ANALYSIS OF LANDSCAPE AND TOPOGRAPHICAL FEATURES ASSOCIATED WITH DEER-VEHICLE COLLISIONS IN KANSAS CITY, MO

by

Michael D. Caby

<u>An Abstract</u>
of a thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science
in the Department of Biology and Agriculture
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November, 2013

ABSTRACT

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Michael D. Caby

As urban sprawl increases, it reduces the amount of natural habitat available for deer species resulting in costly deer-vehicle collisions (DVCs). Pulling insight from previous research, I developed a model to identify locations of frequent DVCs using only remotely sensed data from Kansas City, Mo. I then tested the model in a novel environment, St. Louis, Mo. I used Geographical Information System (GIS) software to analyze and measure landscape features surrounding "hotspots" of DVCs and compare them to control areas with no DVCs. The features that were significantly different were tested using logistic regression to isolate those with the most predictive capability. The two models developed using these features were approximately 65% and 81% successful in identifying hotspots in Kansas City and St. Louis, but misidentified 25% and 56% of the controls. The error is too great to apply these models in future road planning, but they did show a link between DVCs and forests, streams and parks as did the previous research.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figure Page

Introduction

As more and more people move away from the heart of cities, it reduces the amount of natural habitat available for local wildlife. Species are forced to adapt to the changing environment and utilize the resources available to them (Ditchkoff *et al.* 2006). Working as a nuisance wildlife technician, I have seen evidence of deer feeding on expensive landscaping, raccoons turning over trash cans and eating fish out of ponds, and squirrels making nests in attics. These behavioral adaptations to the changing environment are attempts to survive, but they are intolerable to humans in those areas and result in conflicts. Conflicts with wildlife can be very costly to humans by destroying expensive landscaping and damaging houses. In addition to nuisance conflicts, animals may also cross roads and collide with moving vehicles. Smaller wildlife collisions rarely cause damage to vehicles and tend to be a minor inconvenience, but for larger species it can be costly and very dangerous for humans. Conover *et al.* (1995) estimated that 1 million deer-vehicle collisions (DVCs) occur annually in the United States, costing more than $1 billion in vehicle damage and over 200 human fatalities. Bissonette *et al.* (2008) studied DVCs in Utah from 1996 to 2001 involving 20,873 people. Of these, 5.3% sustained some form of injury which Bissonette *et al.* (2008) estimated costs totaling $1 million. There were also 8 fatalities during this time period and using the USDOT statistical value for human life, Bissonette *et al.* (2008) estimated a loss of $24 million.

DVCs have occurred for many years, and earlier researchers looked for patterns within landscape features to predict locations of DVCs and possibly mitigate for them. Early researchers sampled roadside vegetation and other features by hand, which was very time consuming and prevented coverage of a large area. Later research started to incorporate remotely sensed data and mapping software like ArcGIS. Bellis and Graves (1971) studied a newly opened 8.03 mile section of Interstate Highway 80 in Pennsylvania. They divided the highway into 212 contiguous 200 foot sectors for analysis. Data on deer carcasses were collected by the Game Protector that addressed DVCs reported on that road. The game protector filled out a data sheet with the date, location by sector number, highway lane, sex, and age of deer (fawn, yearling or adult). Bellis and Graves (1971) analyzed quality and amount of vegetation, topography, area of right-of-way (ROW), and presence of fences or guardrails along the median, ROWs, and areas adjacent to the ROWs. Another research team used the same stretch of road to study deer abundance and behavior on ROWs by conducting spotlight surveys of the south ROW from May 1968 to May 1969.

Even though the other research team saw deer frequently grazing on the ROWs, Bellis and Graves (1971) could not find a correlation between vegetation type and the number of DVCs per sector. They concluded that in forested areas with limited pasture, ROWs provided an area for deer to graze and increased the chance for DVCs. In areas where crop fields bordered forests, deer had alternative areas in which to forage which reduced the chance of DVCs. Bellis and Graves (1971) did not see any connection between the presence of fences or guardrails and a reduction of DVCs. They determined that the fences and guardrails were too low and limited in extent to hinder the movement of deer. When Bellis and Graves (1971) compared the effects of ROW or median slope on DVCs independently, they found no correlation. However, when they looked at roadside and median slopes together, Bellis and Graves (1971) found that high slopes on both sides of the road created a trough which funneled deer along the road and increased DVCs.

Puglisi *et al.* (1974) studied the entire 313 mile stretch of Interstate 80 within Pennsylvania from August 1970 to January 1972. They classified it as a recently constructed four-lane divided highway. The characteristics for each DVC site were determined by analysis of reports submitted by state game protectors responsible for removal of deer injured or killed along Interstate 80. They described the vegetation immediately adjacent to each side of the ROW as well as the topography of the ROW. The game protectors also recorded the height of any fences, and they estimated the distance from the road to the fence and the fence to the nearest wooded area. The interstate was also surveyed by driving down both east and west bound lanes to determine the vegetation, topography, fence type, and fence location at each of the 16,777 mile markers. Each mile marker consisted of two signs on a metal post; the top one designating the number of miles and the lower number multiplied by 100 being the number of feet into that mile. Each mile marker was 200 feet apart except the last one in each mile which was 80 feet from the next marker and indicated the start of the next mile (Puglisi *et al.* 1974).

After comparing all the variables, they found that the fence location was the most significant factor in their study area. High numbers of DVCs occurred where fences were at the edge of a wooded area or within 25 yards of the wooded edge (Puglisi *et al.* 1974). This provided good cover close to the fence and grazing area on the interstate side of the fence. Deer would readily cross the fence increasing the chance for a DVC. Fewer DVCs occurred where fences were more than 25 yards away from the wooded area. There was less cover by the fence and more grazing area readily available on the non-interstate side of the fence. There were also lower numbers of DVCs where fences were located within the woods. Without grazing areas immediately outside the fence to entice the deer, they were less likely to jump the fence and travel near the roadsides. Puglisi *et al.* (1974) concluded that deer mortality depended more on the amount of existing grazing area available to deer rather than the nearness of travel cover to the highway. However, where fences were absent, they found that vegetation type had a significant impact on the location of DVCs. The researchers felt that this indicated the fences may be effective in reducing deer mortality or redistributing it with respect to vegetation.

Allen and McCullough (1976) studied Michigan State Police accident reports on DVCs in 10 counties for 1966 and 1967. The variables that were analyzed from all accidents included date, day of the week, time, speed of vehicle, sex of deer, and road type. They also selected a section from three different roads in areas of high DVCs for habitat analysis. DVCs were plotted on aerial photos of these road sections, and roadside habitat was classified as forest, cropland, or unimproved field. Habitat was verified by ground check. Traffic volume data representative of the study area were obtained from the Michigan Department of State Highways. Allen and McCullough (1976) focused on daily traffic fluctuations and deer activity cycles as well as seasonal fluctuations in deer activity. The data showed peaks in DVCs in the morning and in the evening which coincided with peaks in deer feeding behavior and peaks in traffic volume. The data also showed seasonal peaks in November and in May which coincided with heightened deer activity during fall mating and spring dispersal of males, respectively. Allen and McCullough did not see any great shift in DVC numbers in relation to the habitats sampled along the three road sections.

With all the focus on interstate highways, Bashore *et al.* (1985) chose to study 2-lane non-interstate highways in four Pennsylvania counties. They examined road-kill locations plotted on highway maps by Pennsylvania game protectors from 1968 to 1982. They also analyzed aerial photos and topographical maps and conducted field studies to gather information about the road-ways and landscape adjacent to the road. Their goal was to develop a model that would predict the probability that a section of highway would be a high kill site and then test its reliability (Bashore *et al.* 1985). They examined 51 paired sample sites, one a kill site and the other a “control” (low kill) site. Control sites were the same length, on the same highway, and within 100 m of kill sights to eliminate potential variations in road traffic and deer population. Control sites had no more than 20% of the total collisions of the kill site with which they were paired. The variables that were measured at each site focused on type and number of buildings, slope along the ROW, vegetation type along the ROW, distance to tree line, visibility along the road segment, speed limit, and length of fence or guardrail along the ROW (Bashore *et al.* 1985).

Prior to building the model, 5 paired kill and control sites were randomly selected and removed for later validation of the model. With the remaining 90.2% of the data they began testing to build their model. They only selected validation sites and designed the model once instead of running multiple trials to see if different variables would have been selected. The 19 variables sampled were run through a stepwise logistic regression to test which had the most influence on the probability of the road segment being designated as a kill site. The following 9 variables were selected as most influential: residences, commercial buildings, other buildings, shortest visibility, in-line visibility, speed limit, distance to woodland, fencing, and non-wooded area. In-line visibility and non-woody vegetation had positive coefficients, therefore increasing the likelihood that a road segment would be a kill site, and the rest had negative coefficients. The level of auto correlation was tested between variables which showed that speed limit and in-line visibility as well as residences and other buildings displayed a high level of correlation. Bashore *et al.* (1985) removed speed limit and other buildings from the model and tested both the 7 variable model and the original 9 variable model on the 5 paired data set for effectiveness. Both correctly identified the five kill sites and 4 of the 5 control sites.

Bashore *et al.* (1985) drew several conclusions about landscape features that influence where DVCs occur. Road segments in wooded areas within kill sites tended to be longer, and there were no discernible areas of concentration of DVCs along these segments. A motorist could expect a high likelihood of encountering a deer along any wooded roadway. Their data also showed a greater concentration of DVCs as vegetation transitioned from woodland to non-woodland habitat. Bashore *et al.* (1985) found that high concentrations of buildings decreased the likelihood that a road segment would be a kill site. They attributed this to the displacement of deer because of high human presence in those areas. Although they were surprised that there was a negative correlation between speed limit and DVCs, Bashore *et al.* (1985) hypothesized that the higher rate of speed for vehicles could scare the deer and prevent them from attempting to cross at those road segments. They also showed as driver visibility along road sides decreased or as the road curves through the landscape, there is an increase in DVCs.

Due to the labor-intensive nature of field sampling and advent of new remote sensing technology, researchers shifted their methodology to include new sampling techniques and data analysis tools. An early example of this shift in methodology was a study by Finder *et al.* (1999). They were supplied information about 86 road segments within 43 counties in Illinois that had 15 or more DVCs between 1989 and 1993. They digitally plotted these high DVC road segments (hotspots) using Topographically Integrated Geographic Encoding and Reference System (TIGER) data files of county roads and Map and Image Processing System (TNTmips: MicroImages 1998) Geographical Information System (GIS) software. Control road segments were randomly selected along the same stretch of road 0.8 to 8 km away from hotspots for comparison. The road segments were overlaid on a landcover layer and a 0.8 km buffer was created around each segment to quantify and compare landscape composition. A spatial pattern analysis program called FRAGSTATS (McGarigal and Marks 1995) was used to calculate the area of each landcover type; density, size, edge, shape, core area and interspersion of landcover patches; and overall landscape diversity and contiguity of landcover patches.

Finder *et al.* (1999) also used high resolution aerial photographs to measure additional landscape and topographic physical features with the 0.8 km buffer zone. They measured adjacent landcover, distance to forest cover, ROW topography, field edges, hedgerows, corridors, residences, other buildings, water, urban area, curvature, straight-away, general topography, public recreation land, and other unusual features. They followed the same procedure as Bashore *et al.* (1985) by randomly selecting five paired sites and removing them from the original data set for later testing of the models' effectiveness. The remaining 94.2% of the data was used to build the models. Paired-sample t-tests were used to determine whether the variables were significantly different between hotspots and controls. Those variables found to be significant were then subjected to the stepwise logistic regression model selection process to obtain a preliminary equation. A second model equation was created using the same method but only examined the digital remotely sensed data. The variables included in the first model were percentage of distant woody cover, percentage of adjacent gully, area of recreational land and width of corridors crossing the road. The second model only utilized the Simpson's diversity index and the woods mean proximity index.

The first model correctly identified five control sites and four hotspots, while the second model correctly selected four controls and two hotspots. The most important predictor for high DVC locations was distance-to-forest cover. Though deer will feed on grasses and other herbaceous vegetation, they will remain close to wooded cover as they forage and move from place to place. Woody cover also decreases visibility for drivers, and therefore increases the chance of a DVC. Finder *et al.* (1999) advised that when planning for future road development, passing through large woodlots should be avoided if at all possible. They hypothesized that public recreation lands act as a refuge from hunting and provide adequate forage and wooded habitat to increase local deer populations. Riparian corridors are often used as travel lanes for deer when moving from one wooded fragment to another or while foraging. The model indicates when a riparian corridor crosses a roadway, there is an increase in DVCs. Finder *et al.* (1999) hypothesized that gullies adjacent to roadways obstruct the visibility of motorists or prevent deer from observing passing vehicles, therefore increasing the occurrences of collisions. For the model that used only digital landscape metrics, the woods mean proximity index and the Simpson's diversity index were the most important landscape metrics. The woods mean proximity index reflects forest patch size and density, and as it increased, so would the number of deer near the roadside. The Simpson's diversity index is a measure of the number of different patch-types and the distribution of area between different patch-types. Diverse landscapes support larger deer populations because they provide sufficient amounts of food, cover, and water.

Hubbard *et al.* (2000) studied the habitat surrounding all state and federally maintained highways within Iowa. The number of DVCs, traffic, and landcover data were collected for all mile post markers within the state (n = 9,575). Habitat maps were generated from automatically classified LANDSAT images with 30 x 30 m resolution provided by the U.S. Geological Survey. They consolidated the habitat types into the following classes: cropland, woody cover, grass, artificial, water, and miscellaneous. The Iowa Department of Transportation provided a database of DVCs on the highways during 1990-97. The database contained location information, and Hubbard *et al.* (2000) were able to create a shape file of DVCs to overlay with the landcover layer. They also included these other characteristics for each DVC location for analysis: traffic volume estimates, distance to nearest town or city, distance to nearest city with a population ≥2,000, number of bridges, and number of lanes of traffic. Each DVC was associated with a mile marker and associated with a 1.61 km segment of road. They randomly selected 1,284 road segments and sampled the landscape within 0.8 km on either side of the road using FRAGSTATS (McGarigal and Marks 1995) for analysis. They broke the data set into two categories for comparison: sites with 13 or fewer DVCs and those with 14 or more DVCs. They used stepwise logistic regression to build a model for selecting high DVC areas and refined their selection of variables by constructing a factor classification tree. They tested the model using 245 randomly selected road sections not included in model development.

Hubbard *et al.*'s (2000) analysis showed that an increase in grass or woody patches related to an increase in DVCs while an increase in cropland patch size related to a decrease in DVCs. The regression model isolated the standard deviation of all patches as an influential factor. Hubbard *et al.* (2000) showed that a higher variation in patch size was indicative of a number of large crop fields with smaller habitat patches intermixed which led to a decrease in DVCs. The regression model also isolated two road characteristics as being influential in the number of DVCs per mile marker segment. As the number of lanes per road segment increased, there was an increase in the number of DVCs. However, the most influential feature in the model was the number of bridges present per road segment which showed a positive correlation with the number of DVCs. In their study, bridges were associated with streams or railroad tracks which often act as corridors for deer as they travel between habitat patches. As deer are funneled into these travel corridors which eventually intersect the roadway at these bridge sites, there is a chance that more deer will cross onto the roadway, resulting in more DVCs. Hubbard *et al.*

(2000) believe that by making bridges with more effective underpasses, deer will be less likely to cross roadways at these intersections, thereby greatly reducing the number of DVCs.

Nielsen *et al.* (2003) chose to focus on DVCs within highly urban areas and selected two suburbs of Minneapolis, Minnesota (Bloomington and Maple Grove) as their study sites. They digitized DVC locations between 1993 and 2000 into an ARCVIEW GIS database from maps provided by each city. Following a similar methodology as Finder *et al.* (1999) and Hubbard *et al.* (2000), they overlaid 0.5 km road segments at the midpoint of DVC clusters with 2 or more collisions; these were called DVC areas. They then overlaid 0.5 km road segments onto areas with 0 or 1 DVC; these were labeled control areas. Both DVC and control areas were buffered at a 0.1 km perpendicular distance on either side of the road in order to sample the landscape features. Nielsen *et al.* (2003) selected 40 DVC and 40 control areas per study area for comparison. They used the Minnesota Landsat-Based Landcover map to determine land-cover information and they consolidated the 9 classes into the following 3: residential/grassland, woodland, and open water. They obtained land-use information from the Generalized Land Use Data Set for the Twin Cities Metropolitan area, and they consolidated the 15 land-use classes into commercial/industrial, residential, and public land. Nielsen *et al.* (2003) analyzed the land-cover and land-use layers within the buffer zones using the Patch Analyst Extension (Elkie *et al.* 1999) and calculated 60 class-and landscape-level variables. They also measured 6 additional variables using U. S. Geological Survey Digital Orthophoto Quadrangles: road curvature, number of buildings in the buffer zone, three categories of speed limit, number of lanes, distance from road to nearest forest patch, and presence of ditches in the ROWs.

Nielsen *et al.* (2003) used univariate analysis to isolate the variables that were significantly different between DVC and control areas. They then used Spearman rank correlation to eliminate variables that were too closely related ($r \geq 0.70$). They used the remaining variables from 60 randomly selected DVC areas and 60 randomly selected control areas in a logistic regression analysis to develop 10 *a priori* models to test the probability that a road segment would be a DVC area. These models were then tested using the remaining 40 road segments left out during model development. Their best fit model showed that DVC areas had fewer buildings, more patches, more forest cover, more public land patches, and a higher Shannon's diversity index, and it was able to correctly classify 31 of the 40 areas left out of model development. Nielsen *et al.* (2003) hypothesized that higher building numbers meant more manicured lawns and less food and cover available for deer. On the other hand, public land had much better deer habitat with more food and cover. Even with municipal efforts to reduce deer population, the public lands had the highest concentrations of deer within the two cities; therefore, any roads adjacent to public lands resulted in higher DVCs.

Unlike the previously mentioned researchers who focused on site-specific factors associated with DVCs, Farrell and Tappe (2007) chose to focus on county-level factors for all 75 counties in Arkansas. They received vehicle accident reports involving deer on state and federal highways from the Arkansas State Police from 1998 to 2001. They obtained highway characteristics from the Arkansas Highway and Transportation Department, such as mean daily traffic count, total highway density, percent of highways that are state maintained, percent of highways located in rural areas, percent of highways with fewer than 4 lanes, percent of highways greater than 5 years old, and percent of highways that were disturbed (e.g., road construction) within the last 5 years. Farrell and Tappe (2007) gathered human population data and urban area per county in 2000 from the United States Census Bureau and the Natural State Digital Database. They also calculated the percent change per county for both the human population and urban area between 1990 and 2000. They calculated a deer density index per county using reported deer harvest, number of legal hunting days and amount of forested area per county. Landcover characteristics were measured using the 1999 Arkansas Land Use/Landcover data set by first condensing the 44 classification into 9 categories similar to previous research: agriculture, barren, coniferous forest, deciduous forest, mixed forest, old-field, pasture, urban, and water. Using ArcGIS 8.0 and FragStats 3.3(McGarigal and Marks 1995), Farrell and Tappe (2007) calculated these class level variables: percent of county, patch density, mean shape index, mean Euclidean nearest neighbor distance with coefficient of variation, and mean edge contrast index with coefficient of variation. They also computed additional landscape-level variables such as edge density, mean shape index, mean edge contrast index, and patch richness density. In addition, they calculated the mean tons harvested per county for both pine and hardwood timber between 1998 and 2001.

Farrell and Tappe (2007) tested for correlation among variables and reduced sets of variables to one representative variable that was most intuitive and most easily interpretable. They then used principle components analysis to form related variable groups (components). They kept the top 5 components and tested regression models developed from each component. Based on statistical analysis, the two regression models that utilized components 1 and 2 had the strongest predictive success. The variables in component 1 were related to urbanization and human population, and as these factors increased, so did DVCs. The regression model based on component 1 showed that as edge density and contrast, forest patch density, and deer density increase, so do DVCs. Farrell and Tappe (2007) also found a negative correlation with DVCs and percent agriculture. Though the majority of research on DVCs focused on a more localized analysis of the factors, Farrell and Tappe (2007) show potential influence of large scale variables on the density of DVCs in an area.

The previous research provided great insight into the factors that may influence the location of DVCs. The first objective of my project was to test as many of these factors as possible using remotely sensed data. With the availability of more public GIS data, this would be the most cost-effective and time-efficient way to analyze DVC locations. My second objective was to develop a predictive model to isolate areas of high DVC occurrence based on this remotely sensed data. I hypothesized that the model would be most accurate and practical if the sample area was large enough to encompass multiple habitat types, but small enough to pinpoint possible applications of DVC mitigation techniques. Ideally, the model and the method of measuring the variables would be versatile enough to allow planners to project and digitize possible habitat changes and use the model to predict locations of potential high occurrences of DVCs. This would allow city planners and developers to isolate areas of concern, and budget for possible road alterations or mitigation techniques before construction. Previous research either tested model validity statistically or with a subset of the original data not used during model development. I chose to use a real-time validation of the model. I used a historical data set to develop the model and then used new data collected for several years after the original data set. The next leap in application of a predictive model is to test it in a novel environment; that was the final step of my project.

Study area

I chose St. Louis, MO on the eastern boundary of the state and Kansas City, MO on the western boundary as my areas of study (Fig. 1). Both are large metropolitan areas with sprawling suburbs and a known DVC problem with recorded data. In St. Louis, I only used

DVC data from St. Louis County, which has an estimated human population of 998,954 per the 2010 census (U.S. Census Bureau 2013). The St. Louis landscape consists of 35.6% low density urban/residential area, 21.5% forest, 13.2% grassland, 11.4% cropland, 6.7% impervious surfaces, 5.4% open water, and 4.6% wetland (MoRAP 2005). The average annual rainfall is 95.63 cm (37.65 inches) with a high of 147.22 cm (57.96 inches) in 2008 and a low of 52.55 cm (20.69 inches) in 1953 (NOAA 2013). The average annual temperature is 13.5ºC (56.3 ºF) with a record high of 46.11 ºC (115 ºF) on July 14, 1954 and a record low of -30.56 ºC (-23 ºF) on January 29, 1873 (NOAA 2013).

In Kansas City, I used DVC data from Platte, Clay, and Jackson Counties, which have population estimates of 89,322; 221,939; and 674,158 respectively (U.S. Census Bureau 2013). The Kansas City landscape consists of 14.3% low density urban/residential area, 15.8% forest, 27.4% grassland, 26.3% cropland, 5.1% impervious surfaces, 3.3% open water, and 2.8% wetland (MoRAP 2005). The average annual rainfall is 93.68 cm (36.88 inches) with a high of 153.04 cm (60.25 inches) in 1961 and a low of 53.16 cm (20.93 inches) in 1953 (NOAA 2013). The average annual temperature is 12 ºC (53.6 ºF) (Climate Zone 2013) with a record high of 44.44ºC (112 ºF) in 1954 and a record low of -28.33ºC (-19 ºF) in 1989 (The Weather Channel 2013).

Figure 1. Study areas, St. Louis and Kansas City, Mo, used to create and validate a predictive model for deer-vehicle collisions.

Methods

I started by gathering some foundation layers to build my initial map from the Missouri Spatial Data Information Service (MSDIS 2008). I downloaded Missouri state and county boundaries, roads, streams, Missouri Department of Conservation (MDC) lands, and Department of Natural Resources (DNR) lands. My advisor provided a land use/landcover layer for the state of Missouri in 2005 from the Missouri Resource Assessment Partnership (MoRAP). I used ArcGIS version 9.2 (Environmental Systems Research Institute 2006) to view and analyze the digital data. I reviewed the state-wide land use/landcover layer which had the following 14 classifications: impervious, high density urban, low density urban, barren or sparsely vegetated, cropland, grassland, deciduous forest, evergreen forest, mixed forest, deciduous woody/herbaceous, evergreen woody/herbaceous, woody-dominated wetland, herbaceous-dominated wetland, and open water. I combined the three different classes of forest into one general forest class, and I also combined the two wetland classes into one. I then overlaid the Kansas City area with a 150 hectare hexagonal grid in order to measure the different landscape features.

I was provided with electronic locations for DVCs in the Kansas City area for 2000, 2001, 2002, 2003, and 2004 from MDC. I also received hard copy data sheets with location descriptions for 2007, 2008, and 2009. The earlier data were digitized by using the description of DVC locations from datasheets to plot a point on an ArcGIS point layer while overlaid with a roads layer. I followed the same methodology to digitize the data from 2007 to 2009 for the Kansas City area. I used the data from 2000 to 2004 to create a predictive model, and I validated that model in Kansas City using the DVC data from 2007 to 2009. I defined a hotspot as a hexagon with five or more DVCs and control grids as a hexagon with no DVCs and at least 1.61 km of roads. When I joined the hexagonal grid layer with the Kansas City DVC layer for 2000-2004, there were 238 hotspots and 1030 controls. I used a random number list to select 238 control grids to compare with my hotspots.

The Patch Analyst extension (Elkie *et al.* 1999) has a whole suite of landcover metrics to measure and test between hotspots and controls. Patch Analyst is a spatial analysis tool that can be downloaded and added to ArcGIS. Some metrics measure all landcover types together within the hexagon and includes diversity and evenness indices. Patch Analyst can also focus on one landcover type at a time and measure such parameters as: number of patches, amount of cover type per hexagon, average patch size, total edge, and mean nearest neighbor. I collected all these measurements for all landcover types mentioned above except impervious, barren, and evergreen woody herbaceous. Impervious areas were often associated with roadways and it would be redundant to measure impervious areas and roadways. There were only a few barren spots in the Kansas City area, and there were not enough data available for testing. There were no patches of evergreen woody herbaceous landcover present in Clay, Platte, or Jackson County for analysis.

I downloaded 10 m digital elevation model (DEM) files for all three counties in Kansas City from MSDIS and merged them together. I then used the Topographic Position Index (TPI); (Jenness 2006) extension in ArcView 3.x to create a landform classification raster layer. I measured the amount of each landform type per hexagon to compare between hotspots and controls. I then vectorized the landform raster layer in order to clip and measure roads within different land forms (i.e. ridge top roads or canyon roads). I also vectorized the landcover layer in order to clip and measure the length of roads and the length of streams passing through all habitat types except open water (i.e. forested roads and forested streams). Also, by vectorizing the landcover types, I was able to overlay two different landcover types and measure the amount of adjoining edge between the two habitats (i.e. forest/grassland edge or forest/cropland edge). I also measured the total length of streams in meters per hexagon and the number of road/stream intersections per hexagon.

I received polygon layers for county parks from the appropriate zoning and planning offices per county. I merged the county parks with the MDC and DNR lands layers and classified it generally as public lands. I measured the area of public lands in each hexagon for comparison. I also measured the area of county parks alone, because the majority of county parks do not allow any hunting. DNR and MDC land s often allow hunting; therefore, in urban areas, county parks provide a concentration of beneficial habitat for deer and a refuge from hunting which could lead to an increase in DVCs in that general area.

Once I collected all these data on the landscape and topographical features, I tested which features were significantly different between hotspots and controls. All of my continuous data were not normally distributed so I used the Mann-Whitney U test. For my discrete data I used contingency tables to test for significance. Once I had all the factors that were significantly different between hotspots and controls, I used forward stepwise logistic regression in SPSS (SPSS 2006) to test which ones had the strongest predictive capability to select hotspot locations.

I used an adaptation of the map algebra technique with raster data to develop a predictive model. Map algebra involves putting a value ranking on a range of measures per raster layer, therefore placing a ranking in each raster cell. Once all raster layers have been ranked, the rankings are totaled for each cell, and that total ranking is used to classify that cell as unlikely, likely or highly likely to be the characteristic for which the researcher is modeling. The majority of the data I collected were vector data, and it would have been difficult and time-consuming to convert vector data into raster data. However, a raster datum is an assessed value over a defined region, in most cases a 30 m by 30 m square. In essence, I created my own defined raster cells by using a hexagonal grid to sample my study area. It was not the conventional method, shape, or size, but in theory similar to the original method. The question was how to link the data from the different layers spatially. With traditional map algebra, the raster cells in each layer have the same coordinates, and therefore lay on top of one another. In my research, all data were collected using the same hexagonal grids for hotspots and controls with each of the different raster and vector layers. Instead of the different layers having the same coordinates, they were all linked to the same hexagon which had a unique hexagon ID. For my research, instead of performing the map algebra in ArcMap, the attribute tables were exported to a Microsoft Excel worksheet. There I could rank each variable from the different layers and then calculate a total ranking for each hexagon.

When deciding how to rank the variables I chose to focus on the range of variables for the hotspots instead of the combined range. Since my goal was to develop a model to predict locations of hotspots, I did not want to skew the ranking system by including the range of values for the controls. To start with an unbiased equal distribution of the range of values, I divided the range into quartiles. The first quartile I gave a rank of 0, the second a rank of 1, the third a rank of 2, and the fourth a rank of 3. If the variable had a negative B value from the logistic regression, it meant there was a negative correlation between that variable and whether the hexagon would be a hotspot. For those variables I used a similar ranking system, but gave negative values for the second, third, and fourth quartile. There were some data sets with a very limited range, and the majority of the values were 0. For these variables, I had to adjust the ranking system accordingly. Once I ranked all the variables and summed the ranks, I broke the totals into quartiles as well. The first quartile was unlikely to be a hotspot, since there is a greater chance of overlap between the hotspots and controls at the lower end of the hotspot range. The second quartile could potentially be a hotspot, the third would likely be a hotpot, and the fourth is highly likely to be a hotspot.

Using this system, I created a series of “if then” statements in Excel to rank the variables measured for each hexagon and to total the ranks. This would be the overall rank for the hexagon and would determine if it should be a hotspot or not. I used the variables from step 6 of the forward stepwise regression to create one model and the variables from step 14 for another. When compared to the original data set of DVCs for Kansas City from 2000 to 2004, the step 14 variables showed a greater success of identifying true hotspots than the step 6 variables. They both had the same percent of error in misidentifying controls as hotspots. In an attempt to increase the success rate of the model and decrease the error, I adjusted the ranking system for the step 14 model based on my theories of the relationship of those variables to deer behavior. I increased the ranked value or "weighted" the characteristics that I perceived had the greatest influence on deer movement. This resulted in a slight drop in success rate and an increase in error with controls.

I explored one more option for breaking the range of variables for ranking in the model. I used ArcMap to identify 5 natural breaks within the range of each variable in order to create a ranking system of 0, 1, 2, 3, or 4 based on those values. When compared to the original data set, there was a 5% drop in success for identifying hotspots, but there was also an 18% drop in the erroneous identification of controls as hotspots. With the acceptable success rate for the natural breaks ranking system and the decrease in the error, it was worthwhile validating both models in Kansas City and testing them in St. Louis.

Results

Table 1 shows the number of correctly and incorrectly identified hotspots and controls, as well as the percentages for each step of the forward stepwise logistic regression. In the table, 0 represents controls and 1 represents hotspots. At step 6 of the process, the variables selected were successful in predicting hotspots and controls 84.2% of the time. There was very little change in the overall success for each consecutive step of the regression, and it stopped at a maximum of 85.1% correct on step 14.

Table 1. Results of a forward stepwise regression using variables to predict hotspot occurrence of deer-vehicular collisions in Kansas City between 2000-2004.

	Observed		Predicted		
			Hotspot		Percentage Correct
			0	1	
Step 1	Hotspot	0	169	69	71.0
		1	84	154	64.7
	Overall Percentage				67.9
Step 2	Hotspot	0	176	62	73.9
		1	66	172	72.3
	Overall Percentage				73.1
Step 3	Hotspot	0	189	49	79.4
		1	50	188	79.0
	Overall Percentage				79.2
Step 4	Hotspot	0	196	42	82.4
		1	47	191	80.3
	Overall Percentage				81.3
Step 5	Hotspot	0	192	46	80.7
		1	51	187	78.6
	Overall Percentage				79.6
Step 6	Hotspot	0	201	37	84.5
		1	38	200	84.0
	Overall Percentage				84.2
Step 7	Hotspot	0	201	37	84.5
		1	39	199	83.6
	Overall Percentage				84.0
Step 8	Hotspot	0	197	41	82.8
		1	41	197	82.8
	Overall Percentage				82.8
Step 9	Hotspot	0	199	39	83.6
		1	39	199	83.6
	Overall				83.6

	Percentage			
Step 10	Hotspot 0	202	36	84.9
	1	36	202	84.9
	Overall Percentage			84.9
Step 11	Hotspot 0	203	35	85.3
	1	38	200	84.0
	Overall Percentage			84.7
Step 12	Hotspot 0	202	36	84.9
	1	37	201	84.5
	Overall Percentage			84.7
Step 13	Hotspot 0	202	36	84.9
	1	32	206	86.6
	Overall Percentage			85.7
Step 14	Hotspot 0	205	33	86.1
	1	38	200	84.0
	Overall Percentage			85.1

Table 2 displays the results for step 6 and step 14 of the forward logistic regression. Step 6 indicated 6 out of the 72 parameters tested contributed significantly to the model. Of those, total length of impervious roads, total length of forest/low density urban edge, total length of grassland/low density urban edge, and total length of low density /high density urban edge were positively associated with hotspots. Number of road /deciduous woody stream intersections and total length of impervious /high density urban edge were negatively associated with hotspots. Step 14 indicated that 12 variables out of the 72 parameters tested contributed significantly to the model. Of those, mean nearest neighbor cropland, total length of forest streams, total area of parks per hexagon, number of road /low density urban stream intersections, total length of impervious roads, total length of grassland /low density urban edge, total length of low density/high density urban edge, total length of impervious/deciduous woody edge, and number of grassland patches per hexagon were positively associated with hotspots. Number of road/

deciduous woody stream intersections, total length of impervious/ high density urban edge, and number of deciduous woody patches per hexagon were negatively associated with hotspots. Table 2 also displays numerous values from the SPSS output of the forward stepwise logistic regression. B is the coefficient for the constant and S.E. is the standard error associated with each coefficient. Wald is the Wald chi-square value and Sig. is the p-value for each Wald statistic where any p-value less than 0.05 is statistically significant. The notation df stands for the degrees of freedom for each test of the coefficients. Exp(B) is the odds ratio for the predictors which is calculated by exponentiation of the coefficients. The notation 95.0% C.I. for EXP(B) represents the upper and lower confidence interval for the Exp(B) value.

Table 2. Variables selected for step 6 and 14 of the forward stepwise logistic regression on characteristics associated with hotspots in Kansas City, Mo from 2000-2004.

		B	S.E.	Wald	df	Sig.	Exp(B)	95.0% C.I.for EXP(B)	
								Lower	Upper
Step 6(f)	Number of Road /Deciduous Woody Stream Intersections	-2.813	0.473	35.390	1	0.000	0.060	0.024	0.152
	Total Length of Impervious Roads	0.002	0.000	62.118	1	0.000	1.002	1.001	1.002
	Total Length of Forest/Low Density Urban Edge	0.000	0.000	15.915	1	0.000	1.000	1.000	1.000
	Total Length of Grassland/Low Density Urban Edge	0.000	0.000	30.856	1	0.000	1.000	1.000	1.001
	Total Length of Low Density /High Density Urban Edge	0.000	0.000	21.795	1	0.000	1.000	1.000	1.001
	Total Length of Impervious /High Density Urban Edge	-0.001	0.000	31.412	1	0.000	0.999	0.999	0.999
	Constant	-2.517	0.282	79.605	1	0.000	0.081		
Step 14(m)	Mean Nearest Neighbor Cropland	0.006	0.002	8.490	1	0.004	1.006	1.002	1.009
	Total Length of Forest Streams	0.001	0.000	6.530	1	0.011	1.001	1.000	1.002
	Total Area of Parks Per Hexagon	0.023	0.007	10.690	1	0.001	1.023	1.009	1.037
	Number of Road /Low Density Urban Stream Intersections	0.290	0.132	4.818	1	0.028	1.337	1.032	1.733

	Number of Road/ Deciduous Woody Stream Intersections	-2.985	0.495	36.319	1	0.000	0.051	0.019	0.133
	Total Length of Impervious Roads	0.002	0.000	46.081	1	0.000	1.002	1.001	1.002
	Total Length of Grassland /Low Density Urban Edge	0.000	0.000	13.558	1	0.000	1.000	1.000	1.000
	Total Length of Low Density/High Density Urban Edge	0.000	0.000	17.772	1	0.000	1.000	1.000	1.001
	Total Length of Impervious/ High Density Urban Edge	-0.001	0.000	26.332	1	0.000	0.999	0.999	0.999
	Total Length of Impervious/Deciduous Woody Edge	0.003	0.001	8.423	1	0.004	1.003	1.001	1.006
	Number of Grassland Patches per Hexagon	0.053	0.024	4.958	1	0.026	1.054	1.006	1.104
	Number of Deciduous Woody Patches per Hexagon	-0.108	0.026	16.630	1	0.000	0.898	0.853	0.946
	Constant	-3.195	0.540	35.013	1	0.000	0.041		

The step 14 quartile rank model correctly identified 74.8% of the hotspots in Kansas City between 2000 and 2004, but incorrectly identified 20.2% of the controls as hotspots. As indicated in Table 3, the step 6 quartile rank model correctly identified 65.1% of the same hotspots, but incorrectly identified 21.4% of the controls as hotspots. The step 14 adjusted rank model correctly identified 73.1% of the hotspots, but incorrectly identified 22.7% of the controls as hotspots. The step 14 natural break rank model correctly identified 69.7% of the hotspots, but incorrectly identified 12.1% of the controls as hotspots. The step 14 quartile rank model had the highest success identifying hotspots, and the step 14 natural break rank model had the lowest error in identifying controls. These two models were used in further testing.

Table 3. Summary of the results after testing the four initial models with the 2000-2004 Kansas City data.

Model description	Percent correctly identified Hotspots	Percent incorrectly identified Controls
Step 14 quartile rank	74.80%	20.20%
Step 6 quartile rank	65.10%	21.40%
Step 14 adjusted rank	73.10%	22.70%
Step 14 natural break rank	69.70%	12.10%

When validating both models using the 2007 to 2009 data for Kansas City (Table 4), the step 14 quartile rank model correctly identified 69.2% of the hotspots, but incorrectly identified 29.6% of the controls as hotspots. The step 14 natural break rank model correctly identified 64.6% of the hotspots, but incorrectly identified 25.0% of the controls. When testing both models using the 2004 to 2007 data for St. Louis, the step 14 quartile rank model correctly identified 83.7% of the hotspots, but incorrectly identified 56.1% of the controls as hotspots. The step 14 natural break rank model correctly identified 81.3% of the hotspots, but incorrectly identified 56.8% of the controls.

Table 4. Summary of results from validation with the 2007-2009 Kansas City data and testing with the 2004-2007 St. Louis data on the two selected models.

Model description	2007-2009 Kansas City data		2004-2007 St. Louis data	
	Percent correctly identified Hotspots	Percent incorrectly identified Controls	Percent correctly identified Hotspots	Percent incorrectly identified Controls
Step 14 quartile rank	69.20%	29.60%	83.70%	56.10%
Step 14 natural break rank	64.60%	25.00%	81.30%	56.80%

Discussion

I chose to combine the three different classes of forest into one general forest class. Since wooded areas are limited in urban areas, deer will use all three categories of forest equally for cover or travel corridors. I also chose to combine the two different classes of wetland into one. Since deer would mainly use wetlands as a source of water, the type of vegetation should not drastically alter the behavior of the deer. I chose to keep high density urban and low density urban separate. High density urban areas would represent densely populated or commercial areas with less vegetation and low density urban would represent more residential areas with more vegetation and other possible green space. I assumed that deer would avoid the high density urban areas, and they could utilize the green space and possible forage in the low density urban areas.

In deciding how to analyze the area around DVCs I had two key strategies to choose from, based on the previous research. I could buffer specific road segments and measure the landscape and topography within the buffer (Bellis and Graves 1971; Finder *et al.* 1999; Neilson *et al.* 2003), or I could use a countywide analysis like Farrell and Tappe (2007). The countywide analysis seemed too coarse of a sampling technique; though one can gain insight on potential impacts of large-scale land or population management, it would make it difficult to extrapolate small scale modifications to local communities to help mitigate occurrences of DVCs. Buffering specific road segments would demonstrate a strong link between specific landscape features and frequency of DVCs, providing insight on potential modifications that could mitigate collisions. However, in viewing the locations of DVCs provided by MDC overlaid with a roads layer from MSDIS, buffering all road types for sampling would be a monumental task and very impractical for city planners if they should want to use a model developed from this research. While viewing the layers in ArcMap 9.2 (ESRI, 2006), I considered selecting only larger roads (state and interstate highways), but that appeared to eliminate a large number of DVCs that were linked with smaller residential roads. I did not want to eliminate these data from analysis for fear that there might be a key component influencing DVC locations within these urban areas.

The next challenge was to work out an intermediate technique to sample these areas. The more current research which used GIS software also used either FRAGSTATS (Finder *et al.* 1999; Hubbard *et al.* 2000; Farrell and Tappe 2006) or Patch Analyst (Neilsen *et al.* 2003) to measure various landcover metrics. For ease of access and use I chose Patch Analyst for my project. One tool within Patch Analyst uses a hexagonal grid placed over a landcover layer to measure different metrics such as percent cover, length of edge type, diversity indices, etc. Using a grid placed over each study area was a functional intermediate method for sampling high occurrences of DVCs in a given area, and by utilizing the same hexagonal grid system from Patch Analyst I could link the metrics by hexagon across the various map layers. In deciding what size to make the hexagons, I relied on literature where researchers looked at deer movement and home range sizes within urban areas.

Swihart *et al.* (1993) pooled figures from various research projects in 1993 and showed that the home range for female white-tailed deer was 8 to 221 hectares in summer and 42 to 345 in winter. The home range for male deer was 27 to 319 hectares in summer and 111 to 300 in winter. Kilpatrick and Spohr (2000) observed that home range for female white-tailed deer was 32 to 44 hectares in two communities in Gorton, Connecticut. Etter *et al.* (2002) observed home ranges to be 10 to 234 hectares in the suburbs of Chicago, IL with 75% of the does having home ranges less than 77 hectares. Grund *et al.* (2002) studied the home range of female deer in Bloomington, MN centered around an urban park and measured an average fall home range of 111 hectares in 1996, 101 in 1997 and 73 in 1998. Porter *et al.* (2004) observed the movements of female white-tailed deer in Rochester, NY, and calculated an average summer home range of 21.4 hectares and an average winter home range of 22.4. Storm *et al.* (2006) studied female deer near Carbondale, IL, and calculated an average fawning home range of 53 hectares and an average winter home range of 91 hectares. After reviewing this information and comparing hexagonal grids of 75, 100, 150, and 200 hectares, I chose to use hexagonal grids of 150 hectares. This was the prevailing average for Swihart *et al.* (1993) and within range of the Grund *et al.* (2002) and Etter *et al.* (2002). The 150 hectare hexagons were large enough to encompass multiple landcover types and small enough to isolate areas for potential mitigation.

When deciding how to define hotspots and controls, I considered the previous research. Farrell and Tappe (2007) used various statistical methods to analyze the relationship between landscape features and the density of DVCs per county. Finder *et al.* (1999), Hubbard *et al.* (2000), and Nielsen *et al.* (2003) all compared road segments with high occurrences of DVCs (hotspots) and segments with lower occurrences of DVCs (controls). These three projects defined the number of DVCs for hotspots and controls differently, but they all allowed for some DVCs in the control segments. For my project I wanted a clear distinction between hotspots and controls, so I defined hotspots as hexagons with 5 or more DVCs and controls as hexagons with 0 DVCs. I also had to ensure there was a minimum length of roads in the controls, since there would be no chance for a DVC without roads. After comparing the three aforementioned projects using road segments, the largest road segment used was 1.61 km by Hubbard *et al.* (2000), and I used it as my minimum road length requirement for control grids. All hotspots had more than 1.61 km of roads.

In reading the previous research that utilized field sampling, many logical connections were made about the landscape and topography, and their influence on DVC location. Bellis and Graves (1971) showed how upward sloping roadsides can funnel deer to travel along with the road and increase the chance of DVCs. Both Finder *et al.* (1999) and Nielson *et al.* (2003) used aerial photos to classify the ROW topography based on slope and tested its potential influence.

For both projects, factors other than the ROW slope were more influential in the location of DVCs. Besides ground sampling and aerial photos, I wanted to find another method to sample topography in relation to DVC location. Digital Elevation Models (DEMs) are an easily accessible and accepted map layer that represents the topography of a given area. The challenge was how to symbolize the information and compare subsections of it. I used an ArcView 3.x extension called Topographic Position Index (TPI); (Jenness 2006) which compares the immediate area surrounding a point to classify its topography or landform (i.e. ridge top or canyon). This method allowed me to test canyon roads which were similar to upward sloping ROWs as in Bellis and Graves (1971), but I would also be able to test for any influence from other topographical land forms.

Of the landform types, my preliminary testing found only midslope ridges and canyons to be significantly different between hotspots and controls. Also, all road/landform types were significantly different between hotspots and controls except upland drainage roads. I was uncertain whether it was the combination of landform and road that made the difference or the roads alone. When the total length of roads was shown to be significantly different between hotspots and controls, I doubted the influence of the landform on the road and only tested total midslope ridges and canyons in the stepwise logistic regression, and they were not selected as being most influential in isolating hotspots.

Bellis and Graves (1971) also showed an increase in DVCs where roads traveled through forested areas. They hypothesized that ROWs provided grazing areas for deer that were not available in predominately forested areas. Bashore *et al.* (1985) and Finder *et al.* (1999) also showed that the closer the forest edge was to the road, the more DVCs occurred. By vectorizing the different landcover types I was able to clip and measure the length of roads passing through forested areas. I also measured the lengths of roads running through the rest of the habitat types except open water. The majority of these would be bridges over bodies of water with no ROW vegetation to draw the deer to these road segments. My data showed roads passing through forests, impervious areas, high density urban areas, low density urban areas, and deciduous woody herbaceous habitat to be significantly different between hotspots and controls. Roads passing through impervious areas were selected by forward stepwise logistic regression as being influential in identifying hotspots. When raster cells are classified, the most dominant landcover type is used to classify the entire 30 m X 30 m cell. This leads me to two possible explanations. Though the majority of the cell is impervious surfaces such as asphalt or concrete, there is enough ROW vegetation to draw deer in and lead to higher DVCs. Secondly, these roads in impervious cell types are larger multilane roads that are difficult for deer to cross and lead to higher numbers of DVCs.

Bashore *et al.* (1985) observed that an increased number of DVCs where woodland/field interfaces were near roads. However, Bellis and Graves (1971) observed a decrease in the number of DVCs when forested areas were found adjacent to cropland within the buffer zone. By vectorizing the landcover types I was able to overlay two different landcover types and measure the amount of adjoining edge between the two habitats (i.e. forest/grassland edge, forest/cropland edge, etc.).   Of the 110 combinations or edge types, 3 forest, 6 grassland, 5 cropland, 3 low density urban, 2 impervious, and 2 deciduous woody herbaceous edge types were shown to be significantly different between hotspots and controls. The logistic regression selected 4 of these as being influential in identifying hotspot locations. Impervious/high density urban edge had a negative correlation with hotspot locations, while grassland/low density urban edge, low density urban/high density urban edge, and impervious/deciduous woody herbaceous edge all had positive correlations to hotspots. Since impervious areas are associated with road surfaces and high density urban areas are associated with an increased number of buildings, the negative correlation of impervious/high density urban edge to hotspots could be similar to Bashore *et al.* (1985) findings on the influence of buildings along roadsides. They found a decrease in the number of DVCs when the number of buildings increased along roadsides and they attributed this to a limited amount of forage and an increase in human presence keeping deer away from these areas.

The positive correlation of the other three edge types was likely a factor of habitat limitations due to urban sprawl. Deciduous woody herbaceous vegetation may have been the key foraging areas in an otherwise impervious landscape leading to an increased number of DVCs associated with impervious/deciduous woody herbaceous edges. As mentioned before, the residential areas in the low density urban landcover type provide some woody cover, potential forage, and refuge from hunting in a highly fragmented landscape. Where these residential areas coincide with additional grassland cover types, this increases the amount of forage for deer. This can lead to a higher concentration of deer and more DVCs near grassland/low density urban edges. Where the residential areas interface with higher density urban areas, there will be an increase in the number of roads resulting in more DVCs near low density urban/high density urban edges.

I was unable to find a map layer showing the location of bridges in order to test the Hubbard *et al.* (2000) observations on the bridge numbers and DVCs. Hubbard hypothesized that the link between bridge number and DVCs was because bridges often indicate where streams or railroads intersect the road. Deer will often use riparian corridors to travel between forest patches, and railroads have also been common travel corridors. Finder *et al.* (1999)

observed that as the width of the riparian corridor increased, so did the occurrences of DVCs. Since I could not find a bridge layer, I overlaid a roads layer with a streams layer and created a point layer showing the intersections of the two. Assuming that these intersections would likely be areas were deer were funneled toward the road, I wanted to test for increased DVCs in hexagons with road/stream intersections. I also thought that by clipping the streams layer with the forest polygons I could symbolize possible riparian corridors and measure their impact on hotspot locations. I clipped streams within all landcover types to measure their influence. The logistic regression showed a positive correlation between hotspots and forest streams and road/low density urban stream intersections. The selection of forested streams supports the findings presented by Hubbard *et al.* (2000) and Finder *et al.* (1999). The low density urban landcover type is dominated by residential housing, but can contain a variety of vegetation types. It is possible that the streams are within the small wooded sections of the residential areas and are smaller riparian corridors within the low density urban landcover type.

Finder *et al.* (1999) observed that with an increase in the amount of public land in the road side buffer, there was an increase in the number of DVCs. Neilsen *et al.* (2003) saw a similar increase in DVCs with relation to county parks specifically. My data did not show a significant difference in the total area of public land per hexagon between hotspots and controls, but it did show one for the total area of county parks per hexagon. The logistic regression even selected the total area of county parks per hexagon as an influential factor of selecting hotspots. I agree with the Neilsen *et al.* (2003) assessment that parks provide wooded areas for cover, forage areas, and refuge from hunting. This leads to localized increases in deer population and increases in DVCs.

It is difficult to directly compare model success from my research to the previous research, since they tested their models on a subset of the original data, and I tested mine on a new data set within the model development area and a novel test area. I was not satisfied with the percent of incorrectly identified controls for either model in Kansas City or in St. Louis. These models would not be practical for city planners to use when assessing where to apply funding for mitigation techniques or rerouting road construction. However, the link between certain landscape features and DVC locations across the different research projects lends support for the influence of these features on DVCs. Forest cover, riparian corridors, and public lands/parks have shown a positive correlation to the occurrence of DVCs in several of the aforementioned research projects. With some improvements in methodology and multiple years of landscape data, a stronger predictive model can emerge.

Conclusion

There are several ways to improve this project for a future study. First would be to record location data using a GPS device or with GPS coordinates. The data sheets provide a wide range of error in regard to location. The descriptions that were linked to a specific mile marker or an intersection had minimal error, but the ones that described a given distance from an intersection had a lot more error. After working with the data sheets, it was obvious that the recorders did not physically measure the distance. There were many times that I measured the distance from one intersection in ArcMap, but passed other intersections before reaching the desired distance. If the true location of the DVC was half a mile from the described location, the cover type and topography linked to that DVC would skew the data set. By using a GPS devise to record latitude and longitude or take a waypoint, it would greatly reduce the amount of location error and improve the assessment of the landscape around DVCs.

Another improvement would be to have equal number of years sampled for model building as well as testing. There were limited data available at the time the project was started. Five years of data were available for model building in Kansas City, but only three years were available for validation in Kansas City, and only four years of data were available for testing in St. Louis. With a shorter timeframe, there is less opportunity for DVCs to occur and usually fewer recorded for that time period. Even though the landscape characteristics match that of hotspots, the area will not be validated as a hotspot because the numbers of recorded DVCs will not meet the minimum requirement for a hotspot.

A third improvement would be to have a different landcover layer for each time period. I was only able to find one landcover layer for all of Missouri for 2005. Each area has a different rate of change of landcover over time. In rural areas there tends to be less change to landcover over time than in urban areas, unless there is a drastic shift of pasture to row crop. The type of row crop may also influence deer movement because some crops are easier to traverse than others and deer feed on types of crops differently. The urban landscape is steadily changing, with new developments being built and sprawl pushing the human footprint further into rural areas. These changes to landcover type could drastically affect deer movement and feeding behaviors. As larger tracts of forest are cut into smaller patches, there may not be wooded corridors to connect these patches which may keep local populations of deer separated as they stay close to the forest patches for shelter. As fields are converted into parking lots, there is less grazing area to support deer populations, and they may migrate out of an area. By having only one landcover layer, this vegetative change over time is not taken into account for this study.

The overall consensus from my research and those that came before is to consider roads near forested areas and public lands as high risk areas, as well as riparian corridors that intersect road ways. Providing effective wildlife underpasses could greatly reduce the occurrences of DVCs. With the development of more remotely sensed data and better accuracy in DVC locations, a more successful model for predicting hotspots can emerge. An alternate management technique for mitigating DVCs would be overall population control in the hotspot areas. With some public lands and residential areas providing refuge from hunting, there is little pressure to keep the deer population in check other than disease, availability of food, or collisions with vehicles. Some communities have tried relocating deer, adding birth control to food or having female deer spayed, which is very costly. Allowing some form of hunting in these areas would be a cost effective way to reduce local deer populations and could lead to a decrease in the number of DVCs. Wildlife provide both an aesthetic and financial benefit to the community, but as habitat continues to decrease or fragment due to urban sprawl, there will always be conflicts between wildlife and humans. This supports the need for continued research to better understand and potentially mitigate these conflicts.

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