Reduced Visibility Related Crashes In Florida: Crash Characteristics, Spatial Analysis And Injury Severity

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REDUCED VISIBILITY RELATED CRASHES IN FLORIDA: CRASH CHARACTERISTICS, SPATIAL ANALYSIS AND INJURY SEVERITY

by

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BSc., Bangladesh University of Engineering and Technology, 2006

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the Department of Civil, Environmental and Construction Engineering in the College of Engineering and Computer Science at the University of Central Florida Orlando, Florida

Fall Term 2009
ABSTRACT

Roadway crashes related to vision obstruction due to fog/smoke (FS) conditions constitute a challenge for traffic engineers. Previous research efforts mostly concentrated on the snow and rain related crashes. Statistics show that Florida is among the top three states in terms of crashes due to vision obstruction by FS. This research culminated in a comprehensive study of fog and smoke related crashes in the state of Florida. The analysis took into account the crashes that occurred between 2003 and 2007 on Florida state roads. Spatial analysis and injury severity analysis have been conducted and significant results have been identified.

The spatial analysis by GIS examines the locations of high trends of FS related crashes on state roads in the State of Florida. Statistical features of the GIS tool, which is used efficiently in traffic safety research, has been used to find the crash clusters for the particular types of crashes that occur due to vision obstruction by FS. Several segmentation processes have been used, and the best segmentation for this study was found to be dividing the state roads into 1 mile segments, keeping the roadway characteristics uniform. Taking into account the entire state road network, ten distinct clusters were found that can be clearly associated with these types of crashes. However, no clear pattern in terms of area was observed, as it was seen that the percentage of FS related crashes in rural and urban areas are close.

The general characteristics of FS related crashes have been investigated in detail. For the comparison to clear visibility conditions, simple odds ratios (in terms of crash frequencies) have been introduced. The morning hours in the months of December to February are found to be the
prevalent time for fog related crashes, while for the smoke related crashes the dangerous time was found to be morning to midday in the month of May. Compared to crashes under clear-visibility conditions, the fog crashes tend to result in more severe injuries and involve more vehicles. Head-on and rear-end crashes are the two most common crash types in terms of crash frequency and severe crashes.

For the injury severity analysis, a random effect ordered logistic model was used. The model in brief illustrates that the head-on and rear-end crash types are the two most prevalent crash types in FS conditions. Moreover, these severe crashes mainly occurred at higher speeds. Also they mostly took place on undivided roads, roadways without any sidewalk and two-lane rural roads. Increase of average daily traffic decrease the severity of FS related crashes.

Overall, this study provides the Florida Department of Transportation (FDOT) with specific information on where improvements could be made to have better safety conditions in terms of vision obstruction due to FS in the state roads of Florida. Also it suggests the times and seasons that the safety precautions must be taken or the FS warning systems to be installed, and the controlling roadway geometries that can be improved or modified to reduce injury severity of a crash due to FS related vision obstruction.
To my mother,
For making me who I am
ACKNOWLEDGMENTS

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Last but not the least I would also like to acknowledge my mother, my grandfather and grandmother. Without your unending support and love from childhood to now, I would never have made it through this process or any of the tough times in my life.
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# LIST OF ACRONYMS/ABBREVIATIONS

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADT</td>
<td>Average Daily Traffic</td>
</tr>
<tr>
<td>CAR</td>
<td>Crash Analysis Reporting System</td>
</tr>
<tr>
<td>DVMT</td>
<td>Daily Vehicle Miles Traveled</td>
</tr>
<tr>
<td>FDOT</td>
<td>Florida Department of Transportation</td>
</tr>
<tr>
<td>FS</td>
<td>Fog/Smoke</td>
</tr>
<tr>
<td>FHWA</td>
<td>Federal Highway Administration</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information Systems</td>
</tr>
<tr>
<td>RCI</td>
<td>Roadway Characteristics Inventory</td>
</tr>
</tbody>
</table>
CHAPTER 1. INTRODUCTION

Transportation has evolved ever since the mankind had the upper-hand on civilization. Faster vehicles, intelligent roads, skilled drivers, and modern machineries making peoples life easy for travelling each and every day. But safety always comes first, and a fine line still exists between the ‘going beyond’ expectations in technology of traffic operations and the safety of the road users. Safety, in itself, has been on focus for decades now, and it is of high priority for the people associated with roadway design, operation and maintenance. 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).

When it comes to driving in adverse weather, safety has always been put into question. Most of the studies though, discussed this key issue in a generic point of view. Some studies discussed climate changing effects on the transportation sector as a whole, while other showed the effect of different weather events on traffic operations, safety, traffic demand, flow and traffic intensity. Effects of weather and weather forecast on driver behavior have been researched as well. CHAPTER 2 provides a detailed idea about the progress in weather effects on traffic safety.

In terms of crash frequencies in the three major inclement weather events, i.e. rain, snow and FS (FS), there are revealing statistics (see Table 1-1) that show the fatal crashes in these weather conditions. The figures show that while snowy weather, as a contributing factor of
traffic crashes, is unsurprisingly more associated with some northern states, the top states in terms of rain or FS related fatal crashes are mostly located in the southern parts of the US, such as Texas, Florida and California.

### Table 1-1: Inclement weather related fatal crashes in United States (2000 to 2007)

<table>
<thead>
<tr>
<th>Rank</th>
<th>Rain State</th>
<th>Fatal crashes</th>
<th>Snow State</th>
<th>Fatal crashes</th>
<th>FS State</th>
<th>Fatal crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Texas</td>
<td>1927</td>
<td>Michigan</td>
<td>572</td>
<td>California</td>
<td>380</td>
</tr>
<tr>
<td>2</td>
<td>Florida</td>
<td>1403</td>
<td>Pennsylvania</td>
<td>429</td>
<td>Texas</td>
<td>356</td>
</tr>
<tr>
<td>3</td>
<td>California</td>
<td>1340</td>
<td>New York</td>
<td>380</td>
<td>Florida</td>
<td>299</td>
</tr>
<tr>
<td>4</td>
<td>Pennsylvania</td>
<td>1060</td>
<td>Ohio</td>
<td>316</td>
<td>North Carolina</td>
<td>168</td>
</tr>
<tr>
<td>5</td>
<td>North Carolina</td>
<td>1025</td>
<td>Wisconsin</td>
<td>304</td>
<td>Georgia</td>
<td>146</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Mean*</th>
<th>447</th>
<th>97</th>
<th>73</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S.D.*</td>
<td>428</td>
<td>121</td>
<td>82</td>
</tr>
<tr>
<td></td>
<td>Total*</td>
<td>22813</td>
<td>4972</td>
<td>3729</td>
</tr>
</tbody>
</table>

Data queried from Fatality Analysis Reporting System (FARS)

* statistics for all 50 states, the District of Columbia, and Puerto Rico

Previous literature (see CHAPTER 2) suggest that even though quite an amount of research have been done on the weather effects on traffic crashes, good and conclusive findings have been prominent only when it comes to rain and snow crashes. As for FS related crashes, there is indeed a good deal of research needed to reveal the crash characteristics and potential outcomes so that proper countermeasures might be proposed. As shown in Table 1-1, Florida is among the top states in the United States in terms of FS related fatal crashes. This study aims at a
comprehensive analysis of FS crashes in Florida. In particular, the method and major results arising from three specific analyses in this study are presented:

(1) Crash Characteristics Analysis examines the characteristics of FS crashes in comparison with crashes occurring at non vision obstruction conditions. Issues investigated include temporal distribution, crash types, and effects of various geometric, traffic and environmental factors. Injury severity was found to be worth more in-depth analysis in terms of other factors, which has been done in-detail in the third part of this study.

(2) Hotspot Identification Analysis concentrates on identifying FS crash hotspots based on spatial distribution of historical crash occurrences. Spatial cluster analysis technique is employed in this analysis. Ten distinct FS crash hotspot areas have been identified on the Florida road network.

(3) Injury Severity Analysis estimates the effects of various traffic and environmental factors on injury severity given an FS crash had occurred, so that appropriate countermeasures could be proposed for proactive actions to reduce the risk of severe crashes at the FS crash prone locations.

The main aims of this thesis are split in two. The first is to provide the Florida Department of Transportation (FDOT) with the hazardous locations of FS related crashes using the Geographic Information System (GIS) tool. This analysis focused specifically on Florida’s state road network. The mapping of the high concentration locations in GIS makes it easier to visually identify those spots. The GIS map is supported by the perimeter boundaries of the areas where the accident hotspots are marked, so that it is useful for the decision makers and planners.
The second aim of this thesis is to establish a relationship that links different factors that are specifically associated with the characteristics of FS crashes and the factors that are specifically affecting the injury severity of those crashes.

To summarize, the following are the main objectives of the thesis:

1. Better understanding of FS crashes in Florida;
2. Comparison of the FS crashes to the clear visibility crashes;
3. Identify and select spots with high trends of FS crashes;
4. Practical implications of FS crashes;
5. Injury severity analysis of FS crashes.

The thesis is organized as follows: CHAPTER 2 provides a review of previous researches that have focused on generic weather related crash studies and also used GIS in assessing safety for hotspot identifications. CHAPTER 3 describes the data collection, data preparation and sampling process carried out for the GIS analysis and injury severity modeling. CHAPTER 4 presents the preliminary analysis of the FS data. It also shows some conclusive results and comparisons of FS crashes to non-FS crashes. CHAPTER 5 presents the methodology and results of the GIS cluster analysis. The result is presented visually as well as describing the perimeter of the clusters found. CHAPTER 6 presents a modeling approach, methodology followed and the results in detail for the injury severity of FS crashes. CHAPTER 7 concludes the findings of this thesis and provides directions for future research.
CHAPTER 2. LITERATURE REVIEW

Even though a lot of research has been done on weather related traffic accidents, very few have been done on FS (FS) specifically, and most of them have no conclusive results. That strengthens the need to dive deep into this particular type of visibility affecting traffic crashes, as is the prime objective of this study.

2.1 General weather related crashes

Koetse and Rietveld (2009) studied the effect of climate change and weather on transportation as a whole. Even though they did not look at fog and smoke in particular, they found that precipitation increases traffic accident frequency, but decreases traffic severity. The effect is particularly large during peak hours and on congested roads.

Maze et al. (2006) showed the effect of different weather events on traffic operations, safety, traffic demand, flow and traffic intensity. They found that depending on the type of traffic (commuter, commercial, long-distance travel) and weather severity, roadway traffic volumes have been shown to be reduced to less than 5% during rainstorms and from 7% to 8% during snowstorms. Crash rates also increases during inclement weather, increasing dramatically during snowstorms.

Cools et al. (2008) assessed the impact of weather on traffic intensity. They found that precipitation, cloudiness and wind speed have a clear diminishing effect on traffic intensity.
Edwards (1999) studied the speed adjustment behavior of commuter traffic in British motorways. The study was done in three weather conditions: fine, rain and misty. It shows significant but insufficient amount of reduction of speed in inclement weather conditions. Interestingly though, a survey for the purpose of this study showed that bad weather generates most concern among the drivers followed by other factors related to roadway geometry.

Effects of weather and weather forecast on driver behavior have been researched as well by Kilpelainen and Summala (2007), and it was concluded that drivers should be informed locally and more specifically of a weather condition rather than a forecast of a whole region.

Considerable research efforts have been made on the rain and snow related crashes in northern states. Qin et al. (2006) did a snowstorm event-based crash analysis on Wisconsin’s state trunk highway system. They showed that the severity of snowstorm increases traffic crashes, whereas a freezing rain event leads to a less number of crashes but more severity. Furthermore, a large percentage of crash occurred during the initial part of snowstorm. Khattak and Knapp (2001) did crash analysis on Iowa state roads, and found that both injury and non-injury crash rates increases during winter snow events, but those crashes are less severe than those during non-snow periods. Oh et al. (2009) focused research on identifying common site features that may have contributed to a high collision rate under wet pavement conditions. They found that speeding is the primary collision factor regardless of pavement conditions, and also stated that visibility played a role in collision for drivers.
2.2 Fog or smoke related crashes

Very few researches have focused specifically on FS related crashes. Even smaller is the amount of the researchers who have focused on the smoke related crashes in particular. So there are inconclusive results for the effects of FS on road crashes. Qui and Nixon (2008) have conducted research on vehicle crashes and how weather is impacting crash rates on highways. This study focused on quantifying the weather impacts on traffic crashes. It shows meta-analysis approach to weather crashes including fog, with no conclusive result. Wanvik (2006) studied the effect of road lighting on crashes and implied that the effect of lighting during foggy conditions may be underestimated in safety studies. Musk (1991) mentioned in his study that fog is still considered the weather hazard that drivers fear most. Moore and Cooper (1972) studied roadways in the UK and noted that despite a drop of 20% in the amount of traffic in dense fog there was an increase of 16% in the total of personal injury crashes. Codling (1971) and Summer (1977) showed that fog crashes tend to involve multiple vehicles; and Perry (1981) found that those fog related crashes often occur in a few “black-spots”, frequently on motorways. Edwards (1998) studied the road crash severity on British motorways in fog and concluded that speed is a major contributing factor in many of the pile-up crashes in foggy conditions. Kang et al. (2008) studied the effects of fog on car following performance. They found that drivers tend to maintain good distance headway under the highest fog condition. Cools et al. (2008) assessed the effect of weather on traffic intensity. They had conclusive results for snowfall and rain but the effect of reduced visibility due to fog and cloudiness remains inconclusive.
2.3 GIS Analysis: Roadway and area level

Abdel-Aty and Radwan (1998) incorporated the use of GIS to analyze crash trends at the county level. The comprehensive study concluded that counties with high population tend to have higher crash frequencies. The percentage of severe crashes to total crashes was also focused in the study. Rural counties tend to have higher percentage of severe crashes compared to urban counties, as found by the study.

GIS mapping tools have been used by Aguero-Valverde and Jovanis (2006) to display the distribution of injury and fatal crashes amongst the 67 counties of the State of Pennsylvania. The study was based on county level GIS maps. The study found highest frequency of severe crashes in the largest Metropolitan areas of the state of Pennsylvania. It was also found highest rates of fatal crashes in counties with an overall lower frequency of total crashes. This observation was explained in the study implying to the fact that fatal crashes are rare events and a small increase in the number of those crashes tends to magnify the crash rate. If the counties have low exposure values (in terms of DVMT (daily vehicle miles traveled)), the crash rate tends to magnify.

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

With respect to crash-type (i.e., harmful event type), there have been some researches. Kant (2005) focused this crash type analysis in Florida. He did a spatial analysis to find the
relationship between crash types and land-use in Florida. The study found that rear-end and right
turn crashes are more common on urban roads than on rural roads. Urban roadway environment
contributes to the number of these crash types than on rural roads, combined with the fact that
urban areas generally have more traffic. The study also found that vehicles running of the
pavements, or “run-off” crashes, were more common on rural roads than on urban roads.

Road safety rating using GIS involves the mapping and visually displaying the varying
safety conditions of road elements in a road network. This nifty process presents a good picture
to the agencies and decision makers about the potential places in a roadway network where
safety improvement can be made. The procedure involves altering the size and the color of
roadway elements in GIS. These elements might be road segments if the spatial analysis is done
on micro level. On a network as a whole, this road safety conditions are marked on cluster of
crashes, commonly known an accident “hotspots”.

Kulikowski and Bejleri (2006) used color coding and varying thicknesses of road
segments to depict varying safety conditions on a road network as shown in Figure 2-1 and
Figure 2-2.
Figure 2-1: Use of Color and Thickness in GIS (Point element) (Kulikowski and Bejleri, 2006)

Figure 2-2: Use of Color and Thickness in GIS (Line element) (Kulikowski and Bejleri, 2006)
2.4 Roadway segmentation

The GIS analysis has been done based on the line density estimation procedure. For this purpose, the roadways had to be segmented in a justified way so that the uniform characteristics of the segments are held. There are, however, several other methods that researchers have followed previously. Following are a few of those literature reviews.

Kulikowski and Bejleri (2006) used a spatial analysis technique to rate the safety condition of road elements. The signalized intersections were separated from road segments in a road network. Then the signalized intersections were ranked according to the rate of crashes per volume of traffic entering the intersection. The authors sorted them in a way that the higher this rate, the higher is the rank, and hence the worse is the intersection. With the incorporation of a normalizing technique, ranking of the road segments was also done. The normalizing parameter for the frequency of crashes on a road segment was VMT of that particular road segment.

Similar approach was also followed by the Minnesota DOT. The researchers (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. Ranking was done according to each of the following criteria:

- Total crashes for intersections; Crash density (i.e., crashes per mile) for road segments;
- Crash rate per VMT for a particular road segment; crash rate per volume of traffic entering an intersection;
• A “crash cost” was introduced, where each crash is multiplied by its monetary cost, and the total sum for all crashes is calculated. The final number was total cost in case of intersections and cost per mile in case of segments.

• Incorporating an index called “Severity Rate”, which is 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;

After ranking the segments based on these individual criteria, sum of the ranks of the criteria for each intersection and road segment were calculated. As per the definition, the higher the ranking (i.e. lowest sum) pertaining to each segment, the worse the safety condition.

Geurts et. al. (2003) did the analysis by splitting a road corridor into equal one mile segments. This method did not separate a corridor’s road segments from signalized intersections. Instead the corridor was treated as a single, homogeneous entity. The one mile segments were ranked according to the frequency of the crashes within the segments, with more weight given to severe crashes. In this study, this particular segmentation process has been followed, except the fact that all the crashes in whole state road network in Florida have been taken into account.

Federal Highway Administration (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 selection of a suitable length of the window is based on frequency. So the window having more number of crashes is more dangerous than the other. The final output of this analysis is a table and an interactive GIS map indicating high crash locations.
As a segmentation method followed in this study, the sliding window analysis proposed by FHWA considers signalized intersections and road segments as one entity.

The segmentation methods that were discussed are widely used by researchers and agencies. However, this study focuses specifically on FS related crashes. In this study manual procedure was taken for the segmentation of roadways based on frequency of FS related crashes. The results of the segments will be displayed in GIS. A cluster analysis will then be conducted.

2.5 Spatial Analysis: Kernel Density Estimation

Previous literatures provide no universally accepted definition of a hotspot for road accident. Road accident hotspot analysis has always focused on road segments or specified junctions (Thomas, 1996), while area-wide hotspot analysis and the spread of risk in the consequence of a collision is somewhat neglected.

Studies by Hauer and Persaud (1987), Miaou (1994), Shankar et al. (1995), Maher and Summersgrill (1996) and Abdel-Aty and Radwan (2000) have extensively used the negative binomial regression models in safety studies. In all these models only the reported number of accidents in the observed time period is used, therefore site location characteristics are modeled as constant within a given time period.

In another study, Flahaut et al. (2003) use the density estimation method and found that the accident hotspots show exposed concentrations. As a result the authors suggest that there is
spatial dependence between individual occurrences which may be due to one or several common causes.

Traditional typologies in road accident analysis have been used a lot throughout the literatures. For instance, delineating road users (Pietro, 2001; Oxley et al., 2005) and classifying by spatial and temporal measures and also type of accidents (Levine et al., 1995) are a few previous studies that can be good examples of the use of those typologies. A study by Pulugurtha et al. (2003) summarized results on ranking for the pedestrian hotspots.

Anderson (2009) used the kernel density estimation and K-means clustering method to profile road accident hotspots. He used similar techniques followed and described by Silverman (1986) and Fotheringham et al. (2000). Figure 2-3 shows the schematic diagram and Figure 2-4 shows the typical result of hotspot identification by clustering in GIS format. In this study, this KDE method by K-means clustering procedure has been used. In CHAPTER 5, the method will be discussed in detail.

2.6 Conclusion

The literatures reviewed for this study has shown that there is a need for extensive amount of research on the characteristics of FS crashes. Specifically in the states where FS is prominent, there are a lot of crashes which needs in-depth study in terms of crash characteristics and spatial distributions of these crashes.
FS crash characteristics have not been analyzed altogether in the previous studies. There is therefore a need for identifying the different factors that affects the FS crashes compared to clear visibility (CV) conditions. This study tries to bridge this research gap.

This research effort aimed at improving the findings of the previous studied on FS crashes. Furthermore, for the purpose of identification of FS crash clusters, the previous methods have been analyzed and the segmentation method for GIS cluster analysis has been followed based on the optimum results found from previous researches following the similar methodology. This is aimed at good use for the different agencies involved in the safety of Florida state roadways when FS prevails in the areas within the clusters.

Injury severity, as found in several literatures before, is an important issue for inclement weather related crashes. It is therefore necessary to look at the factors that contribute to severe crashes in FS conditions. The last and third part of this study addresses injury severity in detail.
Figure 2-3: How the hotspot classification method works (Anderson, 2009)
Figure 2-4: A typical hotspot: An ‘illicit’ late night Zone 1 for pedestrians (Anderson, 2009)
CHAPTER 3. DATA PREPARATION AND SAMPLING

The datasets in this study is a merger of several datasets comprising of different variables pertaining to the roadway characteristics and crash characteristics. In this study, there were three sets of data used: roadway characteristics inventory, crash database 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 secure Crash Analysis Resources (CAR) database. The layers of the GIS datasets were obtained from the FDOT website’s GIS section, which is for public use.

3.1 Crash Data

CAR database of FDOT has wealth of information in different formats about a crash event. For the purpose of the study, crash data on all state road networks of Florida was used from year 2003 to year 2007. The database comes in different options. For this study, option 3 and option 4 were used. Option 3 of CAR contains the characteristics of each crash and the variables associated with that crash (e.g., time, location, direction, drivers involved, particulars of the road condition at that time, some driver information, environmental conditions such as weather, etc.). Option 4 is a special case of option 3 where each driver involvement is an entry in the database. This option was used to extract the information about the crashes involving multiple vehicles.

Some of the variables in the CAR database are as follows:

- 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 3-1.

<table>
<thead>
<tr>
<th>Severity Level</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No injury/PDO (Property damage only)</td>
</tr>
<tr>
<td>2</td>
<td>Possible Injury</td>
</tr>
<tr>
<td>3</td>
<td>Non-incapacitating</td>
</tr>
<tr>
<td>4</td>
<td>Incapacitating (Severe)</td>
</tr>
<tr>
<td>5</td>
<td>Fatal (within 30 days)</td>
</tr>
<tr>
<td>6</td>
<td>Non-traffic fatality</td>
</tr>
</tbody>
</table>

• 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.

For the purpose of this study, all the state roads in Florida are taken into account. Crash data from years 2003 to 2007 were investigated, along with the corresponding RCI data pertaining to each crash location. These two databases have been merged by the unique roadway
identifier in each. Hence, the final database contains a number of different characteristics that can be associated with each specific crash, namely i) driver characteristics (e.g., age, etc.), ii) roadway characteristics (e.g., posted speed, divided/undivided, etc.) and iii) environmental characteristics (e.g., weather conditions, visibility conditions, etc.).

The FS crashes in particular were extracted based on several constraints to ensure that only those crashes that happened in foggy or smoky conditions are selected, thus they do not mingle with the other weather conditions. The “vision obstruction” variable has been used as the secondary filter variable, with “weather condition” being the primary one, so that FS crashes do not intertwine with other poor visibility conditions such as heavy rain or glare from sun or headlight (at night). As a result, a total of 994 FS crashes were identified for the period of 2003-2007. The number of smoke related crashes is very low for the five year period analyzed. Hence it was justifiable to merge the fog and smoke related crashes together, given the fact that the visibility obstructions they create are virtually the same. There is no information available for the level of visibility for FS in the CAR and RCI. So only FS vs. no FS information are the attributes associated with those crashes.

Furthermore, based on the spatial locations of these FS crashes, a total of 597 road segments were manually defined, which have largely uniform road characteristics. The lengths of these segments range from 2 to 5 miles. For the purpose of comparison, a dataset which contains all the “clear-visibility (CV)” crashes (120,053 crashes) that occurred on these 597 road segments was created as a control group to FS crashes. Herein, the CV condition refers to an ambient environment where no vision obstruction is prevalent.
3.2 Roadway Characteristics Inventory Database

RCI database holds a lot of information about the different roadway parameters of the state road network system in 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 functional classification of the roadway. The functional classification parameter also provides information on the level of mobility and accessibility of the road (with freeways providing highest mobility and lowest accessibility). Moreover, it has data about the land-use type, whether the roadway section falls in is a rural or urban road category. Table 3-2 provides a list of the highway functional classifications in RCI.
Table 3-2: FDOT Functional Classification for roadways

<table>
<thead>
<tr>
<th>Functional Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Principal Arterial-Interstate RURAL</td>
</tr>
<tr>
<td>2</td>
<td>Principal Arterial-Other RURAL</td>
</tr>
<tr>
<td>6</td>
<td>Minor Arterial RURAL</td>
</tr>
<tr>
<td>7</td>
<td>Major Collector RURAL</td>
</tr>
<tr>
<td>8</td>
<td>Minor Collector RURAL</td>
</tr>
<tr>
<td>9</td>
<td>Local Roads RURAL</td>
</tr>
<tr>
<td>11</td>
<td>Principal Arterial-Interstate URBAN</td>
</tr>
<tr>
<td>12</td>
<td>Arterial-Freeways and Expressways URBAN</td>
</tr>
<tr>
<td>14</td>
<td>Other Principal Arterial URBAN</td>
</tr>
<tr>
<td>16</td>
<td>Minor Arterial URBAN</td>
</tr>
<tr>
<td>17</td>
<td>Collector URBAN</td>
</tr>
<tr>
<td>19</td>
<td>Local Roads URBAN</td>
</tr>
</tbody>
</table>

Table 3-3 is an example of the RCI data. It can be noticed how Roadway 75080006 is split into several small subsections.

Table 3-3: Example of RCI Data (RCI database, 2006)

<table>
<thead>
<tr>
<th>County</th>
<th>Rdwy ID</th>
<th>Beg Mp</th>
<th>End Mp</th>
<th># of Lanes</th>
<th>ADT</th>
<th>Speed Limit</th>
<th>Section Length</th>
<th>Funclass</th>
</tr>
</thead>
<tbody>
<tr>
<td>75</td>
<td>75080006</td>
<td>0</td>
<td>0.05</td>
<td>6</td>
<td>14500</td>
<td>45</td>
<td>0.05</td>
<td>16</td>
</tr>
<tr>
<td>75</td>
<td>75080006</td>
<td>0.05</td>
<td>0.908</td>
<td>6</td>
<td>14300</td>
<td>45</td>
<td>0.858</td>
<td>16</td>
</tr>
<tr>
<td>75</td>
<td>75080006</td>
<td>0.908</td>
<td>1.288</td>
<td>6</td>
<td>16300</td>
<td>45</td>
<td>0.38</td>
<td>16</td>
</tr>
<tr>
<td>75</td>
<td>75080006</td>
<td>1.288</td>
<td>1.325</td>
<td>6</td>
<td>16300</td>
<td>45</td>
<td>0.037</td>
<td>16</td>
</tr>
<tr>
<td>75</td>
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<td>6</td>
<td>16300</td>
<td>45</td>
<td>0.1</td>
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</tr>
<tr>
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<td>75080006</td>
<td>1.425</td>
<td>1.46</td>
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<td>16300</td>
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</tr>
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<td>1.719</td>
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<td>45</td>
<td>0.259</td>
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</tr>
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<td>75</td>
<td>75080006</td>
<td>1.719</td>
<td>1.819</td>
<td>6</td>
<td>31100</td>
<td>45</td>
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<td>75</td>
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<td>1.819</td>
<td>1.918</td>
<td>6</td>
<td>31100</td>
<td>45</td>
<td>0.099</td>
<td>16</td>
</tr>
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<td>75</td>
<td>75080006</td>
<td>1.918</td>
<td>2.398</td>
<td>6</td>
<td>31100</td>
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</tr>
<tr>
<td>75</td>
<td>75080006</td>
<td>3.663</td>
<td>3.821</td>
<td>6</td>
<td>31100</td>
<td>45</td>
<td>0.158</td>
<td>16</td>
</tr>
</tbody>
</table>

The RCI data used in this study focused specifically on state roads. All the crash data were merged with the corresponding year’s RCI database, with the exception that RCI 2006 has
been used for both the crash database of 2006 and 2007, and it is assumed that no significant changes have occurred in the state road network in these two years. SAS 9.1.3 was used for the data preparation extraction and manipulation process.

3.3 GIS Data

Geographic Information System (GIS) is a graphic representation of data for the purpose of quick decision making, and also a powerful tool for spatial analysis. In its simplest form, a GIS map provides information on different data layers which relates to a specific location. GIS provides data with reference 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 of macro level in nature, such as the location or boundaries of a country or more in-depth, 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 for public use and research which are related to geographical and transportation related factors. 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 map provides the geographical boundaries of the seven districts in the state of Florida, with different color coding for visual reference.
Florida Districts Map

Figure 3-1: GIS map showing Florida district boundaries

- Florida State Road Map (see Figure 3-2): This layer provides a map of the state road network of the state of Florida. The attribute table for this layer also provides the beginning and ending milepoints of the roadway segments and their corresponding roadway ID numbers.
Figure 3-2: GIS map showing Florida State Road Network
Figure 3-3 presents a snapshot of the state road layer attribute table. The highlighted portion is the Roadway ID of the segments selected. The last two columns of the attribute table denote the beginning and ending milepoints of the road.

- County Layer Map (see Figure 3-4): This GIS map was obtained from another source online, Florida Geographic Data Library (FGDL).
The district and county map layers were mainly used in the initial study of the exploratory Macro-GIS analysis of this study. The state road map was used in the Micro-GIS analysis section. Only maps of state roads were displayed in GIS. Several other GIS maps are available from the FDOT website, such as bridge locations and median type maps; however they were not used because of lack of relation to the scope of this study.
CHAPTER 4. FOG/SMOKE RELATED CRASH CHARACTERISTICS

The main objective of this study was to explore the crashes caused by the vision obstruction due to FS (FS). The rich RCI and CAR database has a lot of information pertaining to each crash. Interesting to note though, is that it does not have information about the levels of FS (i.e., dense, light, etc.). Therefore, all the analyses in this study have been done on the basis of two levels of vision obstruction: FS present and clear visibility conditions.

There are several factors that might affect the occurrence or severity of FS related crash. As in the RCI and CAR database, most of the factors can be combined into three types: I) Driver factors (e.g., age), II) Roadway factors (e.g., median type, shoulder width, etc.) and III) Environmental factors (e.g., weather condition, lighting condition etc.). Also there is information on type of the ‘harmful event’, i.e., type of crash. Moreover, another format of the database (Option 4) has the information on the number of vehicles involve in a crash.

For a preliminary analysis point of view, FS related crashes needed a particular attention since these visibility obstruction conditions depend on the time of day and also season. Furthermore, it will be required to investigate the number of vehicles involved in a FS related crash (a pile-up crash), since reduced visibility can cause these sort of crashes. Also important are the injury severity given a FS related crash, and the collision types associated with this vision obstructions. A preliminary analysis is done which can be divided in four parts: temporal distribution, effects of influential factors, injury severity and collision types.
4.1 Temporal Distribution

Visibility obstruction due to FS prevails based on weather conditions. The conditions do not stay the same during all day long. Moreover, there is significant seasonal variation in the occurrence of FS conditions. It is therefore worthwhile to look at the temporal distribution of FS crashes. As seen from Figure 4-1, it is evident that at the early hours of dawn and subsequent hours where fog is prominent, from 5am to 8am in particular, the number of crashes due to fog is on the higher side. For the smoke though, the crashes took place in the long time span between 6am to 2pm. The monthly variations of these crashes gives another important finding (see Figure 4-2). The duration from December to February looks to have a high number of fog related crashes. It is interesting to note that in the month of May there is a sudden inflation of the smoke crash frequency trend. This can be explained by the increase of smoke related crashes in particular, as the dry season prevails at that time of the year increasing the likelihood of wildfires or the propagation of fire. To surmise then, the early hours from 5am to 8am in the months of December to February are the deadliest for fog related crashes, and the early hours from 6am until 2pm in the month on May are likely to have a lot of smoke related crashes.
Figure 4-1: Hourly distribution of FS crashes in Florida (2003 to 2007) (Fog Crashes: Top, Smoke Crashes: Bottom)
4.2 Contributing Factors

Different factors (roadway, driver and environmental factors) may have direct or indirect effect on the occurrence of FS crashes. These factors, when compared to the CV (Clear visibility) crashes, would give an idea about the significant factors that affect the FS crashes in
Figure 4-3 shows the effects of different factors on FS crashes compared to CV crashes.

Figure 4-3: Comparison of the effects of contributing factors on fog/smoke crashes and clear-visibility crashes in Florida (2003 - 2007) (Black bar: % of FS crashes; Grey bar: % of clear-visibility crashes)
Figure 4-3 (contd.): Comparison of the effects of contributing factors on fog/smoke crashes and clear-visibility crashes in Florida (2003 - 2007) (Black bar: % of FS crashes; Grey bar: % of clear-visibility crashes)
Focusing only on the important aspects of the contributing factors, there are some interesting findings from these observations. At posted speeds 55mph and higher there are a high number of FS crashes that are observed compared to those associated with CV conditions. Lighting condition adversely affects the FS crashes, as suggested from Figure 4-3 that at dawn and dark (night) with no street light the frequencies (15.9% and 31.29% of the total FS crashes respectively) are pretty high in foggy or smoky conditions, compared to CV conditions, where out of all CV crashes only 1.56% took place at dawn and 6.83% at dark (with no street light). It again confirms the findings observed from Figure 4-3 and is consistent with conclusions in Wanvik (2009). As for the age group, young and middle age drivers in particular are more prone to be involved in a crash happening in FS conditions. This might be due to the fact that at the dark hours and very early morning where FS prevails, young drivers are driving recklessly. Again, at early morning it is school time for young drivers and middle age drivers going to work, thus they are being involved in high frequency of FS crashes.

As shown in Figure 4-3, FS is very much prevalent in rural areas, confirmed by the fact that 46.68% of FS crashes happened in rural areas compared to only 9.45% of CV crashes there. Looking at the roadway characteristics, 60.26% of FS crashes occurred on roadways with raised median compared to 76.47% of CV crashes. On undivided roadways 9.31% of CV crashes occurred, compared to 27.16% of FS crashes. Accounting for the surface width (number of lanes), most of the FS crashes occurred on four lane roadways, where the statistics is 48.29% compared to 43.38% for CV conditions. But again the key finding is the effect of two-lane roadways, where a hefty 33.8% of the total FS crashes took place, where only 9.4% crashes occurred in CV conditions. Absence of sidewalk also increases the number of FS crashes, as
79.68% of FS crashes occurred in roadways without sidewalk, whereas the statistic is 50.68% for CV crashes. This could also be related to rural highways.

4.3 Injury Severity and Collision Type

To achieve a better understanding of the FS crashes in comparison with CV crashes, it is necessary to delve into more specific analyses. Injury severity of a traffic crash is a key issue. In the absence of adequate studies of the severity of weather related crashes and FS crashes in particular, it is important to look at the severity of these crashes given the crash happened in a FS condition. In the crash database, injury severity is defined with five levels, in which, “none injury”, “possible injury” and “non-incapacitating injury” can be considered as non-severe crashes, and the “incapacitating injury” and “fatal (within 30 days)” can be considered as severe crashes.

Moreover, in the event of a crash, collision type can be unique given a crash happened in FS conditions. The crash databases record a total of forty collision types based on the first harmful event. The major collision types with an acceptable size of crash observations are investigated in this study, which include rear-end, head-on, angle, left turn and sideswipe. The investigation is also done for multiple vehicle crashes, i.e., more than two vehicles involved.

To answer the questions of whether crashes in FS conditions lead to more severe injuries and which types of collisions are more associated with FS crashes, odds ratios are calculated based on the following equation,
\[ O.R.(\text{Type}) = \frac{\text{Type}(FS)}{\text{Type}(CV)} \div \frac{\text{All}(FS)}{\text{All}(CV)} \]

where,

\( O.R.(\text{Type}) \) = Odds ratio of a particular type of crash (severe crash and/or collision types) in FS conditions to that in CV conditions;

\( \text{Type}(FS) \) = Crash number of a particular type in FS conditions;

\( \text{Type}(CV) \) = Crash number of a particular type at the segments in CV conditions;

\( \text{All}(FS) \) = Total number of all types of crashes in FS conditions;

\( \text{All}(CV) \) = Total number of all types of crashes at the segments in CV conditions;

Furthermore, the interaction effects of severe crash and collision types and multiple vehicle crash and collision types are introduced as well, and the odds ratios are calculated for these interactions. The important results of the analyses are summarized in Figure 4-4.

Figure 4-4: Odds ratios of severe crash and collision types in FS conditions to CV conditions in Florida (2003 to 2007)
It is quite revealing that compared to CV conditions, FS poses a deadly threat in terms of crash severity. The elevated odds are as high as 3.24 times. Moreover, a higher probability (O.R. = 1.53) of a crash involving multiple vehicles is found to be associated with FS conditions. As indicated in previous studies (Codling, 1971; Summer et al., 1977), pile-up crashes can be a dominant type during FS conditions due to the reduced visibility. Regarding the collision types, the likelihoods of all typical collision types investigated are higher in FS conditions than that in CV conditions. Notably, the highest odds are associated with head-on crash (O.R. = 3.66). This result is very interesting as we also found a substantial increased proportion of FS crashes on undivided roadways compared to CV crashes as discussed previously (27.16% to 9.31%). The crashes between vehicles from opposite traffic at undivided roads tend to be head-on collisions.

As suggested by the interaction effects, given a head-on, rear-end or multi-vehicle crash happening in FS conditions, there is a significantly higher probability to result in severe injuries in contrast with other types of crash. It implies that the efforts to reduce injury severity of FS crashes will be more effective by focusing on the reduction of head-on, rear-end and multiple vehicle crashes. These results are preliminary to more in-depth analysis of the severity of FS crashes.
4.4 Roadway Ranking

Another important finding of this study was the ranking of the roadways according to the frequency of FS crashes. Irrespective of the segments, it was observed that there are several roadways (routes) which have a higher number of FS related crashes compared to the other routes. Even though it does not directly relate to the analysis of this study (since the study has been focused on the whole state road network), it is worth to have a look at the roadways according to the frequency of these crashes. Agencies will have a better idea of what roadways to deal with at first when a project might deal with reducing the FS related crash happenings. Table 4-1 summarizes the outputs of these ranking.
Table 4-1: Ranking of roadways according to frequency of FS crashes (2003 to 2007)

<table>
<thead>
<tr>
<th>Route ID</th>
<th>No of FS Crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td>SR 93</td>
<td>68</td>
</tr>
<tr>
<td>SR 25</td>
<td>54</td>
</tr>
<tr>
<td>SR 9</td>
<td>39</td>
</tr>
<tr>
<td>SR 60</td>
<td>39</td>
</tr>
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<td>SR 45</td>
<td>33</td>
</tr>
<tr>
<td>SR 10</td>
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<td>12</td>
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<tr>
<td>SR 700</td>
<td>11</td>
</tr>
</tbody>
</table>
CHAPTER 5. GIS CLUSTER ANALYSIS

GIS analysis focused primarily on the general trends of the FS crash distributions on the state road network of Florida. The analysis was state road network level because it was done focusing on the distribution of crashes among the whole state road network of the state of Florida, running statewide along the 67 counties. The main aim of the analysis was to be able to visually identify (using color-coding of clusters in GIS) some hotspots on the road network within the state boundary that experienced high trends of FS related crashes for the years 2003 to 2007. Hence the dataset that was used for the purpose of the analysis consists of all the FS related crashes in these years.

The purpose was to make it possible to visually identify certain spots on the roadways which have experienced a high trend of FS crashes. All the observed FS crashes were used to find these spots. The identification of the areas of those spots would help in pinpointing locations where improvements are necessary in terms of roadway planning and design in order to have better safety conditions. Looking at a planning point of view, it deems very important to blend the safety at an early stage of planning of road network when certain weather conditions as FS might prevail. This particular type of analysis is supposed to yield results that will be very useful at an early stage of new roadway planning. For the existing roadways, the decision making would be benefitted greatly by looking at certain areas where improvements will be necessary, so that a financial outline for safety improvement can be done.
For the GIS analysis tool, ArcMap 9.2 has been used which displays maps of county boundaries, roadway segments and crash locations on the whole network. By using the several graphical tools provided by ArcMap, it becomes convenient to mark spots or sections on the roadway by varying colors along roadway segments to denote the safety condition of a roadway. The less safe a segment is, the darker in color that particular segment is drawn in GIS. Figure 5-1 is an ArcMap 9.2 snapshot presenting an example the crash locations and attributes of a crash in the GIS visual.

Figure 5-1: Example of crash Location and crash attributes in GIS
Figure 5-2 shows the different color coding for the locations of crashes in a GIS visual environment. As observed, the darker the color gets is the more frequency of the crash in that particular roadway segment. In order to achieve this objective, crash data and roadway data had to be merged and prepared properly for analysis in order to display the varying safety conditions on a map. Several roadway section segmentation procedures were examined through the exploration of previous literature and scientific intuition until one consistent method to segment the roadway sections was achieved. The methodology section discusses the steps followed in order to achieve the proper segmentation procedure.

Figure 5-2: Example of road segmentation according to crash frequency in GIS
5.1 Methodology

The following is a breakdown of the methodology followed in order to identify a proper way to rank and find roadway segments according to their safety performance with regards to their crash frequencies.

5.1.1 Selection of proper roadway segment length

The complete crash database (that is, the merger of CAR and RCI) was exhausted for the identification of every crash that occurred due to the fog or smoke related visibility obstruction. Initially for the purpose of GIS analysis, it was found to be convenient that the number of road segments to be as low as possible. But the segments were not of uniform characteristics, that is, within a roadway segment, the roadway characteristics varied. For example, in a five mile long segment, roadway alignment changed from straight to curve or vice versa. Furthermore, sometimes an intersection also came into the segment where most of the length of that segment consists of mid-block roadway. Hence, it was necessary to define uniform segments and therefore was the need of a suitable segment length.

The sliding window analysis is a method used to identify roadway segments with a high crash frequency. The analysis segment is not fixed with respect to location; rather it slides along the route in an incremental fashion. Segment length (the window size) and the increment length can be defined by the user for analysis. The frequency of FS crashes is counted within the window. The end result is this case is a suitable length where the number of FS crashes is maximum keeping the roadway segment of uniform characteristics. The window size used in this
analysis was from 0.5mile to 2.5 mile window. This is basically a non-GIS approach, which is imposed on the GIS map layer later once a suitable segment length is found used to conduct the GIS analysis. Since all the state roadways were chosen for the sliding window analysis, this selection process was done manually by visual inspection with several trials, with 0.5 mile increment in each trial. It was found that a 1mile segment length is optimum which serves both the purposes of uniform segment and number of FS related crashes to the maximum. A GIS map was then plotted with the segments being color-coded according to the frequency of FS related crashes, which is shown in Figure 5-3.
Figure 5-3: Map showing the uniform roadway segments by FS (fog and smoke) crashes on all state roads in Florida
5.1.2 Hotspot Identification: Kernel Density Estimation

ArcGIS 9.2 by ESRI Inc. was used for the GIS mapping and the cluster generation purpose. The Spatial Analyst tool was used to serve the purpose of clustering the crashes and identifying hotspots. There are a number of spatial analysis tools available to perform the cluster analysis and to do the hotspot identification for events in GIS. The most promising of these tools is the Kernel Density Estimation (Chainey and Ratcliffe, 2005). The Kernel Density Estimation (KDE) is a technique which defines the spread of risk as an area around a defined cluster in which there is an increased likelihood of an accident to occur on the basis of spatial dependency. This density method also incorporates the use of an arbitrary spatial unit of analysis (in this study the uniform segment of roadways).

Kernel density estimation method involves placing a symmetrical surface over each point of event and then evaluating the distance from the point to a reference location based on a certain mathematical function and then summing up the values for all the surfaces for that reference location in consideration. The same procedure is repeated for successive points. This procedure therefore allows the user to place a kernel over each observation, and summing these individual kernels gives the result of a density estimate for the distribution of accident points (Fotheringham et al., 2000).

\[
   f(x, y) = \frac{1}{nh^2} \sum_{i=1}^{n} K\left(\frac{d_i}{h}\right)
\]

where \( f(x, y) \) is the density estimate at the location \((x, y)\); \( n \) is the number of observations, \( h \) is the bandwidth or kernel size, \( K \) is the kernel function, and \( d_i \) is the distance between the location
\((x, y)\) and the location of the \(i\)-th observation. Here, main objective of placing these humps or kernels over the events or crash points is to create a smooth, continuous surface. Around each point at which the indicator is observed, a circular area (the kernel) of defined bandwidth is created, the bandwidth is defined by the user. This takes the value of the particular indicator at that particular point spread into it according to some appropriate mathematical function. The next process is that it sums up all of these values at all places, including those at which no incidences of the indicator variable were recorded (and creates it as a base layer in GIS), gives a nice smooth surface of density estimates.

Density can be measured by two methods; simple and kernel. The simple method divides the entire study area to a predetermined number of cells (the number is given by the user) and draws a circular neighborhood around each cell in order to calculate the individual cell density values, which is the ratio of the number of features that fall within the search area to the size of the area. A selection of the radius of the circular neighborhood also affects the resulting density map. If the radius is increased there is a possibility that the circular neighborhood would include more feature points which results in a smoother density surface (Silverman, 1986). The kernel method also divides the entire study area into predetermined number of cells. Instead of considering a circular neighborhood around each cell (the simple method), the kernel method take into account the event points and draws a circular neighborhood around each feature point (the crash) and then a mathematical equation is applied that goes from 1 at the position of the feature point to 0 at the neighborhood boundary (see Figure 5-4).
5.1.3 Spatial Analysis

The ArcGIS Spatial Analyst tool provides the features needed to do the cluster analysis by density estimation methods. The kernel density estimation process needs that the data-points (i.e., the features to be clustered, which is the segments of fog and smoke crash created in a shape-file) to be spatially joint. The data points are shown in Figure 5-5. For the points to be joined spatially, fishnet of square size cells was created using the “create fishnet” tool. The cell size (cell width and height) was selected in such a way that the area under consideration is divided in a finite number of cells that can be calculated without expense. Since the fog and smoke crashes are sparsely populated, the fishnet cells were created such that the number of cells on each side does not exceed 100.

The kernel density function was applied to calculate the boundaries of each cluster, with more number of points (crashes) within the center of each cluster.
Figure 5-5: Fog /smoke crashes in Florida (2003 to 2007)
Figure 5-6: Cluster Outputs of Fog /smoke crashes in Florida (2003 to 2007)
5.2 GIS Analysis Results

Figure 5-6 shows the clustering output from the GIS analysis and Table 5-1 details the locations of FS crash hotspots. The KDE technique presents ten distinct FS crash hotspot areas on Florida road network. The colors represent the density of crashes per square mile area. From the figure, it is notable that the ten clusters are associated with crash densities 0.048 to 0.074 crashes per square mile. In other words, it can be said that in the blue region of the map, considering the spatial uniformity, an FS crash occur at each 13.51 to 20.83 square-mile of state road network.

<table>
<thead>
<tr>
<th>Cluster No.</th>
<th>Area covering the cluster</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Extends from center to north-east corner of Polk and a very small portion in the north-west corner of Osceola county</td>
</tr>
<tr>
<td>2</td>
<td>Heart of Duval county</td>
</tr>
<tr>
<td>3</td>
<td>Almost the whole of Pinellas and some south-western part of Hillsborough</td>
</tr>
<tr>
<td>4</td>
<td>Connects from center of Hillsborough to center of Pasco</td>
</tr>
<tr>
<td>5</td>
<td>Heart of Orange county</td>
</tr>
<tr>
<td>6</td>
<td>Eastern part of Orange and the adjacent portion of Brevard</td>
</tr>
<tr>
<td>7</td>
<td>Center region of Leon</td>
</tr>
<tr>
<td>8</td>
<td>Extends from most of the northern part of Lee to the southern portion of Charlotte</td>
</tr>
<tr>
<td>9</td>
<td>Center region of Alachua</td>
</tr>
<tr>
<td>10</td>
<td>North eastern corner of Volusia county</td>
</tr>
</tbody>
</table>
CHAPTER 6. INJURY SEVERITY ANALYSIS

From CHAPTER 4, it can be observed that the odds of having a severe crash given a crash happens in FS conditions to that of clear visibility conditions is 3.24. Hence, a closer look is needed on the injury severity of FS crashes. As stated before, even though very few studies have focused particularly on FS, a handful of those stated the severity to be on the higher scale when crashes happen in these visibility conditions. So, a model is developed and the contributing factors are presented for injury severity of FS crashes.

6.1 Methodology

All the FS crashes in Florida state roads from 2003 to 2007 were extracted. The injury severity has five levels in CAR database. At first, attempt was made to model the injury severity keeping all the five levels, and an ordered logit model was developed, with severity as a target variable having 5 levels. The variables used in the model development are presented in Table 6-1, with the results in Table 6-2.
Table 6-1: Variables used in the initial crash severity model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td>age_gr</td>
<td>Age group</td>
<td>if age&lt;=19 then age_gr =1; else if 20&lt;=age&lt;=24 then age_gr =2; else if 25&lt;=age&lt;=64 then age_gr =3; else if 65&lt;=age&lt;=79 then age_gr =4; else if 80&lt;=age then age_gr =5;</td>
</tr>
<tr>
<td>div_undiv</td>
<td>Divided/Undivided</td>
<td>Paved=1, Raised =2, Undivided =3</td>
</tr>
<tr>
<td>funclass</td>
<td>Road Functional Class</td>
<td>1-Principal Arterial, 2- Minor Arterial, 3- Collector Roads</td>
</tr>
<tr>
<td>light_cond</td>
<td>Lighting Condition</td>
<td>1=Daylight, 2= Dusk, 3=Dawn, 4=Dark (street light), 5=Dark (no street light), 88=Unknown</td>
</tr>
<tr>
<td>shld_typ</td>
<td>Shoulder Type</td>
<td>1-Paved, 2-Paved warning, 3-Curb and gutter, 4-All Other</td>
</tr>
<tr>
<td>siteloc</td>
<td>Site Location</td>
<td>1-Not at x-section/RR xing, Bridge, 2-At intersection, 3-All other locations</td>
</tr>
<tr>
<td>skid_num</td>
<td>Skid test result</td>
<td>1- skid&lt;=30, 2- skid&gt;30</td>
</tr>
<tr>
<td>trafficway</td>
<td>Trafficway character</td>
<td>1-Straight n level, 2-Straight n UG/DG, 3-Curve n Level, 4- Curve n UG/DG</td>
</tr>
<tr>
<td>ur_rur</td>
<td>Urban/Suburb/Rural</td>
<td>1-Rural, 2-Urban</td>
</tr>
<tr>
<td>vehi_type</td>
<td>Vehicle Type</td>
<td>1-Automobile, 2-Van, 3-Light truck, 4- Other types</td>
</tr>
<tr>
<td>surface_cond</td>
<td>Surface Condition</td>
<td>As the crash report</td>
</tr>
<tr>
<td>NOLANES</td>
<td>No of lanes</td>
<td>1-Two lane; 2-Four lane, 3-Six lane, 4- All other</td>
</tr>
<tr>
<td>sdwlk</td>
<td>Sidewalk</td>
<td>0-No Sidewalk, 1-Sidewalk</td>
</tr>
<tr>
<td>ADT</td>
<td>Section ADT= log(sectadt_num)</td>
<td>Continuous variable</td>
</tr>
<tr>
<td>AVGKFACT_num</td>
<td>K factor</td>
<td>Continuous variable</td>
</tr>
<tr>
<td>AVGTFACT_num</td>
<td>T factor</td>
<td>Continuous variable</td>
</tr>
<tr>
<td>MAXSPEED_num</td>
<td>Posted Speed</td>
<td>Continuous variable</td>
</tr>
<tr>
<td>SLDWIDTH_num</td>
<td>Shoulder Width</td>
<td>Continuous variable</td>
</tr>
<tr>
<td>severity</td>
<td>severity of crash</td>
<td>1-No Injury/PDO, 2-Possible, 3-Non-incapacitating, 4-Incapacitating, 5-Fatal (within 30 days)</td>
</tr>
</tbody>
</table>
It is seen that the results are not good enough, since only one factor came significant, which is the Urban/Rural area type. According to this, severity of a crash happen in FS condition is more in rural area compared to urban area.

From the preliminary analysis done in CHAPTER 4, it is evident that more than one factor affects the injury severity of FS crashes. Later, a multilevel ordered logistic model has been developed, which is a random effect model. The results have been much improved, and the results of that model are presented in this chapter.
6.1.1 Model Description

According to the CAR database, the injury severity levels of the 994 FS crashes are defined as five ordered categories:

Category 1 (C1): no injury/property damage only (PDO),
Category 2 (C2): possible injury,
Category 3 (C3): non-incapacitating injury,
Category 4 (C4): incapacitating injury, and
Category 5 (C5): traffic fatality.

For this ordinal outcome of severity, a multilevel ordered logistic model is specified to examine the effects of various risk factors. Suppose that \( y_{ij} \) is the severity level of \( i^{th} \) crashes which occurred at \( j^{th} \) segments (\( i = 1, \ldots, 994; j = 1, \ldots, 597 \)). In an ordinal response model, a series of latent thresholds are generally formulated. Specifically, the real line is divided into five intervals by four thresholds \( \gamma_{kj}, k = 1, 2, 3, 4 \), corresponding to the five ordered categories \( (C_1 - 5) \). It is noted that differing from ordinary ordered logistic model, the multilevel model accounts for the cross-segment heterogeneities by specifying a set of variable thresholds for individual segments. The thresholds define the boundary between the intervals corresponding to observed severity outcomes. The latent response variable is denoted by \( y^*_{ij} \) and the observed categorical variable \( y_{ij} \) is related to \( y^*_{ij} \) by the “threshold model” defined as,
\[ y_{ij} = \begin{cases} 
1 & \text{if } -\infty < y_{ij}^* \leq \gamma_{1j} \\
k & \text{if } \gamma_{(k-1)j} < y_{ij}^* \leq \gamma_{kj}, \ k = 2, 3, 4 \\
5 & \text{if } \gamma_{4j} < y_{ij}^* < +\infty 
\end{cases} \]

The ordinal models can be written as

\[ y_{ij}^* = \theta_{ij} + \varepsilon_{ij}, \quad \text{and} \quad \theta_{ij} = \sum_{p=1}^{P} \beta_{p} x_{p ij} \]

in which \( x_{p ij} \) is the crash-level covariates and \( \varepsilon_{ij} \) is the disturbance term, which is assumed a logistic distribution with \( F \) as the cumulative density function. Thus, the cumulative response probabilities for the three categories of the ordinal outcome could be denoted as,

\[ P_{ij(k)} = \Pr(y_{ij} \leq k) = F(\gamma_{kj} - \theta_{ij}) = \frac{\exp(\gamma_{kj} - \theta_{ij})}{1 + \exp(\gamma_{kj} - \theta_{ij})}, \quad k = 1, 2, 3, 4. \]

The idea of cumulative probabilities leads naturally to the cumulative logistic model

\[ \text{Logit}(P_{ij(k)}) = \log \left( \frac{P_{ij(k)}}{1 - P_{ij(k)}} \right) = \log \left[ \frac{\Pr(y_{ij} \leq k)}{\Pr(y_{ij} > k)} \right] = \gamma_{kj} - \theta_{ij}, \quad k = 1, 2, 3, 4. \]

In the segment level, \( \gamma_{kj} \) could be specified as random effects,
\[ \gamma_{kj} = \gamma_k + \sum_{q=1}^{Q} \alpha_q z_{qj} + b_j, \quad k = 1, 2, 3, 4. \]

where the intercept \( \gamma_k \) represents a constant component for thresholds for all segments. Given different segment-level covariates \( z_{qj} \), the thresholds vary between segments. Furthermore, to accommodate for the cross-segment heterogeneities, a random effect component \( b_j \) is formulated, which is normally distributed with mean of zero and precision of \( \tau \sim \text{Gamma}(0.01, 0.01) \). As for the parameter estimation \( (\alpha, \beta) \), clearly a positive coefficient indicates an increase of probability of being of higher severity level given an increased value of the corresponding covariate.

Table 6-3 shows the variables that have been used to develop the model.
Table 6-3: Variables used in the final multilevel ordered logistic model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>mean</th>
<th>stdev</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Response variable</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crash severity levels</td>
<td>C1: no injury, property damage only (PDO)</td>
<td>2.22</td>
<td>1.22</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>C2: possible injury</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C3: non-incapacitating injury</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C4: incapacitating injury</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C5: traffic fatality</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Covariates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural area</td>
<td>If road at rural area = 1, otherwise = 0</td>
<td>0.47</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Principle arterial</td>
<td>If road is principle arterial = 1, otherwise = 0</td>
<td>0.47</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>No. of lanes</td>
<td>Continuous variable: number of lanes</td>
<td>3.67</td>
<td>1.46</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>ADT</td>
<td>Continuous variable: average daily traffic (k)</td>
<td>28.1</td>
<td>27.2</td>
<td>0.6</td>
<td>197</td>
</tr>
<tr>
<td>Speed limit</td>
<td>Maximum speed limit on the road segment</td>
<td>55.17</td>
<td>10.12</td>
<td>30</td>
<td>70</td>
</tr>
<tr>
<td>Shoulder width</td>
<td>Continuous variable in feet</td>
<td>5.72</td>
<td>3.00</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Truck factor</td>
<td>Average truck factor</td>
<td>13.12</td>
<td>8.63</td>
<td>0</td>
<td>47.3</td>
</tr>
<tr>
<td>No division</td>
<td>If road undivided = 1, otherwise = 0</td>
<td>0.27</td>
<td>0.44</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Skid</td>
<td>If skid coeff. &lt;= 30, then = 1, otherwise = 0</td>
<td>0.06</td>
<td>0.23</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Curve</td>
<td>If crash at curve = 1, otherwise = 0</td>
<td>0.08</td>
<td>0.26</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Intersection</td>
<td>If crash at intersection = 1, otherwise = 0</td>
<td>0.36</td>
<td>0.48</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Dusk or dawn</td>
<td>If crash at dusk or dawn = 1, otherwise = 0</td>
<td>0.18</td>
<td>0.39</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Dark with street light</td>
<td>If crash at night with street light =1,otherwise=0</td>
<td>0.18</td>
<td>0.38</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Dark w/o street light</td>
<td>If crash at night w/o street light =1,otherwise=0</td>
<td>0.31</td>
<td>0.46</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Vehicle type</td>
<td>If vehicle type is automobile = 0, otherwise =1</td>
<td>0.53</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Young driver</td>
<td>If driver age &lt; 25 then = 1, otherwise = 0</td>
<td>0.33</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Old driver</td>
<td>If driver age &gt; 65 then = 1, otherwise = 0</td>
<td>0.07</td>
<td>0.25</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Alcohol use</td>
<td>If crash with alcohol use = 1, otherwise = 0</td>
<td>0.17</td>
<td>0.38</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
6.2 Model Estimation

Obtained from the CAR and RCI databases, eighteen covariates were used to explain the variations of severity of FS crashes. These variables are listed in Table 6-3, together with their descriptive statistics. The model was estimated via MCMC technique in Bayesian framework, which was implemented using WinBUGS software (Spiegelhalter et al., 2003).

In the model estimation, a backward procedure was employed for variable selection. Specifically, beginning with all the variables considered, each variable was tested for the statistical significance and the insignificant ones were eliminated. Table 6-4 shows the final results of parameter estimation in the model, in which only the statistically significant covariates are retained. The precision parameter $\tau$ is significant judged by the Bayesian Credible Interval (10.06, 145.9). This justifies the specification of the cross-segment heterogeneities and in other words, the within-segment covariance exists among crashes that occurred on a same road segment.
<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>sd</th>
<th>10%</th>
<th>median</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gamma1</td>
<td>-1.169</td>
<td>0.729</td>
<td>-2.116</td>
<td>-1.185</td>
<td>-0.273</td>
</tr>
<tr>
<td>Gamma2</td>
<td>-0.302</td>
<td>0.727</td>
<td>-1.243</td>
<td>-0.317</td>
<td>0.592</td>
</tr>
<tr>
<td>Gamma3</td>
<td>0.944</td>
<td>0.727</td>
<td>0.009</td>
<td>0.928</td>
<td>1.837</td>
</tr>
<tr>
<td>Gamma4</td>
<td>2.267</td>
<td>0.734</td>
<td>1.326</td>
<td>2.252</td>
<td>3.170</td>
</tr>
<tr>
<td>Ln(ADT)</td>
<td>-0.080</td>
<td>0.069</td>
<td>-0.170</td>
<td>-0.083</td>
<td>-0.005</td>
</tr>
<tr>
<td>Rural area</td>
<td>0.438</td>
<td>0.153</td>
<td>0.243</td>
<td>0.439</td>
<td>0.635</td>
</tr>
<tr>
<td>Dark w/o street light</td>
<td>0.216</td>
<td>0.135</td>
<td>0.039</td>
<td>0.218</td>
<td>0.389</td>
</tr>
<tr>
<td>Truck factor</td>
<td>-0.011</td>
<td>0.008</td>
<td>-0.021</td>
<td>-0.011</td>
<td>0.000</td>
</tr>
<tr>
<td>Young driver</td>
<td>-0.225</td>
<td>0.127</td>
<td>-0.390</td>
<td>-0.223</td>
<td>-0.064</td>
</tr>
<tr>
<td>Tau</td>
<td>65.82</td>
<td>63.15</td>
<td>10.06</td>
<td>40.83</td>
<td>145.9</td>
</tr>
<tr>
<td>Deviance</td>
<td>2824</td>
<td>13.79</td>
<td>2806</td>
<td>2827</td>
<td>2837</td>
</tr>
<tr>
<td>DIC</td>
<td>2844.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
6.3 Results

The significant covariates include Ln(ADT), rural area, Dark without street light, Truck factor, and Young driver. As shown in Table 6-4, it was found that the increase in traffic volume, reflected by the ADT, has a positive effect in reducing injury severity level of FS crashes (-0.080). This result may be explained by the generally reduced speed associated with heavy traffic roads. As proven by Edwards et al. (1998), speeding is a major contributing factor leading to severe crashes during pile-ups in foggy conditions. This result is further confirmed by the positive parameters for rural area variable (0.43). Specifically, results show that severe crashes are much more likely to occur in rural areas compared to suburban and urban areas.

On the roads of rural areas, drivers are used to driving at a high speed with low level of alertness due to the low traffic volume. Traveling at a high speed, especially in reduced visibility conditions due to fog or smoke, has been widely proven to be associated with reduced capability of the driver to crash avoidance. Likewise, this problem becomes more serious at night without street light as shown in the parameter estimation (0.216). This is reasonable since drivers may have more reaction time and better perception ability in good street lighting environment (Huang et al., 2008). Wanvik (2009) showed the risk of crash increases by fog in unlit roads by 12%. Combined with the result of this study, therefore, it may be concluded that the installation of street lights at FS prevailing locations will be helpful in reducing both FS crash risk as well as the injury severity. Furthermore, it is surprising to find a negative effect for the Truck factor (-0.011) although the effect is very close to zero. The reason for less severe crashes while trucks are present might be associated with the fact that while trucks are present in the road in FS
conditions, they tend to slow down, which makes the following traffic to slow down as well. This contributes to a less severe crash. Also another inference can be made that trucks normally drive on divided roads, and this study showed that severity is more in rural areas, where roads are typically undivided. So presence of trucks in divided roads also might lessen severity of a crash in FS conditions.

Finally, the result shows that FS crashes involving young drivers tend to be less severe (-0.225). This may be presumably due to the better vision and reaction abilities, and above all stronger physical condition, of young drivers to detect and avoid severe injury in a crash under reduced visibility conditions. Nevertheless, it is worth noting that young drivers were found to be associated with a higher crash risk in FS conditions in contrast with CV conditions as shown in CHAPTER 4.
CHAPTER 7. CONCLUSIONS

Florida is amongst the top states in United States for traffic safety concerns when it comes to crashes due to reduced visibility from FS (fog/smoke). Using the five year crash data record (2003 to 2007), this study presents a comprehensive effort in identifying the characteristics of FS related crashes, and the comparison of that with the clear weather condition crashes. It also looked in-detail at the injury severity of the FS related crashes and the factors associated with this.

The spatial analysis done in this thesis also identified ten distinct clusters or ‘hotspots’ those are prone to FS related crashes. The following summarizes the findings of this thesis:

1. **Comparison of FS and non-FS crashes:** From this analysis, it was found that compared to clear visibility condition crashes, FS crashes tend to result in more injury severity and involve more vehicles. Head-on and rear-end crashes are more prominent crash types in FS conditions in terms of crash risk and severity of crashes. In terms of temporal distributions, morning hours in the months of December to February are prone to have crashes due to fog, whereas morning hours until midday in the month of May are prone to have smoke related crashes.

2. **GIS cluster analysis:** Ten distinct clusters have been found across the whole state of Florida, where FS related crashes are prevalent. It is found that there is no clear pattern observed in the clusters where these types of crashes occur. In terms of the percentage of FS crashes, rural and urban areas share very much equal amount of crashes for FS crashes in terms of frequency.
3. **Injury Severity analysis**: Looking at the severe crashes in detail, it was found that the head-on and rear-end crash types are the two most prevalent crash types in FS conditions. And not surprisingly, these severe crashes mainly occurred at higher speeds. Also they mostly took place on undivided roads, roadways without any sidewalk and two-lane rural roads.

Thus the reduction of speed limits and the installation of road medians are expected to be useful to improve safety at FS prone locations. Another conclusive suggestion is to improve road lighting at the identified hotspots as FS crashes tend to occur more likely at night without street light, which also leads to more severe injury.

7.1 **Engineering implementations**

This study was a part of the Florida Department of Transportation funded research on developing a system for detection of FS on roadways and automation of the driver information system. The system included installation of sensors coupled with transmitter and GPS in locations where FS prevails. The sensors will detect the FS prevalence, transmits to a base station through intermediate radios, and sends data and pictures to TMC (Traffic Management Center). VMS (variable message sign) and DMS (dynamic message sign) will display different FS conditions and associated speed regulations to driver ahead of entering the FS area. Several important findings from this study can be useful for the purpose of the project.
This study found that most of the FS crashes took place on undivided roads in rural areas in Florida. Also, they took place at dark lighting conditions. From the severity analysis, it was also found that severity of a crash in FS conditions is more in rural areas. These findings lead to the fact that the system has to be installed in rural areas. In rural areas though, foggy or smoky conditions can be anywhere in a long stretch of a road network, as seen from the clusters. Hence, it implies that a mobile system is needed which can be transferred anywhere in the FS locations. The mobile system will include the sensor, DMS and VMS.

Another important finding is that as FS crashes are mostly in rural areas, powering the mobile system will have to be through solar and battery. Specially, since FS prevails at dark hours, battery power storage as back-up is needed for the system’s operation at those hours.

### 7.2 Recommendations for Future Research

One of the main objectives of the thesis were accomplished by providing the roadway locations were high trends of FS related severe crashes and displaying them using the Geographic Information System (GIS) tool.

In the future, the methodology used in the GIS cluster analysis could be expanded to include all types of roads. It can also be done on county basis. As a starter, the counties which show high number of clusters and larger areas of clusters can be analyzed in detail, so that within the county boundary, some more distinctive clusters might be identified.
In the preliminary analysis, type of harmful event (i.e., type of crash) was an important finding, and it was showed that head-on and rear-end collisions are prevalent in FS conditions. A detailed collision type analysis can be done on these FS crashes, so that locations associated with these types of crashes can be found, since most of the collision types do not happen in all the portions of the roadway. Agencies would greatly benefit from this analysis.

It is also possible to find the specific factors that contribute to the FS crashes by doing the analysis on county or district basis. Furthermore, spatial correlation analysis can be done for these crashes based on the roadway-level GIS analysis.
LIST OF REFERENCES


39. Roadway Characteristic Inventory (FDOT).


