A Gis Safety Study And A County-level Spatial Analysis Of Crashes In The State Of Florida

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A GIS SAFETY STUDY AND A COUNTY-LEVEL SPATIAL ANALYSIS OF CRASHES IN THE STATE OF FLORIDA

by

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ABSTRACT

The research conducted in this thesis consists of a Geographic Information Systems (GIS) based safety study and a spatial analysis of vehicle crashes in the State of Florida. The GIS safety study is comprised of a County and Roadway Level GIS analysis of multilane corridors. The spatial analysis investigated the use of county-level vehicle crash models, taking spatial effects into account.

The GIS safety study examines the locations of high trends of severe crashes (includes incapacitating and fatal crashes) on multilane corridors in the State of Florida at two levels, county level and roadway level. The GIS tool, which is used frequently in traffic safety research, was utilized to visually display those locations.

At the county level, several maps of crash trends were generated. It was found that counties with high population and large metropolitan areas tend to have more crash occurrences. It was also found that the most severe crashes occurred in counties with more urban than rural roads. The neighboring counties of Pasco, Pinellas and Hillsborough had high severe crash rate per mile.

At the roadway level, seven counties were chosen for the analysis based on their high severe crash trends, metropolitan size and geographical location. Several GIS maps displaying the safety level of multilane corridors in the seven counties were generated. The GIS maps were based on a ranking methodology that was developed in research that evaluated the safety

condition of road segments and signalized intersections separately. The GIS maps were supported by Excel tables which provided details on the most hazardous locations on the roadways. The results of the roadway level analysis found that the worst corridors were located in Pasco, Pinellas and Hillsborough Counties. Also, a sliding window approach was developed and performed on the ten most hazardous corridors of the seven counties. The results were graphs locating the most dangerous 0.5 miles on a corridor.

For the spatial analysis of crashes, the exploratory Moran's I statistic test revealed that crash related spatial clustering existed at the county level. For crash modeling, a full Bayesian (FB) hierarchical model is proposed to account for the possible spatial correlation among crash occurrence of adjacent counties. The spatial correlation is realized by specifying a Conditional Auto-regressive prior to the residual term of the link function in standard Poisson regression.

Two FB models were developed, one for total crashes and one for severe crashes. The variables used include traffic related factors and socio-economic factors. Counties with higher road congestion levels, higher densities of arterials and intersections, higher percentage of population in the 15-24 age group and higher income levels have increased crash risk. Road congestion and higher education levels, however, were negatively correlated with the risk of severe crashes. The analysis revealed that crash related spatial correlation existed among the counties. The FB models were found to fit the data better than traditional methods such as Negative Binomial and that is primarily due to the existence of spatial correlation.

Overall, this study provides the Transportation Agencies with specific information on where improvements must be implemented to have better safety conditions on the roads of Florida. The study also proves that neighboring counties are more likely to have similar crash trends than the more distant ones.

To My Beloved Family

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LIST OF ACRONYMS/ABBREVIATIONS

ADT	Average Daily Traffic
CAR	Crash Analysis Rosources
DVMT	Daily Vehicle Miles Traveled
DIC	Deviance Information Criterion
FDOT	Florida Department of Transportation
FB	Full Bayesian
FHWA	Florida Highway Authority
GIS	Geographic Information Systems
NB	Negative Binomial
RCI	Roadway Characteristics Inventory
VMT	Vehicle Miles Traveled

CHAPTER 1. INTRODUCTION

Traffic safety is one of the most continuously researched topics in the field of transportation engineering. Traffic crashes lead to injuries, some of which can be fatal, and they also cause traffic congestion. An estimated 1.2 million people are killed, and as many as 50 million people are injured in road crashes annually worldwide (Nambisan et. al, 2007). According to the National Highway Traffic Safety Administration, more than 42,600 people were killed in 2006 and about 2.6 million were injured in traffic-related crashes on the roads of the United States (NHTSA, 2006).

There were 256,200 traffic accidents in Florida in 2006; of which 3084 were fatal crashes which resulted in 3,365 deaths (FHSMV, 2006). The fatality rate on Florida roads is 1.65 deaths per 100 million Vehicle Miles Traveled (VMT), which is higher than the national average of 1.42 deaths per 100 million VMT (FHSMV, 2006). Among different road types, principal and minor arterials account for 58% of the total fatal crashes in Florida (NHTSA, 2004). The proportion and total number of fatal crashes on principal arterials (excluding freeways and toll roads) in Florida were highest in the nation (compared to any other state) in 2003.

The U.S. congress passed the 1966 Highway Safety Act in order to improve highway safety, which requires the state Departments of Transportation (DOTs) to develop and implement safety improvement programs. The identification of hazardous locations based on crash history and spatial relationships, is one of the main cornerstones in the process of improving highway safety, guaranteeing proper transportation planning and efficient implementation of improvement programs.

The main objectives of this thesis are:

- Identify severe crash prone locations at macro and micro levels in Florida's state road network using GIS tools.
- Investigate the spatial association of county-level road crash patterns with factors relating to county-level transportation operation and planning and socio-economic factors.

The research steps involved in this thesis are as follows:

1. Perform an exploratory district and county level GIS analysis of crash trends in Florida.
2. Identify and select counties with high trends of severe crashes.
3. Identify hazardous locations on the multilane corridors of the chosen counties.
4. Display those locations in GIS.
5. Present tables and graphs of those locations with more details.
6. Explore whether spatial correlation with respect to crash trends occur among Florida's 67 counties using the Moran's I statistic tool.
7. Generate FB models with spatial attributes.
8. Discuss the results of the FB models and conclude if spatial correlation exists.

The thesis is organized as follows: Chapter 2 provides a review of previous research that used GIS in assessing safety at county and roadway level. It also looks into literature that dealt with spatial association and area-level crash models. Chapter 3 describes the data collection process carried out for the multilane corridor GIS safety analysis. Chapter 4 presents the methodology and findings of the district and county level GIS safety study (Macro-GIS Analysis). Chapter 5 presents the methodology and results of the roadway level GIS analysis (Micro-GIS Analysis). Chapter 6 describes a more detailed approach to roadway level safety analysis (Sliding Window Analysis) and presents its results. Chapter 7 provides a description of the data collection process and the methodology followed in the spatial analysis while Chapter 8 presents the results and discussions. Chapter 9 concludes the findings of this thesis and provides directions for future research.

CHAPTER 2. LITERATURE REVIEW

2.1 County Level GIS Analysis

There are several published studies that used GIS analysis in order to evaluate crash trends. Aguero-Valverde and Jovanis (2006) used county-level GIS mapping to display the distribution of injury and fatal crash trends among the 67 counties of the State of Pennsylvania. The authors found that the highest frequency of fatal crashes occurred in the largest metropolitan areas of the state. It was also found that the highest rates of fatal crashes occurred in counties with low total number of crashes. This observation was attributed to the fact that fatal crashes rarely occur and a small increase in the number of those crashes tends to magnify the crash rate especially if those counties have low exposure, DVMT (daily vehicle miles traveled), values.

Abdel-Aty and Radwan (1998) also used GIS to analyze crash trends at the county level. The study found that counties with high population tend to have higher crash frequencies. The study also looked into the percentage of severe crashes to total crashes. The analysis concluded that rural counties tend to have higher severe crashes percentages than urban counties. Similar results were also found when the study looked at the distribution of drug and alcohol related crashes. The authors suggested that there might be a strong relationship between those two types of crashes.

GIS analysis has also been widely used to analyze crash types at county level. Khan et. al (2008) used GIS in order to select counties that displayed similar ice related crash rates in Wisconsin.

Kant (2005) analyzed the relationship between crash types and land-use in Florida using GIS. The study found that rear-end crashes and right turn crashes are more common on urban roads than on rural roads. This could be attributed to the fact that signalized intersections and traffic jams are more common on urban roads than rural roads. The study also found that "ran-off" road type crashes were more common on rural roads than on urban roads.

2.2 Roadway Level GIS Analysis

The process of rating road safety using GIS involves the mapping of roads and visually displaying the varying safety conditions of road elements. This practice provides a helpful indicator to agencies on locations where improvements to the road are recommended in order to improve the safety condition. This is achieved by altering the size and the color of road elements, namely road segments and signalized intersections, in GIS.

Kulikowski and Bejleri (2006) used color coding and thickness alteration to indicate varying safety conditions on a road network as seen in Figure 2-1 and Figure 2-2.

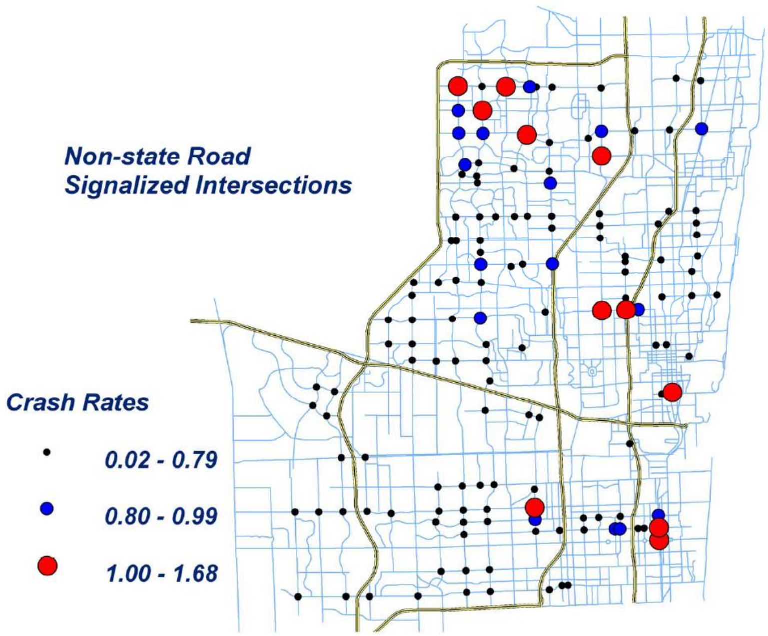

Figure 2-1: Example 1 of Use of Color and Thickness in GIS (Kulikowski and Bejleri, 2006)

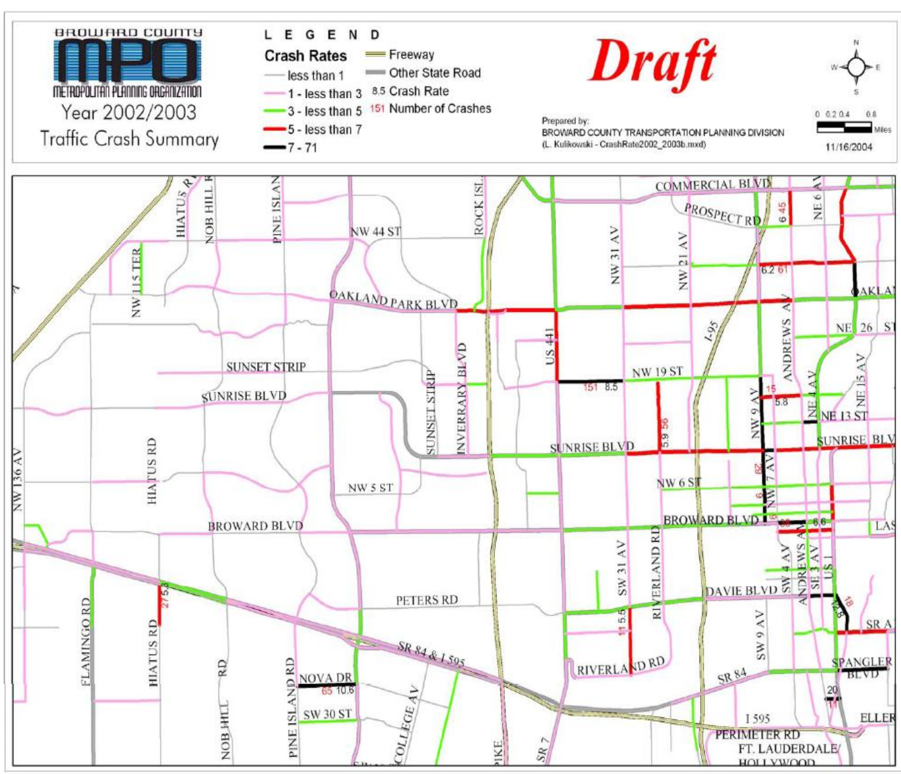

Figure 2-2: Example 2 of Use of Color and Thickness in GIS (Kulikowski and Bejleri, 2006)

2.2.1 Methods of Rating the Safety of Roadway Elements

In order to be able to visually display the varying road safety condition, a methodology had to be devised to reflect the safety condition of a road element in comparison with another.

Kulikowski and Bejleri (2006) used a naive technique to rate the safety condition of road elements. The authors separated signalized intersections from road segments in a road network. Signalized intersections were ranked according to the rate of crashes per volume entering the intersection; the higher the rate, the higher the rank, the worse the intersection. Road segments were also ranked in a similar manner; the frequency of crashes on a road segment was normalized by the VMT of that particular road segment.

The Minnesota DOT (Hallmark et. al., 2002) also separated road segments from signalized intersections to evaluate the safety condition on roadway elements. Road segments and intersections were ranked according to each of the following criteria:

- Crashes per mile for road segments (i.e. crash density); total crashes for intersections
- Crash rate per VMT for road segments; crash rate per volume entering intersection
- Severity Rate: an index similar to crash rate where fatal crashes have a weight of 10, injury crashes a weight of 4, and property damage have a weight of 1.
- Crash Cost: Each crash is multiplied by its monetary cost, and the total sum for all crashes is calculated. The final number is total cost for intersections and cost per mile for segments.

The sum of the ranks of the criteria for each road segment and intersection were calculated; the higher the ranking (i.e. lowest sum) the worse the safety condition.

Geurts et. al. (2003) proposed splitting a road corridor into equal 1 mile segments. This method did not separate a corridor's road segments from signalized intersections. The corridor was treated as a monolithic entity. The 1 mile segments were ranked according to the frequency of the crashes within the 1 mile segments, with more weight given to severe and fatal injury crashes.

The Federal Highway Authority (FHWA) proposed the use of the Sliding Window Analysis. In this type of analysis, the user defines an analysis window which 'slides' along the road in an incremental fashion. The window that has the highest crash frequency is considered to be the most dangerous. The final output of this analysis is a table and a map indicating high crash locations. The FHWA provides a GIS add-on package that performs such type of analysis on its website. The sliding window analysis considered signalized intersections and road segments as one entity.

The safety rating methods that were discussed are widely used by researchers and agencies. However, the roadway level analysis in this thesis focuses specifically on severe type crashes (incapacitating and fatal crashes). Some methods for example, used the VMT in order to calculate crash rates. Since severe crashes occur in low numbers, it is already well established that an increase in VMT tends to decrease the rate of severe crashes which would mask the existence of a problem at a particular location of the road. This study will attempt at devising a ranking methodology for road safety rating that specifically targets severe crashes. The results of the ranking methodology will be displayed in GIS. A Sliding Window Analysis will then be conducted on the most hazardous corridors to specify the exact locations with high severe crashes.

2.3 Spatial Analysis

2.3.1 Area-level Crash models

The use of area-level aggregation such as, states, counties and metropolitan areas in crash models is very common (Quddus, 2008). In most roadway safety studies, crashes are grouped in spatial units ranging from counties and zip-codes to intersection and road section levels (Miaou 2003; Abdel-Aty and Radwan, 2000). The main objective of such a practice is to establish a relationship between road infrastructure, traffic-related factors, socio-economic and demographic factors with the crash frequencies and crash rates at various area units. Noland and Oh (2004) used county-level data for Illinois to estimate the expected number of crashes using infrastructure characteristics and demographic factors as independent variables. Aguero-Valverde and Jovanis (2006) used transportation related factors (e.g. VMT and road lengths), socioeconomic factors (e.g. age breakdown and male population ratio) and environmental factors (e.g. precipitation) to model crash risk at county-level in the State of Pennsylvania. In addition to several traffic related factors, Quddus (2008) suggested several socio-economic factors, such as area depravation and number of employees within 'ward-levels' in London in the models he developed. Hadayeghi et. al. (2003) estimated crashes within planning zones of the city of

Toronto whereas Graham and Glaister (2003) developed macro-level crash prediction models to estimate the number of pedestrian crashes at ward level in England.

Crash disaggregation is also employed in order to explore factors leading to different types of crashes. Crashes can be disaggregated by the type (rear-end or angle crashes), severity (fatal injuries, severe injuries and light injuries) or year of occurrence (temporal). Levin et. al. (1995) looked into the relationship between alcohol consumption and injury severity in geographic units in Honolulu. Aguero-Valverde and Jovanis (2006) disaggregated fatal crashes from injury crashes. It was found that fatal crashes tend to increase with DVMT at a decreasing rate. It was also found that counties with higher poverty levels have higher risk of fatal crashes and variables corresponding to age group breakdown were found to be significant in both fatal and injury crash models. Quddus (2008) also developed separate Negative Binomial (NB) models for fatal, severe and light crashes respectively at 'geographical ward' level in London, U.K.

2.3.1.1 Negative Binomial Models in Crash Predictions

Most of the studies already described used Negative Binomial in crash modeling at area-level. Negative Binomial is very popular with models that involve non-negative count type of data, which is the case in crashes. NB models are an adaptation of Poisson models, taking into account overdispersion that arises in crash count data (e.g. Abdel-Aty and Radwan, 2000; Shankar et. al, 1995). Other studies that employed NB include (Amoros et al., 2003) who developed NB models at county level in France that included interactions between road type and county.

Kim et. al. (2006) integrated NB count models with GIS to link land use, population and economic development with crash using a 0.1 square mile grid structure from Hawaii. The authors also recommended the use of spatial statistical analysis when developing relationships between area-wide variables and traffic crashes.

The main limitation that arises from the use of traditional NB models is that it ignores the existence of spatial correlation between observations which violates the traditional Gauss-Markov assumptions in traditional regression modeling.

2.3.1.2 Moran's I Statistic

The Moran's I statistic is an exploratory statistical tool used to assess whether spatial association for a certain factor (crashes for example) exists among area units. There were several studies that used GIS maps and Moran's I statistic to explore whether spatial correlation between area units exists. Fang et. al. used the Moran's I statistic to explore whether county-level spatial clustering of the Hemorrhagic fever with renal syndrome (HFDR) endemic existed in China. It was found that spatial correlation existed and was significant.

Khan et. al. (2008) used the spatial statistic add-on package in the GIS software ArcMap 9.2 to conduct the Moran's I statistic to investigate whether neighboring counties in Wisconsin exhibited similar trends of ice-related crashes. Crash rates along with the results of the Moran's I analysis were displayed in GIS and used to select counties for which the network cross K-function analysis was conducted to investigate the relationship between ice-related crashes and bridge locations.

Figure 2-3 is an example of incorporating the Moran's I statistic with GIS. It shows a map of the 1999 average verbal Scholastic Aptitude Test (SAT) scores in the lower 48 states of the USA. A visual overview of the map indicates that spatial clustering of SAT scores at state level exists. The middle states tend to have higher scores whereas eastern states have lower scores. The Moran's I result was positive and significant which supports the visual indicators of similar average SAT results among neighboring counties.

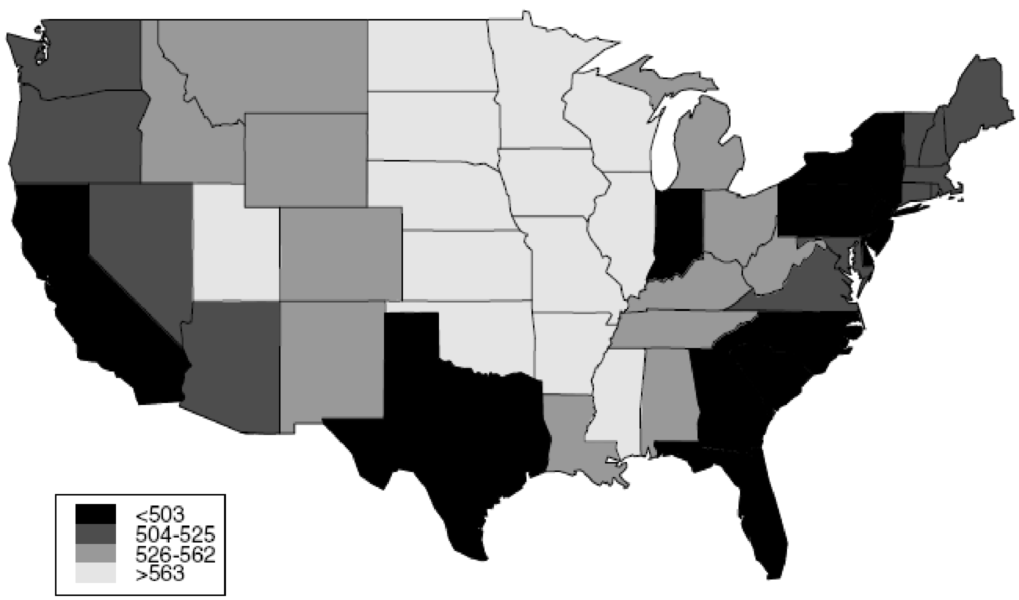

Figure 2-3: GIS Map Example of SAT Scores (Banerjee et. al., 2003)

2.3.1.3 The Full Bayesian Approach

There are several previous studies that took into account the existence of spatial correlation between observations (e.g. crashes) among locations (e.g. roadways or intersections) or area units (e.g. counties). Recently, the FB hierarchical approach has been suggested as a useful, though complex approach that is believed to better account for uncertainty in data used and provides more detailed causal inferences and more flexibility in selecting crash count distributions. The FB approach is a methodology that has become very common in modeling crashes at area level because of their ability to account for spatial correlation.

In their ground-breaking research, Miaou et. al. (2003) adopted a Poisson-based FB methodology to estimate county-level fatal, incapacitating and non-incapacitating vehicle crashes in the State of Texas. The main limitation of this study, however, was the use of several surrogate variables to account for transportation related factors. Aguero-Valverde and Jovanis (2006) also employed a FB approach to estimate county-level injury and fatal crashes risks in Pennsylvania. The authors compared the results with the traditional NB models. It was found that spatial correlation existed in the injury crash models but not in the fatal crash models. Time trend and space-time interactions were also found to be significant. FB models were found to fit the data better than NB. The main limitation of the study, however, is that some of the variables selected for the models appear to be correlated such as DVMT and length of roads in each county.

Quddus (2008) also compared FB models to NB models to estimate the number of crashes at varying severity levels for 'ward' area units. FB model parameter estimates were found to be similar to NB. The spatial correlation parameters also came out to be significant and very high. This was expected since the analysis was at ward-level which are much smaller in size than counties or other common area-aggregated entities. The smaller the aggregated area, the more it shares common features with its neighbors. The main limitation of the study was the use of a surrogate measure to account for exposure to crashes since VMT figures were not available.

The spatial analysis in this thesis follows a similar pattern to the literature that has been presented in this section. FB models were developed and analyzed. The models goodness of fit was compared with traditional NB models. The results of FB model were also checked for consistency with the conclusions of the Moran's I statistic. In this study, however, surrogate measures were not used for traffic related crash risk factors. In addition, new factors and several interaction terms that were not discussed in previous literature were introduced, such as the density of intersections and the average travel time to work within a county.

CHAPTER 3. GIS SAFETY STUDY: DATA PREPARATION FOR THE ANALYSIS

There were three sets of data used in the GIS safety study; roadway data; crash data and GIS data. The roadway data was collected from the Florida Department of Transportation's (FDOT) Roadway Characteristics Inventory (RCI) repository. The crash data was obtained from the FDOT's Crash Analysis Resources (CAR) database available online. The GIS maps were also obtained online from the FDOT website.

3.1 Roadway Data

The FDOT RCI database provides information and description of the state road system in the State of Florida. The main road characteristics used in the analysis include:

- County Number: A unique number given to each of Florida's 67 Counties.
- Roadway ID: A unique 7 or 8 digit number given for a certain length of a state road. One Roadway ID is split into small sections in the RCI database.
- Beginning Milepoint: The beginning milepoint of a section.
- Ending Milepoint: The ending milepoint of a section.
- ADT: The average daily traffic of a section of the roadway.
- Speed Limit: The posted speed limit at a section of the roadway.
- Number of Lanes: The total number of through lanes in both directions.

- Functional Classification: The FDOT highway functional classification of the roadway. The functional classification factor also provides information on the level of mobility and accessibility of the road (with freeways providing highest mobility and lowest accessibility); and its land-use type, whether it's rural or urban. Table 3-1 provides a list of the highway functional classifications in RCI.

Table 3-1: FDOT Highway Classification

Functional Class	Description
1	Principal Arterial-Interstate RURAL
2	Principal Arterial-Other RURAL
6	Minor Arterial RURAL
7	Major Collector RURAL
8	Minor Collector RURAL
9	Local Roads RURAL
11	Principal Arterial-Interstate URBAN
12	Arterial-Freeways and Expressways URBAN
14	Other Principal Arterial URBAN
16	Minor Arterial URBAN
17	Collector URBAN
19	Local Roads URBAN

Table 3-2 is an example of the RCI data. It can be noticed how Roadway 75040002 is split into several small subsections. The VMT is not provided in RCI. It was calculated by multiplying the ADT of the section by the length of the section. The product was then multiplied by 365, the number of days in a year.

Table 3-2: Example of RCI Data

County	Rdwy ID	Beg Mp	End MP	# of Lanes	ADT	Speed Limit	Section Length	VMT	Funclass
75	75040002	0	0.05	6	16300	45	0.05	297475	16
75	75040002	0.05	0.908	6	16300	45	0.858	5104671	16
75	75040002	0.908	1.288	6	16300	45	0.38	2260810	16
75	75040002	1.288	1.325	6	16300	45	0.037	220131.5	16
75	75040002	1.325	1.425	6	16300	45	0.1	594950	16
75	75040002	1.425	1.46	6	16300	45	0.035	208232.5	16
75	75040002	1.46	1.719	6	31100	45	0.259	2940039	16
75	75040002	1.719	1.819	6	31100	45	0.1	1135150	16
75	75040002	1.819	1.918	6	31100	45	0.099	1123799	16
75	75040002	1.918	2.398	6	31100	45	0.48	5448720	16
75	75040002	2.398	2.774	6	31100	45	0.376	4268164	16
75	75040002	2.774	3.52	6	31100	45	0.746	8468219	16
75	75040002	3.52	3.663	6	31100	45	0.143	1623265	16
75	75040002	3.663	3.821	6	31100	45	0.158	1793537	16

The GIS analysis focused specifically on state road multilane corridors. Only year 2006 data was used in the analysis since it was assumed that roadway characteristics do not significantly change over the span of 2 years. Only functional classes 2,6,7,8,14,16 and 17 were included in the analysis. Local roads, freeways and expressways were left out. Roads with posted speed limits of 40 mph and above and with at least 4 lanes in each direction were retained for the analysis. The total centerline miles of multilane corridors came out to be 3977 miles, almost all of which are arterials with only 25 miles of collectors. The software that was used in the data extraction process is SAS version 9.1.

3.2 Crash Data

The FDOT CAR database contains rich information and description about the crashes that occurred over several years on the roads of the State of Florida. Some of the crash characteristics used in the analysis include crash roadway ID, crash location milepoint, crash severity, crash type and functional classification of the roadway on which the crash occurred.

- Crash roadway ID: The crash roadway ID provides the RCI roadway ID of the road on which the crash occurs.
- Milepoint: The milepoint provides the location on the RCI roadway ID section at which the crash occurred. The milepoint is recorded as the distance measured from milepoint 0 of a certain roadway ID to the location of the crash on that same roadway ID.
- Crash severity: The FDOT splits the severity of a crash into the following levels as seen in Table 3-3.

Table 3-3: FDOT Crash Severity Levels

Severity Level	Description
1	PDO (Property damage)
2	Possible Injury
3	Non-incapacitating
4	Incapacitating (Severe)
5	Fatal (within 30 days)
6	Non-traffic fatality

- Crash types: The type of the crash recorded in the CAR database such as rear-end crashes, angle crashes, turning movement crashes, sideswipe crashes and head-on crashes.
- Functional Classification: The functional classification of the roadway on which the crash occurred.

There are many other crash characteristics in the CAR database, such as date and time of the crash, but they were not included in the GIS analysis.

Overall, two years of crash data, 2006 and 2007, were used in the GIS analysis. Since the GIS analysis only involves multilane corridors, only crashes that occurred on multilane roadways which were extracted from the RCI data were considered. Each data entry in CAR has a milepoint where the crash occurred and a Roadway ID. Crash entries in the database, which share the same roadway ID with one of the multilane corridor roadways in RCI and have a milepoint crash location within the range of the RCI beginning and ending milepoint of that same roadway ID, are selected for the GIS analysis. The process of crash selection was achieved using the SAS 9.1 software. Crashes with severity level 6 were not included in the analysis For the Macro-GIS analysis (Chapter 4), only 2006 crashes were considered in the analysis. For the Micro-GIS analysis and Sliding Window Analysis (Chapters 5 and 6), both 2006 and 2007 crashes were used to enrich the dataset since only severe crashes (severity levels 4 and 5) of seven Florida counties were included. The total number of crashes used in the analysis for multilane corridors came out to be 159493 crashes; 80558 in 2006 and 78935 in 2007. The total number of severe crashes was found to be 13132 (8.2% of total crashes); 6946 in 2006 and 6186 in 2007.

3.3 GIS Data

GIS, in its simplest form, provides information which relates to a specific location. GIS provides data which relates to geographic scales of measurement and which are referenced by a coordinate system to location on the surface of the earth. The data could be broad in nature, such as the location or boundaries of a country or more detailed, such as the location of roads within a city network.

The GIS software used in this study is ArcMap 9.2. The FDOT provides on its website several GIS maps of Florida related to geographical and transportation related factors. The maps are saved in compressed file format (.zip) and could be uploaded into GIS in layer file format (.lyr) once extracted. The maps that were used in this analysis were from the year 2006. The following is a list of the maps:

- District Layer Map (see Figure 3-1): This layer provides a map of Florida with the geographical boundaries and areas of the state's seven districts.

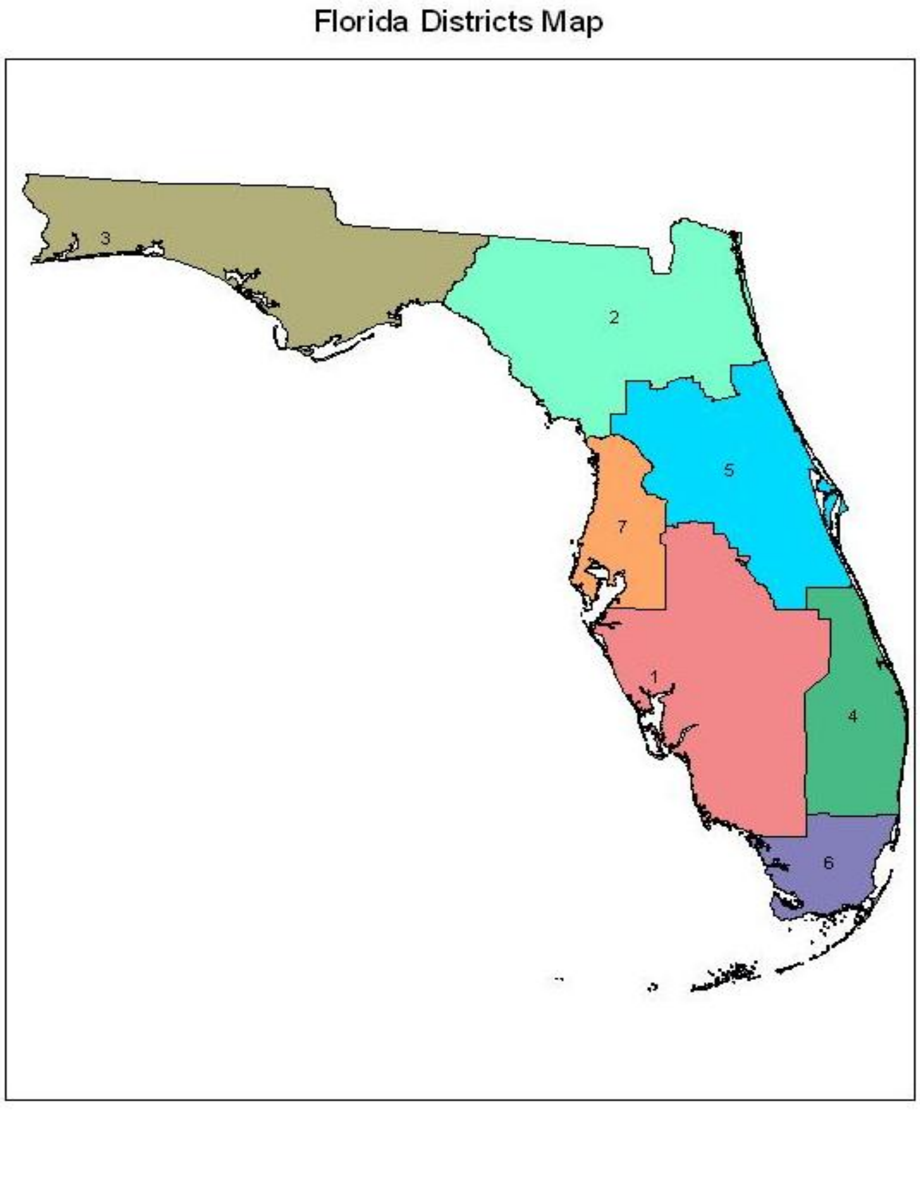

Figure 3-1: Florida Districts Map

- State Road Map (see Figure 3-2): This layer provides a map of the state road system within Florida. The layer's attribute table also provides the beginning and ending milepoint of the roadways and their corresponding roadway ID number.

Figure 3-2: Florida State Road Network

Attributes of state_roads

OBJECTID *	Shape *	state_roads.ROADWAY	state_roads.RANK	state_roads.ROUTE	state_roads.RouteNum	state_roads.BEGIN_POST	state_roads.END_POST
719	Polyline	01010000	1	SR 45	45	15.214	25.946
720	Polyline	01010000	1	SR 45	45	13.247	15.214
721	Polyline	01010000	1	SR 45	45	0	13.247
718	Polyline	01010101	1	SR 45	45	0	2.042
717	Polyline	01030000	1	SR 31	31	0	18.337
715	Polyline	01040000	1	SR 35	35	1.532	6.399
716	Polyline	01040000	1	SR 35	35	0	1.532
714	Polyline	01040101	1	SR 35	35	0	1.668
713	Polyline	01040201	1	SR 35	35	0	4.425
712	Polyline	01050000	1	SR 776	776	2.237	17.549
711	Polyline	01060000	1	SR 776	776	9.23	10.385
710	Polyline	01075000	1	SR 93	93	0	22.008
703	Polyline	02010000	1	SR 45	45	13.177	30.039
704	Polyline	02010000	1	SR 45	45	13.136	13.177
705	Polyline	02010000	2	SR 45	45	12.72	13.136
706	Polyline	02010000	1	SR 44	44	12.72	13.136
707	Polyline	02010000	2	SR 45	45	12.198	12.502
708	Polyline	02010000	1	SR 44	44	12.198	12.502
709	Polyline	02010000	1	SR 45	45	0	12.198

Figure 3-3: Example of State Road Attributes Table

Figure 3-3 is a snapshot of the state road layer attribute table. The highlighted portion is the Roadway ID while the last two columns denote the beginning and ending milepoint of the road.

- Signalized Intersections Map (see Figure 3-4): This layer provides a map of geo-coded signalized intersections on the roads of the State of Florida. The map’s attributes table could be extracted into an excel table format and used in the analysis.

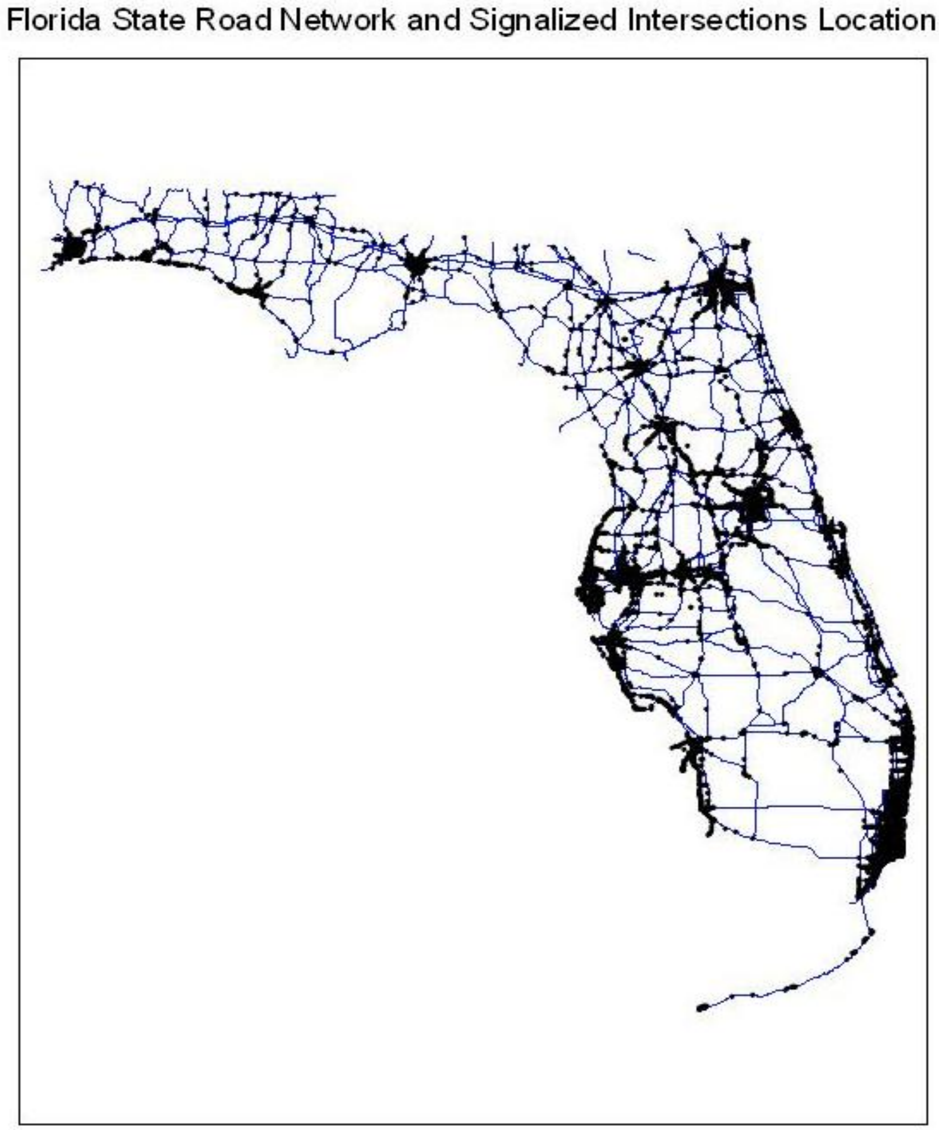

Figure 3-4: Florida Signzalized Intersection Map

- County Layer Map (see Figure 3-5): The FDOT does not provide a map of Florida's 67 counties. The map was obtained from another source online (FGDL).

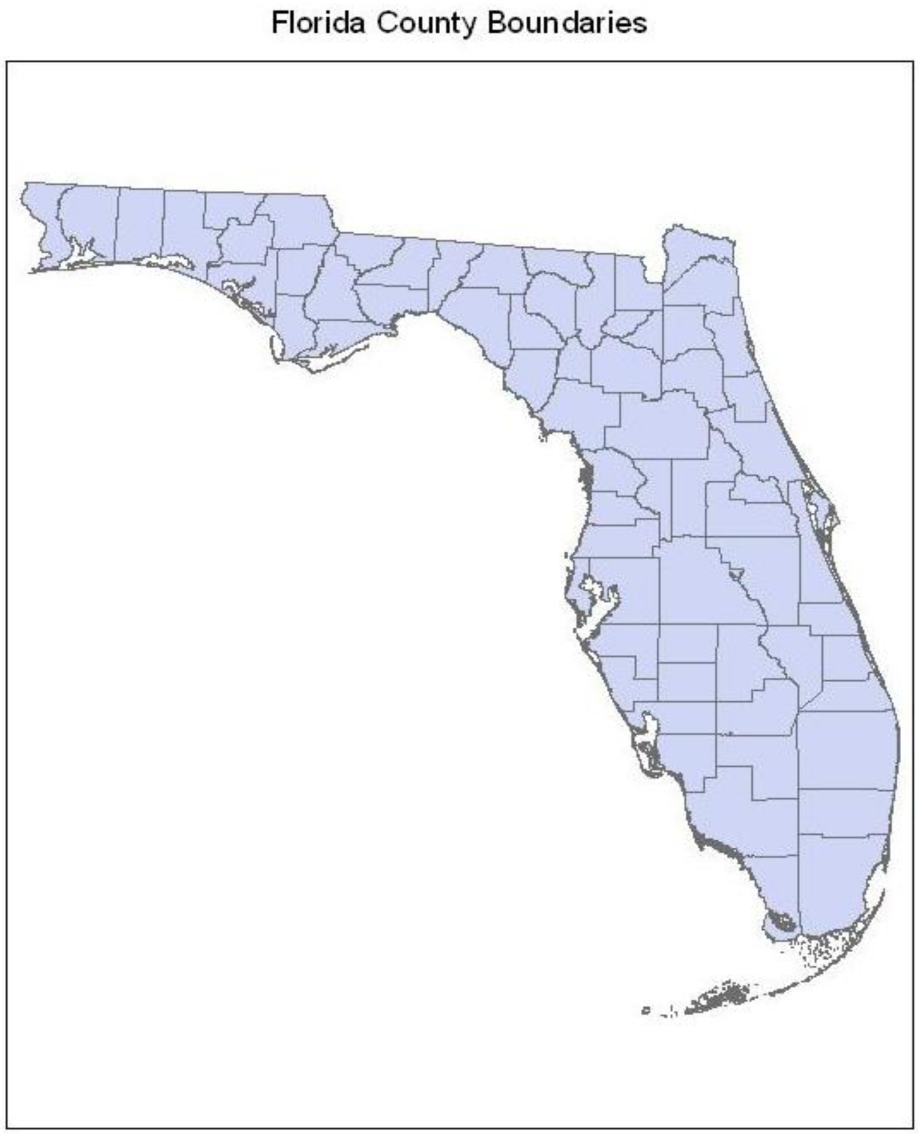

Figure 3-5: Florida Counties Map

The district and county map layers were mainly used in the exploratory Macro-GIS analysis of this study. The state road map and intersection maps were used in the Micro-GIS analysis section. Only maps of state roads and intersections of multilane corridors were displayed in GIS. There are other several maps available from the FDOT website, such as bridge locations and median type maps, however they were not included in the scope of this analysis.

CHAPTER 4. GIS SAFETY STUDY-MACRO GIS ANALYSIS: DISTRICT AND COUNTY LEVEL ANALYSIS OF CRASHES

At the macro level, the main objective of the GIS safety analysis is to provide exploratory maps of crash trends in the state of Florida at District and County level. The use of districts for analysis is too broad because of their large geographical area. The mapping of district crash trends in this study is purely exploratory in nature. The mapping of crash trends at the county levels provides a clear visual indication of areas with relatively unsafe roads. The use of map color degradation, from light to dark, displays variation in crash trends from county to county.

4.1 Methodology

Incorporating crash trends into GIS is very simple. For example, to display the rate of crashes per mile in each county, the total number of crashes in a county is divided by the total centerline miles for that same county. The end result is an excel table with 67 rows (denoting 67 counties in Florida) with the columns being county name, number and rate of crashes per mile. The excel table is then saved in database file format (.dbf) which can be recognized by ArcMap 9.2. Since the attributes table of the county layer map in ArcMap 9.2 also 67 entries, the newly created database table file is linked to the GIS attributes table, as long as both tables have a common field and the same number of rows. In the case of this analysis, the common field is the county name and both tables have 67 rows.

4.2 Results

The District and County level maps generated for this analysis include the following:

- District Crashes Frequency
- District Multilane Corridors Centerline Miles
- District Crash Rate per Mile
- County Crashes Frequency
- County Multilane Corridors Centerline Miles
- County Crash Rate per Mile
- County Crash Rater per 1 Million VMT
- County Crash Frequency vs. Landuse Distribution
- County Severe Crashes Frequency vs. Landuse Distribution
- County Severe Crashes Percentage from Total Crashes
- County Severe Crashes Rate per Mile
- County Severe Crashes Rate per 1 Million VMT

There were six counties that had no multilane corridors, hence no crash occurrences. The counties are Gilchrist, Hamilton, Lafayette, Union, Franklin and Wakulla.

4.2.1 District Crash Frequency Map

As shown in Figure 4-1, the district with the highest crash occurrences in 2006 was District 7 (17869 crashes).

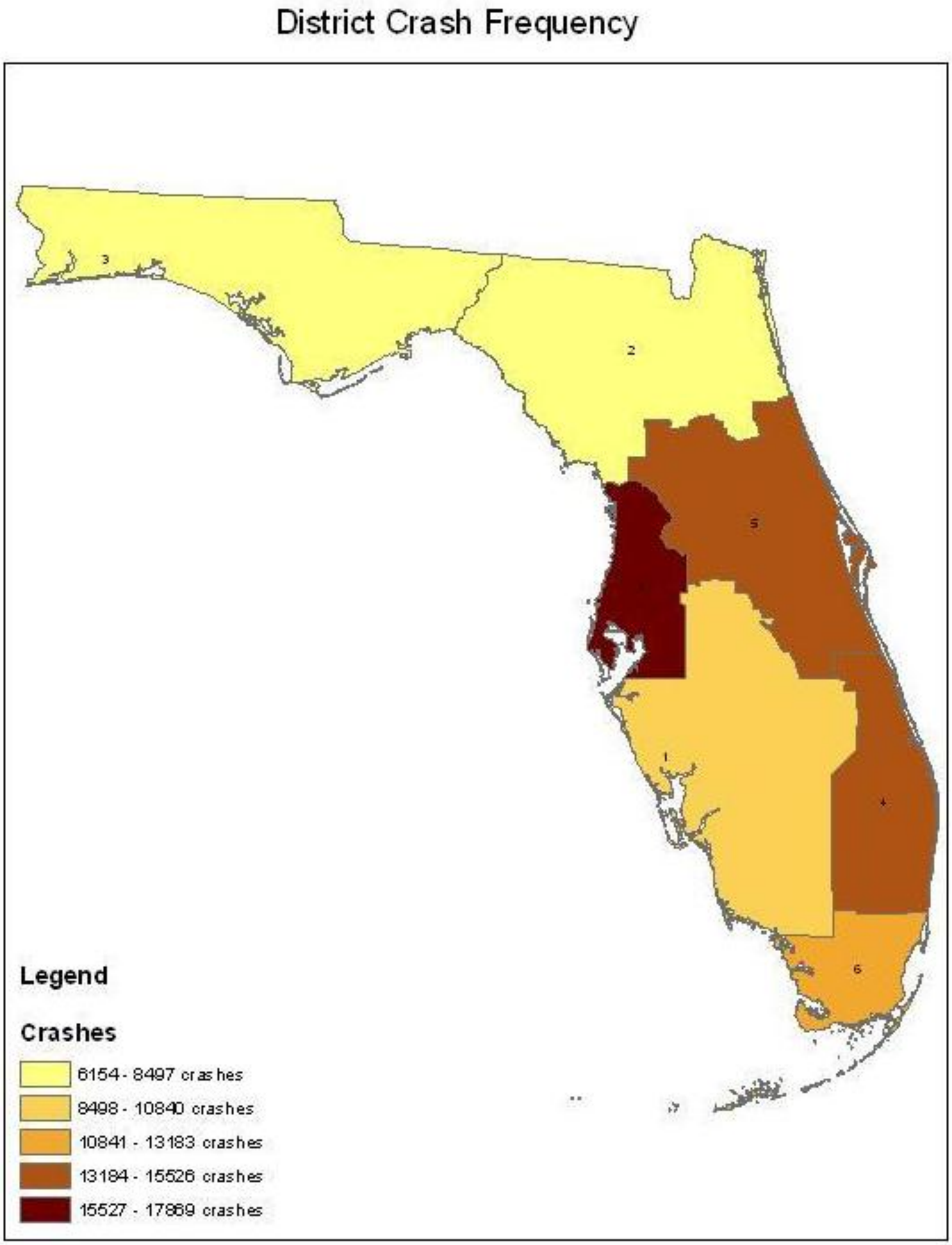

Figure 4-1: Districts Crash Frequency Map

4.2.2 District Multilane Corridors Centerline Miles Map

The District with the highest mileage of corridors in Florida is District 5 (869 miles), as shown in Figure 4-2.

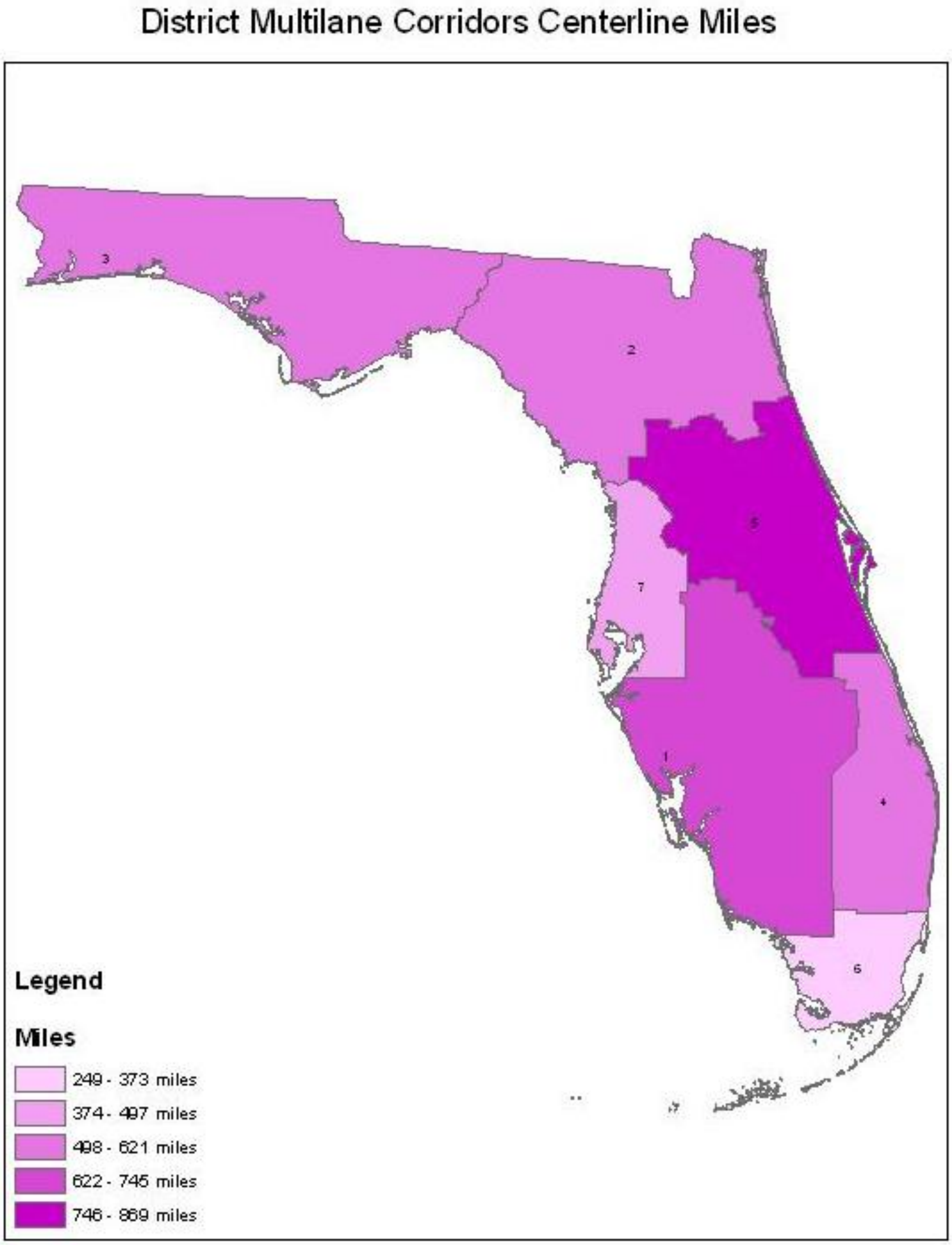

Figure 4-2: Districts Multilane Cooridors Centerline Miles Map

4.2.3 District Crash Rate per Mile Map

As observed in Figure 4-3, the districts with the highest crash rates per mile are District 6 and District 7. This result makes sense since District 6 includes Miami-Dade County and District 7 includes Hillsborough County. Both counties have very high crash frequencies which probably are due to the high population levels there.

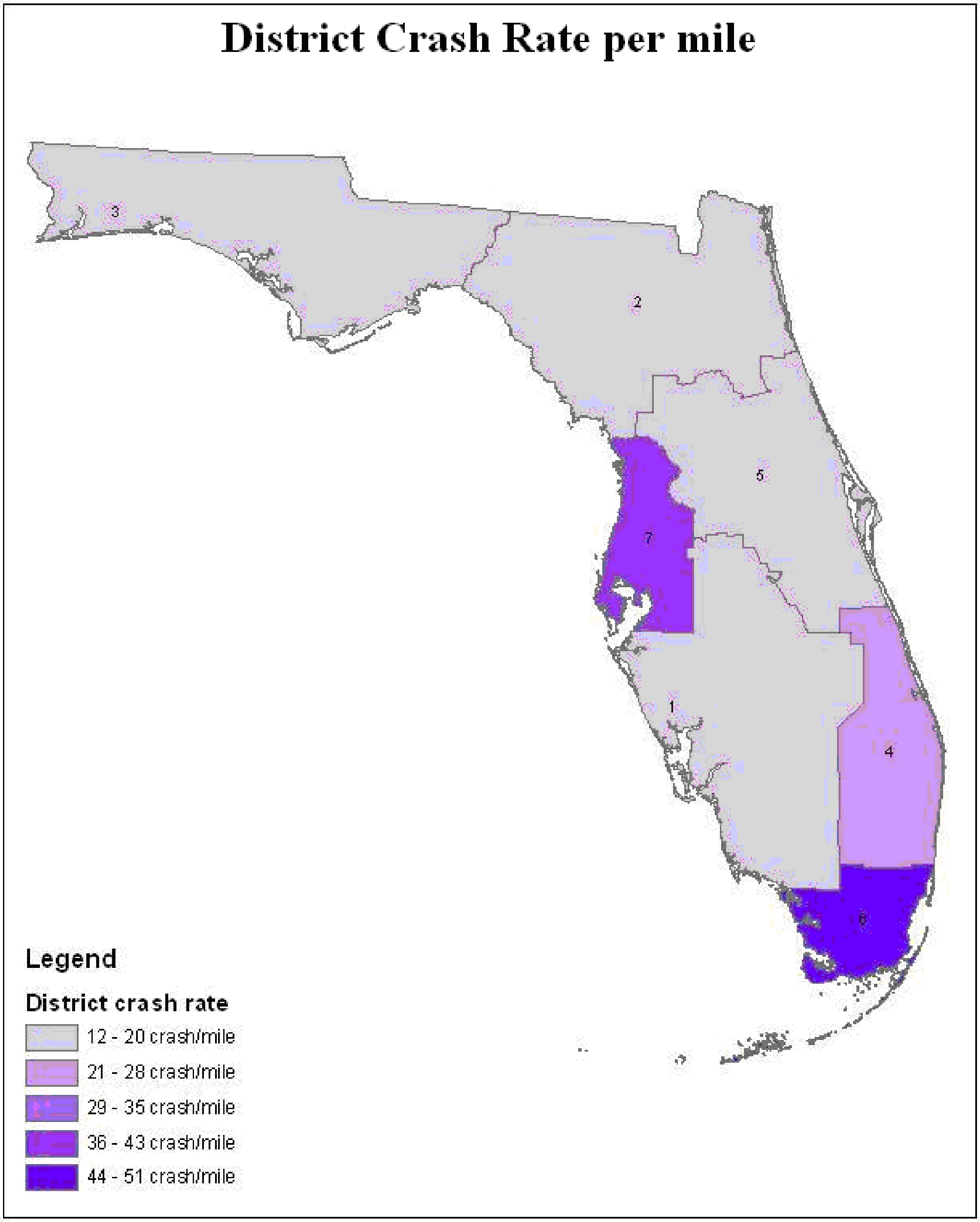

Figure 4-3: Districts Crash Rate per Mile Map

4.2.4 County Crash Frequency Map

As it was expected, the highest number of crashes in 2006 occurred in Miami-Dade County with 12,378 crashes. It is followed by Broward County, which includes the city of Fort-Lauderdale, with 9049, Hillsborough County, which includes the city of Tampa, with 9001 crashes and Pinellas, which includes the city of St. Petersburg, with 5744 crashes (see Figure 4-4). These findings are not surprising since these counties have historically shown high crash trends and due to the high population of the cities within those counties.

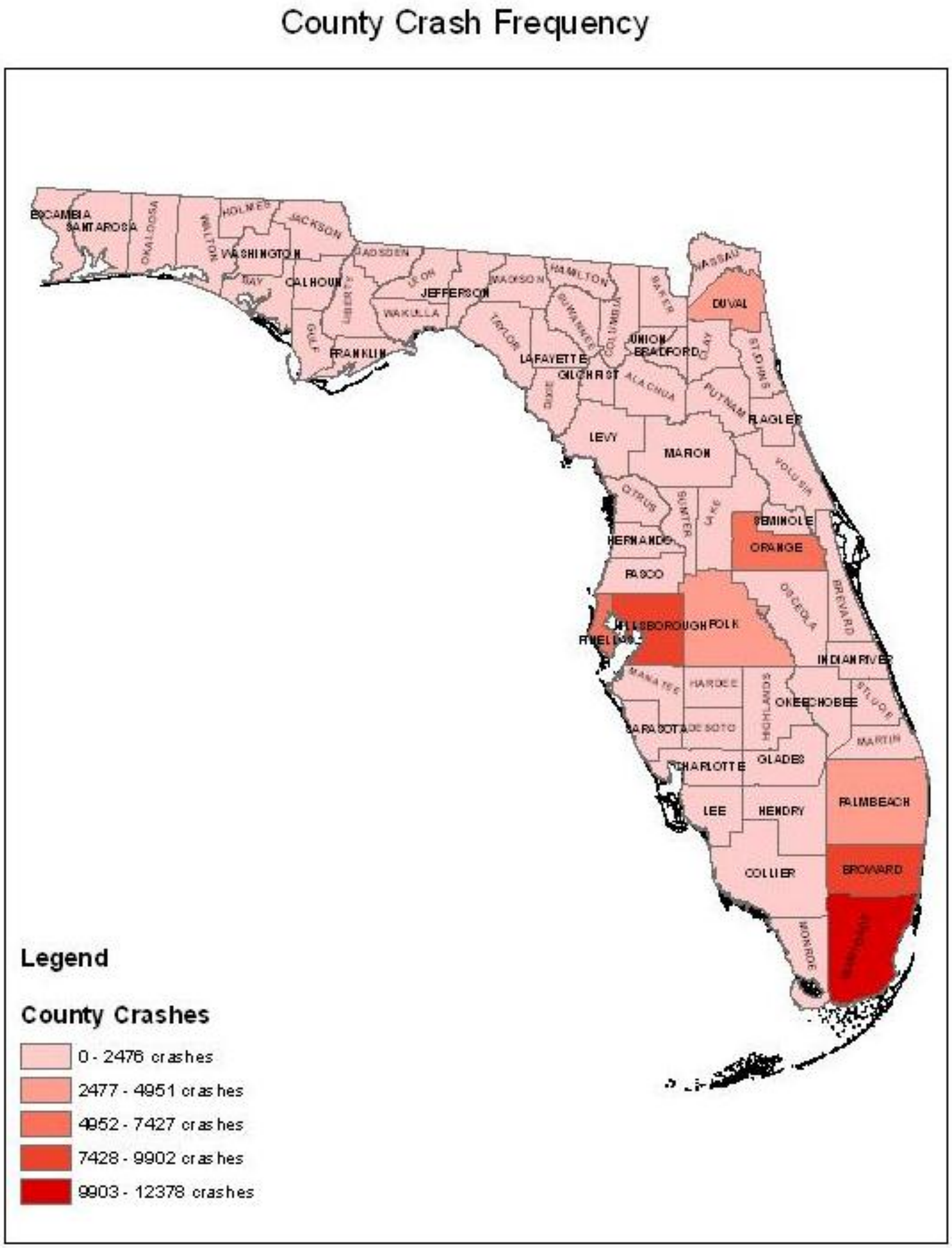

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Figure 4-4: County Crash Frequency Map

4.2.5 County Multilane Corridor Centerline Miles Map

As seen in Figure 4-5, the counties with the highest multilane corridor miles are Polk County (215 miles) and the southern counties of Palm Beach (246 miles), Broward (227 miles) and Miami-Dade (224 miles).

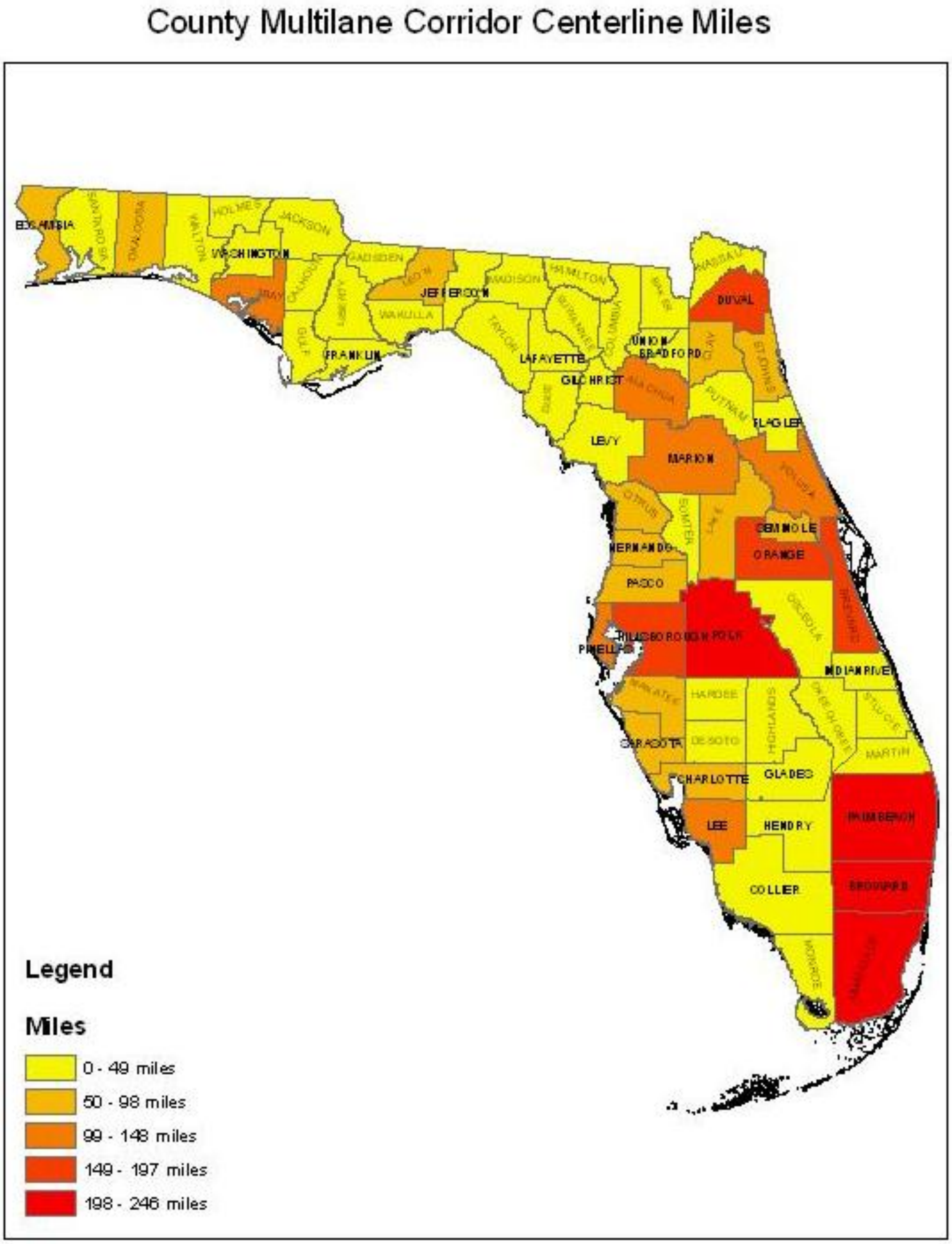

Figure 4-5: County Multilane Corridor Centerline Miles Map

4.2.6 County Crash Rate per Mile Map

The county with highest crash rate per mile was Miami-Dade, at 55 crashes/mile. It was followed by Hillsborough County at 48 crashes/mile, Pinellas County at 43 crashes/mile and Broward County with a rate of 40 crashes/mile (see Figure 4-6).

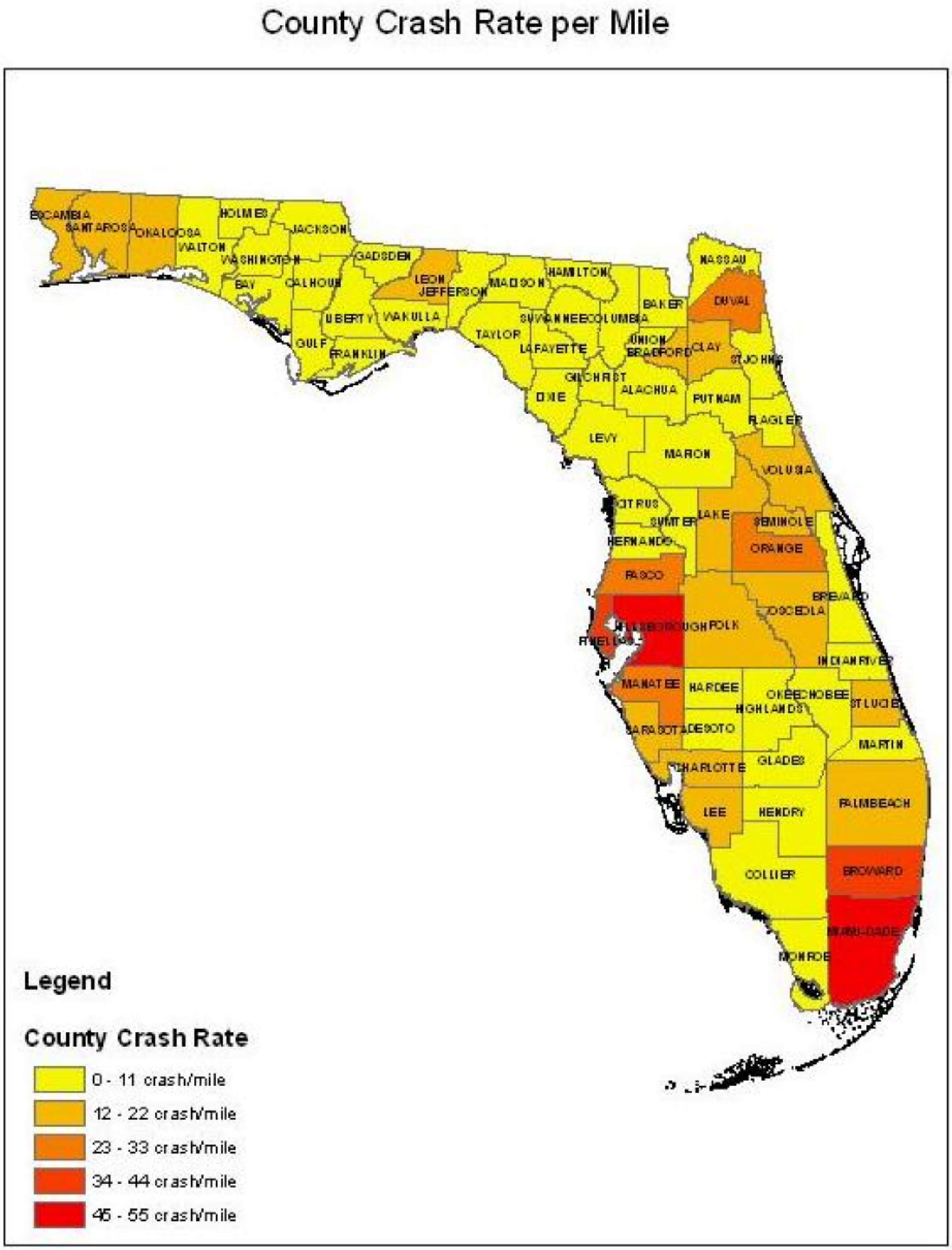

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Figure 4-6: County Crash Rate per Mile Map

4.2.7 County Crashes per 1 million VMT Map

The counties with the highest crash rate per 1 million VMT were Hillsborough County (3.63), Miami-Dade County (3.49), Pinellas County (2.76) and Broward County (2.73) as seen in Figure 4-7.

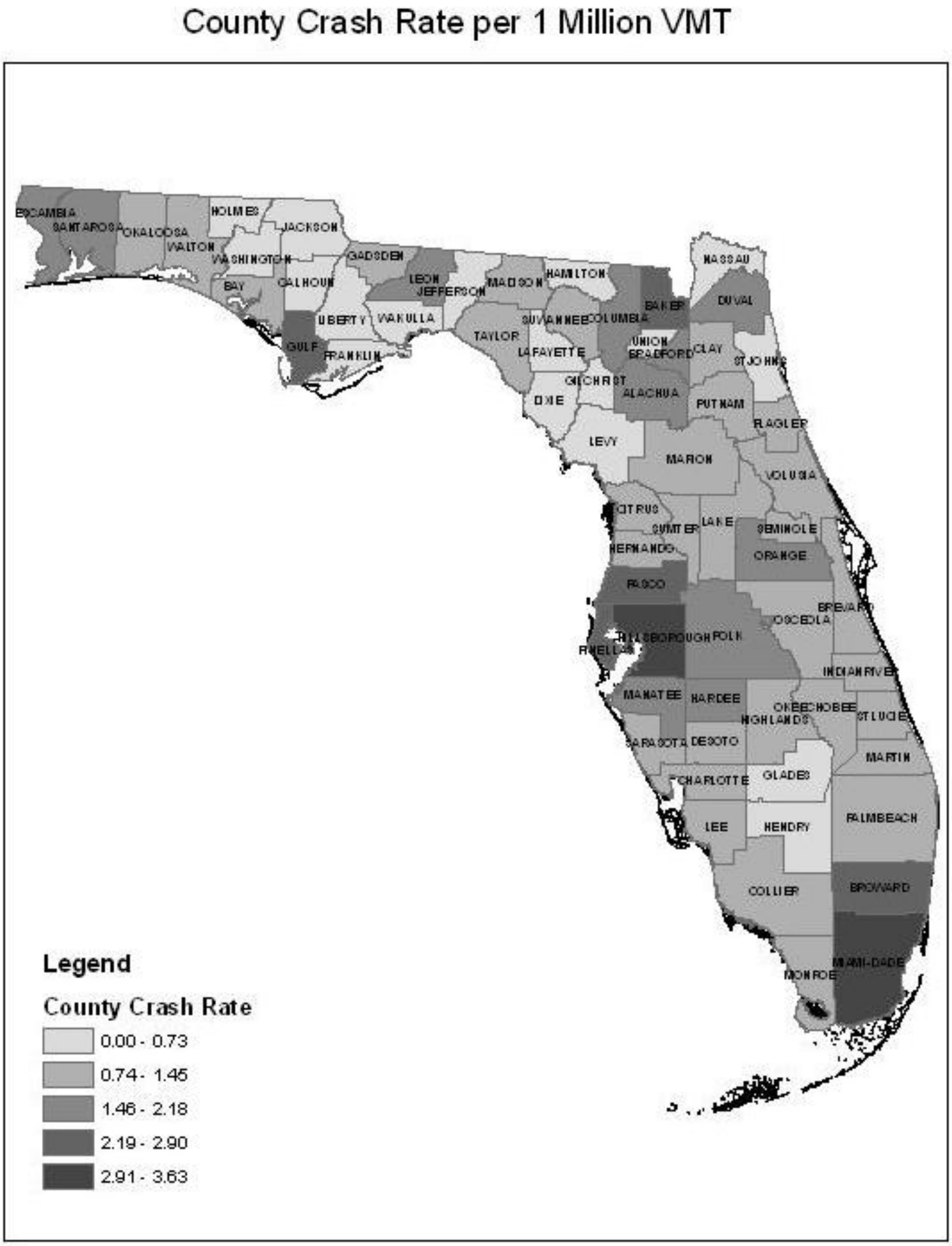


Figure 4-7: County Crash Rate per 1 Million VMT Map

4.2.8 County Crash Frequency vs. Landuse Distribution Map

It is interesting to note in Figure 4-8 that the counties that had high crash frequencies have a much higher ratio of urban roads to rural roads (Miami-Dade, Hillsborough, Broward, Orange). This is expected since urban roads are much more congested and have more intersections which create more accidents risk.

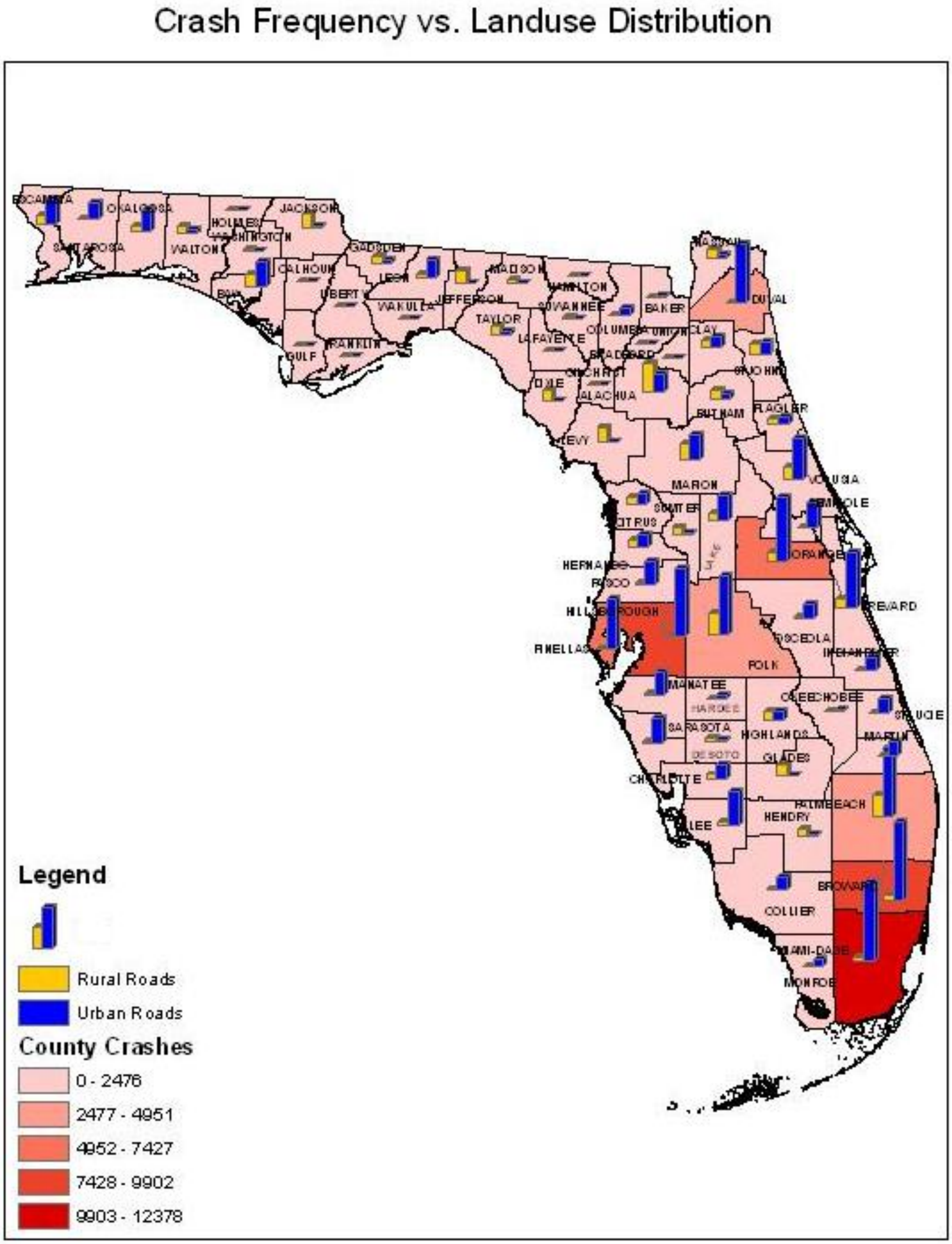


Figure 4-8: County Crash Frequency vs. Landuse Distribution Map

4.2.9 Severe Crashes Frequency vs. Landuse Distribution Map

As seen in Figure 4-9, the counties with the highest frequency of severe crashes are, Hillsborough (705 crashes), Broward (685 crashes), Miami-Dade (620 crashes) and Pinellas (497 crashes). The same four counties had the highest frequency of total crashes (Figure 4-4). It is also observed that counties with more urban roads have higher frequencies of severe crashes compared to counties with more urban roads. This is expected since the traffic volume on urban roads is higher than rural roads which increase the chances of the occurrence of a severe or fatal crash.

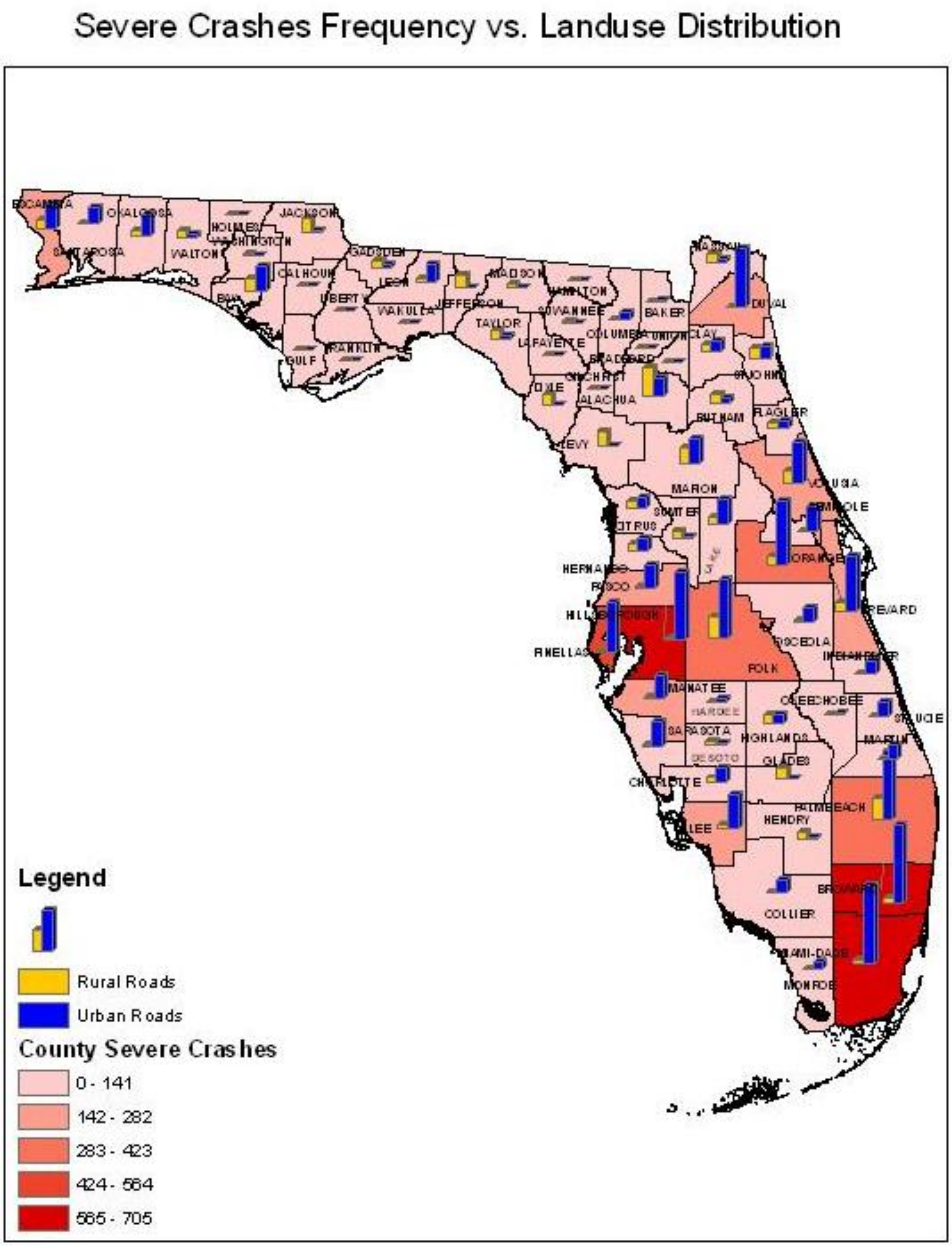


Figure 4-9: County Severe Crashes Frequency vs. Landuse Distribution Map

4.2.10 County Severe Crash Percentage Map

The counties with the highest percentage of severe crashes and fatal crashes to total crashes were Madison County (31%), Jefferson County (31%), Flagler County (29%) and Hernando County (25%) as shown in Figure 4-10. It was found that counties with more rural roads than urban roads tend to have higher percentages due to the low total crash frequencies, thus a small increase of severe crashes translates into a large ratio. On the other hand , Miami-Dade has a low percentage of severe crashes and that is due to the large total number of crash frequencies and the fact that severe crashes are occur at a much lower rate than other crashes.

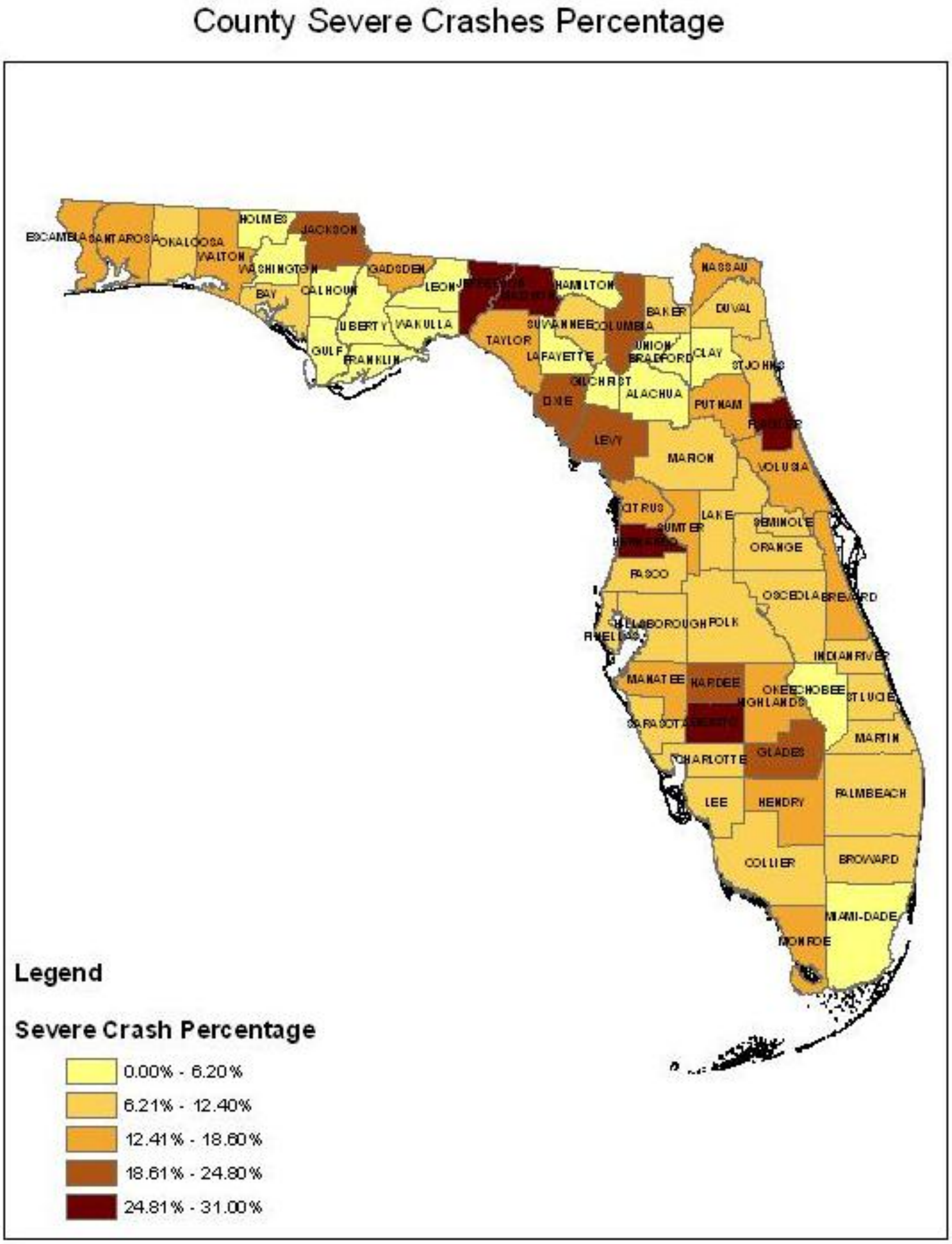


Figure 4-10: County Severe Crashes Percentage from Total Crashes Map

4.2.11 County Severe Crash Rate per Mile Map

The counties with highest rate of severe crashes per mile were Pinellas County (4.09 crashes per mile), Hillsborough County (3.74 crashes per mile) and Pasco County (3.69 crashes per mile) (see Figure 4-11). It is interesting to note that these 3 counties neighbor each other.

County Severe Crashes Rate per Mile

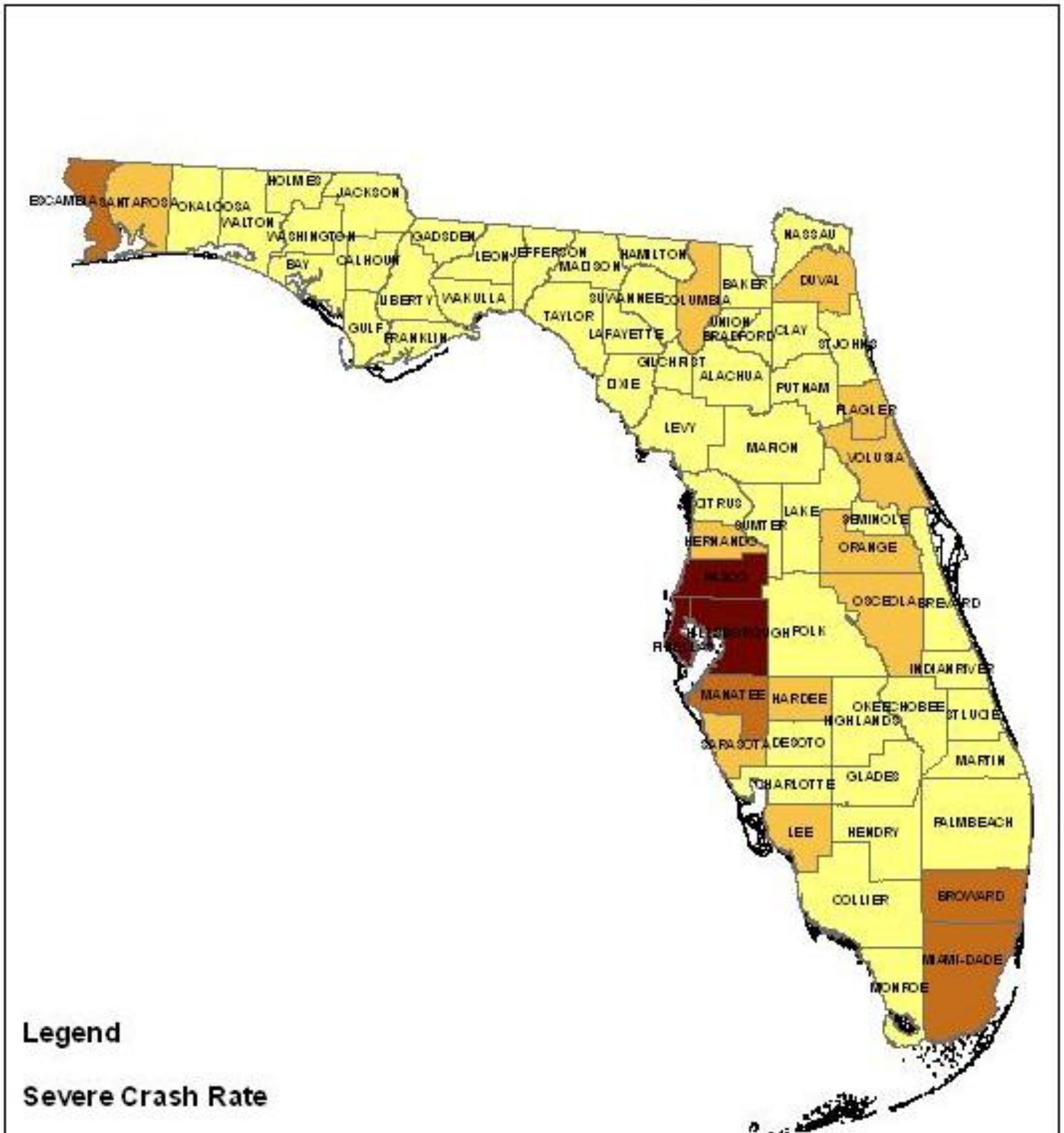


Figure 4-11: County Severe Crashes per Mile Map

4.2.12 County Severe Crash Rate per 10 Million VMT Map

The counties with the highest rate of severe crashes per 10 million VMT were Hardee County (3.53), Escambia County (3.21), Flagler County (3.15) and Columbia County (3.03) as shown in Figure 4-12. With the exception of Escambia, the other 3 counties experience low total severe crash occurrences. The three counties have low VMT values, thus a small increase of one or two severe crashes tends to magnify the rate.

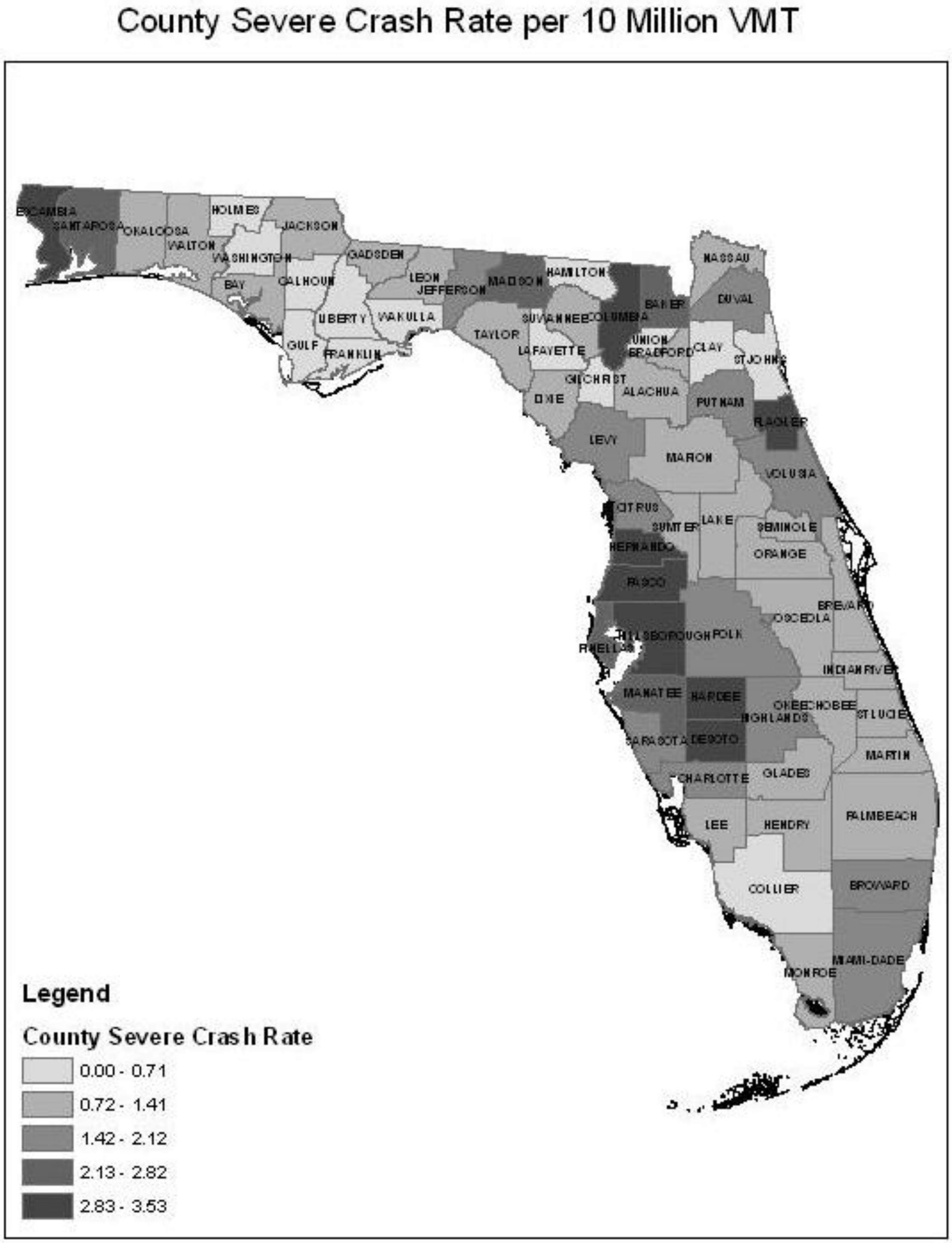


Figure 4-12: County Severe Crashes per 10 Million VMT Map

4.3 Summary

In summary, Miami-Dade, Broward, Palm Beach and Hillsborough Counties had the highest number of total crash occurrences and crash rates in 2006. Counties with urban roads have higher frequencies of total crashes and severe type crashes than the ones with rural roads. Counties with more rural roads tend to have a higher percentage of severe crashes in comparison with urban counties; however this is mainly to low total number of crash occurrences. The neighboring counties of Pasco, Pinellas and Hillsborough have the highest rates of severe crashes per mile. Counties with low number of crash occurrences have higher severe crashes per 10 million VMT and this is mainly due to the low VMT values. Appendix A includes several other county level maps that were generated in GIS.

CHAPTER 5. GIS SAFETY STUDY-MICRO GIS ANALYSIS: ROADWAY LEVEL ANALYSIS OF SEVERE CRASHES

The Macro-GIS analysis focused primarily on the general trends of county crash distribution. The macro analysis was concluded by focusing on the distribution of severe crashes among the 67 counties of the state of Florida. The second stage of the GIS analysis proceeds from there as it specifically focuses on those types of crashes. The Micro-GIS analysis zooms into specific counties and looks at the distribution of severe crashes on multilane corridors within a county. The main aim of the secondary analysis is to be able to visually identify (using color-coding of road links and signalized intersections in GIS) certain sections of roadways within a county that experienced high trends of severe crashes for the years, 2006 and 2007. Two years of data were used for this type of analysis to enrich the dataset.

The main objective of the Micro-GIS analysis is to make it possible to visually identify certain spots on the roadways which have experienced a high trend of severe crashes. These spots could be a roadway section or a signalized intersection area. It will also be possible to identify the beginning and ending mile points of those spots. The identification of the mile posting of those spots would help in specifying locations where road improvements are required in order to have better safety condition.

ArcMap 9.2, is a powerful tool that can display maps of county boundaries, roadway segments and intersection locations. By using the several graphical tools provided by ArcMap, it becomes convenient to mark spots or sections on the roadway by varying colors or altering the size or thicknesses of roadway segments to denote the safety condition of that particular spot.

The less safe a segment or an intersection is, the darker in color and thicker in size that particular segment is drawn in GIS. Figure 5-1 is an ArcMap 9.2 snapshot presenting an example of the main visual objective of the GIS analysis. As observed, the darker and thicker the lines or dots, the worse the safety condition of that particular segment of the roadway.

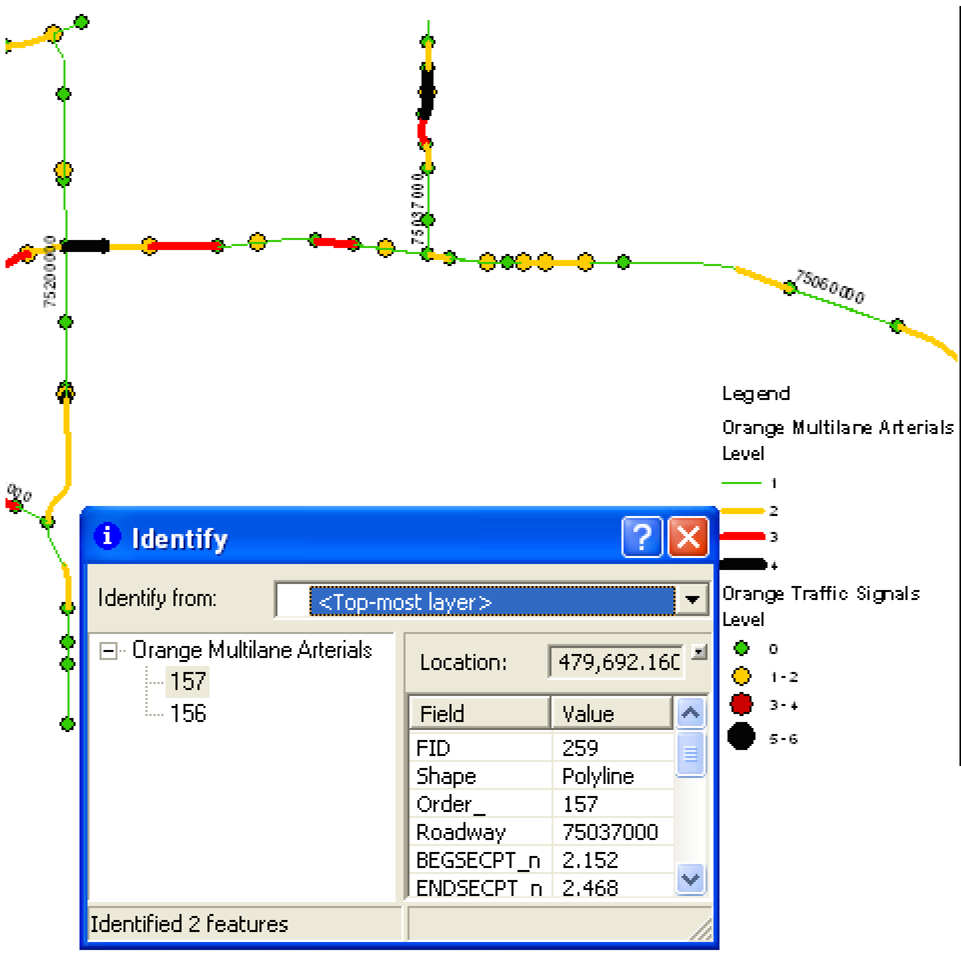


Figure 5-1: Example of Main Visual Objectives of GIS

However in order to achieve this objective, severe crash data and roadway data had to be properly analyzed in order to display the varying safety conditions on a map. Several roadway section ranking procedures were examined through the exploration of previous literature and scientific intuition until one consistent method to rank the roadway sections was achieved. The methodology section discusses the steps followed in order to achieve the proper ranking procedure.

5.1 Methodology

The following is a breakdown of the methodology followed in order to identify a proper way to rank roadway sections according to their safety performance with regards to their severe crash trends.

5.1.1 Selection of a County for Roadway Ranking Trials

The Macro-GIS analysis identified several counties that exhibited alarming severe crash trends in 2006. These counties exhibited relatively high frequencies and crash rates (per road mile and VMT) for such type of crashes. The counties chosen for the Micro-GIS analysis were: Hillsborough, Miami-Dade, Duval, Pinellas, Escambia, Pasco and Orange. There were other counties that also displayed high trends of severe crashes; however the aforementioned counties were chosen because they displayed high trends, spanned different geographic locations and had big metropolitan areas sizes within them. In addition several counties that exhibited high crashes per miles per VMT had a low frequency of severe crashes. They simply ranked high because they had low centerline miles or low VMT. Table 5-1 summarizes the severe crashes trends of the 7 chosen counties.

Table 5-1: Summary Statistics of Selected Counties

County	Geographical Location	Major City	Severe & Fatal Crash Frequency	Rank	Sever & Fatal Crashes per mile	Rank	Severe & Fatal Crashes per 10 million VMT	Rank
Escambia	Florida Panhandle	Pensacola	257	10	2.86	6	3.21	2
Hillsborough	South-West Florida	Tampa	705	1	3.74	2	2.84	8
Miami-Dade	South Florida	Miami	620	3	2.76	7	1.75	17
Orange	Central Florida	Orlando	357	5	1.87	13	1.37	26
Pinellas	South-West Florida	St. Petersburg	497	4	3.69	3	2.38	12
Pasco	West Florida	Dade City	278	8	4.09	1	2.98	6
Duval	North-East Florida	Jacksonville	260	9	1.62	16	1.47	21

Escambia County was chosen in order to test different ranking techniques. Escambia is a county located in the west most section of the Florida panhandle. In 2006, Escambia experienced 257 severe crashes on its multilane arterials (10^{th} highest), of which 10 were fatal. Most of Escambia's multilane corridors are urban (67 miles out of a total of 89) and only 16 severe crashes occurred on rural roads. The 2007 severe crash data for the seven counties was not used in the ranking trial stage. The data was used after finalizing a ranking methodology for the roadways.

5.1.2 Testing Different Ranking Techniques

The first method tested to rank sections of multilane corridors in Escambia was to use the frequency of severe crashes occurrence on road sections provided by the RCI data; however the roadway beginning and end mile-point segments provided by the raw RCI roadway data were found to be too small (see Table 3-2) and more than 90% of those small segments exhibited 0 crash occurrences. The method was found to be far too simplistic and visually unfriendly (see

Figure 5-2). It does not provide a clear way to identify or display very unsafe spots. Thus it was concluded that the roadways had to be split into larger segments than the ones provided in the RCI data.

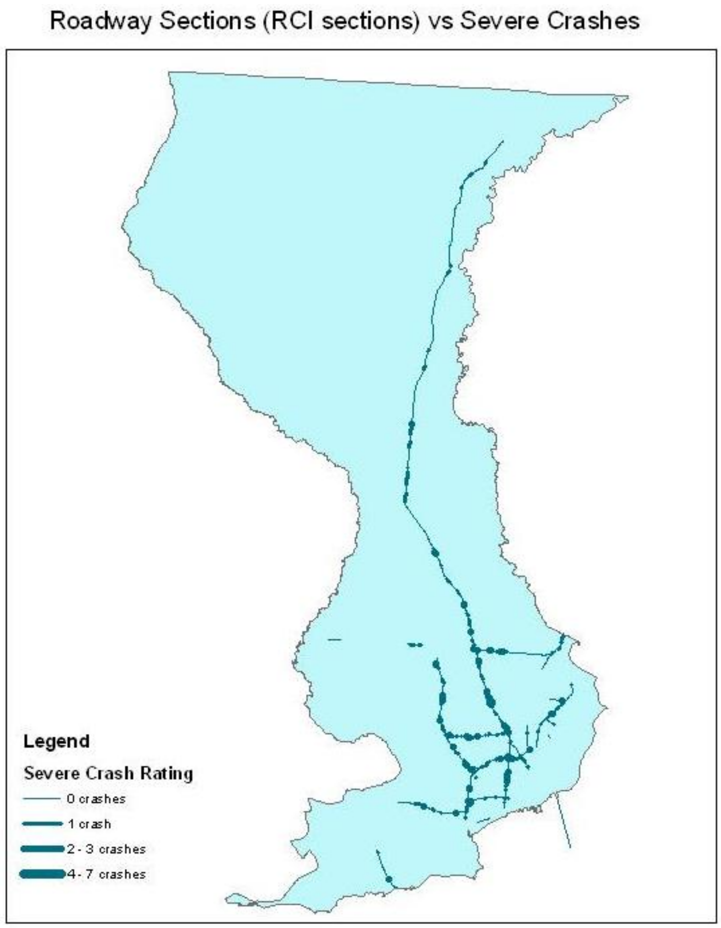


Figure 5-2: Use of RCI Sections for Ranking Methodology

Another ranking technique considered was splitting the roadways into equal 1 mile segments and then ranking the safety of those segments according to the frequency of severe crashes as recommended by Geurts et. al.(2003). It was found that this method is good to rank segments; however it assumes the roadway as a continuous entity without taking the presence of signalized intersections into account.

Another ranking technique tested is the one used by Kilkowski and Bejleri (2006) in which roadways are split into segments between signalized intersections. Signalized intersections would be analyzed separately by taking into account the number of crashes within an intersection's physical boundary and its influence area, whereas road segment analysis take into account crashes that occurred on road sections between 2 consecutive intersection influence areas. However, because sections between traffic signals vary in length, the frequency of severe crashes had to be normalized, either by the length in miles or the VMT of that section or by using both.

For this analysis, it was decided to split roadways into segments between signalized intersections and to analyze those two elements of a corridor separately, which is similar to the procedure followed by the Minnesota and Idaho DOT's (Hallmark et. al., 2002). The frequency of severe crashes was divided by the centerline length of a segment.

The next step was to decide on a weight ratio for fatal (severity level 5) to incapacitating crashes (severity level 4). Geurts et. al. used a 5:3 weight ratio in their study. The Iowa DOT proposed a 7:1 ratio. Illinois DOT used a 10:9 ratio whereas the Minnesota DOT used a 10:4 ratio. It seemed that studies looked at crash severity from several perspectives, which explains the variation in the ratios. From a monetary perspective for example, an incapacitating (severity level 4) crash costs more than a fatal (severity level 5) crash in medical bills. However, a fatal crash costs much more than an incapacitating one in human value. A 2:1 ratio was chosen for this analysis as an approximate average of the ratios discussed previously. The road segment ranking formula used was:

Road Segment Severity Score=[2x(No. of fatal crashes)+1x(No of. incapacitating crashes)]/segment length

(5-1)

As the score increases, the safety level of that road segment deteriorates which implies a higher ranking. This is displayed in GIS with darker colors and thicker lines (denoting road segments). The longest allowable road segments analyzed were 1 mile long. If the distance between 2 signalized intersections exceeded 1 mile, then the segment was split into equal parts less than 1 mile long. Intersection influence areas were subtracted from the segment length in the calculation of road segment scores.

As for signalized intersections, they were ranked according to the frequency of severe crashes within an intersection's physical location and influence area with a (2:1) weighting given to fatal (severity level 4) and incapacitating (severity level 5) crashes respectively.

Signalized Intersection Severity Score=[2x(No. of fatal crashes)+1x(No. of incapacitating crashes)]

(5-2)

As the score increases, the safety level of the intersection deteriorates. This is displayed in GIS with darker colors and thicker dots (denoting intersections). Most studies use a 500 ft as a default value for an intersection's influence area (250 ft upstream and downstream). However, a signalized intersection's influence should be varied according to the volume of traffic entering the intersection from the crossroad. Since information on intersection volumes is not available for all seven counties, the number of lanes of the cross road was used as a surrogate indicator of the length of the influence area (see Table 5-2).

Table 5-2: Signalized Intersection Influence Area

CrossRoad No. of Lanes	Influence Area
<=Two Lanes	150 ft
Three Lanes	200 ft
Four or more Lanes	250 ft

Crashes which occurred upstream of a signalized intersection, within its influence area and 50 ft downstream (to account for right turn crashes) were considered as intersection crashes. The influence area of an intersection was assumed to start from the intersection's actual center. There are cases in which crash location mile points were measured with reference to an intersection's stop bar, however it is extremely tedious to clarify such cases.

Some studies ranked intersections according to the number of crashes divided by the volume of traffic entering the intersection. This approach is recommended for the analysis of intersection crash trends in general. However, similar to the case of using crash rates per VMT for ranking road segments, such a technique would mask the severe crashes hazard.

5.2 Micro-GIS Analysis Results

After choosing a ranking methodology, the severe crash records of 2006 and 2007 were compiled together in order to calculate road segment and signalized intersection scores. Road segment scores and signalized intersection scores were pooled into 2 groups for all 7 counties. Table 5-3 and Table 5-4 provide guidelines to the ranking of roads and intersections. The scores were split into 4 levels according to the 50th, 75th, 90th and 100th percentiles.

Table 5-3: Breakdown of Road Segment Scores

Color in GIS	Score
Black	>17.094 (Rank 1)
Red	6.316-17.094 (Rank 2)
Yellow	2.060-6.315 (Rank 3)
Green	0-2.059 (Rank 4)

Table 5-4: Breakdown of Signalized Intersections Score

Color in GIS	Score
Black	>5 (Rank 1)
Red	4 & 5 (Rank 2)
Yellow	2 & 3 (Rank 3)
Green	0 & 1 (Rank 4)

A new layer had to be created in order to generate a map of the road segments. This is accomplished by using the "Add Route Events" option in ArcMap 9.2. Since there already is a State-Road layer for Florida, the map of the road segments is created by referencing the road segments' excel table to the State-Road map. GIS then uses the Roadway ID and beginning and ending milepoints of the road segments to generate the map. For visual purposes, the beginning and ending milepoints of segments used to draw the maps in GIS include intersection influence areas. This is required in order for road segments to appear continuous. For mapping signalized intersections in GIS, the procedure was much simpler. The signalized intersections of the 7 counties were extracted from their corresponding GIS layer (see Figure 3-4). A new map of the signalized intersections of the 7 counties was then created. Intersection scores were then appended to the signalized intersection attribute table of the newly created map in GIS. The results are shown in the following sections with the tables emphasizing on road segments and intersections that ranked 1 and 2. In the tables, IC stands for incapacitating crashes; FC stands for fatal crashes.

5.2.1 Escambia County

In Figure 5-3 and Figure 5-4, it can be seen that the most dangerous roadway segments and intersections occur in the southern region of the county. Roadway 48040000 (SR 295,727) has the highest number of hazardous road segments according to the analysis. (see Table 5-5).

Table 5-5: Escambia County Worst Road Segments

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
48003000	SR 289	4.053	4.183	1	1	0	7.692308	2
48003000	SR 289	4.586	4.671	4	4	0	47.05882	1
48004000	SR 295	7.131	7.748	3	2	1	6.482982	2
48004000	SR 295	6.871	7.075	3	3	0	14.70588	2
48004000	SR 295	8.341	8.527	3	3	0	16.12903	2
48004000	SR 295	7.804	8.285	8	8	0	16.63202	2
48004000	SR 727	5.989	6.108	6	6	0	50.42017	1
48010000	SR 10	6.589	7.491	6	4	2	8.86918	2
48010000	SR 10	10.431	10.621	3	3	0	15.78947	2
48010000	SR 10	11.098	11.295	4	4	0	20.30457	1
48010000	SR 10	10.265	10.375	3	3	0	27.27273	1
48012000	SR 296	1.456	2.26	8	6	2	12.43781	2
48012000	SR 296	0.653	1.456	10	9	1	13.69863	2
48012000	SR 296	0.028	0.597	11	11	0	19.33216	1
48020000	SR 10A	8.18	8.674	4	4	0	8.097166	2
48020000	SR 10A	10.923	10.98	1	1	0	17.54386	1
48020000	SR 10A	10.522	10.867	11	10	1	34.78261	1
48040000	SR 95	8.177	8.615	3	3	0	6.849315	2
48040000	SR 95	17.869	18.818	5	3	2	7.376185	2
48040000	SR 95	14.741	14.994	2	2	0	7.905138	2
48040000	SR 95	10.231	10.725	3	2	1	8.097166	2
48040000	SR 95	11.787	11.979	2	2	0	10.41667	2
48040000	SR 95	3.571	4.144	9	9	0	15.70681	2
48040000	SR 95	7.631	8.121	8	8	0	16.32653	2
48040000	SR 95	5.236	5.783	11	11	0	20.10969	1
48040000	SR 95	5.963	6.068	3	3	0	28.57143	1
48040000	SR 95	5.839	5.907	4	4	0	58.82353	1
48050000	SR 292	20.92	21.029	1	1	0	9.174312	2
48050000	SR 292	21.029	21.923	14	14	0	15.65996	2
48070000	SR 291	2.55	2.696	2	2	0	13.69863	2
48080000	SR 295	3.07	3.829	5	4	1	7.905138	2
48080000	SR 295	1.717	2.026	4	4	0	12.94498	2
48080000	SR 295	1.3	1.524	3	3	0	13.39286	2
48080060	SR 30	2.398	2.59	2	1	1	15.625	2
48080062	SR 295	0.354	0.482	2	2	0	15.625	2
48190000	SR 297	0.949	1.71	7	7	0	9.198423	2
48190000	SR 297	3.504	3.677	1	0	1	11.56069	2
48280000	SR 30	3.639	4.228	4	4	0	6.791171	2

Table 5-6: Escambia County Worst Signalized Intersections

Roadway ID	State Road	Signal Mp	Total Severe Crashes	IC	FC	Score	Rank
48004000	SR 727	6.136	5	5	0	5	2
48004000	SR 295	7.776	4	4	0	4	2
48004000	SR 295	9.647	5	5	0	5	2
48020000	SR 10A	7.788	7	7	0	7	1
48020000	SR 10A	8.702	11	11	0	11	1
48020000	SR 10A	11.095	4	4	0	4	2
48040000	SR 95	7.603	3	2	1	4	2
48040000	SR 95	9.709	4	4	0	4	2
48040000	SR 95	11.307	5	5	0	5	2
48080060	SR 30	0.434	6	6	0	6	1
48280000	SR 30	2.123	9	9	0	9	1
48280000	SR 30	5.46	5	5	0	5	2
48280000	SR30	3.611	5	4	1	6	1

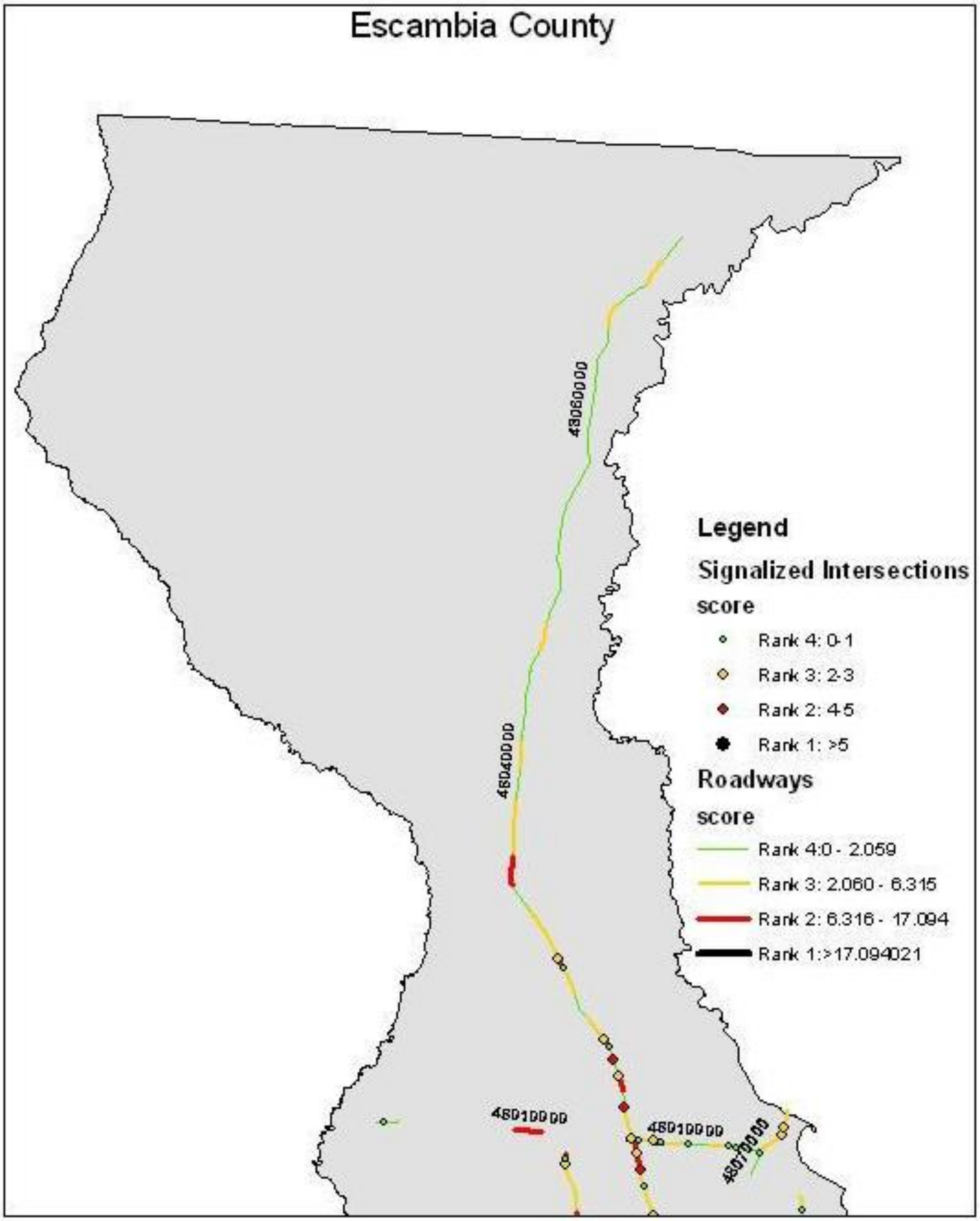


Figure 5-3: Escambia County Map (North)

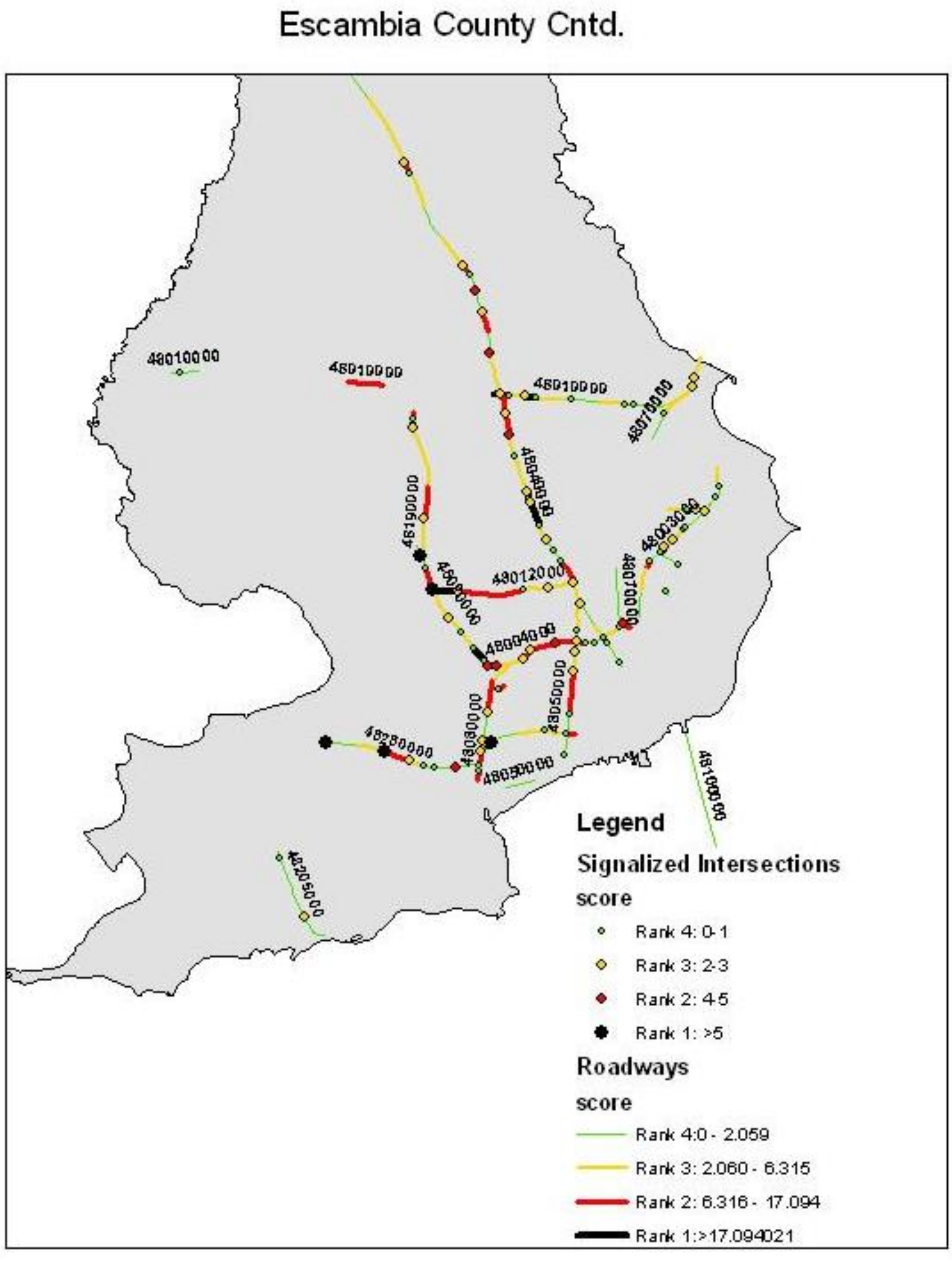


Figure 5-4: Escambia County Map (South)

5.2.2 Duval County

The most hazardous roadways are the ones located in the central region of the county, mainly Roadway 72100000 (SR 10) (see Table 5-7 and Figure 5-5). There are very few dangerous signalized intersections in the county. Overall, Duval County is the safest among the seven chosen counties.

Table 5-7: Duval County Worst Road Segments

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
72014000	SR 109	2.976	3.363	2	1	1	7.751938	2
72014000	SR 109	2.021	2.225	2	1	1	14.70588	2
72014000	SR 109	2.53	2.704	2	1	1	17.24138	1
72014000	SR 109	4.023	4.111	1	0	1	22.72727	1
72028000	SR 152	3.217	3.476	1	0	1	7.722008	2
72028000	SR 152	2.878	2.975	1	1	0	10.30928	2
72028000	SR 152	3.031	3.161	2	2	0	15.38462	2
72028000	SR 152	2.606	2.733	2	2	0	15.74803	2
72030000	SR 15	6.75	7.37	3	2	1	6.451613	2
72030000	SR 15	1.272	2.055	4	1	3	8.939974	2
72030000	SR 15	8.738	9.094	2	0	2	11.23596	2
72070000	SR 5	13.828	14.747	5	3	2	7.616975	2
72080000	SR 15	6.811	7.61	5	3	2	8.760951	2
72080000	SR 139	2.178	2.571	3	2	1	10.17812	2
72100000	SR 10	5.378	5.676	2	2	0	6.711409	2
72100000	SR 10	7.523	7.658	1	1	0	7.407407	2
72100000	SR 10	5.057	5.322	2	2	0	7.54717	2
72100000	SR 10	10.515	10.95	3	2	1	9.195402	2
72100000	SR 10	7.174	7.467	3	3	0	10.23891	2
72100000	SR 10	3.248	3.627	4	4	0	10.55409	2
72100000	SR 10	10.022	10.459	5	5	0	11.44165	2
72100000	SR 10	11.006	11.262	2	1	1	11.71875	2
72100000	SR 10	7.04	7.118	1	1	0	12.82051	2
72100000	SR 10	1.872	2.022	2	2	0	13.33333	2
72100000	SR 10	11.318	11.863	7	6	1	14.6789	2
72100000	SR 10	4.682	4.799	2	2	0	17.09402	1
72100000	SR 10	2.078	2.173	2	2	0	21.05263	1
72100000	SR 10	4.855	5.001	3	2	1	27.39726	1
72100000	SR 10	3.014	3.192	6	6	0	33.70787	1
72120000	SR 228	17.612	17.921	3	3	0	9.708738	2

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
72160000	SR 13	0	0.14	1	1	0	7.142857	2
72160000	SR 13	3.393	3.599	2	2	0	9.708738	2
72160000	SR 13	4.442	4.647	1	0	1	9.756098	2
72160000	SR 13	2.947	3.317	3	2	1	10.81081	2
72160000	SR 13	7.881	8.061	2	2	0	11.11111	2
72170000	SR 21	6.251	6.704	3	3	0	6.622517	2
72170000	SR 21	0	0.147	1	1	0	6.802721	2
72170000	SR 21	1.043	1.44	2	1	1	7.556675	2
72170000	SR 21	5.466	5.683	1	0	1	9.21659	2
72170000	SR 21	6.892	7.382	5	4	1	12.2449	2
72170000	SR 21	5.739	6.069	3	1	2	15.15152	2
72170000	SR 21	0.32	0.665	5	4	1	17.3913	1
72190000	SR 212	7.413	7.716	2	2	0	6.60066	2
72190000	SR 212	8.848	9.622	6	5	1	9.043928	2
72190000	SR 212	4.962	5.047	1	1	0	11.76471	2
72190000	SR 212	11.479	12.056	5	3	2	12.13172	2
72190000	SR 212	6.383	6.671	4	4	0	13.88889	2
72190000	SR 212	6.727	6.795	1	1	0	14.70588	2
72190000	SR 212	5.742	5.998	3	2	1	15.625	2
72190000	SR 212	6.851	7.357	6	4	2	15.81028	2
72220000	SR 134	7.782	8.012	3	3	0	13.04348	2
72220000	SR 134	6.39	6.841	5	4	1	13.30377	2
72220000	SR 134	8.214	8.662	7	4	3	22.32143	1
72220000	SR 134	8.068	8.088	1	1	0	50	1
72220000	SR 134	8.144	8.158	3	3	0	214.2857	1
72230000	SR A1A	2.158	2.272	1	1	0	8.77193	2
72250000	SR 105	0.437	1.323	5	4	1	6.772009	2
72250000	SR 105	6.003	6.32	4	3	1	15.77287	2
72291000	SR 111	5.201	5.89	4	3	1	7.256894	2

Table 5-8: Duval County Worst Signalized Intersections

Roadway ID	State Road	Signal Mp	Total Severe Crashes	IC	FC	Score	Rank
72010000	SR 10	20.213	4	4	0	4	2
72012000	SR 103	0	3	2	1	4	2
72030000	SR 15	0.46	4	4	0	4	2
72160000	SR 13	0.168	2	0	2	4	2
72170000	SR 21	0.693	3	2	1	4	2
72190000	SR 212	6.823	6	4	2	8	1
72190000	SR 212	6.355	3	2	1	4	2
72190000	SR 212	5.075	3	2	1	4	2
72220000	SR 134	6.869	4	4	0	4	2
72230000	SR A1A	2.3	4	4	0	4	2

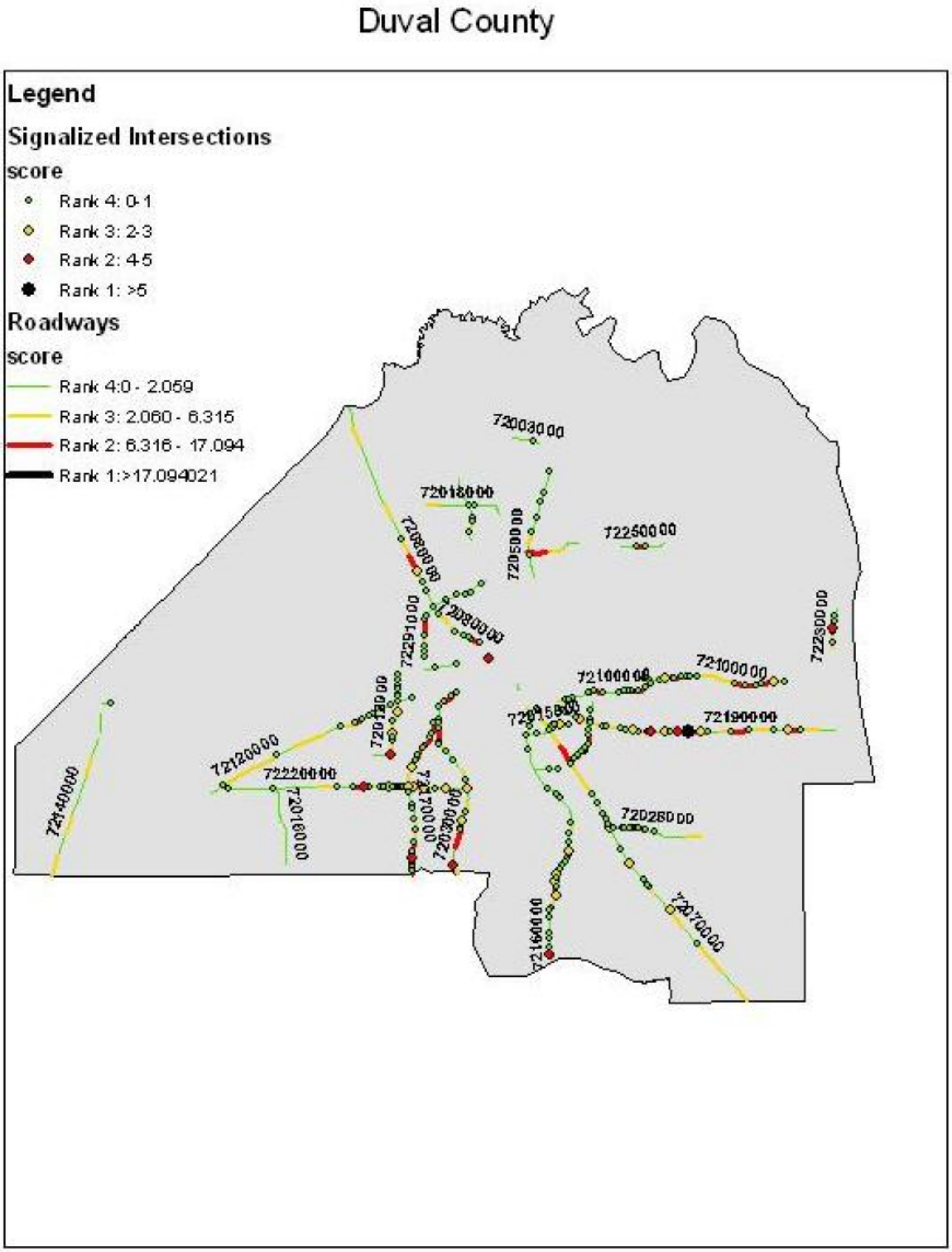


Figure 5-5: Duval County Map

5.2.3 Orange County

From the tables (Table 5-9 and Table 5-10) and figures (Figure 5-6 and Figure 5-7) and it can be clearly observed that the roadways with the most dangerous road segments and intersections are Roadway 75003000 (SR 436), Roadway 75050000 (SR 50) and Roadway 75060000 (SR 50).

Table 5-9: Orange County Worst Road Segments

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
75002000	SR 482	1.261	1.828	4	4	0	7.054674	2
75002000	SR 482	4.447	4.764	3	3	0	9.463722	2
75002000	SR 482	3.009	3.635	5	3	2	11.18211	2
75002000	SR 482	4.82	5.017	2	1	1	15.22843	2
75003000	SR 436	9.636	10.079	3	3	0	6.772009	2
75003000	SR 436	2.076	2.326	1	0	1	8	2
75003000	SR 436	6.554	7.033	3	2	1	8.350731	2
75003000	SR 436	8.57	8.799	2	2	0	8.733624	2
75003000	SR 436	5.302	5.629	2	1	1	9.174312	2
75003000	SR 436	8.855	9.58	5	3	2	9.655172	2
75003000	SR 436	3.8	4.352	4	2	2	10.86957	2
75003000	SR 436	5.685	6.021	3	2	1	11.90476	2
75003000	SR 436	5.023	5.246	2	1	1	13.45291	2
75003000	SR 436	7.512	7.583	2	2	0	28.16901	1
75010000	SR 500	6.411	6.549	1	1	0	7.246377	2
75010000	SR 500	10.811	11.065	2	2	0	7.874016	2
75010000	SR 500	8.01	8.106	1	1	0	10.41667	2
75010000	SR 500	8.666	9.412	4	0	4	10.72386	2
75010000	SR 500	2.97	3.39	5	4	1	14.28571	2
75010000	SR 500	9.468	10.117	9	5	4	20.03082	1
75010000	SR 500	10.173	10.755	12	10	2	24.05498	1
75012000	SR 552	1.841	2.148	2	2	0	6.514658	2
75012000	SR 552	1.029	1.224	1	0	1	10.25641	2
75012000	SR 552	0.17	0.35	2	1	1	16.66667	2
75020000	SR 500	10.359	10.514	1	1	0	6.451613	2
75020000	SR 500	20.269	21.116	4	1	3	8.264463	2
75020000	SR 500	1.973	2.668	5	2	3	11.51079	2
75020000	SR 500	11.76	12.251	4	2	2	12.21996	2
75035000	SR 535	0	0.098	1	1	0	10.20408	2
75035001	SR 535	1.796	1.875	1	1	0	12.65823	2
75037000	SR 434	0.475	1.1	3	1	2	8	2

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
75037000	SR 434	2.19	2.44	2	2	0	8	2
75037000	SR 434	1.476	1.827	2	1	1	8.547009	2
75037000	SR 434	1.156	1.42	2	1	1	11.36364	2
75037000	SR 434	1.883	2.114	3	2	1	17.31602	1
75050000	SR 50	8.793	9.31	2	0	2	7.736944	2
75050000	SR 50	11.817	12.075	1	0	1	7.751938	2
75050000	SR 50	15.086	15.329	2	2	0	8.230453	2
75050000	SR 50	8.427	8.737	2	1	1	9.677419	2
75050000	SR 50	14.523	14.831	3	3	0	9.74026	2
75050000	SR 50	12.853	13.335	4	3	1	10.37344	2
75050000	SR 50	12.615	12.797	2	2	0	10.98901	2
75050000	SR 50	11.129	11.578	4	3	1	11.13586	2
75050000	SR 50	6.028	6.11	1	1	0	12.19512	2
75050000	SR 50	11.634	11.761	2	2	0	15.74803	2
75060000	SR 50	13.31	13.772	2	1	1	6.493506	2
75060000	SR 50	13.828	14.265	3	3	0	6.864989	2
75060000	SR 50	18.074	19.042	5	3	2	7.231405	2
75060000	SR 50	7.473	8.004	3	2	1	7.532957	2
75060000	SR 50	13.021	13.254	2	2	0	8.583691	2
75060000	SR 50	8.08	8.915	7	5	2	10.77844	2
75060000	SR 50	5.24	5.822	6	5	1	12.02749	2
75060000	SR 50	6.972	7.417	4	2	2	13.48315	2
75060000	SR 50	10.251	10.712	6	5	1	15.18438	2
75060000	SR 50	2.173	2.37	3	3	0	15.22843	2
75060000	SR 50	0.167	0.361	2	1	1	15.46392	2
75060000	SR 50	2.952	3.07	2	2	0	16.94915	2
75060000	SR 50	5.822	6.403	7	4	3	17.2117	1
75060000	SR 50	0.028	0.111	3	3	0	36.14458	1
75060000	SR 50	1.047	1.102	2	2	0	36.36364	1
75080000	SR 15	15.124	15.757	4	4	0	6.319115	2
75090000	SR 426	3.485	4.097	4	3	1	8.169935	2
75190000	SR 423	8.136	8.37	2	2	0	8.547009	2
75190001	SR 423	39.542	39.668	1	1	0	7.936508	2
75190001	SR 423	39.724	39.972	3	3	0	12.09677	2
75200000	SR 551	4.434	4.499	1	1	0	15.38462	2
75200000	SR 551	4.527	4.546	1	1	0	52.63158	1
75220000	SR 530	1.487	1.726	2	2	0	8.368201	2
75250000	SR 438	6.145	6.276	2	1	1	22.90076	1
75260000	SR 434	6.448	6.737	1	0	1	6.920415	2
75260000	SR 424	4.253	4.826	4	3	1	8.726003	2
75260000	SR 424	2.311	2.439	2	2	0	15.625	2
75270000	SR 435	1.983	2.258	5	4	1	21.81818	1

Table 5-10: Orange County Worst Signalized Intersections

Roadway ID	State Road	Signal Mp	Total Severe Crashes	IC	FC	Score	Rank
75003000	SR 436	1.245	4	4	0	4	2
75003000	SR 436	3.308	3	1	2	5	2
75003000	SR 436	4.995	5	4	1	6	1
75003000	SR 436	7.324	6	6	0	6	1
75010000	SR 600	8.638	3	2	1	4	2
75010000	SR 600	10.145	6	6	0	6	1
75020000	SR 500	4.835	3	2	1	4	2
75020000	SR 500	10.312	3	2	1	4	2
75050000	SR 50	11.606	4	4	0	4	2
75050000	SR 50	13.739	4	4	0	4	2
75050000	SR 50	14.869	3	2	1	4	2
75050000	SR 50	7.079	5	5	0	5	2
75050000	SR 50	13.872	4	3	1	5	2
75050000	SR 50	12.825	7	7	0	7	1
75060000	SR 50	2.653	3	2	1	4	2
75060000	SR 50	8.943	2	0	2	4	2
75190000	SR 423	4.428	4	4	0	4	2
75270000	SR 435	0.543	5	5	0	5	2

Orange County

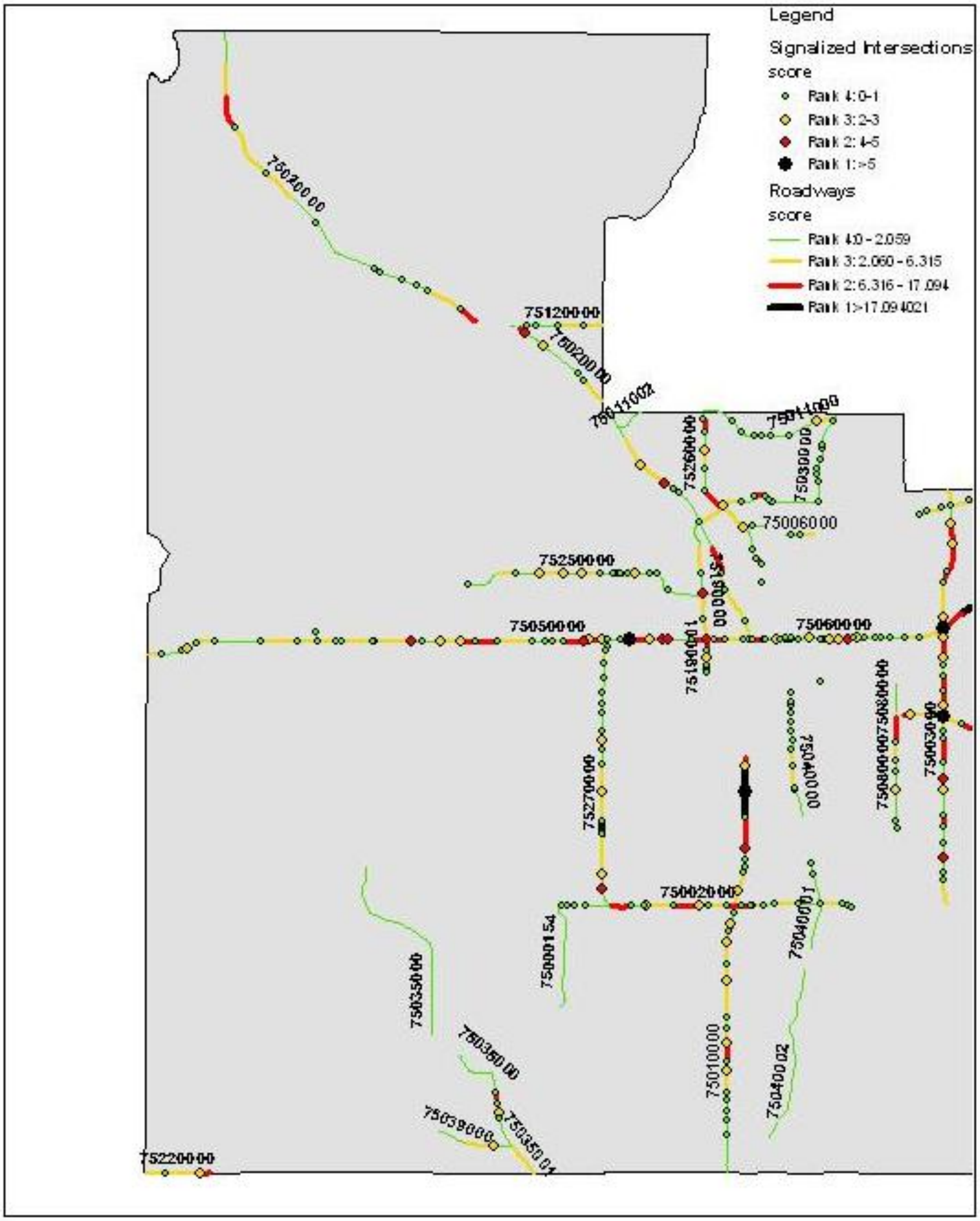


Figure 5-6: Orange County Map (West)

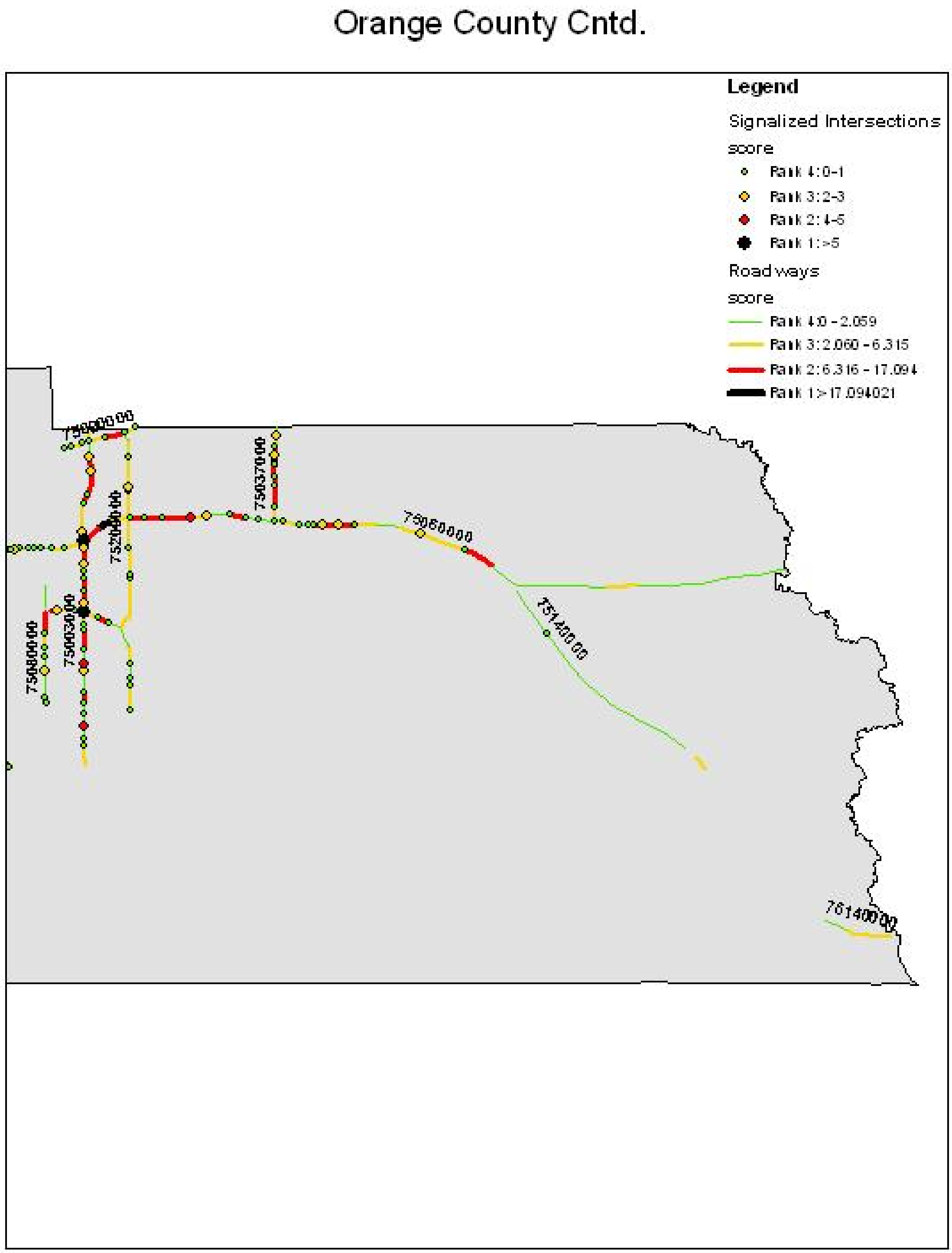


Figure 5-7: Orange County Map (East)

5.2.4 Miami-Dade County

Roadways 87020000 (SR 5) and 87030000 (SR 5) have the most dangerous roadway segments (see Table 5-11, Figure 5-8 and Figure 5-9). In fact both roadways are part of the same corridor near the eastern portion of the county. The most hazardous signalized intersections are spread around the county. There does not seem to be any clusters of unsafe intersections, with the exception of those on Roadway 87020000.

Table 5-11: Miami-Dade Worst Road Segments

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
87001000	SR 94	3.782	3.924	1	1	0	7.042254	2
87001000	SR 94	4.791	4.926	1	1	0	7.407407	2
87001000	SR 94	3.474	3.726	2	2	0	7.936508	2
87001000	SR 94	5.402	5.505	1	1	0	9.708738	2
87001000	SR 94	2.157	2.408	3	3	0	11.95219	2
87001000	SR 94	6.489	7.094	7	6	1	13.22314	2
87001000	SR 94	6.153	6.433	3	2	1	14.28571	2
87002000	SR 823	3.598	3.747	1	1	0	6.711409	2
87002000	SR 823	1.31	1.434	1	1	0	8.064516	2
87002000	SR 823	7.918	8.478	5	5	0	8.928571	2
87002000	SR 823	2.017	2.254	3	3	0	12.65823	2
87002000	SR 823	0.796	0.861	1	1	0	15.38462	2
87002000	SR 823	4.648	4.71	1	1	0	16.12903	2
87002000	SR 823	3.803	3.912	1	0	1	18.34862	1
87008000	SR 916	9.415	9.612	1	0	1	10.15228	2
87008000	SR 916	8.916	8.986	1	1	0	14.28571	2
87015000	SR 989	0.409	1.129	7	5	2	12.5	2
87019000	SR 817	0.87	1.285	4	4	0	9.638554	2
87019000	SR 817	2.267	2.702	4	3	1	11.49425	2
87019000	SR 817	1.788	2.211	5	5	0	11.82033	2
87019000	SR 817	2.778	2.963	3	3	0	16.21622	2
87019000	SR 817	0.586	0.707	2	1	1	24.79339	1
87020000	SR 5	12.203	12.355	1	1	0	6.578947	2
87020000	SR 5	11.685	11.986	1	0	1	6.644518	2
87020000	SR 5	2.453	3.046	4	4	0	6.745363	2
87020000	SR 5	5.724	6.277	3	2	1	7.233273	2
87020000	SR 5	8.243	8.372	1	1	0	7.751938	2
87020000	SR 5	16.848	17.358	3	2	1	7.843137	2
87020000	SR 5	15.265	15.504	1	0	1	8.368201	2
87020000	SR 5	7.64	8.187	3	1	2	9.140768	2
87020000	SR 5	3.102	3.319	2	2	0	9.21659	2

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
87020000	SR 5	12.411	13.046	4	2	2	9.448819	2
87020000	SR 5	12.042	12.147	1	1	0	9.52381	2
87020000	SR 5	3.671	4.295	6	6	0	9.615385	2
87020000	SR 5	18.256	19.042	8	8	0	10.17812	2
87020000	SR 5	10.837	11.122	3	3	0	10.52632	2
87020000	SR 5	7.093	7.64	5	4	1	10.96892	2
87020000	SR 5	19.656	20.014	4	4	0	11.17318	2
87020000	SR 5	6.779	7.037	2	1	1	11.62791	2
87020000	SR 5	8.428	8.637	2	1	1	14.35407	2
87020000	SR 5	13.824	13.934	1	0	1	18.18182	1
87020000	SR 5	6.333	6.685	4	1	3	19.88636	1
87020000	SR 5	13.99	14.139	3	3	0	20.13423	1
87020000	SR 5	5.045	5.098	3	2	1	75.4717	1
87026000	SR 860	6.136	6.537	2	1	1	7.481297	2
87026000	SR 860	8.744	9.186	3	2	1	9.049774	2
87026000	SR 860	6.631	6.735	1	1	0	9.615385	2
87026000	SR 860	5.606	5.752	3	3	0	20.54795	1
87026000	SR 860	6.791	6.806	1	1	0	66.66667	1
87026005	SR 860	1.764	2.362	5	5	0	8.361204	2
87030000	SR 5	4.892	5.026	1	1	0	7.462687	2
87030000	SR 5	22.072	22.602	3	2	1	7.54717	2
87030000	SR 5	1.469	1.6	1	1	0	7.633588	2
87030000	SR 5	8.825	8.942	1	1	0	8.547009	2
87030000	SR 5	2.466	2.568	1	1	0	9.803922	2
87030000	SR 5	6.014	6.506	5	5	0	10.1626	2
87030000	SR 5	7.648	7.745	1	1	0	10.30928	2
87030000	SR 5	3.251	3.504	3	3	0	11.85771	2
87030000	SR 5	2.13	2.293	1	0	1	12.26994	2
87030000	SR 5	3.56	3.721	2	2	0	12.42236	2
87030000	SR 5	23.414	23.567	2	2	0	13.0719	2
87030000	SR 5	23.89	24.039	2	2	0	13.42282	2
87030000	SR 5	20.437	20.502	1	1	0	15.38462	2
87030000	SR 5	21.253	21.488	3	2	1	17.02128	2
87030000	SR 5	24.677	24.777	1	0	1	20	1
87030000	SR 5	0.989	1.037	1	1	0	20.83333	1
87030000	SR 5	23.02	23.145	3	3	0	24	1
87030000	SR 5	2.349	2.39	1	1	0	24.39024	1
87030000	SR 5	0.901	0.933	1	1	0	31.25	1
87030000	SR 5	24.23	24.25	1	1	0	50	1
87034000	SR 915	3.192	3.572	3	3	0	7.894737	2
87038000	SR 932	1.678	1.786	1	1	0	9.259259	2
87038000	SR 932	1.211	1.286	1	1	0	13.33333	2
87038000	SR 932	1.342	1.446	2	2	0	19.23077	1
87038000	SR 932	3.037	3.122	2	2	0	23.52941	1
87039000	SR 992	1.637	2.387	5	4	1	8	2

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
87039000	SR 992	0.121	0.339	1	0	1	9.174312	2
87044000	SR 976	5.228	5.683	2	1	1	6.593407	2
87044000	SR 976	2.179	2.624	3	3	0	6.741573	2
87044000	SR 976	4.4	4.668	2	2	0	7.462687	2
87044000	SR 976	0.328	0.632	2	1	1	9.868421	2
87044000	SR 976	4.724	5.172	4	3	1	11.16071	2
87044000	SR 976	0.213	0.272	1	1	0	16.94915	2
87047000	SR 973	3.949	4.567	3	2	1	6.472492	2
87047000	SR 973	9.15	9.285	1	1	0	7.407407	2
87047000	SR 973	7.805	7.958	1	0	1	13.0719	2
87052000	SR 924	0.553	0.987	2	1	1	6.912442	2
87052000	SR 924	1.043	1.49	4	2	2	13.42282	2
87052000	SR 924	1.546	1.742	3	2	1	20.40816	1
87053000	SR 968	3.596	3.748	1	1	0	6.578947	2
87053000	SR 968	2.032	2.48	3	2	1	8.928571	2
87053000	SR 968	0.28	0.479	2	2	0	10.05025	2
87053000	SR 968	4.446	4.637	2	2	0	10.4712	2
87053000	SR 968	2.536	2.614	1	1	0	12.82051	2
87053000	SR 968	0	0.224	3	3	0	13.39286	2
87053000	SR 968	5.558	5.845	2	0	2	13.93728	2
87053000	SR 968	5.071	5.502	6	5	1	16.2413	2
87053000	SR 968	1.536	1.772	3	2	1	16.94915	2
87053000	SR 968	3.458	3.54	1	0	1	24.39024	1
87053000	SR 968	5.901	6.054	3	2	1	26.14379	1
87054000	SR 972	2.577	2.852	2	1	1	10.90909	2
87055000	SR 986	1.384	1.99	2	0	2	6.60066	2
87060000	SR A1A	0.817	1.606	5	5	0	6.337136	2
87060000	SR A1A	2.482	2.583	1	0	1	19.80198	1
87062000	SR 959	5.37	5.448	1	1	0	12.82051	2
87072000	SR 985	3.535	4.132	4	4	0	6.700168	2
87072000	SR 985	2.542	2.976	2	1	1	6.912442	2
87072000	SR 985	4.208	4.642	3	3	0	6.912442	2
87072000	SR 985	5.985	6.123	1	1	0	7.246377	2
87072000	SR 985	7.354	7.604	1	0	1	8	2
87072000	SR 985	6.217	6.384	1	0	1	11.97605	2
87080900	SR 934	37.807	37.94	1	1	0	7.518797	2
87080900	SR 934	37.996	38.16	2	2	0	12.19512	2
87090000	SR 934	9.618	10.058	3	3	0	6.818182	2
87090000	SR 934	5.014	5.201	2	2	0	10.69519	2
87090000	SR 934	0	0.997	7	3	4	11.0331	2
87090000	SR 934	5.277	6.162	8	6	2	11.29944	2
87090000	SR 934	10.152	10.256	3	3	0	28.84615	1
87090000	SR 934	13.583	13.609	1	1	0	38.46154	1
87091000	SR 994	6.386	6.53	1	1	0	6.944444	2
87091000	SR 994	5.698	5.813	1	1	0	8.695652	2

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
87091000	SR 994	6.586	6.801	2	2	0	9.302326	2
87120000	SR 90	4.497	5	4	4	0	7.952286	2
87120000	SR 90	5.921	6.17	1	0	1	8.032129	2
87120000	SR 90	5.056	5.491	3	2	1	9.195402	2
87120000	SR 90	7.097	7.53	2	0	2	9.237875	2
87120000	SR 90	6.596	6.779	1	0	1	10.92896	2
87120000	SR 90	6.455	6.54	1	1	0	11.76471	2
87120000	SR 90	9.09	9.557	6	5	1	14.98929	2
87120000	SR 90	6.835	7.021	3	3	0	16.12903	2
87140000	SR 7	7.701	8.133	3	3	0	6.944444	2
87140000	SR 7	5.801	6.176	2	1	1	8	2
87140000	SR 7	12.642	12.866	2	2	0	8.928571	2
87140000	SR 7	13.124	13.56	3	2	1	9.174312	2
87140000	SR 7	13.636	13.854	2	2	0	9.174312	2
87140000	SR 7	14.215	14.652	5	5	0	11.44165	2
87140000	SR 7	10.216	10.7	6	6	0	12.39669	2
87140000	SR 7	5.477	5.621	1	0	1	13.88889	2
87190000	SR 909	2.134	2.43	3	3	0	10.13514	2
87190000	SR 909	2.486	2.782	3	3	0	10.13514	2
87220000	SR 948	2.193	2.47	3	3	0	10.83032	2
87220000	SR 948	3.535	3.675	3	3	0	21.42857	1
87240000	SR 9	9.506	9.576	1	1	0	14.28571	2
87240000	SR 9	8.323	8.81	6	5	1	14.37372	2
87240000	SR 9	2.259	2.326	1	1	0	14.92537	2
87240000	SR 9	9.301	9.45	2	1	1	20.13423	1
87250000	SR 944	4.275	4.469	2	2	0	10.30928	2
87250000	SR 944	0.483	0.663	2	1	1	16.66667	2
87281000	SR 953	2.123	2.588	3	1	2	10.75269	2
87281000	SR 953	7.989	8.168	1	0	1	11.17318	2

Table 5-12: Miami Dade-Worst Signalized Intersections

Roadway ID	State Road	Signal Mp	Total Severe Crashes	IC	FC	Score	Rank
87001000	SR 94	3.129	4	4	0	4	2
87002000	SR 823	0.566	3	2	1	4	2
87002000	SR 823	6.058	4	4	0	4	2
87002000	SR 823	8.746	4	4	0	4	2
87002000	SR 823	4.738	6	6	0	6	1
87008000	SR 916	8.637	4	3	1	5	2
87015000	SR 989	2.417	4	4	0	4	2
87019000	SR 817	4.351	4	3	1	5	2
87020000	SR 5	6.305	3	2	1	4	2
87020000	SR 5	7.065	3	2	1	4	2
87020000	SR 5	10.47	4	4	0	4	2
87020000	SR 5	11.647	4	4	0	4	2
87020000	SR 5	13.234	4	4	0	4	2
87020000	SR 5	2.425	3	1	2	5	2
87020000	SR 5	4.323	5	3	2	7	1
87026000	SR 860	8.185	3	2	1	4	2
87026000	SR 860	2.021	6	6	0	6	1
87026000	SR 860	2.519	6	5	1	7	1
87030000	SR 5	7.62	3	2	1	4	2
87030000	SR 5	23.605	4	4	0	4	2
87030000	SR 5	24.649	4	4	0	4	2
87030000	SR 5	3.749	5	5	0	5	2
87030000	SR 5	6.534	5	3	2	7	1
87037000	SR 907	1.54	4	4	0	4	2
87044000	SR 976	4.696	2	0	2	4	2
87044000	SR 976	2.652	3	2	1	4	2
87044000	SR 976	4.175	3	1	2	5	2
87044000	SR 976	0.66	5	5	0	5	2
87053000	SR 968	2.004	3	2	1	4	2
87053000	SR 968	4.031	3	2	1	4	2
87060000	SR A1A	12.733	3	2	1	4	2
87060000	SR A1A	1.634	4	3	1	5	2
87072000	SR 985	5.161	3	1	2	5	2
87090000	SR 25	4.986	3	1	2	5	2
87090000	SR 25	5.239	3	1	2	5	2
87090000	SR 25	8.804	6	5	1	7	1
87091000	SR 994	7.466	4	4	0	4	2
87120000	SR 90	5.874	4	3	1	5	2
87140000	SR 7	12.604	4	4	0	4	2
87240000	SR 9	8.848	2	0	2	4	2
87240000	SR 9	11.809	2	0	2	4	2
87240000	SR 9	9.864	3	2	1	4	2
87240000	SR 9	9.478	4	2	2	6	1
87250000	SR 944	2.967	4	3	1	5	2
87281000	SR 953	8.647	4	4	0	4	2

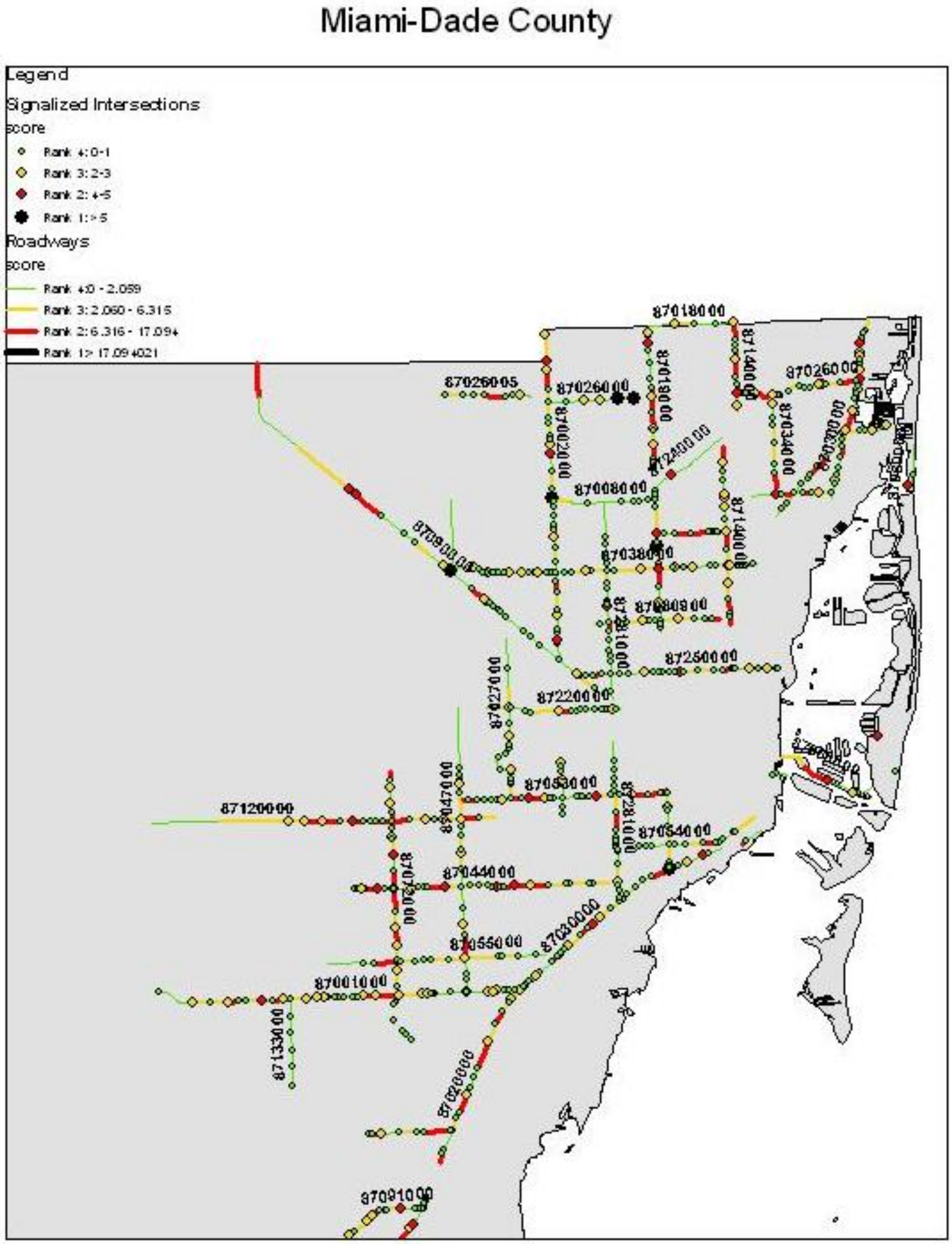


Figure 5-8: Miami-Dade County Map (North)

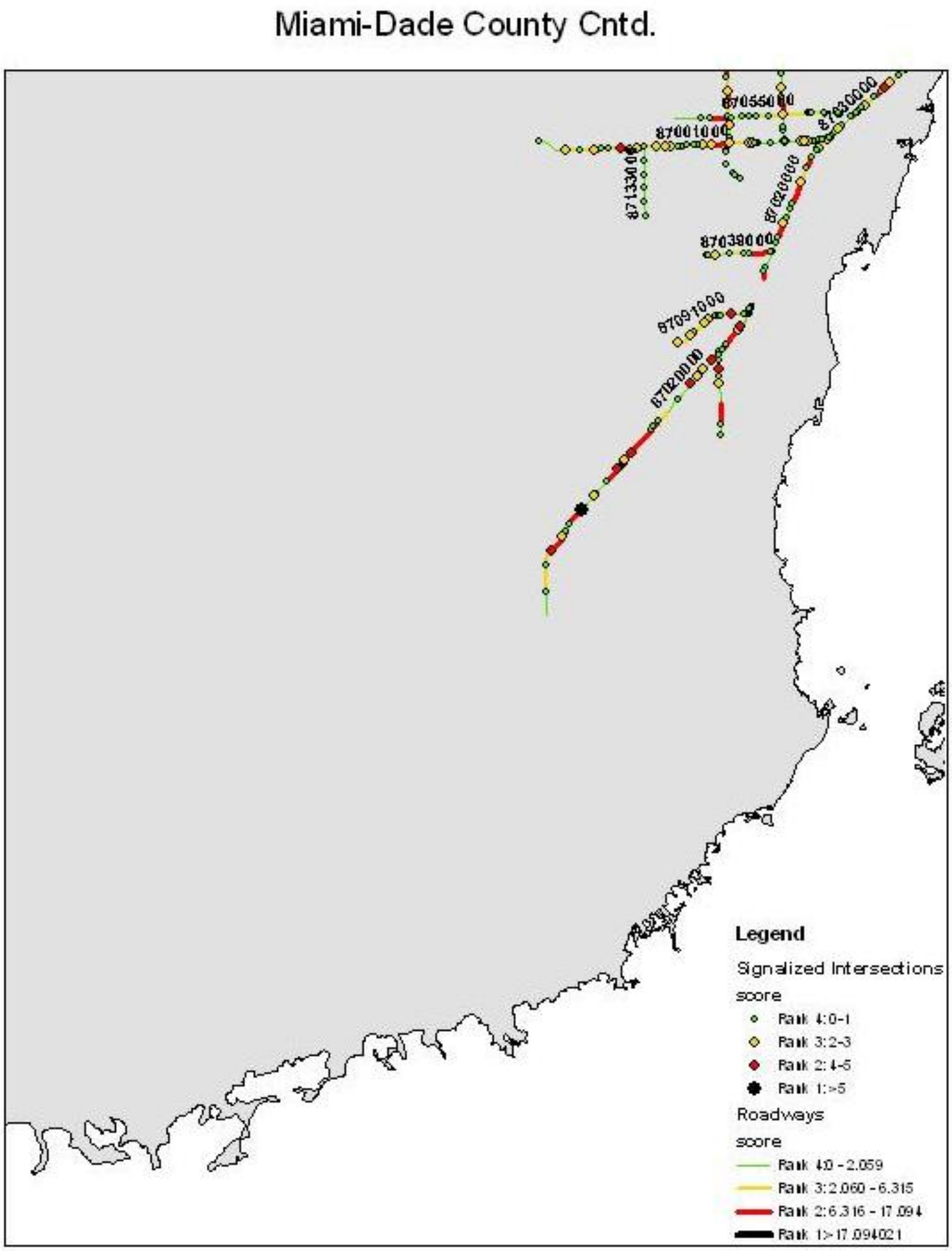


Figure 5-9: Miami-Dade County Map (South)

5.2.5 Pasco County

It is very clear from Table 5-13, Table 5-14 and Figure 5-10 that the west-most corridor (Roadway 14030000, SR 55) that runs from the north to the south of Pasco County has many dangerous roadway segments and intersections. In fact, this corridor is the most dangerous among all seven counties. Crash propagation is evident on this corridor as several 'black' and 'red' segments and intersections appear to be consecutive.

Table 5-13: Pasco County Worst Road Segments

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
14030000	SR 55	2.545	3.005	3	3	0	6.521739	2
14030000	SR 55	4.21	4.635	3	3	0	7.058824	2
14030000	SR 55	1.547	1.683	1	1	0	7.352941	2
14030000	SR 55	9.755	9.964	1	0	1	9.569378	2
14030000	SR 55	12.902	13.81	9	9	0	9.911894	2
14030000	SR 55	10.02	10.455	5	5	0	11.49425	2
14030000	SR 55	0.298	0.627	4	4	0	12.15805	2
14030000	SR 55	8.784	9.023	3	3	0	12.5523	2
14030000	SR 55	7.745	8.454	8	7	1	12.69394	2
14030000	SR 55	13.866	14.469	7	6	1	13.267	2
14030000	SR 55	4.691	4.832	2	2	0	14.1844	2
14030000	SR 55	11.517	11.938	6	6	0	14.25178	2
14030000	SR 55	4.888	5.415	8	7	1	17.0778	2
14030000	SR 55	7.186	7.689	8	7	1	17.89264	1
14030000	SR 55	5.471	6.3	11	7	4	18.09409	1
14030000	SR 55	3.081	3.565	10	9	1	22.72727	1
14030000	SR 55	0.683	0.99	6	5	1	22.8013	1
14030000	SR 55	11.994	12.902	17	13	4	23.12775	1
14030000	SR 55	1.739	2.489	17	16	1	24	1
14030000	SR 55	0	0.242	6	6	0	24.79339	1
14030000	SR 55	6.3	7.13	16	11	5	25.3012	1
14030000	SR 55	10.511	11.441	22	20	2	25.80645	1
14030000	SR 55	1.046	1.491	13	12	1	31.46067	1
14030000	SR 55	9.079	9.528	16	14	2	40.08909	1
14050000	SR 35	15.958	16.886	4	2	2	6.465517	2
14050000	SR 39	7.248	8.016	5	5	0	6.510417	2
14050000	SR 35	16.886	17.814	5	3	2	7.543103	2
14050000	SR 39	8.868	9.692	7	7	0	8.495146	2
14050000	SR 35	15.03	15.958	8	8	0	8.62069	2
14090000	SR 54	0.038	0.889	5	4	1	7.050529	2
14090000	SR 54	9.34	9.554	2	2	0	9.345794	2
14120000	SR 52	2.05	2.49	3	3	0	6.818182	2
14120000	SR 53	3.056	3.465	2	1	1	7.334963	2

Roadway ID	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
14120000	SR 54	0.796	1.289	5	5	0	10.14199	2
14120000	SR 55	0.039	0.473	5	4	1	13.82488	2

Table 5-14: Pasco County Worst Signalized Intersections

Roadway ID	State Road	Signal Mp	Total Severe Crashes	IC	FC	Score	Rank
14030000	SR 55	0.655	3	2	1	4	2
14030000	SR 55	8.756	4	4	0	4	2
14030000	SR 55	11.479	4	4	0	4	2
14030000	SR 55	16.126	4	4	0	4	2
14030000	SR 55	10.483	5	5	0	5	2
14030000	SR 55	1.018	6	6	0	6	1
14030000	SR 55	14.818	7	7	0	7	1
14030000	SR 55	9.727	7	6	1	8	1
14030000	SR 55	13.838	6	4	2	8	1
14030000	SR 55	3.043	7	5	2	9	1
14030000	SR 55	1.711	9	8	1	10	1
14030000	SR 55	1.519	10	9	1	11	1
14090000	SR 54	1.778	3	2	1	4	2
14120000	SR 52	0.501	4	4	0	4	2
14120000	SR 52	0.768	5	5	0	5	2
14120000	SR 52	3.028	5	5	0	5	2
14120000	SR 52	2.012	6	6	0	6	1
14570101	SR 54	0.201	5	5	0	5	2

Pasco/Pinellas/Hillsborough Counties

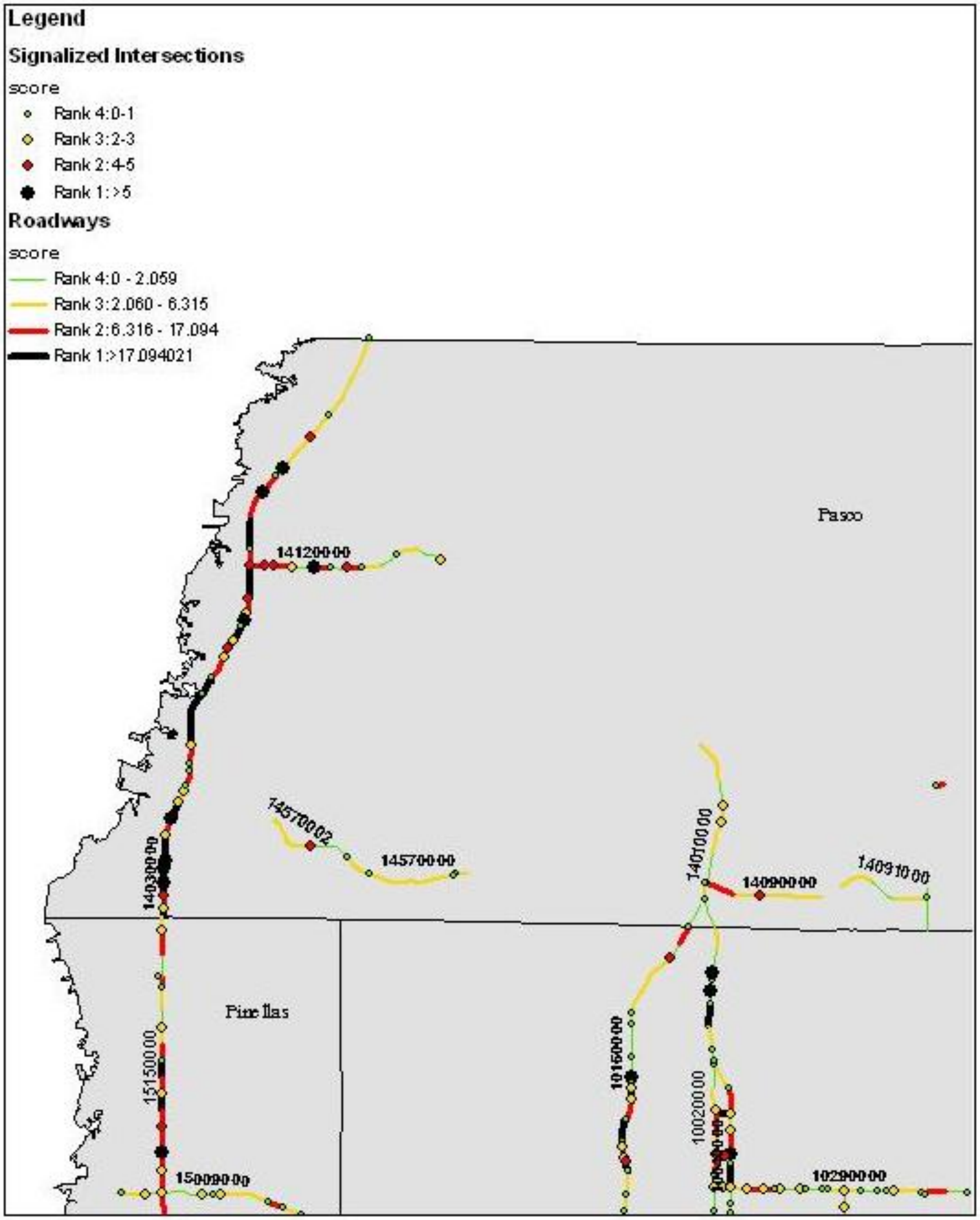


Figure 5-10: Pasco County Map

5.2.6 Pinellas County

As observed in, Table 5-15, Table 5-16 and Figure 5-11 that Roadway 15150000 (SR 55) has the most hazardous road segments and intersections. It seems that severe crashes propagate from road segments to intersections on SR 55. It has to be noted that this roadway is not continuous. Several sections of it do not classify as multilane corridors. It is also interesting to note that Roadway 15150000 is a continuation of Roadway 14030000, from Pasco County (Figure 5-10). Thus both roadways are part of the same corridor system, SR 55, which explains the high trend of crashes on both of them.

Table 5-15: Pinellas County Worst Road Segments

Roadway ID	State Road	Begpt	Endpt	Total Severe Crashes	IC	FC	Score	Rank
15007000	SR 595	0.788	1.091	1	0	1	6.60066	2
15007000	SR 595	0.278	0.732	3	2	1	8.810573	2
15007000	SR 595	1.305	1.507	2	2	0	9.90099	2
15007000	SR 651	3.572	3.77	2	2	0	10.10101	2
15010000	SR 595	5.432	5.921	4	4	0	8.179959	2
15010000	SR 595	13.568	14.014	4	4	0	8.96861	2
15010000	SR 595	11.294	11.493	1	0	1	10.05025	2
15010000	SR 595	15.087	15.286	1	0	1	10.05025	2
15010000	SR 595	10.191	10.484	4	4	0	13.65188	2
15010000	SR 595	6.11	6.617	6	5	1	13.80671	2
15010000	SR 595	14.582	15.031	6	5	1	15.5902	2
15010000	SR 595	18.147	18.366	4	4	0	18.26484	1
15030000	SR 686	1.057	1.52	2	1	1	6.479482	2
15030000	SR 686	2.081	2.529	3	3	0	6.696429	2
15030000	SR 686	9.107	9.683	4	4	0	6.944444	2
15030000	SR 686	3.609	3.74	1	1	0	7.633588	2
15030000	SR 686	2.605	2.86	2	2	0	7.843137	2
15030000	SR 686	3.796	4.033	2	2	0	8.438819	2
15030000	SR 686	2.916	3.239	2	1	1	9.287926	2
15030000	SR 686	4.571	5.112	4	2	2	11.09057	2
15030000	SR 686	5.168	5.401	3	3	0	12.87554	2
15030000	SR 686	4.089	4.515	6	5	1	16.43192	2
15030000	SR 686	5.457	5.501	1	1	0	22.72727	1
15040000	SR 60	5.765	5.916	1	1	0	6.622517	2
15040000	SR 60	4.974	5.675	4	3	1	7.132668	2
15040000	SR 60	3.469	4.134	6	6	0	9.022556	2
15040000	SR 60	2.708	2.903	2	2	0	10.25641	2
15040000	SR 60	2.463	2.652	2	2	0	10.58201	2
15040000	SR 60	4.285	4.379	1	1	0	10.6383	2

Roadway ID	State Road	Begpt	Endpt	Total Severe Crashes	IC	FC	Score	Rank
15040000	SR 60	4.708	4.806	2	2	0	20.40816	1
15040000	SR 60	4.862	4.918	2	1	1	53.57143	1
15050000	SR 590	2.461	2.748	2	2	0	6.968641	2
15050000	SR 590	1.507	2.115	5	5	0	8.223684	2
15050000	SR 580	13.068	13.172	1	1	0	9.615385	2
15050000	SR 590	2.804	2.88	1	1	0	13.15789	2
15050000	SR 590	2.171	2.405	3	2	1	17.09402	1
15050000	SR 580	11.438	11.48	1	1	0	23.80952	1
15070000	SR 580	5.008	5.161	1	1	0	6.535948	2
15070000	SR 580	0.602	1.004	3	3	0	7.462687	2
15070000	SR 580	2.235	2.489	2	2	0	7.874016	2
15070000	SR 580	1.781	1.993	2	2	0	9.433962	2
15070000	SR 580	2.545	2.744	2	2	0	10.05025	2
15070000	SR 580	1.272	1.361	1	1	0	11.23596	2
15080000	SR 584	0.637	1.04	3	3	0	7.444169	2
15090000	SR 687	3.938	4.375	3	3	0	6.864989	2
15090000	SR 687	4.431	5	4	4	0	7.029877	2
15090000	SR 600	6.625	7.103	5	5	0	10.46025	2
15090000	SR 687	2.931	3.882	9	8	1	10.51525	2
15090000	SR 687	5.404	5.688	3	3	0	10.56338	2
15090000	SR 687	2.227	2.373	2	2	0	13.69863	2
15090000	SR 687	5.056	5.348	3	1	2	17.12329	1
15120000	SR 688	2.278	2.891	4	4	0	6.525285	2
15120000	SR 688	7.227	8.071	5	4	1	7.109005	2
15120000	SR 688	0.27	0.677	3	3	0	7.371007	2
15120000	SR 688	8.558	9.083	4	4	0	7.619048	2
15120000	SR 686	10.641	10.762	1	1	0	8.264463	2
15120000	SR 688	6.348	7.028	10	10	0	14.70588	2
15120000	SR 688	7.104	7.171	1	1	0	14.92537	2
15120000	SR 688	4.814	5.013	2	1	1	15.07538	2
15120000	SR 686	10.818	11.113	6	6	0	20.33898	1
15150000	SR 55	30.972	31.262	2	2	0	6.896552	2
15150000	SR 55	23.141	23.851	4	3	1	7.042254	2
15150000	SR 55	23.851	24.55	5	5	0	7.153076	2
15150000	SR 55	31.995	32.672	4	3	1	7.385524	2
15150000	SR 55	24.626	25.267	4	3	1	7.800312	2
15150000	SR 55	26.678	27.155	4	4	0	8.385744	2
15150000	SR 55	1.401	1.846	2	0	2	8.988764	2
15150000	SR 55	25.87	26.622	7	7	0	9.308511	2
15150000	SR 55	15.968	16.274	3	3	0	9.803922	2
15150000	SR 55	5.548	5.85	3	3	0	9.933775	2
15150000	SR 55	25.323	25.814	5	5	0	10.1833	2

Roadway ID	State Road	Begpt	Endpt	Total Severe Crashes	IC	FC	Score	Rank
15150000	SR 55	7.928	8.119	2	2	0	10.4712	2
15150000	SR 55	12.482	12.766	3	3	0	10.56338	2
15150000	SR 55	8.175	8.351	2	2	0	11.36364	2
15150000	SR 55	18.886	19.317	3	1	2	11.60093	2
15150000	SR 55	9.862	10.445	6	5	1	12.00686	2
15150000	SR 55	10.501	11.164	7	6	1	12.06637	2
15150000	SR 55	27.688	28.164	6	6	0	12.60504	2
15150000	SR 55	28.696	29.177	5	3	2	14.55301	2
15150000	SR 55	11.164	11.827	10	10	0	15.08296	2
15150000	SR 55	11.883	12.406	7	6	1	15.29637	2
15150000	SR 55	3.152	3.342	2	1	1	15.78947	2
15150000	SR 55	8.677	8.867	3	3	0	15.78947	2
15150000	SR 55	7.398	7.872	7	6	1	16.87764	2
15150000	SR 55	6.409	6.849	8	7	1	20.45455	1
15150000	SR 55	27.155	27.632	9	8	1	20.96436	1
15150000	SR 55	28.164	28.64	9	8	1	21.0084	1
15150000	SR 55	8.961	9.171	6	6	0	28.57143	1
15150000	SR 55	9.278	9.862	19	18	1	34.24658	1
15150000	SR 55	8.445	8.621	7	7	0	39.77273	1
15230000	SR 693	3.662	4.092	3	3	0	6.976744	2
15230000	SR 693	1.653	1.793	1	1	0	7.142857	2
15230000	SR 693	3.161	3.606	3	2	1	8.988764	2
15230000	SR 693	5.169	5.354	2	2	0	10.81081	2
15230000	SR 693	4.669	5.113	5	5	0	11.26126	2
15230000	SR 693	0.647	0.845	2	1	1	15.15152	2
15240000	SR 687	3.31	4.108	7	7	0	8.77193	2
15240000	SR 693	0.038	0.633	9	9	0	15.12605	2

Table 5-16: Pinellas County Worst Signalized Intersections

Roadway ID	State Road	Signal Mp	Total Severe Crashes	IC	FC	Score	Rank
15010000	SR 595	6.072	4	4	0	4	2
15010000	SR 595	8.033	4	4	0	4	2
15010000	SR 595	14.042	4	4	0	4	2
15030000	SR 686	1.029	3	2	1	4	2
15040000	SR 60	3.441	3	2	1	4	2
15040000	SR 60	2.435	6	6	0	6	1
15070000	SR 580	5.199	6	4	2	8	1
15120000	SR 688	2.25	2	0	2	4	2
15120000	SR 688	10.613	3	2	1	4	2
15120000	SR 688	10.79	6	5	1	7	1
15120000	SR 688	11.141	8	8	0	8	1
15150000	SR 55	2.628	4	4	0	4	2
15150000	SR 55	2.879	4	4	0	4	2
15150000	SR 55	8.649	4	4	0	4	2
15150000	SR 55	8.914	4	4	0	4	2
15150000	SR 55	9.199	4	4	0	4	2
15150000	SR 55	11.855	4	4	0	4	2
15150000	SR 55	8.398	5	5	0	5	2
15150000	SR 55	9.25	5	5	0	5	2
15150000	SR 55	20.418	5	5	0	5	2
15150000	SR 55	26.65	4	3	1	5	2
15150000	SR 55	25.842	6	5	1	7	1
15150000	SR 55	12.444	11	11	0	11	1
15230000	SR 693	4.139	4	4	0	4	2
15230000	SR 693	3.133	5	5	0	5	2

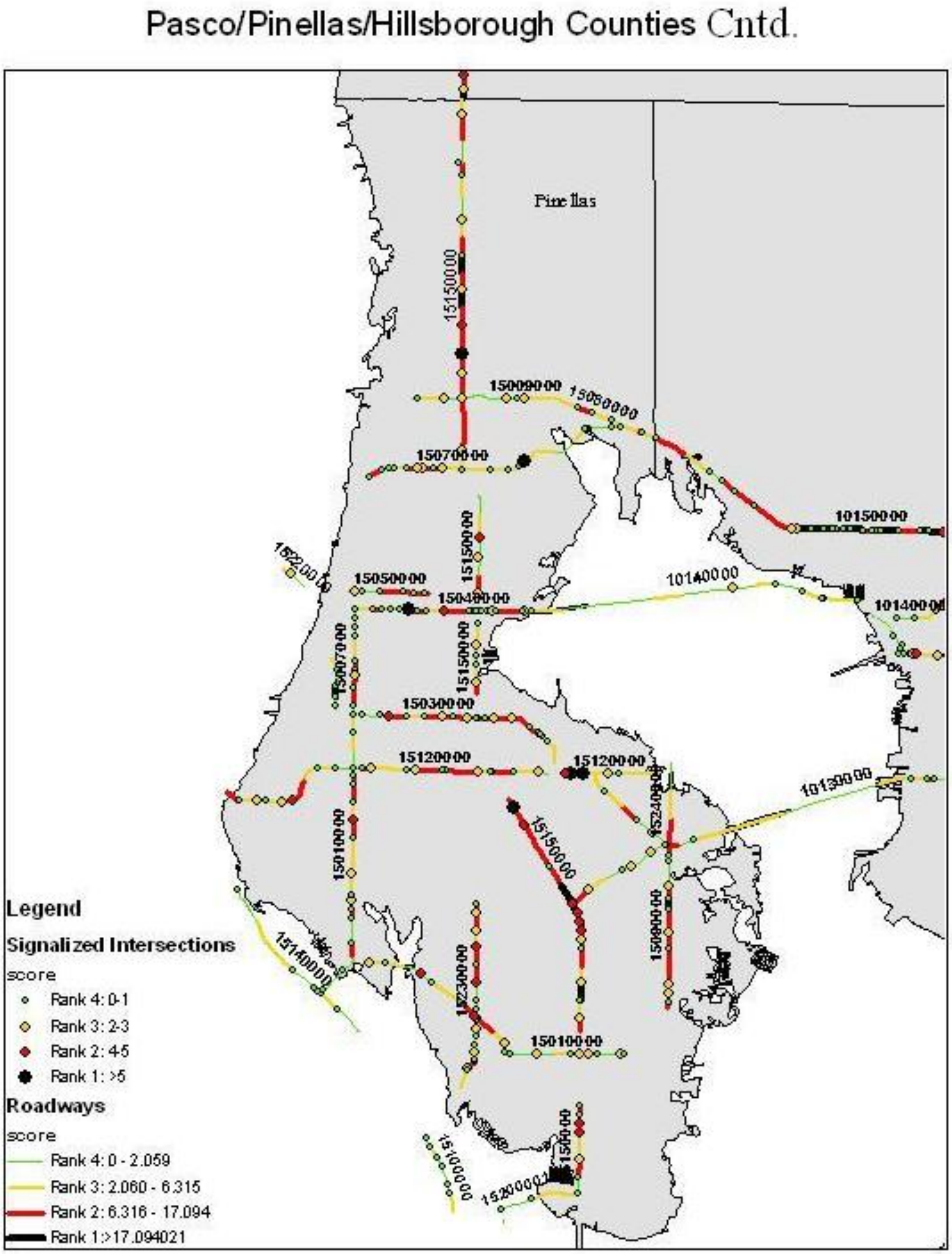


Figure 5-11: Pinellas County Map

5.2.7 Hillsborough County

Hillsborough County has many dangerous roadway segments and intersections. The most notable are Roadway 10110000 (SR 60) and Roadway 10150000 (SR 600).

Table 5-17: Hillsborough County Worst Road Segments

Roadway	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
10005000	SR 569	1.184	1.385	2	2	0	9.950249	2
10005000	SR 599	2.2	2.397	1	0	1	10.15228	2
10005000	SR 599	1.948	2.144	3	3	0	15.30612	2
10005000	SR 599	2.453	2.521	2	1	1	44.11765	1
10005000	SR 569	0.778	0.819	1	0	1	48.78049	1
10010000	SR 43	17.287	17.866	4	4	0	6.908463	2
10010000	SR 43	19.185	19.897	4	3	1	7.022472	2
10010000	SR 43	16.716	17.231	4	4	0	7.76699	2
10010000	SR 43	16.294	16.66	3	3	0	8.196721	2
10010000	SR 43	21.221	21.848	5	4	1	9.569378	2
10010000	SR 43	19.897	20.573	6	5	1	10.35503	2
10010000	SR 41	25.36	26.225	9	9	0	10.40462	2
10010000	SR 43	22.503	23.28	9	9	0	11.58301	2
10010000	SR 43	20.649	21.089	6	5	1	15.90909	2
10010000	SR 43	21.904	22.447	9	9	0	16.57459	2
10010000	SR 43	15.598	15.642	1	1	0	22.72727	1
10020000	SR 685	3.868	4.303	3	3	0	6.896552	2
10020000	SR 685	2.967	3.307	3	3	0	8.823529	2
10020000	SR 685	3.363	3.812	3	2	1	8.908686	2
10020000	SR 685	4.397	4.704	3	3	0	9.771987	2
10020000	SR 685	7.773	8.36	6	5	1	11.92504	2
10020000	SR 685	9.049	9.672	8	7	1	14.44623	2
10020000	SR 685	5.197	5.334	2	2	0	14.59854	2
10020000	SR 685	5.39	5.592	3	3	0	14.85149	2
10030000	SR 600	0.522	0.971	3	3	0	6.681514	2
10030000	SR 600	0.028	0.466	2	1	1	6.849315	2
10030000	SR 600	2.9	3.494	4	3	1	8.417508	2
10030000	SR 600	2.316	2.9	5	5	0	8.561644	2
10030000	SR 600	4.08	4.494	3	2	1	9.661836	2
10030000	SR 600	3.938	4.024	1	1	0	11.62791	2
10030000	SR 600	4.55	4.744	2	1	1	15.46392	2
10030000	SR 600	21.143	21.249	1	0	1	18.86792	1

Roadway	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
10030000	SR 600	1.779	2.24	9	9	0	19.52278	1
10040000	SR 45	5.198	5.424	2	2	0	8.849558	2
10040000	SR 45	5.745	6.167	4	4	0	9.478673	2
10040000	SR 45	8.242	8.957	7	7	0	9.79021	2
10040000	SR 45	9.531	10.237	8	7	1	12.74788	2
10040000	SR 45	5.48	5.669	3	3	0	15.87302	2
10040000	SR 45	4.418	4.521	1	0	1	19.41748	1
10040000	SR 45	12.312	12.975	13	13	0	19.60784	1
10040000	SR 45	7.256	7.933	13	12	1	20.67947	1
10060000	SR 45	6.34	7.077	5	5	0	6.784261	2
10060000	SR 45	17.257	18.212	6	5	1	7.329843	2
10060000	SR 45	11.688	12.494	5	4	1	7.444169	2
10060000	SR 45	3.717	4.646	6	4	2	8.61141	2
10060000	SR 45	15.061	15.852	6	5	1	8.849558	2
10060000	SR 45	8.161	8.661	5	5	0	10	2
10060000	SR 45	23.575	24.235	6	4	2	12.12121	2
10070000	SR 39	3.328	3.51	2	2	0	10.98901	2
10080000	SR 685	1.64	1.707	1	1	0	14.92537	2
10090000	SR 574	4.154	4.306	2	2	0	13.15789	2
10110000	SR 60	11.475	11.927	3	3	0	6.637168	2
10110000	SR 60	21.53	22.248	5	5	0	6.963788	2
10110000	SR 60	7.118	7.396	2	2	0	7.194245	2
10110000	SR 60	5.584	6.098	4	4	0	7.782101	2
10110000	SR 60	4.121	5.014	7	7	0	7.838746	2
10110000	SR 60	6.154	6.275	1	1	0	8.264463	2
10110000	SR 60	17.479	18.479	7	4	3	10	2
10110000	SR 60	7.957	8.152	2	2	0	10.25641	2
10110000	SR 60	9.71	9.903	2	2	0	10.36269	2
10110000	SR 60	12.474	13.449	12	12	0	12.30769	2
10110000	SR 60	5.07	5.584	7	6	1	15.5642	2
10110000	SR 60	10.083	10.912	13	12	1	16.88782	2
10110000	SR 60	9.453	9.654	4	4	0	19.9005	1
10110000	SR 60	8.63	8.904	7	7	0	25.54745	1
10110000	SR 60	6.331	6.496	6	6	0	36.36364	1
10110000	SR 60	6.895	7.062	9	8	1	59.88024	1
10120000	SR 674	5.068	5.219	1	1	0	6.622517	2
10120000	SR 674	0.907	1.662	5	4	1	7.94702	2
10120000	SR 674	1.718	2.424	7	6	1	11.33144	2
10130000	SR 600	4.287	4.411	1	1	0	8.064516	2
10130000	SR 600	9.866	9.989	1	1	0	8.130081	2
10130000	SR 600	8.542	8.745	2	2	0	9.852217	2
10130000	SR 600	5.903	5.998	1	1	0	10.52632	2
10130000	SR 600	11.084	11.84	8	7	1	11.90476	2
10130000	SR 600	9.192	9.271	1	1	0	12.65823	2

Roadway	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
10130000	SR 600	9.327	9.495	3	3	0	17.85714	1
10130000	SR 600	11.896	11.986	2	2	0	22.22222	1
10130000	SR 600	9.551	9.81	6	6	0	23.16602	1
10140000	SR 616	8.678	9.015	3	3	0	8.902077	2
10150000	SR 600	11.394	11.701	2	2	0	6.514658	2
10150000	SR 600	0.069	0.958	6	6	0	6.749156	2
10150000	SR 580	12.703	12.85	1	1	0	6.802721	2
10150000	SR 600	2.358	2.748	3	3	0	7.692308	2
10150000	SR 600	2.804	3.437	5	4	1	9.478673	2
10150000	SR 600	4.109	4.724	6	6	0	9.756098	2
10150000	SR 600	6.847	7.029	2	2	0	10.98901	2
10150000	SR 600	9.098	9.42	3	2	1	12.42236	2
10150000	SR 600	7.851	8.412	7	7	0	12.47772	2
10150000	SR 600	3.493	4.109	8	8	0	12.98701	2
10150000	SR 600	4.78	4.848	1	1	0	14.70588	2
10150000	SR 600	6.077	6.211	2	2	0	14.92537	2
10150000	SR 580	10.618	10.751	1	0	1	15.03759	2
10150000	SR 600	4.924	5.271	6	6	0	17.29107	1
10150000	SR 600	7.348	7.795	8	8	0	17.89709	1
10150000	SR 600	5.327	5.652	6	6	0	18.46154	1
10150000	SR 600	5.708	5.901	4	4	0	20.72539	1
10150000	SR 600	8.723	9.042	7	7	0	21.94357	1
10150000	SR 580	11.147	11.319	4	4	0	23.25581	1
10150000	SR 580	9.861	10.562	17	16	1	25.6776	1
10150000	SR 600	6.457	6.791	10	10	0	29.94012	1
10150000	SR 600	8.468	8.667	5	4	1	30.15075	1
10150000	SR 580	10.845	11.072	5	3	2	30.837	1
10150000	SR 580	9.626	9.805	7	7	0	39.10615	1
10150000	SR 600	5.957	6.021	3	3	0	46.875	1
10150000	SR 600	7.169	7.292	5	4	1	48.78049	1
10150000	SR 600	6.267	6.401	7	5	2	67.16418	1
10150000	SR 580	12.613	12.627	1	1	0	71.42857	1
10150000	SR 600	7.085	7.113	5	5	0	178.5714	1
10150000	SR 600	0	0.013	3	3	0	230.7692	1
10160000	SR 597	7.184	7.335	1	1	0	6.622517	2
10160000	SR 597	12.197	12.767	4	4	0	7.017544	2
10160000	SR 597	6.207	6.801	5	5	0	8.417508	2
10160000	SR 597	4.968	5.287	4	4	0	12.53918	2
10160000	SR 580	2.328	2.822	7	7	0	14.17004	2
10160000	SR 580	1.318	2.007	9	8	1	14.51379	2
10160000	SR 597	5.516	6.151	12	11	1	20.47244	1
10160000	SR 597	5.343	5.46	3	3	0	25.64103	1
10160000	SR 597	6.857	7.128	7	7	0	25.83026	1
10160000	SR 580	2.953	3.098	4	4	0	27.58621	1

Roadway	State Road	Beg Mp	End Mp	Total Severe Crashes	IC	FC	Score	Rank
10160000	SR 597	7.391	7.482	3	3	0	32.96703	1
10160000	SR 597	4.603	4.79	7	7	0	37.43316	1
10160000	SR 597	4.846	4.912	4	4	0	60.60606	1
10180000	SR 573	1.162	1.776	4	4	0	6.514658	2
10250000	SR 676	3.081	3.145	1	1	0	15.625	2
10270000	SR 60	2.483	2.702	2	2	0	9.13242	2
10270000	SR 60	3.027	3.334	3	3	0	9.771987	2
10290000	SR 582	1.041	1.49	3	3	0	6.681514	2
10290000	SR 582	6.54	7.142	5	5	0	8.305648	2
10290000	SR 582	1.546	1.842	3	3	0	10.13514	2
10310000	SR 580	3.348	4.328	7	6	1	8.163265	2
10310000	SR 580	6.398	6.835	2	0	2	9.153318	2
10310000	SR 580	4.384	4.591	3	3	0	14.49275	2
10330000	SR 583	2.148	2.62	3	3	0	6.355932	2
10330000	SR 583	4.977	5.127	1	1	0	6.666667	2
10340000	SR 574	9.65	10.382	3	1	2	6.830601	2
10340000	SR 574	8.123	8.852	5	5	0	6.858711	2
10340000	SR 574	11.947	12.139	2	2	0	10.41667	2
10340000	SR 574	4.348	4.702	3	2	1	11.29944	2
10340000	SR 574	7.555	7.688	2	2	0	15.03759	2
10340000	SR 574	10.438	10.771	6	6	0	18.01802	1
10350000	SR 579	0.352	0.471	1	1	0	8.403361	2
10350000	SR 579	0.028	0.212	3	3	0	16.30435	2
10360000	SR 678	0	0.501	9	8	1	19.96008	1

Table 5-18: Hillsborough County Worst Signalized Intersections

Roadway ID	State Road	Signal Mp	Total Severe Crashes	IC	FC	Score	Rank
10010000	SR 43	18.473	5	5	0	5	2
10010000	SR 43	15.67	6	6	0	6	1
10010000	SR 43	5.685	5	2	3	8	1
10020000	SR 685	4.35	3	2	1	4	2
10020000	SR 685	8.388	4	4	0	4	2
10020000	SR 685	5.362	6	6	0	6	1
10020000	SR 685	5.887	6	6	0	6	1
10030000	SR 600	0.999	4	4	0	4	2
10030000	SR 600	4.052	4	4	0	4	2
10030000	SR 600	3.522	5	5	0	5	2
10030000	SR 600	1.751	5	4	1	6	1
10040000	SR 45	3.668	3	2	1	4	2
10040000	SR 45	13.993	6	6	0	6	1
10040000	SR 45	8.214	7	7	0	7	1
10040000	SR 45	13.401	6	5	1	7	1
10060000	SR 45	7.6	4	4	0	4	2
10060000	SR 599	24.924	3	2	1	4	2
10060000	SR 45	17.229	5	4	1	6	1
10070000	SR 39	0	5	5	0	5	2
10110000	SR 60	7.09	4	4	0	4	2
10110000	SR 60	10.94	5	5	0	5	2
10110000	SR 60	11.447	6	6	0	6	1
10110000	SR 60	11.955	6	5	1	7	1
10120000	SR 674	3.497	4	4	0	4	2
10150000	SR 580	9.07	4	4	0	4	2
10160000	SR 580	2.3	4	4	0	4	2
10160000	SR 597	4.818	4	4	0	4	2
10160000	SR 597	11.628	3	2	1	4	2
10160000	SR 580	0.785	5	5	0	5	2
10160000	SR 597	7.51	6	6	0	6	1
10270000	SR 60	1.608	3	2	1	4	2
10330000	SR 583	3.15	4	4	0	4	2
10330000	SR 583	2.648	5	5	0	5	2
10340000	SR 574	11.418	3	2	1	4	2
10340000	SR 574	12.167	4	4	0	4	2
10340000	SR 574	10.41	5	5	0	5	2
10340000	SR 574	11.919	7	7	0	7	1
10350000	SR 579	0.314	5	5	0	5	2

Pasco/Pinellas/Hillsborough Counties Cntd.

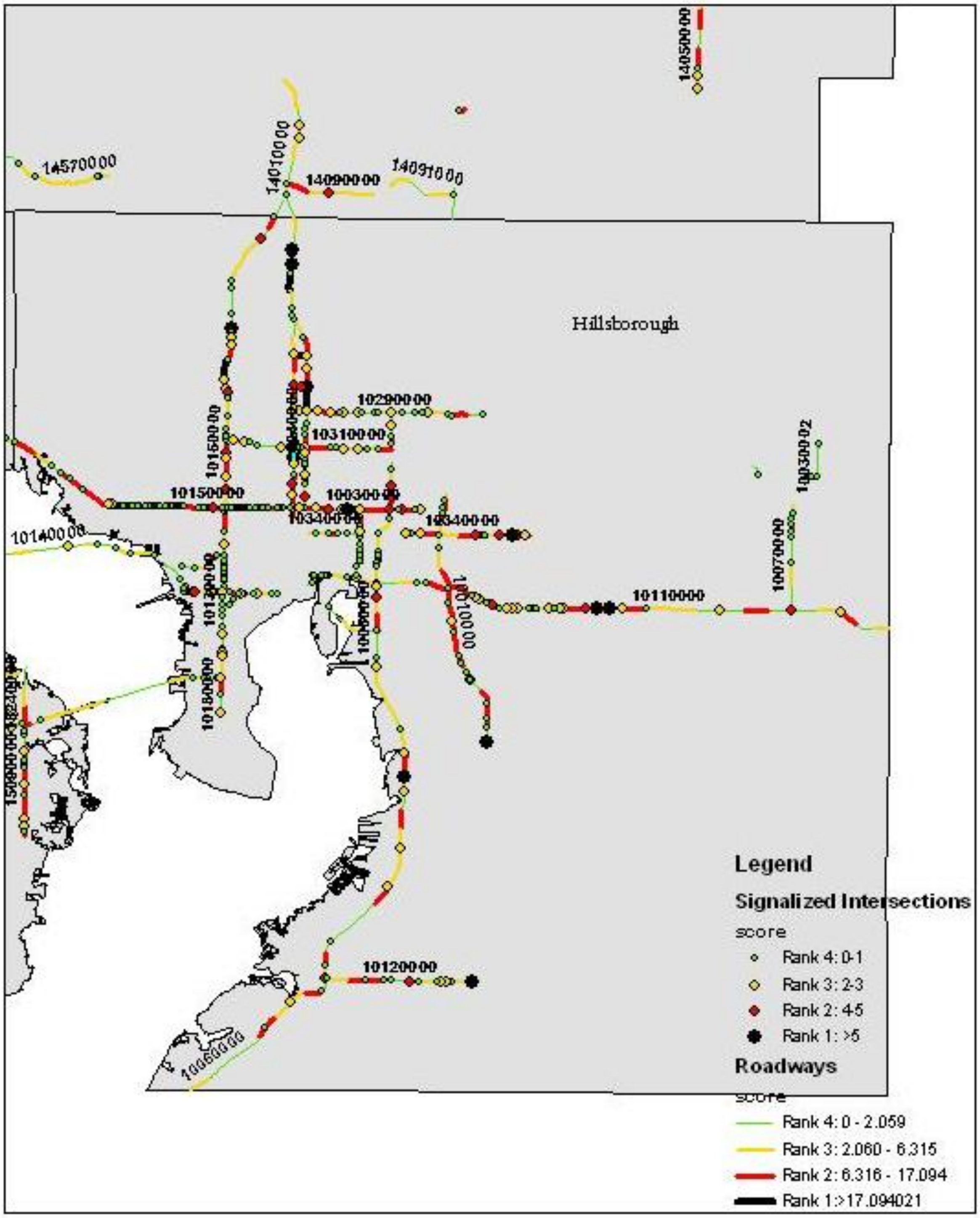


Figure 5-12: Hillsborough County Map

It is interesting to note that the three neighboring counties, Pinellas, Pasco and Hillsborough have more dangerous road elements than the other four counties and this is evident from the crash frequency and score values of road segments and intersections in several locations of those three counties. These findings are also consistent with Table 5-1 which ranked those three neighboring counties in the top three from a severe crash per mile perspective.

CHAPTER 6. GIS SAFETY STUDY: SLIDING WINDOW ANALYSIS OF SEVERE CRASHES ON ROADWAYS

The sliding window analysis is a method used to identify roadway segments with a high severe crashes occurrence. The analysis segment is not fixed but rather slides along the route in an incremental fashion. The user defines the segment length (the window size) and the increment length for analysis. The frequency of severe crashes is counted within the window. The end result of the analysis includes a plot showing high crash locations. The window size used in this analysis was 0.5 miles long with an increment of 0.1 miles. The aim of the sliding window analysis is to narrow down the most hazardous 0.5 mile range on a roadway that has already been established to be of high risk in the Micro-GIS analysis. The FHWA Sliding Window add-on package to ArcMap 9.2, which conducts the sliding window analysis, did not run properly, so a different non-GIS approach was used to conduct the analysis. The final result is graphs that display the 0.5 mile ranges on a roadway that experienced the highest severe crash frequencies.

6.1 Methodology

Ten corridors (roadway IDs) were chosen for the sliding window analysis. These corridors were chosen using the results of the Micro-GIS Analysis. Only corridors longer than 3 miles were selected for the analysis. A corridor sum of ranks procedure was developed for this analysis. A corridor's sum of rank is determined by a combination of a weighted score for the segments and intersections within that corridor (see Chapter 5, section 5-1 on score calculation). A high corridor road segment or intersection rank (i.e. rank 1, 2 etc.) reflects a high score (i.e. bad safety rating). The corridors with the highest sum of ranks (lowest combined value) were chosen for the sliding window analysis as they represented the corridors with the worst safety rating. Table 6-1 and Table 6-2 present an example for the calculation of the worst corridor in Pasco county (Roadway ID: 1403000, SR 55)

Table 6-1: Sample Calculation of Rank for Roadway ID: 14030000, Road Segments

Roadway	Beg Mp	End Mp	Total Severe & Fatal Crashes	Severe Crashes	Fatal Crashes	Sectlength	Score	Product: Sectlength *score
14030000	0	0.242	6	6	0	0.242	24.79339	6
14030000	0.298	0.627	4	4	0	0.329	12.15805	4
14030000	0.683	0.99	6	5	1	0.307	22.8013	7
14030000	1.046	1.491	13	12	1	0.445	31.46067	14
14030000	1.547	1.683	1	1	0	0.136	7.352941	1
14030000	1.739	2.489	17	16	1	0.75	24	18
14030000	2.545	3.005	3	3	0	0.46	6.521739	3
14030000	3.081	3.565	10	9	1	0.484	22.72727	11
14030000	3.621	3.945	2	2	0	0.324	6.17284	2
14030000	4.001	4.154	0	0	0	0.153	0	0
14030000	4.21	4.635	3	3	0	0.425	7.058824	3
14030000	4.691	4.832	2	2	0	0.141	14.1844	2
14030000	4.888	5.415	8	7	1	0.527	17.0778	9
14030000	5.471	6.3	11	7	4	0.829	18.09409	15
14030000	6.3	7.13	16	11	5	0.83	25.3012	21
14030000	7.186	7.689	8	7	1	0.503	17.89264	9
14030000	7.745	8.454	8	7	1	0.709	12.69394	9
14030000	8.51	8.728	1	1	0	0.218	4.587156	1
14030000	8.784	9.023	3	3	0	0.239	12.5523	3
14030000	9.079	9.528	16	14	2	0.449	40.08909	18
14030000	9.584	9.699	0	0	0	0.115	0	0
14030000	9.755	9.964	1	0	1	0.209	9.569378	2
14030000	10.02	10.455	5	5	0	0.435	11.49425	5
14030000	10.511	11.441	22	20	2	0.93	25.80645	24
14030000	11.517	11.938	6	6	0	0.421	14.25178	6
14030000	11.994	12.902	17	13	4	0.908	23.12775	21
14030000	12.902	13.81	9	9	0	0.908	9.911894	9
14030000	13.866	14.469	7	6	1	0.603	13.267	8
14030000	14.525	14.79	1	1	0	0.265	3.773585	1
14030000	14.846	15.472	2	1	1	0.626	4.792332	3
14030000	15.472	16.098	3	3	0	0.626	4.792332	3
14030000	16.154	16.968	3	3	0	0.814	3.685504	3
14030000	17.024	17.888	4	3	1	0.864	5.787037	5
14030000	17.888	18.78	4	3	1	0.892	5.605381	5
14030000	18.78	19.645	2	0	2	0.865	4.624277	4
					Sum:	17.981	Sum:	255

The sum of the products is 255 whereas the sum of the section lengths of the roadway is 17.981. The weighted score value for the corridor is 255/17.981=14.181 which ranks as the 4th worst corridor from a road segment perspective among all corridors in the seven chosen counties.

Table 6-2: Sample Calculation of Rank for Roadway ID: 14030000, Signalized Intersections

Roadway ID	Signal Mp	Total Severe & Fatal Crashes	Severe Crashes	Fatal Crashes	Score
14030000	0.27	2	2	0	2
14030000	0.655	3	2	1	4
14030000	1.018	6	6	0	6
14030000	1.519	10	9	1	11
14030000	1.711	9	8	1	10
14030000	2.517	2	2	0	2
14030000	3.043	7	5	2	9
14030000	3.593	2	1	1	3
14030000	3.973	2	2	0	2
14030000	4.182	1	1	0	1
14030000	4.663	1	1	0	1
14030000	4.86	0	0	0	0
14030000	5.443	3	3	0	3
14030000	7.158	1	1	0	1
14030000	7.717	1	1	0	1
14030000	8.482	3	3	0	3
14030000	8.756	4	4	0	4
14030000	9.051	2	2	0	2
14030000	9.556	1	1	0	1
14030000	9.727	7	6	1	8
14030000	9.992	2	2	0	2
14030000	10.483	5	5	0	5
14030000	11.479	4	4	0	4
14030000	11.966	1	1	0	1
14030000	13.838	6	4	2	8
14030000	14.497	0	0	0	0
14030000	14.818	7	7	0	7
14030000	16.126	4	4	0	4
14030000	16.996	1	1	0	1
14030000	19.673	1	1	0	1
				Sum:	107

The sum of the scores is 107 and the number of the signalized intersections on the roadway is 30 signals. The weighted intersection score value is 107/30=3.57 which ranks as the 6th worst intersection score among the corridors of the seven counties.

The sum of ranks for Roadway 14030000 in Pasco County is, 4+6=10, which is the highest sum of ranks (lowest combined value) and translates to the worst corridor among all the corridors in the 7 chosen counties.

Following the process described above, the 10 worst corridors were:

Table 6-3: The Ten Worst Corridors

Roadway	State Road	Corridor length	#of intersections in corridor
14030000	SR 55	17.981	30
15150000	SR 55	23.175	36
48020000	SR 10A	3.086	8
10030000	SR 600	4.477	13
48004000	SR 295	3.179	10
10160000	SR 597	11.403	21
10020000	SR 685	7.318	16
10010000	SR 43	9.903	14
10110000	SR 60	22.096	25
10040000	SR 45	10.406	24

It is interesting to note that 6 out of the 10 corridors were located in Hillsborough County.

A 2:1 weight ratio of fatal to incapacitating injury crashes was used again in the calculation of crash frequency within the sliding window. The weighted frequency total was called ‘Score’ in the analysis. The severe crash score values within every 0.5 mile analysis window were then plotted against the midpoints of each 0.5 mile window. Ten plots were generated corresponding to the ten selected corridors.

6.2 The Use of the Kernel Regression Smoothing Technique for the Plots

The ten plots that were generated came out to be somehow visually unfriendly and too noisy.

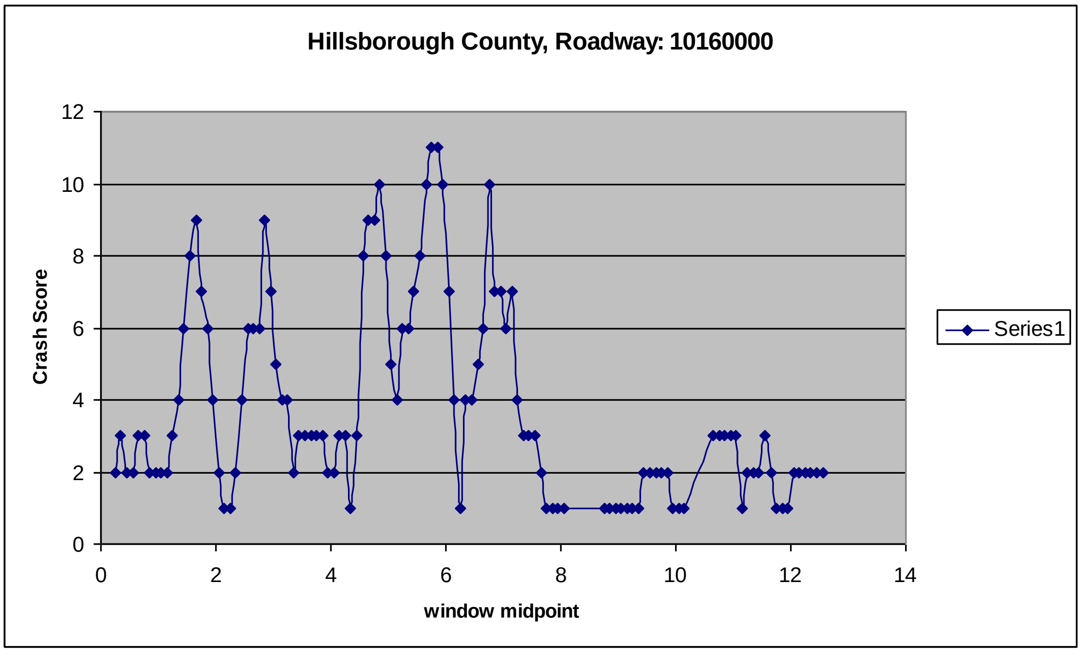


Figure 6-1: Roadway 10160000

As observed in Figure 6-1, there are several repeated peaks on adjacent midpoints. Kernel Regression is a smoothing technique that fits a curve to a given set of data (x_i,y_i). In this case the y_is are the crash score whereas the x_is are the midpoints of the 0.5 mile window range. The aim of Kernel smoothing is to find a regression function, f, which best fits the given data set.

Kernel smoothing is classified as a non-paramteric regression technique because it does not assume any underlying distribution to estimate the function, as in linear or polynomial regression (Teknomo, 2006).

Kernel regression places identical weighted function called ‘kernel’ local to each observational data point. The kernel assigns weight to each location based on distance from the data point. The kernel basis function depends only on the radius or width (or variance) from the ‘local' data point X to a set of neighboring locations x (Teknomo, 2006).

The most common type of kernel basis function is the Gaussian Kernel function as seen in Equation 6-1.

$$K(x,X) = \exp(-\frac{(x-X)^2}{2\alpha^2}) \tag{6-1}$$

where x is an incremental value starting from 0 and whose increment width , dx, is defined by the user; the smaller the value of dx, the smoother the curve. X are the observations (window midpoint values), and α is the kernel width.

The kernel regression formula used in this analysis is called the Nadaraya-Watson regression formula:

$$\hat{y}_j = f_j(x,w) = \frac{\sum_{i=1}^{n} w_i K(x_j, X_i)}{\sum_{i=1}^{n} K(x_j, X_i)} \tag{6-2}$$

where w_i is the weight assigned for the kernel function and $\hat{y}$ is the estimated value at x. Using the R-2.7.2 statistical software, the optimal combination of dx, α, and w_i are computed in a manner that minimizes the Sum of Square Errors (SSE) between the estimated observation, $\hat{y}$, when $x_j=X_i$, and the actual observed value y_i.

6.3 Results

Only road segment severe crashes were included in the sliding window analysis. The results would have been biased if signalized intersection severe crashes were included since those types of crashes happen within the small proximity (i.e. influence area) of the intersection. Thus the results presented in Chapter 5 of this thesis for signalized intersections were considered sufficient since they display the exact mile points of intersections with high severe crash frequency scores.

6.3.1 Roadway 10160000 (SR 597)

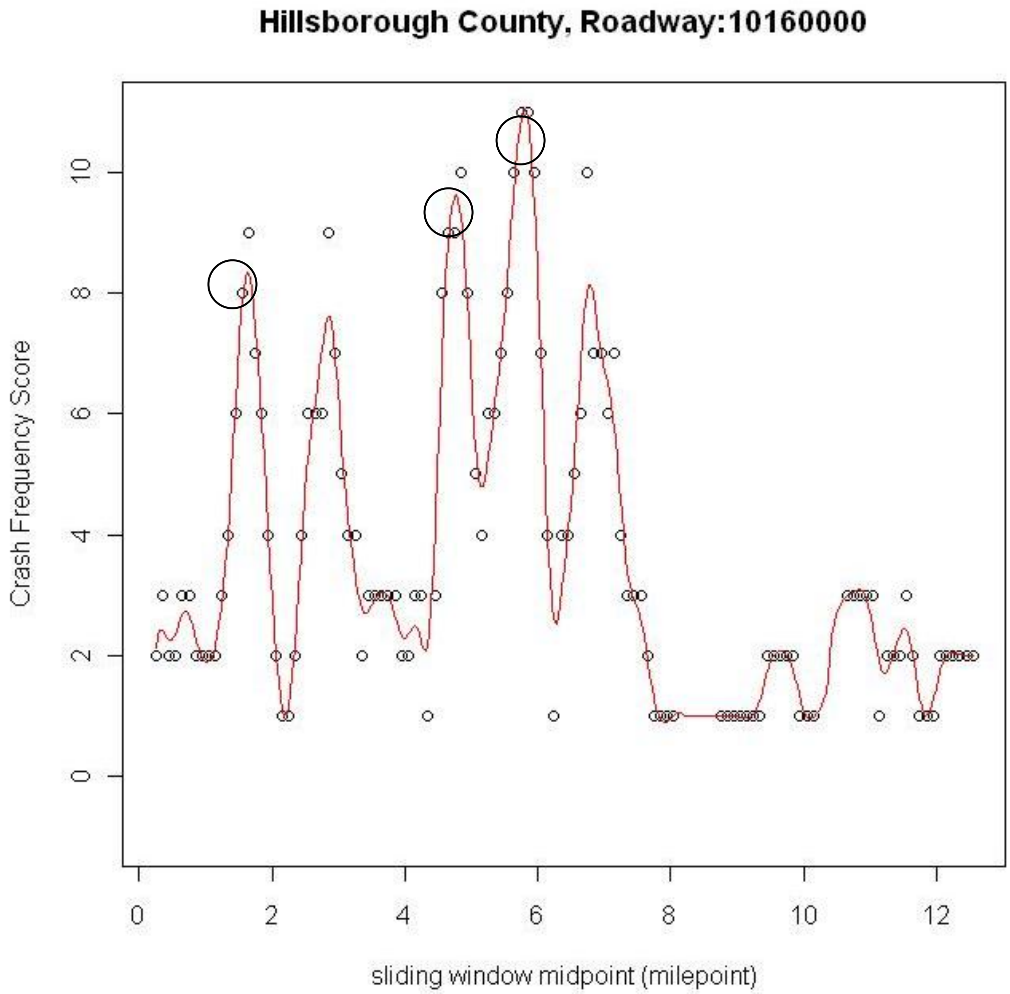


Figure 6-2: Hillsborough County, Roadway 10160000 (SR 597)

The locations with the highest 0.5 mile frequency crash scores of severe crashes are:

- Midpoint Milepoint: 1.63, corresponding to milepoints' range (1.38-1.88)
- Midpoint Milepoint: 4.77, corresponding to milepoints' range (4.52-5.02)
- Midpoint Milepoint: 5.82, corresponding to milepoints' range (5.57-6.07)

6.3.2 Roadway 10010000 (SR 43)

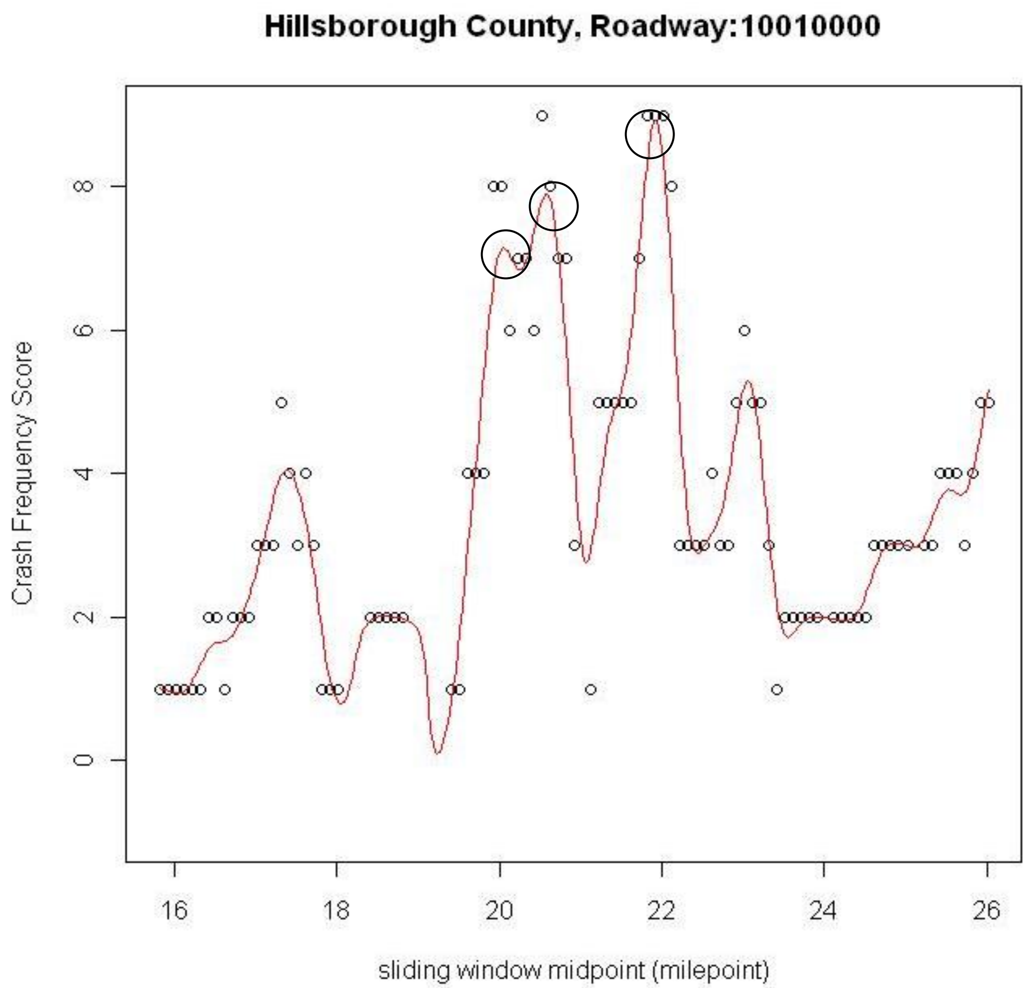


Figure 6-3: Hillsborough County, Roadway 10010000 (SR 43)

The locations with the highest 0.5 mile frequency crash scores of severe and crashes are:

- Midpoint Milepoint: 20.05, corresponding to milepoints' range (19.8-20.3)
- Midpoint Milepoint: 20.59, corresponding to milepoints' range (20.34-20.84)
- Midpoint Milepoint: 21.91, corresponding to milepoints' range (21.66-22.16)

6.3.3 Roadway 10020000 (SR 685)

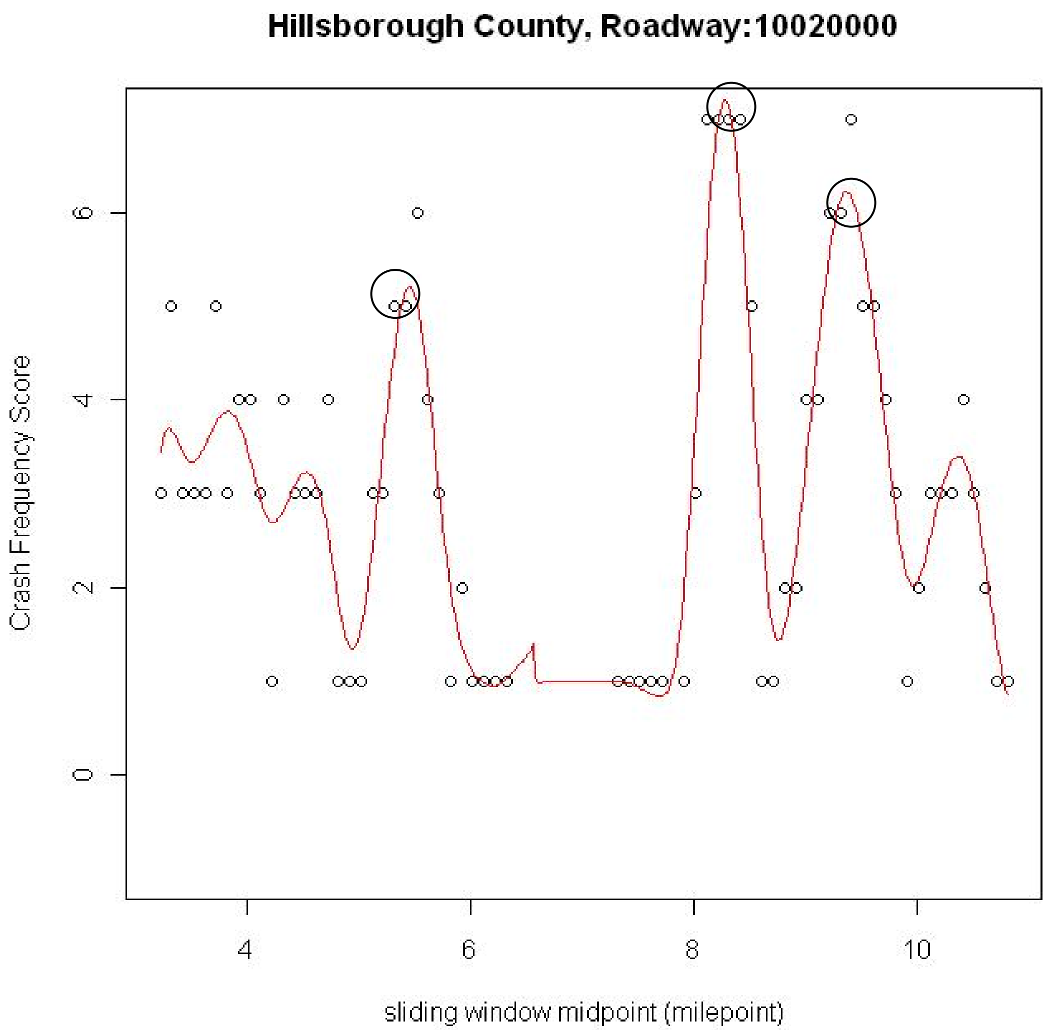


Figure 6-4: Hillsborough County, Roadway 10020000 (SR 685)

The locations with the highest 0.5 mile frequency crash scores of severe crashes are:

- Midpoint Milepoint: 5.46, corresponding to milepoints' range (5.21-5.71)
- Midpoint Milepoint: 8.27, corresponding to milepoints' range (8.02-8.52)
- Midpoint Milepoint: 9.37, corresponding to milepoints' range (9.12-9.62)

6.3.4 Roadway 10030000 (SR 600)

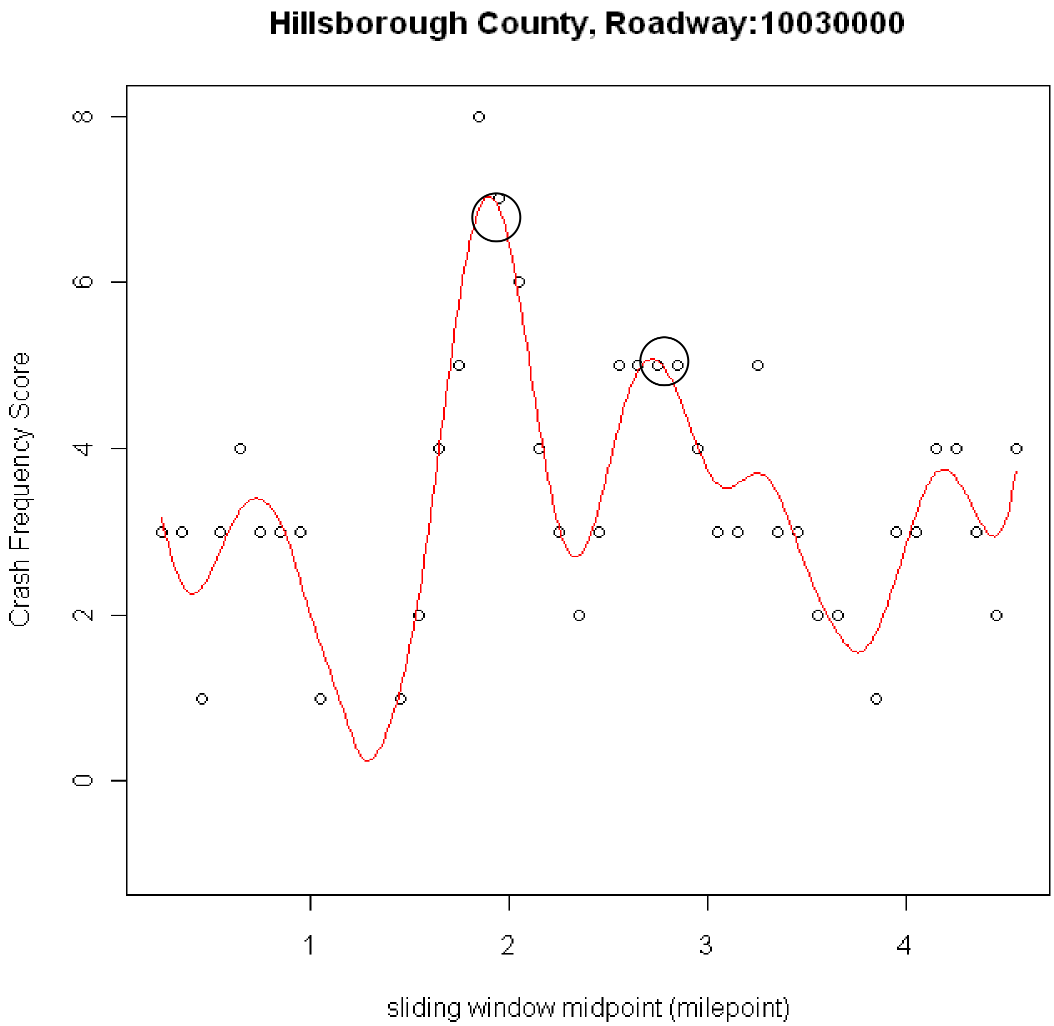


Figure 6-5: Hillsborough County, Roadway 10030000 (SR 600)

The locations with the highest 0.5 mile frequency crash scores of severe crashes are:

- Midpoint Milepoint: 1.89, corresponding to milepoints' range (1.64-2.14)
- Midpoint Milepoint: 2.72, corresponding to milepoints' range (2.47-2.97)

6.3.5 Roadway 10040000 (SR 45)

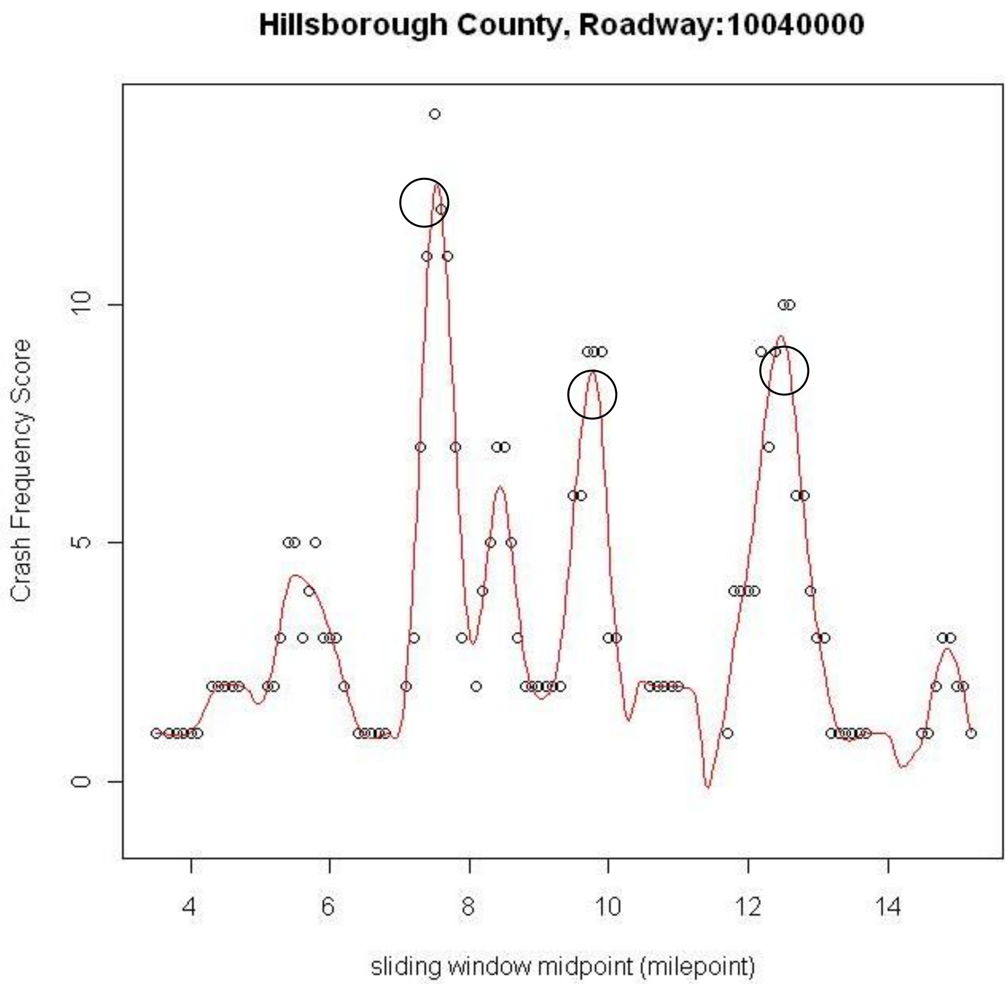


Figure 6-6: Hillsborough County, Roadway 10040000 (SR 45)

The locations with the highest 0.5 mile frequency crash scores of severe crashes are:

- Midpoint Milepoint: 7.53, corresponding to milepoints' range (7.28-7.78)
- Midpoint Milepoint: 9.78, corresponding to milepoints' range (9.53-10.03)
- Midpoint Milepoint: 12.47, corresponding to milepoints' range (12.22-12.72)

6.3.6 Roadway 10110000 (SR 60)

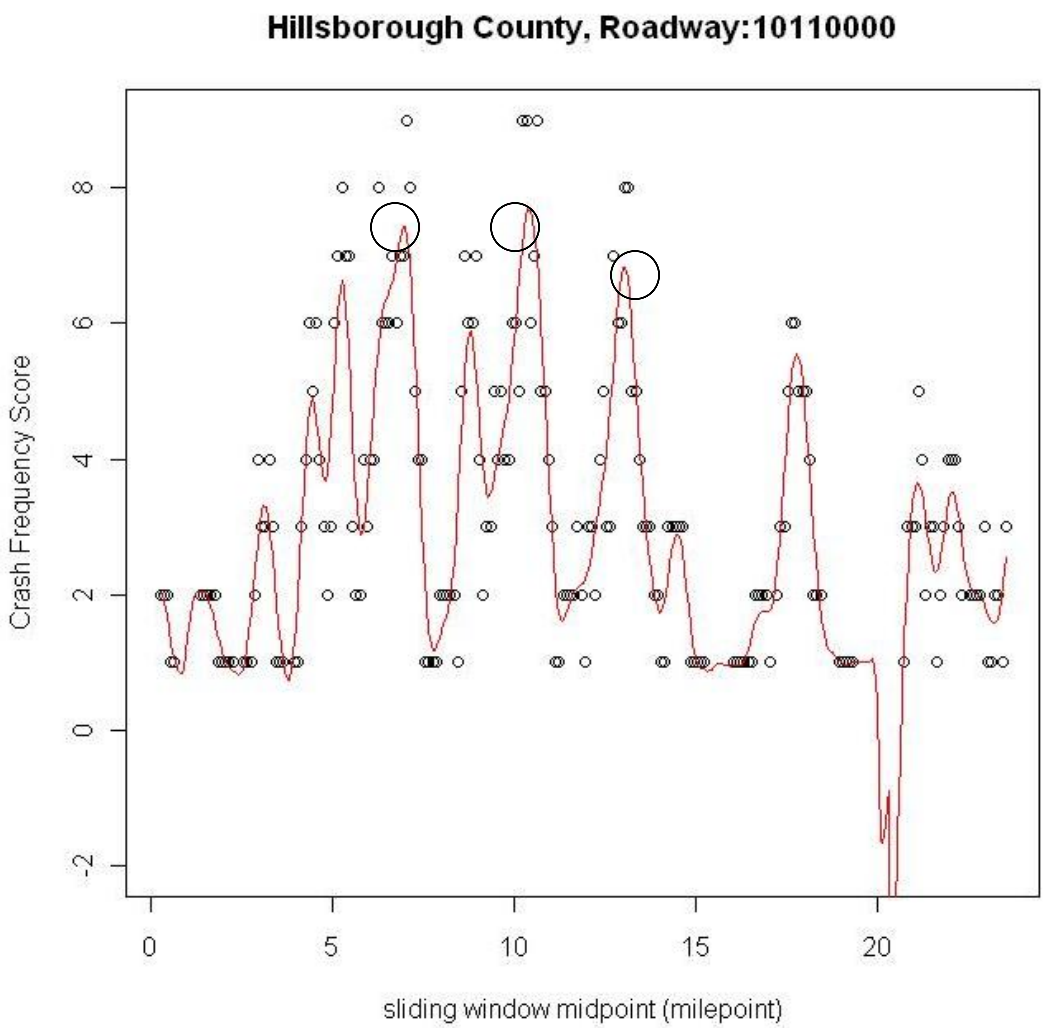


Figure 6-7: Hillsborough County, Roadway 10110000 (SR 60)

The locations with the highest 0.5 mile frequency crash scores of severe crashes are:

- Midpoint Milepoint: 6.95, corresponding to milepoints' range (6.70-7.20)
- Midpoint Milepoint: 10.39, corresponding to milepoints' range (10.14-10.64)
- Midpoint Milepoint: 13.07, corresponding to milepoints' range (12.82-13.32)

6.3.7 Roadway 14030000 (SR 55)

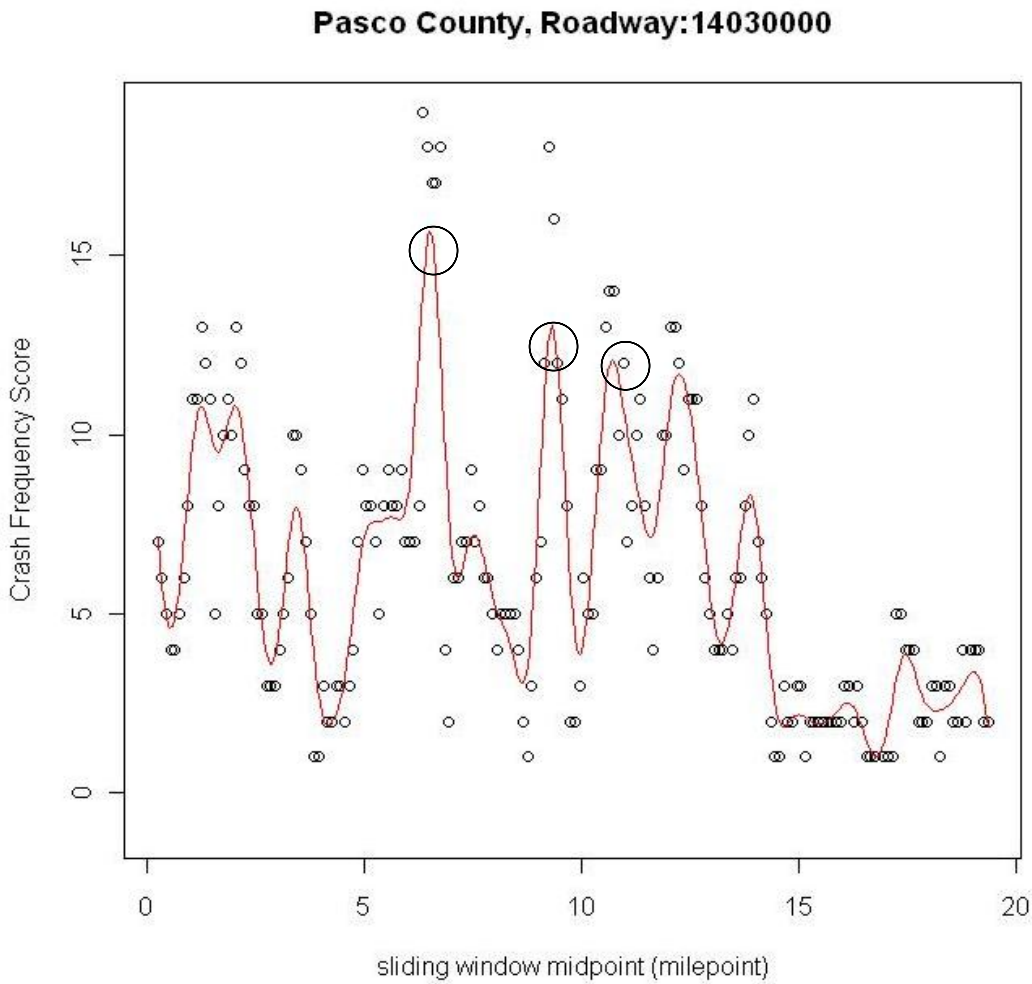


Figure 6-8: Pasco County, Roadway 14030000 (SR 55)

The locations with the highest 0.5 mile frequency crash scores of severe crashes are:

- Midpoint Milepoint: 6.51, corresponding to milepoints' range (6.26-6.76)
- Midpoint Milepoint: 9.32, corresponding to milepoints' range (9.07-9.57)
- Midpoint Milepoint: 10.71, corresponding to milepoints' range (10.46-10.96)

6.3.8 Roadway 15150000 (SR 55)

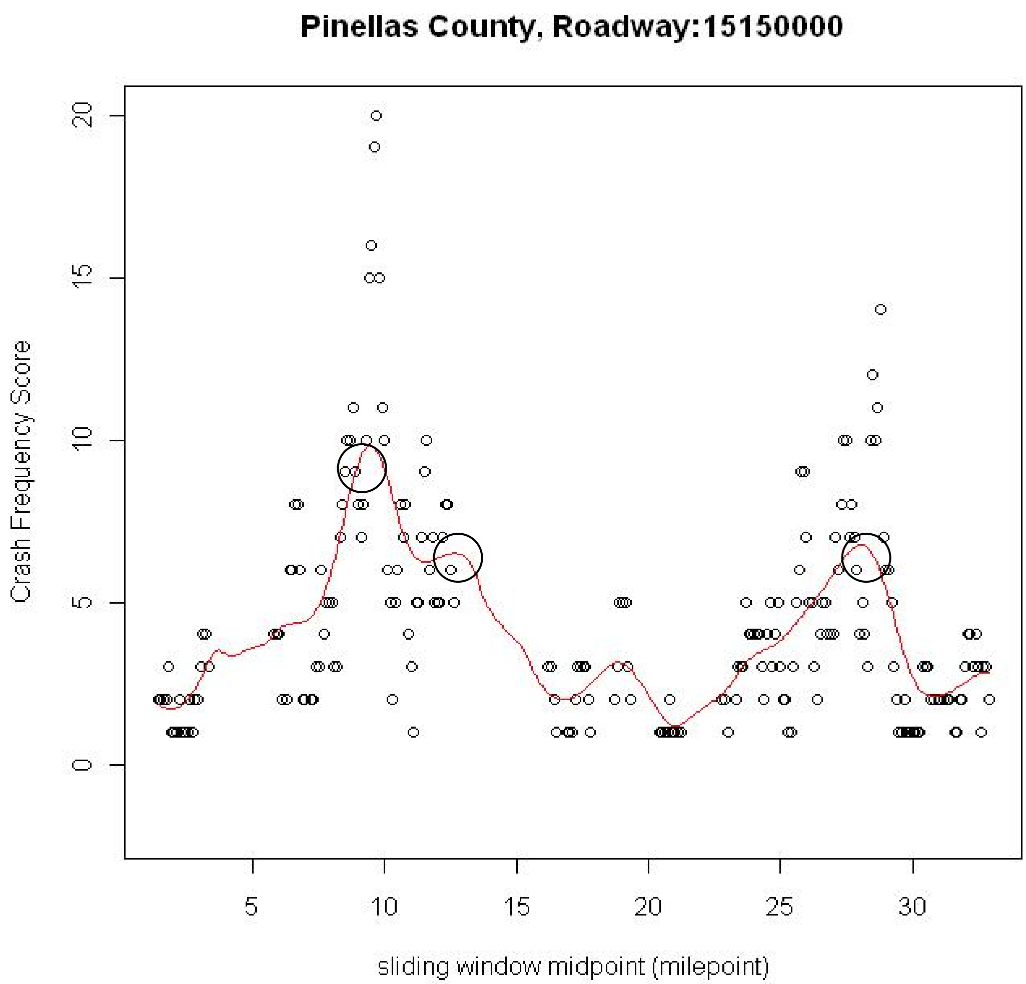


Figure 6-9: Pinellas County, Roadway 15150000 (SR 55)

The locations with the highest 0.5 mile frequency crash scores of severe crashes are:

- Midpoint Milepoint: 9.44, corresponding to milepoints' range (9.19-9.69)
- Midpoint Milepoint: 12.59, corresponding to milepoints' range (12.34-12.84)
- Midpoint Milepoint: 28.02, corresponding to milepoints' range (27.77-28.27)

6.3.9 Roadway 48004000 (SR 295)

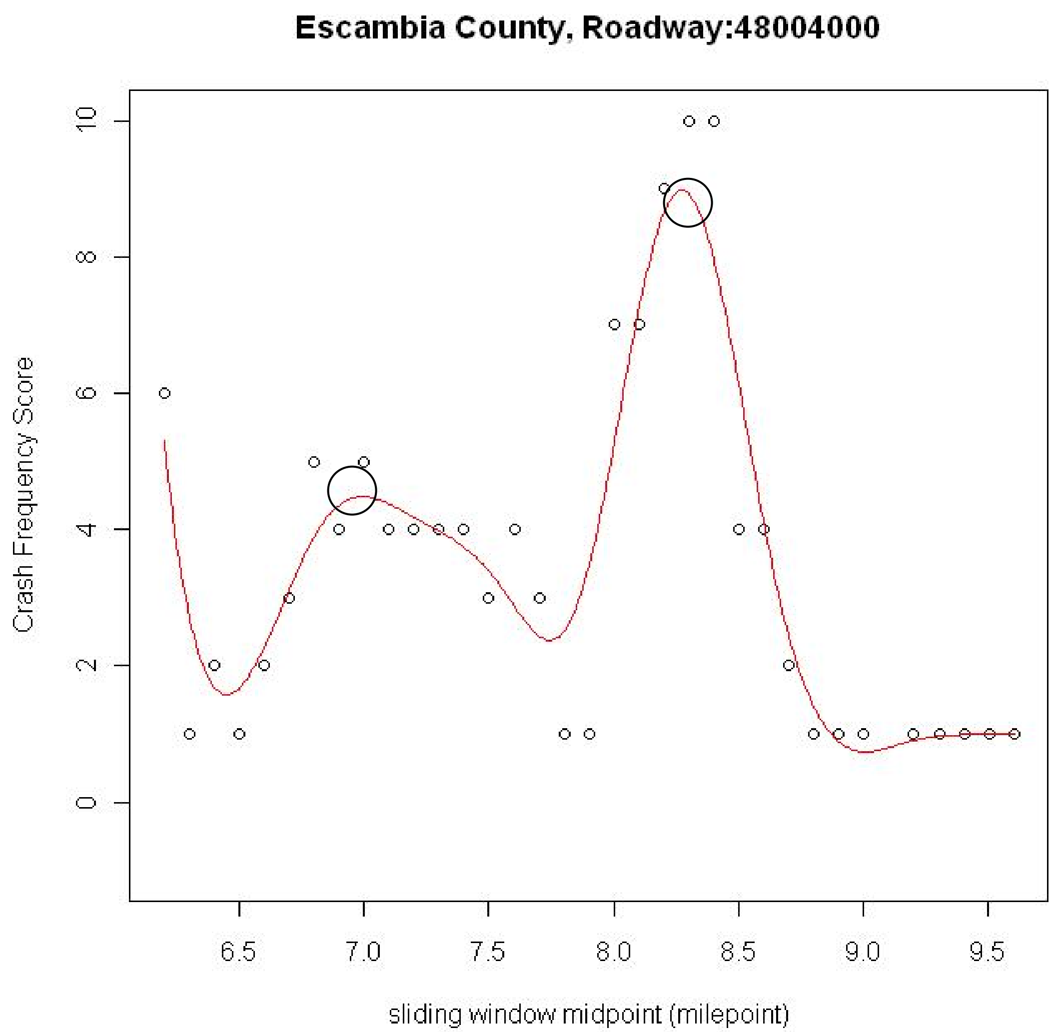


Figure 6-10: Escambia County, Roadway 48004000 (SR 295)

The locations with the highest 0.5 mile frequency crash scores of severe crashes are:

- Midpoint Milepoint: 6.99, corresponding to milepoints' range (6.74-7.24)
- Midpoint Milepoint: 8.27, corresponding to milepoints' range (8.02-8.52)

6.3.10 Roadway 48020000 SR(10A)

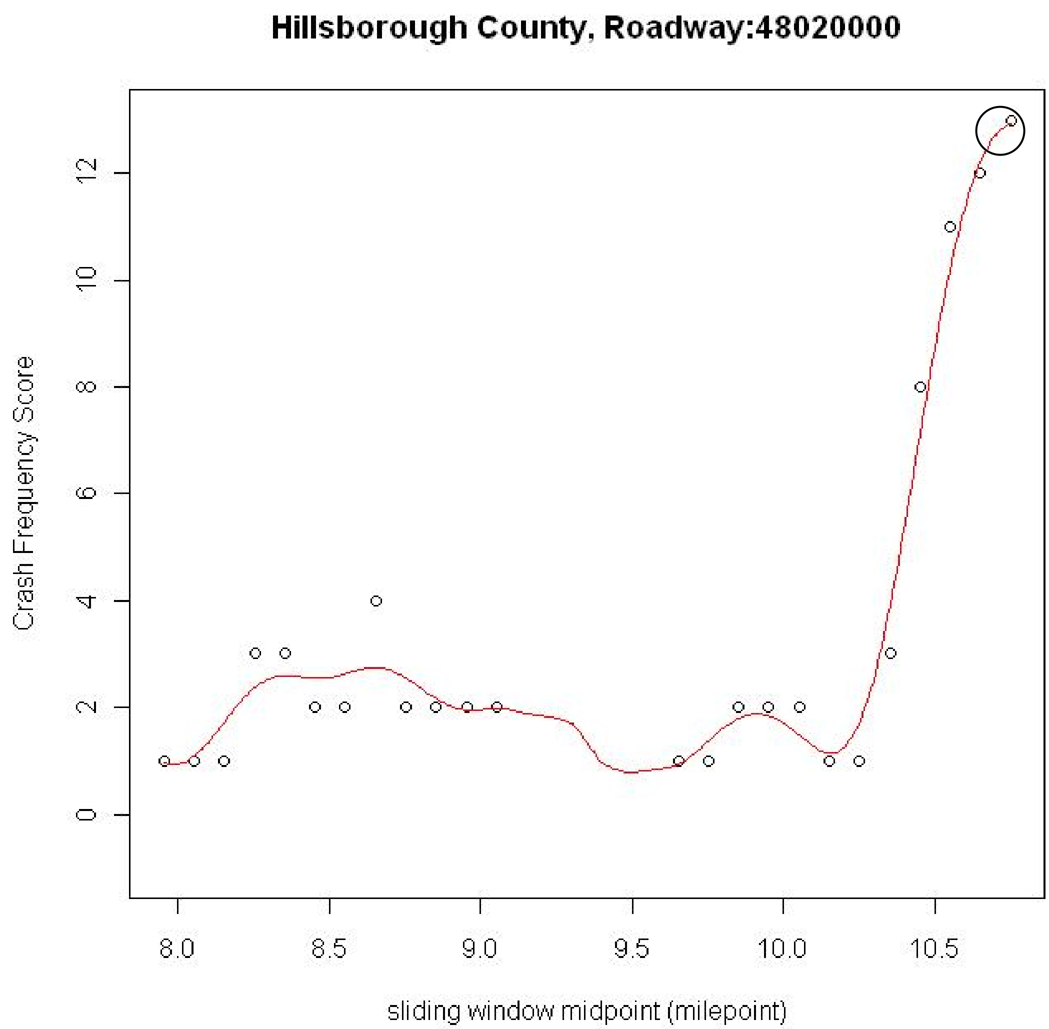


Figure 6-11: Escambia County, Roadway 48020000 (SR 10A)

The locations with the highest 0.5 mile frequency crash scores of severe crashes are:

- Midpoint Milepoint: 10.75, corresponding to milepoints' range (10.5-11.00)

CHAPTER 7. COUNTY-LEVEL SPATIAL ANALYSIS: DATA PREPARATION AND METHODOLOGY

The first objective of the spatial analysis is to establish county-level relationships between traffic-related factors and socio-economic factors with crashes by developing a set of models. The second objective is to observe whether neighboring counties tend to display similar crash trends; in other words assert whether crash related spatial correlation at county-level exists.

7.1 Data Preparation

Four different sets of data were used for the county-level spatial analysis. They include crash related data (response variables), traffic-related factors, socio-economic factors (predictors) and the neighbor structure of Florida's 67 counties. In total, five years of data were used for the analysis (2003-2007). In some cases, values had to be assumed or projected since not all data was available for all the years. To avoid having many 0 observations, all state road related data was included in this analysis, unlike the GIS safety study which focused on multilane corridors. All data was aggregated at county level. It would have been even better to also include non state road data in the analysis; however traffic-related factors were not available for these crashes.

7.1.1 Crash Data

Five years of crash data (2003-2007) were downloaded from the FDOT CAR database. The most important information provided by the crash data was the county in which the crash occurred and its severity (levels 1 through 5, see). Table 7-1 provides an example of the crash data arrangement for the analysis. Crashes with severity level 4 (i.e. incapacitating crashes) and 5 (i.e. fatal crashes) were considered severe crashes.

Table 7-1: Example of Crash Data Arrangement

County Name	Year	Total Crashes	Severe Crashes
Miami-Dade	2003	30294	1617
Miami-Dade	2004	32233	1585
Miami-Dade	2005	32810	1570
Miami-Dade	2006	29750	1435
Miami-Dade	2007	29607	1307
Orange	2003	7941	707
Orange	2004	8791	685
Orange	2005	9714	596
Orange	2006	9350	612
Orange	2007	9969	579

7.1.2 Traffic-Related Factors

Traffic related factors are always expected to be highly correlated with crash occurrences. The factors, as shown below, were collected from several sources. The main source of data was FDOT's RCI repository.

- Roadway length: The total centerline miles of roads per county
- Highway Classification: The centerline miles of roads for each type of highway functional classification per county (see Table 3-1 for FDOT highway functional classifications)
- Daily Vehicle Miles Traveled: Similar to the process explained in Chapter 3, the DVMT was calculated by multiplying each RCI section's ADT by its centerline mile length and then summing up all the DVMT values for each county.

It must be noted that only 4 years (2003-2006) of RCI data were used. The 2007 data was still not available at the time of the analysis. The year 2006 data was used for 2007, since it was observed that roadway trends do not significantly change in two consecutive years.

The second source for traffic related data were the GIS maps found on FDOT's website. The following provides the maps that were used and the information that was extracted from them.

- Signalized Intersections Map: The number of signalized intersections per county
- Non-signalized intersections Map: The number of non-signalized intersection per county
- Truck AADT Map: The average annual daily traffic of trucks per county
- Interchanges Map: The number of interchanges per county

Only 2006 GIS data was available. The same values were used for all the remaining years. The GIS data was made available in Excel by exporting the attributes table of each GIS map into a text file (.txt) and then transforming it to Excel (.xls) format.

The last source of traffic related data was the U.S. Census Bureau website (http://quickfacts.census.gov/). The website is an excellent repository for state and county level socioeconomic and demographic statistics. There was only one traffic related factor extracted from the website, the county-level average travel time to work. Only year 2000 data is available for this factor. The same values had to be assumed for all 5 years.

7.1.3 Socio-economic Factors

The second set of model predictors were socio-economic factors. All those factors were obtained from one single source, the U.S. Census Bureau website (http://quickfacts.census.gov/). There were several studies which linked socio-economic factors to crash risk. Aguero-Valverde and Jovanis (2006) and Kam (2003) suggested age and sex as some of those factors. Noland and Quddus (2004) also found area depravation to be positively correlated with crash risk. Socioeconomic factors were divided into 3 subsets, demographics, age distribution and economic factors.

1. Demographics:

- Area: The Geographical area of each of Florida's 67 counties in square miles.
- Population
- Sex: The percent of males and females

2. Age Distribution:

- In this analysis, several age group ratios are considered; the proportion of population younger than 14, between 15 and 24 (surrogate for young drivers), between 25 and 64 which is used as a base case in modeling and 65 years and older (surrogate for senior drivers).

3. Economic Factors:

- Median Income: The average yearly income per household
- Poverty Level: The percent of people living under the poverty line. This factor is used as a surrogate indicator of area deprivation level.

- Bachelor's Degree Ratio: The percent of people older than 25 with a bachelor's degree or higher (surrogate for education level).
- Unemployment Rate

For the area factor, only year 2000 data was available. The same figures were used for (2003-2007) since geographic areas do not change over a short period of time which makes the assumption logical. For the population factor, year 2000 and 2006 figures were available. The population levels for the remaining years were extrapolated by assuming simple linear growth. For the sex, race and age distributions, only 2006 data was available. However, since these are ratio figures, they are not expected to change significantly over a five year period; thus the same values were used for all the years. Due to information unavailability also, the median income and poverty levels of 2004 were used all throughout. For the same reason the year 2000 education levels were also assumed for years 2003-2007 and the year 2006 unemployment figures were used for all the years.

7.1.4 Counties Neighbor Structure

A 67*67 matrix table was setup with Florida's counties as its rows and columns. A binary response was used to indicate if two counties were adjacent. If a county shared a border with another then the response value is 1, otherwise it is 0.

7.2 Methodology

7.2.1 Negative Binomial Regression Model

Count data is usually modeled using a Poisson Distribution. Crash frequency is one example of the typical count data. The main characteristic of the Poisson Distribution is that its mean is equal to its variance. Crash data have a gamma-distributed mean for a population of systems, allowing the variance of the crash data to be more than its mean (Shen, 2007).Several studies found that a negative binomial distribution fits crash frequency data better. NB is similar to a Poisson Distribution, however its variance is greater than its mean. The NB model can be used to estimate crashes at locations, such as roadway sections or at area level such as counties.

Equation 7-1 presents the NB probability distribution function.

P(y_i) ~ Negbin (λ_i, k)

$$P(y_i|\lambda_i, k) = \frac{\Gamma(1/k + y_i)}{y_i!\Gamma(1/k)}\left(\frac{k\lambda_i}{1+k\lambda_i}\right)^{y_i}\left(\frac{1}{1+k\lambda_i}\right)^{1/k} \tag{7-1}$$

Where, y = number of crashes on a certain location at a certain period,

λ= Expected number of crashes on a certain location at a certain period

k= over-dispersion parameter.

The NB estimation equation is given as follows;

$$\log\lambda_i=\log(EV_i)+(\beta_0+\beta X_i+\varepsilon_i). \tag{7-2}$$

where λ_i is the estimated number of crashes at location i; β is a vector of explanatory variables EV_i is the exposure variable which is included in models as an offset term to account for unequal exposure to crashes among counties (Quddus, 2008). Count models such as NB need a mechanism to deal with different exposure scenarios. DVMT or expected number of crashes for example can be included as an exposure offset term in NB models. By offsetting the exposure, the response variable becomes the log crash rate (offset is DVMT) or log crash risk (offset is expected number of crashes) at a certain location. ε_i is the term adjusting for overdispersion and it is Gamma distributed. It is an error term due to a combination of variables omitted from the model and pure randomness. Maximum Likelihood Estimation (MLE) is used to estimate the coefficients of the explanatory variables and the overdispersion parameter. The goodness of fit of the NB model is measured by analyzing the overdispersion parameter. NB models, however, do not take into account spatial correlation among area units such as counties.

7.2.2 Moran's I Statistic

One of the objectives of the county-level spatial analysis is to find out whether observed crashes are spatially correlated among neighboring counties. One of the most commonly used statistical tools to measure the strength of spatial association among area units at an exploratory level is the Moran's I statistical test. Moran's I takes the form:

$$I = \frac{n \sum_i \sum_j w_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{\left(\sum_{i \neq j} w_{ij}\right) \sum_i (Y_i - \overline{Y})^2} \quad . \tag{7-3}$$

where,

n is the number of observations and $\sum w_{ij}$ is a binary weight value matrix; if area units i and j are neighbors than the weight value is 1 , otherwise it would be 0 (Banerjee et. al., 2003). The $\sum w_{ij}$ matrix reflects whether two units share a common border. The w_{ij} can also represent the centroidal distances’ between two neighboring units while still returning a binary value. For example if 2 units share a border and the centroidal distance between them is less than a defined threshold, then w_{ij} is equal to 1. In this analysis, if two counties share a border then they are considered to be neighbors. Y_i and Y_j are the respective total number of observations of a parameter (crash occurrences) in units (counties) i and j. $\bar{Y}$ is the average number of those occurrences. If the I value is positive and (I values range from -1 to +1) then this indicates positive spatial correlation, or clustering, within a study area. If the value is negative then this indicates negative spatial autocorrelation, or dispersion.

Under the assumption of i.i.d. (independent and identically distributed) Y_is, I is normally distributed with a mean of -1/(n-1) and a variance,

$$Var(I) = \frac{n^2(n-1)S_1 - n(n-1)S_2 - 2S_0^2}{(n+1)(n-1)^2 S_0^2} \tag{7-4}$$

where

$$S_0 = \sum_{i \neq j} w_{ij},\ S_1 = \frac{1}{2}\sum_{i \neq j}(w_{ij} + w_{ji})^2,\ S_2 = \sum_k \left(\sum_j w_{kj} + \sum_i w_{ik}\right)^2$$

The significance of the I value is estimated using a Z score equation, which is associated with any normal distribution (Lembo Jr.).

$$Z(I) = \frac{I - E(I)}{S_{E(I)}} \tag{7-5}$$

where,

$$S_{E(I)} = SQRT[\frac{N^2 \sum_{ij} w_{ij}{}^2 + 3(\sum_{ij} w_{ij})^2 - N \sum_i (\sum_j w_{ij})^2}{(N^2 - 1)(\sum_{ij} w_{ij})^2}]$$

Values of z greater than +1.96 or less than -1.96 indicate significant positive and negative spatial autocorrelation respectively, at the 5% level.

The Moran's I statistic is global in the sense that it indicates whether spatial correlation occurs in general over the whole study area. The Moran's I statistic equation structure could also be rearranged to find whether spatial correlation occurs at a local level. In other words I values and z values could be calculated for each area unit (county) and thus it could be observed whether a unit has spatial association with its neighbors (Anselin ,2006, Khan, 2008). The Local Moran's I equation takes the form:

$$I_i = (Y_i - \overline{Y} / S^2) \sum_{j=1}^{n} w_{ij} (Y_j - \overline{Y}) \qquad (7\text{-}6)$$

where, Ii is the I value at area i and

$$S^2 = [\sum_{j=1, j \neq i}^{n} Y_j^2 / (n-1)] - \bar{Y}^2$$

7.2.3 Full Bayesian Conditional Auto-regressive models

7.2.3.1 Model Specification

In this study, a FB hierarchical model is proposed to account for the possible spatial correlation among crash occurrence of adjacent counties. Hierarchical model is a regression (a linear or generalized linear model) in which the parameters, the regression coefficients, are given a probability model. Hence, this higher-level model has parameters of its own, the hyperparameters of the model, which are also estimated from the data. In the context of generalized linear models as in this study, the hierarchical modeling is mainly working on the link function: residual terms are added to the model corresponding to different sources of variation in the data structure. Bayesian approach is the process of fitting a probability model to a set of data and summarizing the result by a probability distribution on the parameters of the model and on unobserved quantities. Instead of giving "maximum likelihood" estimates for the studied unknowns totally based on the sample data in MLE inference, the essential characteristic of Bayesian methods is its explicit use of probability for quantifying uncertainty in inferences based on statistical data analysis. Specifically, the ultimate aim of Bayesian data analysis is to obtain the marginal posterior distribution of all unknowns, and then integrate this distribution over the unknowns that are not of immediate interest to obtain the desired marginal distribution. The Bayesian inference is recommended for the proposed hierarchical models in this study. As indicated from a large number of theoretical studies and applications, Bayesian approach shows numerous theoretical and practical advantages over the "classical" likelihood-based inference methods especially for hierarchical models as applied in this study.

Specifically, the spatial correlation is realized by specifying a Conditional Auto-regressive prior to the residual term of the link function in standard Poisson regression as shown in Equation 7-7.

$$
\begin{aligned}
&y_i \sim Poisson(\mu_i) \\
&\mu_i = E_i \times R_i \\
&\log(\mu_i) = \log(E_i) + \beta_0 + \beta_1 X_i + \theta_i + \Phi_i
\end{aligned}
\tag{7-7}
$$

Where the μ_i is the parameter of Poisson model whereas E_i is the expected number of crashes at county i. It is calculated using the equation:

$$E(i)= \bar{Y} * DVMT(i) / \overline{DVMT} \tag{7-8}$$

Risk = $R_i = \mu_i / E_i$

Thus it is clear that the R_i is the relative crash risk of county i. A crash risk greater than 1 indicates a higher relative risk. θ_i is a site-specific random effect, which is assumed as independently and identically distributed among different counties. Φ_i is the spatial correlation residual or in other words, the correlated heterogeneity. This model allows the data to decide how much of the residual crash risk is due to spatially structured variation. Φ_i is assigned an auto-regressive prior $N(\overline{\Phi_i}, \tau_i^2)$ as recommended by Besag (1974) where τ_i^2 is the precision, 1/variance, and

$$\overline{\Phi}_i = \frac{\sum_j \Phi_j w_{ij}}{\sum_j w_{ij}} \quad \text{and} \quad \tau_i^2 = \frac{\tau_\Phi^2}{\sum_j w_{ij}} \quad \text{for } i \neq j \tag{7-9}$$

in which w_{ij}=1 if areas i and j are adjacent (i.e. county i shares a border with county j) or 0 otherwise; τ_i^2 is assumed a gamma prior, Ga(0.5, 0.0005) as recommended by Wakefield et. al.

(2000). This formulation is proposed by Besag et. al. (1991) and has been applied successfully in traffic safety research field in several studies such as Quddus (2008) and Lit et al. (2007).

7.2.3.2 Model Calibration and Assessment

The general computing approach for Bayesian models is Markov chain Monte Carlo (MCMC) methods. MCMC is a general method based on drawing values of unknowns from approximate distributions and then correcting those draws to better approximate the target posterior distribution. Gibbs sampler and the Metropolis-Hastings algorithm are the most widely used simulation algorithms in MCMC. BUGS modeling language (Bayesian Inference using Gibbs Sampling) is a prevailed tool to allow the computation using MCMC algorithms for all sorts of Bayesian models, including most of the hierarchical models applied. WinBUGS software (Spiegelhalter et al. 2003) provides a flexible and simplified platform to modeling with the BUGS programs. In particular, since specification of the full conditional densities is not necessary in WinBUGS, small changes in program code can achieve a wide variation in modeling options and thus facilitating sensitivity analysis and prior assumptions.

For model comparison, Deviance Information Criterion (DIC), proposed by Spiegelhalter et al. (2003) can be used. In complex hierarchical models where parameters may outnumber observations, DIC provides a Bayesian measure of model complexity and fit that can be combined to compare models of arbitrary structure (Spiegelhalter et al., 2003). This can overcome the problems of classical criteria, such as AIC and BIC. These classical criteria require the specification of the number of parameters in each model. Specifically, DIC is defined as:

$$DIC = D(\bar{\gamma}) + 2p_D = \overline{D(\gamma)} + p_D \tag{7-10}$$

where $D(\bar{\gamma})$ is the deviance evaluated at the posterior means of estimated unknowns ($\bar{\gamma}$), and posterior mean deviance $\overline{D(\gamma)}$ can be taken as a Bayesian measure of fit or "adequacy". p_D is motivated as a complexity measure for the effective number of parameters in a model, as the difference between $\overline{D(\gamma)}$ and $D(\bar{\gamma})$, i.e., mean deviance minus the deviance of the means. As a generalization of AIC (Akaiki Information Criterion), DIC can thus been considered a Bayesian measure of fit or adequacy, penalized by an additional complexity term p_D. As with AIC, models with lower DIC values are preferred.

CHAPTER 8. SPATIAL ANALYSIS RESULTS

8.1 Moran's I Statistic Result

The main aim of conducting the Moran's I statistic is purely exploratory in nature. The results indicate whether spatial association exists among Florida's counties with respect to crash trends, taking into account the county neighborhood structure only. Other variables that might affect the spatial correlation such as traffic and socio-economic factors are not included. ArcMap 9.2, the GIS software, was used to calculate the Moran's I values. One of the advantages of ArcMap is the Arc ToolBox package which performs several spatial statistical operations such as analyzing patterns and mapping clusters. The data of year 2006 was chosen to conduct the preliminary Moran's I statistic analysis. In order to be able to compare trends, crashes had to be normalized by the DVMT. Figure 8-1 and Figure 8-2 display the rates of crashes and severe crashes, respectively. It can be observed in Figure 8-1 that counties in the northern portion of Florida share similar low crash rates while the southern ones have higher rates. In Figure 8-2 clusters of counties with similar severe crashes trends can be observed towards the east (around Hillsborough County) and in the Florida Panhandle. Figure 8-3 and Figure 8-4 display the GIS outputs of the results of the Moran's I statistic for the rates of all crashes and severe crashes, respectively. Table 8-1 summarizes those findings.

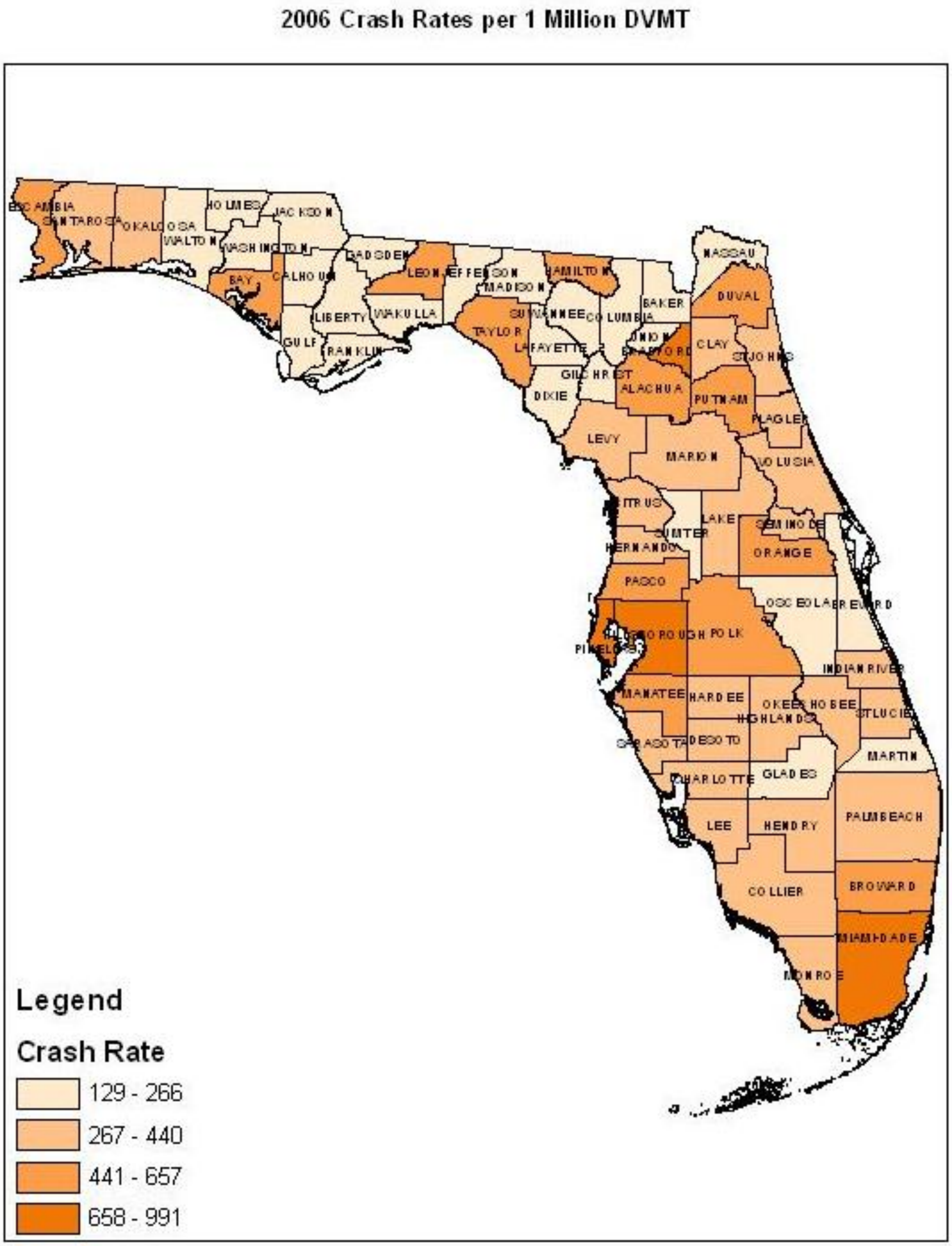


Figure 8-1: 2006 Crash Rates per 1 Million DVMT

2006 Severe Crashes Rate per 1 Million DVMT

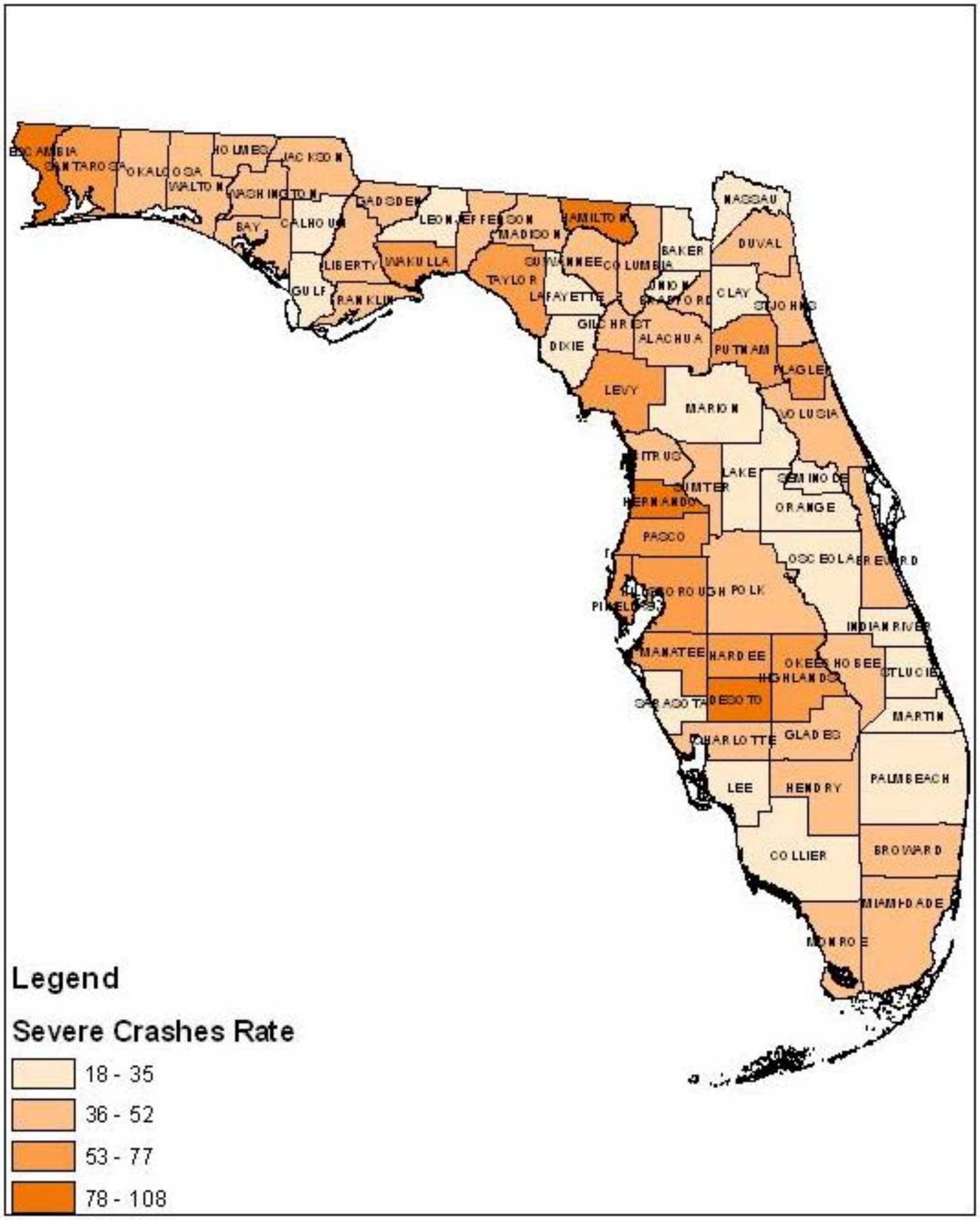


Figure 8-2: 2006 Severe Crashes Rate per 1 Million DVMT

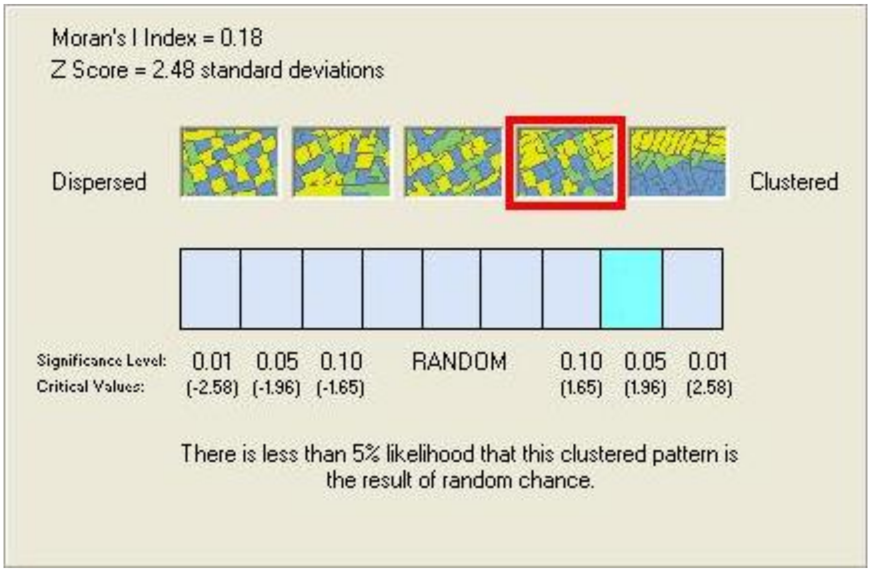


Figure 8-3: GIS Ouput for Moran's I Test on Crash Rate

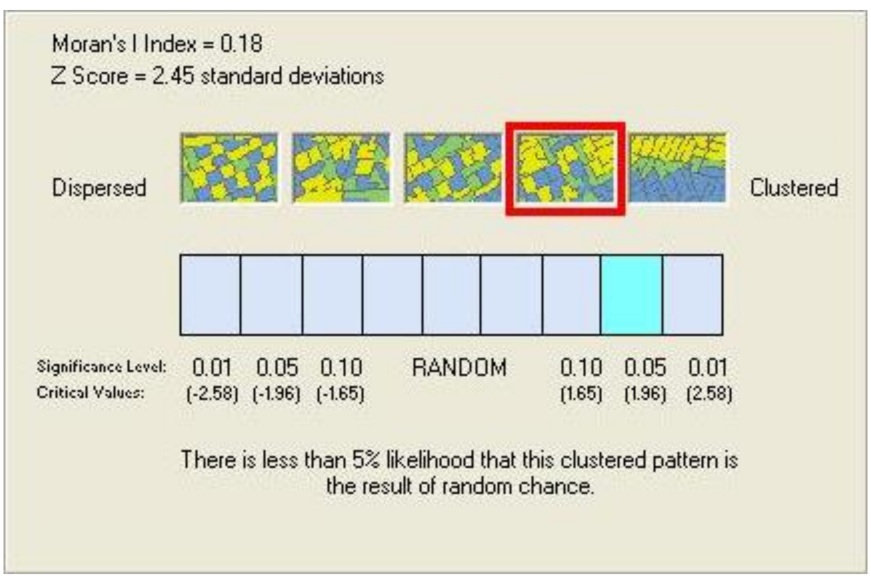


Figure 8-4: GIS Output for Moran's I Test on Severe Crash Rate

Table 8-1: Results of Global Moran's I Statistic

	Global Moran's I	Z Score
All Crashes	0.18	2.48
Severe Crashes	0.18	2.45

The results indicate that substantial positive spatial correlation does exist among the counties in Florida since I values are positive and since the Z scores are both higher than 1.96, which indicate that there is less than 5 % chance that spatial association is due to random chance. These results justify investigating spatial trends in the assembly of the FB crash models.

8.2 Full Bayesian Models

A series of FB models were fitted using WinBugs. There were two FB models developed, one for all the crashes and one for severe crashes exclusively. The variables shown in Table 8-2 were initially included in the FB models. The final set of parameter estimates that were selected for both models are the ones that were found significant and produced the lowest DIC.

Table 8-2: Summary of Variables Descriptive Statistics

Type	Risk Factors	Description	Min	Median	Mean	Max	Std Deviation
Response Variables	All Crashes	The frequency of all types of crashes	25	603	2353	32810	4821.472
	Severe Crashes	The frerquency of severe crashes	3	98	203.4	1617	304.449
Traffic-Related Risk Factors	log DVMT	Natural logarithm of (Daily Vehicle Miles Traveled/1000)	5.067	7.710	7.612	10.345	1.324
	Road_Cong	Road Congestion: (DVMT/1000)* 1/road length	1.9	14.8	16.59	56.7	12.221
	Dens_Road	Road Density: (road length*1/Area)*1000	5.6	22.3	25.23	96	13.521
	UoverR	Urban Road length * 1/Rural Road length	0.5	36.7	528.3	26882	3113.807
	Dens_FW	Freeway density: freeway length*1/Area	0	2.911	3.464	18.004	4.018
	Dens_PA	Principle arterial density: PA Length*1/Area	0.2	10.315	10.71	37.062	7.062
	Dens_MA	Minor Arterial density: MA Length*1/Area	0	7.328	8.063	35.547	5.536
	Dens_X	Intersection Density: (No. of signal+nonsignal intersect)*1/Road length)	0.083	10.007	10.97	27.25	5.013
	Truck AADT	Truck AADT*1/Total AADT	3.98	9.95	11.16	40.22	5.624
	TTTW	Avg. Travel Time to Work (minutes)	18.4	26.5	26.55	35.5	3.665
	Interchange	The number of interchanges	0	5	16.85	187	35.759
Socio-economic Risk Factors	Dens_pop	Population Density: Population*1/Area	8.86	137.03	316.5	3304.2	501.71
	fourteen	Age group under 15: (population younger than 15*1/population)*100	12.06	17.378	17.52	24.383	2.488
	young	Age group (15-24): (population between 15 and 24*1/population)*100	13	19.4	19.7	36.8	4.1809
	Sixtyfive	Age group over 64: (population 65 and older*1/population)*100	8	15.1	16.93	31.2	5.78
	Female	Female population: (Female population*1/population)*100	34.4	50.5	48.71	52.5	3.654
	MIC	Median income (in thousands)	26.41	36.743	37.19	55.712	6.882
	Poverty	Population under poverty line ratio: (population under poverty line*1/population)*100	7.1	12.5	12.79	20.9	3.387
	Bachelor	Population above 25 with bachelor's degree: (population above 25with bachelor*1/population above 25)*100	6.8	15.1	16.73	41.7	8.028
	Uerate	Unemployment rate	2.1	3.2	3.304	6.2	0.634

There were several transformations used in order to reduce the variances within the independent variables. The highway functional classifications were also pooled to reduce zero observations. Functional classifications (1, 11 and 12) were classified as freeways; (2, 14) principle arterials and (6, 16) minor arterials (for highway classification see Table 3-1). Local roads and collectors were disregarded because very few state roads are designated as local roads and more than one third of those observations were zeros. It was initially thought to combine principle and minor arterials together. However, those two types of roads serve slightly different purposes. Principal arterials are designed for the movement of large traffic volumes over relatively long distances. Such facilities also carry many trips not destined or originating within a county. Principal arterials do provide access management, unlike freeways, however it is controlled to the maximum extent possible. Minor arterials, on the other hand, carry moderate volumes of traffic and provide an intermediate connection between principle arterials and collectors and local roads (FDOT). Several variables were included as interaction terms (all of them being ratios). Road congestion is the ratio between the DVMT and road length. Density of the road, freeway density, principle arterial density and minor arterial density are interactions between road lengths and geographical area as shown in Table 8-2. Intersection density is an interaction between number of intersections and road length. Population density is the ratio of population to area. Age factors are also interactions between age group population and total population. The female, poverty, bachelor and unemployment terms represent interactions between certain types of populations and total population.

A correlation test was conducted for the potential risk factors. There are several factors that are potentially good predictors but were found to be insignificant due to multicollinearity.

For example, it is expected that crashes tend to increase in counties with higher population densities; however this factor is highly correlated with road congestion, hence it was dropped.

8.2.1 All Crashes Model

Table 8-3: All Crashes Model

Variable	Estimate	Credible Set 95%	
	Mean	2.50%	97.50%
Road_Cong: Road Congestion	0.0076	0.0003	0.0149
Dens_FW: Freeway density	-0.0787	-0.0917	-0.0647
Dens_PA: Principle arterial density	0.0236	0.0178	0.0293
Dens_MA: Minor Arterial density	0.0218	0.0151	0.028
DensX: Intersection Density	0.022	0.0118	0.0317
TTTW: Avg. Travel Time to Work	-0.0218	-0.0309	-0.0109
Interchange: The number of interchanges	0.0055	0.0042	0.0068
MIC: Median income	0.0059	0.0001	0.0115
Young: Age group (15-24) ratio	0.0264	0.0202	0.0328
Stdev(Φi): Spatial Correlation Term	0.19	0.112	0.2438
Stdev(θi): Site Specific Random Effect	0.174	0.0514	0.3486
Ratio:Stdev(Φi)/(Stdev(Φi)+Stdev(θi))	0.5219		

Table 8-3 presents the FB model for all crashes. Several traffic-related factors came out to be significant with the expected signs. A parameter is determined to be significant if its 95% credible set does not contain 0. The coefficient for road congestion came out to be positive. As the roads become more congested (traffic jams), the risk of vehicle crashes, especially rear-ends and angle crashes, tend to increase. Crash risk is negatively correlated with freeway density but positively correlated with the densities of other road types (principal and minor arterials and collectors). This finding could be attributed that freeways are generally better designed, have full access control, and low speed variance; whereas arterials have intersections and experience more traffic jams which increase crash risk. The coefficients for intersection density and number of interchanges are also positive and significant. This indicates that the more intersections on a road and the higher number of interchanges within a county, the higher the chances of crash occurrences. This is expected since higher densities of intersections and interchanges indicate higher traffic flows and exposure of vehicles to conflicting movement or red light running which in turn would result in higher crash incidents. The average travel time to work came out to be negatively correlated with crash risk. One might think this finding to be somewhat surprising since it would seem logical that the probability of crash involvement increases as the average time spent traveling on the road increases. Recent research established that most people tend to live close to their workplace which would result in lower average travel times to work (Strillacci, 2004). Most crashes have been found to occur within a close area of home. Strillacci (2004) attributed this to the fact that people tend to be less attentive when driving short distances due to a false sense of security that arises from proximity. With more people preferring to travel shorter distances to work, which could be a surrogate for shorter travel time, and with higher proportions of crashes occurring in close proximity, the probability of a crash increases with shorter travel times.

Two socio-economic factors were found to be significant: median income and percent of young population. The median income coefficient is positively correlated with a higher crash risk. This finding could be explained by the fact that counties with higher median incomes tend to have higher economic activity. This leads to higher traffic flow which increases crash risk. The percentage of young population, surrogate for young drivers, was found to be positive and significant which is consistent with previous research Quddus 2008, Aguero-Valverde and Jovanis, 2006). This is expected since young population (surrogate for young drivers) tends to have a high level of mobility, whether as drivers, passengers, cyclists or pedestrians. They also are more risk taking and aggressive in driving. Contrary to previous studies, however, the percentage of population 65 years or older was found to be insignificant.

The Poisson extra variation due to spatial correlation, **Stdev(**Φi), came out to be significant as shown in the model. This indicates that crash risk is spatially correlated among neighboring counties. This result is consistent with the findings of the Moran's I statistic (see Figure 8-3) which indicated that crash related spatial correlation existed.

8.2.2 Severe Crashes Model

Table 8-4: Severe Crashes Model

Variable	Estimate	Credible Set 95%	
	Mean	2.50%	97.50%
Road_Cong: Road Congestion	-0.014	-0.0212	-0.0067
Dens_FW: Freeway density	-0.0122	-0.0253	-0.0003
Dens_PA: Principle arterial density	0.0182	0.0111	0.0253
DensX: Intersection Density	0.0273	0.0131	0.041
Interchange: The number of interchanges	0.0097	0.0015	0.0181
Bachelor: Percent of population above 25 with bachelor's degree	-0.0125	-0.0187	-0.0065
Stdev(Φi): Spatial Correlation Term Stdev	0.1493	0.0825	0.21
Stdev(θi): Site Specific Random Effect Stdev	0.2838	0.1486	0.365
Ratio:Stdev(Φi)/(Stdev(Φi)+Stdev(θi))	0.3447		

Table 8-4 presents the FB model for severe crashes. Less crash risk factors were found to be significant in this model compared with the previous one. With the exception of the education level variable (i.e. bachelor) all the parameters in this model were also significant in the previous one. Overall, the signs of the coefficients came out as expected. The coefficient for road congestion came out to be negative in this model. This means that the risk of severe crashes decrease with higher congestion on the roads. This finding is logical since higher congestion lowers the speeds at which vehicles travels, which in turn lowers the risk of a serious injury or a fatality in the case of a crash. Freeway density is negatively associated with severe crashes and this is probably due to the lower vehicle to vehicle speed variation on freeways and because those types of roads have wide medians and no intersections which reduce conflict points. The coefficient for principle arterials is positive and is consistent with previous findings (NHTSA, 2004). As expected, the coefficient for intersection density is positive and significant. The number of interchanges is also positively correlated with crash risk. This could be explained by the fact that conflicting movement at interchanges, such as weaving, happens at high speeds which increases the risk of a severe or fatal injury in the case of an accident.

The only socio-economic factor that came out to be significant was the education level variable. At county-level, severe crashes risk is negatively associated with higher population ratios holding at least a bachelor's degree. This is an interesting finding since it implies that people (25 years or older) with a higher degree of education are less likely to be involved in severe crashes than those with only a high school diploma or less at the same age level. People with higher levels of education, for example, are more likely to use seatbelts or less likely to drive under the influence, which can reduce the severity of injury in the case of a crash.

The Poisson extra variation (i.e. standard deviation) due to spatial correlation, **Stdev**(Φi), came out to be significant as shown in the model and consistent with the findings of the Moran's I statistic (see Table 8-1). The spatial correlation term is slightly higher in the all crashes model compared to the severe crashes model. This is consistent with the findings of Quddus (2008) and Aguero-Valverde and Jovanis (2006).

8.2.3 FB Models Goodness of Fit

For the sake of comparison, two NB models with Bayesian inference, but which do not account for spatial correlation, were fitted.

Table 8-5: DIC Goodness of Fit Results

All crashes Model	**Dbar**	**Dhat**	**pD**	**DIC**
NB Model (non-spatial model)	2360.56	2138.38	222.179	2582.74
FB Model (spatial model)	1390.23	1351.81	38.427	1428.66
Severe crashes Model				
NB Model (non-spatial model)	1634.04	1540.68	93.362	1727.4
FB Model (spatial model)	1515.94	1466.91	49.03	1564.97

As shown in Table 8-5, FB models provides lower DIC values for both the all crashes model and severe crashes model, indicating that the FB approach fits the data better. This is attributed to the presence of extra variation due to spatial correlation which the FB approach can accommodate, unlike the traditional NB approach.

CHAPTER 9. CONCLUSIONS

This thesis consisted of a GIS safety study and a spatial analysis of crashes in the State of Florida. The GIS safety study focused on identifying counties and roadway locations where high trends of severe crashes were observed. This was accomplished in order for the transportation agencies to target roadway sections where improvements are required in order to enhance the safety performance and reduce road fatalities.

The spatial analysis established a relationship that linked traffic-related factors and socio-economic factors with crashes at the county level. The analysis also investigated the existence of similarities in crash risk (i.e. spatial correlation) among neighboring counties. The following summarizes the findings of this thesis:

1. **District and County Level GIS Analysis**: At the macro level of the analysis, it was found that the counties with the highest trends of severe crashes were mostly urban. It was also found that the counties with the highest trends of such type of crashes were neighbors (Pasco County, Pinellas County and Hillsborough County).

2. **Roadway Level GIS Analysis**: There were seven counties chosen for this type of analysis; all exhibited high trends of severe crashes. The locations of dangerous road segments and signalized intersections were identified for all seven counties. It was found that the worst road safety conditions were in the neighboring counties of Pasco, Pinellas and Hillsborough. By identifying those locations, transportation agencies can look afterwards for the underlying reasons behind

the high trends of severe crashes. The reasons can be related to road geometry (e.g. shoulder width, median width), road condition (lighting, road surface condition) or intersection properties. The results of the roadway level also help in increasing cooperation among counties. Several corridors that showed severe crashes trends run through several counties (e.g. SR 55 which passes through Pasco and Pinellas Counties). Cooperation among counties would help identify the causes behind such trends and whether they are similar. Such an approach would provide efficient solutions to improve the safety conditions on corridors.

3. **Sliding Window Analysis**: This type of analysis identified the ten worst corridors in the seven selected counties. It was found that 6 out of the 10 worst corridors were in Hillsborough County. The sliding window analysis provided the locations of the worst 0.5 mile ranges on those 10 corridors.

4. **County-level Spatial Analysis:** In the all crashes model, counties with higher road congestion levels, higher densities of arterials and intersections, higher percentage of population in the 15-24 age group and higher income levels have increased crash risk. For the severe crashes model, crash risk is positively correlated with arterial density, intersection density and the number of interchanges. Spatial correlation is significant in the all-crash FB model and the severe crashes model. Both of those results were consistent with the findings of the Moran's I exploratory analysis of spatial association. The DIC values of both models indicated that the FB approach fits the data better than a traditional NB. This is primarily due to the existence of spatial correlation which is not accounted for by NB. There were several more significant variables in the all-crash

model than the severe crashes model. This is expected since the occurrences of severe crashes are much lower.

The results of the spatial analysis provides counties that are within close proximities the opportunity to share ideas at the transportation planning stage and collectively implement new measures that can help improve roadway safety; especially if those counties have similar crash history.

9.1 Recommendations for Future Research

The main objectives of the thesis were accomplished by providing the roadway locations were high trends of severe crashes occurred and displaying them using the Geographic Information System (GIS) tool. The existence of crash-related spatial correlation among the counties of Florida was also verified.

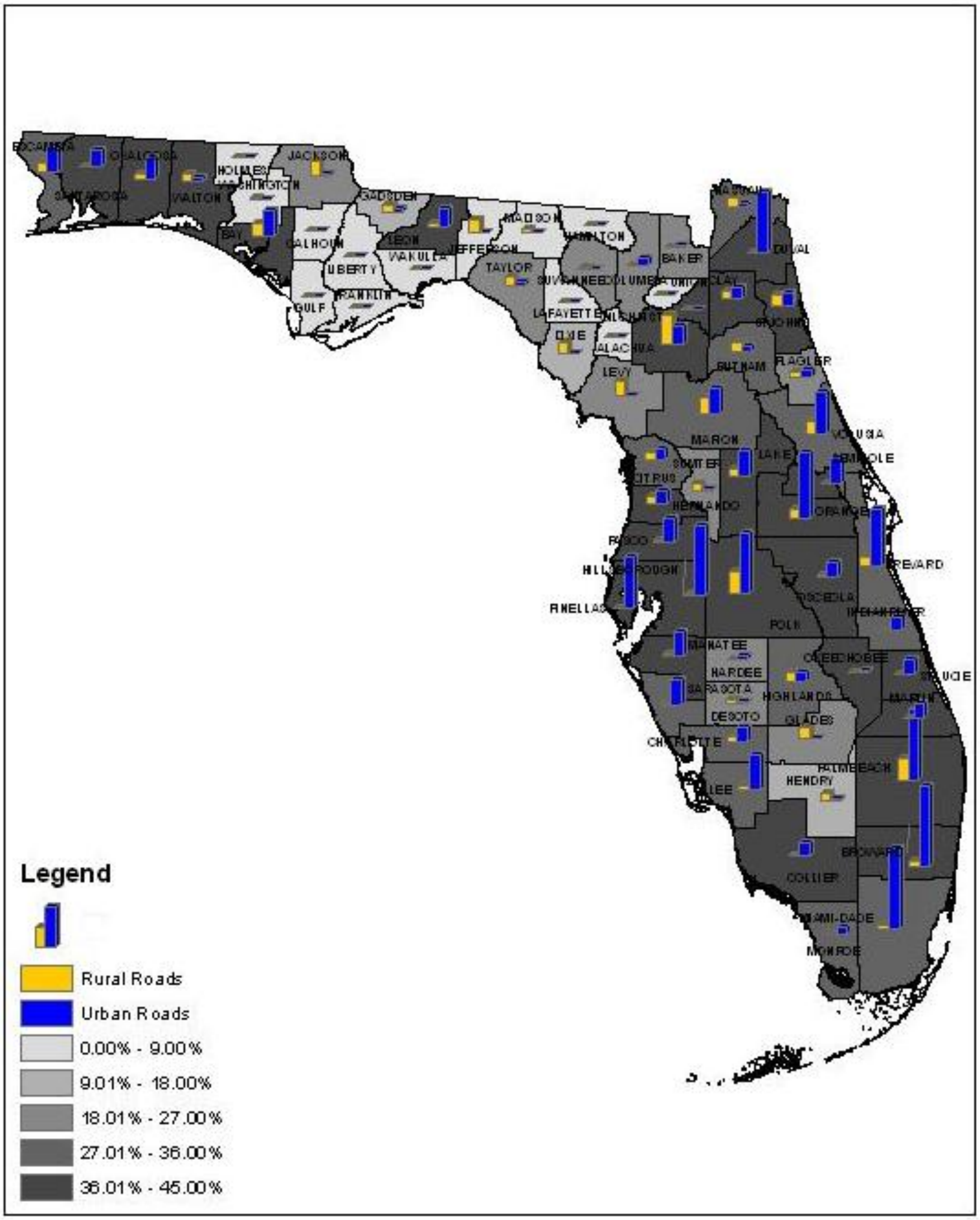
In the future, the methodology used in the roadway-level GIS analysis could be expanded to include all the counties in Florida and all types of roads. The same recommendation applies for the sliding window analysis. Another direction for future research would aim at studying the correlation between signalized intersections and roadway segments prior to applying a ranking methodology to identify the most hazardous locations in a road network.

There are several extensions that could be made for the spatial analysis. The FB models presented in this study only focused on total crashes and severe crashes. In the future, separate models for different crash types can be developed and analyzed to observe the different factors that affect different crash types and observe whether spatial correlation is still significant after performing crash segregation.

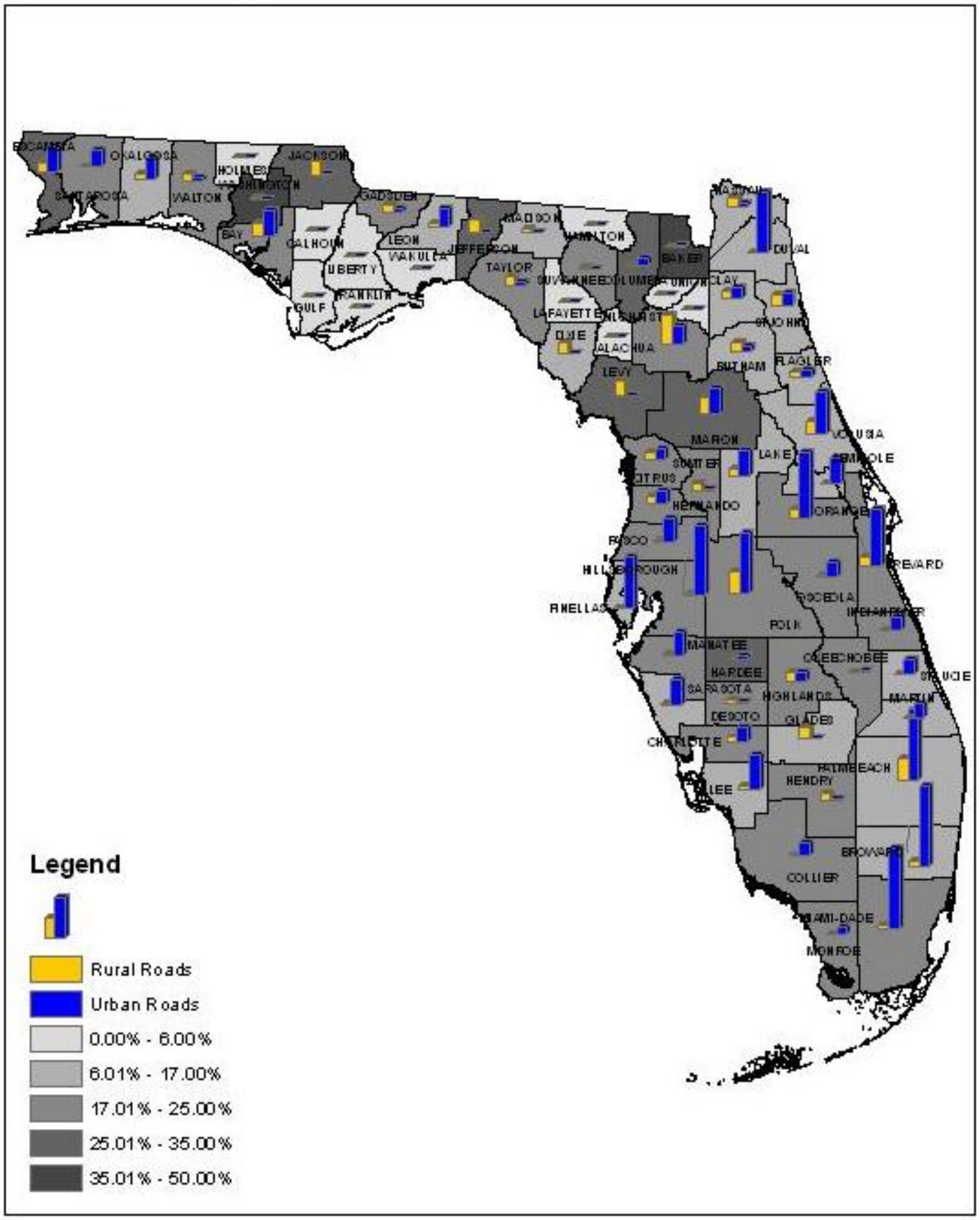
It is also possible to conduct a spatial-temporal analysis following an FB approach to investigate whether time trends affect crash risk over the years and observe whether space and time interactions exist. This will require collecting data for several years. The values of several crash risk factors were assumed to be the same over a five year period in this analysis, which is a limitation for a spatial-temporal modeling. It would also be better to limit the use of surrogate measures for socio-economic factors such as using actual figures of the number of drivers within an age group. It is also recommended to use both state and non state road data and include more factors related to land use within counties, such as the amount of commercial, tourist and industrial areas.

APPENDIX
MACRO-GIS ANALYSIS: COUNTY LEVEL GIS MAPS

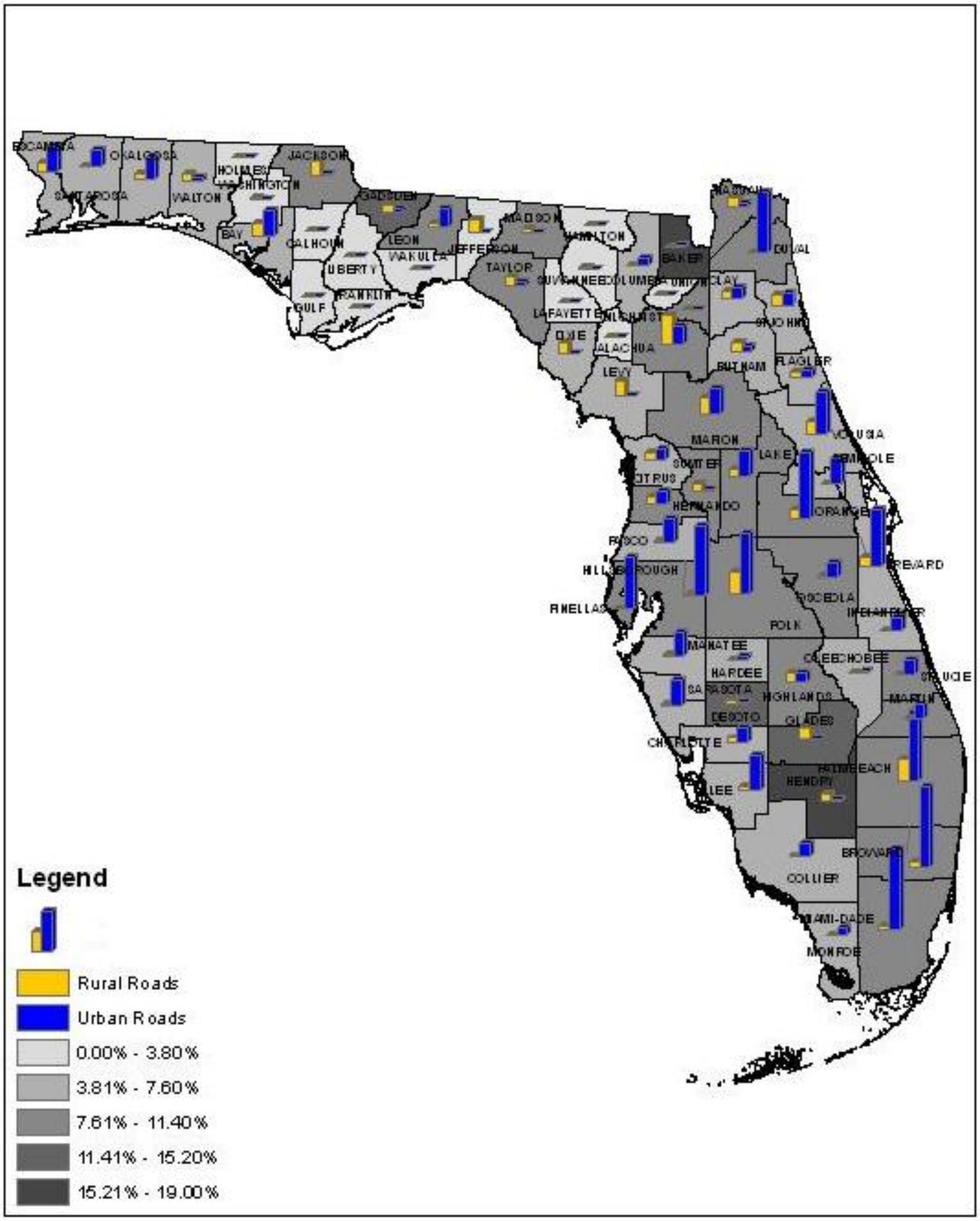
Ratio of Read-end Crashes to Total Crashes vs. Landuse



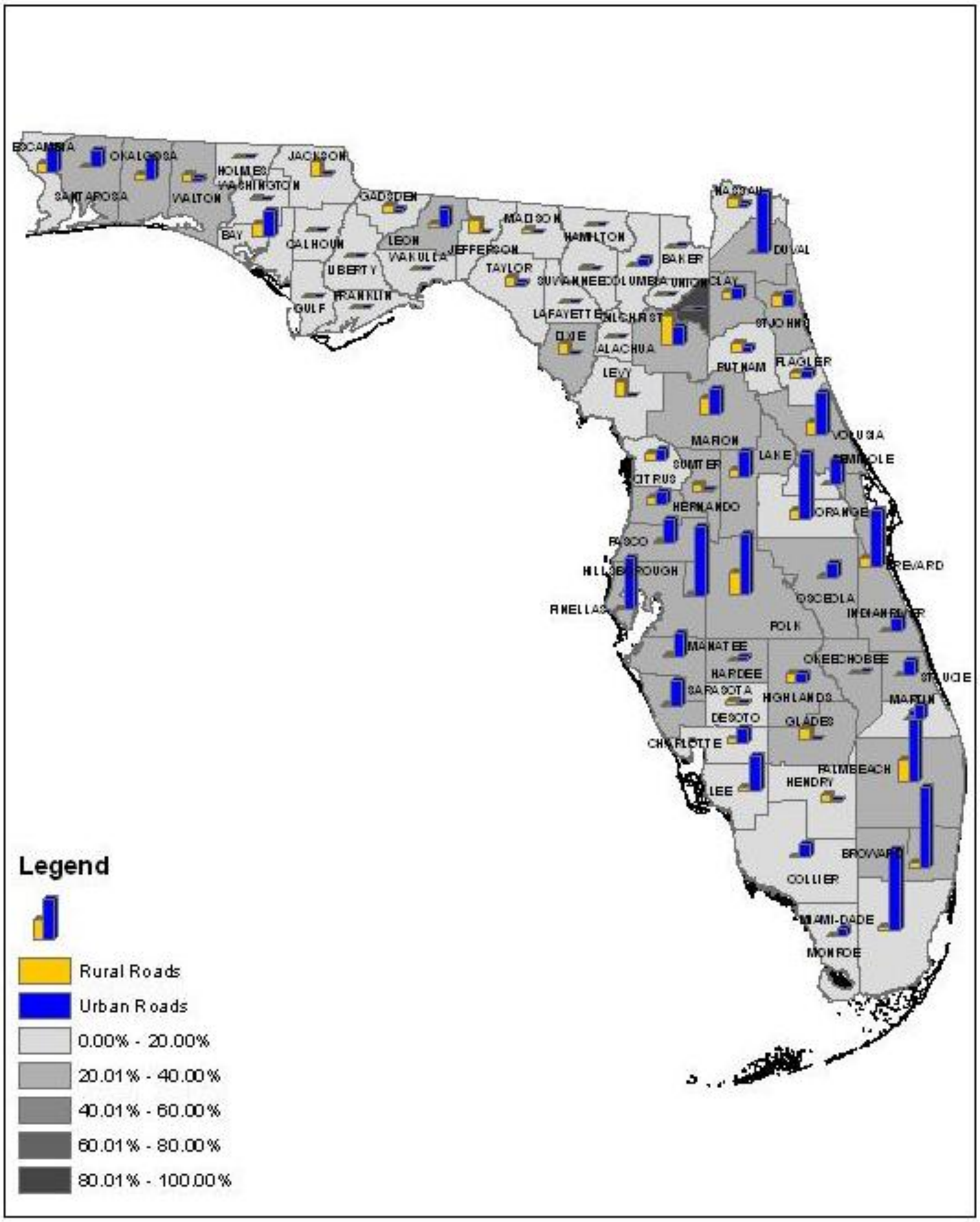
Ratio of Angle Crashes to Total Crashes vs. Landuse



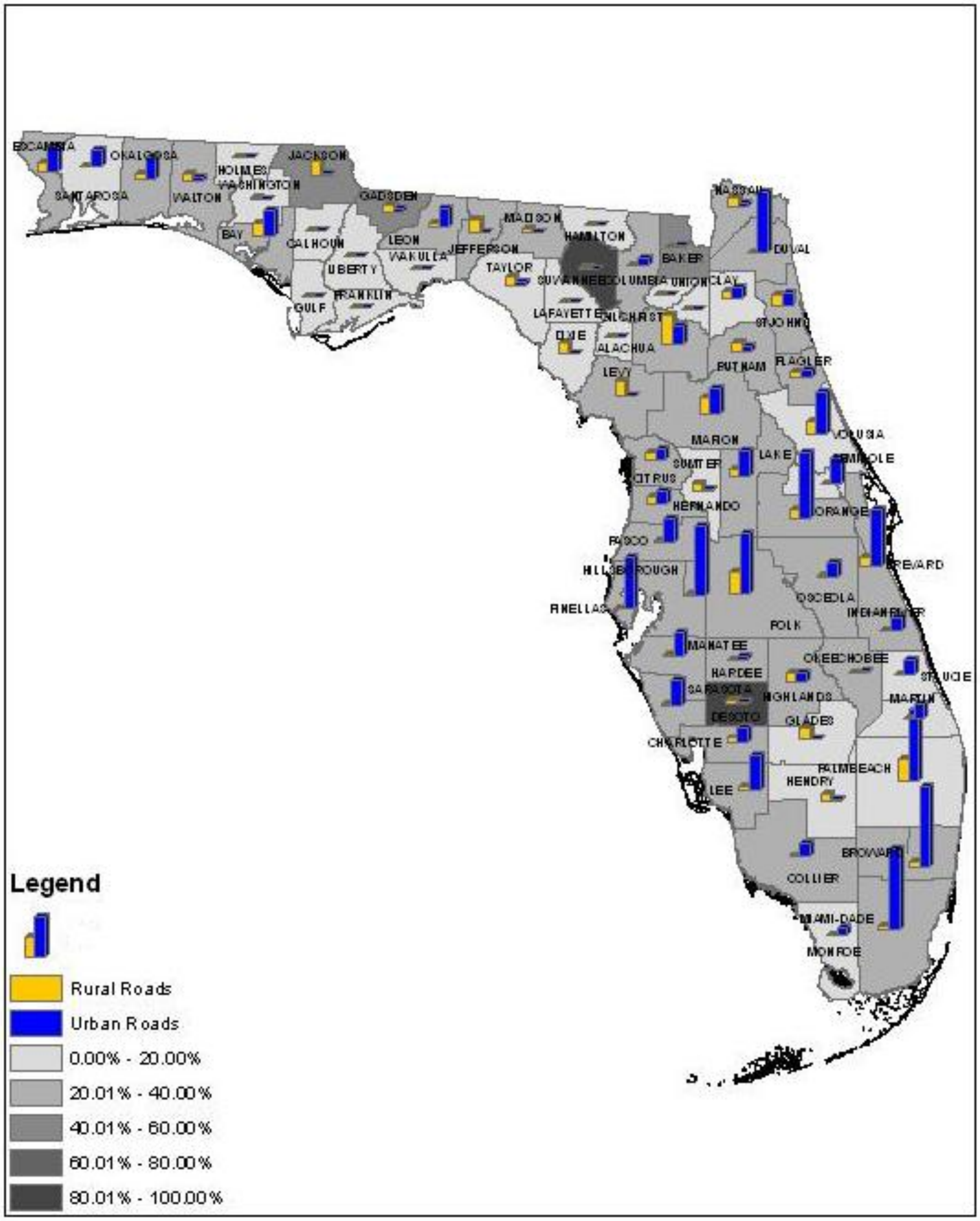
Ratio of Sideswipe Crashes to Total Crashes vs. Landuse



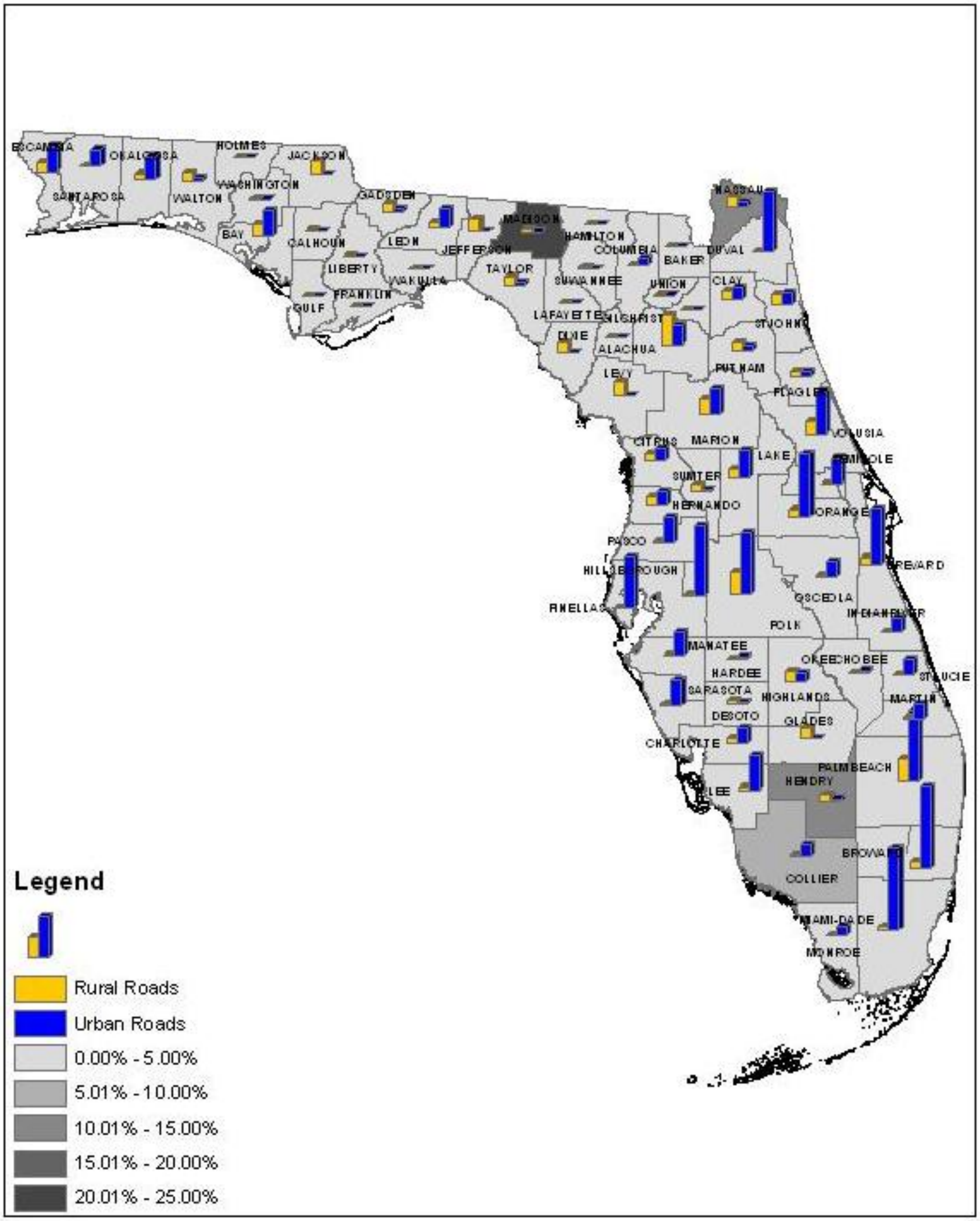
Ratio of Severe Rear-end Crashes to Total Severe Crashes vs. Landuse



Ratio of Severe Angle Crashes to Total Severe Crashes vs. Landuse



Ratio of Severe Sideswipe Crashes to Total Severe Crashes vs. Landuse



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