11-2017

Influence of Street Trees on Roadway User Safety

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INFLUENCE OF STREET TREES ON ROADWAY USER SAFETY

by

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A THESIS

Presented to the Faculty of

The Graduate College at the University of Nebraska

In Partial Fulfillment of Requirements

For the Degree of Master of Community and Regional Planning

Major: Community and Regional Planning

Under the Supervision of Professor Daniel Piatkowski

Lincoln, Nebraska

November, 2017

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University of Nebraska, 2017

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This thesis aims to understand trends of trees in transportation planning and to determine if street trees have a negative or positive influence on crash frequency and severity. As roadways become more walkable and livable, they become safer. Street trees are a vital component of this trend. Planners must understand the impacts of trees on roadway user safety as they work to reduce crash risk. Although spatial analysis suggests there may be a negative relationship between trees and crash frequency, correlation models find a significant correlation between trees and crash severity, but no significant correlation between trees and crash frequency. Regression models of crash reports, tree inventory data, and other related variables in the city of Des Moines, Iowa, show that the presence of trees has a positive relationship on crash severity but no relationship on crash frequency. For every one unit increase in trees there is a 1.428 increase in predicted severe crashes, but an increase in trees does not result in any statistically significant influence on crash frequency. These findings are useful in gaining an understanding of tree influences on crash frequency and severity at the block group level, but further analysis of other variables is necessary for any further conclusions to occur.

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List of Abbreviations

American Association of State Highway and Transportation Officials (AASHTO)

Diameter at Breast Height (DBH)

Federal Highway Administration (FHWA)

Geographically Weighted Regression (GWR)

Iowa Department of Transportation (Iowa DOT)

Ordinary Least Squares (OLS)

Right-of-Way (ROW)

Introduction

Trees have the potential to provide communities significant social, economic, and environmental benefits including storm water capture and retention, filtration of water and air pollutants, aesthetic benefits, softening of hard architectural lines, soil improvements, and reduction of the urban heat island effect (Simons & Johnson, 2008). While trees can positively affect a community, an urban tree canopy is not made up of park and backyard trees alone. Street trees are a vital component of an urban community tree canopy as well, and thus hold the potential for many of these same benefits. Although street trees are considered important in an overall urban forest system, they pose implications on traffic safety for both vehicular and pedestrian traffic (Dixon & Wolf, 2007). The purpose of this thesis is to explore the influence of urban street tree canopy management on traffic and pedestrian safety and quality of life.

Research Intent, Hypothesis, and Questions

The intent of this thesis is to investigate the influence of street trees on driver and pedestrian safety issues through analysis of crash reports, demographic data, street tree inventory, and other related variables for the city of Des Moines, Iowa. The research aims to understand trends of trees in transportation planning and to determine to what extent street trees positively or negatively influence traffic safety issues. This thesis analyzes the relationships between multiple variables related to traffic crash instances to establish correlations and relationships between trees and traffic safety. If the right trees are planted in the right places, they may instead foster positive influences on the safety of roadway users. The purpose of this thesis is to generate data that supports planning options that maximize urban canopy and minimize traffic and safety issues.

- **Research Question**: Is there a relationship between street trees and roadway safety?
- **Hypothesis 1**: There is a positive relationship between street trees and crash frequency.
- **Hypothesis 2**: There is a positive relationship between street trees and crash severity.

CHAPTER 1 LITERATURE REVIEW

Roadway Design Background

Attempts to minimize perceived traffic hazards caused by an urban grid (gridiron) street network that was made popular in the 19th Century resulted in these disconnected residential neighborhoods and the placement of retail along arterial roadways as the desire to move traffic quickly and separate land uses grew in the 20th century (Dumbaugh & Rae, Safe Urban Form: Revisiting the Relationship Between Community Design and Traffic Safety, 2009). Early planning for traffic safety resulted in issues such as disconnected neighborhoods and retail on arterial roadways, creating conditions that inhibit pedestrian mobility and favor the personal vehicle as a primary mode of transport (Rifaat, Tay, & de Barros, 2012).

The purpose of the grid network was to promote rapid land development by maximizing the number of corner lots (Rifaat, Tay, & de Barros, 2012). Cities like New York and Chicago continued to expand these grid networks as they quickly grew. (Dumbaugh & Rae, Safe Urban Form: Revisiting the Relationship Between Community Design and Traffic Safety, 2009)

As growth of the personal automobile increased during the 20th century, Fredrick Law Olmstead Jr. lead efforts to move street planning away from the traditional grid pattern (Dumbaugh & Rae, Safe Urban Form: Revisiting the Relationship Between Community Design and Traffic Safety, 2009). A goal of transitioning from a grid system to a disconnected system with limited side road access was to create roads that serve specific functions (Elvik, 2001). For example, the function of high speed highways and thoroughfares was to move traffic as quickly and efficiently as possible (Elvik, 2001). Around the same time period efforts took place to beautify and reforest urban areas (Simons & Johnson, 2008). These efforts were met with the conflict of keeping high speed roadways open and clear of visual obstruction, resulting in much of the greening and beautification remaining confined to residential neighborhoods (Simons & Johnson, 2008).

The new planning strategy separated high speed roadways from neighborhoods, with new neighborhoods characteristic of disconnected features such as cul-de-sacs (Rifaat, Tay, & de Barros, 2012). By promoting traffic on high speed thoroughfares and highways, intersections are eliminated, and drivers are given greater sight lines and stopping distances in order to improve safety conditions (Rifaat, Tay, & de Barros, 2012). Over time land use changes associated with this new planning strategy led to a phenomenon referred to as "homogenization", where urban and residential ecosystems and landscapes all tend to be alike, replacing the diverse ecosystems that used to occupy those spaces across the nation (Groffman, 2014). Impacts of urbanization, and consequently homogenization, have led to both ecological and social trends (especially related to transportation safety) at both regional and global scales (Groffman, 2014).

One method of improving roadway safety conditions is called traffic calming. The concept of area wide traffic calming was developed in the 20th Century by Frederick Law Olmstead Jr. and is aimed at increasing safety on both arterial and suburban roadways by moving traffic from neighborhoods to arterials (Elvik, 2001). Area-wide traffic calming schemes are road systems such as street closures, one-way systems, or speed reducing devices that aim to move traffic volume away from residential streets and onto main arterial roadways (Ewing & Brown, Traffic Calming Progress Report, 2009). In traffic calming systems, arterial roads are improved to safely and efficiently handle increased traffic load.

Traffic calming schemes can reduce injury accidents by 15% (averaged between approximately 25% on residential streets and 10% on main roads) (Elvik, 2001). With a goal of moving residents in and out of neighborhoods rather than through them by moving roadway traffic to arterial streets to increase safety, it became increasingly difficult for pedestrians to walk or bike to these services (Dumbaugh & Rae, Safe Urban

Form: Revisiting the Relationship Between Community Design and Traffic Safety, 2009). While the goal of these systems was to improve safety and efficiency on arterials, the system may foster unintended consequences on neighborhood streets. By reducing traffic on neighborhood streets and improving sight distances, drivers may become comfortable with increasing their speeds, heightening the risk for increased crash frequency and severity.

Pedestrian and Vehicle Safety

Although the purpose of these design changes was to improve roadway safety, the movement of commercial and retail uses to arterial roads and the redesign of neighborhoods into suburbs has brought new, more severe safety issues to light (Ewing & Dumbaugh, The Built Environment and Traffic Safety, 2009). Pedestrians no longer have easy or safe walkable access to services located along the arterial roadways, and crashes along these roadways have become more severe and frequent due to increased traffic speeds (Dumbaugh & Rae, Safe Urban Form: Revisiting the Relationship Between Community Design and Traffic Safety, 2009). Dense, lower speed urban areas are actually found to be safer than higher speed and less dense suburbs due to higher crash severity along higher speed suburban roadways (Ewing & Dumbaugh, The Built Environment and Traffic Safety, 2009). Traditional urban roadways characteristic of narrow lanes, developed street tree canopies, and other traffic calming measures are also considered more forgiving in the instance of a crash than faster suburban roadways (Ewing & Dumbaugh, The Built Environment and Traffic Safety, 2009).

There are many benefits to planning for a healthy street tree canopy within a transportation plan. Trees offer great social, economic, and environmental benefits to a neighborhood. They also provide a great aesthetic addition to a roadway by softening hard architectural lines, providing shade, and adding color to a landscape. As beautiful as they may seem along streets and sidewalks though, there is a fear that trees pose a threat to both pedestrians and vehicles. It is commonly argued by roadway engineers that trees should be removed along arterial streets to increase driver visibility and increase safety (Simons & Johnson, 2008). This opinion is not well supported and should not be cause alone to eliminate trees from roadway planning all together (Macdonald, Williams, Harper, & Hayter, 2006-2011). When appropriately selected and maintained, the benefits of trees may outweigh the costs, and these benefits should all be considered in transportation planning (McPherson, Simpson, Peper, Maco, & Xiao, 2005).

Strategies to Improve Pedestrian and Vehicle Safety

Increased traffic has led to an increased need for traffic calming techniques (Garrick, 2005). Traffic calming techniques are important for improving the safety of both pedestrians and drivers through reduction in traffic speed and volume (Knapp, 2000). Some examples of these techniques include traffic circles and speed humps (Knapp, 2000). There is currently a national debate regarding the use of traffic calming schemes on large arterial roadways when they have traditionally been limited to residential roads (Ewing & Brown, Traffic Calming Progress Report, 2009). When implementing these types of traffic calming designs it is important that users are notified of upcoming physical roadway changes such as speed bumps or speed changes with signage in order to decrease negative impacts of changes in daily driving routines (Ewing & Brown, Traffic Calming Progress Report, 2009).

Two traditional methods of performing “traffic calming” measures are by traffic volume control (examples: barriers, cul-de-sacs, dead ends) and by speed control (examples: speed humps and speed bumps) (Knapp, 2000). Speed humps are the most common form of traffic calming control in the US. They are also the only traffic control measure that has national guidelines (Knapp, 2000). In 2009 the American Society of Civil Engineers published the *U.S. Traffic Calming Manual*, a national guide for engineers and planners to use in traffic calming roadway design (Ewing & Brown, Traffic Calming Progress Report, 2009). In some cases speed reduction traffic calming measures may promote the use of alternative modes of transportation (bus, bicycle, etc.) by reducing speeds and supporting sustainable alternatives as feasible methods of commuting (Randall, Churchill, & Baetz, 2005). The traffic calming techniques suggested here are all designed by engineers, but have argued that trees successfully function as a more affordable traffic calming measure due to their aesthetic appeal (Simons & Johnson, 2008).

Traffic calming is one method of protection for pedestrians, but for planners an alternative to this is neighborhood and roadway design safety considerations. The safest street pattern for pedestrians is the gridiron pattern because of its walkable and connected design (when compared to loop and lollipop designs that are characteristic of disconnected streets and sidewalks), but crashes between two vehicles are more common on this street pattern because of the increased number of intersections (Rifaat, Tay, & de Barros, 2012). Although the loop and lollipop street pattern is designed to increase safety by decreasing through traffic, it may decrease safety by decreasing driver line of sight distance (Rifaat, Tay, & de Barros, 2012).

Traffic calming measures and roadway design considerations may be implemented differently based on location and situation. Techniques may also be used on their own or in combination with others. Design standards for traffic calming devices may be set locally, but there are no nationally set standards for any traffic calming measures other than speed humps. Some factors that may influence the design of traffic calming measures include traffic safety and mobility, street maintenance and emergency vehicle accessibility, rule enforcement (police involvement or self-enforcement), and how the system will impact the neighborhood and connecting streets. Development of a plan and design should be an open and multi-disciplinary process that involves all stakeholders. (Knapp, 2000)

An alternative to traffic calming measures for improving safety is roadway design that focuses on multi-use roadways that optimize social controls such as legible streets, self-explaining streets, or shared streets, rather than structural controls such as stop lights (Garrick, 2005). These concepts lower traffic speeds and optimize physical guidance for users along the roadway rather than traditional signs and markings (Garrick, 2005). This method allows for integration of streets into the urban form (where all users have shared access) rather than just as a mode of moving traffic through a space (Ewing &

Dumbaugh, The Built Environment and Traffic Safety, 2009). Although speeds are reduced, shared streets often improve movement efficiency by eliminating street signs and promoting continual flow of all users (Garrick, 2005).

Environmental Safety Concerns

Traffic fatalities are one of the most common causes of preventable death in the US, and crash severity increases as vehicular speed increases, especially with crashes involving fixed objects (Elvik, 2001). Trees are the least likely to become a safety hazard when they are planted in areas that do not obstruct driver visibility and are located on low-speed residential streets (Simons & Johnson, 2008). Because collisions are more severe as traffic speed increases, trees pose the most risk when located along high speed roads. It is important to give the greatest care to tree plantings in areas of high speed traffic to avoid planting trees in spaces that block driver visibility. It is also important to keep clear zones and horizontal clearance areas free of vegetation that may inhibit the utilization of these spaces by vehicles in need of safely exiting a roadway (Artimovich, Clear Zones and Roadside Terrain, 2011).

A roadway design should be linked to its environmental setting. A roadway will always exist within an environment, and an environment can foster a natural ecosystem, meaning wildlife and other ecosystem features may be present (Dumbaugh, Safe Streets, Livable Streets, 2005). Vegetation is a naturally occurring part of every ecosystem and an important component of environmental health and sustainability. Because of this it should be given adequate consideration in transportation management (Artimovich, Highway

Safety and Trees: The Delicate Balance, 2011). Community design impacts roadway safety greatly, and future design trends will continue to be important in the safety of future communities.

Tree Collisions

According to the Federal Highway Administration (FHWA) and the American Association of State Highway and Transportation Officials (AASHTO), single-vehicle collisions with trees make up about 25% of all fixed-object accidents each year, making them the reported object involved in 48% of all fixed-object accident fatalities (based on 1990 data) (Wolf & Bratton, 2006). Trees are commonly involved in many vehicular accidents, but the cause of the accident is not the tree itself. A crash is a consequence of road design and driver behavior (Wolf K. , Trees in Urban Streetscapes: Research on Traffic Safety and Crash Risk, 2005). Trees are sometimes a casualty of a crash, and drivers who hit them as a fixed object are often subject to increased injury severity. Roadways designed for increased speeds are increasing crash risk, thereby increasing the severity of fixed object crashes with trees. It is important for planners to weigh the pros and cons of including trees in transportation planning as well as allow for design that optimizes these benefits and minimizes the risks.

Wolf and Bratton (2006), made distinctions between urban and rural data used in descriptive, comparative, and predictive analysis to determine the influences of trees on crashes and found that tree collisions accounted for about 1.9% of all traffic accidents analyzed. Collisions with trees occur the least frequently overall, but injury rates for these instances are higher than all other crashes with 61% of tree collisions resulting in definite injury. Accidents in rural areas also have a higher chance of resulting in serious injury. About 6.1% of rural crashes were with fixed objects, while only 3.8% of urban crashes were with fixed objects. Although the rate of fixed-object collisions was higher in rural areas than urban areas, the percentages of these incidents involving trees was relatively the same in both cases (1.1% in rural and 0.7% in urban) (Wolf & Bratton, 2006).

This comparison of urban to rural environments found that rural roadside crashes are more frequent than those in urban areas, collisions with fixed objects are more frequent in rural than urban areas, and crashes in urban areas are more likely to result in more serious injury or death than those in urban areas. Risk assessment as well as consideration for community values should both be a consideration when planning for trees along roadways. This balance is important as cities attempt to plan for walkable and livable communities that are tied together by multi-use transportation and green corridors, thus promoting safer multidiscipline oriented transportation systems. (Wolf & Bratton, 2006)

Urban Design

Throughout time the most practiced method of improving roadway safety was through roadside design. Some ways of increasing safety by design include removing an obstacle, redesigning to avoid an obstacle, reducing crash severity by allowing breakaway devices, or shielding obstacles with barriers (Dumbaugh, Safe Streets, Livable Streets, 2005).

Clear Zones

One method of making roadways safer through urban design is by creating a clear zone. A clear zone is the buffer space along a roadside that is open for vehicles to safely move off the roadway when needed, allowing for horizontal clearance (Dumbaugh, Safe Streets, Livable Streets, 2005).

Horizontal clearance is the lateral area adjacent to a roadway necessary to provide vehicles with clearance when parked along a roadside, and this clearance area must safely accommodate the width of a vehicle with open doors. This area can be referred to as a shoulder, recoverable slope, non-recoverable slope, or a clear run-out area. The design of a clear zone is situational, project specific, and dependent on speed, traffic volume, and natural roadside slope and curvature. Design may also be limited to location, environmental and built surroundings, and available right-of-way. (Artimovich, Clear Zones and Roadside Terrain, 2011)

The recommended clear zone width for high volume roads with a level right-of-way is about 29.7 feet, and the recommended clear zone for low volume and low speed roads is only about 9.9 feet (Federal Highway Administration, 2017). These clearance distances vary based on individual cases and variables (grade of the space, presence of fixed objects, etc.) (Wolf & Bratton, 2006). Although a clear zone was a commonly used method for increasing safety along roadways, professionals are now considering the possibility that clear zones may actually decrease safety by allowing traffic to stop along the roadway and act as a hazard (Wolf K. , Trees in Urban Streetscapes: Research on

Traffic Safety and Crash Risk, 2005). Traffic calming measures such as clear zones may also create dangerous road conditions by promoting a false sense of security in drivers, resulting in increased roadway speeds.

Designing for Trees

Trees and green spaces are a vital component of urban design (Nadera, Kweon, & Praveen, 2008). Only 2 out of 91 national standardized crash reports include data about roadside vegetation, making it difficult to analyze the impact of vegetation on traffic safety at a national scale (Wolf K. , 2010). Because trees are fixed objects and allow for little buffer or padding to vehicles upon impact, they have the potential to increase injury and fatality risk in vehicle accidents (FDA, 1990). Driver choice and behavior influences the outcomes of moving vehicles and safety, but roadway design can minimize the risk of accidents (Dumbaugh, Safe Streets, Livable Streets, 2005). Wolf (2010) speculated that roadways lined with trees may provide an edge effect that results in positive influences on driver behavior and perception, leading to better driver safety and awareness (Wolf K. , 2010).

An analysis of national collision data was used to look at urban trees in relation to traffic safety, specifically in crash incidence and severity (Wolf & Bratton, 2006). The goal of the analysis was to use its conclusions as guiding tools for future flexible transportation design that aligns with Context Sensitive Solutions (national policy to integrate local values with transportation planning) (Wolf & Bratton, 2006). The fifth edition of the AASHTO Policy on the Geomentric Design of Highways and Streets, known as the

"Green Book" is a set of highway and road design guidelines adopted by the FHWA (Wolf & Bratton, 2006). The goal of the Green Book is to provide uniform criteria for design that follows safety and operational consistency in a way that is economically friendly (Wolf & Bratton, 2006).

Roadway design includes details for streetscape materials (e.g. signage, lighting, and traffic signals). Engineers may design urban and rural roadways in a manner that minimizes the use of trees, when the standards set along high speed roads may not be necessary along residential streets where speeds are slower and trees are less likely to cause safety issues or block visibility (Wolf & Bratton, 2006). By keeping trees and other visual barriers away from roadways, sight distances are increased. One goal of improving sight distances is to improve safety by improving a driver's ability to analyze their surroundings. Like the concept of clear zones, this traffic calming measure may actually lower roadway safety by providing drivers with a false sense of security, leading to an increase in driving decisions like speeding and increasing the vehicle's crash risk (Wolf & Bratton, 2006).

Designing for Community Values

A growing trend in transportation planning is the incorporation of community values and needs into the planning process while still planning for safety. Values and needs of pedestrians, cyclists, mass transit, and individual vehicles should all be integrated into a transportation plan. The national policy called Context Sensitive Solutions promotes the integration of these local needs and values into transportation plans. A component of satisfying local needs in transportation is the inclusion of trees and landscaping along roadsides. The inclusion of properly managed vegetation along roadways gives economic, social, and environmental benefits to a community. If properly planned, planted, and managed, this vegetation does not result in obstructed driver visibility or decreased traffic safety. (Wolf K. , 2010)

In transportation planning trees are often only analyzed for their aesthetic benefits and not always given consideration for their other economic and environmental benefits. Safety is the most important concern when planning for successful roadways that serve the public, and when trees are viewed as a safety hazard they are often omitted from transportation plans (Dumbaugh, Safe Streets, Livable Streets, 2005). Roads with well-maintained street trees give communities a better perception to drivers, and shoppers tend to travel further to shops with better landscapes and spend more money at these shops (Dumbaugh, Safe Streets, Livable Streets, 2005). Because of the sense of relaxation and calmness of a scenic road lined with trees, drivers also prefer these routes over faster expressways not buffered by rows of trees and vegetation (Dumbaugh, Safe Streets, Livable Streets, 2005). Commuting can be a stressful part of an individual's day, and the added calmness of driving along a scenic route can reduce stress, frustration, and aggression when driving (Wolf K. , 2010).

Streets and Street Trees

Impact of Trees on Driver Safety

More than 4,000 fatalities and more than 100,000 injuries are the result of vehicle collisions with trees each year (Artimovich, Highway Safety and Trees: The Delicate Balance, 2011). Balancing the preservation of trees for environmental benefits and the removal of trees for traffic safety is a delicate process. Governing bodies, planners, and the public must work together to reach consensus when managing such a sensitive issue.

A pilot study was conducted in 2008 to determine the impact of street trees on driver safety by measuring the effect of perception of safety and edge on driver safety using a simulated environment that guided users through a series of four worlds that varied in city form (urban and suburban) and landscape type (with and without trees) (Nadera, Kweon, & Praveen, 2008). The simulation and its preliminary questions found that on average the presence of trees had a greater influence on driver perception of safety than other surrounding land uses and that average simulation cruising speeds dropped 3.02 miles per hour in simulations where trees were present (Nadera, Kweon, & Praveen, 2008). A similar study conducted by the University of California at Berkeley Experimental Social Science laboratory tested 96 participants using a drive-through simulation to study the effects of street trees and other fixed objects on intersection visibility and found that the presence of parked cars and newspaper racks near intersections has a greater impact on driver visibility than the presence of high branching trees along sidewalks (Macdonald, Williams, Harper, & Hayter, 2006-2011).

Minimizing Tree Hazards (FHWA Standards)

Trees are dangerous traffic hazards because they act as a stagnant or “fixed” object in a vehicle collision (FDA, 1990). Because trees are sturdy and large they have little to no cushioning effect in the event of a collision (FDA, 1990). Trees create unsafe conditions that lead to more frequent accidents by acting as visual obstructions to drivers and are often planted at safe distances from a roadway to avoid the potential of collision (Dixon & Wolf, 2007). Sight distances, sign visibility, and visibility of pedestrians are most likely to be blocked by trees at intersections, driveways, and curves (FDA, 1990).

Local ordinances typically set requirements for line-of-sight clearance at intersections (Simons & Johnson, 2008; Tempelton & Rouse, 2015). This clearance restriction is often referred to as an intersection sight triangle, and the distance required to allow for a safe driver line of sight is dependent on traffic speed (FDA, 1990). High speed roadways require more line-of-sight clearance than slower streets (FDA, 1990). Clearance restrictions may set requirements for spacing between vegetation or other objects and the roadway (Simons & Johnson, 2008). Jurisdictions may also restrict vegetation or object height within the sight triangle area where vegetation or object placement is allowed, and restrictions can be set along roadways as well as within roadway medians (FDA, 1990).

Trees may become an overhead hazard if large limbs are allowed to grow or overhang a roadway, and local or state ordinances often set standards for overhead clearance dependent on roadway usage (the FHWA recommends a 9-foot clearance over roadways and sidewalks) (FDA, 1990). For example, roadways that often accommodate large trucks will require more clearance than residential streets (FDA, 1990). In some cases, pruning is not necessary because trees are constantly disturbed by passing traffic and growth is restricted by contact and interference by vehicles (Tempelton & Rouse, 2015).

In some cases, trees cause accidents due to falling branches or failure of entire trees into roadways endangering pedestrians or vehicles and blocking roadways (FDA, 1990) Trees are most likely to drop limbs or fall into roadways when they are structurally damaged and at risk (FDA, 1990). Proper forestry management techniques and regular monitoring and maintenance should occur along roadsides to minimize the risk of tree failure (FDA, 1990).

It is better to be proactive in designing and maintaining a healthy street tree canopy now than to be reactive in responding to failing trees in the future from both a financial and a safety perspective (Simons & Johnson, 2008). Trees can successfully be maintained along roadsides if they are properly managed and kept a safe distance away from the roadside's edge (Dumbaugh, Safe Streets, Livable Streets, 2005). To successfully utilize trees to their fullest potential along streets the right tree must be planted in the right place (Simons & Johnson, 2008).

Evidence of traffic accidents where sight lines are restricted indicates trees should not block driver visibility (Artimovich, Clear Zones and Roadside Terrain, 2011). Strategies to keep sight lines clear of blockage by trees include clearance restrictions set by local regulations as well as design consideration that utilize vegetation that will not grow large enough to block driver visibility or the installation of plantings behind sidewalks

(Artimovich, Highway Safety and Trees: The Delicate Balance, 2011). In addition to tree planting and maintenance considerations drivers should also be educated on the importance of safe driving techniques to minimize any distraction or inattentiveness that may result in collisions (Wolf K. , Freeway Roadside Management: The Urban Foresty Behond the White Line, 2003).

Along with driver safety education and landscape vegetation design that allows for clear visibility, roadways may be made safer by flattening curves, adding signage, repainting pavement markings, and other infrastructure safety improvements (Rifaat, Tay, & de Barros, 2012). All of these improvements are beneficial in improving road safety, but collisions may still occur. Although residents and environmental advocates may support the preservation of trees to maintain environmental benefits and aesthetic value, trees may still need to be removed in areas where they are the main cause of driver visibility limitation (Wolf K. , Trees in Urban Streetscapes: Research on Traffic Safety and Crash Risk, 2005). Open discussion meetings with all involved stakeholders should occur to address these situations, and decisions should be made collaboratively on a case-by-case basis (Artimovich, Highway Safety and Trees: The Delicate Balance, 2011).

A Study of Methodologies Used in Similar Research

Spatial and Regression Analysis

Dumbaugh and Rae (2009) completed a GIS-based spatial analysis of crash reports in San Antonio, CA and analyzed the impacts of community design on traffic safety using ESRI's ArcGIS (ESRI, 2011). In their research, private and public roadway data was overlaid with parcel-level land use data and demographic data for the spatial analysis. Neighborhoods were defined by census block groups (Dumbaugh & Rae, Safe Urban Form: Revisiting the Relationship Between Community Design and Traffic Safety, 2009).

Dumbaugh and Rae (2009) encountered spatial issues where some roadways ran along the border of a census block group making it difficult to define in which block group an accident fell. To remedy this situation Dumbaugh and Rae (2009) created buffers around each of the census block groups, treating those entire areas each as their own neighborhoods. If a crash fell within the buffer, it was counted within that neighborhood's analysis (Dumbaugh & Rae, 2009). This methodology resulted in some crashes being analyzed within multiple neighborhoods (Dumbaugh & Rae, 2009). Dumbaugh and Rae (2009) analyzed each neighborhood separately instead of the entire city as a whole, meaning each crash could be represented more than once if it influenced more than one neighborhood.

Negative binomial regression models using ArcGIS were also used by Dumbaugh and Rae (2009) to analyze crash frequency and severity. This is a linear model of the percentage change of dependent variables (the count of times an event occurs) occurring with each unit of change in the independent variable (Dumbaugh & Rae, 2009). Dumbaugh and Rae (2009) found crashes increased with an increase in speed. Human behavior also played an uncountable role in crash rates (Dumbaugh & Rae, 2009). Safety improvements such as roundabouts decreased the rate of fatal crash occurrences;

however, the rate of less severe crashes increased (this may also be due to human behavior and issues of unfamiliarity with new intersection designs) (Dumbaugh & Rae, 2009).

Rifaat, Tay, and de Barros (2012) analyzed crash data from the city of Calgary, Alberta to examine the impacts of urban street pattern and design on traffic safety. Crashes were overlain with the 227 community and included streets, schools, liquor stations, and train stations GIS layers for the City of Calgary (Rifaat, Tay, & de Barros, 2012). Rifaat, Tay, and de Barros (2012) focused on the variables of street pattern, driver age, driver sex, driver condition, traffic control device present, environmental condition, road surface condition, collision location, and other special road conditions in their work to understand relationships between urban street pattern and design on traffic safety (Rifaat, Tay, & de Barros, 2012).

Rifaat, Tay, and de Barros (2012) found the street pattern safest for pedestrians was the gridiron pattern, but that crashes between two vehicles are more common on this street pattern because of the increased number of intersections. The study found that although the loop and lollipop street pattern was designed to increase safety by decreasing through traffic, it may decrease safety by decreasing driver line of sight distance. Some final findings were that crashes were more severe under extreme weather conditions or in cases where drivers were under the influences of alcohol (Rifaat, Tay, & de Barros, 2012).

Brooks, Kelley, and Amiri (2016) investigated relationships between socio-economic status and street trees using ArcGIS., finding an inverse relationship between socio-economic status and the number of street trees decreased in an area of Spokane, WA. Brooks et al. (2016) used ordinary least squares (OLS) regression models as an indicator of inequality and for spatial autocorrelation by utilizing a hot spot analysis to search for density of tree canopy and other variables in relation to pedestrians. The study area in Spokane was analyzed at the census tract level. The spatial analysis delineated the pedestrian realm within the city, identified and quantified trees within that that area, and assessed socio-economic status within the area (Brooks, Kelley, & Amiri, 2016).

Brooks et al. (2016) modeled crash occurrences on median home value, household density, and average year structures built. Ordinary least squares regression and exploratory regression (ArcGIS function to model linear regression to build OLS models) were used to analyze percent tree canopy (Brooks, Kelley, & Amiri, 2016). Spatial autocorrelation of variables was analyzed using a hot spot analysis to identify areas of where the socio-economic features are densely aggregated (indicating a high presence of the factor in that area in comparison to surrounding areas) (Brooks, Kelley, & Amiri, 2016).

Other Methods of Analysis

Dumbaugh (2005) tested his hypothesis that livable streetscapes are less safe due to their reduction in clear zone width by examining crash data for Colonial Drive (a major connector between downtown Orlando, FL and eastern and western suburbs). Dumbaugh

(2005) did not consider Colonial Drive as a livable street, but believed it had many attributes of a livable street due to its continuous sidewalk, narrow lane widths, on street parking, and protections for pedestrians (Dumbaugh, 2005). Dumbaugh (2005) compared the section between the downtown of Orlando and surrounding suburbs to a section of similar distance (0.9 miles) along Colonial Drive located less than 4 miles east (Dumbaugh, 2005). The comparison section of roadway was similar in all characteristics such as street design, average number of crashes per intersection, and mean age of driver (Dumbaugh, 2005). The difference between the two sections was that the section located further from downtown Orlando had wider lanes and a wider clear zone (Dumbaugh, 2005). The posted speed limit on this section was also 45 mph where the posted speed limit along the livable section was only 40 mph, but this was considered a minor difference and did not inhibit the study (Dumbaugh, 2005).

Dumbaugh (2005) found the livable section of roadway to be safer, supporting his hypothesis that livable streets with more narrow lanes and clear zones are safer than roadways with wider lanes and clear zones. Dumbaugh (2005) also found no fatal mid-block crashes along the livable section of roadway while there were 6 fatal crashes along the comparison section. Pedestrian and cycling accidents were also lower in the livable section where there is a greater buffer between these users and drivers (Dumbaugh, 2005).

A major benefit of the Dumbaugh (2005) study was that the two comparison areas were located along the same roadway, giving better control of driver population. To compare the two sections of roadway the crash numbers were normalized by determining the number of crashes per 100 million vehicle miles traveled. Safety was also analyzed based on the number of mid-block crashes per mile to minimize the influences of traffic volume on crash rates. There was no significant difference between crash rates in either analysis model, and the general finding was that the livable street section was safer than the comparison street section. (Dumbaugh, Safe Streets, Livable Streets, 2005)

To further support this finding, Dumbaugh also analyzed roadways utilizing similar livable conditions to those studied in downtown Orlando (dense development, narrow lanes and clear zones) by analyzing two 0.5 mile sections located within the historic districts of DeLand and Ocala, FL (Dumbaugh, 2005). These 0.5 mile sections were each compared to 5-miles sections (10 mph faster) of the same roadway located on either side of each historic district, and in both cases the average number of crashes reported was lower in the livable sections within the historic districts (Dumbaugh, 2005). There were also no fatal crashes reported within the historic districts (Dumbaugh, 2005). From these findings Dumbaugh concludes that wider lanes and clear zones may reduce driver's perception of risk, causing them to not focus as much on driving safety and possibly engage in riskier driving behaviors (Dumbaugh, 2005). This conclusion suggests that further research should be conducted on drivers' perceptions of risk (Dumbaugh, 2005).

In another case Kathleen Wolf and Nicholas Bratton (2006) utilized archived crash data to discern the influences of trees on crashes and whether or not there are differences in these trends between urban and rural settings. Data from 2002 was taken from the

General Estimates System (GES) database generated by the National Automotive Sampling System and collected by the U.S. National Center for Statistics and Analysis (Wolf & Bratton, 2006). In total, 91 variables were analyzed including driver gender and age, alcohol consumption, posted speed, and road characteristics (Wolf & Bratton, 2006). Accidents on roadways in areas where the population was greater than 50,000, the number of travel lands was four or less, and speeds were posted at less than 45 miles per hour were considered urban (Wolf & Bratton, 2006). All other accidents were considered rural (Wolf & Bratton, 2006).

Wolf and Bratton (2006) found that rural roadside crashes are more frequent than those in urban areas, collisions with fixed objects are more frequents in rural than urban areas, and crashes in urban areas are more likely to result in more severe injury or death than those in urban areas. Risk assessment as well as consideration for community values should both be a consideration when planning for trees along roadways; this balance is the true goal of Context Sensitive Solutions, especially as cities attempt to plan for walkable and livable communities (Wolf & Bratton, 2006). The comparison of urban to rural environments as well as considerations for community values in planning for trees along roadways in this case was a successful method of comparing different street design and its impact on traffic safety (Wolf & Bratton, 2006).

CHAPTER 2 METHODS

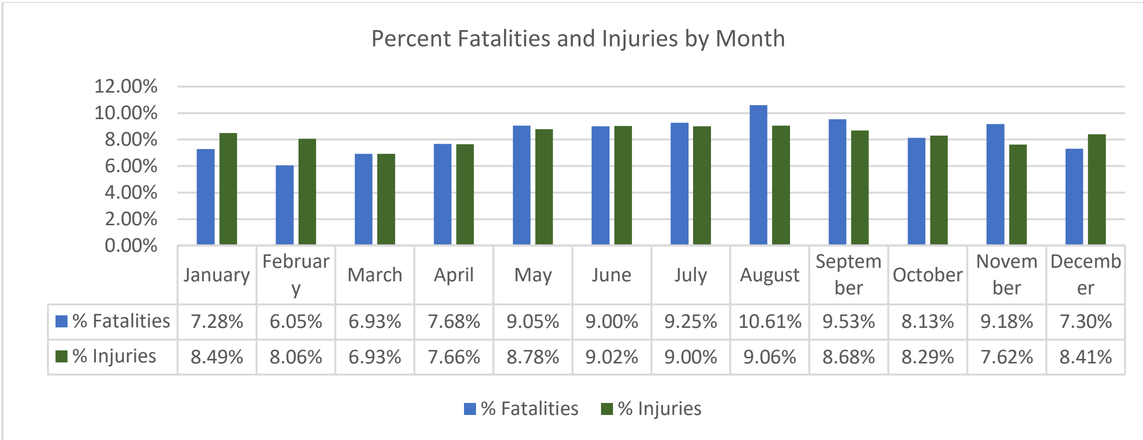
Many studies described in the review of methodologies have analyzed influences of trees on crash severity and frequency, but have not directly analyzed the relationship between street tree density and crash occurrences. Crash reports are required components of this research. These are important in analyzing crash occurrences in relation to street trees. This data is available in varying levels of detail at the city level. Another essential component in this thesis is the analysis of the community's public tree canopy, that is, canopy provided by trees in the public right-of-way. Of these, public trees along roadways are the primary focus in this research.

Study Area and Data

Des Moines, Iowa was the chosen study area for due to the city's availability of crash statistics and tree inventory data. The tree inventory data provided by the Des Moines City Public Works Department, 2010 U.S. income and population data, and crash report data generated by the Iowa Department of Transportation was mapped and analyzed both numerically using SPSS® as well as spatially using ArcGIS®.

Initial Des Moines City crash data analysis displays a uniform distribution of crash frequencies over a 12 month period with the greatest number of both fatalities and injuries in the months of August and September and the lowest crash frequencies in the months of February and March (Table 1). Based on the uniform distribution of crash frequencies over a 12 month period, it is decided that seasonal influences will not be included in this analysis.

Table 1 Percent Fatalities and Injuries by Month



	January	February	March	April	May	June	July	August	September	October	November	December
% Fatalities	7.28%	6.05%	6.93%	7.68%	9.05%	9.00%	9.25%	10.61%	9.53%	8.13%	9.18%	7.30%
% Injuries	8.49%	8.06%	6.93%	7.66%	8.78%	9.02%	9.00%	9.06%	8.68%	8.29%	7.62%	8.41%

Spatial Analysis

Crash data, tree inventory data, and land use data were input into ArcGIS® software using a 1984 World Geodetic System Geographic Coordinate System (GCS_WGS_1984) to address Hypothesis 1: there is a positive relationship between trees and crash frequency. ArcGIS® was used to display crash data spatially as well as to aid in the analysis itself by working as a tool to group the data by Census Block Groups. A hot spot analysis of crash location frequency was then completed (ESRI, 2011). Tree inventory data was plotted by latitude and longitude coordinates and displayed using green point symbology. Likewise, crash data was plotted using latitude and longitude coordinates and displayed using red point symbology. The Des Moines city boundary is indicated using a black polygon outline, and data sources are described in the figure.

Figure 1 Des Moines, IA Public Tree Locations and Vehicular Crash Occurrences. clearly displays where trees are located and where crashes have occurred across the city, giving initial visual understanding of the research question if street trees influence roadway safety. After identifying relationships between the variables a hot spot analysis by aggregate polygon block groups of vehicular crash occurrences was conducted using the ESRI Moran's I model to identify spatial autocorrelation (Figure 2; Appendix A). In order to analyze feature locations and feature values in unison to identify clustering of crash occurrences in Des Moines, IA Global Moran's I was the chosen model for hotspot analysis.

The Moran's I model generated by ArcGIS® calculates an index value and evaluates the significance of the index using z-scores and p-scores. The goal of the hot spot analysis was to help determine sample zones for spatial analysis, and the goal of including spatial analysis in this thesis was to work as a visual aid to provide readers with a connection to Des Moines at the neighborhood level by ultimately displaying the difference between what can be viewed on a map and what statistical numbers show. The hot spot map shows a clear area of high crash frequencies in the center of the city. The remainder of the city shows crash frequencies at a rate that is non-significant, and the northwest corner of the city displays an area of low crash frequency.

Results of the Moran's I analysis indicate that, with an R square value of 0.497, about 50% of the variation in crash occurrences in Des Moines, IA is explained by the independent variables (Appendix A). This is evidence that countless other unknown variables are also attributable to crash occurrences. The Significance F is 0.000. Because this value is less than 0.5 the model finds that there is statistical significance between crash rates and the independent variables. The model z-score of 11.98 is relatively high, indicating significant relationship between the dependent and independent variables. Further analysis and interpretation of these relationships is warranted and is evaluated using SPSS® software.

The initial hot-spot analysis was conducted at a city level in order to identify areas of highest crash frequency, and deeper analysis was conducted over areas of high interest (referred to as "sample zones") at the block group level to give simple insight as to where crashes are happening most frequently. Sample zone block groups were chosen at random within areas of high (most number of crashes when compared to the city totals), medium (average number of crashes when compared to the city totals), and low crash frequencies (lowest number of crashes when compared to the city totals). Traffic counts were not included in this analysis due to limitations in data availability. Roadway speeds were displayed using line segments. Spatial analysis also includes additional variable layers such as trails, land use, neighborhood boundaries, zoning, and street centerlines to complete the spatial analysis. The additional variables add depth to understanding outside influences on traffic crashes.

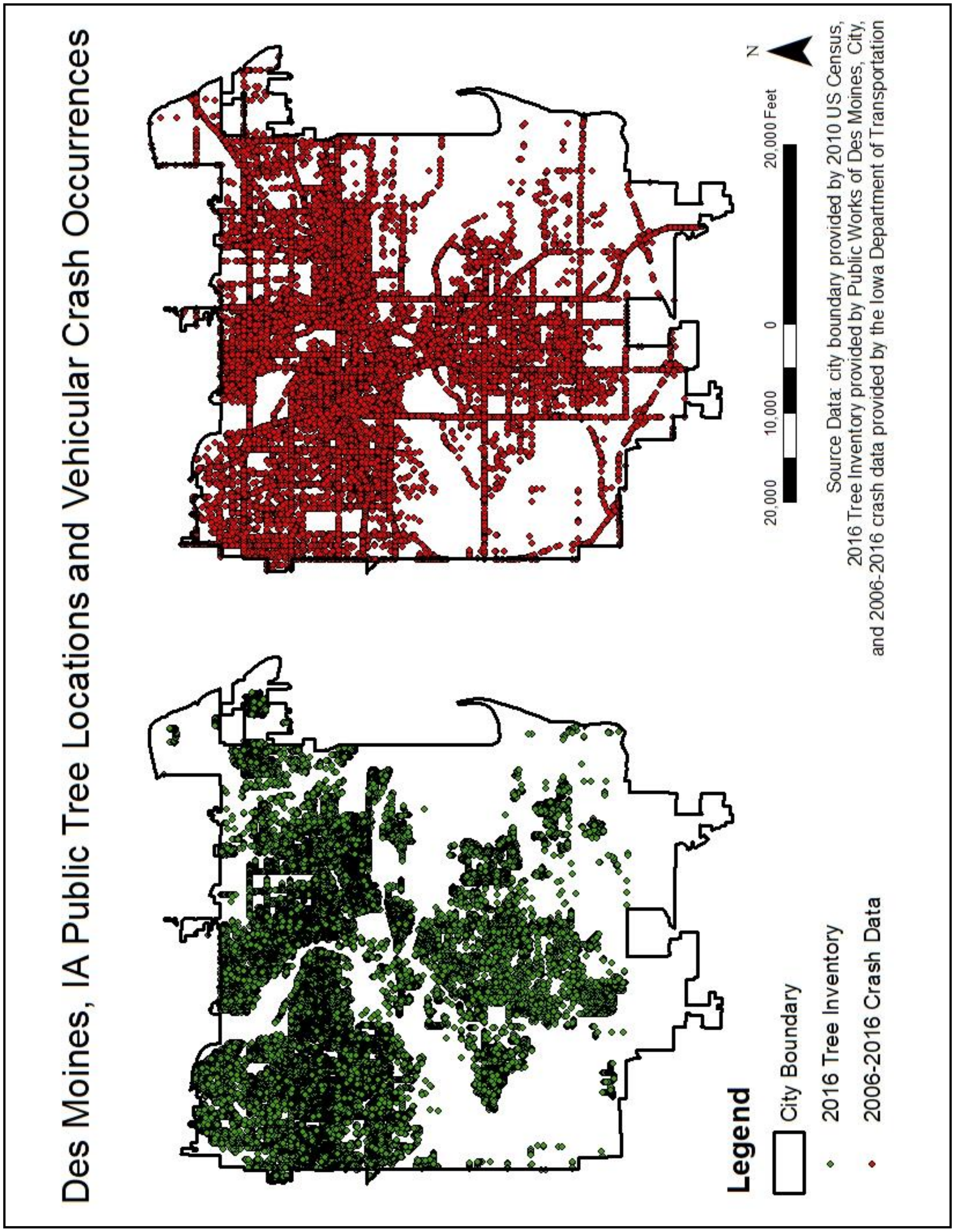


Figure 1 Des Moines, IA Public Tree Locations and Vehicular Crash Occurrences.

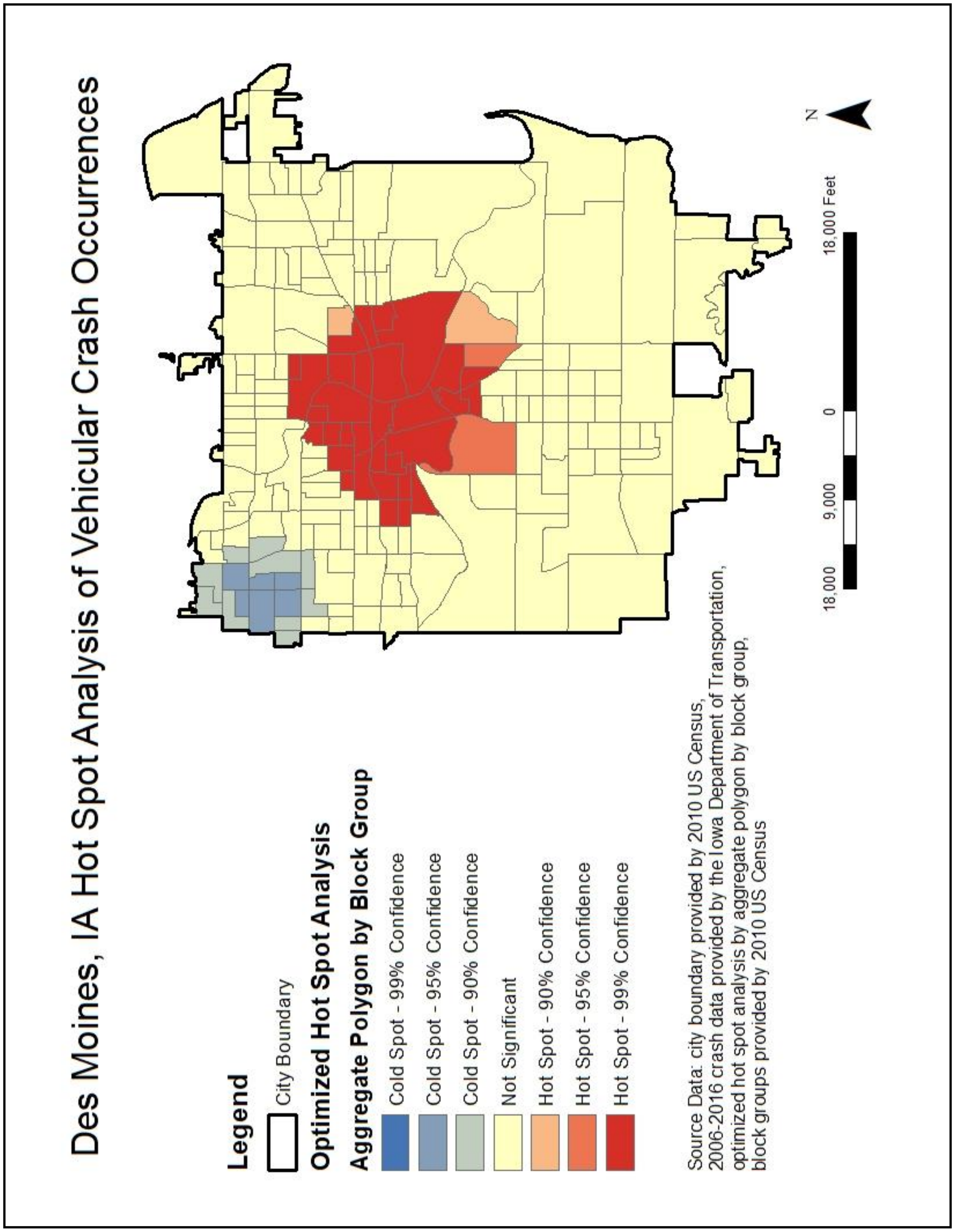


Figure 2 Des Moines, IA Hot Spot Analysis of Vehicular Crash Occurrences using Morans I.

In determining study sample locations in Des Moines, IA it was decided that six selections would be made in the North East quadrant of the city to help minimize location variables. Cold spots block groups, not significant block groups, and hot spot block groups are all found within the North East quadrant, making this an ideal area for further analysis. Research sample zones are identified in Figure 3 in yellow polygon outline symbology. There are two cold spot sample zones, two not significant sample zones (referred to as “neutral areas”), and two hot spot sample zones chosen, all of them encompassing a variety of speed limits. After determining sample zones, further analysis and mapping was completed. Variables mapped include crash data, street centerlines, 2016 tree inventory data, health centers, education buildings, fire stations, police stations, city facilities (libraries, juvenile centers, parks, shelters, community centers, parking ramps, pools, recreational centers, armories, laboratories, event centers, city buildings, etc.), and park trail systems.

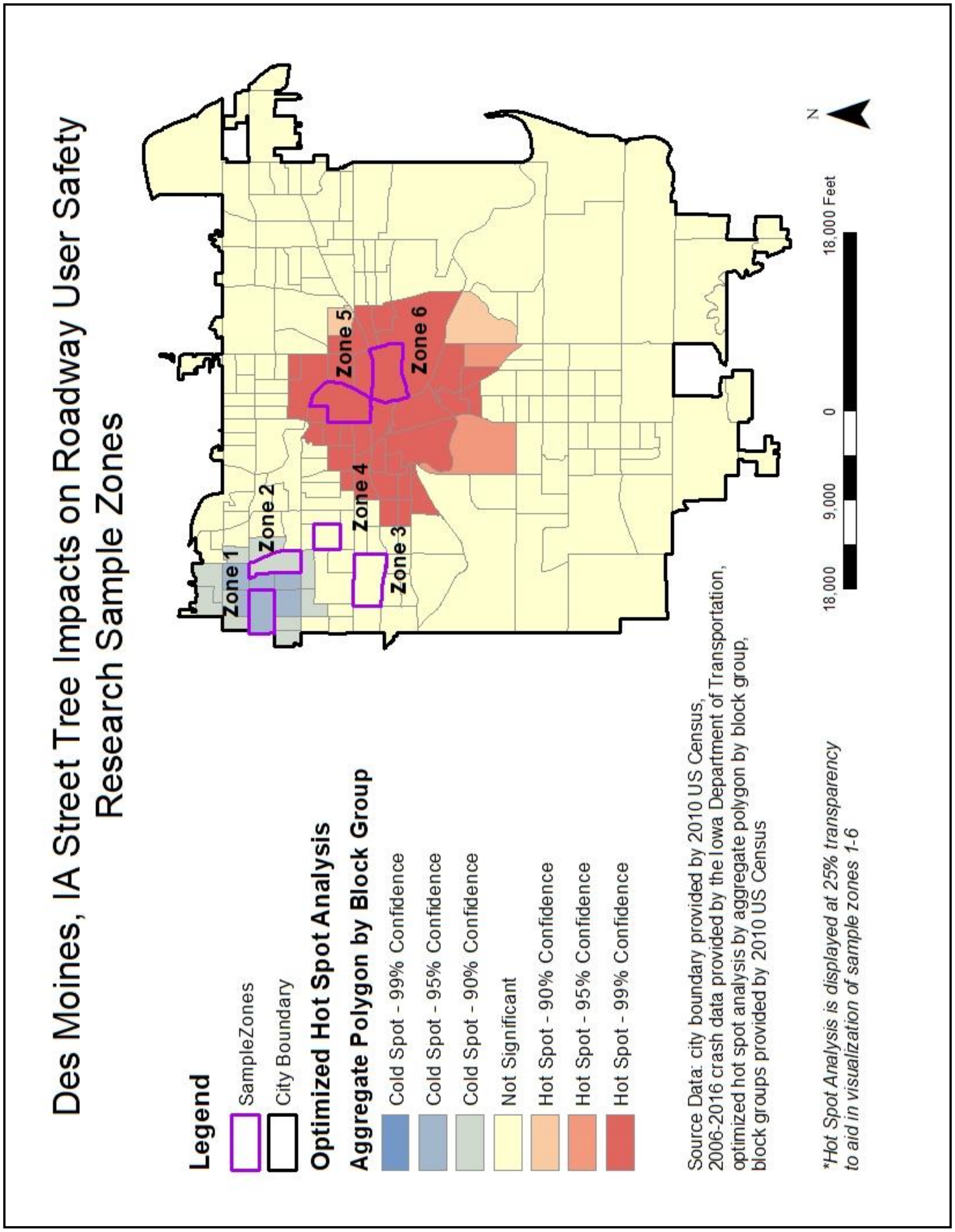


Figure 3 Des Moines, IA Street Tree Impacts on Roadway User Safety Research Sample Zones

Statistical Analysis

All of the steps in the statistical analysis are used to answer the research question "is there a relationship between street trees and roadways safety" by either supporting or failing to support Hypothesis 1 that there is a positive relationship between street trees and traffic frequency and Hypothesis 2 that there is a positive relationship between street trees and traffic severity. To do this, crash data is standardized in order to address spatial issues and discrepancy at the block group level using street distances as the standardization value, and the dependent variable of traffic crashes per mile is considered in relation to the independent variables of population density, income, tree size, and tree density by block group (IBM Corp., 2016). Des Moines, IA is comprised of 200 block groups, all of different shapes and sizes, and all of varying road lengths. These spatial differences may play a role in the rate of crashes per block group. For example, a block group with limited street miles may report fewer crashes than a larger block group comprised of more street miles. Differences in crash frequency per block group may be influenced by the number of street miles per block group, and this spatial attribute must be accounted for in analysis. By dividing total crashes by street miles per block group, the crashes are standardized by street mile to account for spatial differences between block groups. Analysis at the block group level allows for a "neighborhood" analysis suitable for the questions posed in this research.

To test Hypothesis 1, independent variables of income and population density are used to provide a proxy for how urban and dense a place is, and the independent variable of tree size and density and the dependent variable of crash density control for built environment characteristics. The independent variable of roadway speeds (included in the spatial analysis) was omitted from further statistical analysis due to its inability to be generalized at the block group level.

Analysis at the block group level testing Hypothesis 1 includes a descriptive analysis using t-tests to compare sample means with data standards (test values that are used to compare variable data mean values to a locally accepted or comparable standard), a histogram to identify normal distribution, correlation tests to identify correlations between variables, a multicollinearity test to identify issues between variable relationships, and regression tests (linear and negative binomial) of the data to identify relationships between the independent and dependent variables (IBM Corp., 2016). Because the distribution of the crash data per mile is not normal, a negative binomial regression model is found to be more appropriate than the linear regression model, but both outputs are included in results and discussion as an exploratory measure and comparison. The negative binomial regression model is used to provide a more conservative test of the coefficients than a traditional linear regression model. In the negative binomial regression model the dependent variable Crashes per Mile values were rounded to the nearest integer in order to perform the analysis, and 200 cases were analyzed using the Generalized Linear Model (negative binomial regression with log rate of 1) function in SPSS (IBM Corp., 2016). The output also included analysis of interactions between independent variables. The goal of this process is to test Hypothesis 1: there is a positive relationship between trees and crash frequency.

After these relationships were identified, a similar analysis took place testing only relationships between severe crashes (dependent variable) and trees by selecting only crashes identified as “severe” to be included in the statistical models (IBM Corp., 2016). The first step in this final analysis included descriptive tests, frequency tests, and histograms to understand distribution and descriptive characteristics of the variables. Next, linear and negative binomial regression models are used to better understand this relationship and its significance in order to test Hypothesis 2: there is a positive relationship between trees and crash severity and to test interaction between the variables. Because the data is found to be skewed, a negative binomial regression model is found to be more appropriate than the linear regression model, but both outputs are included in results and discussion. In the negative binomial regression model the dependent variable Severe Crashes per Mile values were rounded to the nearest integer in order to perform the analysis, and 200 cases were analyzed using the Generalized Linear Model (negative binomial regression with log rate of 1) function in SPSS (IBM Corp., 2016).

CHAPTER 3 RESULTS AND DISCUSSION

Spatial Analysis

The first in a series of sample zone maps is of Zone 1, an area of lowest crash frequencies in the city of Des Moines (Figure 4). Various amenities including a school, health facility, and park are all located in or near Zone 1. As shown in the map, more crash occurrences are located along roadways with higher roadway speeds than lower speed roads. There are also more trees located along lower speed roadways than higher speed roadways, where the crashes are occurring.

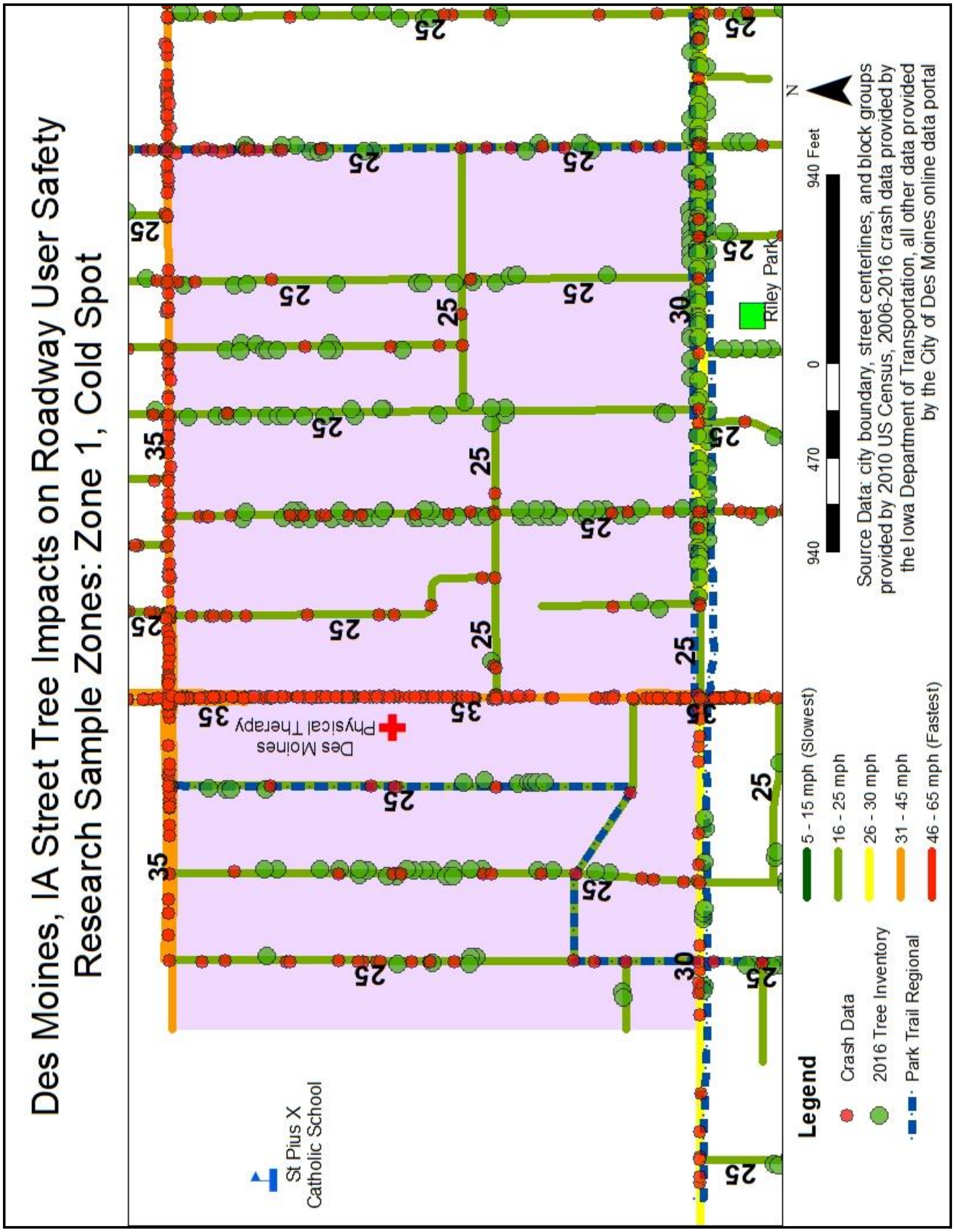


Figure 4 Des Moines, IA Street Tree Impacts on Roadway User Safety Research Sample Zones: Zone 1, Cold Spot

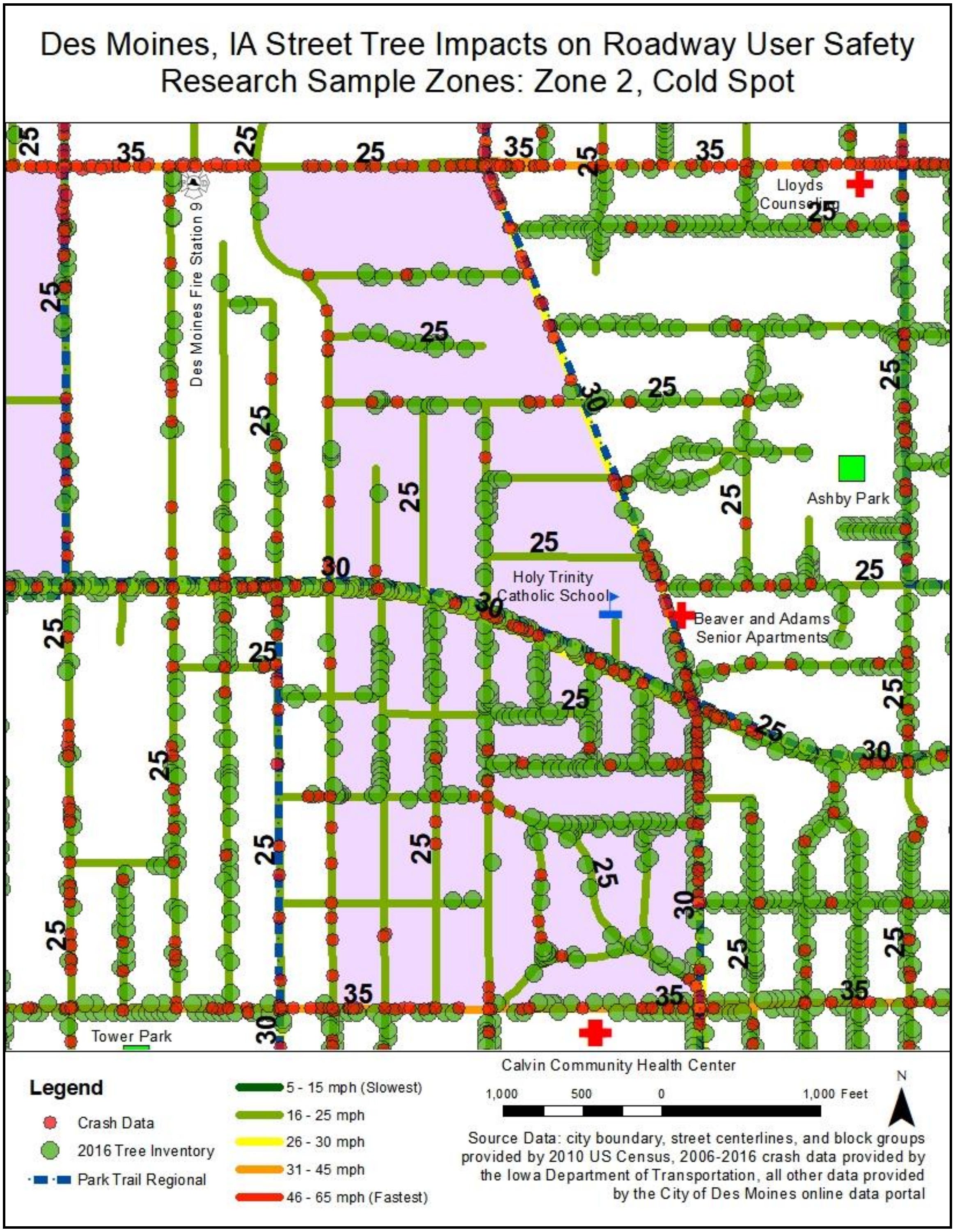


Figure 5 Des Moines, IA Street Tree Impacts on Roadway User Safety Research Sample Zones: Zone 2, Cold Spot

Alike to Zone 1, Zone 2 is a sample of an area of low crash frequency within the city (Figure 5). Trends are also similar in that more occur along high speed roadways than at slower speeds. One notable difference between Zones 1 and 2 is that there is a greater population of street trees along higher speed roadways in Zone 2 than there was in Zone 1. The presence or absence of street trees does not seem to influence the trend of more crashes occurring on higher speed roadways than lower speed roadways.

A notable feature of Zone 3 is the 55 mile per hour speed zone running along the lower boundary of the sample area where there is a high frequency of traffic crashes and where no trees are present in the public right-of-way (Figure 6). This suggests that crashes occur within the zone whether or not trees are present along the roadways. Zone 3 is the first study area located in the neutral area where crash occurrences are occurring at rates considered average for the city. Although crashes are happening at a higher rate than Zones 1 and 2, the trend is the same. More crash occurrences are located along roadways with higher roadway speeds and fewer trees than lower speed roads.

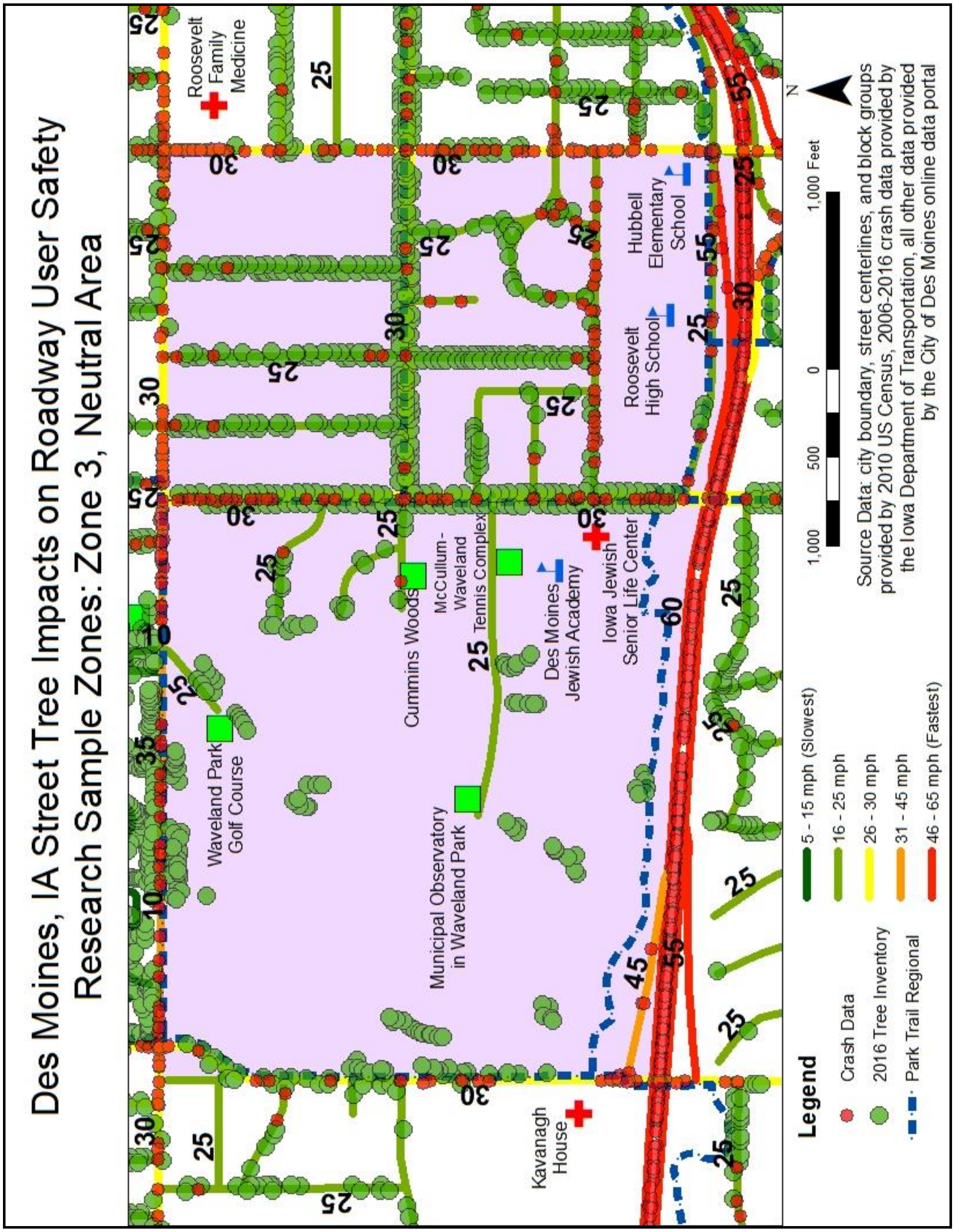


Figure 6 Des Moines, IA Street Tree Impacts on Roadway User Safety Research Sample Zones: Zone 3, Neutral Area

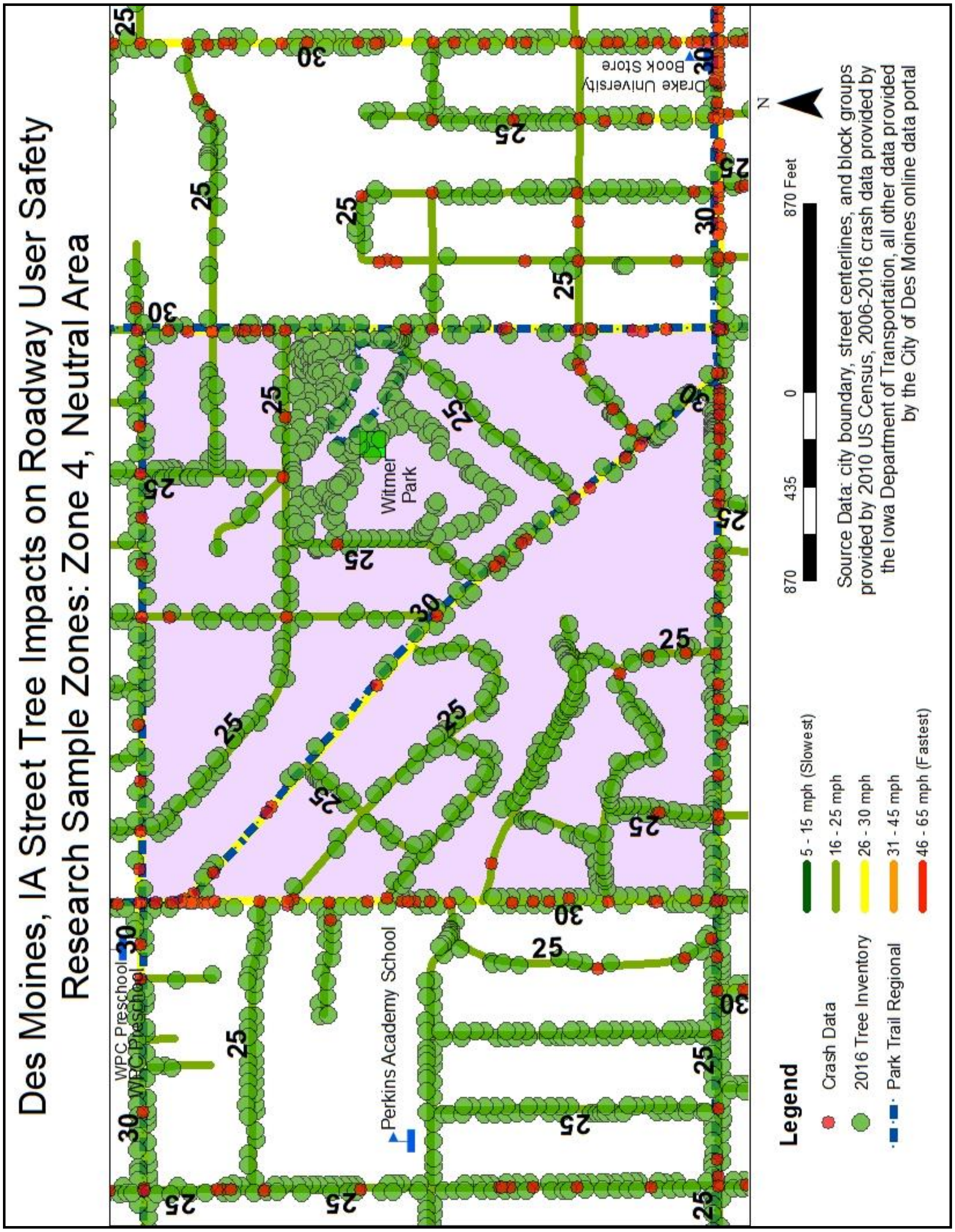


Figure 7 Des Moines, IA Street Tree Impacts on Roadway User Safety Research Sample Zones: Zone 4, Neutral Area

Zone 4 is the second area reviewed in what is considered as the neutral area where crash frequencies are similar to averages found across the city (Figure 7). A notable feature of Zone 4 is the park trail system that runs within and along the perimeter of the study zone, introducing additional conflict into the transportation system. Although the trail system is present, crashes still tend to occur along the higher speed roadways (where fewer trees are present than lower speed roadways) rather than where trails run.

Zone 5 is the first sample area mapping a part of the city where crashes are most frequent (Figure 8). Crashes in the Zone 5 map seem to occur along every roadway. City amenities, parks, trails, and other variables plotted on the map are also more frequent in this zone than previous areas reviewed, indicating a more active environment. The busyness of this map makes trends harder to discern than Zones 1-4. Historical practices of maintaining trees along lower speed roadways but removing them from busier and faster roads can still be noted. More crashes still appear to occur along high speed roadways where fewer trees are present than at lower speeds, although an overall increase in all crashes within the zone is apparent (as compared to Zones 1-4).

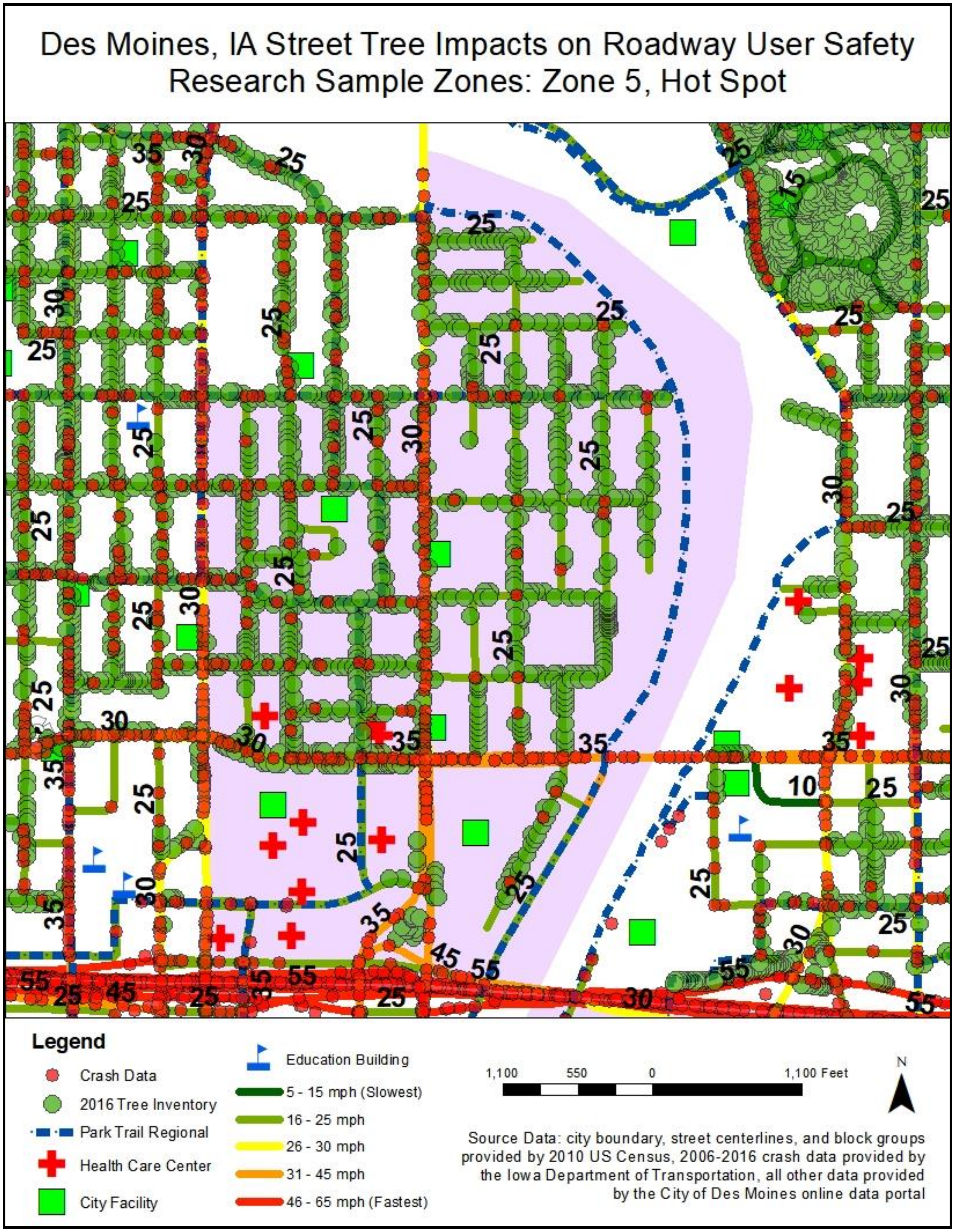


Figure 8 Des Moines, IA Street Tree Impacts on Roadway User Safety Research Sample Zones: Zone 5, Hot Spot

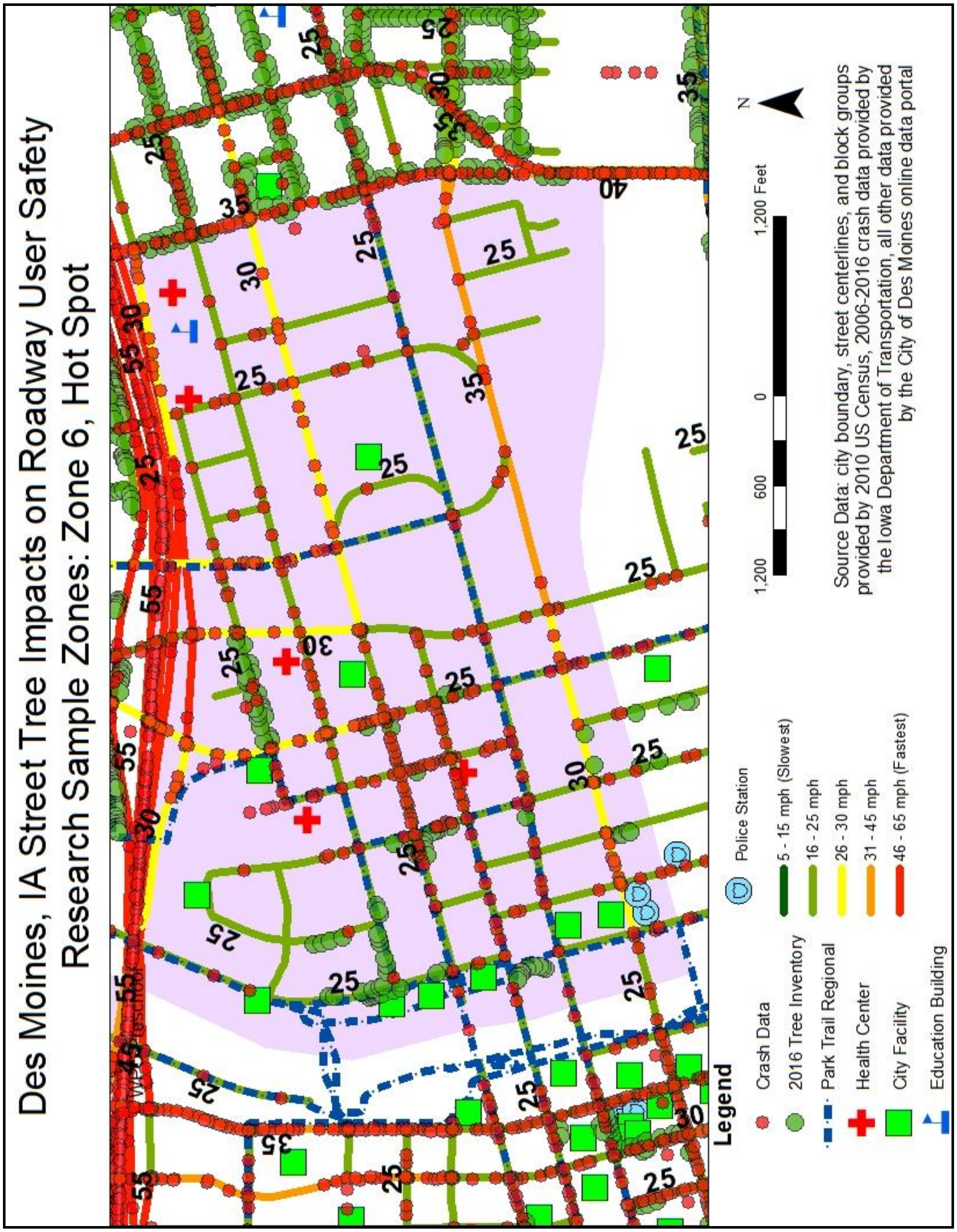


Figure 9 Des Moines, IA Street Tree Impacts on Roadway User Safety Research Sample Zones: Zone 6, Hot Spot

Findings in Zone 6, another area of highest crash frequency within the city, are comparable to findings in Zone 5 (Figure 9). Crashes tend to occur more along higher speed roads than slower roads. There is a notable lack of trees within this zone compared to that of Zones 1-5. There are factors other than roadway safety that may be influencing this lack of street trees. However, the decision to not maintain trees within the area may have been in part in attempt to improve traffic safety in a high-traffic area of the downtown area. It is clear though that crashes are still occurring, even in the absence of street trees.

It is important to remember that the 2016 tree inventory only includes public tree information. Public trees are only those found in the public right-of-way (ROW), so this map is not a depiction of all trees found within the city. It is mainly a depiction of only street and park trees. With this understanding it does make sense that crashes would occur in the same vicinity as trees because many of the trees displayed here are those located along streets.

In all six sample zones trees are absent from street edges in high speed areas, but have been maintained in lower speed zones (Artimovich, Highway Safety and Trees: The Delicate Balance, 2011). The goal of maintaining greater clearance of street trees along high speed roadways is to minimize risk of fixed object crashes at higher speeds as well as to promote safety by improving sight lines along roadways that are designed to move traffic faster (Dixon & Wolf, 2007). A significant finding in these maps, however, is that crashes are still occurring at higher frequencies along these faster streets. This suggests then that simply removing street trees is not a viable option for making streets safer. If crashes occur with or without street trees present, then their presence may be of more overall environmental, social, and economic value to a city than their absence.

Statistical Analysis

Analysis of street tree and crash data gives spatial understanding of locations of crashes in relation to street trees. However, spatial analysis alone is not enough to support or fail to support either Hypothesis 1: there is a positive relationship between street trees and crash frequency or Hypothesis 2: there is a positive relationship between street trees and crash severity. After gaining an overall spatial understanding of traffic crashes in relation to the independent variables, the statistical analysis is used to scientifically identify and quantify relationships and answer the research question "is there a relationship between street trees and roadway safety?" (IBM Corp., 2016).

To understand Hypothesis 1, there is a positive relationship between street trees and crash frequency, a t-test was first conducted. The t-test is used to understand descriptive information about the variables by identifying if the difference between variable means is statistically significant. Each variable was analyzed and compared to a normally accepted mean average. Sources for mean comparisons (test values) are listed within the tables. Crash data per mile is available at a state-wide level, but this does not serve as a suitable mean comparison to the city of Des Moines due to the rural nature of the state. Mean crashes per mile in Cedar Rapids, Iowa is the chosen standard of measurement because Cedar Rapids is the closest city in population to Des Moines in the state. Cedar Rapids reported a population of 126,714 in 2010 and is made up of 108 Block Groups, and in 2010 Des Moines reported a population of 203,433 and is made up of 200 block groups (US Census Bureau). Tree inventory data is not available at a national or statewide level, so test values for this variable are compared to Madison, WI values (average number of trees by block group) (Madison, 2017). Madison was chosen as the standard comparison for the tree density t-test because of its availability of data, proximity, and relative size to Des Moines. In 2010 Madison reported a population of 233,631, and the city is comprised of 196 total block groups, and in 2010 Des Moines reported a population of 203,433 and is comprised of 200 block groups (US Census Bureau).

Results of the t-test in Table 2 show that the p-value (Sig. [2-tailed]) is 0.000, a value less than 0.05 (standard measure at a 95% confidence interval), indicating that mean value of crash frequencies in Des Moines, Iowa is statistically different than standard test value mean of crash occurrences for the entire state (Department of Transportation, 2015). With a t-value of 6.536 evidence shows that there is a positive difference between the variable mean and the test value, suggesting that the mean value of crash frequency in Des Moines, Iowa is higher than the mean value of crash frequencies for the entire state. This information it important in understanding the significance of crash frequency in Des Moines relative to the state as a whole. In this case, crashes appear to happen more frequently in Des Moines than the source city for the test value, Cedar Rapids. This may be due to the larger population in Des Moines, but it still raises awareness of the high crash frequency in Des Moines relative to the second most populated city in the state.

Table 2 Crash count data t-test

T-Test (Crashes per mile)

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Crashes per mile	200	107.24274359165	100.455170375906	7.103253217805

One-Sample Test

	Test Value = 60.814 Data Source: Iowa DOT; US Census 2010 Block Group Data					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper
Crashes per mile	6.536	199	.000	46.428743591645	32.42143692332	60.43605025997

According to the t-test in Table 3, the p-value value is 0.000, a value less than 0.05 indicating that the observed mean of tree density in Des Moines, Iowa is statistically different than the standard test value mean *(Madison, 2017; US Census Bureau)*. A t-value of -15.540 suggests that the mean value of tree density in Des Moines is significantly lower than the mean value of the test value of tree density in Madison, WI. This difference in mean tree density between these cities may be reason to think that there is room for canopy growth in Des Moines when compared to Madison. Other variables are involved in understanding the potential for tree density increase in Des Moines and the associated risks and benefits, especially in relation to traffic safety and crash frequency.

Table 3 Tree count data t-test

T-Test (Tree Count)

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Tree Count	200	259.02	286.649	20.269

One-Sample Test

	Test Value = 574 Data Source: City of Madison, WI open data portal, 2017 tree inventory data					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Tree Count	-15.540	199	.000	-314.985	-354.95	-275.02

Table 4 shows a p-value of 0.217, a value greater than 0.05, indicating that the observed mean of population density in Des Moines, Iowa is not statistically different than the standard test value mean *(US Census Bureau)*. This data concludes that population density in Des Moines is similar to population across the entire state of Iowa. Incorporating characteristics of population density into this research process helps to give a better degree of understanding to how urban and dense Des Moines is in relation to the rest of the state. Although crashes occur more frequently in Des Moines when compared to the standard (Table 2), the city's population density is similar to that of Iowa as a whole, giving reason to believe that population density may not be the cause of increased crash frequency, but not reason enough to eliminate it entirely from statistical analysis.

Table 4 Population Density t-test

T-Test (Population Density)

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Population Density	200	1868179.05533 5171	21319061.0630 326300	1507485.264620 0461

One-Sample Test

	Test Value = 1192 Data Source: 2015 US Census Block Group Data and state averages					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper
Population Density	1.238	199	.217	1866987.05533 51708	-1105708.37759 4692	4839682.488265 034

Findings in the t-test in Table 5 show a p-value of 0.000, a value less than 0.05 indicating that the observed mean value of median household income in Des Moines, Iowa is statistically different than the standard test value mean *(US Census Bureau)*. With a t-value of -58.339, the t test in Table 5 concludes that the mean of median household income in Des Moines is significantly lower than the mean of median household income for the entire state of Iowa. This finding suggests that there is a significant difference between income in Des Moines and that of the state, a factor that warrants further investigation of the independent variable and its relationship with crash frequency per mile.

Table 5 Median household income t-test

T-Test (Median Household Income)

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Median Household Income	199	15224.56	9554.141	677.275

One-Sample Test

	Test Value = 54736 Data Source: 2010 US Census Block Group Data and state averages					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Lower
Median Household Income	-58.339	198	.000	-39511.442	-40847.04	-38175.84

Scatterplots of independent variables (population density, median household income, tree density, and tree size based on diameter at breast height) along a line of best fit determined by the dependent variable (crashes per mile) were created to determine linear relationships (Appendix B). Finding no statistically significant correlations between the variables at a 95% confidence interval, a correlation model was next conducted to give further understanding of variable relationships. The p-values (Sig. [2-tailed]) for all independent variables are greater than 0.05, indicating no statistical significance in correlation between crash counts and population density, median household income, tree count, or average DBH at a 95% confidence level (Table 6). This model observes slight correlations between each independent variable and the dependent variable, but there is not enough evidence to conclude that this correlation exists in the population based on the non-significant p-values for all variables. This finding fails to support Hypothesis 1: there is a positive relationship between trees and crash frequency.

Table 6 Correlation analysis of crash counts per mile, tree counts, population density, and median household income variables.

Correlations

		Crashes per mile	Population Density	Median Household Income	Tree Count	Average DBH
Crashes per mile	Pearson Correlation	1	-.015	.018	.132	-.054
	Sig. (2-tailed)		.828	.796	.062	.445
	N	200	200	200	200	200

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

A test of multicollinearity is found in Table 7. In the Coefficients portion of the Table 7 output, no VIF values are greater than 5, indicating no significant issues with multicollinearity. Likewise, there are no tolerance levels below 0.20, another indication that there is not multiple correlation between the variables. Finally, no Eigenvalues in the diagnostic test are close to 0, indicating that the predictors are not inter-correlated and will not cause issues in further statistical testing.

Table 7 Test of multicollinearity of variables

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Tolerance	VIF
		B	Std. Error	Beta	t	Sig.	Collinearity Statistics	
1	(Constant)	90.826	15.570		5.833	.000		
	Population Density	-3.725E-7	.000	-.079	-1.024	.307	.839	1.192
	Median Household Income	.000	.001	.029	.399	.690	.967	1.034
	Tree Count	.055	.027	.157	2.055	.041	.859	1.164
	Average DBH	-.873	1.472	-.042	-.593	.554	.991	1.009

a. Dependent Variable: Crashes per mile

Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	Population Density	Median Household Income	Variance Proportions	Variance Proportions
1	1	2.621	1.000	.03	.01	.03	Tree Count	Tree Count
	2	1.070	1.565	.00	.50	.00	.05	.05
	3	.780	1.833	.01	.26	.02	.03	.03
	4	.401	2.558	.01	.13	.21	.02	.02
	5	.127	4.536	.95	.10	.74	.71	.71

a. Dependent Variable: Crashes per mile

A linear regression model was next performed to test linear relationships between the dependent and independent variables in order to address Hypothesis 1: there is a positive relationship between trees and crash frequency (Appendix B). In the linear regression model testing Hypothesis 1, the Pearson Chi-Square value in the Goodness of Fit value is greater than 0.05, concluding that the model does fit the data and further interpretation of the results is useful to research (Table 8). However, the Test of Model Effects finds the only independent variable in the model to be statistically significant is the tree count variable. The dispersion parameter set by the statistic package is 1. This adjusts the standard error, creating a more conservative test of the coeffecients than a linear regression model. Based on the parameter estimate results, for every one unit increase in tree count there is a 0.055 increase in predicted crash occurrences per mile, and this is statistically significant because the p-value for this variable is less than 0.05. Although this data is part of the exploratory process of developing statistical analysis to answer the research question "is there a relationship between trees and traffic safety", this model is only appropriate when distribution of the data is normal and interaction effects are not further assessed in this model, so the identification of distribution trends is necessary.

Table 8 Generalized Linear Model test of linear regression to test Hypothesis 1

Goodness of Fit[a]

	Value	df	Value/df
Deviance	1958550.315	195	10043.848
Scaled Deviance	200.000	195	
Pearson Chi-Square	1958550.315	195	10043.848
Scaled Pearson Chi-Square	200.000	195	
Log Likelihood[b]	-1202.727		
Akaike's Information Criterion (AIC)	2417.455		
Finite Sample Corrected AIC (AICC)	2417.890		

Bayesian Information Criterion (BIC)	2437.245		
Consistent AIC (CAIC)	2443.245		

Dependent Variable: Crashes per mile

Model: (Intercept), Population Density, Median Household Income, Tree Count, Average DBH[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Test of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	34.877	1	.000
Population Density	1.084	1	.298
Median Household Income	.163	1	.687
Tree Count	4.338	1	.037
Average DBH	.360	1	.548

Dependent Variable: Crashes Per Mile

Model: (Intercept), Population Density, Median Household Income, Tree Count, Average DBH

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square
(Intercept)	90.802	15.3753	60.667	120.937	34.877

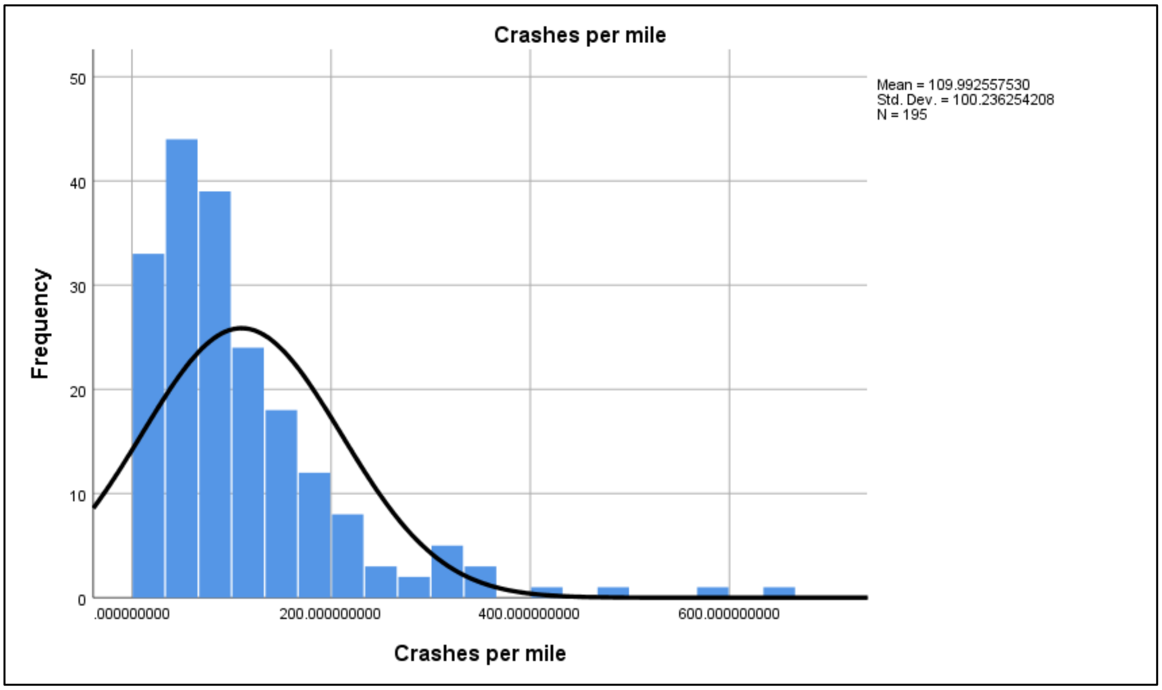
Population Density	-3.740E-7	3.5920E-7	-1.078E-6	3.301E-7	1.084
Median Household Income	.000	.0007	-.001	.002	.163
Tree Count	.055	.0264	.003	.107	4.338
Average DBH	-.872	1.4532	-3.721	1.976	.360
(Scale)	9792.752[a]	979.2752	8049.791	11913.103	

Parameter Estimates

Parameter	Hypothesis Test df	Sig.
(Intercept)	1	.000
Population Density	1	.298
Median Household Income	1	.687
Tree Count	1	.037
Average DBH	1	.548
(Scale)		

The histogram in Table 9 shows a skewed dataset of Des Moines crash frequency per mile. Because the data is skewed toward the 0 y-axis the dataset was checked to determine if the skew comes from an abnormal number of 0's in the data. No block groups report 0 crash reports, leading to the conclusion that a negative binomial regression model is appropriate due to over-dispersion of count variable (not normal distribution; the mean is lower than the variance of the variable).

Table 9 Histogram of dependent variable: crashes per mile



In the negative binomial regression model testing Hypothesis 1, the Pearson Chi-Square value in the Goodness of Fit value is greater than 0.05, concluding that the model does fit the data and further interpretation of the results is useful to research (Table 10). The regression model was run a second time to test for interaction effects between tree counts and the other independent variables (Appendix B). Finding issues with effects of interaction between the Median Household Income and Tree Count variables, Median Household Income was removed from the model and the model was re-computed (Appendix B). Omitting this variable from the analysis is acceptable as relationships between it and the dependent variable were not statistically significant in the first model. The dispersion parameter set by the statistic package is 1. This adjusts the standard error, creating a more conservative test of the coeffecients than a linear regression model. In the second run of the regression model, the Pearson Chi-Square value in the Goodness of Fit value is greater than 0.05, indicating the model still fits the data. The Test of Model Effects finds no relationships between the dependent and independent variables in the model to be statistically significant (all p-values are greater than 0.05). Based on these results, no parameter estimates are useful in further analysis and it is concluded that trees do not have a significant positive relationship on crash frequency, failing to support Hypothesis 1: there is a positive relationship between trees and traffic safety.

Table 10 Generalized Linear Model test of negative binomial regression to test Hypothesis 1

Goodness of Fit[a]

	Value	df	Value/df
Deviance	211.709	194	1.091
Scaled Deviance	211.709	194	
Pearson Chi-Square	174.210	194	.898
Scaled Pearson Chi-Square	174.210	194	
Log Likelihood[b]	-1131.857		
Akaike's Information Criterion (AIC)	2275.715		
Finite Sample Corrected AIC (AICC)	2276.150		
Bayesian Information Criterion (BIC)	2295.505		
Consistent AIC (CAIC)	2301.505		

Dependent Variable: Crashes per mile
Model: (Intercept), Population Density, Tree Count, Average DBH, Population x Tree Count Interaction, Average DBH x Tree Count Interaction
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	1238.474	1	.000
Population Density	.935	1	.334
Tree Count	3.112	1	.078
Average DBH	1.837	1	.175
Population x Tree Count Interaction	1.402	1	.236
Average DBH x Tree Count Interaction	1.319	1	.251

Dependent Variable: Crashes per mile
Model: (Intercept), Population Density, Tree Count, Average DBH, Population x Tree Count Interaction, Average DBH x Tree Count Interaction

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	Upper	Hypothesis Test Wald Chi-Square
(Intercept)	4.506	.1280	4.255	4.757	1238.474
Population Density	-3.549E-9	3.6709E-9	-1.074E-8	3.645E-9	.935
Tree Count	.001	.0006	.000	.002	3.112
Average DBH	-.034	.0252	-.084	.015	1.837
Population x Tree Count Interaction	-2.298E-7	1.9407E-7	-6.101E-7	1.506E-7	1.402
Average DBH x Tree Count Interaction	.000	.0001	-9.152E-5	.000	1.319
(Scale)	1[a]				
(Negative binomial)	1[a]				

Parameter Estimates (cont.)

Parameter	Hypothesis Test df	Sig.
(Intercept)	1	.000
Population Density	1	.334
Tree Count	1	.078
Average DBH	1	.175
Population x Tree Count Interaction	1	.236
Average DBH x Tree Count Interaction	1	.251
(Scale)		
(Negative binomial)		

Dependent Variable: Crashes per mile
Model: (Intercept), Population Density, Tree Count, Average DBH, Population x Tree Count Interaction, Average DBH x Tree Count Interaction
a. Fixed at the displayed value.

Crashes defined as “severe” were next pulled from the crash dataset (dependent variable) and analyzed alongside tree density (independent variable) to aid in furthering the understanding of the influence of tree density on crash severity. Descriptive statistics and histograms of the variables found skewed distributions for both (Appendix B).

Next a correlation model was run to determine if there is a statistically significant relationship between tree density and crash severity in Des Moines, IA (Table 11). The p-value for relationships between trees and crash severity per mile by block group is 0.045, a value statistically significant at the 95% confidence level. This finding supports the idea that there is a relationship between trees and crash severity, but details of this relationship are yet unclear.

Table 11 Correlation descriptive statistics of severe crashes and tree density

Correlations		Tree Count
Severe Crashes Per Mile	Pearson Correlation	.142*
	Sig. (2-tailed)	.045
	N	200

*. Correlation is significant at the 0.05 level (2-tailed).

A linear regression model was next performed to test linear relationships between the dependent and independent variables in order to address Hypothesis 2: there is a positive relationship between trees and crash severity (Table 12, Appendix B). In the linear regression model testing Hypothesis 1, the Pearson Chi-Square value in the Goodness of Fit value is greater than 0.05, concluding that the model does fit the data and further interpretation of the results is useful to research (Table 12). The Test of Model Effects finds the relationship between trees and severe crashes per mile to be statistically significant. The dispersion parameter set by the statistic package is 1. This adjusts the standard error, creating a more conservative test of the coeffecients than a linear regression model. Based on the parameter estimate results, for every one unit increase in tree count there is a 0.002 increase in predicted severe crashes per mile, and this is statistically significant because the p-value for this variable is less than 0.05. Although this data is part of the exploratory process of developing statistical analysis to answer the research question “is there a relationship between trees and traffic safety”, this model is only appropriate when distribution of the data is normal and interaction effects are not further assessed in this model.

Table 12 Generalized Linear Model test of linear regression to test Hypothesis 2

Goodness of Fit[a]

	Value	df	Value/df
Deviance	3778.505	198	19.083
Scaled Deviance	200.000	198	
Pearson Chi-Square	3778.505	198	19.083
Scaled Pearson Chi-Square	200.000	198	
Log Likelihood[b]	-577.664		
Akaike's Information Criterion (AIC)	1161.329		
Finite Sample Corrected AIC (AICC)	1161.451		
Bayesian Information Criterion (BIC)	1171.224		
Consistent AIC (CAIC)	1174.224		

Dependent Variable: Severe crashes per mile

Model: (Intercept), Tree Count[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Tests of Model Effects

		Type III	
Source	Wald Chi-Square	df	Sig.
(Intercept)	75.582	1	.000
Tree Count	4.114	1	.043

Dependent Variable: Severe crashes per mile

Model: (Intercept), Tree Count

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df
(Intercept)	3.605	.4147	2.793	4.418	75.582	1
Tree Count	.002	.0011	7.333E-5	.004	4.114	1
(Scale)	18.893[a]	1.8893	15.530	22.983		

Parameter Estimates (cont.)

	Hypothesis Test
Parameter	Sig.
(Intercept)	.000
Tree Count	.043
(Scale)	

Dependent Variable: Severe crashes per mile

Model: (Intercept), Tree Count

a. Maximum likelihood estimate.

In the negative binomial regression model test for Hypothesis 2, the Pearson Chi-Square value in the Goodness of Fit value is greater than 0.05, concluding that the model does fit the data and further interpretation of the results is useful to research (Table 13). Likewise, the Test of Model Effects finds the model to be statistically significant at the 95% confidence level with a p-value less than 0.05. The dispersion parameter set by the statistic package is 1. This adjusts the standard error, creating a more conservative test of the coeffecients than a linear regression model.

Based on these results, for every one unit increase in trees there is a 1.428 increase in predicted severe crashes, and this is statistically significant because the p-value for this variable is less than 0.05. Although results from the linear regression model in Table 12 were not assumed to be definite due to the model's inappropriate nature when analyzing a skewed dataset, findings in the negative binomial regression support initial linear regression results. Based on this model it is concluded that an increase in trees results in an increase in predicted severe crashes, supporting Hypothesis 2: there is a positive relationship between trees and crash severity.

Table 13 Generalized Linear Model test of negative binomial regression to test Hypothesis 2

Goodness of Fit[a]

	Value	df	Value/df
Deviance	199.984	199	1.005
Scaled Deviance	199.984	199	
Pearson Chi-Square	178.869	199	.899
Scaled Pearson Chi-Square	178.869	199	
Log Likelihood[b]	-507.848		
Akaike's Information Criterion (AIC)	1017.697		
Finite Sample Corrected AIC (AICC)	1017.717		
Bayesian Information Criterion (BIC)	1020.995		
Consistent AIC (CAIC)	1021.995		

Dependent Variable: Severe Crashes Per Mile
Model: (Intercept)[a]
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	328.913	1	.000

Dependent Variable: Severe Crashes Per Mile
Model: (Intercept)

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
Tree Count	1.428	.0787	1.274	1.582	328.913	1	.000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Dependent Variable: Severe Crashes Per Mile
Model: (Intercept)
a. Fixed at the displayed value.

CHAPTER 4 CONCLUSIONS AND PROFESSIONAL APPLICATIONS

By comparing the frequencies of recorded crashes with the Des Moines tree inventory and other related variables this thesis explores the research question "is there a relationship between street trees and roadway safety" by supporting or failing to support Hypothesis 1 that there is a positive relationship between street trees and crash frequency and Hypothesis 2 that there is a positive relationship between street trees and crash severity. Data findings here show that mean crash frequency is higher in Des Moines than the standard (Table 2). One reason for this finding may be due to the fact the Des Moines is the most populated city in the state, but this issue should still be a cause of concern for planners and decision makers in the city. Findings also show that population density in Des Moines is not statistically different from that of the entire state, supporting the idea that population count is not the sole reason for high crash frequency in Des Moines (Table 3). As planners work to minimize risk of crash occurrences in Des Moines, understanding the impacts of trees on roadway user safety will be an important component of the planning process.

If human beings had no error in decision making, cars would never speed, stop signs would never be ignored, and theoretically there would be no road conflict. Although this seems ideal, this concept is not a reality. In the future, cars may evolve enough to remove human error from the equation. Currently, technologies that eliminate the chance of error such as adaptive cruise control and lane departure warning systems are common. However, it will be many years before driverless cars become widespread. As long as humans are maneuvering the roadways, conflict will occur and accidents will happen. The duty of the planner is to work to minimize the risk of conflict when attempting to design safer systems.

Historical trends for planning safer and more productive transportation systems discussed in the literature review have resulted in greater sight lines, wider shoulders, and consequently increased speed limits (Dumbaugh & Rae, Safe Urban Form: Revisiting the Relationship Between Community Design and Traffic Safety, 2009). By providing drivers with an increased sense of security and safety, drivers are more comfortable with allowing themselves to increase their speeds even more and succumb to other distractions such as cell phones, ultimately worsening safety conditions rather than improving them (Dumbaugh, Safe Streets, Livable Streets, 2005).

Increased risk of accidents combined with increased speeds results in more severe collisions, especially those involving fixed objects (Federal Highway Administration, 2017). When a vehicle strikes a tree at a high speed the likelihood of the accident becoming fatal increases because trees are sturdy and provide no cushion upon impact (FDA, 1990). It is easy then to conclude that if a tree is located along a roadway, that roadway may be made safer by removing that tree, but this is not enough cause to assume correlation.

Similar to findings in the literature review, spatial maps reviewed here indicate that crashes on roadways with high traffic speeds and fewer street trees are more frequent than in areas of lower speed limits with more street trees, providing initial support to

Hypothesis 1: there is a positive relationship between street trees and crash frequency, with this relationship being negative. However, correlation analysis for Des Moines finds no statistical significance between tree density and crash frequency per mile, failing to support the hypothesis that there is a positive relationship between street trees and crash frequency. The linear regression model testing Hypothesis 1 finds that trees have a positive relationship with crash frequency, but further interpretation of this model is not warranted due to issues related to running a linear regression model with a skewed dataset. Finally, the negative binomial regression model finds no statistically significant relationships between trees and crash frequency, failing to support Hypothesis 1: there is a positive relationship between trees and crash frequency.

The correlation model used to determine if there is a statistically significant relationship between tree density and crash severity in Des Moines, IA shows that the p-value for relationships between trees and crash severity per mile by block group falls below 0.05, indicating statistical significance for correlations between these variables. Likewise, the linear and negative binomial regression models find that for every one unit increase in tree density there is an increase in predicted severe crashes (a 0.002 increase in the linear regression model and a 1.428 increase in the negative binomial regression model), supporting Hypothesis 2 that there is a positive relationship between trees and crash severity.

With these findings in mind, any planning for street trees at a neighborhood level cannot be supported by decision makers if it is not supported by the public. Awareness of the issues is important in fostering public support, and it is critical for all stakeholders to understand the potential benefits as well as risks of maintaining a street tree canopy along any roadway (Dixon & Wolf, 2007). If the right tree is planted in the right place, and continued proper pruning and care is maintained, the tree should be considered an asset to a community rather than a risk (Macdonald, Williams, Harper, & Hayter, 2006-2011).

Evidence in this research ultimately fails to support Hypothesis 1: there is a positive relationship between street trees and crash frequency but supports Hypothesis 2 that there is a positive relationship between street trees and crash severity. Although the presence of trees in this analysis doesn't prove a statistically significant influence on crash frequency, it is apparent that the presence of trees increases the risk of crashes becoming more severe.

This thesis does not present enough evidence to place blame on trees for causing traffic accidents, but it does present conclusions that suggest trees should be given valuable consideration as to planting location, species selection, pruning techniques, and other best management practices that may reduce the risk of trees along roadways by improving tree structure and optimizing driver sightlines. As long as there is potential for driver error, there will always be driver error. It is not reasonable to plan for the same type of urban tree canopy along a high speed freeway as what can be found along a lower speed multi-use street. However, the environmental, social, and economic benefits of maintaining street trees in livable and walkable areas outweigh the potential costs, and deserve to be included in any transportation planning discussion.

Research Limitations

There are many research limitations involved when assessing crash statistic data. Issues related to crash data are extremely complex and involve countless outside variables and influences. One important component of understanding the influence of trees on crash frequency is the understanding of whether or not trees were the cause of the accidents in these cases. A second important component in understanding this topic is understanding driver perceptions of trees on traffic safety. Both of these issues are increasingly complex and beyond the scope of this research.

Another limitation in this thesis is the use of Global Moran’s I hot spot analysis rather than a local hot spot analysis method (such as Getis-Ord Gi*). When analyzing each feature in a Global Moran’s I analysis, only neighboring feature values are considered in each feature analysis, whereas a local hot spot model would include both the value being analyzed and its neighboring values in the analysis. This difference may result in significantly different results between models depending on the scale of analysis. Hot spots may be occurring where traffic is most frequent, and the inclusion of traffic counts within the analysis would be a method of addressing this issue that was omitted from this analysis due to availability of the data.

This thesis researches conditions relevant to neighborhood planning decisions rather than street level design decisions due to the limiting nature of available crash data. It is impossible to conclude or assume every detail involved with every variable in all Des Moines crash reports, especially at the street level. Completing a block group level analysis provides a picture of conditions as the neighborhood level and is a method of analyzing the data presented. Standardizing the data by street mile helps account for spatial variances between block groups. Further analysis of outside variable relationships such as traffic speed, traffic counts, driver behavior, and other built environment conditions, would provide greater understanding to both hypotheses and is an opportunity for future research potential. The main reason for data omissions in this thesis were due to data availability.

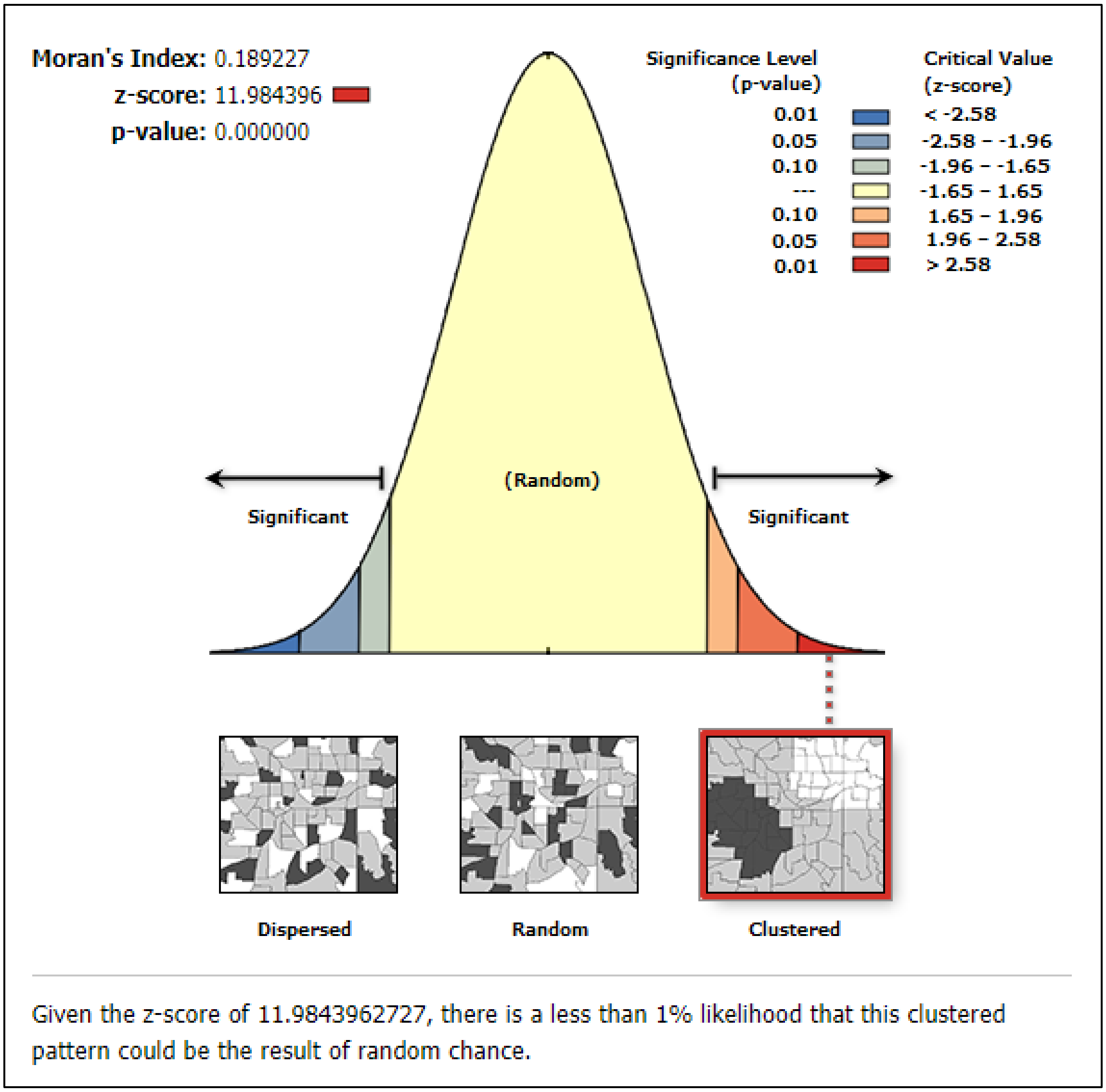
Future Research Potential

As a potential future research project, a study that included a series of cities offering opportunities for comparison between the areas could be completed. An alternative option is to conduct an analysis at an even smaller scale. This would involve a comparison analysis between livable streets and other segments of roadway with wider lanes and clear zones along just one segment of road. A local scale analysis would require the comparison of segments along the same roadway to help control outside variables such as traffic population. An analysis at this scale would require a greater level of detail in the crash reports, and this level of detail is not available in Des Moines, Iowa. This thesis focuses on data for the city of Des Moines, leaving the door open for future comparisons between cities as part of a larger project. Any future research would also benefit from additional variable analysis omitted from this research including roadway speeds, driver behavior, and other build environment conditions. It would be important to consider all research limitations developed within this thesis when approaching any future research.

APPENDIX

APPENDIX A: MORAN'S I SPATIAL AUTOCORRELATION OUTPUT

Spatial Autocorrelation Report



Global Moran's I Summary

Moran's Index:	0.189227
Expected Index:	-0.005495
Variance:	0.000264
z-score:	11.984396
p-value:	0.000000

Dataset Information

Input Feature Class:	BlockGroup_Crash_Tree_Street1
Input Field:	COUNT_
Conceptualization:	ZONE_OF_INDIFFERENCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	10387.4222 US_Feet
Weights Matrix File:	None
Selection Set:	False

APPENDIX B: SPSS OUTPUT

Hypothesis 1 Statistical Data Analysis

Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
Crashes per mile	195	.673429774	648.888056500	109.99255752989	100.236254207746	2.222	.174
Population Count	200	0	5169	1192.21	630.390	2.602	.172
Median Household Income	200	0	81695	15148.44	9590.716	2.574	.172
Tree Count	200	0	2345	259.02	286.649	3.491	.172
Average DBH	200	.000000	19.640449	1.91321026	4.848367460	2.411	.172
Valid N (listwise)	195						

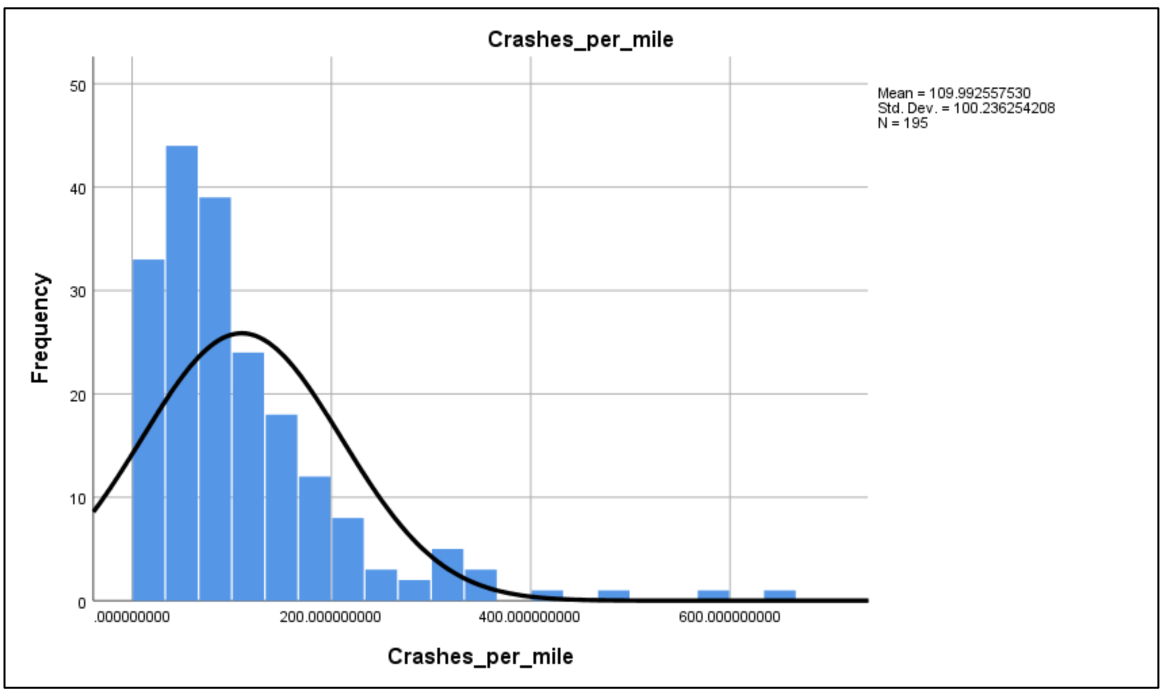
Frequencies

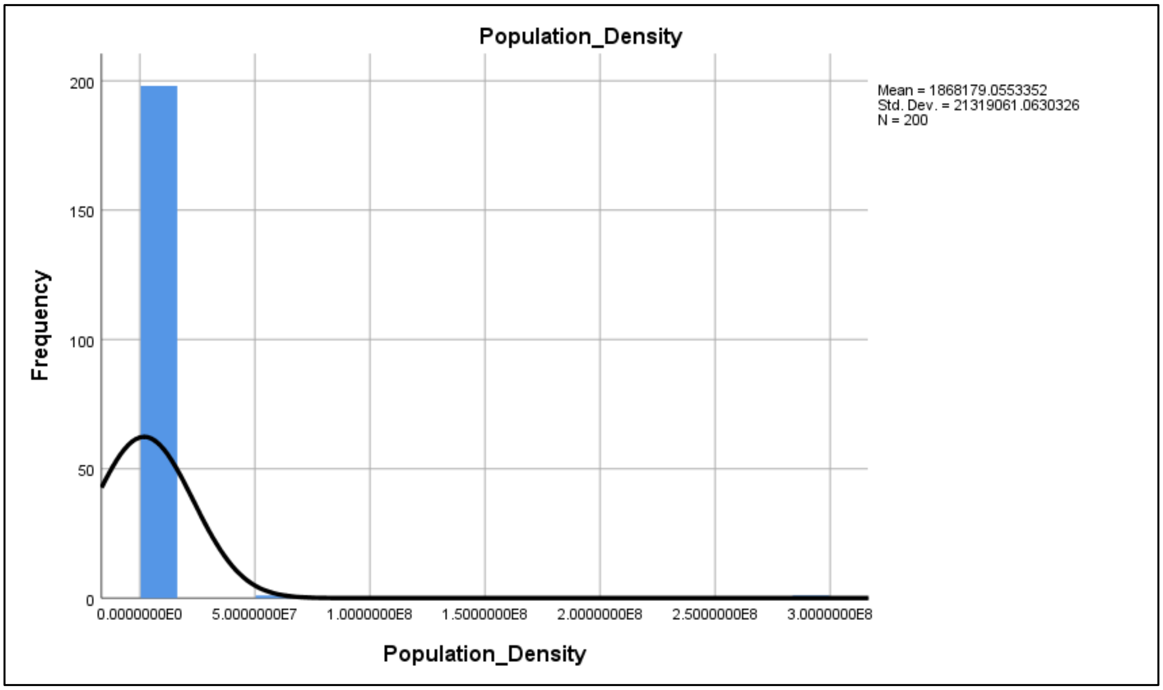
Frequency Statistics

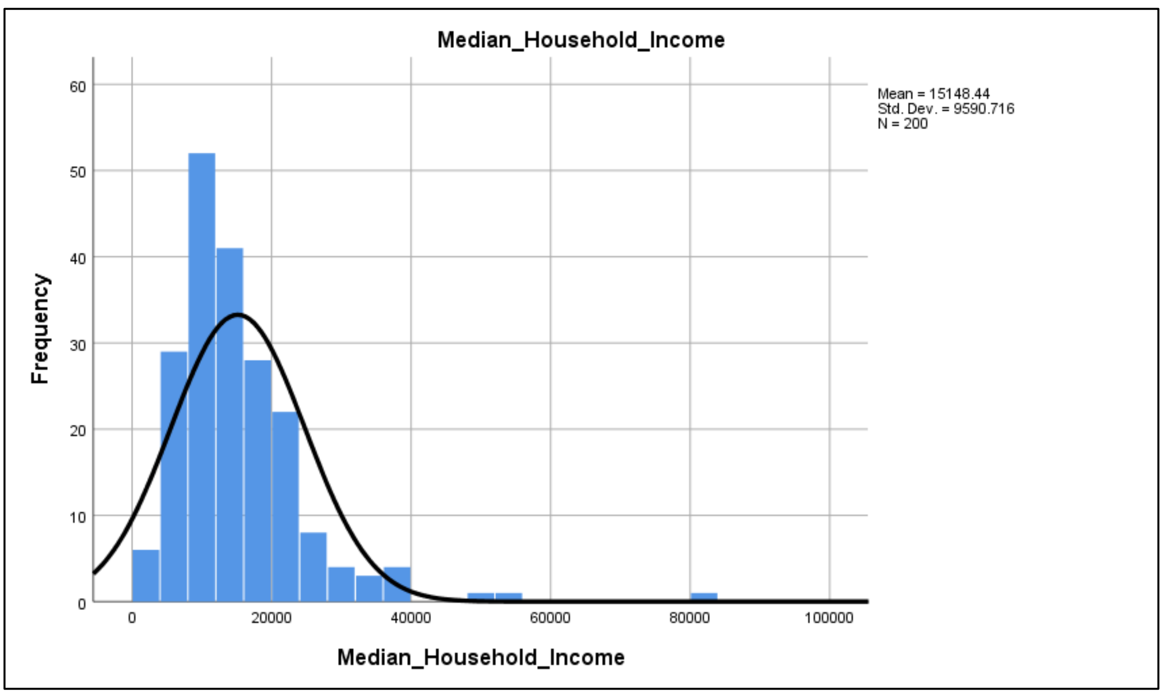
		Crashes per mile	Population Density	Median Household Income	Tree Count	Average DBH
N	Valid	200	200	200	200	200
	Missing	0	0	0	0	0
Mean		107.24274359164	1868179.055335173	15148.44	259.02	1.91321026
Median		83.43820490500	4790.228499000	13204.00	196.50	.00000000
Mode		.000000000	.0000000[a]	13278[a]	0	.000000

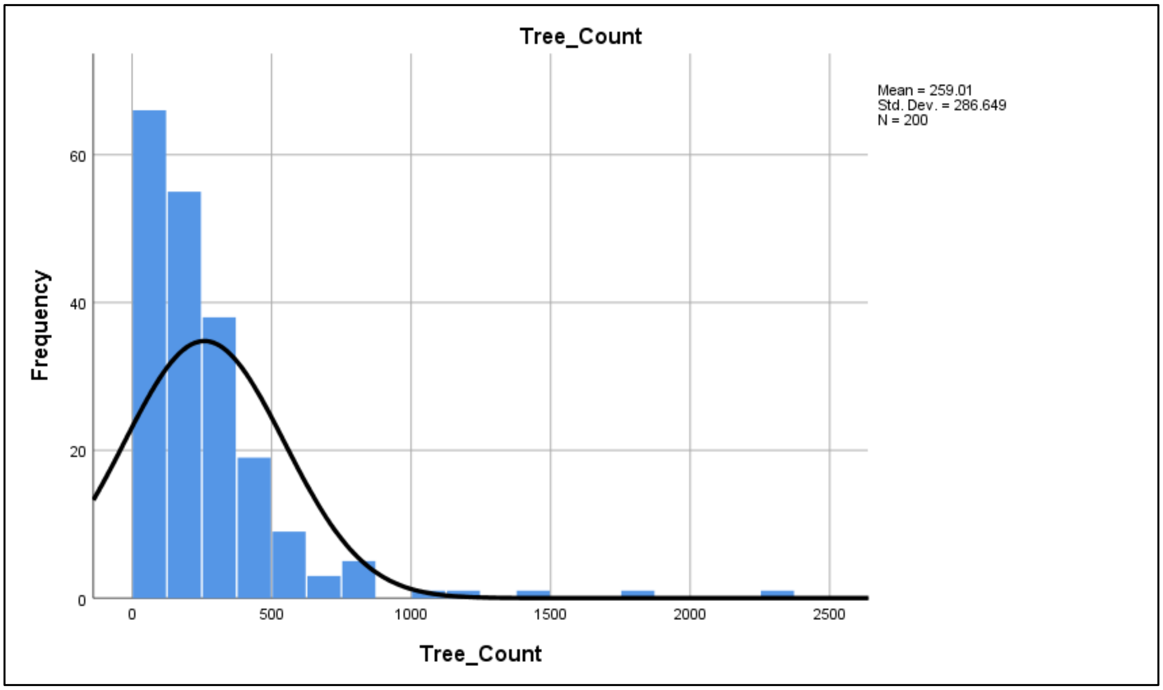
Std. Deviation		100.455170375906	21319061.0630326300	9590.716	286.649	4.848367460
Skewness		2.201	13.551	2.574	3.491	2.411
Std. Error of Skewness		.172	.172	.172	.172	.172
Kurtosis		7.056	187.740	12.623	18.513	4.383
Std. Error of Kurtosis		.342	.342	.342	.342	.342
Percentiles	25	44.14715208250	2588.303532250	9103.75	90.75	.00000000
	50	83.43820490500	4790.228499000	13204.00	196.50	.00000000
	75	141.37288667500	8132.621594000	18946.25	326.00	.00000000

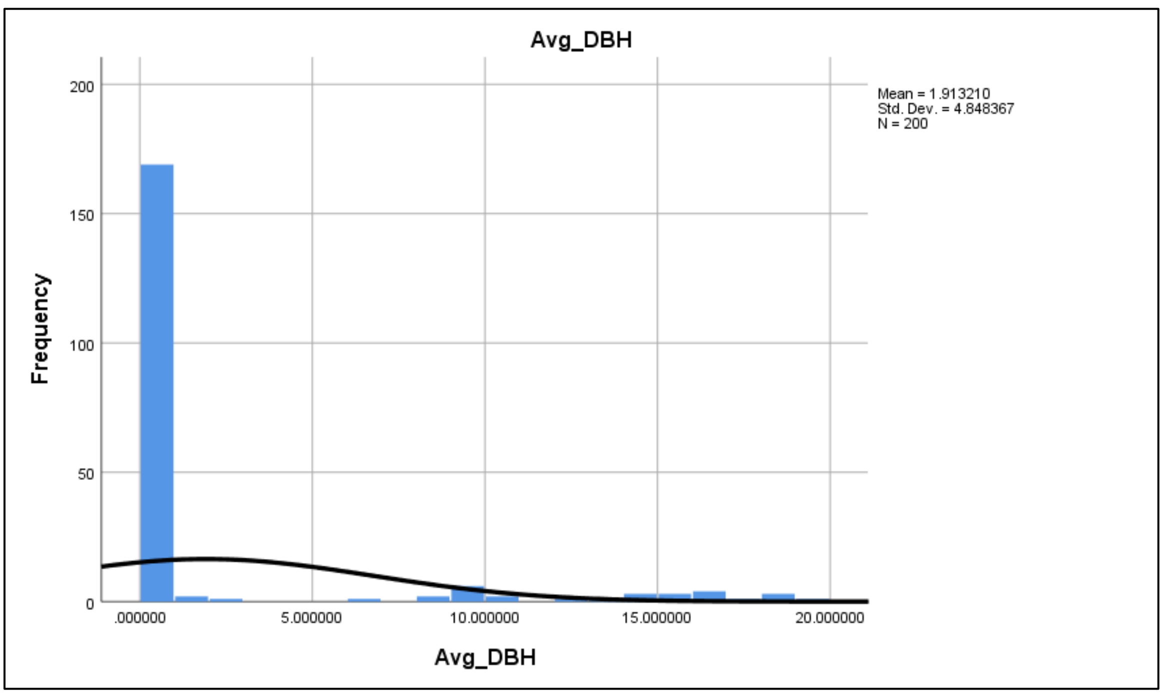
Histograms



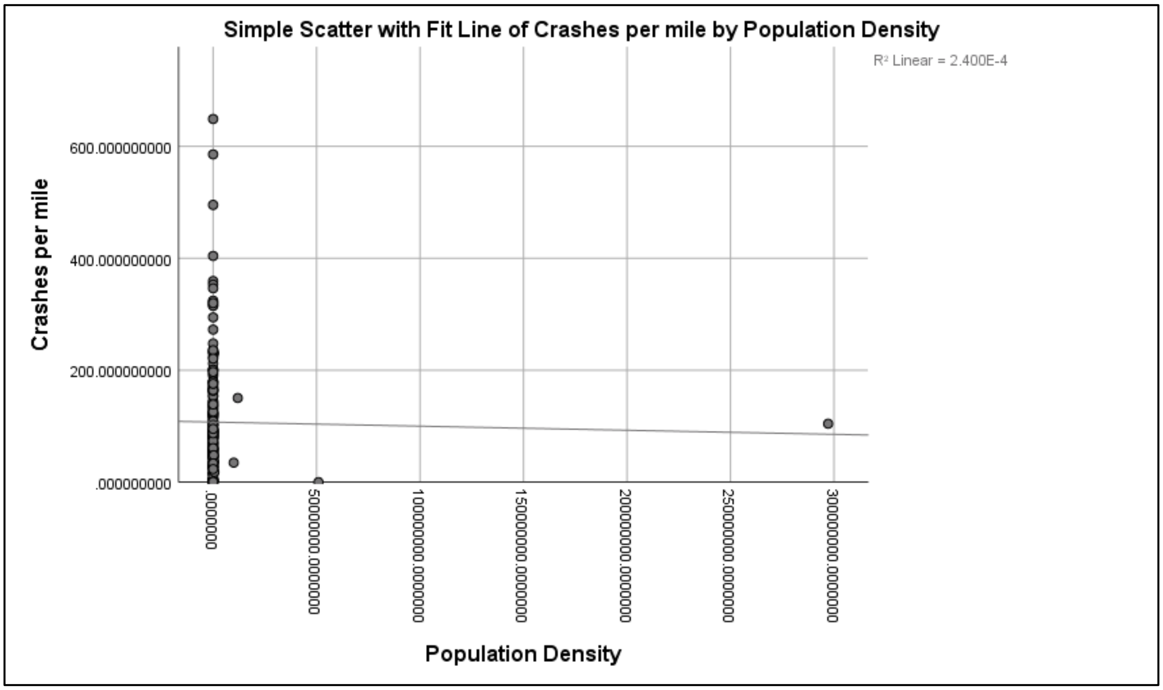

Population_Density
Mean = 1868179.0553352
Std. Dev. = 21319061.0630326
N = 200
Frequency
200
150
100
50
0
0.0000000E0
5.0000000E7
1.0000000E8
1.5000000E8
2.0000000E8
2.5000000E8
3.0000000E8
Population_Density

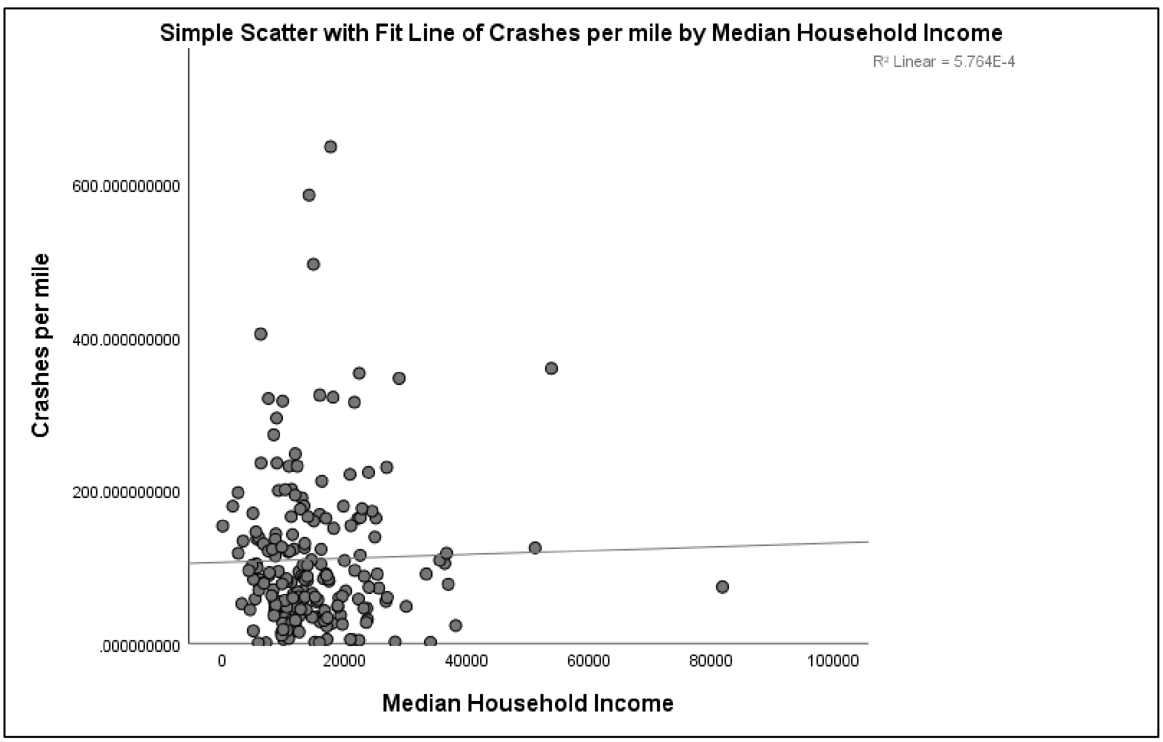

Median_Household_Income
Mean = 15148.44
Std. Dev. = 9590.716
N = 200
Frequency
60
50
40
30
20
10
0
0
20000
40000
60000
80000
100000
Median_Household_Income

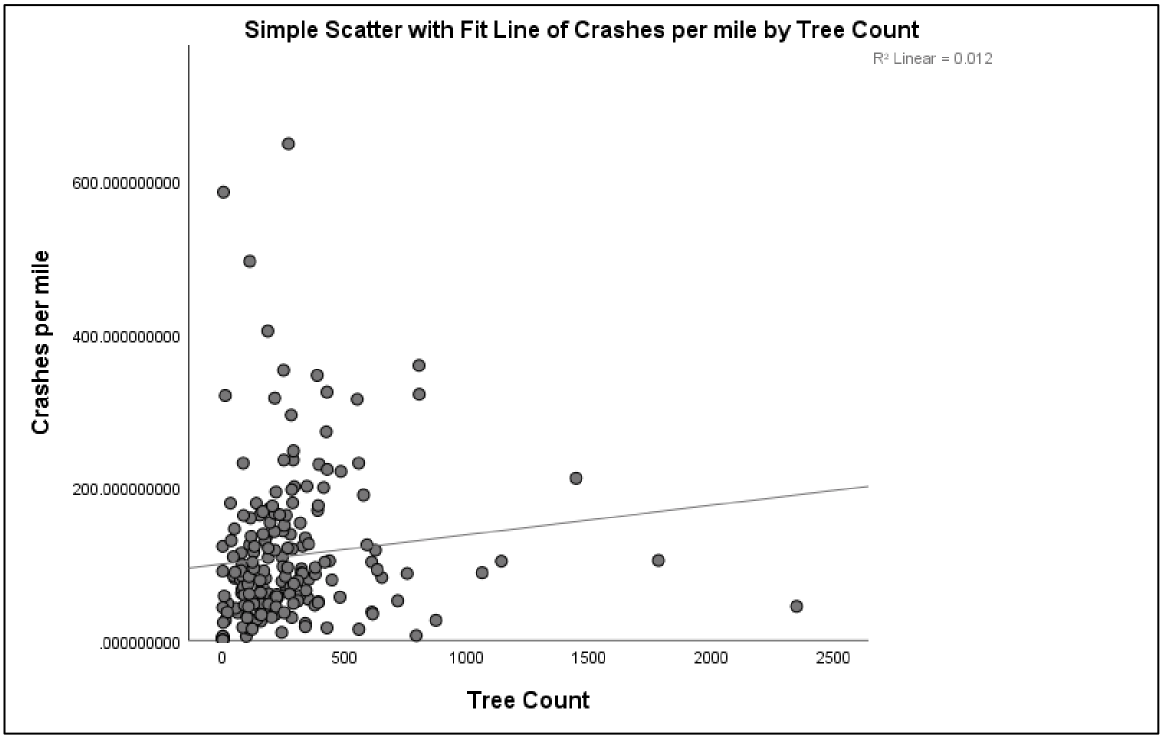

Tree_Count
Mean = 259.01
Std. Dev. = 286.649
N = 200
Frequency
0
20
40
60
0
500
1000
1500
2000
2500
Tree_Count


Avg_DBH
Mean = 1.913210
Std. Dev. = 4.848367
N = 200
Frequency
0
50
100
150
200
.000000
5.000000
10.000000
15.000000
20.000000
Avg_DBH

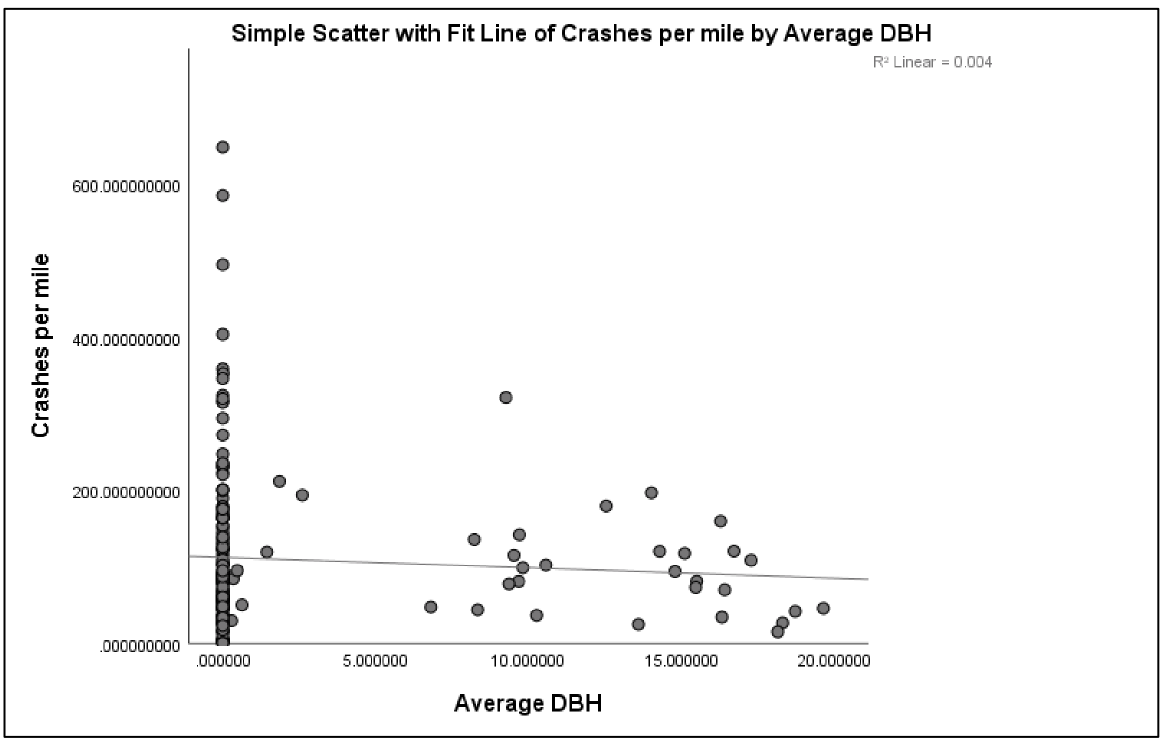
Scatterplots







Simple Scatter with Fit Line of Crashes per mile by Tree Count
R² Linear = 0.012
Crashes per mile
600.000000000
400.000000000
200.000000000
.000000000
0
500
1000
1500
2000
2500
Tree Count



Simple Scatter with Fit Line of Crashes per mile by Average DBH
R² Linear = 0.004
Crashes per mile
600.000000000
400.000000000
200.000000000
.000000000
.000000
5.000000
10.000000
15.000000
20.000000
Average DBH

Correlations

Variable Correlations

		Crashes per mile	Population Density	Median Household Income	Tree Count	Average DBH
Crashes per mile	Pearson Correlation	1	-.015	.018	.132	-.054
	Sig. (2-tailed)		.828	.796	.062	.445
	N	200	200	200	200	200
Population Density	Pearson Correlation	-.015	1	.175*	.364**	-.035
	Sig. (2-tailed)	.828		.013	.000	.626
	N	200	200	200	200	200
Median Household Income	Pearson Correlation	.018	.175*	1	.019	-.013
	Sig. (2-tailed)	.796	.013		.785	.851
	N	200	200	200	200	200
Tree Count	Pearson Correlation	.132	.364**	.019	1	-.092
	Sig. (2-tailed)	.062	.000	.785	.132	.194
	N	200	200	200	.062	-.054
Average DBH	Pearson Correlation	-.054	-.035	-.013	200	.445
	Sig. (2-tailed)	.445	.626	.851	.364**	200
	N	200	200	200		-.035

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

T-Tests

T-Test (Crashes per mile)

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Crashes per mile	200	107.24274359165	100.455170375906	7.103253217805

One-Sample Test

	Test Value = 60.814 Data Source: Iowa DOT; US Census 2010 Block Group Data					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper
Crashes per mile	6.536	199	.000	46.428743591645	32.42143692332	60.43605025997

T-Test (Tree Count)

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Tree Count	200	259.02	286.649	20.269

One-Sample Test

	Test Value = 574 Data Source: City of Madison, WI open data portal, 2017 tree inventory data					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Tree Count	-15.540	199	.000	-314.985	-354.95	-275.02

T-Test (Population Density)

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Crash_Count	200	273.59	312.745	22.114
Population_Density	200	1868179.055	21319061.06	1507485.265

One-Sample Test

	Test Value = 1192 Data Source: 2015 US Census Block Group Data and state averages					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Crash_Count	-41.530	199	.000	-918.415	-962.02	-874.81
Population_Density	1.238	199	.217	1866987.055	-1105708.38	4839682.488

T-Test (Median Household Income)

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Median Household Income	199	15224.56	9554.141	677.275

One-Sample Test

	Test Value = 54736 Data Source: 2010 US Census Block Group Data and state averages					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Lower
Median Household Income	-58.339	198	.000	-39511.442	-40847.04	-38175.84

Test of Multicollinearity

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.157[a]	.025	.005	100.213940251003

a. Predictors: (Constant), Average DBH, Median Household Income, Tree Count, Population Density

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	49804.415	4	12451.104	1.240	.295[b]
	Residual	1958352.595	195	10042.834		
	Total	2008157.010	199			

a. Dependent Variable: Crashes per mile

b. Predictors: (Constant), Average DBH, Median Household Income, Tree Count, Population Density

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	90.826	15.570		5.833	.000		
	Population Density	-3.725E-7	.000	-.079	-1.024	.307	.839	1.192
	Median Household Income	.000	.001	.029	.399	.690	.967	1.034
	Tree Count	.055	.027	.157	2.055	.041	.859	1.164
	Average DBH	-.873	1.472	-.042	-.593	.554	.991	1.009

a. Dependent Variable: Crashes per mile

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	Population Density	Median Household Income	Variance Proportions	Variance Proportions
1	1	2.621	1.000	.03	.01	.03	Tree Count	Tree Count
	2	1.070	1.565	.00	.50	.00	.05	.05
	3	.780	1.833	.01	.26	.02	.03	.03
	4	.401	2.558	.01	.13	.21	.02	.02
	5	.127	4.536	.95	.10	.74	.71	.71

a. Dependent Variable: Crashes per mile

Generalized Linear Model (Linear Regression)

Model Information

Dependent Variable	Crashes Per Mile
Probability Distribution	Normal
Link Function	Identity

Case Processing Summary

	N	Percent
Included	200	100.0%
Excluded	0	0.0%
Total	200	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean
Dependent Variable	Crashes Per Mile	200	0	649	107.22
Covariate	Population Density	200	.0000000	297166666.7000000	1868179.055335173

	Median Household Income	200	0	81695	15148.44
	Tree Count	200	0	2345	259.02
	Average DBH	200	.000000	19.640449	1.91321026

Continuous Variable Information

		Std. Deviation
Dependent Variable	Crashes Per Mile	100.462
Covariate	Population Density	21319061.0630326300
	Median Household Income	9590.716
	Tree Count	286.649
	Average DBH	4.848367460

Goodness of Fit[a]

	Value	df	Value/df
Deviance	1958550.315	195	10043.848
Scaled Deviance	200.000	195	
Pearson Chi-Square	1958550.315	195	10043.848
Scaled Pearson Chi-Square	200.000	195	
Log Likelihood[b]	-1202.727		
Akaike's Information Criterion (AIC)	2417.455		
Finite Sample Corrected AIC (AICC)	2417.890		
Bayesian Information Criterion (BIC)	2437.245		
Consistent AIC (CAIC)	2443.245		

Dependent Variable: Crashes per mile

Model: (Intercept), Population Density, Median Household Income, Tree Count, Average DBH[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
5.031	4	.284

Dependent Variable: Crashes per mile

Model: (Intercept), Population Density, Median Household Income, Tree Count, Average DBH[a]

a. Compares the fitted model against the intercept-only model.

Test of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	34.877	1	.000
Population Density	1.084	1	.298
Median Household Income	.163	1	.687
Tree Count	4.338	1	.037
Average DBH	.360	1	.548

Dependent Variable: Crashes Per Mile

Model: (Intercept), Population Density, Median Household Income, Tree Count, Average DBH

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square
(Intercept)	90.802	15.3753	60.667	120.937	34.877
Population Density	-3.740E-7	3.5920E-7	-1.078E-6	3.301E-7	1.084
Median Household Income	.000	.0007	-.001	.002	.163
Tree Count	.055	.0264	.003	.107	4.338
Average DBH	-.872	1.4532	-3.721	1.976	.360
(Scale)	9792.752[a]	979.2752	8049.791	11913.103	

Parameter Estimates

Parameter	Hypothesis Test df	Hypothesis Test Sig.
(Intercept)	1	.000
Population Density	1	.298
Median Household Income	1	.687
Tree Count	1	.037
Average DBH	1	.548
(Scale)		

Test of Interaction Effects

Tests of Model Effects (Interaction Effects)

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	405.005	1	.000
Population Density	5.372	1	.020
Median Household Income	5.512	1	.019
Tree Count	1.050	1	.306
Average DBH	1.765	1	.184
Population x Tree Count Interaction	.956	1	.328
Median Household Income and Tree Count Interaction	5.651	1	.017
Average DBH x Tree Count Interaction	1.213	1	.271

Dependent Variable: Crashes per mile

Model: (Intercept), Population Density, Median Household Income, Tree Count, Average DBH, Population x Tree Count Interaction, Median Household Income x Tree Count Interaction, Average DBH x Tree Count

Parameter Estimates (Interaction Effects)

			95% Wald Confidence Interval		Hypothesis Test
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square
(Intercept)	5.027	.2498	4.537	5.516	405.005

Population Density	-1.575E-8	6.7966E-9	-2.907E-8	-2.432E-9	5.372
Median Household Income	-3.312E-5	1.4108E-5	-6.078E-5	-5.472E-6	5.512
Tree Count	-.001	.0009	-.003	.001	1.050
Average DBH	-.034	.0256	-.084	.016	1.765
Population x Tree Count Interaction	-1.982E-7	2.0276E-7	-5.956E-7	1.992E-7	.956
Median Household Income and Tree Count Interaction	1.180E-7	4.9657E-8	2.072E-8	2.154E-7	5.651
Average DBH x Tree Count Interaction	.000	.0001	-9.920E-5	.000	1.213
(Scale)	1[a]				
(Negative binomial)	1[a]				

Parameter Estimates (Interaction Effects Continued)

	Hypothesis Test	
Parameter	df	Sig.
(Intercept)	1	.000
Population Density	1	.020
Median Household Income	1	.019
Tree Count	1	.306
Average DBH	1	.184
Population x Tree Count Interaction	1	.328
Median Household Income and Tree Count Interaction	1	.017

Average DBH x Tree Count Interaction	1	.271
(Scale)		
(Negative binomial)		

Generalized Linear Modal (Negative Binomial Regression)

Model Information

Dependent Variable	Crashes per Mile
Probability Distribution	Negative binomial
Link Function	Log

Case Processing Summary

	N	Percent
Included	200	100.0%
Excluded	0	0.0%
Total	200	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Crashes per mile	200	0	649	107.22	100.462
Covariate	Population Density	200	.0000000	297166666.7000000	1868179.055335173	21319061.0630326300
	Tree Count	200	0	2345	259.02	286.649
	Average DBH	200	.000000	19.640449	1.91321026	4.848367460
	Population x Tree Count Interaction	200	.00	5887491.00	358883.6050	620306.23637

Average DBH and Tree Count Interaction	200	.00	7440.00	367.8850	1070.85780

Goodness of Fit[a]

	Value	df	Value/df
Deviance	211.709	194	1.091
Scaled Deviance	211.709	194	
Pearson Chi-Square	174.210	194	.898
Scaled Pearson Chi-Square	174.210	194	
Log Likelihood[b]	-1131.857		
Akaike's Information Criterion (AIC)	2275.715		
Finite Sample Corrected AIC (AICC)	2276.150		
Bayesian Information Criterion (BIC)	2295.505		
Consistent AIC (CAIC)	2301.505		

Dependent Variable: Crashes per mile
Model: (Intercept), Population Density, Tree Count, Average DBH, Population x Tree Count Interaction, Average DBH x Tree Count[a] Interaction
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
8.117	5	.150

Dependent Variable: Crashes per mile
Model: (Intercept), Population Density, Tree Count, Average DBH, Population x Tree Count Interaction, Average DBH x Tree Count[a] Interaction
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	1238.474	1	.000
Population Density	.935	1	.334
Tree Count	3.112	1	.078
Average DBH	1.837	1	.175
Population x Tree Count Interaction	1.402	1	.236
Average DBH x Tree Count Interaction	1.319	1	.251

Dependent Variable: Crashes per mile
Model: (Intercept), Population Density, Tree Count, Average DBH, Population x Tree Count Interaction, Average DBH x Tree Count Interaction

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test
			Lower	Upper	Wald Chi-Square
(Intercept)	4.506	.1280	4.255	4.757	1238.474
Population Density	-3.549E-9	3.6709E-9	-1.074E-8	3.645E-9	.935
Tree Count	.001	.0006	.000	.002	3.112
Average DBH	-.034	.0252	-.084	.015	1.837
Population x Tree Count Interaction	-2.298E-7	1.9407E-7	-6.101E-7	1.506E-7	1.402
Average DBH x Tree Count Interaction	.000	.0001	-9.152E-5	.000	1.319
(Scale)	1[a]				
(Negative binomial)	1[a]				

Parameter Estimates

Parameter	Hypothesis Test	
	df	Sig.
(Intercept)	1	.000
Population Density	1	.334
Tree Count	1	.078

Average DBH	1	.175
Population x Tree Count Interaction	1	.236
Average DBH x Tree Count Interaction	1	.251
(Scale)		
(Negative binomial)		

Dependent Variable: Crashes per mile
Model: (Intercept), Population Density, Tree Count, Average DBH, Population x Tree Count Interaction, Average DBH x Tree Count Interaction
a. Fixed at the displayed value.

Hypothesis 2 Statistical Data Analysis

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Severe Crashes Per Mile Rounded	200	0	27	4.17	4.402	2.049
Tree Count	200	0	2345	259.02	286.649	3.491
Valid N (listwise)	200					

Descriptive Statistics (cont.)

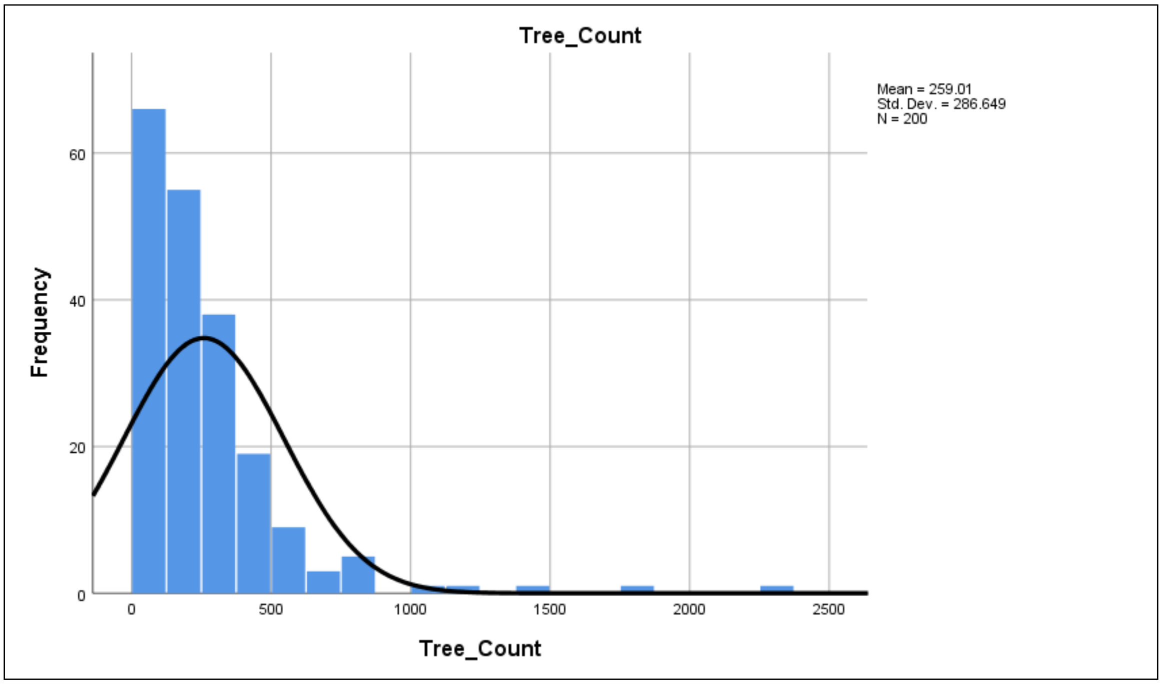
	Skewness	Kurtosis	
	Std. Error	Statistic	Std. Error
Severe Crashes Per Mile Rounded	.172	5.803	.342
Tree Count	.172	18.513	.342
Valid N (listwise)			

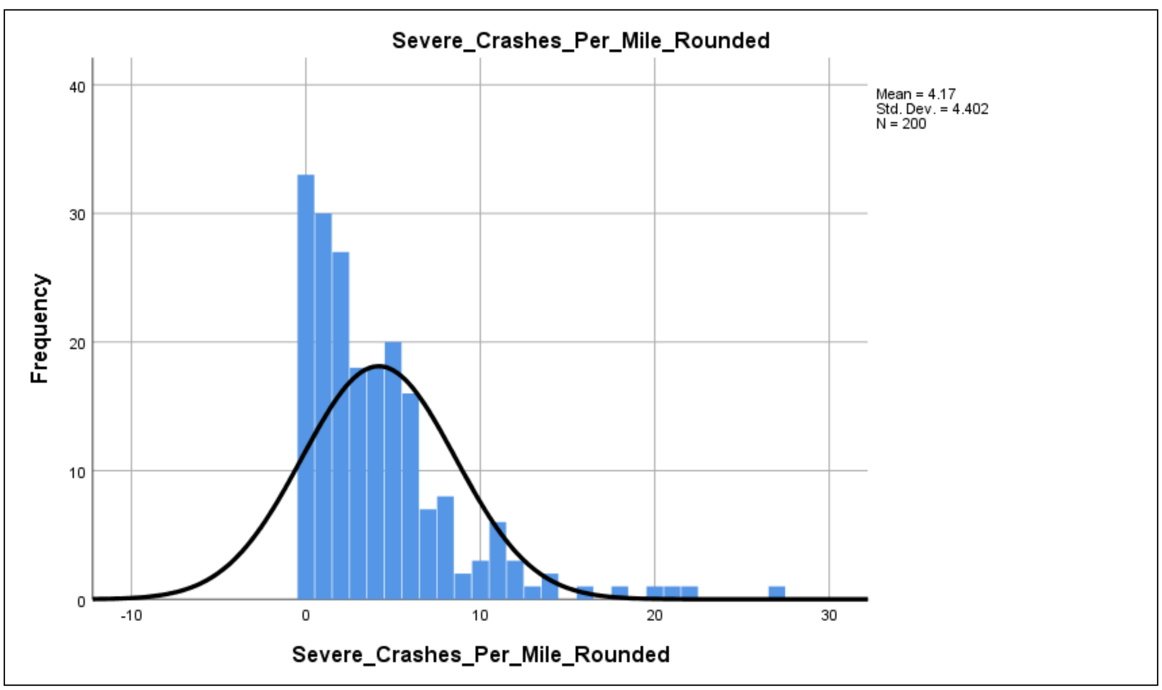
Frequencies

Frequency Statistics

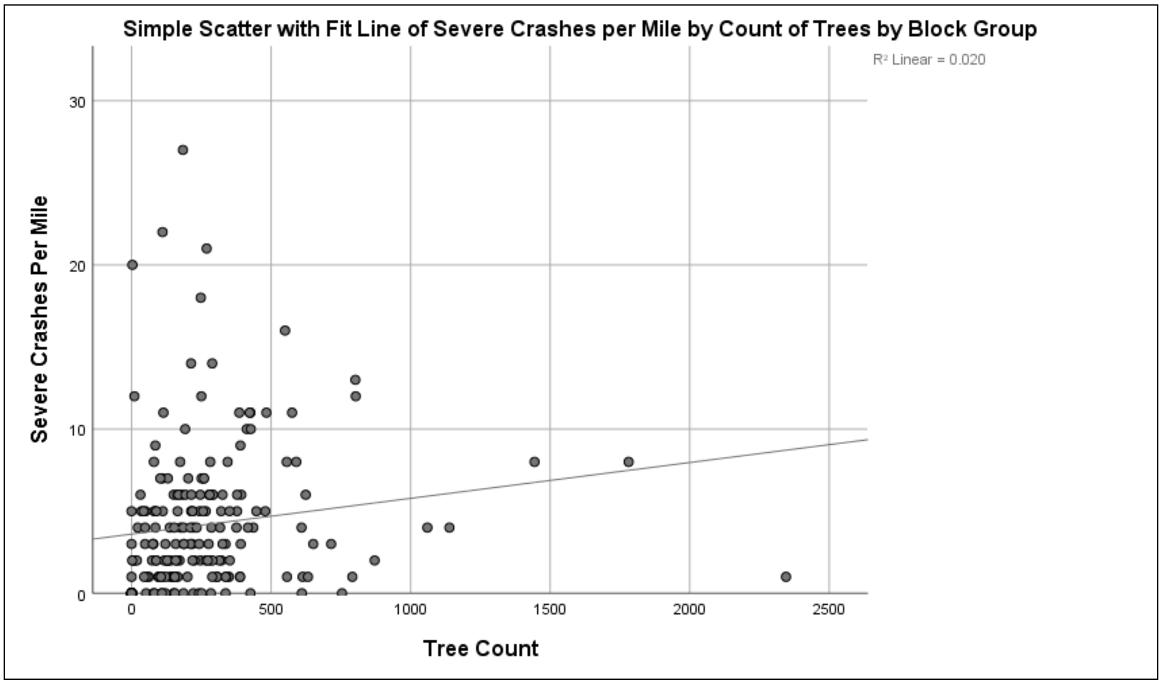
		Tree Count	Severe Crashes Per Mile
N	Valid	200	200
	Missing	0	0
Mean		259.02	4.17
Median		196.50	3.00
Mode		0	0
Std. Deviation		286.649	4.402
Skewness		3.491	2.049
Std. Error of Skewness		.172	.172
Kurtosis		18.513	5.803
Std. Error of Kurtosis		.342	.342

Histograms


Tree_Count
Mean = 259.01
Std. Dev. = 286.649
N = 200
Frequency
60
40
20
0
0
500
1000
1500
2000
2500
Tree_Count


Severe_Crashes_Per_Mile_Rounded
Mean = 4.17
Std. Dev. = 4.402
N = 200
Frequency
40
30
20
10
0
-10
0
10
20
30
Severe_Crashes_Per_Mile_Rounded

Scatterplot



Correlation Descriptive Statistics

	Mean	Std. Deviation	N
Severe Crashes Per Mile	4.17	4.402	200
Tree Count	259.02	286.649	200

Correlations

		Severe Crashes Per Mile	Tree Count
Severe Crashes Per Mile	Pearson Correlation	1	.142*
	Sig. (2-tailed)		.045
	N	200	200
Tree Count	Pearson Correlation	.142*	1
	Sig. (2-tailed)	.045	
	N	200	200

*. Correlation is significant at the 0.05 level (2-tailed).

Generalized Linear Model (Linear Regression)

Model Information

Dependent Variable	Severe crashes per mile
Probability Distribution	Normal
Link Function	Identity

Case Processing Summary

	N	Percent
Included	200	100.0%
Excluded	0	0.0%
Total	200	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean
Dependent Variable	Severe crashes per mile	200	0	27	4.17
Covariate	Tree Count	200	0	2345	259.02

Continuous Variable Information

		Std. Deviation
Dependent Variable	Severe crashes per mile	4.402
Covariate	Tree Count	286.649

Goodness of Fit[a]

	Value	df	Value/df
Deviance	3778.505	198	19.083
Scaled Deviance	200.000	198	
Pearson Chi-Square	3778.505	198	19.083
Scaled Pearson Chi-Square	200.000	198	
Log Likelihood[b]	-577.664		
Akaike's Information Criterion (AIC)	1161.329		
Finite Sample Corrected AIC (AICC)	1161.451		
Bayesian Information Criterion (BIC)	1171.224		
Consistent AIC (CAIC)	1174.224		

Dependent Variable: Severe crashes per mile

Model: (Intercept), Tree Count[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
4.072	1	.044

Dependent Variable: Severe crashes per mile

Model: (Intercept), Tree Count[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	75.582	1	.000
Tree Count	4.114	1	.043

Dependent Variable: Severe crashes per mile

Model: (Intercept), Tree Count

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df
(Intercept)	3.605	.4147	2.793	4.418	75.582	1
Tree Count	.002	.0011	7.333E-5	.004	4.114	1
(Scale)	18.893[a]	1.8893	15.530	22.983		

Parameter Estimates (cont.)

	Hypothesis Test
Parameter	Sig.
(Intercept)	.000
Tree Count	.043
(Scale)	

Dependent Variable: Severe crashes per mile

Model: (Intercept), Tree Count

a. Maximum likelihood estimate.

Generalized Linear Model (Negative Binomial Regression)

Model Information

Dependent Variable	Severe Crashes Per Mile
Probability Distribution	Negative binomial (1)
Link Function	Log

Case Processing Summary

	N	Percent
Included	200	100.0%
Excluded	0	0.0%
Total	200	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean
Dependent Variable	Severe Crashes Per Mile	200	0	27	4.17
Covariate	Tree Count	200	0	2345	259.02

Continuous Variable Information (cont.)

		Std. Deviation
Dependent Variable	Severe Crashes Per Mile	4.402
Covariate	Tree Count	286.649

Goodness of Fit[a]

	Value	df	Value/df
Deviance	199.984	199	1.005
Scaled Deviance	199.984	199	
Pearson Chi-Square	178.869	199	.899
Scaled Pearson Chi-Square	178.869	199	
Log Likelihood[b]	-507.848		
Akaike's Information Criterion (AIC)	1017.697		
Finite Sample Corrected AIC (AICC)	1017.717		
Bayesian Information Criterion (BIC)	1020.995		
Consistent AIC (CAIC)	1021.995		

Dependent Variable: Severe Crashes Per Mile

Model: (Intercept)[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
.000	.	.

Dependent Variable: Severe Crashes Per Mile

Model: (Intercept)[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	328.913	1	.000

Dependent Variable: Severe Crashes Per Mile
Model: (Intercept)

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	1.428	.0787	1.274	1.582	328.913	1
(Scale)	1[a]					
(Negative binomial)	1[a]					

Parameter Estimates (cont.)

Parameter	Hypothesis Test Sig.
(Intercept)	.000
(Scale)	
(Negative binomial)	

Dependent Variable: Severe Crashes Per Mile
Model: (Intercept)
a. Fixed at the displayed value.

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