A Thesis

entitled

Spatial Patterns of Deer Roadkill in Lucas County, Ohio

by

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Submitted to the Graduate Faculty as partial fulfillment of the requirements for the

Master of Arts Degree in

Geography

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An Abstract of
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Roadkill is a widespread occurrence in the United States. Particularly, deer-vehicle collisions (DVCs) pose societal, economic, and traffic safety concerns. DVC data was combined with landscape and roadway variables in a geographic information system (GIS) to examine factors associated with deer roadkill in Lucas County, Ohio. To explore patterns of DVCs, the data was analyzed for distribution, space-time trends, and hot spot clustering. Two regression methods were developed from 13 candidate variables to find contributing factors of landscape and roads experiencing statistically significant DVC incidents. In Ordinary Least Squares (OLS) regression, distance to parks & water, forest & habitat areas, traffic volume, time of year & day, and road contour were variables that significantly contributed to DVCs. In another method, Geographically Weighted Regression (GWR), it was found forest & building area, population, length of street networks, and distance to parks & water influenced DVCs. It is recommended to implement enhanced deer-crossing signage on the identified, critically high DVC routes.
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Make haste, my beloved, and be like to a roe or to a young hart upon the mountains of spices.
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List of Abbreviations

AADTC……………………………...Annual Average Daily Traffic Count
AVC(s)………………………………Animal Vehicle Collision(s)
CROS………………………………...California Roadkill Observation System
DVC(s)……………………………….Deer Vehicle Collision(s)
DOT………………………………...Department of Transportation
FHWA………………………………..Federal Highway Administration
GIS…………………………………...Geographic Information System
GWR………………………………....Geographically Weighted Regression
NCHRR………………………………National Cooperative Highway Research Program
ODOT………………………………...Ohio Department of Transportation
OLS………………………………....Ordinary Least Squares
VIF…………………………………..Variance Inflation Factor
Chapter 1

Introduction

Before the age of industrialization and modernization in the U.S., the landscape was widely non-fragmented with fewer man-made structures. Trail blazing, and later the construction of roads, contributed to the rift in land fragmentation - reducing habitat for some species and creating new habitat for others. In the case of deer, urbanization removes habitat, while clearing dense forest creates sought-after mixed cover habitat. As deer thrive best in mixed habitat, Lucas County is an ideal place of transitional forest, agriculture, grazing, waterway, riparian land covers.

In general, both humans and wildlife need space to move and disperse across the land. People have primarily used roads for ease of travel. Fragmentation of habitable spaces via roadways may inhibit this free movement for wildlife. When the land is not able to bear the substance of people and wildlife that they may dwell together, they must scatter abroad. Inability to journey across the landscape and spread out can lead to unhealthy clustering or breach of carrying capacity. While nature conservation is important, land development is also vital. People build, demolish, plant, uproot, destroy, create, sow, and harvest as they desire. At times and locations, there have been
devastative effects on the environment from pollution and resource depletion, while at
others people have been good stewards of the environment and have practiced sustainable
development. Inside Lucas County, is a city with trees, wetlands, rivers that flow through
it, and other natural habitats, making nature and urbanization inseparable.

From the age of indigenous exploration and discovery of the Americas, to
colonization, pioneering, and modern development, wildlife abundance and land cover
have certainly been transformed due to human activities. A good example of this
transitional people-environmental interaction is roadkill, which has contributed to
decreasing wildlife populations over time (Beaudry, n.d.). At first glance, roadkill may
seem to be a minor problem – a small notch in wildlife population decline overcome by
breeding in the next season. However, it is estimated by the Humane Society that
millions of vertebrate are killed each week in the US alone (as cited in National
Geographic, 2011), which is an indicator that roadkill can be a significant issue in regard
to wildlife population levels. Without proper stewardship of the environment in
developed areas, the natural environment can be impacted dramatically by less animal
species. Although many factors have influenced wildlife variety and abundance, roadkill
has been a contributing factor to decline (Lombardo, 2013). Among the other elements
imposing on wildlife are hunting for market consumption, pollution of natural resources,
and human density beyond the sustainability of the land. By implementing strategic
improvement plans aimed to reduce roadkills, the natural and developed areas can be
properly stewarded to restore a healthy balance of nature and modernization.

Roadkill is an unsightly and potentially hazardous problem all over the world
wherever vehicles and animals coincide. People and animals dwell together, sharing
aquatic, tellurian, and atmospheric spaces. As mobile beings, humans and wildlife will cross paths while roving through this space. It is at these intersections of contact where animals and vehicles collide, causing undesirable outcomes at times. Demonstrated in various environments, direct people-wildlife contact can lead to disastrous outcomes, especially for the animals that are involved. Travel by water has disturbed specific animals in the aqueous wildernesses such as the manatee, highly prone to boat propeller injuries and deaths, especially with increasing boat traffic (Wells, 1997). In the vast skies above, avian flocks and aircraft are not exempt from collisions. Canadian geese are capable of downing an airplane from power failure loss when ingested by an engine (Alge, 1999). Smaller birds and insects are susceptible to automobile smashes both on and above ground as well as to the large blades of wind turbines. Most commonly, animal-vehicle collisions (AVCs) take place on land, where traffic utilizes roads.

According to estimates of the United States Department of Transportation (n.d.), there are presently over 8.5 million lane miles of roads in the entire U.S. In the contiguous 48 states, roads average 11 feet lane width, resulting in land cover of roads to an area of 17,590 mi². The American Road & Transportation Builders Association (2010) ascribes road cover to less than 1% of the nation’s land area. However, fragmentation of the landscape by roads is clearly evident. The farthest one can go on land space before meeting a road in the coterminous U.S. is 21.8 miles, occurring in Wyoming near the southeast corner of Yellowstone National Park (Watts, 2007).

Roads have ecological implications as well. Forman (1998) estimates 15-20% of the U.S. is ecologically impacted by roads. Toxic chemicals from vehicles and road composition are introduced to water, land, and air. Road construction changes water
drainage networks and contributes to pollutants in stormwater runoff (Coffin, 2007). Ecological effects of roads extend to include: elevated concentrations of salt in water and soil; micro-climatization; decreased wetland volume; and noise disturbance (Forman, 2000).

Such anthropogenic constructions as roads can have profound effects on wildlife. Sometimes inhibiting population survival as with the threatened Florida scrub-jay (Mumme, 1999) and at other times regulating species over-population. Roadkill may serve as an institutional balance to breached wildlife population thresholds when the urbanizing environment diminishes the sustenance of the land. Roads may deplete the feral instincts of wildlife by facilitating increased interactions with humans and access to non-natural food sources. Roadkills can be viewed as an impact to species population where hunting and fur trapping once took place. Roads play a dynamic role affecting wildlife in regard to habitat fragmentation and interactions with humans.

During a period of one year the California Road Observation System (CROS) study counted over 6,000 roadkills of 196 different species from various routes in California (CROS, 2010). In attempt to understand the effects of roads on wildlife at Saguaro National Park, located in Tuscon, Arizona, Kline (2003) used a mathematical model to estimate roadside mortality. It was estimated 51,000 animals are killed annually on the 50 miles of roads that lie in or adjacent to both districts of the park, including around 17,000 amphibians, 27,000 reptiles, 1,000 birds, and 6,000 mammals. The Federal Highway Administration (FHWA) claims AVCs present an immediate danger to individual wildlife survival for some species, and certain threatened and endangered
species are faced with a further reduction in their population survival probability (Huijser, 2008).

AVCs are significant enough that each state department of transportation (DOT) has wildlife crossing signage as part of its traffic regimen. For example, the amphibian population decline, largely attributed to roadkill, because they often migrate en masse to or from breeding grounds or wetlands (Glista, 2007). Prior to implementing wildlife crossings, the endangered Florida Panther faced severe decline in numbers directly linked to AVCs and habitat genetic isolation (Huijser, 2008).

AVCs represent a serious conservation issue for wildlife, they also impact people to some extent. According to research carried out by the FHWA, almost all (95.4%) of AVCs result in zero human injury. Collisions with deer and other large animals can have a higher likelihood of resulting harm to the vehicle and riders. Furthermore, in review of national trends in AVC data, the FHWA has reported an increase in these crashes by 50% from 1990 to 2004. AVCs now represent almost 5% (or 1 in 20) of all reported motor vehicles collisions. Almost all collisions with larger wildlife result in substantial vehicle damages averaging $1,840 for a deer crash and even more costly for a crash with moose or elk. An estimated 200 people die annually from AVCs in the U.S. Some drivers also experience emotional trauma as a result of the danger they encountered and the killing of an animal (Huijser, 2008).

AVC studies take a nature-conservational approach. These studies emphasize wildlife corridor connectivity and reestablishing wildlife resilience in remnants of wildernesses. The ideal goal is to invigorate the remnants of wildernesses before animal species recede and disappear. Mech (1988) determined regions in Minnesota with road
densities exceeding 0.58 km² do not contain wolves whereas similar areas nearby with fewer roads do contain wolves. Wolf range and territory is limited by road density. To raise awareness of habitat fragmentation, conservationists formed a coalition known as “Freedom to Roam” as an initiative to integrate the science and stories of wildlife movement across North America. Among the organization’s partners is the Center for Large Landscape Conservation, ESRI, and the National Geographic Society. The wildlife corridors are passages that allow regular travel, seasonal migration, or population dispersal of different species. Without connectivity, species movements become constricted and wildlife cannot find food, reproduce, migrate, or adapt to habitat fragmentation or development; and may thus disappear. Essentially the Corridor Commons paints a picture of the need for wildlife corridors and landscape connectivity across all geographies of the continent. The maps of corridors created by naturalist anecdotes, projects, and people support scientific analysis, sustainable land use decision, and inspired strategies. So far, 400 corridors have been identified and mapped in Corridor Commons (World Wildlife Fund, 2016).

The National Park Service has been tracking mountain lion populations in California. Biologists have seen evidence of the cats roaming around on one side of Highway 101, believing they were looking for safe places to cross the freeway. Requiring up to 100 mi² to hunt, man-made obstacles such as the 101 or 118 freeways can prove dangerous for mountain lions when exploring territories and maintaining healthy gene pools. It is critical to provide linkages between intermittent habitats because urbanized areas cannot sustain the current mountain lion population according to Magruder (2009). Quite often the method of conservationist approaches include wildlife
capture and tagging by biologists, GPS satellite monitoring, and motion cameras to detect activity.

On a similar note, Peacock (2006) describes the journey of a “grizzly bear who crossed the freeway” journeying 50 miles back to the land in which he was raised as a cub. The observed bear is documented at dawn waiting for traffic to subside in the quiet hours after midnight before dashing across Highway 287. Managing through fence lines and two towns, the grizzly encounters another highway with link fences and only a vehicle or two pass every five minutes, but the fences make darting across the pavement impractical. Instead the bear followed railroad tracks below a freeway bridge to reach the land on the other side.

From the national parks to the outskirts of cities, AVC mitigation techniques have been the focus of many reports and studies. In order to understand where mitigation is needed, data must be collected to support decision making to protect wildlife and reduce AVCs. The National Cooperative Highway Research Program (NCHRP, 2007) has an extensive report on U.S. and Canada roadkill related data collection standards. Surveyed data were obtained from each state and province from transportation and natural resource management agencies. Generally, there are two types of data source related to roadkill: (1) AVC data from accident reports with or without animal carcass data; and (2) animal carcass data observed and/or removed from the road, usually collected by road maintenance or natural resource personnel. Excluded from their survey is data gathered by individuals or other organizations. Parameters collected among the agencies are not uniform, altering the usefulness and applicability of the data. Furthermore, it is unattainable to record all AVCs, the most thorough data collection is even underreported.
NCHRP (2007) identifies the main usages for roadkill data. One of the most basic uses of the data is gauging the magnitude of the problem. Knowing how many accidents are occurring, level of severity, and involved members is the first necessary step toward identifying and addressing the issue. Measuring the type of AVCs allows for calculation of associated monetary costs and can justify the expense of mitigation measures.

When the precise locations of AVCs are known, the data are often plotted on maps using GIS. The analyst can then use a clustering algorithm to find statistically different hot spots. Usually hot spots and certain times of day exhibit higher AVCs. Spatial statistic tests can be employed to analyze the roadkill locations such as a density analysis used by Hardy (2008). Predictive models based on landscape characteristics and habitat preferences of specific species helps to identify potential areas susceptible to many AVCs. After roadkill hot spots are revealed, the characteristics of hot spots and cold spots can be compared. This provides for recognition of road facility, traffic, and landscape attributes with high AVCs. Conditions prompting hot spots are indicated by adjacent vegetation and land use, topography, traffic volume and speed, road features, and visibility, to name a few. Road planners can use this information to design safer roads and accurate mitigation places. Roadkill data is of course necessary for evaluating mitigation techniques before and after implementation. Lastly, road mortality rates have been used as an index to assess species population size (Gehrt, 2005).

Since AVCs are a direct result of roads, it helps to be aware of road designs that are especially troublesome to wildlife. Two lane rural/suburban roads and low to medium capacity highways that pass through wildlife habitat already have high likelihood for AVCs. In addition to the placing of roads in habitats, Huijser (2008) sets
out considerations for road design. He suggests that roads with steep side slopes can hide approaching animals from a driver’s view. Roads that cut into the terrain are typically within hilly or mountainous topographies or simply located near hydrology. Secondly, anticipated problem sites will likely be near drainage crossings, migration corridors, or known animal habitat. If road placement is unavoidable in these zones, the roads should be designed with minimal curves, avoiding steep side slopes, and ample clear zones away from the road. Culverts below roads should be wide enough to include opportunities for wildlife to cross under the road. Roadside ditches, water drainage sources, and ornamental vegetation from road construction may actually be an attractive nuisance.

Although median barriers and retaining walls significantly improve safety to drivers, these are deadly barricades for animals, and all the more when the barriers provide a way in, but no way out. Concrete median barriers are most often used on highways and are temporarily erected during construction. Temporal construction medians are especially harmful because it can throw off the animals’ past learning curve of familiar crossing paths. Detriments of barriers can be reduced by having large cutouts at the bottom of the concrete blocks for safer passage of small to mid-sized species and placing gaps in the barrier at strategic hot spot locations for large animals. As for incorporating better management practices for wildlife corridors Beier (2008) offers a good set of guidelines in his research.

Huijser et al., (2007) provide a number of mitigation measures for safe wildlife crossing ranging from modifying driver and wildlife behavior to substantial infrastructure changes. To reduce traffic volume during seasonal and temporal peaks in AVCs, drivers are advised to choose an urbanized alternate route, lower speed, or heighten alertness.
Standard wildlife crossing signs are generally ignored. Non-standard graphical and variable message signs are more affective at grabbing drivers’ attention. With seasonal signs set up during migration or mating times, driver habituation is less likely to occur. Additionally, roadway lighting and clearing side vegetation mitigate AVCs but contribute to natural landscape degradation. Likewise, many such aversion techniques are available, ranging from culling to intercept feeding, but do equal damage to wildlife and habitat. Sometimes public education is a necessary step and roads throughout national parks require cross guards when animal migration occurs.

Mitigation efforts are further limited by cost and practicality. Culverts, underpasses, and overpasses, though deemed effective, are rather expensive to implement. Additionally, the fencing needed to funnel wildlife into appropriate crossing zones may indeed be another barrier. Each of these mitigation measures require another round of research to examine real world effectiveness and cost-benefit analysis. For example, animals may be apprehensive to share an overpass bridge if a natural predator is using the same crossing structure waiting on the other side (Clevenger, 2007).

As discussed so far, the widely known AVC studies are documented around the remaining “wildernesses” of North America. This part of the introduction will divert attention away from these kinds of environments to AVC studies in urbanized settings less associated with pristine environments and will include an overview of novel data collection methods.

Primarily, the collection of roadkill data has been left up to various state agencies. With a limited number of individuals recording roadkill data, the data sets are in no way thorough or comprehensive, and are limited in area. Recent advancements in technology
have opened the doors to a broader group of potential data collectors and volunteers of geographic information (Elwood, 2008). Expanding access to GPS devices have spawned what Goodchild (2007) calls “citizen censors.” Coupled with web interface data repositories, volunteering citizen sensors contribute their scientific observations of roadkill. Thereby mounting the level of participation and improving the scope of roadkill data collection.

One such volunteered citizen scientist program is CROS, a California initiated roadkill study aimed at unifying the participants of roadkill data collectors, both freelance and agency members alike. The wildlife-crossing.net website provides a common survey sheet to ensure uniform data collection. The observations are later entered on the website providing an open access database and interactive map powered by Google where aggregate observations are viewed. Participants range from casual commuters spotting roadkill to enthusiastic professional researchers. Already in its early stages CROS (has contributed to the understanding of ecological, wildlife behavior, and transportation issues associated with roadkill (CROS, 2010). As sister website for state of Maine has emerged as result. Persistent and routine roadkill surveying adds an important temporal aspect to research (Smith-Patten, 2008; Caro, 1999). Seasonal trends and time of day variability of AVCs may otherwise go unnoticed among wildlife species.

Mass publicity is essential for volunteered GIS roadkill data collection to be most affluent. Several citizen science websites exist but may be ineffective due to lack of consistency of the same spatial-temporal participation. Where citizens science collaborations lack, scrupulous field surveys make up ground. Field surveys usually occur on a local or regional scale. For example, Kanda (2005) recruited volunteers to
assist with a Virginia Opossum roadkill survey and then used logistic regression to determine landscapes associated with roadkill. Various topographic features around roadkill hotspots are useful for conducting logistic regression analysis (Finder, 1999). Anywhere roads and wildlife cross paths, roadkill is an inevitable part of negotiating the landscape; causing property damage now and then and mortality. Most roadkill studies have centered on national park wildlife, ungulates, or singular species. Investigating site and situation characteristics of roadkill locations will lead to better understanding of landscape cover inducing road mortality, areas devoid of both roadkill and wildlife, and planning measures to reduce negative impacts of roads on wildlife.

1.1 Research Questions and Objectives

Provided the context of Deer Vehicle Collisions (DVCs) in Lucas County in chapter two of this study, this research explores the following questions: (1) What are the spatial distribution patterns of DVCs? (2) What areas are more prone to DVCs than others? (3) What factors are contributing to deer roadkill? (4) What trends are found in DVC occurrences? (5) What can be done do reduce and mitigate DVCs in Lucas County?

In order to address the research questions this study focuses on five main objectives: (1) incorporate DVC, roadway, and land use data into a GIS to identify patterns reflected in deer roadkill; (2) contribute to the body of knowledge on deer roadkill for a county level scale; (3) conduct spatial & temporal analyses of DVCs in Lucas County; (4) perform regression analysis to identify leading predictive factors of DVCs; and (5) interpret the data to offer planning solutions for DVC prone areas and provide insights for the implications of DVCs.
It is inferred that particular landscape and roadway variables are associated with DVCs. Quantitative data representing these variables assist to identify where roads are susceptible to high DVC rates. Variables calculated for this study build upon prior research to establish prominent surrounding variables affecting DVCs. Researchers have used both field-measured and GIS derived variables (Clevenger, Hardy, & Gunson, n.d.) Using GIS provides an array of tools for analysis of a county-wide rundown of DVCs. Studies have looked at a variety of habitat and landscape characteristics and road parameters to explain roadkill. The main roadway variables considered are: speed limit, barriers, traffic counts, visibility, fencing; and as for landscape: area of residences and buildings, proximity to habitat, proportion of public lands or agriculture, and landcover diversity (Gunson, Mountrakis, & Quackenbush, 2010). Conducting data analysis in a GIS for such variables will confirm the results of other research and offer new insights for DVCs in Lucas County, Ohio.

Few other deer roadkill studies have focused on a single county. DVC research reports have previously been aggregated by counties statewide for Ohio (ODOT, 2016). This study focuses on deer vehicle collisions (DVCs) in Lucas County of northwest Ohio. Results of other ungulate roadkill studies may be difficult to parallel with Lucas County for the reason of varying spatial scales and regional characteristics of the study areas. A county-level scale provides an encompassing analysis for metropolitan, suburban, and rural areas. Ranges of other roadkill study areas have covered expanses over national parks (Clevenger, Chruszcz, & Gunson, 2003), statewide (Hubbard, Danielson, & Schmitz, 2000; Iverson & Iverson, 2009), groups of counties (Grovenburg et al., 2008), metropolitan areas (Nielsen, Anderson, & Grund, 2003; Ng, Nielsen, & St. Clair, 2008),
and dissects of highways or streets (Glista, DeWoody, DeVault, & Rhodes 2006; Shilling, 2015).

A new facet contributing to the body of knowledge of roadkill research is space-time pattern mining, to measure flux of roadkill overtime per location. Alongside with spatial-temporal analysis, mapping spatial DVC densities offers a visual clarification of places with higher rates of DVCs. To detect patterns of statistically significant clustering or dispersion, hot spot analysis is a handy tool. Often, hot spot interpretation is an initial step before regression modeling in order to explore which variables may contribute to DVCs.

A spatial-temporal analysis identifies how DVCs have changed over time and place in Lucas County. This helps to assess the temporal direction and position of DVCs, whether trends are waxing or waning. When the spatial relationships of DVCs are understood, solutions can be made to help curb them. Hot spot analysis addresses where higher than expected DVC occur in Lucas County, while regression analysis allows further modeling, examination, and exploration of factors behind observed DVCs (Scott & Janikas, 2010).

Researchers desire to understand factors influencing DVCs in order to prevent them, regression modeling is a step toward achieving that goal. In order to achieve the research goals, regression analyses test the hypothesis that certain landscape and roadway characteristics are more prone to DVCs than others. Identifying spatial relationships can assist planners to lower the DVC problem.

Regression analysis models the factors that contribute to DVCs. Numerous studies have used some form of linear regression with various software to find
contributing factors to roadkill. For example, Barrientos & Miranda (2012) employed multiple regression analysis to explain around 25% of variation in pole-cat roadkills. Logistic regression was used by Clevenger et al., (n.d.) to identify significant parameters predicting ungulate collisions. Nielsen, Anderson, & Grund (2003) modeled landscape factors influential to deer-vehicle accidents. As each of these study areas are different, similar regression modeling with locally measured variables are expected to produce an outcome specific to Lucas County. So far, researchers have found variables influencing the location and rate of roadkills. This particular study hopes to identify significant factors of DVCs associated with Lucas County, and compare results with other studies for greater understanding. Results from the data and regression analyses will provide direct assessment of DVCs for Lucas County, offering locally applied mitigation strategies.
Chapter 2

Study Area and Methodology

2.1 Study Area

Lucas County is situated in the southwest corner of Lake Erie. Sharing a state line with Michigan to the north and a border with the Maumee River to the south before extending east of the river. The City of Toledo is the main urban district of the county. The Ohio Development Services Agency reports Lucas County is home to around 430,000 residents and nearly 400,000 registered motor vehicles using 2,330 miles of road. Its three greatest land uses are urban (36.69%), cropland (36.56%), and forest (14.88%); also having over 4,311 acres of wildlife areas within a total of 340.4 mi² (Ohio Development Services Agency, 2014). The topography of Lucas County is relatively flat and it has a temperate climate. In modern times, Lucas County is no longer a vast expanse of unsubdued wilderness, having been modified by the indelible human footprint. It is therefore appropriate to adequately manage its resources in order to keep a healthy balance of modernization and nature in the land.
2.2 A Focus on Deer

Though all roadkill studies are important, this study focuses on deer. Being the largest ungulates found in Lucas County, deer pose the risk of significant economic and societal impacts. Ohio’s population of deer is estimated recently at 700,000 (Ohio Division of Wildlife, n.d.). According to Ohio Insurance Institute (2013), 20,683 DVCs were reported in Ohio during 2012. State Farm has ranked Ohio 19th as a high risk state for DVCs with a 1 in 131 chance of hitting a deer. Approximately 1.25 million DVC claims occurred in the U.S. over 1 year with the upward national cost per claim for DVCs averaging $4,135 (State Farm, 2015). In addition to vehicle repairs, medical costs,
towing and law enforcement services, deer carcasses strung on the roads must be removed and discarded by work crews. Not only do DVCs cause immediate wreckage, but they also pose threats to safety for fellow travelers passing by the collision scene. Adverse reactions may ensue as drivers swerve to avoid the carcass, and accident sites could slow down the flow of traffic.

Considered rampant by some in Lucas County, DVCs are actually even more prolific in the northeastern counties of Ohio. In 2012, Lucas County ranked no. 19 out of 88 counties in Ohio for highest number of DVCs (ODOT, 2012). Statewide in the year 2012, DVCs were reported bringing about 1,013 injuries and six fatalities (ODOT, 2013). Lucas County had the corridor with the highest level of DVCs in 2014 for ODOT District 2, located on State Route 64 between US-20 Airport Hwy and Reed Rd (ODOT, 2014).

Before proceeding to details, it is important to have a foundational understanding of deer profiling for this study. White-tailed deer are currently the largest ungulate wildlife in Lucas County. Breeding season among deer begins in mid-October. The doe’s gestation lasts 200 days on average, bringing forth 1 to 3 fawns from mid-May through July (Ohio Department of Natural Resources, n.d.). Deer typically live gregariously, excepting that bucks roam more independently. Home ranges for deer can average about 1mi² (Bowhunter, 2010), but can be more or less depending on habitat quality and population size (Piccolo et al., 2000). White-tails ruminate a wide variety of natural grasses, barks, fruits, crop grains, and fungi. And may be either lured by or prey on suburban gardens. They prefer successional forest cover with transition areas of grassy openings, shrub lands, and agriculture (VerCauteren, 2003), and thrive near natural habitats with nearby rivers and streams. White-tailed deer can sail over fences,
leaping as high as 10ft., as far as 30ft., and are swift up to 30mph (National Geographic, 2016).

In the past, the deer population was in decline. According to VerCauteren (2003) deer were over-hunted to endangerment status around 1900, but today they have rebounded to pre-European settlement levels because of restrictions on hunting. Wildlife managers aim to avoid eradicating deer completely and also to prevent unnecessary population abundance. In essence, this strategy is pursued because it is undesirable for white-tail deer to become overly common so as to displace the breeds of other wildlife or to cause an imbalance in the ecosystem from over-foraging plants. Wildlife managers are concerned with finding the ideal level of deer population - appeasing both human enjoyment for deer while limiting the overpopulation dilemma. High levels of deer can cause increased risk of motor vehicle crashes, and damage to vegetation through over-foraging by deer. In addition, the quality of life for deer is diminished as a result of inadequate space and nutrition. In these conditions a doe may abandon her fawn. Complaints of traffic safety and damage to lawns, plants, crops, and trees can lead to the labeling of deer as a 'nuisance. In fact, deer roaming in spaces close to human contact may impose threats to safety. In the community of Lucas County, a 110 pound dog was gored to death by a stag due to elevated aggression in mating season (ABC 13 News, 2015).

When cultural and/or land conditions are unable to support the level of deer, wildlife experts implement strategies to reach a safe carrying capacity. Roadkill is an operative, or an effect of overpopulation in urban areas, but it is an unfavorable approach to controlling deer population. Natural predators, such as coyotes prey on deer fawn.
However, there are a limited number of coyotes in Lucas County compared to fawn. Introducing these kinds of natural predators into urban areas is also inappropriate. People don’t want to mix with coyotes in their everyday lives either. Without natural predators, hunting seasons are introduced to moderate the size of deer herds. Lowering the urban population of deer via harvesting or controlled kills could ultimately decrease DVCs. As deer come into close proximity to humans, their behavioral instincts become modified. In Findlay, Ohio (a city less than 35 miles south of Lucas County), a stag leaped through a glass window at a town center restaurant, causing damage throughout the building (Sanctorum, 2015). Naturally, deer avoid such places because they typically avoid people in general. However, deer are lured by people’s gardens, diversified trees, crops, ornamental flower beds, and other lawn edibles. In addition, they simply need more roaming space as a result of an ever-encroaching society.

Drawing near to human settlements puts deer at risk for vehicle collisions and over time may cause reluctance to move away from noisy scenery. According to Shilling and Waetjen (2012), wildlife is affected by traffic volume noise and vehicle emissions. One result of wildlife traversing through human populated areas is increased resistance to human-place avoidance. Thereby assimilating wildlife to dwell in close proximity to humans. Likewise, providing feed to wildlife immensely alters their behavioral temperament. Handing out routine portions of feed causes wildlife to become dependent upon people, and reduces their fear of humans as well as contributes to an unbalanced diet.

White-tailed deer have adaptive ability and are somewhat willing to live in close proximity to urban regions and people. As deer become acclimated to residential streets
and adapt their behavior, they are often welcomed as visitors in people’s yards in urban areas. Occasionally one even hears quaint news stories of a person keeping an orphaned deer, bird, or some other wild animal as a domestic pet. This is a controversial, yet mostly un-harmful practice. However, still others go beyond this benign practice, and keep dangerous animals as pets. For example, there was a case of a person in Ohio, who kept illegal & exotic animals and released them into the open (Kendall, 2012). These instances can be harmful to society and to the exotic animals.

The taming of feral animals, not useful for domestication, is generally inefficacious. Deer have not been widely considered agreeable partners for domestication, but this trend is on the rise in the United States. Unlike oxen, deer are not suitable to be harnessed for plowing nor do they possess the strength to serve as beasts of burden. Within industrialized societies, cattle are raised for meat or dairy. Deer are not ridden like horses or kept as house pets, but venison and related by-products are growing in popularity. In fact, there is a growing niche market for exotic game, sustainably raised, and healthier meats, and venison falls into the category of alternative food stock to the commonplace beef, pork, and poultry. Since hunted or wild-caught venison cannot be commercially sold in the U.S. without being inspected, some have turned to deer farming. Conveyed by Schmitt (2014), raising deer can be more profitable than traditional livestock as they are “low-care”, adaptable to different terrains, consume less fodder, and are less damaging to pastures. A deer farmer in Vermont turned his land lot more lucrative by selling farmed venison and antler velvet, a popular medicinal by-product sold in Asian markets (Schmitt, 2014).
This changing perception of deer and their adaptation to urban environments has led to an increase in DVCs and other clashes between people and the deer population. This thesis will provide a more in-depth examination of these overlapping environments from a geographic perspective. The conclusion will provide planning strategies for mitigating the effects of these relationships.

2.3 Deer Vehicle Collision (DVC) Observations

In order for deer roadkill to occur, it must be assumed there are deer present with nearby traffic on roads. Equally important to identifying deer roadkill locations, is knowing where deer roadkill incidences do not occur. There are a variety of circumstances that negate the presence of roadkill (Table 2.1). In particular, areas of successful deer crossings are attributable to safe-crossing implements, favorable roadway characteristics, landscape surroundings, and time & chance. Areas of unsuitable deer habitat are important in the dialogue of marking environmental shifts. Urban centers represent areas generally free from deer collisions but portray a landscape devoid of wildlife. Whereas the land once made room for nature, it becomes a concrete settlement, driving out nature. For example, the research shows relatively fewer deer collisions in the Toledo city urban center, an area seldom occupied by deer.

Table 2.1 explores possible places where deer may be found on the globe. For instance, deer are not usually found in the ocean, nor are they frequently found in dense urban areas, therefore drivers are free from DVCs in those places. Deer in a forest without roads equates to a place of zero roadkills because vehicles have not traversed it.
As a creative thinking exercise, presence or absence of deer may be better illustrated by a game of tic-tac-toe as a grid system overlaying a hypothetical place. \( X = \text{deer}; \ O = \text{no deer in proposed situations.} \) Each game played is a stalemate. Taken a step further, deer roadkill may only occur in one ‘X’ place, where deer and driver meet together.

*Table 2.1* Matrix of deer locations.

<table>
<thead>
<tr>
<th>Unoccupied / Abandoned Zones (i.e. roads without traffic, reverting to nature)</th>
<th>Unconnected Habitat / Absence of Deer (i.e. land is sustainable for deer, but is beyond range or otherwise inaccessible)</th>
<th>Deer and driver travel paths intersect at the same time and space (roadkill)</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>O</td>
<td>X</td>
</tr>
<tr>
<td>Unsuitable Habitat / Absence of Deer (e.g. Barrenness, Dense Urban, Concrete, Industrial Zones)</td>
<td>Isolated Habitat (e.g. deer on an island with very limited traffic)</td>
<td>Successful road crossings (both deer and vehicles traversed the landscape without incident)</td>
</tr>
<tr>
<td>O</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Wilderness as a large water body or sky (no roads travelled and no deer)</td>
<td>Wilderness / Suitable habitat (without roads)</td>
<td>Wilderness as land devoid of both deer and roads (out of home range for both deer and humans)</td>
</tr>
<tr>
<td>O</td>
<td>X</td>
<td>O</td>
</tr>
</tbody>
</table>
2.4 Methodology

2.4.1 Data Source and Processing

Calculating spatial parameters addresses the research objective to develop regression models for finding quantified contributing factors of DVCs. Variables were extracted from DVC data sets, as well as remotely sensed land use classification, census tracts, hydrology, building footprints, park lands, and street network geospatial vector data.

Ohio motorists are required by law to report DVCs within 24 hours. Deer collision data was retrieved from the Ohio Department of Transportation (2015) via the Highway Safety - GIS crash analysis tool. Data for this study was gathered for years 2011 through 2015, comprising a 5 year study period. Queried results were inspected for completeness and locational accuracy. Crash reports with invalid coordinates were removed, along with duplicate reports. For instance, if two vehicles were involved in a deer collision, two separate crash reports would recount the same incident, therefore a selected report would be omitted from the study. However, it was unknown how many deer were sighted attempting to cross a road from the traffic accident reports, as typically they are gregarious travelers. Furthermore, it could be two or more drivers hit the same deer, or multiple drivers collided with more than one deer. Figure 2-2 illustrates the locations of DVCs over five years in Lucas County, Ohio. 1,707 records of DVCs were utilized for the study. There were actually >1,707 DVCs in Lucas County for that time period but records with missing details were omitted. Deer roadkills are not always
reported, and combined with the omitted records, it can be estimated closer to 1,800 DVCs occurred in Lucas County from 2011-2015.

*Figure 2-2* Deer vehicle collisions in Lucas County, Ohio, 2011-2015.

Also contained in the deer collision data were important details regarding vehicle speed, road conditions, date, time, and weather. Five variables were extracted from the crash details and were assigned dummy values. Posted speed limit was partitioned as low (≤40 mph) or high (≥41 mph). Road contour had four categories (straight-level, straight-grade, curve-level, and curve-grade). The road grade indicates change in elevation as compared to a level segment of street. Any missing road-related values were ascertained and verified using Google Street View for a complete and accurate table. Seasonal attributes were divided into three month increments beginning with January. The deer collision data also captures reported light condition at the time of incidence (dawn,
daylight, dusk, dark-lighted, and dark-no lights). Weather related conditions were grouped into three categories (1-clear; 2-cloudy, fog, smog, smoke, & other; and 3-rain, sleet, hail, snow). As for these categorical attributes, binary values were assigned for each classification in order to prepare the data fields for testing significance while running regression.

A population density variable was implemented from 2010 census data within block groups for Lucas County. Population reflects change across landscape. Suburban areas are more densely populated than rural places. The DVC points were conferred a population density value from the block groups they fell within. Not many other deer roadkill studies have regarded a variable for population density.

As DVCs have been found to cluster near public lands (Nielsen et al., 2003), a variable for distance to nearest park was computed from state park, forest, nature preserves, and wildlife areas extracted from various shapefiles. Distance to nearest water resource (i.e. rivers, creeks, and streams) was calculated from ESRI hydrology data and unpublished Lucas County floodplains data. The nearest distance to parks and water resource was measured for each roadkill data point.

Four additional variables were tabulated from 1 mile diameter buffers around each DVC point. The sum of street lengths, building area, forest area, and habitat area features were extracted from the surrounding buffers and assigned to the DVC points. Each feature class was measured by intersecting and tabulating the layers that were encompassed within the buffers. The length of street arcs were summed within the buffers as well as building areas of Lucas County. From 30 meter resolution Landsat satellite TM imagery, forest and deer habitat variables were derived. After converting the
raster set into vector data, forest was classified to include deciduous, evergreen, and mixed cover. Likewise, deer habitat coverage was defined as forest, pasture/hay, row crops, and woody wetlands. The areas for these two variables were also tabulated within the buffers. Densities were not used because the calculations were made in equal buffer areas. Unlike research sectoring roadkill counts per road segment on individual survey routes (Glista et al., 2006; Markolt, 2012; Shilling, 2015), this study measures DVCs for the Lucas County street network as a whole.

Traffic analysis zones were used as the polygon aggregation for hotspot counts. The traffic analysis zones represent areas of similar characteristics, providing for meaningful analysis. Another polygon count method for incidence data is uniform grid cells used by Barrentos & Miranda (2012). Selecting an appropriate polygon layer to count the incident points is crucial, having influence on the study results.

Traffic count data was retrieved from Toledo Metropolitan Area Council of Governments (2016), while traffic counts for the Ohio turnpike traversing Lucas County were sourced from Ohio DOT (2013). Annual average daily traffic count (AADTC) data points from the streets were assigned to the nearest DVC, then were reviewed and edited to ensure correct AADTC location values were attributed to each crash point. Very few DVC locations did not have an associated street AADTC. In these cases, nearby similar functional classes of roads were compared to assign an appropriate traffic count.

There were also several other potential candidate variables considered for this research, but were constrained due to limitations of datasets and availability. For example, Clevenger et al. (n.d.) considered road width, barrier lengths, and average distance to vegetative cover from sides of roads in their study. Hubbard et al. (2000)
included a variable for number of street lanes and bridges. Additionally, locations of every deer crossing sign already in place would be an important variable and would help to assess effectiveness of mitigation. Furthermore, data containing deer abundance counts and places allowing deer culling would be beneficial to see the influence on nearby deer roadkills.

2.4.2 Preliminary Expectations

The author expects lower speed limits to decrease DVCs, providing a higher rate of successful deer crossings. Higher speed limits may be associated with greater DVCs depending on the surrounding area – particularly whether or not it is urbanized. Higher speeds in a rural area may lead to more DVCs. On a similar note, increase of traffic volume (AADTC), may either indicate higher DVCs or could deter crossing attempts. An increase of road networks and buildings (Nielsen et al., 2003) marked by less habitat may lower DVC probabilities. Greater surrounding forest and habitat should also mark an increase in DVCs. As for temporal variables, higher DVCs are expected to be associated with the season of autumn and at night or dusk and dawn.
Chapter 3

Data Analysis

After preparing the data and calculating variables, multiple analyses can be performed, extracting valuable understanding of DVCs in Lucas County, Ohio. First, temporal statistics furnish information of the times and seasons with the highest number of DVCs. Second, visual density provides clues of spatial distribution of where DVCs are taking place. Third, Space-time pattern mining finds significant hot or cold spots over time. Fourth, aside from the time element, hot spot analysis covers high and low clustering values for aggregate incident data. Last, in chapter four, regression analyses can be performed from the calculated variables and output from hot spot analysis.

3.1 Temporal Analysis

Consistent with other seasonal collision data (Ng, Neilsen, & St. Clair, 2008), DVCs peak in the fourth quarter of the year (Figure 3-1). In summation, >45% of DVCs in Lucas County occur in the months of October through December. Typically the public is informed to be alert for deer crossings during this time of year, aligning with rutting in male ruminants and broadened travel ranges.
The histogram of total DVCs per year (Figure 3-2), provides a linear trend line for the past five years in Lucas County. Overall, deer roadkill has slightly increased. This means more should be done to alleviate the number of DVCs so that the trend declines, for an overall improvement in traffic safety. Mitigation remarks in the conclusion section offer effective strategies to reduce DVCs in the study area.

Figure 3-1 Lucas County, Ohio DVCs by season, 2011-2015.
3.2 Cluster Analysis

In order to identify patterns in DVC incidences, the spatial distribution of DVCs must be evaluated. To help establish whether the data show clustering patterns, the average nearest neighbor analysis provides a key index of spatial distribution. The resultant nearest neighbor ratio was 0.413, since this value is <1, it means the pattern exhibits clustering, and are statistically significant with a p-value of 0.

For a more visual interpretation of clustering, a point density analysis identifies places where DVC points are greatest within a specified distance (Figure 3-3). It provides a better pattern recognition than looking at the points themselves. Places where high DVC densities are correlated with higher densities of certain landscape features, may suggest an element increasing roadkill. Several of the highly dense clusters are coincident with metroparks. Low values appear to be associated with rural agricultural
lots and the Toledo urban area. Greatest densities are places in need of further exploration because they account for areas of especially recurrent DVCs. This study has detected the top five trouble routes for DVCs per mile for Lucas County based on densities per road length. (*Table 3.1*).

*Figure 3-3 Greatest densities of DVCs*
Table 3.1 Top five DVC corridors in Lucas County 2011-2015.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Route</th>
<th>Beginning / End Reference</th>
<th>Length (Miles)</th>
<th>Total DVCs</th>
<th>DVCs / Mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>SR 64</td>
<td>From Reed Rd to US 20 Airport Hwy</td>
<td>2.25</td>
<td>85</td>
<td>37.8</td>
</tr>
<tr>
<td>2</td>
<td>Navarre Ave</td>
<td>From S Lallendorf Rd to S Wynn Rd</td>
<td>1.00</td>
<td>36</td>
<td>36.0</td>
</tr>
<tr>
<td>3</td>
<td>Central Ave</td>
<td>From Reynolds Rd to Talmadge Rd</td>
<td>1.50</td>
<td>32</td>
<td>21.3</td>
</tr>
<tr>
<td>4</td>
<td>Dorr St</td>
<td>From Eileen Rd to N Byrne Rd</td>
<td>1.57</td>
<td>28</td>
<td>17.8</td>
</tr>
<tr>
<td>5</td>
<td>SR 64</td>
<td>From Waterville-Swanton Rd to S Berkey Southern Rd</td>
<td>2.05</td>
<td>35</td>
<td>17.1</td>
</tr>
</tbody>
</table>

Depicted in the map below (Figure 3-4) are the routes with the greatest densities of DVCs referenced in Table 3.1.

*Figure 3-4 Lucas County top five DVC corridors 2011-2015.*
3.3 Space Time Pattern Mining

DVCs can be measured according to location and also with an added time dimension, resulting in an emerging hotspot analysis. Figure 3-5 gives a visual of data aggregated into space-time bins, each bin contains a count of points that occurred at the location for the specified time step interval (ESRI, 2016a).

![Space Time Cube Diagram](image)

Figure 3-5 Visualizing the space time cube (ESRI, 2016a).

The space time cube, created for DVC trends over 3 month time was sliced into 774 time bin locations, resulting in 20 time steps for a five year period. Overall, the trend direction was not significant, meaning the DVCs have stayed relatively constant in their respective count locations over the past five years in Lucas County. According to the space time cube characteristics, generally DVCs have not been on the rise in Lucas County, nor have they been reduced. Planners may aim to not only stabilize the occurrence of DVCs, but proactively drive down incidences annually.
After the space time cube is formed, the emerging hot spot analysis identifies statistically significant hot and cold spot trends over time from the cube input (*Figure 3-6*) (ESRI, 2016b).

*Figure 3-6* Space time cube into emerging hot spot analysis (ESRI, 2016b).

Display of the trend bin values from the resultant emerging hot spot analysis in *Figure 3-7* reveals a statistically significant increasing or decreasing trend for the count values at each location. A few locations in blue have seen a downward trend while most locations have remained constant, without a significant trend value. In red color, there appears an upward swath of hot spots through Lucas County indicating values have increased in these bin locations over time. Areas of upward shifting trends as seen in the figure, may indicate deer are dispersing through central Lucas County in recent times.
Another result of the emerging hot spot analysis categorizes patterns of the data (Figure 3-8). A few areas seen in red are new hot spots, with the most recent time step interval hot for the first time. A section of the Ohio Turnpike is one of the new hot spots. Another new hot spot is near to a past demolished mall site, now an empty brownfield, that has been slowly reverting to natural ground. Most other locations were non-emergent, having no patterns detected over time. The sporadic hot spots are intermittently hot throughout the time step intervals. Two main sporadic hot spots occur around Oak Openings Metropark and Side Cut Metropark.
3.4 **Optimized Hot Spot Analysis**

Whereas the emerging hot spot tool shows a time component, the optimized hot spot analysis displays spatially high or low clustering values. Since DVCs are incident data, they must be grouped to form counts of incidences for the values analyzed. Two different aggregation methods were used to compare output. Different results were obtained depending on the polygon aggregation method used.

The first optimized hot spot analysis counted incidents within the traffic analysis zone bounding polygons (*Figure 3-9*). The hot spots show where a statistically significant number of unsuccessful deer crossings take place. Interestingly, low clusters
occurred in the urban center of Lucas County and high clusters were concentrated in the southwestern rural region.

*Figure 3-9* Lucas County optimized hot spot analysis bound by traffic zones.
The second aggregation method utilized a fishnet grid overlay to count incidences, within bounding traffic analysis zone underlying polygons, wherein incidents are possible (Figure 3-10). The locations of these particular hot spots in the above figure are coincident with large metropolitan parks and parcels of moderately undisturbed areas. Major routes identified within statistically significant hot spots of the fishnet polygon bound by traffic zones method include Airport Hwy, State Route 64, Ohio Turnpike, Anthony-Wayne Trail, Glendale Ave, Central Ave, Sylvania Ave, and Navarre Ave.

Comparing two aggregation methods, the incident counts differ in output depending on which polygons are used. The traffic analysis zones create larger count groups whereas the fishnet combined with traffic zones method has more narrow cells aligning routes. Upon examining the results of the optimized hot spot analyses, maps...
were further investigated to explore possible influential landscape and roadway characteristics among high values of DVCs.

The hot spots direct where to look for clues of environmental surroundings that may lead to more DVCs. The purpose of this study is to suggest why DVCs are higher in some places than in others, postulating that higher speed limits and forested or suitable habitat surroundings prompt more DVCs. Discovering characteristics of places experiencing a higher rate of DVCs, helps to find contributing factors of higher than expected DVCs, and confirm results of other similar research.

Now that significant hot spot clusters of DVCs have been identified, the results of the hot spot analysis can be input for regression modeling along with the quantified variables. Regression analysis discovers spatial relationships prompting DVCs, particularly in these hot spot areas.
Chapter 4

Spatial Relationship Models

4.1 Ordinary Least Squares (OLS) & Geographically Weighted Regression (GWR)

The regression modeling portion of this research is used to help determine what landscape and roadway characteristics promote DVCs. Whereas spatial patterns and trends have been identified through cluster analyses, regression analysis seeks to model the influential factors contributing to observed spatial patterns. The OLS tool creates a single equation to model a dependent variable and each explanatory variable (Scott & Janikas, 2010). In this case, the research intends to model DVCs as a function of the independent variables in Table 4.1, to test the hypothesis that certain landscape and roadway characteristics are more prone to DVCs than others. As referred to in the research objectives, a list of 13 variables were compiled from intrinsic deer collision data, GIS processing, and other factors considered by prior researchers.
**Table 4.1 Independent variables.**

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Classification</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Weather Condition</td>
<td>Environmental</td>
<td>Categorical value for weather condition at time of deer collision.</td>
</tr>
<tr>
<td>2. Seasons</td>
<td>Temporal</td>
<td>Categorical value for collision dates grouped quarterly.</td>
</tr>
<tr>
<td>3. Light Condition</td>
<td>Temporal/Road</td>
<td>Categorical value for magnitude of light at time of deer collision.</td>
</tr>
<tr>
<td>4. Road Contour</td>
<td>Road</td>
<td>Categorical value for grade and curvature of road.</td>
</tr>
<tr>
<td>5. Posted Speed Limit</td>
<td>Road</td>
<td>Categorical value for high ≥41mph; low ≤40mph speed.</td>
</tr>
<tr>
<td>6. AADTC</td>
<td>Road</td>
<td>Annual Average Daily Traffic Counts</td>
</tr>
<tr>
<td>7. Linear Feet of Streets</td>
<td>Road</td>
<td>Tabulation of street arc lengths in ft within 0.5 mile radius buffers.</td>
</tr>
<tr>
<td>8. Population Density</td>
<td>Landscape</td>
<td>Tabulation of population per mi² within census block groups.</td>
</tr>
<tr>
<td>9. Distance to Nearest Park</td>
<td>Landscape</td>
<td>Length to nearest park in ft.</td>
</tr>
<tr>
<td>10. Distance to Nearest Water Source</td>
<td>Landscape</td>
<td>Length to nearest river, stream, creek, or floodplain in ft.</td>
</tr>
<tr>
<td>11. Forest Area</td>
<td>Landscape</td>
<td>Tabulation of forested area within 0.5 mile radius buffers in ft².</td>
</tr>
<tr>
<td>12. Habitat Area</td>
<td>Landscape</td>
<td>Tabulation of habitat area within 0.5 mile radius buffers in ft².</td>
</tr>
<tr>
<td>13. Building Area</td>
<td>Landscape</td>
<td>Tabulation of building square footage within 0.5 mile radius buffers.</td>
</tr>
</tbody>
</table>

The independent, non-categorical variables in Table 4.1 were transformed to remove skewness and to make as normally distributed as possible for a better working OLS model. DVCs are incident data and therefore a weighted value must be assigned to show variance among the points. In order to apply a value from hot spots to use in OLS
regression as the dependent variable, the z-score result from the optimized hot spot analysis of Figure 3-10 was used for regression. A high z-score with a low p-value reflects spatial clustering, and a z-score near zero means no significant clustering. Since a z-score represents standard deviations above or below the mean, these values were applied as a spatial weight to the individual DVC incidences. The z-score values from the hot spot analysis were spatially joined to their respective nearest DVC points. The values were all shifted upward as positive numbers. The purpose of applying a value to the DVC point incidents is to represent the magnitude of DVCs belonging to the polygons from the hot spot analysis. The significant clusters receive heavier weights for consideration of the variables in the regression models. Initially, the DVC aggregated counts within the hot spot analysis polygons was considered for a dependent variable. However, the counts not being normally distributed, the z-score values performed better as a dependent variable in regression. The magnitude of DVCs became the dependent variable to test the hypothesis that DVCs are a function of the above mentioned independent variables, with applied greater weight to DVC points of hot spot clusters.

When running the regression model, all of the independent variables were added, with exception of the categorical fields (i.e. weather, season, light, road contour, and speed limit). Out of 13 independent variables, 5 were categorical variables. From these 5 came 17 sets of binary classifications, and out of them, 3 were significant (i.e. the January through March season, daylight, and curve-level road contour). The binary classification fields of the categorical variables were added one by one with the other independent variables to test for significance. The categorical binary fields that did not have a significant robust probability were excluded from subsequent OLS regression.
tests. The Weather Condition variable did not show any significant p-values from the binary classifications and therefore was not included in the regression model. Speed Limit was already a binary field and did not need to be tested separately for significance. In total, 12 independent variables were input into the OLS regression model as shown in Table 4.2.
Table 4.2 OLS results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>StdError</th>
<th>t-Statistic</th>
<th>Probability</th>
<th>Robust StdError</th>
<th>Robust_t</th>
<th>Robust Probability</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-11.495697</td>
<td>1.604912</td>
<td>-7.162822</td>
<td>0.000000*</td>
<td>1.699203</td>
<td>-6.765349</td>
<td>0.000000*</td>
<td>---</td>
</tr>
<tr>
<td>SPEEDLIMIT</td>
<td>0.034675</td>
<td>0.339190</td>
<td>0.10223</td>
<td>0.91857</td>
<td>0.316302</td>
<td>0.109627</td>
<td>0.912702</td>
<td>1.364303</td>
</tr>
<tr>
<td>POPULATION</td>
<td>-0.019207</td>
<td>0.045450</td>
<td>-0.422608</td>
<td>0.67265</td>
<td>0.043196</td>
<td>-0.444661</td>
<td>0.656637</td>
<td>2.030386</td>
</tr>
<tr>
<td>PARK_DISTANCE</td>
<td>-0.254662</td>
<td>0.019260</td>
<td>-13.222523</td>
<td>0.000000*</td>
<td>0.022588</td>
<td>-11.274235</td>
<td>0.000000*</td>
<td>1.277941</td>
</tr>
<tr>
<td>LNFTST</td>
<td>0.173564</td>
<td>0.149196</td>
<td>1.163329</td>
<td>0.244858</td>
<td>0.156363</td>
<td>1.110011</td>
<td>0.267146</td>
<td>4.642778</td>
</tr>
<tr>
<td>WATER_DISTANCE</td>
<td>0.154301</td>
<td>0.024710</td>
<td>6.244529</td>
<td>0.000000*</td>
<td>0.023505</td>
<td>6.564529</td>
<td>0.000000*</td>
<td>1.05004</td>
</tr>
<tr>
<td>FOREST_AREA</td>
<td>0.672911</td>
<td>0.044636</td>
<td>15.075524</td>
<td>0.000000*</td>
<td>0.074124</td>
<td>9.078219</td>
<td>0.000000*</td>
<td>1.261229</td>
</tr>
<tr>
<td>HABITAT_AREA</td>
<td>0.000637</td>
<td>0.000101</td>
<td>6.312122</td>
<td>0.000000*</td>
<td>0.000105</td>
<td>6.082832</td>
<td>0.000000*</td>
<td>3.304057</td>
</tr>
<tr>
<td>BUILDING_AREA</td>
<td>0.097002</td>
<td>0.075949</td>
<td>1.277194</td>
<td>0.201716</td>
<td>0.06445</td>
<td>1.505063</td>
<td>0.132509</td>
<td>3.639956</td>
</tr>
<tr>
<td>AADTC</td>
<td>0.336604</td>
<td>0.049931</td>
<td>6.741378</td>
<td>0.000000*</td>
<td>0.05054</td>
<td>6.660157</td>
<td>0.000000*</td>
<td>1.549573</td>
</tr>
<tr>
<td>SEASON</td>
<td>0.44704</td>
<td>0.126636</td>
<td>3.530115</td>
<td>0.000441*</td>
<td>0.130866</td>
<td>3.416024</td>
<td>0.000666*</td>
<td>1.042267</td>
</tr>
<tr>
<td>DAYLIGHT</td>
<td>-0.248863</td>
<td>0.127029</td>
<td>-1.959112</td>
<td>0.050258</td>
<td>0.119647</td>
<td>-2.079983</td>
<td>0.037665*</td>
<td>1.017306</td>
</tr>
<tr>
<td>CURVE-LEVEL</td>
<td>-0.594128</td>
<td>0.234511</td>
<td>-2.533475</td>
<td>0.011373*</td>
<td>0.23594</td>
<td>-2.518138</td>
<td>0.011879*</td>
<td>1.012253</td>
</tr>
</tbody>
</table>
Table 4.3 OLS statistical output of variables.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Observations</td>
<td>1707</td>
</tr>
<tr>
<td>Akaike's Information Criterion (AIC)</td>
<td>7345.381952</td>
</tr>
<tr>
<td>Multiple R²</td>
<td>0.34402</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.339373</td>
</tr>
<tr>
<td>Joint F-Statistic</td>
<td>74.033077</td>
</tr>
<tr>
<td>Probability (&gt;F), (12,1694) degrees of freedom:</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Joint Wald Statistic</td>
<td>784.106092</td>
</tr>
<tr>
<td>Probability (&gt;chi-squared), (12) degrees of freedom:</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) Statistic</td>
<td>59.596709</td>
</tr>
<tr>
<td>Probability (&gt;chi-squared), (12) degrees of freedom:</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Jarque-Bera Statistic</td>
<td>205.544764</td>
</tr>
<tr>
<td>Probability (&gt;chi-squared), (2) degrees of freedom:</td>
<td>0.000000*</td>
</tr>
</tbody>
</table>

*Statistically significant p-value < 0.01
Figure 4-1 Scatterplots of independent variables and dependent variable.
4.2 OLS Model Performance and Discussion of Results

The OLS analysis was conducted and variables with significant or insignificant robust p-values were identified. The adjusted R² value was 33.9%, interpreted as the independent variables are telling 33.9% of DVC story. It means that DVCs are also a function of some other omitted variables required for a properly fitted model and are able to show about 34% of the variation in the dependent variable.

The spatial autocorrelation report of the Moran’s Index test statistic confirms the residuals are not spatially random, having a statistically significant z-score above 48. The Moran’s Index was 0.817. A value close to +1 indicates clustering and a value near to -1 shows dispersion. When the resultant output shows clustering of under or over predictions, the model is still missing key explanatory variables. Therefore evidencing an improperly specified model and rendering bias.

Another form of model bias, exhibited by a significant Jarque-Bera statistic, is non-normal distribution of residuals, making the p-value unreliable. The Jarque-Bera statistic can also be significant when there are non-linear relationships or strong heteroscedasticity.

In linear regression methods, the candidate independent variables should have a linear relationship with the dependent variable. However, the scatterplot matrices revealed non-linear relationships (Figure 4-1). Since OLS and GWR are linear methods, it makes the model difficult to perform well. Influential outliers in the data can also cause model bias. The Building Area and Forest Area variables both contained an outlier. However these values were in fact accurate and should not be removed. AADTC was corrected for an outlier value, but did not have a large impact on the results.
Multicollinearity was not a problem in the model as none of the variables had a variance inflation factor (VIF) statistic >7.5. The Koenker statistic was significant, indicative of non-stationarity, or regional variation within the study area. Non-stationarity causes the standard errors to be artificially inflated and may be remedied by the GWR method, which allows for regional variance as a local method of regression. It may be that the set of variables work well in one region of the study area but are less important predictors in others.

The results of regression modeling are foremost only as strong as the representational ability of the variables to accurately reflect true reality describing the DVC surroundings. When variables are quantified into understandable study areas, it should be taken into consideration that boundaries and generalization may influence the analysis results.

It is important to satisfy the requirements of regression model specification. Otherwise, results could be unreliable or backward. As discussed in this model performance section, some aspects of the regression model were misspecified.

4.3 GWR Model Performance and Discussion of Results

The GWR method computes a regression equation for each feature. The non-transformed version of the variables were input, excluding any categorical variables. The best performing model revealed seven key variables: (1) Population Density, (2) Distance to Nearest Water Source, (3) Distance to Nearest Park, (4) Linear Feet of Streets, (5) Forest Area, (6) Building Area, and (7) AADTC. With a lower Akaike’s Information Criterion score of 5,465 (Table 4.4), the GWR model performed better than OLS by a
difference of 1,880. The Habitat Area variable was excluded because of multicollinearity. GWR yielded an adjusted $R^2$ value of 78.8%. Again, spatial autocorrelation was objectionable at a z-score $>48$, showing non-random distribution of the residuals. Statistically significant clustering of residuals shows the GWR model is misspecified, having yet unaccounted variables. With a local regression equation for each feature, the GWR model is able to express 78.8% of the DVC story. Mapping the coefficients of each variable allows further investigation of the way DVCs change across the study area.

Table 4.4 GWR result.

<table>
<thead>
<tr>
<th>Neighbors</th>
<th>300</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residual Squares</td>
<td>2189.3371114</td>
</tr>
<tr>
<td>Effective Number</td>
<td>117.4388918</td>
</tr>
<tr>
<td>Sigma</td>
<td>1.1735935</td>
</tr>
<tr>
<td>AIC</td>
<td>5465.1659959</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.8023846</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.7879089</td>
</tr>
</tbody>
</table>

**4.4 Assessment of Variables**

Of the 12 variables tested in the OLS method, 8 were found to have statistically significant robust probabilities as contributors to DVCs: (1) January through March Season, (2) Daylight, (3) Curve-level Road Contour, (4) Distance to Nearest Park, (5) Distance to Nearest Water Source, (6) Forest Area, (7) Habitat Area, and (8) AADTC.

A slightly curious coefficient was the distance to water, having a positive relationship to DVCs. Also Clevenger et al., (n.d.) found that less open water was
associated with high roadkill zones. Deer thrive around water resources. But DVCs increase farther away from water probably due to roads are not built very close to water to avoid potential flooding or erosion. Contrariwise, Ng et al. (2008) found DVCs were more likely to take place closer to water in a metropolitan study area.

The Seasons variable was only significant for the January through March period. It was unusual to find this result because more DVCs take place from October through December in Lucas County. It may be that the clusters of hot spots had more DVCs occurring in the winter season and the fall season DVCs were dispersed in other places of the study area.

The Light variable was to capture time of day and whether streets are well-lit at night or not. Deer prefer quiet, dark, natural areas as opposed to city lights and noise. Only the daylight classification of the Light variable was found significant with a negative relationship to the dependent variable. It means daylight reduces the likelihood of DVCs. It makes sense because DVCs are known to occur more at dawn, dusk, and night.

Weather Condition was also found to be an insignificant predictor. Apparently atmospheric conditions such as precipitation do not play a major role in the outcome of DVCs. Clear skies or clouds of rain, drivers should be attentive for deer crossings. Rather, time after gestation and rutting season contribute more to increased deer roaming, leading to seasonal shifts in DVC abundance. Intriguingly, a drought phenomenon was attributed to a peak in roadkills of mule deer in California, which consequently raised distance traveled in farther search of water or vegetative provender (Rocha, 2014).
The findings of this research determined that the curve-level classification of the Road Contour variable was a significant predictor. The vast majority of roads in Lucas County are straight and level grade owing to the flat topography. The curve-level classification of roads significantly predicted a negative relationship to DVCs. The coefficient sign was not as expected, as other research demonstrates locations with a curve in the road can lead to higher roadkills due to shorter line of sight and visibility of oncoming traffic (Grilo et al., 2011). On the other hand, Barrientos & Bolonio (2009) maintain roadkill increases on straight roads because they call for higher speeds. Yet, in this study straight-level, straight-grade, and curve-grade road classifications were not found significant. Clevenger et. al. (2003) suggested raised or buried topography adjacent to roads decreased roadkills associated with the snowshoe hare.

As far as Posted Speed Limit goes, it was found to be an insignificant predictor of DVCs. The results for speed limit variable performance are diverse in other findings. For instance, Bashore et al. (1985) found higher speeds were negatively correlated with DVCs, whereas Ng et al. (2008) uncovered a strong positive correlation to speed limit. According to Seiler (2005), speed limits of 55mph held the greatest densities of moose vehicle collisions. Mixed results occur depending on which descriptors are used, and per the stance taken by Bissonnette & Kassar (2008), neither speed limit nor traffic volume metrics provide reliable results.

Furthermore, this study detected a strong positive correlation with AADTC. Traffic volume is an important characteristic since roadkills are not predictable by landscape factors alone (Markolt, Hervai, Havas, Szemethy, & Heltai 2012). The majority of other studies also discovered higher traffic volumes impelled animal
collisions (Barrientos and Bolonio, 2009; Clevenger et al., n.d.; Gunson and Clevenger, 2003; Gunson, Mountrakis, Quackenbush 2010; Seiler, 2005). Interestingly, at a high enough threshold, large traffic volumes may also deter wildlife from crossing roads (Gagnon, Theimer, Dodd, Boe, Schweinsburg 2006).

In the GWR method, Linear Feet of Streets strongly predicted DVCs in a transitional swath of Lucas County having more forest and less roads. This variable was not found significant in the OLS method most likely due to non-stationarity. Ng et al. (2008) also observed that lower road density added to DVCs, typically on higher speed freeways and on township roads that were surrounded by suitable deer habitat.

The Population Density variable was not a significant predictor in the OLS method, but did contribute in GWR. The presence of non-stationarity for this variable likely gave way to better performance with the GWR method. Few other studies included this particular social variable.

In a similar way, Building Area did not have a significant performance in OLS regression, but did with GWR. In general, building and urban areas were associated with lowering the probability of wildlife collisions (Bashore et al., 1985; Neilsen et al., 2003; Grilo et al. 2009; Seiler 2005). Mapping the coefficients from the GWR revealed Building Area was a weak predictor in what can be described as the outskirts of urban sprawl before the landscape transitions into rural/agricultural (Figure 4-2). And was a strong predictor in the building-sparse area of Oak Openings Metropark.
Figure 4-2 Coefficients of Building Area variable.

Distance to Nearest Park captures prime deer habitat and abundance. It is commonly reported that auto accidents occur within a 2 mile radius of residence, as it is usually an area more frequently travelled. The same may reasonably be inferred for deer roadkills. Most DVCs would occur close to their habitat grounds. With a high number of the deer population living in metroparks in Lucas County, many DVCs occur on the roads adjacent to the parks. It was an important variable since DVCs densely clustered around Lucas County Metroparks. These are well-known areas for deer crossings and have implemented signage. Bashore et al. (1985) and Nielsen et al. (2003) confirm proximity to public lands increase DVCs.

Forest coverage had a strong positive correlation in OLS regression. Along with areas of mixed habitat (forest, shrub, grass, and wetlands) Forest Area is known as one of
the strongest predictors of DVCs and other species of roadkills (Bashore et al. 1985; Choi, Park, Lee 2015; Finder et al 1999; Gunson et al. 2010; Gunson et al 2009; Malo et al. 2004; Seiler 2005).

The Habitat Area variable was a combination of forest, pasture/hay, row crops, and wooded wetlands. Deer visit cropland (37% area of Lucas County) to forage but it is not their predominant habitat. The purpose of this variable was to represent travel ranges by deer. Therefore, in OLS Habitat Area has a weak, but positive correlation with DVCs. Hubbard et al. (2000) noted DVCs decreased with a greater proportion of crop fields. In GWR, Habitat Area outfitted local multicollinearity.

4.5 Regression Model Evaluation

The models may be enhanced by introducing any missing variables to describe the DVC story. For example, a deer population abundance variable could increase model performance (Barrientos & Miranda, 2011), as suitable deer habitat does not necessarily entail the existence of deer in that location.

Perhaps other candidate variables include level of deer wisdom and experience for crossing roads. It is conceivable that deer have a learning curve on frequented corridors, knowing to approach the road when clear of traffic. On the other hand, a frightened deer could dash suddenly into oncoming traffic without pausing at the roadside. An Index of driver attentiveness or individual awareness of deer problems in a neighborhood may add color to the incidence of DVCs. There are additional considerations - factors difficult to quantify - such as time and chance, for both the driver
and deer. Not every person may happen to have an equal chance of hitting a deer, in congruence to timing and circumstance.

A misspecified model often indicates there are more complex issues behind the phenomena than a linear equation can adequately demonstrate. Issues such as societal awareness of deer crossings and abundance of deer are likely intertwined in the DVC story.

The regression models could also be improved by controlling for spatial autocorrelation within other spatial statistic software. Additionally, the OLS model may perform better by redefining the study area into smaller groups and running the analysis, thereby removing regional variation. Overall, regression modeling assisted to explore quantifiable spatial parameters and learn of factors heralding DVCs in Lucas County.

Comparing the two methods, OLS provides statistical diagnostic output, detailing how each variable influences the regression equation. It also permits the use of binary value fields whereas the GWR method does not. But because of non-stationarity, the coefficients could be non-representational for the whole region or cancel out by the change in the sign of direction across the study area. GWR allows for mapping the coefficients. Viewing the coefficient maps reveals where the variables are strong or weak predictors of the dependent variable. Since there was heteroscedasticity, the GWR method is recommended for the Lucas County study area. Usually spatial data is not uniform, rather, geographically near features have more similarities than with those far away. Thus, the GWR model is better for this study because it provides calculations for regional variation.
Chapter 5

Discussion and Recommendations

5.1 Local Community Example

In order to relate the results of this study to an area in Lucas County currently undergoing conflicts with deer, the Village of Ottawa Hills is an appropriate place of consideration. The location of this community is within a hot spot zone of Figure 3-10. Based on the GIS data, the village is proximate to a large forested park, intersected by a river water source for deer, is marked by quality habitat, and has moderately high traffic volume – characteristics that lead to an increase of DVCs from the regression analyses.

There were approximately 50 DVCs from 2011-2015 on the perimeter and inside the Village of Ottawa Hills. Among those, 11 DVCs from this data set specifically befell within the village limits. There are many successful deer crossings within the village area, notwithstanding, the high deer population pose safety risks to motorists. Often, two way traffic in the village yields to allow for successful deer crossings. On the outskirts of the village, on the major roads, there are a high number of DVCs. The population of deer in this community is high because it is situate along the Ottawa River basin, connected to a metropark, has diverse vegetation, and therefore abundant of wildlife. Local knowledge about deer frequently treading through the streets raises awareness to use
caution while driving to avoid DVCs. However, even a few DVCs are a few too many to constituents. The speed limit throughout the village is rather low, ranging from 25-35mph. It is easier for traffic to yield and halt for animal crossings on low speed streets rather than on high speed streets. Even a deer feeding ban had been implemented. This local area evidences how community awareness of frequent deer crossings has curbed a potentially greater risk of DVCs given the abundance of deer.

Yet further, recent legislation was passed to allow bow hunting for deer in Ottawa Hills (Rowland, 2015). It is expected to lower the abundance of deer along with the associated nuisances. The Village of Ottawa Hills Wildlife Management Task Force (2015) reported approximately 76 deer in the village, detected by Forward Looking Infrared Radar. According to the “White Tailed Deer” (2015) report, nearly 38 deer/mi² is above the cultural, biological, and ecological carrying capacities for the village. The sought after rate for the village is about 20 deer/mi². Compatibility with deer in the village should improve when the deer abundance is reduced through the controlled bow hunting. After bow hunting is carried out, it would be interesting to see if the overall deer population in the village decreases and if DVCs decrease in subsequent years also.

Since landscape and roadway characteristics in the area are not likely to alter, it is hoped that culling can minimize conflicts with deer. In such a case, keeping record of deer population counts is a worthwhile variable to utilize in future studies to explore the impact on the rate of DVCs.
5.2 Mitigation

It is beneficial for the transportation system officials to know the identified hot spot clusters of roadkill. After reviewing the outputs of this study, the author recommends placing flashing crossing signage on the I-80 turnpike and on Airport Hwy Route 20 – north of the Toledo Express Airport. Modified signage is especially important for non-local traffic on the Ohio Turnpike. The enhanced signage should flash during peak DVC times (1700-0000 and 0500-0800). Traffic engineers can install solar powered message boards, cautioning drivers to be aware of deer crossings on the Ohio Turnpike. The area is also rather dark and not well-lit. Planners can consider the tradeoff between more light pollution with additional lamp fixtures providing light to roads and enhancing deer visibility, or letting the natural area be. There are also stands of forest close to the road in the area. Clearing tree cover from the road edge possibly creates more forage space, but at least gives drivers better visibility of approaching deer and more reaction time. In this same area, it may be advisable to allow targeted hunting to reduce the herd population. Consultation with wildlife biologists can help determine whether deer are overly abundant in the area and in need of herd reduction.

The route with the most DVCs in Lucas County is on State Route 64 between Airport Hwy. and Reed Rd. It is a two lane road next to Oak Openings Metropark, the largest forested area in Lucas County. This route has three posted deer crossing signs. It is recommended to swap them for flashing signage to warn drivers.

Other hot spot clusters were found adjacent to metroparks. These areas already have posted deer crossing signage in place. Typically streets next to nature areas have less light pollution and are darker at night. It’s not always practical do use high beams
when there is frequent oncoming traffic. Occasionally, drivers involved in a DVC report ‘the deer came out of nowhere’, or ‘the deer ran into the side of the vehicle’ – indicating the unpredictability of deer. Motorists are not likely to drive at much slower speeds on wide roads with five or more lanes. When possible, drivers may be advised to drive more slowly with greater visual attentiveness on two lane roads during peak collision times of day. If travelling on wider arterial streets next to parks, drivers should use the inside lane, distancing themselves from the forested or shadowy edges, allowing for more reaction time. It is recommended that these driving tips be issued in the Ohio Bureau of Motor Vehicles public offices and literature. Drivers are required to appear before the agency periodically or receive mailings via postal service. This way, drivers may be reminded and receive suggested counsel to avoid collisions with deer.

Fueling the challenge of controlling the rate of deer collisions, DVCs are widespread in many places outside of hot spots in Lucas County. Given landscape richness and diversity in Lucas County, deer traverse almost anywhere they are willing, even venturing into suburban and commercial areas. Adding more crossing signage is not practical for every street since deer can cross almost anywhere. What is more helpful, is to be aware of intermittent patches of forest or habitat along roads, places with fewer street lights, and overall driver attentiveness.

5.3 Future Research

Furthermore, the procedures followed for this research may be applied to other counties in the state and greater region. DVCs are even more problematic in other counties of Ohio. Localized assessments help identify target routes in need of
improvement. Future applications include analyzing distribution of DVCs across a region, and predicting DVC location hot spots for other counties as well. Results are useful to DOTs and Insurance agencies for measuring DVC trends. Also DVCs help to assess deer population levels when coupled with deer harvesting data. It is worthwhile to examine also where DVCs are the lowest in Ohio and compare the characteristics with the highest places.

This research serves as documentation of DVC trends in Lucas County. Future years of DVC data may be compiled to this study to keep track of changes in the local DVC trend. Implemented remediation efforts are expected to improve traffic safety in Lucas County.
References


Scott, L. M., & Janikas, M. V. (2010). Spatial statistics in ArcGIS. In M. M. Fischer & A. Getis (Eds.), Handbook of applied spatial analysis: Software tools, methods and applications (pp. 27-41). doi:10.1007/978-3-642-03647-7_2


