magnitude of its effect on collisions was highly variable. This was particularly evident among the individual roadways and functional classifications models. The variation in magnitude most likely is related to changes in driver visibility or speed; however, this relationship was not examined. A future comparison of how sinuosity and slope affect vehicle speed could potentially elicit a more complete understanding of how these three predictors are related to each other, as well as their effect on wildlife-vehicle collisions.

The results of the robustness test on the maximum road segment length in the roads data provide another interesting finding. In the all roads, the roadway-specific, and functional classification data, the predictive power of the models generally increased as the maximum segment length increased from 400 to 1,600 m. This finding suggests the presence of the Modifiable Areal Unit Problem (MAUP). The MAUP describes the scenario when a change in the "partitioning scheme" of spatial data affects the results of a statistical analysis (Openshaw and Taylor 1979). In this case, while the data are not areal units, varying the maximum length of the segments in the roads data did have a very clear effect on the model results, even when segment length is used as a control variable in the model. While these results may be simply due to central tendency leveling occurring in the larger spatial features (longer road segments), they also indicate that the spatial variation in wildlife-vehicle collisions may operate at a larger scale (e.g., the width of wildlife crossing areas).

The MAUP is commonly present in analysis using spatial data and aggregated units. Therefore, prior to a robustness analysis, the maximum lengths of the road segments should be determined by ecology or wildlife managers. Wildlife may cross roads at specific points because of an existing wildlife corridor (Austin et al. 2006). Depending on the size of road segment, multiple corridors or crossing locations may be captured by a single segment. This presents a challenge to management strategies if policymakers are trying to target individual crossing locations. Mitigation efforts are dependent on the type of wildlife and crossing location (Mata et al. 2008). This research demonstrated very clearly that the maximum road segment length in the data affected the results. While only three maximum lengths were tested here, a more expansive examination of how maximum road segment length affects the observed relationships with collision density is warranted in further studies. While initial selection of the length should be based on the ecology of the wildlife or management strategies, this is another opportunity in which GIS-based analysis can assist in informing the proper approach.

Roads were investigated by functional classification as a proxy for road characteristics, such as the width and number of lanes of the roads. The relationship between each of the independent variables and WVCD differed by functional classification, which warrants further investigation. Consideration of additional road characteristic-based independent variables in future studies may clarify the differences in WVCD between classifications of road.

By evaluating wildlife-vehicle collisions for all roads in VT as well as for specific roadways and functional classifications, this analysis solidified the importance of considering place and classification in understanding the conditions that affect collisions. While the wildlife crossing index had a consistently positive and significant effect on collision density, the other variables demonstrated varying levels of inconsistency across models. Traffic volume and slope showed variation in sign and magnitude (respectively) across models. These findings demonstrate that the conditions influence wildlife-vehicle collisions are not consistent across space and may be due to specific local characteristics of regions or roads. Although this analysis did not investigate the genesis of these variations, the results do highlight the importance of understanding the place-to-place variation of these relationships for developing effective prevention or mitigation efforts.

Limitations

There were several limitations to this research. While habitat-based wildlife crossing areas, traffic density, sinuosity, and slope are commonly used predictors of wildlife-vehicle collisions, further analysis should consider additional conditions: the presence of median strips, the speed of vehicles the width and height of a road, habitat diversity, or the number of the road lanes (Clevenger et al. 2003; Mata et al. 2004; Malo et al. 2005). Some of these conditions may be collinear or linked back to the functional classification of a road. However, additional conditions describing animal abundance near roads, high road traffic volume, and reduced driver awareness may explain a larger portion of the variability of the observed rate of wildlife-vehicle collisions (Farmer and Brooks 2012; Seiler 2005). Notably though, time and cost are the main drivers of GIS-based analysis for wildlife-vehicle collisions. Obtaining data for these additional conditions as spatial layers may not be easy or even possible for some study areas. Any future research should consider standardizing the procurement and evaluation of each theoretical condition as one of its objectives, as the previous literature demonstrated a high amount of variation in attempts to measure or model them using existing data.

This research examined collisions over a long temporal period and did not incorporate how temporal factors might have an effect on the findings. Wildlife populations in some areas may have declined to the extent that crossing attempts rarely or no longer occurred (Clevenger et al. 2003). However, without extensive historical data, it is difficult to account for the effect of past events. One resolution to this issue and an avenue for future research is to extend this study using a robustness analysis that accounts for time by comparing model results among decades or at different time scales (e.g., one year worth of collisions). The relationships between the evaluated conditions and wildlife-vehicle collisions may also vary by season and species (Clevenger et al. 2003; Grilo et al. 2009). However, the methods used in this research were partly driven by suitability for policymakers and state conservation efforts, which is why it was conducted at the landscape scale, for large mammals, and over a long-time period. While a more in-depth examination of the temporal aspects discussed here but not examined (length of time period and seasonality) would likely provide additional information, the results of this research do provide a base from which future studies focused on targeted areas or species can be launched.

CONCLUSION

Successful mitigation and recovery efforts have the potential to alleviate the negative consequences for wildlife caused by increasing road infrastructure. As these efforts are costly and time-intensive, extensive consideration is required to determine the sites at which action should be taken (Clevenger et al. 2002; Clevenger 2005; Mata et al. 2008). The ability to predict and verify these sites using GIS has dramatically improved mitigation efforts (Clevenger et al. 2002; Clevenger 2005).

Predicting wildlife-vehicle collision sites requires an understanding of which landscape and road conditions contribute to the occurrence of collisions. Using GIS capabilities, this research demonstrated that road traffic volume, wildlife crossing areas based on habitat suitability, and specific road characteristics do help to explain the variation in wildlife-vehicle collisions; however, their effects did vary across the models, highlighting the roadway- and place-specific variation in the processes that lead to collisions. Controlling for the length of the road was demonstrated to be of vital importance as it had a significant relationship with wildlife-vehicle collisions across the models.

This research extended previous studies of wildlife-vehicle collisions in several important aspects. First, wildlife crossing areas were calculated based on habitat suitability at three separate spatial extents to evaluate whether the results of the statistical analysis were sensitive to changes in extent. Specifically, a wildlife crossing index value was calculated based on habitat suitability within 400, 800, and 1,200 meters (m) of each spatial line feature used to represent roads. Second, this study acknowledged that the length of the road features might have an influence on the statistical results. Therefore, rather than simply using the original data, the road features were split into segments based on maximum segment lengths of 400, 800, and 1,600 m. This split permitted an evaluation of the MAUP and whether the statistical results are sensitive to changes in the maximum length of the road features in the data. Previous studies did not perform such tests of robustness. The significant results of the robustness tests in this research signify the need for such consideration in future research. Third, this study compared the relationship of wildlife-vehicle collisions and each factor at the state-scale and on individual roads, which few previous studies have done (Clevenger et al. 2015; Malo et al 2004). Lastly, this analysis considered specific classifications of road based on the federal highway classification system (FHWA 1989). In previous studies, road type was observed to be a positive indicator of wildlife-vehicle collisions (Clevenger et al. 2003; Myers et al. 2008). The empirical evidence has been mixed regarding the relationship between wildlife-vehicle collisions and each of the conditions tested in this research, possibly due to the scale or road classification used by previous studies (Clevenger et al. 2003; Clevenger et al. 2015; Malo et al 2004; Myers et al. 2008). In this research, differences were evident between the whole road network, individual roads, and road classifications, demonstrating the need to consider scale and road classification during analysis.

This research used a case study set in the state of VT, where state agencies have been focusing efforts to address the effects of roads on wildlife (Austin et al. 2010; Kart et al. 2005).

As this study focused on a single state, further analysis is required to extrapolate these results for other species or regions. Although an extensive analysis should be performed prior to any mitigation effort, this study has demonstrated that it is possible to use existing spatial data, GIS, and statistical analysis to better understand the relationships among wildlife-vehicle collisions, wildlife habitat suitability, and road characteristics.

APPENDIX

Table A.1. Land Use Land Cover (LULC) reclassification scheme for habitat suitability model.

LULC class	Score
Deciduous Forest	10
Evergreen Forest	10
Mixed Forest	10
Woody Wetlands	10
Emergent Herbaceous Wetlands	10
Shrub/Scrub	9
Grassland/Herbaceous	9
Cultivated Crops	6
Pasture/Hay	5
Barren Land (Rock/Sand/Clay)	5
Open Water	5
Developed, Open Space	3
Developed, Low Intensity	1
Developed, Medium Intensity	1
Developed, High Intensity	1

Table A.2. Core area reclassification scheme for habitat suitability model.

Definition	Score
Large core (+10,000 acres)	10
Medium core (1,500-10,000 acres)	8.875
Small core (0-1,500 acres)	7.75
Buffer 1	6.625
Buffer 2	5.5
Buffer 3	4.375
Buffer 4	3.25
Buffer 5	2.125
Outside core area and buffer	1

Table A.3. Structure density reclassification scheme for habitat suitability model.

Structure density (houses #/mi^2)	Score
0	10
0.1 - 10	9
10.1 - 20	8
20.1 - 30	7
30.1 - 40	6
40.1 - 50	5
50.1 - 60	4
60.1 - 70	3
70.1 - 80	2
80.1 - 5000	1

Table A.4. Descriptive statistics for variables used in the I-91 multiple regression models.

Model variables	Minimum	Maximum	Mean	Std. Devation
I-91, 400 m (n=147)				
WVCD	0.003	0.018	0.004	0.003
AADT	3,417.353	24,180.882	8,920.268	5,023.778
WCI (400 m)	1.895	8.992	6.322	1.839
WCI (800 m)	2.110	9.377	6.584	1.786
WCI (1200 m)	2.074	9.530	6.762	1.730
Sinuosity	1.000	1.023	1.002	0.004
Slope	2.000	34.341	11.580	6.770
Segment length	203.094	400.000	395.045	27.774
I-91, 800 m (n=127)				
WVCD	0.001	0.015	0.002	0.002
AADT	3,417.353	25,997.059	9,228.455	5,220.475
WCI (400 m)	1.055	9.056	6.104	1.782
WCI (800 m)	1.028	9.415	6.337	1.724
WCI (1200 m)	1.247	9.541	6.599	1.768
Sinuosity	1.000	1.061	1.006	0.011
Slope	3.000	27.605	11.323	5.190
Segment length	203.094	800.000	770.169	114.935
I-91, 1600 m (n=104)				
WVCD	0.001	0.009	0.001	0.001
AADT	3,417.353	25,997.059	9,370.057	5,210.005
WCI (400 m)	1.057	8.832	5.920	1.715
WCI (800 m)	1.061	9.223	6.139	1.677
WCI (1200 m)	2.459	9.436	6.385	1.597
Sinuosity	1.000	1.122	1.015	0.020
Slope	2.728	22.617	11.630	4.348
Segment length	271.094	1,600.000	1,499.133	285.150

Table A.5. Descriptive statistics for variables used in the US-2 multiple regression models.

Model variables	Minimum	Maximum	Mean	Std. Devation
US-2, 400 m (n=84)				
WVCD	0.003	0.028	0.005	0.004
AADT	2,190.000	20,322.353	4,055.560	2,857.394
WCI (400 m)	1.245	9.339	6.828	1.849
WCI (800 m)	1.618	10.000	7.542	1.628
WCI (1200 m)	1.578	10.000	7.835	1.571
Sinuosity	1.000	1.091	1.009	0.016
Slope	2.000	36.842	10.507	5.891
Segment length	207.479	400.000	386.569	40.479
US-2, 800 m (n=69)				
WVCD	0.001	0.016	0.003	0.003
AADT	2,190.000	20,322.353	4,193.116	2,901.967
WCI (400 m)	1.304	9.168	6.748	1.868
WCI (800 m)	1.498	10.000	7.581	1.554
WCI (1200 m)	1.626	9.810	7.619	1.569
Sinuosity	1.000	1.089	1.018	0.021
Slope	2.056	25.675	8.719	4.476
Segment length	244.146	800.000	726.304	163.042
US-2, 1600 m (n=52)				
WVCD	0.001	0.014	0.002	0.003
AADT	2,190.000	20,322.353	4,608.829	3,191.386
WCI (400 m)	1.866	9.161	6.455	1.953
WCI (800 m)	1.677	10.000	7.352	1.653
WCI (1200 m)	1.846	10.000	7.666	1.588
Sinuosity	1.000	1.156	1.033	0.034
Slope	2.056	28.435	9.275	5.141
Segment length	244.146	1,600.000	1,323.454	454.370

Table A.6. Descriptive statistics for variables used in the VR-114 multiple regression models.

Model variables	**Minimum**	**Maximum**	**Mean**	**Std. Devation**
VR-114, 400 m (n=83)				
WVCD	0.003	0.028	0.006	0.005
AADT	604.412	3,734.706	939.245	643.044
WCI (400 m)	2.557	9.318	7.914	1.409
WCI (800 m)	3.179	9.635	8.395	1.318
WCI (1200 m)	4.665	9.747	8.685	1.080
Sinuosity	0.927	1.000	0.991	0.012
Slope	2.195	32.732	11.726	6.337
Segment length	204.479	400.000	393.595	29.802
VR-114, 800 m (n=61)				
WVCD	0.001	0.015	0.004	0.003
AADT	604.412	3,734.706	964.368	659.707
WCI (400 m)	2.557	9.432	7.813	1.340
WCI (800 m)	3.1150	9.70	8.299	1.315
WCI (1200 m)	5.101	9.788	8.736	0.896
Sinuosity	1.000	1.114	1.018	0.022
Slope	4.049	26.506	11.242	5.489
Segment length	285.139	800.000	775.051	88.217
VR-114, 1600 m (n=41)				
WVCD	0.001	0.014	0.003	0.003
AADT	604.412	3,734.706	1,033.271	758.158
WCI (400 m)	2.557	9.379	7.559	1.420
WCI (800 m)	3.179	9.662	8.153	1.257
WCI (1200 m)	3.070	9.763	8.389	1.348
Sinuosity	1.001	1.106	1.029	0.029
Slope	4.625	25.891	11.222	4.905
Segment length	285.139	1,600.000	1,434.070	360.850

Table A.7. Descriptive statistics for variables used in the Functional 7 multiple regression models.

Model variables	Minimum	Maximum	Mean	Std. Devation
Functional 7, 400 m (n=340)				
WVCD	0.003	0.028	0.004	0.003
AADT	122.941	4,851.765	1,146.866	854.870
WCI (400 m)	2.142	9.880	7.625	1.571
WCI (800 m)	2.237	10.000	8.192	1.415
WCI (1200 m)	2.907	10.000	8.406	1.334
Sinuosity	1.000	2.142	1.018	0.068
Slope	2.000	60.667	11.786	7.451
Segment length	203.637	400.000	393.456	29.059
Functional 7, 800 m (n=299)				
WVCD	0.001	0.015	0.002	0.002
AADT	122.941	4,851.765	1,185.240	877.613
WCI (400 m)	2.557	9.872	7.528	1.496
WCI (800 m)	2.856	10.000	8.127	1.342
WCI (1200 m)	2.856	9.946	8.308	1.241
Sinuosity	1.000	1.809	1.033	0.0063
Slope	2.000	53.038	11.112	56.043
Segment length	215.821	800.000	765.703	110.989
Functional 7, 1600 m (n=256)				
WVCD	0.001	10.014	0.001	0.002
AADT	122.941	4,851.765	1270.941	949.910
WCI (400 m)	2.147	9.881	7.266	1.493
WCI (800 m)	2.331	10.000	7.911	1.361
WCI (1200 m)	1.500	10.000	8.178	1.309
Sinuosity	1.000	1.508	1.049	0.067
Slope	2.000	54.075	11.121	5.628
Segment length	215.821	1,600.000	1,427.757	339.255

Table A.8. Descriptive statistics for variables used in the Functional 6 multiple regression models.

Model variables	Minimum	Maximum	Mean	Std. Devation
Functional 6, 400 m (n=231)				
WVCD	0.003	0.028	0.004	0.003
AADT	625.294	14,227.647	2,910.024	2,327.265
WCI (400 m)	1.876	9.850	6.874	1.785
WCI (800 m)	3.274	9.967	7.555	1.605
WCI (1200 m)	3.124	9.985	7.916	1.530
Sinuosity	1.000	1.087	1.016	0.027
Slope	2.00	101.158	10.845	7.981
Segment length	214.609	400.000	390.247	34.728
Functional 6, 800 m (n=210)				
WVCD	0.001	0.025	0.002	0.003
AADT	625.294	14,227.647	3,051.018	2,384.773
WCI (400 m)	1.876	9.902	6.778	1.715
WCI (800 m)	3.158	9.974	7.487	1.535
WCI (1200 m)	3.056	9.984	7.811	1.472
Sinuosity	1.000	1.455	1.033	0.048
Slope	2.000	62.416	10.129	5.226
Segment length	214.609	800.000	749.530	132.273
Functional 6, 1600 m (n=181)				
WVCD	0.001	0.025	0.002	0.002
AADT	625.294	14,227.647	3,249.770	2,481.834
WCI (400 m)	1.876	9.784	6.578	1.676
WCI (800 m)	3.282	9.954	7.322	1.472
WCI (1200 m)	3.954	9.988	7.694	1.410
Sinuosity	1.000	1.285	1.045	0.048
Slope	2.056	40.051	10.170	4.265
Segment length	214.609	1,600.000	1,385.918	388.467

Table A.9. Descriptive statistics for variables used in the Functional 2 multiple regression models.

Model variables	Minimum	Maximum	Mean	Std. Devation
Functional 2, 400 m (n=168)				
WVCD	0.003	0.028	0.004	0.003
AADT	2,190.000	12,995.588	5,052.043	2,582.670
WCI (400 m)	2.285	9.583	7.072	1.675
WCI (800 m)	2.630	10.000	7.707	1.439
WCI (1200 m)	1.621	10.000	8.016	1.433
Sinuosity	1.000	1.236	1.011	0.025
Slope	2.140	59.744	11.300	7.127
Segment length	229.967	400.000	393.668	27.283
Functional 2, 800 m (n=145)				
WVCD	0.001	0.016	0.002	0.002
AADT	2,190.000	12,995.588	5,219.795	2,540.025
WCI (400 m)	2.594	9.721	6.918	1.678
WCI (800 m)	2.885	10.000	7.579	1.456
WCI (1200 m)	3.869	10.000	7.859	1.368
Sinuosity	1.000	1.344	1.027	0.045
Slope	2.537	53.610	10.507	6.149
Segment length	244.146	800.000	766.949	110.808
Functional 2, 1600 m (n=108)				
WVCD	0.01	0.014	0.002	0.002
AADT	2,190.000	12,995.588	5,534.047	2,615.607
WCI (400 m)	2.562.670	9.447	6.798	1.559
WCI (800 m)	2.552	10.000	7.457	1.449
WCI (1200 m)	1.557	10.000	7.706	1.529
Sinuosity	1.000	1.562	1.051	0.094
Slope	3.553	37.225	10.774	5.305
Segment length	244.146	1,600.000	1,433.181	329.437

Table A.10. Descriptive statistics for variables used in the Functional 1 multiple regression models.

Model variables	Minimum	Maximum	Mean	Std. Devation
Functional 1, 400 m (n=252)				
WVCD	0.003	0.018	0.004	0.003
AADT	3,417.353	26,629.412	12,286.370	6,750.259
WCI (400 m)	1.895	8.992	6.229	1.721
WCI (800 m)	2.110	9.377	6.612	1.655
WCI (1200 m)	2.074	9.530	6.905	1.608
Sinuosity	1.000	1.025	1.002	0.004
Slope	2.000	34.341	11.386	6.217
Segment length	203.094	400.000	395.897	24.342
Functional 1, 800 m (n=216)				
WVCD	0.001	0.015	0.002	0.002
AADT	3,417.353	26,629.412	12,344.450	6,716.599
WCI (400 m)	1.055	9.056	6.086	1.677
WCI (800 m)	1.028	9.415	6.445	1.604
WCI (1200 m)	1.247	9.541	6.853	1.667
Sinuosity	1.000	1.072	1.007	0.014
Slope	2.000	27.605	11.506	5.166
Segment length	203.094	800.000	774.348	102.566
Functional 1, 1600 m (n=171)				
WVCD	0.001	0.009	0.002	0.001
AADT	3,417.353	26,629.412	12,246.214	6,704.722
WCI (400 m)	1.057	8.832	5.943	1.600
WCI (800 m)	1.061	9.223	6.288	1.563
WCI (1200 m)	2.459	9.436	6.600	1.506
Sinuosity	1.000	1.372	1.018	0.034
Slope	2.000	23.692	11.634	4.530
Segment length	205.097	1,600.000	1,500.733	290.739

Table A.11. Results of Lagrange Multiplier test for the all roads models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
LM-Error	39.334	***	41.824	***	39.687	***	48.633	***	48.034	***	47.217	***	79.506	***	78.909	***	77.452	***
LM-Lag	44.874	***	46.896	***	45.434	***	58.873	***	58.272	***	55.573	***	86.315	***	83.968	***	81.889	***
Robust LM-Error	0.149		0.104		0.227		0.137		0.257		0.0002		1.390		1.635		1.667	
Robust LM-Lag	5.689	*	5.177	*	5.974	*	10.378	**	10.495	**	8.355	**	8.198	**	6.694	**	6.103	*

Table A.12. Results of Lagrange Multiplier test for I-91 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						1600			
Buffer distance (WCI)	400		800		1200		400		800	
LM-Error	3.938	*	4.024	*	3.986	*	4.730	*	7.174	**
LM-Lag	3.052		2.986		3.066		5.039	*	6.111	*
Robust LM-Error	1.048		1.307		1.110		0.184		1.099	
Robust LM-Lag	1.620		0.269		0.190		0.493		0.036	

Table A.13. Results of Lagrange Multiplier test for VR-114 models. The p-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400					
Buffer distance (WCI)	400		800		1200	
LM-Error	1.643		1.923		1.862	
LM-Lag	2.013		2.208		2.325	
Robust LM-Error	0.289		0.147		0.335	
Robust LM-Lag	0.659		0.432		0.799	

Table A.14. Results of Lagrange Multiplier test for Functional 7 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
LM-Error	22.998	***	26.221	***	24.285	***	23.417	***	25.397	***	21.354	***	29.113	***	30.273	***	29.709	***
LM-Lag	25.274	***	28.078	***	26.472	***	26.021	***	27.099	***	24.266	***	33.735	***	33.487	***	32.532	***
Robust LM-Error	0.002		0.010		0.001		0.056		0.138		0.023		0.031		0.144		0.101	
Robust LM-Lag	2.776		1.867		2.188		2.659		1.839		2.935		4.653	*	3.358		2.925	

Table A.15. Results of Lagrange Multiplier test for Functional 6 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200	
LM-Error	2.988		3.317	*	3.097		6.818	**	7.363	**	7.446	**
LM-Lag	4.6222	*	4.4479	*	4.115	*	8.764	**	8.537	**	8.231	**
Robust LM-Error	0.337		0.079		0.047		0.000004		0.069		0.147	
Robust LM-Lag	1.972		1.210		1.066		1.946	*	1.244		0.932	

Table A.16. Results of Lagrange Multiplier test for Functional 2 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400						800						1600					
Buffer distance (WCI)	400		800		1200		400		800		1200		400		800		1200	
LM-Error	11.950	***	12.458	***	11.024	***	20.269	***	21.785	***	22.510	***	14.517	***	15.048	***	14.911	***
LM-Lag	10.396	**	10.887	***	10.561	**	20.775	***	21.295	***	21.771	***	14.719	***	14.871	***	14.700	***
Robust LM-Error	1.645		1.677		0.494		0.350		0.799		1.000		0.424		0.524		0.517	
Robust LM-Lag	0.091		0.107		0.031		0.856		0.310		0.261		0.626		0.347		0.306	

Table A.17. Results of Lagrange Multiplier test for Functional 1 models. The *p*-values are represented as follows: $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

Max Road Feature Length	400				800				1600					
Buffer distance (WCI)	400		800		400		800		400		800		1200	
LM-Error	16.945	***	13.296	***	18.817	***	13.165	***	16.473	***	13.326	***	11.091	***
LM-Lag	15.925	***	13.499	***	20.718	***	16.771	***	21.276	***	18.283	***	26.116	***
Robust LM-Error	1.024		0.221		0.025		0.165		0.064		0.108		0.267	
Robust LM-Lag	0.004		0.424		1.925		3.771		4.867	*	5.065	*	5.292	*

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