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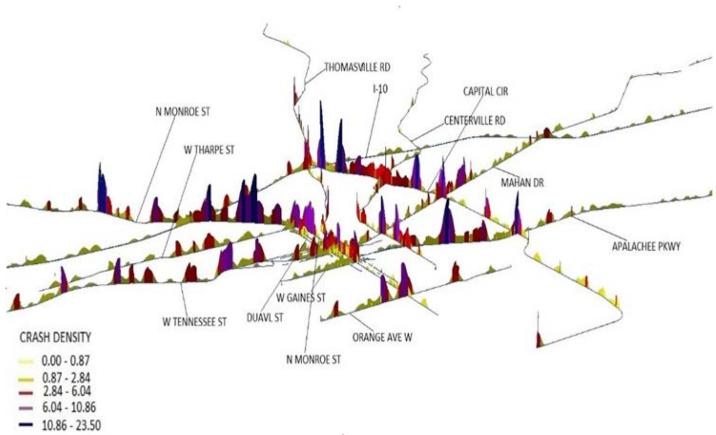
RESEARCH FINAL REPORT

Analyzing Crash Clusters near Senior Destination Sites Using a GIS Approach

Thobias Sando
Eren Ozguven
Yassir Abdelrazig
Ren Moses
Sai Saylesh Vemulapalli
Michelle Angel



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Dr. T. Sando
Associate Professor
School of Engineering
University of North Florida

Dr. E. Ozguven
Assistant Professor
Civil and Environmental Engineering
FAMU-FSU College of Engineering

Dr. Y. Abdelrazig
Associate Professor
Civil and Environmental Engineering
FAMU-FSU College of Engineering

Dr. R. Moses
Professor
Civil and Environmental Engineering
FAMU-FSU College of Engineering

Sai Saylesh Vemulapalli
Graduate Student
FAMU-FSU College of Engineering
Florida State University

Michelle Angel
Research Associate
School of Engineering
University of North Florida

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Roadway crashes claim more than 30,000 lives each year in the United States, and they continue to affect the lives of people adversely. This problem becomes even more challenging when aging populations are considered due to their vulnerability and fragility to crashes. This is especially a principal concern in Florida since the crash risk for the aging population is increasing day by day, proportional to the population growth of aging Floridians. This study investigates the spatial and temporal patterns of aging-involved crashes to identify aging related crash hotspots, using Geographical Information Systems (GIS)-based methods on a case study of ten urban counties in Florida. The counties were selected based on the high aging-involved crash rates, as identified by the Safe Mobility for Life Coalition of Florida. Both different spatial and temporal methods were employed. Among the methods studied, SANET, a network distance-based kernel density estimation method, was identified as a very effective tool in providing an unbiased distribution of the crashes by calculating the actual distances between the crashes over the roadway network. GIS-based results were also supported with a binary logistic regression analysis to identify the significant factors affecting aging-involved crash occurrence when compared to other age group crashes. Results indicate that high risk locations for aging-involved crashes show different spatial and temporal patterns than those for other age groups. These pattern specific differences include the following: (a) Intersections have an adverse effect on the 65+ populations more than other adult age groups, and the locations of high crash risk intersections are different than those of other age groups, (b) Aging-involved population crashes occur during the mid-day rather than the peak hours, which is not a similar pattern for other adult age groups, especially for the working populations, and (c) Week days have more aging-involved crashes than the weekends contrary to the other age group crashes.</td></tr>
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Planar Kernel Density Estimation

$\hat{f}(x)$: density estimator
K : Kernel function
h : bandwidth
n : number of observation points
$x\ldots x(i)$: observation points

Network Kernel Density Estimation
N : roadway network
V : nodes on the network N from $v_1, v_2, v_3, \ldots v_n$
L : roadway links on the network N
$\check{L}$: union of all links
L_q : subnetwork
p : arbitrary point on an link L
h : bandwidth
dp : integration operator
$K_q\ (p)$: network Kernel density function at q, with q as kernel center
$K\ (p)$: network Kernel density estimator for $f\ (p)$ at p
s : shortest path from q to b_i
b_i : boundary point
n_{i1} : degree of node v_i
$d_s(q,p)$: shortest path distance from q to p on $\check{L}$

Getis-Ord (Gi*)
$G_i\ (d)$: Getis-Ord statistic
d : distance from the original weighted point
i : area subdivided into n regions (1, 2, 3…..n)
x : weight associated for all links i,
j : points
w_{ij} : spatial weigh matrix with 1 for all the links within the distance d for given i, and 0 for all others.
$G_i{*}$: Getis-Ord Z-score value at site i,
x_j : attribute value for feature j,
$w_{i,j}$: spatial weight between feature i and j,
$\bar{X}$: average crash frequency, and
S : standard deviation of x_j.

Logistic Regression Analysis
Y : response variable
$X_{(n)}$: regressor variables ($X_1, X_2 \ldots X_n$)
F : cumulative standard logistic distribution function
β_n : coefficients of $X_{(n)}$

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Abstract

Roadway crashes claim more than 30,000 lives each year in the United States, and they continue to affect the lives of people adversely. This problem becomes even more challenging when aging populations are considered due to their vulnerability and fragility to crashes. This is especially a principal concern in Florida since the crash risk for the aging population is increasing day by day, proportional to the population growth of aging Floridians. This study investigates the spatial and temporal patterns of aging-involved crashes to identify aging related crash hotspots, using Geographical Information Systems (GIS)-based methods on a case study of ten urban counties in Florida. The counties were selected based on the high aging-involved crash rates, as identified by the Safe Mobility for Life Coalition of Florida. Both different spatial and temporal methods were employed. Among the methods studied, SANET, a network distance-based kernel density estimation method, was identified as a very effective tool in providing an unbiased distribution of the crashes by calculating the actual distances between the crashes over the roadway network. GIS-based results were also supported with a binary logistic regression analysis to identify the significant factors affecting aging-involved crash occurrence when compared to other age group crashes. Results indicate that high risk locations for aging-involved crashes show different spatial and temporal patterns than those for other age groups. These pattern specific differences include the following: (a) Intersections have an adverse effect on the 65+ populations more than other adult age groups, and the locations of high crash risk intersections are different than those of other age groups, (b) Aging-involved population crashes occur during the mid-day rather than the peak hours, which is not a similar pattern for other adult age groups, especially for the working populations, and (c) Week days have more aging-involved crashes than the weekends contrary to the other age group crashes.

Investigating these distinct patterns thoroughly can lead to better aging-focused transportation plans and policies, thereby reducing aging related crashes in Florida.

Chapter 1 Introduction

1.1 Background and Motivation

Traffic crashes are one of the leading contributors to the social and economic costs for the society. According to the Federal Highway Administration (FHWA, 2015), roadway crashes in the United States (U.S.) are the leading cause of death. Despite substantial efforts towards implementing preventive solutions, crashes still remain a serious problem (Plug et al., 2011). This problem becomes even more challenging and complex when aging people (persons age 65 and over) are considered since they are more vulnerable to traffic crashes than other adult age groups due to their cognitive, behavioral, and health limitations.

As the population increases in the U.S., so does the number of individuals age 65 and older (U.S. Census Bureau, 2010). Decennial data between the years 2000 and 2010 indicate that the number of residents in this age group increased by 15.1 % over the ten-year period, while the overall population increased by 9.7 % nationwide (U.S. Census Bureau U.S. Census Bureau-May, 1995 revised on October, 2011). Currently, the aging population growth rate is at a moderate pace. However, this rate is expected to grow rapidly in the future. By 2030, the 65 and older (65+) population is projected to be more than 20 % of the total U.S. population, a substantial increase from 13 % and 9.8% in 2010 and 1970, respectively. By 2050, the estimations show that the 65+ population will have nearly doubled, from 43.1 million to 83.7 million (Jennifer et al., 2014). This increase in the 65+ population is mainly attributed to the aging of people who were born during the post-World War II era, between 1946 and 1964, and are generally referred to as the “baby boomers”. The first baby boomer turned 65 in 2011, indicating that the growth rate of 65+ population will significantly rise in the coming years. In 2029, all of the baby boomers will be over age 65 and constitute more than 20% of the total U.S.

population (Sandra and Jennifer, 2014). Advancements in the field of medicine have also improved the survival rate, especially in the U.S. In 1972, life expectancy at age 65 was at approximately 15.2 additional years, whereas today, it reaches up to 19.1 additional years. Thus, the 65+ age group in the U.S. continue to live while other age groups turn 65 years of age (Jennifer et al., 2014). It is projected that by year 2056, the population of the 65+ age group will become larger than the population under 18 years (Sandra and Jennifer, 2014). This increased population will have a critical effect on U.S. roadways, especially on the number of crashes. At present, there are 34 million licensed drivers age 65 and older in the U.S., 16 % of the total number of licensed drivers. This percentage is projected to increase to 20% by the year 2025 (Sandra and Jennifer, 2014). Hence, there is a need to focus more on aging-involved crashes so that planners and engineers can explore ways to mitigate future crashes and provide safety for aging road users.

This issue is even more critical for States with high aging populations such as Florida. The aging population growth rate in Florida is higher than the national average, consisting of 19% of the total State population (U.S. Census Bureau- May, 1995 revised on October, 2011). The percentage of population in the age group of 50 to 64, on the other hand, is 20% of the State population, indicating a significant increase in the 65+ population in the coming years. By 2030, the 65+ group population is estimated to be over 27%. Moreover, Florida is one state where nearly 20% of the drivers are over the age 65, and also the second largest state for total number of licensed 65+ drivers. Consequently, the number of aging road users and aging-related crashes on Florida roadways increases every year. Florida traffic crash statistics reflect an 11.3 % increase in aging-involved crashes from 2008 to 2012 (FDOT, 2015). Statistics also show an increase in the number of crash related fatalities. In 2008, 447 aging road users were killed in the crashes, nearly 15 % of all fatalities. From 2007 to 2009, the traffic fatalities involving the aging population increased from 18.3% to 20.6% (Florida Department of Highway Safety and Motor Vehicles, 2013).

According to the U.S. Census Bureau (2010) and the Safe Mobility for Life Coalition (SMLC) (2013), the number of 65+ people will almost double in Florida from 2010 to 2040 (Florida Demographic Research, 2014). As the number of aging people become a greater share of the population, aging-involved crashes will also be more than present. Therefore, it is important for transportation agency officials to understand the spatial and temporal patterns of aging-involved traffic crashes, to aide with the implementation of more effective preventive measures.

1.2 Research Objective

To study the high risk of death and injuries posed by the roadway crashes, Geographical Information Systems (GIS) has emerged as a vital tool, allowing agencies to better identify roadways associated with high crash risks while providing visual illustrations of crash clusters on maps. However, no studies focusing specifically on the spatial and temporal patterns of aging-involved crashes have been undertaken. The objectives of this research were to:

- Identify and study the locations of crashes that pose high crash risks for aging road users,
- Identify the temporal patterns of the aging-involved crashes,
- Analyze the spatial and temporal clusters of crash hotspots that possess high risks for aging road users, and
- Conduct statistical analyses to determine the significant factors contributing to the occurrence of aging-involved crashes.

To achieve these objectives, GIS-based spatial, temporal, and spatio-temporal methods were applied with a focus on aging people. Following a review of existing literature, the GIS-based comparative methodology was based on the following methods: (a) Spatial analysis with the Kernel Density Estimation (KDE), (b) Temporal analysis with the spider graphs, and (c) Spatio-temporal analysis with the Comap method. Roadway networks in ten urban counties and one rural county in Florida were examined to identify high crash risk locations containing crash clusters (hotspots). The counties were selected based on the high aging-related crashes with respect to the aging population, and designated as priority counties by the SMLC of Florida. A regression-based statistical analysis was conducted on the crash hotspots to identify significant factors relating to aging-involved crashes. These analyses can assist transportation officials with understanding the contributing factors surrounding crash occurrence in the 65+ age group, and focus deeper on aging driver behavior to pinpoint road characteristics that are problematic for aging road users.

1.3 Report Overview

This report consists of 5 chapters. Chapter 1 provides a brief introduction and discussion of the research objectives. Chapter 2 concentrates on the review of existing spatial, temporal and spatio-temporal GIS-based crash analyses, as well as, the statistical methods used to identify the significant contributing factors. Chapter 3 presents the proposed methodology in the context of aging-focused transportation operations, including the data collection, extraction, and preparation processes. Chapter 4 includes the application of spatial, temporal and spatio-temporal methods, and regression methods for the selected Florida counties. Results from the spatial, temporal and regression analyses are discussed in Chapter 5, followed by the conclusion, contributions, and future tasks discussed in Chapter 6.

Chapter 2 Literature Review

Over the last two decades, the high risk for aging people associated with crashes has been a growing concern. This concern is especially prominent in Florida, where the population of 65+ increased 16% from 2000 to 2010, and expected to double by the year 2020 ((U.S. Census Bureau, 2010, SMLC, 2013). With this increasing 65+ population, statistics show that the crash rates for the 65+ age group, projected to 10,000 licensed drivers, increased by 30.8% from 2008 to 2011 (Florida Department of Highway Safety and Motor Vehicles, 2013). These statistics highlight a crucial focus area, aging-involved crashes. Previous research recognized this need; however, most of these studies focused only on behavior-related problems, regression models that include age as a factor, and the effects of aging on the crash occurrence and injuries (Abdel-Aty et al., 1998; Preusser, 1998; Hu and Baker, 2010; Centers for Disease Control and Prevention, 2007; National Center for Health Statistics (NCHS), 2007; Dissanayake and Lu, 2002; Braitman et al., 2007; Boufous et al., 2008; Cook et al., 2000; McGwin and Brown, 1991; Williams and Shabanova, 2003; Alam and Spainhour, 2008; Abdel-Aty et al., 1999; Abdel-Aty and Radwan, 2000; Abdel-Aty et al., 1999). Consequently, there is a definite need for methodologies that focus on the spatial and temporal distribution of aging-involved crashes.

Traffic crashes on the roadways exhibit distinct spatial and temporal patterns, and are said to form clusters in the geographical space and time (Black, 1991). An extensive knowledge and analysis of these patterns is therefore important for developing appropriate crash prevention strategies. According to McGuigan (1981), the relationship between traffic crashes and roadway attributes allows for the identification of locations prone to a higher number of crashes, or hotspots. These hotspots can be determined spatially, temporally and spatio-temporally using different methods. The first and foremost element in identifying crash hotspots using any method is the designation of the crash point on a geographical space. Once crash points are plotted in the space, they can be analyzed for clustering and significance. The variables associated with each crash such as location, timing, traffic data, and speed limit can be used for interpreting traffic patterns. After hotspots are identified, some of the variables can also be included in statistical analyses to determine possible contributing factors for the crash clusters.

Geographical Information System (GIS) is one tool employed to analyze crashes using crash information converted specifically for spatial mapping. For such a conversion, information regarding the number, time, and location of crashes are needed. With this information, crash data can be analyzed spatially, temporally and spatio-temporally, using GIS. These methods can pinpoint crash hotspot locations and the times when most crashes occur. Recently, a number of studies successfully implemented GIS techniques to identify clusters of various roadway incidents (Dai et al., 2010, Steenberghen et al., 2010, Plug et al., 2011, Larsen, 2010, Pulugurtha et al., 2007). However, studies that focused on identifying crash hotspots involving aging drivers were very limited. Hence, more research directed at analyzing aging-involved crashes, identifying high risk locations, and determining appropriate safety measures for reducing aging road user crashes is needed. The following sections present a review of several existing spatial, temporal, and spatio-temporal methodologies.

2.1 Spatial Analysis

Any formal statistical technique that focuses on data based on spatial details, such as topological geometry or geographic properties, falls under spatial analysis methods. In other disciplines, in order to detect the geographic domains with high density (hotspots) spatially, studies have been conducted which implement Geographical Information Systems (GIS)-based methods. Examples include studies involving crime-related hotspots (Kuo et al., 2011, Nakaya and Yano, 2010, Turnbull et al., 2000) and medical observations, mostly for cancer cell detection (Jarrahi et al., 2007, Kulldroff et al., 1997, Kulldroff et al., 2005).

Similarly, GIS can also be used to analyze roadway crashes to identify high risk locations, hotspots and/or clusters. Crash analyses can be done in two different ways:

- Locating the high crash risk locations,
- Using crash information to arrive at a methodology for predicting future crashes.

The central advantage in using GIS is that it can associate the high crash locations. GIS can provide the means to analyze crashes by either using buffering or cluster analyses (crash concentrations), or by spatial queries. Cluster analyses form clusters that are graphically recognizable and may reflect a circular, elliptical, or contour type shape depending on the analysis method used (Michael, 2006). In each case, clusters can be examined for statistical significance using the observed number of crashes within the cluster (Michael, 2006). These methods measure distances between the crash points and compare them to available random crash distributions.

Point pattern analysis is the most popular approach for identifying hotspots. Analyses can be broadly divided into two categories (O'Sullivan and Unwin, 2002, Manepalli et al., 2011). The first category examines the first-order effects, i.e. measures the variation in the average crash value. Kernel Density Estimation (KDE), Nearest K-means, Quadrant count analysis and Neighbor Method (NNM) fall under this method. Other methodologies examine the second-order effects, i.e. spatial dependency of points. Spatial autocorrelation techniques such as Moran's I, Getis-Ord G statistic examine the second-order effects. (Xie and Yan, 2008, O'Sullivan and Unwin, 2002).

A number of studies have concentrated on using spatial analysis methods. Previous studies have evaluated crash hotspots to determine possible roadway design deficiencies (Dai et al., 2010; Steenberghen et al., 2010; Plug et al., 2011; Larsen, 2010; Pulugurtha et al., 2007). Other studies have also been conducted to identify crash hotspots using GIS techniques to examine pedestrian-, truck-, young driver-, and weather-related crashes (Dai, 2012; Khan et al., 2008; Huang et al., 2010; Siddiqui et al., 2011; Shalini and Geetam, 2013).

The next section describes Kernel Density Estimation method.

2.1.1 Kernel Density Estimation (KDE)

There are a variety of spatial methods used to identify crash hotspots, including the Kernel Density Estimation (KDE), Getis-Ord (Gi*), K-means, nearest neighbor method, and point cluster method (Larsen, 2010). This study focuses on the evaluation of the most popular approach for spatial analysis, Kernel Density Estimation (KDE). Due to its simplicity and ease of application, KDE has generally been the most popular approach to study the first-order effects of crashes. KDE is fundamentally a density estimation and uses a distance-based technique that analyzes a point dataset, and creates a density surface for each point (i.e., crash occurrence). For each individual point, a Kernel density surface is defined with the highest value at its location center. The density value decreases as it moves away from the center, and finally becomes zero after it reaches a pre-specified radius. Conceptually, each of these individual density surfaces are added to create a continuous smooth curved surface across the entire study area (Silverman, 1986). Although there are a wide range of Kernel functions available, Silverman (1986) argued that the choice of Kernel function would not significantly affect the results.

For the KDE-based spatial approach, distances between two crash locations can be calculated in two distinct ways: (a) Planar KDE, (b) Network KDE. Planar KDE uses Euclidian distance measure while analyzing the traffic crashes (Plug et al., 2011; Asgary et al., 2010; Pulugurtha et al., 2007; Prasannakumar et al., 2011; Anderson, 2006; Anderson, 2009; Truong and Somenahalli, 2011; Pulugurtha et al., 2007; Flahaut et al., 2003; Shalini and Geetam, 2013). Shalini and Geetam (2013) also concentrated on pedestrian crashes using GIS techniques. Plug et al. (2011) studied spatial and temporal techniques on single vehicular crashes for identifying hotspots. The planar KDE approach calculates the crash density in a circular window moving across the study area, and the crashes inside the window area are weighted based on the Euclidean distances from the center where the density values are assigned. This produces a biased estimation based on confining the estimation of the Kernel density values in a planar scale. With the network KDE approach, on the other hand, crashes are weighed based on their network distances along the roadway, not by the Euclidean (planar) distance. That is, the network KDE approach assumes that the crashes occur on or alongside the roadways. This approach was applied on GIS-based roadway networks by Okabe et al. (1995, 2006, 2009) as an improvement to the planar KDE method, and also to overcome the biased estimation encountered when planar KDE method is used for roadway networks. For this purpose, Okabe et al. (2006) created a GIS-based application referred to as SANET. See Okabe et al. (2009) for a more detailed discussion on the SANET tool. Satoh and Okabe (2005) pinpointed the drawbacks of using planar methods in analyzing the points that took place on a roadway network (on a planar space), showing that the planar estimation produces a bias. Recently, several researchers employed this approach to calculate the kernel density distributions for crashes (Larsen, 2010; Xie and Yan, 2008). Other studies by Yamada and Thill (2004), Mohaymany et al. (2013), Loo et al. (2011) , Loo and Yao (2013), Yang et al. (2013), Dai et al. (2010), Timothee et al. (2010), Steenberghen (2010), Larsen (2010), Flahaut et al. (2003), Xie and Yan (2008), Borruso (2005), and Borrus (2008) also employed network KDE approach in their research. Okabe et al. (2009) formulated three types of Kernel function: the 'similar shape', the 'equal split', and the 'equal split continuous' methods for the estimation along the networks. They also argued that the 'equal split' and 'equal split continuous' methods produce unbiased results unlike the 'similar shape' kernel function, which is an extension of the planar KDE. Larsen (2010) studied traffic crashes in the Philadelphia using the Nearest Neighbor, K-function, and KDE methods, and presented a comparison between planar KDE and network KDE methods that explained the biased estimation produced by planar KDE. Steenberghen et al. (2010) showed the difference between planar KDE and network KDE more clearly by examining crash hotspots identified by each method and explained the benefits of using network KDE. They employed a new network-based approach known as the moving segment approach, where the roads are not necessarily divided into equal segments. Comparisons between ED and RND were also presented when analyzing crash hotspots for an whole population by Mohaymany et al. (2013), Dai (2012), and Yamada and Thill (2007). These studies show the relatively better performance of the network KDE approach over the planar KDE approach while estimating the crash distributions accurately.

2.1.1 Spatial Autocorrelation: Getis-Ord (Gi)*

In spatial analysis, failure to look at the effects of the spatial scale may lead to serious errors (Anselin and Griffith, 1988, Getis and Ord, 1992). There are generally two ways of assessing spatial patterns within geographical space: (a) "global" measure, and (b) the "local" measure. Global statistics evaluate the entire dataset and report the presence, if any, of the spatial autocorrelation, displaying the overall pattern of the data in the study region. Moran's I index and Getis-Ord General G statistic are two types of global measures that can be used within GIS. These global measures identify the statistically significant patterns of high risk (hot spots) or low risk (cold spots) frequency locations. The Getis-Ord (Gi*) statistic is a spatial autocorrelation method used to identify statistically significant spatial clusters. Getis and Ord (1992, 1995) introduced a family of G statistics which measures the spatial association of crashes. Getis and Ord (1992) compared the Moran's I statistic and General G statistics. They explained that G statistics and Moran's I measures differ significantly, and concluded that G statistics provide a better understanding of the spatial data when used in conjunction with the Moran's I. The local measure of the spatial association, on the other hand, quantifies the spatial autocorrelation at a relatively smaller scale to determine the high risk clusters. The Getis-Ord Gi statistic and local Moran's I are the indicators of local measures used in the literature (Getis and Ord, 1992, Anselin, 1995).

Several studies used spatial autocorrelation techniques to identify and analyze hotspots (Manepalli et al., 2011; Mohaymany et al., 2013; Flahaut et al., 2003; Khan et al., 2008; Erdogan, 2009; Deshpande et al., 2011; McCullagh, 2006; Black and Thomas, 1998; Kuo et al., 2011). Flahaut et al. (2003) compared two different statistical techniques, local autocorrelation index and the KDE method to locate the black zones resulting from road crashes. From this study, Flahaut et al. (2003) argued that autocorrelation techniques can investigate the local spatial structure of roadway crashes better than KDE methods by allowing the length of the black zones to vary locally. Manepalli et al. (2011) also made a similar comparison between the KDE and Getis-Ord (Gi*). This study supported the findings of Flahaut et al. (2003). Fixed distance band, inverse distance band, and inverse square distances were used to determine the Gi* statistics. Results showed that inverse distance and inverse square distances identify hotspots more accurately (Manepalli et al., 2011). Khan et al. (2008) used the Getis-Ord (Gi*) method in order to correlate crash patterns with different weather conditions. Results showed a positive spatial autocorrelation suggesting that weather was a contributor to the high number of crashes in the study area. Deshpande et al. (2011) also presented a comparison between planar KDE and spatial autocorrelation methods, and concluded that Kernel Density is more appropriate in crash analysis. The most thorough comparison study reviewed was conducted by Kuo et al. (2011) where a comparison of the planar KDE, Getis-Ord, and network KDE methods were presented. Crash and crime data were used in the study to identify the clusters for both data sets. According to this study, KDE showed the high risk locations more accurately than the Gi* which only shows a large area covered in clusters. Moreover, Gi* defined a point and/or an area where incidents were clustered together by high values only. Finally, Plug et al. (2011) mentioned that the drawback of Gi* was that it needed the aggregation of data rather than using the individual crashes. A review of the existing studies clearly express the better performance of the KDE methods.

2.2 Temporal Analysis

The majority of existing studies reviewed used spatial clustering to analyze traffic crashes. Few researchers focused on investigating the temporal patterns for analyzing the crash data sets, which are as critical as spatial patterns (Li et al., 2007; Plug et al., 2011; Corcoran et al., 2008; Asgary et al., 2010; Kuo et al., 2011). Temporal representation of data points is not only used for crashes and crime, but also in other fields such as fire safety. Studies like Corcoran et al. (2014) and Asgary et al. (2010) used spider graphs to represent fire incidents temporally. They showed that the fire incidents followed different spatial and temporal patterns. Results proved to be important for fire prevention planning and response management.

Asgary et al. (2010) stated that there were four general forms of analysis in temporal analyses: the “panel”, “event-count”, “event-sequence”, and “event-history” methods. Panel analysis shows the state of a sample of units at two or more points, while event-count analysis shows the number of different types of crashes in the selected interval. Event-sequence analysis shows the sequence of patterns that occur with a high frequency, and event-history analysis shows the timing of changes in a sequence. Temporal analyses concentrate on the units of time, such as hourly, daily, monthly, and yearly units of measure, to visualize the crash rates and crash frequencies (Plug et al., 2011; Li et al., 2007; Asgary et al., 2010). There are several ways of representing temporal relationships such as line graphs, bar graphs and spider plots. Several recent studies discuss the usefulness of spider graphs that illustrate the chronological nature of the temporal data, highlight the temporal hotspots, and provide a better visualization and understanding of crash variation over time (Plug et al., 2011; Li et al., 2007; Asgary et al., 2010).

2.3 Spatio-temporal Analysis

Roadway crashes require a keen understanding of both temporal and spatial components simultaneously. When two or more crashes occur at a close proximity, but differ in their time periods, they may not likely represent a significant cluster. Likewise, two crashes that occur in the same time period, but differ spatially are also not likely to represent a significant cluster. Hence, a good knowledge of both the spatial and temporal information is necessary for effectively representing the hotspots to develop better mitigation strategies. However, few researchers have concentrated on the spatio-temporal analysis for analyzing crash clusters (Wang and Abdel-Aty, 2006; Prasannakumar et al., 2011; Plug et al., 2011; Dai, 2012; Corcoran et al., 2008; Asgary et al., 2010; Kuo et al., 2011). Two widely used methods in spatio-temporal analyses consist of the Comap method and SaTScan method.

2.3.1 The Comap Method

Among the few available methods, the Comap method is one effective method in representing both spatial and spatio-temporal information simultaneously. The Comap method explores the crash data at an ordered time interval such as the hours of a day, days of a week, or months of a year. The method works by first sub-dividing the crash data according to time of occurrence based on a chosen interval, followed by a spatial analysis such as the Kernel Density Estimation (KDE). Results are presented in a sequential order to highlight the changes over time in order to identify the variation of spatial distribution of crashes over time. Plug et al. (2011) employed the Comap method for investigating single vehicle crash patterns. The study visually showed how crashes vary on space at different hours of a day. Several other studies (Asgary et al., 2010; Plug et al., 2012) also used the Comap method to successfully illustrate how the spatial distribution of crashes varies with time. Due to its simplicity of application, the Comap method is commonly preferred over other methods.

2.3.2 The SaTScan Method

The SaTScan method, developed by Kulldorff (1997), is another effective method in representing both spatial and spatio-temporal information together. SaTScan is reasonably sensitive and specific when compared to the other cluster detection methods (Song and Kulldroff, 2003, Dai, 2012). This method calculates a log-likelihood ratio statistic using a Poisson distribution in order to create the events needed for further analysis. Depending on the nature of the data, it allows for different probability distributions such as the Bernoulli, discrete Poisson, or space-time permutation model, and chooses either elliptical or circular shapes to conduct the spatial scan statistics for the base of the study area. Conversely, the time period is taken as its height, and different time periods can be selected for the analysis. The circular or elliptical window moves in space and time across the study area. For each circle, a log-likelihood statistic is calculated, and the circles, which are statistically significant, are reported as clusters. Spatial randomness is accounted for by carrying out Monte Carlo simulations (Ribeiro et al., 2012), a commonly used method to approximate the probability of outcomes by running multiple trial runs through simulations. The SaTScan method is widely practiced in the field of health science (Kulldorff et al., 2005, Molina et al., 2012, Ngui et al., 2013, Curtis et al., 2014, Roth et al., 2013, Zeng et al., 2004). Additionally, Cheng and Williams (2012) presented interesting results from the analysis of crime patterns with a combination of the SaTScan with visual inquiry tools such as space-time cubes, animations, and map matrices. The results were effectively displayed using space-time cylinders in a space-time cube.

2.4 Statistical Regression Analysis of Crash Data

While most of the studies concentrated on identifying the crash clusters or hotspots, several studies focused on identifying the significant factors (e.g. roadway and traffic characteristics) that influence the occurrence and severity of roadway crashes. A very comprehensive review on the evolution of these statistical methodologies was presented by Mannering and Bhat (2014). Since the crash counts are basically non-negative integers, Poisson regression approach was first adopted in order to determine the significant factors. However, due to the fact that the Poisson regression cannot handle overdispersed data, negative binomial and zero-inflated Poisson models became more popular (Mannering and Bhat, 2014). Recently, many statistical models have emerged enabling transportation researchers to extract more information from crash databases. However, the choice of statistical model remains a significant aspect in analyzing the factors that affect crashes. Lord and Mannering (2010) and Mannering and Bhat (2014) reviewed various statistical methodologies that can be used in identifying factors associated with crash frequency data. Lao et al. (2014) used generalized nonlinear models for rear-end crash analysis to elaborate non-monotonic relationships between independent and dependent variables. They argue that the generalized nonlinear models provide a better understanding and explanation of contributing factors. The results also indicated a non-monotonic relationship between the crash frequency and the percentage of trucks in the traffic stream. Abdel-Aty and Keller (2005) used ordered probit modeling and tree-based regression techniques to explore the crash severity levels at signalized intersections. They adopted the ordered probit model to illustrate the naturally ordered injury levels, and the tree-based regression model to explore the significant factors that affect crashes. Results found a high prediction rate for injury levels using a combination of crash information and intersection characteristics.

Abdel-Aty et al. (1998) used log linear models to assess the effect of driver age on traffic crashes. The results found a specific relationship between the driver age, Average Daily Traffic (ADT) volume, speed, alcohol involvement, and roadway characteristics. Similarly, Lee and Abdel-Aty (2005) used log-linear models to identify the factors correlated with high pedestrian crashes. An ordered probit model was also employed to estimate the likelihood of pedestrian injury severity in pedestrian-involved crashes. Findings point to a correlation between middle-age male drivers and pedestrians, and increased pedestrian crashes, compared to other age group drivers. Results also found that adverse weather and lighting conditions had an effect on pedestrian injury severity. Abdel-Aty and Radwan (2000) used a negative Binomial model to study the factors affecting crashes. The study determined that Annual Average Daily Traffic (AADT), degree of horizontal curvature, median width, lane curvature, and section length had significant influence on the frequency of crash occurrence. Wang and Abdel-Aty (2006) performed temporal and spatial analyses on rear-end crashes particularly at intersections. They used the negative binomial link function to model rear-end crashes in order to account for temporal or spatial autocorrelation. A model was also developed to identify the relationship between the rear-end crashes, intersection geometric features, traffic operational features, and traffic characteristics. Their results revealed that high volume intersections, with a larger number of phases per cycle and right and left turn lanes, had a direct influence on rear-end crashes in high population areas. Yang et al. (2015) focused on modeling the crash risk of highway work zones by developing a model based on the logistic regression. They developed a model to explore the relationship between the contributing factors and crash risk in work zones. Findings revealed that work zone crash risk is significantly influenced by traffic volume, work zone length and lane closures.

While there are many previous statistical analysis studies available in the literature, few studies focused on aging-involved crashes (Oxley et al., 1997; Abdel-Aty et al., 1988; McGwin and Brown, 1999). Oxley et al. (1997) studied judgment differences between young and old adult pedestrians, whereas Abdel-Aty (1988) and McGwin and Brown (1999) discussed the effect of driver age and characteristics on the occurrence of crashes.

2.5 A Review of the Practice

Older drivers experience deterioration in physical, perceptual and cognitive skills; therefore, many agencies have developed strategic plans to accommodate aging road users. National Cooperative Highway Research Program (NCHRP, 2005), one of the major areas of the AASHTO Strategic Highway Safety Plan, addressed this issue, performed extensive literature review and surveys, and provided implementation strategies to reduce the number of crashes involving aging populations. Some of the studies include several measures for implementation:

(a) providing advance warning signs, (b) increasing the size and letter height of roadway signs, (c) providing all-red clearance intervals at signalized intersections, (d) improving roadway delineation, (e) reducing the intersection skew angle, and (f) improving lighting at intersections. U.S. Department of Transportation provides design guidelines for the aging population, and included all roadway segments, particularly at intersections, where aging population crashes are more frequent. Some State transportation agencies consider the population group of age 45 and over as elderly, and have implemented license renewal rules for drivers age 45+. Florida Department of Transportation (FDOT) implemented a program, the Safe Mobility for Life Coalition (SMLC), in 2004 to improve safety, access and mobility of Florida's aging population, and to identify transportation safety problems for the aging population (SMLC, 2013). Many interdisciplinary agencies have joined this program to create awareness among the aging population. SMLC program also conducts research to identify and develop plans to reduce aging-related issues. Several measures and strategies have been implemented to reduce aging-involved crashes; however, the benefits of these plans have not been fully utilized. Thus, this area of practice and research is still worthy of investigation.

2.6 Summary

The review of existing literature reveals a gap in terms of identifying crash hotspots with a specific focus on the aging population. As a result, there is definitely a need for studies that focus on aging-involved crashes to identify high risk locations. Additional research in this area can facilitate the development of appropriate safety measures targeted at reducing the number of aging-related crashes and associated risk of injury. The next section presents the methodology used in the current study.

Chapter 3 Methodology

The focus of this research was to develop a GIS-based spatial and temporal evaluation methodology for aging-involved roadway crashes. Unlike previous approaches found in literature, the current methodology, illustrated in Figure 3.1, concentrates specifically on crashes involving aging population groups to systematically determine the most hazardous locations for crashes. Hazardous location analysis refers to the identification of aging-involved crash hot spots and clusters on a given roadway network. Different spatial, temporal and spatio-temporal methods were considered to analyze the crash data, and identify the high crash risk locations using ArcGIS 10 mapping software. Statistical analyses were conducted using MATLAB 2014 and Minitab 17. Section 3.1 describes the areas analyzed in this study.

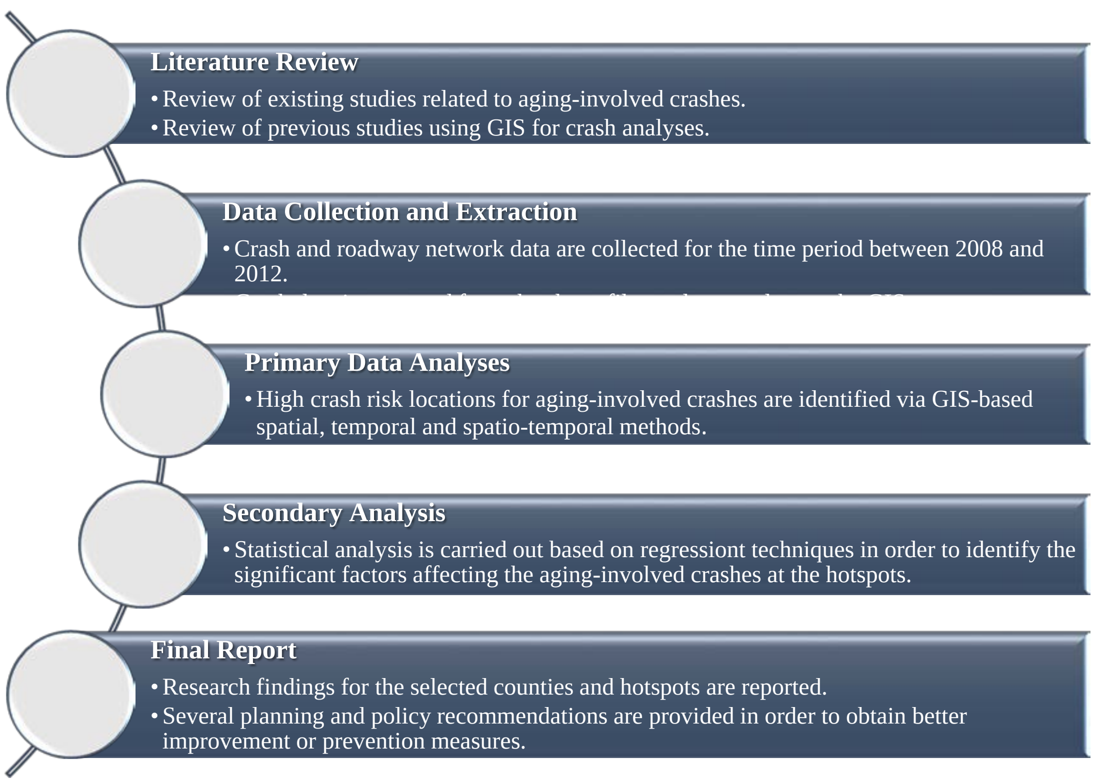


Figure 3.1 Research Methodology

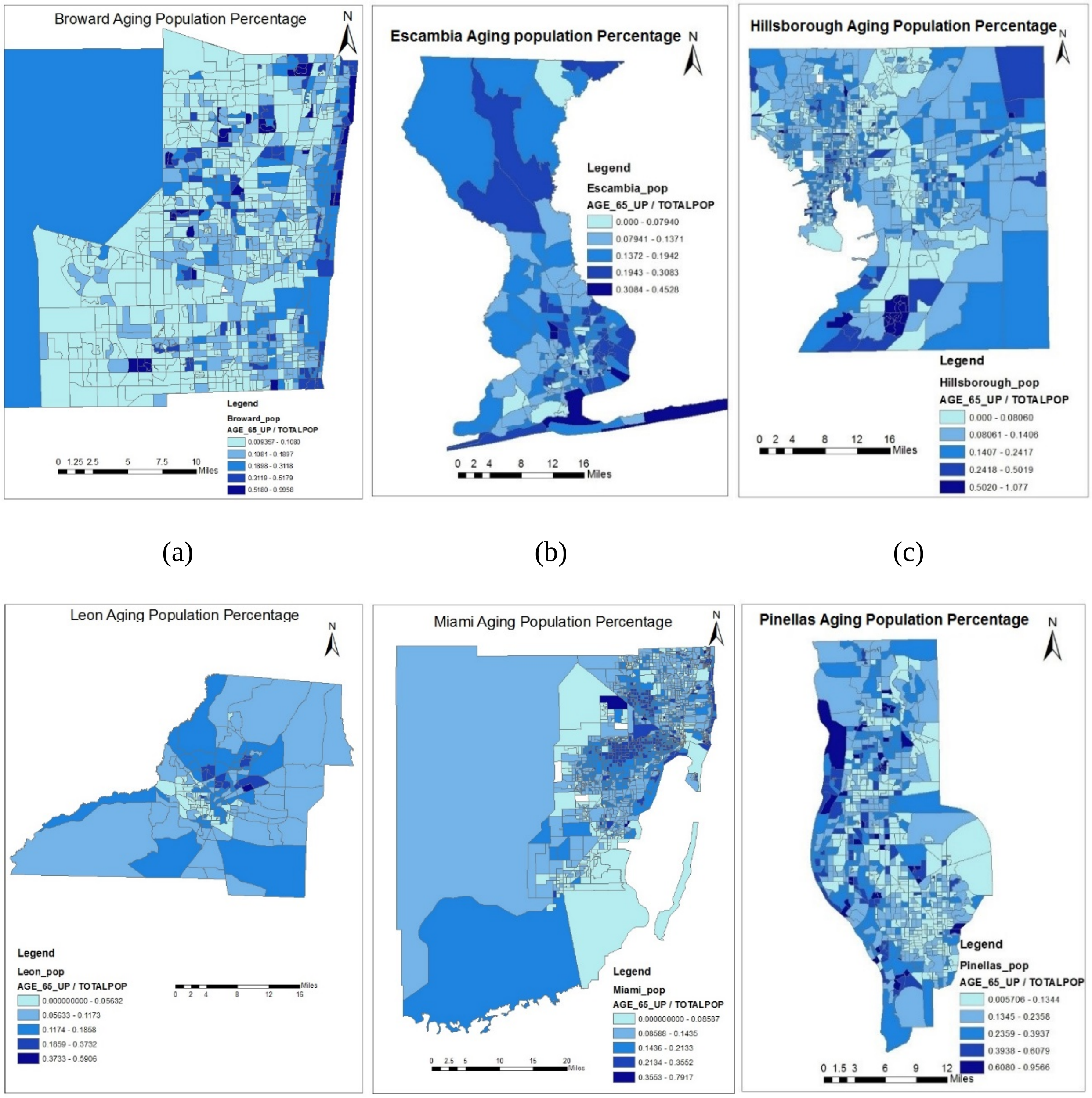
3.1 Study Areas

Aging-involved crashes in Florida were examined for ten urban counties, Alachua, Bay, Broward, Duval, Escambia, Hillsborough, Leon, Miami-Dade, Monroe, and Pinellas, and one rural county, Walton County. The counties were selected based on the high number of 65+ age group crashes with respect to the age group population. Moreover, these counties were identified as priority counties by the Safe Mobility for Life Coalition Program (SMLC, 2013).

Concentrated analysis efforts were placed on six of the eleven study counties, and included Broward, Escambia, Hillsborough, Leon, Miami-Dade and Pinellas County. Graphical analyses on the remaining five counties, Alachua, Bay, Duval, Monroe, and Walton, are presented in Appendix A through E. Figure 3.2 illustrates the 65+ population demographics in terms of percentages with respect to the total population in each of the selected six counties (U.S. Census, 2010). The 65+ population density is clearly recognizable in each county map, allowing for targeted geographical area analyses.

3.2 Data Collection and Extraction

Roadway network and crash data were obtained from the FDOT Safety Office in the format of GIS shape files with associated databases, and a query tool with crash data separated by age groups, 65+, 50-64, and less than 50 years of age for a study period of five years (2008-2012). Traffic flow information was obtained from the data collected at the Telemetered Traffic Monitoring Sites (TTMS) locations operated by the FDOT. After the crash hotspots were identified, traffic flow information, using the date and time attributed to the crashes within each hotspot, was extracted from the relevant traffic stations and aggregated with the crash data.



(d) (e) (f)

Figure 3.2 Population Demographics of +65 populations

Figures 3.3 through 3.8 illustrate the total number of crash occurrences in each of the selected six counties from 2008-2012, for age groups 50+, 65+, and All ages. Broward (Figure 3.3), Escambia (Figure 3.4), and Pinellas County (Figure 3.8) show increases in aging-involved crashes from 2008 to 2010, followed by slight decreases in 2011, and increasing again in 2012. Alternatively, Hillsborough, and Miami-Dade counties (Figures 3.5 and 3.7) experienced annual increases in aging-involved crashes over the full five year study period. Aging-involved crash occurrence remained fairly consistent in Leon County (Figure 3.6) among each study year, with only slight variations. Crashes for age groups 50+ and 65+ also demonstrate similar patterns. This observation is significant since aging of baby boomers are expected to produce a 79% increase in 65+ population over the next 20 years (Koffman et al., 2010). Consequently, crash risks associated with the aging population is expected to increase accordingly.

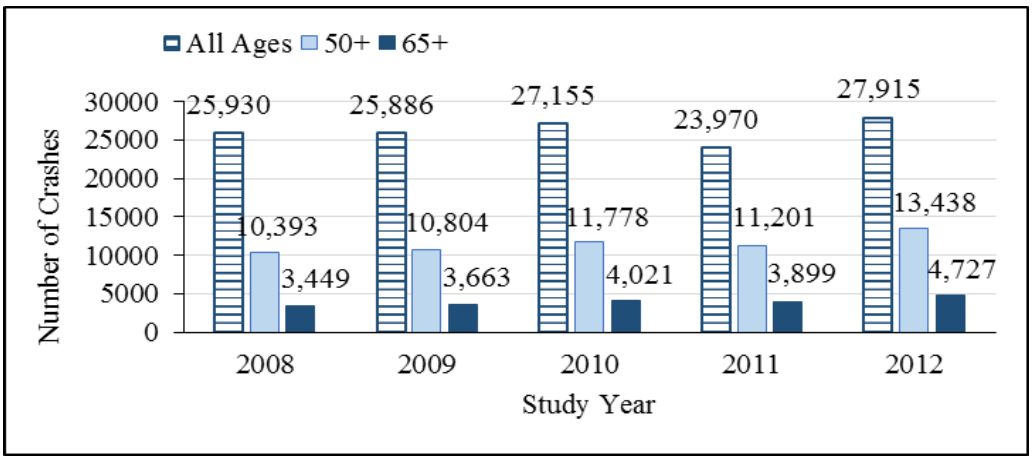


Figure 3.3 Yearly Crash Variations: Broward County

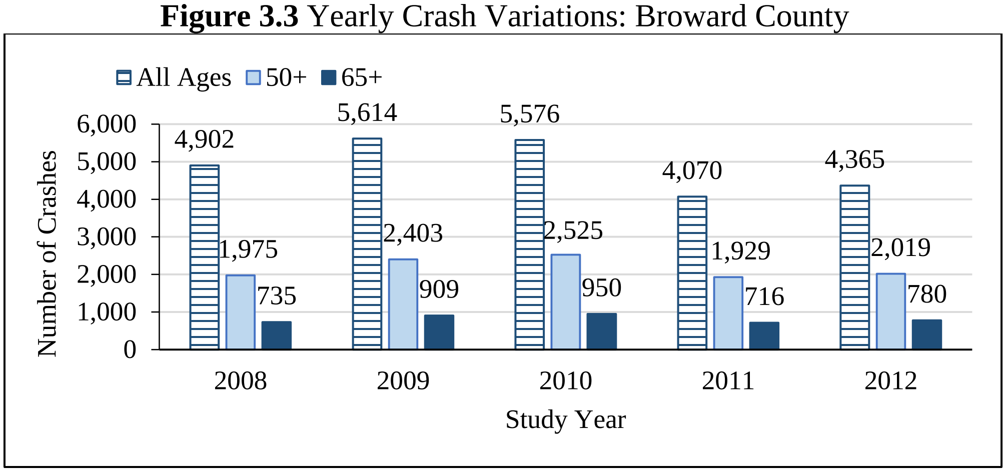


Figure 3.4 Yearly Crash Variations: Escambia County

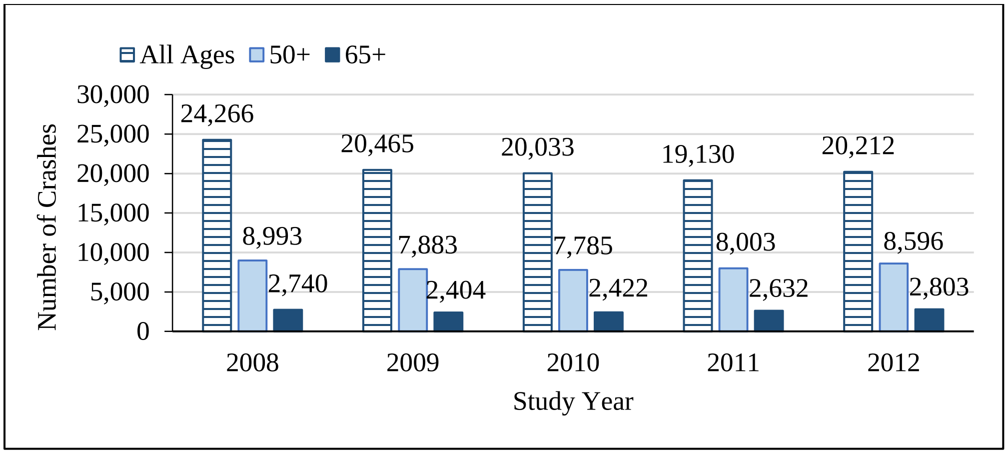


Figure 3.5 Yearly Crash Variations: Hillsborough County

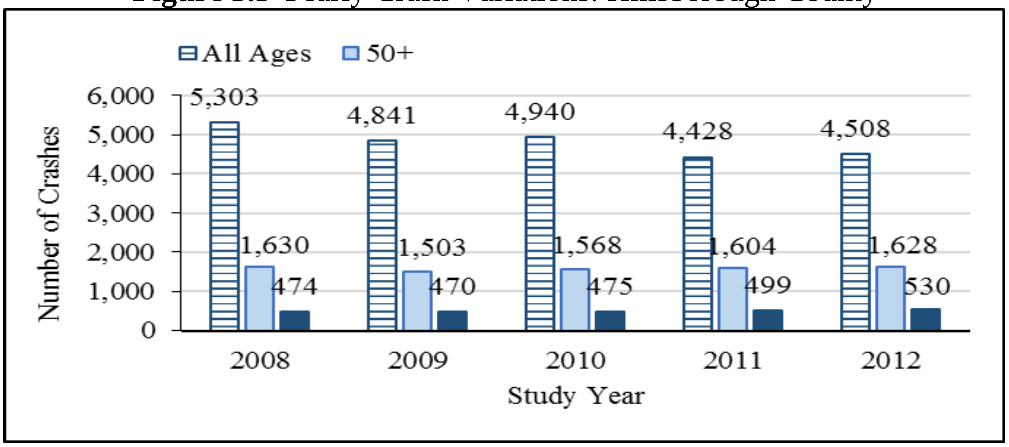


Figure 3.6 Yearly Crash Variations: Leon County

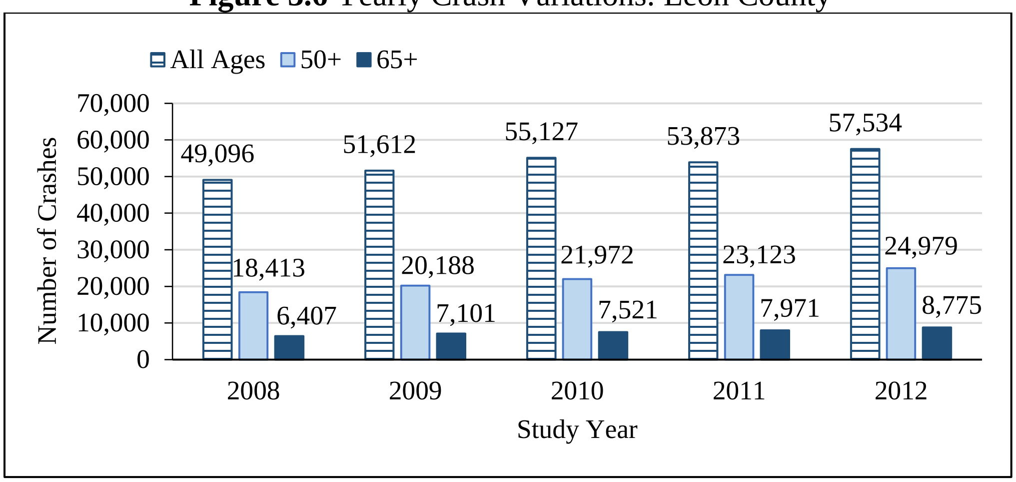


Figure 3.7 Yearly Crash Variations: Miami-Dade County

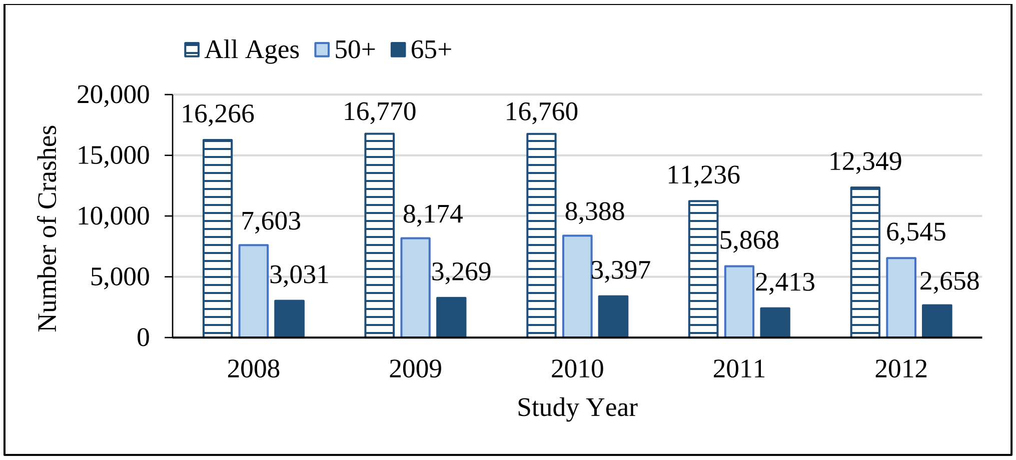


Figure 3.8 Yearly Crash Variations: Pinellas County

3.3 Analytical GIS-based Approach

For the GIS-based approach, spatial, temporal, and spatio-temporal methods were applied first to reveal crash patterns, high risk locations, and time periods of the crash clusters for the six counties of Broward, Escambia, Hillsborough, Leon, Miami-Dade and Pinellas. Geo-spatial aging-involved crash density maps were first created to provide visual illustrations of the intensity clusters of crashes involving aging populations. Three Kernel density spatial analysis methods were employed within the ArcGIS software, based on the following approaches: (a) planar KDE, (b) network KDE, and (c) Getis-ord Gi*. Results from these spatial analyses were compared to identify the advantages and disadvantages of each individual method.

The second step included the use of spider graphs to obtain the temporal distribution of the aging-involved crashes. Temporal units of hours, days, and months were examined to reveal the trends in the crash data, and to display the number of crashes and crash clusters in a selected time interval.

The third step involved the examination of the relationship between the spatial and temporal distributions of aging-involved crashes using a spatio-temporal technique called the

Comap method. For each spatial distribution of crashes, the Comap method determines the temporal pattern in the crashes by examining the effect of different time periods on the spatial data. Spatio-temporal maps were created for different time periods of the day.

Figure 3.9 outlines the basic structure of the spatial and temporal GIS methodology used in this research. Based on the evaluation of these techniques, several important conclusions were reached with regards to the spatial and temporal patterns of aging-involved crashes. The case study application results are discussed in Chapter 4.

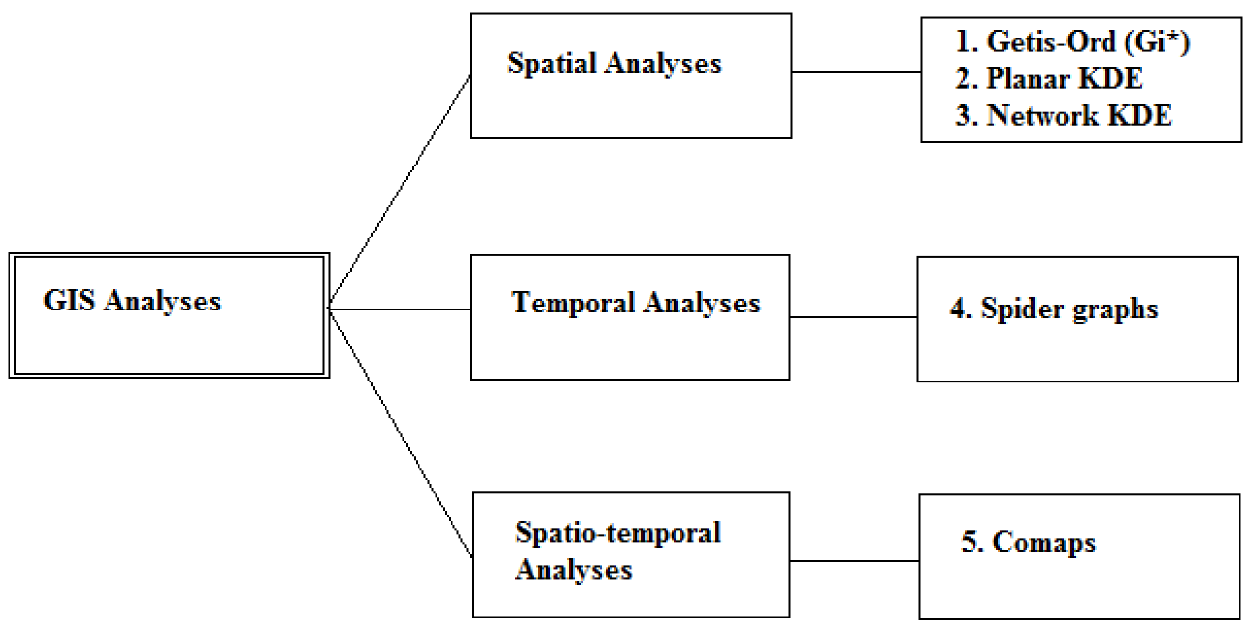


Figure 3.9 Basic Structure for the GIS-based Methodology

3.4 Spatial Analysis

3.4.1 Planar Kernel Density Estimation (KDE)

Planar Kernel Density Estimation (KDE) is a non-parametric density estimation where there are no fixed structures, and the analysis depends on all of the data points, contrary to parametric estimation which has a fixed functional structure. Unlike spatial auto-correlation which uses the aggregation of data, planar KDE uses disaggregated data by treating individual events as centers to create mole hills. Planar KDE can be useful in identifying the density of high crash occurrence locations, or hotspots. As described in Chapter 2, the planar KDE method first takes an individual point and creates a density surface which peaks at the surface center. The surface value tends to become smaller as it moves away from the center point, thus creating mole hills surrounding each crash point. Once a surface is created for each individual crash point, a continuous density surface is created by combining the mole hills to develop a heaping surface across the entire study area. Crash events are weighted based on their distance from the Kernel center using the Euclidean distance, and a density value is assigned to the center point. The density estimator function which is used in the analysis is shown in Equation (1) as follows:

$$\hat{f}(x) = \frac{1}{n} \sum_{i=1}^{n} K\left(\frac{x-x(i)}{h}\right) \tag{3.1}$$

where

$\hat{f}$(x): density estimator,
h: chosen bandwidth,
n: number of observation points,
K: Kernel function,
x…x(i): observation points.

In this $\int K(t)dt = 1$ equation, to ensure that *f*(*x*) integrates to 1 with a peak at zero. There are various choices in Kernel functions ranging from Gaussian, Quartic, Conic, Uniform, Epanechnikov, and Negative Exponential (O’Sullivan and Unwin, 2002; Mohaymany et al., 2013). Silverman (1986) argues that the choice of Kernel function will not significantly affect the results. This study employs the quadratic Kernel function (Silverman, 1986) incorporated into the ArcGIS 10 software. It should be noted that when selecting the bandwidths, smaller bandwidths are more likely to produce inadequate smoothing by just simply highlighting the individual points. Hence, bandwidths are generally selected based on trial and error for the planar KDE method (Plug et al., 2011, Pulugurtha et al., 2007).

3.4.2 Network Kernel Density Estimation (KDE)

Contrary to planar KDE, Network Kernel Density Estimation (KDE), locates the crash hotspots (high risk locations where the crash densities are higher) on a network. The basic principle of network KDE is the same, except that it works on the roadway networks rather than a planar space. This method was first developed by Okabe et al. (2006) and applied successfully by several researchers such as Okabe and Sugihara (2011). The network KDE method attempts to estimate a nonparametric estimation when the only known information is the location of points. Let *N* be a roadway network with *V* (v_1, v_2, v_3, …. v_n) nodes on the network and *L* (l_1, l_2, l_3, …. l_n) roadway links on that network connecting the nodes. A sub-network L_q is created such that the shortest-path distance between *q* and any point on L_q is less than or equal to *h*, where *q* is an arbitrary point connected on any link *L*, and *h* is the chosen bandwidth. For a given point *q* and some arbitrary point *p* on any link *L*, the function K_q (*p*) is defined as follows:

$$\int K_q\,(p)\,dq = 1 \begin{Bmatrix} \geq 0\ for\ q \in L_q \\ = 0\ for\ q \in \tilde{L}\,/L_q \end{Bmatrix}$$

K_q (*p*) , (3.2)

$\tilde{L}\check{L}$where , the union of all links, $p \in L_q$ is the integration of K_q (*p*) d_p along the line segment of L_q. Here, K_q (*p*) is the network Kernel Density function value at *q*, with *q* as the kernel center. For the given sample points *p*1, *p*2……, p_n on , a function *K* (*p*) is given as follows:

$$K\,(p) = \frac{1}{n}\sum_{i=1}^{n} K_{pi}\,(p) \tag{3.3}$$

where $K(p)$ is the network kernel density estimator for $f(p)$ at p. This creates a kernel function for all of the individual points on the network. However, this type of calculation changes if the point has more than two degrees, i.e., if it comes across as a node where it has to create a function on two roadway links. In such situations, Okabe et al. (2006) proposed two methods: (a) 'Equal- split discontinuous kernel density function', and (b) 'Equal-split continuous kernel density function'. A key disadvantage of the latter method is an increase in computational time over the former method. Therefore, the first method, the Equal- split discontinuous kernel density function is applied in this study. Two possible cases arise when using this method:

1. The kernel center q does not coincide with a node in V.
2. The kernel center q coincides with a node in V.

In the first case, a buffer network of q with a width of h is constructed with the shortest path s from q to the boundary points of the buffer network b_i. If the boundary distance $0 \leq d_s(q, p) \leq d_s(q, v_{i1})$ it creates the function as $K_q = K(ds(q, p))$ but when it reaches a node v_{i1}, it splits the link which comes from the center q into $n_{i1} - 1$, where n_{i1} is the degree of node v_{i1}. Next, it distributes the value to every link that is attached to node v_{i1}. This process continues until it reaches the boundary b_i. The function $K_q(p)$ is defined as follows:

$$K_q(p) = \begin{cases} \dfrac{K\ (d_s(q,p))}{(n_{i1}-1)\ ((n_{i2}-1)\ \dots ((n_{ik-1}-1)} \ for\ d_s\ (q,(v_{ik}-1) \leq d_s(q,p) < \ d_s(q,(v_{ik}), \\ o\ for\ d_s(q,p) \geq h \end{cases} \tag{3.4}$$

where $k = 1\dots, m$, $v_{i0} = q$ and $v_{im} = b_i$.

In the second case, the value of function $K_q(v_{i1})$ is divided by n_{i1} and assigned to the roadway links. The function in this case is defined as follows:

$$K_q(p) = \begin{Bmatrix} \dfrac{2k\,(d_s(q,p))}{n_{i1}\,(n_{i2-1})\,\ldots.(n_{ik-1}-1)}\; for\; d_s(q, v_{ik-1}) \leq\; d_s(q,p) <\; d_s(q, v_{ik}), \\ 0\; for\; d_s(q,p) \geq h. \end{Bmatrix} \tag{3.5}$$

where $k = 2, \ldots.., m$.

The computation of the equal-split discontinuous method is used when there are more than two paths available, and is critical when the length is less than h from the center q. For example, when the paths overlap on the network, N is carried out in three steps. In the first step, the method modifies the given network by creating dummy nodes for every link nearest to the nodes that have more than two degrees such that these dummy nodes further divide the existing links to manage the multiple values at every node with a degree more than two. In the second step, it computes the split ratio at every node with the length of the bandwidth h starting from the kernel center q. Third step sums up all the densities obtained from the previous steps with respect to all kernel centers. As the choice of bandwidth effects the density estimation, studies suggest using a 100-300 meter bandwidth (Okabe and Sugihara, 2011), which can be taken as a rule of thumb when applying the methodology on the urban areas. A 250-meter bandwidth was used in the current study for the network Kernel estimation analysis, and was determined based on trial and error.

3.4.3 Spatial Autocorrelation (Gi)*

As mentioned in Chapter 2, spatial autocorrelation works based on the first law of geography, that “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970). Moran’s I, Getis-Ord G, Geary’s C and Anselin Moran’s I statistics belong to this family. All of these statistics require attribute values and the aggregation of data. Since we are working on the crash data points, we only have the physical location of the crash data point without any attribute values associated to it. To overcome this and identify the clusters based on those points, the "Optimized Hot Spot Analysis" option, available in ArcGIS 10 was used. The hot spot analysis uses the Getis-Ord Gi* analysis, developed by Getis and Ord (1992). This statistic can be used to evaluate spatial association of a variable within a specified distance of a single point (Getis and Ord, 1992). Getis-Ord Gi* is a second order statistic which examines the pattern locally. This is important if the process is spatially nonstationary. The G statistic measures the degree of association that results from the concentration of weighted points, which are included within a distance *d* (Getis and Ord, 1992). The Gi (*d*) statistic is calculated based on the following formula:

$$G_i(d) = \frac{\sum_{j=1}^{n} w_{ij}(d) x_j}{\sum_{j=1}^{n} x_j}, j \text{ not equal to } i, \tag{3.6}$$

where;

w_{ij} is the spatial weigh matrix with 1 for all the links within the distance d for given *i*, and 0 for all others.

x = the weight associated for all links *i*,

d = distance from the original weighted point.

This method identifies the statistically significant clusters of high values and low values based on the *Z*-scores and *p*-values, which determine whether or not to reject the null hypothesis. Complete spatial randomness defines the null hypothesis for the pattern toolset by either the features themselves or the values associated with the features. The desired result of this analysis is to reject the null hypothesis, which indicates that the features exhibit statistically significant clusters (High or Low), rather than a random pattern. If the given point *i* is among the high value

x_{js},, then Gi (d) is high with a large positive Z-score. This indicates a cluster of high attributes. If the given point i has a low value x_{js},, then Gi (d) is low with a large negative Z-score, which indicates a cluster of low attribute values. Therefore, the larger the absolute value Z-score, the higher the significance. The Gi* is given as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}\ x_j - \bar{X}\ \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\ \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{3.7}$$

where;

G_i* is the Getis-Ord Z-score value at site i,

x_j is the attribute value for feature j,

$w_{i,j}$ is the spatial weight between feature i and j,

n is the total number of features,

$\bar{X}$ is the average of crash frequency, and

S is the standard deviation of x_j.

$\bar{X}$ and S can be calculated using the following equations:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{3.8}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \tag{3.9}$$

Since no attribute values are defined, the optimization method aggregates the incident points, thus creating an attribute value to determine the statistic by utilizing one of three methods: “incident count with fishnet polygons”, “incident count with aggregation polygons”, or “snap-to nearby incidents” to obtain weighted points. The large dataset used in the current study required the last method, snap-to nearby incidents, to successfully aggregate the data. Therefore, each hotspot analysis in this study was analyzed using the Getis-Ord statistic.

3.4.4 Summary

Roadway crashes events are constrained to networks. In planar spatial statistics, we assume that the events occur on a continuous plane and the distance between these events are measured by Euclidean distance. For convenience, planar spatial methods are often applied to network events. However, these methods may lead to potential false conclusions because the distance between the events used in the calculations is the Euclidean distance. In reality, this result is not typically the case, since the events occur on a network indicated by line segments. Satoh and Okabe (2009) in their research proved that this estimation produces bias. This bias can be compromised by the use of network based spatial analysis, where the events are mapped onto a network, and the distance between the events will be the shortest path. In another study, Maki and Okabe (2005) state that both the Euclidean and shortest path measures the same, however, this holds true only if the measurement is less than 400 meters (Maki and Okabe, 2005). Network based Kernel Density Estimation method was used in the current study.

<u>3.5 Temporal Analysis</u>

Temporal analysis provides more understanding, can assist in visualizing the change in aging-involved crashes over time (Plug et al., 2011), and also reveal the temporal trends involved in aging-involved crashes. Temporal units of hours, weeks and months were examined to reveal these trends in the spatial data. There are several ways of representing this temporal relationship, such as line graphs, bar graphs and spider plots. Several recent studies discuss the usefulness of spider graphs. Spider graphs were used in the current study to locate high crash locations (hotspots) based on the selected time periods for each county. Event count analysis was also used to display the number of crash events in the selected time interval.

3.6 Spatio-temporal Analysis

Roadway crashes require a keen understanding of both temporal and spatial components simultaneously. When two or more crashes occur at a close proximity, but differ in their time periods, they may not likely represent a significant cluster. Likewise, two crashes that occur in the same time period, but differ spatially, are also not likely to represent a significant cluster. Therefore, a good working knowledge of both the spatial and temporal information is necessary for effectively representing the hotspots to develop better mitigation strategies.

3.6.1 The Comap Method

Comaps, also known as co-plots, can be used to explore the relationship between spatial and temporal data via the Comap method. This method allows the effect of the time period change on the crash hotspots for a given set of spatial data to be examined. In the current study, hourly temporal units were used for creating the Comaps for different hours of the day to observe the effect of the hourly time change on hotspots. Two conditions must be met to conduct this type of spatio-temporal analysis. First, the range of each chosen time period must overlap with the subsequent periods. Second, the number of crashes in each time period must be approximately equal. The two conditions are the only limitations of the Comap technique (Corcoran et al., 2007), and are necessary to represent the distribution of crashes spatially over time (Corcoran et al., 2007). Therefore, the analysis was performed by first separating the hourly crash data for chosen counties, and arranging them in a chronological order according to the chosen class. Class boundaries should be chosen in such a way that, each class should have approximately equal number of events. Once the data was arranged in the chronological order, these subsets were then analyzed using the planar KDE method to identify the spatial and temporal variation in the aging-involved crashes.

3.7 Regression Analysis

Three regression analyses were performed to determine the significant factors influencing crashes in the 65+ age group compared with other adult age groups. Figure 3.10 shows the structure of the regression analyses used to identify the factors in this study.

Regression analysis explains the effect of independent variables on the dependent variable. In this study, the effect of independent variables such as traffic characteristics, roadway characteristics, and weather conditions on the occurrence of crashes were explored for both the 65+ and 65- age groups. In the analyses, the goal was to identify how the independent variables affect the probability of having an aging-involved crash versus a crash involving people under the age 65. Therefore, the dependent variable was coded as 1, for a 65+ crash, and 0, if otherwise (65-). Since the dependent variable and several other independent variables are binary, nonlinear logistic regression models such as Logit or Probit were appropriate to use.

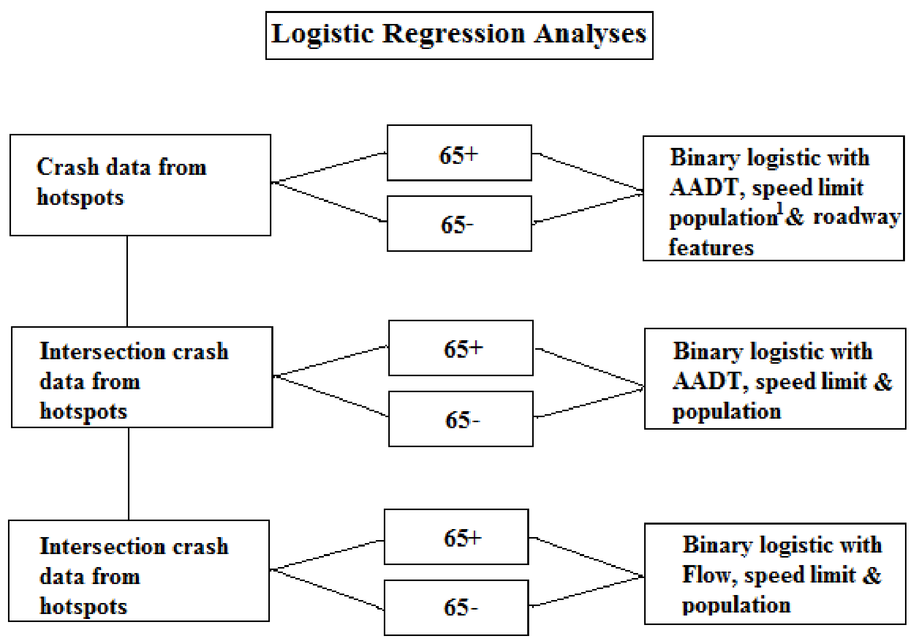


Figure 3.10 Regression Analysis Structure

These methods are different from linear regression, and can be solved explicitly using a formula. They also iterate several times to improve the fit of the model. Once the improvement from one step to the next is relatively small, the algorithm stops.

In this study, logistic regression was used. Developed by Cox (1958), logistic regression is widely used to identify the effect of traffic characteristics (Amemiya, 1985). Several factors can be used for such a study including: (a) traffic characteristics, such as the AADT and speed, (b) roadway characteristics, such as lane width, median width, shoulder width, and number of lanes, and (c) population characteristics. The formulation of the logit model for a binary dependent variable with multiple regressors is as follows:

$$\Pr(Y = 1|\, X_1, X_2 \ldots\ldots X_n) = F\,(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n\,)$$
$$= \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n)}} \tag{3.10}$$

where *F* is the cumulative standard logistic distribution function.

Here, *Y* is the response variable, and takes a value of 1, for a 65+ crash, and 0, if otherwise. The regressors make no assumption about the distribution of the independent variables. The coefficients can be estimated by maximum likelihood. The maximum likelihood estimator for unknown regressor coefficients maximizes the probability of drawing the data which is actually observed. The hypothesis testing for the estimated values is conducted using the *t*- statistics and *p*- values. The measures of fit for the logistic model is conducted through pseudo-R2, and uses the maximum likelihood function. It measures the quality of fit of a model by comparing the maximized likelihood function with all of the regressors to the value of likelihood with none.

Three different regression approaches were pursued in this study. In the first approach, once the hotspots were identified, the crashes that happened inside the hotspots were separated from the whole data in the form of two age groups: above 65 (65+) and below 65 (65-). A 5 mile buffer zone was created surrounding the hotspot to identify the population age living in the zone using Census population figures (U.S. Census, 2010). Along with the population information, the following independent factors were also evaluated: AADT and speed, and roadway features such as lane width, median width, and shoulder width. These factors were used in the first regression analysis to observe the effect of the factors on aging-involved crashes compared to other adult age groups. For the second regression analysis, all intersections (161) inside the hotspots were selected, and the same approach was applied on these intersections, where intersection crashes were separated from the hotspots to determine the significant factors effecting intersection crashes only. In the third regression analysis, instead of using the specified AADT, actual hourly flow data, extracted from the TTMS locations by the FDOT, was used. The the case study application results are discussed in Chapter 4.

Chapter 4 Case Study Application Results

In this chapter, we present a case study application on the Broward, Escambia, Hillsborough, Leon, Miami-Dade and Pinellas counties of Florida where we aim to identify the spatial, temporal and spatio-temporal distributions of aging-involved crashes. This application will also enable us to identify those high risk locations both spatially and temporally in terms of visual illustrations. Six primary counties of interest, Broward, Escambia, Hillsborough, Leon, Miami-Dade and Pinellas County, with an aging population percentage of 14%, 14%, 12%, 9%, 14%, 21% (U.S. Census, 2010) respectively, are studied in this section. These counties are documented to have a high number of documented crash events involving aging persons. They also include the following major cities in the State of Florida: Fort Lauderdale, Pensacola, Tampa, Tallahassee, Miami and St. Petersburg, respectively. Figures 3.2 through 3.7 compare the number of crash occurrences between the years 2008-2012 within each county for adult age groups. Table 4.1, on the other hand, presents the aging-involved (65+) crash characteristics within the study period (2008-2012) for the six counties selected. Table 4.1 shows that the majority of aging crashes occurred during the daylight hours (under clear weather conditions and good roadway conditions) in all the counties. We can also see that more than 50% of the aging crashes happened at the intersections or at those locations influenced by intersections. Similar to the findings of Braitman et al. (2007) and Preusser et al. (1998), intersections appear to increase the risk of crashes among the aging populations.

Table 4.1 Crash Characteristics (65+ group)

	Counties					
Characteristics	**Broward**	**Escambia**	**Hillsborough**	**Leon**	**Miami**	**Pinellas**
2010 Pop: 65+	249,424	42,929	145,237	25,980	352,033	194,099
Total crashes:65+	19,759	4,090	13,000	2.448	37,775	14,768
Factors						
Alcohol/Drugs	382	108	290	30	382	411
No Alcohol/Drugs	19,377	3,982	12,710	2,418	37,393	14,357
Intersection	10,393	2,825	6,815	1,413	20,453	9,111
Daylight	15,747	3,456	10,777	2,049	30,966	12,537
Other light conditions: Dusk, Dark	3,935	634	2,223	389	6,554	2,231
Clear Weather	15,057	2,806	9,639	1,712	29,380	11,544
Rainy Weather	4,622	370	967	230	2,546	953

In order to identify the crash hotspots in Broward, Escambia, Hillsborough, Leon, Miami and Pinellas County, the next section will present the results of the GIS-based spatial, temporal and spatio-temporal applications on the selected counties.

4.1 Spatial Analysis

In this study, we implement the Getis-Ord (Gi*) and Kernel Density Estimation (KDE) methods in order to analyze the aging-involved crashes spatially. The following sections will present the results of this analysis for the six counties studied, starting with the Gi* applications. Spatial results for other counties can be found in Appendix B.

4.1.1 Getis-Ord (Gi)*

4.1.1.1 Broward County

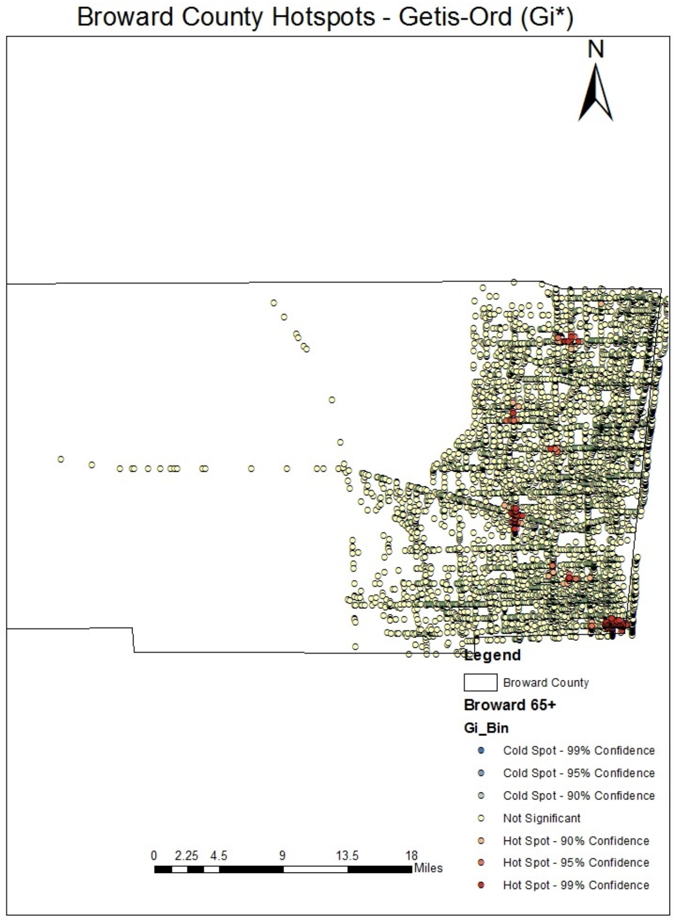


Figure 4.11 Gi* Analysis for the Broward County

Figure 4.1 shows the results obtained from the Gi* application on the Broward County, where Gi* methodology can be used to show the hot (shown as red) and cold (shown as green) spots regarding the crash clusters. These spots are presented with three levels of confidence in this analysis: 90%, 95% and 99% (95% confidence interval is the one mostly used). Please note that hot spots indicate the high crash risk locations for the Broward County. Figure 4.1 shows three major statistically significant hotspots with more than 90% confidence intervals, from this county. The hotspots identified are the Hallandale Beach, Nova Dr., and the W Sample Rd areas, with the 95% confidence.

4.1.1.2 Escambia County

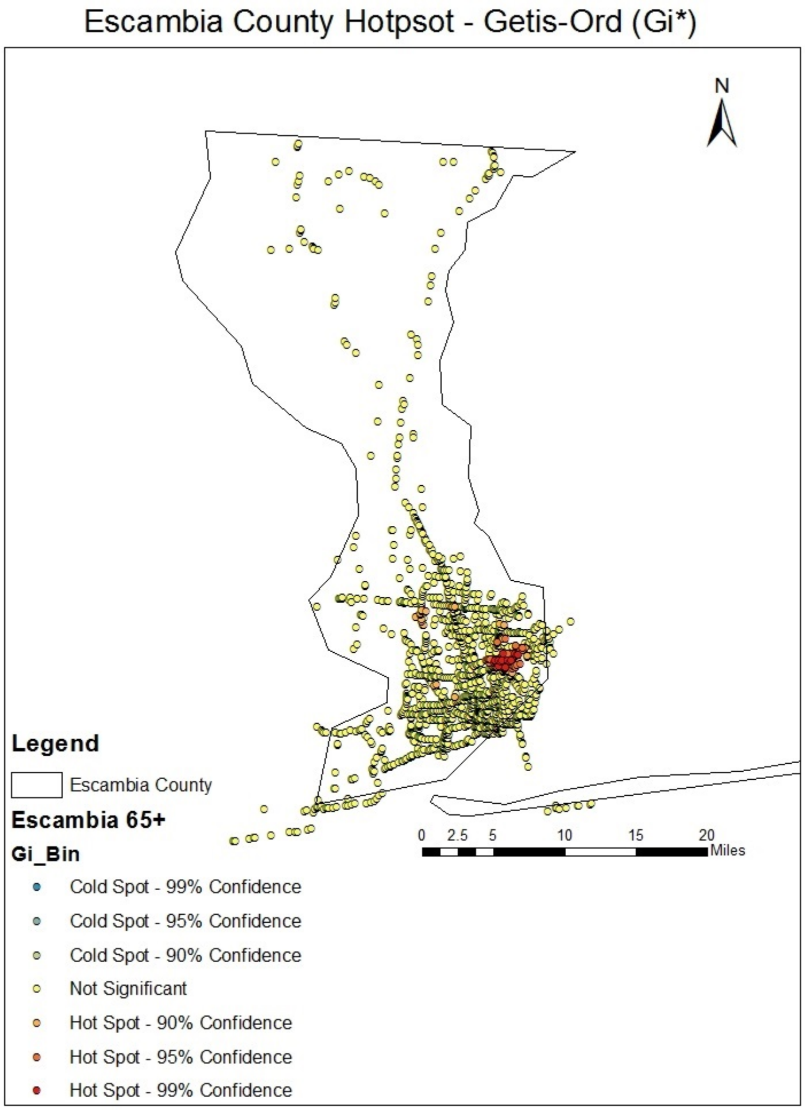


Figure 4.12 Gi* Analysis for the Escambia County

Similar results are obtained after analyzing the Escambia County based on the Gi* analysis are shown in Figure 4.2 for the given confidence levels. One major hotspot is detected near the downtown Pensacola region with more than 90% confidence interval in the Escambia County.

4.1.1.3 Hillsborough County

Gi* method is also applied on the roadway network of the Hillsborough County, which revealed the locations of the hotspots (Figure 4.3). This method identified 4 major hotspots in the Hillsborough County with the 95% confidence level: (1) Sun City Center, (2) Brandon, (3) University of South Florida, and (4) Greater Northdale regions.

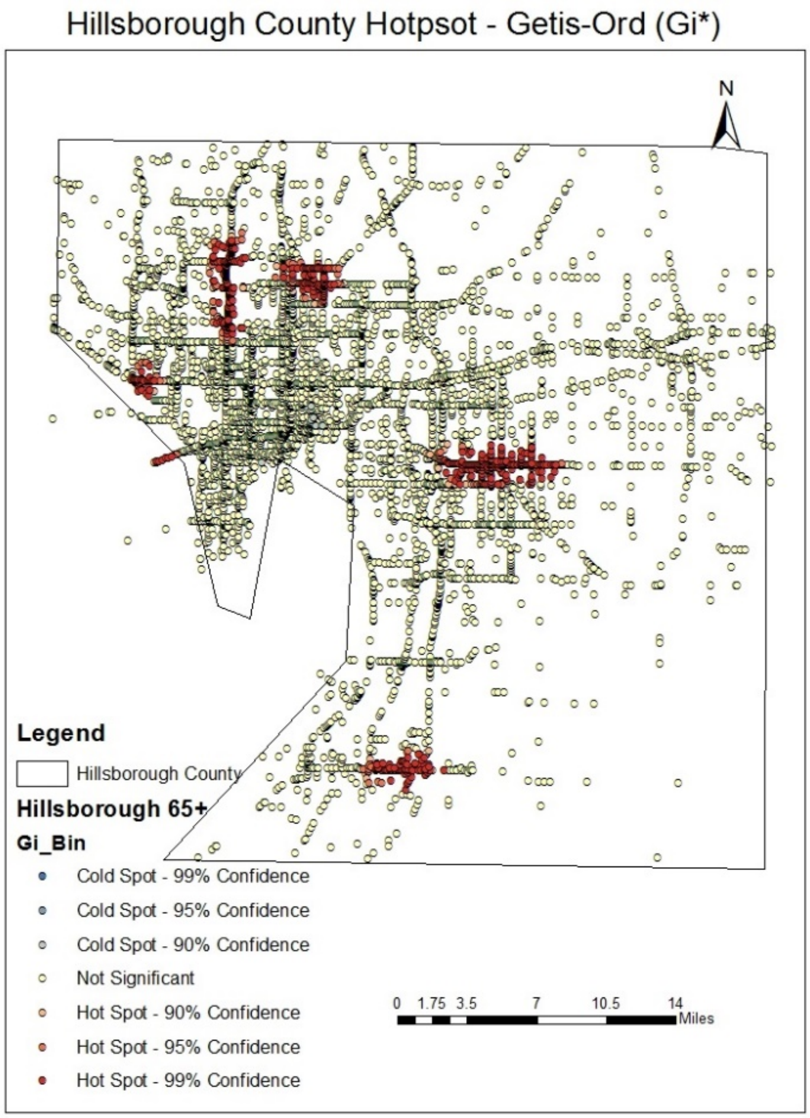


Figure 4.13 Gi* Analysis for the Hillsborough County

4.1.1.4 Leon County

Figure 4.4 shows the hot and cold spots identified after the Gi* analysis for the Leon County. Two major hotspots are detected in the Leon County: The first one is around the Raymond Diehl Rd extended to the Capital Circle NE, and the second hotspot is at the intersection of N Monroe St and N Duval St.

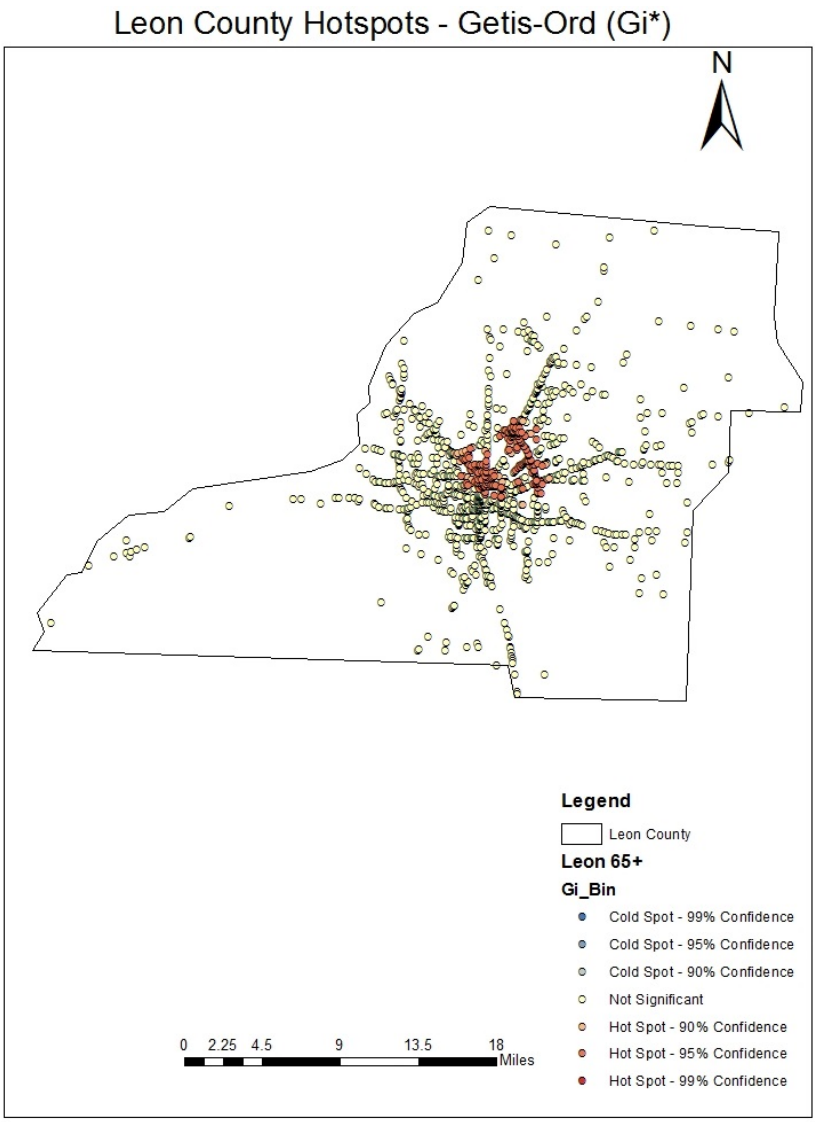


Figure 4.14 Gi* Analysis for the Leon County

4.1.1.5 Miami-Dade County

Hotspots detected for the Miami-Dade County are shown in the Figure 4.5. Four hotspots identified using the Gi* application are located at North Miami, Hialeah, Coral Gables and Miami International Airport regions.

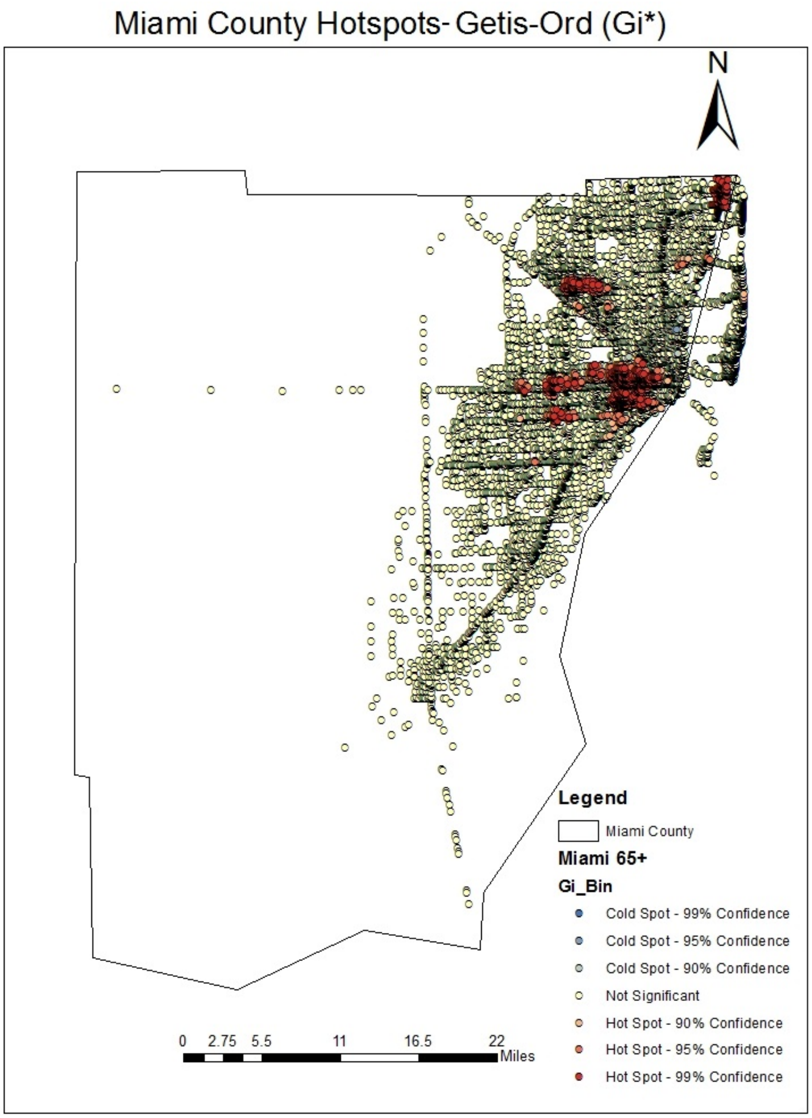


Figure 4.15 Gi* Analysis for the Miami-Dade County

4.1.1.6 Pinellas County

Figure 4.6 shows the hotspots identified for the Pinellas County. Two hotspots are identified with the 95% confidence level: Palm Harbor region on the US Highway 19 and Kenneth City region.

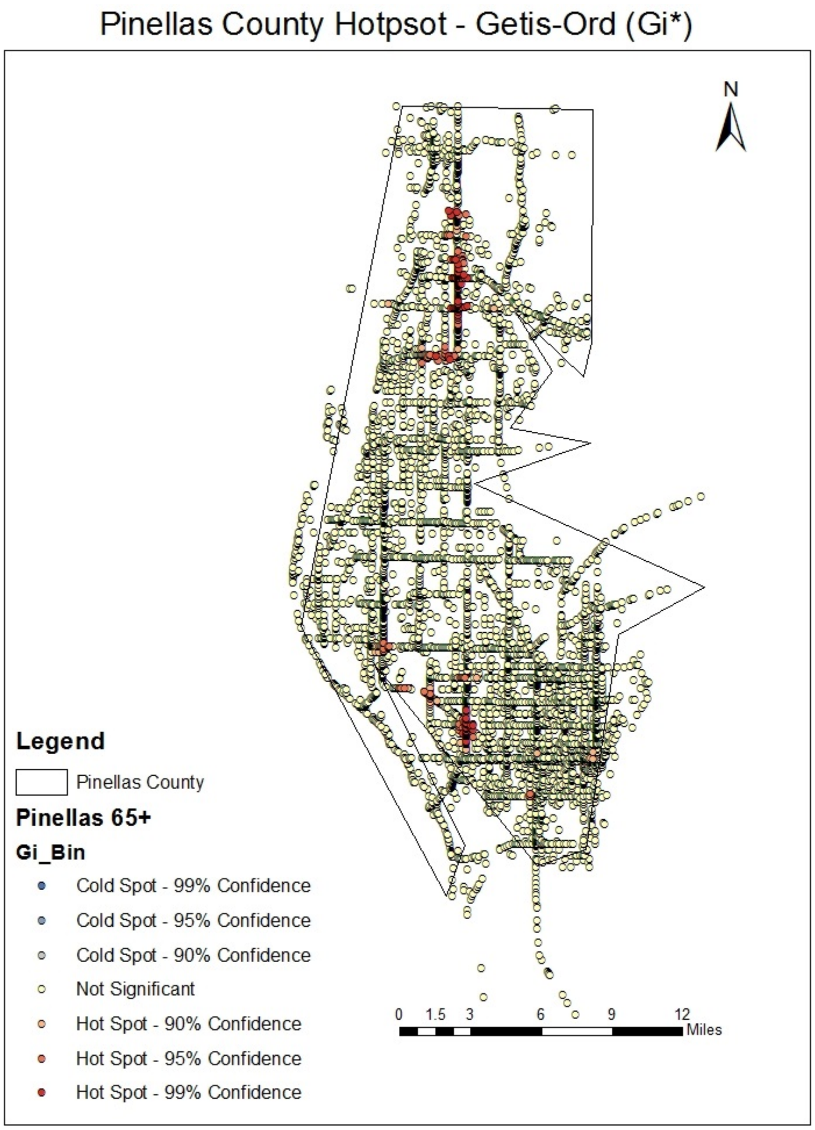


Figure 4.16 Gi* Analysis for the Pinellas County

4.1.2 Planar Kernel Density Estimation (KDE)

Planar KDE works by creating the mole hills for every individual crash point. Next, a continuous density surface is created heaping those hills across the study area. In this section, planar KDE is used for all the counties in order to identify the hotspots.

4.1.2.1 Broward County

Figure 4.7 shows the hotspots identified from the planar KDE application on the Broward County. Basically, dark blue areas in Figure 4.7 indicate more high crash risk locations. The most risky locations compared to others are identified as follows: (1) at the Hallandale Beach area, and (2) at the town of Davie.

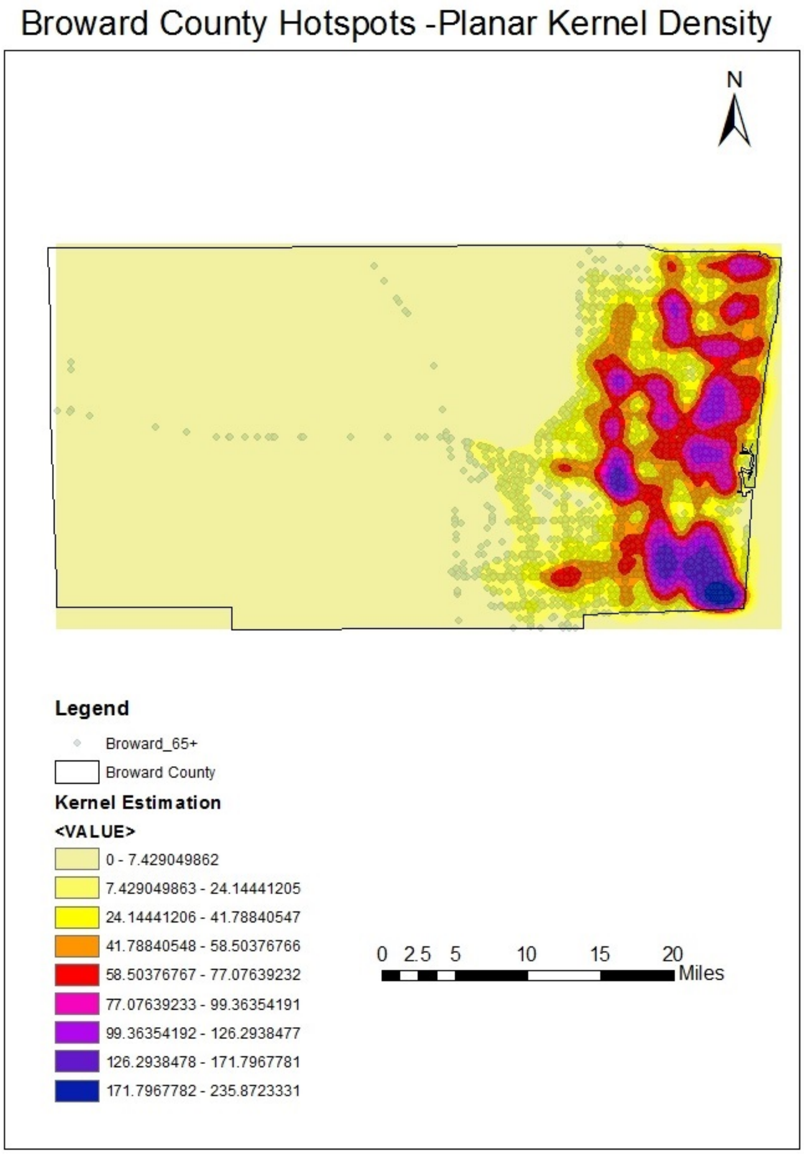


Figure 4.17 Planar KDE Application for the Broward County

4.1.2.2 Escambia County

The hotspots for the Escambia County are identified via the planar KDE method in the Figure 4.8. The highest risk associated with the aging-involved crashes is identified near the northeast of the City of Pensacola, between the 9th Avenue and Creighton Road. Some parts of the southeast Pensacola also appear to be critical.

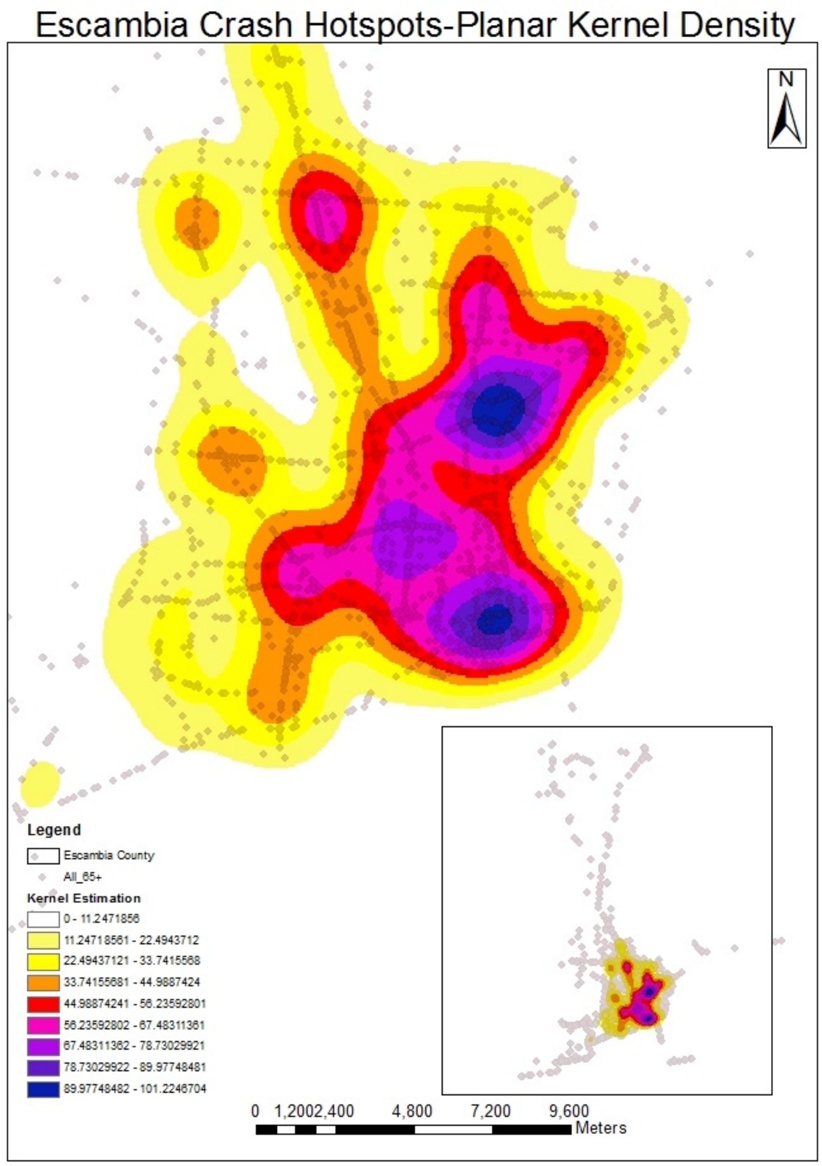


Figure 4.18 Planar KDE Application for the Escambia County

4.1.2.3 Hillsborough County

Hillsborough County hotspots with respect to the aging-involved crashes can be seen in Figure 4.9. From this analysis, two major hotspots are identified in the Brandon area and in the City of Tampa whereas two minor hotspots near the Sun City Center and the University of South Florida are observed.

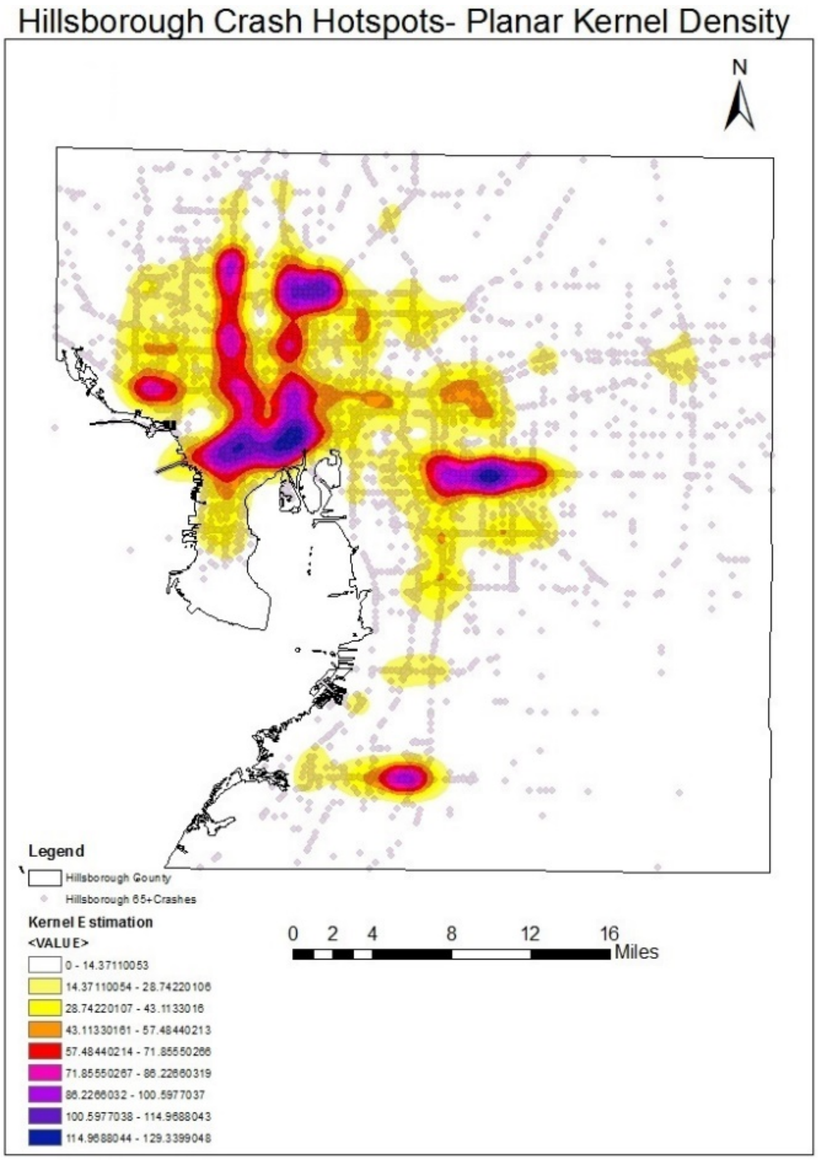


Figure 4.19 Planar KDE Application for the Hillsborough County

4.1.2.4 Leon County

Leon County hotspots are identified from the planar KDE, and are shown in Figure 4.10. The hotspots are observed in the downtown area as well as the northeast of the City of Tallahassee. Highest risk locations are found at the following locations: (1) Downtown Tallahassee, (2) N Monroe Corridor, and (3) I-10 intersection with the Capital Circle and Raymond Diehl Rd.

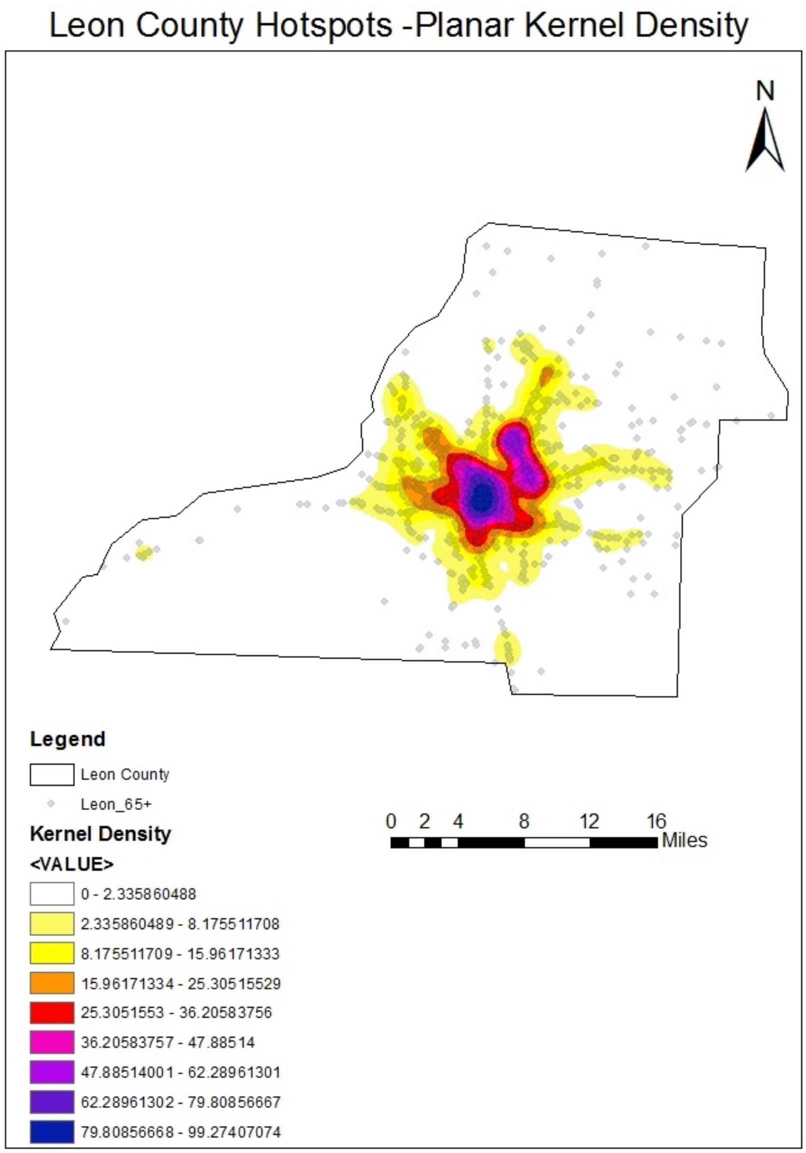


Figure 4.20 Planar KDE Application for the Leon County

4.1.2.5 Miami-Dade County

The hotspots identified for the Miami-Dade County are shown in the Figure 4.11. The most significant hotspot in the Miami-Dade County is identified near the Coral Gables and Fontainebleau regions.

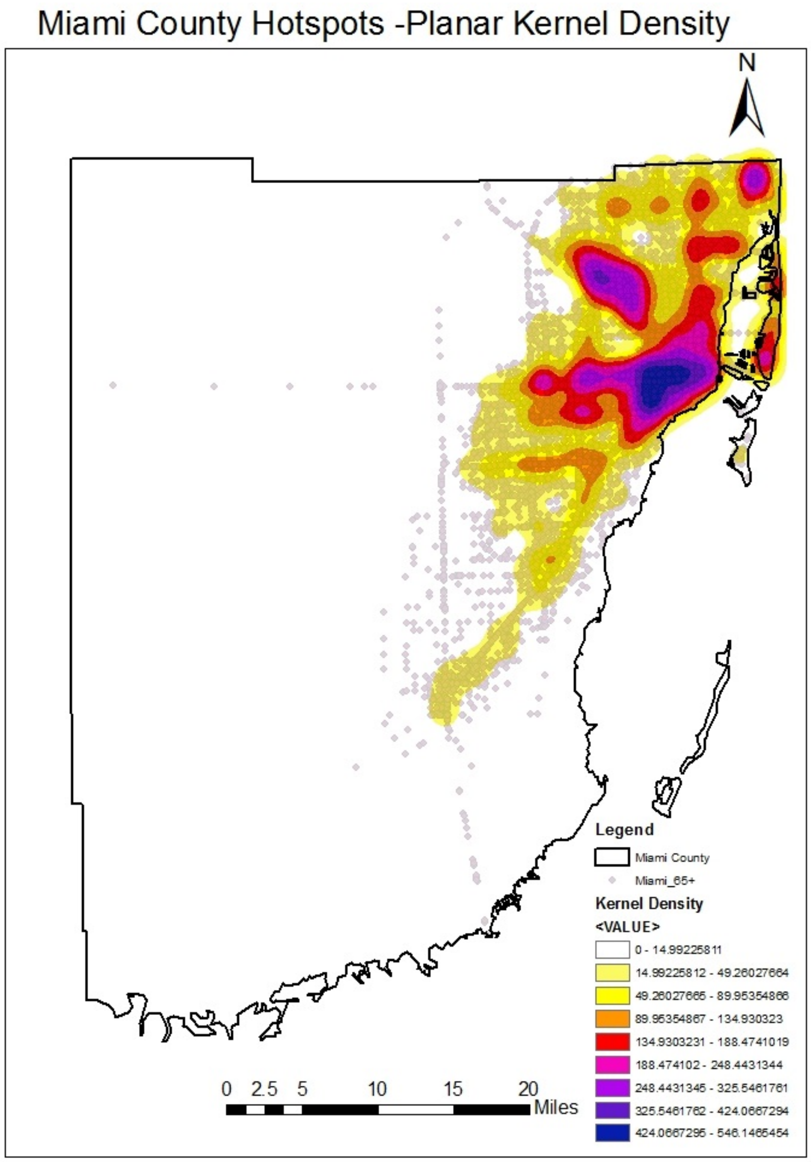


Figure 4.21 Planar KDE Application for the Miami-Dade County

4.1.2.6 Pinellas County

Figure 4.12 shows the hotspots identified in the Pinellas County based on the planar KDE approach. Figure 4.12 shows three major hotspots near the Palm Harbor, St Petersburg and Kenneth City regions.

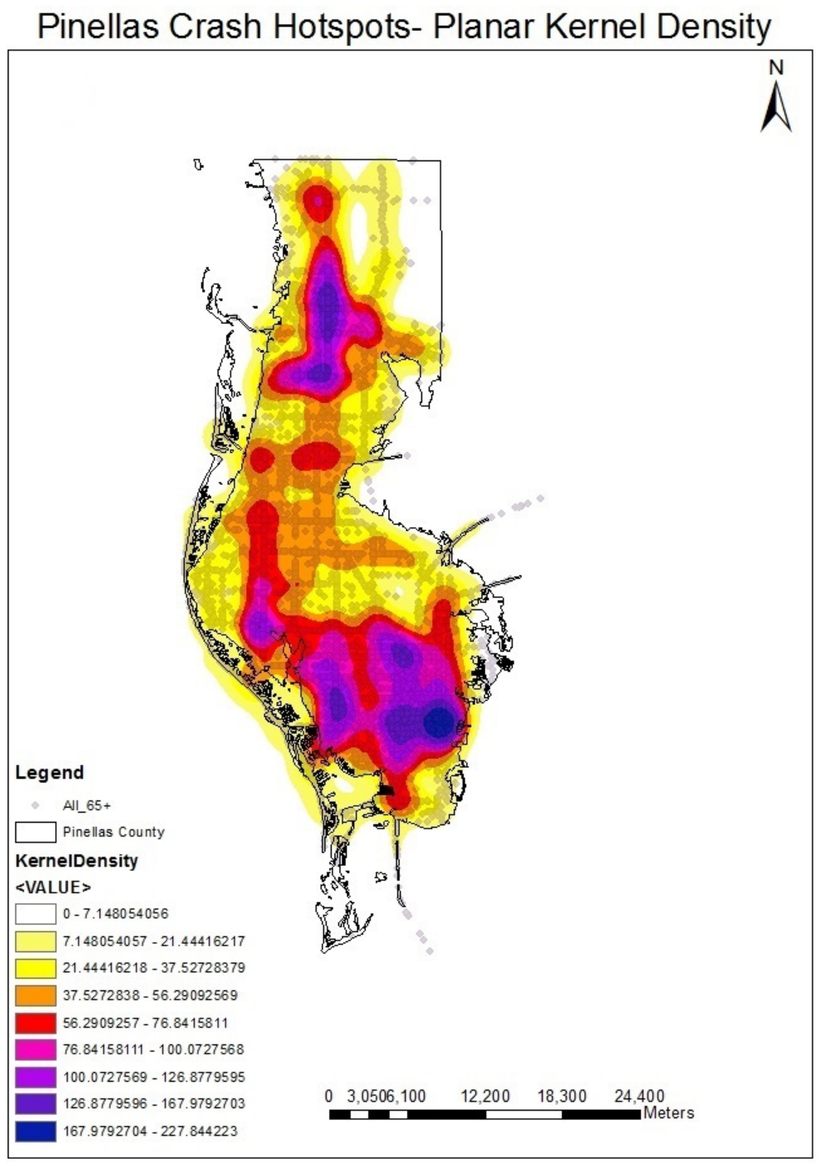


Figure 4.22 Planar KDE Application for the Pinellas County

*4.1.2.7 Comparison of the Planar Methods: Kernel Density and Gi**

As clearly described in Chapter 2 and 3, planar KDE is a non-parametric estimation that makes use of the individual data points, and it uses the Euclidean (network) distance for calculating the distance between two crash points. The points that are closer to each other tend to form a cluster and therefore have more chance to create a hotspot region. On the other hand, Gi* statistics creates the statistically significant spatial clusters by aggregating the data points, and cannot directly work on the individual data points. It is also a second order estimate which examines the spatial dependency of the crash points.

In this study, we use the Hillsborough County as an example to compare these two planar methods. Figure 4.13 illustrates the visual differences and similarities between these two methods.

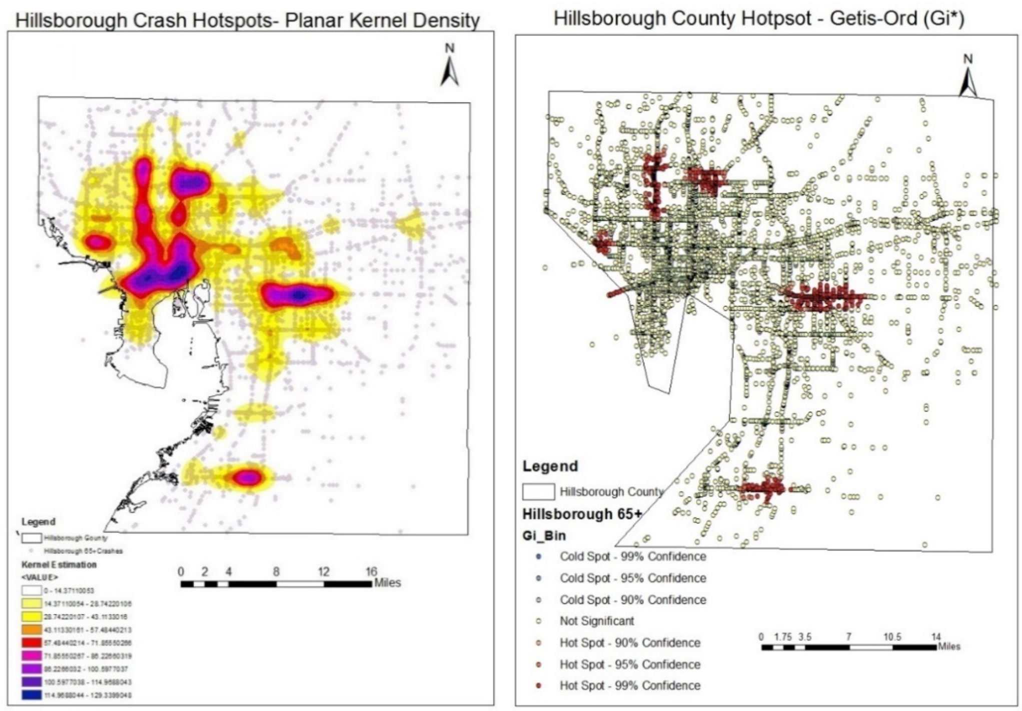


Figure 4.23 Comparison of Planar KDE and Gi* Methods for the Hillsborough County

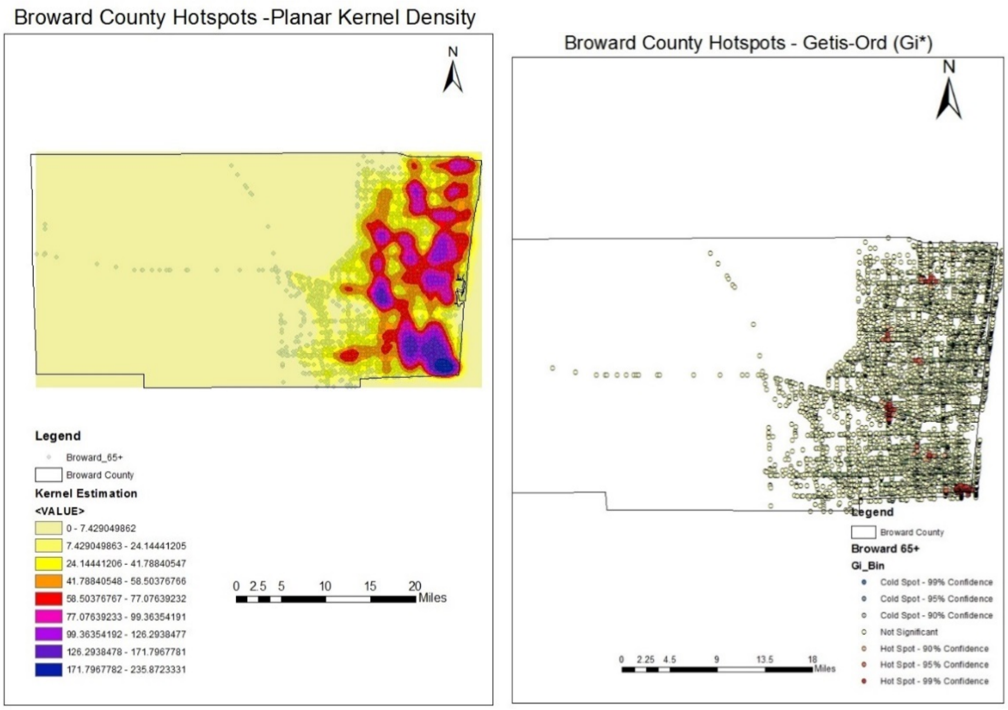


Figure 4.24 Comparison of Planar KDE and Gi* Methods for the Broward County

Figure 4.13 shows that Gi* method identified four major hotspots with the 95% confidence level: (1) Sun City Center, (2) Brandon, (3) University of South Florida, and (4) Greater Northdale regions. Planar KDE method, on the other hand, identified two major hotspots in the Brandon area and the City of Tampa as well as two minor hotspots near the Sun City Center and the University of South Florida. Hotspots identified in the City of Tampa are not identified by the Gi* method. This is clearly a drawback of the Gi* method since the downtown Tampa possesses a high crash risk for aging-involved accidents based on the data available.

Similar results are obtained for other counties as well. Gi*method does not show those major hotspots that are identified by the planar KDE. Such an example can also be presented for the Broward County where two major hotspots identified by the planar KDE method (namely Hollywood and Fort Lauderdale regions) are not detected by the Gi* method (Figure 4.14).

Similarly, in the Pinellas County, the downtown St Petersburg is identified as a critical hotspot based on the planar KDE, which is not detected by the Gi* method (Figure 4.15).

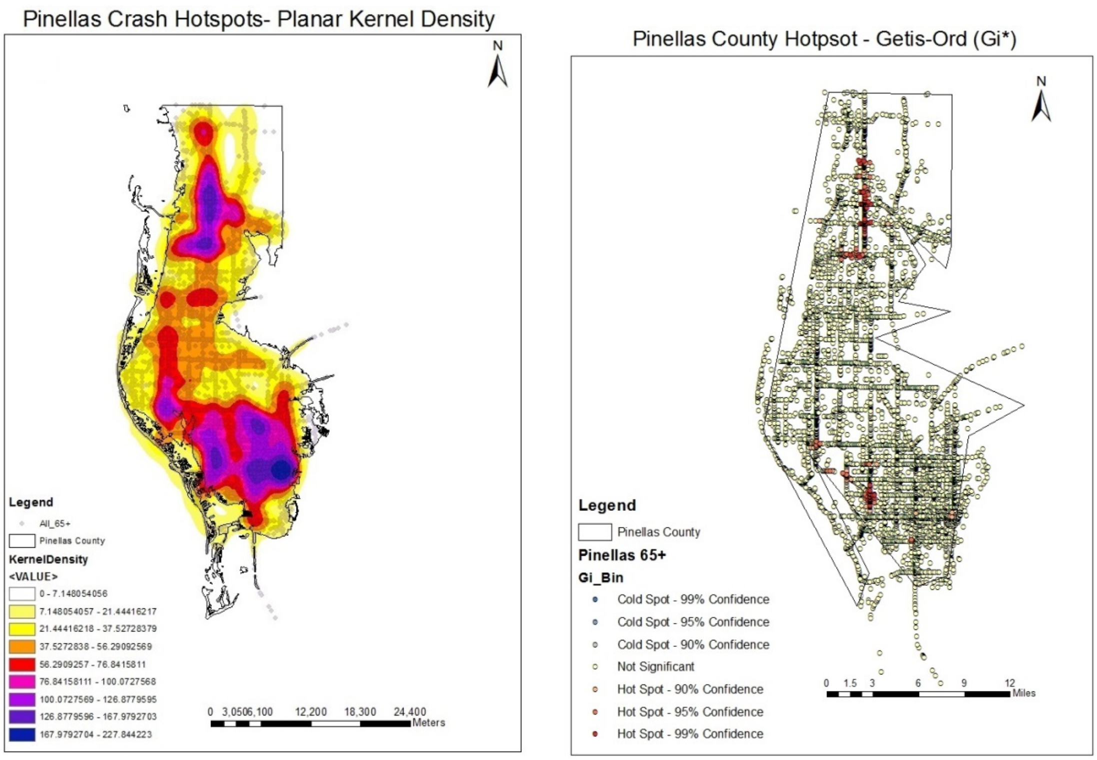


Figure 4.25 Comparison of Planar KDE and Gi* Methods for the Pinellas County

4.1.3 Network Kernel Density Estimation (KDE)

We will present the results of network KDE approach in this section. These are implemented using ArcGIS 10 where the SANET method (Okabe, 2006) is used to conduct the network KDE approach. The SANET method also provides a means of visualizing the accident distributions over the whole roadway network in 3-D. The peaks in these maps represent those locations that have higher number of accidents than others. In order to determine the hotspot locations, we first focus on each whole county. Next, based on the network distance-based kernel density estimates, we determine the high risk regions, and finally the hotspot locations. These hotspots are shown for the selected six counties. Hotspots for the remaining counties are shown in Appendix C. Then, five-mile and three-mile buffer zones are created in order to investigate the effect of 65+ population on the crash occurrence at the hotspots.

4.1.3.1 Broward County

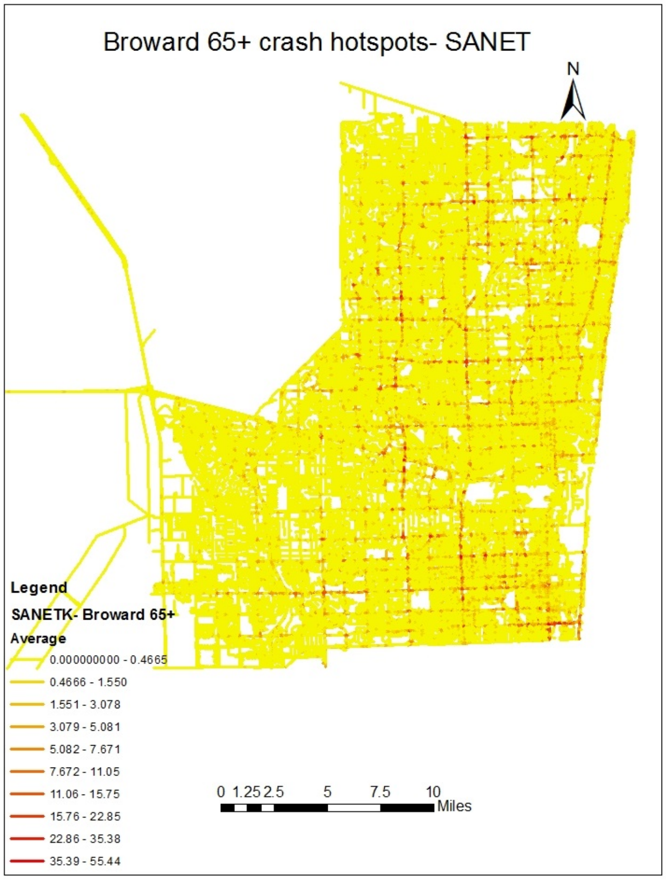


Figure 4.26 Network KDE (2D) Application for the Broward County

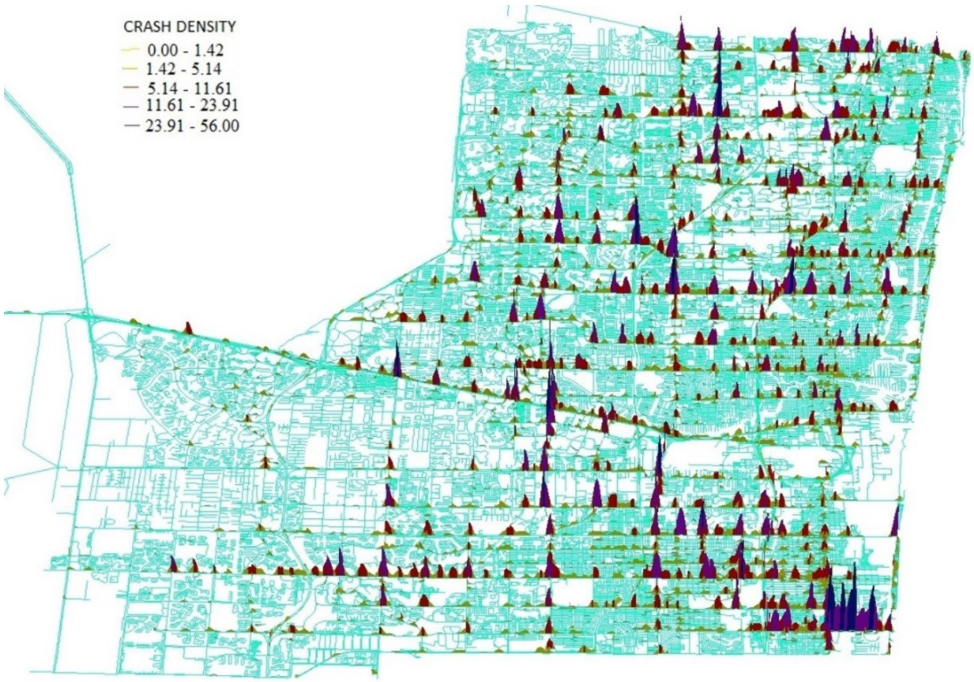


Figure 4.27 Network KDE (3D) Application for the Broward County

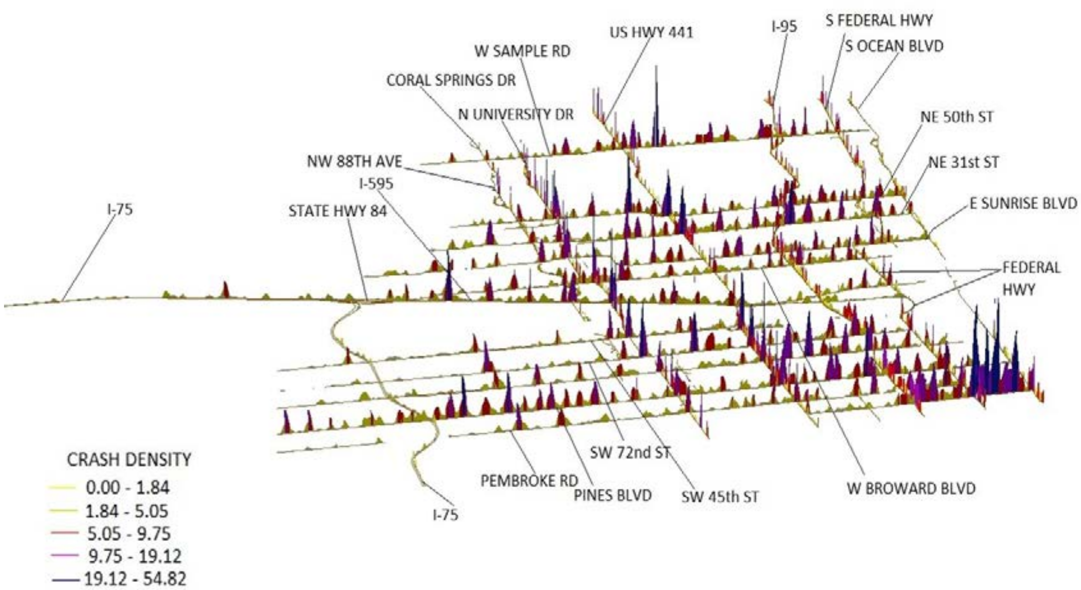


Figure 4.28 High Crash Risk Location for Broward County

Table 4.2 Hotspots for the Broward County

Broward County- Hotspot-1									
Age Group	County Crashes		Hallandale Beach Blvd. Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	19,759	8,912	328	36,079	59,345	9	6	192 (58.5%)	211 (64.3%)
65-	111,097	41,546	651	120,443	225,146	5	3	385 (59%)	412 (63.2%)
	Hotspot- Hallandale Beach Blvd. : Federal Hwy. to S Ocean Drive								

Broward County- Hotspot-2									
Age Group	County Crashes		W Sample Rd. Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	19,759	8,912	162	23530	61409	7	3	100 (61.7%)	114 (70%)
65-	111,097	41,546	532	78693	252457	7	2	297 (55.8%)	349 (65.6%)
	Hotspot- W Sample Rd from US HWY 441 to NW 42ND AVE								

Figure 4.16 shows the hotspot locations identified based on the network KDE application on the Broward County. Figure 4.17 shows the 3-D view of the hotspots over all the county whereas Figure 4.18 shows high crash risk locations are selected based on the high density values: Southeast of the Broward County, which includes the City of Fort Lauderdale. Figures

4.16 through 4.18 clearly show that aging-involved accidents mostly occur at the intersections for the Broward County. This indicates that intersections appear to be significantly problematic for the aging populations. Please note that other adult aging populations may also have relatively more accidents on the intersections; however, the locations of those intersections may differ for the aging and other adult age groups.

Analyzing the high peaks in the hotspot region, two major hotspots are selected for further analysis. Hallandale Beach (from Federal Highway to S. Ocean Drive) and W. Sample Rd (From US Highway 441 to NW 42nd Avenue). The crash characteristics in these hotspots are presented in Table 4.2. Out of the 328 aging-involved crashes that occurred at the Hotspot 1, 64.3% of these crashes happened at the intersections and those areas influenced by the intersections. The number of crashes per 1000 residents of 65+ is almost doubled compared to 65- people. For the second hotspot, similarly, 70% of the overall crashes (162) took place at the intersections, and the number of crashes per 1000 residents of 65+ are higher than the 65- age group.

4.1.3.2 Escambia County

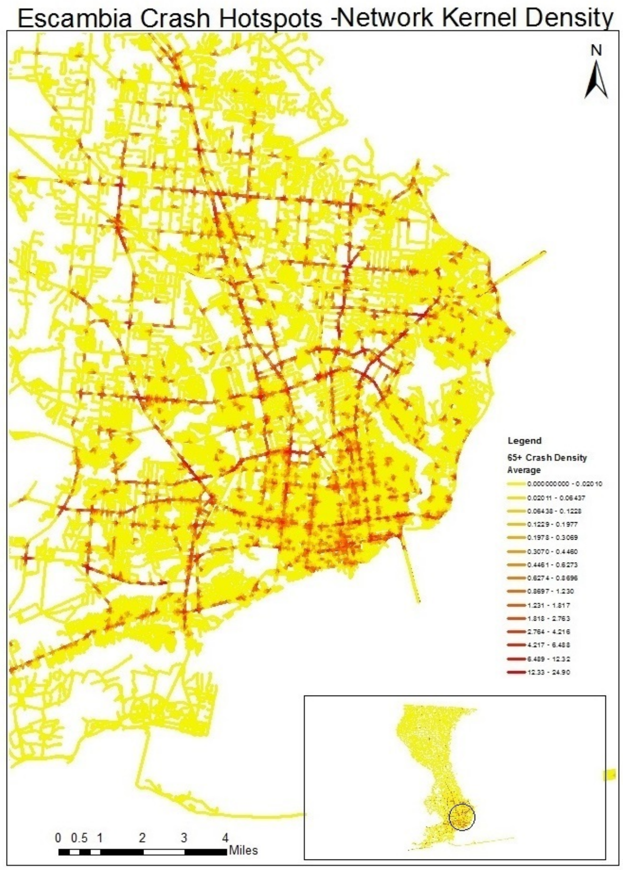


Figure 4.29 Network KDE (2D): Escambia County

Figure 4.30 Network KDE (3D): Escambia County

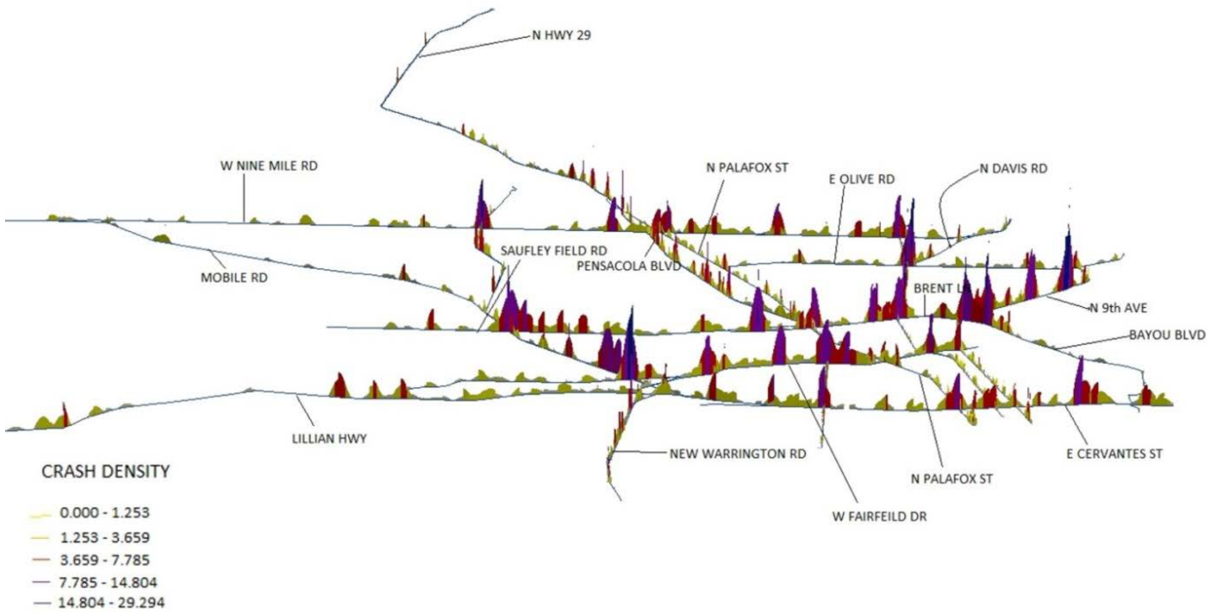


Figure 4.31 High Crash Roadways: Escambia County

The hotspots identified for the Escambia County are shown in Figure 4.20 based on the network KDE method. For the Escambia County, the 3-D view of the hotspots is shown in the Figure 4.21, and high crash risk locations are shown in the Figure 4.22. Similar to the Broward County, aging-involved accidents mostly occur at the intersections for the Escambia County, too.

Based on the results of the network KDE analysis, two major hotspots are identified: N. 9th Ave (from Creighton Rd. to Bayou Blvd.) and N. Davis Hwy (from University Parkway to Brent Ln.). Table 4.3 shows the crash and population characteristics for these hotspots in the Escambia County. 175 crashes took place in the Hotspot 1, out of which 70.2 % are those crashes at the intersections and at those locations influenced by the intersections. Hotspot 1 shows that 65+ intersection crashes are more than those for other age groups. Crash rate for 1000 residents for 65+ and 65- populations is almost the same. For Hotspot 2, out of 203 aging-involved crashes, 166 crashes are at the intersections and at those locations influenced by the intersections. Population crash rates are approximately equal for both age groups.

Table 4.3 Hotspots for the Escambia County

Escambia County- Hotspot-1									
Age Group	County Crashes		N 9th Ave Road Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	4090	2257	175	12370	21286	14	8	93 (53%)	123 (70.2%)
65-	20437	9601	654	52179	88556	13	7	335 (51.2%)	493 (75%)
	Hotspot- N 9th Ave- Creighton Rd to Bayou Blvd								

Escambia County- Hotspot-2									
Age Group	**County Crashes**		**N Davis Hwy Road Crashes**						
	Total	**Intersection Crashes**	**Total**	**No. of Residents in 3-Mile Radius**	**No. of Residents in 5-Mile Radius**	**No. of Crashes per 1000 Residents**		**Intersection Crashes**	**Crashes at Intersection/ Influenced by Intersection**
						3-Mile	**5-Mile**		
65+	**4090**	**2257**	**203**	**12991**	**24789**	**16**	**8**	**113 (55.6%)**	**166 (81.7%)**
65-	**20437**	**9601**	**791**	**54179**	**89751**	**15**	**9**	**415 (52.4%)**	**577 (73%)**
	Hotspot- N Davis Hwy- University Pkwy to Brent Ln								

4.1.3.3 Hillsborough County

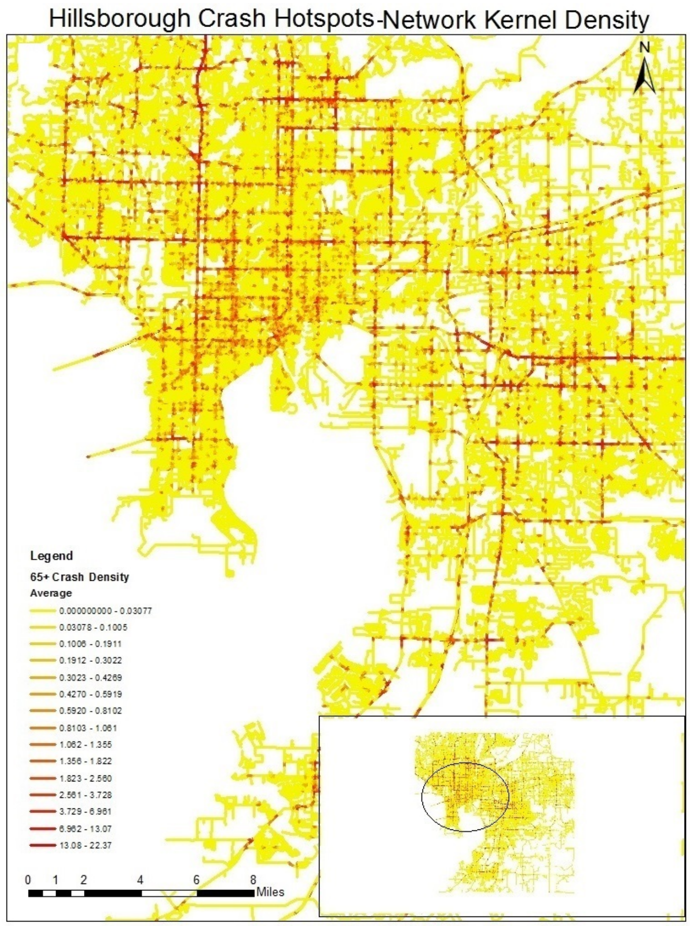


Figure 4.32 Network KDE (2D) Application for the Hillsborough County

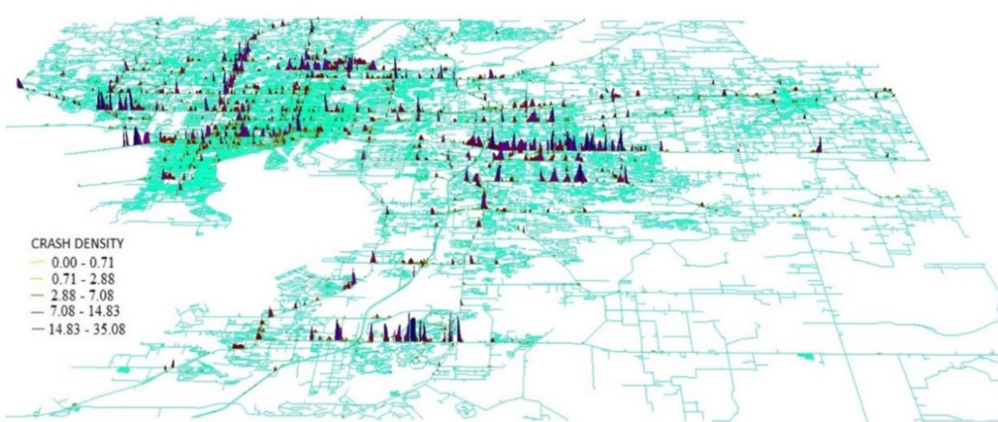


Figure 4.33 Network KDE (3D) Application for the Hillsborough County

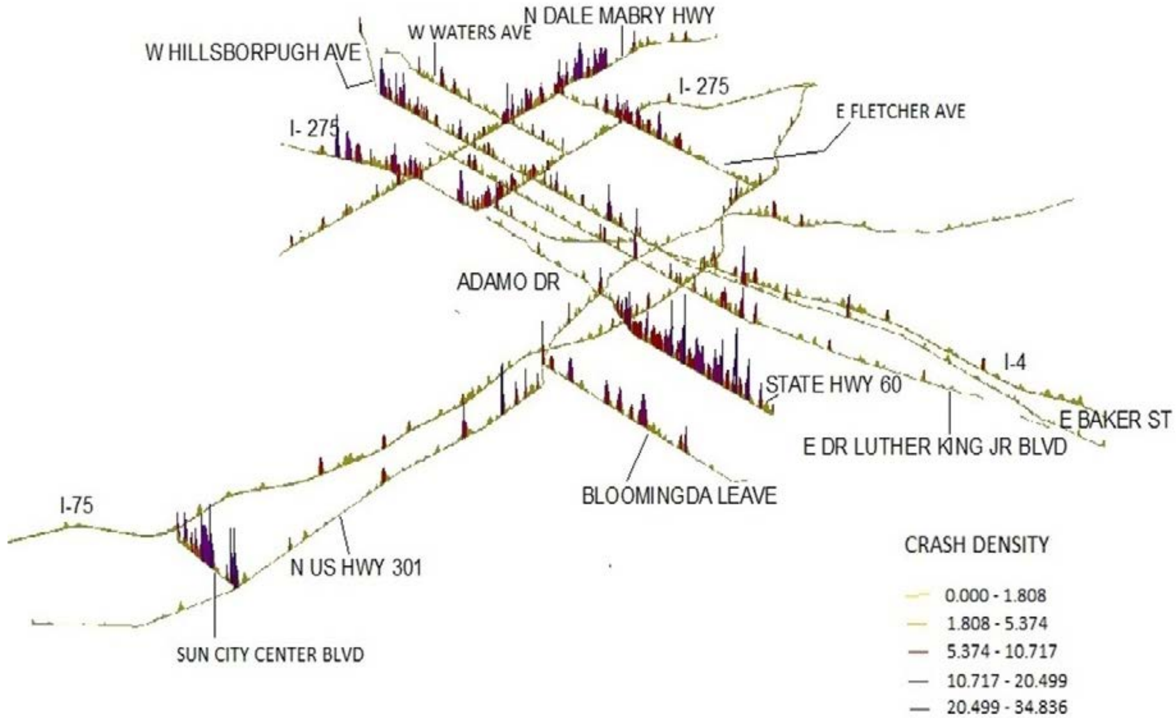


Figure 4.34 High Crash Roadways Application for the Hillsborough County

Figure 4.22 shows those hotspots for the Hillsborough County that is identified by the network KDE method. The 3-D view of the hotspots is shown in the Figure 4.23 whereas Figure 4.24 shows high crash risk roadways of the Hillsborough County.

From the network KDE analysis, two major hotspots are identified for deeper analysis: Brandon Blvd and State Hwy (from I-75 to N. Miller Rd.) and Sun City Blvd (from I-75 to N. US Highway 301). Table 4.4 presents the characteristics of the crashes that took place inside these hotspots. 4,552 crashes occurred in the Hotspot 1, out of which 54.3% crashes happened at the intersections or at those locations influenced by the intersections. Table 4.4 shows that crashes per 1000 residents are higher for the 65+ age group. Similarly, 316 crashes took place at the second hotspot, and 73.7% of those crashes occurred at the intersections and other locations influenced by the intersections. This rate is significantly high for the 65+ populations compared to other age group crashes. Crash rates per 1000 residents are also more for the 65+ age group.

Table 4.4 Hotspots for the Hillsborough County

Hillsborough County- Hotspot-1

Age Group	County Crashes		Brandon Blvd & State Hwy Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	13000	5480	552	15574	24949	35	22	228 (41.3%)	300 (54.3%)
65-	91105	31043	2552	102160	165216	25	15	1019 (40%)	1332 (52%)
	Hotspot - Brandon Blvd & State Hwy- 60 from I-75 to N Miller Rd								

Hillsborough County- Hotspot-2

Age Group	County Crashes		Sun City Blvd Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	13000	5480	316	15979	20158	20	16	208 (65.8%)	233 (73.7%)
65-	91105	31043	315	13588	30676	23	10	158 (50%)	189 (60%)
	Hotspot- Sun City Blvd- from I-75 to N US Hwy 301								

4.1.3.4 Leon County

Using the network KDE analysis, aging-involved crash hotspots are identified as shown in Figure 4.27. Figure 4.28 shows the 3-D view of the hotspots and Figure 4.29 shows the high crash risk roadways of the Leon County.

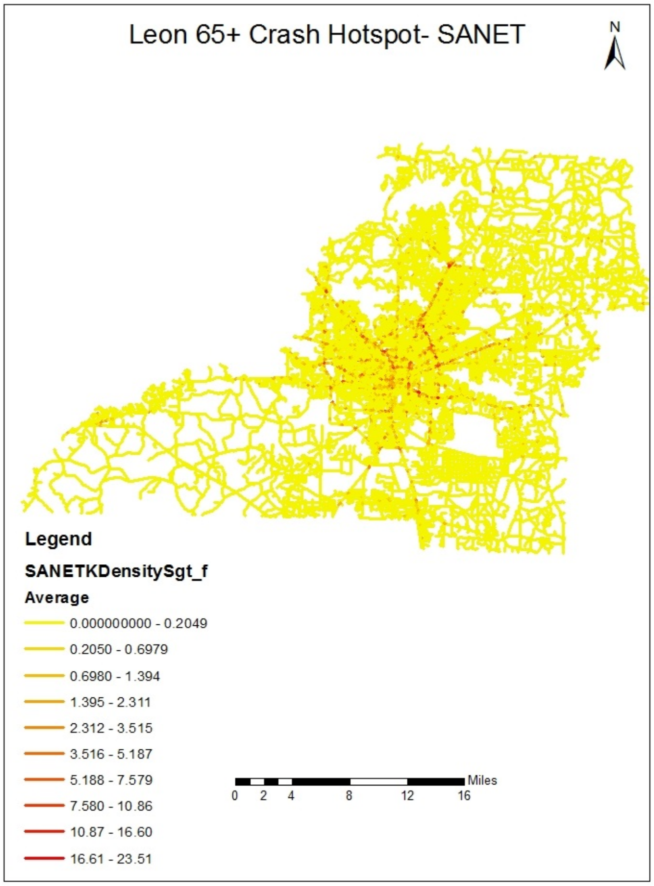


Figure 4.35 Network KDE (2D) Application for the Leon County

Figure 4.27 shows that the roadways containing the most number of crashes (hotspots) are as follows: Capital Circle and Thomasville Rd intersection with I-10, and N. Monroe Road (from John Knox Rd. to Callaway Rd.). Table 4.5 shows the crash and population characteristics for these two hotspots. Out of 75 crashes that occurred within the Hotspot 1, 63 crashes are at the intersections/locations that are influenced by intersections (84%). The 65+ crash rate per 1000 residents is higher than other age group crashes for the Hotspot 1; however, this rate is the same for the Hotspot 2. The aging-involved intersection crashes at the Hotspot 2 is 74% of the total crashes that took place at that hotspot.

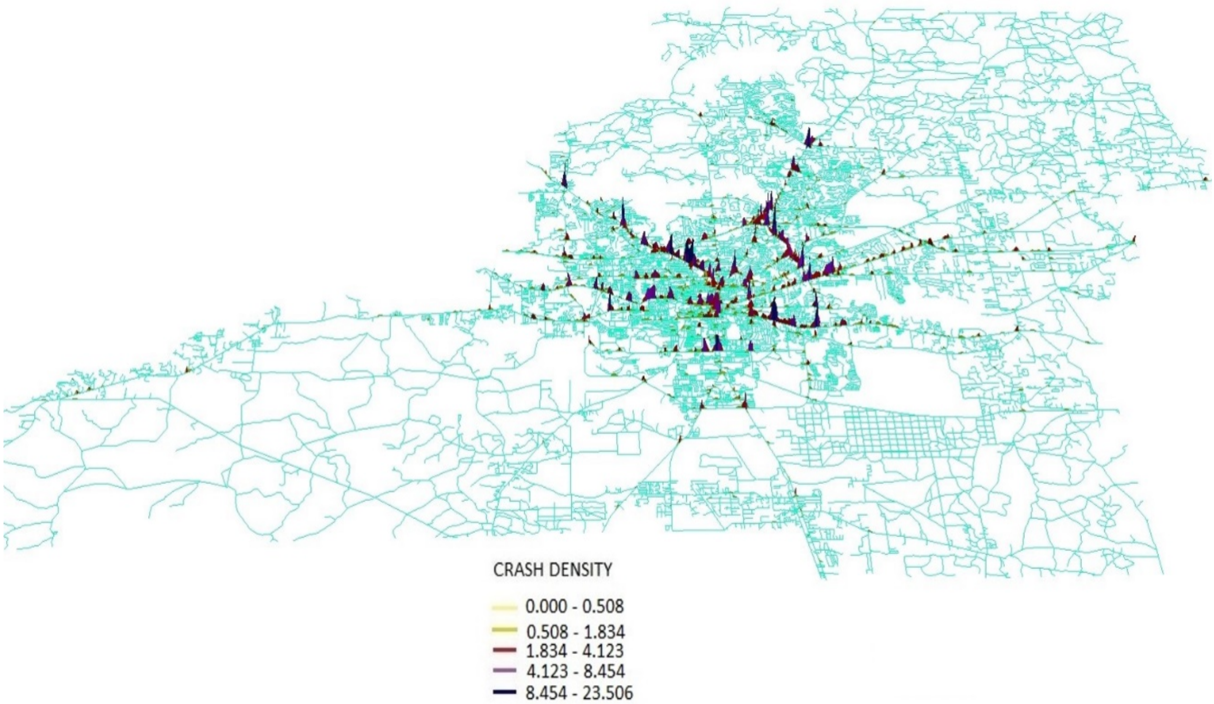


Figure 4.36 Network KDE (3D) Application for the Leon County

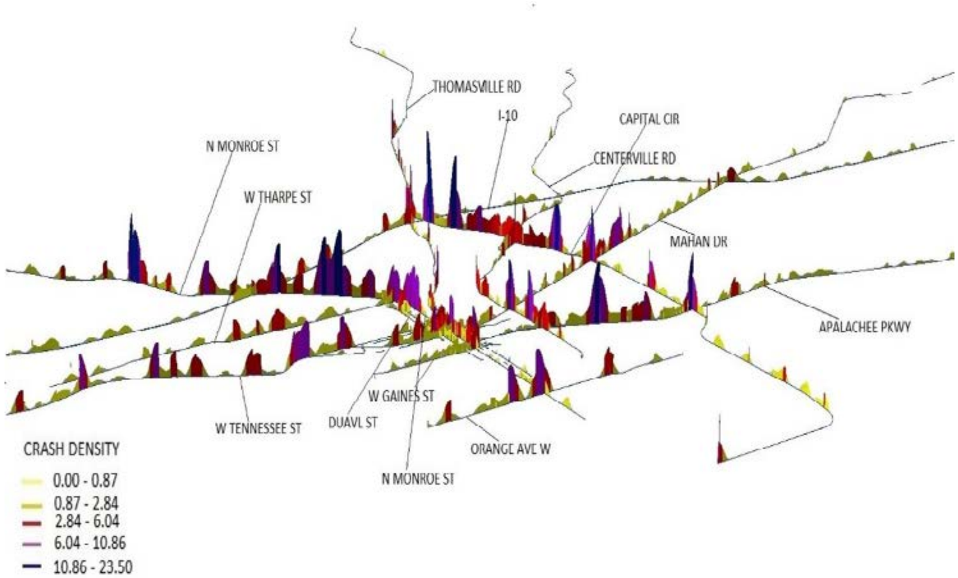


Figure 4.37 High Crash Roadways Application for the Leon County

Table 4.5 Hotspots for the Leon County

Leon County- Hotspot-1									
Age Group	County Crashes		Capital Circle Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	2448	1169	75	7906	14858	9	5	52 (69.3%)	63 (84%)
65-	21572	8886	312	29370	94603	11	3	204 (65.3%)	235 (75.3%)
	Hotspot- Capital Circle: at Thomasville Rd., at I-10, at Raymond Diehl Rd.; Thomasville Rd at Timberlane Rd., Thomasville Rd. at Raymond Diehl Rd., and Raymond Diehl Rd at Lonnbladh Rd.								

Leon County- Hotspot-2									
Age Group	County Crashes		N Monroe						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	2448	1169	66	8651	14645	8	5	39 (59%)	49 (74.2%)
65-	21572	8886	378	26099	127353	14	3	190 (50.2%)	244 (64.5%)
	Hotspot - N Monroe- N Monroe/John Knox Rd to N Monroe/Callaway Rd								

4.1.3.5 Miami-Dade County

Aging-involved crash hotspots in Miami-Dade County are identified by the network KDE (Figure 4.28). Figure 4.31 and Figure 4.32 show the 3-D view of these hotspots and the high crash risk roadways in the Miami-Dade County, respectively.

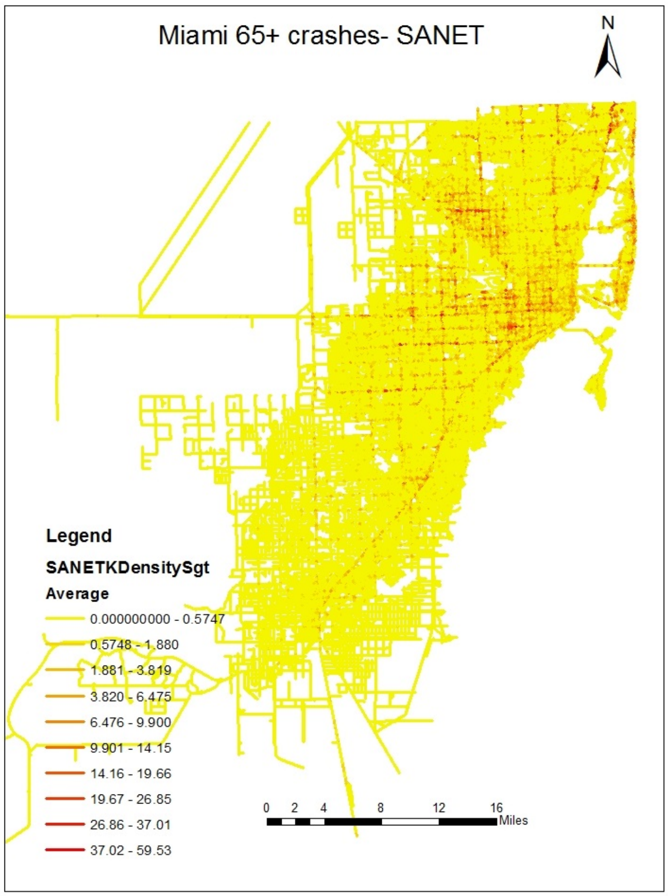


Figure 4.38 Network KDE (2D) Application for the Miami-Dade County

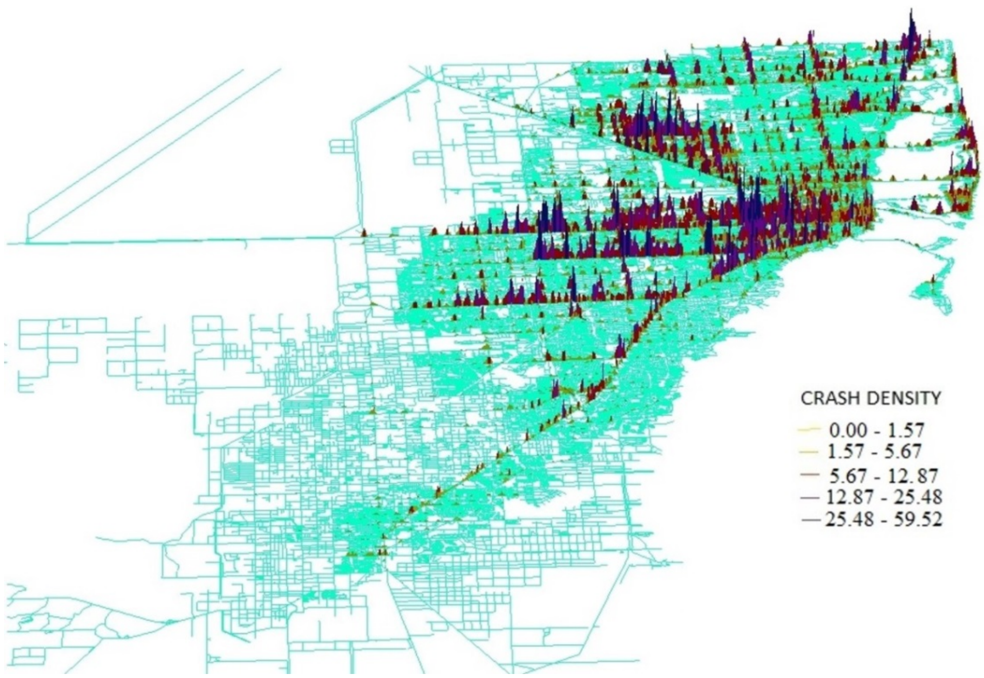


Figure 4.39 Network KDE (3D) Application for the Miami-Dade County

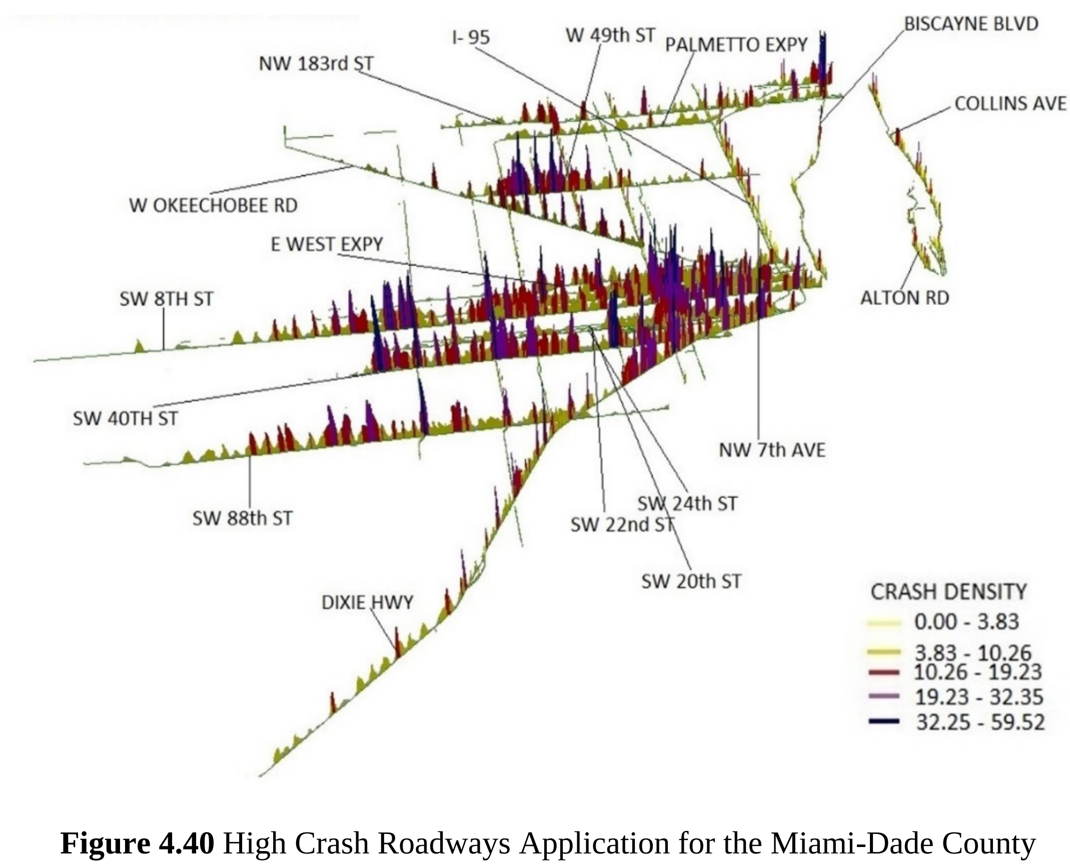


Figure 4.40 High Crash Roadways Application for the Miami-Dade County

As seen from Figure 4.30, Biscayne Rd. (from NE 213th St. to NE 183rd St.) and W. 49th St (from W. 17th St. to W. 6th Ave.) are selected as the major hotspots shown in Table 4.6. Although there are other roadways with relatively more peaks, these hotspots show the highest peaks for shorter roadway lengths. This indicates substantially higher intensities in these areas. Therefore, these locations are selected for further analysis. There were 556 crashes involving drivers age 65+ along Biscayne Boulevard (Hotspot 1), 57.7% of these crashes belong to the 65+ populations. The number of crashes at intersections were also higher in the age 65+ group (65.6%) compared with the crashes involving drivers under the age 65 (63%). Similarly, for the Hotspot 2, 295 crashes occurred involving the aging populations where 68.8% of those crashes were at the intersections or those areas that were influenced by the intersections. The other age group also showed a similar result with a percentage of 68.5%.

4.1.3.5 Pinellas County

Figure 4.31 shows the hotspots identified from the network KDE for the Pinellas County. A 3-D view of network KDE give a clear picture of the hotspots, which is presented in Figure 4.32. Figure 4.33, on the other hand, shows the high crash risk roadways in the Pinellas County.

For the Pinellas County, two hotspots are identified: U.S. HWY 19 N. (from Alderman Rd. to Curlew) and Main St. (from Keene Rd. to Belcher Rd.). These locations are observed to have high number of aging-involved crashes. The crashes at these hotspots are analyzed in Table 4.7. For the Hotspot 1, out of 537 crashes, 36.3% crashes occurred at the intersection and at those locations influenced by the intersections, which is approximately the same for other age groups. In the second hotspot, 72% and 74.5% of the crashes are at the intersection and those locations influenced by the intersections for the 65+ and 65- populations, respectively. Table 4.7 also shows that the crash rate percentages/1000 residents for the 65+ and 65- populations are approximately the same.

Table 4.6 Hotspots for the Miami-Dade County

Miami-Dade County- Hotspot-1									
Age Group	County Crashes		Biscayne Road Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection / Influenced by Intersection
						3-Mile	5-Mile		
65+	37,775	19,203	556	41,054	43,076	14	13	321 (57.7%)	365 (65.6%)
Under 65	229,467	100,000	2,006	143,042	185,205	14	11	1,111 (55.3%)	1,264 (63%)
	Hotspot- Biscayne Rd.: NE 213th St. to NE 183rd St.								
Miami-Dade County- Hotspot-2									
Age Group	County Crashes		W 49th St road crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection / Influenced by Intersection
						3-Mile	5-Mile		
65+	37,775	19,203	295	46,597	77,542	6	4	193 (65.4%)	203 (68.8%)
Under 65	229,467	100,000	1,182	159,019	337,465	7	4	776 (65.6%)	810 (68.5%)
	Hotspot- W 49th St- W 17th Ct to W 6th Ave.								

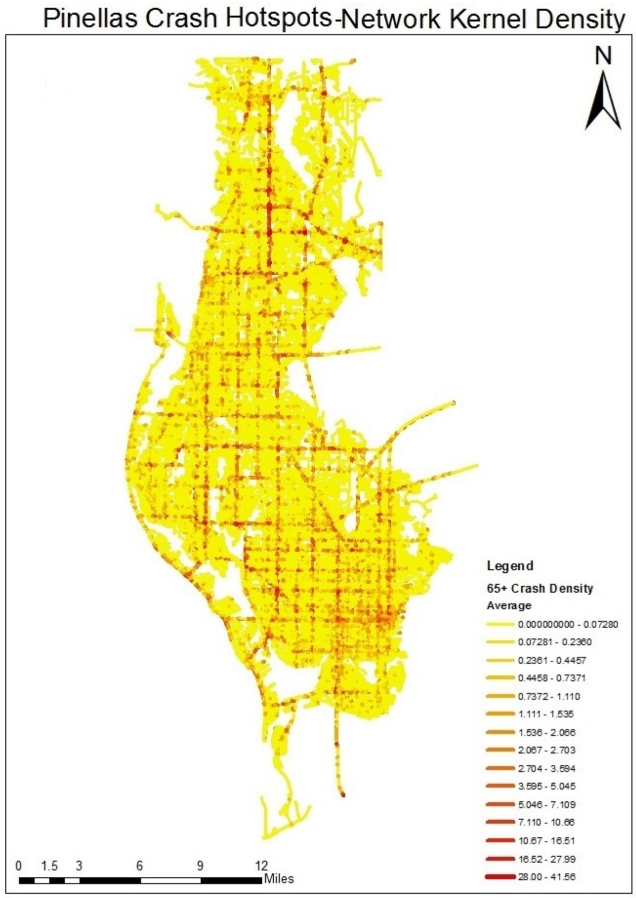


Figure 4.41 Network KDE (2D) Application for the Pinellas County

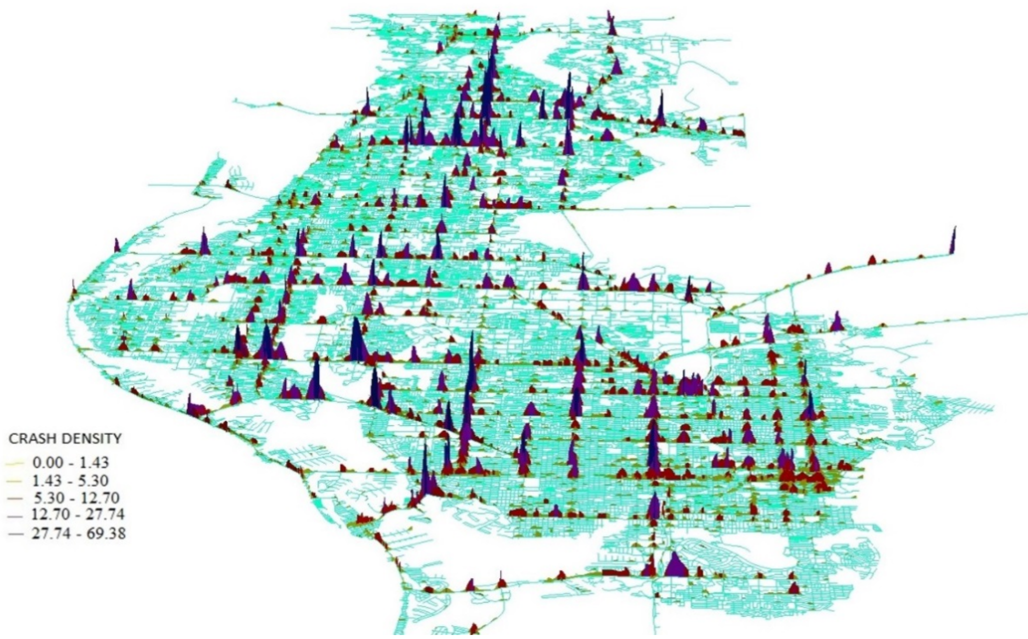


Figure 4.42 Network KDE (3D) Application for the Pinellas County

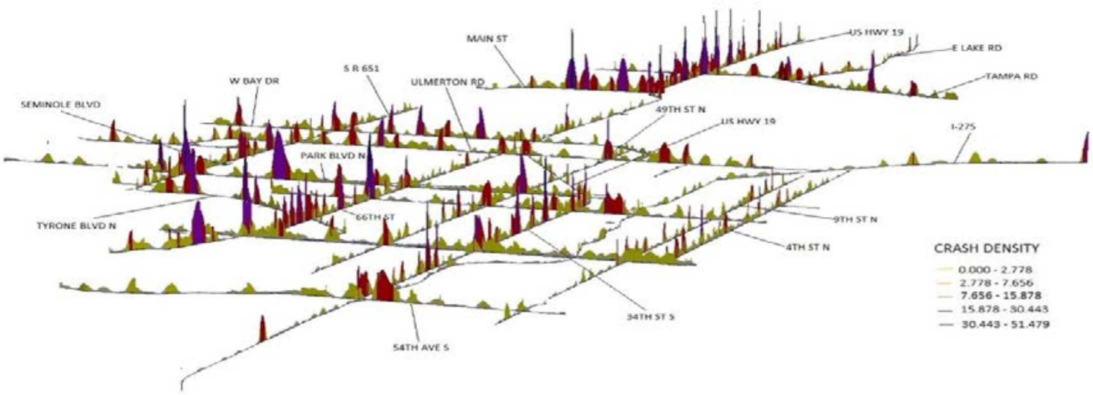


Figure 4.43 High Crash Roadways Application for the Pinellas County

Table 4.7 Hotspots for the Pinellas County

<table>
<tr><th colspan="10">Pinellas County- Hotspot-1</th></tr>
<tr><td rowspan="3">Age Group</td><td colspan="2">County Crashes</td><td colspan="7">U.S. HWY 19 N road crashes</td></tr>
<tr><td rowspan="2">Total</td><td rowspan="2">Intersection Crashes</td><td rowspan="2">Total</td><td rowspan="2">No. of Residents in 3-Mile Radius</td><td rowspan="2">No. of Residents in 5-Mile Radius</td><td colspan="2">No. of Crashes per 1000 Residents</td><td rowspan="2">Intersection Crashes</td><td rowspan="2">Crashes at Intersection/ Influenced by Intersection</td></tr>
<tr><td>3-Mile</td><td>5-Mile</td></tr>
<tr><td>65+</td><td>14,768</td><td>7,322</td><td>537</td><td>34,473</td><td>55,518</td><td>16</td><td>10</td><td>195 (36.3%)</td><td>285 (53%)</td></tr>
<tr><td>65-</td><td>58,613</td><td>24,769</td><td>1,667</td><td>77,070</td><td>139,802</td><td>22</td><td>12</td><td>619 (37%)</td><td>894 (53%)</td></tr>
<tr><td></td><td colspan="9">Hotspot- U.S. HWY 19 N- from Alderman Rd to Curlew</td></tr>
<tr><th colspan="10">Pinellas County- Hotspot-2</th></tr>
<tr><td rowspan="3">Age Group</td><td colspan="2">County Crashes</td><td colspan="7">Main St road crashes</td></tr>
<tr><td rowspan="2">Total</td><td rowspan="2">Intersection Crashes</td><td rowspan="2">Total</td><td rowspan="2">No. of Residents in 3-Mile Radius</td><td rowspan="2">No. of Residents in 5-Mile Radius</td><td colspan="2">No. of Crashes per 1000 Residents</td><td rowspan="2">Intersection Crashes</td><td rowspan="2">Crashes at Intersection/ Influenced by Intersection</td></tr>
<tr><td>3-Mile</td><td>5-Mile</td></tr>
<tr><td>65+</td><td>14,768</td><td>7,322</td><td>191</td><td>30,211</td><td>53,121</td><td>6</td><td>4</td><td>121 (63.3%)</td><td>138 (72%)</td></tr>
<tr><td>65-</td><td>58,613</td><td>24,769</td><td>358</td><td>68,374</td><td>136,485</td><td>5</td><td>5</td><td>231 (64%)</td><td>277 (74.5%)</td></tr>
<tr><td></td><td colspan="9">Hotspot- Main St- from Keene Rd to Belcher Rd</td></tr>
</table>

4.1.3.6 Comparison of the KDE Methods: Planar and Network KDE

It is important to reiterate the differences between the planar KDE and network KDE methods here. Basically, the planar KDE method obtains the density maps based on the planar (Euclidean) distance calculations without using the roadway network itself. That is, the distances from the center of the hotspot are still calculated without considering the existing roadway network structure. The accident density maps also extend over the areas like parks, residential areas, and lakes where there are no roadways and therefore no accidents. In order to overcome these drawbacks, the SANET method is introduced to identify the accident hotspots more accurately. Through this methodology, it is possible to detect the roadways that have a high number of aging-involved accidents where every distance between the accidents is calculated based on the actual roadway (network) distance.

Moreover, the planar KDE method identifies all the roadways and intersections that reside in the peak density region as 'high accident' risk locations. This is critical since it may cause the following problems: (a) Overestimation: Some roadways that do not actually possess high risk are shown to be risky, (b) Underestimation: Since multiple roadways are shown as critical locations rather than the actual roadways that have high accident risk, one may not give the needed attention to the actual high risk locations. The network KDE approach, on the other hand, solves these two problems using the actual roadway distances for kernel density estimation.

Figure 4.34 shows the comparative results between the planar and network KDE approaches. The planar KDE approach for Escambia County shows the accident hotspots located in the Northeast and Southeast areas of the largest city of Escambia, namely Pensacola. The network KDE approach, on the other hand, enables us to identify the exact locations of the most critical hotpot corridors such as the N. Davis Road corridor between the 9th Avenue and Highway 29. This hotspot location in the Northeast Pensacola is basically the one that has the highest number of accidents for those aged 65 and over. However, the network KDE approach does not show any critical hotspots in the Southeast of Pensacola as identified by the planar KDE approach. Although this may not be entirely visible from the 2-D maps, they are typically identifiable by the high surface peaks in a three-dimensional (3D) view of accidents (Figure 4.20 and Figure 4.21). This can lead us to a more detailed assessment of aging population-involved accidents via another feature offered by the SANET method: 3-D visualization of the accidents on the roadway network. This approach allows us to observe high accident risk locations more clearly and accurately.

The drawbacks of the planar KDE approach is more visible for the Hillsborough and Pinellas counties. For example, Sun City Center Boulevard of Hillsborough County, which is shown as a moderate hotspot in the planar KDE-based maps of Figure 3, has the highest peak (highest accident risk) in the 3-D view based on the network KDE approach (Figure 4.23). Similarly, in Pinellas County, the Saint Petersburg area is shown as a hotspot location based on the planar KDE approach; however, the whole area is not actually a hotspot but rather certain roadways have higher accident rates than others in that area, which is more precisely shown through using the SANET method (Figure 4.33).

The comparison maps reveal other interesting trends. Accidents where aging populations are involved do not necessarily cluster the same areas where there are clusters for other age groups such as the downtown areas or other typically congested regions. This is an interesting pattern for aging road users which suggests that they may not necessarily prefer driving on congested or busy roadways as other age groups may do. Many aging drivers may actually prefer to use familiar nearby streets while shopping, volunteering or socializing, which can be the prominent reason behind how aging-involved accident spatial patterns differ from other adult age groups. This finding is also correlated with temporal patterns of aging-involved accidents, which will be discussed in the Section 4.2.

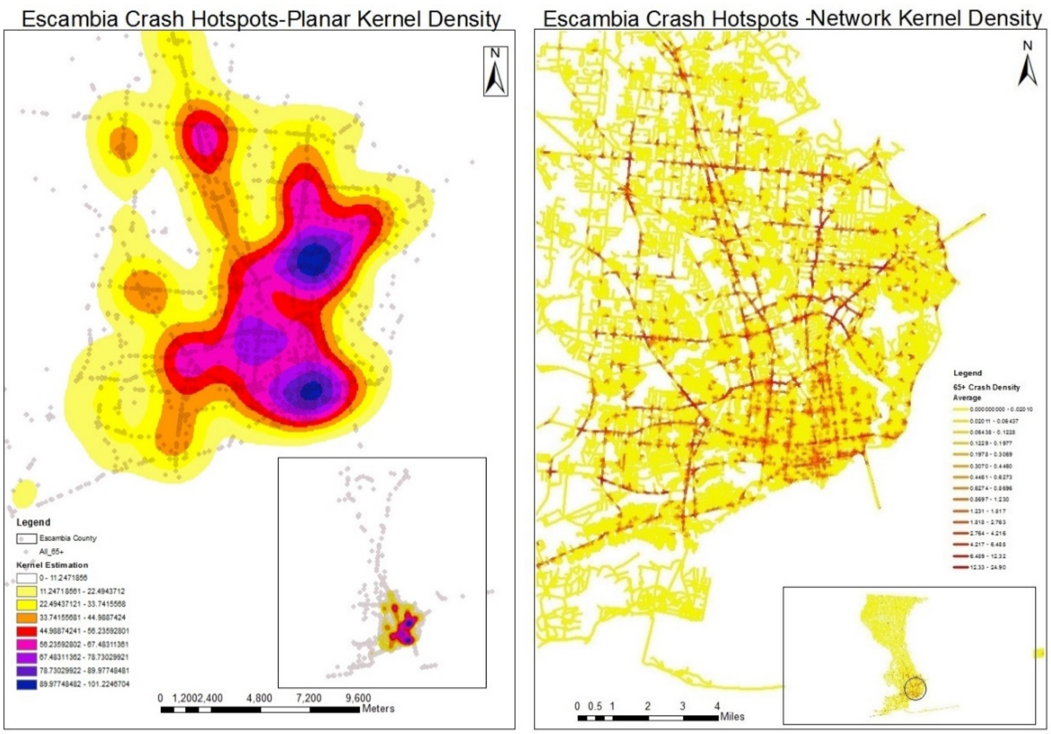


Figure 4.44 Planar and Network KDE Comparison for the Escambia County

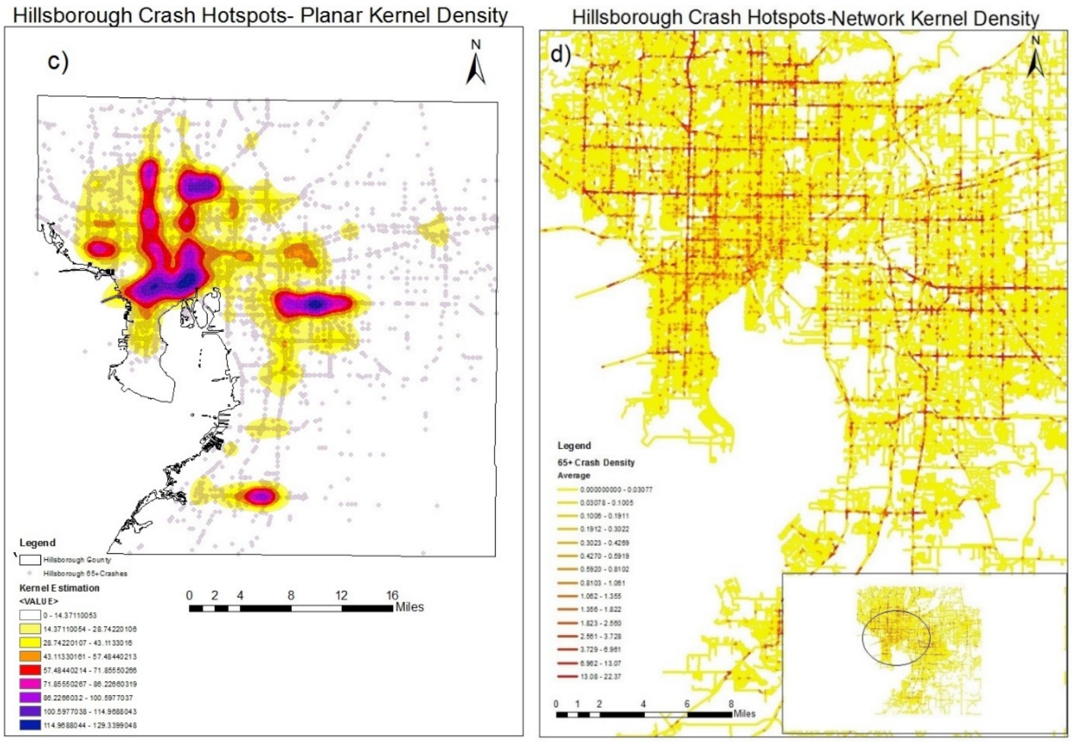


Figure 4.45 Planar and Network KDE Comparison for the Hillsborough County

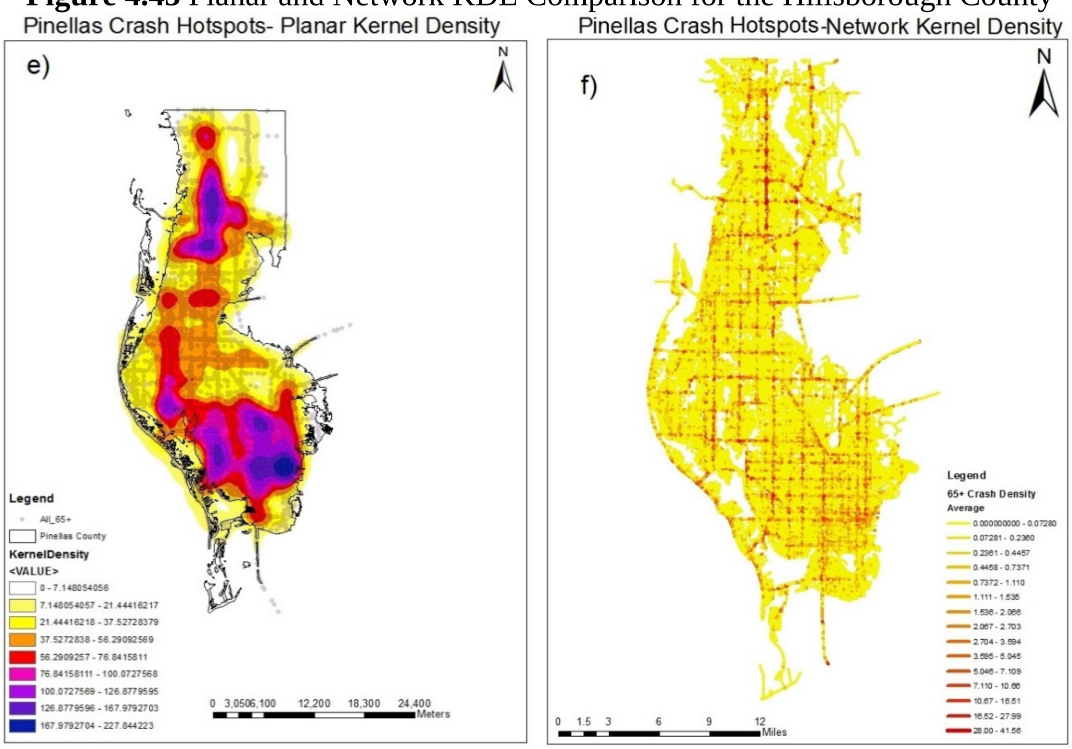


Figure 4.46 Planar and Network KDE Comparison for the Pinellas County

4.1.3.6 Comparison of Crashes based on Different Adult Age Groups

This section presents a comparative analysis based on identifying the differences in the high crash risk locations for different age groups: 65+, 50-64, and 50- populations. Especially 50-64 age group is critical since they represent the Baby Boom generation. We will present our application for the Leon and Miami-Dade counties. Figure 4.37, Figure 4.38 and Figure 4.39 show the resulting 3-D SANET maps via the network KDE analysis for the 65+, 50-64 and 50- age group, respectively for Leon County whereas Figure 4.40, Figure 4.41, Figure 4.42 present the same results for Miami-Dade County.

Figure 4.37 and Figure 4.38 show that the two hotspots identified for the 65+ age group are also critical for the 50-64 age groups: Raymond Diehl Rd., Capital Circle, Thomasville Rd and I-1 intersection as well as the N. Monroe Corridor. However, there is also another major hotspot for the 50-64 age group, which is the downtown Tallahassee region. This area is also critical for the 50- age group (Figure 4.39). On the other hand, in Miami-Dade County, Figure 4.40, Figure 4.41 and Figure 4.42 show two major hotspots: Biscayne Rd (from NE 213th St. to NE 183rd St.) and W. 49th St (from W. 17th St to W. 6th Ave) for all age groups. This comparison reveals an interesting pattern for 65+ populations. They do not have hotspots at those locations such as downtowns and heavily congested areas. Rather, 65+ crashes tend to occur away from those areas heavily used by the working class populations. Hotspot locations for the 50- age group are totally different than those for the 65+ populations. There are hotspots around the W. Tennessee St, W. Pensacola St. and around the Florida State University for Leon County whereas Miami Beach is a major hotspot for Miami-Dade County. This shows the effect of working age groups as well as the students of the Florida State University, which shifts the major hotspots towards the west of Tallahassee. This type of analysis will benefit the transportation agencies by providing the vital information with regards to the age-specific differences in the major hotspots.

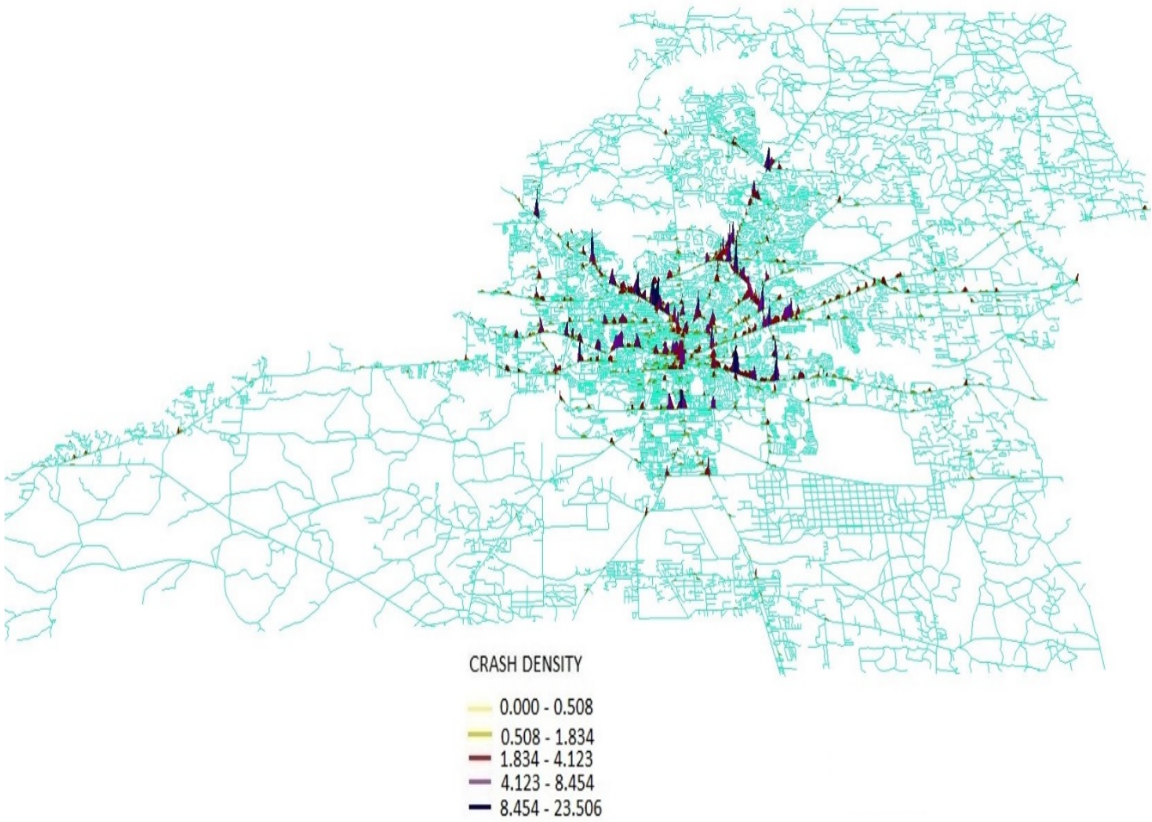


Figure 4.47 3-D Network KDE Application for the 65+ Age Group in the Leon County

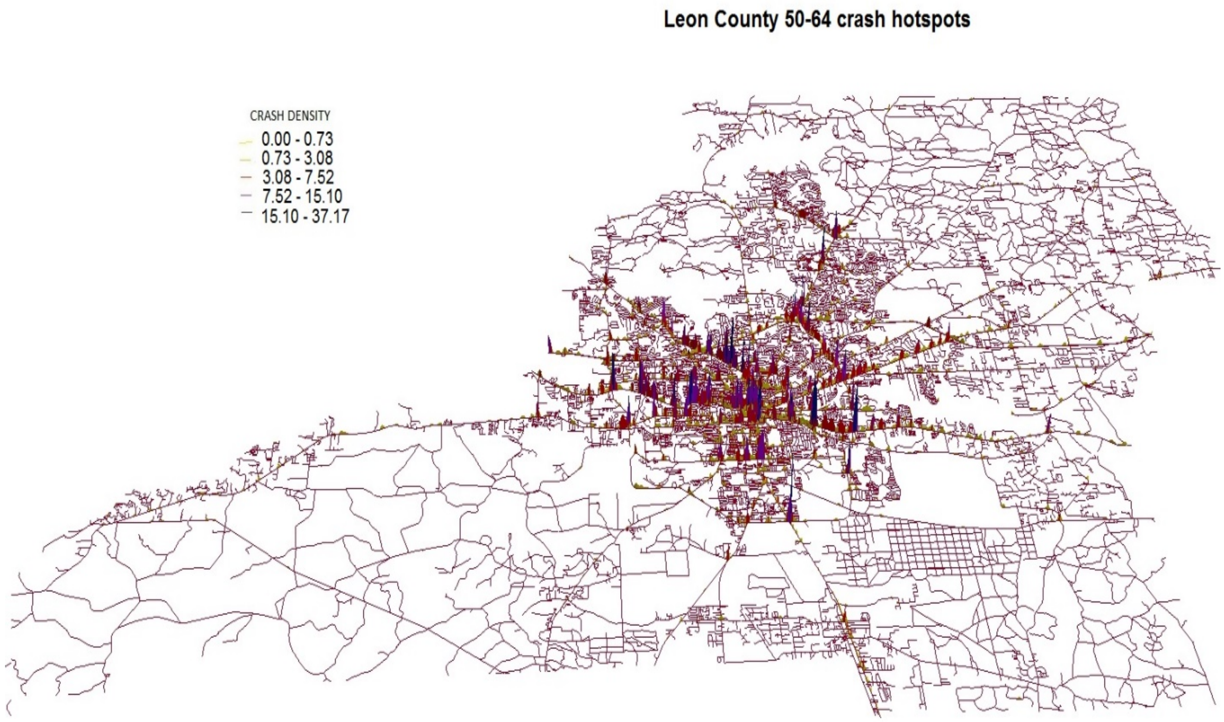


Figure 4.48 3-D Network KDE Application for the 50-64 Age Group in the Leon County

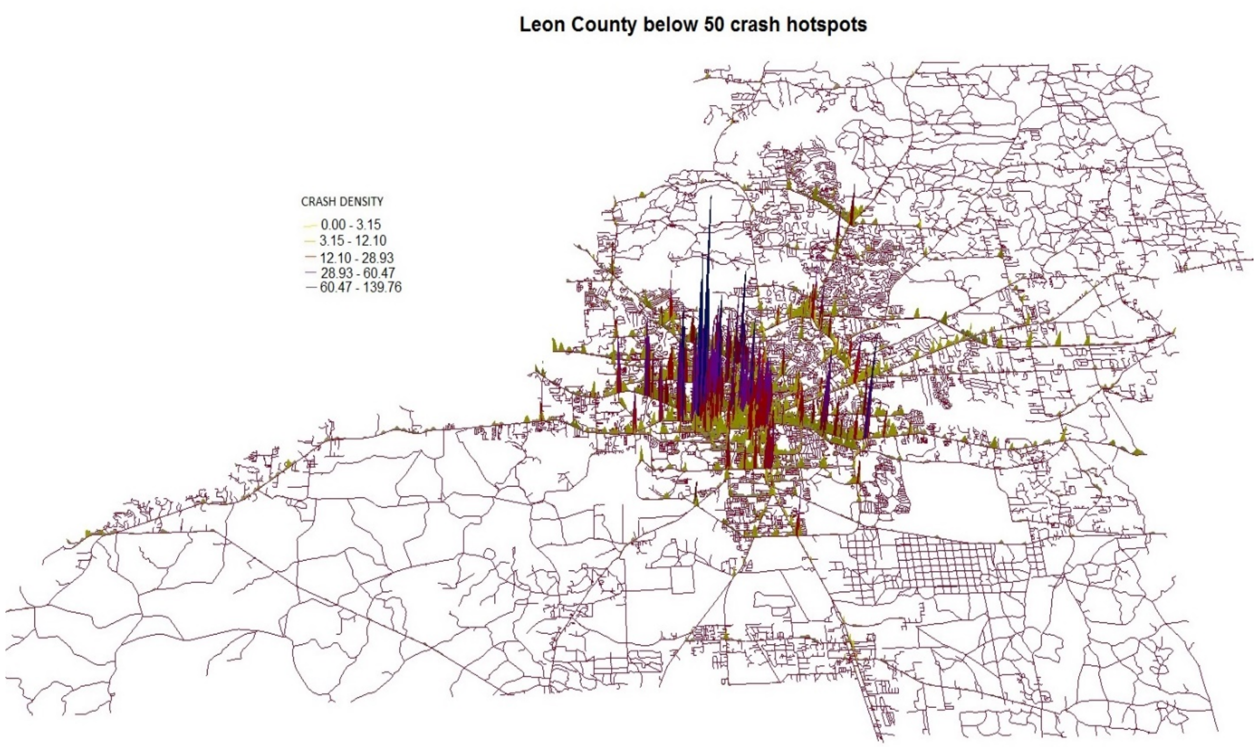


Figure 4.49 3-D Network KDE Application for the 50- Age Group in the Leon County

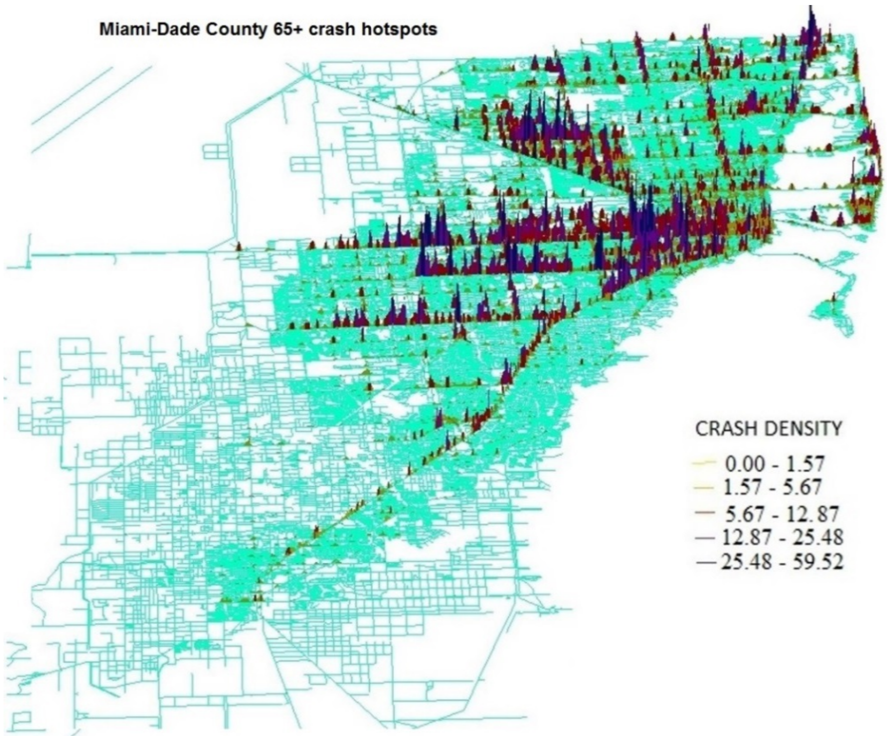


Figure 4.50 3-D Network KDE Application for the 65+ Age Group in the Miami-Dade County

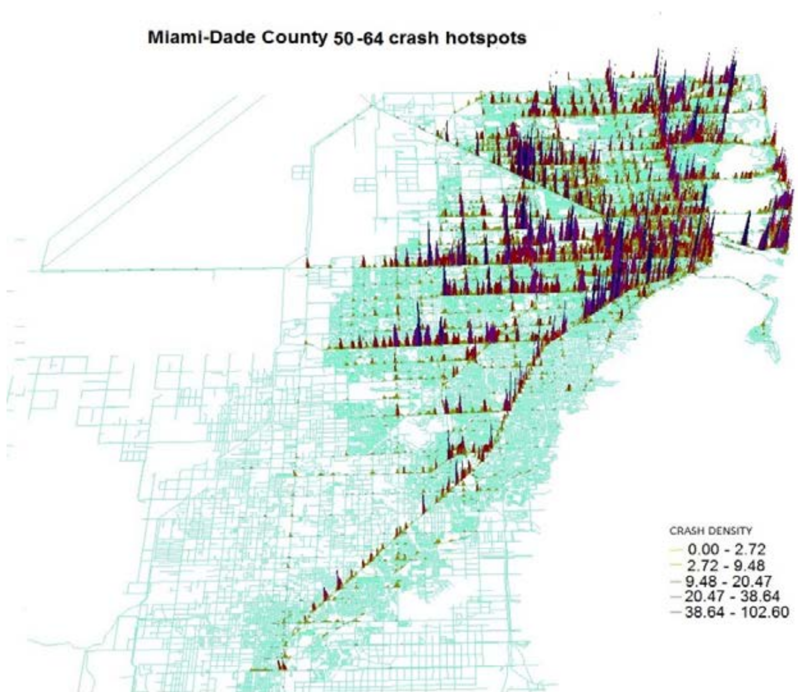


Figure 4.51 3-D Network KDE Application for the 50-64 Age Group in the Miami-Dade County

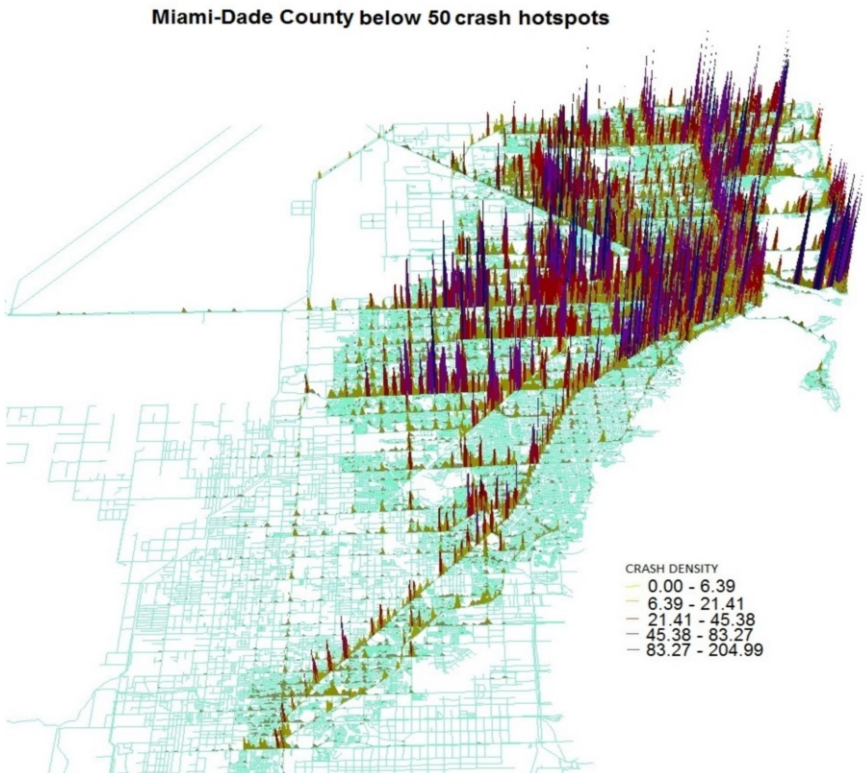


Figure 4.52 3-D Network KDE Application for the 50- Age Group in the Miami-Dade County

4.2 Temporal Analysis

In this section, temporal analysis is provided through the use of spider plots for the selected six counties selected. Temporal results for other counties studied can be found in Appendix D.

4.2.1 Broward County

Figure 4.43 shows the hourly, daily and monthly variations in the aging-involved accidents for the Broward County, respectively. Most of these accidents occur during the mid-hours of the day (between 11:00 AM and 04:00 PM), not during the peak hours, the peak being usually before the evening rush hours. From the daily variation plots, we observe that higher accident rates during the weekdays when compared to the weekends. Monthly variation plots, on the other hand, do not really show a significant change in the accident rates between the months.

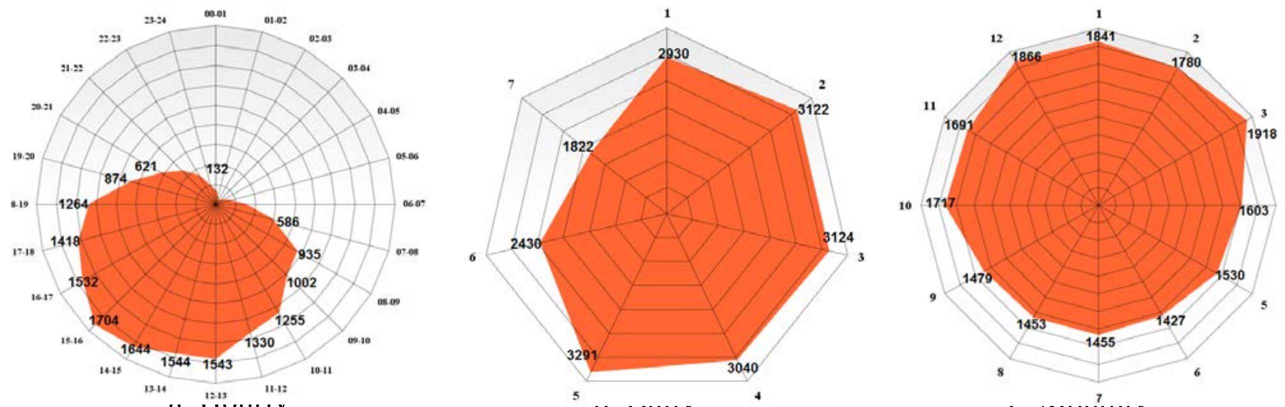
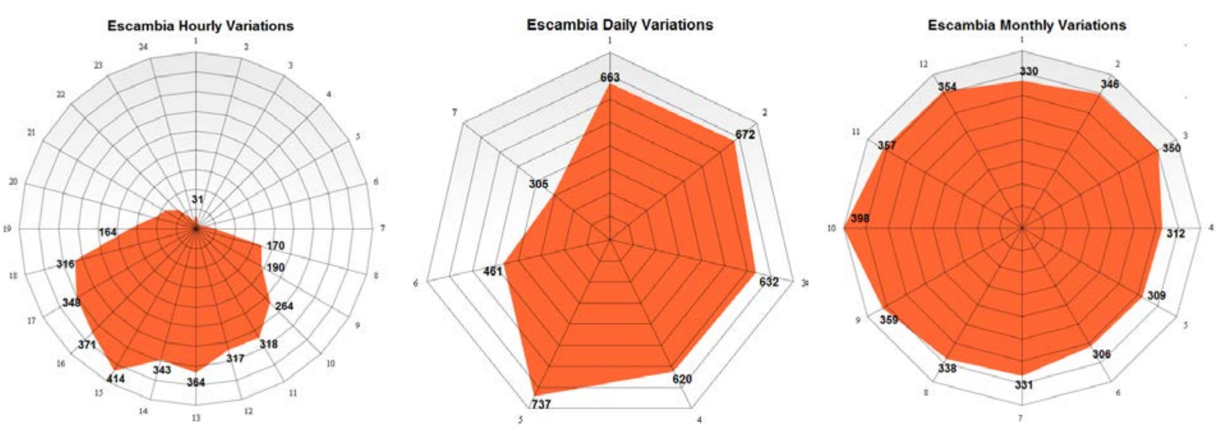


Figure 4.53 Temporal Analysis of the Broward County

4.2.2 Escambia County

Figure 4.44 shows the hourly, daily and monthly variations in the aging-involved accidents for the Escambia County, respectively. Most of these accidents occur during the mid-hours of the day (between 11:00 AM and 06:00 PM), not during the peak hours, the peak being usually before the evening rush hours. From the daily variation plots, we observe that higher accident rates during the weekdays when compared to the weekends. Monthly variation plots, on the other hand, do not really show a significant change in the accident rates between the months.

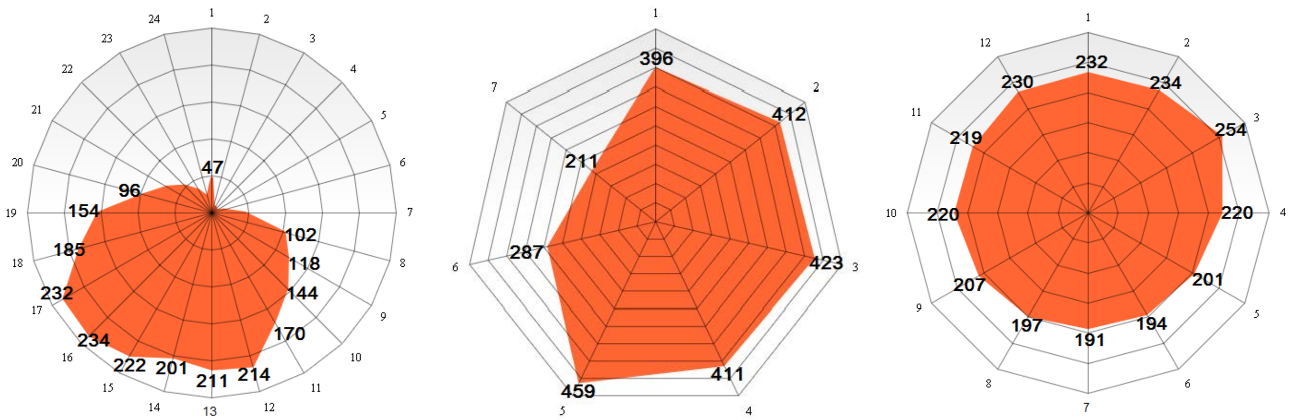


a. Hourly b. Daily c. Monthly

Figure 4.54 Temporal Analysis of the Escambia County

4.2.3 Hillsborough County

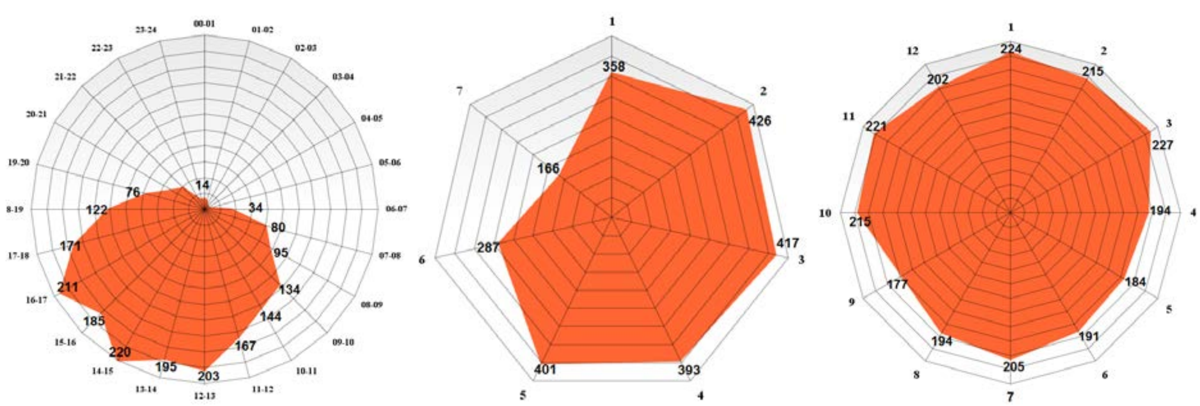
Figure 4.45 shows the hourly, daily and monthly variations in the aging-involved accidents for the Hillsborough County, respectively. Most of these accidents occur during the mid-hours of the day (between 12:00 AM and 05:00 PM), not during the peak hours, the peak being usually before the evening rush hours. From the daily variation plots, we observe that higher accident rates during the weekdays when compared to the weekends. Hillsborough County also shows a slight decrease in the aging-involved accidents during the summer months.



a. Hourly b. Daily c. Monthly

Figure 4.55 Temporal Analysis of the Hillsborough County

4.2.4 Leon County

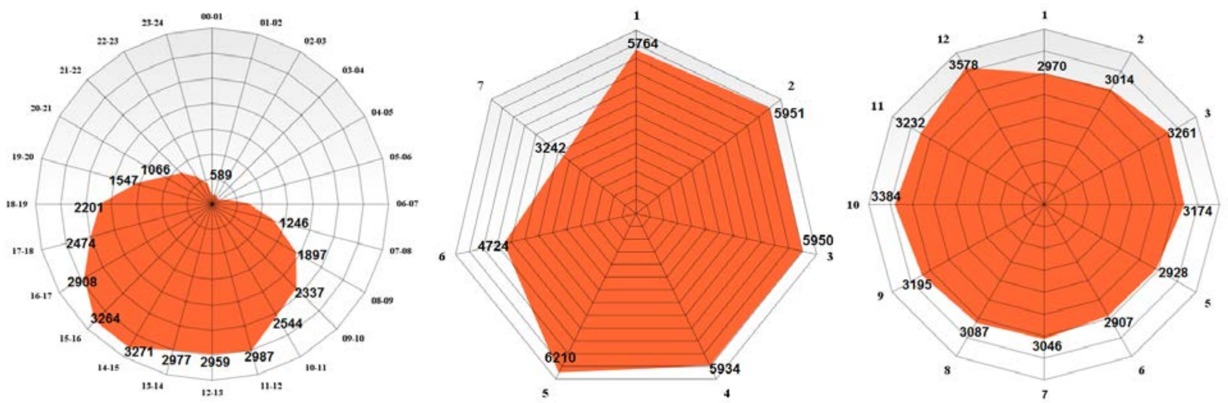


a. Hourly b. Daily c. Monthly

Figure 4.56 Temporal Analysis of the Leon County

Figure 4.46 shows the hourly, daily and monthly variations in the aging-involved accidents for the Leon County, respectively. Most of these accidents occur during the mid-hours of the day (between 12:00 AM and 05:00 PM), not during the peak hours, the peak being usually before the evening rush hours. From the daily variation plots, we observe that higher accident rates during the weekdays when compared to the weekends. Hillsborough County also shows a decrease in the aging-involved accidents between April and September.

4.2.5 Miami-Dade County



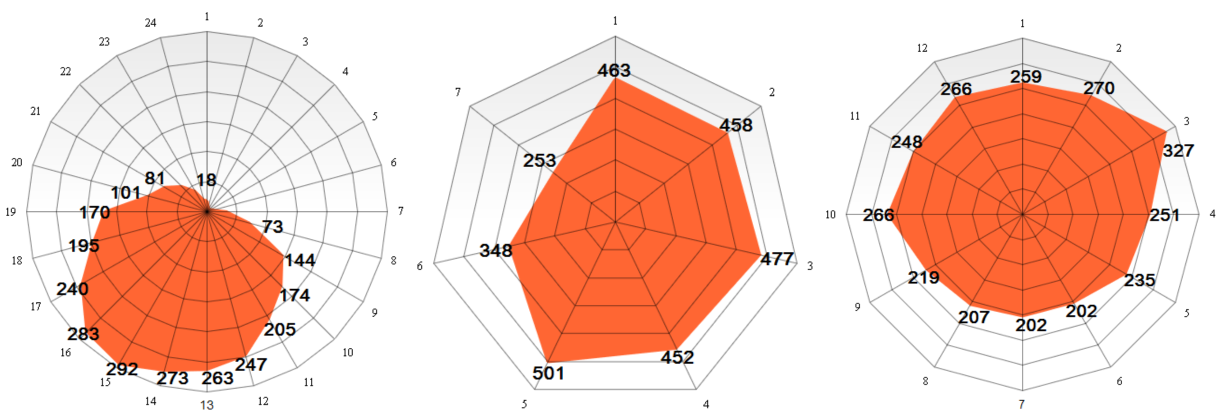
a. Hourly b. Daily c. Monthly

Figure 4.57 Temporal Analysis of the Miami-Dade County

Hourly, daily and monthly variations in the aging-involved accidents for the Miami-Dade County is presented in Figure 4.47. Most of these accidents occur during the mid-hours of the day (between 10:00 AM and 04:00 PM), not during the peak hours, the peak being usually before the evening rush hours. From the daily variation plots, we observe that higher accident rates during the weekdays when compared to the weekends. Hillsborough County also shows an increase in the aging-involved accidents between September and December.

4.2.6 Pinellas County

Figure 4.48 shows the hourly, daily and monthly variations in the aging-involved accidents for the Pinellas County, respectively. Most of these accidents occur during the mid-hours of the day (between 12:00 AM and 04:00 PM), not during the peak hours, the peak being usually before the evening rush hours. From the daily variation plots, we observe that higher accident rates during the weekdays when compared to the weekends. Monthly variation plots do not really show a significant change in the accident rates between the months except the month of March. Pinellas County also show a slight decrease in the aging-involved accidents during the summer months.



a. Hourly b. Daily c. Monthly

Figure 4.58 Temporal Analysis of the Pinellas County

4.2.7 Summary

This analysis reveals an interesting hourly pattern for the aging-involved accidents. Most of these accidents occur during the mid-hours of the day, not during the peak hours, the peak being usually before the evening rush hours. That is, we do not observe a peak in the morning and evening rush hours as we would expect for the working age group accidents. This makes the aging-involved accidents unique in the sense they do not follow the usual pattern. This may be due to the fact that most aging Floridians are retirees and/or they do not prefer to drive in the rush hours.

From the daily variation plots, we also observe higher accident rates during the weekdays when compared to the weekends. This may reveal a specific preference for aging people: driving during the weekdays more than weekends. Monthly variation plots, on the other hand, do not really show a significant change in the accident rates between the months except the month of March for Pinellas and the month of December for Miami-Date. Broward, Hillsborough, Miami-Dade and Pinellas counties also show a slight decrease in the aging-involved accidents during the summer months whereas the Escambia and Leon counties show slightly increasing number of accidents in the fall and spring seasons, respectively. However, we do not observe a clear picture on the accident variation like the hourly and weekly plots. It is clear that this temporal analysis can provide us with a better understanding for the variations in the aging-involved accidents between hours of the day, days of the week, and months of the year.

4.3 Spatio-temporal Analysis

In order to even better comprehend the spatial and temporal patterns of aging-involved accidents, an analysis that makes use of both approaches is needed, such as the Comap method. The Comap method is used to conduct the spatio-temporal analysis shown in this section, where maps are shown for four different time periods of the day. For each time period, spatial distribution of the aging-involved accidents are presented for each county, which leads us to the temporal hotspots.

Therefore, this time-based variety for the hotspots can be determined using the Comap method efficiently. Identifying accident distribution patterns both spatially and temporally can provide better guidance to the planners on where and when the accident prevention remedies and strategies should be applied. Two drawbacks associated with the Comap method is as follows: (a) The time periods should always overlap each other, and (b) The number of crashes in each time period should be approximately the same. In order to overcome these drawbacks, other spatio-temporal methods such as SatScan method can be implemented and compared with the results presented in this paper. Spatio-temporal results for other counties studied can be found in Appendix E.

Broward County

Figure 4.49 shows the spatio-temporal analysis results for Broward County. First, we observe that Hallandale Beach area is a major hotspot, and some minor hotspots are also observed near Fort Lauderdale. In the afternoon, the intensity of the Ford Lauderdale hotspot increases. We also observe that another hotspot is forming around the Dave areas. When we reach the evening, the Fort Lauderdale hotspot intensifies even further. At night, the intensity of hotspot at near Hallandale Beach decreases while the one for Fort Lauderdale stays the same.

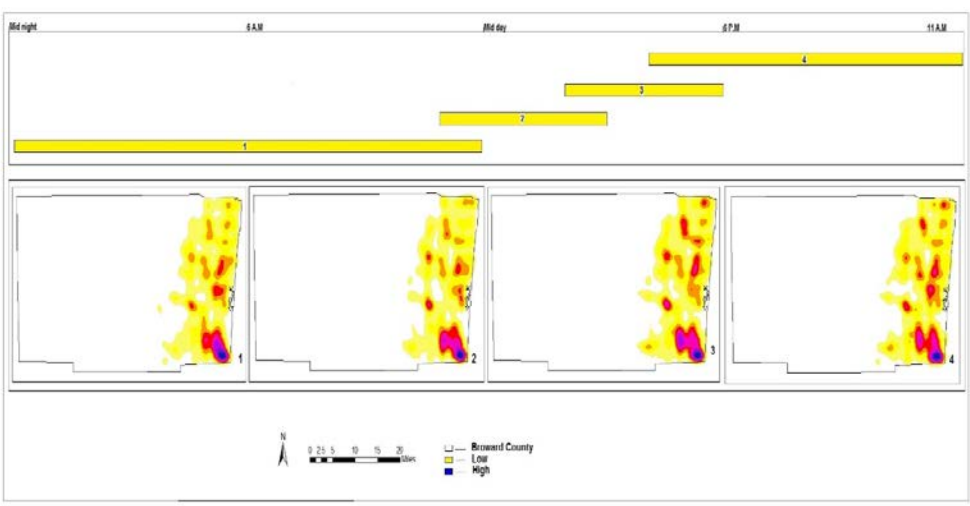


Figure 4.59 Spatial-temporal Analysis for the Broward County

Escambia County

Figure 4.50 shows the spatio-temporal analysis results for the Escambia County. Escambia County has two hotspots in the morning, namely the downtown Pensacola and Brent areas; however, as the time progresses, a new hotspot is detected near the Northwest of Pensacola.

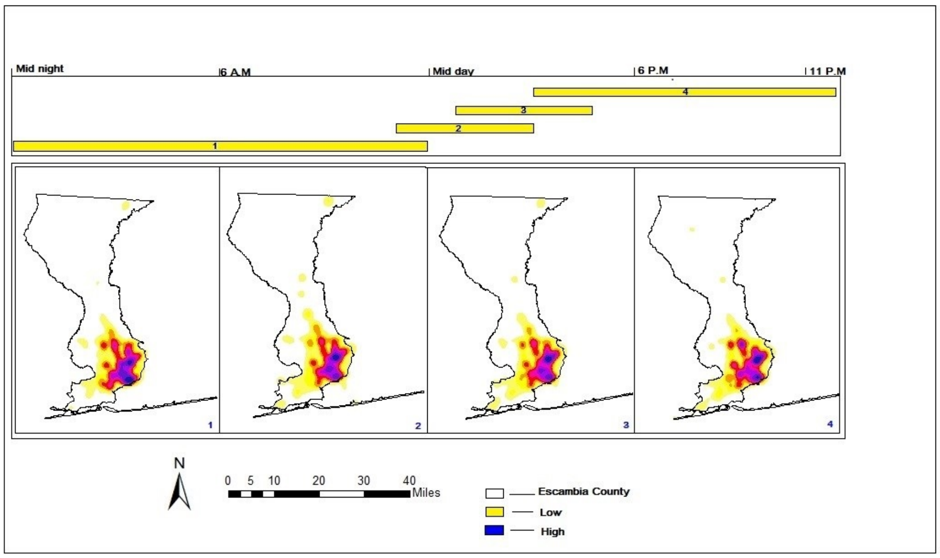


Figure 4.60 Spatio-temporal Analysis for the Escambia County

Hillsborough County

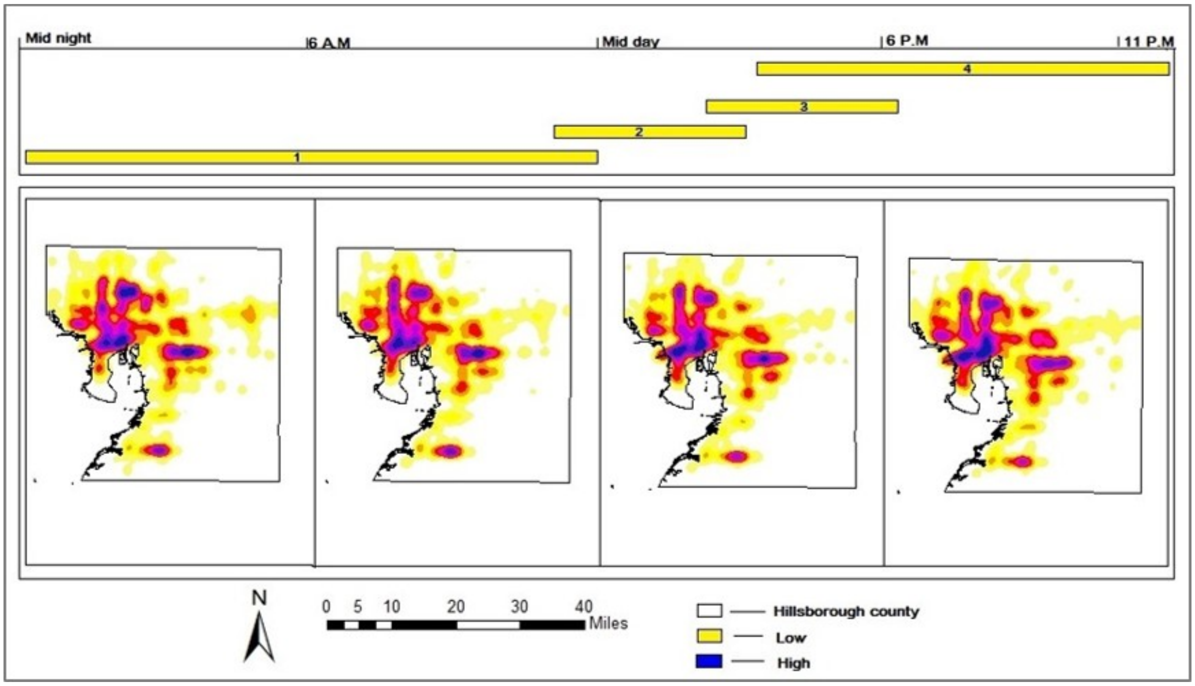


Figure 4.61 Spatio-temporal Analysis for the Hillsborough County

Figure 4.51 shows the spatio-temporal hotspots for the Hillsborough County. For this county, the hotspots are detected around New Tampa, Brandon and Sun City Center regions; however, they start to fade away as the time passes.

Leon County

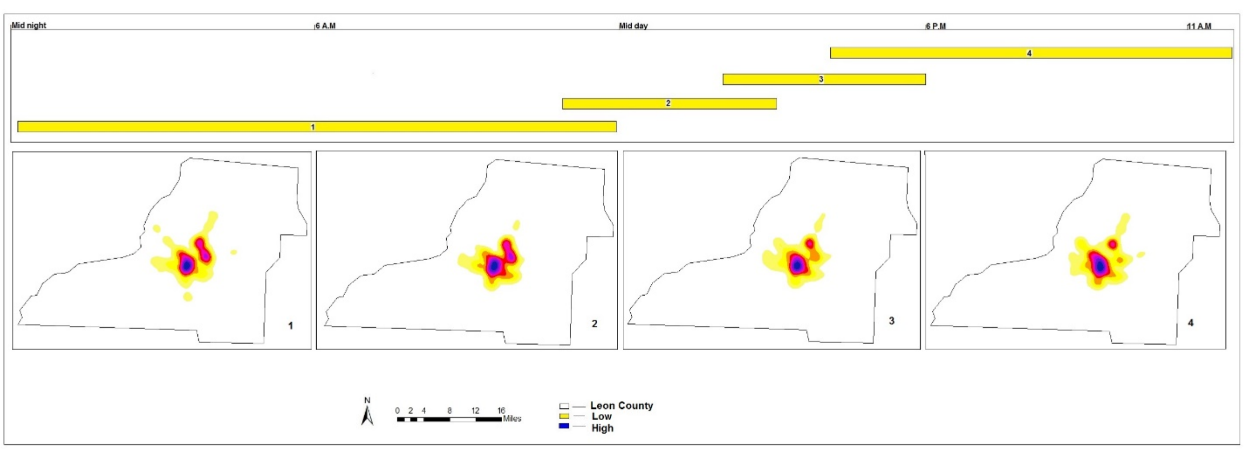


Figure 4.62 Spatio-temporal Analysis for the Leon County

For Leon County, day time hotspots are identified near the N. Monroe Rd., around the Florida State University, and the Raymond Diehl Rd. and I-10 intersection (Figure 4.52). As time passes, the hotspot near the N. Monroe gets more risky with higher density values whereas the hotspot near the Raymond Diehl Rd. loses its intensity.

Miami-Dade County

Figure 4.53 shows the hotspots identified from the spatio-temporal analysis conducted for the Miami-Dade County. During the day, we observe hotspots near the downtown Miami downtown and Haileah region. The intensity of these hotpots reduce in the afternoon and gets intensified again in the evening.

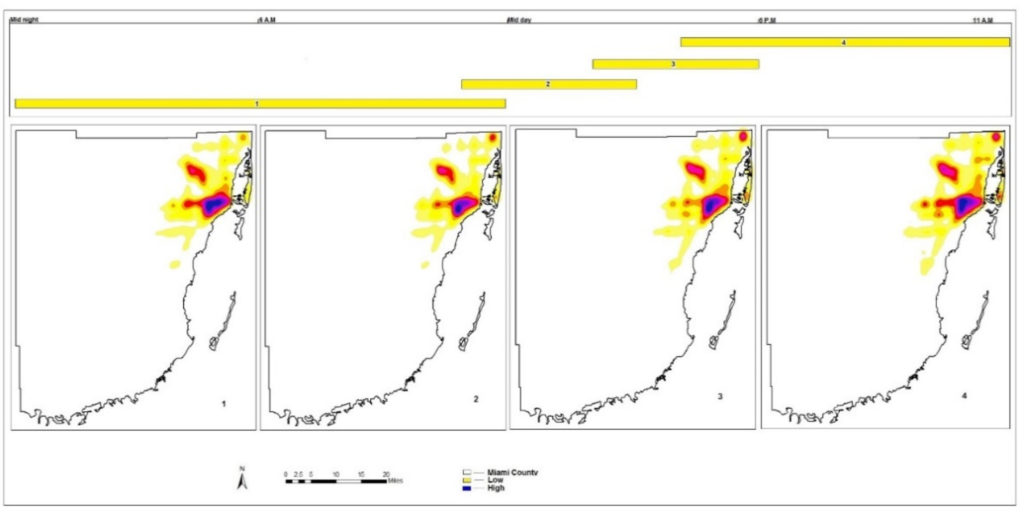


Figure 4.63 Spatio-temporal Analysis for the Miami-Dade County

Pinellas County

Hotspots for the Pinellas County are shown in Figure 4.54. In Pinellas, we do not observe any change on the hotspot locations; however, the intensity of the accidents around Palm Harbor and Tarpon Springs regions clearly increase.

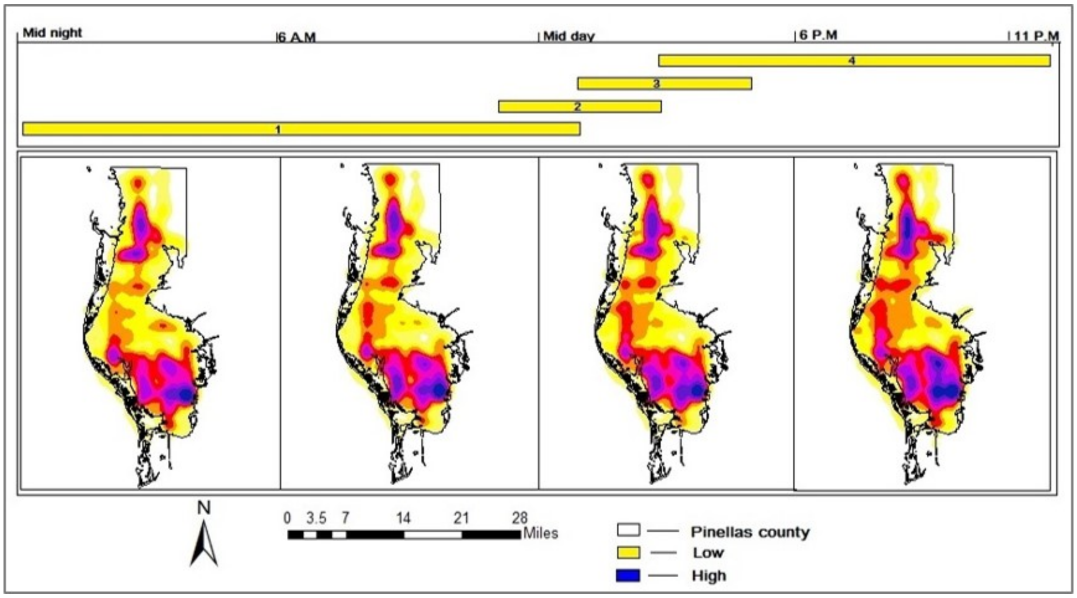


Figure 4.64 Spatio-temporal analysis for the Pinellas County

Summary

This time-based variety for the hotspots can be determined using the Comap method efficiently. Identifying accident distribution patterns both spatially and temporally can provide better guidance to the planners on where and when the accident prevention remedies and strategies should be applied. Two drawbacks associated with the Comap method is as follows: (a) The time periods should always overlap each other, and (b) The number of crashes in each time period should be approximately the same. In order to overcome these drawbacks, other spatio-temporal methods such as SatScan method can be implemented and compared with the results presented in this thesis.

4.4 Regression Analysis

In order to support the GIS-based approach and achieve a more comprehensive analysis of the aging-involved crashes, the significant factors that influence these crashes should be analyzed with regression techniques. The utmost importance is given to answer the following question: How do aging (65+) crash influencing factors compare with those affecting the crashes involving the 65- age group? This statistical analysis, combined with the GIS-based results, can assist state and local agencies in strategic planning efforts for developing appropriate preventive measures to improve safety and enhance mobility for aging road users. The knowledge gained from the results of this research will not only help identifying the critical factors contributing to aging-involved crashes, but can also contribute to the development of more reliable aging-focused safety plans and models.

4.4.1 Analysis for the Hotspots

Among the hotspots identified for Alachua, Bay, Broward, Duval, Escambia, Hillsborough, Leon, Miami-Dade, Monroe, Pinellas and Walton counties, two high crash risk locations are identified for further analysis. For this purpose, a total of 17,376 aging-involved crashes, within the 22 hotspots selected for these eleven counties, are studied via the binary logistic regression technique. Here, the dependent variable is 1, if the crash is an aging-involved (65+) crash, and 0, otherwise (65-). Table 4.8 presents the proposed binary logit model results for the spatial analysis of aging-involved crashes. Please note that the preliminary approach included other geometric design characteristics as well as the light and weather conditions; however, the insignificant factors are eliminated, which leads to the following independent variables (factors) that are used for this analysis:

- Peak term is a binary variable, which takes a value of 1, if the crash occurs in the peak hour, and 0, otherwise. Peak hours in this study are selected as AM Peak (07:00 AM – 10:00 AM) and PM Peak (04:00 PM – 07:00 PM).
- Week factor is a binary variable that indicates whether the crash occurs in a weekday or weekend. It is 1, if the crash occurs at a weekday, and 0, otherwise.

- AADT is a continuous variable, and represents the Average Annual Daily Traffic for the crash location.
- Speed is a continuous variable, and represents the posted speed limit at the crash location.
- Population is a continuous variable and represented as follows: Proportion of the 65+ Population over the total population is calculated for a 5-mile buffer zone around the hotspot location.
- Site location is a binary variable, and takes a value of 1, if the crashes occur at the intersections, and 0, otherwise.
- Median is a continuous variable indicating the median width at the crash location.
- Shoulder width is a continuous variable, indicating the shoulder width at the crash location.
- Lane width is a continuous variable, indicating the lane width at the crash location.

Table 4.8 indicate the factors that are significant and insignificant for the aging-involved crashes based on the p-values given the 95% confidence interval. There is a negative coefficient for the “Peak hour factor”, which implies that aging-involved crashes are more likely to occur in off-peak hours rather than peak hours, when compared to the other age group crashes. This is consistent with the previous GIS-based results. There is a positive coefficient for the “Week day factor”, suggesting that aging-involved crashes are more likely to occur during the week days rather than the weekends, which is also consistent with the GIS-based temporal results.

Table 4.8 Logistic Regression Results for Hotspots

Variable	Description	Type/Scale	Coefficient	p-value	t-statistics
Intercept		Constant	-2.4473	1.89E-98	-21.05
Peak	Peak Hours	Binary	-0.354912	6.21E-16	-8.085073
Week	Weekday/ Weekend	Binary	0.3461327	9.25E-14	7.45126
AADT	AADT	Continuous	-0.004418	0.00178	-3.124878
Speed	Posted Speed	Continuous	0.0019	0.4648	0.7309
Pop	Population	Continuous	4.823712	1.20E-61	16.56715
Sitloc	Site Location	Binary	0.089197	0.00109	3.26619
Medwid	Median Width	Continuous	0.0079	6.55E-05	3.992247
Lanewid	Lane Width	Continuous	-3.778E-04	0.8923	-0.1354
Shuldwid	Shoulder Width	Continuous	-0.0117	0.1943	-1.2981
Number of Valid Observations				1.74E+04	
Pseudo R-square				2.78E-02	
Hosmer-Lemeshow				1.57E+01	
Significance of Model				4.70E-02	

There is a negative coefficient for the "AADT", which indicates that aging-involved crashes are more likely to occur on the roadways having less "AADT" than other age groups. However, please note that aging populations may not prefer to drive on the heavily congested roadways that usually have higher traffic volumes. The "Population coefficient", with the high positive coefficient, has a significantly high effect on the aging-involved crashes. This is very interesting since it reveals another location-specific effect that should be analyzed further: More aging-involved crashes occur at those areas that have higher aging populations. "Site location" has a positive coefficient, from which we can infer that the probability for an aging crash to occur at an intersection is more than other age group crashes. "Median width" is observed to have a positive coefficient indicating the strong influence of median width on the aging crashes with a positive correlations. From the analysis results, “Posted speed limit”, “Lane width” and “Shoulder width” appear to be the insignificant factors.

4.4.2 Analysis for the Hotspot Intersections with AADT as a Factor

Table 4.9 Logistic Regression Results for the Hotspot Intersections with AADT as a Factor

Variable	Description	Type/Scale	Coefficient	p-value	t-statistics
Intercept		Constant	-1.7759	2.61E-31	-11.63895
Peak	Peak Hours	Binary	-0.2958	3.47E-09	-5.907773
Week	Weekday/ Weekend	Binary	0.3455	2.30E-11	6.685755
AADT	AADT	Continuous	1.215E-05	0.9217	0.0983
Speed	Speed	Continuous	-0.0230	1.35E-08	-5.680046
POP	Population	Continuous	6.0006919	1.42E-64	16.96769
Number of Valid Observations				1.46E+04	
Pseudo R-square				2.49E-02	
Hosmer-Lemeshow				9.46E+00	
Significance of Model				2.21E-01	

Both the GIS-based results and the regression analysis provided in the previous section indicate that intersections are more critical and therefore possess more risk for aging populations. Therefore, all the 161 intersections that reside within the hotspots are selected and separated for a deeper regression analysis. Similarly, binary logistics regression analysis is implemented in order to identify the factors contributing to the aging-involved intersection crashes compared to other age group crashes. Table 4.9 shows the results of this analysis. Only the “Population factor” and traffic-related factors are considered for this analysis in order to observe how the change in the traffic characteristics influence the aging-involved crashes when compared to other age group crashes. Similar to the hotspot regression analysis, “Peak hour” and “Week day” factors have positive coefficients, which indicates that aging-involved intersection crashes occur at off-peak hours and on weekdays mostly. “Speed factor” has a negative coefficient indicating that the higher posted speed limits lead to less aging-involved crashes. This is also related to the fact that aging populations may not prefer to drive on the heavily congested roadways that usually have higher posted speed limits. “Population factor”, similar to the hotspot regression, has a high positive coefficient, which shows that population is a very significant factor that influences the intersection crashes for aging. “AADT” appears to be very insignificant, therefore hourly traffic volume will be added to the regression analysis instead of the “AADT” in the next section.

4.4.3 Analysis for the Intersections with the Traffic Flow as a Factor

Results presented in Section 4.4.2 indicate that “AADT” does not appear to be a significant factor for the aging-involved crashes. However, the number of vehicles on the roadway should be critical for the occurrence of crashes. Therefore, we use the actual hourly flow data for the regression analysis. This flow data is collected through the Telemetric Traffic Monitoring Sites (TTMS) locations, and obtained from the Florida Department of Transportation. Since only some of the hotspots had the TTMS locations, those hotspots were selected for further analysis. These hotspots belong to the Broward, Miami-Dade, Alachua, Monroe and Walton counties. The flow data is extracted from the traffic stations near the hotspots. Table 4.10 presents the logistics analysis results where the “Traffic flow factor” also appears to be a significant factor given the 90% confidence level. The negative coefficient indicates that aging-involved populations have more crashes when lower volumes are observed. The effect of the remaining factors are similar to the previous regression analysis presented in Table 4.9.

Table 4.10 Logistic Regression Results at the Intersections with the Flow as a Factor

Variable	Description	Type/Scale	Coefficient	p-value	t-Statistics
Intercept			0.404	0.3659	0.9041
Peak	**Peak Hours**	Binary	-0.21871	0.00204	-3.084992
Week	**Week day/ Weekend**	Binary	0.2619942	0.00045	3.508759
Flow	**Flow**	Continuous	-0.076346	0.07434	-1.784498
Speed	**Speed**	Continuous	-0.071234	1.10E-22	-9.801925
POP	**Population**	Continuous	4.1874177	0.00287	2.980998
Number of Valid Observations				8.27E+03	
Pseudo R-square				1.77E-02	
Hosmer-Lemeshow				1.03E+02	
Significance of Model				0.00E+00	

Further analysis is needed in order to identify the effect of average speed of the vehicles when the crash occurs, rather than the posted speed limit, which will be obtained from the Florida Department of Transportation for those TTMS locations as a future work.

4.4.4 Summary

In order to find the factors influencing aging-involved crashes at the county hotspots, a binary logistic regression-based analysis is conducted. Results show that "Peak hour factor", "Week day factor", "AADT", "Population", "Intersection factor", and "Median width" are found to be significant factors for aging-involved crashes (@ 95% confidence level). The regression analysis for the hotspots also indicate that aging-involved crashes are more likely to happen at the intersections. Therefore, in order to provide a more detailed evaluation, 161 intersections that reside within the hotspots are selected for further analysis. Only traffic factors and the population factor are considered for this intersection-focused crash analysis. First, we consider "AADT" as one of the factors. Results show that Peak hour factor", "Week day factor", "Posted Speed Limit", and "Population" has a significant influence on the aging-involved crashes at the intersections, when compared to other age group crashes (@ 95% confidence level). However, “AADT”, which is a measure of traffic volume, does not appear to be significant. Therefore, a second regression analysis is conducted with and addition of the hourly traffic flow as one of the factors instead of the “AADT”. In order to conduct such an analysis, those intersection locations, that have hourly traffic flow data, are selected. Results show that “Traffic flow” is a significant factor that affects the aging-involved crashes compared to other age groups with a 90% confidence level. Therefore, it is meaningful to suggest that the actual hourly traffic flow at the crash locations can provide more accurate results than the “AADT” while conducting a regression analysis on the crashes.

Chapter 5 Discussion

This study is conducted to fill the void of knowledge related to the aging-involved crashes. The proposed methodology is applied with the following objectives: (a) identify the crash hotspots and time periods in the eleven Florida counties with high crash rates involving aging road users, (b) conduct a statistical analysis in order to identify the significant factors that affect aging-involved crashes. For this purpose, spatial, temporal and spatio-temporal methods as well as a logistic regression-based statistical approach are implemented based on the Florida Department of Transportation crash database recorded between the years 2008 and 2012. There are several important findings of this study that can assist the transportation officials and policy makers for better planning and management of traffic operations with a focus on aging populations:

- Intersections have an adverse effect on the 65+ populations more than other adult age groups. This is critical since popular places like grocery stores and pharmacies for aging people are often located in the commercial areas that often contain numerous intersections for access. This problem can become even more complex when multiple intersections, complex signalizations and unexpected design features are present. Since redesigning a roadway intersection would be very costly to the transportation agencies, it can be more appropriate to maintain and operate the current intersections in a better and smarter way, especially in the regions that have high aging populations such as the counties studied in this paper. These strategies include better signalization, signing and communication through IT-based systems such as Intelligent Transportation Systems. This will definitely help communicating vital roadway/traffic information to the 65+

population sufficiently and timely, which can be critical for their safety and survival.

- Aging-involved population crashes occur during the mid-day rather than the peak hours, which is not a similar pattern for other adult age groups, especially for the working populations. This is again related to the aging-specific behavior since they may want to visit those places like grocery stores and pharmacies in the least congested time periods and with the least traffic present on the roadways. Since the 65+ Floridians are mostly comprised of retirees, it is possible for them to avoid the rush hours and complete their daily chores within the day. Weekday crashes that involve aging people are also more than those of weekend crashes. This can also be due to the fact that aging populations prefer to drive and/or complete their daily activities like shopping mostly on weekdays rather than weekends. Transportation officials, especially those that maintain and operate the roadways close to senior living communities, should be aware of the consequences of this high crash risk for aging populations during the mid-day hours of the weekdays. One strategy that can help solving this problem is providing better information to the aging people with regards to the design and operational characteristics of the critical and risky intersections.
- Kernel density analysis based on the Euclidean (planar) distance calculation is the most widely used geo-spatial analysis method in the literature and practice in order to determine the crash clusters. Results indicate that this may not be the most appropriate approach since crashes actually occur on the roadway network where distances between two points are not necessarily Euclidean. This approach

also overestimates the problem by presenting all the roadways located in the peak density regions as risky. Therefore, it is appropriate to suggest that the SANET analysis, which makes use of the network (taxi cab) distances, can create more accurate density maps. Transportation officials can efficiently use the proposed methodology to analyze the aging-specific spatial and temporal characteristics of the crashes, which can help identifying the possible reasons behind the high risk associated with the hotspot locations. Using this aging-focused application, better crash prevention and reduction strategies can be prepared by transportation officials.

- The binary logistic regression analysis supports the GIS-based results, and identifies the intersection, peak hour and weekday factors as statistically significant. This suggests that aging-involved crashes occur more (a) on intersections, (b) during the mid-day, and (c) on the weekdays, compared to other adult age groups. Results also suggest that the hourly traffic volume (hourly flow), rather than the AADT, provides better insight and understanding for the aging-involved crashes.

Chapter 6 Conclusions and Future Recommendations

This study presents a methodology to evaluate and analyze the aging-involved roadway accidents via GIS-based spatial and temporal techniques and regression models. This can help officials decide how to identify the locations that have high risk in terms of aging-involved accidents. Following a review of the spatial and temporal methods, the methodology is applied on the roadway network of eleven counties in Florida, namely Alachua, Bay, Broward, Duval, Escambia, Hillsborough, Leon, Miami-Dade, Monroe, Pinellas and Walton, based on three distinct GIS-based approaches: (a) Spatial analysis in order to reveal the hotspot locations, (b) Temporal analysis in order to reveal time-based patterns, and (c) Spatio-temporal analysis in order to investigate the relationship between the location and the time of the accidents. This is followed by an extensive logistic regression analysis on the major hotspots of the selected counties in order to identify the significant factors that affect the aging-involved crashes. Results of this research not only highlights the risky accident locations and time periods to the transportation officials but can also contribute to the development of more reliable aging-focused transportation plans and policies.

Spatially, identifying high accident risk locations such as critical intersections (hotspots) is vital in order to explore ways to reduce and/or prevent the aging-related accidents at those locations. With this knowledge, transportation officials can work on the possible reasons behind the occurrence of high number of aging-involved accidents. This, in turn, can be used to identify the significant factors that contribute to these accidents including driver behaviors and roadway characteristics. Leveraging the findings of this study into transportation plans, agencies can use this vital information in order to identify the possible deficiencies and therefore improve the roadway design at the hotspot regions which can possibly lead to a reduction in the aging-involved accidents. This information can also help Departments of Elderly Affairs and Safe Mobility for Life Coalition of Florida to develop better mitigation and educations plans for aging populations. Among the spatial methods, SANET method, which is based on the roadway network-based distance calculations, solves the overestimation and underestimation problems associated with the planar (ED)-based kernel density estimation approach, and therefore provides more accurate hotspots.

For the temporal analysis, temporal spider graphs provide a better understanding of the time-based accident patterns. For the spatio-temporal approach, Comap method is used in order to get a better insight for the critical hotspots in terms of space as well as time. These hotspots involving aging populations reveal both locations and time periods where accidents are more frequent. Results of this analysis indicate the following: (a) a substantial amount of aging-involved accidents happen at the intersections, and (b) they happen during the mid-hours of the day rather than the peak hours. This temporal result is an unusual pattern for accidents, which basically separates aging-involved accidents from other adult age groups. This knowledge can allow planners and engineers to focus on those high risk areas and time periods for safety-focused intervention efforts to assist aging drivers. This can also help increasing the efficiency of the traffic operations towards obtaining better policies and plans that focus on aging populations.

The analysis is extended to identify the significant factors that affect the aging-involved accidents via the binary logistic regression models. The regression analysis supports the GIS-based results in the sense that aging-involved crashes occur more (a) at the intersections, (b) during the off-peak hours rather than the rush hours, and (c) on the weekdays rather than the weekends. Results also suggest that traffic flow is a more significant factor that affects the aging-involved crashes than the AADT. This can help transportation officials understand the prominent reasons behind the occurrence of these accidents, focus deeper on the aging driver behavior, and pinpoint which road characteristics are unsuitable for aging drivers.

Many agencies have recognized the need to analyze the aging-involved crashes, and several strategic plans have been developed and implemented that can help reduce and avoid these crashes. Florida Department of Transportation (FDOT), including several other organizations in the State of Florida, have developed the Safe Mobility for Life Coalition (SMLC) program to improve safety, access and mobility of Florida's aging population (SMLC, 2013). With the help of these agencies, this type of study can be extended by applying the spatial, temporal and spatio-temporal methodologies to other counties in Florida and also to other states, which are reported to have high aging populations, in order to identify aging-involved crash hotspots. In addition to the methods used in this study, other spatial methods such as K-means and Nearest Neighbor method, and other spatio-temporal methods such as SatScan can be implemented, and compared with the results presented in this thesis. Using the network KDE approach within the Comap methodology instead of the planar KDE can also help identifying the exact hotspot location on the roadway for different time periods. The regression analysis presented in this study can be improved with the addition of other factors such as light and weather conditions, and other roadway and traffic factors. This study can also be extended in order to identify the spatial and temporal patterns of other age group drivers, such as teenagers.

Appendix A Yearly Crash Variations

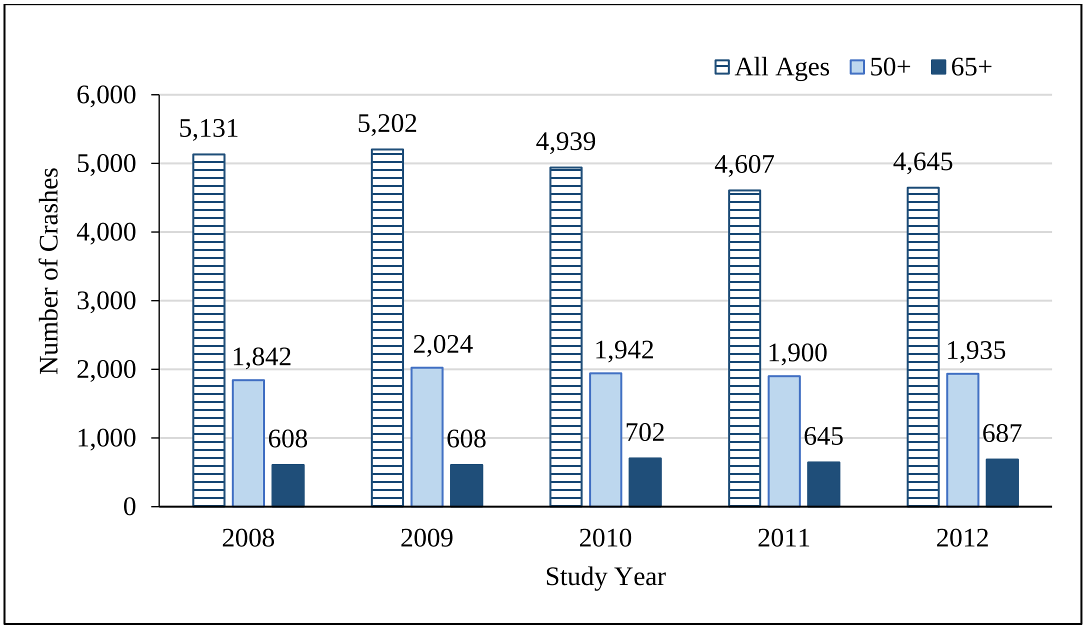


Figure A.65 Yearly Crash Variations: Alachua County

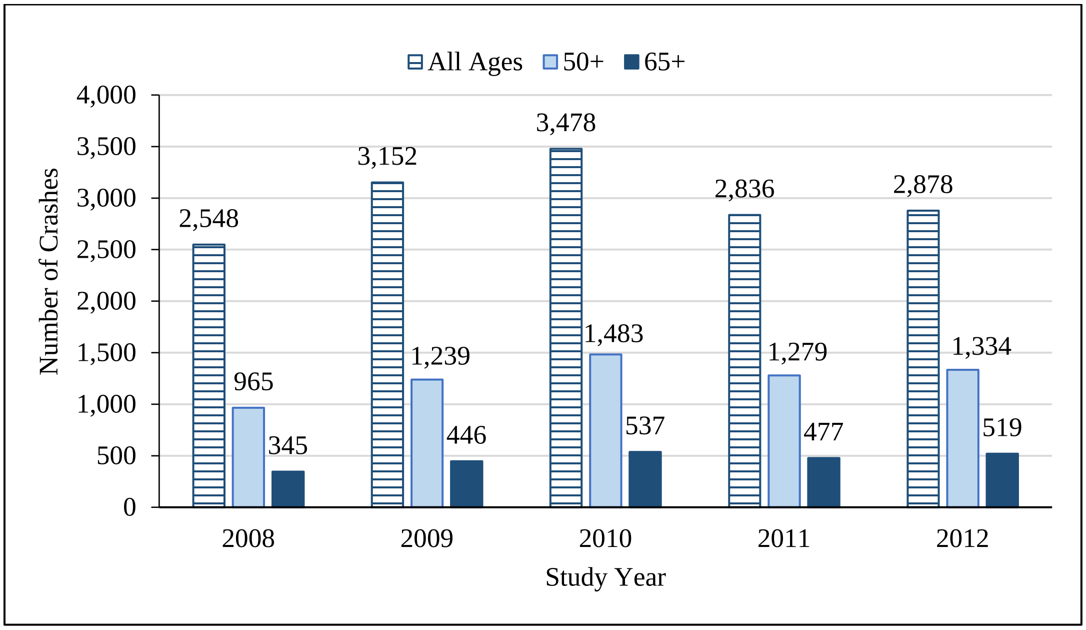


Figure A.66 Yearly Crash Variations: Bay County

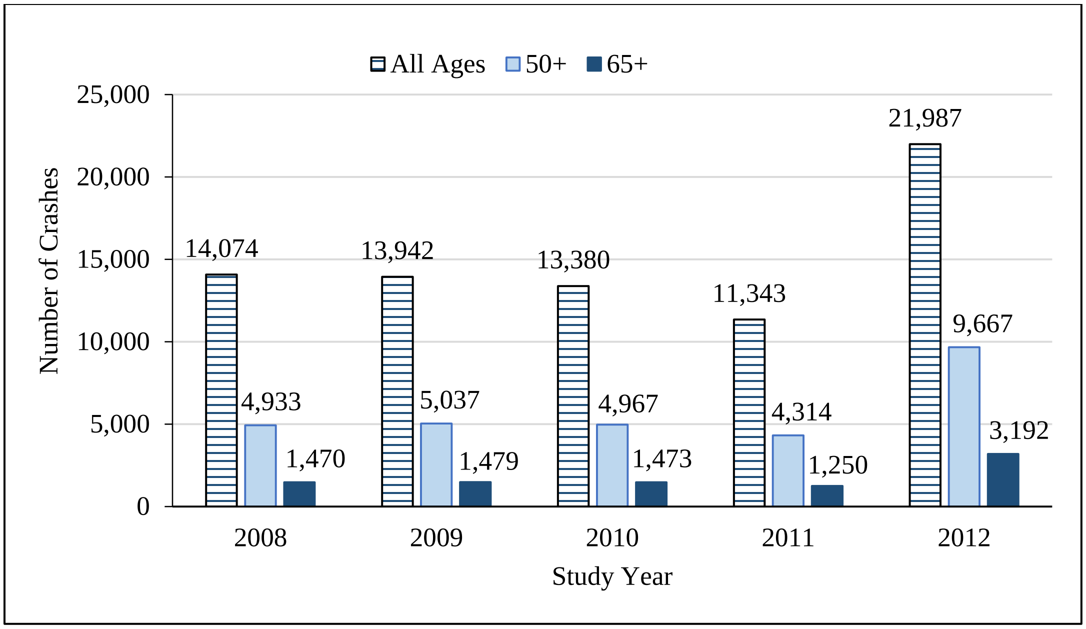


Figure A.67 Yearly Crash Variations: Duval County

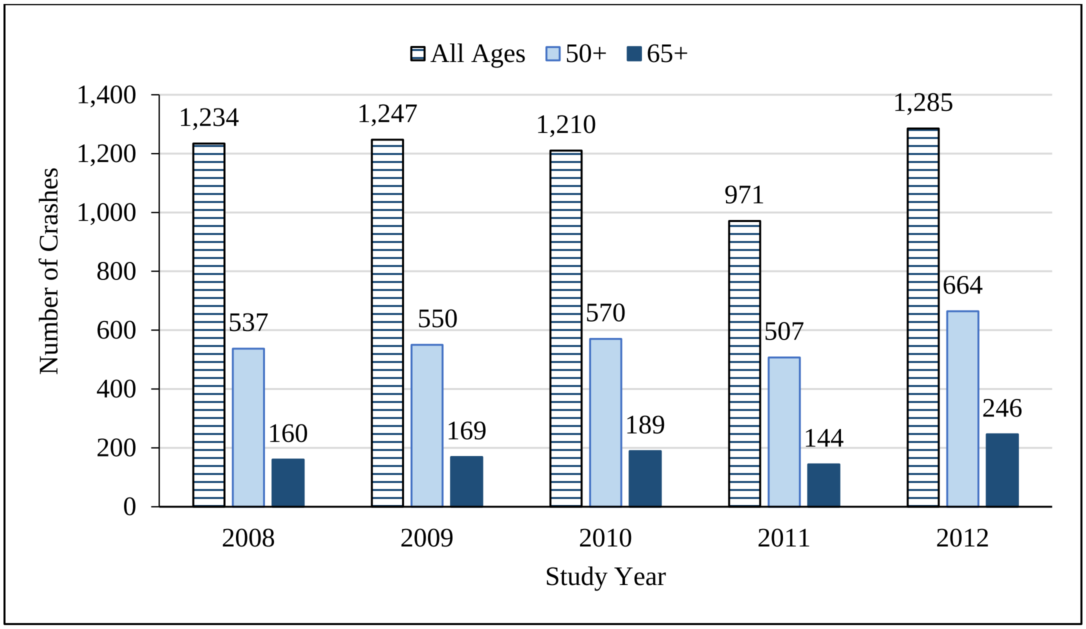


Figure A.68 Yearly Crash Variations: Monroe County

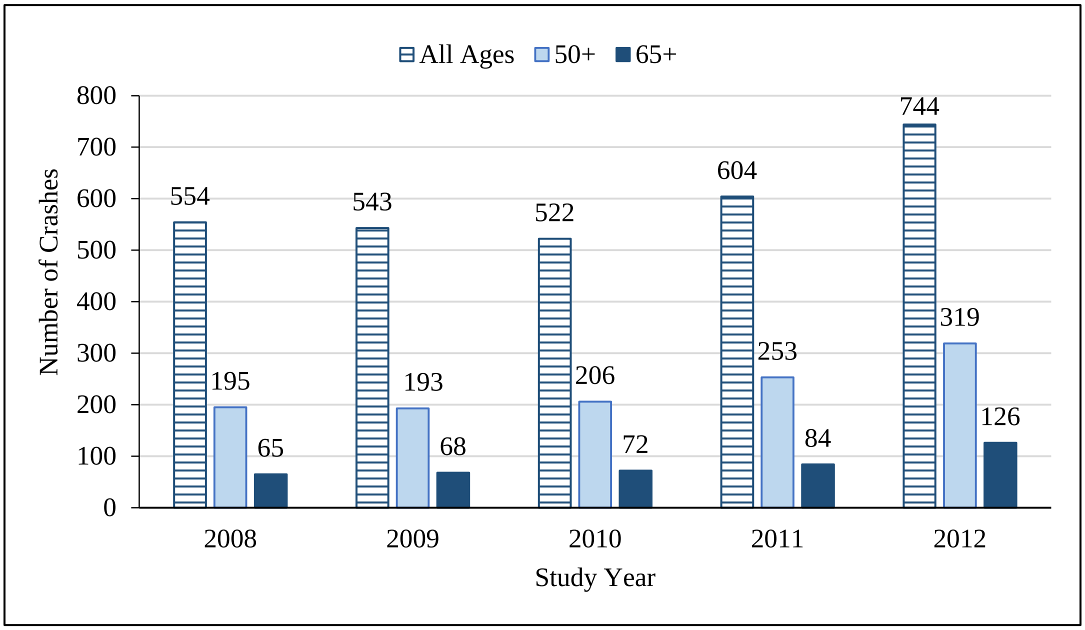


Figure A.69 Yearly Crash Variations: Walton County

Appendix B Spatial Analysis

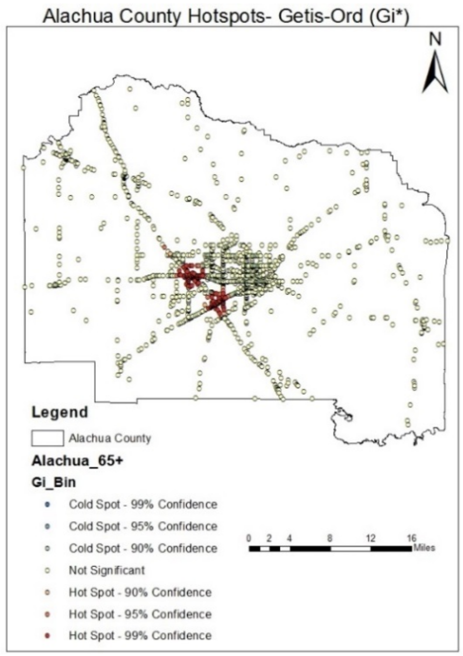


Figure B.70 Gi* Analysis for the Alachua County

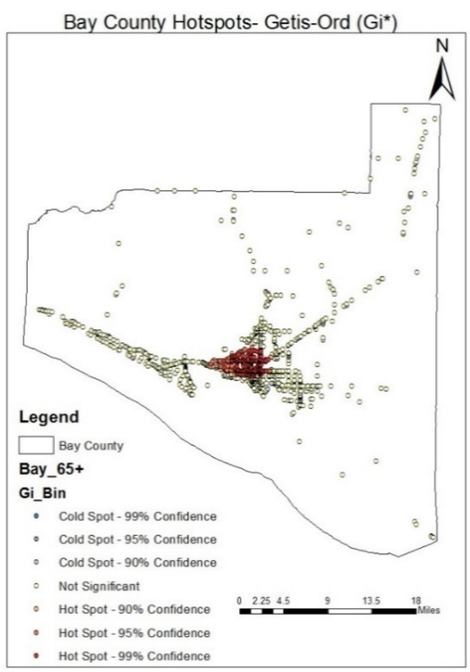


Figure B.71 Gi* Analysis for the Bay County

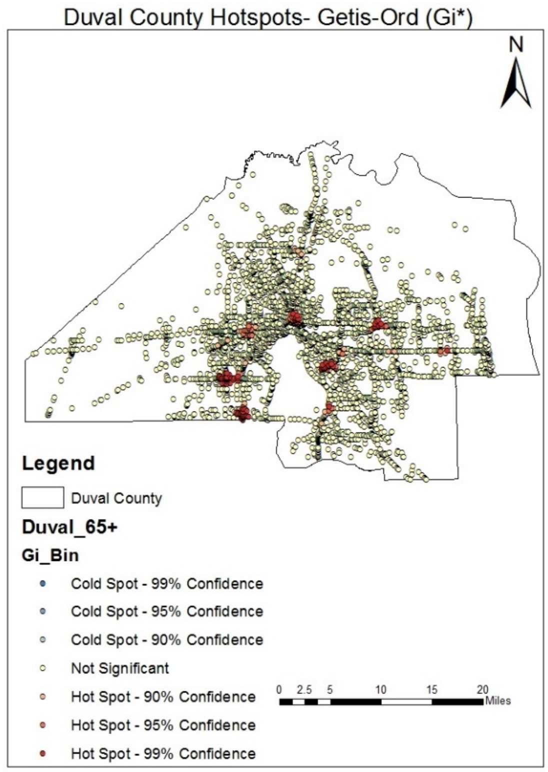


Figure B.72 Gi* Analysis for the Duval County

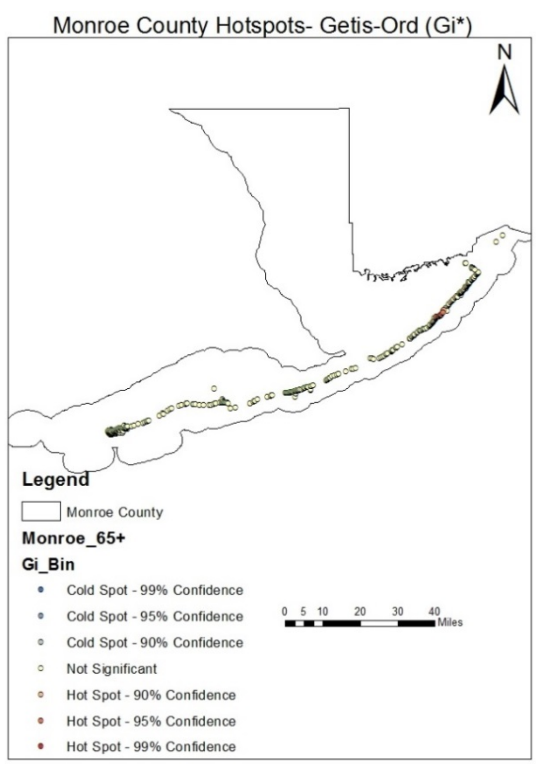


Figure B.73 Gi* Analysis for the Monroe County

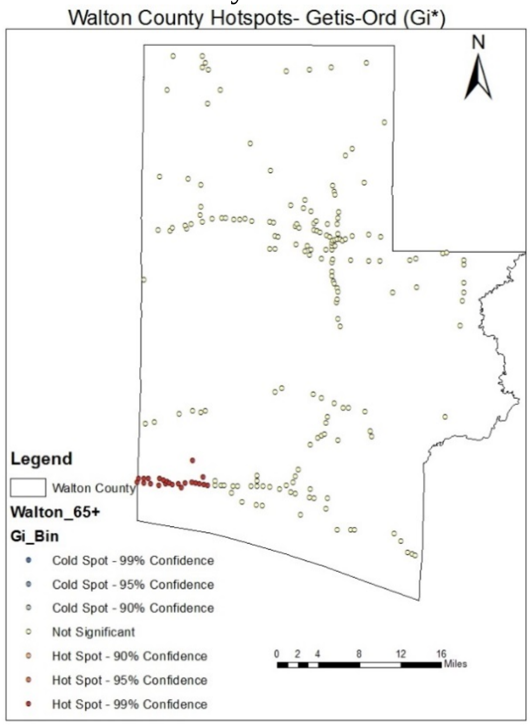


Figure B.74 Gi* Analysis for the Walton County

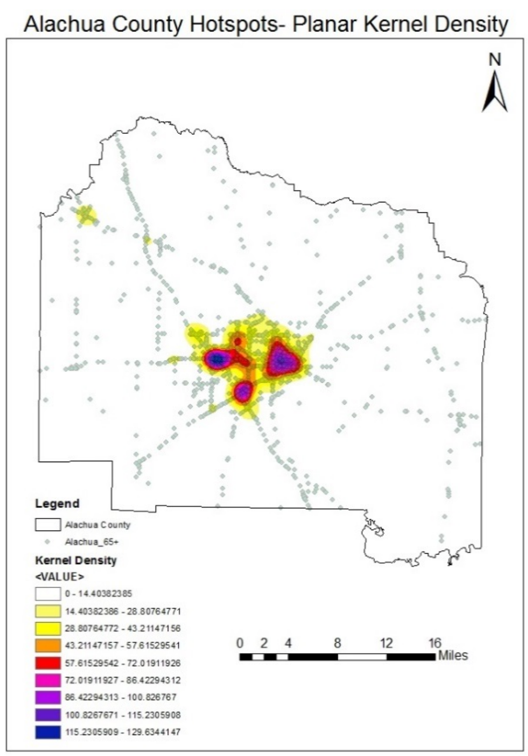


Figure B.75 Planar KDE Application for the Alachua County

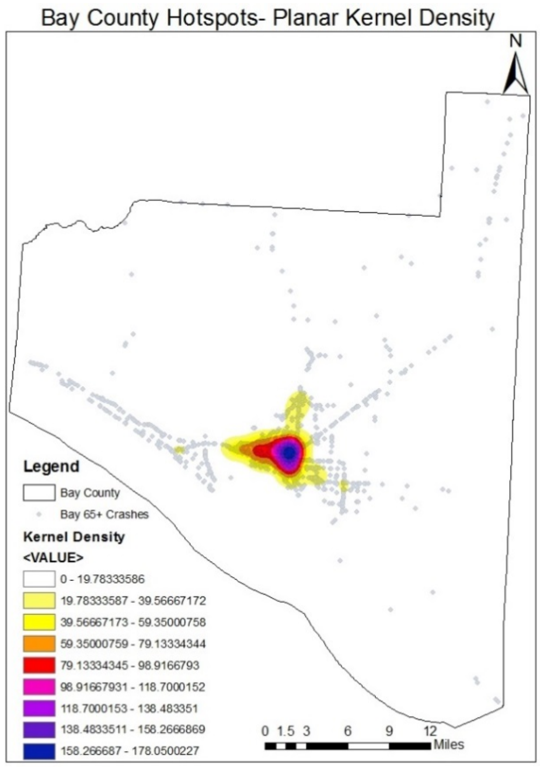


Figure B.76 Planar KDE Applications for the Bay County

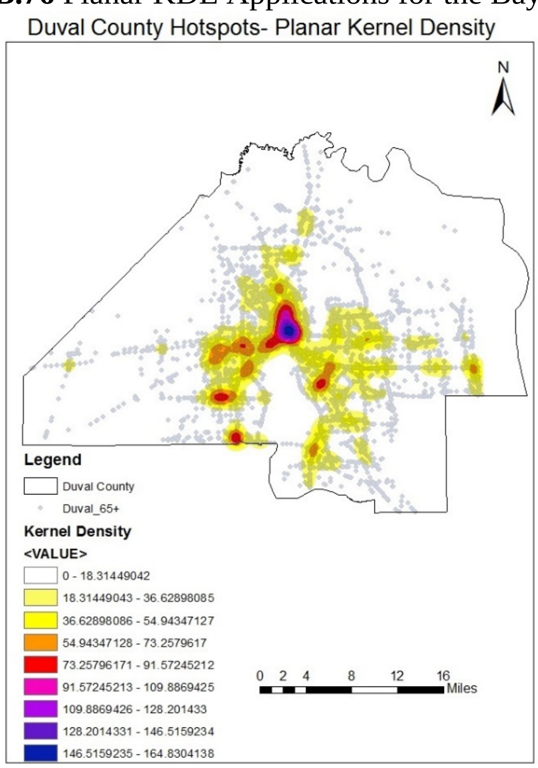


Figure B.77 Planar KDE Applications for the Duval County

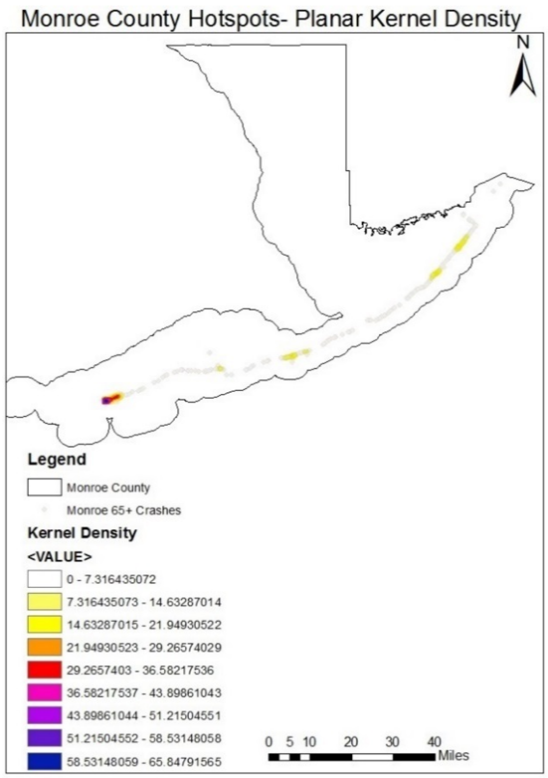


Figure B.78 Planar KDE Application for the Monroe County

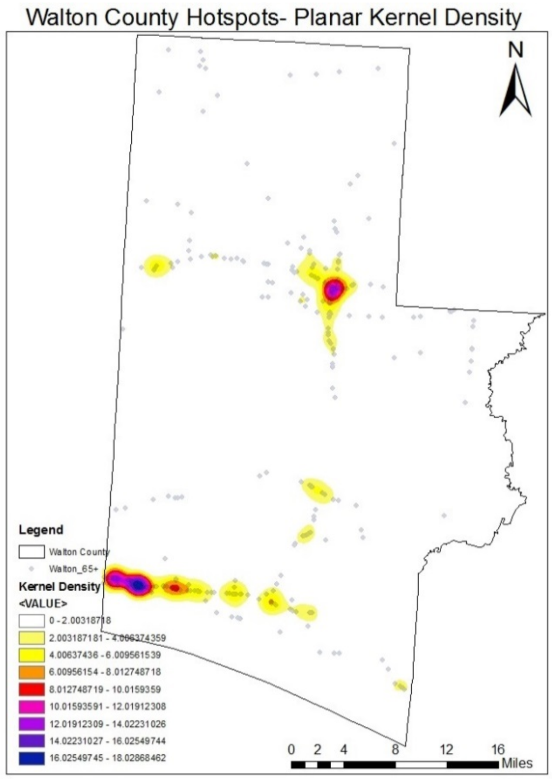


Figure B.79 Planar KDE Application for the Walton County

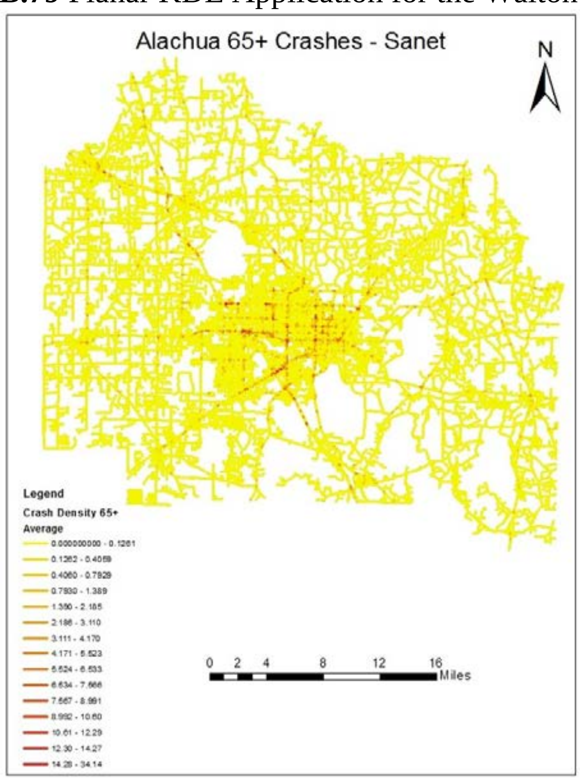


Figure B.80 Network KDE (2D) Application for the Alachua County

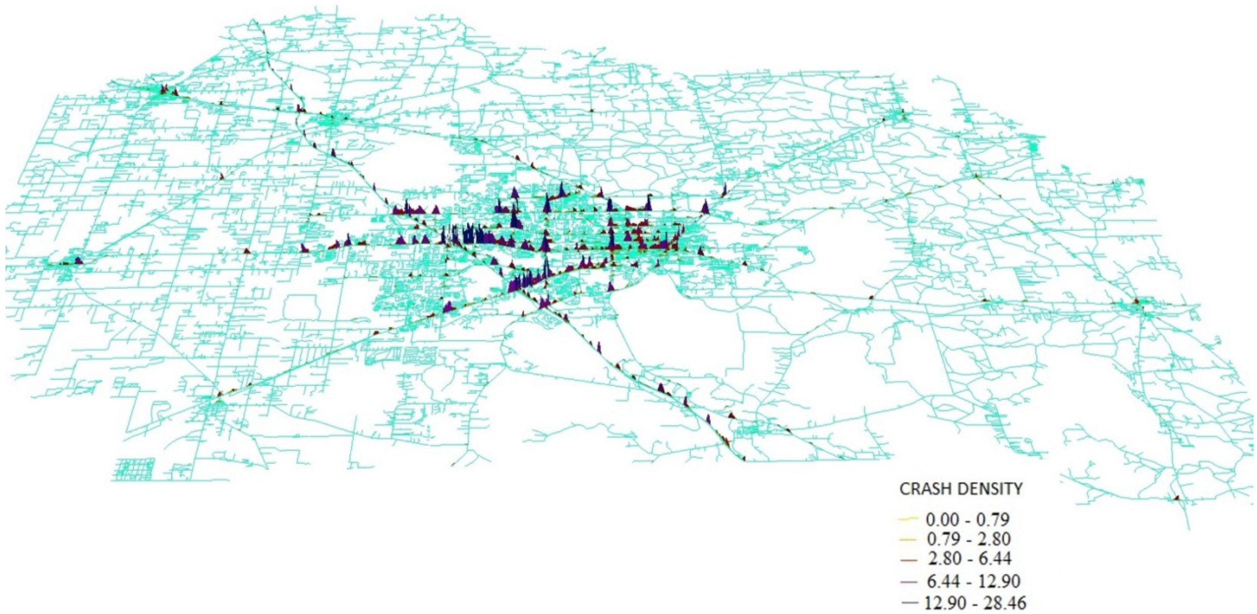


Figure B.81 Network KDE (3D) Application for the Alachua County

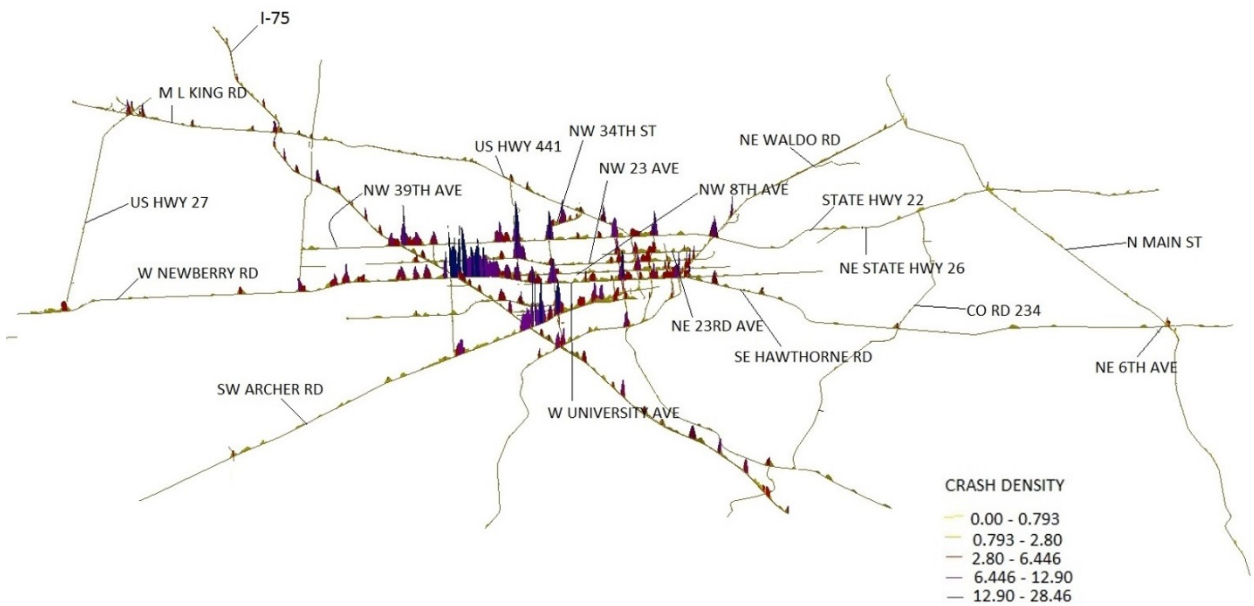


Figure B.82 High Crash Roadways Application for the Alachua County

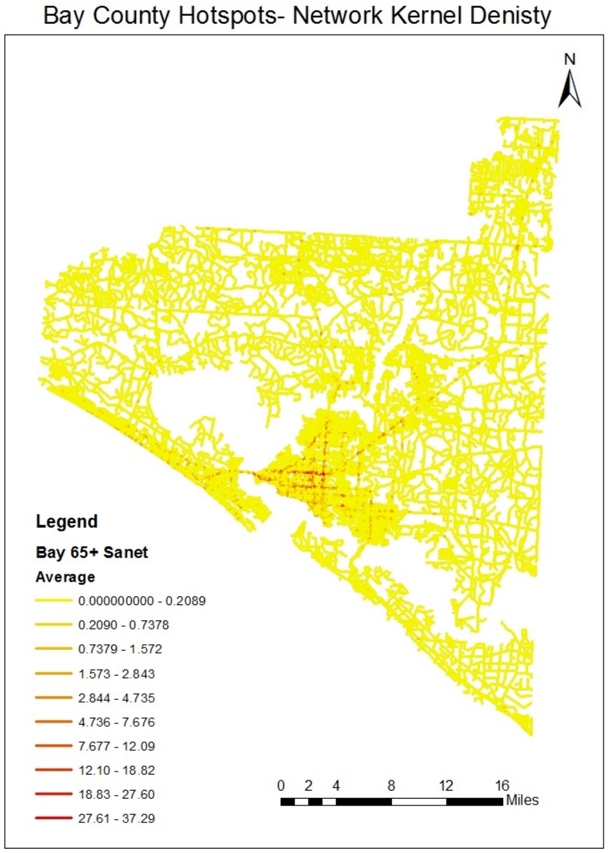


Figure B.83 Network KDE (2D) Application for the Bay County

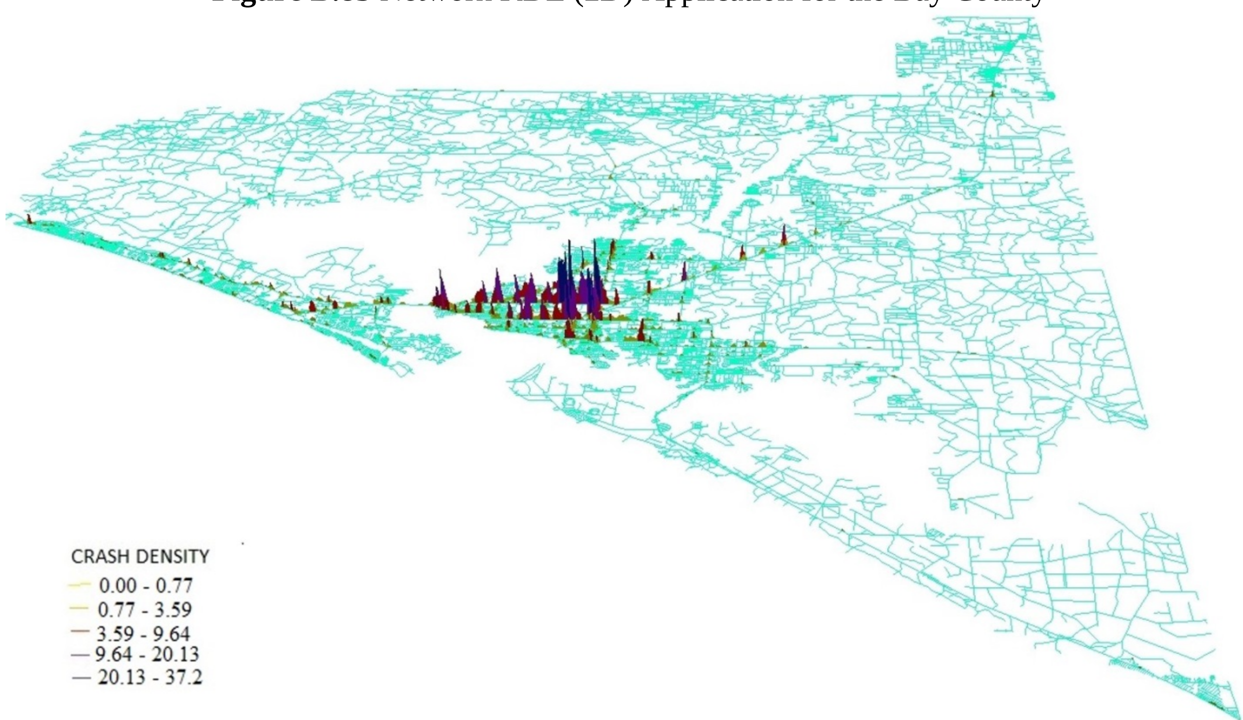


Figure B.84 Network KDE (3D) Application for the Bay County

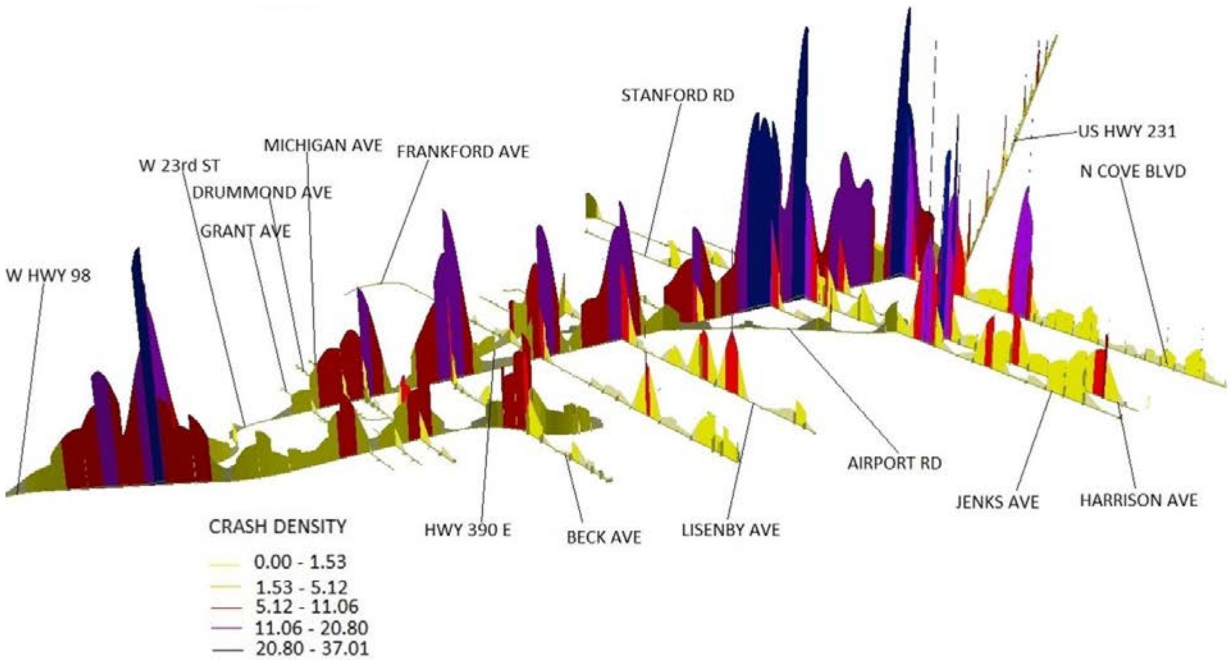


Figure B.85 High Crash Roadways Application for the Bay County

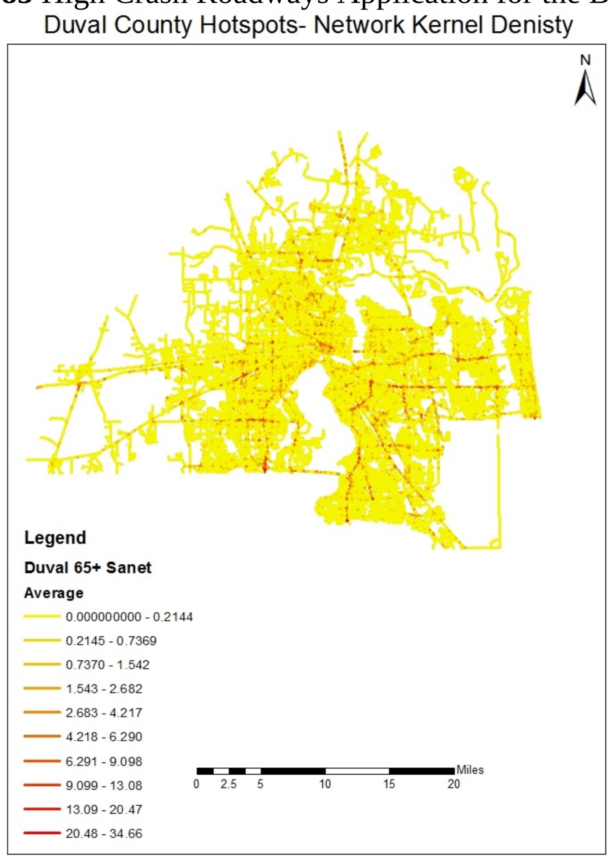


Figure B.86 Network KDE (2D) Application for the Duval County

Figure B.87 Network KDE (3D) Application for the Duval County

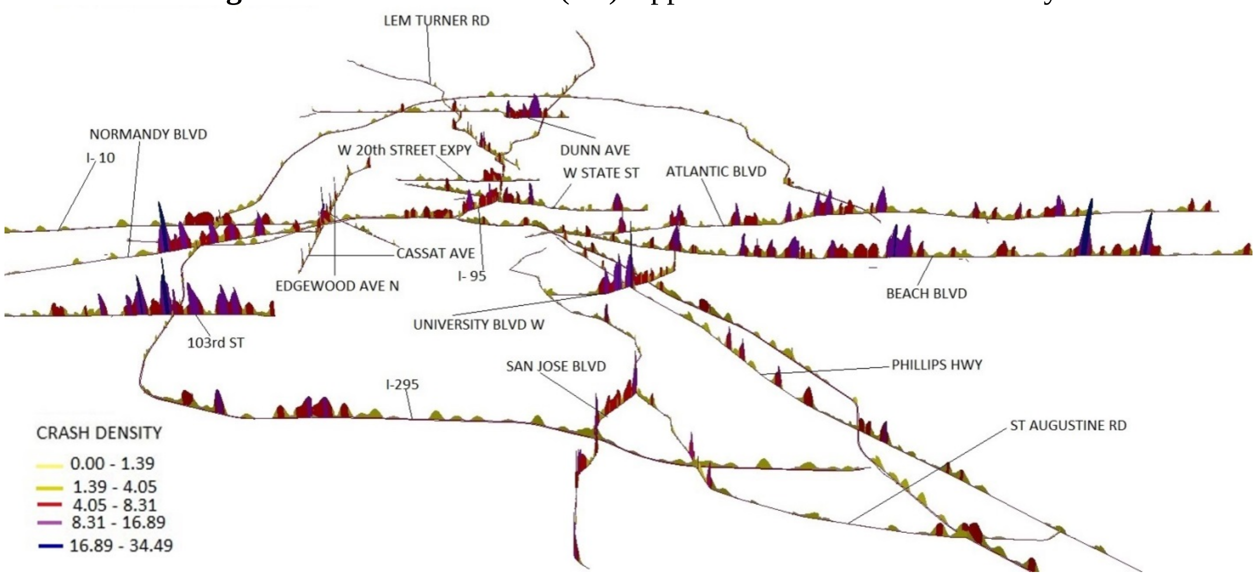


Figure B.88 High Crash Roadways Application for the Duval County

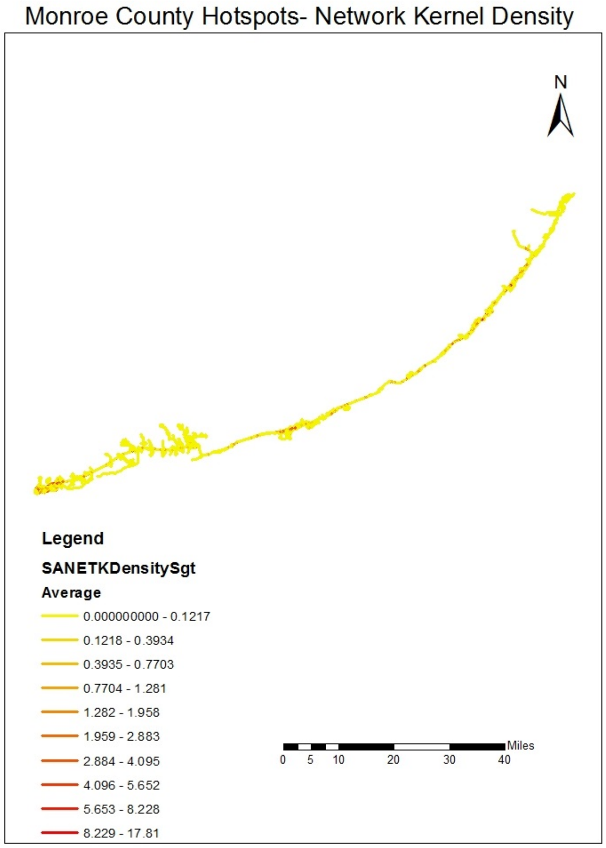


Figure B.89 Network KDE (2D) Application for the Monroe County

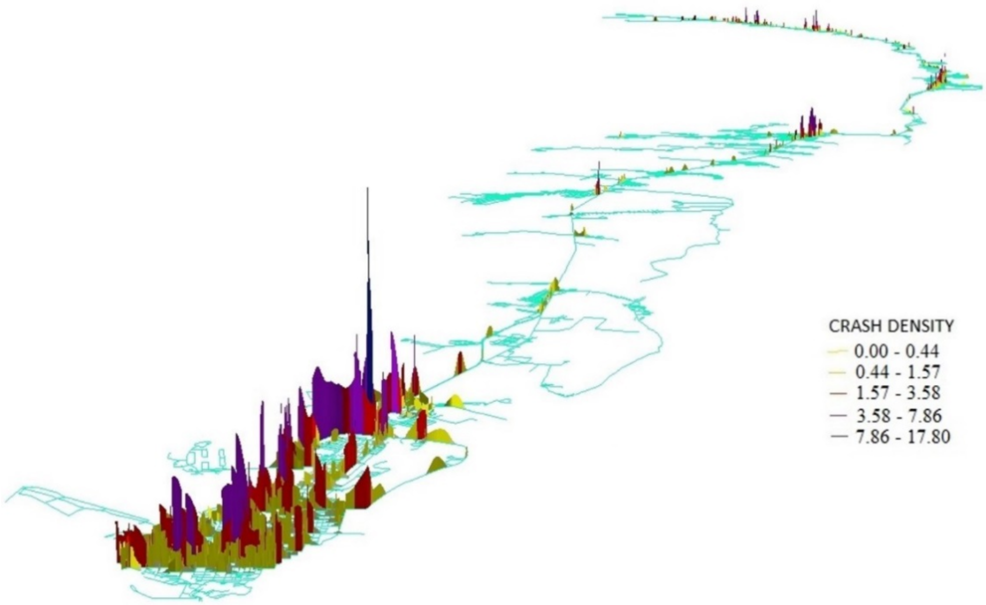


Figure B.90 Network KDE (3D) Application for the Monroe County

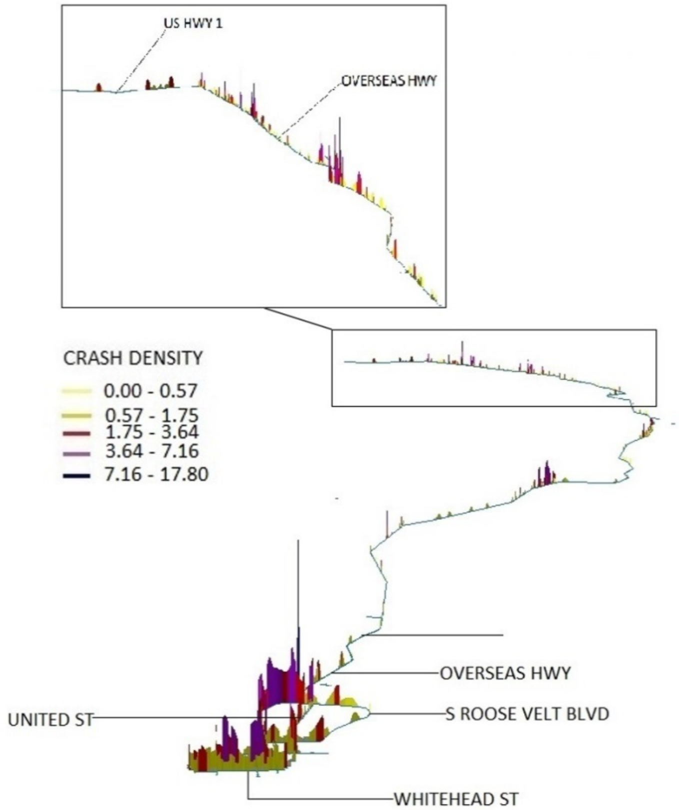


Figure B.91 High Crash Roadways Application for the Monroe County

Walton County Hotspots- Network Kernel Density

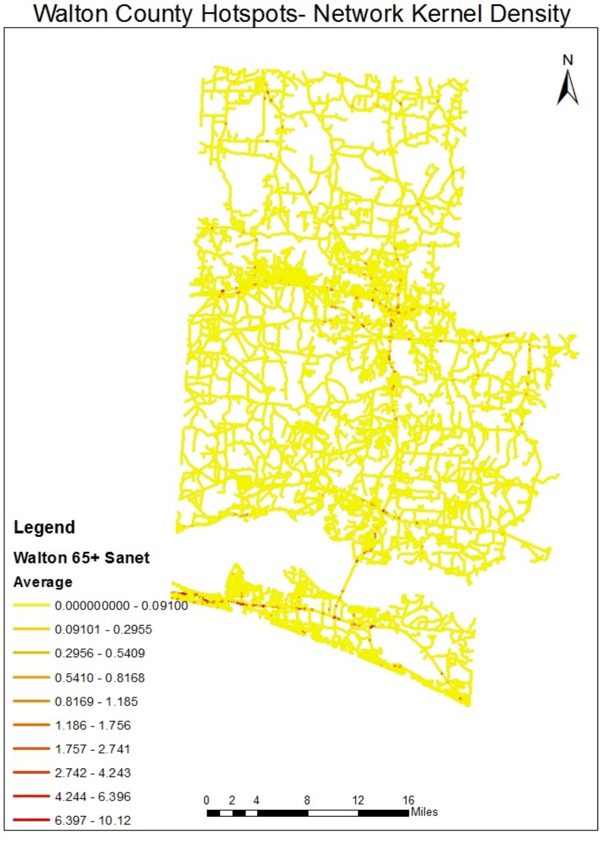


Figure B.92 Network KDE (2D) Application for the Walton County

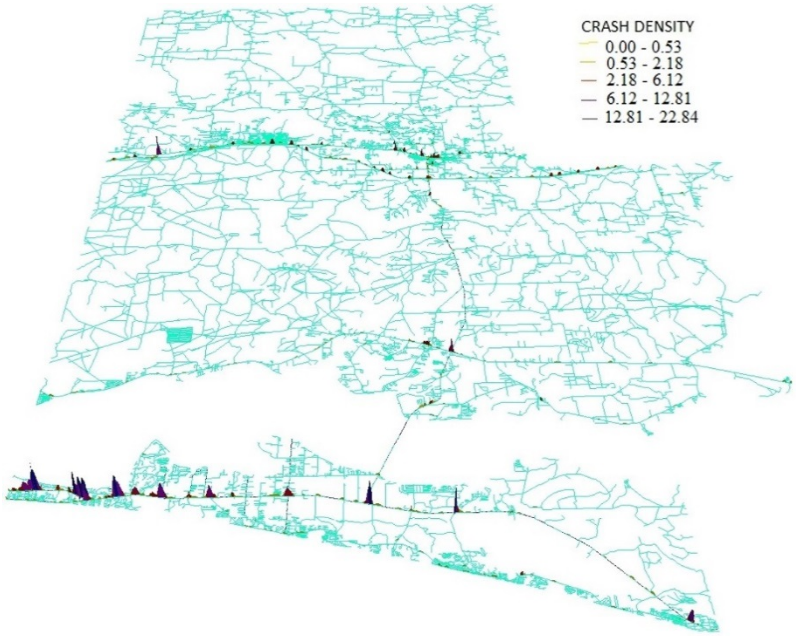


Figure B.93 Network KDE (3D) Application for the Walton County

Appendix C Hotspots

Table C.1 Hotspots for the Alachua County

Alachua County – Hotspot-1

Age Group	County Crashes		Newberry Road Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents 3-Mile	No. of Crashes per 1000 Residents 5-Mile	Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
65+	3,305	1,465	235	7,432	15,265	32	15	110 (46.8%)	145 (61.7%)
65-	21,219	8,166	1,033	48,655	119,973	21	9	492 (47.6%)	666 (64.4%)
	Hotspot- Newberry Rd: NW 76th Blvd. to NW 57th St.*								

Alachua County – Hotspot-2

Age Group	County Crashes		SW ARCHER RD						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents 3-Mile	No. of Crashes per 1000 Residents 5-Mile	Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
65+	3,305	1,465	163	5,091	13,796	32	12	66 (40.5%)	89 (54.6%)
65-	21,219	8,166	1,098	71,237	115,213	15	10	466 (42.4%)	611 (55.6%)
	Hotspot- SW Archer Rd: From SW 44 ST to SW 34th ST								

Table C.2 Hotspots for the Bay County

Bay County – Hotspot-1

Age Group	County Crashes: Total	County Crashes: Intersection Crashes	W 23rd Street Crashes: Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents: 3-Mile	No. of Crashes per 1000 Residents: 5-Mile	Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
65+	2,324	1,191	212	8,383	13,882	25	15	88 (41.5%)	126 (59.4%)
65-	12,568	5,235	682	34,058	54,679	20	12	263 (38.5%)	392 (57.4%)
	Hotspot- W 23rd St.: Stanford Rd. to Hwy. 77								

Bay County – Hotspot-2

Age Group	County Crashes: Total	County Crashes: Intersection Crashes	15th ST: Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents: 3-Mile	No. of Crashes per 1000 Residents: 5-Mile	Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
65+	2,324	1,191	95	6,761	12,154	14	8	61 (64.2%)	76 (80%)
65-	12,568	5,235	426	25,701	48,441	17	9	261 (61.2%)	322 (75.5%)
	Hotspot - 15th St. :From Chandlee Ave to Harrison Ave								

Table C.3 Hotspots for the Duval County

Duval County – Hotspot-1

Age Group	County Crashes		103rd Street Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	8,864	3,681	196	9,493	17,951	21	11	102 (52%)	115 (58.6%)
65-	65,862	21,369	1,214	58,853	113,617	21	11	589 (48.5%)	679 (56%)
	Hotspot- 103rd St. : Hillman Dr./McManus Dr. to Blanding Blvd.								

Duval County – Hotspot-2

Age Group	County Crashes		University Blvd W						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	8,864	3,681	220	13,797	28,508	16	8	103 (46.8%)	121 (55%)
65-	65,862	21,369	1,036	66,206	150,506	16	7	474 (45.7%)	554 (53.4%)
	Hotspot- University Blvd W: From Saint Augustine Rd to Beach Blvd								

Table C.4 Hotspots for the Monroe County

Monroe County – Hotspot-1

Age Group	County Crashes: Total	County Crashes: Intersection Crashes	Overseas Hwy/ College Road Crashes: Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents: 3-Mile	No. of Crashes per 1000 Residents: 5-Mile	Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
65+	908	407	21	2,882	3,629	7	6	18 (85.7%)	19(90.4%)
65-	5,039	1,785	59	17,498	21,091	3	3	31 (52.5%)	36 (61%)
	Hotspot- Overseas Hwy/ College Rd								

Monroe County – Hotspot-2

Age Group	County Crashes: Total	County Crashes: Intersection Crashes	Overseas Hwy/ Tarpon Basin Dr.: Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents: 3-Mile	No. of Crashes per 1000 Residents: 5-Mile	Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
65+	908	407	18	998	1,789	18	10	13 (72.2%)	16 (88.8%)
65-	5,039	1,785	46	4,308	6,352	11	7	32 (69.5%)	35 (76%)
	Hotspot- Overseas Hwy/ Tarpon Basin Dr.								

Table C.5 Hotspots for the Walton County

Walton County – Hotspot-1

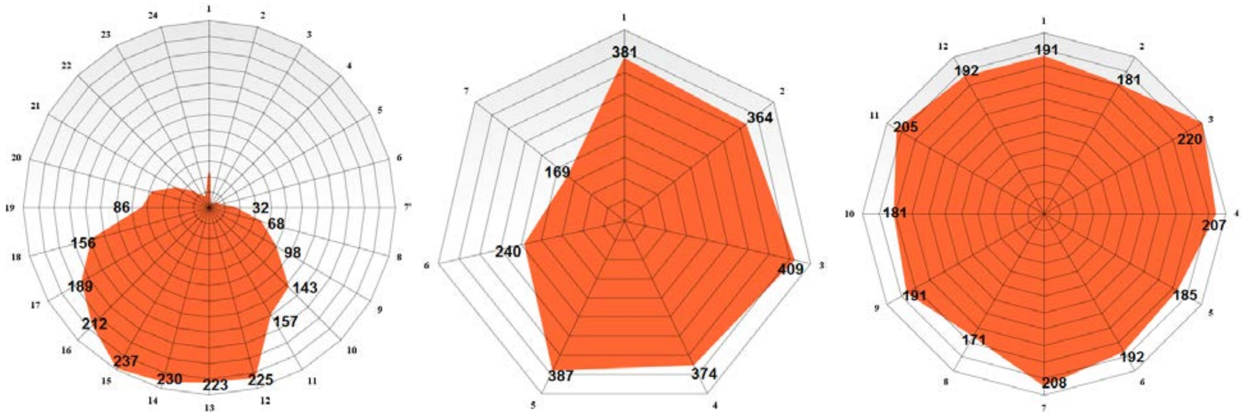
Age Group	County Crashes		U.S. Hwy. 98/ U.S. Hwy 331 S Crashes						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
65+	1,166	442	22	1070	2545	21	9	14 (63.6%)	20 (91%)
65-	1,801	530	22	1127	3134	20	7	12 (54.5%)	16 (72.7%)
	Hotspot- U.S. Hwy. 98/ U.S. Hwy 331 S								

Walton County – Hotspot-2

Age Group	County Crashes		Emerald Coast PKWY W						
	Total	Intersection Crashes	Total	No. of Residents in 3-Mile Radius	No. of Residents in 5-Mile Radius	No. of Crashes per 1000 Residents		Intersection Crashes	Crashes at Intersection/ Influenced by Intersection
						3-Mile	5-Mile		
50+	1,166	442	174	4,036	4,883	43	36	89 (51%)	113 (65%)
50-	1,801	530	200	3,365	4,157	59	48	95 (47.5%)	127 (63.5%)
	Hotspot- Emerald Coast PKWY W: From Professional to Sandestin Blvd N								

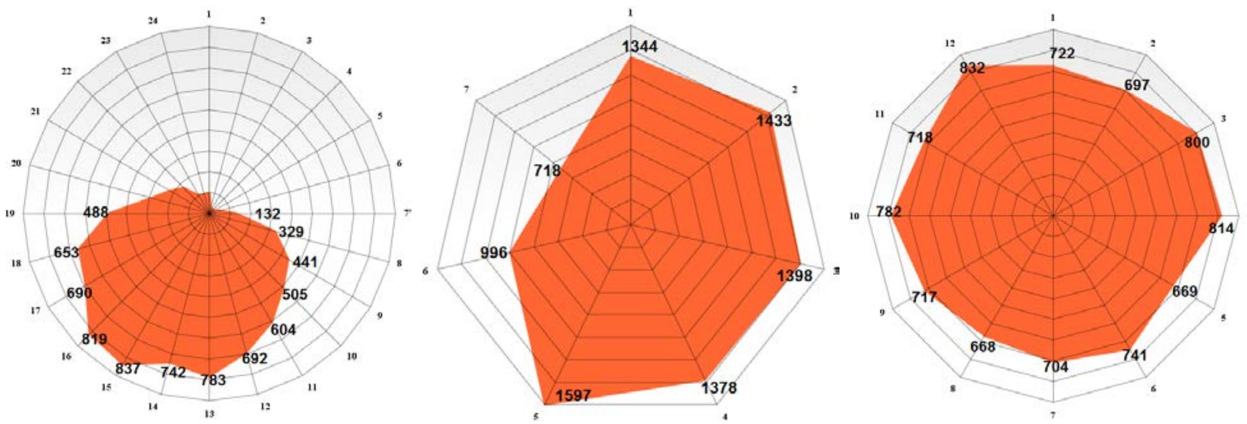
a. Hourly b. Daily c. Monthly

Figure D.94 Temporal Analysis of the Alachua County



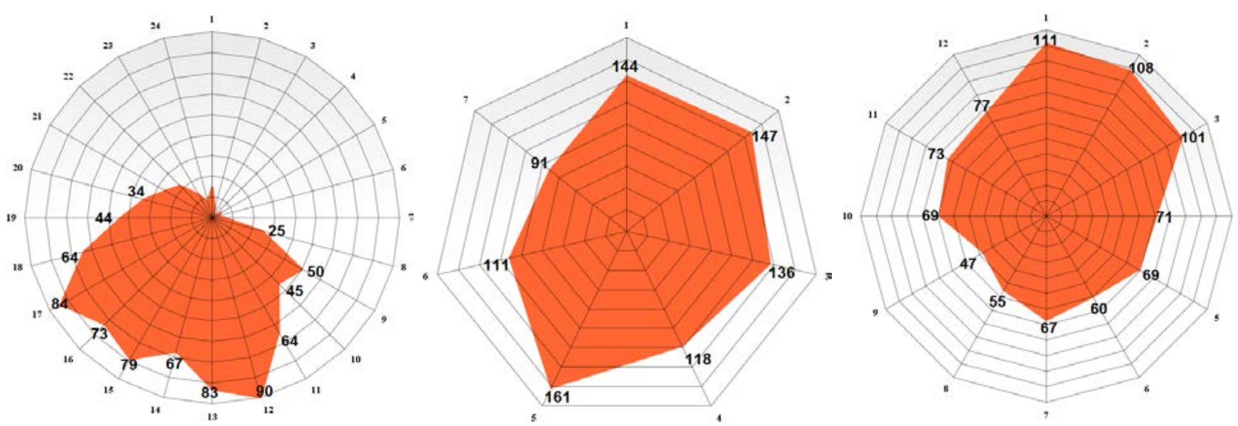
a. Hourly b. Daily c. Monthly

Figure D.95 Temporal Analysis of the Bay County



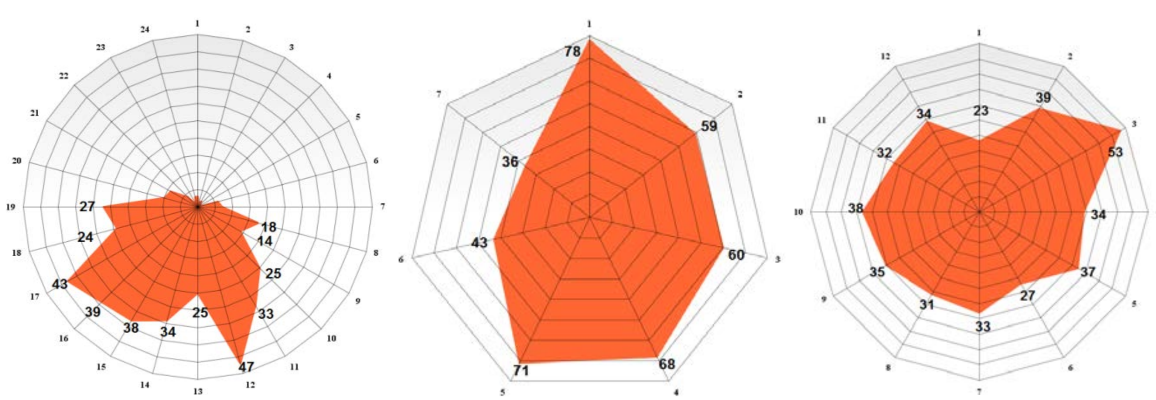
a. Hourly b. Daily c. Monthly

Figure D.96 Temporal Analysis of the Duval County



a. Hourly b. Daily c. Monthly

Figure D.97 Temporal Analysis of the Monroe County



a. Hourly b. Daily c. Monthly

Figure D.98 Temporal Analysis of the Walton County

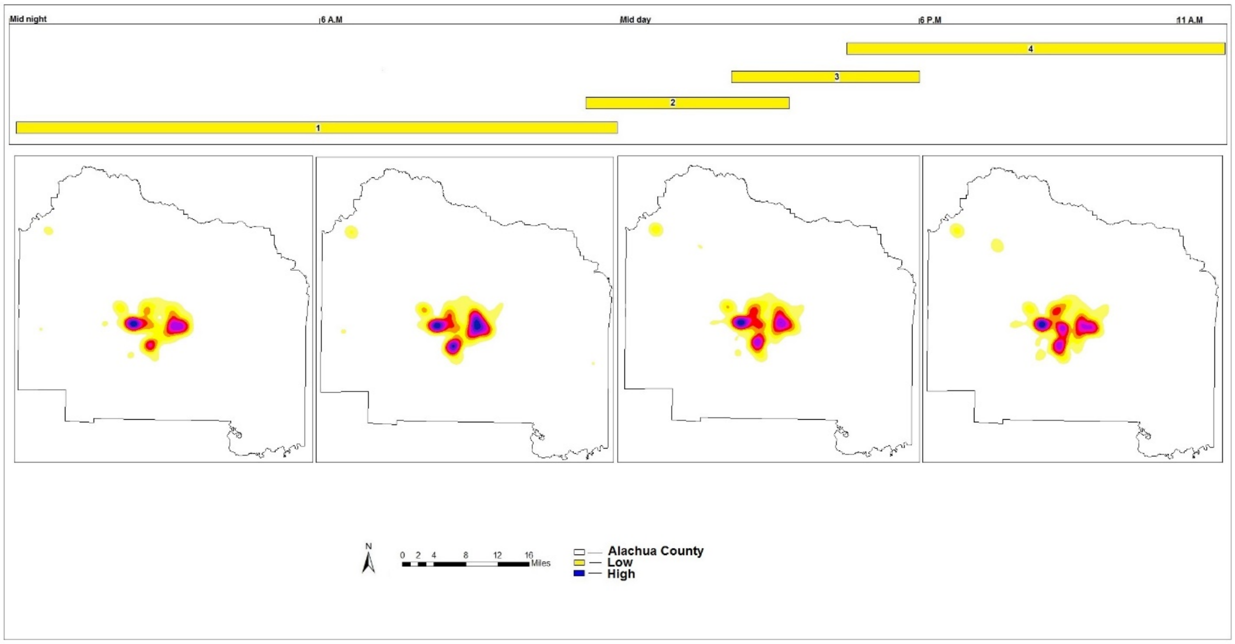


Figure E.99 Spatio-temporal Analysis for the Alachua County

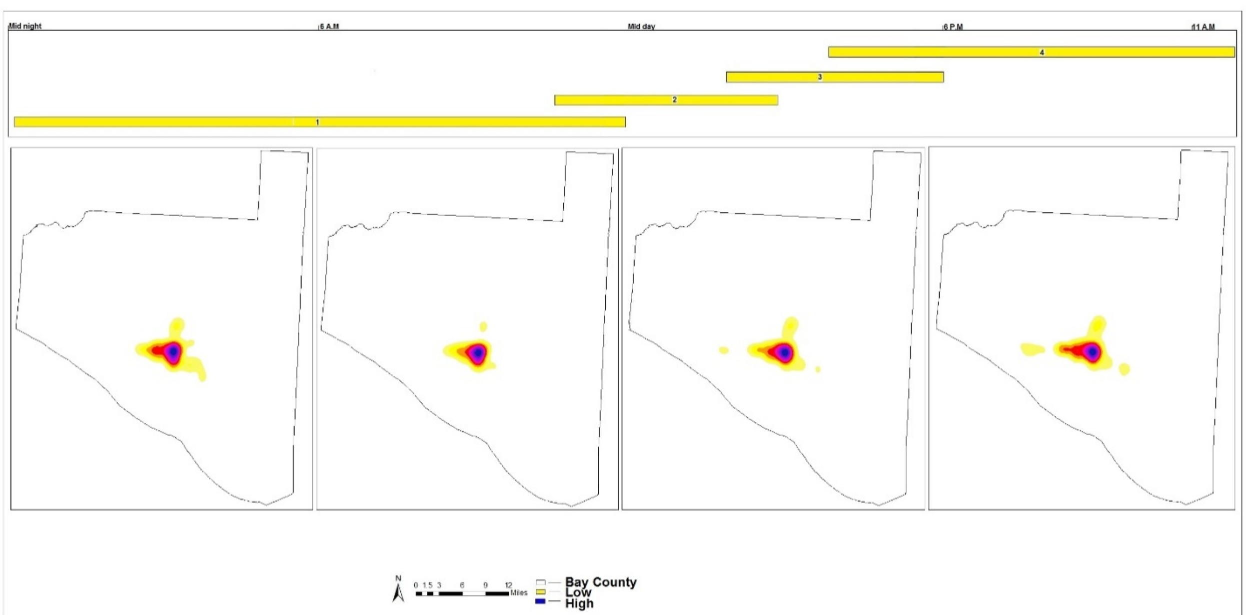


Figure E.100 Spatio-temporal Analysis for the Bay County

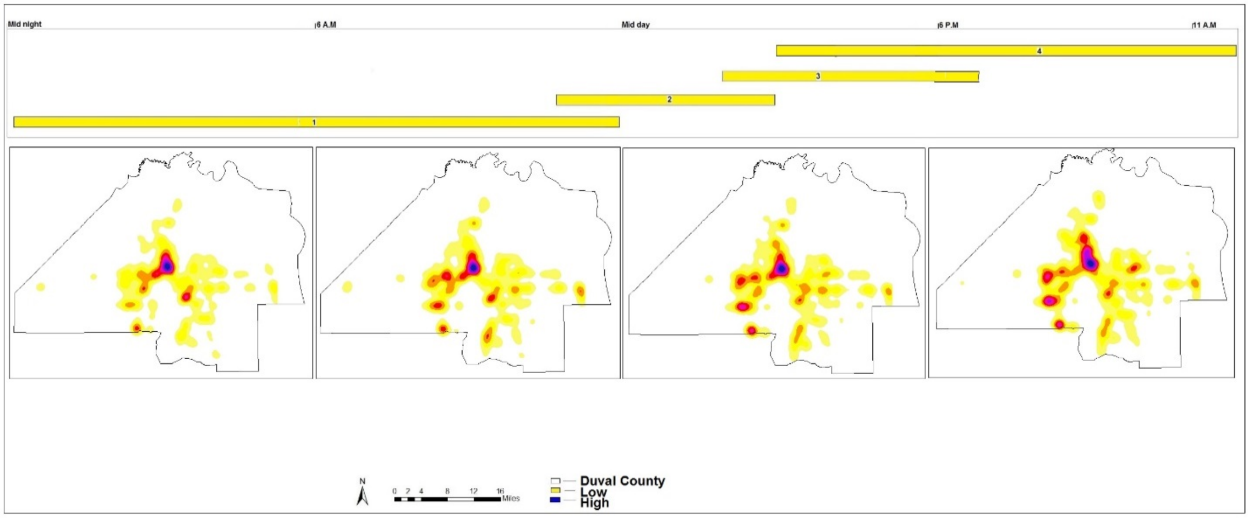


Figure E.101 Spatio-temporal Analysis for the Duval County

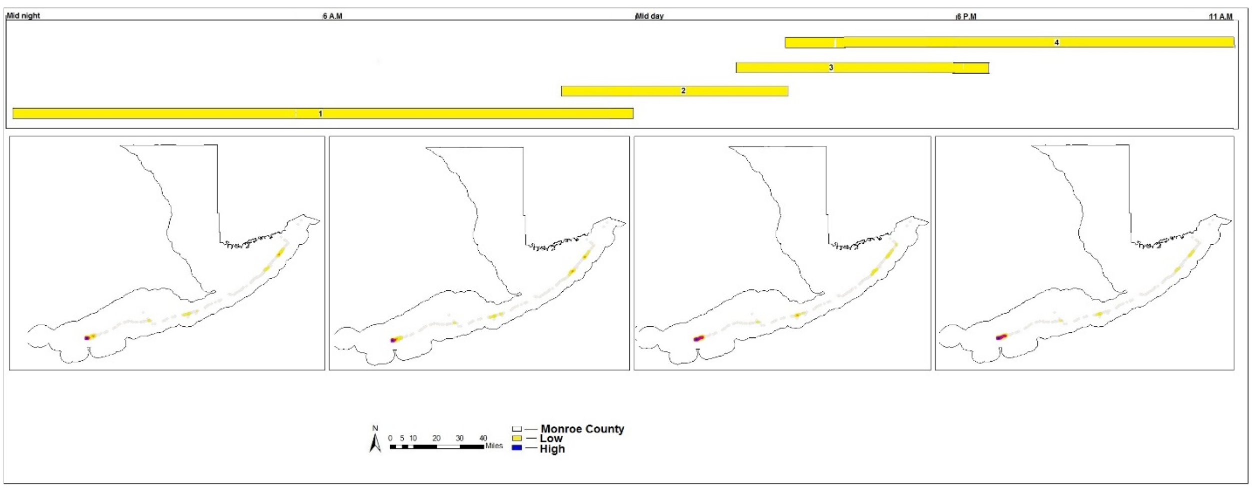


Figure E.102 Spatio-temporal Analysis for the Monroe County

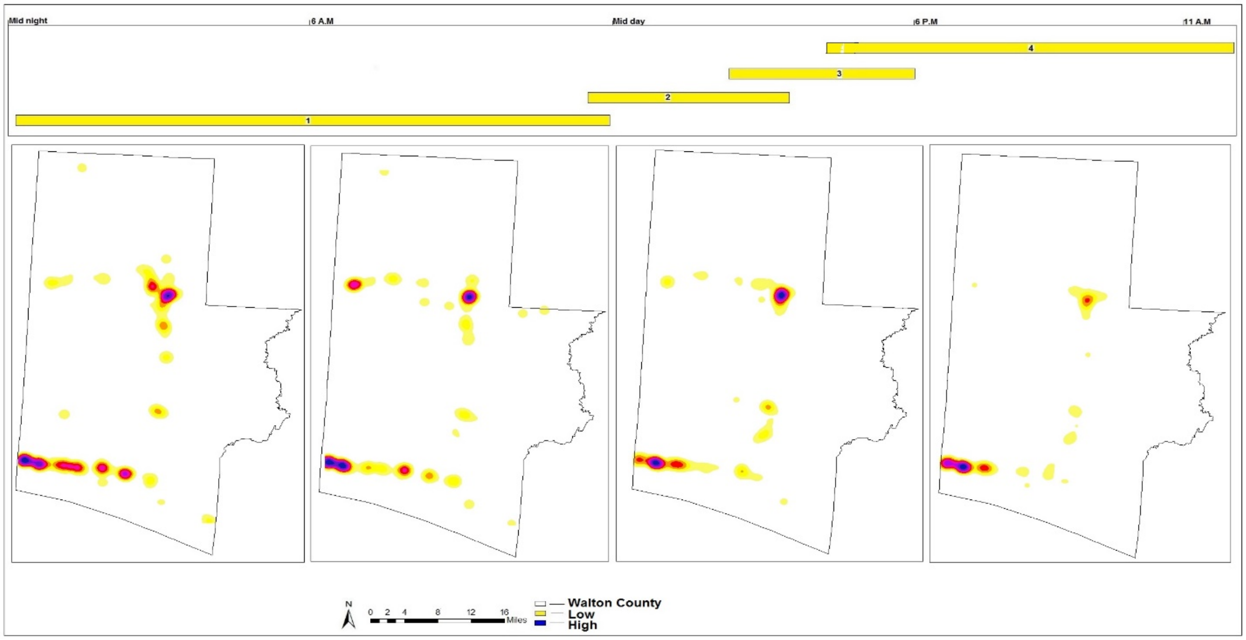


Figure E.103 Spatio-temporal Analysis for the Walton County

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