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Investigating the Effects of Rainfall on Traffic Operations on Florida Freeways

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INVESTIGATING THE EFFECTS OF RAINFALL ON TRAFFIC OPERATIONS ON FLORIDA FREEWAYS

By

Lucia Andrew

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DEDICATION

Special dedication to the Almighty God. It was only by his grace that I could reach this far.

ACKNOWLEDGEMENTS

I am so grateful for managing to complete this thesis. Accomplishment to this point is a product of endless efforts and support of so many individuals. I am overwhelmed to thank all who participated to make this work a success.

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Above all, I thank God the father – through him all things are possible!

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ACRONYMS

AMS	American Meteorological Society
ASOS	Automated Surface Observing System
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GIS	Geographic Information System
HCM	Highway Capacity Manual
ID	Identification
JIA	Jacksonville International Airport
KJAX	Radar site at Jacksonville International Airport
NAS Jax	Naval Air Station Jacksonville
NEXRAD	Next Generation Radar
NCDC	National Cimatic Data Center
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service
RTMS	Remote Traffic Microwave Sensors
RWIS	Road Weather Information Systems
RWMP	Road Weather Management Program
UK NWS	United Kingdom National Weather Service
U.S. NWS	United States National Weather Service
VSL	Variable Speed Limits
WCT	NOAA Weather Climatic Toolkit
WSR	Weather Surveillance Radar

ABSTRACT

Rainfall affects the performance of traffic operations and endangers safety. A common and conventional method (rain gauges) for rainfall measurements mostly provide precipitation records in hourly and 15-minute intervals. However, reliability, continuity, and wide area coverage pose challenges with this data collection method. There is also a greater likelihood for data misrepresentation in areas where short duration rainfall is predominant, i.e., reported values may not reflect the actual equivalent rainfall intensity during subintervals over the entire reporting period. With recent weather and climate patterns increasing in severity, there is a need for a more effective and reliable way of measuring rainfall data used for traffic analyses. This study deployed the use of precipitation radar data to investigate the spatiotemporal effect of rainfall on freeways in Jacksonville, Florida. The linear regression analysis suggests a speed reduction of 0.75%, 1.54%, and 2.25% for light, moderate, and heavy rainfall, respectively. Additionally, headways were observed to increase by 0.26%, 0.54%, and 0.79% for light, moderate, and heavy rainfall, respectively. Measuring precipitation from radar data in lieu of using rain gauges has potential for improving the quality of weather data used for transportation engineering purposes. This approach addresses limitations experienced with conventional rain data, especially since conventional collection methods generally do not reflect the spatiotemporal distribution of rainfall.

Key words: precipitation radar data, adverse weather, freeway operation

CHAPTER 1: INTRODUCTION

Background

Adverse weather conditions, specifically rainfall, affect the performance of traffic operations and reduces highway safety. Rainfall influences traffic operations by affecting pavement conditions, vehicle performance, and driver behavior. Consequently, three primary aspects of traffic operations are negatively impacted: traffic safety, mobility, and efficiency (Hammit, Ghasemzadeh, Ahmed, & Young, 2017).

The characteristics and behavior of road users are among the most important elements that influence the task of driving. The driving task involves performing several activities, such as guiding the vehicle within the road, detecting other vehicles, detecting other motorized and non-motorized users, judging the speed, position, and possible behavior of other road users, and reacting accordingly (Chakrabarty & Gupta, 2013). Inclement weather affects the driving conditions by either reducing the friction between the tires and pavement surface, impairing driver visibility, and/or making vehicle handling difficult. Reduction in friction is caused by the hydroplaning effect due to the formation of a thin layer of water on the roadway which may lead to skidding. Road user perception of risk influences their behavioral responses to not only natural changes in weather conditions, but road surface conditions as well.

Inclement weather may disturb a driver's comfort of driving. Weather conditions, such as rainfall, snow, and fog, require drivers to adjust their driving behavior to reduce the associated risks with each condition. These adjustments vary from trip cancellation to on-road adjustments, such as increased driver attention, speed reduction, and greater gap distances between other vehicles. However, some of these adjustments have been insufficient in alleviating the hazards posed by inclement weather (Andrey, Hambly, Mills, & Afrin, 2013).

It is well known that the performance of any transportation system is gaged primarily by the traffic flow characteristics. Traffic performance indicators, such as speed, flow, and capacity are affected by rainfall and other adverse weather conditions (Ibrahim & Hall, 1994; Li, Elefteriadou, & Kondyli, 2014; Maze, Agarwai, & Burchett, 2006). Drivers' response to inclement weather affects traffic operations in terms of speed, reaction time, lane maintenance, and visibility, since drivers tend to be more cautious. Moreover, weather and traffic conditions were found to be the most significant factors contributing to driver behavior (Chakrabarty & Gupta, 2013)

Rainfall is spatiotemporal by nature, i.e., it varies with respect to time and area. Consequently, this implies that the effect of rain at a given time in a given area may differ. The spatiotemporal impact of rainfall on traffic operations is of interest in transportation research, planning, and management. Previous studies have examined the spatiotemporal effects of rain on traffic by analyzing the changes in speed and flow patterns due to rain using available radar map and rainfall data from hydrological stations (Dhaliwal et al., 2017).

A study by Tsapakis et al. (2013) examined the spatiotemporal correlation of rainfall in Greater London using hourly rainfall data from weather stations. The study found that weather effects on speeds and travel times vary considerably, depending on the target area, geometric, traffic, and driver characteristics, socioeconomic factors, roadway functional class, the season of the year, and the climate of the examined region (Tsapakis, Cheng, & Bolbol, 2013). However, despite the informative findings by Tsapakis et al. (2013) on variations of the effects of rainfall with different factors, the study based the analyses on hourly data, and excluded sub-hourly variations in weather, which are essential in gaining a full understanding of the effects of rainfall on traffic operations. Similar studies also used hourly data (Maze et al., 2006); (Gillette, Fitzpatrick, & Raul, 2017); (Angel, Sando, Chimba, & Kwigizile, 2014).

The analysis of weather impacts on traffic flow where Automated Surface Observing System (ASOS) was used for measurement of hourly rainfall reported some data issues associated with ASOS, whereby some observations were missing in the dataset. Authors also pointed out that study sites were located as far as 25 miles from the weather stations at three airport stations, which implies that they could not capture the roadway weather conditions fully ever since weather could vary throughout the road segment (Stern, Vaishal, Goodwin, & Pisano, 2002).

Problem Statement

Precipitation values that are frequently reported in hourly intervals may not reflect the rainfall intensity throughout the entire 60-minute duration. For example, in Florida, short duration rainfall events are common, where heavy rain may occur for 10 minutes or less, followed by sunny conditions for the remainder of the hour. Consequently, hourly rainfall data may not correspond to actual real-time rain conditions used in conjunction with other variables used for analysis.

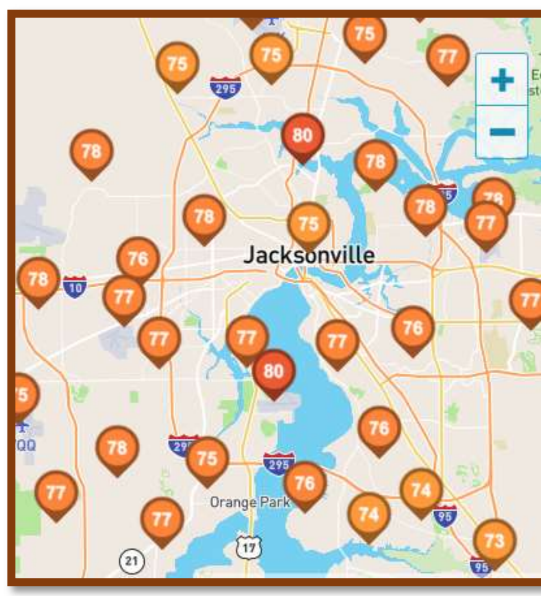
Typically, stations used to collect rainfall data are sparsely spaced. For example, in Jacksonville, Florida, with a total land area of 875 square miles, there are only two reliable rainfall stations: Naval Air Station Jacksonville (NAS Jax) and Jacksonville International Airport (JIA). These stations cover not only a large area, but also are subject to mechanical breakdown, either due to physical damage (natural or manmade), mechanical wear, or severe icing during winter weather, requiring repair or replacement. During these system outages, some data may be unavailable or physical observations may be misinterpreted.

Changes in weather patterns and extreme climate events may contribute to heavy precipitation events in some areas. It has also been suggested that the frequency and intensity of heavy precipitation has increased in North America and Europe (Pachauri & Meyer, 2014).

Therefore, developing a rainfall quantification approach that facilitates the effectiveness of spatiotemporal analysis on issues relating to transportation systems is essential, especially in anticipation of future extreme weather effects (Pachauri & Meyer, 2014).

Radar data provide the spatial temporal distribution of rainfall over the road network. It also offers a higher resolution data (Stern et al., 2002). Radar data is available in short time intervals of 4.5, 5, 6 and 10 minutes. The availability of radar data in such small-time intervals provides an opportunity to associate rainfall data with real-time traffic data, which is available in small time intervals as well. With these benefits of radar data, it can be well exploited and applied in quantification of the impact of rainfall on the transportation system. Figure 1 below shows the coverage of radar station and that of conventional weather stations. Conventional weather stations do not provide full coverage over the entire area, hence radar can be used to fully capture the effect of rainfall on road networks.

NOAA Radar Data from KJAX



Underground Weather Stations[1]

Figure 1: Radar and Conventional Weather Stations Coverage

[1] Reprinted from Weather Underground (2019). Retrieved from: https://www.wunderground.com/dashboard/pws/KFLJACKS129

Objective

Quantifying the effect of weather on driver response is important in the evaluation of traffic operations (Angel et al., 2014). A common practice for quantifying rainfall uses data collected by surface meteorological stations which typically represent a wide area. The recent availability of improved quality radar-based precipitation data is providing a momentum for better and relevant quantification of rainfall in a spatial context, which can be helpful in analyzing the impact of rainfall on traffic operations. Additionally, radar provides an opportunity for estimating shorter durations of rainfall based on reflectivity data records of four to six minutes intervals, considering the sub-hourly variations. This study presents an approach for quantifying rainfall using weather radar data to examine the effects of rainfall on traffic operations along freeways, including short rainfall events common in Florida, and reports the spatiotemporal effects on traffic parameters.

Significance of the study

Evaluating the spatiotemporal effects of rainfall on freeway traffic operations will be useful for weather responsive management of transportation networks. This analysis can better establish the actual effects of rainfall on freeway operations, thus allowing for appropriate response measures based on the need.

Organization of the Manuscript

After identifying the knowledge gap and potential benefits of this study, the following section, Chapter 2, provides a thorough review of relevant past studies related to the effect of rainfall on traffic safety, freeway traffic operations, and the deployment of weather radar for traffic studies. The methodology framework for this study is presented in Chapter 3. Chapter 4 discusses the analysis of speed and headway, and model evaluation is presented in Chapter 5. Chapter 6 presents the summary of the study, conclusions, and recommendations for future work.

CHAPTER 2: LITERATURE REVIEW

The effects of rainfall on traffic operations has been discussed by different scholars in the past. Additional research is still ongoing, primarily due to climatic changes leading to uncertainties, unresolved issues, advancements in technology impacting analysis methods, and previous research findings inspiring further investigation. This chapter explores different works related to the effects of rainfall on traffic operations and is divided into six sections.

Effect of weather on safety

Precipitation can greatly affect transportation safety. Previous studies reported an increase in collision rates, typically by 50-100%, resulting in serious injury or fatality under inclement weather conditions. Many weather-related crashes occur during rainfall events and/or when the pavement is wet (Hjelkrem & Ryeng, 2016). The U.S. Federal Highway Administration (FHWA) reported that on average, more than 573,784 and 907,831 weather-related vehicle crashes occur each year in United States (U.S.), due to rain and wet pavement respectively, resulting in property damage, injuries and fatalities. About 74% and 46% of weather-related crashes in U.S. occur during wet surface conditions and rainfall, respectively (Federal Highway Administration, 2018). Also, a study in China reported that weather-related crashes account for 25% of total vehicle crashes (Shi, 2015).

Rainfall Impact on Freeway Traffic Speed

Vehicle speed is one of the key parameters in determining traffic performance of a transportation system. Speed reduction is cited as a primary response to inclement weather, as drivers attempt to compensate for the negative effects on the driving task, such as insufficient time for appropriate response to unexpected situations. Relative to the number of trips, driving below the posted speed limit has been observed more often during heavy rainfall, compared to light rain and clear weather,

by 85.2%, 65.2%, and 37%, respectively (Ahmed, Mohamed M.; Ghasemzadeh, 2015). Studies on the impact of rain on highway and freeway traffic flows revealed that reduction in vehicle speed increases travel time and traffic delays significantly, resulting in increased traffic congestion (Smith, Brian L.; Byrne, Kristi G.; Copperman, Rachel B.; Hennessy, Susan M.; Goodall, 2003; Zhou, 2016). Furthermore, under inclement weather conditions, the associated risks increase as the posted speed limit increases (Andrey et al., 2013). To account for speed reductions under adverse weather conditions, such as medium and heavy rainfall, speed adjustment factors are presented for facility free flow speed (Highway Capacity Manual, 2016; Zegeer et al., 2013).

Several studies reported the impact of rainfall on traffic speed as a function of the rain intensity, thus, speed reduction increases as the intensity increases. Table 1 briefly summarizes the results of several studies on the impact of rainfall on traffic speeds.

Table 1: Summary of the Effects of Rainfall on Speed and Capacity from Different Studies

	Facility type & Location	Rain Intensity Level	Speed reduction
(Ibrahim & Hall, 1994)	Freeway	Light Heavy	3%-5% 14%-15%
(Brilon & Ponlet 1996)	Freeway	Dry condition Wet condition	- 6mph–four-lane 7.5mph-Six-lane
(HCM, 2000)	Freeway	Light rain Heavy Rain	10km/hr 19km/hr
(Smith, Brian L.; Byrne, Kristi G.; Copperman, Rachel B.; Hennessy, Susan M.; Goodall, 2003)	Freeway Hampton, Virginia	None < 0.01 in/hr Light 0.01-0.25 in/hr Heavy > 0.25 in/hr	No speed reduction 5%-6.5% 5%-6.5%
(Agarwal, Maze, & Souleyrette, 2005)	Freeway-Minneapolis, Minnesota	Trace < 0.01 in/hr Light 0.01-0.25 in/hr Heavy > 0.25 in/hr	1%-2% 2%-4% 4%-7%
(Rakha, Farzaneh, Arafeh, & Sterzin, 2008)	Freeway Minneapolis, Minnesota	Light ≤ 0.1 in/hr Medium 0.1-0.25 in/hr Heavy>0.25 in/hr	2%-3.65% - 6%-9%
(HCM, 2016)	Freeway	Light Heavy 0-0.01 in/hr 0.1-0.25 in/hr >0.25 in/hr	3%-5% 14%-15% - - -
(Akin, Sisiopiku, & Skabardonis, 2011)	Freeway (Istanbul)	Rainy conditions	8%-20%
(Angel et al., 2014)	Freeway Jacksonville, Florida	Light Medium Heavy	1.8-2.5mph for I-295 1.5-3.5mph for I-95
(Li et al. (2014)	Freeway & Arterial section Tallahassee, Orlando and Miami, Florida	Light Heavy	6% 12%
(Dhaliwal et al., 2017)	Freeway (Los Angeles)	Light Medium Heavy	8.65 17.4% 15.34%
(Wang & Luo, 2017)	Expressway Hainan, China	Light Moderate Heavy	4.4%, 7.3% 10.6%

Headway

Driver behavior affects the driving task. Headway selection depends on the driver's ability to see objects (the dynamic visual acuity) and the reaction process, both of which influence the driving task. During inclement weather, it is important for drivers to keep greater than the minimum safe vehicle gap. As such, drivers tend to keep longer following distances during rainfall events. Adverse weather conditions, such as rainfall, reduces visibility, as brightness decreases and the glare increases. Consequently, a drivers' perception reaction time increases to compensate for the increased risk (Ahmed, Mohamed M.; Ghasemzadeh, 2015; Andrey et al., 2013).

Wet pavement during and after rainfall events reduces the traction between the pavement surface and the vehicle tires, causing slippery conditions and difficulty braking. Weather related crashes in China contribute to nearly 25 percent of total vehicle crashes, one-third of which are rear-end, which are more likely to occur on rainy days (Shi, 2015). Two primary reasons for this are increased driver perception response times due to reduced visibility and less pavement friction, both affecting the minimum safe gap typically required between vehicles.

The fact that human error and driver behavior have been identified as key factors contributing to more than 60% of crashes, the general nature of headway selection can have a significant effect on freeways in terms of safety and operational performance (Ahmed & Ghasemzadeh, 2015). Therefore, it is important to examine the impact of rainfall on headways.

Weather Radar in Traffic Studies

Although few, several researchers (Hooper et al., 2007; Jaroszweski & McNamara, 2014) have attempted to examine spatiotemporal aspects of rainfall on traffic issues using weather radar data. A study by Hooper et al. (2007) was conducted on United Kingdom (UK) motorways to determine the impact of precipitation on traffic speeds in an effort to establish failure precipitation thresholds.

Precipitation data was obtained after creating a geographic information system (GIS) map using weather data and motorway links. Speed data were collected at 15-minute intervals, while the precipitation data were in five-minute intervals. Higher speeds were observed in periods without rain, and a decrease in speeds were reported when precipitation was present. However, the analysis did not include several important factors, such as traffic flows (volume) and precipitation durations, which are significant factors required to gain a better understanding of the impacts of precipitation on travel speeds (Hooper et al., 2007).

Another UK study by Jaroszweski and McNamara (2014) incorporated weather radar images in the accident analyses. The study used a 3-hour rainfall event and superimposed the weather radar images onto an urban area map. The effect of rainfall was expressed in relative accident rates, the ratio of accidents recorded during precipitation to those that occurred during normal conditions. Study findings revealed that the matching analysis of weather radar images onto urban areas produced a more representative measure of rainfall than the station-based data approach. However, the metrics to support this argument were not provided.

A study conducted in Washington DC, used radar data to compliment weather data for the missing ASOS data in the analysis of weather impact on traffic flow. Level III reflectivity data we used from the National Climatic Data Centre (NCDC). Correlation of radar data on road segment was done by overlaying radar on road network through Geographic Information system (Stern et al., 2002).

A report on weather integration by (Federal Highway Administration, 2006) for weather stated that weather integration in Traffic Management Centers (TMC) will enhance operators ability to manage traffic in a more responsive and effective way. The improved weather integration within TMCs will help reduce the effects of weather on transportation systems. Integration of current and

future weather information in a TMC depends on the institutional landscape, weather exposure, transportation infrastructure, and weather information need in the state or region, hence it is expected to vary from one center to another. Weather information requires a comprehensive understanding of weather data and forecast accuracy so as to be useful in decision making in the TMCs . Weather radar images is among the operational strategies in use, which provides a visual access for operators to see where adverse weather may be developing (Federal Highway Administration, 2006). Apart from the weather images for visualization, weather radar data, can be effectively quantified as well as the corresponding traffic parameters for better management of the transportation systems.

In summary, rainfall affects freeway traffic flow in various ways, both at the micro level and the macro level. This study focuses on the micro level, whereby two parameters, speed and headways, will be examined.

Regression Analysis

Previous studies have applied different approaches to model the effects of rain on traffic operations, such as analyzing vehicle speeds before, during, and after a rain event, or utilizing binary logistic regression to determine factors affecting the speed variance during and after rain events. Wang and Luo (2017) used a linear regression analysis to develop weather influence factors for traffic flow parameters. Another study by Shi et al. (2011) explored the effects of rainfall and road environmental factors on urban freeway traffic using the same approach.

To understand driver behavior under different rain and traffic conditions, Ahmed and Ghasemzadeh (2015) used the ordered probit model to model speed and headway. A multiple regression approach was used by Ibrahim and Hall (1994) to study speed reduction during rain and snow conditions. Shi (2015) investigated the effects of rain on the average vehicle gap using a

quadratic regression model, and a stepwise regression analysis was performed by Rakha et al. (2012) to study the impact of weather on traffic stream behavior. Findings of these studies are briefly summarized in Table 1.

CHAPTER 3: METHODOLOGY

Site Selection

The study location was selected based on the availability of traffic detectors for traffic data and within radar range for rainfall data. A segment along the I-95 corridor, a north-south freeway that travels through Jacksonville, Florida was selected for study. As shown in Figure 1, the selected segment is located between Southside Boulevard and Baymeadows Road, south of downtown, and spans approximately two miles in length. This segment of I-95 is a 6-lanes facility with a posted speed of 65 mph. Both traffic directions of travel were considered in this study.

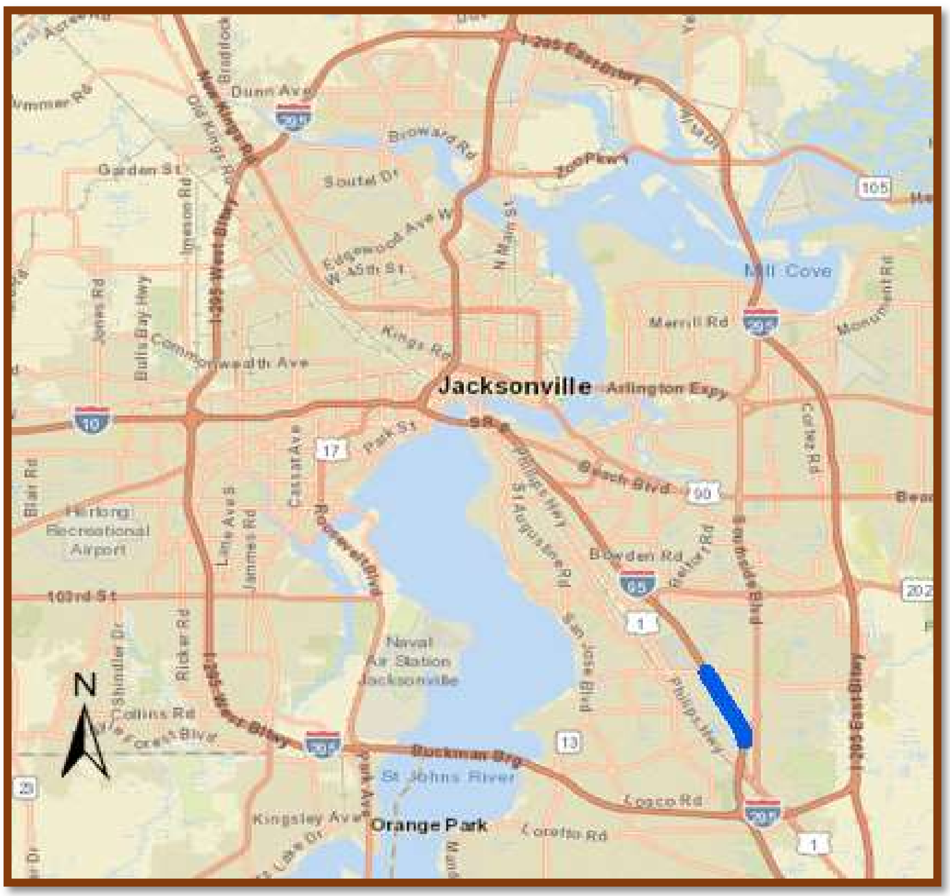


Figure 2: Study Location along I-95 in Jacksonville, Florida

Data Collection

Data were collected for eight rainy days in 2018: June 12, June 28, July 05, July 17, October 10, December 03, December 14, and December 20. These days were selected based on previous video recordings and historical weather information from websites that provide archived weather data, such as Weather Underground (Weather Underground, n.d.). Data for eight days in 2018 where the weather condition was dry also collected: June 05, June 07, July 12, July 10, October 03, December 17, December 28, and December 13. These dates were selected based on the time-period that coincided with the rain event days in terms of day of the week, and one or two weeks before or after the rain event, as suggested by other studies (Andrey et al., 2013; Dhaliwal et al., 2017). This was accomplished through accessing archived weather records available online (Weather Underground, n.d.).

Data were collected between 7:00 AM to 7:00 PM for each date included in the study. Holidays, such as New Year's Day, Christmas Day, Independence Day, and Thanksgiving were avoided and not included in the dataset. Additionally, weekend days (Saturday and Sunday) were not included in the analyses to avoid the possible effect of non-weekday traffic patterns.

Rainfall Data

Areas such as Jacksonville experience short rain events which may last for only few minutes. This study used radar data to capture short duration and location-specific (spatiotemporal) rainfall data at the freeway study segment.

Weather radar data available from the National Weather Service (NWS), a division of the National Oceanic and Atmospheric Administration (NOAA), was reviewed to obtain the spatiotemporal rainfall data. Radar is a detection system that uses radio waves to determine the range, angle, or velocity of objects for different purposes such as the detection of aircraft, ships,

spacecraft, guided missiles, motor vehicles, weather formations, and terrain, and has been used to estimate rainfall amounts since 1960. There are several weather radars around the world. For this study, the preferred weather radar was determined to be Weather Surveillance Radar 88-Doppler (WSR 88-D), also known as Next Generation Radar (NEXRAD). Figure 2 shows the general location of Doppler radar sites in U.S., with one NEXRAD site located in Jacksonville at the Jacksonville International Airport (JIA), and called KJAX. These weather radars can locate and follow precipitation within a range of 127.274 to 248.548 miles (200-400 km) (Teegavarapu & UNESCO, 2012).

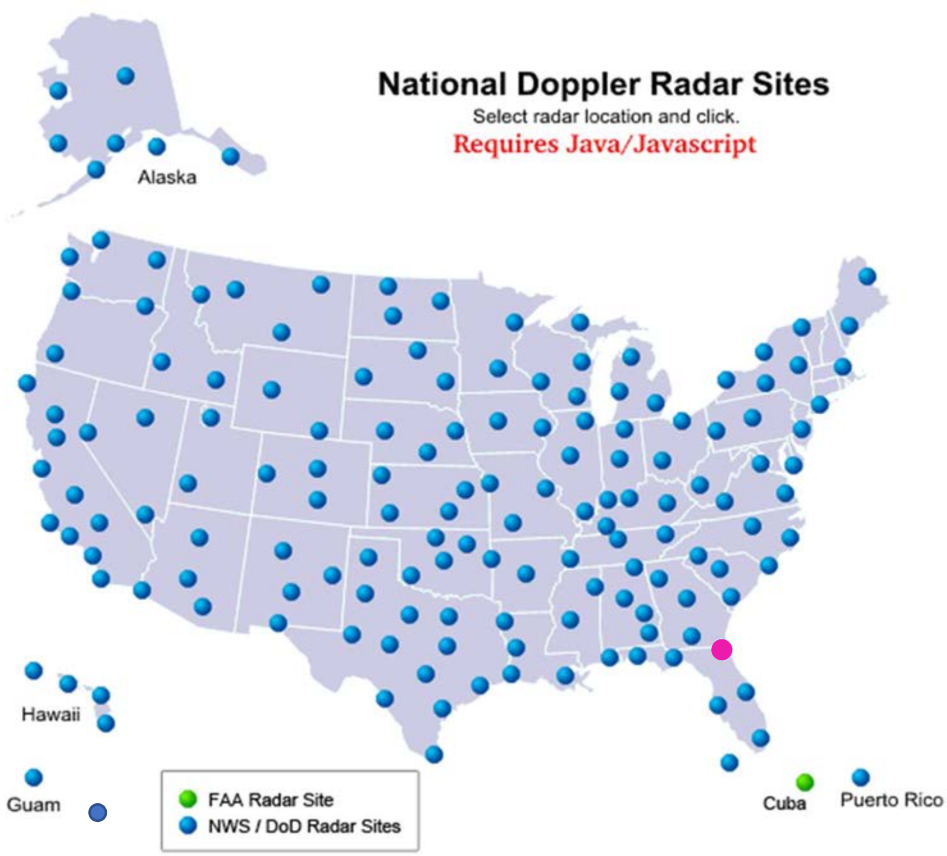


Figure 3: Radar Sites
(National Oceanic and Atmospheric Administration [NOAA], n.d.)

Radiations emitted by radar are detected and reflected by the precipitation targets. The degree of detection depends on atmospheric conditions between the radar and the target, the distance from the radar to the target, target characteristics, and radar characteristics. The measure of efficiency of a target in intercepting and returning radio frequency energy is referred to as reflectivity. Reflectivity can simply be defined as a measure of fractions of radiations reflected by a given surface, and expressed as the ratio of the radiant energy reflected to the total amount of energy incident upon that surface (National Weather Service Training Centre, n.d.).

Limitations of a Radar Method of Estimating Rainfall Rate

When using weather radar, underestimation of rainfall data may occur in case of:

- Distant targets, small targets, and wide radar beams directly resulting from the target and not filling the radar beam.
- Sub-refraction of the beam, attenuation by intervening targets, and wet radomes (protective domes). Sub-refraction is caused when the radar beam may be "bent", causing the energy to propagate over a target. Attenuation factors depend upon the extent (and intensity) of precipitation between the radar and the desired target. Radome wetness attenuation is usually small, but may become significant if the exterior of the dome is not well maintained (National Weather Service Training Centre, n.d.).
- In regions where echo contains mixed phase particles. The physical interpretation of radar reflectivity factors is more complicated than in regions containing mixed precipitation, such as mixed snow and rain than in regions with exclusive snow or rain.

These limitations can be avoided through frequent calibration and maintenance of the radar. Well maintained radar equipment is necessary for accurate radar estimations.

Data Acquisition Procedure

Data was requested from the NOAA website using the following steps:

1. Go to weather website (NOAA, n.d.).
2. Select the site, either by map (KJAX) or by city, county, or zip code.
3. Choose time of event and the radar product required-base data.
4. Enter an email address and order the data.
5. Once the application is completed, an order confirmation and the product code number will be sent to the email entered. When data processing is complete, the data will be sent to the email entered (Duda, 2005).

Alternatively, one can directly download data by simply writing a script using java or python programming language to obtain data from the NOAA website.

Radar Data Extraction and Processing

Since NEXRAD level II files come in binary file format, the data was extracted and processed using the NOAA weather climatic toolkit (WCT). The WCT enables conversion and visualization of NEXRAD files into various file formats. Each file contains reflectivity, mean radial velocity, and spectrum width data collected for the entire range of the radar station. Data files are available for the intervals of four, five, six, or ten minutes.

To obtain the spatial distribution data, the extracted arc polygon files were exported to ArcGIS, and a layer for the road polygon was created for the study site using the imagery base map. This segment was further divided into sub-polygons. Arc polygon files from NOAA were combined with the road polygon to obtain a joint file providing reflectivity data (from which rainfall was derived) for every sub-polygon, in tabular form. Figure 3 shows a map extracted from ArcGIS with rainfall data in in/h for different locations along the I-95 study segment.

Polygon ID	Detector ID	Distance (miles)	Time		
			7:00:14 AM	7:05:14 AM	7:10:14 AM
1	1-2049	0 (reference)	0.223	0.223	0.12
2	2-2109	0.61 (1-2)	2.445	0.269	0.167
3	3-2114	0.43 (2-3)	3.946	0.138	0.138

Rainfall intensity (in/h)

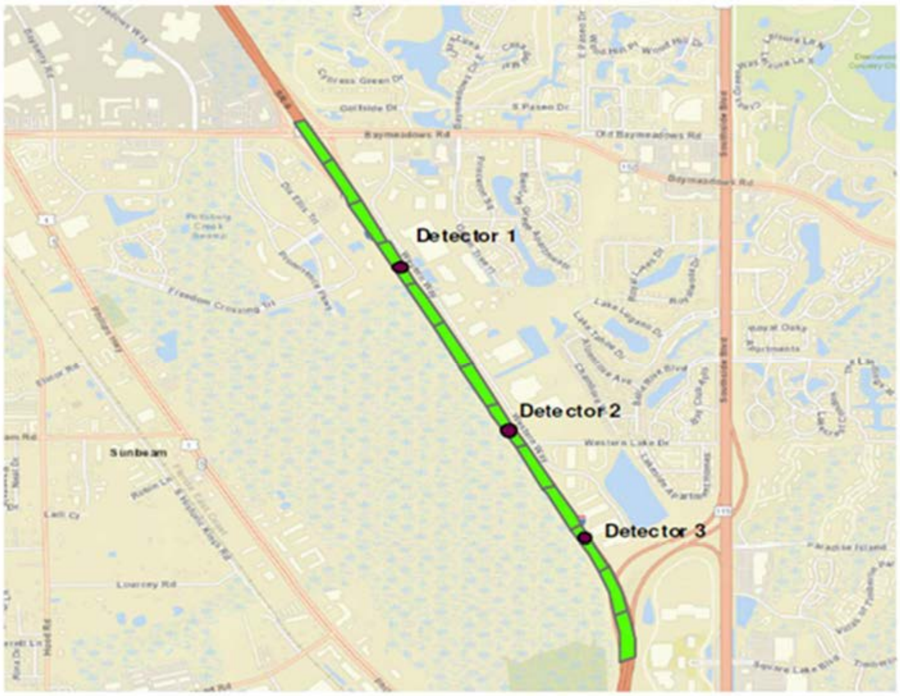


Figure 4: Spatiotemporal Effect of Rainfall

Reflectivity Rainfall Relationship

Reflectivity is also referred to as the sixth power of the diameter of rain drops (mm^6) per cubic meter of atmosphere. The relationship between reflectivity and rainfall rate is through the drop size distribution, and is given by two parameters in a Z-R relationship as follows:

$$Z = aR^b \tag{1}$$

where, Z is the reflectivity (mm^6/m^3),

R is the rainfall rate (mm/hr), and

a and *b* are fitting coefficients.

The coefficient *a* varies between 100 and 900, and exponent b varies between 1 and 2. In practice, specifically in the U.S., reflectivity values (Z) are reported as decibels of reflectivity (dBZ), and the reflectivity can range over many orders of magnitude. For operational use, Z is converted to decibels (Equation 2) (Teegavarapu & UNESCO, 2012). Note that anytime Z is less than 1 mm^6/m^3, dBZ becomes negative, which implies that the radar is detecting very small hydrometeors.

$$Z = 10 \log dBZ \tag{2}$$

Table 2: Typical Observed Radar Reflectivity Factors for Varying Precipitation Rates (https://www.weather.gov/jetstream/refl)

dBZ	**Rain Rate (in/hr)**	**Rain Rate (mm/hr)**
65	16+	420+
60	8	205
55	4	100
50	1.9	47
45	0.92	24
40	0.45	12
35	0.22	6
30	0.1	3
25	0.05	1
20	0.01	Trace
< 15	No rain	No rain

For Jacksonville, with a sub-tropical climate, the Z-R relationship was computed using Equation 3, as follows:

$$\mathrm{Z} = 250R^{1.2} \tag{3}$$

The conversion of reflectivity to rainfall rate was computed as follows:

$$R = \frac{10^{\frac{dBZ^{\frac{1}{2}}}{10}}}{250} \tag{4}$$

Figure 4 illustrates the data extraction process used to obtain the rainfall rates used in the analyses.

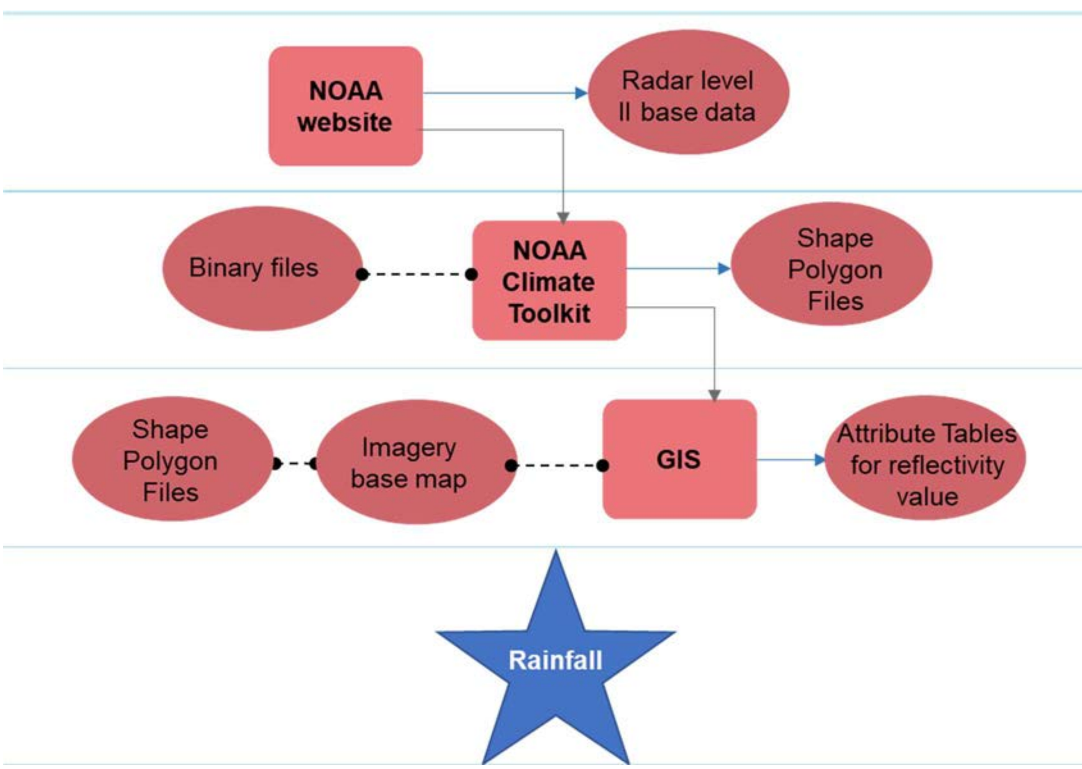


Figure 5: Rainfall Data Extraction Process

In addition, weather station data was also obtained from the Weather Underground weather forecasting website (Weather Underground, n.d.) for the rainfall intensity classifications shown in Table 3. Rainfall intensity rates defined by the American Meteorological Society (AMS) for *Light*, *Moderate*, and *Heavy* rain classifications were adopted in this study for comparison with findings from previous studies. The intensity range for each category is listed in Table 3, with comparative ranges used by other agencies and resources.

Table 3: Rainfall Intensity Classification by Different Agencies

(Angel et al., 2014)

Rain Category (in/h)	**AMS**	**U.S. NWS**	**HCM**	**Canada**	**UK NWS**
Light	Trace - 0.10	> 0.11 - 0.20	> 0-0.10	≤ 0.1	> 0-0.08
Moderate	0.10 - 0.30	0.21 - 0.50	> 0.10-0.25	> 0.10-0.30	> 0.08-0.39
Heavy	> 0.30	> 0.50	> 0.25	> 0.30	> 0.39-1.96

Note: American Meteorological Society (AMS), United States National Weather Service (U.S. NWS), United Kingdom National Weather Service (UK NWS), Highway Capacity Manual (HCM)

Traffic Data

For this study, traffic information was obtained from the Regional Integrated Transportation Information System (RITIS), which provides data gathered by Remote Traffic Microwave Sensors (RTMSs). RITIS is a database that collects traffic information from a network of detectors located along the freeways. Figure 5 shows the location of traffic detectors installed along freeways in Jacksonville, including the I-95 study segment, as they appear in RITIS. Mounted on road-side poles for traffic detection, RTMSs are small radar sensors that operate in a microwave band. The detection principle is based on the detector sending (emitting) radio frequency waves. Once these waves hit a vehicle(s), they are reflected back to the detector, and information is recorded, such as vehicle speeds. Data from these detectors are then archived in the RITIS database (Regional Integrated Transportation Information System [RITIS], n.d.).

Information provided by RTMS sensors include per-lane presence indication, volume, occupancy, vehicle speed, and classification information for up to eight lanes or detection zones. For the I-95 study site, six traffic sensors (three for each travel direction) were available for capturing traffic information. At the study site, northbound detectors with RITIS identification (ID) numbers 2049, 2109, and 2114 were used, and detectors, ID-2050, 2010, and 2115, were used for the southbound travel direction. The sensor data collected was aggregated in 20-second

intervals. From the primary speed, volume, and occupancy data, other traffic variables, such as density, headway, and traffic flow can be derived. Traffic flow was aggregated into 15-minute intervals and then converted to hours for computation purposes. Equations 3 and 4 were used to calculate headway and density, respectively, as follows:

$$\text{Headway (s)} = \frac{3600}{\text{Flow (vph)}} \tag{3}$$

$$\text{Density (veh/mi/ln)} = \frac{\text{Flow (vph)}}{\text{Speed (mi/h)}} \tag{4}$$

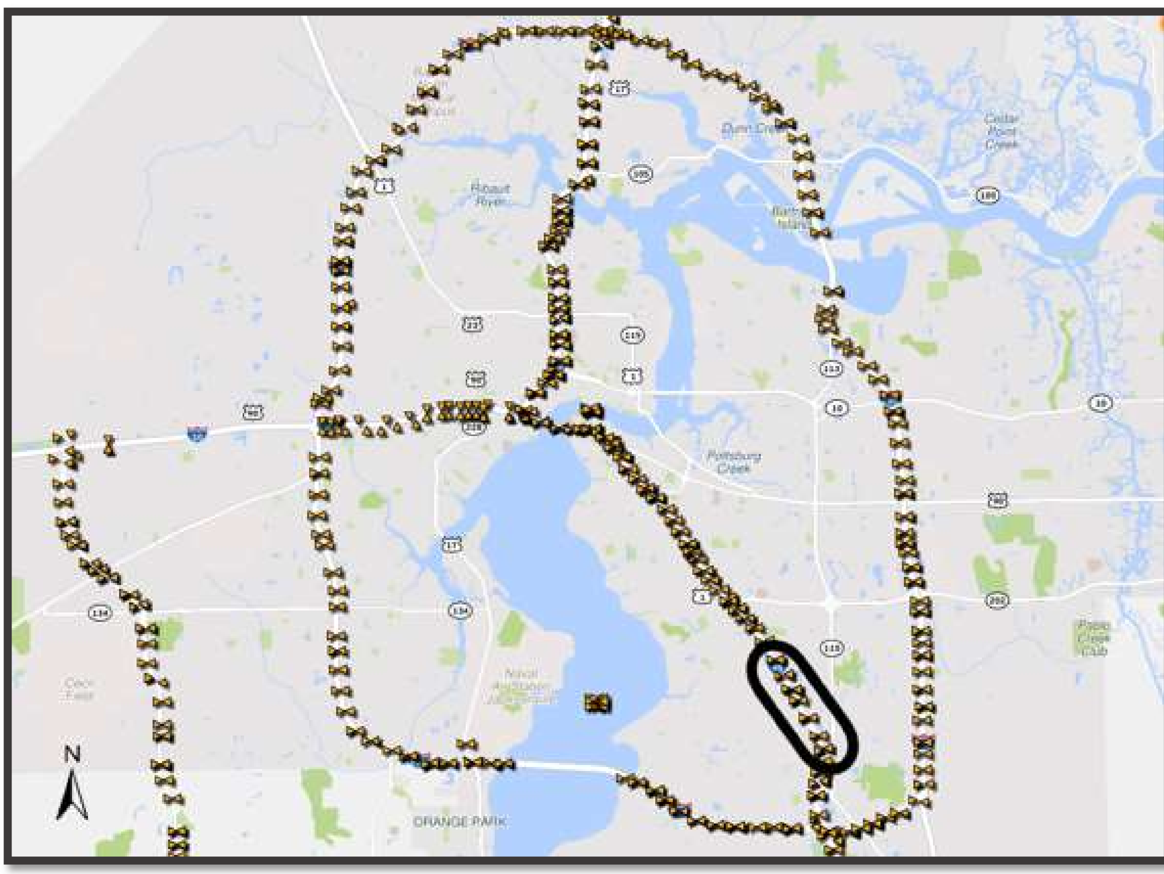


Figure 6: Network of Detectors in RITIS
(RITIS, n.d.)

Data Reduction

Both the collected traffic and rainfall data were obtained in form of Excel files. Since the traffic data obtained from RITIS were in 20-second intervals, and rainfall data were in 4- to 6-minute intervals, the two datasets had to be carefully merged for the traffic condition parameters to correlate with the rainfall intensity data. Therefore, each 5-minute interval for each rainfall intensity category (*Light*, *Moderate*, and *Heavy*) was carefully matched with the corresponding 5-minute traffic data interval, aggregated from the 20-second data delivered in the Excel file.

Outliers and other data discrepancies, such as missing data and rainfall intensity greater than 3.95 in/hr were removed from the dataset. After merging the traffic and rain data, the final dataset used for analysis contained a total of 69,546 and 67,526 data points in 20 seconds interval for northbound and southbound, respectively, at the I-95 study site.

CHAPTER 4: DATA ANALYSIS

Variable Description

In this study, data were grouped into two main groups: categorical variables and continuous variables. Categorical variables included time of day, lane position (lane ID), and rainfall category. Continuous variables included traffic volume, occupancy, speed, density, traffic flow, headway, and rainfall intensity. Categorical variables were further subcategorized, as shown in Tables 4 and 5, and descriptive statistics for both variable groups are also presented.

Zone identification (zone ID) was also included in the analyses as a categorical variable. Zone depicts the locations where traffic detectors are located within the study segment (see Figure 3). Information on the direction of travel, northbound or southbound, was determined for each zone ID.

The study site selected along I-95 is a 6-lane section with three lanes in each direction of travel. Therefore, each lane position (i.e., innermost, middle, and outermost lane) was considered in the analyses to incorporate common trends of different vehicle speeds in different lanes. In general, vehicles are expected to exhibit different behavior with respect to lane position. Higher speeds are typically observed in the innermost lane (adjacent to the median) compared to the middle lane and outermost lane (adjacent to the shoulder). The outermost lane, also referred to as the shoulder lane, is characterized with lower speeds, especially in merging areas, such as at interchanges, where vehicles are entering or exiting the freeway. Vehicles in this lane must adjust their speeds to accommodate these scenarios. Average speeds shown in Table 4 corroborate this speed-lane phenomenon typically observed on freeways.

Data was also categorized with respect to the rain intensity using the AMS classification system (see Table 3). Four subgroups were analyzed within the rainfall category: no rain, light

rain, moderate rain, and heavy rain. Traffic parameters were analyzed with respect to the time of a day for peak and off-peak traffic conditions. Peak travel time was assigned to the hours of 0700 to 1000 for morning peak and 1500 to 1900 hours for the evening peak. However, the categorization did not specify the type of peak (morning or evening).

The traffic volume continuous variable was collected by the detector as the number of vehicles passing in 20-second intervals. Occupancy, also collected by the detector, refers to the amount of time a detector is occupied by vehicles, and is expressed as a percentage. Traffic flow was derived from the traffic volume value, an hourly equivalent to the number of vehicles passing through a detector in a 20-second interval. The headway was obtained by reciprocating the flow, and density was also derived from the computed traffic flow.

Variable Selection

A correlation coefficient analysis was conducted using R programming language to check the correlation between rainfall and traffic variables. The variables used to examine the correlation included speed, volume, headway, flow, occupancy, density, zone ID, and lane ID (lane position). The resulting correlation coefficients are shown in Figure 6.

Interpretation of correlation coefficient differs greatly in different research areas. There are no absolute rules for interpreting their strength, and it is unclear where a relationship changes from good to strong (Akoglu, 2018). However, some highly correlated factors were observed from the correlation model. A threshold of 0.8 was adopted, based on correlation thresholds presented in a study by Shi et al. (2011), where the correlation coefficient, r, was defined as follows: $|r|\leq 0.3$ indicates a weak correlation, $0.3<|r|\leq 0.5$ indicates a low correlation, $0.5<|r|\leq 0.8$ suggests a significant correlation, and $0.8<|r|\leq 1$ indicates a high correlation.

Table 4: Descriptive Statistics for Northbound Variables

Categorical Variable	Factor	Count	Average (mph)	SD (mph)	Min (mph)	Max (mph)
Time-of-day	Off Peak	32357	68.14 (4.61)	8.15 (3.76)	26 (1)	90 (20)
	Peak	37189	62.46 (4.04)	15.38 (3.33)	10 (0.91)	90 (20)
Lane position	Innermost	23264	70.01 (3.97)	12.74 (3.1)	10.00 (0.91)	90.00 (20.00)
	Middle	23455	65.00 (3.08)	11.82 (1.60)	10.00 (1.05)	88.00 (20.00)
	Outermost	22827	60.21 (5.91)	12.01 (4.65)	10.00 (1.00)	90.00 (20.00)
Rainfall Category	No rain	33228	69.98 (4.08)	8.05 (3.46)	10.00 (0.91)	90.00 (20.00)
	Light	25625	62.18 (4.48)	14.00 (3.60)	10.00 (1.05)	90.00 (20.00)
	Moderate	6142	57.33 (4.50)	16.59 (3.63)	10.00 (1.25)	89.00 (20.00)
	Heavy	4551	56.46 (4.73)	14.19 (3.70)	10.00 (1.25)	86.00 (20.00)
Continuous Variable		**N**	**Mean**	**SD**	**Min**	**Max**
Volume (veh/20 sec)		69546	7	3	1	22
Occupancy (%)		69546	9	7	0	96
Rainfall Intensity (in/h)		69546	0.09	0.31	0	3.95
Density (veh/mi/ln)		69546	20	13	2	165
Flow(veh/h)		69546	1165	542	180	3960
Headway (sec)		69546	4.3	3.5	0.9	20
Speed (mph)		69546	65.10	12.86	90	10

Note: For categorical variables, values in brackets represent headway in seconds.

Table 5: Descriptive Statistics for Southbound Variables

Categorical Variable	Factor	Count	Average (mph)	SD (mph)	Min (mph)	Max (mph)
Time of a day	Off Peak	31330	71.12 (4.61)	8.05 (3.76)	24 (1)	90 (20)
	Peak	36196	66.18 (4.04)	13.12 (3.33)	10 (0.91)	90 (20)
Lane position	Innermost	22850	72.88 (4.59)	10.89 (3.31)	10.00 (1.11)	90.00 (20.00)
	Middle	21869	67.37 (3.42)	10.73 (2.04)	10.00 (1.05)	90.00 (20.00)
	Outermost	22807	65.10 (4.06)	10.91 (3.69)	10.00 (0.91)	90.00 (20.00)
Rainfall Category	No rain	30895	72.40 (3.86)	9.00 (2.98)	10.00 (0.91)	90.00 (20.00)
	Light	25879	66.16 (4.08)	11.94 (3.17)	10.00 (1.05)	90.00 (20.00)
	Moderate	6194	64.57 (4.36)	11.34 (3.37)	10.00 (1.18)	90.00 (20.00)
	Heavy	4558	60.20 (4.52)	12.02 (3.68)	15.00 (1.33)	90.00 (20.00)
Continuous Variable		**N**	**Mean**	**SD**	**Min**	**Max**
Volume (veh/20 sec)		67526	7	4	1	22
Occupancy (%)		67526	10	6	0	93
Rainfall Intensity (in/h)		67526	0.09	32	0	3.95
Density (veh/mi/ln)		67526	19	12	2	252
Flow(veh/h)		67526	1212	559	180	3960
Headway (sec)		67526	4.03	3.15	0.91	20
Speed (mph)		67526	68.47	11.33	90	10

From the correlation analysis, two sets of variables revealed a correlation greater than 0.8. Occupancy and density had a high correlation coefficient (0.9), while the correlation coefficient between lane ID and zone was 1.0, as shown in Figure 6. Therefore, only one variable from each was selected for analysis based on parameter importance. A high correlation (0.9) was found between flow and volume. This was expected since flow and volume are derivative of one another. The final variables selected for modeling were flow, density, lane position (lane ID), rainfall intensity, speed, and headway.

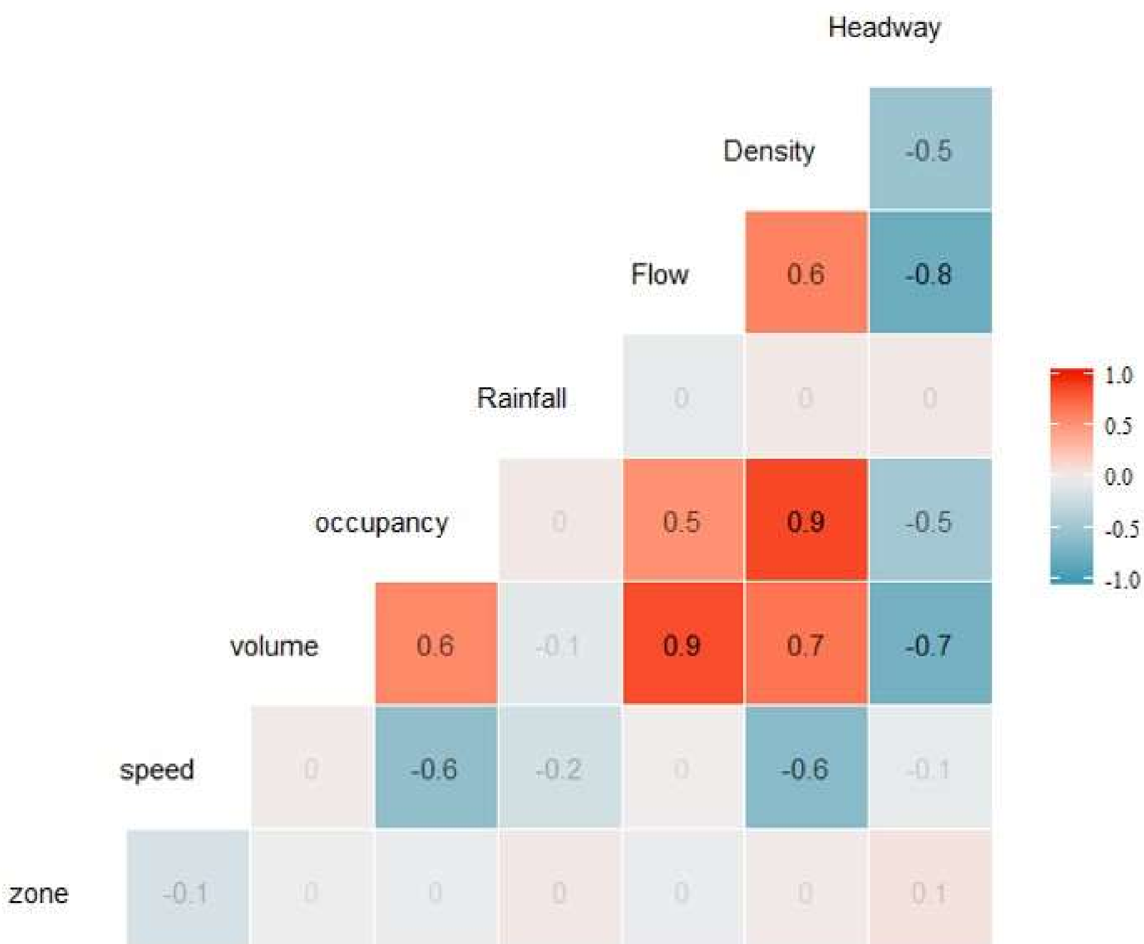


Figure 6: Variable Correlation Model

Data Distribution

Using Minitab software, speed and headway data were plotted to determine the data distribution, one of the factors guiding the selection of a suitable model. As illustrated in Figure 7, the speed data distributions were observed to follow a 3-parameter Weibull distribution.

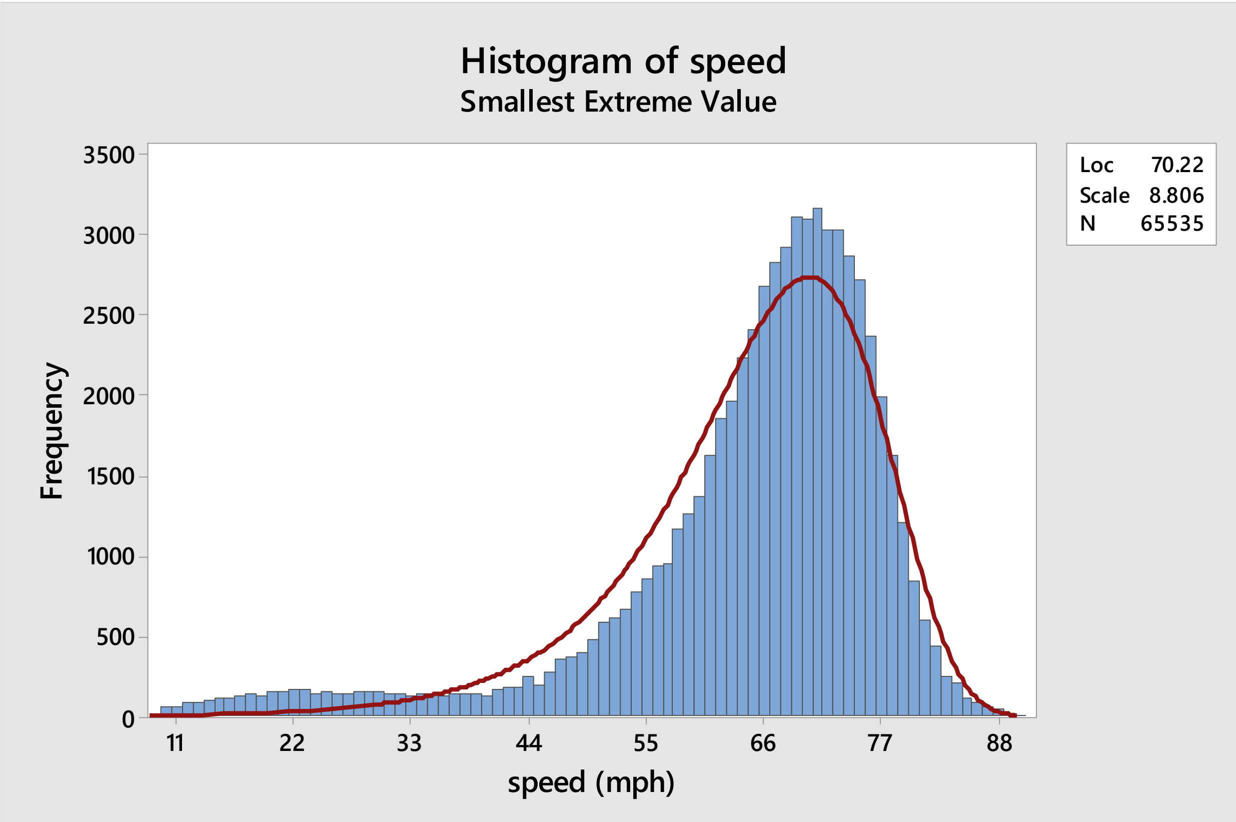


Figure 7: Speed Distribution

Relationship between Radar and Conventional Weather Station Rain Data

As expected, the Minitab software analysis revealed that the rainfall data was non-parametric, as they are not normally distributed. For this reason, an Analysis of Variance (ANOVA) test, which works under the assumption that the data is normally distributed, was not suitable for the comparison of weather radar data and rainfall data obtained from conventional collection stations (i.e., sites that utilize rain gages). The application of ANOVA for non-normal distributions may

result in false results; however, several previous studies have found that when the sample size is large, the test is not very sensitive to moderate variations from normality (Dhaliwal et al., 2017; Glass et al., 1969). Therefore, a more suitable test to analyze the rain data was determined to be the Friedman non-parametric test. The Friedman test is a non-parametric alternative to a two-way ANOVA test. Similar to other non-parametric tests, the Friedman test does not assume data to follow any specific distribution.

The Friedman test requires data to have two categorical factors: experimental treatments and blocks. These two factors determine the test statistic *S*, which is used to compute the *p*-value. Another requirement for the Friedman test is for the number of experimental treatments (k) to be greater than or equal to two ($k \geq 2$). The blocks (n) are normally used to display the observations, and are randomly assigned to each treatment. Also, only one observation for each treatment and block observation is required. Table 6 illustrates the block-treatment matrix for the Friedman test (Hollander et al., 2013).

Table 6: Example of Block-Treatment Matrix

Blocks	**Treatments**		
	1	**2 ...**	***K***
1	X_{11}	X_{12} ...	X_{1k}
2	X_{21}	X_{22} ...	X_{2k}
3	X_{31}	X_{32} ...	X_{3k}
...	...	... ...	...
n	X_{b1}	X_{b2} ...	X_{bk}

Note that the response variable should be continuous or ordinal and for the approximation of the Friedman test statistic *S* to be accurate, and the randomized block design should have at least five blocks or treatments. Hypotheses tested using the Friedman test are:

Null hypothesis, H_0: The treatments have equal effects

Alternative hypothesis, H_1: Not all treatments have equal effects

The first step in computing the Friedman statistic *S*, is to rank the observations (k) within each block (n) in ascending order (i.e., the smallest to the largest). Let r_{ij} be the rank of X_{ij} in the joint observation within block i. The sum of the ranks of (R_j) and the average within blocks rank ($R_{.j}$) is given as follows:

$$R_j = \sum_{i=1}^{n} r_{ij} \ \ and \ \ R_{.J} = \frac{R_J}{n} \quad (5)$$

The Friedman *S*-statistic is computed as follows:

$$S = \frac{12n}{k(k+1)} \sum_{j=1}^{k} (R_{.j} - \frac{k+1}{2})\, 2 = \left[\frac{12}{nk(k+1)} \sum_{j=1}^{k} R_j^2\right] - 3n(k+1) \quad (6)$$

To test the hypotheses, H_0 against H_1 at α level of significance for large sample approximation, the *S*-statistic follows an asymptotic chi-square distribution with k-1 degrees of freedom. Therefore,

Reject H_0 if $S \geq \chi^2_{k-1,\alpha}$; otherwise do not reject,

where, $\chi^2_{k-1,\alpha}$ is the upper α percentile point of a chi-square with k-1 degrees of freedom.

For the analysis of rainfall data in this study, the null and alternative hypotheses were formulated as follows:

H_0: Rainfall intensities measured by different methods are equal.

H_1: Rainfall intensities measured by different methods are not equal.

Block-Treatment matrix for methods of measuring rainfall is presented in Table 7, whereby rainfall values from three different radar location; radar 1, 2 and 3 along the segment were compared with the rainfall measurement from the nearest rain gage station (conventional station).

Table 7: Radar Rainfall Data versus Conventional Rainfall Data

Time ID	Method of Measuring Rainfall			
	Conventional	Radar_1	Radar_2	Radar_3
1	0	0	0	0
2	0	0	0	0
.				
.				
120	0.09	0	0	0

Table 8: Friedman Results for Radar and Conventional Rainfall Data

Method	**N**	**Median**	**Sum of Ranks**
Conventional station	120	0.0000550	253.0
Radar_1	120	0.0003020	375.0
Radar_2	120	0.0000080	181.0
Radar_3	120	0.0003737	391.0
Overall	480	0.0001847	
Chi-square, χ^2_r= 163.36 DF=3 p-value =0.00			

From statistical table, with three degrees of freedom at a 95% confidence level, the critical Chi-Square value is 7.81. The Friedman test analysis conducted in Minitab produced a test statistic value, χ^2_r= 163.36, as listed in Table 8. This value is greater than the critical chi-square; therefore, there is strong evidence to reject the null hypothesis. Conclusively, the Friedman test shows that conventional rainfall stations and weather radar produce different precipitation values.

Figure 8 shows a graphical presentation of the rainfall amount for radar and conventional stations. The observation shows higher values for the rain gage relative to the radar values, meanwhile radar readings were generally observed to decrease from upstream (radar_4) to downstream (radar_10). Higher readings of rain gage represent the rainfall condition over the

entire road segment which is not actually the case as shown by radar values that the rainfall intensity varies from upstream to downstream.

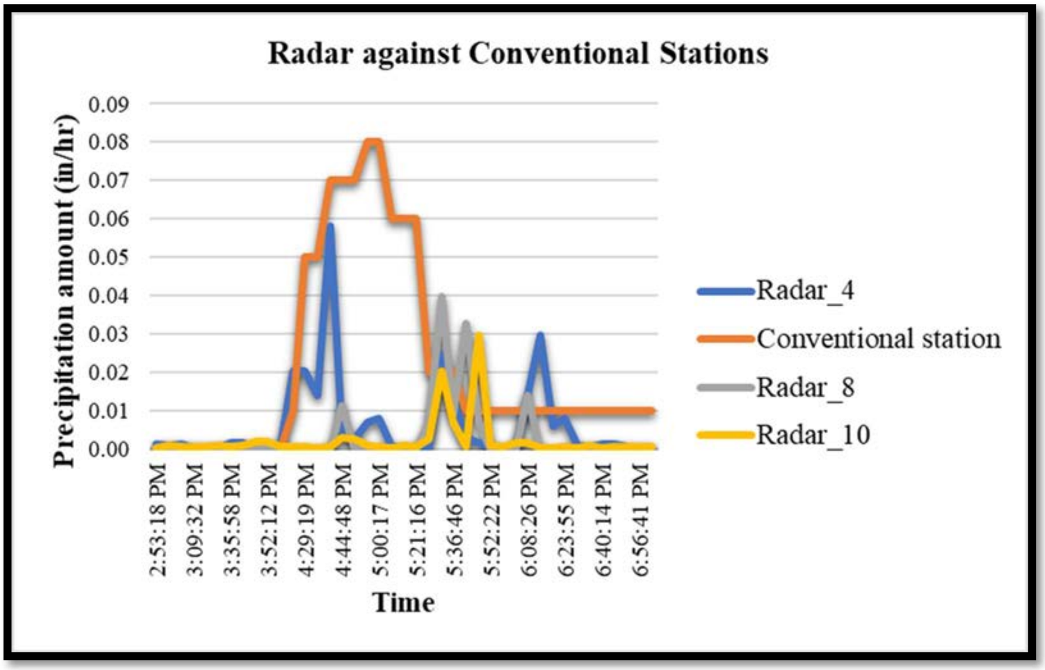


Figure 8: Rainfall Amount for Radar and Conventional Station

Speed and Headway Modeling

Linear regression models indicate the linear relationship between a continuous dependent (response) variable and one or more independent variables. One application for this regression method is to develop predictive models using observational data. Equation 5 shows a simple linear regression model (Washington et al., 2011).

$$Y_i = \beta_o \sum_{i=1}^{n} \beta_i X_i + \varepsilon_i \tag{5}$$

where, Y_i - Continuous dependent variable,

B_o – Constant term,

β_i – Coefficient for independent variable $X_{i,}$

X_i – Independent variable X,

ε_i – Disturbance term, and

i - Observation $i=1,2,3\ldots,n$.

In many cases, the dependent variable is a function of many explanatory variables. Sample estimated betas give information on parameter properties, which helps to explain the relationship with the response variable.

The response variables for this study were speed and headway. A linear regression analysis was performed using the *r* programming language for two functions, as shown in Equations 6 and 7. The coefficients and statistics for the best model were obtained from the analysis.

$$Speed = \beta_o + \beta_l Laneid + \beta_r Rainfall + \beta_f Flow + \beta_d Density \quad (6)$$

$$Headway = \beta_o + \beta_l Laneid + \beta_r Rainfall + \beta_f Flow + \beta_d Density \quad (7)$$

where, $\beta_o, \beta_l, \beta_r, \beta_f$ *and* β_d are notations for estimate factors for lane position, rainfall intensity, flow, density, headway, and speed.

Logarithmic Transformation

For the regression analysis to yield better results, flow data, which were observed to have values much higher than other variables, had to be transformed. A natural logarithm was applied to flow values, and then the new log flow data set, along with other variables, were used for modeling.

CHAPTER 5: RESULTS AND FINDINGS

Traffic Characteristics

Plots of traffic variables (speed, flow, and occupancy) were used for validation to ensure that data follows the expected traffic flow characteristics. Figure 9 shows the plots of traffic flow characteristics exhibited by the data collected for both northbound and southbound directions at the study site. The speed-occupancy relationship is similar to that of speed-density and follows standard diagrams that depict low occupancy at higher speeds. When speeds are lower, vehicles occupy more time.

The flow-occupancy and flow-speed relationship show the uncongested condition and the congested condition just before and after reaching the maximum traffic flow, respectively.

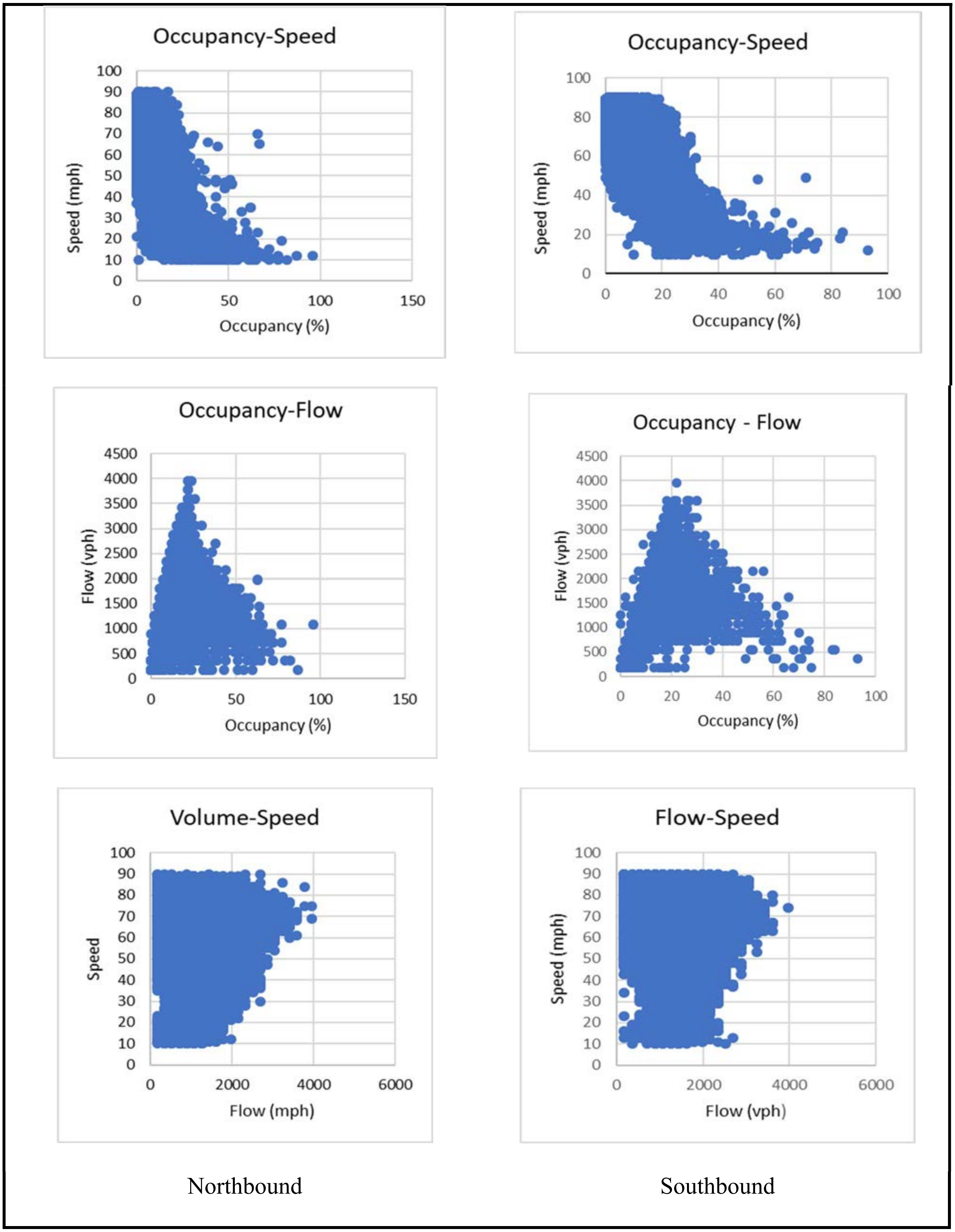


Figure 9: Traffic Flow Characteristics

Descriptive Analysis

Speed, flow, density and headway data were sorted with respect to no rain, light rain, moderate rain, and heavy rain. The descriptive analysis for these traffic parameters that were considered in the model is discussed in Table 9. The general trend shows reduction in speed, in both northbound and southbound as rainfall intensity increases. For speed, a reduction of 11.1%, 18.1% and 19.3% were reported for light, moderate and heavy rainfall relative to no rain condition. Headway was observed to increase from light to heavy rain as drivers tend to slow down and keep larger gaps. Increase in headway ranged from 9.8% to 15.9%. Flow was observed to decrease with the increase of rainfall intensity, a percentage change of 10.3, 11.6 and 16.2 as depicted from the data for light, moderate to heavy rainfall. As it rains drivers slow down, consequently increasing the traffic density. This scenario has been observed in the data, as traffic density increases by 16.7%, 27.8% and 22.2% when comparing the no rain condition relative to light, moderate and heavy rainfall.

Table 9: Traffic Parameters Statistical Summary for Northbound and Southbound

Rainfall Category	**Count**	**Average**	**% change**	**Count**	**Average**	**% change**
		Northbound			**Southbound**	
Speed (mph)						
No rain	33228	69.98		30895	72.40	
Light	25625	62.18	-11.1%	25879	66.16	-8.6%
Moderate	6142	57.33	-18.1%	6194	64.57	-10.8%
Heavy	4551	56.46	-19.3%	4551	60.2	-16.9%
Headway (s)						
No rain	33228	4.08		30895	3.86	
Light	25625	4.48	9.8%	25879	4.08	5.7%
Moderate	6142	4.50	10.3%	6194	4.36	13.0%
Heavy	4551	4.73	15.9%	4551	4.52	17.1%
Flow(vph)						
No rain	33228	1238		30895	1238	
Light	25625	1111	-10.3%	25879	1111	-10.3%
Moderate	6142	1094	-11.6%	6194	1094	-11.6%
Heavy	4551	1037	-16.2%	4551	1037	-16.2%
Density (veh/h/ln)						
No rain	33228	18		30895	18	
Light	25625	21	16.7%	25879	21	16.7%
Moderate	6142	23	27.8%	6194	23	27.8%
Heavy	4551	22	22.2%	4551	22	22.2%

Model Results

Speed and headway models were analyzed using *r* programming language. Results for the linear regression analyses for northbound and southbound are presented in Tables 10 through 14. Generally, the models show that the lane position, rainfall intensity, traffic flow, and density have

a significant influence on vehicle travel speeds and headways. All models have a goodness-of-fit coefficient (R-square) greater than 0.5.

Speed Model

Rainfall intensity had a significant influence on the speed model. A unit increase in rain intensity was observed to cause a decrease in speed by 5.1 mph in the northbound direction (see Table 10), while in the southbound direction, the model reports a decrease of 5.4 mph for a unit increase in rainfall intensity (see Table 11). In general, the relative speed percentage decreased by 0.75% to 2.25% from light to heavy rainfall, as shown in Table 13. A decrease in speed with an increase in rainfall intensity is consistent with previous studies (Angel et al., 2014; Rakha et al., 2008). This suggests that drivers are less comfortable driving under rainfall conditions, and thus, are more likely to slow down to compensate for the associated risks of rainy conditions, such as skidding and reduced visibility.

For other factors, such as lane position, the developed model predicts that vehicle speeds decrease from the middle lane to the outermost lane (shoulder lane). An average decrease of 4.9 mph and 8.8 mph was found for the middle and outermost lanes, respectively, with respect to the innermost lane (adjacent to the median) in the northbound direction. While a mean decrease of 5.5 mph and 8.1 mph was observed in the southbound direction. These results were expected since normal traffic trends exhibit higher driving speeds in the innermost lane (median lane) compared to the middle or outermost lane. Speed lowering maneuvers are common in the outermost lane (shoulder lane) as drivers adjust their speeds to accommodate incoming or exiting traffic.

For the flow variable, estimates indicate that a unit percentage change of flow results in an increase in speed by 0.0929 mph and 0.0809 mph for northbound and southbound directions, respectively. This suggests that vehicles are operating under congested traffic conditions. It is

noteworthy to mention that during the development of this model; the speed threshold analysis was not conducted in order to provide enough evidence for each identified traffic condition.

Density results indicate that a unit increase in traffic density decreases vehicle speeds in the northbound and southbound directions by 0.94 mph and 0.933 mph, respectively. This increase in traffic density as the rainfall intensity increases comes as the result of decrease in vehicles speed due to the effect caused by rain and drivers being more cautious which may also result in traffic congestion.

The goodness-of-fit is given by the pseudo R-square value which shows how well the data exhibit a linear relationship. The R-square values for northbound and southbound were found to be 0.69 and 0.6, respectively.

Table 10: Linear Regression Results for Speed - Northbound

		Estimate	**Std. error**	**Upper Limit**	**Lower Limit**	***p*-value**
Intercept		15.869	0.313	15.871	15.887	<0.0001
	Innermost lane					
Lane position	Middle lane	-4.859	0.070	-4.860	-4.858	<0.0001
	Outermost lane	-8.807	0.068	-8.808	-8.806	<0.0001
Rainfall Intensity		-5.091	0.087	-5.090	-5.092	<0.0001
Ln Flow		9.929	0.055	9.929	9.929	<0.0001
Density		-0.940	0.003	-0.940	-0.90	<0.0001
$R^2 = 0.69$						

Table 11: Linear Regression Results for Speed - Southbound

		Estimate	**Std. error**	**Upper Limit**	**Lower Limit**	***p*-value**
Intercept		38.984	0.363	39.347	38.621	<0.0001
Lane position	Innermost lane					
	Middle lane	-5.492	0.068	-5.424	-5.560	<0.0001
	Outermost lane	-8.123	0.068	-8.055	-8.191	<0.0001
Rainfall Intensity		-4.931	0.087	-4.844	-5.018	<0.0001
Ln Flow		8.093	0.062	8.155	8.031	<0.0001
Density		-0.933	0.003	-0.936	-0.930	<0.0001
$R^2 = 0.60$						

Headway Model

For the developed headway model, all factors (lane position, rainfall intensity, flow, and density) are statistically significant at the 95% confidence level. Expected outcomes from the model are shown in Tables 12 and 13. The effect of rainfall is shown to cause an increase in headway, where drivers allow longer following distances behind the leading vehicle (the vehicle ahead). An increase in headway was observed to be 0.26% for the light rain events, while under moderate and heavy rain, headway increased by 0.26% to 0.79%, respectively (see Table 14).

In addition, other factors that were considered to affect the headway, such as lane position, show a decreasing trend. As indicated in Tables 12 and 13, headway decreases from the outermost lane (shoulder lane) to the innermost lane (median lane). Interestingly, vehicles in the outermost lane are typically characterized as having lower speeds, yet results indicate greater headways than observed in the other higher speed lanes. Also, traffic flow is observed to result in a decrease in headway, which is typically observed during congested traffic conditions.

Table 7: Regression Analysis for Headway - Northbound

		Estimate	Std. error	Upper Limit	Lower Limit	*p*-value
Intercept		29.718	0.097	29.815	29.621	<0.0001
Lane position	Innermost lane					
	Middle lane	-0.590	0.022	-0.568	-0.612	<0.0001
	Outermost lane	-0.453	0.021	-0.432	-0.474	<0.0001
Rainfall		0.064	0.027	0.091	0.037	0.018
Ln Flow		-3.861	0.017	-3.844	-3.878	<0.0001
Density		-0.022	0.008	-0.014	-0.174	<0.0001
$R^2 = 0.62$						

Table 8: Regression Analysis for Headway - Southbound

		Estimate	Std. error	Upper Limit	Lower Limit	*p*-value
Intercept		27.854	0.098	27.952	27.756	<0.0001
Lane position	Innermost lane					
	Middle lane	-0.433	0.018	-0.415	-0.451	<0.0001
	Outermost lane	0.244	0.018	0.262	0.226	<0.0001
Rainfall		0.153	0.024	0.177	0.129	<0.0001
Flow		-3.601	0.017	-3.584	-3.618	<0.0001
Density		-0.025	0.001	-0.024	-0.026	<0.0001
$R^2 = 0.62$						

Table 9: Speed Reduction and Headway Increase per Rain Category

	Light Rain	Moderate Rain	Heavy Rain
Speed Reduction	0.75%	1.50%	2.25%
Headway Increase	0.26%	0.53%	0.79%

Findings

Based on the spatiotemporal analysis on the effects of rainfall on I-95, the estimation results reveal that vehicle speeds decrease with increased rainfall intensity. In general, speeds were observed to be much lower during heavy rainfall. However, the amount to which vehicle speeds are reduced, as indicated in Table 14, are comparably lower than reported values in previous studies (see Table 1). However, the trend is similar to findings from previous studies that speed decreases as rainfall intensity increases. Several factors may have contributed to the observed low percentages in speed reductions, such as spatiotemporal differences where the effect of rain varies from one region to another or one segment to another.

An increase in headway was observed as rain intensity increased. This depicts a change in driving behavior under varying rainfall conditions, whereby the results identified longer following gaps relative to greater rainfall intensities.

These findings can help in freeway management to improve safety and operational performance of the freeway system. The spatial effect of rainfall can be useful in developing appropriate strategies in response to inclement weather, such as the use of variable speed limit technology, which enhances speed homogeneity of traffic flow and can potentially improve freeway safety and efficiency in adverse weather (Zhou, 2016). The use of road signs to advise or enforce lower speed limits during heavy rainfall, as applied in Germany and the UK, can also help to reduce the risk of collision (Andrey et al., 2013).

CHAPTER 6: CONCLUSIONS

This study introduced a new approach for examining the effects of rainfall on traffic operations by for quantifying rainfall intensity from Doppler radar. Being a traffic mobility-related study, specifically, the study examined the effects of rainfall spatiotemporal variations on vehicle speeds and headways. Traffic data were collected from the microwave sensors along a freeway section selected for study. Rainfall intensities were computed from reflectivity values obtained from the Doppler radar.

Linear regression was applied to associate the relationships between the traffic parameters analyzed (vehicle speeds and headways) and rainfall intensity categories (no rain, light rain, moderate rain, and heavy rain), together with other independent variables. Analysis results reveal that of the factors analyzed, rainfall intensity, density, and lane position were found to affect vehicle speeds. Reduction in speed was observed as rainfall intensity increased. While increase in rainfall intensity was associated with longer headways, flow and density were found to associate with shorter headways.

With respect to rainfall intensity, on average, a unit increase in rainfall decreases average vehicle speed by 0.75%, 1.50%, and 2.25%, and increases average vehicle headway by 0.26%, 0.53%, and 0.79% for light, moderate, and heavy rainfall, respectively. This suggests that heavy rainfall significantly results in lower speeds and longer headways.

Study Limitations

The following limitations were observed:

- Since rainfall intensity is spatially and temporarily distributed, the effect on traffic operations is expected to follow the magnitude of both rainfall and traffic, as well as the roadway geometric characteristics, which was not captured in this study.

- The same quantity of rain is assumed per a given area.
- Weather radar rainfall method is only applicable in areas with weather radar coverage.
- This method of analysis requires a considerable amount of time to analyze rainfall radar data; therefore, only few days were analyzed.
- Overestimation of rain quantities was observed for some cases; therefore, additional research is needed to reconcile this issue.

Recommendations

The weather radar approach discussed in this work has potential to improve freeway traffic management and transportation analyses, as it provides insight into how weather radar data can be useful and efficient in traffic studies, operations, and management. Further work is recommended to investigate and expand techniques that can be used to fully exploit weather radar for transportation systems management.

Apart from utilizing the weather radar images for visualization of adverse weather on, Traffic management centers can benefit from this work by incorporating anticipated traffic operation needs based on rainfall predictions to estimate traffic conditions, such as the expected level of congestion, travel time, and drop in travel speed, since this approach can estimate precipitation and provide the amount of rainfall that is expected in a much higher resolution compared to the conventional method. Moreover, if used for predictive purposes, it promotes proactive transportation management by allowing appropriate measures to be taken in advance, hence improving the safety and efficiency of the transportation systems.

In addition, during adverse weather, this approach can play a significant role in identifying areas within the transportation network that may be subject to major rainfall events that would require additional assistance to help the motoring public. Service patrols, such as Road Rangers in

Florida, and highway patrol officers can be dispatched in advance when traffic conditions are expected to be affected by adverse conditions.

For effective advisory, control, and treatment strategies to mitigate mobility and safety challenges due to adverse weather, the Federal Highway Administration's (FHWA) Road Weather Management Program (RWMP) can incorporate the findings of this study to improve its initiatives. Also, the use of rainfall radar data in transportation system can help in improving the navigation data especially during the adverse weather as during these times road users encounter uncertainties on traffic parameters such as travel times and travel speed. A thorough exploitation of these data will help predictions of the expected speed and travel time; hence road users will be aware of the delays due to reduction in speed and longer travel times that they will encounter for their trips.

There is a need to investigate further on how radar data can easily be used for rain quantification as the current method consumes a considerable amount of time. Also, placement of weather stations along the freeways can be used in conjunction with radar for surveillance of freeway weather system. This will result in high reliability and a more comprehensive understanding of the impact of rain on freeway operations.

Several groups of transportation engineering officials had an opportunity to comment on the usefulness of this study. The first group was the 2019 Florida Section Institute of Engineers (FSITE) judges during the shark tank presentation. This research topic won a second place for shark tank competition after being presented at the Florida Puerto Rico Institute of Transportation Engineers meeting on June 25, this year. Generally, the shark tanks indicated that weather radar data will make a positive change in traffic management. In additional to that the shark tanks thought that this study could prove of value, in that it will support the consensus of many colleagues in the ITS arena that weather does play a role in performance of the roadway system.

Mr. Pete Vega, District 2 TSMO engineer indicated that the use of high-resolution weather data could help improve management of traffic operations especially for the incoming fronts and storms involving severe weather. However, skepticism in the accuracy of weather radar products calls upon more investigation to this method of tracking weather. Another transportation official suggested that, hiring of meteorologist in highway agencies can help reduce the error for misinterpretations of weather radar products which was pointed out to be one of the challenges.

Personnel at the RTMC see these events daily and prepare for the worst when large storm fronts are on the way. The bigger challenge throughout Florida is when the afternoon "pop-up" severe rain events occur because it's a moving target with short periods of impact. All it takes is about 10-minutes of heavy rain and lightning to create chaos on the roadway system".

Further research work is needed to validate this method in order to put it into practice as it has potential to enhance continuity and provide a wide area coverage of rain data hence capturing the spatiotemporal distribution of rain and its effects on transportation system.

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