NATIONAL CENTER FOR TRANSPORTATION SYSTEMS PRODUCTIVITY AND MANAGEMENT

A Comprehensive Investigation of Visibility Problems on Highways: Developing Real Time Monitoring and Prediction System for Reduced Visibility and Understanding Traffic and Human Factors Implications

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Developing Real Time Monitoring and Prediction System for Reduced Visibility and Understanding Traffic and Human Factors Implications

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EXECUTIVE SUMMARY

Visibility is one of the most important impacts weather can have on road systems; weather-related visibility reduction is most often due to fog. Florida is among the top-rated states in the United States with regards to traffic safety problems resulting from adverse visibility conditions caused by fog or smoke (F/S). The reduced visibility also has a negative impact on traffic flow.

One of the goals of the research project is develop a low cost deployable fog prediction system. An array of low-cost environmental sensors, arranged at varying levels above the ground surface, could effectively detect the onset of fog and meet or exceed existing performance of traditional and much more expensive technologies. The fog detection algorithm and the updated algorithm is efficient to detect the fog days but it is still likely to make false positive alarms when the day is actually clear.

Both weather data and traffic data are collected in this research project to explore traffic flow pattern under reduced visibility conditions. The mean headway and headway variation are significantly higher while the mean speed and volume are significantly lower in fog cases compared to clear cases. There isn't significant difference in speed variation based on the comparison of a single case.

Overall, the impact of reduced visibility on passenger cars is more significant compared to trucks. The mean headway, variation of headway and speed are significantly higher while the mean speed

is significantly lower in the fog case compared to the clear case for the cars. In comparison, there isn't significant difference in the standard deviation of speed for the trucks and the difference of mean speed, headway and standard deviation of headway between fog cases and clear cases for passenger cars are all larger than trucks.

The differences of mean of headway, speed and standard deviation of headway are all significant under different visibility levels. The mean of headway increases when the visibility drops. The mean speed decreases when the visibility drops. The mean of standard deviation of headway increases when the visibility drops.

The effect of reduced visibility on both directions is similar. The effects of reduced visibility on different lanes are different. For the outer lane, the mean speeds under good visibility and moderate visibility levels are both significantly higher than mean speed under low visibility level. The difference of mean speed under good and moderate visibility levels is not significant. The mean headway under good visibility level is significantly higher than both mean headways under low and moderate visibility levels. The difference of mean headway under low and moderate visibility levels is not significant. For the middle lane, the mean speeds increases as the visibility increases. The mean headway increases as the visibility drops and the mean headway under good visibility level are significantly higher than both mean headways under low and moderate visibility levels. The difference of mean headway under low and moderate visibility levels is not significant. For the inner lane, the mean speeds under good and moderate visibility levels are both significantly higher than the mean speed under low visibility level. The difference of mean speed under good and moderate visibility levels is not significant. The mean headway decreases as the visibility increases.

The crash risks analysis is also conducted. “TTC1” and “TTC2” are selected to describe the crash risks, which represent the “time to collision” value at two different situations. Both TTC1 and TTC2 for all the vehicles decrease significantly as the visibility is reduced and the standard deviation of headway increases significantly as the visibility is reduced from good to low visibility. This means that the crash risk would be higher during reduced visibility and the crash risk keeps increasing when visibility drops.

The TTC would decrease significantly as the visibility and mean of headway decrease while it would decrease significantly as the mean speed and volume increase, from the modeling results. Meanwhile, the decrease of mean headway would increase the crash risk because the TTC will decrease significantly. The effect of mean headway on TTC is more significant compared to mean speed.

Several areas were identified with frequent fog and/or smoke crashes that occurred during low-visibility conditions on Florida state highways using Kernel Density Estimation (KDE) in macroscopic analysis. Subsequently, we zoomed in the macro-level hotspots and identified specific hotspots for the target crashes for one-mile segments, ramps and intersections. Both maps and tables are provided to easily locate these hotspots for fog and/or smoke crashes. It is recommended to pay attention to the identified hotspots and offer appropriate countermeasures to minimize the number of traffic crashes under low-visibility conditions due to fog or smoke.

The results of matched control case logistic regression model indicated that higher mean of headway, variance of speed and headway and higher occupancy were related to the increase of the likelihood of reduced visibility while lower mean speed was related to the increase of the likelihood of reduced visibility.

The driving simulator experiment is conducted through the use of the NADS Minisim. A six variables and levels included experimental design was created. The goal of the driving simulator experiment is to analyze the driver behavior under low visibility conditions and test the effects of fog warning systems on drivers. Currently, twenty-four (24) participants has been tested. The preliminary analysis shows a strange relationship between average speeds and visibility conditions.

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1. INTRODUCTION

Adverse weather events related to fog has become a serious problem for the safety and operation of Florida highways. Florida was the third after California and Texas, with 299 fatal crashes occurring due to fog or smoke (F/S) between 2002 and 2007. The most recent example for visibility related crashes in Florida was the pileup involving a dozen cars and six tractor-trailers on I-75 near Gainesville in January, 2012. At least 10 people were killed, and another 18 were taken to a nearby hospital. The poor visibility also made it extremely difficult for rescuers to find victims, and the segment was shut down for an extended time. The problem derives from the inadequacy of traffic control techniques to provide guidance for drivers and the unpredictability of locations and times of reduced visibility on highways.

Therefore, the major objectives of this research are as follows:

-To develop and evaluate the fog detection algorithm and the corresponding software by using an array of low-cost environmental sensors

-To analyze the impact of reduced visibility on traffic flow characteristics and crash risks based on real-time traffic data and corresponding weather information

-To identify area/locations with frequent fog and/or smoke crashes that occurred during low-visibility conditions on Florida state highways

-To analyze the viability of using airport weather data in reduced visibility detection

-To analyze the driver behavior under reduced visibility condition, and the effects of Dynamic Message Sign (DMS) & beacons based on driving simulator experiment.

This report is divided into nine chapters. A review of currently visibility systems in the US and around the world is provided in Chapter 2. The development and evaluation of fog detection algorithm are introduced in Chapter 3. Data collection and preparation are presented in Chapter 4. Chapter 5 mainly analyzes the effect of weather parameters on reduced visibility. A comprehensive study of fog or smoke related crashes in Florida using four-year crash data based on screening method is presented in Chapters 6. Chapter 7 provides further explores the relationship between reduced visibility and traffic parameters based on airport weather information. The driving simulator experiment information is provided in Chapter 8. Finally, conclusions and further research are provided in Chapter 9.

2. REVIEW OF STATE-OF-THE-ART

Recently, there have been several reports on comprehensive low visibility/fog detection systems in the US and other countries. Abdel-Aty et al. (2010) designed a portable visibility warning and detection system to identify the reduction in visibility and convey specific warning messages to drivers. In addition, a comprehensive study of fog/smoke crashes in Florida is provided in this study. Abdel-Aty et al. (2012a) provides an overview of the current systems in the US and around the world. Limitations of these systems were pointed out in this report. In 2014, Abdel-Aty et al. updated the new systems that were employed and reviewed previous research about the impacts of reduced visibility on traffic flow and driver behavior. This report also offers an introduction about the fog-related meteorological theories and the fog detection algorithms. The distribution of fog, factors for fog duration, and effects of reduced visibility on traffic flow characteristics were explored in the study.

2.1 Visibility Systems in the US

A typical visibility system includes four components (Figure 2-1). The visibility systems are highly dependent on the weather and traffic information. After gathering the data, decisions will be made at the Central Management Center to inform drivers about the current visibility conditions and maintain road safety.

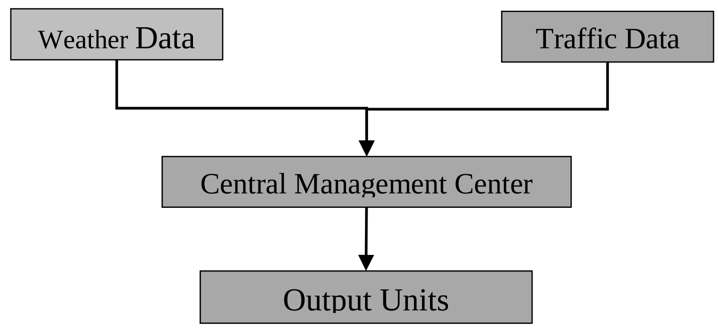


Figure 2-1 Components of a visibility system

Figure 2-2 shows the system architecture of the visibility system in Florida (Abdel-Aty et al. 2013). There are four stations in the system, while one of the stations works as a base station. The stations detect the road visibility and continuously send information to the base station. Strategies, which include displaying warning messages on Dynamic Message Signs (DMSs) and changing speed limits by Variable Speed Limit (VSL) signs, could be implemented when specific hazardous conditions are detected.

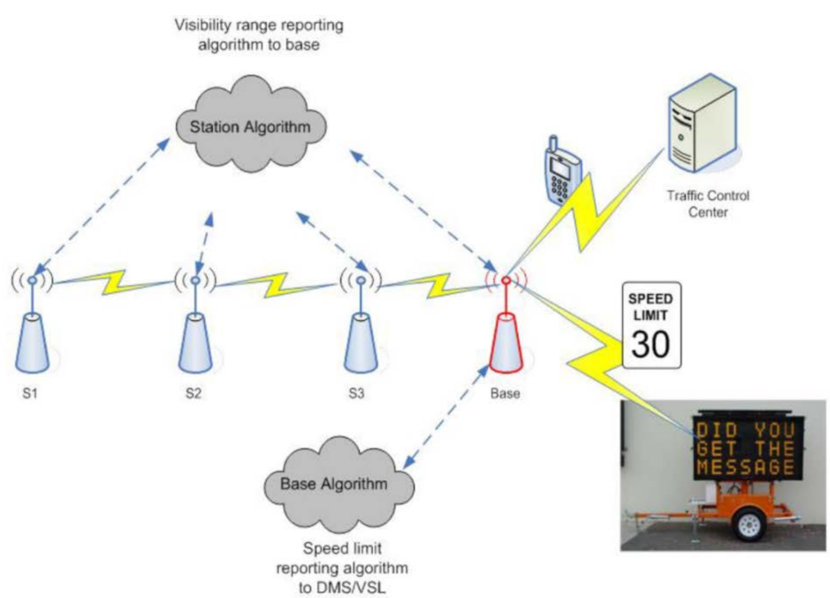


Figure 2-2 Visibility system proposed to FDOT (Abdel-Aty et al., 2012a)

Weather Data Collection

Low visibility is usually related to the presence of dust, smoke, haze or pollution (Hautire et al., 2013), which can cause many traffic safety problems. In meteorological studies, the visibility distance is defined as the greatest distance that a black object can be seen. There are four common types of fog, which are radiation fog, advection fog, upslope fog and evaporation fog (sea fog) (Table 2-1). In Florida, the fog is usually formed during cold months by air cooling and mixing with air parcels, which is known as radiation fog (Pietrzyk et al., 1997).

Table 2-1 Fog types

Fog Types	Causes	Characteristics
Radiation Fog	During night, the heats from earth's surface radiates into space, and the cooler earth's surface lead to the presence of the moist air layer. When the humidity reaches 100% the fog will be present.	It tends to dissipate very quickly once the sun comes up. This type of fog can be very dense and make driving dangerous in the low visibility environment.
Advection Fog	The condensation is caused by the horizontal movement of warm moist air, when the surface temperature is low.	It is prevalent on the Pacific coast of North America.
Upslope Fog	It occurs when moist air flows up a hillside or mountainside by light winds and becomes saturated.	It occurs in all mountain ranges in North America during winter.
Evaporation Fog	It occurs when the moist air, which contains sufficient water vapor, mixes with cooler air.	It leads to smoke rising off the surface of water, or frontal fog, which has the raindrops evaporate into the cool air near the ground.

A Road Weather Information System (RWIS) is used to detect the weather and pavement conditions. A typical RWIS usually includes Remote Processing Units (RPU), communication links and Environmental Sensor Stations (ESS) for collecting different types of weather data, such as temperature, precipitation, visibility, etc. Visibility sensors play an important role in the visibility systems. Figure 2-3 provides an example of a visibility sensor in Idaho.

Figure 2-3 Idaho DOT visibility sensor (Goodwin, 2003)

Other important weather information sources are the Automated Weather Observing System (AWOS), the Automated Surface Observing System (ASOS), and the Automated weather Sensor System (AWSS). Rivard (2014) gathered the AWOS/ASOS stations' data in Florida to analyze the Prospective Fog Warning Systems. He explained the meteorological data sources in Florida (Figure 2-4), which include primary stations (AWOS, ASOS, Florida Automated Weather Network, South Florida Water Management District site), and secondary sites (individual and privately owned weather stations). Florida has a total of 93 AWOS and ASOS stations, and 77 of them are located at airports.

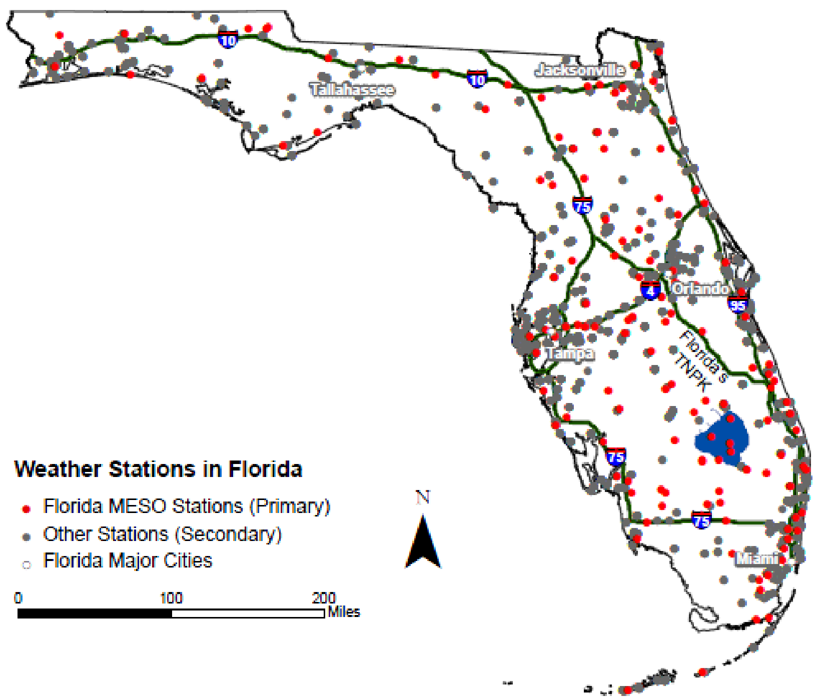


Figure 2-4 All mesonet station in Florida (Rivard, 2014)

In general, the fog sensors can be divided into two types:

Transmissometers: A receiver is located 50 meters away from the transmitter, and collects the transmitted light source. During the fog conditions, the receiver will collect less light because the light will be scattered along the path. This type of sensor is normally used at airports, which is more expensive, inconvenient for transit when installing the sensors, and a long time of accurate alignment is needed (Figure 2-5).

Figure 2-5 Transmission method (Weisser, 1999)

Backscatter and forward scatters: the other method of fog detection is measuring the light scattered. These two types of sensors will get the data from a small area of air, which are also called "point" detectors (Figure 2-6). The disadvantage of the sensors is that the maintenance should be done regularly.

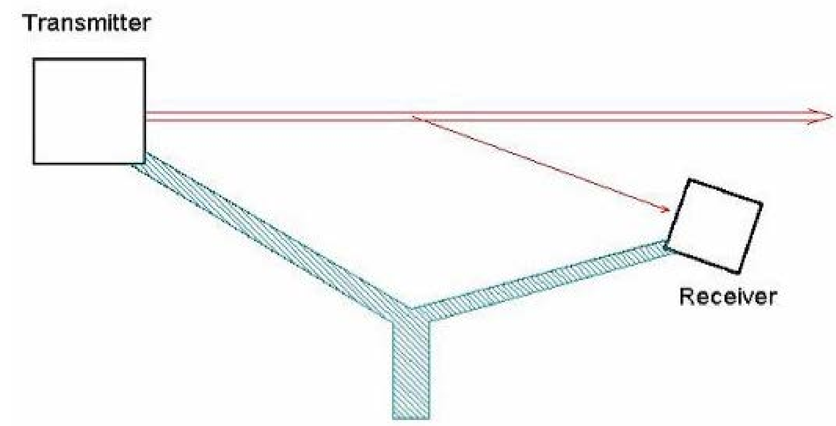


Figure 2-6 Backscatter and forward scatter methods (Weisser, 1999)

Road Traffic Monitor

Different types of road detectors can be employed to monitor the road traffic conditions, such as loop detectors, radar detectors, CCTVs, etc. Loop detectors are used to detect traffic to obtain the traffic parameters, while radar detectors can also be deployed to get the information about traffic flow and speed, and are recently more common. CCTVs are widely applied to confirm the weather conditions and road conditions. Meanwhile, video imaging is another technique that has recently drawn much attention. The technique is designed to monitor the traffic even during low visibility conditions. However, the performance of this technique is still far from satisfactory and improvements are needed.

Decision Making Process and Output Units

The operational strategies during fog conditions are implemented based on both weather information and traffic information. Different weather conditions can affect the road safety in different levels. In 1995, Lavdas and Achtemeier proposed the "Low Visibility Occurrence Risk

Index (LVORI)”, and they also presented LVORI values as a function of Relative Humidity (RH) as well as Dispersion Index (DI) (Table 2-2). The Dispersion Index values describe the atmosphere’s ability to ventilate smoke from areas of prescribed burning activity. From Table 2-2, we can find that the highest risk is presented when the DI value is low and the RH value is high.

Table 2-2 LVORI as a function of RH and DI (Lavdas and Achtemeier, 1995)

	DISPERSION INDEX											
	1-1	2-2	3-4	5-6	7-8	9-10	11-12	13-16	17-25	26-30	31-40	> 40
R.H.												
<55	2	2	2	2	2	2	2	2	2	2	1	1
55-59	3	3	3	3	3	2	2	2	2	2	1	1
60-64	3	3	3	3	3	3	2	2	2	2	1	1
65-69	4	3	3	3	3	3	3	3	3	3	3	1
70-74	4	3	3	3	3	3	3	3	3	3	3	3
75-79	4	4	4	4	4	4	4	4	3	3	3	3
80-82	6	5	5	4	4	4	4	4	3	3	3	3
83-85	6	5	5	5	4	4	4	4	4	4	4	4
86-88	6	6	6	5	5	5	5	4	4	4	4	4
89-91	7	7	6	6	5	5	5	5	4	4	4	4
92-94	8	7	6	6	6	6	5	5	5	4	4	4
95-97	9	8	8	7	6	6	6	5	5	4	4	4
>97	10	10	9	9	8	8	7	5	5	4	4	4

Note: 10 point scale is based on proportions of smoke and/or fog related accidents

In meteorological studies, the road visibility denotes the horizontal visibility 1.2 m above the roadway. The international classification of visibility is as follows (Table 2-3).

Table 2-3 International classification of visibility (Meteorological Office, 1969)

Visibility	Description
Less than 40 m	Dense fog
40-200 m	Thick fog
200-1000 m	Fog
1-2 km	Mist (if mainly due to water droplets)
	Haze (if mainly due to smoke or dust)
2-4 km	Poor visibility
4-10 km	Moderate visibility
10-40 km	Good visibility
Over 40 km	Excellent visibility

In practice, the visibility can be classified into different levels by different visibility systems, and the information would be reported to the Central Management Center to implement different operational strategies. The display messages on the DMSs or the speed limit information on the VSLs would be based on the current visibility levels. After collecting the information, the visibility system would implement corresponding strategies automatically or manually, which include displaying warning messages, speed advisories, changing speed limit, road closure, etc.

The DMSs, which are also known as Variable Message Signs (VMSs) or Changeable Message Signs (CMSs), are widely adopted in visibility systems nowadays. DMS can provide information about the possible issues ahead and give corresponding advice to drivers. Williams et al. (2015) examined the effects of different color configuration, brightness levels, and flashing beacons on a VMS on drivers during the day and night under fog conditions (Figure 2-7). The experiments were carried out on Virginia Smart Road. The Virginia Smart Road is a 2.2 miles test road, and it was built to interstate standards. The smart road can produce fog, rain and snow in order to test their effects on traffic. During most of the situations in the experiment in this study, the VMSs with black-on-white, white-on-black, and amber-on-black color combinations had longer detection and legibility distances. The VMSs with flashing beacons, high brightness, and red-on-black color configurations would make the drivers feel more urgency.

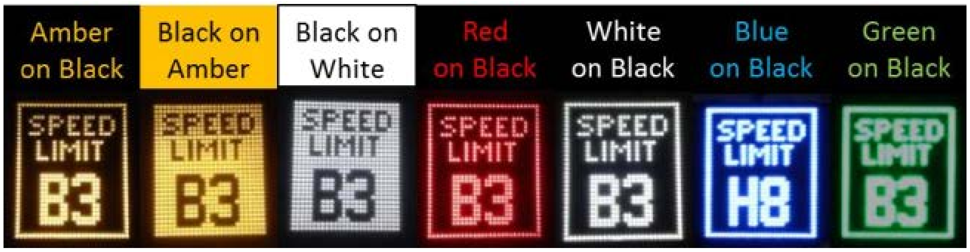
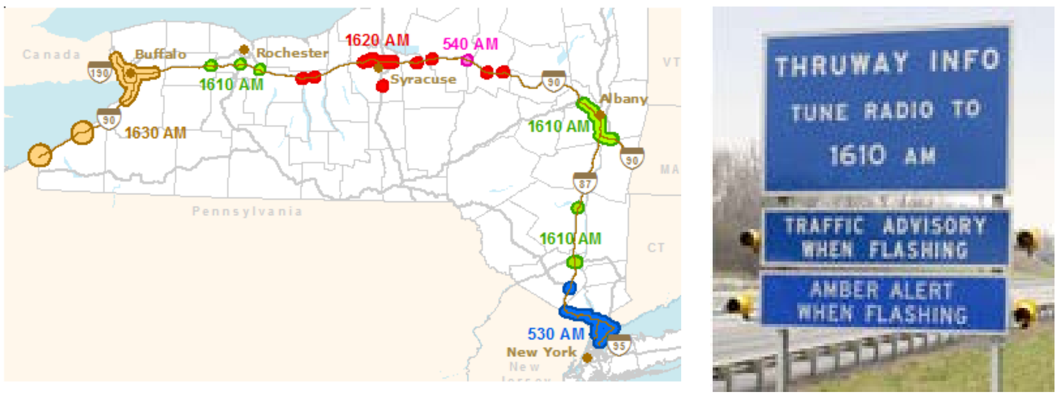


Figure 2-7 Tested color configurations (Williams et al., 2015)

The warning sign is an alternative treatment for reduced visibility conditions, which includes Dynamic Message Sign (DMS) and static message sign. Figure 2-8 is the fog area sign in the Manual on Uniform Traffic Control Devices (MUTCD). The signs are typically located before the area where fog is likely to form frequently. In practice, the signs are sometimes placed with flashing beacons to draw drivers' attention during fog.

Figure 2-8 MUTCD fog area sign (MUTCD, 2009)

Highway advisory radio (HAR), which is also called Traveler Information Station (TIS), also plays an important role of communicating with vehicles. Permanent HAR transmitters are typically located on the Interstate and can be updated instantly during an emergency. The system provides road users with information such as incidents, fire, weather and other traffic conditions. For example, Virginia Department of Transportation (VDOT) broadcasts information on 1620 AM in VDOT's Northern, Southwestern and Central regions, and on 1680 AM in the Eastern Region. Figure 2-9 describes the locations of HAR stations in New York State and offers an example of current HAR signs. When the lights are flashing, the traffic information will be broadcasted.



(a) HAR stations (b) HAR signs

Figure 2-9 HAR (Highway Advisory Radio) system in New York State

In vehicle Camera Based Visibility Techniques

Recent years have seen a trend in research on exploring the in-vehicle fog detection techniques, which still have not commonly been applied. The basic concept of the camera-based visibility detection compresses the information from a 3D space to a two-dimension space. The depth information is lost during the compression process, so many studies are focusing on the methods of how to extract the depth information. However, the fog detection becomes more difficult when the vehicles are moving.

Advanced Driver Assistance System (ADAS), which is developed to help in the driving process, heavily rely on the camera-based detection technology to provide information during adverse weather conditions in order to improve safety and help the drivers have a better driving experience. Lane Departure Warning Systems (LDWSs) are one of the ADASs that can provide a warning to drivers when they are driving out-of-lane. Figure 2-10 shows an example of the LDWS, which is named AutoVue. AutoVue can track the visible lane lines using the cameras, and it is designed to cope with the adverse weather conditions, such as rain, fog, etc.

(a) Camera and ECU

(b) Lane Tracking

Figure 2-10 Bendix AutoVue (NHTSA, 2014)

2.2 Visibility Systems in Other Countries

In addition to the visibility systems that have been employed in the US, there are some other visibility systems around the world. This section of the literature review introduce the visibility systems in other countries.

Visibility Systems in South Korea

A 100-vehicle pile-up happened in foggy weather near South Korea's Incheon International Airport in 2015. Two people died and about sixty-five people injured due to the crash. The Korean authorities at this time aim at developing a new visibility measuring and fog monitoring system using CCTV cameras. Figure 2-11 describes its image processing procedure.

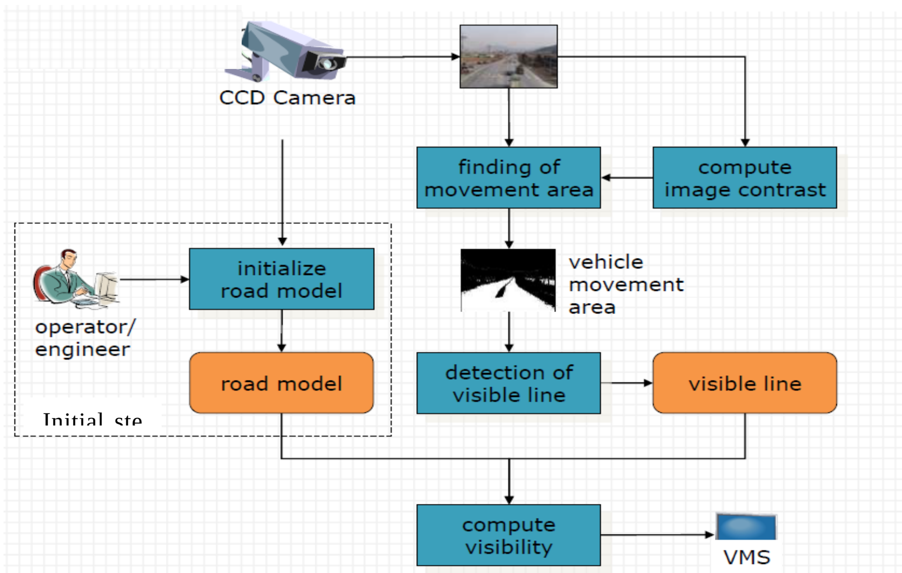


Figure 2-11 Image processing procedure in Korean visibility system (Lee & Kim, 2014)

One important part of the system is to determine the current visibility by the images from cameras. Figure 2-12 offers an example of the system that they employed to determine the current visibility levels.

Figure 2-12 Road model (Lee & Kim, 2014)

The Fog Detection and Warning System (FDWS) in South Korea includes a main controller, a visibility meter, a light bar, and a vehicle detector. The light bar is installed at every 30 m intervals to detect vehicles. If a vehicle passes the detection zone, the light bar will display red warning lights to inform the following vehicle of the leading vehicle's position in fog (Figure 2-13). Lee et al. *(2012)* conducted a study to evaluate the effects of FDWS on a section of National Highway No.37. The results indicate that FDWS will reduce the mean speed by about 3 kph during daytime and 10 kph during nighttime.

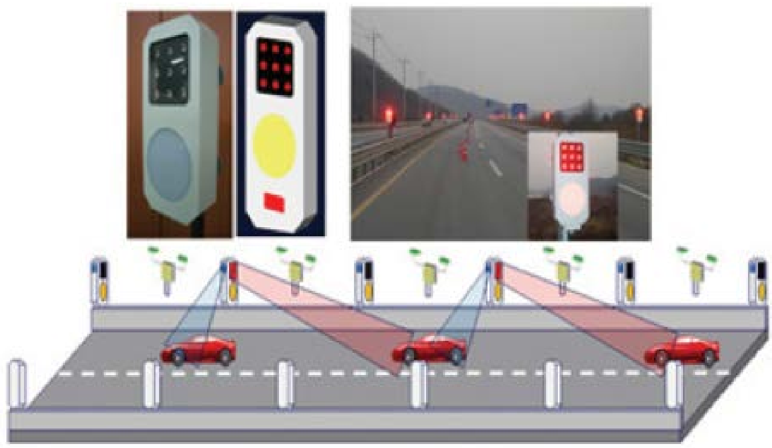


Figure 2-13 Light bars in FDWS (Lee et al., 2012)

Visibility systems in China

In 2005, a severe multi-vehicle involved traffic crash happened in foggy weather in Sichuan, China. Two people died and thirty-four people were injured in the crash. Fog monitoring and warning system has been employed in many places of China. The weather information are collected based on CCTVs and satellite images. Both the real-time weather data and the fog forecasting data are sent to the traffic management center under low visibility conditions. The visibility conditions are divided into two levels: 1) visibility less than 200 m; 2) Visibility greater than 200 m and less than 500 m. The traffic management center implements relative strategies based on the weather information to cope with the situations. The traffic control strategies during fog conditions include: reducing the speed limits by DMSs or VSLs, road network management, roadway closing, etc. Sometimes, when fog last for a long time at mountainous regions, the road managers arrange that the vehicles pass the fog region by groups. The lead vehicle and the last vehicle of each group should be police cars, and other vehicles cannot pass the police cars when driving in the fog area. This method can increase the road capacity under fog conditions.

Visibility Systems in Japan

The Japanese government has funded many efforts to keep improving their Intelligent Transport Systems (ITSs) in order to help resolve road traffic problems. The ITSs include many parts, such as advances in navigation systems, electronic toll collection systems, assistance for safe driving, increasing efficiency in road management, support for public transport, etc. Figure 2-14 shows the structure of the Vehicle Information and Communication System (VICS). The basic concept of the system is using intelligent transportation technology to connect people (road users), vehicles and roads together.

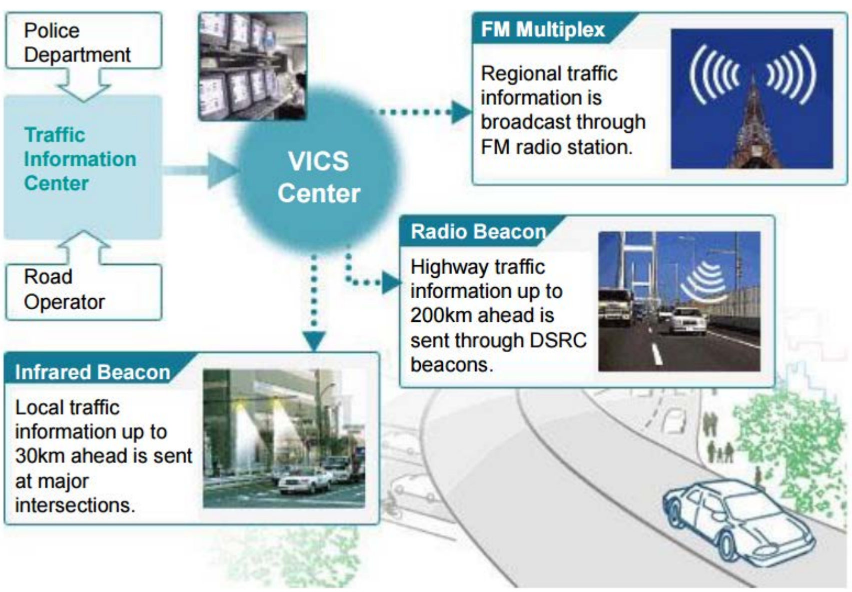


Figure 2-14 Structure of vehicle information and communication systems (MLIT, 2013)

For example, the information of traffic and weather conditions can be provided to drivers' in-vehicle devices to inform drivers about the potential issues ahead (Figure 2-15).

Figure 2-15 In-vehicle device in Japan (MLIT, 2013)

Meanwhile, a guide-light delineation system has been employed in Japan since 2012 to overcome the problem of road marking being covered by snow. A green LED lamp is installed at the road shoulder and provides cues to drivers about the road geometry (Figure 2-16). Hagiwara et al. (2015) evaluated the effects of the guide-light delineation system by driving simulator, and found significant positive effects of the system on driver mental workload under snow cover condition during nighttime.

Figure 2-16 Guide-light delineation system in Japan (Hagiwara et al., 2015)

2.3 Studies of Visibility Systems

Several new procedures has been proposed in recent year, and more advanced visibility-related studies have been conducted. This section of the literature review discusses the current studies of visibility systems.

Traffic Flow in Inclement weather conditions

Low visibility conditions will have significant impacts on the road traffic flow (Table 2-4). Some of the drivers would decrease their speed, while others will not during the low visibility conditions (Al-Ghamdi, 2007). It was reported that the average speeds of the freeway traffic flow during the low visibility could be reduced by 10%-12% (DOT, 2014).

Table 2-4 Weather impacts on roads, traffic and operational decisions (Goodwin and Pisano, 2003)

Road Weather Variable	Roadway Impacts	Traffic Flow Impacts	Operational Impacts
Fog	• Visibility • Distance	• Traffic speed • Speed variance • Travel time delay • Accident risk	• Driver capabilities/behavior • Road treatment strategy • Access control • Speed limit control

Agarwal et al. (2005) analyzed the capacities and speed reduction due to fog, and revealed the significant impacts of fog. From Table 2-5, we can observe that low visibility conditions will have negative effects on road capacities and average speeds.

Table 2-5 Comparison of percentage reductions in capacity and average operating speeds (Agarwal et al., 2005)

Variable	Range	Capacities (percentage reduction)	Average operating speeds (percentage reduction)
Visibility	1-0.51 mile	9	6
	0.50–0.25 mile	11	6
	< 0.25 mile	10.5	11

Abdel-Aty et al. (2013) explored the relationship between reduced visibility and traffic flow characteristics. The study concluded that the variation of both headway and speed, and the average headway are higher while the average speed is lower in reduced visibility conditions.

Differences in traffic flow patterns are also pointed out under adverse weather conditions. Seeherman and Skabardonis (2015) studied the variability in bottleneck discharge flow during adverse weather that includes rainfall, wind and reduced visibility. The study found that reduced visibility would lead to a lower discharge flow. Elhenawy et al. (2015) developed an automated congestion identification algorithm that includes the weather and visibility impacts using a mixture linear regression model to identify and rank traffic bottlenecks. Bartlett et al. (2015) tried to validate the traffic model during the inclement weather conditions. They attempted to model the average speed and the hourly volume while taking weather into consideration. From the results, they recommended that a separate speed prediction model under the inclement weather condition could improve the model performance. Weng et al. (2015) attempted to study the traffic flow at signalized intersections under adverse weather conditions. The study concluded that the saturation flow rate would be decreased while the start-up lost time will increase under the adverse weather conditions. Qing et al. (2015) conducted a GPS based trip analysis and taxi services analysis during adverse weather in New York City. The results indicate that average trips of the travelers will be shorter and slower during the storm conditions. However, the taxi trips in the storm conditions during the regular work hours are similar to the taxi trips during the regular workdays.

Theofilatos et al. (2014) offers a review of the current studies about the effects of weather characteristics on road safety. They found that there is a trend of using real-time data to conduct the traffic safety impact analysis. However, the combined effects of the weather and other factors are needed to be identified, while the different effects in different areas (rural/urban or different countries) are needed to be explored. Also, more attentions should be paid to the vulnerable road users during the adverse weather conditions.

Driver Behavior in Inclement Weather Conditions

Under the fog conditions, drivers are prone to adjust their driving behavior, including changing their speeds and headways (White and Jeffery, 1980; Van der Hulst et al., 1998). One important behavior during the low visibility condition is the drivers' car following behavior. The car following performance is found to be related to the drivers' age, experience and some other factors. The results from a questionnaire (Shepard, 1996) indicated that 46% drivers were more prone to follow other vehicles, 29% drivers were prone to follow the pavement strips, and 5% of drivers said they will pull their vehicles off the road during low visibility conditions.

Previous studies have found that some drivers are likely to maintain shorter headways in the low visibility conditions. Some researches were trying to figure out the reason for the decrease in headway. Their results indicate that the drivers are trying to follow the front car and hope to maintain a visual contact with the front car (Evans and Rothery, 1976; Saffarian et al., 2012).

Even though drivers are prone to reduce their speed during the low visibility conditions, the reduction of the speeds is found to be insufficient. Sumner et al. (1977) found that the driver will reduce their speed when the visibility is below 100m. However, half of the drivers were driving at a higher speed, which they could not stop safely. Yan et al. (2014) conducted a driving simulator experiment and found that the drivers' speed control behavior will vary at different risk levels. They also concluded that the professional drivers tend to have lower speeds when they are facing low visibility conditions. Some researchers have made efforts to find the reasons about the relatively high operating speeds of the drivers in reduced visibility conditions. The current studies reveal that the drivers could have false perspective of their operating speed when they are driving in a low visibility condition (Kang et al., 2008; Brooks et al., 2011). Their studies show that the low visibility will decrease the drivers’ ability to perceive speed (Snowden et al., 1998; Kang et al., 2008).

Li et al. (2015a) investigated the driver behavior on s-curved road segments under fog conditions. The experiment results reveal the differences in control abilities between the professional drivers and the non-professional drivers. The results also indicated that non-professional drivers are less skilled in both longitudinal and lateral vehicles control.

Visibility-related Crashes

In recent years, the number of the fatal crashes involving fog shows a decreasing trend. However, there are still about 300-400 fog involved crashes happening every year in the United States (Hamilton et al., 2014). Previous studies have found that there are more severe injury crashes and multi-vehicles involved crashes during fog (Abdel-Aty et al., 2011).

More and more studies use the combined weather and real-time traffic data to analyze the traffic conditions during fog (Hourdos et al., 2006. Abdel-Aty et al. (2012b) examined the relationship between the traffic data and the reduced visibility crashes. The data was collected from Loop/radar detectors and Automatic Vehicle Identification (AVI) sensors. The model has good prediction accuracy of the reduced visibility crashes. Ahmed et al. (2014) developed a Bayesian logistic regression model using six years’ (2005-2010) crash data and the weather data from eight airports in Florida. The results show reliable prediction for the visibility conditions within 5 nautical miles radium around the airports.

There are some studies that have been conducted to examine the relationship between weather and crashes (Edwards, 1999; Golob and Recker, 2003). However, most of the current studies are focusing on precipitation, snow and some other weather conditions, but few address the low visibility conditions. Yu et al. (2013) analyzed the hazardous factors of the mountainous freeways, and suggested that the weather condition, especially precipitation, has significant impact on crash occurrence. Li et al. (2015b) attempted to identify the weather-sensitive-hotspots in order to find better locations to place the environmental sensor stations.

Huang et al. (2010) conducted a hotspots analysis for the low visibility related crashes in Florida. They found that the morning hours in December to February are more likely to have fog-related crashes, while head-on and rear-end crashes are the two most prevalent types of crashes. They also concluded that the road with higher speeds, undivided road segments and road without sidewalk are more prone to have crashes under reduced visibility conditions. In addition, low visibility related crashes are more likely to happen on two-lane rural roads.

Zheng et al. (2015) studied the secondary crashes on statewide freeway networks in Wisconsin and revealed that low visibility can probably lead to secondary crashes, while the rear-end type of crashes is the most common secondary crash type.

Meanwhile, the increasing use of the multi-type of data has made the combined effect analysis more possible. There are many factors that may have influences on the crash likelihood or the crash severity. Wang et al. (2015) examined the crashes that happened on the expressway ramps and the results indicate that visibility is a significant factor for both single-vehicle and multi-vehicle crash occurrence. There are also some efforts to develop the reduced visibility related crash prediction models. Hassan et al. (2013) developed a prediction model based on random forests and matched case-control logistic regression model. They concluded that the higher occupancy rate of the downstream at 10-15 minutes before the crashes will increase the low visibility crash occurrence likelihood. Xu et al. (2013) analyzed the crash likelihood in rainy and fog conditions. The results indicate that the reduced visibility crashes is highly related to the crash-prone speed difference between the upstream and the downstream.

2.4 Chapter Summary

This chapter introduced the state-of-practice of visibility systems in the US and around the world. Previous studies that are related to the low visibility effects on traffic flow and driver behavior are also reviewed. There are some limitations of the current visibility studies. First, many of the recent studies are based on driving simulator experiments, and there are few efforts that are based on field studies. In addition, most of the visibility systems are only based on the current visibility conditions, few systems take fog prediction into consideration. Combing the information of real-time visibility conditions and fog forecasting information may help improve the performance of visibility systems.

3. FOG PREDICTION SYSTEM

3.1 Introduction

The presence of fog, smoke, and heavy rain contribute to an increase in the potential for traffic crashes. Improved detection and prediction of visibility obstructions can help avoid crashes, improve traffic management from reduced congestion, save money and most importantly save lives via more efficient advance deployment of law enforcement or other crews necessary to monitor deteriorating visibility conditions. The purpose of this chapter was to validate that an array of alternative low-cost environmental sensors combined with decision support logic specifically designed to detect the onset of fog, can meet or exceed existing performance of traditional technologies to identify fog and also provide the potential for short-term fog prediction.

An analysis of existing technologies indicates that most states have achieved some degree of improvement in safety via the deployment of visibility sensors and cameras along select sections of highways that can send information to dynamic message signs and traffic management centers. These traditional implementations are however expensive, purely reactive in nature, and typically limited to only very few locations due to budget constraints. These traditional approaches do not provide the necessary spatial coverage nor do they provide predictive guidance that is desired for optimum safety.

During this project PraxSoft worked to refine current low-cost environmental sensor array, interfaced it with an innovative communications system for real-time data collection, determined necessary supplemental data, developed initial decision support software algorithms to process and analyze the data, and deployed a prototype system at a test site on I-4 in Polk County, FL. A traditional visibility sensor and camera were used as a baseline “ground truth” to determine the presence of restricted visibility. Initial results confirmed the ability of the PraxSoft system to identify the presence of fog with promising potential for at least short term prediction of fog formation.

3.2 Sensor Array Architecture, Placement and Installation

Since a correlation of certain environmental conditions were derived from the historical data set analysis, specialized environmental sensor arrays were designed to measure certain parameters. A schematic of the Fog Monitoring System (FMS) is shown in Figure 3-1.

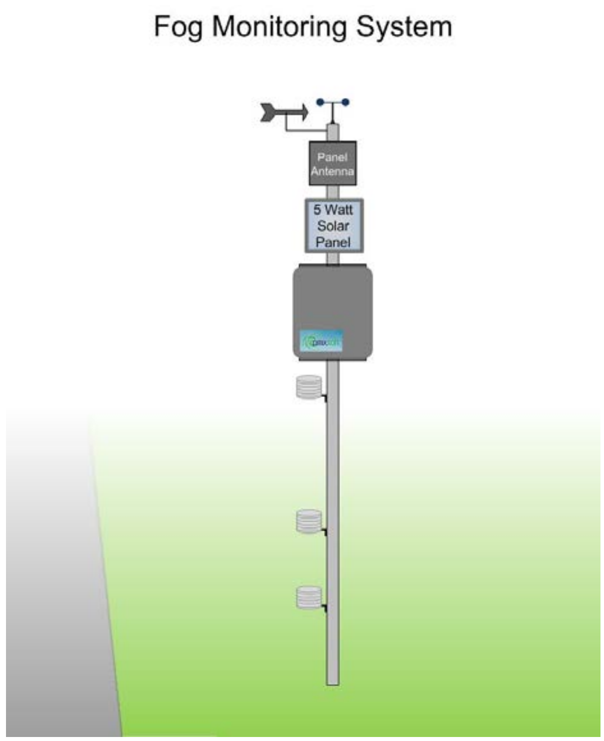


Figure 3-1 Fog monitoring system

For purposes of this project, a Fog Monitoring Station (FMS) consists of three sensors at increasing elevations beginning at one foot one inch. A soil probe is inserted under the immediate ground surface. An anemometer is placed at every other FMS at a height of eight feet above the ground. The anemometer used was specifically chosen for its low-speed detection capabilities. A 5-watt solar panel and 12AH battery keep the FMS powered at all times so data is reported at 5-minute intervals 24/7. There are a total of eight FMS's spaced 0.25 miles apart. All sensors are secured to a 2-inch aluminum pole and a NEMA enclosure houses the battery, wiring, 802.15.4 radio, and Wireless Sensor Node Microprocessor circuit board to handle the multiple sensor inputs while providing extremely low power consumption. This enables a high rate of data transmissions because of the very low power budget of the system. A photograph of one of the FMSs is shown in Figure 3-2 below.

Figure 3-2 Fog monitoring station

A more traditional meteorological sensor array, visibility sensor and camera were installed at the center point of the Fog Monitoring Stations to validate the data from the FMS units. Figure 3-3 is a diagram that illustrates the complete sensor architecture and layout of the system.

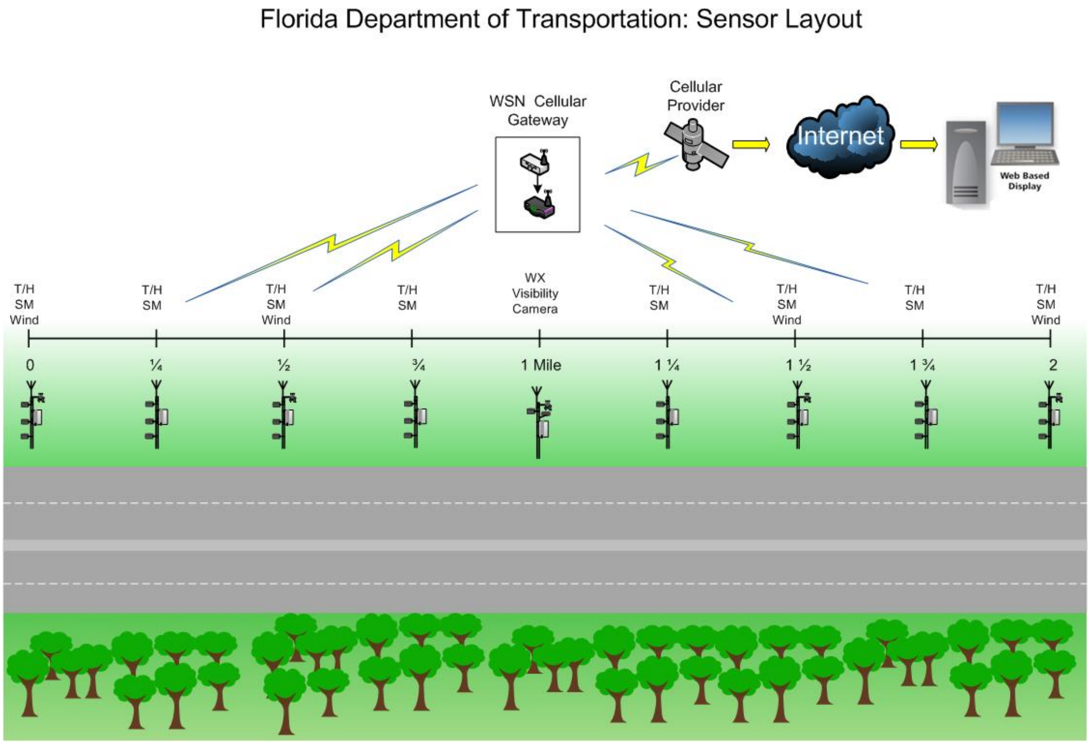


Figure 3-3 Sensor architecture and layout of the system

Also installed at the center location is the cellular back-haul and RF communications receiver that is responsible for collecting the data from the FMSs and delivering it to the PraxSoft database server via an "always-on" cellular gateway. This allows real-time access of data and images from the instrumented site. Each FMS communicates with the receiver via a point-to multipoint RF link with data packets sent out every 5 minutes (adjustable down to 1 minute). As each packet is received and acknowledged, it is sent to the server and inserted into an SQL database where the data is made available to selected users via a web application. The following photograph (Figure 3-4) shows the central collection point with the camera, visibility sensor, and meteorological sensor stack.

Figure 3-4 Camera, visibility sensor, and meteorological sensor stack

Figure 3-5 below is the aerial view of the project study area located on I-4 between milepost 19 and milepost 23. The study area is roughly situated between State Road 559 and State Road 557. Each pinpoint marker represents the location of a multi-array sensor stack, and the distance between two consecutive yellow pinpoints is 0.25 miles.

Figure 3-5 Aerial view of the study area

Web Application

The web application is based on previous software developed by PraxSoft and modified for this project. It can be accessed at the following URL:

http://fdot.weatheractive.net:81/login.aspx

Credentials are required to login and access the data.

The web application provides real-time access to the data from the FMSs and other sensors via a GIS-based map interface as shown in Figure 3-6 below.

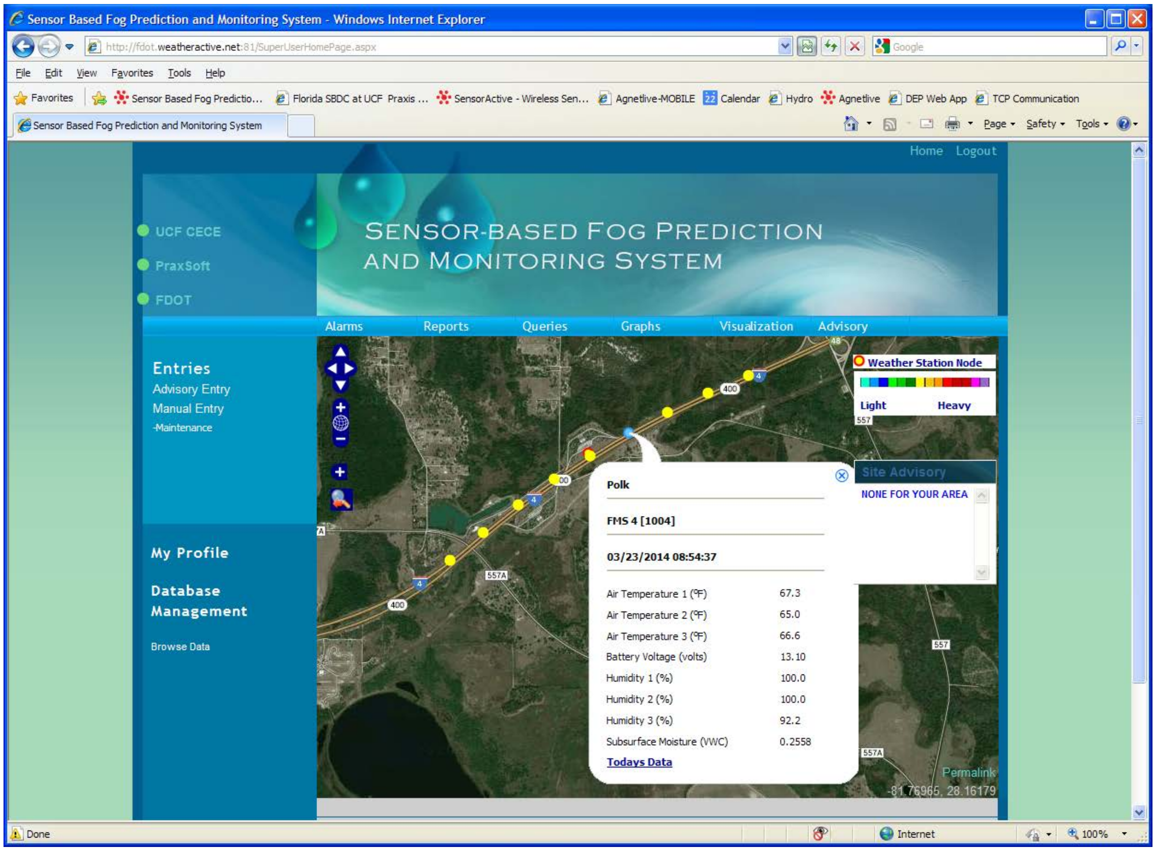


Figure 3-6 GIS-based map interface

The web application includes an "Administrative" mode where the metadata used in determination of the Fog Detection Thresholds can be defined and adjusted.

This information along with the analysis of the data collected during the project will be explained in the following section.

3.3 Fog Algorithm and Visibility Determination

Measurements of environmental parameters from the Fog Measurement Stations were collected from sensors at different elevations above the ground. This data provided an objective micro-level assessment of the current state of the thermodynamic profile near the ground surface along with soil conditions to determine if a visibility constraint (fog) existed or was likely forming. The FMS sensor measurements were interrogated each 5-minute update cycle, seeking to identify conditions that exceeded certain defined fog detection thresholds for each unique location where FMS sensors are deployed.

Critical "threshold" values were identified for each measured FMS parameter, at each vertical level, that correlated to the presence of fog. Three distinct thresholds, one for low fog probability, one for medium fog probability, and one for high probability are assigned for each meteorological parameter (Table 3-1). FMS measurements are continually monitored. As atmospheric conditions change, each FMS measurement at every vertical level along with soil moisture is compared to their corresponding fog thresholds. A resultant consolidated Mean Fog Index (MFI) is derived and is further refined by other geospatial factors. The MFI is then converted into an easy-to-understand numerical range value from 0 (no fog) to 3 (fog likely).

Table 3-1 MFI value

	Mean Fog Index	Description
High	3	Fog Likely
Moderate	2	Fog Likely Forming
Low	1	Monitor Trends
None	0	Good Visibility Likely

Initial test results have been encouraging. Once correlations of the presence of fog were validated by the FMS instrumentation, then continuous monitoring of the FMS measurements occurred over time looking for trends where parameters approached critical thresholds. This provided the opportunity for short-term prediction of the onset and dissipation of fog events. In some cases the system was able to not only indicate the onset of fog, but also provided a much longer pre-warning than we had originally anticipated. This is encouraging as it would allow officials more advance time to prepare for localized dense fog events. More research and more test data are suggested to further refine algorithms and also to reduce the chances of "false positives".

There were several data sets available for initial analysis to correlate observed fog episodes with the data gathered by the 8 FMS sites with "ground-truth" by the meteorological sensor array, visibility sensor and camera images.

In the initial test data sets shown below, two examples of radiation fog occurred on February 2nd and February 4th. In both cases the Mean Fog Index provided at least one hour advance notice prior to the formation of dense fog. Another shorter duration fog event occurred on January 20th which also showed the system at work.

Observed day 2-February 2

On February 2nd, the data from the FMS sensors verified the presence of fog with the Mean Fog Index at "High" starting at 4:00 am, with all three FMS humidity sensors at 100% saturation and calm winds. The conventional visibility sensor started indicating lower readings at FMS station 1 at about 5:30 am. In this case the test FMS system provided over a full hour of advance warning of an ensuing fog event that ultimately became very dense.

Table 3-2 FMS data 2/2/2014

Date	Time	FMS Station	SM	H1	H2	H3	Fog Index
2/2/2014	4:02:44	1	0.3701	100	100	100	High
2/2/2014	4:08:40	1	0.3701	100	100	100	High
2/2/2014	4:14:36	1	0.3701	100	100	100	High
2/2/2014	4:20:32	1	0.3701	100	100	100	High
2/2/2014	4:26:31	1	0.3701	100	100	100	High
2/2/2014	4:32:24	1	0.3701	100	100	100	High
2/2/2014	4:44:16	1	0.3701	100	100	100	High
2/2/2014	4:56:09	1	0.3701	100	100	100	High
2/2/2014	5:02:05	1	0.3701	100	100	100	High
2/2/2014	5:25:49	1	0.3701	100	100	100	High

Table 3-3 Visibility data 2/2/2014 (visibility sensor readings)

Visibility		
2/2/2014	5:27:51	2000
2/2/2014	5:34:35	1060
2/2/2014	5:48:03	2000
2/2/2014	6:01:31	274
2/2/2014	6:14:59	1074
2/2/2014	6:21:54	315
2/2/2014	6:28:38	96
2/2/2014	6:35:22	153
2/2/2014	6:42:06	241
2/2/2014	7:02:18	261
2/2/2014	7:09:03	184

Camera images from this dense fog event are captured below:

5:34 am

7:15 am

9:30 am

Some time after sunrise (which occurred at 7:15 am) the fog began to lift and disperse as the winds increased. The humidity levels soon followed and the high risk was lowered.

Table 3-4 Continued

Date	Time	FMS Station	SM	H1	H2	H3	Fog Index
2/2/2014	8:35:42	1	0.3653	100	100	100	High
2/2/2014	8:41:40	1	0.3653	100	100	100	High
2/2/2014	8:47:34	1	0.3653	100	100	100	High
2/2/2014	8:53:33	1	0.3653	100	100	100	High
2/2/2014	8:59:27	1	0.3653	100	100	100	High
2/2/2014	9:11:21	1	0.3653	100	100	100	High
2/2/2014	9:17:17	1	0.3653	100	100	100	High
2/2/2014	9:23:14	1	0.3653	100	100	100	High
2/2/2014	9:29:11	1	0.3653	100	100	100	High
2/2/2014	9:35:08	1	0.3653	100	100	100	High
2/2/2014	9:41:06	1	0.3653	100	100	100	High
2/2/2014	9:47:08	1	0.3653	98.2	100	100	High
2/2/2014	9:53:03	1	0.3653	98.6	100	100	High
2/2/2014	9:58:58	1	0.3653	98	98.8	100	High
2/2/2014	10:16:51	1	0.3653	93.8	94.4	96.4	Moderate
2/2/2014	10:22:48	1	0.3653	89.8	91.3	92.5	Moderate
2/2/2014	10:28:48	1	0.3653	86.7	88	89.3	Moderate

Observed day 2-February 4

The February 4th episode followed a similar pattern with a “High” Fog Index that preceded a fog event by more than one hour. Very light winds persisted for much of the night with saturated humidity levels resulting in fog in the early morning hours. This was followed by an increase in wind after sunrise, a decrease in humidity, and the lifting of the fog whereupon the Mean Fog Index was reduced.

Table 3-5 FMS data 2/4/2014

Date	Time	FMS Station	SM	H1	H2	H3	Fog Index
2/4/2014	5:47:27	8	0.2796	100	100	100	High
2/4/2014	5:53:25	8	0.2796	100	100	100	High
2/4/2014	5:59:23	8	0.2796	100	100	100	High
2/4/2014	6:05:23	8	0.2796	100	100	100	High
2/4/2014	6:29:14	8	0.2796	100	100	100	High
2/4/2014	6:35:14	8	0.2749	100	100	100	High
2/4/2014	6:41:12	8	0.2749	100	100	100	High
2/4/2014	6:47:08	8	0.2796	100	100	100	High
2/4/2014	6:53:06	8	0.2796	100	100	100	High
2/4/2014	6:59:04	8	0.2796	100	100	100	High
2/4/2014	7:05:03	8	0.2796	100	100	100	High
2/4/2014	7:11:01	8	0.2796	100	100	100	High
2/4/2014	7:28:55	8	0.2796	100	100	100	High
2/4/2014	8:04:47	8	0.2749	100	100	100	High
2/4/2014	8:16:44	8	0.2749	100	100	100	High
2/4/2014	8:28:38	8	0.2749	100	100	100	High
2/4/2014	8:34:36	8	0.2749	100	100	100	High
2/4/2014	8:40:34	8	0.2749	100	100	100	High
2/4/2014	8:46:35	8	0.2749	100	100	100	High
2/4/2014	8:52:31	8	0.2749	100	100	100	High
2/4/2014	8:58:30	8	0.2749	100	100	100	High
2/4/2014	9:10:27	8	0.2749	100	100	100	High
2/4/2014	9:16:26	8	0.2749	100	100	100	High
2/4/2014	9:22:24	8	0.2749	100	100	100	High
2/4/2014	9:28:23	8	0.2749	100	100	100	High
2/4/2014	9:34:22	8	0.2749	100	100	100	High
2/4/2014	9:40:21	8	0.2749	100	100	100	High
2/4/2014	9:46:42	8	0.2749	100	100	100	High
2/4/2014	9:52:19	8	0.2749	100	100	100	High
2/4/2014	9:58:19	8	0.2749	98.1	98.2	99	High
2/4/2014	10:04:18	8	0.2749	94.4	92.5	96.3	High
2/4/2014	10:10:18	8	0.2749	86.9	86.3	92.3	Moderate
2/4/2014	10:16:19	8	0.2796	82	82.3	91.6	Moderate
2/4/2014	10:22:20	8	0.2749	79.6	80	87.4	Low

One note, the soil moisture (SM column) ticked down from 0.2796 to 0.2749 which may be expected as the fog persists and moisture slowly evaporates out of the soil. This was also noted in some of the FMS stations during the February 2nd event.

Table 3-6 Visibility data 2/4/2014 (visibility sensor readings)

Visibility		
2/4/2014	5:46:46	1271
2/4/2014	5:53:30	2000
2/4/2014	6:00:14	1188
2/4/2014	6:06:58	89
2/4/2014	6:20:26	242
2/4/2014	6:27:10	95
2/4/2014	6:33:54	258
2/4/2014	6:40:38	182
2/4/2014	6:47:22	220
2/4/2014	6:54:06	195
2/4/2014	7:00:51	216
2/4/2014	7:14:18	276
2/4/2014	7:27:46	177
2/4/2014	7:34:30	226
2/4/2014	7:41:14	149
2/4/2014	8:01:26	2000
2/4/2014	8:14:54	136
2/4/2014	8:28:22	289
2/4/2014	8:35:06	326
2/4/2014	8:41:50	1190
2/4/2014	8:48:34	1126
2/4/2014	8:55:18	198
2/4/2014	9:02:02	1190
2/4/2014	9:08:47	2000
2/4/2014	9:15:32	2000
2/4/2014	9:22:17	2000
2/4/2014	9:29:02	2000
2/4/2014	9:35:51	2000
2/4/2014	9:42:32	2000

The lower visibility in this event, also correspond well with the visibility sensor readings, which just lag 40 or so minutes when the fog lifted. Below are camera images of the fog event for February 4th:

5:46 am	7:00 am	9:15 am

Observed day 3 - January 20

On January 20th there was a short duration radiation fog event. Even though it was of short duration, it was a radiation fog event with significantly reduced visibility. The event occurred right around sunrise. When the winds increased at just after 8:20 am, it began to break it up. The visibility sensor began indicating reduced visibility at 7:41 am, however the FMS indicated a "High" fog index at 6:06 am. From the pictures below it can be seen that there is indeed the beginning of reduced visibility at 6:06 am. Winds were calm and humidity levels were at saturation on all three levels of the FMS.

Table 3-7 Visibility data 1/20/2014 (Visibility sensor for January 20th)

Visibility		
1/20/2014	6:06:49	2000
1/20/2014	6:26:58	2000
1/20/2014	6:33:41	2000
1/20/2014	6:40:24	2000
1/20/2014	6:47:07	2000
1/20/2014	6:53:50	2000
1/20/2014	7:00:33	2000
1/20/2014	7:07:16	1222
1/20/2014	7:13:59	2000
1/20/2014	7:20:42	2000
1/20/2014	7:27:25	2000
1/20/2014	7:41:02	174
1/20/2014	7:54:28	211
1/20/2014	8:07:57	72
1/20/2014	8:14:37	53
1/20/2014	8:21:20	2000
1/20/2014	8:28:06	2000
1/20/2014	8:34:49	2000
1/20/2014	8:41:31	2000
1/20/2014	8:48:18	2000
1/20/2014	8:54:59	2000

Weather from station 1 for January 20th:

Table 3-8 FMS data 1/20/2014

Date	Time	FMS Station	SM	H1	H2	H3	Fog Index
1/20/2014	6:06:32	1	0.332	100	100	100	High
1/20/2014	6:24:19	1	0.332	100	100	100	High
1/20/2014	6:30:14	1	0.332	100	100	100	High
1/20/2014	6:36:10	1	0.332	100	100	100	High
1/20/2014	6:42:05	1	0.332	100	100	100	High
1/20/2014	6:48:01	1	0.332	100	100	100	High
1/20/2014	6:59:52	1	0.332	100	100	100	High
1/20/2014	7:05:50	1	0.332	100	100	100	High
1/20/2014	7:11:45	1	0.332	100	100	100	High
1/20/2014	7:17:39	1	0.332	100	100	100	High
1/20/2014	7:23:35	1	0.332	100	100	100	High
1/20/2014	7:41:22	1	0.332	100	100	100	High
1/20/2014	7:53:13	1	0.332	100	100	100	High
1/20/2014	8:11:00	1	0.332	100	100	100	High
1/20/2014	8:16:57	1	0.332	100	100	100	High
1/20/2014	8:22:51	1	0.332	100	100	100	High
1/20/2014	8:34:42	1	0.332	100	100	100	High
1/20/2014	8:40:38	1	0.332	100	100	100	High
1/20/2014	8:46:36	1	0.332	100	100	100	High

6:06 am

7:40 am

8:21 am

Additionally, other events on the 21st and 28th of January, though they did not have a strong signature for radiation fog, produced reduced visibilities which started improving around sunrise with increased wind speeds.

3.4 Evaluation of the Performance of the Fog Detection Algorithm

3.4.1 Evaluation of the Performance of the Initial Fog Detection Algorithm

The performance of the initial fog detection algorithm completed around April 11 was first evaluated in general by using the Table 3-9 for classification. The major purpose of this evaluation is to figure out whether the fog detection algorithm can be used to predict the reduced visibility by showing high or moderate fog index.

The following four measures were used as performance criteria to evaluate the relative performances of the fog detection algorithm (Miranda-Moreno, 2006):

False Discovery Rate (FDR): the ratio of false positives (Type I errors) among all detected fog events by a model. Smaller values are better.

$$\text{FDR}=\frac{V}{D} \qquad \text{Equation 3-1}$$

False Negative Rate (FNR): the ratio of false negatives (Type II errors) among all detected non-fog events by a model. Smaller values are better.

$$\text{FNR}=\frac{R}{X} \qquad \text{Equation 3-2}$$

Sensitivity (SENS): the ratio of correctly detected fog events. Larger values are better.

$$\text{SENS}=\frac{S}{n_1} \qquad \text{Equation 3-3}$$

Specificity (SPEC): the ratio of correctly detected non-fog events. Larger values are better.

$$\text{SPEC}=\frac{U}{n_0} \qquad \text{Equation 3-4}$$

n_0: number of "true" good visibility

n_1: number of "true" reduced visibility

Table 3-9 Possible outcomes of classification

	Number of observation "detected" as high fog index	Number of observation "detected" as moderate fog index	Number of observation "detected" as low fog index
Number of reduced visibility	U		V
Number of good visibility	R		S
	X		D

U: number of observations of reduced visibility correctly identified as high fog index
V: number of Type I errors
R: number of Type II errors
S: number of observations of good visibility correctly identified as low fog index
D: number of observations of visibility identified as low fog index
X: number of observations of visibility identified as high fog index

Table 3-10 Results of all the observations

	Number of observation "detected" as high fog index	Number of observation "detected" as moderate fog index	Number of observation "detected" as low fog index
Number of reduced visibility(<2000)	425	6	6
Number of good visibility(>=2000)	6997	3182	1544

The performance of the algorithm was first evaluated in general by using the above tables of classification and criteria. The total number of observations is 12160. It can be seen from Table 3-10 that the number of Type II error that the observation of good visibility was detected as high fog index in the prediction algorithm was 6997. In addition, the observation of good visibility was detected as moderate fog index was also 3182. The number of Type I error that the reduced visibility was detected as low fog index was 6. The result of four performance criteria measurements was shown in Table 3-11. It then can be concluded from the results that this algorithm can be used to detect the fog days but it is very easy to make a false alarm when the day is actually clear.

Table 3-11 Results of four performance criteria measurements

Criteria	Value
FDR (smaller is better)	0. 4%
FNR (smaller is better)	57.5%
SENS (larger is better)	13.2%
SPEC (larger is better)	97.2%

Next, In order to further validate the predictions of the fog index in the cases with reduced visibility, the visibility in the days with reduced visibility are matched by the prediction of the fog index in the same days. Fourteen cases with reduced visibility were studied. The starting date and time and ending date and time for the 14 cases are summarized in Table 3-12.

From the summary of starting date and time and ending date and time for the 14 cases are in Table 3-12, we can conclude that when there is a reduced visibility the fog index is showing high fog in 100% of the cases. However, the problem is that the fog index starts to predict high fog before the visibility drops by a period of time in the range of 5 hours to 3 days and it keep showing high fog after the visibility is normal by a period of time in the range of 45 minutes to 23 hours, which means a lot of time was falsely detected as fog period.

Table 3-12 The Starting date and time and ending date and time for the 14 fog cases

Case	Limits	Fog Index (High)		Reduced Visibility	
		Date	Time	Date	Time
1	Starting	01/28/2014	20:30:48	02/01/2014	0:08:44
	Ending	02/01/2014	15:03:54	02/01/2014	08:39:15
2	Starting	02/01/2014	16:15:28	02/02/2014	01:38:44
	Ending	02/02/2014	10:38:36	02/02/2014	09:23:42
3	Starting	02/02/2014	22:13:43	02/03/2014	08:15:40
	Ending	02/03/2014	10:17:52	02/03/2014	08:49:20
4	Starting	02/03/2014	19:18:26	02/04/2014	01:03:58
	Ending	02/04/2014	09:49:16	02/04/2014	09:02:02
5	Starting	02/06/2014	19:17:29	02/08/2014	22:06:16
	Ending	02/09/2014	09:50:36	02/08/2014	23:54:21
6	Starting	02/06/2014	19:17:29	02/09/2014	0:54:56
	Ending	02/09/2014	09:50:36	02/09/2014	01:35:20
7	Starting	02/11/2014	21:01:19	02/12/2014	03:21:30
	Ending	02/13/2014	04:01:13	02/12/2014	20:27:59
8	Starting	02/19/2014	19:15:05	02/20/2014	05:14:08
	Ending	02/20/2014	08:36:08	02/20/2014	06:08:00
9	Starting	02/21/2014	19:29:13	02/22/2014	02:45:28
	Ending	02/22/2014	20:24:49	02/22/2014	18:46:20
10	Starting	02/25/2014	20:41:15	02/26/2014	04:58:59
	Ending	02/27/2014	16:30:00	02/26/2014	16:41:05
11	Starting	03/03/2014	20:45:02	03/04/2014	05:54:31
	Ending	03/04/2014	10:48:00	03/04/2014	07:50:05
12	Starting	03/04/2014	19:46:19	03/05/2014	06:21:28
	Ending	03/05/2014	10:54:56	03/05/2014	09:16:43
13	Starting	03/08/2014	19:14:15	03/09/2014	0:31:55
	Ending	03/09/2014	09:29:10	03/09/2014	4:52:00
14	Starting	03/10/2014	09:43:11	03/11/2014	09:32:24
	Ending	03/11/2014	11:58:25	03/11/2014	09:59:20

3.4.2 Evaluation of the Performance of the Modified Fog Detection Algorithm

The fog detection algorithm was modified recently by PraxSoft after we identified the above problem. Therefore, the performance of the modified algorithm was evaluated again by using the same method and criteria. The total number of observations is 10493 which include the analysis period from 1/2/2014 to 04/01/2014 in the new dataset. It can be seen from Table 3-13 that the number of Type II error that the observation of good visibility was detected as high or moderate fog index in the prediction algorithm was 2058 and 2778 separately. The number of the reduced visibility detected as low fog index or none fog index was only 12 in total. The result of four performance criteria measurements was shown in Table 3-14. It then can be concluded from the results that this updated algorithm is still efficient to detect the fog days but it is still easy to make a false alarm when the day is actually clear. The total number of the observations of good visibility detected as high or moderate fog index was 4836 which consists 46.1% of all the observations. Overall, it can be seen from the Table 3-14 that the performance of the updated algorithm was much better compared to the original one.

Table 3-13 Results of observations of the updated algorithm

	Number of observation "detected" as high fog index	Number of observation "detected" as moderate fog index	Number of observation "detected" as low fog index	Number of observation "detected" as none fog index
Number of reduced visibility(<2000)	132	177	3	9
Number of good visibility(>=2000)	2058	2778	2546	2790
Total	2190	2955	2549	2799

Table 3-14 Comparison of four performance criteria measurements for two algorithm

Criteria	Original algorithm	Modified algorithm
FDR (smaller is better)	0. 4%	0. 32%
FNR (smaller is better)	57.5%	19.6%
SENS (larger is better)	13.2%	52.4%
SPEC (larger is better)	97.2%	96.2%

Next, in order to further validate the predictions of the fog index in the cases with reduced visibility, the visibility in the days with reduced visibility are matched by the prediction of the fog index in the same days. Fifteen cases with reduced visibility were studied. The starting date and time and ending date and time for the 15 cases are summarized in Table 3-15.

From the summary of starting date and time and ending date and time for the 15 cases are in Table 3-15, we can conclude that when there was a reduced visibility the fog index showed high fog or at least moderate index in 100% of the cases before the fog began. In most cases, the fog index starts to predict high or moderate fog before the visibility drops by a period of several hours and it keeps showing high or moderate fog index for several hours after the visibility is back to normal. There are only three cases that the fog index starts to predict high or moderate fog before the visibility drops by a period of three days, which is not so accurate for the prediction. Overall, it also can be seen from the analysis of these detailed fog cases that the performance of modified algorithm is much better compared to the original one, but still need much adjustment and validation.

Table 3-15 The starting date and time and ending date and time for the 15 fog cases

Case	Limits	Fog Index (High or moderate)		Reduced Visibility	
		Date	Time	Date	Time
1	Starting	01/28/2014	20:30:48	02/01/2014	0:08:44
	Ending	02/01/2014	12:40:48	02/01/2014	08:39:15
2	Starting	02/01/2014	17:21:00	02/02/2014	01:38:44
	Ending	02/02/2014	10:58:36	02/02/2014	09:23:42
3	Starting	02/02/2014	22:13:43	02/03/2014	08:15:40
	Ending	02/03/2014	9:30:14	02/03/2014	08:49:20
4	Starting	02/03/2014	19:28:22	02/04/2014	01:03:58
	Ending	02/04/2014	09:31:25	02/04/2014	09:02:02
5	Starting	02/06/2014	19:29:21	02/08/2014	22:06:16
	Ending	02/09/2014	08:45:19	02/08/2014	23:54:21
6	Starting	02/06/2014	19:19:21	02/09/2014	0:54:56
	Ending	02/09/2014	08:45:19	02/09/2014	01:35:20
7	Starting	02/11/2014	21:01:19	02/12/2014	03:21:30
	Ending	02/12/2014	09:40:38	02/12/2014	09:18:55
8	Starting	02/19/2014	19:21:02	02/20/2014	05:14:08
	Ending	02/20/2014	08:00:29	02/20/2014	06:08:00
9	Starting	02/21/2014	21:40:12	02/22/2014	02:45:28
	Ending	02/22/2014	20:24:49	02/22/2014	18:46:20
10	Starting	02/25/2014	22:45:52	02/26/2014	04:58:59
	Ending	02/26/2014	09:08:42	02/26/2014	08:00:47
11	Starting	03/03/2014	22:43:53	03/04/2014	05:54:31
	Ending	03/04/2014	09:13:12	03/04/2014	07:50:05
12	Starting	03/04/2014	20:33:54	03/05/2014	06:21:28
	Ending	03/05/2014	10:07:19	03/05/2014	09:16:43
13	Starting	03/08/2014	19:26:42	03/09/2014	0:31:55
	Ending	03/09/2014	08:53:32	03/09/2014	4:52:00
14	Starting	03/10/2014	23:25:12	03/11/2014	09:32:24
	Ending	03/11/2014	09:52:28	03/11/2014	09:59:20
15	Starting	03/18/2014	20:19:12	03/19/2014	03:57:24
	Ending	03/19/2014	09:03:28	03/19/2014	07:49:20

3.5 Chapter Summary

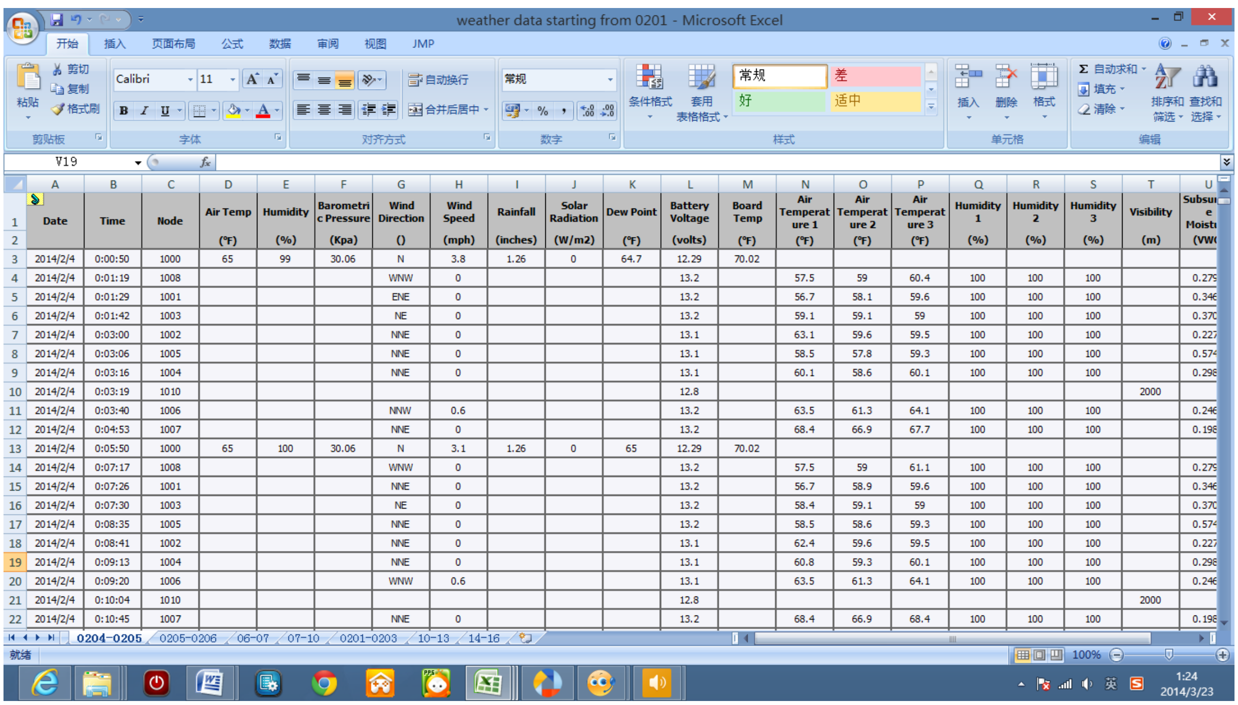
The purpose of this chapter was to develop a proof of concept to validate that an array of low-cost environmental sensors, arranged at varying levels above the ground surface, could effectively detect the onset of fog and meet or exceed existing performance of traditional and much more expensive technologies. A combination of sensors and software algorithms were refined and augmented to work in concert to create derivative products that detect and provide the basis to predict the onset of fog. In this chapter, we evaluated the performance of the fog detection algorithm developed by PraxSoft. Four measures: False Discovery Rate, False Negative Rate, Sensitivity and Specificity were used as performance criteria to evaluate the relative performances of the fog detection algorithm. A comparison of original and modified fog detection algorithm was presented in the chapter and it can be seen that the performance of modified algorithm is much better compared to the original one. The modified algorithm is efficient to detect the fog days but the percentage of making a false alarm when the day is actually clear is still a little bit high.

4. DATA COLLECTION AND PREPARATION

4.1 Weather Data

The weather data was then collected from those installed weather sensors in I-4 rest area.

There are mainly two kinds of weather datasets. The first kind of dataset consists of twenty-one variables including air temperature, dew point, surface moisture, humidity, wind speed and some other important weather parameters such as barometric pressure and rainfall. The second kind of dataset consists of twelve variables including air temperature, surface moisture, humidity, wind speed and fog index which is used to predict the fog event. The Figure 4-1 and Figure 4-2 show a sample of these two kinds of datasets.



Date	Time	Node	Air Temp (°F)	Humidity (%)	Barometric Pressure (Kpa)	Wind Direction ()	Wind Speed (mph)	Rainfall (inches)	Solar Radiation (W/m2)	Dew Point (°F)	Battery Voltage (volts)	Board Temp (°F)	Air Temperature 1 (°F)	Air Temperature 2 (°F)	Air Temperature 3 (°F)	Humidity 1 (%)	Humidity 2 (%)	Humidity 3 (%)	Visibility (m)	Subsure Moistu (VW
2014/2/4	0:00:50	1000	65	99	30.06	N	3.8	1.26	0	64.7	12.29	70.02								
2014/2/4	0:01:19	1008				WNW	0				13.2		57.5	59	60.4	100	100	100		0.279
2014/2/4	0:01:29	1001				ENE	0				13.2		56.7	58.1	59.6	100	100	100		0.346
2014/2/4	0:01:42	1003				NE	0				13.2		59.1	59.1	59	100	100	100		0.370
2014/2/4	0:03:00	1002				NNE	0				13.1		63.1	59.6	59.5	100	100	100		0.227
2014/2/4	0:03:06	1005				NNE	0				13.1		58.5	57.8	59.3	100	100	100		0.574
2014/2/4	0:03:16	1004				NNE	0				13.1		60.1	58.6	60.1	100	100	100		0.298
2014/2/4	0:03:19	1010									12.8								2000	
2014/2/4	0:03:40	1006				NNW	0.6				13.2		63.5	61.3	64.1	100	100	100		0.246
2014/2/4	0:04:53	1007				NNE	0				13.2		68.4	66.9	67.7	100	100	100		0.198
2014/2/4	0:05:50	1000	65	100	30.06	N	3.1	1.26	0	65	12.29	70.02								
2014/2/4	0:07:17	1008				WNW	0				13.2		57.5	59	61.1	100	100	100		0.279
2014/2/4	0:07:26	1001				NNE	0				13.2		56.7	58.9	59.6	100	100	100		0.346
2014/2/4	0:07:30	1003				NE	0				13.2		58.4	59.1	59	100	100	100		0.370
2014/2/4	0:08:35	1005				NNE	0				13.2		58.5	58.6	59.3	100	100	100		0.574
2014/2/4	0:08:41	1002				NNE	0				13.1		62.4	59.6	59.5	100	100	100		0.227
2014/2/4	0:09:13	1004				NNE	0				13.1		60.8	59.3	60.1	100	100	100		0.298
2014/2/4	0:09:20	1006				WNW	0.6				13.1		63.5	61.3	64.1	100	100	100		0.246
2014/2/4	0:10:04	1010									12.8								2000	
2014/2/4	0:10:45	1007				NNE	0				13.2		68.4	66.9	68.4	100	100	100		0.198

Figure 4-1 Sample of weather data

	Date	Time	Soil Moisture (VWC)	Temperature Level 1 (°F)	Humidity Level 1 (%)	Temperature Level 2 (°F)	Humidity Level 2 (%)	Temperature Level 3 (°F)	Humidity Level 3 (%)	Wind Speed (mph)	Wind Direction (&)	Fog Index
2	03/12/2014	0:00:19	0.232	64.7	86.4	65.3	85.9	64.6	87.4	0.6	SSW	Low
3	03/12/2014	0:11:52	0.232	64.7	87.6	65.3	86.8	64.6	88.7	1.5	SSW	Low
4	03/12/2014	0:17:48	0.232	64.7	88	65.3	87.3	64.6	89.1	0.9	SW	Low
5	03/12/2014	0:23:45	0.232	64.7	88.3	65.3	87.6	64.6	89.2	0.9	SW	Low
6	03/12/2014	0:29:43	0.232	64.7	88.3	65.3	87.5	64.6	89.3	0	SSW	Low
7	03/12/2014	0:35:38	0.232	64.7	88.4	65.3	87.6	65.3	89.3	0.3	WSW	Low
8	03/12/2014	0:59:24	0.232	64.7	88.7	65.3	87.9	64.6	89.6	1.8	SW	Low
9	03/12/2014	1:11:17	0.232	64.7	88	65.3	87.5	64.6	89.2	0.9	SW	Low
10	03/12/2014	1:17:14	0.232	64.7	87.3	65.3	86.6	64.6	88.2	2.1	WSW	Low
11	03/12/2014	1:23:10	0.232	64.7	87.5	65.3	86.7	64.6	88.4	1.5	SW	Low
12	03/12/2014	1:29:07	0.232	65.4	87.4	65.3	86.7	65.3	88.4	3.4	SSW	Low
13	03/12/2014	1:35:03	0.232	64.7	87.9	65.3	87.3	65.3	89.1	1.2	S	Low
14	03/12/2014	1:41:00	0.232	65.4	88.3	65.3	87.6	65.3	89.2	2.5	SSW	Low
15	03/12/2014	1:46:56	0.232	65.4	88.3	65.3	87.7	65.3	89.5	0.6	SSW	Low
16	03/12/2014	1:52:53	0.232	65.4	88.8	65.3	88.1	65.3	90	1.2	E	Low
17	03/12/2014	1:58:51	0.232	65.4	89.1	65.3	88.4	65.3	90.2	1.2	SW	Low
18	03/12/2014	2:22:36	0.232	65.4	91.3	65.3	90.7	65.3	92.7	1.5	ENE	Low

Figure 4-2 Sample of weather data including fog index

4.2 Traffic Data

4.2.1 Installation of Wavetronix SmartSensor

In order to investigate the relationship between weather and traffic flow, a vehicle-based detector, Wavetronix SmartSensor HD, was installed to collect accurate traffic flow data, including vehicle speed, vehicle length and lane assignment. Augmenting the system with the unit Click 514 enables us to collect data for every vehicle so we can also calculate the headway.

The Installation Site

Figure 4-3 depicts is the aerial view of the selected study area on I-4 from milepost 19 to milepost 23. It is roughly situated between State road 559 and State road 557. The selected light pole to install the traffic detector is near the entrance of the rest area on the eastbound side (Figure 4-4). The offset from first detection lane to the light pole is 54 feet. The pictures of the street view of the light pole are provided from Figures 4-5 to 4-7.

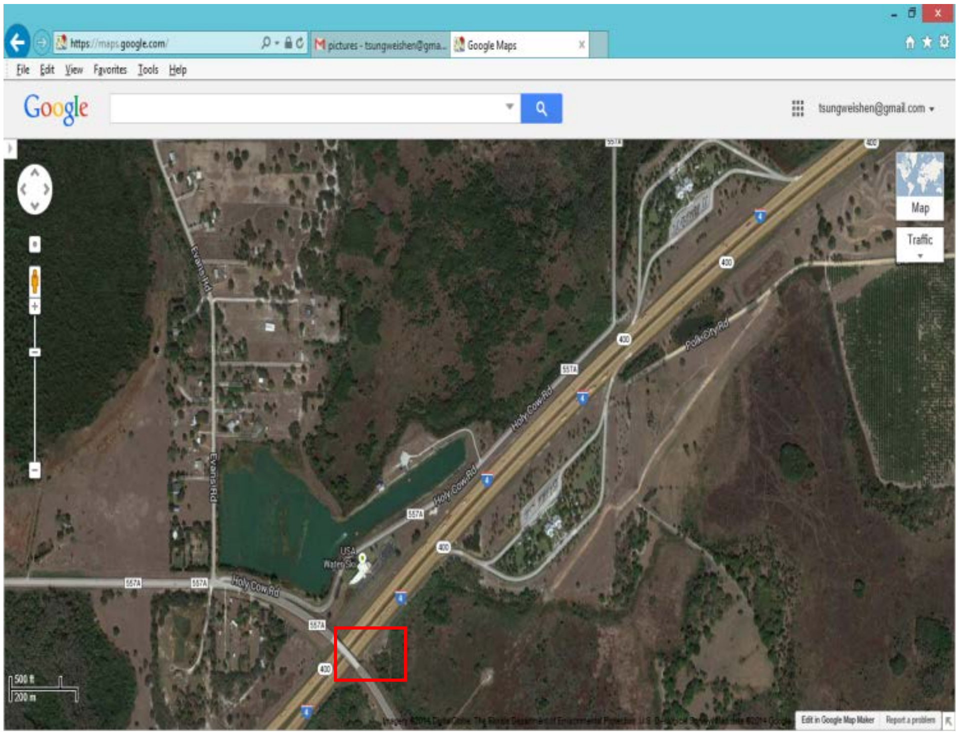


Figure 4-3 Rest area on the eastbound side of I-4

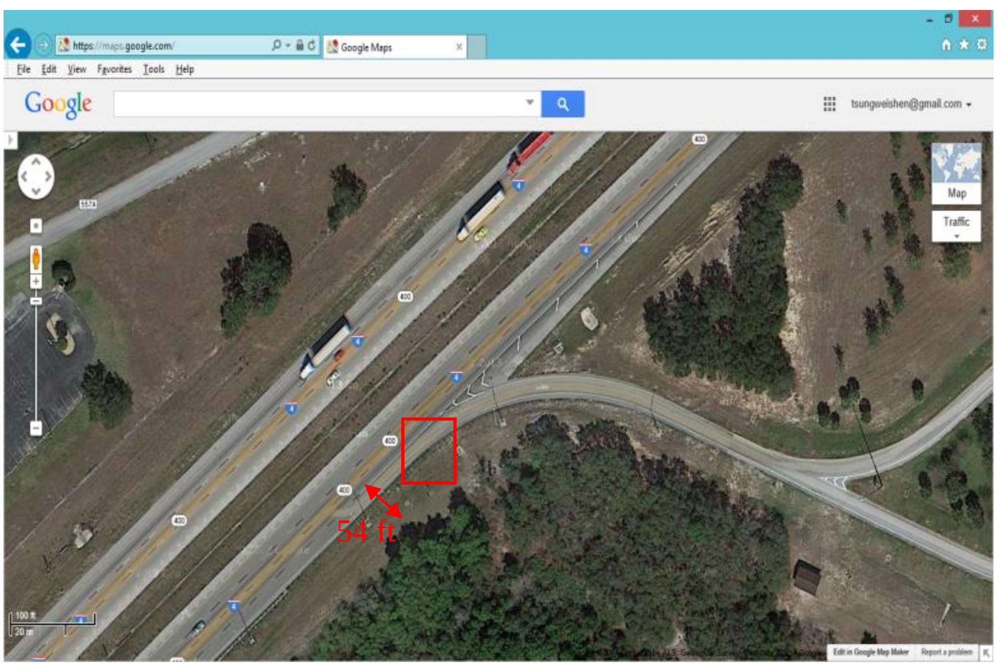


Figure 4-4 Light pole near the entrance of rest area

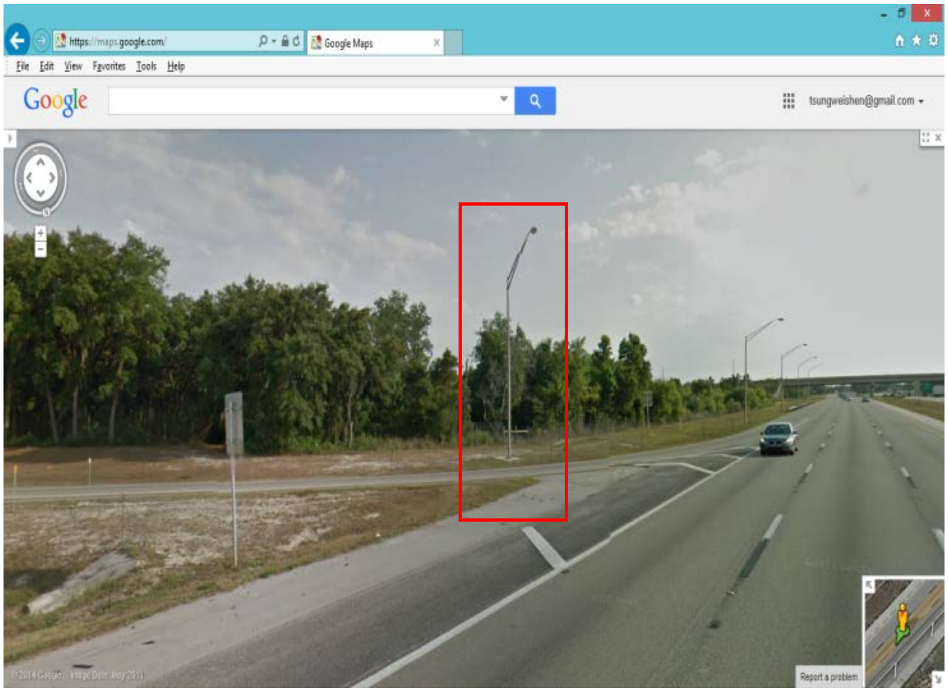


Figure 4-5 Street view of the light pole (1)

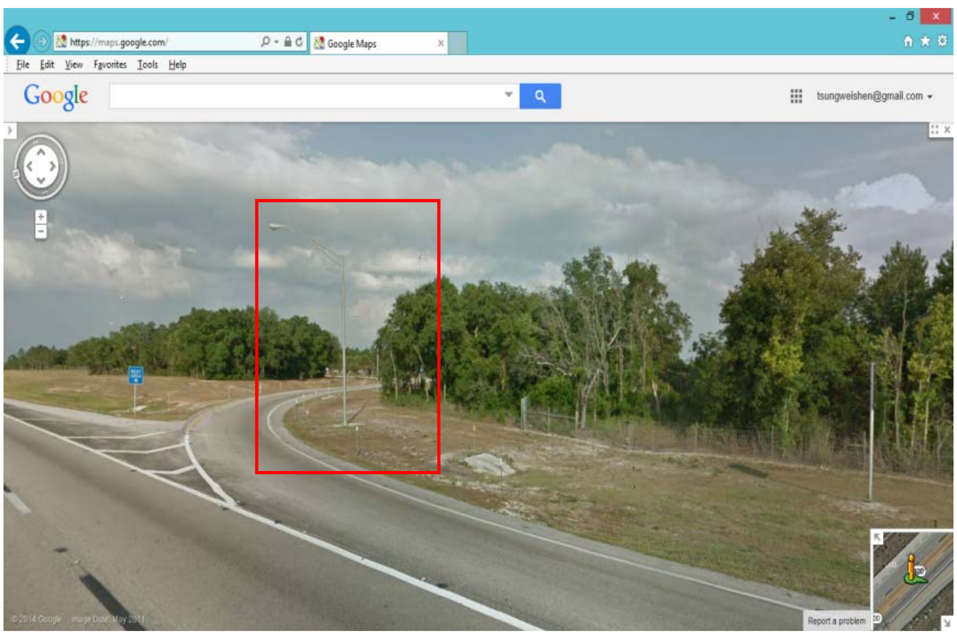


Figure 4-6 Street view of the light pole (2)

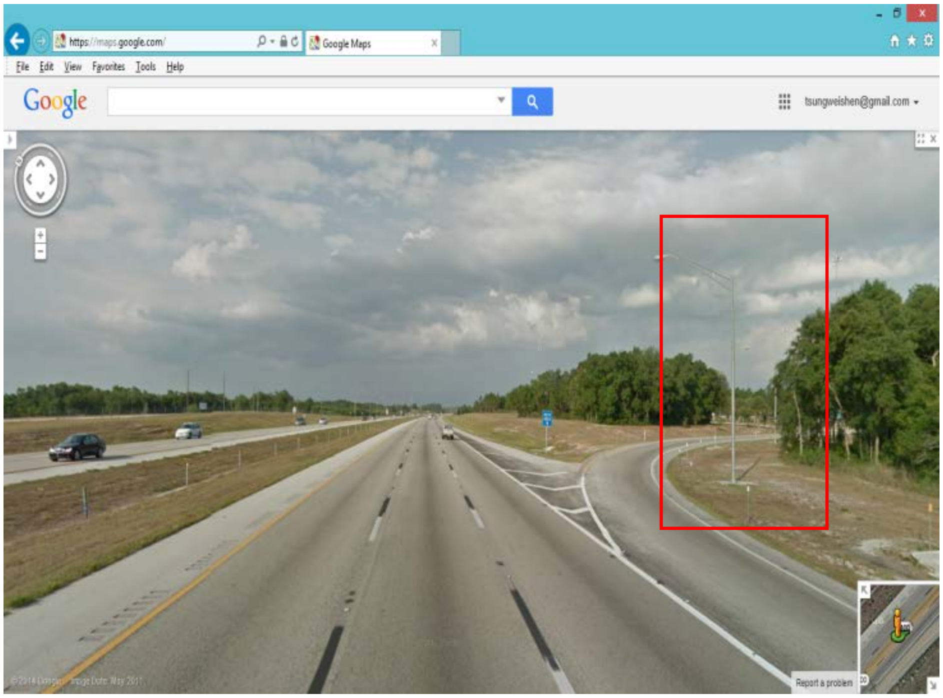


Figure 4-7 Street view of the light pole (3)

Components of the Traffic Sensor

There are three main parts of the detection systems: Wavetronix SmartSensor HD, pole-mount cabinet and power. The Wavetronix SmartSensor HD is a HD Digital Wave Radar, which has a detection range of 250 feet and the ability to simultaneously detect up to 22 lanes of traffic (Figure 4-8). In the pole-mount cabinet, it has the Lightning surge protector (Click 200) and the Event logger (Click 514). Lightning surge protector (Click 200) protects devices from power surges over DC power and serial communication lines (Figure 4-9). Event logger (Click 514) monitors individual vehicle data pushed from SmartSensor HD and forwards it to data logger devices (Figures 4-10 to 4-12). In addition to the above two components, a DataBridge SDR-CF data logger was installed to save the vehicle-based traffic flow data (Figures 4-13 and 4-14). DataBridge SDR-CF is the tool for adding storage to any device. Two 12 V car batteries were connected in series to provide the power of the SmartSensor, event logger and data logger (Figure 4-15).

Figure 4-8 Wavetronix SmartSensor HD

Figure 4-9 Lightning surge protector (first from left)

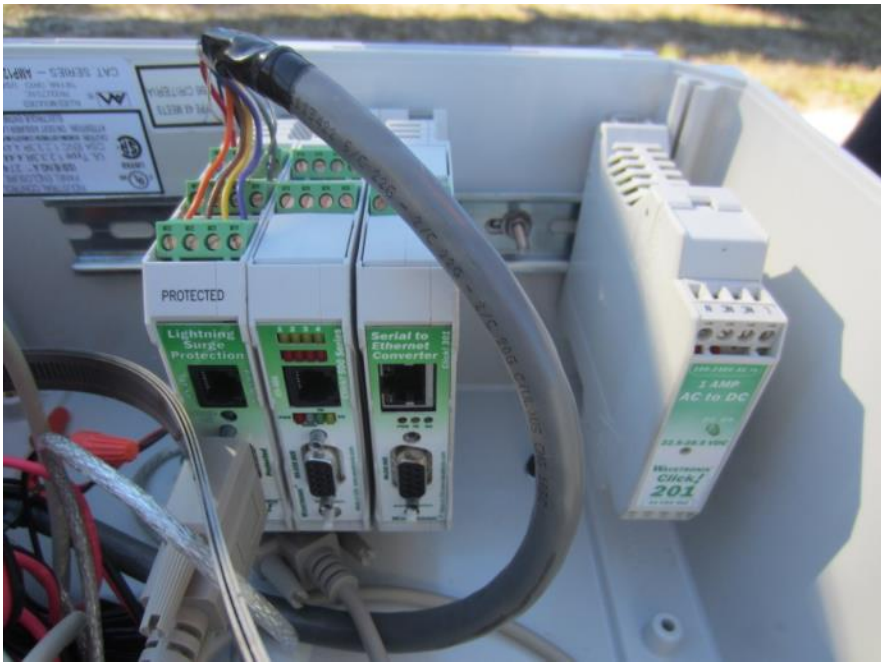


Figure 4-10 Event logger (second from left)

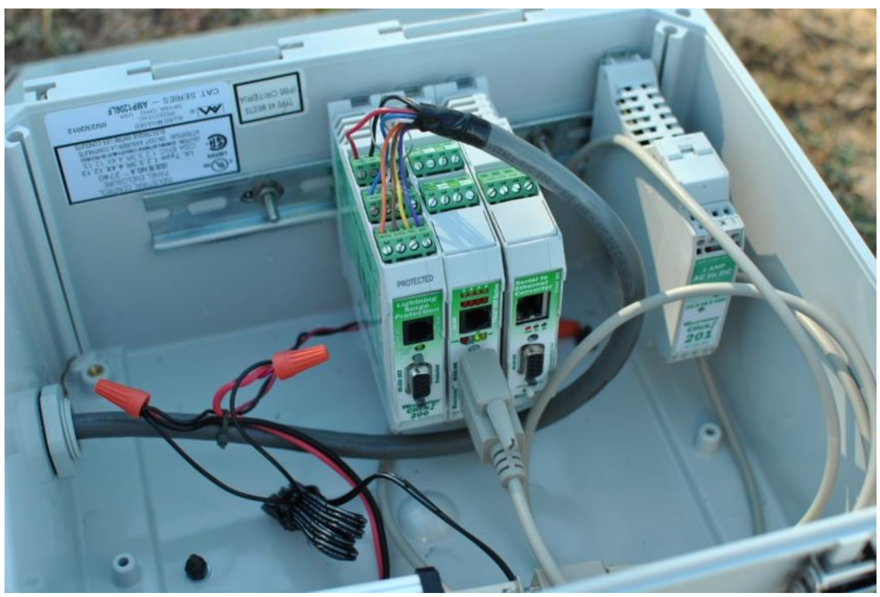


Figure 4-11 The connection between the lightning surge protector and the event logger

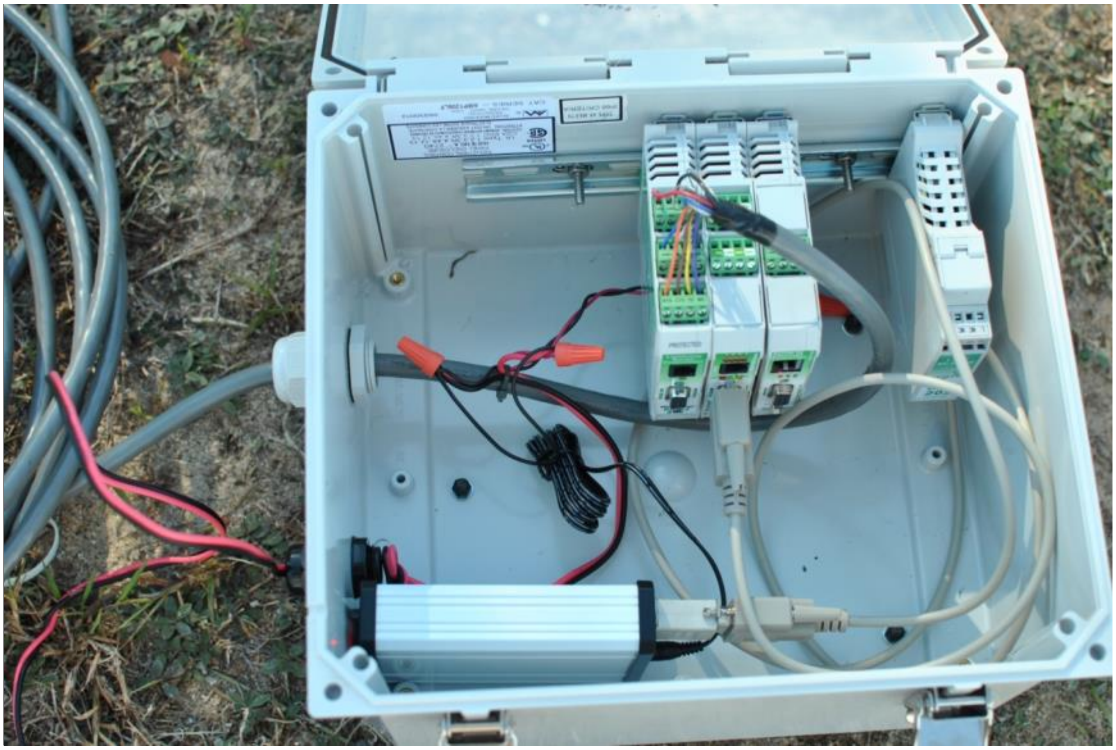


Figure 4-12 All components inside the cabinet

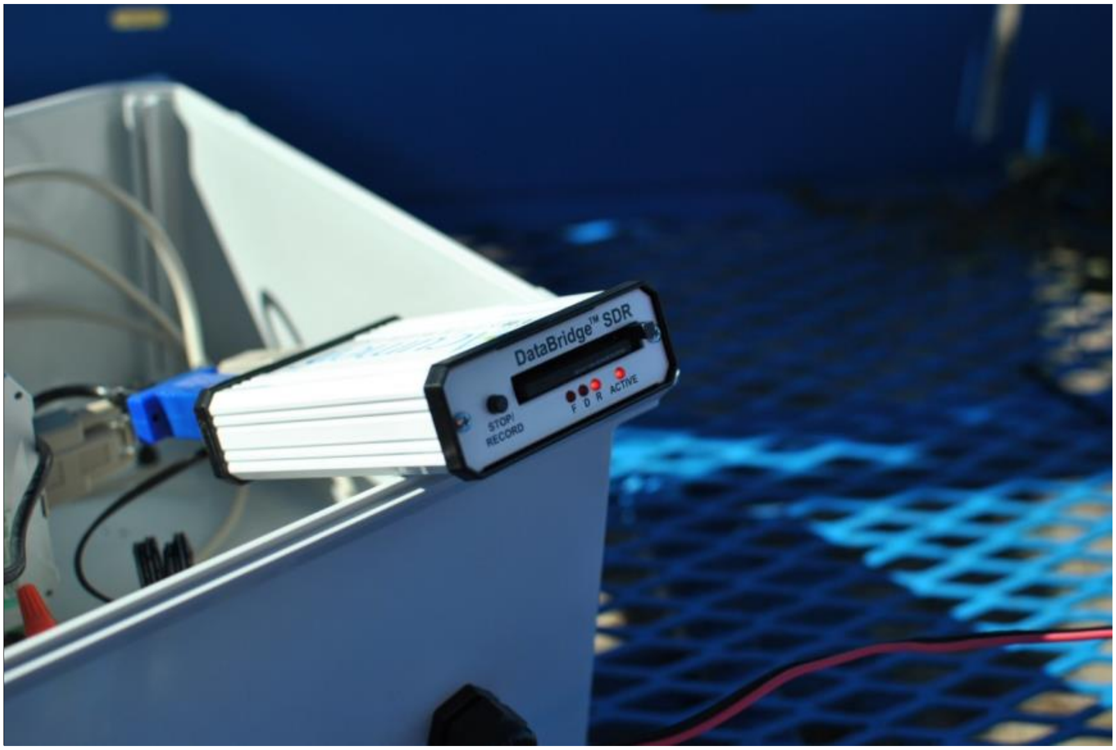


Figure 4-13 DataBridge SDR-CF data logger

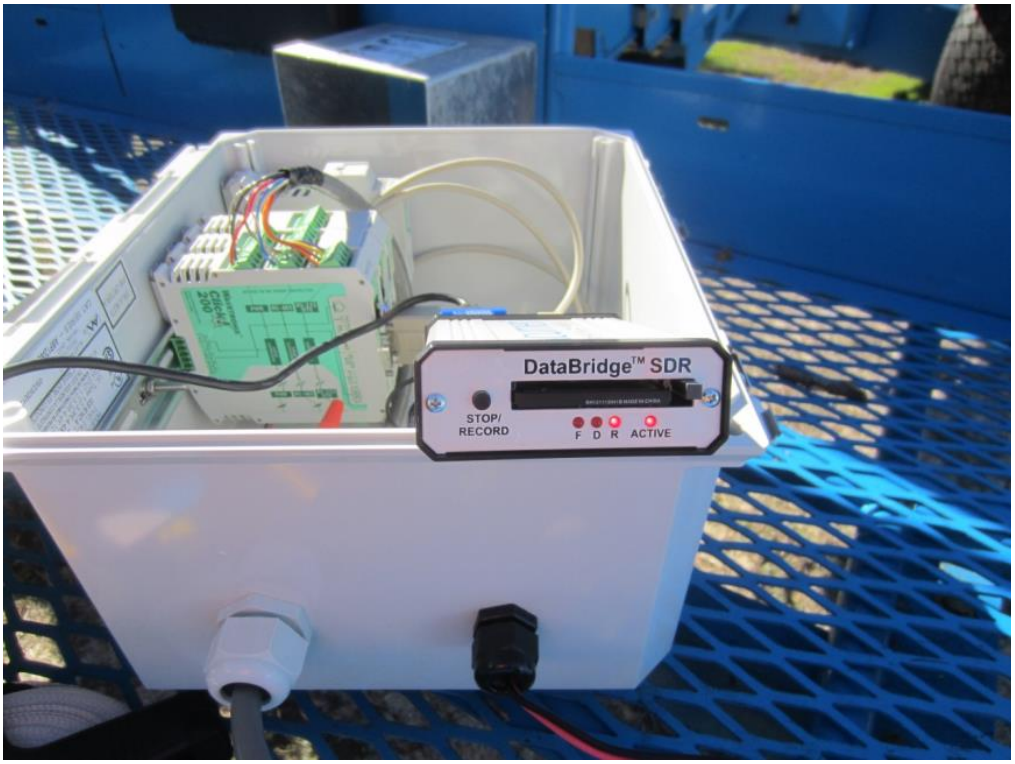


Figure 4-14 The LED indicators show the SDR's current recording status

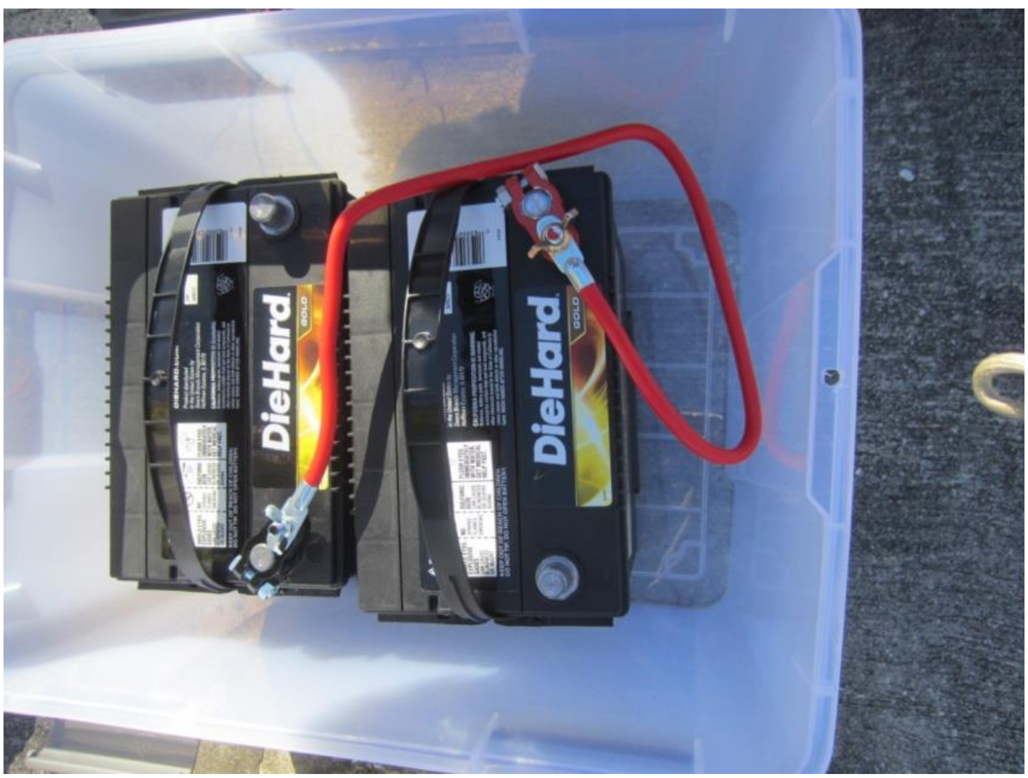


Figure 4-15 Batteries were connected in series

4.2.2 Traffic Data Collection

The traffic data was then collected by Wavetronix SmartSensor HD installed in the above mentioned rest area. The dataset includes eight important variables related to traffic flow characteristics including vehicle speed, vehicle length, duration of detection and lane assignment. The headway of each vehicle can also be calculated from the original dataset. The dataset covers the period from January 31st, 2014 till April. Figure 4-16 shows a sample of the dataset.

	A	B	C	D	E	F	G	H	I
1	date	time	lane	speed	length	range	classification	duration	
2	02/12/201	21:08.8	1	73.7	17.8	72	1	219	
3	02/12/201	21:09.0	2	81.6	15.4	84	1	179	
4	02/12/201	21:09.6	3	76.7	18.1	157.1	1	213	
5	02/12/201	21:11.3	4	68.9	19.4	170.1	1	251	
6	02/12/201	21:11.6	1	80	16	72	1	187	
7	02/12/201	21:12.4	5	68.7	16.5	182.1	1	222	
8	02/12/201	21:15.5	2	77.8	17.4	85	1	205	
9	02/12/201	21:16.1	1	69.2	16.8	74	1	224	
10	02/12/201	21:18.0	4	70	22.6	170.1	1	278	
11	02/12/201	21:18.7	3	81.1	19.5	157.1	1	214	
12	02/12/201	21:19.6	4	76.4	18.7	169.1	1	220	

Figure 4-16 Sample of traffic dataset

4.3 Chapter Summary

This chapter presented the site selection and installation of weather sensors and the traffic sensor. The components of the traffic sensor were also introduced in detail. After that, a sample of collected weather data, traffic data and combined datasets were shown in this chapter.

5. DATA ANALYSIS OF IMPACT OF REDUCED VISIBILITY ON TRAFFIC FLOW AND CRASH RISKS

The impact of reduced visibility on traffic flow characteristics is analyzed in this section. Two fog cases were selected and analyzed by comparing them with clear cases to figure out the difference of traffic flow characteristics under different situations. Moreover, the vehicles were divided into two types including passenger cars and trucks in order to identify whether the impact of visibility on traffic flow characteristics is different for different vehicle types. After that, the traffic flow characteristics under different visibility levels and the effects of reduced visibility on different lanes were analyzed.

5.1 Preliminary Analysis of a Fog Case

5.1.1 Analysis of Traffic Flow Characteristics in a Fog Case

The fog case was selected on Feb 2nd morning. The period of fog formation is from 6:30am to 9:00am in the morning. The relationship between mean speed and visibility is shown in Figure 5-1. It can be seen from that there is a slight drop in speed during reduced visibility. The mean speed drops to around 70 mph during the fog period. The relationship between speed variation and visibility is shown in Figure 5-2. It is shown from this figure that the speed variation increases at the beginning of the fog formation and the speed variation is larger during the fog period.

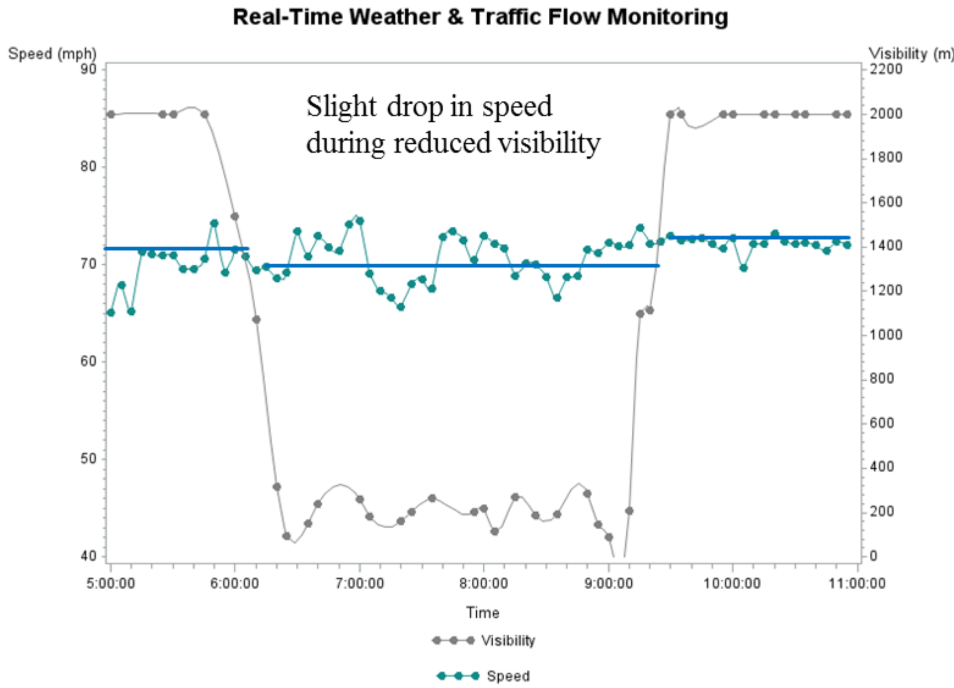


Figure 5-1 Relationship between mean speed and visibility

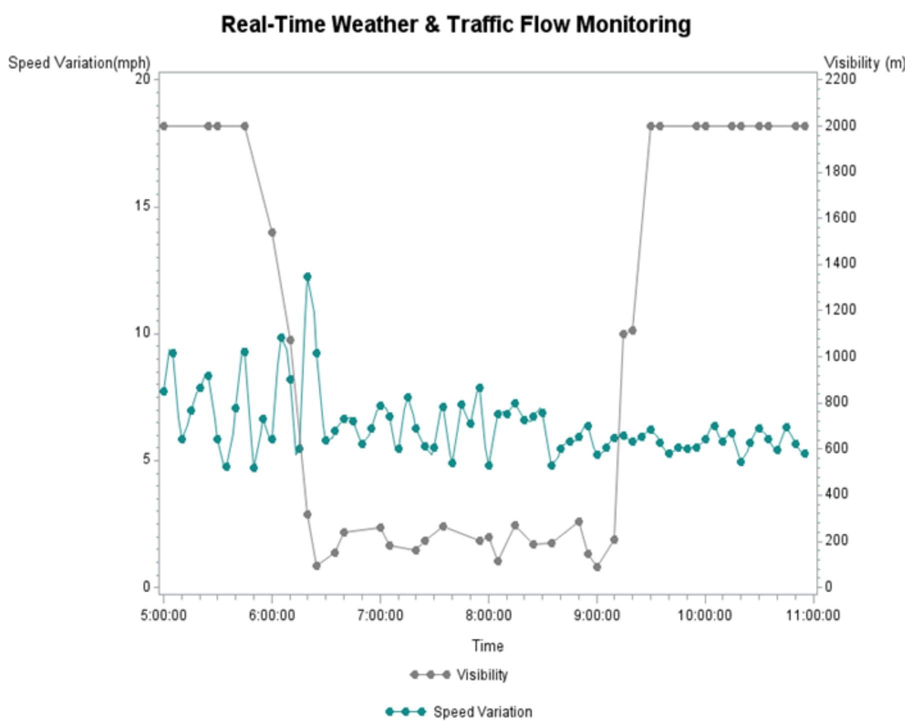


Figure 5-2 Relationship between speed variation and visibility

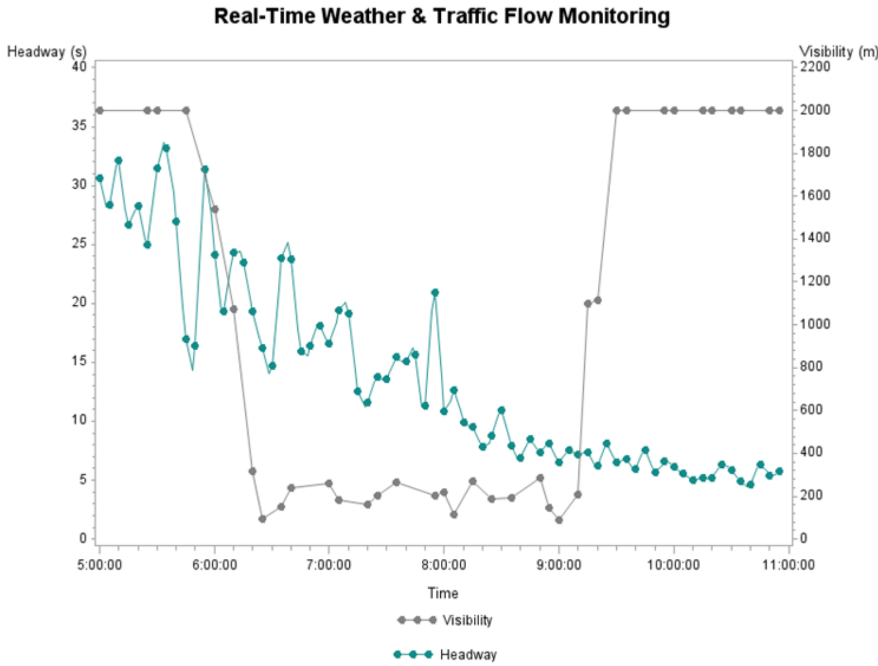


Figure 5-3 Relationship between headway and visibility

The relationship between headway and visibility is shown in Figure 5-3. It seems that the headway keeps decreasing during the fog period. The main reason for this is that the traffic volume also increases during this period. Therefore, the impact of reduced visibility on mean headway was not clearly shown from this Figure. It is easier to figure out the impact of reduced visibility on mean headway when the volume is more stable during the fog period. It can be seen from the figure that the headway variation is larger in the fog period.

5.1.2 Comparison of Traffic Flow Characteristics between Fog Case and Clear Case

The same period from 6:30am to 9:00am on Feb 9th morning was selected as the clear case to compare the traffic flow characteristics between fog case and clear case. The reason to choose this date is that it is the same weekday as Feb 2nd. Therefore, the volume is expected to be similar in those two days and it will be easier to investigate the effect of reduced visibility. Five important traffic flow variables including headway, speed, speed variation, headway variation and volume were compared using t-tests to identify the difference of these variables in fog case and clear case.

5.1.2.1 Headway

The comparison of the headway under the fog and clear cases is carried by comparing the mean value of the logarithm of headway using the t-test. The value of the mean in fog case is 2.6708 seconds, while the value of the mean in clear case is 2.4351 seconds. The P- value showed to be less than 0.0001 which indicates that the mean value is significantly different in both cases.

Table 5-1 Summary of t-test for logarithm of headway

Parameter	Analysis Cases	
	Fog Case	Clear Case
Sample size	300	300
Mean	2.6708	2.4351
95% CL Mean	2.6125-2.7290	2.3836-2.4866
Maximum Value	4.2729	3.7710
Minimum Value	1.5064	1.3863
Standard deviation	0.5129	0.4535
P-Value	<.0001	

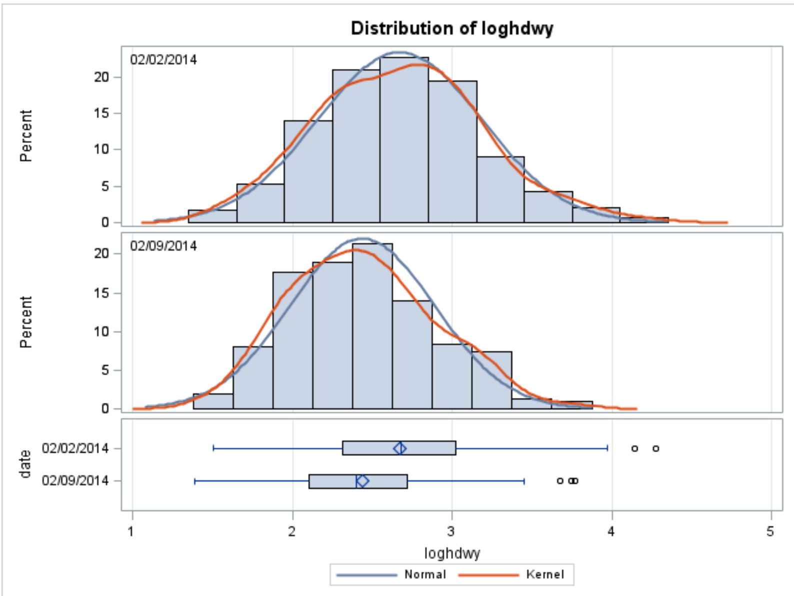


Figure 5-4 Distribution of logarithm of headway

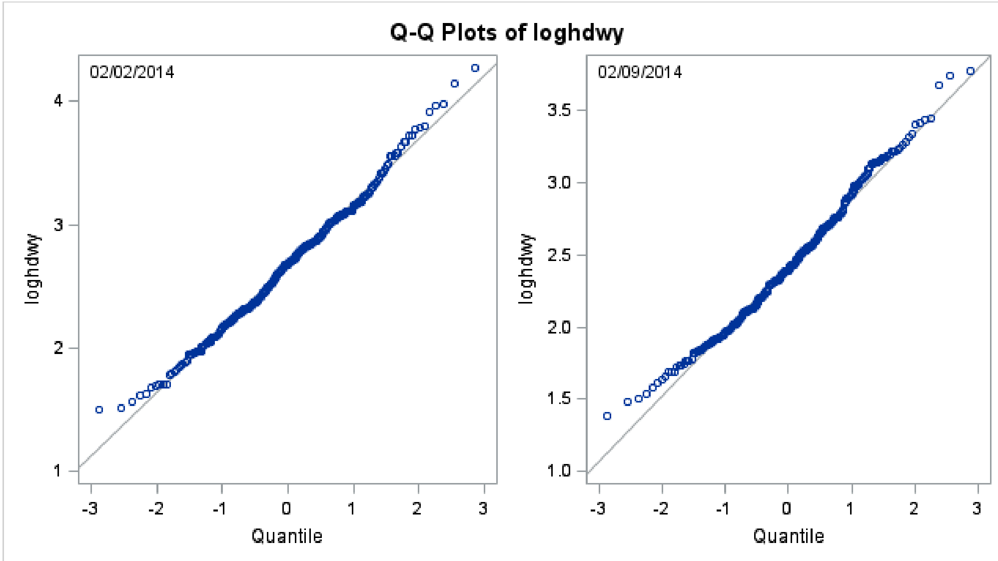


Figure 5-5 Q-Q plots of logarithm of headway

The distribution of logarithm of headway in both cases is shown in Figure 5-4. The top one is the distribution for the fog case and the bottom one is the distribution for the clear case. It can be seen from above figure that the mean headway is significantly higher in the fog case. The Q-Q plot in shown in Figure 5-5 indicates that the logarithm of headway in both cases follows the normal distribution.

6.1.2.2 Mean Speed

The comparison of the mean speed under fog case and clear case is carried out by comparing the mean value of the mean speed using the t-test. The value of the mean in fog case is 70.61 mph, while the value of the mean in clear case is 73.37 mph. The P- value showed to be less than 0.0001 which indicates that the mean value is significantly different in both cases.

Table 5-2 Summary of t-test for mean speed

Parameter	Analysis Cases	
	Fog Case	Clear Case
Sample size	300	300
Mean	70.6139	73.3785
95% CL Mean	70.2258-71.0020	73.1235-73.6334
Maximum Value	84.1500	78.5658
Minimum Value	60.9567	65.5000
Standard deviation	3.4156	2.2442
P-Value	<.0001	

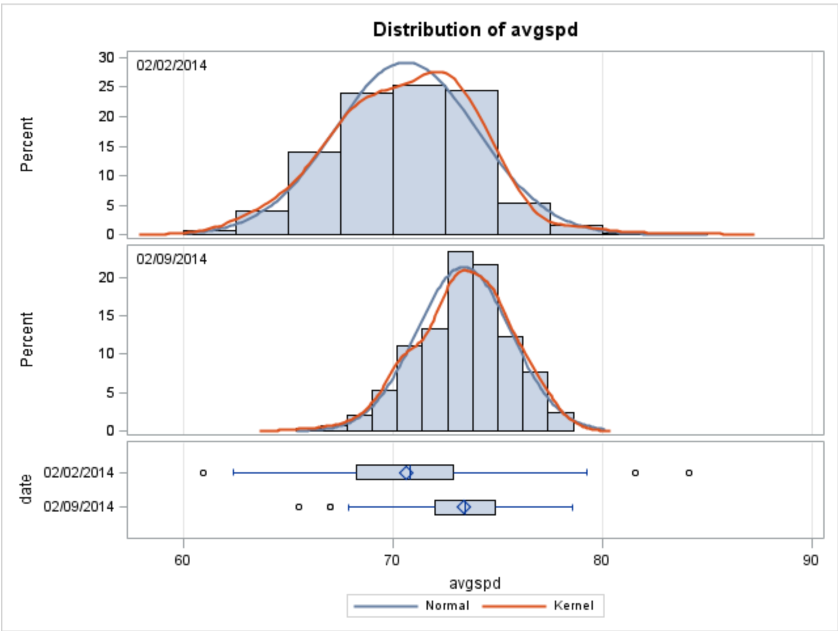


Figure 5-6 Distribution of mean speed

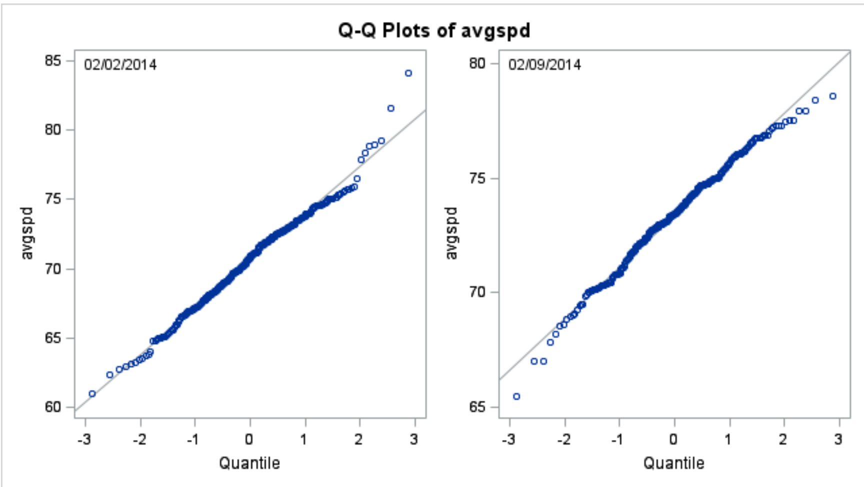


Figure 5-7 Q-Q plots of mean speed

The distribution of mean speed in both cases is shown in Figure 5-6. The top one is the distribution for the fog case and the bottom one is the distribution for the clear case. It can be seen that the mean speed is significantly lower in fog case. The Q-Q plot illustrated in Figure 5-7 indicates that the mean speeds in both cases follows the normal distribution.

6.1.2.3 Standard Deviation of Speed

The comparison of the standard deviation of speed under fog case and clear case is carried out by comparing the mean value of the standard deviation of speed using the t-test. The P-value showed to be 0.48 which indicates that the mean value is not significant different in both cases, although it appears that the standard deviation of speed is higher in the fog condition.

Table 5-3 Summary of t-test for standard deviation of speed

Parameter	Analysis Cases	
	Fog Case	Clear Case
Sample size	300	300
Mean	5.7945	5.6975
95% CL Mean	5.5828-6.0063	5.5226-5.8724
Maximum Value	12.4364	12.0994
Minimum Value	0.1768	1.8385
Standard deviation	1.8606	1.5397
P-Value	0.4871	

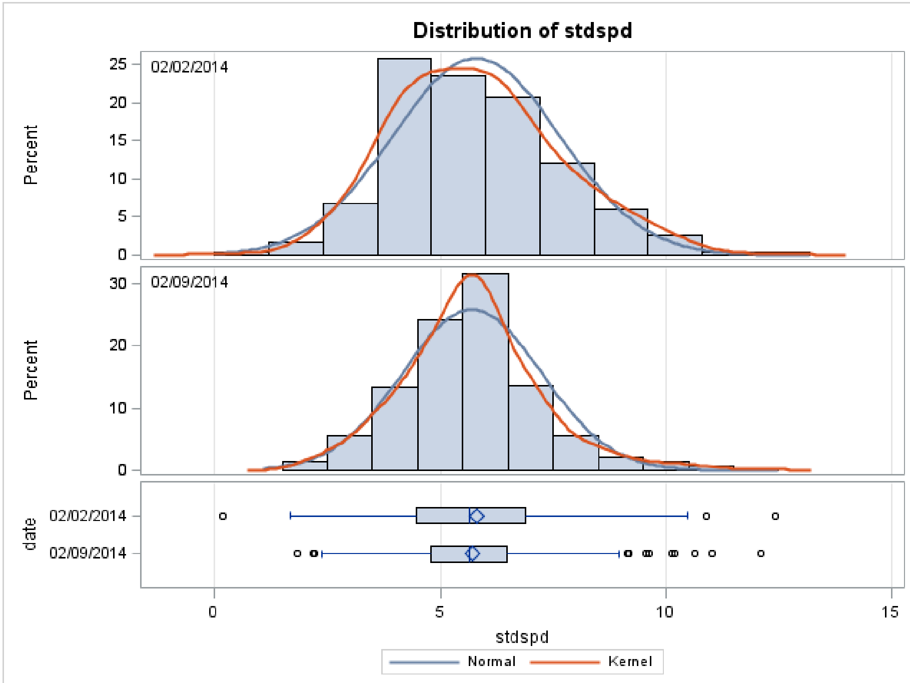


Figure 5-8 Distribution of standard deviation of speed

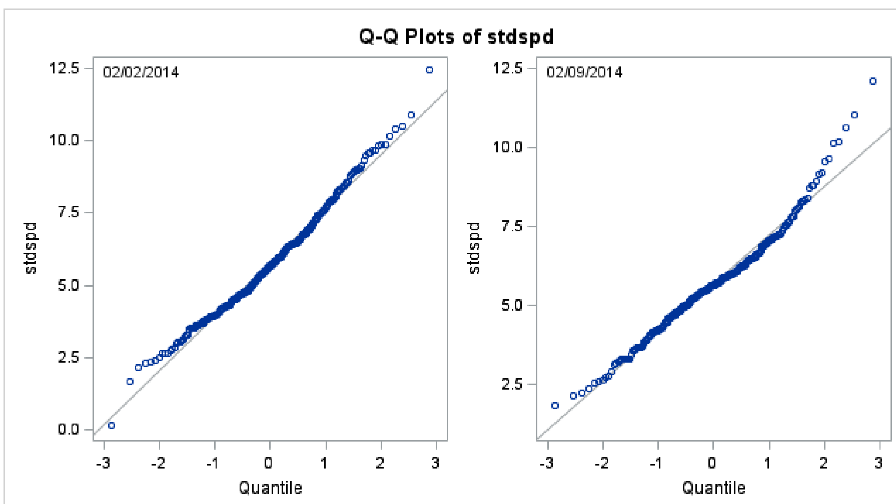


Figure 5-9 Q-Q plots of standard deviation of speed

The distribution of standard deviation of speed in both cases is shown in Figure 5-8. The top one is the distribution for the fog case and the bottom one is the distribution for the clear case. It can be seen that standard deviation of speed is slightly higher in fog case. The impact of reduced visibility on standard deviation of speed is not significant**.** The Q-Q plot in Figure 5-9 indicates that standard deviation of speed in both cases follows the normal distribution.

6.1.2.4 Standard Deviation of Headway

The comparison of the standard deviation of headway under fog case and clear case is carried by comparing the mean value of the standard deviation of headway using the T-test. The value of the mean in fog case is 15.705 s, while the value of the mean in clear case is 11.892 s. The P-value showed to be less than 0.05 which indicates that the mean value is significant different in both cases. The variance of standard deviation of headway is larger in fog case.

Table 5-4 Summary of t-test for standard deviation of headway

Parameter	Analysis Cases	
	Fog Case	Clear Case
Sample size	300	300
Mean	15.705	11.892
95% CL Mean	14.623-16.786	11.026-12.758
Maximum Value	68.32	74.74
Minimum Value	3.65	3.54
Standard deviation	0.8232	1.8632
P-Value	<0.0001	

The distribution of standard deviation of standard deviation of headway in both cases is shown in Figure 5-10. The top one is the distribution for the fog case and the bottom one is the distribution for the clear case. It can be seen that standard deviation of headway is higher in fog case.

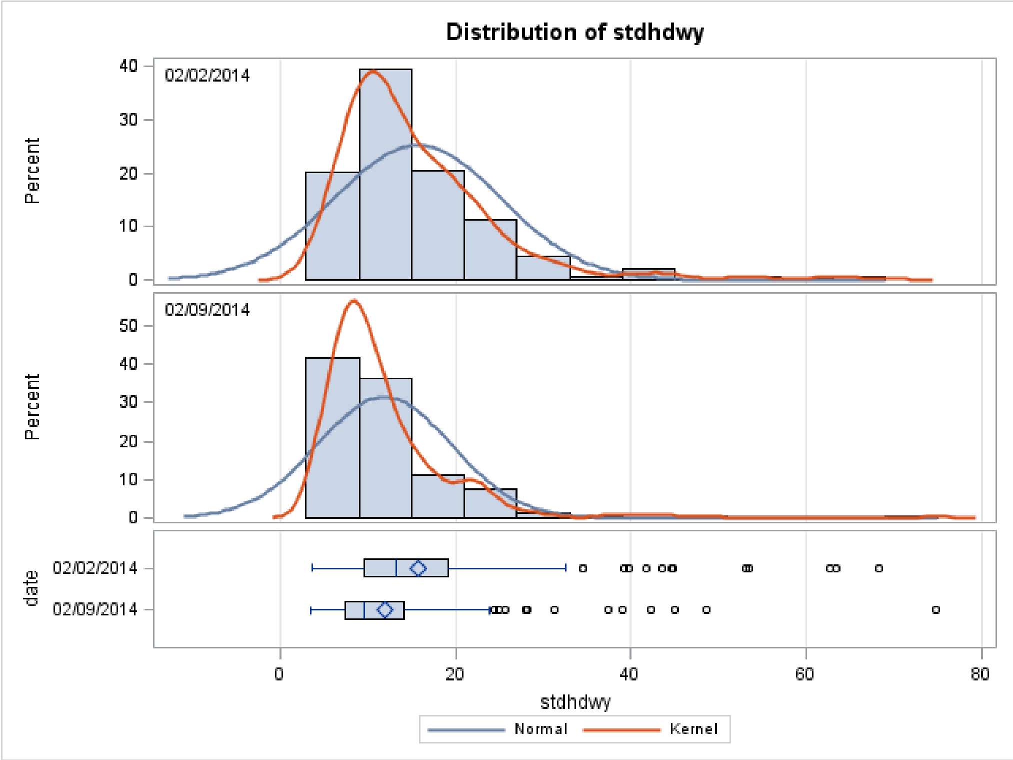


Figure 5-10 Distribution of standard deviation of headway

6.1.2.5 Volume

The comparison of the volume under fog case and clear case is carried out by comparing the mean value of the volume using the t-test. The value of the mean in fog case is 13.85 vehicles per minute per direction, while the value of the mean in clear case is 17.15 vehicles per minute per direction. The P-value showed to be less than 0.0001 which indicates that the mean value is significantly different in both cases.

Table 5-5 Summary of t-test for volume

Parameter	Analysis Cases	
	Fog Case	Clear Case
Sample size	300	300
Mean	13.8500	17.1500
95% CL Mean	12.9926-14.7074	16.2881-18.0119
Maximum Value	42.0000	42.0000
Minimum Value	1.0000	2.0000
Standard deviation	7.5461	7.5859
P-Value	<.0001	

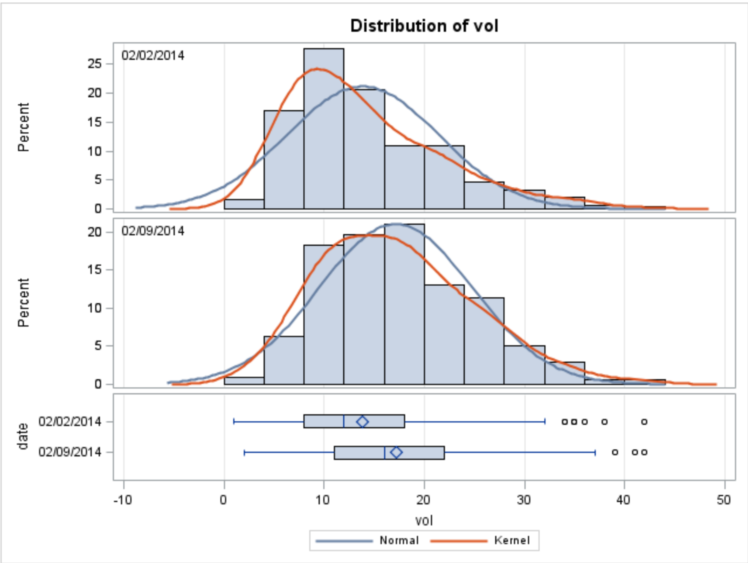


Figure 5-11 Distribution of volume

The distribution of volume in both cases is shown in Figure 5-11. The top one is the distribution for the fog case and the bottom one is the distribution for the clear case. It can be seen that the volume is significant lower in fog case. The Q-Q plot in Figure 5-12 indicates that volume in clear case follows the normal distribution very well while the volume in fog case does not follow the normal distribution very well.

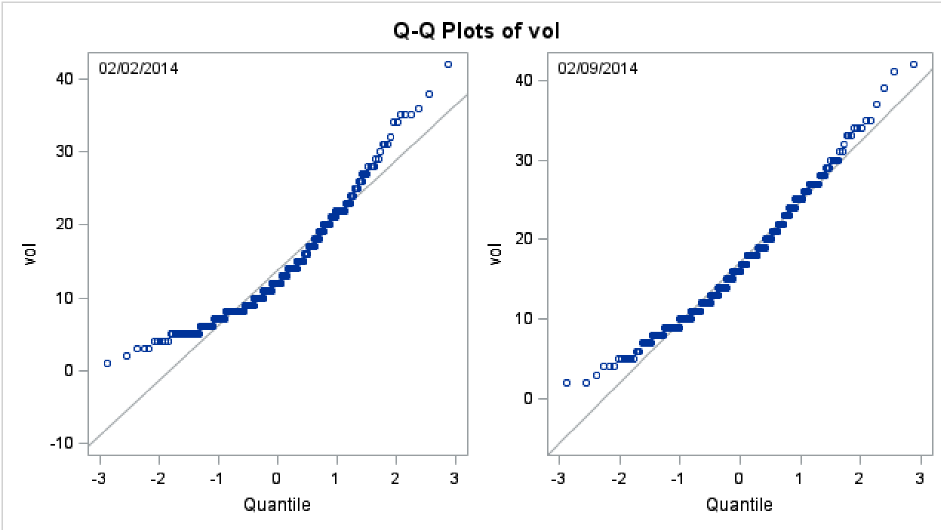


Figure 5-12 Q-Q plots of volume

5.1.3 Scatterplot Analysis

The scatterplot was used to analyze the relationship between several traffic flow characteristics including speed, headway and volume in both fog case and clear case. The research team wants to figure out whether the relationship between several traffic flow characteristics is different in both cases.

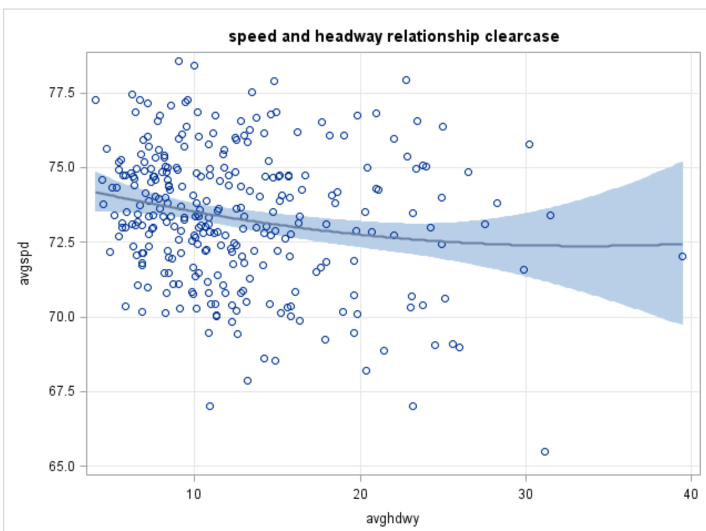


Figure 5-13 Speed and headway relationship in clear case

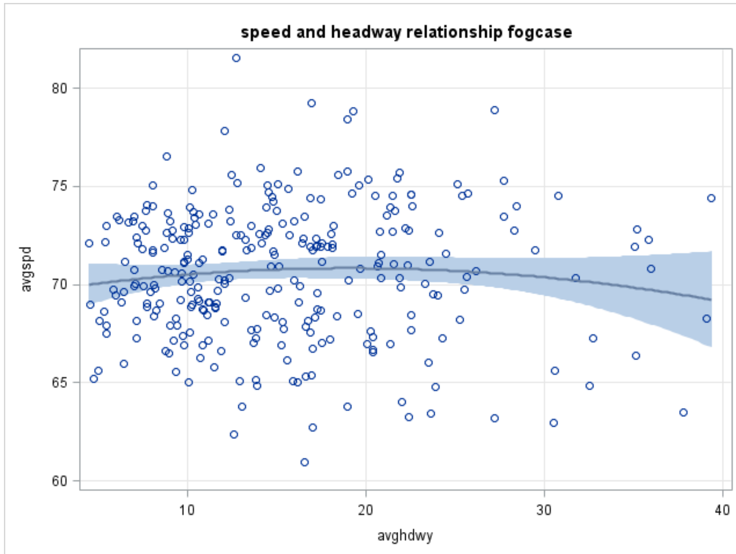


Figure 5-14 Speed and headway relationship in fog case

The speed and headway relationship in both cases is shown in Figures 5-13 and Figure 5-14. There is obvious difference in the relationship between speed and headway in both cases. It can be seen from the Figure 5-13 that the headway increases as the mean speed decreases in the clear case while this trend is not that obvious as it is shown in Figure 5-14. There is not significant change for the mean speed as the headway increases in the fog case.

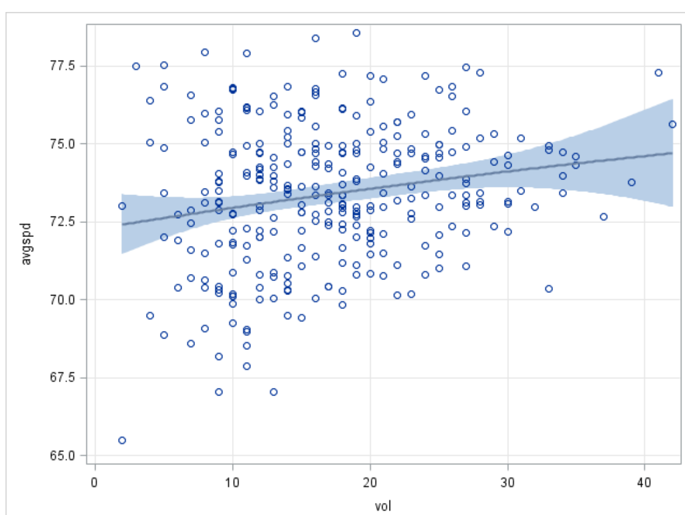


Figure 5-15 Speed and volume relationship in clear case

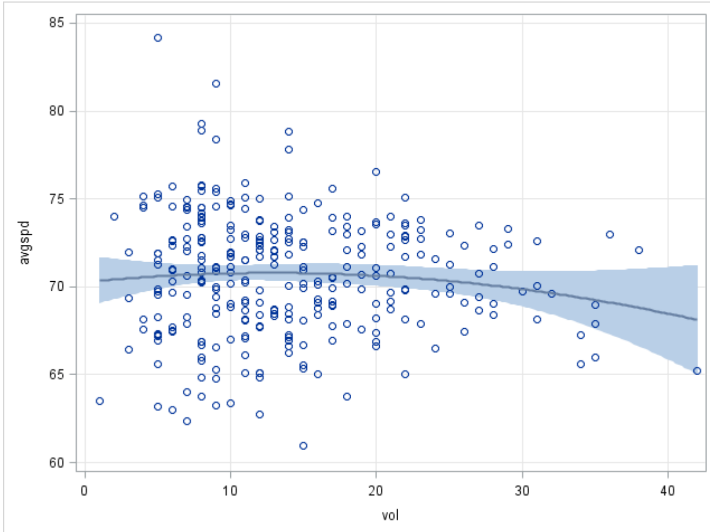


Figure 5-16 Speed and volume relationship in fog case

The speed and volume relationship in both cases is shown in Figures 5-15 and 5-16. There is also obvious difference in the relationship between speed and volume in both cases. It can be seen from Figure 5-15 that the volume increases as the mean speed increases in the clear case while the trend is not the same as it is shown in Figure 5-16. The mean speed remains constant or even slightly drops as the volume increases in the fog case.

5.2 Analysis of Impacts of Reduced Visibility on Different Types of Vehicles

In this section, the vehicles were divided into two types including passenger cars and trucks in order to figure out whether the impact of visibility on traffic flow characteristics is different in different vehicle types. The type of vehicles was divided based on the length of vehicles. The vehicle is considered as truck when the length of vehicle is above 30 feet and it is considered as passenger cars when the length of vehicle is equal to or less than 30 feet. The datasets used in this section were the combined data of weather data and traffic data, which covers the period from Jan 31th to Mar 11th.

5.2.1 Comparison of Reduced Visibility on Speed

The comparison of the speed of both vehicle types under fog case and clear case is carried by comparing the mean value of the speed using T-test. The value of the mean for the passenger cars in fog case is 72.01 mph, while the value of the mean in clear case is 73.18 mph. The value of the mean for the trucks in fog case is 65.79 mph, while the value of the mean in clear case is 66.89 mph. It can be seen that the mean speed of both vehicle types decreases around 1.1 mph during the fog case. The P-value for both vehicle types showed to be less than 0.001 which indicates that the mean value is significantly different in both cases.

Table 5-6 Summary of t-test for speed

Vehicle Type	Parameter	Analysis Cases	
		Fog Case	Clear Case
Passenger Cars	Sample size	367	7177
	Mean	72.01	73.18
	95% CL Mean	71.67-72.37	73.15-73.22
	Maximum Value	76.90	78.65
	Minimum Value	47.97	45.86
	Standard deviation	3.42	1.57
	P-Value	<0.001	
Truck	Sample size	365	7174
	Mean	65.79	66.89
	95% CL Mean	65.53-66.03	66.84-66.92
	Maximum Value	72.25	75.30
	Minimum Value	49.03	40.76
	Standard deviation	2.65	1.73
	P-Value	<0.001	

The distribution of speed in both cases is shown in Figure 5-17 and Figure 5-18. The top one in each figure is the distribution for the fog case and the bottom one is the distribution for the clear case. It can be seen from these two figures that the mean speed of both vehicle types is significantly lower in the fog case.

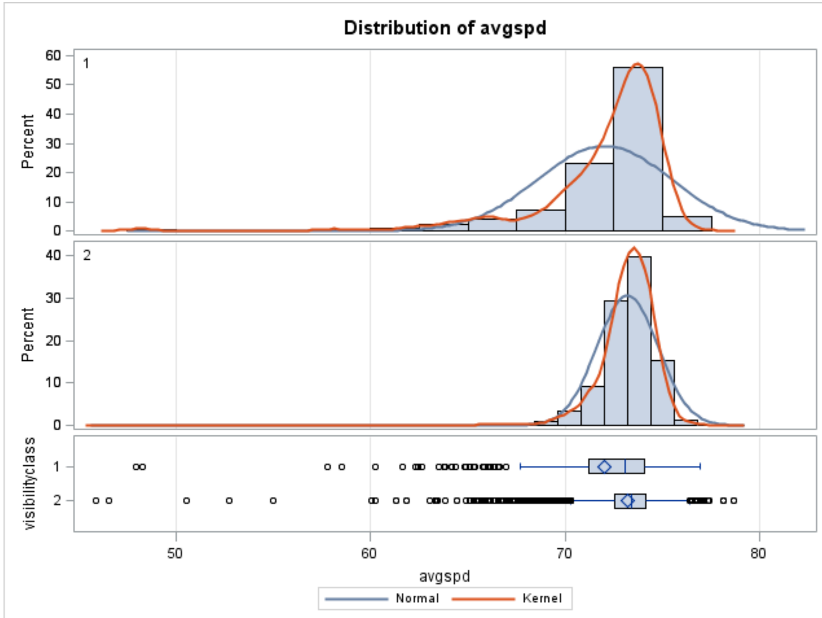


Figure 5-17 Distribution of mean speed

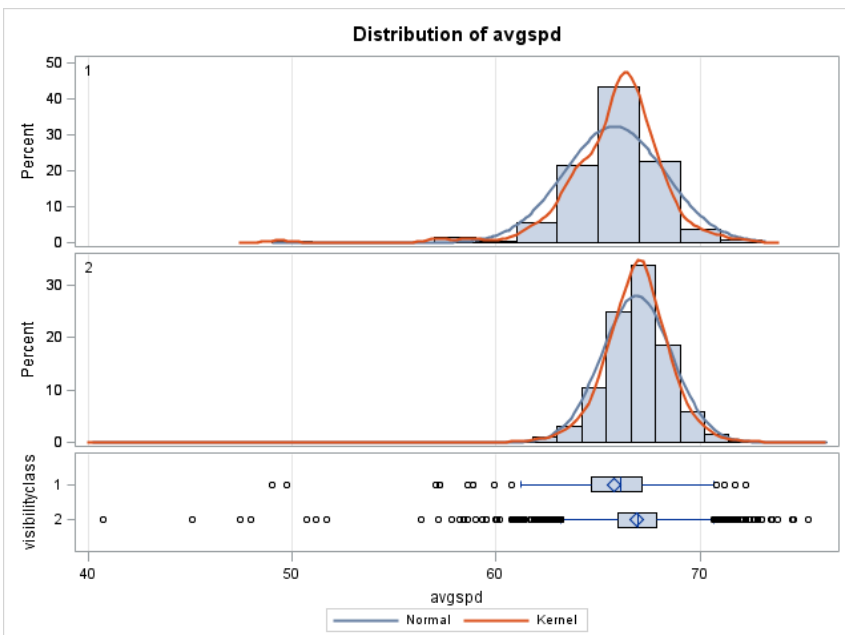


Figure 5-18 Distribution of mean speed for trucks

5.2.2 Comparison of Reduced Visibility on Headway

The comparison of the headway of both vehicle types under fog case and clear case is carried by comparing the mean value of the logarithm of headway using T-test. The value of the mean for the passenger cars in fog case is 2.36 seconds, while the value of the mean in clear case is 1.99 seconds. The value of the mean for the trucks in fog case is 2.56 seconds, while the value of the mean in clear case is 2.27 seconds. It can be seen that the mean headway of passenger cars and trucks increases 0.37 seconds and 0.29 seconds separately during the fog case. The effect of reduced visibility on headway of passenger cars is larger compared to trucks. The P-value for both vehicle types showed to be less than 0.001 which indicates that the mean value is significant different in both cases.

Table 5-7 Summary of t-test for logarithm of headway

Vehicle Type	Parameter	Analysis Cases	
		Fog Case	Clear Case
Passenger Cars	Sample size	367	7177
	Mean	2.36	1.99
	95% CL Mean	2.29-2.44	1.97-2.00
	Maximum Value	3.81	0.82
	Minimum Value	1.27	4.10
	Standard deviation	0.78	0.79
	P-Value	<0.001	
Truck	Sample size	365	7174
	Mean	2.56	2.27
	95% CL Mean	2.50-2.63	2.25-2.29
	Maximum Value	4.05	4.26
	Minimum Value	1.60	0.35
	Standard deviation	0.67	0.64
	P-Value	<0.001	

The distribution of logarithm of headway in both cases is shown in Figure 5-19 and Figure 5-20. The top one in each figure is the distribution for the fog case and the bottom one is the distribution for the clear case. It can be seen from these two figures that the headway of both vehicle types is significantly higher in the fog case.

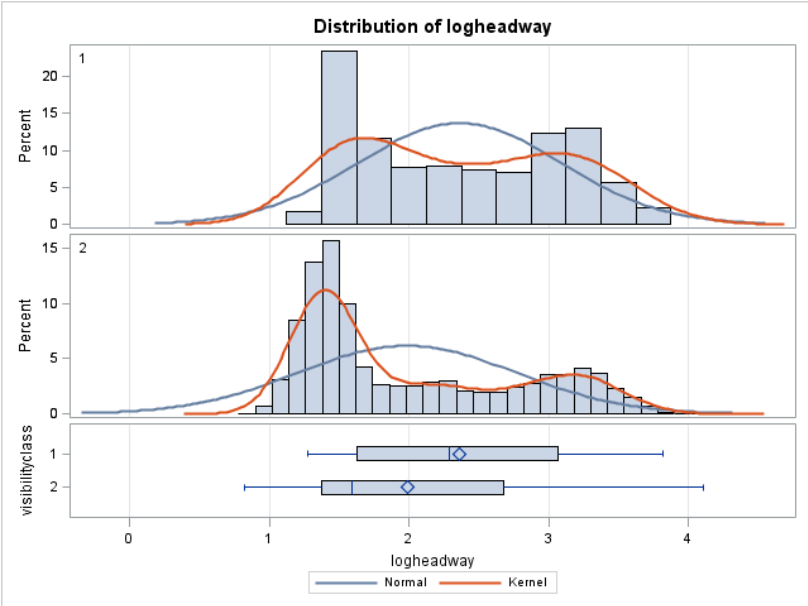


Figure 5-19 Distribution of logarithm of headway for cars

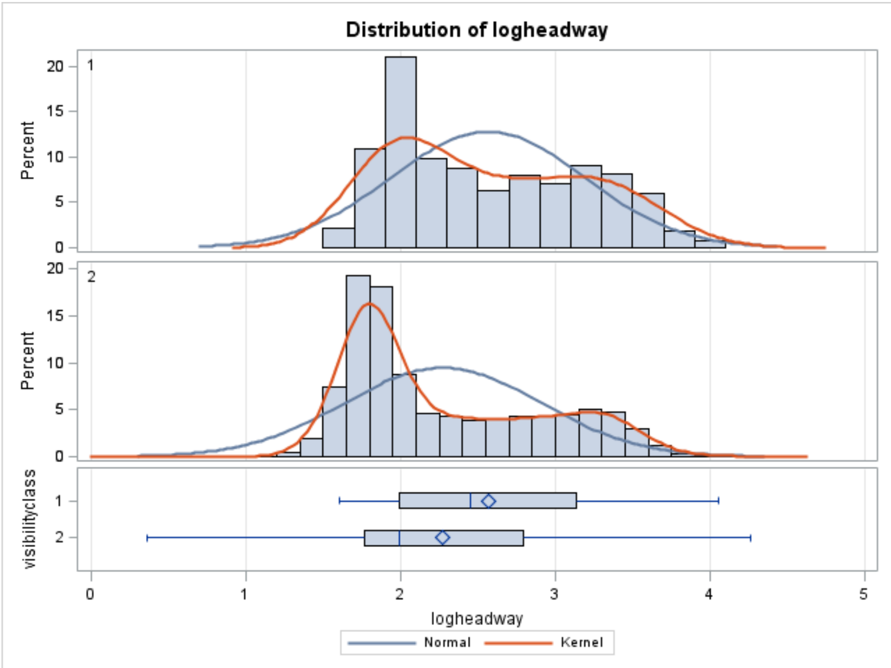


Figure 5-20 Distribution of logarithm of headway for trucks

5.2.3 Comparison of Reduced Visibility on Speed Variation

The comparison of the speed variation of both vehicle types under fog case and clear case is carried by comparing the mean value of the standard deviation of speed using T-test. The value of the mean for the passenger cars in fog case is 6.10 mph, while the value of the mean in clear case is 5.77 mph. The value of the mean for the trucks in fog case is 5.62 mph, while the value of the mean in clear case is 5.60 mph. It can be seen that the standard deviation of speed of passenger cars and trucks increases 0.33 mph and 0.02 mph separately during the fog case. The effect of reduced visibility on standard deviation of trucks is not significant. The P-value for passenger cars showed to be less than 0.001 which indicates that the mean value is significantly different.

Table 5-8 Summary of t-test for standard deviation of speed

Vehicle Type	Parameter	Analysis Cases	
		Fog Case	Clear Case
Passenger Cars	Sample size	367	7177
	Mean	6.10	5.77
	95% CL Mean	6.01-6.20	5.75-5.79
	Maximum Value	11.82	20.64
	Minimum Value	3.71	2.52
	Standard deviation	1.01	0.91
	P-Value	<0.001	
Truck	Sample size	365	7174
	Mean	5.62	5.60
	95% CL Mean	5.48-5.77	5.57-5.63
	Maximum Value	14.99	15.99
	Minimum Value	0.99	0.05
	Standard deviation	1.51	1.39
	P-Value	0.78	

The distribution of logarithm of headway in both cases is shown in Figure 5-21 and Figure 5-22. The top one in each figure is the distribution for the fog case and the bottom one is the distribution for the clear case. It can be seen from both figures that the speed variation of passenger cars is significantly higher in the fog case while the speed variation for the trucks is not.

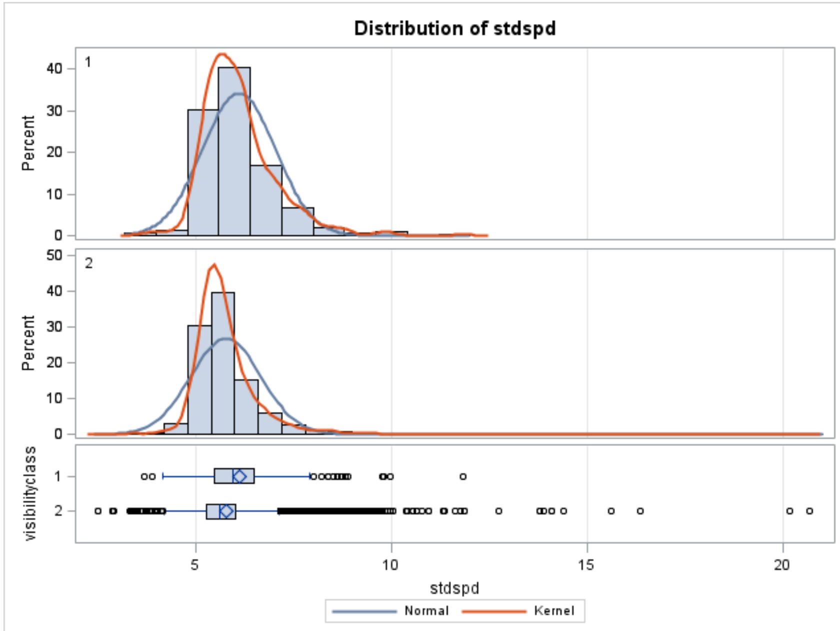


Figure 5-21 Distribution of standard deviation of speed

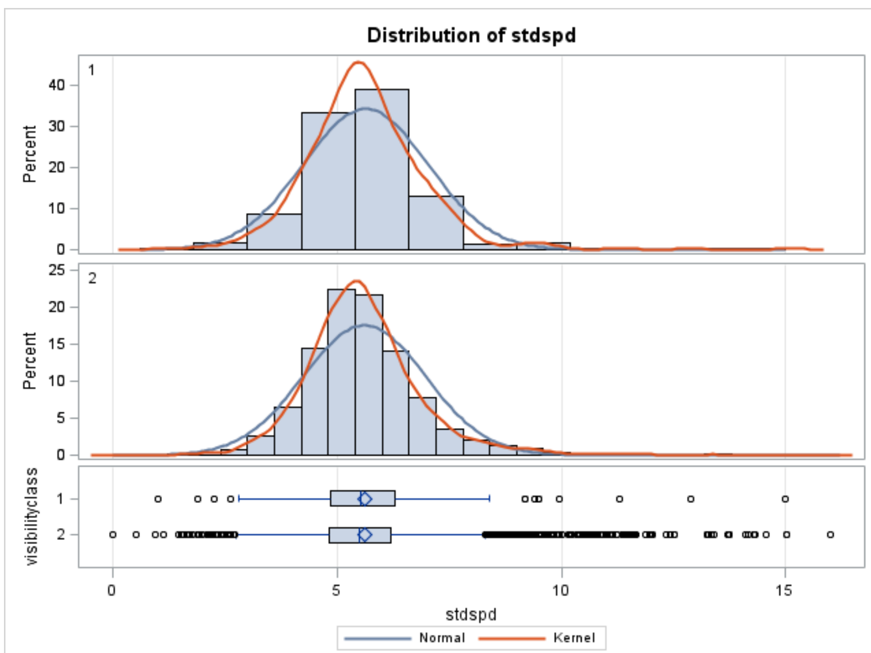


Figure 5-22 Distribution of standard deviation of speed for trucks

5.2.4 Comparison of Reduced Visibility on Headway Variation

The comparison of the standard deviation of headway under fog case and clear case is carried by comparing the mean value of the standard deviation of headway using the T-test. The value of the mean for the passenger cars in fog case is 13.03 seconds, while the value of the mean in clear case is 9.48 seconds. The value of the mean for the trucks in fog case is 12.59 seconds, while the value of the mean in clear case is 9.64 seconds. It can be seen that the standard deviation of headway of passenger cars and trucks increases 3.55 seconds and 2.95 seconds separately during the fog case. The effect of reduced visibility on standard deviation of headway of passenger cars is larger compared to trucks. The P-value for both vehicle types showed to be less than 0.001 which indicates that the mean value is significant different in both cases.

Table 5-9 Summary of t-test for standard deviation of headway

Vehicle Type	Parameter	Analysis Cases	
		fog Case	clear Case
Passenger Cars	Sample size	367	7177
	Mean	13.03	9.48
	95% CL Mean	12.20-13.88	9.31-9.66
	Maximum Value	40.14	37.74
	Minimum Value	3.71	1.81
	Standard deviation	8.83	7.65
	P-Value	<0.001	
Truck	Sample size	365	7174
	Mean	12.59	9.64
	95% CL Mean	11.81-13.36	9.48-9.80
	Maximum Value	39.19	48.11
	Minimum Value	3.27	0.32
	Standard deviation	8.13	7.05
	P-Value	<0.001	

The distribution of standard deviation of headway in both cases is shown in Figure 5-23 and Figure 6.24. The top one in each figure is the distribution for the fog case and the bottom one is the distribution for the clear case. It can be seen from these two figures that standard deviation of headway of both vehicle types is significantly higher in the fog case.

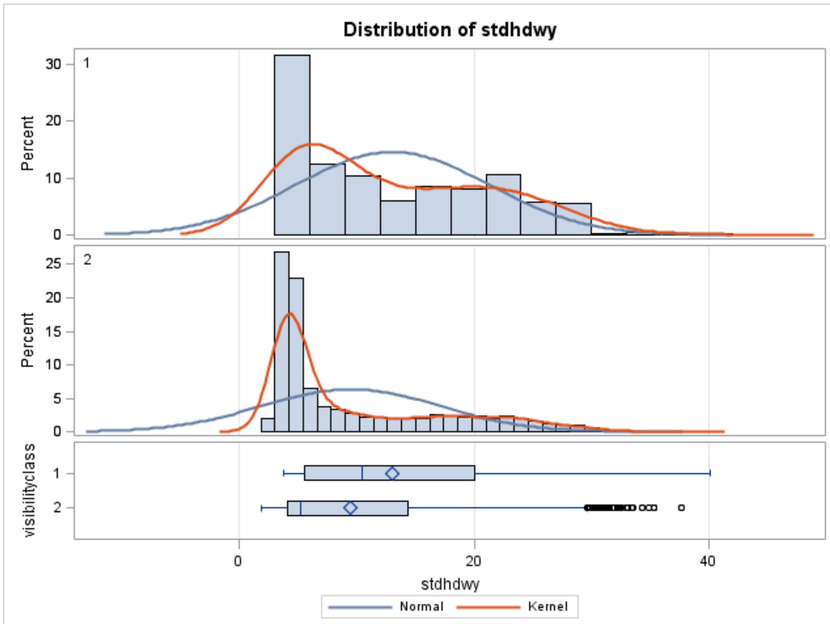


Figure 5-23 Distribution of standard deviation of headway for cars

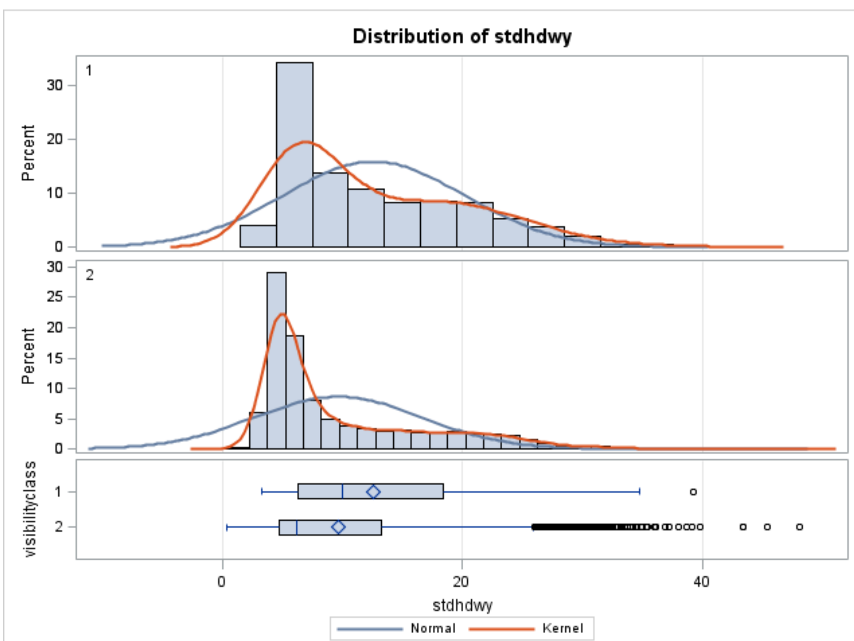


Figure 5-24 Distribution of standard deviation of headway for trucks

5.3 Effects of Reduced Visibility on Traffic Flow Characteristics using ANOVA

The method of Analysis of variance (ANOVA) is used in this project to compare the differences between several group means and their associated variations. This method provides a powerful statistical test of comparing means of more than two groups and it is a generalization of t-test. As doing multiple two-sample t-tests is not convenient and would result in an increased chance of errors, ANOVA is useful in comparing means of three or more groups for statistical significance. In this section ANOVA is used to further analyze the traffic flow characteristics under different visibility levels and the effects of reduced visibility on different lanes. The datasets used in this section were the combined dataset mentioned in section 4.5 which covers the period from Jan31th to Mar 26th.

5.3.1 Analysis of Effects of Different Visibility Levels

According to the characteristics of the weather dataset and some previous literature (Hassan and Abdel-Aty, 2011a), we divided the visibility into three levels using the same combined dataset analyzed above in order to further investigate the difference of traffic flow characteristics under different visibility levels. The visibility is considered as good visibility and classified as 1 in the ANOVA analysis when the visibility is greater than or equal to 2000 m. The visibility is considered as moderate visibility and classified as 2 if the visibility is less than 2000 m but greater than 300 m. The visibility is considered as low visibility and classified as 3 if the visibility is less than or equal to 300 m.

Headway comparison

The comparison of the headway under different visibility levels is carried out by comparing the mean value of the headway per direction. The distribution of means of headway under three different visibility levels is shown in Figure 5-25. It can be seen from the figure that the mean headway is significantly higher under low visibility.

It also can be seen in Table 5-10 that the differences of means of headway are all significant under different visibility levels. The mean of headway increases when the visibility drops. The difference of headway between good visibility and moderate headway is 2.0176 seconds and the difference between moderate visibility and low visibility is 1.8945 seconds.

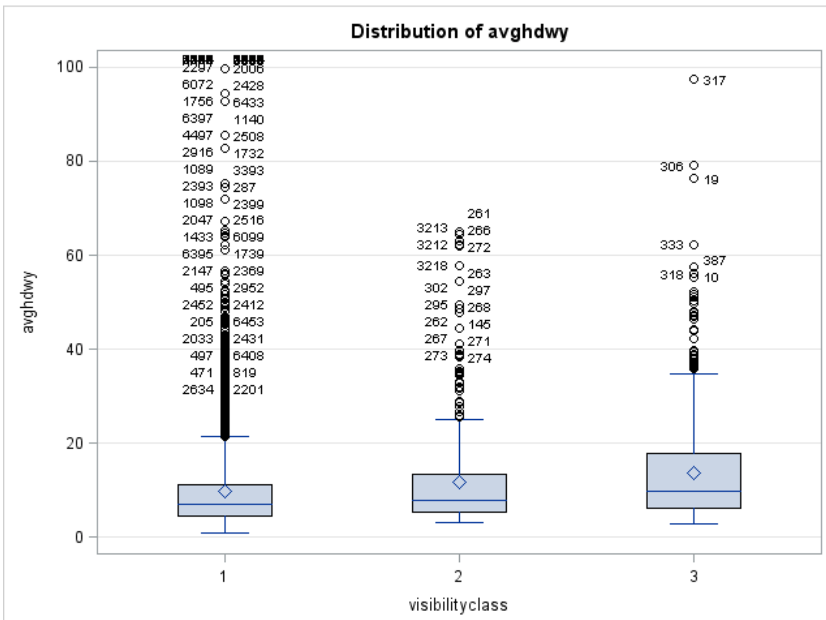


Figure 5-25 Distribution of means of headway under different visibility levels

Table 5-10 Comparison of means of headway under different visibility levels

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
3 - 2	1.8945	0.6497	3.1392	***
3 - 1	3.9120	3.1780	4.6461	***
2 - 3	-1.8945	-3.1392	-0.6497	***
2 - 1	2.0176	0.9487	3.0864	***
1 - 3	-3.9120	-4.6461	-3.1780	***
1 - 2	-2.0176	-3.0864	-0.9487	***

*Note that *** indicates that the result is significant*

Speed comparison

The comparison of the speed under different visibility levels is performed by comparing the mean value of the speed per direction. The distribution of means of speed under three different visibility levels was shown in Figure 5-26. It can be seen that the mean speed is significantly lower under low visibility.

It also can be seen from Table 5-11 that the differences of mean speed are all significant under different visibility levels. The mean speed decreases when the visibility drops. The difference of speed between good visibility and moderate visibility is 0.2929 mph and the difference between moderate visibility and low visibility is 0.6588 mph.

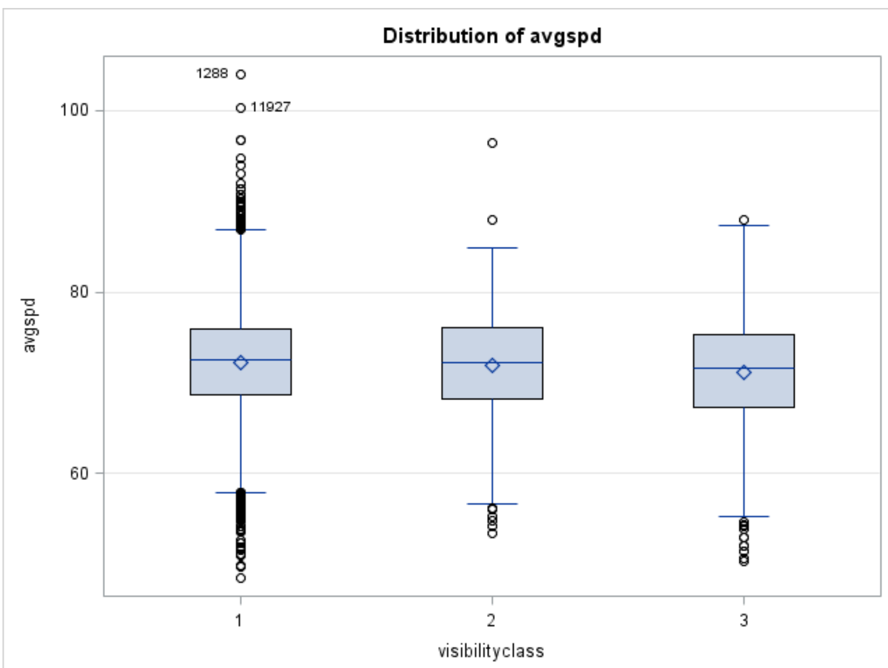


Figure 5-26 Distribution of means of speed under different visibility levels

Table 5-11 Comparison of means of speed under different visibility levels

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
1 - 2	0.29297	0.01564	0.57029	***
1 - 3	0.95181	0.76093	1.14268	***
2 - 1	-0.29297	-0.57029	-0.01564	***
2 - 3	0.65884	0.33533	0.98234	***
3 - 1	-0.95181	-1.14268	-0.76093	***
3 - 2	-0.65884	-0.98234	-0.33533	***

Variance of Headway comparison

The comparison of the variance of headway under different visibility levels is carried by comparing the mean value of the standard deviation of headway per direction. The distribution of standard deviation of headway under three different visibility levels was shown in Figure 5-27. It can be seen that the standard deviation of headway is significantly higher in low visibility.

It also can be seen from Table 5-12 that the differences of standard deviation of headway are all significant under different visibility levels. The mean of standard deviation of headway will increase when the visibility drops. The difference of standard deviation of headway between good visibility and moderate visibility is 0.8115 seconds and the difference between moderate visibility and low visibility is 1.7449 seconds.

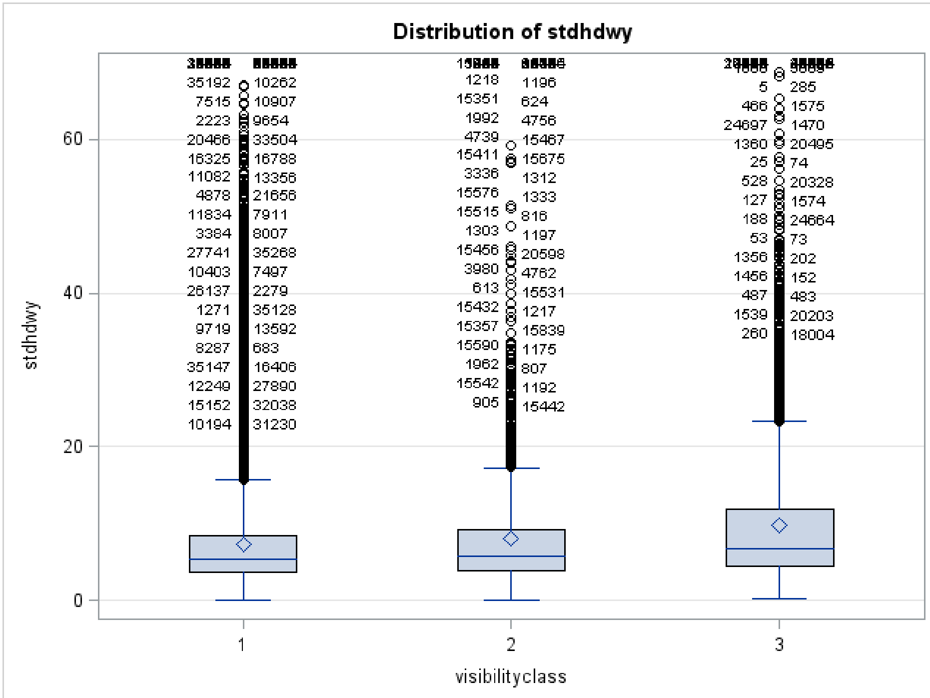


Figure 5-27 Distribution of standard deviation of headway under different visibility levels

Table 5-12 Comparison of standard deviation of headway under different visibility levels

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
3 - 2	1.74495	1.29903	2.19087	***
3 - 1	2.55647	2.29213	2.82082	***
2 - 3	-1.74495	-2.19087	-1.29903	***
2 - 1	0.81152	0.43065	1.19239	***
1 - 3	-2.55647	-2.82082	-2.29213	***
1 - 2	-0.81152	-1.19239	-0.43065	***

It is noted that the variance of speed under different visibility levels is also analyzed using the same method but the result shows that there is not significantly difference of variance of speed under different visibility levels.

5.3.2 Analysis of Effects of Reduced Visibility on Different Lanes

There are three lanes in each direction for the site. The outer lane is labeled as 0 and the inner lane is labeled as 2 while the middle lane is labeled as 1 for the East Bound direction. The outer lane is labeled as 5 and the inner lane is labeled as 3 while the middle lane is labeled as 4 for the West Bound direction. In this section we will mainly make comparisons about the traffic flow characteristics in different lanes under different visibility levels. At first, the distributions of average speed and headway were compared for both directions. It can be seen from the Table 5-13 to Table 5-16 that the distribution of average speed and headway are very similar in both directions. The average speed for the inner lane is significantly higher than middle lane and outer lane while the average headway for the outer lane is significantly higher than middle lane and inner lane. In addition, further comparison under different visibility levels presents the similar results for both directions, therefore, this study focused on presenting the effects of reduced visibility on different lanes for the EB.

Table 5-13 Comparison of means of speed in different lanes for EB

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
2 - 1	4.41505	4.28185	4.54826	***
2 - 0	8.75264	8.61856	8.88672	***
1 - 2	-4.41505	-4.54826	-4.28185	***
1 - 0	4.33759	4.20458	4.47060	***
0 - 2	-8.75264	-8.88672	-8.61856	***
0 - 1	-4.33759	-4.47060	-4.20458	***

Table 5-14 Comparison of means of headway in different lanes for EB

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
0 - 2	5.1770	4.6939	5.6602	***
0 - 1	8.4569	7.9776	8.9362	***
2 - 0	-5.1770	-5.6602	-4.6939	***
2 - 1	3.2798	2.7998	3.7599	***
1 - 0	-8.4569	-8.9362	-7.9776	***
1 - 2	-3.2798	-3.7599	-2.7998	***

Table 5-15 Comparison of means of speed in different lanes for WB

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
5 - 3	-1.5589	1.1048	2.0131	***
5 - 4	4.6358	4.1876	5.0839	***
3 - 5	1.5589	-2.0131	-1.1048	***
3 - 4	3.0768	2.6234	3.5302	***
4 - 5	-4.6358	-5.0839	-4.1876	***
4 - 3	-3.0768	-3.5302	-2.6234	***

Table 5-16 Comparison of means of headway in different lanes for WB

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
5 - 3	1.5589	1.1048	2.0131	***
5 - 4	4.6358	4.1876	5.0839	***
3 - 5	-1.5589	-2.0131	-1.1048	***
3 - 4	3.0768	2.6234	3.5302	***
4 - 5	-4.6358	-5.0839	-4.1876	***
4 - 3	-3.0768	-3.5302	-2.6234	***

Speed comparison of outer lane in different visibility levels

The speed comparison of the outer lane under different visibility levels is carried out by comparing the mean speed. The distribution of means speed under three different visibility levels for the outer lane is shown in Figure 5-28. It is hard to see the difference of mean speed under different visibility levels but it can be seen from Table 5-17 that the mean speeds under good visibility level and moderate visibility level are both significantly higher than mean speed under low visibility level while the difference of mean speed under good visibility level and moderate visibility level is not significant. The difference of mean speed between good visibility and low visibility is 1.28 mph and the difference between moderate visibility and low visibility is 0.84 mph.

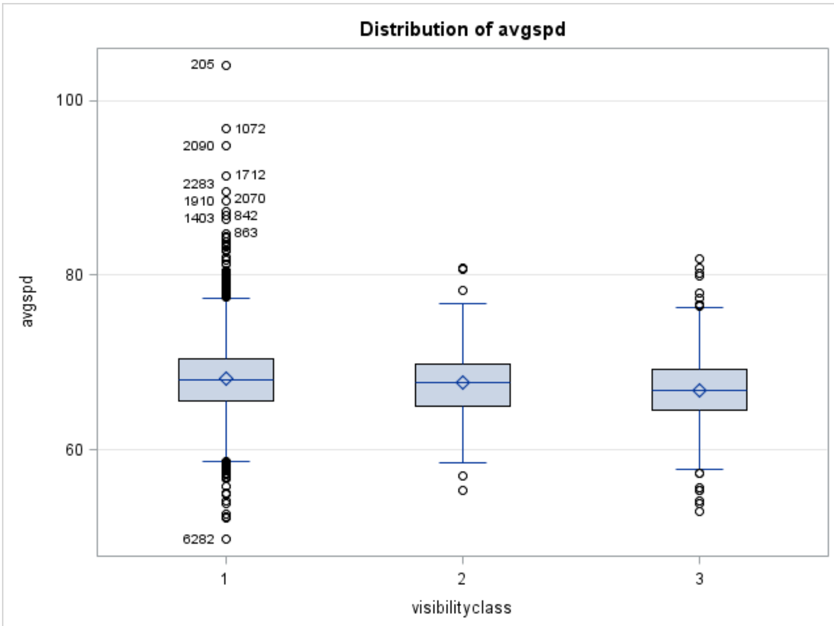


Figure 5-28 Distribution of means of speed for outer lane under different visibility levels

Table 5-17 Comparison of means of speed for outer lane under different visibility levels

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
1 - 2	0.44000	-0.08060	0.96061	
1 - 3	1.28185	0.92093	1.64277	***
2 - 1	-0.44000	-0.96061	0.08060	
2 - 3	0.84185	0.23303	1.45066	***
3 - 1	-1.28185	-1.64277	-0.92093	***
3 - 2	-0.84185	-1.45066	-0.23303	***

Speed comparison of middle lane in different visibility levels

The speed comparison of the middle lane under different visibility levels is also carried by comparing the mean speed. The distribution of means speed under three different visibility levels for the outer lane was shown in Figure 5-29. It can be seen from the Figure 5-29 that there is obvious difference of mean speed under different visibility levels. It also can be seen from the Table 5-18 that the mean speeds will increase as the visibility increases. The difference of mean speed between good visibility and low visibility is 1.01 mph and the difference between good visibility and moderate visibility is 0.36 mph.

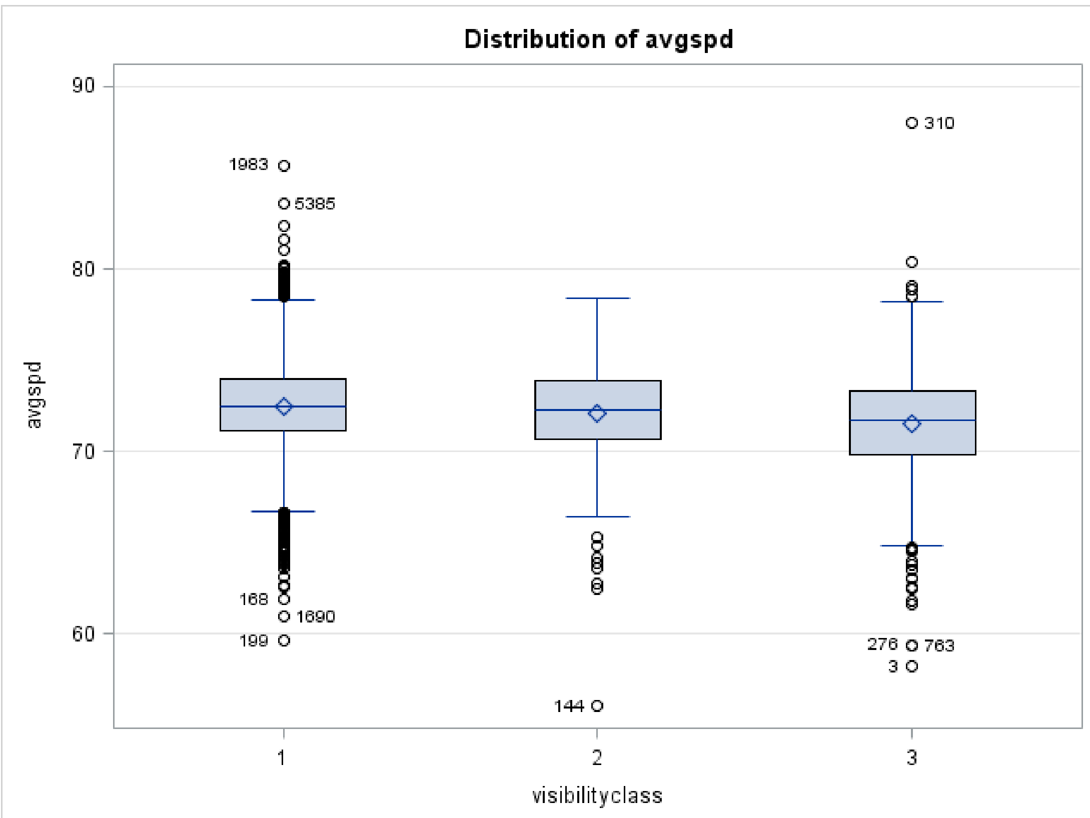


Figure 5-29 Distribution of means of speed for middle lane under different visibility levels

Table 5-18 Comparison of means of speed for middle lane under different visibility levels

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
1 - 2	0.36757	0.03969	0.69546	***
1 - 3	1.01375	0.78870	1.23881	***
2 - 1	-0.36757	-0.69546	-0.03969	***
2 - 3	0.64618	0.26424	1.02813	***
3 - 1	-1.01375	-1.23881	-0.78870	***
3 - 2	-0.64618	-1.02813	-0.26424	***

Speed comparison of inner lane in different visibility levels

The speed comparison of the inner lane under different visibility levels is shown in the Figure 5-30 and Table 5-19. The distribution of means speed under three different visibility levels for the inner lane was shown in Figure 5-30. It is hard to see the difference of mean speed under different visibility levels but it can be seen from Table 5-19 that the mean speeds under good visibility level and moderate visibility level are both significantly higher than mean speed under low visibility level while the difference of mean speed under good visibility level and moderate visibility level is not significant. The difference of mean speed between good visibility and low visibility is 0.96 mph and the difference between moderate visibility and low visibility is 0.77 mph.

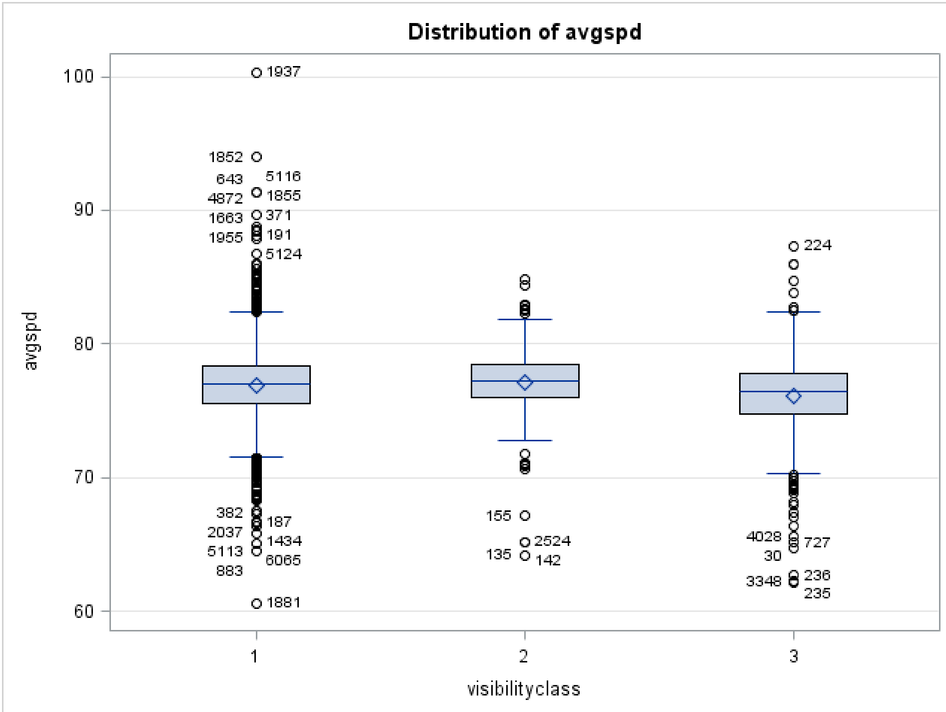


Figure 5-30 Distribution of means of speed for inner lane under different visibility levels

Table 5-19 Comparison of means of speed for inner lane under different visibility levels

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
2 - 1	0.18868	-0.14793	0.52528	
2 - 3	0.96323	0.57122	1.35524	***
1 - 2	-0.18868	-0.52528	0.14793	
1 - 3	0.77455	0.54413	1.00497	***
3 - 2	-0.96323	-1.35524	-0.57122	***
3 - 1	-0.77455	-1.00497	-0.54413	***

In summary, we can conclude that the mean speed will not drop significantly as the visibility starts to decrease especially in inner lane and outer lane. The mean speed will reduce significantly as the visibility drop to below 300m for all the lanes.

Headway comparison of inner lane in different visibility class

The headway comparison of the inner lane under different visibility levels is shown in the Figure 5-31 and Table 5-20. The distribution of means speed under three different visibility levels for the inner lane was shown in Figure 5-31. It can be seen from that there is obvious difference of headway under different visibility levels. It also can be seen from the Table 5-20 that the mean headway will decrease as the visibility increases. The difference of mean headway between good visibility and low visibility is 4.4734 seconds and the difference between good visibility and moderate visibility is 2.4157 seconds.

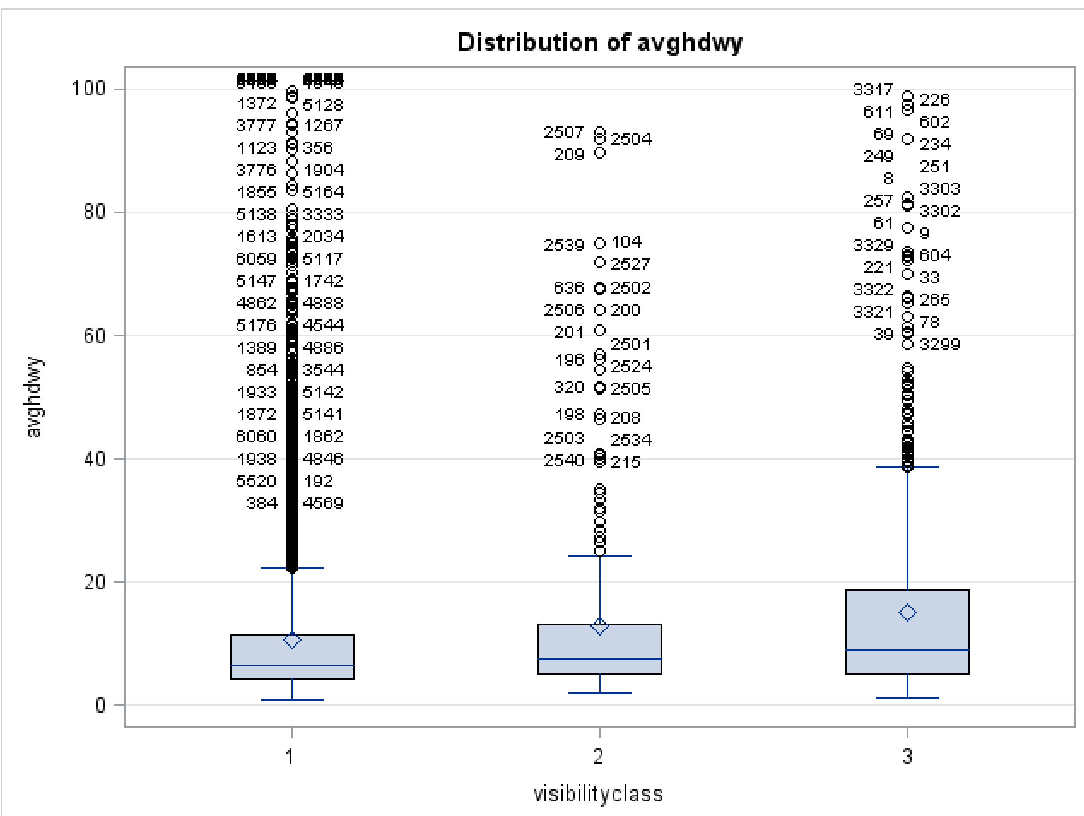


Figure 5-31 Distribution of means of headway for inner lane under different visibility levels

Table 5-20 Comparison of means of headway for inner lane under different visibility levels

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
3 - 2	2.0577	0.0936	4.0218	***
3 - 1	4.4734	3.3189	5.6279	***
2 - 3	-2.0577	-4.0218	-0.0936	***
2 - 1	2.4157	0.7292	4.1022	***
1 - 3	-4.4734	-5.6279	-3.3189	***
1 - 2	-2.4157	-4.1022	-0.7292	***

Headway comparison of middle lane in different visibility class

The headway comparison of the middle lane under different visibility levels is shown in the Figure 5-32 and Table 5-21. The distribution of means speed under three different visibility levels for the middle lane was shown in Figure 5-32. It can be seen that the mean headway increases as the visibility drops and it can be seen from Table 5-21 that the mean headway under good visibility level are significantly higher than both mean headways under low visibility level and moderate visibility level while the difference of mean headway under low visibility level and moderate visibility level is not significant. The difference of mean headway between good visibility and low visibility is 2.48 seconds and the difference between good visibility and moderate visibility is 2.12 seconds.

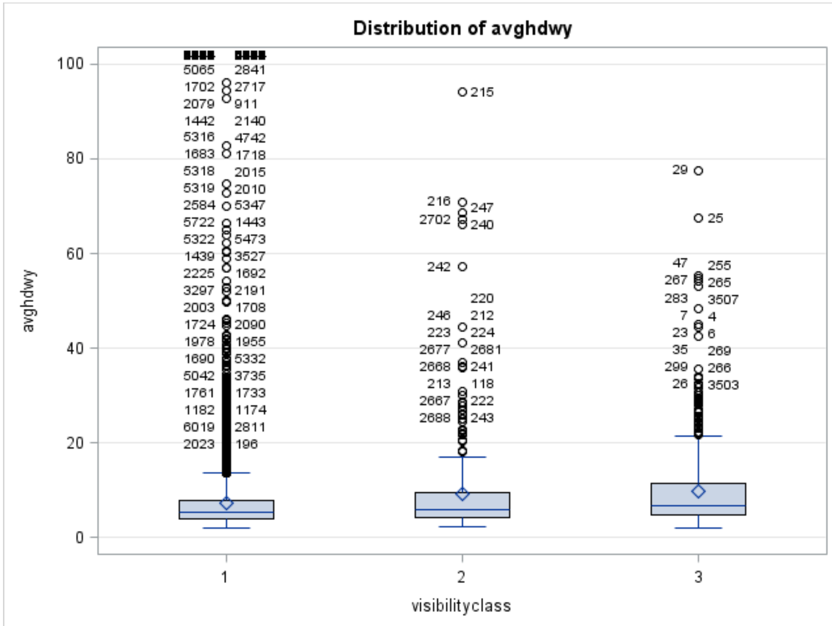


Figure 5-32 Distribution of means of headway for middle lane under different visibility levels

Table 5-21 Comparison of means of headway for middle lane under different visibility levels

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
3 - 2	0.3600	-0.7359	1.4558	
3 - 1	2.4892	1.8435	3.1349	***
2 - 3	-0.3600	-1.4558	0.7359	
2 - 1	2.1292	1.1885	3.0700	***
1 - 3	-2.4892	-3.1349	-1.8435	***
1 - 2	-2.1292	-3.0700	-1.1885	***

Headway comparison of Outer lane in different visibility class

The headway comparison of the inner lane under different visibility levels is shown in the Figure 5-33 and Table 5-22. The distribution of mean headway under three different visibility levels for the inner lane was shown in Figure 5-33. The results are very similar to the results related to middle lane. The mean headway increases as the visibility drops and it can be seen from Table 6.22 that the mean headway under good visibility level are significantly higher than both mean headways under low visibility level and moderate visibility level while the difference of mean headway under low visibility level and moderate visibility level is not significant. The difference of mean headway between good visibility and low visibility is 4.70 seconds and the difference between good visibility and moderate visibility is 3.17 seconds, which are both larger than those of middle lane.

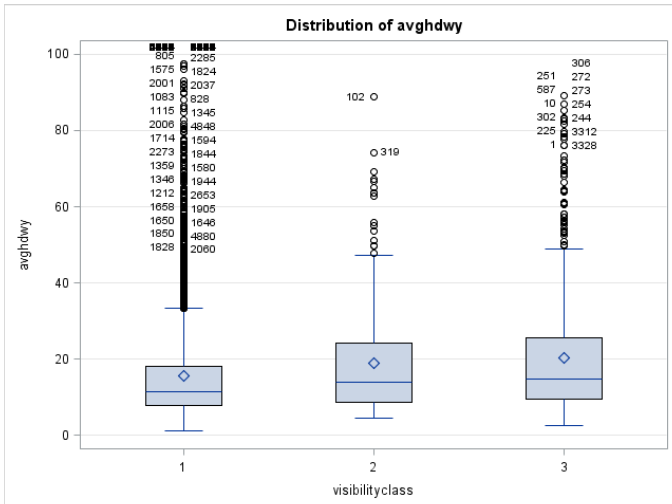


Figure 5-33 Distribution of means of headway for outer lane under different visibility levels

Table 5-22 Comparison of means of headway for outer lane under different visibility levels

Comparison of different visibility levels	Difference Between Means	Simultaneous 95% Confidence Limits		
3 - 2	1.5334	-0.5493	3.6161	
3 - 1	4.7072	3.4726	5.9419	***
2 - 3	-1.5334	-3.6161	0.5493	
2 - 1	3.1738	1.3929	4.9548	***
1 - 3	-4.7072	-5.9419	-3.4726	***
1 - 2	-3.1738	-4.9548	-1.3929	***

5.4 Analysis of effects of Reduced Visibility on Traffic Crash Risk

In this section, two durations are included in this study, which are Jan31st, 2014 to March 12th, and 2014 and Mar 2nd 2015 to May 20th 2015. Crash risks which are based on real-time traffic data are estimated during reduced visibility conditions.

5.4.1 Comparison Results of Surrogate Measures of Safety

In addition to time to collision (TTC), Speed variance and headway variance were considered as three surrogate measures of safety in this paper. It was well recognized that the higher a TTC value and the lower a speed and headway variance is, the safer a situation. There are two definitions of TTC and both were calculated in this paper. The following equation (5-1) was used to calculate both kinds of TTC:

$$TTC = L / (V_1 - V_2) \qquad \text{Equation 5-1}$$

L is the clearance which is the distance between the rear bumper of the leading vehicle and the front bumper of the following vehicle. V_1 is the speed of leading vehicle and V_2 is the speed of the following vehicle. TTC1 was calculated when V_1 maintained its own speed and TTC2 which was also called TTC at braking was calculated when the leading vehicle suddenly stopped. It is noted that the visibility distance was used to replace the actual clearance when the visibility distance is less than clearance because the following car will not make any changes as long as the driver will be able to see the leading vehicle.

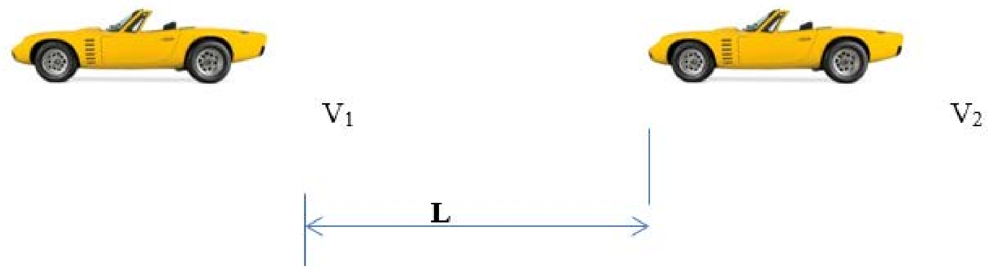


Figure 5-34 TTC calculation

Analysis of variance (ANOVA) was applied in this study to compare the differences between several group means and their associated variations, which provides a powerful statistical test of comparing means of more than two groups. As doing multiple two-sample t-tests is not convenient and would result in an increased chance of errors, ANOVA is applied to analyze the three surrogate measures of safety under different visibility classes and the effects of reduced visibility on different vehicle types and lanes.

For the purpose of exploring the relationship between TTC and visibility together with other traffic parameters, four different types of regression modeling (Normal, Log-Normal, Log-Gamma and Log-Inverse Gaussian) were applied and the goodness of fit compared. The Log-Inverse Gaussian regression model shows the best fit and was applied in this paper. The density function of Inverse Gaussian distribution is defined by

$$f(x,\theta) = (\frac{\lambda}{2\pi x^3})^{\frac{1}{2}} \left\{ -\frac{\lambda(x-\mu)^2}{2\mu^2 x} \right\}, \qquad x \geq 0, \theta = (\mu, \lambda)^T \subset R^2 \qquad \text{Equation 5-2}$$

μ is the mean and λ is the shape parameter for the above equation.

3.1 Comparison Results of All the Vehicles

Table 5-23 shows the comparison of three surrogate measures of safety by dividing the whole period into different cases based on the value of visibility. According to the characteristics of the weather dataset and previous literature (Hassan and Abdel-Aty, 2013), we divided the visibility into three classes. The visibility is considered as good visibility and classified as 1 when the visibility is greater than or equal to 2000 m. The visibility is considered as moderate visibility and classified as 2 if the visibility is less than 2000 m but greater than 100 m. The visibility is considered as low visibility and classified as 3 if the visibility is less than or equal to 100 m. The duration of one minute was considered as a sample of good visibility, moderate visibility or low visibility. The sample size of good visibility, moderate visibility and low visibility is 13701, 1662, and 211, respectively. It can be seen from the Table that the both TTC1 and TTC2 will decrease significantly as the visibility is reduced and the standard deviation of headway will increase significantly as the visibility is reduced from good to low visibility, which means that the crash risk will be higher during the reduced visibility and the crash risk keeps increasing when visibility drops. The standard deviation of speed is higher in reduced visibility but the result is not significant.

Table 5-23 Comparison of surrogate measures of safety under different visibility classes

Visibility classes	TTC1			TTC2		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	7.36*	5.54	9.18	0.95*	0.83	1.07
2-3	18.24*	14.06	22.41	1.20*	0.93	1.47
1-3	25.60*	21.66	29.54	2.15*	1.90	2.41

	Standard Deviation of Speed			Standard Deviation of Headway		
Visibility classes	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	-0.07	-0.26	0.11	-0.78*	-1.18	-0.36
2-3	-0.13	-0.54	0.27	-0.61*	-1.12	-0.11
1-3	-0.21	-0.58	0.16	-1.39*	-1.70	-1.08

Note * means the difference is significant

Table 5-24 Mean and standard deviation of TTC under different visibility classes

Visibility classes	TTC1		TTC2	
	Mean(s)	Standard deviation(s)	Mean(s)	Standard deviation(s)
1	75.65	68.00	3.89	4.68
2	68.29	62.41	2.93	2.97
3	50.05	50.75	1.73	0.77

ASSHTO required stopping sight distance

Design or Operating speed(mph)		50	60	70	80	90	100	110
Stopping distance(m)	t_p=2.5s	63	85	111	139	169	205	246

Table 5-25 Proportion of speeding under different visibility classes

Visibility classes	Mean speed(mph)	Proportion of Speeding
1	71.61	62.65%
2	70.71	68.31%
3	70.24	95.4%

It can be seen from Table 5-24 that the TTC1 drops from 75s to 50s and TTC2 decreases from 3.89s to 1.73 s when visibility drops from 2000 m to below 100m. The average human perception-reaction time t_p is 2.5 seconds according to ASSHTO's Green Book (2011) and the required stopping sight distance for the vehicles is shown in Table 5-24. The proportion of speeding was calculated by comparing the actual stopping distance for each vehicle with the required stopping sight distance. It is noted that the reduced visibility was used to replace the required stopping sight distance when the visibility drops below the required sight distance. It can be shown from Table

2d that the proportion of speeding under low visibility condition is 95.4%, which means the crash risk would increase significantly during low visibility conditions because most of the vehicles will not be able to stop in time to avoid a rear-end crash once the leading vehicle stops suddenly. Although the average speed is slightly reduced when visibility drops, most of the vehicles were still speeding especially under low visibility conditions, which explains the reason that the 70 vehicles pileup on I-4 in Polk County, Florida in 2008.

Comparison Results of Different Types of Vehicles

The vehicles were then divided into two types: passenger cars and trucks in this section in order to figure out whether the impact of visibility on Surrogate Measures of Safety is different for different vehicle types. The type of vehicles was divided based on the length of vehicles. The vehicle is considered as truck when the length of vehicle is above 30 feet and it is considered as passenger cars when the length of vehicle is equal to or less than 30 feet. Table 3 shows the summary for the results of comparison. The datasets used in this section were the same as the above section 3.1 and the sample size of good visibility, moderate visibility and low visibility is 13701, 1662, and 211, respectively. It can be seen from the Table 5-26 that both TTC1 and TTC2 would decrease significantly as the visibility is reduced and the standard deviation of headway would increase significantly as the visibility is reduced from good to low visibility, which means that the crash risk would be higher during the reduced visibility and the crash risk keeps increasing when visibility drops for both types of vehicles. The standard deviation of speed significantly increases when the visibility drops for the passenger cars while the change is not significant for trucks. Compared to passenger cars, the effect of reduced visibility on standard deviation of headway and speed are smaller while the effect on TTC is larger for trucks. Specifically, the value of TTC1 and TTC2 decrease to 25.82s and 2.09s for passenger cars while it decreases to 26.58s and 2.89s for trucks when the visibility drops from class1 to class3. The standard deviation of headway and speed increase by 1.44s and 0.24 mph, respectively, for passenger car while increase only by 0.98s and 0.01mph, respectively, for trucks. Therefore, considering the larger decrease of TTC and relatively larger response and perception time, truck drivers should be more careful about speeding during the reduced visibility conditions.

Table 5-26 Comparison of surrogate measures of safety for different vehicle types

a. Passenger car

Visibility classes	TTC1			TTC2		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	6.42*	4.54	8.30	0.89*	0.77	1.01
2-3	19.40*	15.02	23.79	1.19*	0.91	1.48
1-3	25.82*	21.68	29.97	2.09*	1.82	2.35

Visibility classes	Standard Deviation of Speed			Standard Deviation of Headway		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	-0.16*	-0.30	-0.02	-0.83*	-1.33	-0.33
3	-0.08	-0.54	0.38	-0.63*	-1.11	-0.15
1-3	-0.24	-0.76	0.28	-1.44*	-1.86	-1.02

b. Truck

Visibility classes	TTC1			TTC2		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	14.09*	7.06	21.12	1.31*	0.81	1.81
2-3	12.49*	0.687	24.311	1.58*	0.61	2.55
1-3	26.58*	14.665	39.507	2.89*	2.01	3.78

Visibility classes	Standard Deviation of Speed			Standard Deviation of Headway		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	0.02	-0.04	0.08	-0.36*	-0.66	-0.06
2-3	-0.03	-0.07	0.01	-0.52*	-0.83	-0.21
1-3	-0.01	-0.05	0.03	-0.98*	-0.62	-1.35

Note * means the difference is significant

Comparison Results of Vehicles on Different Lanes

The vehicles were then divided into three different lanes including outer lane that is close to the roadside, middle lane and inner lane in this section in order to understand whether the impact of visibility on surrogate measures of safety is different for different lanes.

It can be seen from Table 5-27 that the both TTC1 and TTC2 decrease significantly as the visibility is reduced from good to low visibility, which means that the crash risk would be higher during the reduced visibility. The crash risk keeps increasing when visibility drops for all the lanes. The standard deviation of speed significantly increases when the visibility drops from good to low visibility for the middle and inner lanes while the change is not significant for outer lane. Compared to outer lane, the effect of reduced visibility on the standard deviation of headway and speed are larger while the effect on TTC is smaller for the vehicles in middle and inner lanes. Specifically, the value of TTC1 and TTC2 decrease to 32.96s and 4.24s for vehicles in outer lane while it decreases only to 25.44s and 1.73s for vehicles in middle lane, respectively. The TTC1 and TTC2 decrease only to 22.71s and 1.53s for vehicles in the inner lane when the visibility drops from class1 to class3. The change of standard deviation of speed is not significant in the outer lane while it is increases significantly in the middle and inner lanes when the visibility drops from class1 to class3. For the headway variance, the effect of reduced visibility on the inner and outer lanes is higher than the effect on the middle lane. It is noted that although the decrease of TTC value is largest in the outer lane, the mean value of both TTC1 and TTC2 under low visibility condition are still smallest in the inner lane. Overall, the drivers in the inner lane should be more careful about speeding during the reduced visibility condition.

Table 5-27 Comparison of surrogate measures of safety for different lanes

a. Outer Lane

Visibility classes	TTC1			TTC2		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	7.36*	5.54	9.18	1.89*	1.53	2.24
2-3	25.60*	21.66	29.54	2.35*	1.58	3.13
1-3	32.96*	26.06	39.86	4.24*	3.51	4.97

Visibility classes	Speed variance			Headway variance		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	-0.05	-0.37	0.27	-1.16*	-1.78	-0.54
2-3	-0.12	-0.56	0.32	-0.64	-1.42	0.12
1-3	-0.18	-0.74	0.38	-1.81*	-2.28	-1.33

b. Middle Lane

Visibility classes	TTC1			TTC2		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	7.91*	5.16	10.67	0.74*	0.59	0.89
2-3	17.52*	11.16	23.89	0.98*	0.64	1.34
1-3	25.44*	19.45	31.43	1.73*	1.40	2.06

Visibility classes	Speed variance			Headway variance		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	-0.19	-0.41	0.02	-0.64	-1.37	0.09
2-3	0.005	-0.25	0.26	-0.26*	-1.15	-0.62
1-3	-0.18*	-0.33	-0.03	-0.90*	-1.43	-0.38

c. Inner Lane

Visibility classes	TTC1			TTC2		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	4.71*	1.77	7.66	0.63*	0.47	0.78
2-3	17.98*	11.06	24.91	0.89*	0.52	1.28
1-3	22.71*	16.13	29.27	1.53*	1.17	1.88

Visibility classes	Speed variance			Headway variance		
	Mean Difference	95% Confidence Interval		Mean Difference	95% Confidence Interval	
1-2	-0.21*	-0.29	-0.13	-0.17	-0.98	0.64
2-3	-0.05	-0.25	0.15	-1.09*	-2.10	-0.08
1-3	-0.26*	-0.47	-0.05	-1.26*	-1.88	-0.64

Note * means the difference is significant

5.4.2 Modeling the Relationship between TTC, Reduced Visibility and Traffic Parameters

The above analysis was based on vehicle based traffic data. However, since most of archived traffic data available are aggregated, it is meaningful to further explore the relationship between average TTC and these aggregated traffic parameters. Transportation authorities would then be able to identify the effect of reduced visibility as well as traffic conditions with high risk based on the results. Four different approaches of regression modeling including Normal, Log-normal, Log-Gamma and Log-Inverse Gaussian were applied and compared. It is noted that visibility was converted to categorical variable (class 3 is low visibility class when average visibility is less than 100m, class 2 is moderate visibility class when average visibility is less than 2000m but greater than or equal to 100m and class 1 is good visibility class when average visibility is 2000m). The dependent variable is the mean of TTC of all the vehicles in five minutes. The independent variables are mean headway, mean speed, volume per lane in five minutes and visibility class. The basic statistics of the five parameters used in the model are summarized in Table 5-28 and the comparison results of the four different regression analyses are shown in Table 5-29. It can be shown from Table 5-29 that the performance of the Inverse-Gaussian regression model achieved the best fit. Therefore, the Inverse-Gaussian regression model was applied to explore the relationship between time to collision and visibility together with the other traffic parameters.

Table 5-28 Summary of statistics of parameters

Parameter	Min	Mean	Max	Std.
Averaged TTC at Break(s)	1.16	8.46	69.23	8.45
Visibility Class	1	1.22	3	0.46
Average Headway(s)	1.28	10.15	96.52	10.37
Average Speed(mph)	40.82	71.98	87.70	4.42
Volume Per Lane Per five Minutes	1	43	152	27

Table 5-29 Comparison of performance of different kinds of modeling

Model Comparison	AIC	BIC
Normal	15550	15592
Log-Normal	15395	15437
Log-Gamma	11585	11627
Log-Inverse Gaussian	11475	11517

Table 5-30 Modeling results of log-inverse Gaussian model

Parameter		DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept		1	1.0525	0.0913	0.8736	1.2314	132.96	<.0001
Visibility Class	1	1	1.1361	0.0206	1.0958	1.1765	3045.19	<.0001
Visibility Class	2	1	0.8790	0.0222	0.8356	0.9224	1573.46	<.0001
Visibility Class	3	0	0.0000	0.0000	0.0000	0.0000	.	.
Average Headway		1	0.0702	0.0021	0.0661	0.0743	1126.09	<.0001
Average Speed		1	-0.0088	0.0011	-0.0110	-0.0066	59.12	<.0001
Volume Per Lane Per five Minutes		1	-0.0067	0.0003	-0.0072	-0.0062	677.61	<.0001
Scale		1	0.1037	0.0013	0.1012	0.1064		

The results in Table 5-30 indicate that that the TTC will decrease significantly as the visibility and mean of headway are reduced while it will decrease significantly as mean speed and volume increase. There are few research efforts exploring the relationship between crash risk and headway. The result concludes that the decrease of mean headway will increase the crash risk because the TTC will decrease significantly. The effect of mean headway on TTC is more significant compared to mean speed.

5.5 Chapter Summary

This chapter mainly analyzed the effect of reduced visibility on traffic flow characteristics. The mean headway and headway variation are significantly higher while the mean speed and volume are significantly lower in fog case. The impact of reduced visibility on passenger cars is more significant compared to trucks. In comparison, there isn't significant difference in the standard deviation of speed for trucks. The difference of mean speed, headway and standard deviation of headway between fog cases and clear cases for passenger cars are all larger than trucks.

The differences of means of headway are all significant under different visibility levels. The mean of headway will increase when the visibility drops. The mean speed will decrease when the visibility drops. The mean of standard deviation of headway will increase when the visibility drops.

The distribution of traffic flow characteristics is very similar in both directions and the effect of reduced visibility on both directions is also similar. The effects of reduced visibility on different lanes are different.

The Inverse Gaussian modeling results indicate that the TTC would decrease significantly as the visibility and mean of headway decrease while it would decrease significantly as the mean speed and volume increase. The result also concludes that the decrease of mean headway would increase the crash risk because the TTC will decrease significantly. The effect of mean headway on TTC is more significant compared to mean speed.

6. MACROSCOPIC/MICROSCOPIC SCREENING ANALYSIS

6.1 Data Collection and Preparation

In order to conduct a series of screening analyses, fog related crashes in 2008-2012 were collected from both the Crash Analysis Reporting system (CAR) of the Florida Department of Transportation (FDOT) and Signal Four Analytics which is an interactive, web-based system designed to support the crash mapping in the State of Florida. The variable weather condition in both CAR and Signal Four Analytics was used to extract fog crashes. It was considered as fog crashes when the value of weather condition was 4: fog. Considering the fact that it is impossible to differentiate smoke crashes from fog crashes in Signal Four Analytics, we only use CAR to collect smoke crashes and combination of fog and smoke (FS) crashes. Two variables visibility1 and visibility2 were used to extract smoke and FS crashes. It was considered as smoke crashes if the value of either one of the variable is 09: smoke. It was considered as FS crashes if the value of one variable is 08: fog while the other one is 09: smoke. Overall 5,078 fog or smoke crashes were collected, among them 4,945 crashes were fog-related, 162 crashes were related to smoke, and 29 crashes were due to FS. They are summarized by year in Table 6-1.

Table 6-1 Number of fog and smoke crashes on the State Highway System in Florida (2008-2012)

Year	Number of Crashes			
	Fog	Smoke	Fog and Smoke (FS)	Total
2008	1009	39	17	1031
2009	1016	23	9	1030
2010	572	32	2	602
2011	1130	28	1	1157
2012	1218	40	0	1178
Total	4945	162	29	5078

6.2. Macroscopic Screening Analysis

The first step of hotspot identification is to examine the spatial distribution and as such the crash hotspots could be identified and focused on for further investigation. The statewide map with frequent Fog and smoke crash clusters was also presented for better visualization and understanding of the spatial distribution of fog and smoke crashes. The Kernel Density Estimation was used to serve the purpose of clustering the crashes and identifying the hotspots for the macroscopic analysis. The KDE defines the spread of risk as an area around a defined cluster in which there is an increased likelihood of a crash to occur based on spatial dependency. It places a symmetrical surface over each point and then evaluates the distance from the point to a reference location based on a mathematical function and then sums the value for all the surfaces for that reference location. This procedure is repeated for successive points, which allows us to place a kernel over each observation, and summing these individual kernels gives us the density estimate for the distribution of crash 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 ith observation. The main objective of placing these kernels over the 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. This takes the value of the particular indicator at that particular point spread into it according to some appropriate function. Then it sums up all of these values at all places, including those at which no incidences of the indicator variable were recorded, and gives a surface of density estimates.

The ArcGIS spatial analyst tool provides the features needed to do the cluster analysis by density estimation methods. The KDE process needs that the data points be spatially jointed. For the points to be joined spatially, a fishnet of square 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. 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 (Abdel-Aty et al. 2012; Ahmed et al., 2014).

6.2.1 KDE Analysis of Fog Crashes

Figure 6-1 shows the statewide map with clustering output from the GIS analysis and Table 6-2 illustrates the locations of fog crash hotspots. The KDE technique presents seven distinct Fog crash hotspot areas on Florida road network. The colors represent the density of crashes per square mile area. The seven clusters identified are associated with fog crash densities above 0.18 crashes per square mile. The most dangerous areas have fog crash densities higher than 0.5 crashes per square mile.

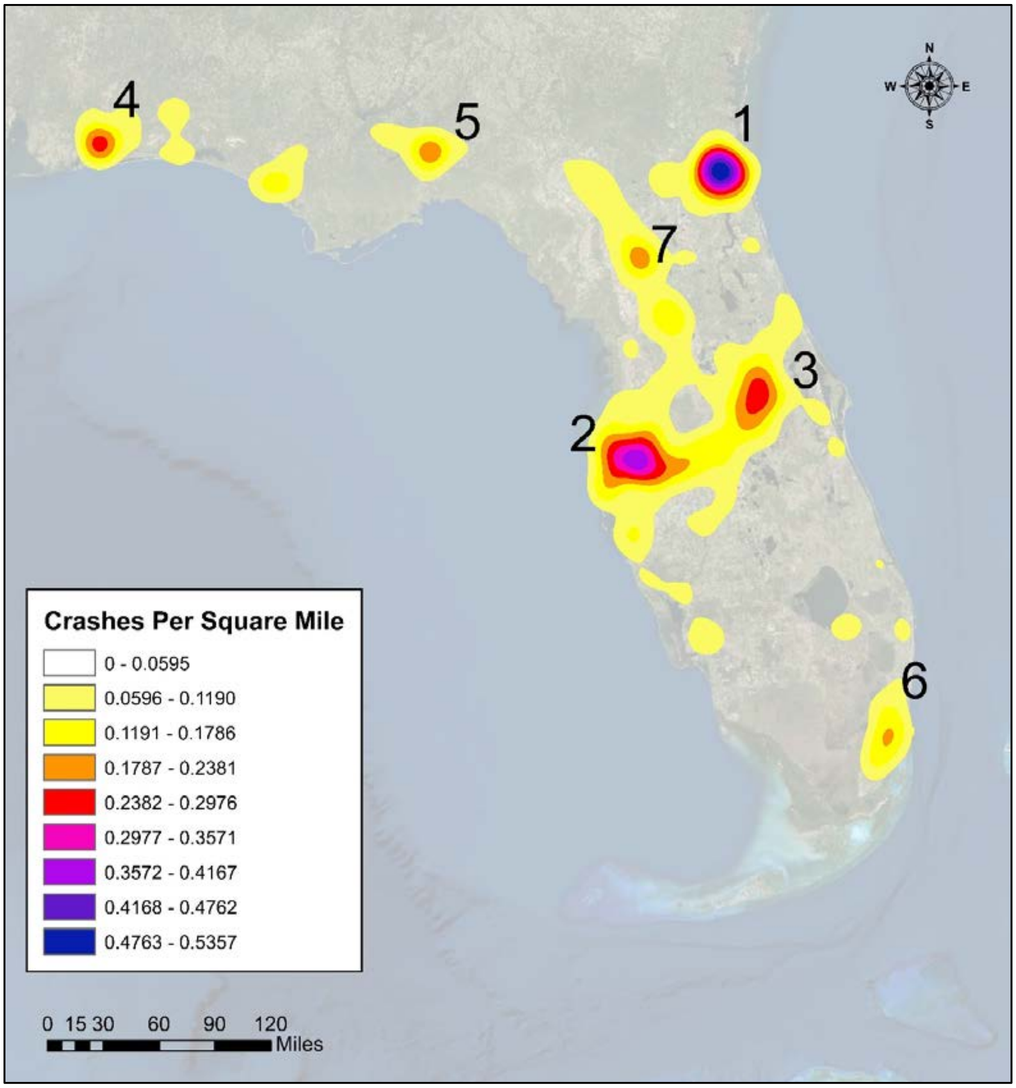


Figure 6-1 KDE analysis of fog crashes on Florida State Highway System

Table 6-2 Areas for fog crashes on Florida State Highway System

Cluster No.	County	Area
1	Duval	Center of Duval County
2	Pinellas, Hillsborough and Pasco	Almost whole of Pinellas and Connects from center of Hillsborough to center of Pasco
3	Polk and Osceola	Extends from the center to the northeast corner of Polk and a portion in the northwest corner of Osceola County
4	Escambia	Southern part of Escambia
5	Leon	Center of Leon County
6	Miami-Dade and Broward	Northern part of Miami-Dade and southern part of Broward
7	Alachua	Center of Alachua County

6.2.2 KDE Analysis of Smoke Crashes

Figure 6-2 exhibits smoke crash hotspot clusters and Table 6-3 illustrates the locations of smoke crash hotspots. The KDE analysis revealed five distinct smoke related crash hotspot areas on Florida road network. In Figure 6-2, the clusters identified are associated with smoke crash densities above 0.01 crashes per square mile. It is notable that the most hazardous areas have smoke crash densities higher than 0.045 crashes per square mile.

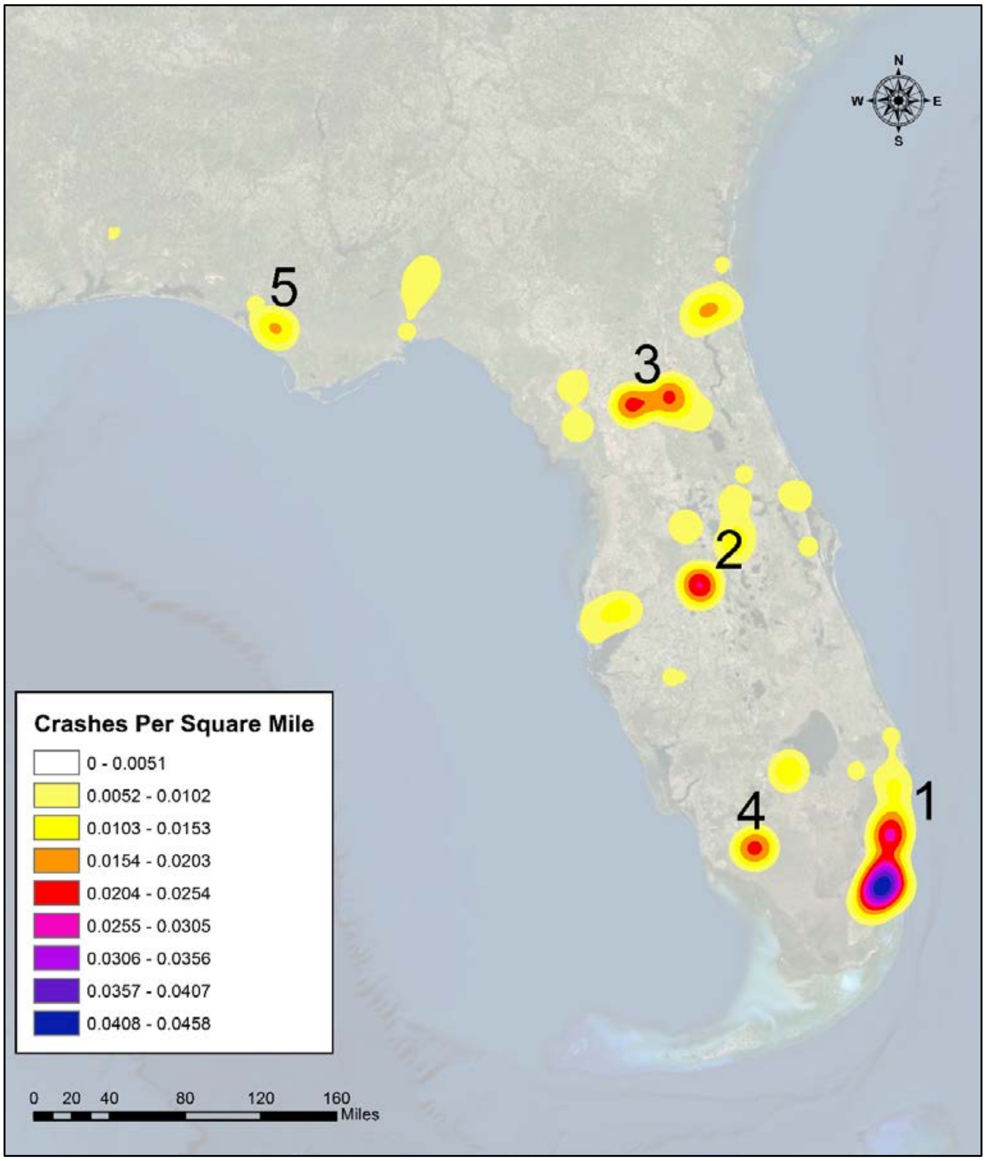


Figure 6-2 Cluster analysis of smoke crashes on Florida State Highway System

Table 6-3 Areas for smoke crashes on Florida State Highway System

Cluster No.	County	Area
1	Miami-Dade and Broward	Northern part of Miami-Dade and southern part of Broward
2	Polk	Northern part of Polk County
3	Alachua	Southeastern part of Alachua County
4	Collier	Center of Collier County
5	Bay	Eastern part of Bay County

6.2.3 KDE Analysis of FS Crashes

Figure 6-3 displays fog and smoke (FS) hotspot clusters using KDE and Table 6-4 illustrates the locations of FS crash hotspots. There are only 29 crashes related to FS crashes. The KDE identified three hotspot clusters related to FS crashes.

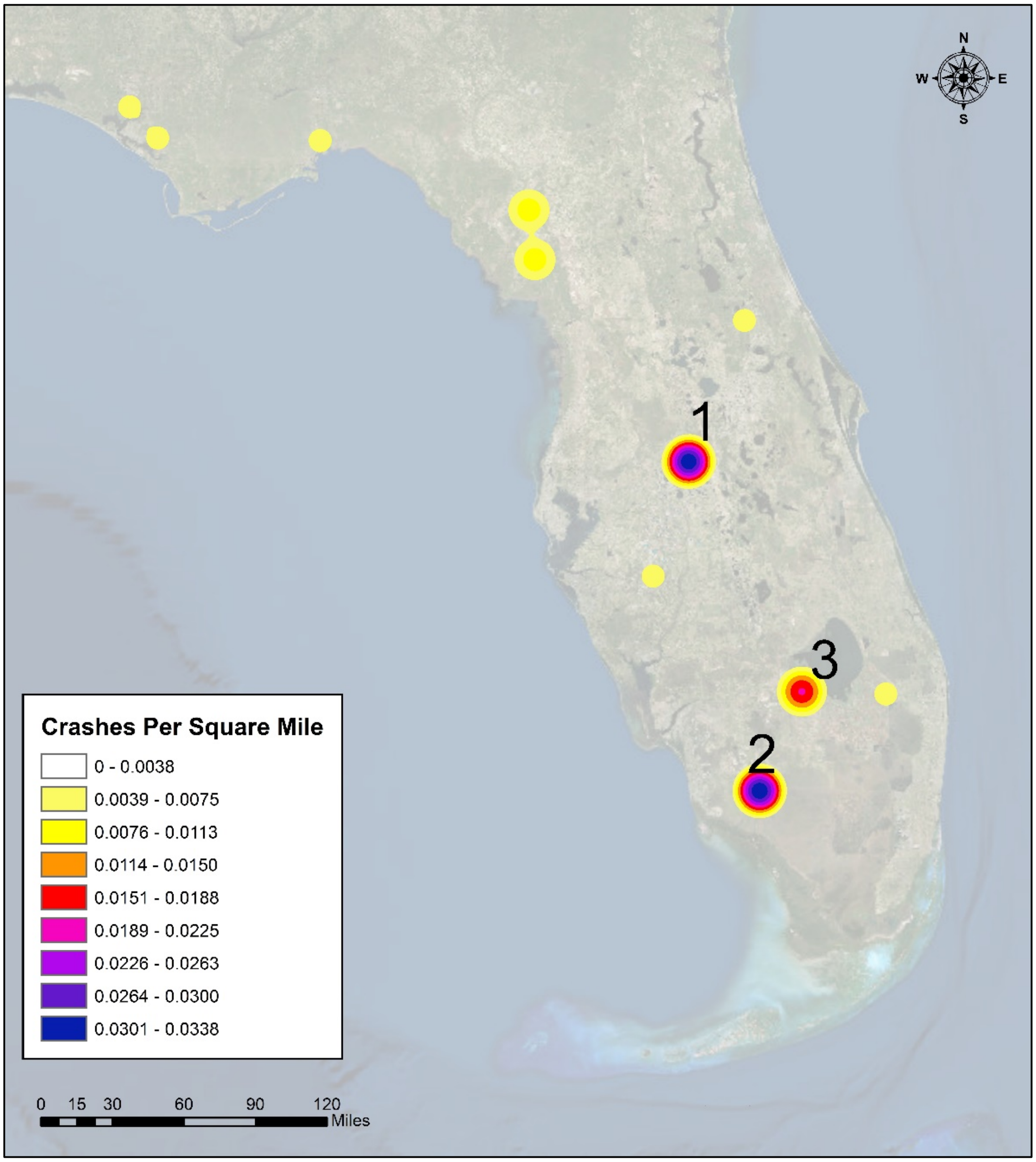


Figure 6-3 Cluster analysis of FS crashes on Florida State Highway System

Table 6-4 Areas for FS crashes in Florida State Highway System

Cluster No.	County	Area
1	Polk	Northern part of Polk County
2	Collier	Center of Collier County
3	Hendry and Glades	Intersecting parts between Hendry and Glades

6.3 Microscopic Screening Analysis

After macroscopic screening analysis using KDE method, each cluster was zoomed in for microscopically investigating the one mile based roadway segments with frequent fog and smoke crashes. The hotspots about fog and smoke crashes on ramp and intersections were also screened in this section.

6.3.1 Microscopic Screening of Fog Crashes

Fog Crashes on One-Mile Segments

Seven areas were identified with frequent fog related crashes on Florida state highways using KDE in macroscopic analysis. We then magnified these areas and divided all state highways into one-mile segments and thus fog crashes were counted based on these segments. All segments with two or more fog crashes were defined as a hotspot in the analysis.

Cluster 1 Duval County

Cluster 1 covers the center of Duval County. Overall 30 segments were discovered as a hotspot in Cluster 1 and were shown in Figure 6-4 and Table 6-5. It is noted that one segment have five fog crashes, four segments have four fog crashes and five segments have three fog crashes per mile.

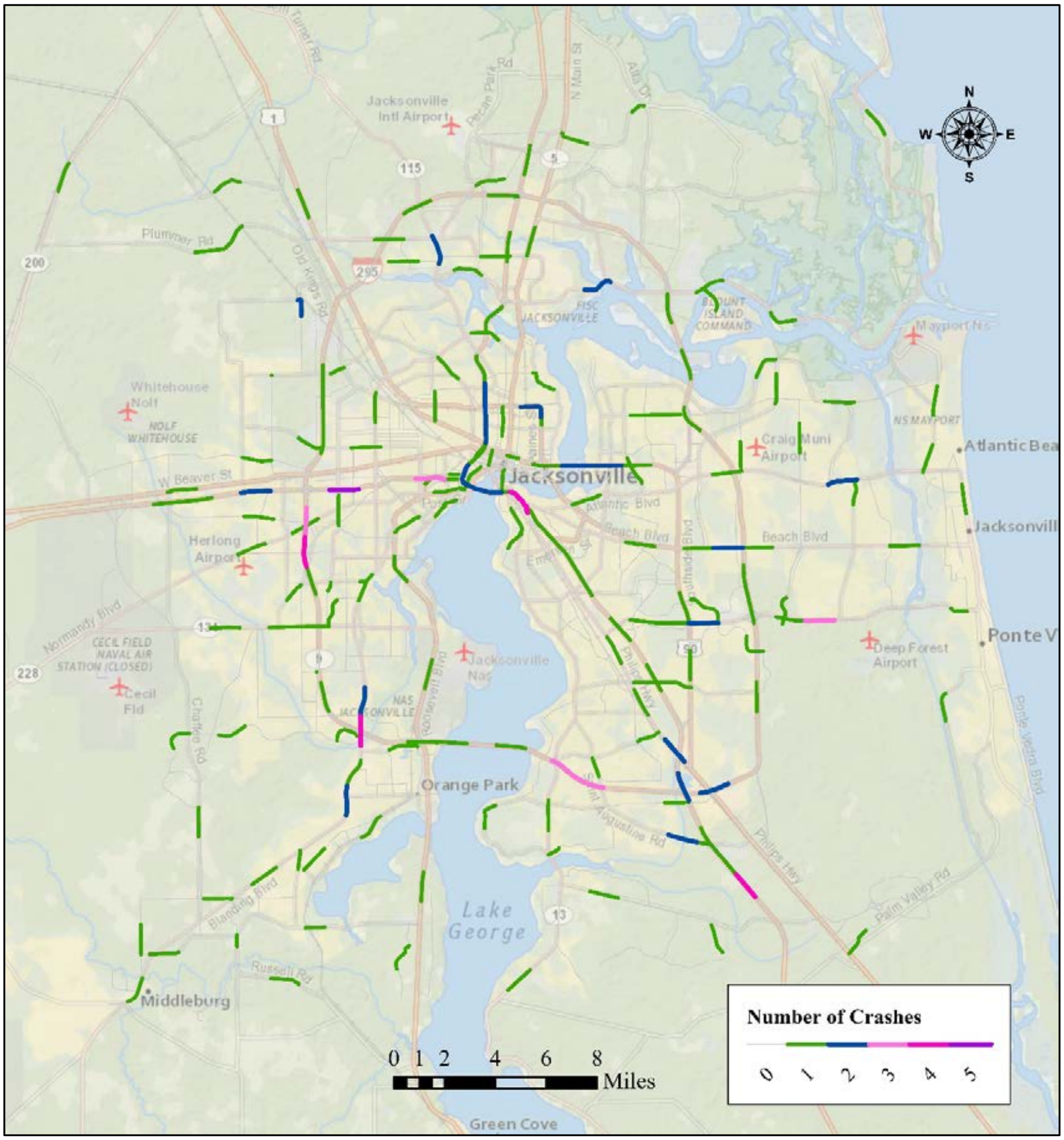


Figure 6-4 Microscopic analysis of fog crashes based on one-mile segment in cluster 1

Table 6-5 One-mile segments with frequent fog crashes in cluster 1

Roadway ID	Begin Milepost	End Milepost	Number of Crashes
72270000	17.000	18.000	5
72070000	0.012	0.715	4
72280000	0.998	1.996	4
72170000	0.000	1.000	4
72001000	18.018	19.019	4
72270000	20.000	21.000	3
72292000	7.000	8.000	3
72001000	19.019	20.019	3
72001000	4.004	5.005	3
72001000	3.003	4.004	3
72090000	4.000	5.000	2
71070000	12.002	13.003	2
72040000	13.009	14.009	2
72040000	12.008	13.009	2
72250000	3.017	4.043	2
72150000	5.512	6.510	2
72070000	6.999	7.999	2
72020000	5.007	6.009	2
72020000	4.006	5.007	2
72020000	2.003	3.005	2
72020000	1.001	2.003	2
72270000	13.850	14.978	2
72292000	3.000	4.000	2
72000110	2.002	2.630	2
72000083	0.996	1.994	2
72280000	4.992	5.990	2
72190000	6.018	7.021	2
72100000	10.984	11.983	2
72170000	1.000	2.001	2
72002000	24.046	25.048	2

Cluster 2 Pinellas, Hillsborough and Pasco Counties

Cluster 2 extends over Pinellas, Hillsborough and Pasco County. Overall 36 segments were discovered as a hotspot in Cluster 2 and were shown in Figure 6-5 and Table 6-6. It is noted that three segments have four fog crashes and nine segments have three fog crashes per mile.

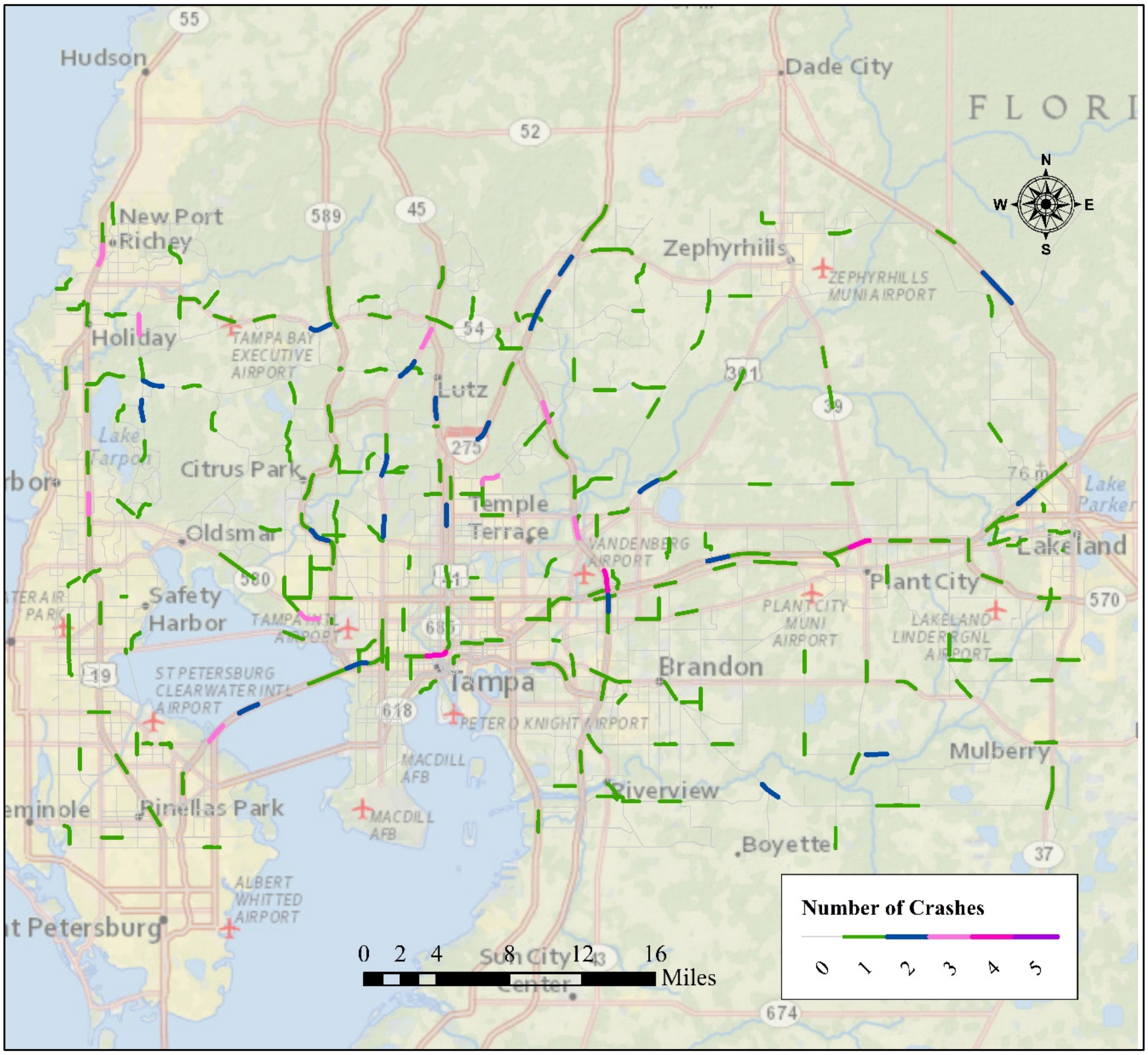


Figure 6-5 Microscopic analysis of fog crashes based on one-mile segment in cluster 2

Table 6-6 One-mile segments with frequent fog crashes in cluster 2

Roadway ID	Begin Milepost	End Milepost	Number of Crashes
10190000	5.997	6.996	4
10190000	27.985	28.985	4
10075000	26.997	27.997	4
14040000	0.000	1.009	3
14000049	0.000	1.000	3
10075000	29.997	30.997	3
10075000	35.996	36.996	3
15150000	25.000	26.000	3
10590000	3.005	4.007	3
14030000	4.002	5.002	3
10517000	1.004	2.008	3
15190000	13.997	14.997	3
15560000	3.001	4.001	2
15000028	7.006	8.007	2
16210000	12.993	13.992	2
16210000	11.993	12.993	2
10190000	20.989	21.988	2
10160000	6.001	7.001	2
10160000	3.000	4.009	2
10160000	11.001	12.001	2
10320000	10.994	11.994	2
10320000	5.997	6.996	2
10075000	25.997	26.997	2
10508000	7.004	8.002	2
10210000	0.999	1.999	2
10190800	2.001	3.001	2
10000017	2.997	3.996	2
14571000	2.001	3.002	2
16320000	4.001	5.003	2
10040000	12.004	13.004	2
10010000	13.002	14.003	2
10470000	4.996	5.995	2
14140000	4.015	5.016	2
14140000	2.003	2.995	2
14140000	0.997	2.003	2
15190000	15.997	16.996	2

Cluster 3 Polk and Osceola Counties

Cluster 3 extends from Polk to Osceola Counties. Overall 15 segments were discovered as a hotspot in Cluster 3 and were shown in Figure 6-6 and Table 6-7.

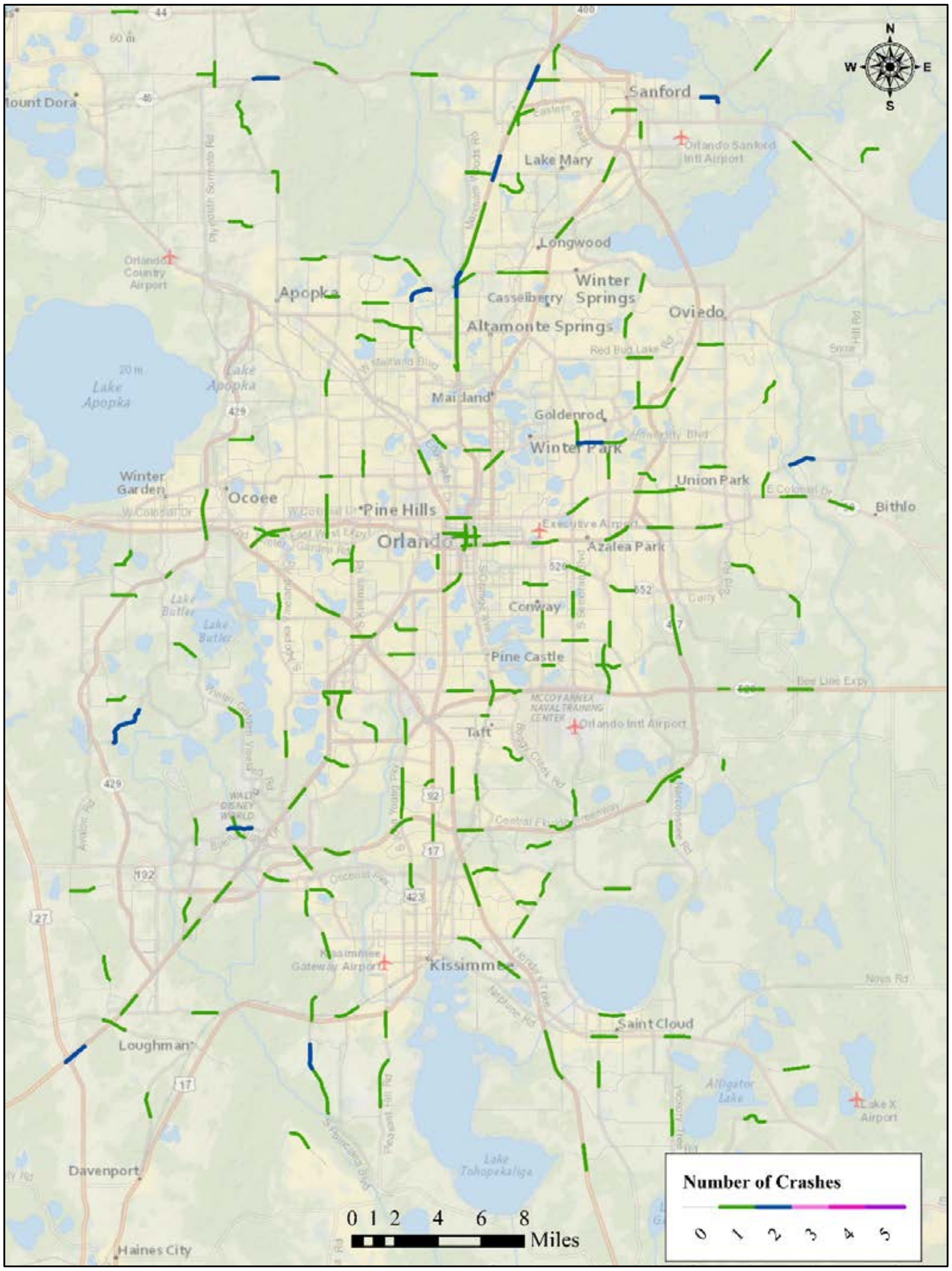


Figure 6-6 Microscopic analysis of fog crashes based on one-mile segment in cluster 3

Table 6-7 One-mile segments with frequent fog crashes in cluster 3

Roadway ID	Begin Milepost	End Milepost	Number of Crashes
11130000	7.001	8.001	2
77160000	2.998	4.001	2
77160000	12.002	13.002	2
77160000	7.988	9.013	2
77120000	3.002	4.002	2
92605000	5.998	6.993	2
75000323	3.008	4.010	2
75000082	1.998	2.997	2
75000082	0.999	1.998	2
77160800	2.998	3.998	2
75160501	2.003	3.004	2
75000034	0.000	0.999	2
16320000	29.019	30.020	2
11010000	19.992	20.991	2
77050000	2.995	3.865	2

Cluster 4 Escambia County

Cluster 4 mainly covers Escambia County. Overall 7 segments were discovered as a hotspot in Cluster 4 and were shown in Figure 6-7 and Table 6-8.

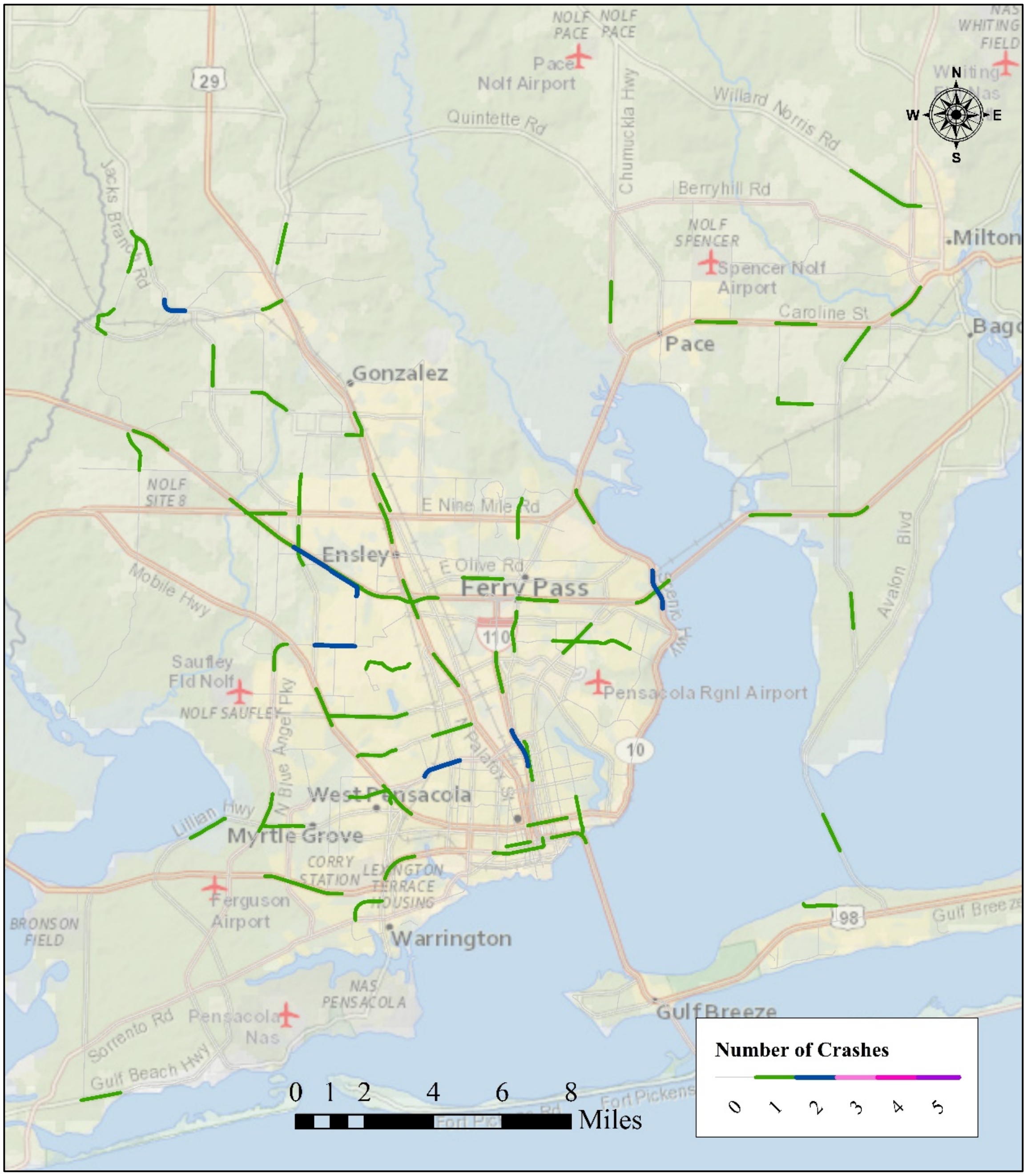


Figure 6-7 Microscopic analysis of fog crashes based on one-mile segment in cluster 4

Table 6-8 One-mile segments with frequent fog crashes in cluster 4

Roadway ID	Begin Milepost	End Milepost	Number of Crashes
48270000	1.990	2.985	2
48000012	0.000	0.999	2
48260000	6.982	7.980	2
48000060	0.000	0.997	2
48020000	22.908	23.904	2
48004000	6.970	7.966	2
48590000	14.234	14.934	2

Cluster 5 Leon County

Cluster 5 is located in the center of Leon County. Overall 9 segments were discovered as a hotspot in Cluster 5 and were shown in Figure 6-8 and Table 6-9. It is noted that there is one segment with three fog crashes per mile.

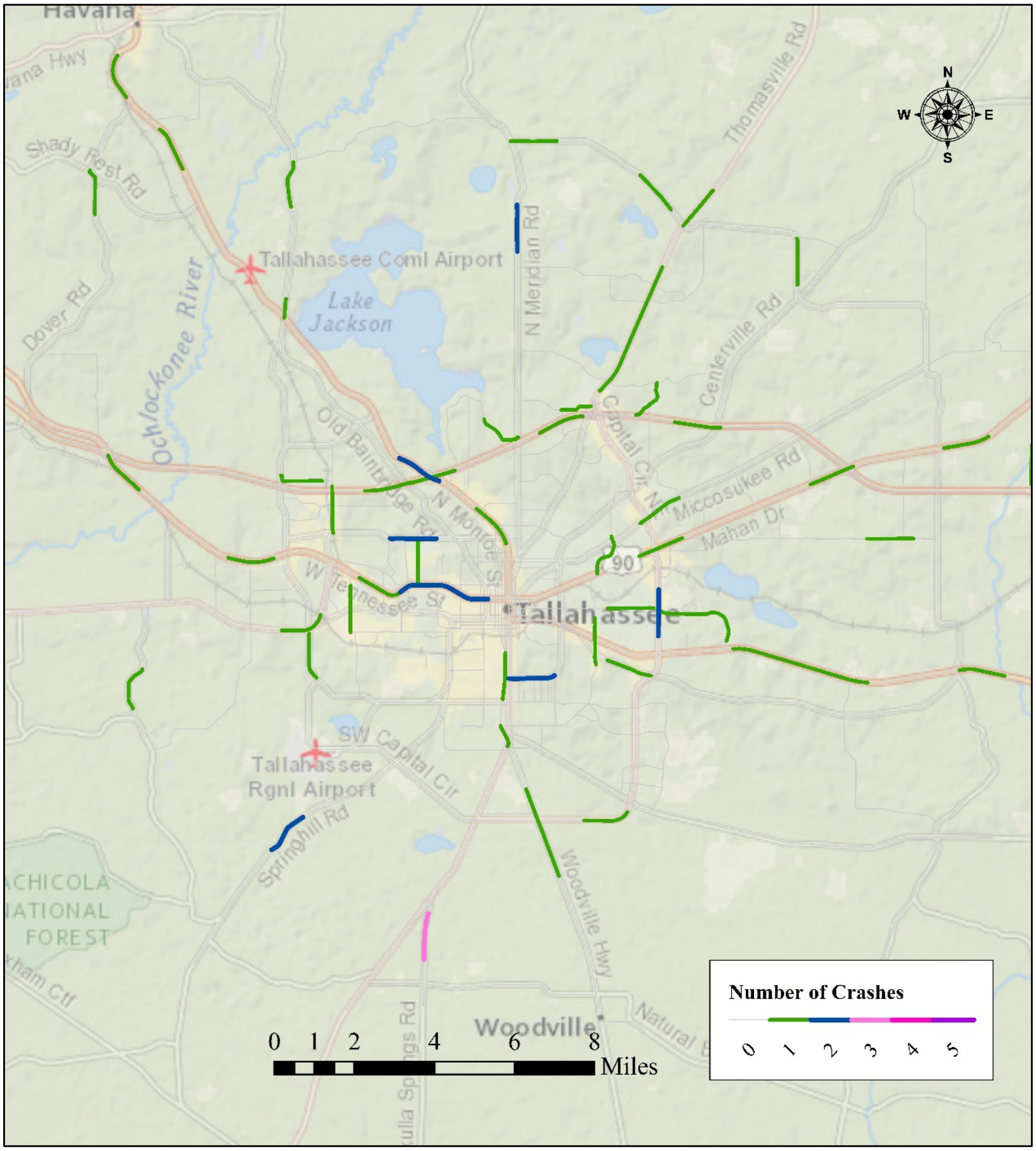


Figure 6-8 Microscopic analysis of fog crashes based on one-mile segment in cluster 5

Table 6-9 One-mile segments with frequent fog crashes in cluster 5

Roadway ID	Begin Milepost	End Milepost	Number of Crashes
55120000	1.999	2.999	3
55550000	0.000	1.001	2
55003000	6.003	7.004	2
55520000	4.998	5.997	2
55060000	7.002	8.003	2
55060000	6.001	7.002	2
55010000	6.011	7.012	2
55516000	4.003	5.004	2
55580000	1.995	2.993	2

Cluster 6 Miami-Dade and Broward Counties

Cluster 6 stretches over Miami-Dade and Broward Counties. Overall 4 segments were discovered as a hotspot in Cluster 6 and were shown in Figure 6-10 and Table 6-11. It is noted that there is one segment with 3 fog crashes per mile.

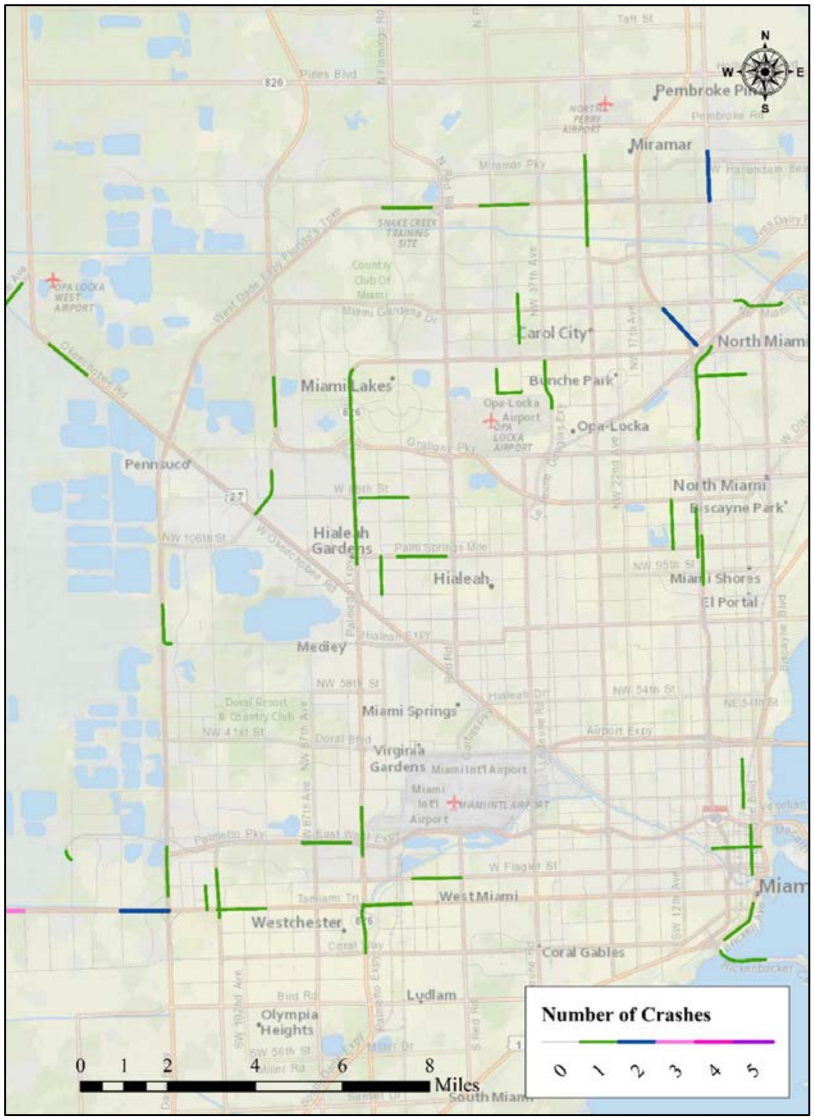


Figure 6-9 Microscopic analysis of fog crashes based on one-mile segment in cluster 6

Table 6-10 One-mile segments with frequent fog crashes in cluster 6

Roadway ID	Begin Milepost	End Milepost	Number of Crashes
87120000	2.003	3.005	3
86100000	0.000	1.000	2
87120000	5.008	6.009	2
87470000	0.000	1.002	2

Cluster 7 Alachua County

Cluster 7 is placed at the center of Alachua County. Overall 8 segments were discovered as a hotspot in Cluster 7 and were shown in Figure 6-10 and Table 6-11. It is noted that there are two segments with four fog crashes per mile and there is one segment with three fog crashes per mile.

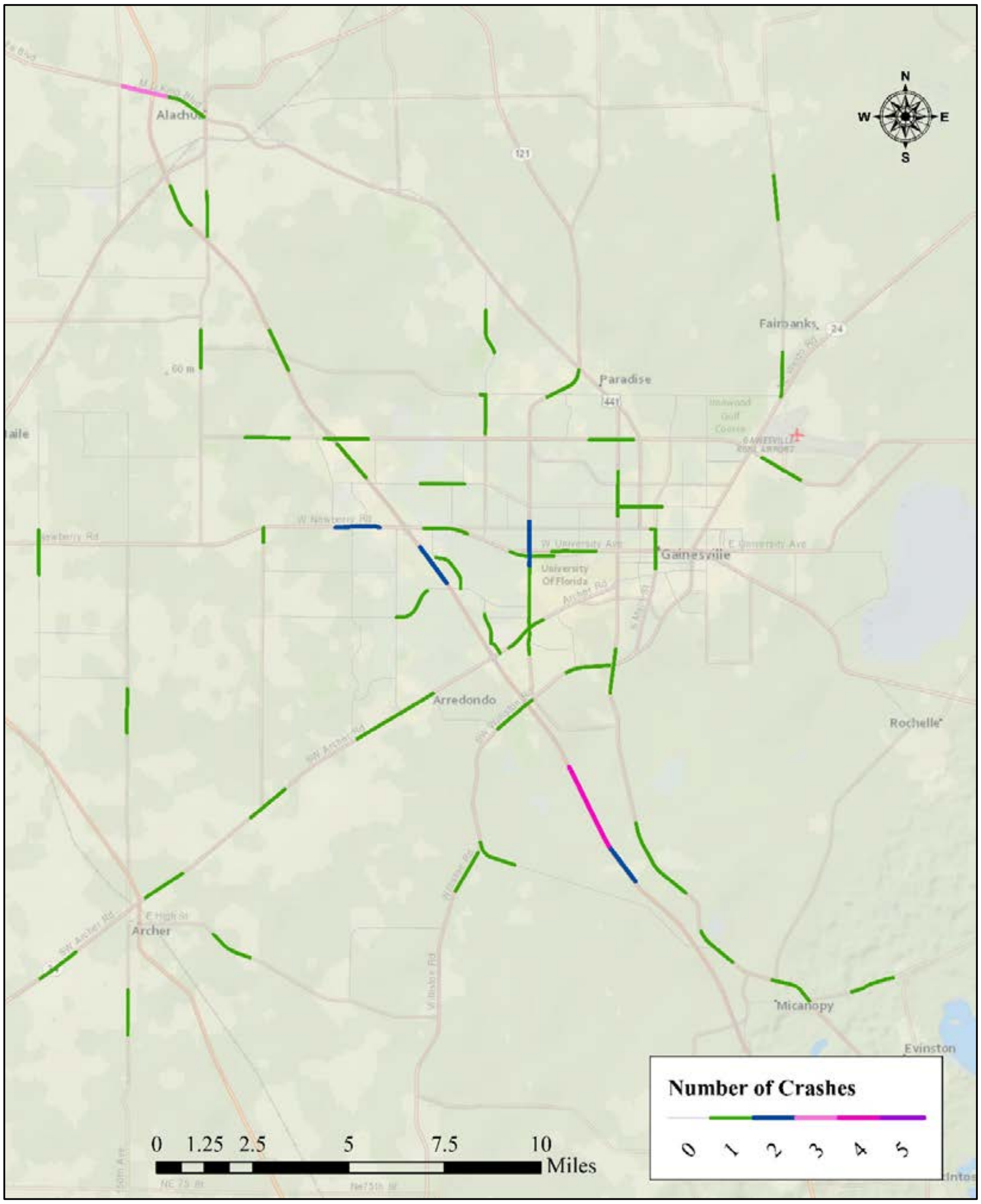


Figure 6-10 Microscopic analysis of fog crashes based on one-mile segment in cluster 7

Table 6-11 One-mile segments with frequent fog crashes in cluster 7

Roadway ID	Begin Milepost	End Milepost	Number of Crashes
26260000	6.003	7.003	4
26260000	7.003	8.004	4
26020000	18.997	19.997	3
26070000	12.999	13.999	2
26250000	3.007	4.009	2
26260000	5.002	6.003	2
26260000	13.006	14.060	2
26500000	3.997	4.997	2

Fog Crashes on Ramps

Similarly as the above analysis, ramps with frequent fog crashes were discovered. All ramps with more than two fog crashes were defined as a hotspot in the analysis. The locations of hotspots are summarized in Table 6-12.

Cluster 1 Duval County

Three ramps were detected as a hotspot in Cluster 1 and are shown in Figure 6-11.

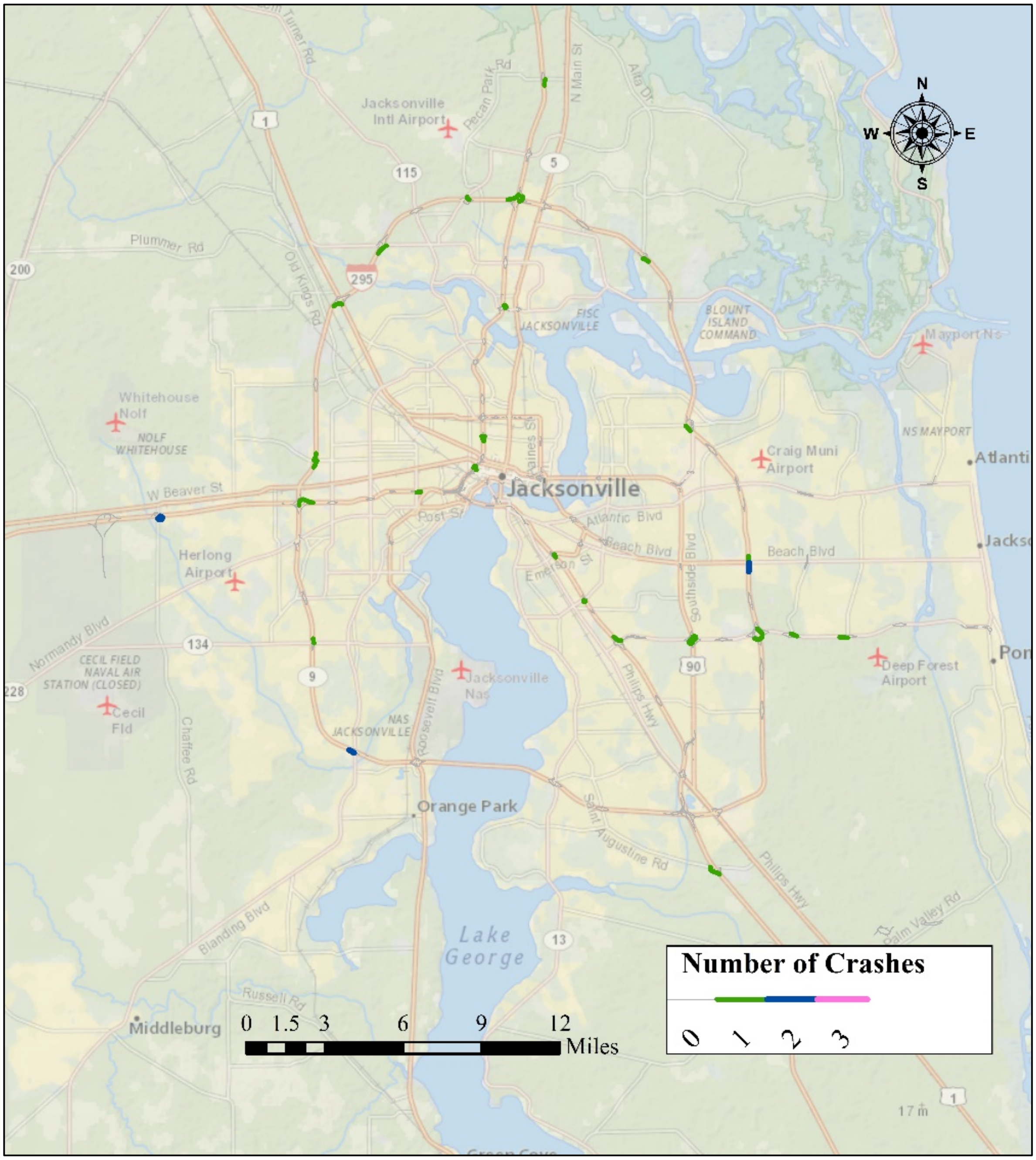


Figure 6-11 Microscopic analysis of fog crashes based on ramp in cluster 1

Cluster 2 Pinellas, Hillsborough and Pasco Counties

Two ramps were revealed as a hotspot in Cluster 2 and are displayed in Figure 6-12.

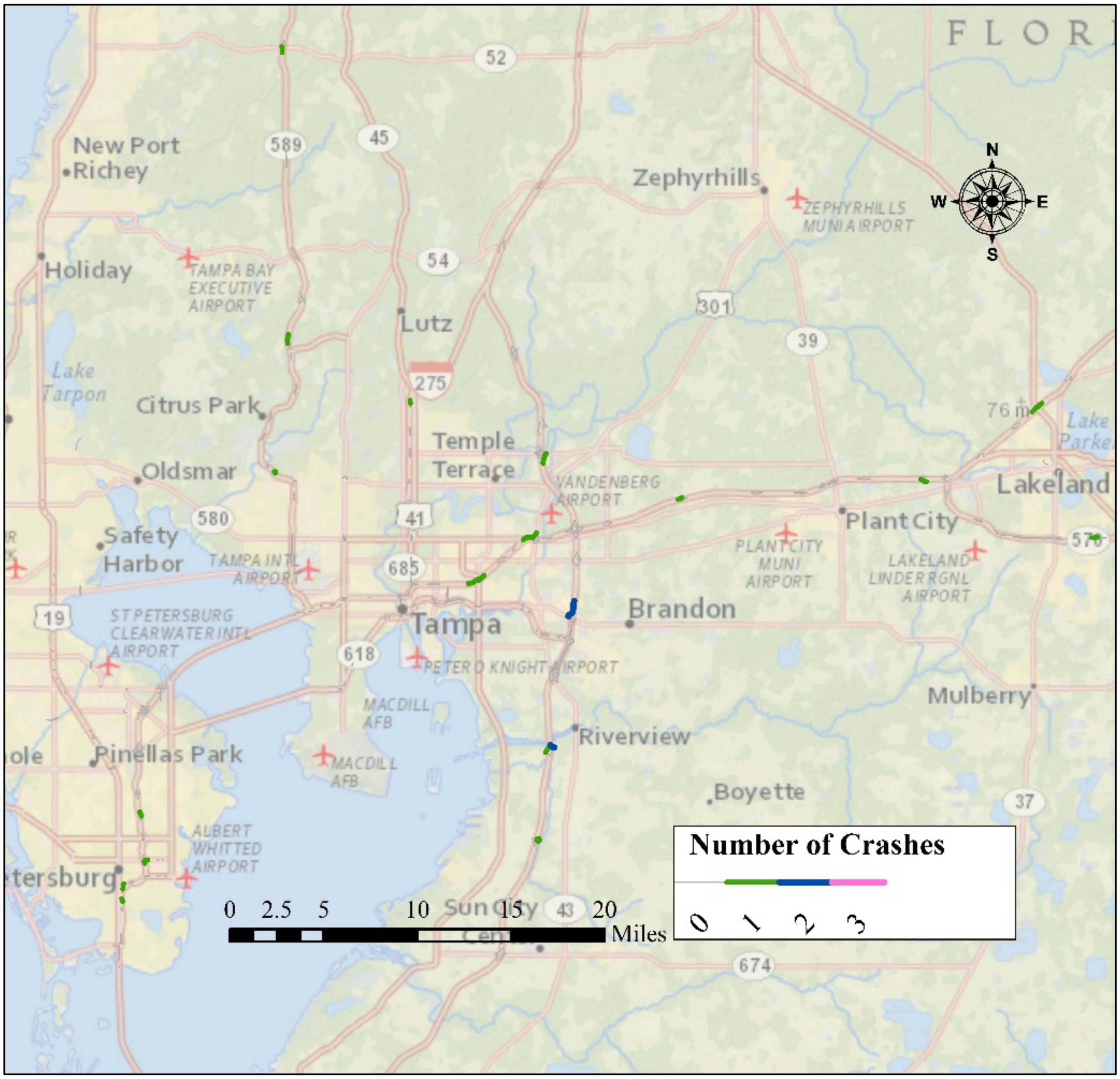


Figure 6-12 Microscopic analysis of fog crashes based on ramp in cluster 2

Cluster 3 Polk and Osceola Counties

Overall 3 ramps were identified as a hotspot in Cluster 3 and are shown in Figure 6-13.

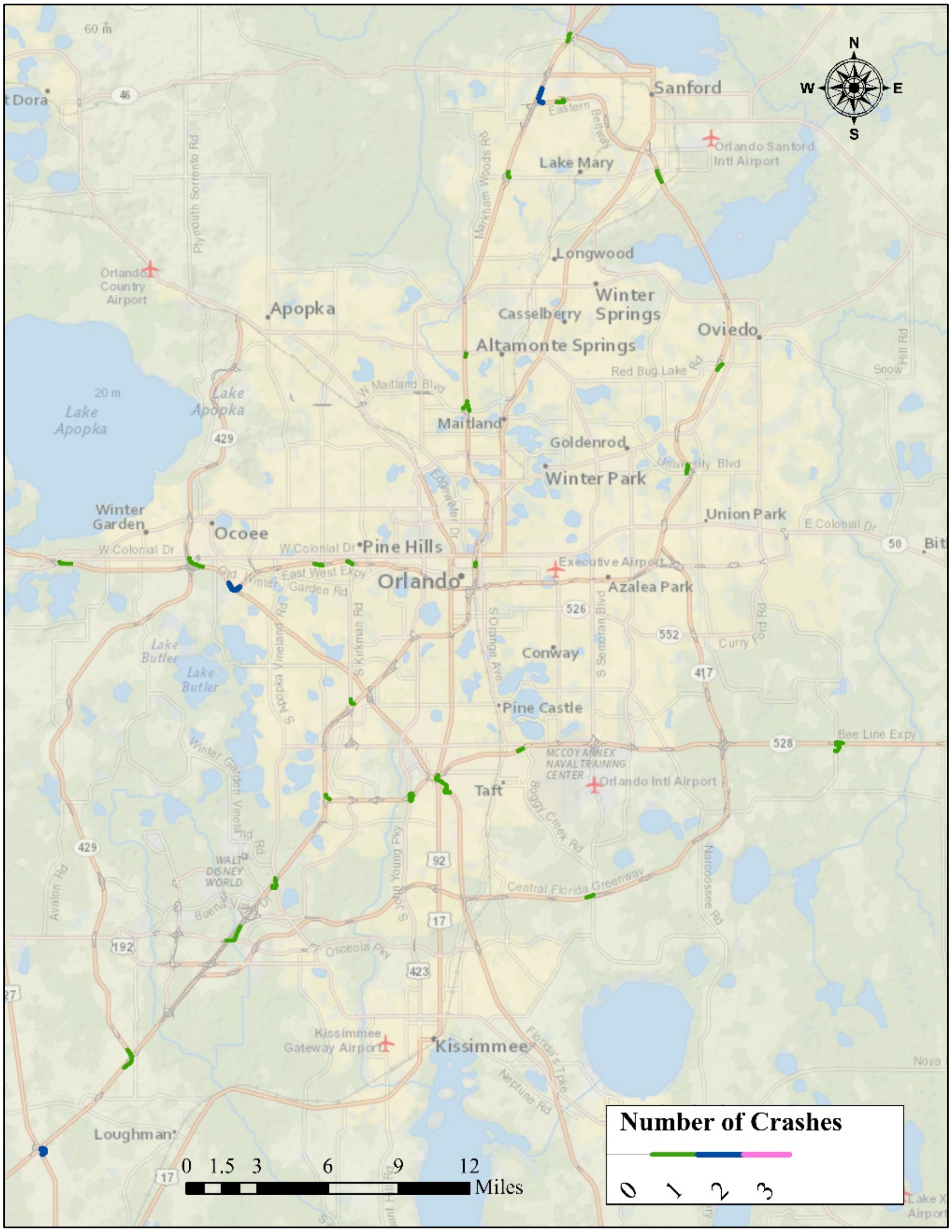


Figure 6-13 Microscopic analysis of fog crashes based on ramp in cluster 3

Cluster 4 Escambia County

Totally two ramps were discovered as a hotspot in Cluster 4 and are depicted in Figure 6-14.

Figure 6-14 Microscopic analysis of fog crashes based on ramp in cluster 4

Cluster 5 Leon County

No ramps were uncovered as a hotspot in Cluster 5 (Figure 6-15).

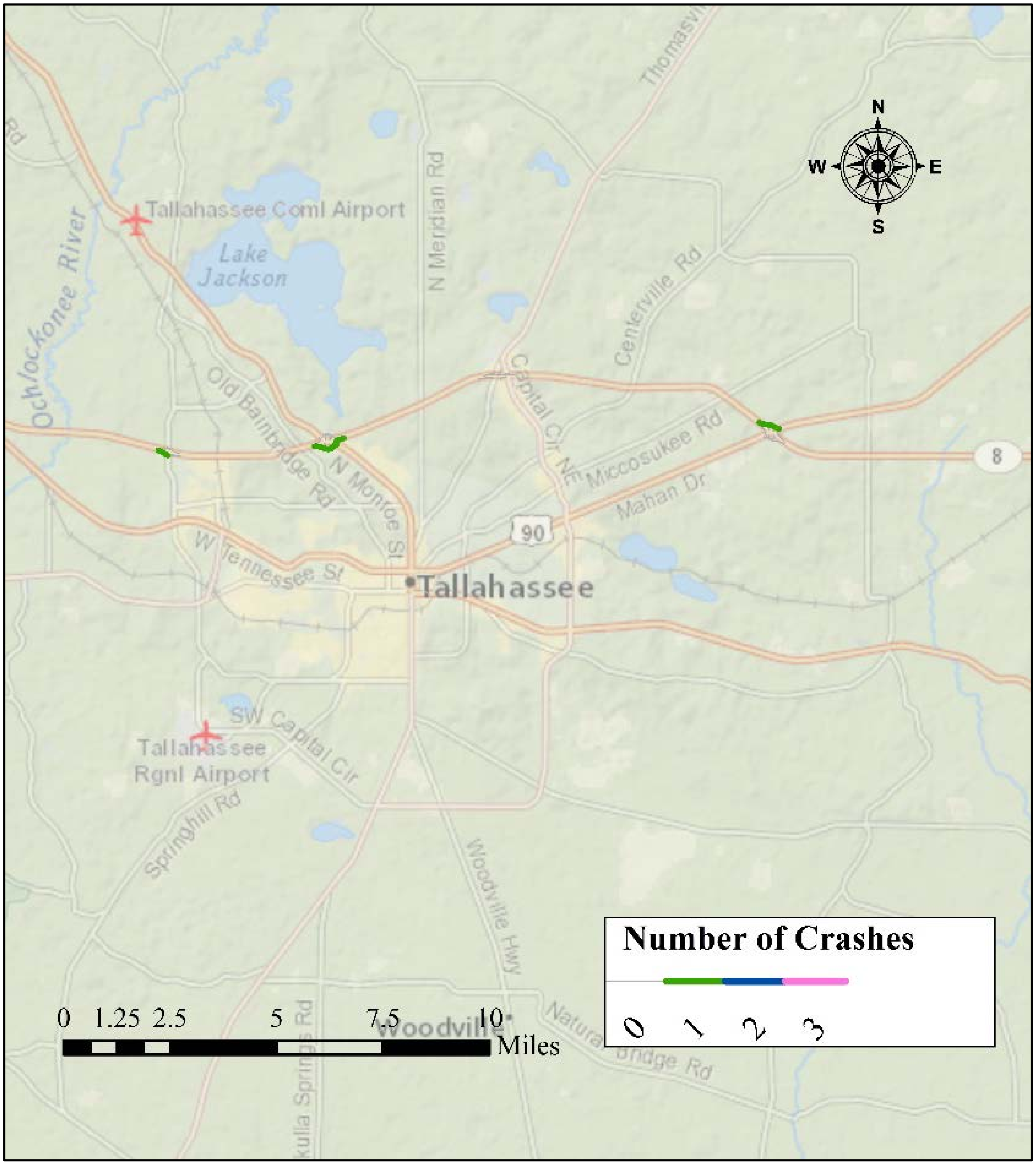


Figure 6-15 Microscopic analysis of fog crashes based on ramp in cluster 5

Cluster 6 Miami-Dade and Broward Counties

It was shown that no ramps were discovered as a hotspot in Cluster 6 (Figure 6-16).

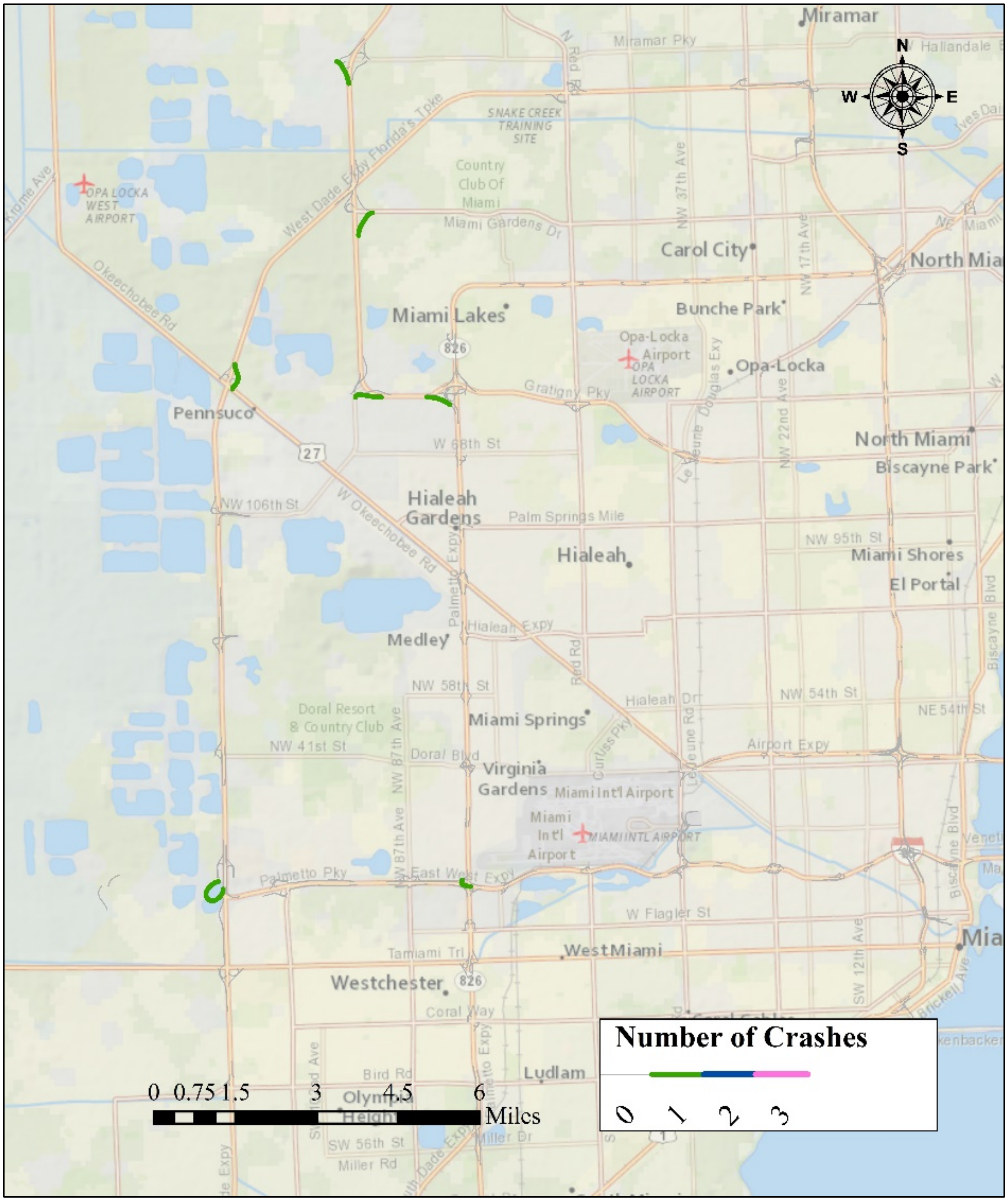


Figure 6-16 Microscopic analysis of fog crashes based on ramp in cluster 6

Cluster 7 Alachua County

Two ramps were identified as a hotspot in Cluster 7 and are shown in Figure 6-17. It was found that the two ramps identified as a hotspot are located on I-75.

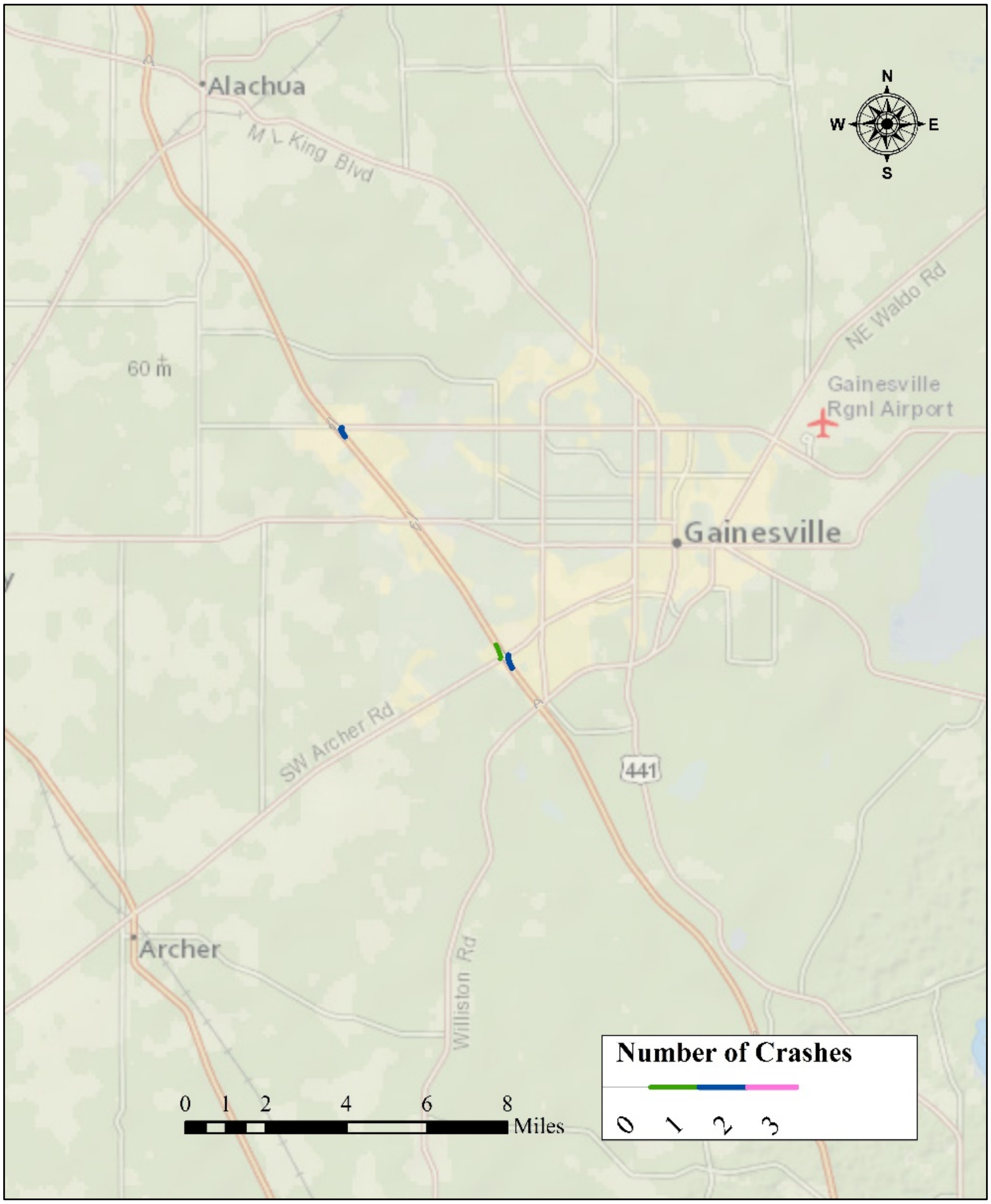


Figure 6-17 Microscopic analysis of fog crashes based on ramp in cluster 7

Table 6-12 Ramps with frequent fog crashes

Cluster	Roadway ID	Begin Milepost	End Milepost	Number of Crashes
1	72002039	0.000	0.293	2
	72001023	0.000	0.190	2
	72270191	0.000	0.247	2
2	10075336	0.000	0.819	2
	10075014	0.000	0.230	2
3	75470151	0.000	0.585	2
	77300001	0.000	0.624	2
	16320103	0.000	0.416	2
4	48260054	0.000	0.449	3
	48260028	0.000	0.175	2
7	26260026	0.000	0.225	2
	26260050	0.000	0.297	2

Fog crashes at Intersections

Intersections with frequent fog crashes were analyzed as previously. All intersections with two or more fog crashes were defined as a hotspot in the analysis. All the hotspots of intersections in the seven clusters were shown in Figures 6-18 to 6-24 and are summarized in Table 6-13.

Cluster 1 Duval County

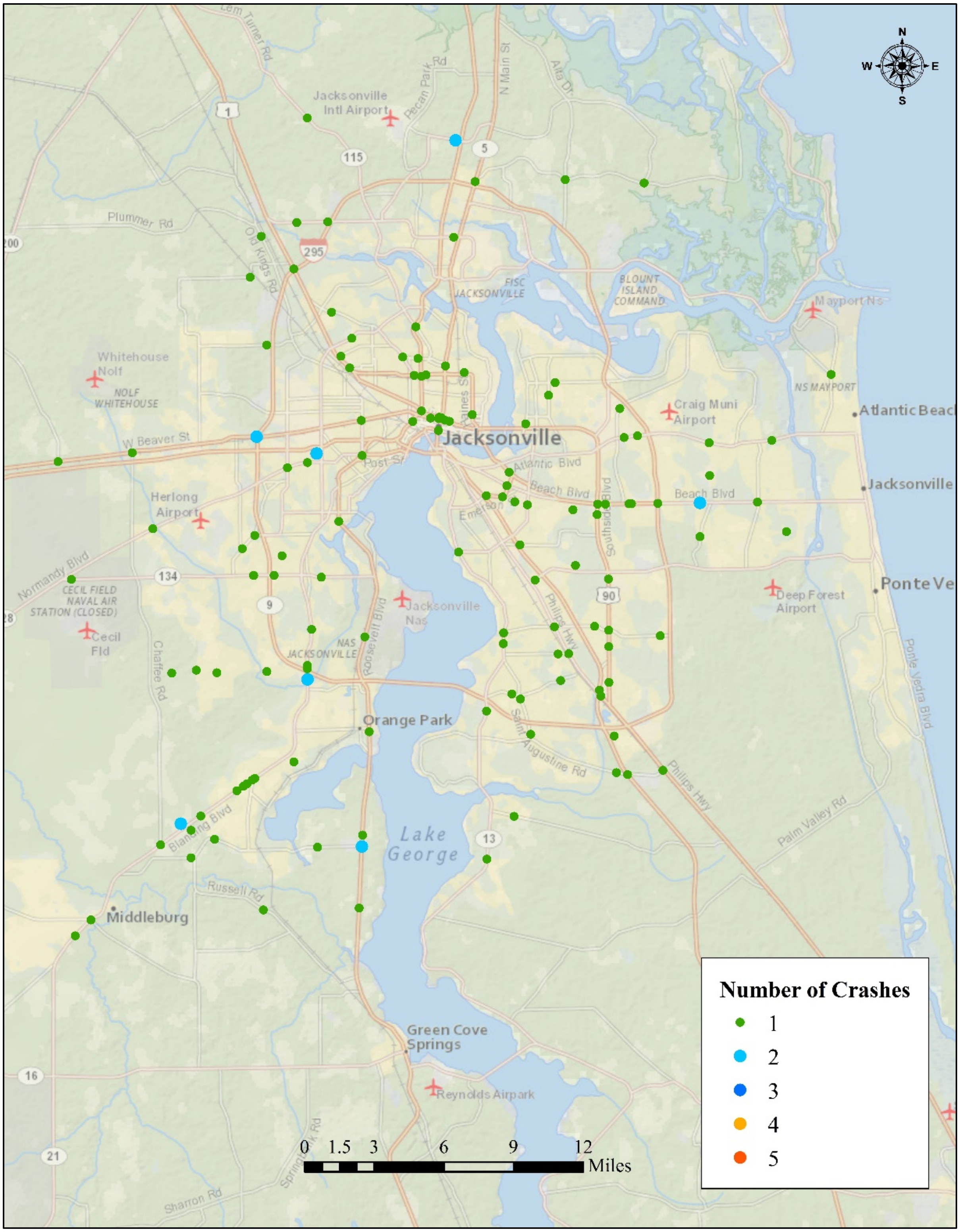


Figure 6-18 Microscopic analysis of fog crashes at intersections in cluster 1

Cluster 2 Pinellas, Hillsborough and Pasco Counties

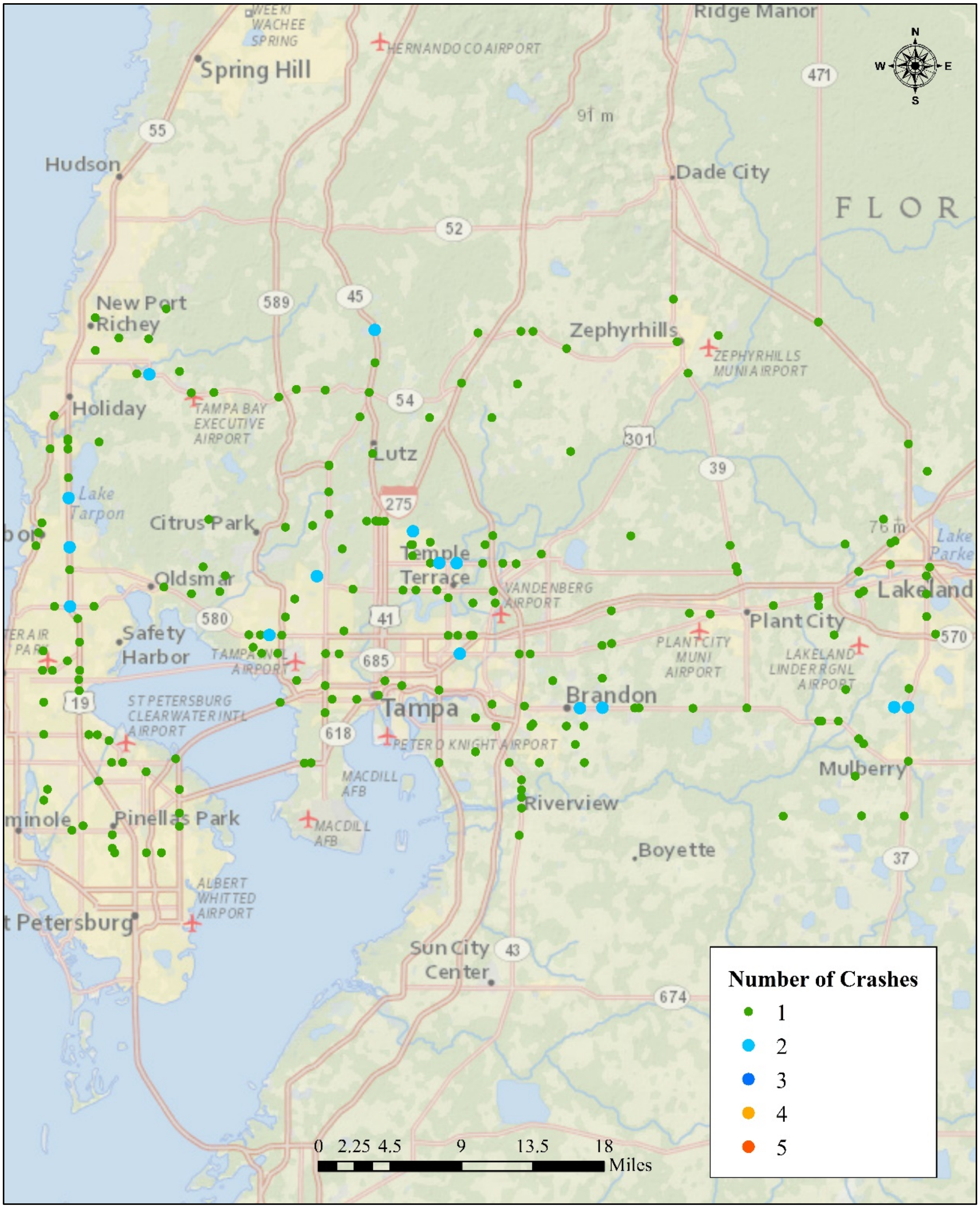


Figure 6-19 Microscopic analysis of fog crashes at intersections in cluster 2

Cluster 3 Polk and Osceola Counties

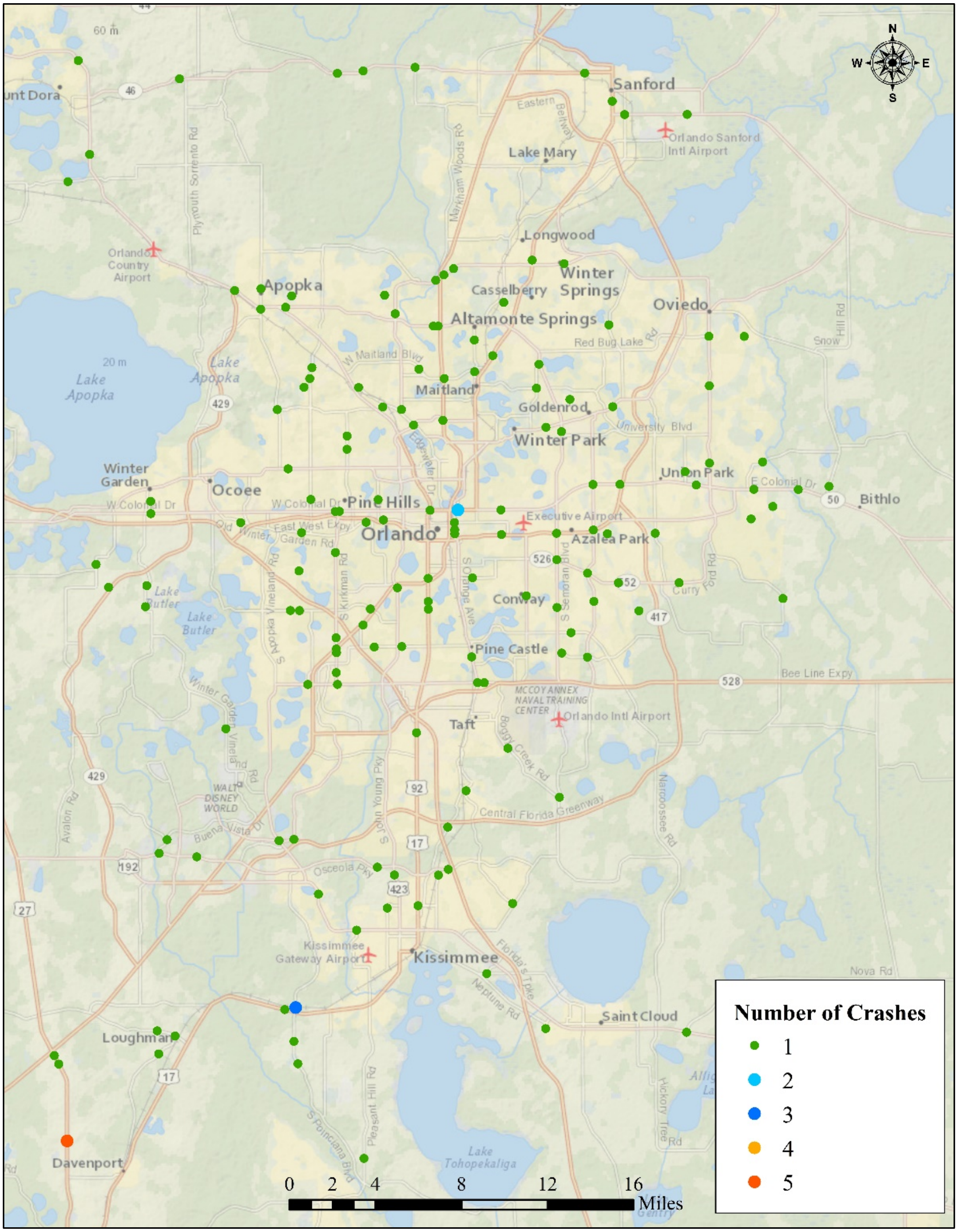


Figure 6-20 Microscopic analysis of fog crashes at intersections in cluster 3

Cluster 4 Escambia County

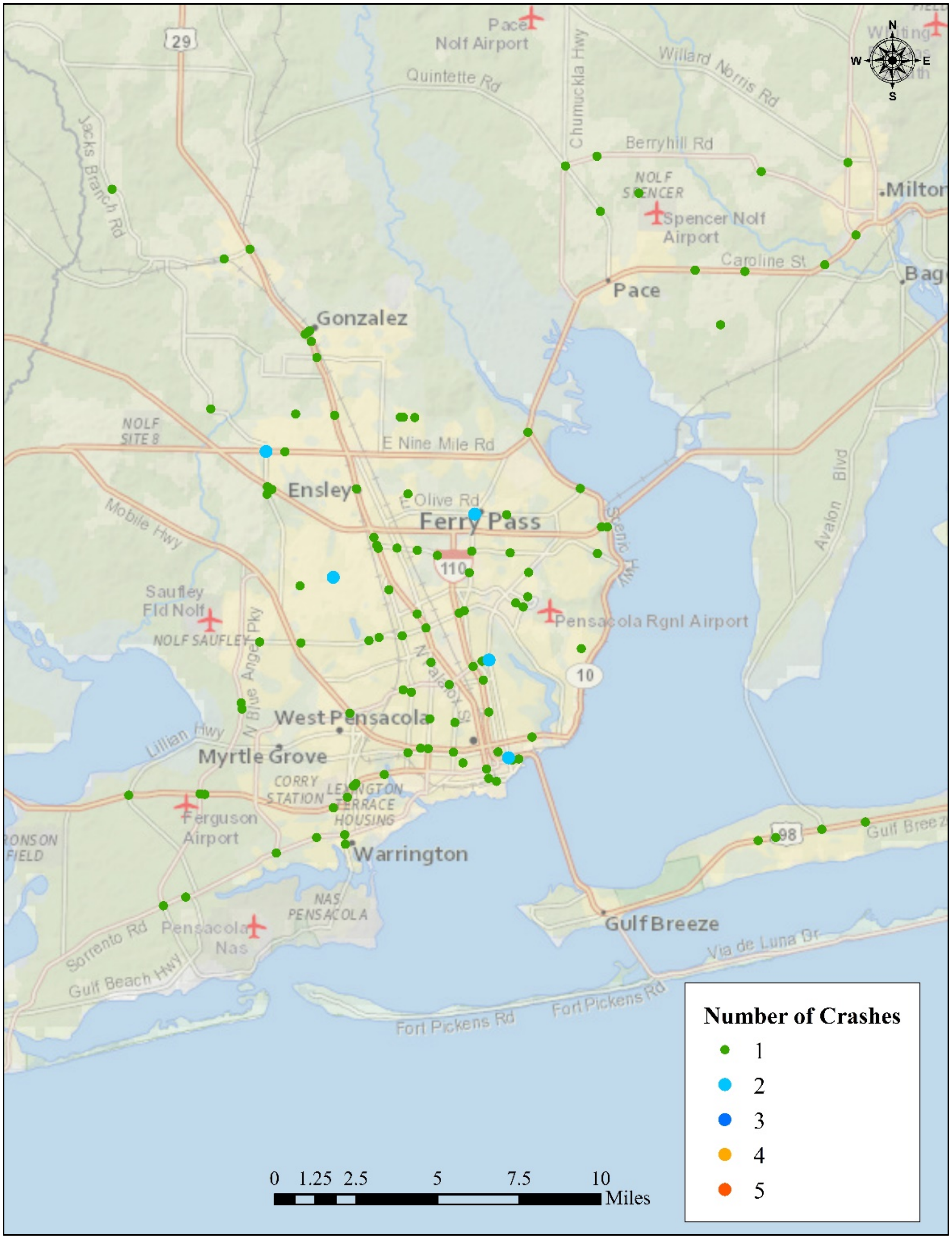


Figure 6-21 Microscopic analysis of fog crashes at intersections in cluster 4

Cluster 5 Leon County

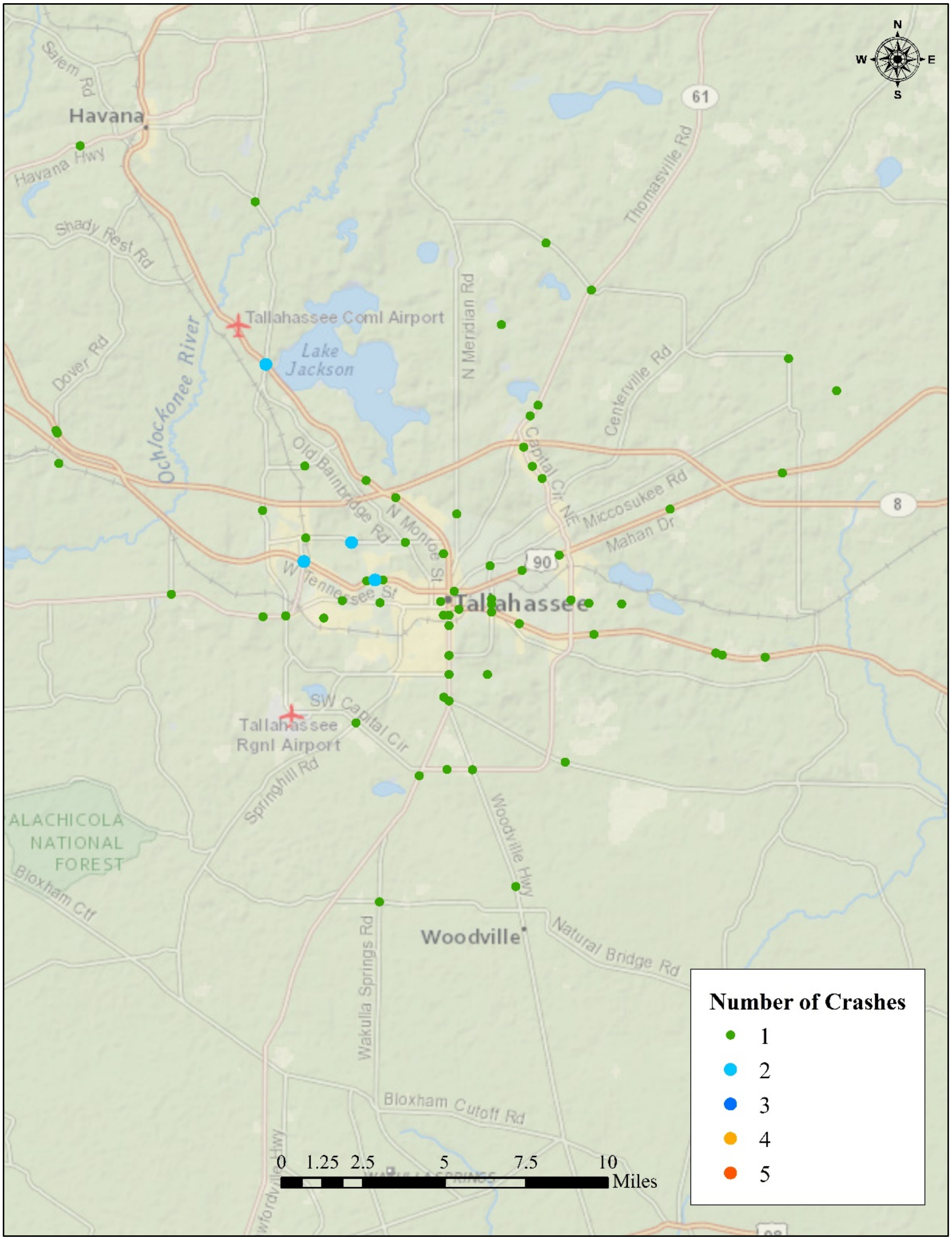


Figure 6-22 Microscopic analysis of fog crashes at intersections in cluster 5

Cluster 6 Miami-Dade and Broward Counties

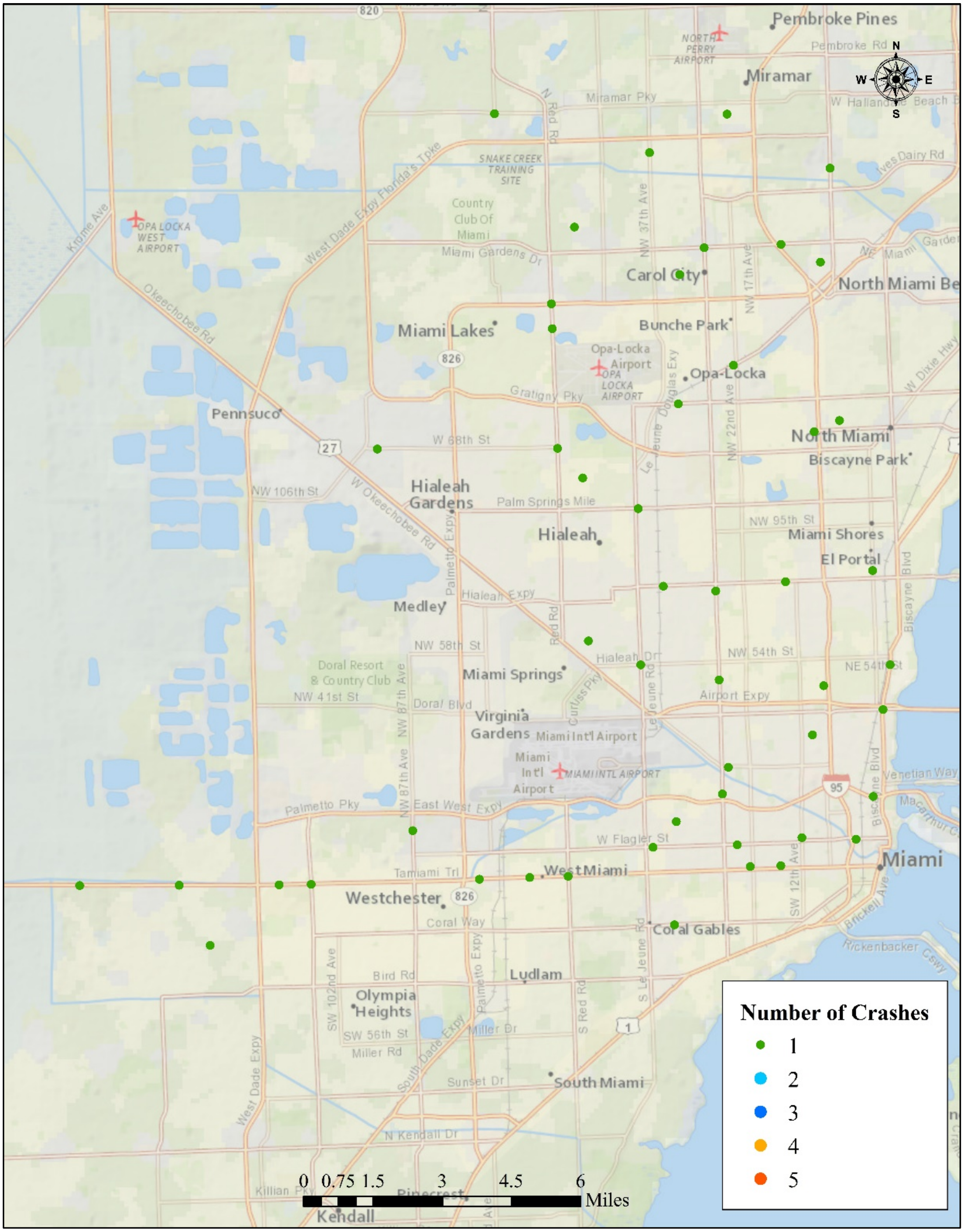


Figure 6-23 Microscopic analysis of fog crashes at intersections in cluster 6

Cluster 7 Alachua County

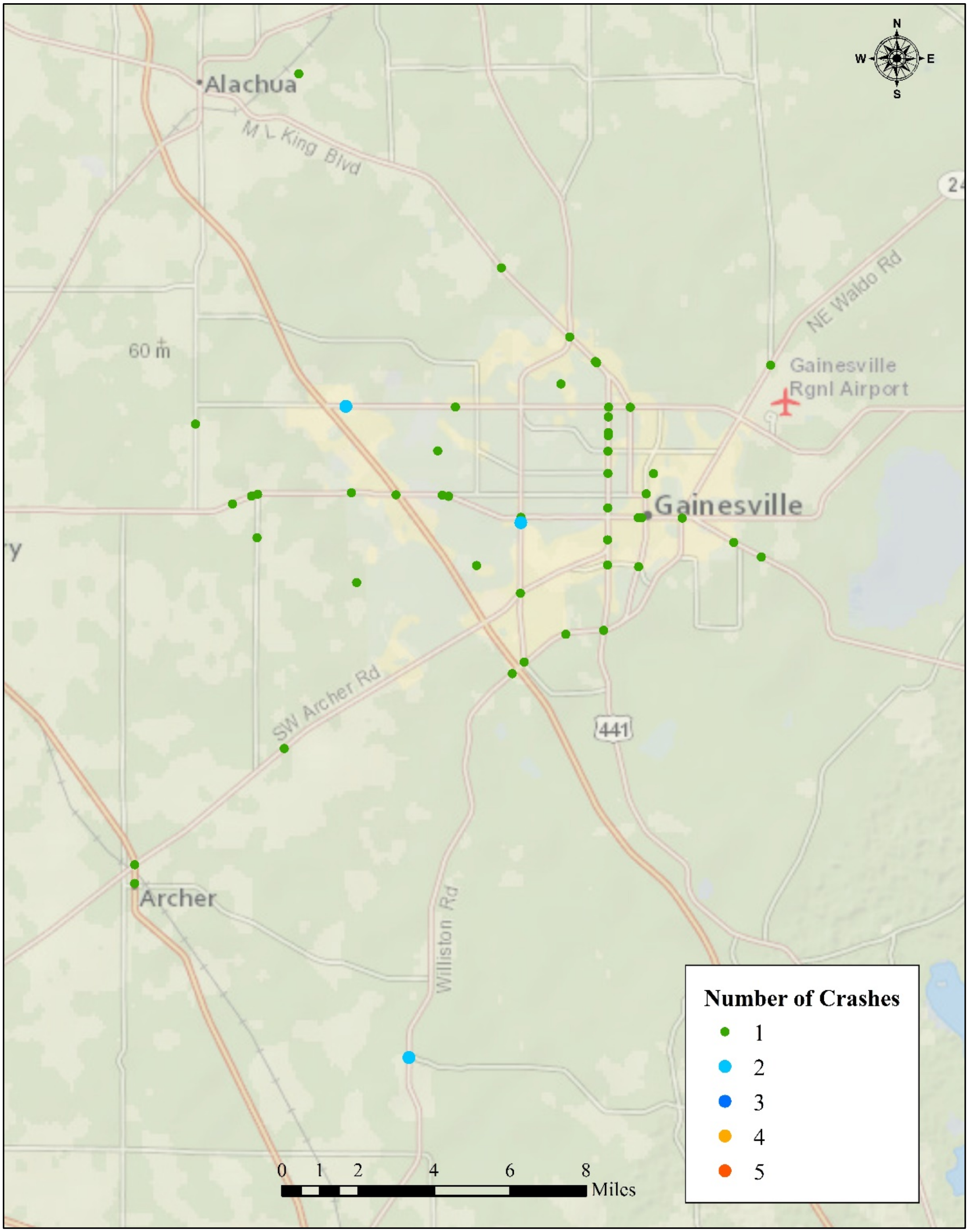


Figure 6-24 Microscopic analysis of fog crashes at intersections in cluster 7

Table 6-13 Intersections with frequent fog crashes

Cluster	Roadway ID	Milepost	Number of Crashes
1	72170000	0.181	2
	72190000	8.631	2
	72580000	5.599	2
	71020000	8.261	2
	71504000	4.621	2
	72003000	3.186	2
	72010000	14.741	2
2	10110000	10.189	2
	10504000	5.455	2
	10000645	0.742	2
	10150000	6.395	2
	10000144	11.444	2
	10340000	7.479	2
	10290000	4.499	2
	10290000	3.524	2
	14010000	4.976	2
	14570101	0.192	2
	15150000	28.564	2
	15070000	3.314	2
	16250000	21.207	2
	15080500	1.529	2
	16000342	4.211	2
3	16180000	20.154	5
	92000019	3.002	3
	75060000	1.135	2
4	48100000	3.901	2
	48004000	10.043	2
	48010000	8.299	2
	48000013	0.383	2
	48030000	2.409	2
5	55000020	6.435	2
	55060000	4.3	2
	55010000	2.005	2
	55580000	1.98	2
7	26005000	0.651	2
	26070068	0.458	2
	34080000	6.305	2

6.3.2 Microscopic Screening of Smoke Crashes

Smoke Crashes on One-Mile Segments

It was shown that five areas were identified with frequent smoke related crashes on Florida state highways using KDE in macroscopic analysis. We zoomed in these areas and then smoke related crashes were counted based on these one-mile segments. All segments with more than two smoke crashes were defined as a hotspot in the analysis. The locations of the hot segments are summarized in Table 6-14. There is no smoke crashes occurred on ramps or at intersections in the macro-level hotspot clusters.

Cluster 1 Miami-Dade and Broward Counties

Cluster 1 stretches over Miami-Dade and Broward Counties. Overall two segments were discovered as a hotspot in Cluster 1 and are exhibited in Figure 6-25.

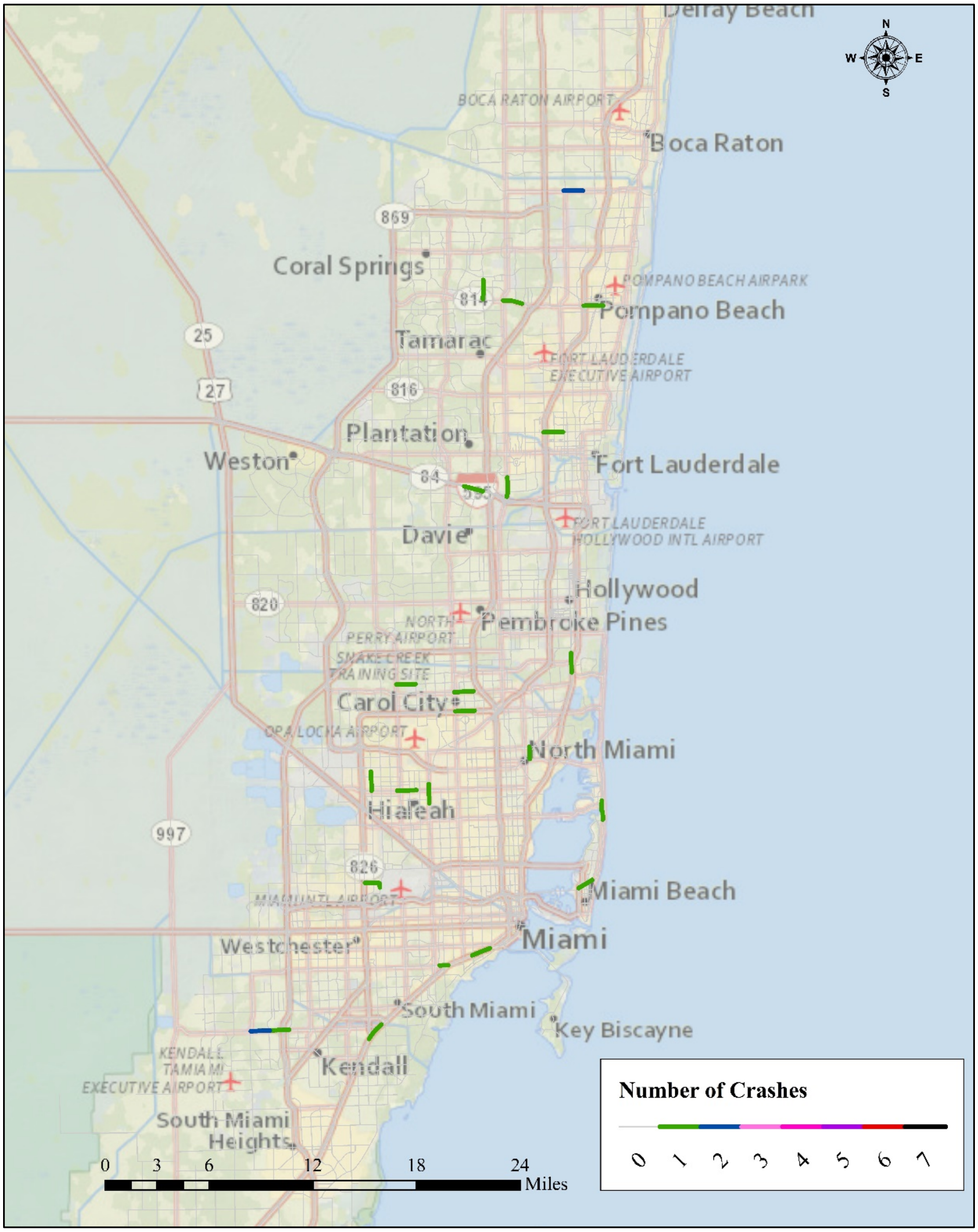


Figure 6-25 Microscopic analysis of smoke crashes based on segments in cluster 1

Cluster 2 Polk County

Cluster 2 mainly covers Polk County. Overall two segments were uncovered as a hotspot in Cluster 2 and are shown in Figure 6-26.

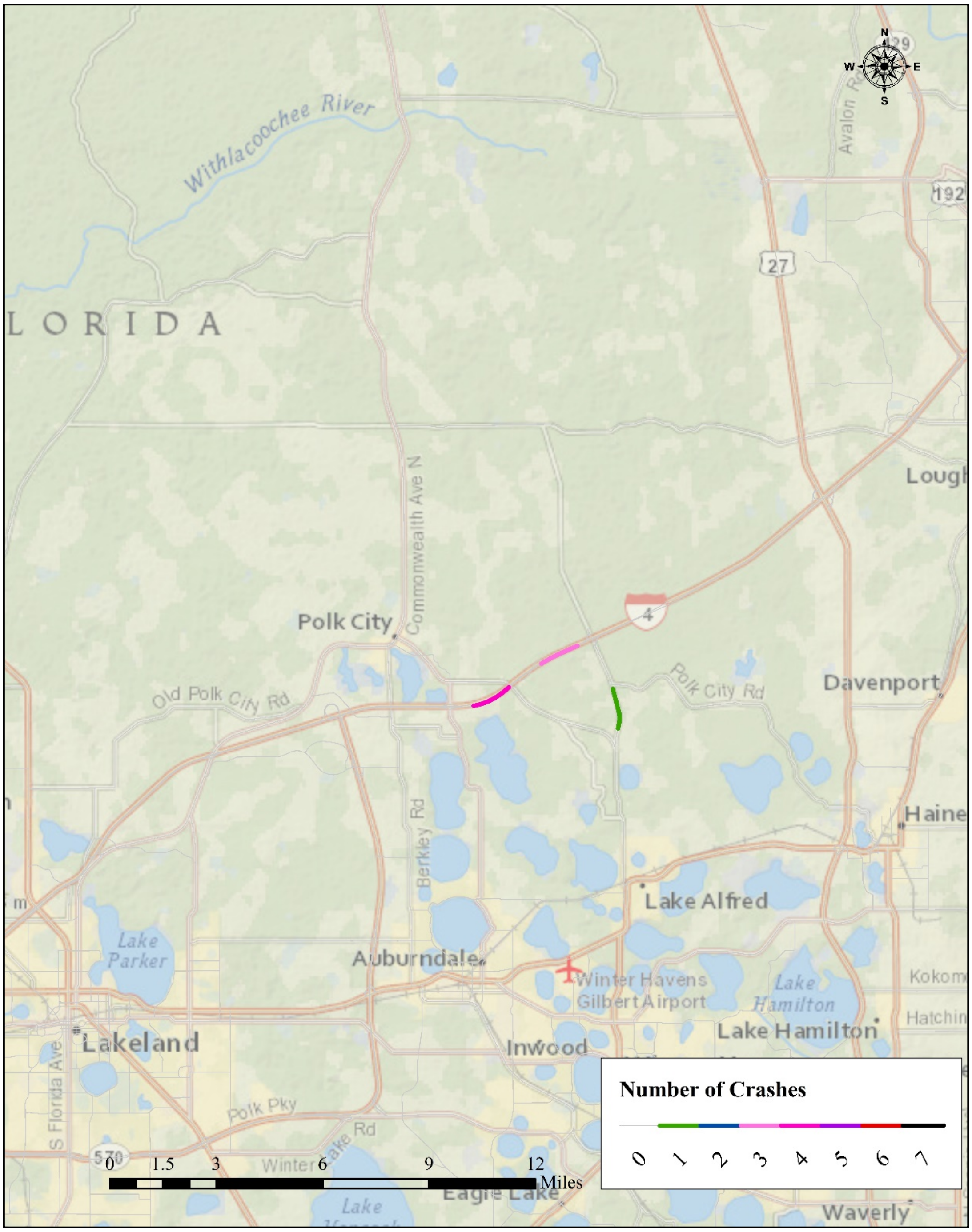


Figure 6-26 Microscopic analysis of smoke crashes based on segments in cluster 2

Cluster 3 Alachua County

Cluster 3 is located in the southeastern part of Alachua County. Overall two segments were identified as a hotspot in Cluster 3 and are displayed in Figure 6-27. It is noteworthy to mention that there are two consecutive segments on I-75 have six smoke crashes. Moreover, there was a smoke crash on SR-441 just next to the I-75 two hotspots.

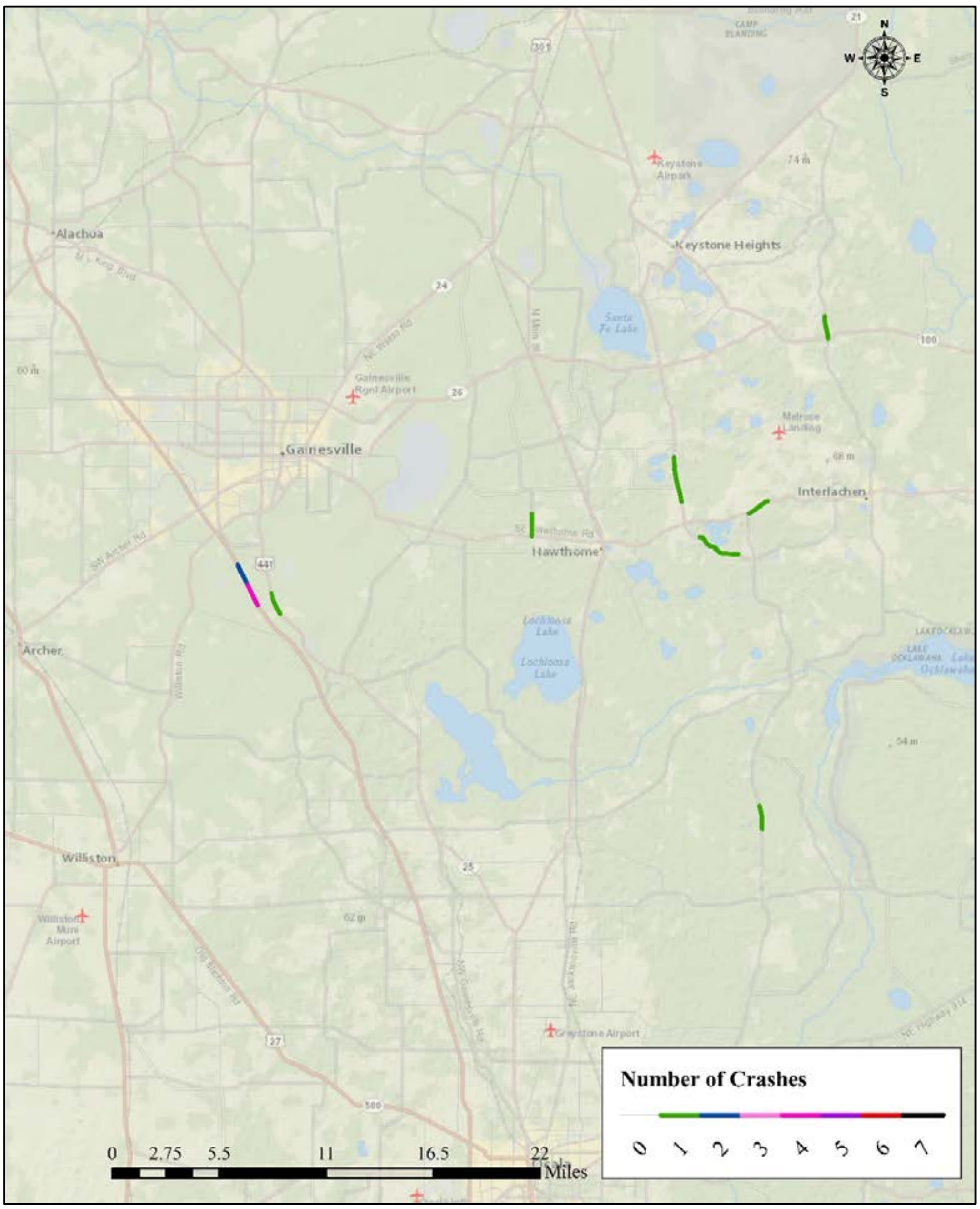


Figure 6-27 Microscopic analysis of smoke crashes based on segments in cluster 3

Cluster 4 Collier County

Cluster 4 is located in the center of Collier County. There is only one segment discovered as a hotspot in Cluster 4; however, the hotspot has 7 smoke crashes. (Figure 6-28).

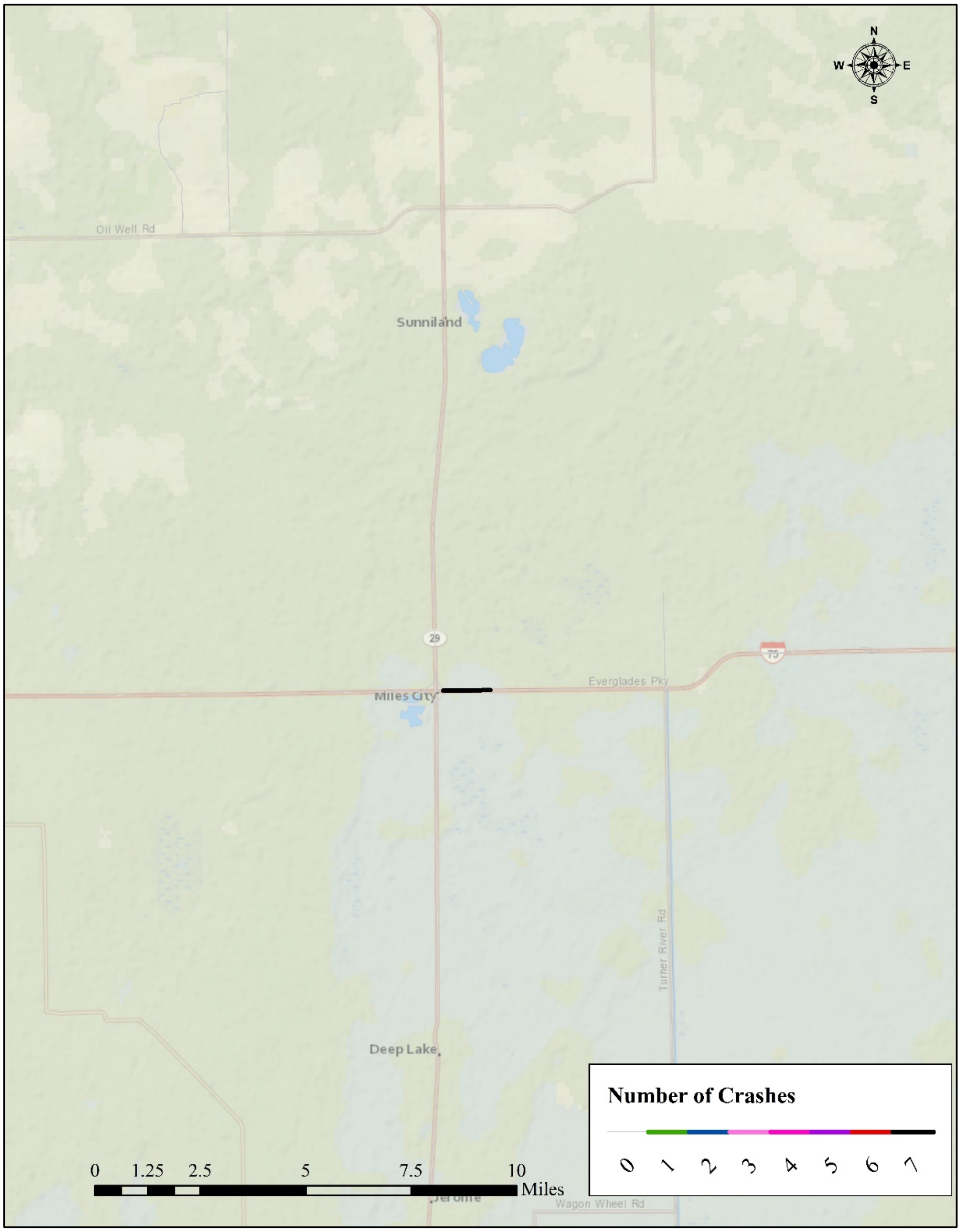


Figure 6-28 Microscopic analysis of smoke crashes based on segments in cluster 4

Cluster 5 Bay County

Cluster 5 is placed at the eastern part of Bay County. Only one segment was identified as a hotspot in Cluster 5 and is shown in Figure 6-29. There have been 5 smoke crashes and they occurred on the consecutive segments on SR-22.

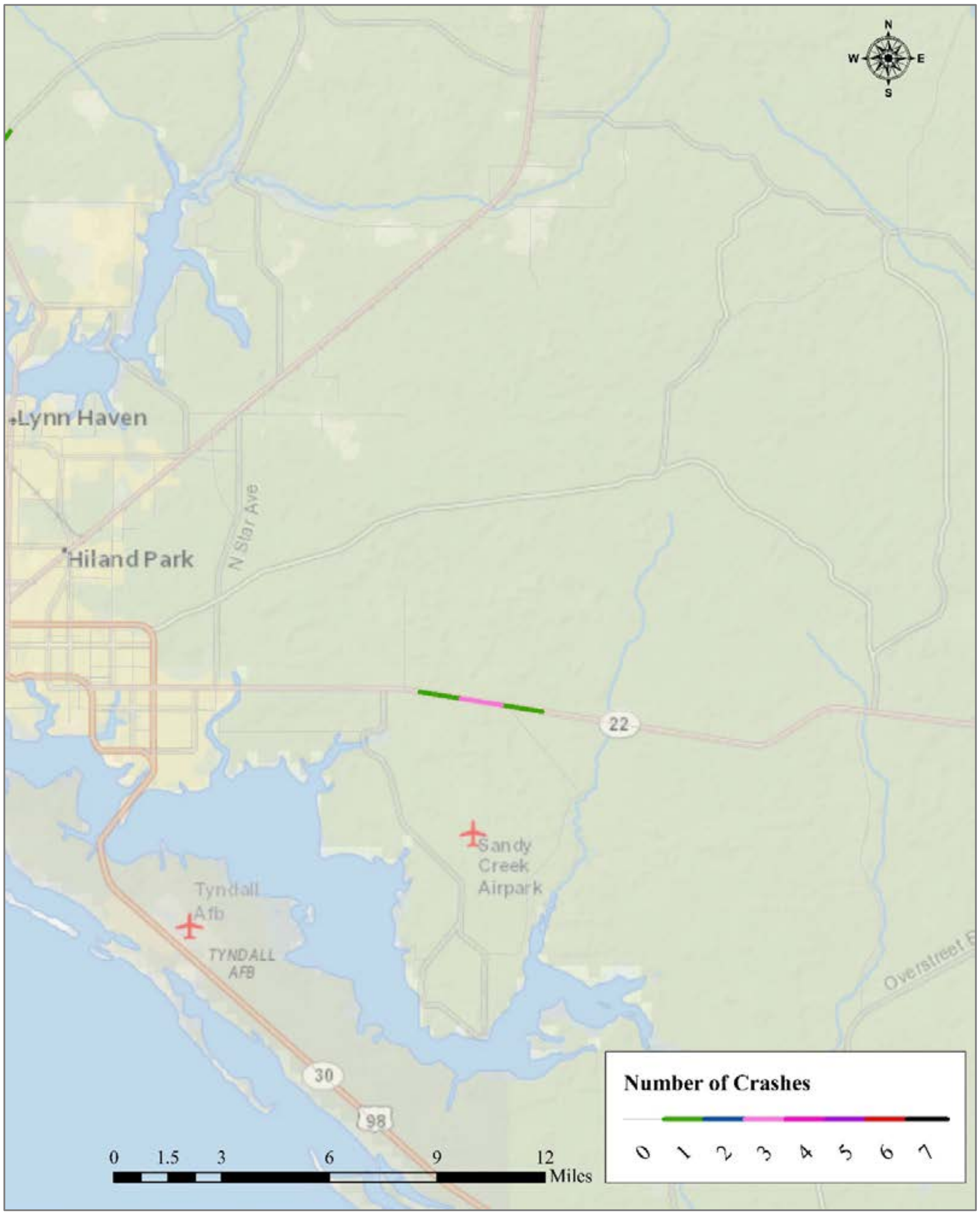


Figure 6-29 Microscopic analysis of smoke crashes based on segments in cluster 5

Table 6-14 One-mile segments with frequent smoke crashes

Cluster	Roadway ID	Begin Milepost	End Milepost	Number of Crashes
1	86120000	3.0022	4.0028	2
	87001000	3.9964	4.9955	2
2	16320000	19.0122	20.0129	4
	16320000	21.0136	22.0142	3
3	26260000	6.0029	7.0034	4
	26260000	7.0034	8.0039	2
4	3175000	28.0628	29.0624	7
5	46080000	8.9807	9.9785	3

6.3.3 Microscopic Screening of FS Crashes

FS Crashes on One-Mile Segments

It was shown that three clusters were identified with frequent FS related crashes on Florida state highways using KDE in macroscopic analysis. We magnified these areas and FS related crashes were counted based on these one-mile segments. All segments with two or more smoke crashes were defined as a hotspot in the analysis. The locations of FS hotspot segments are summarized in Table 6-15. It was revealed that there are no FS crashes on ramps or at intersections in the macro-level hotspot clusters.

Cluster 1 Polk County

Cluster 1 is placed in the northern part of Polk County. Overall two segments were uncovered as a hotspot in Cluster 1 and were shown in Figure 6-30. The two hotspots are located on I-4.

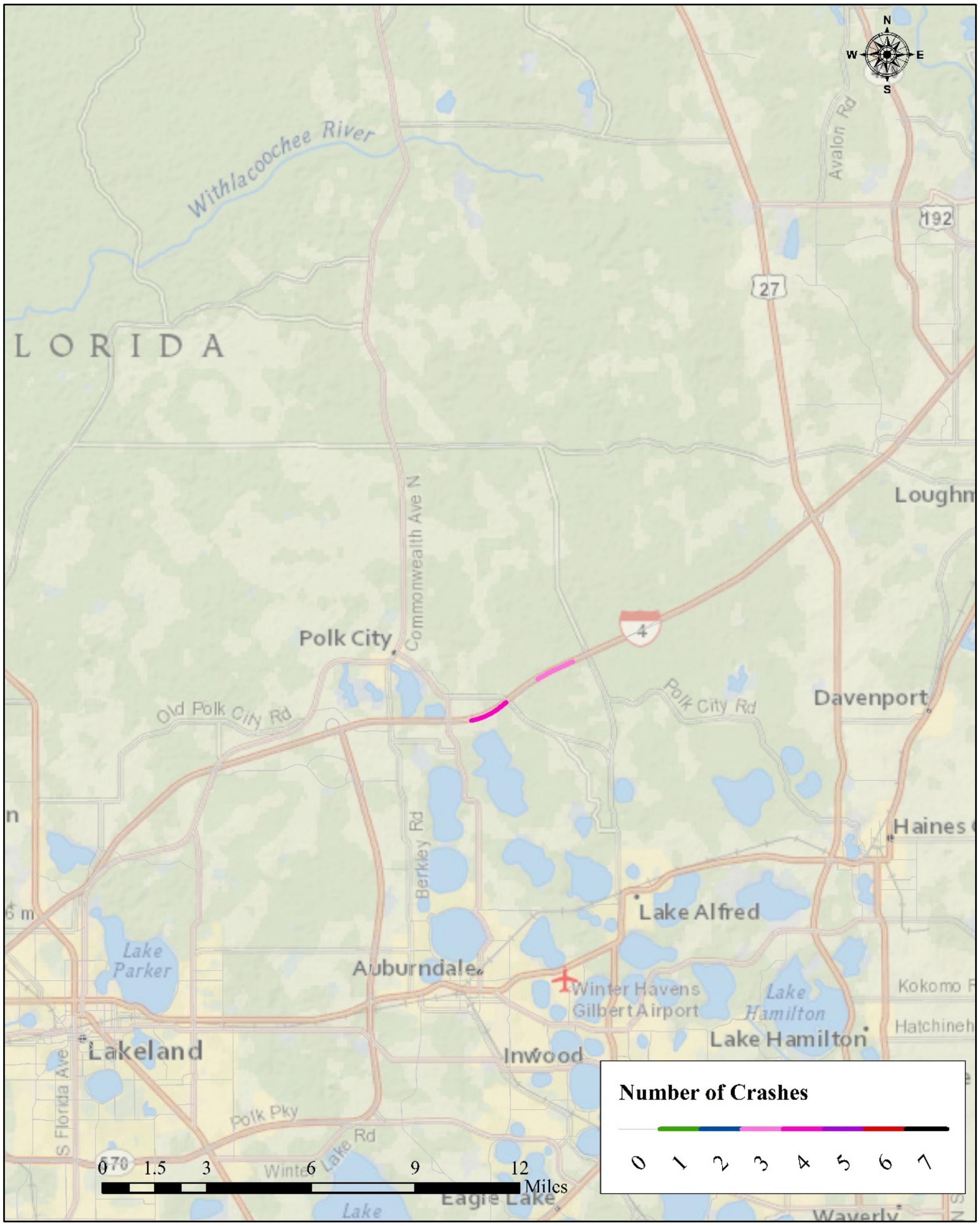


Figure 6-30 Microscopic analysis of FS crashes Based on segments in cluster 1

Cluster 2 Collier County

Cluster 2 is located at the center of Collier County. Only one segment was discovered as a hotspot in Cluster 2 and was shown in Figure 6-31. The hotspot is placed on I-75 near SR-29.

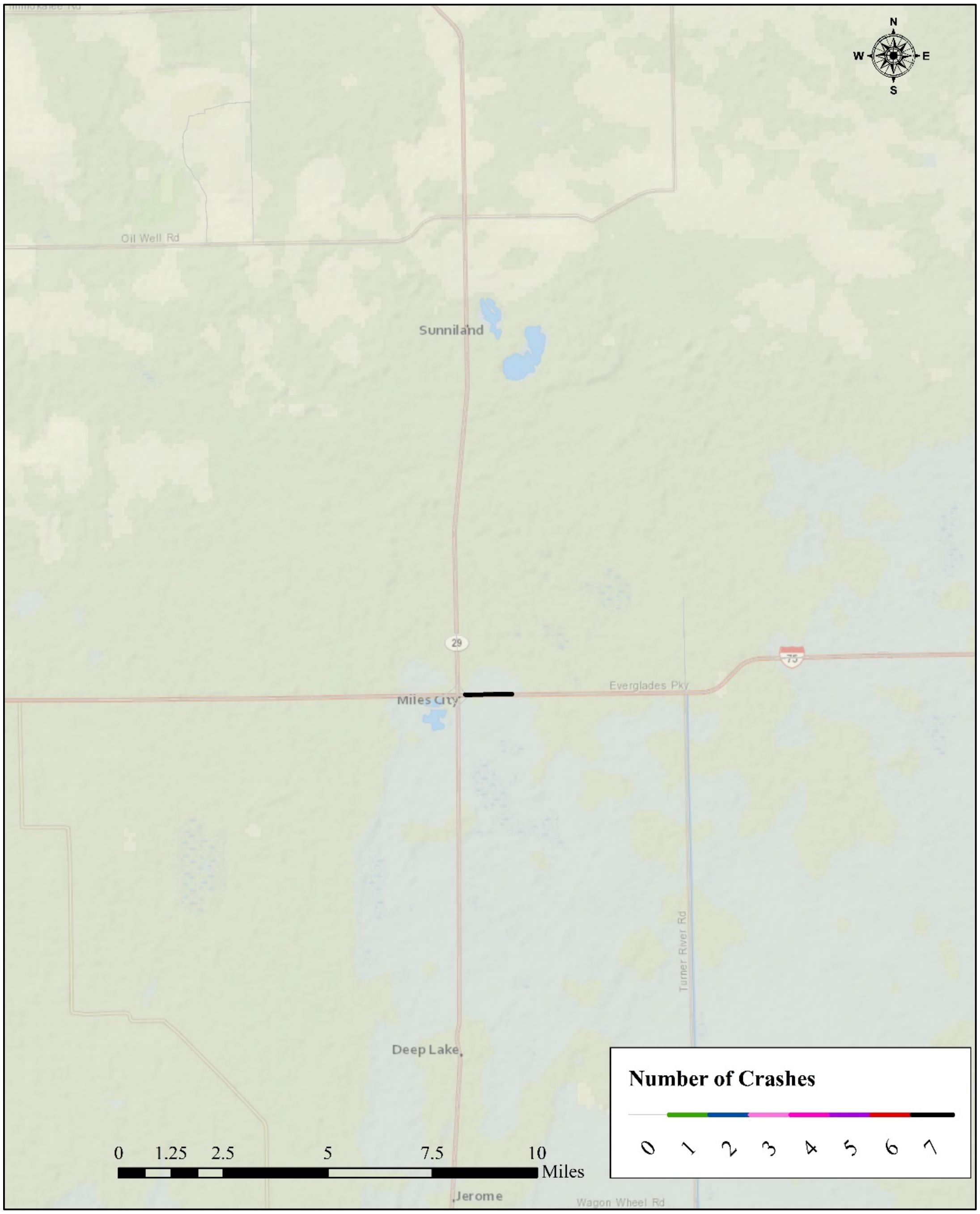


Figure 6-31 Microscopic analysis of FS crashes based on segments in cluster 2

Cluster 3 Hendry and Glades Counties

Cluster 3 stretches over Hendry and Glades Counties. Only one segment was detected as a hotspot in Cluster 3 and is shown in Figure 6-32. It is noted that 4 FS crashes occurred on the consecutive segments on US-27.

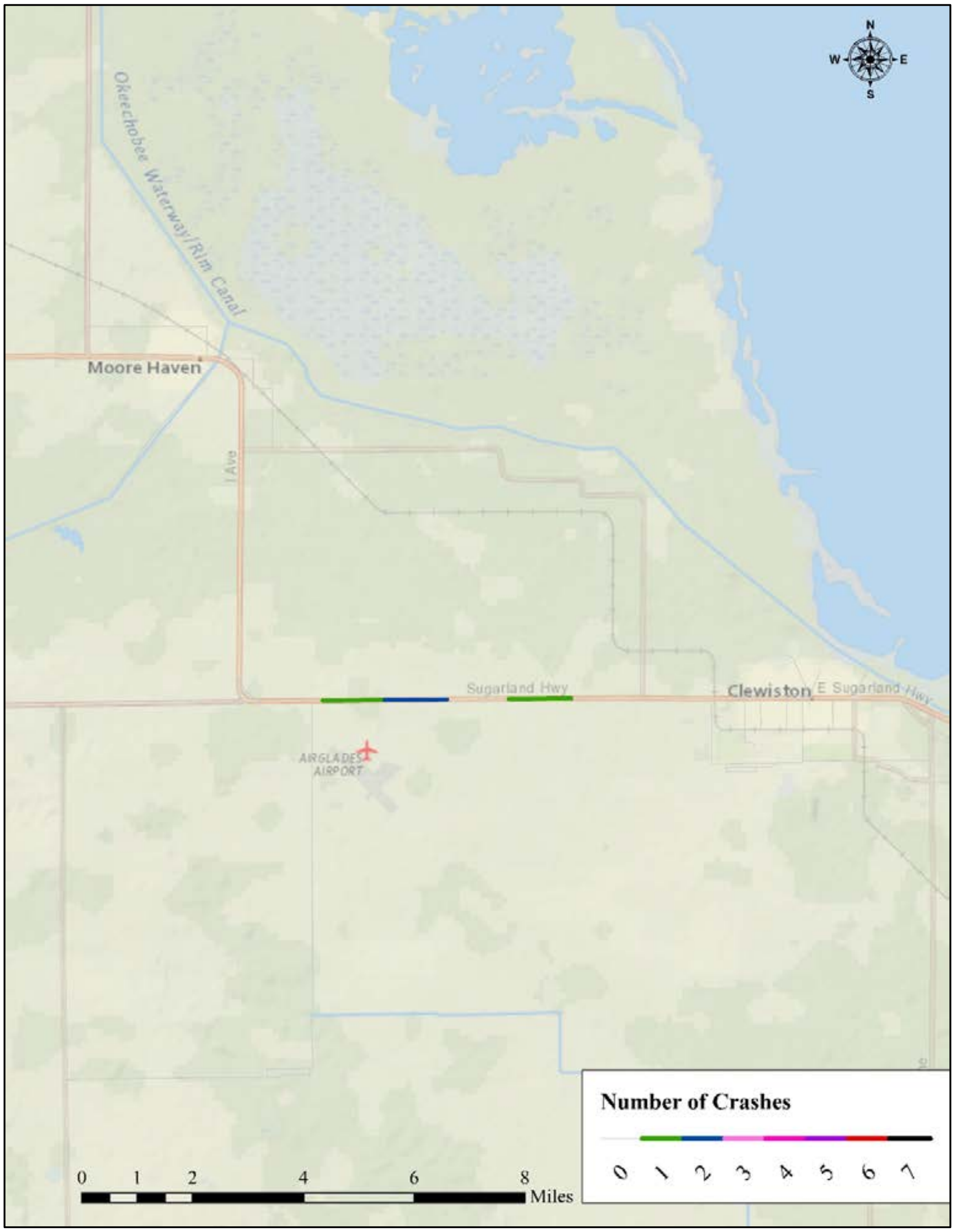


Figure 6-32 Microscopic analysis of FS crashes based on segments in cluster 3

Table 6-15 One-mile segments with frequent FS crashes

Cluster	Roadway ID	Begin Milepost	End Milepost	Number of Crashes
1	16320000	19.0122	20.0129	4
	16320000	21.0136	22.0142	3
2	3175000	28.0629	29.0625	7
3	7030000	9.0356	10.0396	2

6.4 Chapter Summary

Areas with frequent Fog, smoke and FS crashes were identified separately using the KDE technique in macroscopic analysis. Several areas were identified with frequent fog/smoke related crashes on Florida state highways. We zoomed in these areas and conducted a micro-level screening. Both maps and tables are provided to locate these hotspots. It is recommended to pay attention to the identified hotspots and offer appropriate countermeasures to minimize the number of traffic crashes under low-visibility conditions due to fog or smoke.

7. EXPLORATION OF THE RELATIONSHIP BETWEEN TRAFFIC PARAMETERS AND REDUCED VISIBILITY BASED ON AIRPORT DATA

The matched case control logistic regression models were used in this section to further explore the relationship between reduced visibility and traffic flow characteristics. The results may help in monitoring the reduced visibility in real time and reducing the negative effects of reduced visibility accordingly by sending warning messages to the motorists. The main objective of this study is to quantify the relationship between traffic flow characteristics and visibility and therefore we may be able to determine the change of visibility levels only by using traffic flow parameters. The advantage of using this conditional logistic regression models is to better explore the relationship between traffic flow variables and visibility while controlling the effect of other confounding variables such as location, time and the geometric design elements of highway sections (i.e., horizontal and vertical alignments).

7.1 Data Preparation of Polk County

Similar to the datasets used for the aforementioned analysis of impact of reduced visibility on traffic flow characteristics, the combined dataset was composed of two components which include the traffic data and weather data for the whole Polk County.

7.1.1 Weather Data

There are two airports in Polk County. One is Bartow Municipal airport and the other is Lakeland Linder Regional airport. The location of two airports was identified and we draw two buffer circles based on the center of these two airports. The weather condition in one circle was considered as the same and the weather information was obtained from the weather reports for these two airports.

The radius of the circle is 5 miles. Figure 7-1 shows the location of these two airports and Figures 7-2 and 7-3 show the sample of weather data in these two airports. There are twenty variables in total for the weather report which includes visibility, wind speed and some other important weather related variables.

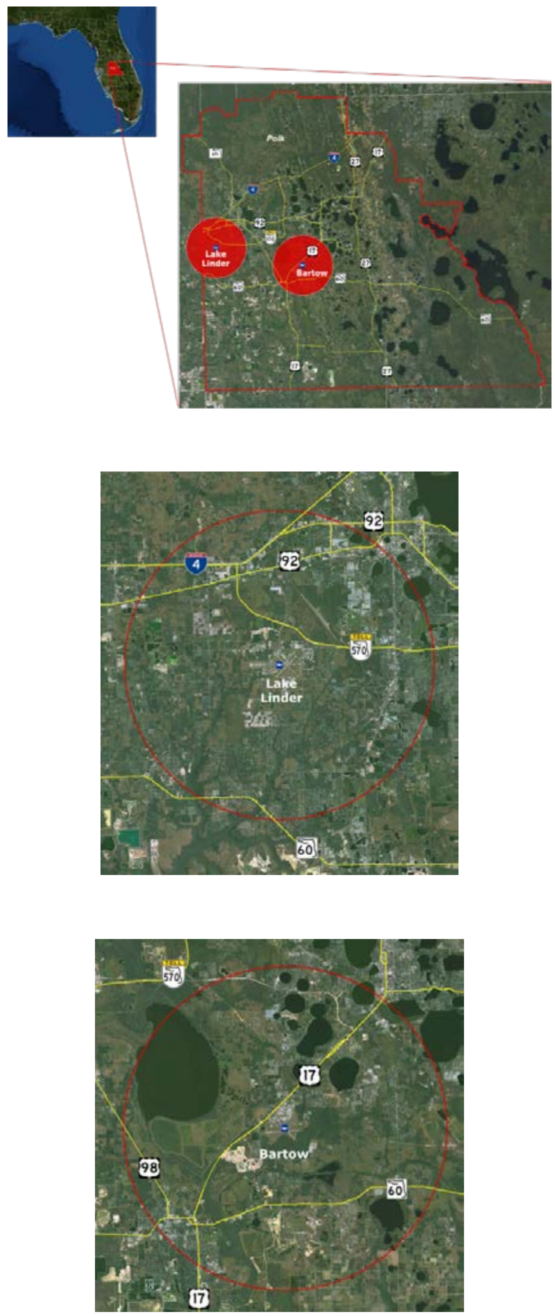


Figure 7-1 Location of two airports in Polk County

U.S. Department of Commerce
National Oceanic & Atmospheric Administration

QUALITY CONTROLLED LOCAL CLIMATOLOGICAL DATA
(final)
HOURLY OBSERVATIONS TABLE
BARTOW MUNICIPAL AIRPORT (12809)
BARTOW, FL
(01/2014)

National Climatic Data Center
Federal Building
151 Patton Avenue
Asheville, North Carolina 28801

Elevation: 125 ft. above sea level
Latitude: 27.95
Longitude: -81.783
Data Version: VER2

Date	Time (LST)	Station Type	Sky Conditions	Visibility (SM)	Weather Type	Dry Bulb Temp (F)	Dry Bulb Temp (C)	Wet Bulb Temp (F)	Wet Bulb Temp (C)	Dew Point Temp (F)	Dew Point Temp (C)	Rel Humd %	Wind Speed (MPH)	Wind Dir	Wind Gusts (MPH)	Station Pressure (in. hg)	Press Tend	Net 3-hr Chg (mb)	Sea Level Pressure (in. hg)	Report Type	Precip. Total (in)	Alti-meter (in. hg)
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
01	0015	0	SCT100	10.00		61	16.0	55	12.8	50	10.0	67	5	030		30.12			M	AA		30.26
01	0035	0	BKN100	10.00		61	16.0	55	12.8	50	10.0	67	8	020		30.14			M	AA		30.27
01	0055	0	SCT100	10.00		61	16.0	56	13.3	52	11.0	72	7	040		30.12			M	AA		30.26
01	0115	0	SCT090	10.00		61	16.0	56	13.3	52	11.0	72	8	020		30.12			M	AA		30.26
01	0135	0	OVC090	10.00		61	16.0	56	13.3	52	11.0	72	6	040		30.11			M	AA		30.25
01	0155	0	FEW070 OVC090	10.00		61	16.0	56	13.3	52	11.0	72	7	010		30.11			M	AA		30.25
01	0215	0	BKN070 BKN090	10.00		59	15.0	55	12.8	52	11.0	78	8	030		30.10			M	AA		30.24
01	0235	0	FEW047 SCT070 BKN090	10.00	-RA	59	15.0	56	13.4	54	12.0	84	7	020		30.10			M	AA		30.24
01	0255	0	BKN090	10.00		59	15.0	56	13.4	54	12.0	84	9	030		30.10			M	AA		30.24
01	0315	0	BKN090	10.00		59	15.0	56	13.4	54	12.0	84	6	020		30.11			M	AA		30.25
01	0335	0	FEW070 BKN090	10.00		59	15.0	56	13.4	54	12.0	84	8	030		30.10			M	AA		30.24
01	0355	0	FEW070 BKN090	10.00		59	15.0	57	13.7	55	13.0	87	8	030		30.10			M	AA		30.24
01	0415	0	FEW031 BKN070 OVC090	10.00		59	15.0	57	13.7	55	13.0	87	9	020		30.10			M	AA		30.24
01	0435	0	OVC070	10.00		57	14.0	55	12.9	54	12.0	90	7	020		30.10			M	AA		30.24
01	0455	0	SCT070 BKN085	10.00		57	14.0	56	13.2	55	13.0	93	9	020		30.09			M	AA		30.23
01	0515	0	BKN085	10.00		57	14.0	55	12.9	54	12.0	90	10	030	16	30.09			M	AA		30.23
01	0535	0	BKN070 BKN085	10.00		57	14.0	55	12.9	54	12.0	90	11	020		30.09			M	AA		30.23
01	0555	0	OVC070	10.00	-DZ	57	14.0	55	12.9	54	12.0	90	13	020	18	30.10			M	AA		30.24
01	0615	0	SCT033 OVC070	10.00		57	14.0	56	13.2	55	13.0	93	10	030		30.10			M	AA		30.24
01	0750	0	SCT020 OVC060	5.00	-RA	57	14.0	56	13.2	55	13.0	93	8	040		30.11			M	AA		30.25
01	0850	0	SCT017 OVC023	3.00	-RA	57	14.0	57	13.8	57	14.0	100	8	030		30.11			M	AA		30.25
01	0955	0	SCT013 OVC025	10.00		59	15.0	59	15.0	59	15.0	100	8	030		30.12			M	AA		30.26
01	1050	0	SCT013 OVC023	10.00		61	16.0	61	16.1	61	16.0	100	7	020		30.12			M	AA		30.26
01	1247	0	BKN006 OVC023	8.00		63	17.0	M	M	M	M	M	8	040		30.06			M	AA		30.20
01	1350	0	OVC006	10.00		63	17.0	63	17.2	63	17.0	100	5	040		30.02			M	AA		30.16
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01	1450	0	CLR005	10.00		63	17.0	M	M	63	17.0	M	6	010		M			M	AA		30.15
01	1455	0	OVC005	10.00		63	17.0	63	17.2	63	17.0	100	5	020		30.01			M	AA		30.15

Figure 7-2 Weather data at Bartow Airport

U.S. Department of Commerce
National Oceanic & Atmospheric Administration

QUALITY CONTROLLED LOCAL CLIMATOLOGICAL DATA
(final)
HOURLY OBSERVATIONS TABLE
LAKELAND LINDER REGIONAL AIRPORT (12883)
LAKELAND, FL
(01/2014)

National Climatic Data Center
Federal Building
151 Patton Avenue
Asheville, North Carolina 28801

Elevation: 142 ft. above sea level
Latitude: 28
Longitude: -82.05
Data Version: VER2

Date	Time (LST)	Station Type	Sky Conditions	Visibility (SM)	Weather Type	Dry Bulb Temp (F)	Dry Bulb Temp (C)	Wet Bulb Temp (F)	Wet Bulb Temp (C)	Dew Point Temp (F)	Dew Point Temp (C)	Rel Humd %	Wind Speed (MPH)	Wind Dir	Wind Gusts (MPH)	Station Pressure (in. hg)	Press Tend	Net 3-hr Chg (mb)	Sea Level Pressure (in. hg)	Report Type	Precip. Total (in)	Alti-meter (in. hg)
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
01	0015	0	OVC100	10.00		59	15.0	53	11.7	48	9.0	67	8	040		30.12			M	AA		30.27
01	0035	0	OVC100	10.00		59	15.0	53	11.7	48	9.0	67	7	020		30.11			M	AA		30.26
01	0055	0	SCT070 OVC100	10.00		59	15.0	54	12.3	50	10.0	72	8	030		30.11			M	AA		30.26
01	0115	0	OVC090	10.00		59	15.0	54	12.3	50	10.0	72	7	040		30.11			M	AA		30.26
01	0135	0	OVC090	10.00		59	15.0	54	12.3	50	10.0	72	6	030		30.10			M	AA		30.25
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01	0255	0	SCT070 OVC090	10.00		57	14.0	54	12.3	52	11.0	83	9	030		30.09			M	AA		30.24
01	0315	0	SCT070 OVC090	10.00		59	15.0	55	12.8	52	11.0	78	8	030		30.09			M	AA		30.24
01	0335	0	SCT070 OVC090	10.00		59	15.0	55	12.8	52	11.0	78	9	030		30.09			M	AA		30.24
01	0355	0	OVC090	10.00		59	15.0	55	12.8	52	11.0	78	9	020		30.09			M	AA		30.24
01	0415	0	BKN080 OVC090	10.00		59	15.0	55	12.8	52	11.0	78	7	020		30.09			M	AA		30.24
01	0435	0	OVC080	10.00		59	15.0	55	12.8	52	11.0	78	10	030		30.09			M	AA		30.24
01	0455	0	SCT070 OVC080	10.00		59	15.0	56	13.4	54	12.0	84	9	030		30.08			M	AA		30.23
01	0515	0	OVC080	10.00	-DZ	57	14.0	55	12.9	54	12.0	90	9	020		30.09			M	AA		30.24
01	0535	0	BKN075 OVC085	10.00		57	14.0	54	12.3	52	11.0	83	11	030		30.08			M	AA		30.23
01	0555	0	BKN075 OVC085	10.00	-RA	57	14.0	55	12.9	54	12.0	90	10	030		30.09			M	AA		30.24
01	0645	0	BKN038 OVC075	10.00	-RA	57	14.0	55	12.9	54	12.0	90	10	030		30.09			M	AA		30.24
01	0755	0	SCT035 OVC065	10.00	DZ	59	15.0	57	13.7	55	13.0	87	8	040		30.10			M	AA		30.25
01	0845	0	SCT015 BKN037 OVC046	5.00	DZ	59	15.0	57	13.7	55	13.0	87	7	060		30.11			M	AA		30.26
01	0950	0	SCT007 OVC028	5.00	DZ	59	15.0	59	15.0	59	15.0	100	8	030		30.11			M	AA		30.26
01	1050	0	BKN007 OVC020	4.00	DZ	61	16.0	61	16.1	61	16.0	100	10	030		30.10			M	AA		30.25
01	1150	0	OVC005	4.00	-RA	61	16.0	61	16.1	61	16.0	100	9	030		30.08			M	AA		30.23
01	1255	0	OVC005	5.00	BR	63	17.0	63	17.2	63	17.0	100	10	030		30.03			M	AA		30.18
01	1354	0	OVC005	6.00	BR	63	17.0	63	17.2	63	17.0	100	5	020		30.01			M	AA		30.16
01	1454	0	OVC007	6.00	BR	63	17.0	63	17.2	63	17.0	100	8	040		30.00			M	AA		30.15
01	1550	0	OVC007	7.00		64	18.0	63	17.4	63	17.0	97	9	050		29.98			M	AA		30.13
01	1650	0	OVC007	7.00		64	18.0	63	17.4	63	17.0	97	9	030		29.98			M	AA		30.13
01	1750	0	OVC003	4.00	BR	63	17.0	63	17.2	63	17.0	100	10	030		29.98			M	AA		30.13

Figure 7-3 Weather data at Lakeland Airport

7.1.2 Traffic Data

Traffic flow data used in this study were collected from the RITIS system which is shown in Figure 7-4. There are over 10000 loop detectors for the whole Florida State and we collected traffic data information from the 60 detectors which are located in Polk County and also within those circles of two airports close to the Polk County. In this way the extracted traffic data can be merged with weather data mentioned above to create the combined dataset. There are fifteen detectors of them within the buffer circle of Barton airport and forty-five detectors of them within the circle of Lakeland airport.

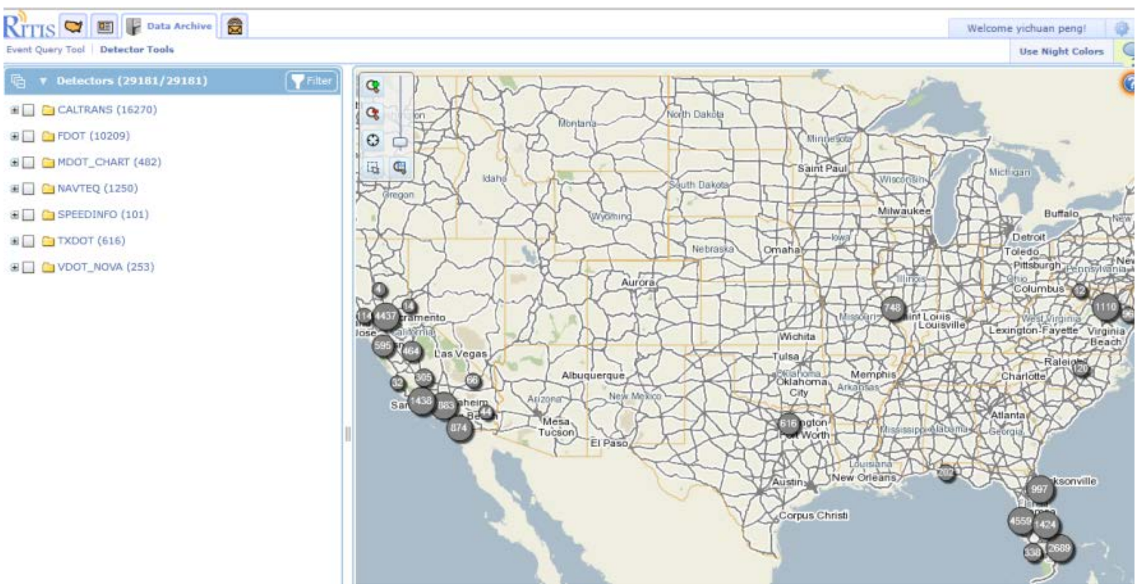
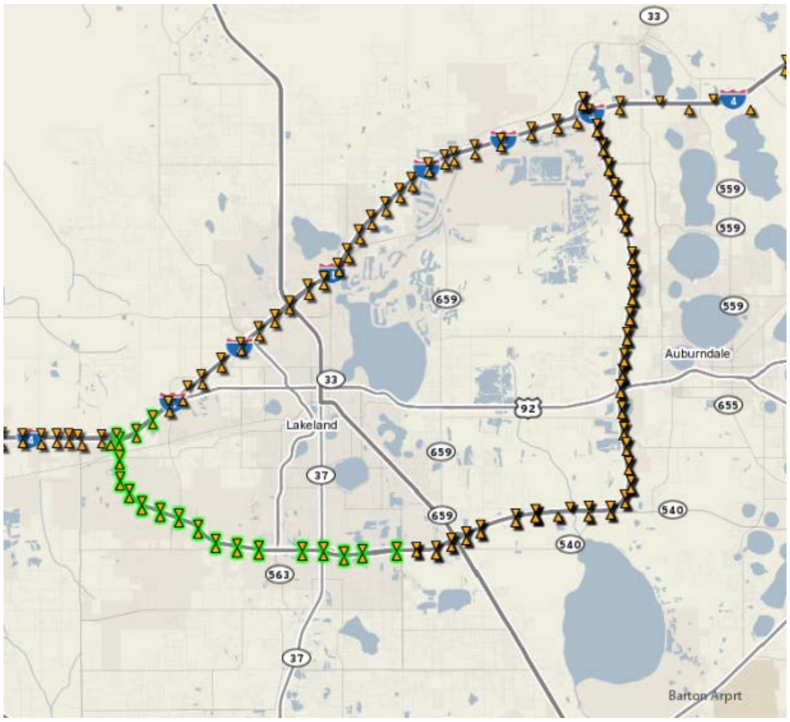
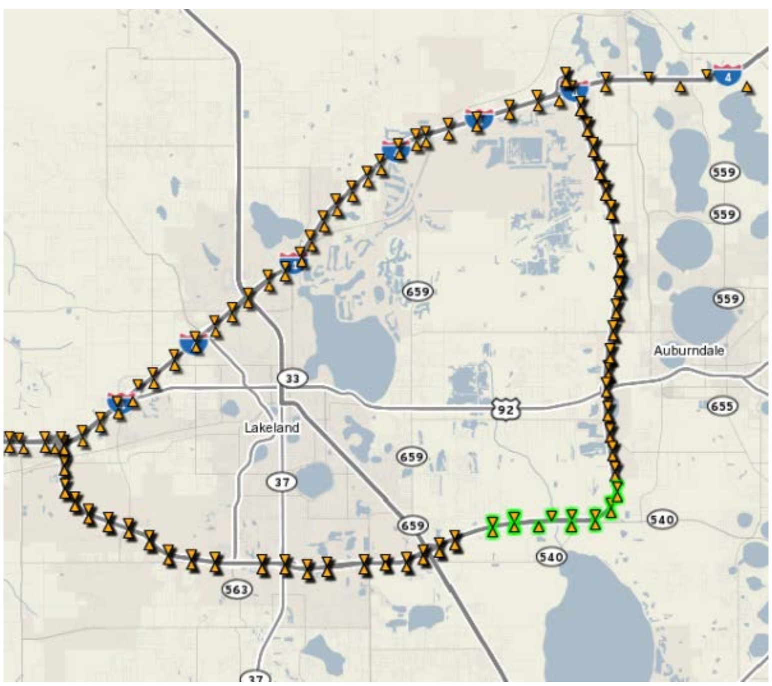


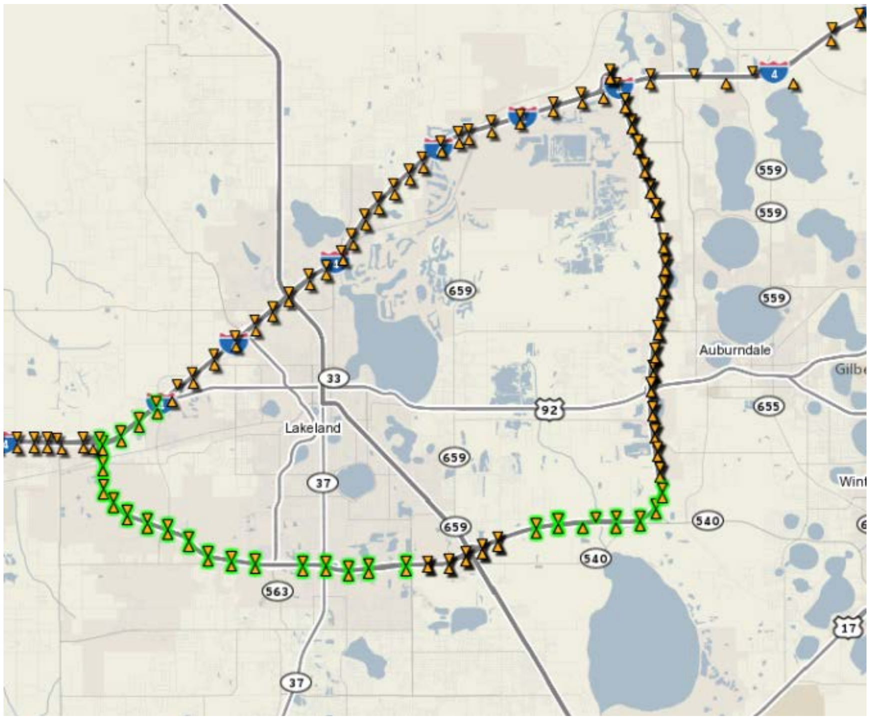
Figure 7-4 Data of all detectors in RITIS



(a) 45 detectors within five miles of Lakeland airport in Polk County



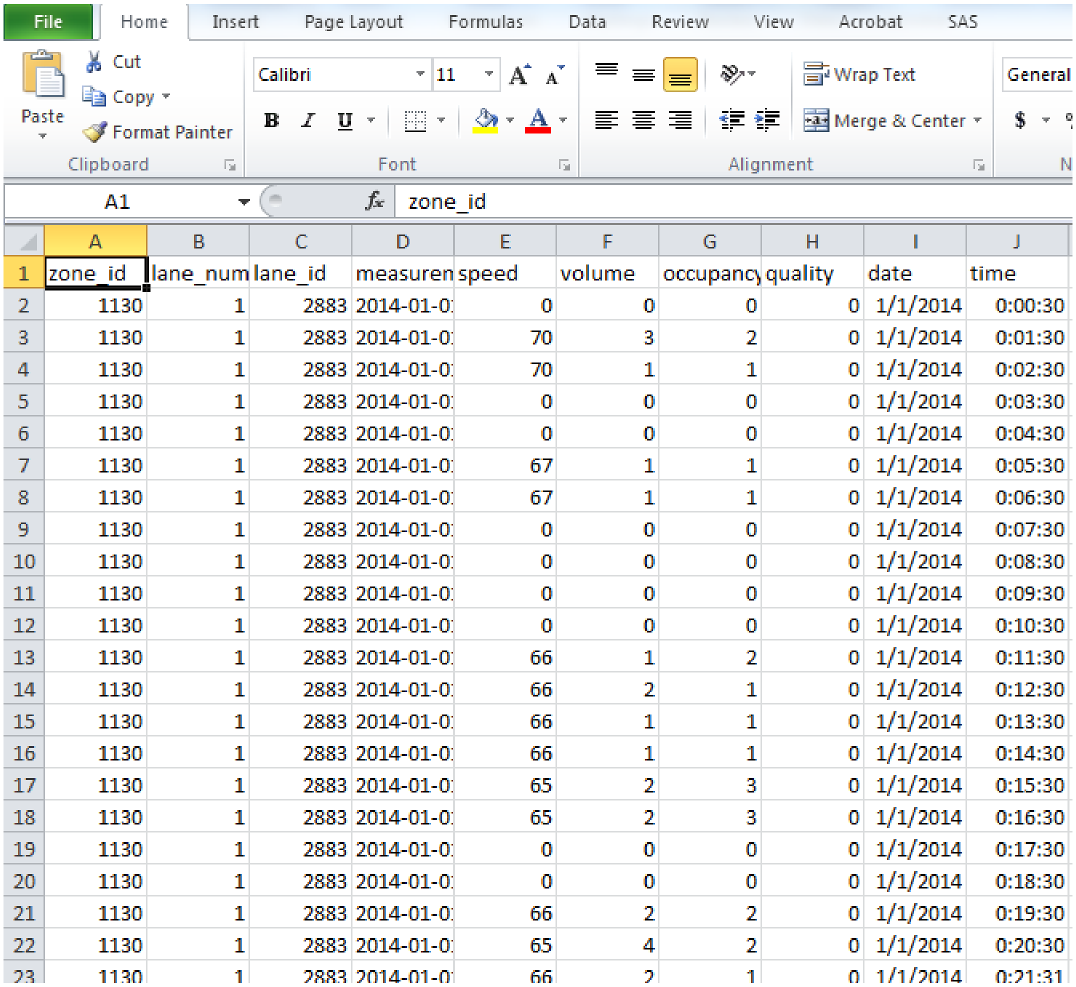
(b) 15 detectors within five miles of Bartow airport in Polk County



(c) 60 detectors within five miles of two airports in Polk County

Figure 7-5 Traffic detectors in Polk County

Figure 7-6 shows the original raw traffic dataset which contains the following traffic flow variables: every 1 minute for each lane in each direction: 1) average speed 2) volume and 3) lane occupancy (percentage of time interval, 1 minute, the loop detector was occupied).



	A	B	C	D	E	F	G	H	I	J
1	zone_id	lane_num	lane_id	measuren	speed	volume	occupancy	quality	date	time
2	1130	1	2883	2014-01-0	0	0	0	0	1/1/2014	0:00:30
3	1130	1	2883	2014-01-0	70	3	2	0	1/1/2014	0:01:30
4	1130	1	2883	2014-01-0	70	1	1	0	1/1/2014	0:02:30
5	1130	1	2883	2014-01-0	0	0	0	0	1/1/2014	0:03:30
6	1130	1	2883	2014-01-0	0	0	0	0	1/1/2014	0:04:30
7	1130	1	2883	2014-01-0	67	1	1	0	1/1/2014	0:05:30
8	1130	1	2883	2014-01-0	67	1	1	0	1/1/2014	0:06:30
9	1130	1	2883	2014-01-0	0	0	0	0	1/1/2014	0:07:30
10	1130	1	2883	2014-01-0	0	0	0	0	1/1/2014	0:08:30
11	1130	1	2883	2014-01-0	0	0	0	0	1/1/2014	0:09:30
12	1130	1	2883	2014-01-0	0	0	0	0	1/1/2014	0:10:30
13	1130	1	2883	2014-01-0	66	1	2	0	1/1/2014	0:11:30
14	1130	1	2883	2014-01-0	66	2	1	0	1/1/2014	0:12:30
15	1130	1	2883	2014-01-0	66	1	1	0	1/1/2014	0:13:30
16	1130	1	2883	2014-01-0	66	1	1	0	1/1/2014	0:14:30
17	1130	1	2883	2014-01-0	65	2	3	0	1/1/2014	0:15:30
18	1130	1	2883	2014-01-0	65	2	3	0	1/1/2014	0:16:30
19	1130	1	2883	2014-01-0	0	0	0	0	1/1/2014	0:17:30
20	1130	1	2883	2014-01-0	0	0	0	0	1/1/2014	0:18:30
21	1130	1	2883	2014-01-0	66	2	2	0	1/1/2014	0:19:30
22	1130	1	2883	2014-01-0	65	4	2	0	1/1/2014	0:20:30
23	1130	1	2883	2014-01-0	66	2	1	0	1/1/2014	0:21:31

Figure 7-6 Sample of traffic data for the Polk County

Finally, a merged dataset consisting of both traffic data and visibility data was created to be applied into matched case control logistic regression models. Since the one minute raw traffic data was noticed to have random noise and are difficult to work with in a modeling framework (Abdel-Aty et al. 2008), therefore, the raw data were aggregate into 5-minutes levels to obtain averages and standard deviations for speed, volume, and occupancy.

7.2 Methodology

As already mentioned at the beginning of this chapter, the matched case control logistic regression model was applied in this study to further explore the relationship between visibility and traffic flow characteristics. In this study, observations with reduced visibility are selected first. Then, for each selected observation, some non-traffic flow variables associated with each fog are selected as matching factors. In this study the variables used to match cases and controls are: location, day of the week and time of reduced visibility. Using these matching factors, a total of non-fog cases are then selected randomly from each subpopulation of non-fog cases.

Matched case-control logistic regression has been adopted in epidemiological studies. In addition, it was used in few transportation related studies such as Abdel-Aty et al. (2004). The detailed description of the modeling can be seen in Abdel-Aty et al. (2004). The data of all corresponding reduced visibility were extracted from the combined dataset and a total of three times of observations with good visibility were randomly selected from the combined dataset. The final created datasets were then applied with matched case logistic regression models. In this study, SAS package (procedure PHREG) was used to fit the proposed stratified conditional logistic regression model, widely known as matched case-control analysis in epidemiological studies (the reader is referred to SAS Institute Inc, 2008).

7.3 Modeling Results

The following five traffic flow variables: mean speed and headway, variance of speed and headway and average occupancy in five minutes were used as input in the model. It is noted that the headway data was calculated based on the volume in one minute. The visibility was divided into two levels: the visibility level was considered as 0 for the good visibility (>=1Statue Mile(SM)) and the visibility level was classified as 1 for the reduced visibility (<1(SM)). The modeling result was show in the Table 7-1.

Table 7-1 Modeling results for two visibility levels

Analysis of Maximum Likelihood Estimates						
Parameter	**DF**	**Parameter Estimate**	**Standard Error**	**Chi-Square**	**Pr > ChiSq**	**Hazard Ratio**
speed	1	-0.03708	0.00993	13.9293	0.0002	0.964
Speed standard deviation	1	0.01618	0.00533	9.2011	0.0024	1.016
headway	1	0.02940	0.00486	36.6278	<.0001	1.030
Headway standard deviation	1	0.22346	0.06713	11.0810	0.0009	1.250
Average Occupancy	1	0.00716	0.00357	4.0209	0.0449	1.007

The results indicated that higher mean of headway, variance of speed and headway and higher occupancy were related to the increase of the likelihood of a reduced visibility while lower mean speed was related to the increase of the likelihood of a reduced visibility.

After that, the visibility was further divided into three levels to further investigate the relationship between traffic flow characteristics and visibility. The visibility level was considered as 0 for the good visibility (>=1(SM)) and the visibility level was classified as 1 for the moderate visibility (0.25(SM)<=visibility<1 (SM)) and the visibility level was classified as 2 for the low visibility (visibility<0.25).The modeling result was shown in the Table 7-2:

Table 7-2 Modeling results for three visibility levels

Parameter	DF	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio
speed	1	-0.03857	0.01075	12.8625	0.0003	0.962
Speed standard deviation	1	0.02152	0.00602	12.7908	0.0003	1.021
headway	1	0.03039	0.00497	37.4117	<.0001	1.031
Headway standard deviation	1	0.30653	0.07281	17.7224	<.0001	1.359
Average Occupancy	1	0.00594	0.00374	2.5189	0.1125	1.006

Similar results indicated that higher mean of headway, variance of speed and headway were related to the increase of the likelihood of a reduced visibility while lower mean speed was related to the increase of the likelihood of a reduced visibility. The relationship between average occupancy and visibility was not significant in this result.

7.4 Chapter Summary

This chapter applied matched case control logistic regression models to the combined traffic and weather datasets for the Polk County. The variables used to match cases and controls are: location, day of the week and time of reduced visibility. The results indicated that higher mean of headway, variance of speed and headway were related to the increase of the likelihood of a reduced visibility while lower mean speed was related to the increase of the likelihood of a reduced visibility.

8. DRIVING SIMULATOR EXPERIMENT OF REDUCED VISIBILITY

8.1 Experimental Design

The design for our scenarios breaks them down into specific variables of multiple levels related to the simulation scenario environment. These variables and levels are as follows:

- Roadway Type: (Freeway / Arterial)
- Fog Visibility: (Light – 500ft / Moderate – 300ft / Heavy – 150ft)
- Number of Dynamic Message Signs (DMSs): (0 / 1 / 2)
- Signage Text: (Null / Warning / Advised)
- Beacon Presence (0 / 1)
- Traffic Setting (Light / Heavy)

Considering that no sign text can be displayed on a sign that is not present, and every combination of variables is used, 108 scenarios can be run on the freeway and 108 on the arterial. This number of scenarios can then be further reduced when we assume that any signs beyond a single one within a light fog condition would prove insignificant in effect to the more severe conditions. We can also assume that beacons will not be necessary for light fog conditions and can be ignored in the study. Removing these conditions further reduces the number of possible scenarios for both road types allowing us to test the remaining scenarios to a further extent. Attempting to use this many scenarios in testing, as seen in Table 8-1, would require more participants to run, especially when considering that these scenarios must be ran for both freeways and arterials as well as different traffic settings. To avoid this issue, multiple scenarios will be run by each participant using experimental block analysis. It can also be considered that each participant would have the same driving habits based on the fog and sign conditions rather than the road itself.

As previously discussed, the 'Fog Visibility' variable deals with how thick the fog in the simulation appears to be and the levels will be based off overall sight distance in feet to determine a measureable intensity. The 'Number of DMS' variable indicates how many DMS signs are present, and the signage text tells what type of message is displayed on them. The 'Traffic Setting' variable is used in order to test light and heavy traffic scenarios that are likely to occur during the timeframe fog forms. Since fog typically occurs in the very late to early morning hours due to the rapid cooling and heating of the air, it was important to reflect the traffic volumes of these times for further analysis and validation. In this case, the setting used will reflect an early morning scenario that occurs between 6:00AM and 8:30AM, as fog is more likely to be present during this time of day with traffic available, and is consistent with the data collected. The light traffic setting uses data observed between 6:00AM and 7:00AM which has average headways of 20 seconds, while the heavy setting occurs between 7:30AM and 8:00AM with headways of 10 seconds. Based on past research and the traffic data collected, we also know that traffic speeds will vary depending on the severity of the fog in the scenario. To reflect this, the simulated traffic will have its speed adjusted as it enters the fog region from the initial clear segment. These changes are summarized in Table 8-1 below.

Table 8-1 Fog – speed relationship

I-75 (Speed Limit = 70 MPH)				
Visibility (ft.)	clear	500	300	150
Speed (MPH)	72	70	68	65
Std. (MPH)	6.5	6.8	6.8	7
I-4 (Speed Limit = 65 MPH)				
Visibility (ft.)	clear	500	300	150
Speed (MPH)	67	65	63	60
Std. (MPH)	6.2	6.5	6.5	6.8

The scenarios generated with the restrictions, seen in Table 8-2, follows:

Restrictions:

1. If Light Fog and 2 Signs present then scenario is not needed.
2. If No Signs present then No Message can be displayed.
3. If 1 or 2 Signs are present then No Message (Null) can be displayed.
4. If Light Fog then no Beacon needed.

Table 8-2 Full scenario list with marked restrictions

Run	Fog	#DMS	Message	Setting	Beacon	Run	Fog	#DMS	Message	Setting	Beacon
1	light	0	Null	heavy	0	37	light	0	Null	heavy	1
2	moderate	0	Null	heavy	0	38	moderate	0	Null	heavy	1
3	heavy	0	Null	heavy	0	39	heavy	0	Null	heavy	1
4	light	1	Advised	heavy	0	40	light	1	Advised	heavy	1
5	moderate	1	Advised	heavy	0	41	moderate	1	Advised	heavy	1
6	heavy	1	Advised	heavy	0	42	heavy	1	Advised	heavy	1
7	light	2	Advised	heavy	0	43	light	2	Advised	heavy	1
8	moderate	2	Advised	heavy	0	44	moderate	2	Advised	heavy	1
9	heavy	2	Advised	heavy	0	45	heavy	2	Advised	heavy	1
10	light	0	null	heavy	0	46	light	0	null	heavy	1
11	moderate	0	null	heavy	0	47	moderate	0	null	heavy	1
12	heavy	0	null	heavy	0	48	heavy	0	null	heavy	1
13	light	1	Mandatory	heavy	0	49	light	1	Mandatory	heavy	1
14	moderate	1	Mandatory	heavy	0	50	moderate	1	Mandatory	heavy	1
15	heavy	1	Mandatory	heavy	0	51	heavy	1	Mandatory	heavy	1
16	light	2	Mandatory	heavy	0	52	light	2	Mandatory	heavy	1
17	moderate	2	Mandatory	heavy	0	53	moderate	2	Mandatory	heavy	1
18	heavy	2	Mandatory	heavy	0	54	heavy	2	Mandatory	heavy	1
19	light	0	Null	light	0	55	light	0	Null	light	1
20	moderate	0	Null	light	0	56	moderate	0	Null	light	1
21	heavy	0	Null	light	0	57	heavy	0	Null	light	1
22	light	1	Advised	light	0	58	light	1	Advised	light	1
23	moderate	1	Advised	light	0	59	moderate	1	Advised	light	1
24	heavy	1	Advised	light	0	60	heavy	1	Advised	light	1
25	light	2	Advised	light	0	61	light	2	Advised	light	1
26	moderate	2	Advised	light	0	62	moderate	2	Advised	light	1
27	heavy	2	Advised	light	0	63	heavy	2	Advised	light	1
28	light	0		light	0	64	light	0		light	1
29	moderate	0		light	0	65	moderate	0		light	1
30	heavy	0		light	0	66	heavy	0		light	1
31	light	1	Mandatory	light	0	67	light	1	Mandatory	light	1
32	moderate	1	Mandatory	light	0	68	moderate	1	Mandatory	light	1
33	heavy	1	Mandatory	light	0	69	heavy	1	Mandatory	light	1
34	light	2	Mandatory	light	0	70	light	2	Mandatory	light	1
35	moderate	2	Mandatory	light	0	71	moderate	2	Mandatory	light	1
36	heavy	2	Mandatory	light	0	72	heavy	2	Mandatory	light	1

This scenario set up will be useful in developing scenarios specific to testing a certain variable under any of the possible conditions. A good example of this would include scenarios that have no signs present but have different fog densities. This develops scenarios that are focused primarily on how the fog impacts the driver. Similarly, the light fog condition is expected to not have much of an impact on the driving behavior due to visibility distance, so some scenarios most likely will not see a majority of driving behavior being affected ideally by the message the sign presents.

Based on how the scenarios are currently established, the actual design that is used for this experiment represents a simple factorial design. Due to the amount of scenarios present and the limitation of the number of participants, these scenarios will need to be reduced further in order to generate an acceptable balanced design. To accomplish this, 12 scenarios were generated via randomized variables through statistical software. These 12 scenarios create the Block design that will be used throughout the experiment. Since each participant is expected to complete 3 scenarios, each block will test 4 different participants. By repeating each block 9 times with different randomized orders and for each roadway type, we end up with a total of 72 participants running a total of 216 scenarios.

Table 8-3 Scenario variable levels' reference

	Attribute	Description	Attribute Levels
x1	Roadway Type	Roadway types for simulation	1. Freeway 2. Arterial
x2	Fog/Visibility	Fog intensity based on visibility	1. Low, 500ft 2. Moderate, 300 ft 3. High, 150 ft
x3	No. of DMS	Number of DMS used for warning	1. 0 sign 2. 1 sign 3. 2 signs
x4	Content of DMS	Message displayed on DMS	1. Null 2. Warning 3. Advised
x5	Traffic Setting	Traffic conditions	1. High Volume 2. Low Volume
x6	Flashing beacons	Presence of flashing beacons along road	1. No 2. Yes

With these variable levels seen in Table 8-3, we will randomly generate 12 scenarios separately for each roadway type and then randomly choose from the pool of 24 scenarios to generate the testing blocks.

From table 8-4, the scenarios that will be tested are shown. These 24 scenarios will be used in the block design to determine how the scenarios will be tested. Table 9-5 lists how many times the specific variable levels are tested within these scenarios.

Table 8-4 Scenario testing scheme (freeway)

Scenarios	Road Type	Fog	#DMS	Message	Setting	Beacon
1	1	1	1	1	2	1
2	1	1	2	2	2	1
3	1	2	1	1	2	1
4	1	2	2	2	1	2
5	1	2	2	3	1	1
6	1	2	2	3	2	2
7	1	2	3	2	1	1
8	1	3	1	1	2	1
9	1	3	2	3	2	2
10	1	3	3	2	1	2
11	1	3	3	3	1	1
12	1	3	3	3	1	2
13	2	1	1	1	1	1
14	2	1	2	3	1	1
15	2	2	1	1	1	2
16	2	2	2	3	1	1
17	2	2	3	2	2	1
18	2	2	3	2	2	2
19	2	2	3	3	2	2
20	2	3	1	1	1	2
21	2	3	2	2	1	1
22	2	3	2	2	2	1
23	2	3	2	2	2	2
24	2	3	3	3	2	1

Table 8-5 Testing scheme data counts

Levels	Road Type	count
1	1	12
2	2	12

Levels	Fog	count
1	1	4
2	2	10
3	3	10

Levels	#DMS	count
1	1	6
2	2	10
3	3	8

Levels	Message	count
1	1	6
2	2	9
3	3	9

Levels	Traffic Setting	count
1	1	12
2	2	12

Levels	Beacon Present	count
1	1	14
2	2	10

Table 8-6 Scenario testing order

Block	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24
1	23	4	1	18	10	13	11	20	24	16	17	6	8	7	12	19	21	3	15	9	14	2	5	22
2	11	24	9	1	8	19	23	13	5	7	21	12	20	17	16	18	3	10	4	22	2	6	14	15
3	21	5	23	7	12	3	16	20	8	6	24	2	19	9	13	22	10	18	11	4	15	17	1	14
4	4	10	1	17	13	6	18	12	5	24	15	2	20	8	23	14	22	11	7	16	21	19	9	3
5	7	8	1	5	2	13	15	9	12	6	24	19	10	3	11	16	18	20	14	21	22	17	4	23
6	12	14	23	2	24	5	8	4	16	6	20	21	19	7	10	9	3	18	22	1	11	17	13	15
7	2	16	9	6	23	4	18	24	3	17	20	1	19	11	7	10	12	13	22	14	15	5	8	21
8	11	10	9	19	5	24	3	20	6	16	1	18	14	21	4	13	22	17	12	15	2	7	23	8
9	16	18	23	6	20	5	7	13	22	1	14	21	3	2	4	10	15	24	12	8	9	17	11	19

As can be seen from the resulting scenario testing order in table 8-6, each block contains 9 blocks of multiple 3 scenarios to test, which indicate the scenarios each participant will be running.

As previously mentioned, the experimental design of the simulation experiment will follow a factorial design in order to effectively analyze the results from this experiment. Overall, we are looking for driver behavior trends based on severity of fog and the whether the DMS presence affects or significantly impacts these trends. This involves comparing how drivers act with no DMS presence and vice versa for each fog condition. We expect to see variability in driver speed and vehicle headway as the fog condition worsens, however the impact of the DMS sign on the drivers reaction to the fog is not very well known. Ideally, as the fog condition becomes more severe, driving speed is expected to reduce due to the reduced visibility. These reactions are hopefully going to be much more apparent under DMS conditions as the driver will have forewarning of the upcoming conditions. Depending on these findings, the demographic variables can be referenced to see if any trends can be noticed between the collected data and the results.

The final part of the experimental analysis will involve the validation of the simulation and resulting data. This can be done in many different ways, but in the case of this experiment data will be collected from the real world site discussed previously. Through comparing the data between the simulator and sensors, we hope to see similarity and common trends of the data. Since the real world scenario will not have any DMS presence, the two sources will be compared with the base, zero signage, condition.

To observe a participants reaction in the scenarios, driver actions involving sudden percent change in acceleration or deceleration rates, braking, and vehicle headways will play a vital role in this analysis and require great focus. These variables are modeled independently during analysis and will be focused on the locations where Dynamic Message Signs are present and where the clear condition begins to transition into foggy conditions. By doing this, we develop cases of drivers responding to these given variables from a constant base condition that can be compared with the scenario of interest.

Population and Sample

The population that are observed in this experiment will consist of both male and female participants with ages ranging from 18 to late 60's who have their drivers' licenses and live in the State of Florida. In order for this experimental design to be performed properly approximately 72 participants will be needed where each will be expected to run 3 random scenarios involving different visibility, DMS, or other roadway conditions. Also, since this research experiment tests two different scenario environments (freeways and arterial roads), both are equally represented in terms of the number of scenarios tested. In terms of gender, though not a variable we are ultimately focusing on, we will attempt to get as close to a fair balance between genders as possible. Similarly with age, it is expected that a majority of the participants will be ages 20-30's, so extra effort must be put into finding older participants through recruitment. To combat this issue, older friends, family, and working faculty and staff were recruited to participate in the study.

The decided age and gender distribution used for this study is based on observed crashes along interstate 408, I75, and SR441. These results can be seen in table 8-7, and although it does not completely represent the participant sample, it is still used as an estimate in selecting which participants are to be tested. Overall, approximately half of the participants tested are in the 20's and 30's age group representing the majority of our testing sample. Likewise, older participants in their 60's will be the smallest sample tested making up about 10 percent of the population sample.

Table 8-7 Population age and gender percentage

age group	Male	Female	Total
18-24	23.50%	18.00%	30.20%
25-34	21.10%	21.10%	21.20%
35-44	16.80%	17.30%	16.30%
45-54	17.70%	18.80%	16.30%
55-64	13.10%	15.40%	10.30%
65+	7.70%	9.50%	5.70%

8.2 Scenario Design

The scenarios tested will begin with the driver under clear conditions. Before the driver encounters any obstacles or variables, they are given a clear segment of roadway allowing them to get up to speed and into the flow of traffic. Farther down the roadway, the driver will begin to encounter DMS and beacons, if present in the scenario, which alerts the driver of upcoming fog conditions; this part of the roadway spans for about 4-5 miles. Following this, the driver will enter a fog 'transition' zone where the visibility will steadily reduce until the desired visibility distance is achieved. Driver behavior can be observed in the segment and view their initial reaction to the fog onset and can be compared to their overall behavior in the previous 'clear' segment. Once the desired visibility distance is met, the driver will continue for approximately 2.5 miles under fog conditions where their speed and car following behavior can be observed and analyzed. The distance of this segment was very important as it is determined that driver behavior can change as they grow more comfortable within the foggy condition.

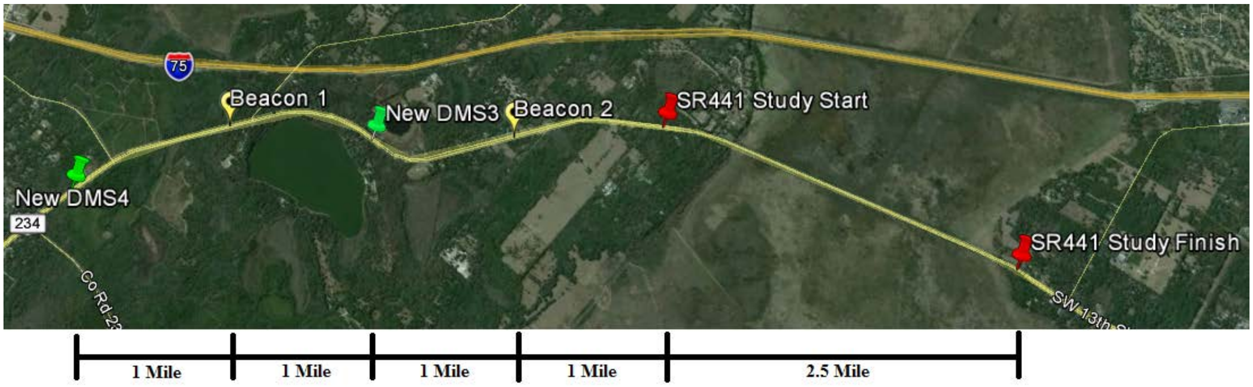


Figure 8-1 Simulation scenario plan for SR441

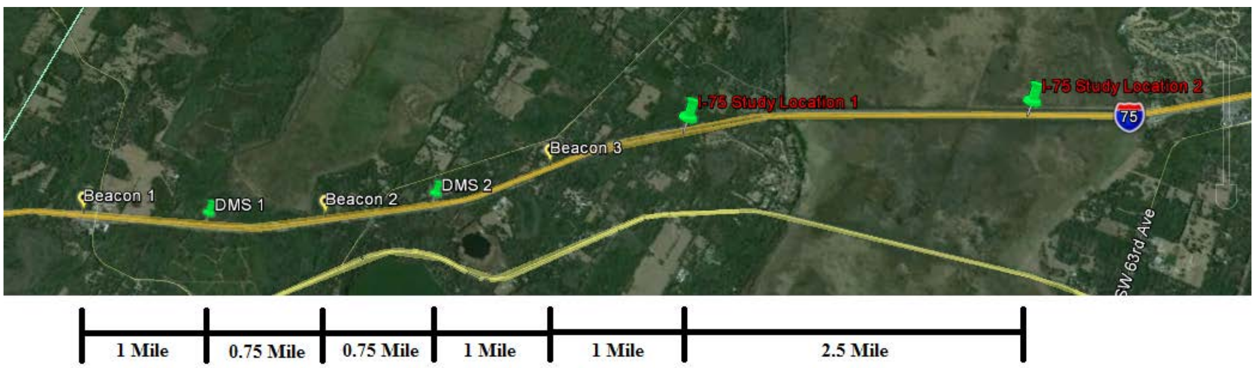


Figure 8-2 Simulation scenario plan for I-75

As it is mentioned in Chapter 8.1, six variables are considered in this study.

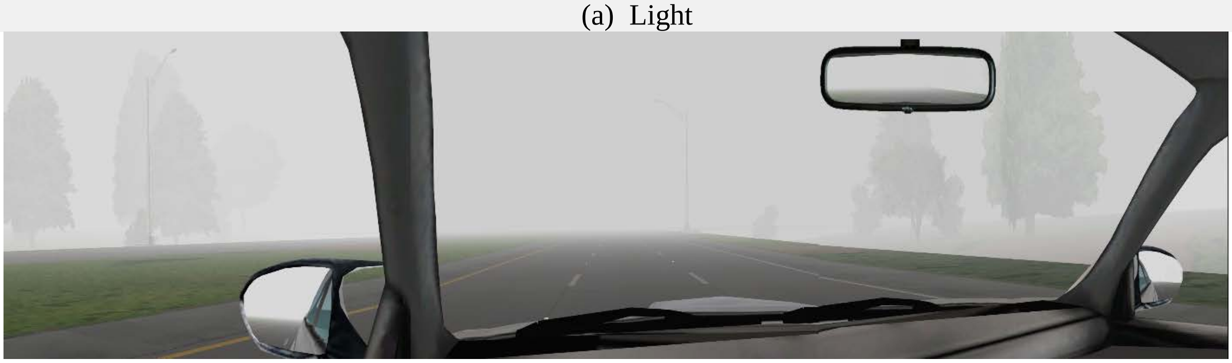
- Roadway Type

Based on the area of interest for the FDOT plan, two roads are tested for the early warning system; SR441 and I-75. SR441 is a two lane arterial road with a speed limit of 65 MPH and I-75 is a three lane highway with a speed limit of 70MPH. By comparing driver behavior changes between the clear and fog conditions, we hope to see a clear trend in terms of speed reduction between the two roadways.

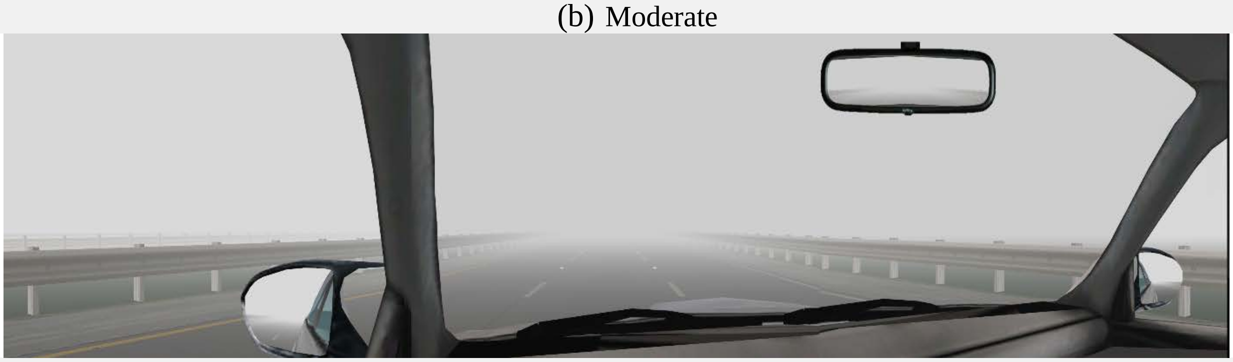
- Fog Visibility

In order to test driver reactions to different severities of fog, varying visibility levels are established. These levels include visibility distances of 500ft, 300ft, and 150ft (Figure 8-3). These distances were chosen in order to see a clear reaction from drivers as it was learned from other studies that drivers will not react to reductions in visibility if sight was not limited to a certain distance.

(a) Light



(b) Moderate



(c) Dense

Figure 8-3 Different fog levels

- Number of DMS

Three different levels of DMS presence were tested; 0, 1, and 2. Each DMS is located approximately 2 miles from each other, and by varying the number present, we wish to observe if DMS or additional DMS have an impact on a driver behavior between the clear and fog conditions. Figure 8-4 provides an example of DMS sign.

Figure 8-4 An example of DMS in scenarios

- Sign Text

Two different DMS messages are tested to also observe if they have an impact on driver behavior as well. One message contains a simple 'warning' indicating that foggy conditions are ahead along the roadway. The other is an 'advised' message which warns the driver of fog and advises the driver to reduce their speed.

- Traffic Setting

Since fog is hard to predict and can occur during a large timeframe in the mornings, two traffic settings were chosen to be studied. A light volume scenario is established to represent a very early morning scenario where vehicles are widely spaced and allow for observation of driver behavior without the interference of other vehicles. A high volume scenario is used to provide a slight obstacle to the driver and allows for the study of possible car following behavior while under the fog conditions.

- Beacon Presence

Beacons are also placed within some of the scenarios to observe if there is an impact on driver behavior, similar to the effect studied on the DMS presence.

Figure 8-5 An example of beacon in scenarios

8.3 Experiment Procedures and Current Data Analysis

Experiment Procedures

Participants will complete the informed consent document and parts of the questionnaire before the experiments. After finishing the paperwork, an instruction will be provided to the participants. After they have read the instruction, a 5-8 minutes test scenario will be provided to the participants to help them be familiar with the driving simulator. Once they finish the test scenario, the participants need to report if they are feeling OK are that time. If they do not feel good, the participants will have a 10-15 minutes rest or stop the experiment. Meanwhile, the participants can stop the experiment whenever they want or feel uncomfortable.

If the participants feel good, the real test scenarios will be provided to drivers. The participants will report their feeling and need to fill in the between scenarios survey every time that they finish one scenario. A 5-10 minutes rest will be provided if they feel good.

After completing the scenarios, the “after experiment survey” will be conducted for each participants. About 20 minutes rest is recommended for the participants, before they leave and drive back.

Current Results and Analysis

Currently, 24 participants have been tested, and each of them had 3 three fog related scenarios. Thus, a total of 72 scenarios has been tested until now. Table 8-8 shows the descriptive statistics of some dependent variables. The speed limit for the Arterial segment (SR. 441) is 65 mph, and the speed limit is 70 mph for the studied freeway segment (I-75). As we can see from the table, people will drive about 3 mph higher than the speed limit, while the freeway segment has higher speed standard deviation ,which indicating that speeds under reduced visibility are much more varied than the clear behavior. Meanwhile, participants are prone to drive at lower speed under fog condition. There is a clear trend that when the visibility decrease, participants are more likely to drive at lower speeds. We can also notice that the average speed is relatively higher if the traffic volume is relatively lower.

Table 8-8 Descriptive statistics of some of the dependent variables

Factors	Parameters	Speed (mph)
Roadway Type (Under clear condition)		
Freeway (N=35)	Mean	73.71
	S.D.	6.98
Arterial (N=37)	Mean	68.03
	S.D.	4.84
Visibility conditions		
Fog (N=72)	Mean	58.68
	S.D.	6.58
Clear (N=72)	Mean	70.75
	S.D.	13.41
Fog levels		
Light (N=13)	Mean	66.37
	S.D.	6.82
Moderate (N=30)	Mean	64.76
	S.D.	11.94
Dense (N=29)	Mean	49.32
	S.D.	11.10
Traffic (Under clear condition)		
Low (N=37)	Mean	71.28
	S.D.	8.2
High (N=35)	Mean	70.2
	S.D.	4.32

Two type ANOVA for average speeds under fog conditions indicates significant F ratio for fog levels (F=19.2, p=0.000, 2 d.f.) (Table 8-9). Table 8-8 shows that the averages speeds decrease significantly at dense fog conditions. The speed difference between light fog conditions and moderate fog conditions is only about 1.5 mph.

Table 8-9 ANOVA results

	d.f.	F-ratio	P-value
roadway type	1	1.48	0.229
fog level	2	19.2	0.000*
traffic	1	0.07	0.795
roadway type*fog level	2	0.13	0.877

*Significant at the 0.05 level.

8.4 Chapter Summary and Future Plan

This chapter discussed the driving simulation experimental design and scenario design for the reduced visibility conditions. Preliminary analysis is conducted based on current 24 participants' data. Strong impacts of visibility conditions on drivers' speed choices is observed from the results.

Meanwhile, once the remainders of the participants are tested, Matlab can be used to determine for accurate average speeds in the different visibility zones of the scenarios. This includes the speeds in the clear condition, DMS and Beacon region, the fog transition region, and the fog zone. Looking at the speeds separately for the fog and transition zone is especially important, as it is observed that drivers will greatly reduce speeds at the initial fog onset and then gradually increase their speeds as they grow more comfortable within the fog zone. Comparison of the scenario variables will also be more available as a much larger sample size is needed for the experimental design analysis.

9. CONCLUSION

In summary, there are several major conclusions based on the analyses above:

1. An array of low-cost environmental sensors, arranged at varying levels above the ground surface, could effectively detect the onset of fog and meet or exceed existing performance of traditional and much more expensive technologies. The updated algorithm is efficient to detect the fog days but it is still likely to make a false alarm when the day is actually clear. Overall, the performance of the updated algorithm was much better compared to the original one and it can be used to detect almost all the fog cases.

3. The mean headway and headway variation are significantly higher while the mean speed and volume are significantly lower in fog case compared to clear case based on the analysis of one fog case in the morning. There isn't significant difference in speed variation in both cases.

4. It is shown from scatter plot analysis that the relationship between speed and headway as well as the relationship between speed and volume is different in fog case compared to the pattern in clear case. It is meaningful to conduct more scatter plot analysis in further to figure out the relationship of this traffic flow characteristics under fog situations.

5. The impact of reduced visibility on passenger cars is more significant compared to trucks. The mean headway, variation of headway and speed are significantly higher while the mean speed is significantly lower in the fog case compared to the clear case for the cars. In comparison, there

isn't significant difference in the mean headway for the trucks and there isn't significant difference in the standard deviation of speed and headway lower in the fog case compared to the clear case for the trucks.

6. It also can be concluded that the differences of mean of headway, speed and standard deviation of headway and are all significant under different visibility levels. The mean of headway will increase when the visibility drops. The mean speed will decrease when the visibility drops. The mean of standard deviation of headway will increase when the visibility drops.

7. The distribution of traffic flow characteristics is very similar in both directions and the effect of reduced visibility on both directions is also similar. The effects of reduced visibility on different lanes are different. For the outer lane, the mean speeds under good visibility level and moderate visibility level are both significantly higher than mean speed under low visibility level. The difference of mean speed under good visibility level and moderate visibility level is not significant the mean headway under good visibility level are significantly higher than both mean headways under low visibility level and moderate visibility level. The difference of mean headway under low visibility level and moderate visibility level is not significant. For the middle lane, the mean speeds will increase as the visibility increases. The mean headway increases as the visibility drops and the mean headway under good visibility level are significantly higher than both mean headways under low visibility level and moderate visibility level. The difference of mean headway under low visibility level and moderate visibility level is not significant. For the inner lane, the mean speeds under good visibility level and moderate visibility level are both significantly higher

than mean speed under low visibility level. The difference of mean speed under good visibility level and moderate visibility level is not significant. The mean headway will decrease as the visibility increases.

9. Inverse Gaussian regression modeling was applied to explore the relationship between time to collision and visibility together with other traffic parameters. It was concluded that reduced visibility would significantly increase the traffic crash risk especially rear-end crashes and the impact on crash risk was different for different vehicle types and different lanes.

10. Based on kernel density estimation (KDE) technique, Areas with frequent Fog, smoke and FS crashes were identified. Areas with frequent fog/smoke related crashes on Florida state highways were identified. A micro-level screening is conducted at those area. Both maps and tables are provided to locate these hotspots. It is recommended to pay attention to the identified hotspots and offer appropriate countermeasures to minimize the number of traffic crashes under low-visibility conditions due to fog or smoke.

11. The matched case control logistic regression model was used to further explore the relationship between traffic flow characteristics and different visibility levels. The results indicated that higher mean of headway, variance of speed and headway and higher occupancy were related to the increase of the likelihood of a reduced visibility while lower mean speed was related to the increase of the likelihood of a reduced visibility.

12. Driving simulator experiment has been designed to test driver behavior under fog conditions, and the effects of Dynamic Messages Signs (DMSs) and beacons. Six variables are considered in this experiment, which include the fog levels, traffic volume, the number of DMSs, the contents of DMSs, the beacon present or not, and the roadway types. Current results indicate drivers' speed choices are highly relative to the visibility conditions.

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