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Safety Investigation of Crash Rates During Hurricane Evacuations

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SAFETY INVESTIGATION OF CRASH RATES DURING HURRICANE EVACUATIONS

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ABSTRACT

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This study aimed to investigate crash rates across four distinct periods—evacuation, re-entry, emergency, and non-emergency—during Hurricanes Matthew (2016), Irma (2017), and Michael (2018). A notable gap in existing research pertains to understanding crash rates during these critical phases of hurricane events. By addressing this gap, this research contributes to a deeper comprehension of evacuation transportation safety. The methodology employed ArcMap to construct an interactive map for data collection, encompassing key variables such as the number of crashes, traffic volumes, duration of each period under analysis, and roadway segment lengths for each hurricane. Evaluating the crash rate per million vehicular miles was a crucial analysis tool and finding of this research, enabling a comprehensive evaluation of segment safety across different periods. Non-emergency periods exhibited crash rates two orders of magnitude higher than those observed during evacuation, re-entry, and emergency periods. While a correlation between non-emergency and emergency period crash rates was apparent, the same could not be concluded for non-emergency and re-entry periods.

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1.0 INTRODUCTION

Emergency evacuations are more frequent than many realize, on average an evacuation of 1,000 or more people occurs once every two to three weeks in the United States (Dotson, Jones, Schneck, & Sullivan, 2004). During evacuations, individuals typically travel along the same route in the same direction, resulting in a significant concentration of vehicles on a single roadway segment. Crashes in these conditions can lead to substantial delays and disrupt the flow of traffic. On average, estimated travel time during evacuations increases between 7.2 percent to eight percent (Collins, Foytik, Frydenlund, Robinson, & Jordan, 2014).

Traffic crash patterns typically exhibit a clear correlation: as vehicle volume rises, so does the number of crashes (Martin, 2002). During evacuation periods, traffic stream follows oscillatory speed, which contributes to rear-end crashes (Hasan & Rahman, 2020). The high volume traffic during evacuations, along with oscillatory speeds, amplifies the likelihood of crashes, especially when distracted driving or speeding are involved (Hasan & Rahman, 2020). The two major factors that contribute to crashes are the driver and the roadway condition (Abdel-Aty & Radwan, 2000). With the oscillating speed on the roadways and distracted behaviors of drivers, elevated crash frequencies may be seen during evacuations and could present a significant challenge.

Driver characteristics, evacuation route characteristics, and traffic conditions factor into driving performance during emergency evacuations (Dublebenets, et al., 2019). Research contributing to emergency evacuations brings more understanding and valuable insights into roadway conditions during times of crisis. The increasing frequency of major hurricanes in recent years raises concern for the safety of the public (Landsea, 1993). With this knowledge, and the gap in crash frequency research, concerns have been raised from policy makers and transportation agencies.

The safety of the public is the paramount concern when it comes to policy makers and transportation agencies. The Florida Department of Transportation (FDOT) recently adopted the goal "Target Zero". Target Zero was a goal set by the FDOT whose initiative is to reduce the number of serious injuries or death on the roadways across the state of Florida to zero (Target Zero, n.d.). Crash frequency is the number of crashes that happen along some geographical space, typically a road segment, over a specific period (Lord & Mannering, 2010). The heightened traffic volume and subsequent increase crashes as a result pose a significant risk to public safety. Given FDOTs Target Zero initiative, there is a need to better understand the factors influencing crashes and crash frequencies within the state of Florida, given the presence of hurricanes. On average there are roughly seventeen hurricanes that make landfall every decade in the United States. Along with this, of the five most deadly and destructive hurricanes, four have made landfall in Florida (Blake, Rappaport, Jarrell, & Landsea, 2005). Considering this, the gaps in knowledge over crash frequencies during hurricane evacuations must be closed.

During Hurricane Irma, 6.5 million Florida residents were under evacuating orders, causing extensive delays and severe traffic congestion (Rahman R. , Bhowmik, Eluru, & Hasan, 2021). These conditions resulted in 221 reported crashes on I-75, a major North/South evacuation corridor over a three-day span (Rahman, Hasan, & Zaki, 2021). However, it is unknown if these crashes represent an increase in crash frequency or if the number of crashes was simply a product of increased roadway volume. Despite the seeming heightened risk of crashes during evacuations, little research has been conducted on crash frequency during such events. Research into temporary safety measures to move along traffic during hurricane evacuations has been completed. Past research includes emergency shoulder use (ESU) implementation (Sharma, Faruk, & El-Urfali, 2020), Adaptive Cruise Control (ACC) systems (Rahman, Hasan, & Zaki, 2021), and contraflow operation (Wolshon, 2002). Furthermore, it's unknown if the underlying factors of these crashes (severity, speeding, crash type, weather, drug/alcohol use, seat-belt use, etc.) are similar to crashes which occur during routine conditions. Such information would be beneficial in tailoring public service messaging to reduce any unique risk of crashes posed by evacuating roadway conditions.

The delimitations in this research encompass selecting hurricanes that impacted the state of Florida and gathering crash data exclusively from the zones within the mandatory evacuated counties subjected to mandatory evacuations. The geospatial limitation of the study encompasses all roadway segments encompassed by or within 10 miles of a mandatory evacuation zone during a hurricane evacuation, for which continuous count data was available. The data used in this research is open source and was collected from the FDOT databases for traffic crashes (FDOT State Safety Office GIS, n.d.), continuous count, and road network shapefiles (Geographic Information System (GIS), n.d.) for the hurricanes Matthew (2016), Irma (2017), and Michael (2018). This study does not encompass the collection of data. Moreover, the selection of evacuation routes was based on their proximity, within ten miles, to the mandatory evacuated zones within Florida counties, as well as the presence of an FDOT Traffic Site camera on the roadway segment.

Additionally, the study's temporal scope focused on analyzing crash data for each entire year that a hurricane is incorporated in, in efforts to investigate crash rates during hurricane evacuations in Florida. Specifically, this research seeks to answer how evacuation and re-entry event crash rates are different or indifferent when compared to non-emergency periods.

Crash rates were investigated by collecting traffic volumes and crashes on roadway segments in the lead up to several hurricanes in Florida. The including criteria for segment selection was:

- Segments had to have a continuous count station which actively collected data during the evacuation and reentry periods.
- Segments must be located on designated evacuation routes.
- Segments must be on or within 10 miles of an evacuating zone during a given hurricane.

The data was then divided into two analysis periods: emergency period and non-emergency period. The emergency period encompasses both evacuation and re-entry. The evacuation phase is delineated as the interval preceding landfall when traffic patterns deviate from historical norms, with base traffic levels defined within one standard deviation above and below the typical range for a given day of the week. Conversely, the re-entry phase spans from landfall onwards until traffic patterns revert to base levels. The non-emergency period encompasses all remaining intervals during the calendar year of a specific hurricane, where traffic volume and crash data are available, but do not coincide with the defined emergency phases.

The FDOT crash data was mapped using ArcMap 10.8 to create an interactive map of the crashes state-wide during emergency and non-emergency periods during 2016, 2017, and 2018. This software was used to add the geospatial component to the crash data provided by the FDOT Crash Database. The software allowed processing data, which included selecting crashes that relate to hurricane evacuations. This allowed for more accurate analysis, leading to understanding the phenomenon of how crash rates increase, decrease, or remains the same when comparing evacuation periods to non-emergency periods.

It's crucial to acknowledge that the timing of evacuation orders by county authorities may influence crash rates during hurricane evacuations, as the heightened stress and urgency of drivers could be a contributing crash factor. The hypothesis posits that crash rates would not be significantly different during hurricane evacuations compared to non-emergency periods.

By gaining an understanding of crash rates during hurricane evacuations, it becomes possible to implement preventative measures. These measures can effectively reduce the number of incidents, along with the severity of delays during evacuations. Additionally, this enhanced understanding leads to increased safety for first responders and emergency personnel. During hurricanes, first responders must remain on station and on duty to assist anyone who may not have evacuated. Their primary responsibility is to ensure the safety of the public. When a crash occurs on the roadways, first responders are thrust into an already hazardous situation, compounded by the adverse weather conditions caused by the hurricane. Armed with insights into crash rates during hurricane evacuations, policy makers can develop strategies to enhance the safety of both the public and first responders during these critical periods.

Along with this, the deeper understanding of crash rates during an emergency evacuation provided from this study allows for future research. Future work could include finding ways to decrease crashes and ensure the safety of the public on roadways during future emergency evacuations. Understanding the relationship between when the evacuation orders were sent relative to landfall of the hurricane can also allow for safety management in the future, allowing for preventative measures to be taken and taking one more step towards Target Zero.

1.1 Background

Hurricane Irma was one of the strongest storms in history to have come from the Atlantic Ocean. This hurricane was classified as a Category 5 hurricane for three continuous days, longer than any other storm from the Atlantic Ocean, recording wind speeds higher than 180 mph (Bloch, 2017). Hurricane Irma hit the state of Florida twice. The first time it made landfall was in Cudjoe Key on September 10th, 2017 as a Category 4. Irma made it's second landfall later the same day in the Gulf Coast as a Category 3, and weakened as it traveled north (Pinelli, et al., 2018). Hurricane Irma caused a total of 123 deaths in Florida and federal assistance to households and communities that sustained damage from Hurricane Irma topped at $5.58 billion (Feito & Ballard, 2022).

Hurricane Michael was the third-strongest storm to make landfall in the United States. The storm made landfall on October 11th, 2018 in the panhandle of Florida, near Mexico Beach, as a category 5 hurricane, with winds reaching 160 mph and 17.5 ft storm surge (Allen, 2022). Hurricane Michael was the 13th major storm during the 2018 Atlantic hurricane season (Gibbens, 2018). The death toll of Hurricane Michael was 16, and roughly 325,000 or more people were estimated to have been given mandatory evacuation orders from local authorities (Winsor, 2018). Hurricane Michael was responsible for approximately $25 billion in damage (Haddad, 2018).

Hurricane Matthew never officially made landfall in the state of Florida, yet its sheer size and intensity unleashed historically high surges and winds, even as it skirted along the eastern coast. The highest storm surge height was seven feet height in Fernandina Beach, and winds maxing out in Cape Canaveral at 107 mph (Brouillette, 2016). During Hurricane Matthew, more than 1.5 Florida natives were under evacuation orders (Huricane Safety and Preparedness, 2016).

2.0 LITERATURE REVIEW

There are several key ideas to grasp when it comes to safety analysis and crash rates. Understanding transportation safety for this research includes considering how safety is impacted with a high volume of vehicles on roadways and factors that play into crashes. Information crucial over hurricane evacuations such as understanding how evacuations work, transportation safety during evacuations and statistical analysis used in past research is vital to this research.

2.1 Effects of High Volume on Roadways

It is important to understand how transportation safety is affected by a high volume of vehicles on the roadways and even more so during hurricane evacuations. The usual two-way traffic on a given roadway segment during an evacuation is condensed into a single direction. Before delving into crash rates, understanding this phenomenon is crucial.

A study concluded that with heavy volumes, when the number of travel lanes, water on the roadways, and rear-end crashes increases and slow grade is present, crash severity increases (Jung, Jang, Yoon, & Kang, 2014). When large amounts of vehicles are surging on roadways, these factors make it difficult to navigate in a safe and timely manner. When multiple vehicles hit their brakes in a congested area, a wave motion of people accelerating, breaking, and then accelerating again occurs. Vehicles that have passed the point of the “braking” spot are accelerating back to normal speed. While vehicles that are approaching the braking section are approaching other vehicles quickly, this results in having to press the brakes in a rather forceful manner. If this same scenario were to happen when cars are traveling up grade, thus their lights do not illuminate out as far, and it is raining, causing little traction to be available and blurred lights, this can make for a dangerous situation.

Excluding weather and topographic effects, a study has been performed to investigate the relationship between traffic volume and the number of crashes. The results showed that there is a strong relationship when there is a high vehicle volume present and when crash numbers are high. Along with this, it was shown that the relationship between high volume and high crash numbers is the strongest on freeways (Hoya & Hesjevoll, 2020). This information is not only crucial in everyday road planning, but this is ever present during emergency evacuations. When a mandatory evacuation is ordered, surges in traffic volume are expected to occur in a short period.

2.2 Crash Rates

Crash rate analysis of the safety of a segment takes into consideration the exposure data and is calculated to determine relative safety compared to other segments. This analysis uses exposure data in the form of vehicle volumes and roadway milage (Golembiewski & Chandler, 2011). Crash rates are used in transportation engineering to equally assess the safety of the road as it considers the differences in traffic and geometric conditions (Zhang, Xie, & Li, 2012). Not all roadways are designed for the same reasons, some roadway segments have different characteristics. For instance, principle arterial roadways have a limited number of access points but offer high speeds of travel. While the opposite of this is local roads, which provide a high degree of access, but offer significantly lower speeds (Chakroborty & Das, 2017). Thus, considering geometric variables and exposure data, crash rates find the number of crashes per million vehicle miles in order to compare all segments equally (Zhang, Xie, & Li, 2012).

Literature on crash rate studies has delved into examining various external factors and their impact on crash rates. Notably, a study conducted in New Jersey focused on investigating the individual and combined influences of licensing age, driving experience, and post-Graduated Driver Licensing (GDL) phases on crash rates per ten thousand drivers. The findings of this study revealed individuals within the initial month of acquiring their driver's license exhibited the highest crash rates, reaching 229 per 10,000 licensed drivers (Curry, Pfeiffer, Durbin, & Elliott, 2015). Another study observed crash rates by age in injury crashes and found that older drivers have a higher than average rate. This study calculated rates by dividing crash numbers by distance driven (Keall & Frith, 2004).

One study compared crash rates across three different periods to understand the effect of safety rest areas (SRAs) on crash rates. In Washington and Idaho, crash rates were investigated by looking at the number of crashes per month and per 10,000 AADT to compare rates before, during, and after closures of SRAs in three different locations. SRAs aid highway users to rest during trips and limit fatigue-related crashes. The results showed that there was not a significant increase in fatigue-related crashes during shutdown periods. However, total crash rates and fatigue-related crash rates increased in one location, decreased in another, and there was no change in the other location during closure periods (Shrestha, 2023). The results from studies such as this can help policymakers aid in the decrease of crashes due to fatigue.

Another piece of literature compares vehicular crashes and occupant injuries on highways in Iowa during winter snow events and equivalent nonsnow event periods. The study found a significant increase in crash rates (crashes per million vehicle kilometers) during winter snow events compared to nonsnow event periods. Additionally, the analysis revealed that crash injury occurrence depends on factors such as traffic volume, road geometry, and number of vehicles involved. Using a logit model, the study concluded that crashes during snow events were found to have less injuries compared to nonsnow event crashes (Khattak & Knapp, 2001).

2.3 Crash Factors Prevalent during Hurricane Evacuations

In addition to transportation safety being affected by the volume of vehicles on the roadways, it is important to understand what other factors play into crashes that could be prevalent during hurricane evacuations. In the US, adverse weather and topographic conditions has been a large factor and heavily weighs into the blame for many single-vehicle crashes every year (Chen, Cai, & Wolshon, 2009). Topographic conditions consist of grade, speed limit, geometry, pavement material (concrete, asphalt), etc. If there is slow grade incline and curves on an interstate while raining, it can impair visibility and affect traction, resulting in dangerous conditions for heavy traffic. Along with weather and geometric factors, driving behaviors during evacuations can affect delays and crashes.

During evacuation periods, traffic stream follows oscillatory speed, which contributes to rear-end crashes (Hasan & Rahman, 2020). Along with oscillating speeds, heavy congestion, lane changes, reduced travel speeds, and the pursuit for alternative routes can cause gridlock on evacuation routes and surrounding segments (Collins, Foytik, Frydenlund, Robinson, & Jordan, 2014). With these topographic factors and driving behaviors, during emergency evacuations, crashes are impacted. Considering the heightened situation and the reason for the vehicular trips, distracted driving could be at an all-time high. These risks amplify mistakes on roadways, causing an increase in rear-end or sideswipe crashes.

During an evacuation period, instead of peak morning and evening periods, traffic consists of unpredictable pattern and heavy traffic throughout the period (Rahman R. , Bhowmik, Eluru, & Hasan, 2021). This is due to all zones within counties receiving mandatory evacuation orders at different times. However, with the FDOT evacuation routes, all traffic eventually travels in the same direction if evacuating on the same coast. Eventually, resulting in surges of vehicles on evacuation routes, leading to severe congestion and infrequent speeds.

Studies have shown that infrequent traffic flow and deviating traffic speed are two main factors that contribute to freeway crashes (Golob, Recker, & Alvarex, 2004), (Tanishita & Van Wee, 2017). These conditions are normal when an emergency evacuation is occurring. Considering this study and the fact that the segments used during evacuations are freeways, one can conclude the problem and see as to why there may be an increase in crashes during these periods.

2.4 Understanding Hurricane Evacuations

Hurricanes have paved the way to infrastructure damages, such as road segments, residential areas, power outages, and more (Ghorbanzadeh, Koloushani, Ulak, Ozguven, & Arghandeh, 2020). Since from 1953 to 2020, there have been 39 hurricanes, 22 severe storms, and 13 floods in Florida (FEMA, Federal Emergency Management Agency, n.d.). Understanding how hurricane evacuations work and its effect on traffic is imperative to this research.

Hurricane forecasts originate from the National Weather Service's Tropical Prediction Center in Miami, Florida (Gladwin, Lazo, Morrow, Peacock, & Willoughby, 2007). The structure of the hurricane behavior is relevant to evacuations, and local authorities must understand this in order to decide which geographic areas are at risk. The area is configured by the hurricane's intensity, which is classified by the Saffir-Simpson Categories 1-5 (Lindell & Prater, 2007). From here, officials release word through live news, the weather channel, news articles, etc. to make known to the public what counties and what zones within those counties are under a mandatory or voluntary evacuation. A mandatory evacuation is when all residents must be evacuated. A voluntary evacuation is not enforced, it only encourages and advises residents to evacuate.

Features related to evacuation traffic demand include distance from the evacuation zone, time to landfall, and other zonal level features (Rahman & Hasan, 2023). Hurricanes are unpredictable in the sense meteorologists hypothesize where the hurricane will make landfall and order evacuations in the vicinity. However, if a hurricane's trajectory shifts and a late evacuation is ordered for a county, one can expect heavy traffic due to the short-time interval moving the high density of people. Within each county in the state of Florida the amount of evacuation zones varies, however, the range is roughly from four to six zones. The most exposed zone in all counties is Zone A, which includes the barrier islands and the outer part of the inland area. Over five million people live in government-designated flood or hurricane evacuation zones, and nearly two million live in mobile homes, most of whom are elderly or live in low-lying or coastal areas (Zone A) (Younes, Darzi, & Zhang, 2021).

2.4.1 Effect of Hurricane Evacuations on Traffic

During evacuations, traffic is frequently interrupted by crashes, resulting in jeopardizing the safety of those who are delayed in congestion on evacuation routes (Chen, Cai, & Wolshon, 2009). Two regression models were used to indicate that there is roughly a 7.2 percent to 8 percent increase of travel time in evacuations (Collins, Foytik, Frydenlund, Robinson, & Jordan, 2014). Although this percent increase in time seems minimal, over a long distance, this is problematic. For example, if an individual is fleeing Miami and drives to Atlanta, the typical drive is roughly nine and a half hours, without stopping or traffic. With the percent increase, without stopping, the drive now takes over ten and a half hours.

Hurricane trajectory shifts can cause an issue in congestion on roadways during evacuations. During 2017, Hurricane Irma shifted, creating a new projection path which forced people to evacuate out of Naples, Cape Corals, Tampa, Levy, and Jacksonville, resulting in significant congestion (Rahman & Hasan, 2023).

2.5 Past Research and Temporary Safety Methods for Evacuations

It is essential not only to consider ongoing research aimed at improvement but also to assess the temporary safety measures implemented in past hurricanes and their effectiveness or lack thereof in alleviating traffic congestion. Research has been conducted to explore temporary safety measures during hurricane evacuations. A safety impact analysis was performed to evaluate the crash types, severity, and other relevant factors during ESU (emergency shoulder use). ESU is a temporary relief method used by transportation management to relieve freeway congestion during emergencies. The simulation model showed that incorporating ESU causes more crashes to occur, however, there were no serious fatalities. Crashes that occurred with implementing ESU were mainly property damage only and some were injury-only crashes. (Sharma, Faruk, & El-Urfali, 2020). While this would help FDOT with Target Zero, moving towards zero fatal crashes, an increase in crashes is not a permanent solution to relief methods for emergency evacuations.

Furthermore, simulation models have also been used to determine if crash frequencies can be reduced using Adaptive Cruise Control (ACC) systems during evacuation scenarios, using real-world data from hurricane Irma evacuation in Florida. The results indicated that there could be a potential 49.7 percent reduction in traffic collisions with a 25% market penetration of ACC-equipped vehicles during evacuations. (Rahman, Hasan, & Zaki). Adaptive Cruise Control (ACC) systems could potentially be implemented in the future as a safety measure for evacuees during hurricane evacuations. One limitation of this method is whether the public would have accessibility to the ACC system in their own vehicles. Currently, this is not a realistic and viable option. However, with future research and technology, this holds promise.

Contraflow operation was a method used in Louisiana after it was performed in South Carolina and Georgia during evacuations for Hurricane Floyd. This method allowed for the inbound travel lanes on the freeway to be used for the outbound direction. This was proved to be successful while in state, however, evacuations are not statewide, the contraflow ended once Georgia was reached, resulting in sever bottlenecking (Wolshon, 2002). Bottlenecking occurs when vehicles moving quickly catch up to vehicles moving exponentially slower and congested, resulting in the fast cars not being able to pass and as time goes on the impacts become worse (Zhou, 2018).

Contraflow could potentially be a viable option for alleviating traffic during emergency evacuation if implemented nationwide. However, because it is only within the state being evacuated, bottlenecking could pose as a risk to the safety of evacuees and significant delays.

2.6 Transportation Safety Statistical Analysis

When it comes to statistical analysis there are numerous available methods. However, not all methods will be of help when it comes to analyzing transportation safety data. Methods such as multiple linear regression, multinomial logistic regression, and Poisson regression models estimate and compare parameters for crash factors to identify significant factors and how they compare to other factors involved in crashes (Diaz-Corro, Moreno, Mitra, & Hernandez, 2021).

In the realm of transportation safety, it is imperative to choose one that allows for comparison with non-numerical variables.

Most early traffic safety studies performed to understand key factors contributing to the crashes involved focusing on post-mortem analysis based on historical accident data and combining them with driver behaviors (Chu & Zhang, 2018). This made for a steppingstone in research in transportation safety. Understanding factors that play into crashes allows for policies and reinforcements to be put into place, allowing for the reduction of crashes in the future. This is the step needed in emergency evacuations. Understanding the factors that contribute to crashes during hurricane evacuations is the first step to preventing and reducing crash rates.

Taking this into consideration, a cross-correlation and prioritization of crash factors was performed on the national crash database. This study found that alcohol/drugs, illness or blackout, and sleepy/drowsiness were the leading contributing factors to driver incapacitation and impairment (Campbell, Smith, & Najm, 2003). Considering these factors found in this study, the crash factors, such as sleepy/drowsiness, distracted driving, speeding, drinking/drugged driving, fatigue, etc., could be a potential factor during hurricane evacuations. In single vehicle off-road (SVOR) crashes, factors contributing to crashes resulted in speeding and inattention (Campbell, Smith, & Najm, 2003). Among cross-correlation studies, negative binomial approach has proven to be effective when examining factors contributing to crashes.

Kassu and Hasan used negative binomial regression to analyze crashes on freeways and the factors that contributed to crashes of all magnitudes, such as traffic volume, median type, and the number of lanes (Kassu & Hasan, 2020). Negative binomial regression is a common statistical analysis the transportation engineering world is familiar with. This model allows for not only understanding crashes but provides evidence of what the significant factors are that lead to crashes. Reducing crashes and the safety of the public is at the heart of transportation safety research. Using statistical analysis to understand crash rates during hurricane evacuations is important, thus correlation analysis is important to see how crash rates during hurricane evacuations compares to non-emergency periods.

Correlation analysis is used to assess the degree of association among data (Asuero, Sayago, & Gonzalez, 2006). The values of correlation coefficient range from -1 to 1. If the correlation coefficient is +1, this shows the data set is in a perfect positive linear relationship, showing if one increases then the other will increase. On the counter, if the coefficient is -1 then the data set has a negative linear relationship, as one increases the other decreases (Ratner, 2009). This statistical analysis allows crash rates to be compared and possibly demonstrate if crash rates during evacuation and re-entry periods are correlated to non-emergency period crashes. This is relevant in the sense of seeing if driving patterns and characteristics are the same or different during these two time periods. If proven that the time periods are correlated, using the different time periods can lead to a growth of information over crash rates and potential for future safety precautions to aid in the reduction of crash rates not only during hurricane evacuations but also during non-emergency periods.

Another statistical analysis that is important to findings in transportation engineering that is relevant to comparing crash rates and the statistical significance between two populations is a paired t-Test. A two-sample t-Test for equal means can be used to determine if two population means are equal. A paired test is used to when there is a one-to-one correspondence between values in two samples (NIST/SEMATECH e-Handbook of Statistical Methods, 2012). This is important to a crash rate analysis to observe if crash rates are significantly different and if the findings omit randomness.

In conclusion, this literature review has provided analysis that crashes are significantly influenced by factors such as traffic volume, road geometry, weather conditions, and driver behaviors. Studies have shown that heavy traffic congestion and oscillating speeds contribute to more crashes, and these traffic patterns are present during evacuations. Additionally, factors such as driver fatigue, distracted driving, and impaired visibility could be concerns raised during emergency evacuations. The forefront research in hurricane evacuations has been investigating the effectiveness of temporary safety measures during evacuations. Such as adaptive cruise control systems and emergency shoulder lane usage. However, it is imperative to see if crash rates vary across different periods. Research into crash rates across different periods is an effective way to research how different periods are affected and influenced by different conditions during respective periods. Looking into crash rates during evacuations, re-entry, and non-emergency periods will aid in making transportation systems safer during such events. Using statistical analysis such as correlation analysis aids in the understanding and investigating if crash rate results are significant and correlated across different periods.

3.0 METHODOLOGY

This study was conducted in several stages to collect input data for crash rates. These stages involved gathering information on volumes, crashes, and segment lengths to analyze crash rates across three distinct periods, evacuation, re-entry, and non-emergency. The segment lengths were found using the evacuation route shapefiles and FDOT telemetered traffic sites, both of which were provided by the FDOT. Mandatory evacuation zones for each storm were identified through comprehensive review of national, state, and local announcements from governmental agencies and news outlets. The volumes were provided using the FDOT traffic volumes collected by the FDOT telemetered traffic sites. Volumes were processed and sorted into the respective three periods, evacuation, re-entry, or non-emergency. The volumes were then used to sort the crashes by period. Subsequently, crash data was sorted according to these periods, allowing for the calculation of crash rates during non-emergency, evacuation, and re-entry phases.

A statistical analysis using correlation and paired t-test was performed to evaluate the accuracy of the findings. The motivation for this methodology is to provide the inputs required for crash rates in the three different periods. The methodology flow chart can be seen in Figure 1. The crash rates were found using the following equation (U.S. Department of Transportation, 2011):

$$R = \frac{C\ x\ 100{,}000{,}000}{\mathrm{V}\ x\ 365\ x\ N\ x\mathrm{L}}$$

$where,$
$R = Roadway\ crash\ rate\ for\ the\ road\ segment\ as\ crashes\ per\ million\ vehicle - miles\ or\ travel$
$C = Total\ number\ of\ roadway\ crashes\ in\ the\ study\ period$

$V = Traffic\ volumes\ using\ Average\ Annual\ Daily\ Traffic\ (AADT)\ volumes$
$N = Number\ of\ years\ of\ data$
$L = Length\ of\ raodway\ segment\ in\ miles$

Using the summation of volume in a period, divided by the number of days in the period, average daily traffic (ADT) was calculated. Multiplying ADT by three hundred sixty-five gives AADT. The segments within this study were measured in feet, to convert to miles the length of the segments were divided by 5,280 to obtain L.

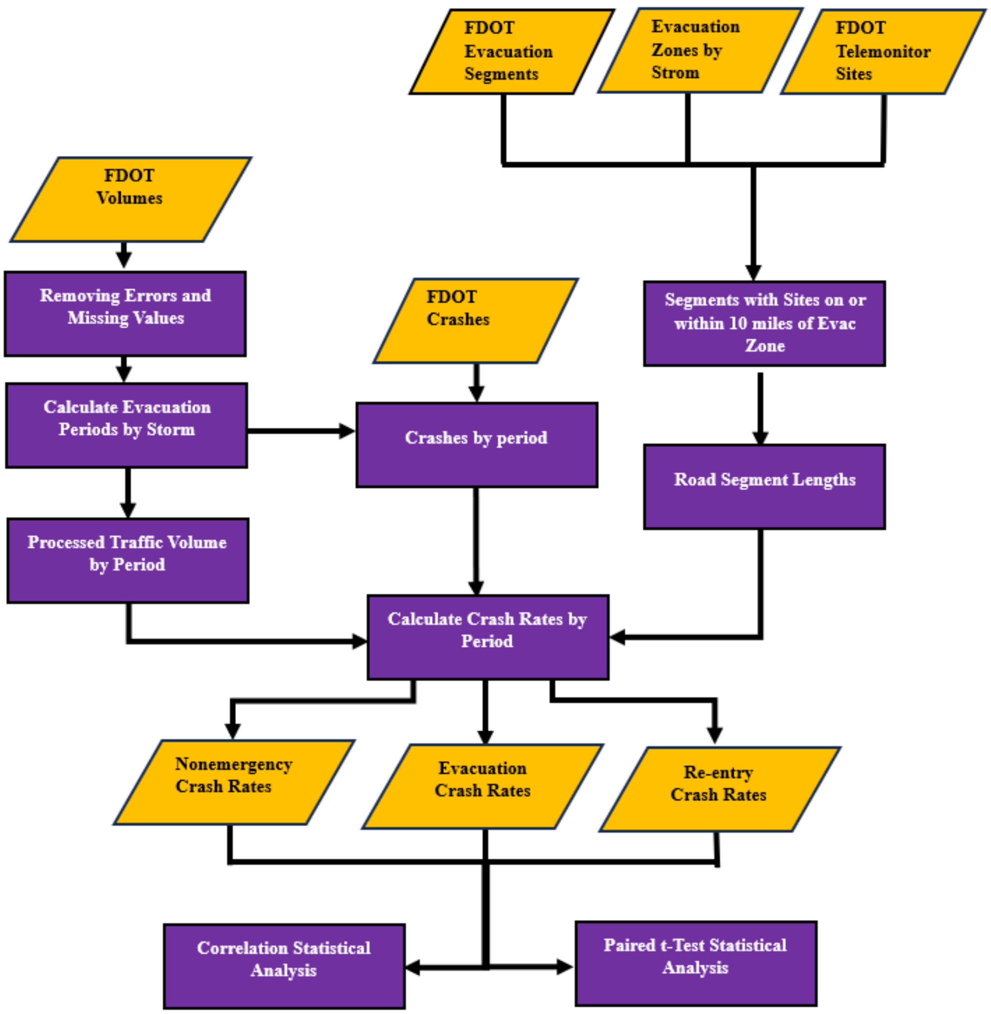

Figure 1: Flow Chart of Study

3.1 Road Segments

Hurricane Matthew, Irma, and Michael were chosen to be studied due to the relevance and magnitude of these storms. Hurricane Michael, Irma, and Matthew in 2016, 2017, and 2018 respectively. Phase one of this research consisted of collecting data relevant to hurricanes Matthew, Irma, and Michael. Segments were considered for this study if they resided within ten miles of a mandatory evacuated road and if there was a FDOT telemeter site. This was made possible by using the FDOT evacuation route shapefile, the FDOT telemeter site shapefile, and barriers made around mandatory evacuation zones in ArcMap. A process was then performed to isolate single segments and no intersections were apart of the study segments. This was done to reduce a skew crash count that resulted on roadways that were not evacuation routes that intersected with an FDOT evacuation route.

Using the FDOT shapefile, the state evacuation routes were also added to the software. Regional boundaries were placed using ArcMap on what roadway segments were going to be considered in this study. The last input needed to calculate the crash rates for all segments for all three periods are segment lengths. Using the measuring tool in ArcMap, each segment length was calculated for the segments that held crashes and volumes. The segment lengths were recorded in feet. The segments for each individual hurricane that were considered in this study can be seen in Figure 2. While not clearly visible in the figure, some segments are common between storms.

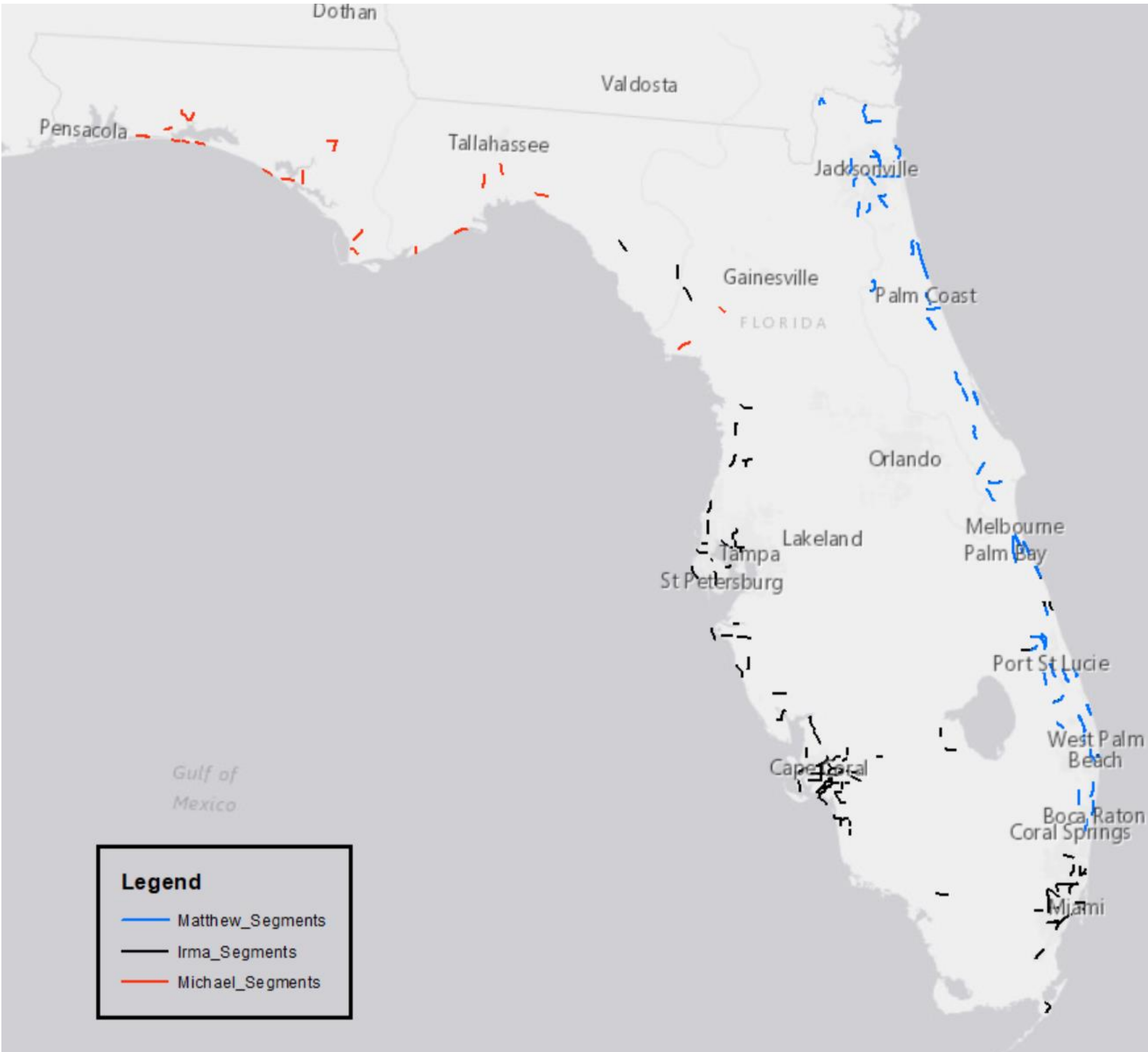

Figure 2: Segments Considered For Study

3.2 Traffic Volumes

The continuous count volumes for each FDOT telemetered traffic monitoring sites were collected for every site in Florida. For an FDOT telemeter traffic monitoring site, and its corresponding volume data, to be considered for this research it had to reside on a study segment. A data cleaning was then performed to remove all days that did not contain volume counts during peak traffic hours (8 AM, 9AM, 10AM, 4PM, 5PM, and 6PM).

Another step in the volume data cleaning process was to remove days that collected only one direction of volume counts per site. This was performed to eliminate the statistical analysis being skewed in efforts to find the evacuation and re-entry periods. As well as removing probable reasoning for crash rates to be impacted. For instance, if on one day a telemeter site failed to collect south direction volumes and only collected north direction volumes, including this day would allow for a low volume observation would artificially increase crash rates.

An example of this can be seen in Table 1 for Hurricane Irma. The example illustrates FDOT telemeter cosite 040145 was missing the North direction volume counts on the days of April 24th, 25th, and 26th in 2017. Resulting in the removal of these days in the volume dataset. This was carried out through the volume processing stage.

Table 1: Traffic Volume Data Cleaning Example

Cosite	Date	Direction	Total Volume
040145	4/24/2017	N	0
040145	4/24/2017	S	4396
040145	4/25/2017	N	0
040145	4/25/2017	S	4487
040145	4/26/2017	N	0
040145	4/26/2017	S	4596

3.3 Study Periods

After cleaning the data, the next process was to find the evacuation, re-entry, and non-emergency period. The first step in this process was to sum the volume counts for each site for every day of the year in the north direction. Using the total volumes for each day of the year, the average, standard deviation, one standard deviation above and below the mean were found for each day of the week in the north direction. The actual volumes one week before and one week after each hurricane made landfall in Florida were graphed and compared to the day of week volume average, one standard deviation above the mean, and one standard deviation below the mean. This was performed to view when the evacuation and re-entry periods started and ended for each storm. This process was continued for all other directions for all hurricanes. An example of the results can be found in Figure 3: Hurricane Irma East Period Analysis. See Appendix A for the rest of the results.

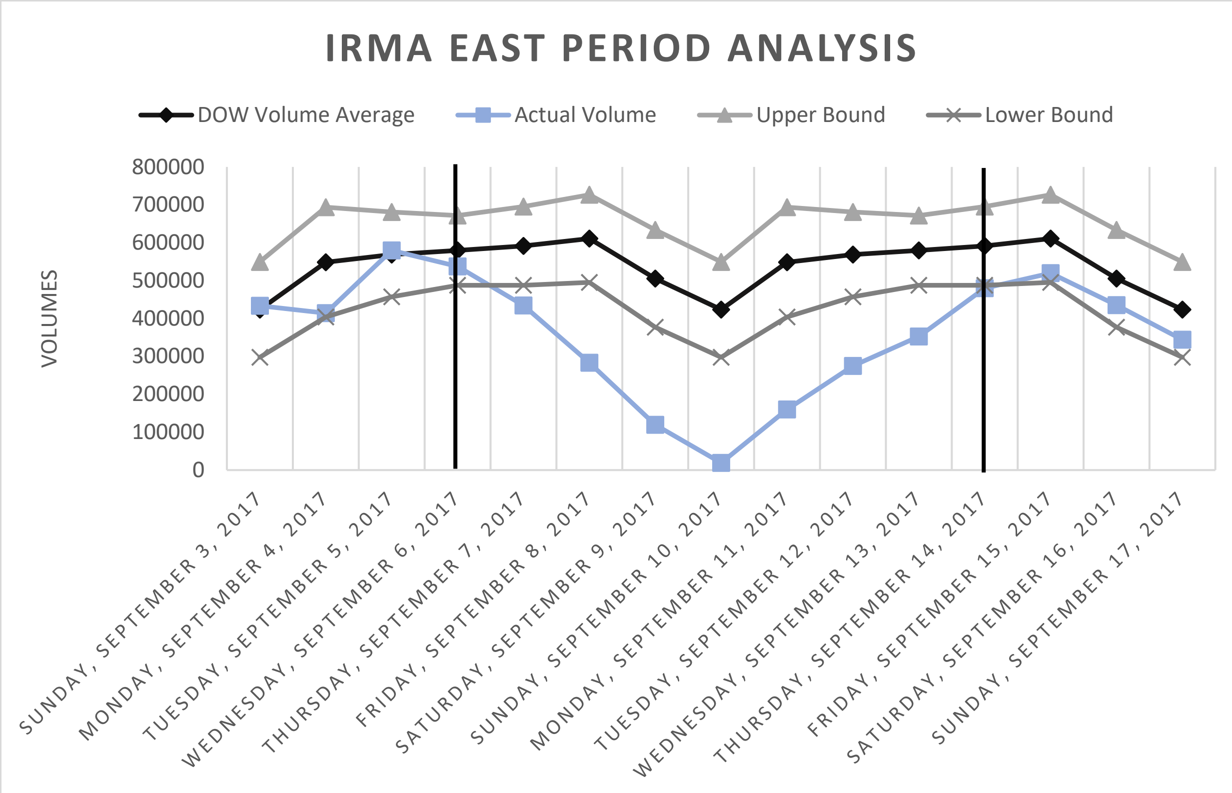

Figure 3: Hurricane Irma East Period Analysis

Figure 3 illustrates the east period analysis performed for Hurricane Irma. Day of week (DOW) average, the actual volume counts corresponding to the date, and the upper and lower bounds were graphed to see when traffic deviated from typical patterns. It should be noted that one standard deviation above the mean is referred to as the "upper bound", and one standard deviation bellow the mean is referred to as "lower bound". On September 6th, the actual volume started to deviate from the Wednesday volume average. Thus, this was determined to be the start of the evacuation period.

After the period dates were established, the volume data was organized into three periods: evacuation, re-entry, and non-emergency. A final cleaning was performed to remove the volumes and FDOT sites that were missing volume counts during an evacuation or re-entry period. The dates for each period for each storm were established as follows:

Table 2: Hurricane Evacuation, Re-entry, and Non-emergency Periods

Hurricane	Evacuation Period	Re-entry Period	Non-emergency Period
Michael (2016)	October 8–10	October 11–13	Remaining days in 2016
Imra (2017)	September 6–10	September 11–14	Remaining days in 2017
Michael (2018)	October 5 –7	October 8–10	Remaining days in 2018

The total volume counts for each segment were recorded for each period, along with how many days were in each period. This is relevant to find the crash rate for each segment during each period.

3.4 Crash Counts

The database used to access the crash data for each hurricane was the FDOT crash database (FDOT State Safety Office GIS, n.d.). The key categories that were considered when downloading the crash data were the crash dates, type of crash, and x-y coordinate system. The coordinate system used was the NAD 1983-2011 UTM Zone 17N, in US feet. This coordinate system was used to map all crashes. Using ArcMap, crashes that were to be considered for this study per hurricane had to meet a certain criteria:

- The crash occurred on an FDOT evacuation segment within the regional boundary set.
- The crash was on a segment that has an FDOT telemeter traffic site with consecutive volumes counts.

These criteria were put into place to minimize skewing the number of crashes compared to volume counts. For instance, if a crash were to occur on a day when there were no volume counts recorded, this would cause an elevated crash rate due to missing data. The crashes that met these criteria were sorted by date into the corresponding periods. The number of crashes that occurred on each segment during each period were recorded.

During 2016, Hurricane Matthew's calendar year, there were a total of 87,772 crashes in Florida. However, only 2,083 of these occurred on the study segments. The same process was followed for Irma which started with 373,114 crashes in and data processing resulted in 23,534 crashes. Michael calendar years recorded 14,843, and crashes along the segments chosen for the study was 1,744. Table 3 shows the summary of all crashes in the state of Florida during respective hurricane year, number of crashes that were on an evacuation route, evacuation, re-entry, and non-emergency crashes relevant to this study.

Table 3: Crash Summary

Year	Storm	All Crashes	Crashes on Segments	Evacuation Crashes	Re-entry Crashes	Non-emergency Crashes
2016	Matthew	87,772	2,083	16	25	5,095
2017	Irma	373,114	23,534	72	87	11,092
2018	Michael	14,843	1,744	3	8	1,384

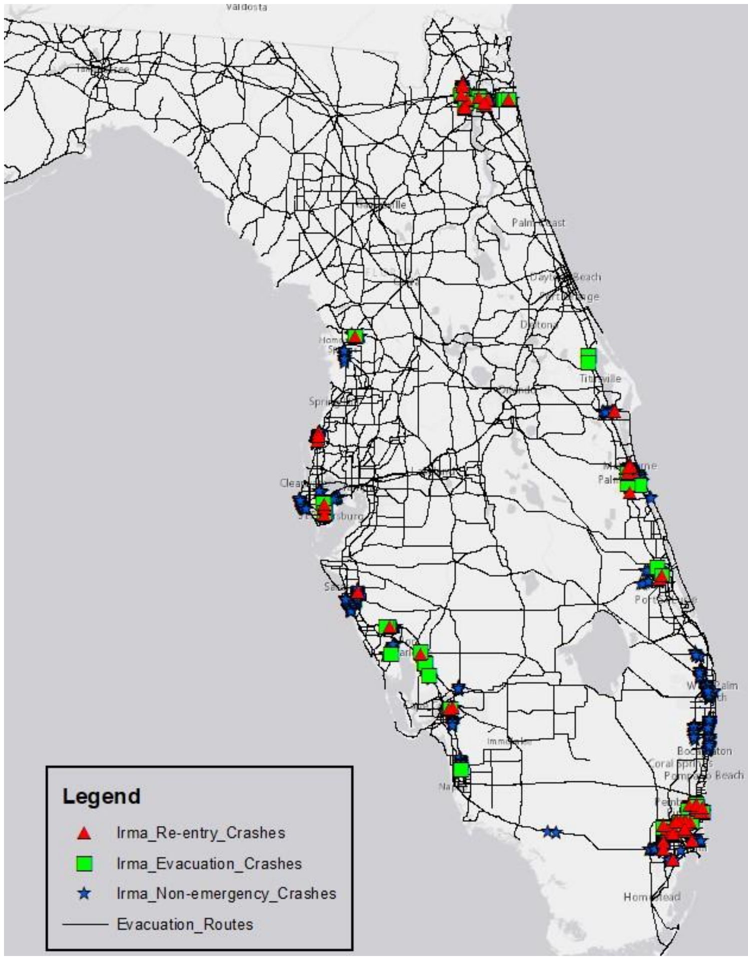

Figure 4: Hurricane Irma Period Crash Map

Figure 4 displays the crashes during the re-entry, evacuation, and non-emergency periods along the FDOT evacuation routes. Hurricane Matthew and Michael's period crash map can be found in Appendix D. With the number of crashes, days in each period, segment length, and volume counts known, crash rates were calculated. Hurricane Michael, Irma, and Matthew crash rates can be found in Table 4, Table 5, and Table 6.

3.5 Statistical Analysis

A statistical analysis was performed after the crash rates were found for all hurricanes. A Pearson correlation test was performed for all hurricanes between non-emergency period and evacuation period, non-emergency and re-entry period, and evacuation and re-entry period. The results of this can be found in Table 8, Table 9, and Table 10. This was done to investigate correlation of crash rates between periods.

Along with this, a paired two-sample t-Test for equal means was performed to verify or reject the null hypothesis. The hypothesis was that crash rates would remain the same between evacuation, re-entry, and non-emergency periods. The summarized results for all hurricanes studied can be found in Table 7. This process was performed for individual hurricanes and all hurricane data combined, comparing non-emergency and evacuation period, non-emergency and re-entry period, evacuation and re-entry period, and non-emergency and emergency period. An alpha value of 0.5 was given to assure the significance level is outside the 95th percentile.

The emergency period combined both evacuation and re-entry periods. The paired two-sample t-Test for equal means that encompasses all crash rates combined per period for hurricanes Irma, Michael, and Matthew can be found in Appendix C.

4.0 RESULTS

After the process of collecting volumes, segment lengths, number of days in each period, and the number of crashes in each period for every storm, the US Department of Transportation equation for crash rates could be used to find the crash rate for all study segments during non-emergency, evacuation, re-entry, and emergency periods. The results concluded that crash rates during non-emergency periods were two orders of magnitude larger than rates during evacuations and re-entries. Using a paired t-test, all crash rates per period were compared. The results concluded that there is a significant difference in crash rates between non-emergency when compared to evacuation, re-entry, and emergency periods. However, this test also concluded that evacuation and re-entry crash rates are insignificantly different.

Table 4 lists the crash rates per period for Hurricane Michael for each cosite and its corresponding segment. A cosite is the composite of the Florida county number and section number. Non-emergency crash rates were an order of magnitude higher than crash rates during the evacuation and re-entry periods. The right column shows the entire emergency period crash rates. This was performed by encompassing all data during the evacuation and re-entry periods per segment.

Table 4: Hurricane Michael Crash Rates

Cosites	Non-Emergency Period Crash Rates	Re-Entry Period Crash Rates	Evacuation Period Crash Rates	Emergency Period Crash Rates
20044	116.39	0	0	0
20324	119.44	0	0	0
340239	220.06	0	0	0
340278	99.48	0	0	0
349909	96.23	0	0	0
340116	88.01	0	0	0
300234	292.16	0	0	0
490369	47.12	0	0	0
380280	0	0	0	0
460305	154.62	0	2.67	2.65
590296	203.41	2.79	0	3.09
460308	668.98	12.71	0	11.64
460166	260.36	0	0	0
550300	0	0	0	0
570385	138.59	0.50	0	0.60
570250	311.64	3.96	5.46	9.18
570219	129.39	0	0	0

Table 5 consists of all the crash rates for each period per segment for Hurricane Irma. Due to the magnitude of the storm, and the shift in path, Hurricane Irma contained the largest data set out of all storm analyses.

Table 5: Hurricane Irma Crash Rates

Cosites	Non-Emergency Period Crash Rate	Evacuation Period Crash Rate	Re-entry Period Crash Rate	Emergency Period Crash Rates
010228	128.27	2.60	0	2.36
010350	64.92	3.74	0.87	4.54
010367	95.30	3.77	0	3.58
020324	96.83	2.60	2.99	5.52
030191	53.20	1.51	0	1.75
120203	423.24	1.59	4.61	6.25
140199	308.89	0	3.04	3.25
150295	884.98	13.32	8.96	22.12
170225	61.84	0	0.52	0.56
170361	53.81	1.68	0.80	2.46
700114	284.06	2.47	11.57	14.37
700134	38.85	1.03	0.93	1.96
700322	16.94	3.73	0	3.58
700345	479.04	2.54	3.92	6.73
700370	45.32	0	2.76	3.00
720062	220.33	3.02	2.97	5.99
720171	194.90	4.25	1.36	5.56
720172	391.36	5.54	12.67	18.30
729914	103.08	2.86	2.13	4.99
860176	916.98	12.15	0.0000	10.34
860306	360.53	0	23.64	26.19
860331	197.08	2.67	1.48	4.01
860384	1077.27	16.02	7.40	21.95
870096	615.72	0	17.13	18.69
870108	176.63	0	2.63	2.64
870137	259.40	2.14	2.93	5.33
870193	156.17	0	4.78	5.09
879947	777.40	11.70	12.92	25.09
940260	47.3897	1.3595	1.1572	2.5229
970267	68.0024	0.3780	0.8240	1.2953
970403	78.8327	0.7087	0.5211	1.2218

Table 6 displays the results of Hurricane Matthew's crash rates. The results found were consistent with Irma and Michael, in that non-emergency period crash rates are much higher than the crash rates during evacuations, re-entries, and emergency periods.

Table 6: Hurricane Matthew Crash Rates

Cosites	Non-Emergency Period Crash Rates	Evacuation Period Crash Rates	Re-entry Period Crash Rates	Emergency Period Crash Rates
700114	403.78	0	4.70	5.32
710189	166.48	1.78	2.78	4.68
720062	276.10	1.29	2.52	4.07
720171	258.71	1.88	2.13	4.03
720172	400.80	4.29	0	3.98
720216	17.97	1.72	0.73	2.36
729905	129.52	2.90	0	2.57
740047	78.65	0	9.40	9.70
780311	303.61	0	5.97	7.26
780360	134.32	0	2.92	3.32
890259	104.47	0	8.45	10.44
930010	328.82	2.50	0	2.25
930174	105.42	0.39	0.81	1.27
930198	100.24	0.40	0	0.33
970416	62.25	0	1.46	1.70
979913	52.99	1.45	0	1.23

The results of the paired t-test, found in Table 7, suggest that the differences between the populations was significant. The results of the paired t-test statistical analysis for all storm crash rates combined can be found in Appendix C. This was done to compare period to period crash rates for all hurricanes. All crash rates for all storms were compiled and a paired t-test was used to compare the results for non-emergency and evacuation periods, non-emergency and re-entry periods, evacuation and re-entry periods, and non-emergency and emergency periods, respectively. The mean, variance, number of observations, coefficient of correlation, and P(T<=t) two tailed were among the most important values considered.

In Table 7, the p values less than 0.05 suggests that the differences observed between the two-population means was statistically significant. Therefore, it is reasonable to suggest that the crash rates between the evacuation period and non-emergency period were significantly different. This also was concluded when comparing re-entry period to non-emergency periods and emergency periods to non-emergency periods. Thus, the results of the paired t-test rejected the null hypothesis of equal means, suggesting that the means of the two populations were likely different. This is consistent across all three storms within this study, furthering the argument that crash rates during emergency periods, evacuations and re-entries, were significantly lower than non-emergency periods.

Table 7: Paired T-Test Analysis Results

Hurricane Irma

Metric	Non-Emergency vs Emergency		Non-Emergency vs Evacuation		Evacuation vs Re-entry		Non-Emergency vs Re-entry	
	Non-Emergency	Emergency Period	Non-Emergency	Evacuation	Evacuation	Re-entry	Non-Emergency	Re-entry
Mean	279.889	7.783	289.644	4.307	4.190	4.263	287.148	5.212
Variance	84395.932	59.503	99171.139	18.712	19.845	18.179	77881.059	34.620
Observations	31	31	24	24	19	19	26	26
P value	<0.0001		0.0002		0.9337		<0.0001	

Hurricane Michael

Metric	Non-Emergency vs Emergency		Non-Emergency vs Evacuation		Evacuation vs Re-entry		Non-Emergency vs Re-entry	
	Non-Emergency	Emergency Period	Non-Emergency	Evacuation	Evacuation	Re-entry	Non-Emergency	Re-entry
Mean	295.446	5.434	233.127	4.065	N/A	N/A	330.653	4.990
Variance	48174.322	22.290	12328.193	3.891	N/A	N/A	55968.609	28.557
Observations	5	5	2	2	N/A	N/A	4	4
P value	0.0394		0.2067		N/A		0.0669	

Hurricane Matthew

Metric	Non-Emergency vs Emergency		Non-Emergency vs Evacuation		Evacuation vs Re-entry		Non-Emergency vs Re-entry	
	Non-Emergency	Emergency Period	Non-Emergency	Evacuation	Evacuation	Re-entry	Non-Emergency	Re-entry
Mean	182.759	4.031	182.759	1.162	1.288	3.108	191.410	2.791
Variance	16035.619	8.596	16035.619	1.679	1.914	10.021	15897.987	9.366
Observations	16	16	16	16	13	13	15	15
P value	<0.0001		<0.0001		0.1512		<0.0001	

All Storms

Metric	Non-Emergency vs Emergency		Non-Emergency vs Evacuation		Evacuation vs Re-entry		Non-Emergency vs Re-entry	
	Non-Emergency	Emergency Period	Non-Emergency	Evacuation	Evacuation	Re-entry	Non-Emergency	Re-entry
Mean	251.498	6.403	266.082	3.735	3.625	3.817	252.407	4.756
Variance	60301.068	42.292	72700.863	15.611	16.225	14.914	57993.313	25.640
Observations	52	52	38	38	25	25	39	39
P value	<0.0001		<0.0001		0.7752		<0.0001	

Table 8, Table 9, and Table 10 present the results of Pearson correlation analyses examining the relationships between crash rates during different periods for hurricanes Irma, Matthew, and a combined dataset including hurricanes Irma, Matthew, and Michael. Hurricane Michael was not examined independently in this statistical analysis due to the limited availability of crash rate data, comprising only five rates, which precluded a meaningful correlation analysis. The results indicate that non-emergency are correlated with evacuation and emergency period crash rates. When a segment displays a high crash rate, relatively during non-emergency periods, it also tends to display a high crash relative rate during the evacuation period. However, it was concluded that non-emergency and re-entry period crash rates are not necessarily correlated.

For the correlation analysis involving evacuation and re-entry periods, only segments with available crash rate data for both periods were included. Similarly, segments without crash rate data were excluded from analyses involving non-emergency and emergency periods. The number of observations for each analysis can be seen next to the correlation coefficients in each table.

Table 8: Hurricane Irma Pearson Correlation Test

	Non-Emergency Period Crash Rate	Evacuation Period Crash Rate	Re-entry Period Crash Rate	Emergency Period Crash Rates
Non-Emergency Crash Rate	1.0			
Evacuation Crash Rate	0.91 (24)	1.0		
Re-entry Crash Rate	0.57 (26)	0.62 (19)	1.0	
Emergency Crash Rates	0.78 (31)	0.89 (24)	0.91 (26)	1.0

Table 9: Hurricane Matthew Pearson Correlation Test

	Non-Emergency Period Crash Rate	Evacuation Period Crash Rate	Reentry Period Crash Rate	Emergency Period Crash Rate
Non-Emergency Crash Rate	1.0			
Evacuation Crash Rate	0.63 (10)	1.0		
Reentry Crash Rate	0.10 (11)	0.47 (5)	1.0	
Emergency Crash Rate	0.15 (16)	0.73 (10)	0.95 (11)	1.0

Table 10: All Hurricane Crash Rates Pearson Correlation Test

	Non-Emergency Period Crash Rate	Evacuation Period Crash Rate	Re-entry Period Crash Rate	Emergency Period Crash Rates
Non-Emergency Crash Rate	1.0			
Evacuation Crash Rate	0.79 (38)	1.0		
Re-entry Crash Rate	0.45 (39)	0.65 (25)	1.0	
Emergency Crash Rates	0.74 (52)	0.90 (38)	0.92 (38)	1.0

5.0 DISCUSSION

An important note to acknowledge is the size of hurricane Irma compared to hurricanes Michael and Matthew. As previously mentioned, Hurricane Irma's trajectory shifted prior to landfall, necessitating more widespread mandatory evacuations. Consequently, a greater number of segments were available for study, and the evacuation period emerged as the largest in this investigation. It is crucial to acknowledge that when amalgamating crash rates across all hurricanes and conducting statistical analyses, Hurricane Irma's dominance in terms of both the number of segments and the duration of the evacuation period may have introduced bias into the results.

The Pearson Correlation test was performed for each hurricane and for all crash rates from all hurricanes combined to see if the crash rate results are correlated between all periods. The test suggested that the crash rates have a strong positive correlation. This suggests that when a segment has a high crash rate, the crash rate during evacuation, re-entry, or during the entire emergency period, while it is smaller than during the non-emergency period, it is high on the scale for the evacuation period. These results are illustrated in Table 8, Table 9, and Table 10.

The results from Table 12, Table 13, and Table 14, indicated by the paired t-test, conclude there is significant difference between non-emergency and evacuation period crash rates, non-emergency and re-entry crash rates, and non-emergency and emergency crash rates. The mean for all three analyses were significantly different, and the correlation coefficient indicated that these three different comparisons are likely correlated. Roadways that have high crash rates during non-emergency periods are still functioning at a high crash rate during evacuations, however, the difference is that non-emergency crash rates are significantly higher than during these periods.

Table 13 illustrates that evacuation and re-entry crash rates are directly correlated based on the correlation coefficient. However, interestingly the mean and variance of these crash rates are almost equivalent. This indicates that the safety aspect for drivers during evacuations and re-entry is relatively consistent.

To review, the original hypothesis was thought that crash rates would be similar during all periods: non-emergency, evacuation, re-entry, and emergency. The paired t-test illustrated in APPENDIX C – PAIRED t-TEST RESULTS

Table 11, Table 12, and Table 14 rejected the null hypothesis of equal means for these three tests. However, Table 13's paired t-test on evacuation and re-entry crash rates failed to reject the null hypothesis of equal means.

The results illustrated in Table 4, Table 5, and Table 6 conclude that crash rates during non-emergency periods are roughly two orders of magnitude higher when compared to crash rates for evacuation, re-entry, and non-emergency periods. Due to the extreme of the situation during emergency periods, distracted driving could be less present on the roadways. Along with this, volumes and the flow of traffic is out of the normal traffic patterns during an emergency period, perhaps causing an impact on crash rates.

Psychological factors that could impact driving patterns and crash rates during emergency periods are stress, fear, anxiety, urgency, among others. Along with this, physical factors could also affect crash rates such as drunk/drugged driving, the small period of analysis, slower speeds, day versus night driving, weather, etc. For instance, most evacuees travel during the daytime and there is better weather before and after a hurricane. This allows for more visible and safe driving conditions. Speeding may not be as common during the emergency period compared to non-emergency due to visible police enforcing speed limits. Higher vehicle occupancy during evacuations could result in lower crash rates during evacuations and re-entries.

It is important to note that since evacuation and re-entry periods are less than a week, the bulk of crashes that happen throughout the year take place during the non-emergency period for each year. Along with this, because evacuations and re-entries are during emergencies, vehicle operators may be less likely to report minor crashes during these periods.

With the number of days being an input into the crash rates, this could suggest that more observations are needed during emergency periods. With this, the evacuation and re-entry periods were suggested based off a traffic volumes and government orders, as discussed. If more days were involved during an evacuation or re-entry, then this could result in different crash rates. However, using statistical analysis and observing the flow of traffic across all sights within ten miles of an evacuated zone was considered the best process to suggest the duration of the evacuation and re-entry periods for all storms. Considering the mass of evacuation routes available to the public within ten miles of a zone, the percentage of evacuees who took these routes was considered high. As most evacuees would choose the most convenient and efficient exit from the area at risk of hurricane damage.

The limitations of this study include the database used to access crashes in the counties that was under a mandatory evacuation order for Hurricane Michael, Irma, and Matthew. The FDOT crash data is based on police reports of the crashes that occur in Florida, along with vehicle operators reporting all crashes. Technology limitations also applied in the sense that FDOT telemeter traffic sites were damaged or unresponsive during certain times of the year, resulting in a loss of volume counts. Specifically, if traffic sites are damaged and did not record vehicle volumes on any day during the evacuation or re-entry periods, the sites had to be removed due to error, resulting in the loss of viable data. An example of this can be seen in Appendix B, Figure 5. Thus, resulting in the loss of potential segments, observations, and crash rates.

Although there were limitations in this study, measures were taken to assure the accuracy of this research through data processing, geospatial boundaries, and error removals. The same process that was used for one storm was carried out thoroughly for the remaining storm evaluations. Statistical analysis was then used to compare the results and show that the chance of the crash rates being a result of randomness was likely less than a 0.02 percent chance. Resulting in reassuring findings and furthering the future of transportation safety during emergency periods.

6.0 CONCLUSION

In general, the results of this research showed that non-emergency period crash rates are two orders of magnitude larger than rates during evacuations, re-entries, and emergency periods. An example of this is illustrated in Table 4. These findings were unexpected, which leads to the need for future work to be completed to understand and further these observations. These results likely stemmed from evacuees being more observant and having lower speeds when fleeing or returning to residential areas during emergency periods compared to non-emergency periods (Collins, Foytik, Frydenlund, Robinson, & Jordan, 2014). A significant finding was the relationship between non-emergency period crash rates to evacuation and re-entry rates were correlated throughout all three storms studied. Non-emergency period crash rates were considerably higher compared to all other emergency period rates. Hurricane Irma, Matthew, and Michael affected a different part of the start of Florida. Driving patterns can vary between different areas within a state. Although the hurricanes hit different parts of the state, resulting in different zones being evacuated per storm, crash rate patterns were consistent across all periods for all three hurricane studies.

It should be noted that the road segment that has the highest crash rate during the non-emergency period also tended to have the highest crash rate in the evacuation period. This can be seen in Table 5, cosite 860384 has the highest non-emergency and evacuation ranked crash rate. This trend persists across Hurricanes Michael and Matthew datasets. Given the observed correlation (0.91) between crash rates during non-emergency and evacuation periods for

Hurricane Irma, enhancing safety measures on a segment would not only mitigate risks during non-emergency periods but also significantly enhance safety during evacuations.

This research suggests the crash rates during evacuation and re-entry periods were significantly smaller when compared to crash rates during non-emergency periods for hurricanes Irma, Matthew, and Michael. Investigating this was important as there are gaps in research over understanding crash rates during evacuations, re-entry, and non-emergency periods. As well as the large population this research relates to. Those that live along coastal waterways are affected every year by evacuations as there are often several hurricanes that threaten the public's safety. Hurricane evacuations affect a large portion of the population as the coastline of the United States is over 95,000 miles (NOAA, 2023). This research was important to perform to learn about the conditions present in relation to crashes during emergency periods for different hurricanes. However, along with this, understanding crash rates, and how rates are smaller during emergency periods, could lead to more safety precautions and safer roadways during non-emergency periods with further research.

Recommendations for future research would be to widen the regional boundary of segments studied, along with looking at zones and counties that had volunteer evacuations to see if these crash rate results stayed consistent. This research is relevant on a national level in the United States. By investigating crash rates during emergency periods in all states residing on coasts that experience hurricane threats could lead to a deeper understanding of evacuation and re-entry safety.

Based on the findings of this research it is expected that a deeper investigation into the phenomenon as to why and if crash rates during non-emergency periods are consistently higher than rates during emergency periods. Future researchers will be able to build upon this work by investigating past and future hurricanes based in Florida, along with investigating this phenomenon nationally. An area in particular that this research could be of significance is hurricane vulnerable areas that carry dense populations. For example, Louisiana is below sea level, leaving this state vulnerable during hurricanes and storm surges, resulting in large scale evacuations. This was proven of relevance in New Orleans by past research of living below sea level (Link, 2010). From an application perspective it is suggested that these results can be used for adding safety measures to driving in non-emergency periods, as well as looking to improve driving and safety conditions during emergency periods. This would improve the current practice of transportation safety because a deeper understanding of a decline in crash rates during different driving environments and time periods was observed.

7.0 REFERENCES

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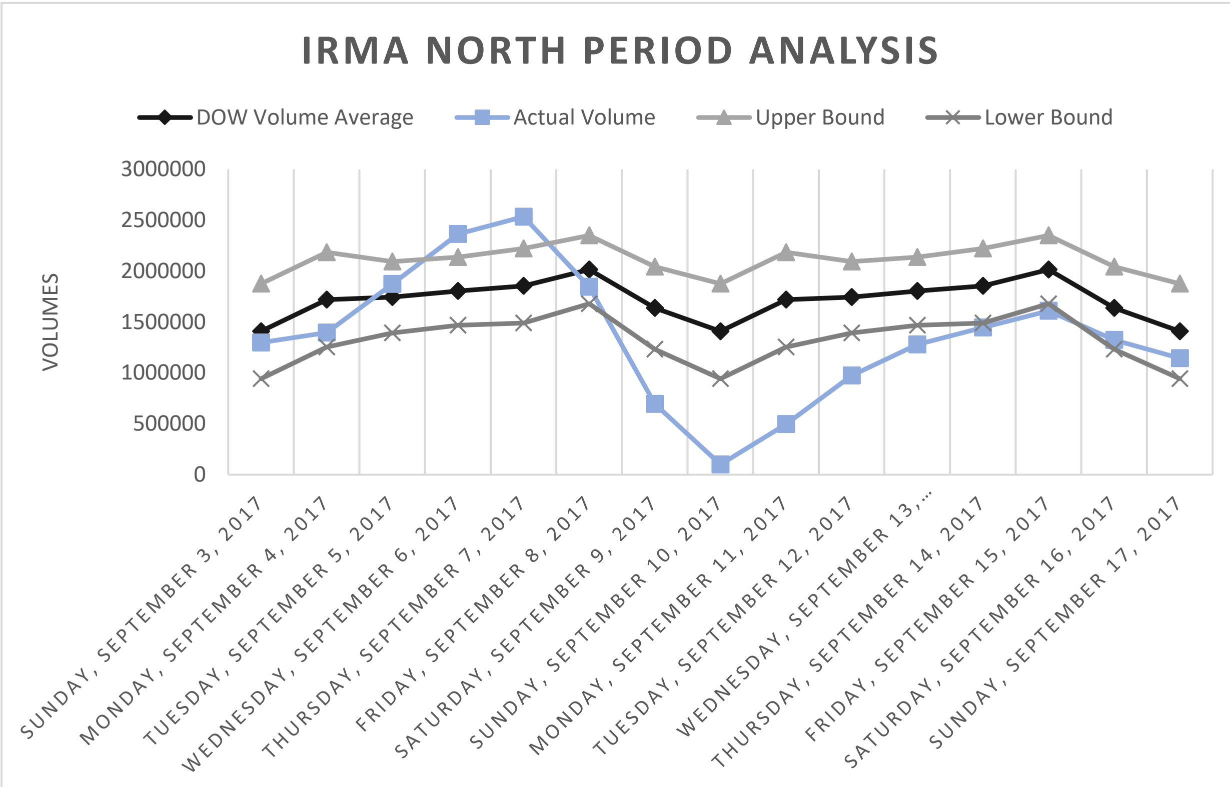
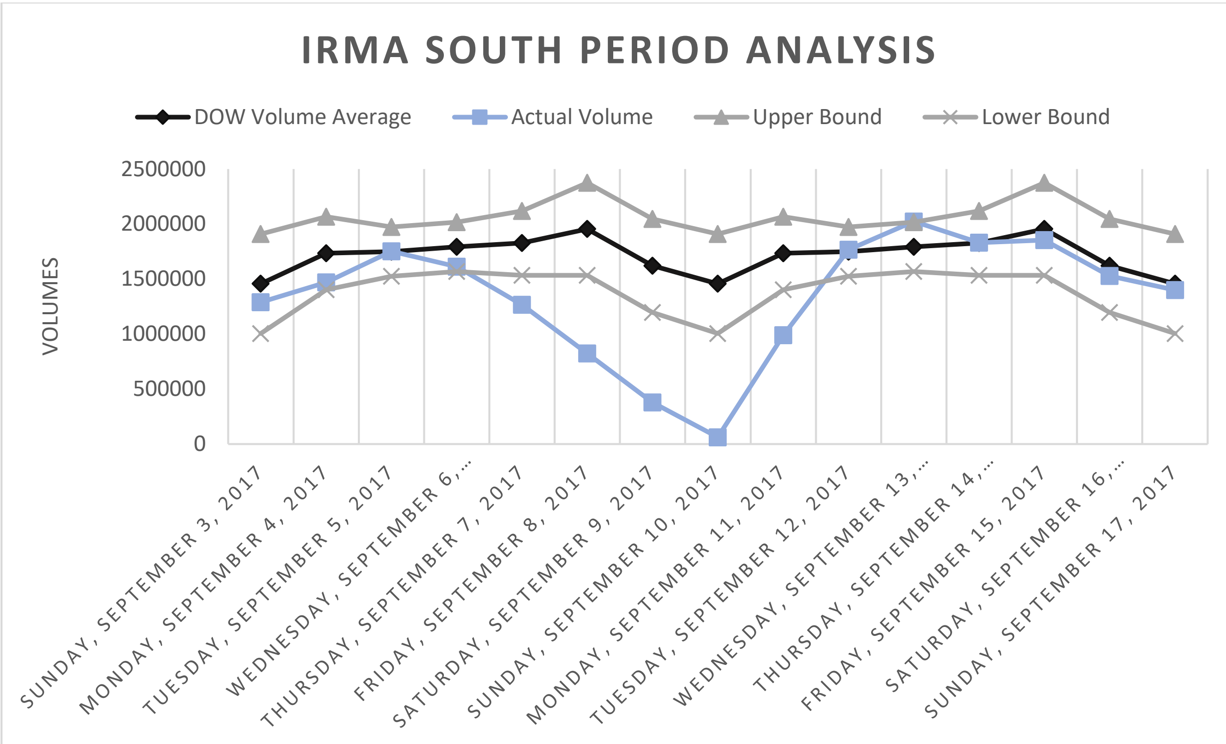
APPENDICIES

APPENDIX A – HURRICANE THREE PERIOD ANALYSES

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TUESDAY, SEPTEMBER 5, 2017
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THURSDAY, SEPTEMBER 7, 2017
FRIDAY, SEPTEMBER 8, 2017
SATURDAY, SEPTEMBER 9, 2017
SUNDAY, SEPTEMBER 10, 2017
MONDAY, SEPTEMBER 11, 2017
TUESDAY, SEPTEMBER 12, 2017
WEDNESDAY, SEPTEMBER 13,…
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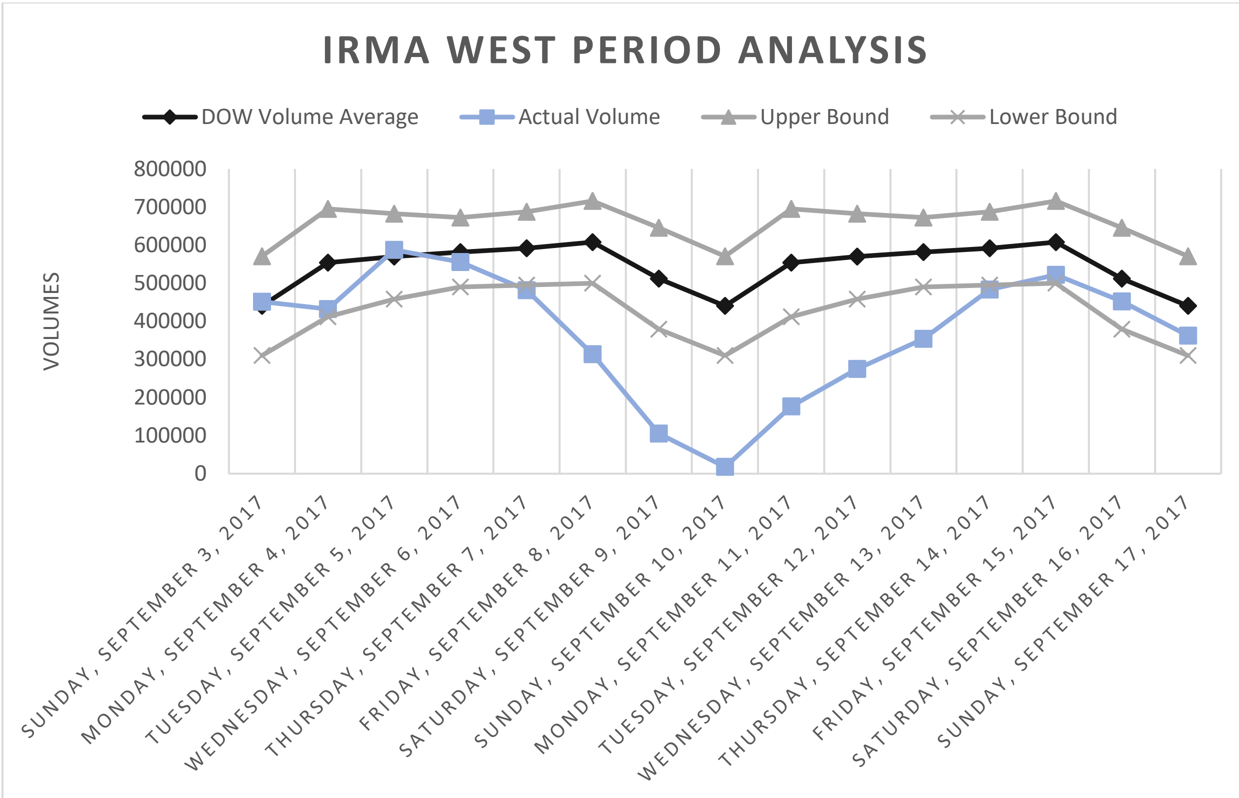
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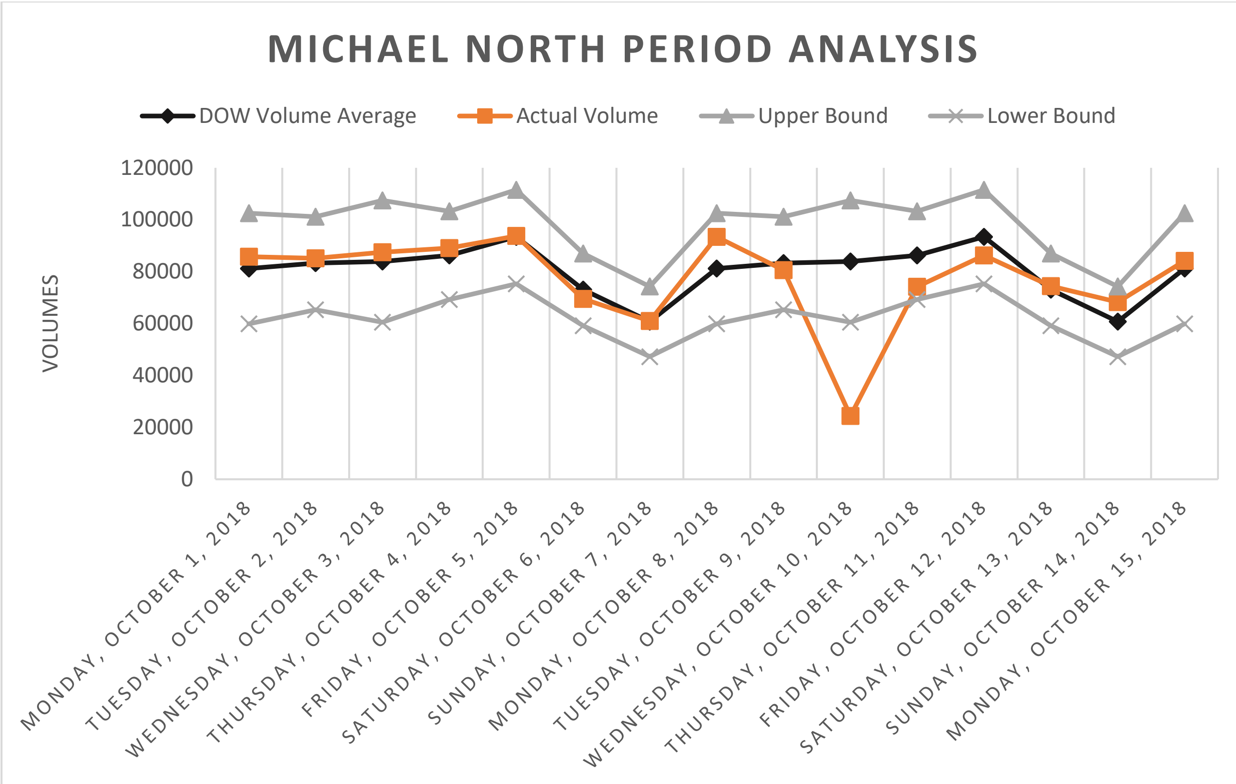
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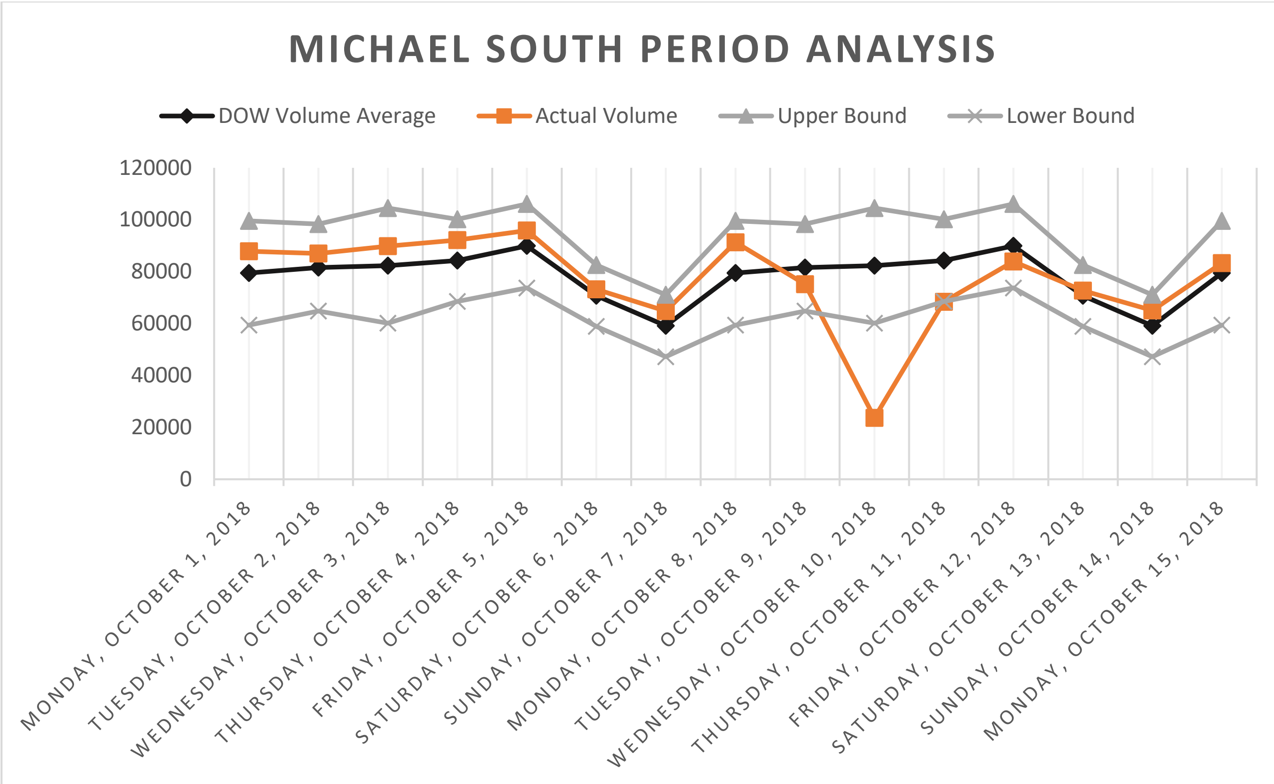
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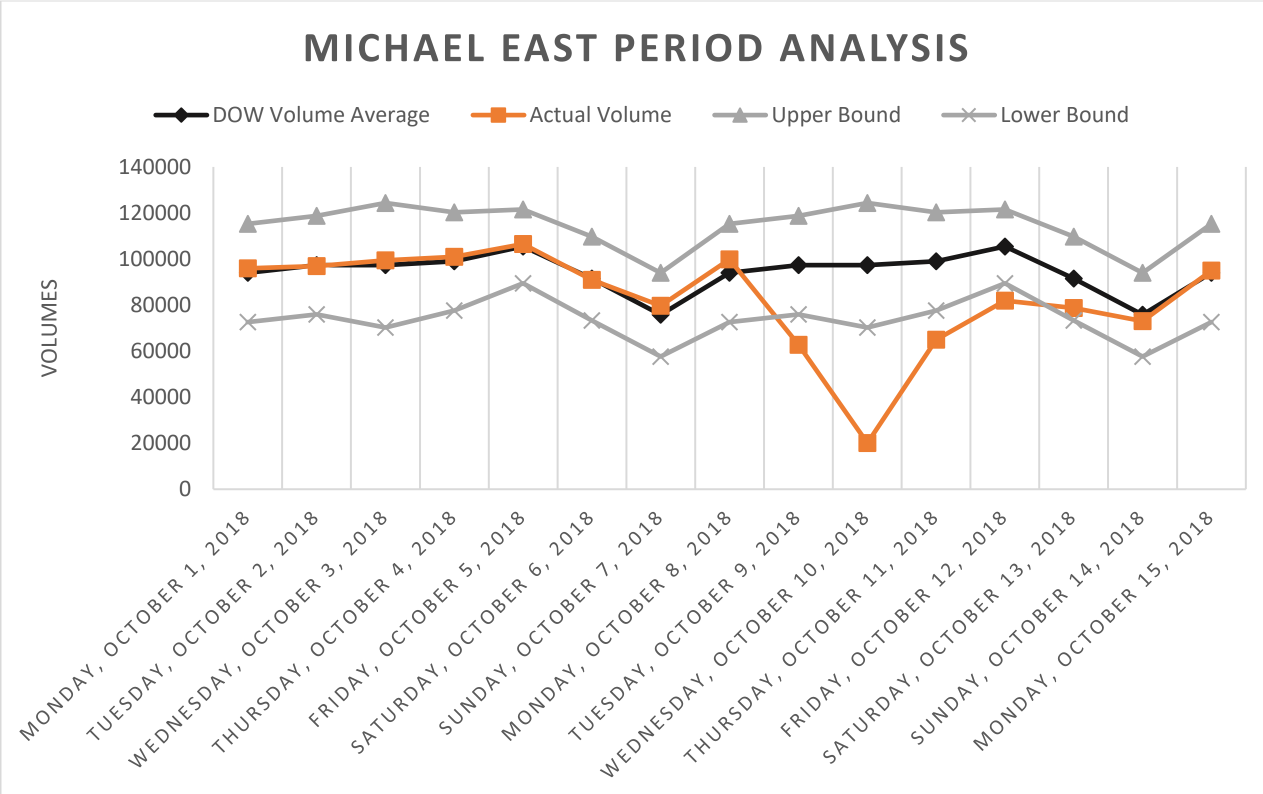
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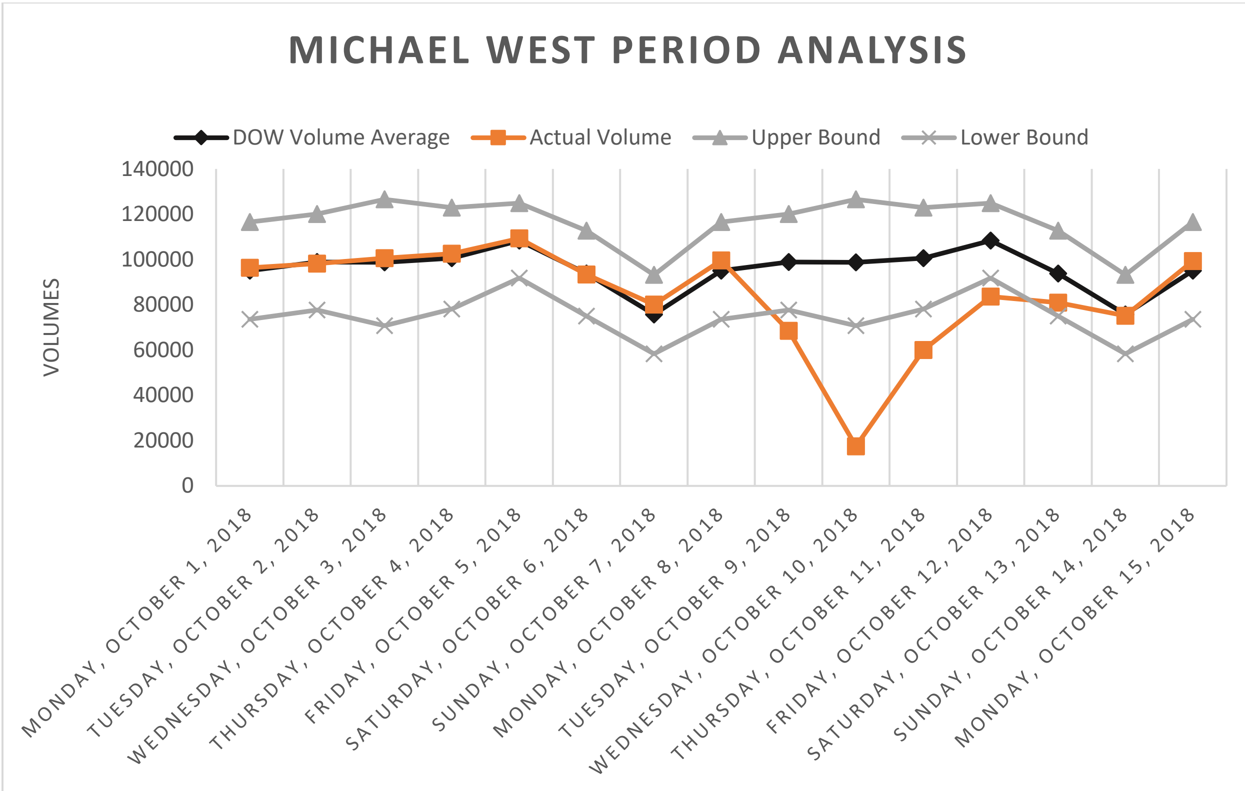
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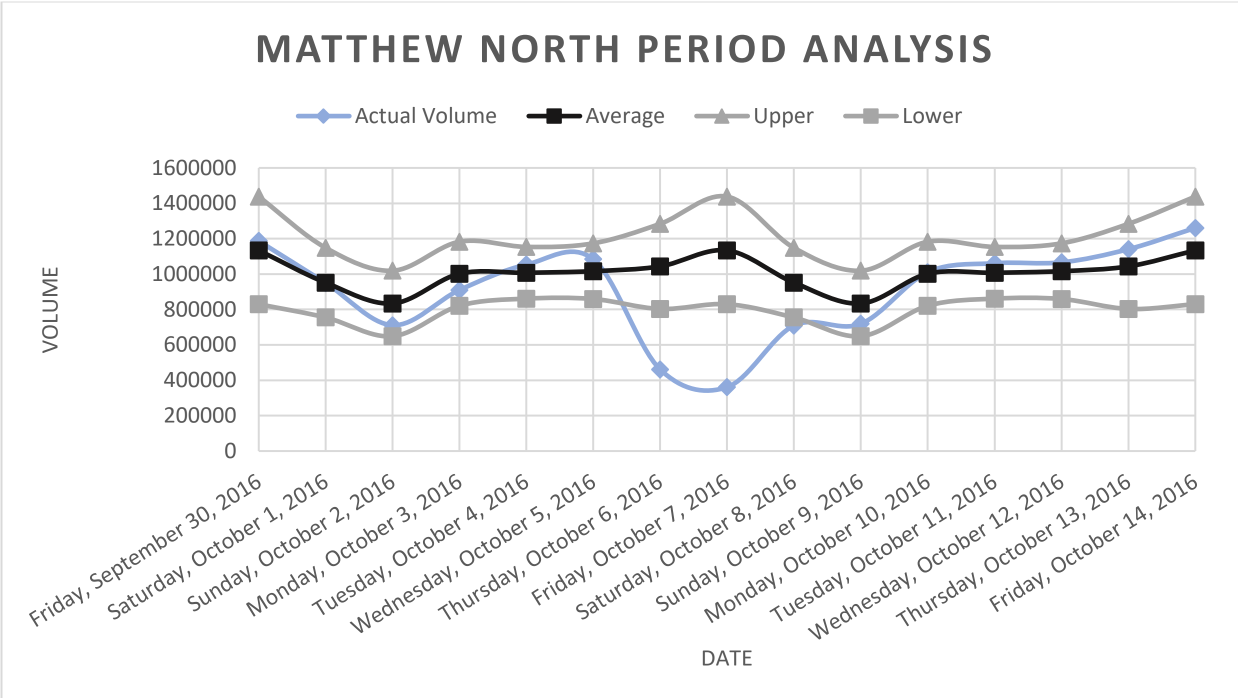
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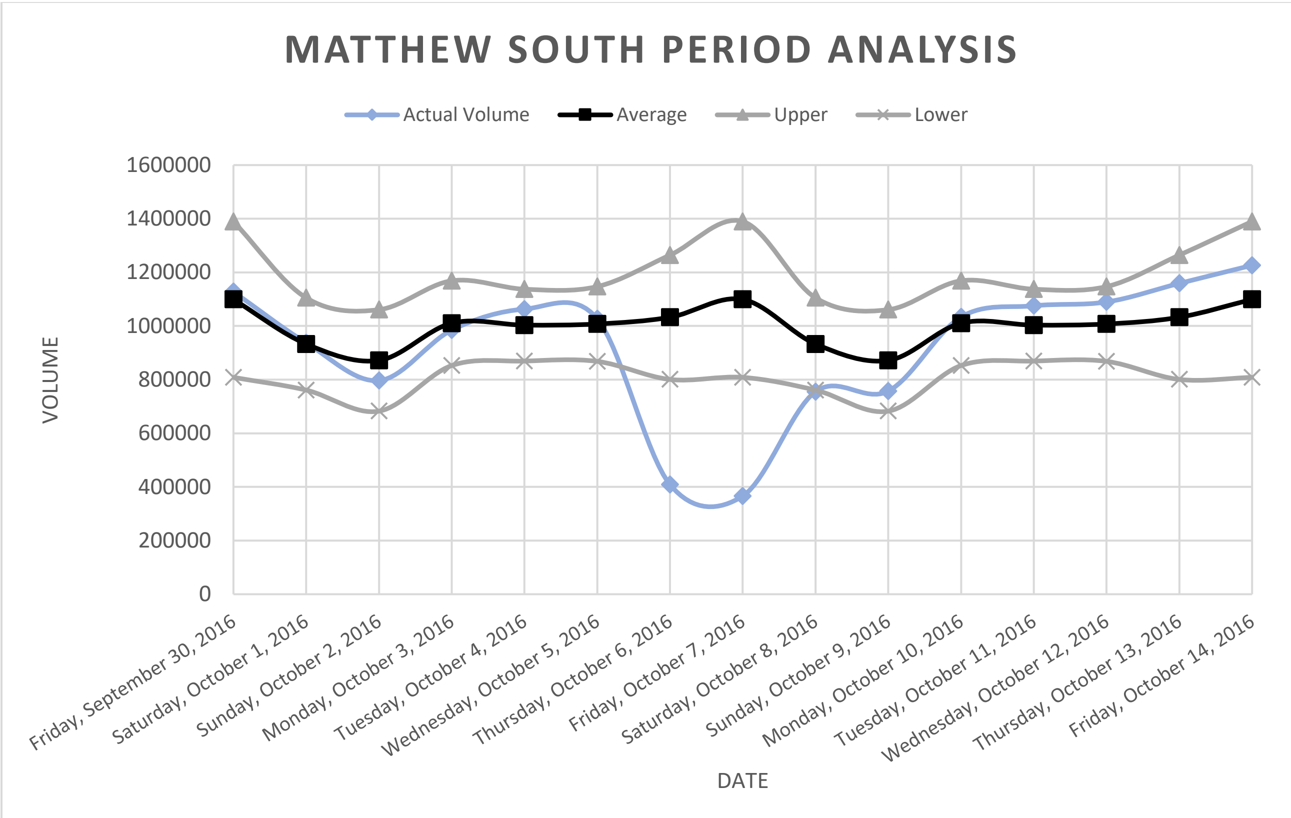
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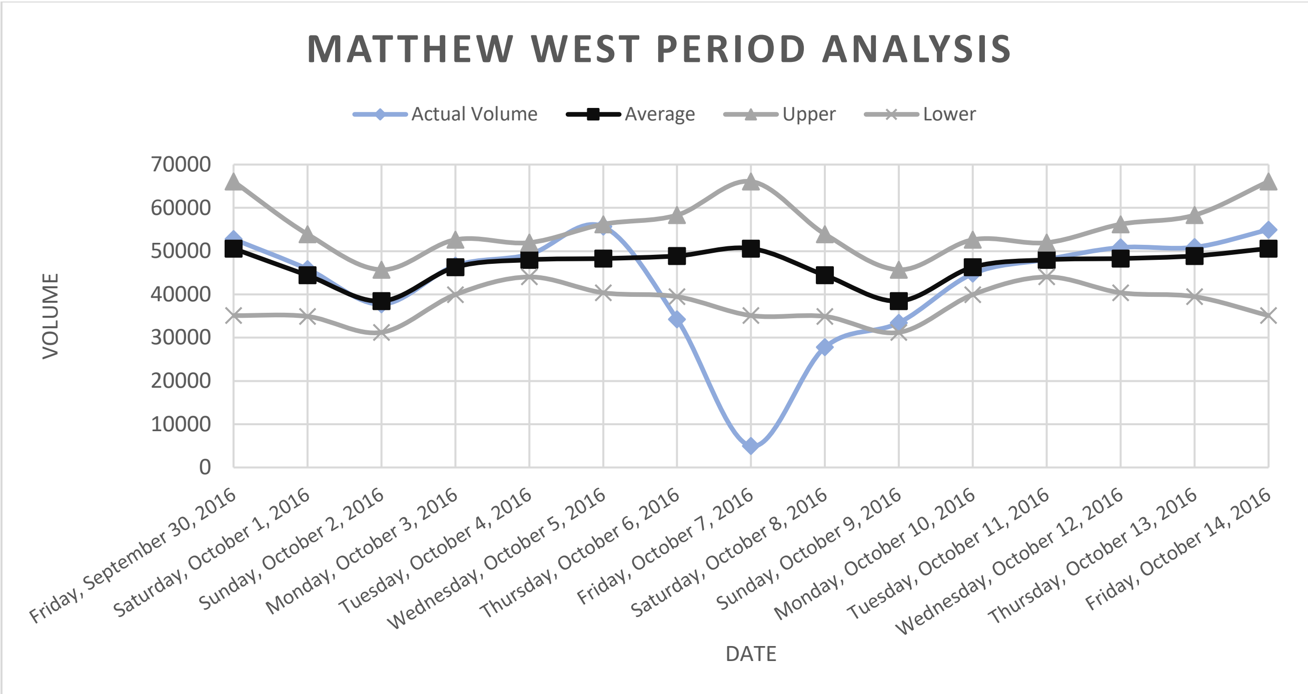

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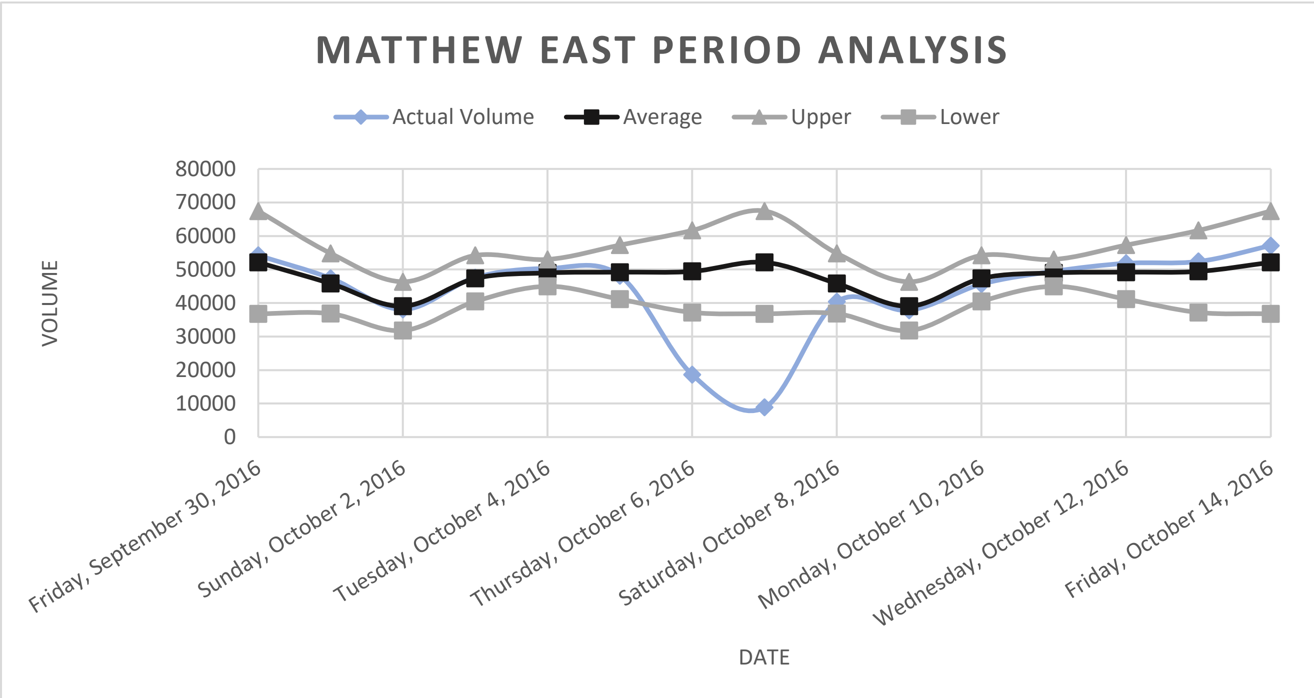
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APPENDIX B – COSITE EMERGENCY PERIOD TRAFFIC SITE ERROR

Cosite	County	COUNT	Site	SITE	BEGDATE	DIR	HR1	HR2	HR3	HR4	HR5	HR6	HR7	HR8	HR9	HR10	HR11	HR12	HR13	HR14	HR15	HR16	HR17	HR18
340116	34	34	0116	116	1-Sep-17	N	38	30	27	32	35	83	144	233	305	391	549	573	586	661	669	763	773	815
340116	34	34	0116	116	1-Sep-17	S	46	37	26	31	63	85	192	422	435	465	521	544	561	583	570	620	572	569
340116	34	34	0116	116	2-Sep-17	N	117	67	39	35	34	51	106	173	270	376	456	581	603	627	559	445	436	370
340116	34	34	0116	116	2-Sep-17	S	67	54	37	24	29	68	128	189	285	438	512	614	514	499	408	468	348	327
340116	34	34	0116	116	3-Sep-17	N	60	30	12	21	12	38	63	92	176	239	357	416	413	420	462	402	339	345
340116	34	34	0116	116	3-Sep-17	S	43	28	39	21	18	28	78	111	210	315	368	420	465	465	416	421	369	394
340116	34	34	0116	116	4-Sep-17	N	31	24	17	17	14	37	81	111	164	254	363	453	498	537	569	510	475	407
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340116	34	34	0116	116	5-Sep-17	N	40	29	23	23	35	95	153	214	299	362	391	440	492	520	548	579	568	559
340116	34	34	0116	116	5-Sep-17	S	43	26	17	45	79	102	203	435	411	450	453	496	496	502	513	568	437	379
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340116	34	34	0116	116	13-Sep-17	N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	358	380	424
340116	34	34	0116	116	13-Sep-17	S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1505	1373	998
340116	34	34	0116	116	14-Sep-17	N	55	18	17	19	34	67	100	174	205	253	342	350	397	390	432	431	406	440
340116	34	34	0116	116	14-Sep-17	S	187	114	104	116	88	170	239	412	554	627	744	886	853	833	879	851	746	694
340116	34	34	0116	116	15-Sep-17	N	38	24	16	35	28	58	99	184	258	277	362	423	463	431	489	577	535	579
340116	34	34	0116	116	15-Sep-17	S	78	49	49	55	63	112	213	404	429	525	604	708	741	794	748	713	672	641
340116	34	34	0116	116	16-Sep-17	N	77	42	24	25	29	46	67	164	159	297	330	395	434	463	426	436	367	325
340116	34	34	0116	116	16-Sep-17	S	87	46	43	51	43	65	124	186	307	410	548	603	618	651	539	541	504	421

Figure 5: Cosite 340116 Error, Missing Volume Counts During Evacuation Period

APPENDIX C – PAIRED t-TEST RESULTS

Table 11: Pair t-Test between Non-emergency and Evacuation Period

	Non-emergency	Evacuation
Mean	302.6195891	4.178552027
Variance	88969.10559	18.80300812
Observations	20	20
Pearson Correlation	0.914773362	
Hypothesized Mean Difference	0	
df	19	
t Stat	4.534824783	
P(T<=t) one-tail	0.0001133	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.0226562%	
t Critical two-tail	2.093024054	

Table 12: Pair t-Test between Non-emergency and Re-entry Period

	Non-emergency	Re-entry
Mean	302.6195891	4.323284429
Variance	88969.10559	17.29330158
Observations	20	20
Pearson Correlation	0.692603797	
Hypothesized Mean Difference	0	
df	19	
t Stat	4.515801692	
P(T<=t) one-tail	0.000118275	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.02366%	
t Critical two-tail	2.093024054	

Table 13: Paired t-Test between Evacuation and Re-entry Period

	Evacuation	Re-entry
Mean	4.178552027	4.323284429
Variance	18.80300812	17.29330158
Observations	20	20
Pearson Correlation	0.618873403	
Hypothesized Mean Difference	0	
df	19	
t Stat	-0.174383913	
P(T<=t) one-tail	0.431704234	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	86.3408%	
t Critical two-tail	2.093024054	

Table 14: Paired t-Test between Non-emergency and Emergency Period

	Non-emergency	Emergency
Mean	302.6195891	8.470464924
Variance	88969.10559	56.98553486
Observations	20	20
Pearson Correlation	0.885219473	
Hypothesized Mean Difference	0	
df	19	
t Stat	4.510988993	
P(T<=t) one-tail	0.000119573	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.000239147	
t Critical two-tail	2.093024054	

APPENDIX D – HURRICANE CRASHES PER PERIOD

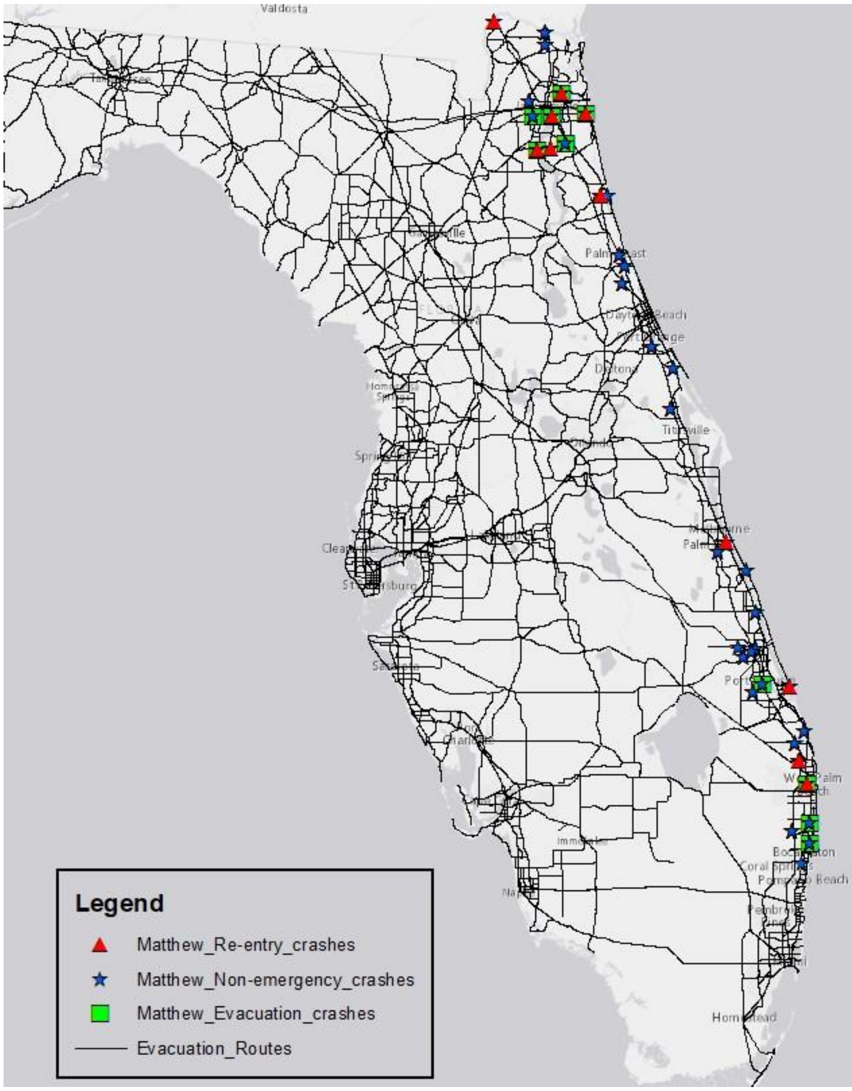

Figure 6: Hurricane Matthew Period Crash Map

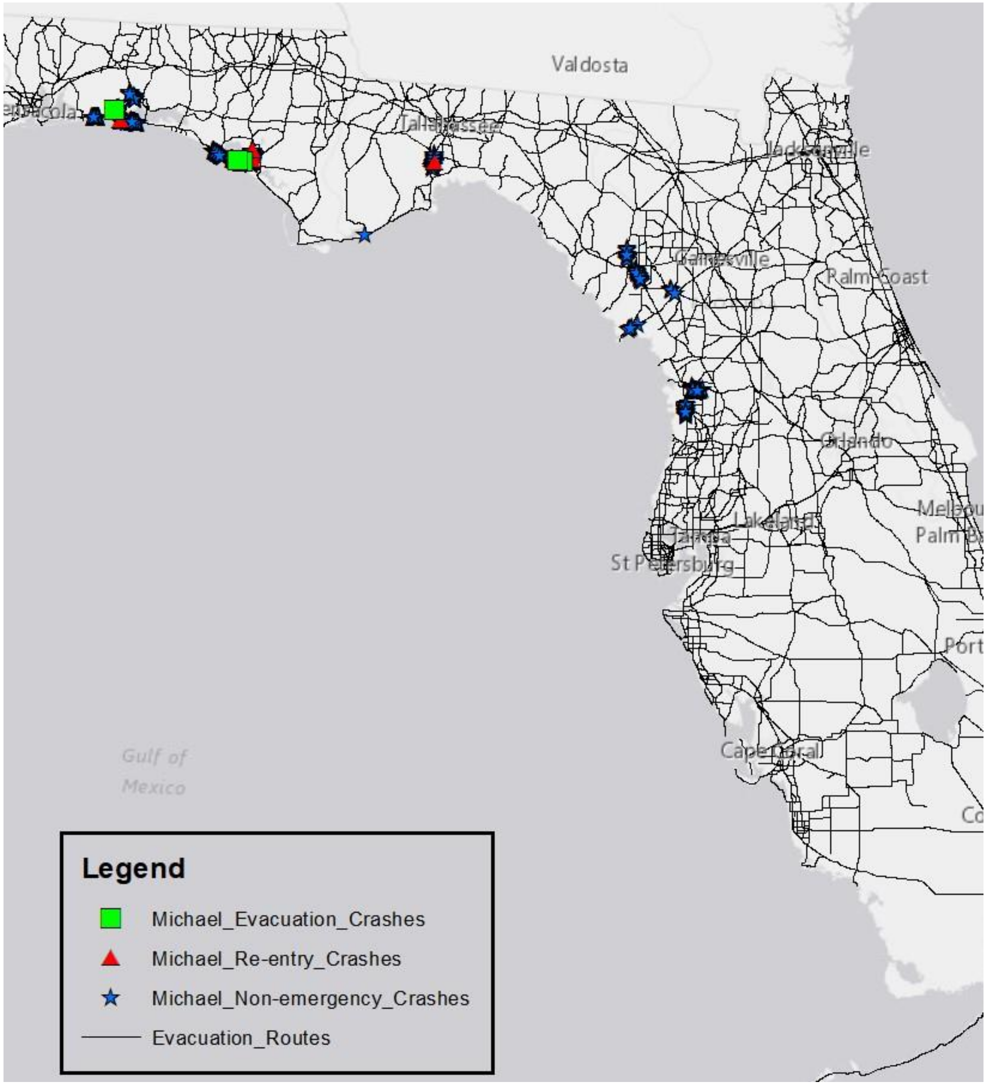

Figure 7: Hurricane Michael Period Crash Map