Understanding Network Wide Hurricane Evacuation Traffic Pattern from Large-scale Traffic Detector Data

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Abstract— **In this study, we develop a data pipeline incorporating automated data quality checking, data imputation, and spatiotemporal visualization of large-scale traffic data to understand the changes in traffic patterns during hurricane evacuation as it unfolds. We collect large-scale Microwave Vehicle Detection System (MVDS) data during Hurricane Irma from four highways in Florida: I-75, I-95, I-4, and Florida Turnpike that served majority of the evacuation traffic. Based on an extensive analysis, we provide insights on network wide spatiotemporal evacuation traffic patterns of Hurricane Irma. Such insights will help transportation agencies recognize the utility of large-scale real-time data, previously unused, to better understand the extent and spatiotemporal distribution of evacuation traffic. To demonstrate this, we analyze the processed data to understand the influence of different spatiotemporal factors on the changes in evacuation traffic pattern. Our results show at least an 18-hour (approximately) time lag between the time of issuing an evacuation order and the time when people first started to evacuate in large numbers. Such findings have potential implications to deal with the challenges of mass evacuation in real time and allows us to develop large-scale network level evacuation traffic prediction model.**

I. Introduction

In recent times, coastal regions of the United States have faced major hurricanes such as Hurricanes Matthew, Harvey, Irma, and Dorian. Devastating experiences from these recent hurricanes, for instance, extensive damage to property and loss of lives [1], have induced a major concern to improve the efficiency of evacuation management systems. During Hurricane Irma, about 6.5 million residents of Florida evacuated, from major cities including Key West, Miami, and Tampa. With only two major interstate highways (I-75 and I-95) available for leaving Florida, evacuation caused a significant amount of traffic congestion and crashes affecting the physical and mental health of evacuees. Under a hurricane evacuation, it is critical for emergency agencies to ensure smooth operations of infrastructure systems and emergency services. Efficient traffic operations can maximize the utilization of existing transportation infrastructure, reducing evacuation time and stress due to massive congestion.

Efficient evacuation traffic management requires detailed evacuation plan [2] including proactive measures to overcome unexpected events such as traffic incidents, a change of hurricane path causing unexpected demand surge etc. Failure to address these factors could result in potentially sub-optimal traffic operation causing severe traffic congestion and delay. For example, during hurricane Katrina, only 60% of the projected vulnerable people were able to evacuate, while during Hurricane Rita enormous response to evacuation orders created excessive traffic problems (e.g., 100-mile-long traffic jams, out of fuel etc.) and dozens of accidents or heat related deaths [3]. Optimal evacuation planning largely depends on better understanding of evacuation traffic behavior from historical data, proactive measures incorporating real-time data, and reliable models to project evacuation travel demand.

However, previous hurricane evacuation studies mainly focused on understanding the factors relating to evacuation decisions [4]–[9], mobilization time [10], departure time [11], [12], and destination choice [13], [14]. Although many studies have been conducted on individual-level evacuation decision making [8], [15]–[20] to forecast evacuation demand, these approaches highly depend on survey data that are difficult to collect as a hurricane unfolds in real time. Although traffic detectors have widely been deployed in major highways in the USA, previous studies did not explore the capacity of these detectors data for network level traffic analysis and modeling for real time evacuation traffic prediction. Lack of confidence on the reliability of these data sources, lack of tools to automatically test the data quality, and challenges to deal with such massive multiresolution data, may discourage transportation agencies and researchers to utilize these data sources for large-scale traffic modeling.

In this study, we build a data pipeline incorporating automated data quality checking, data imputation, and spatiotemporal visualization of network wide traffic to understand the changes in traffic patterns during hurricane evacuation. We collect Microwave Vehicle Detection System (MVDS) data for four major highways in Florida: I-75, I-95, I-4 and Florida Turnpike, these routes serve most of the evacuation traffic during Hurricane Irma and extensively analyze these data to understand the nature and extent of Hurricane Irma's evacuation traffic and the quality of these data for evacuation traffic modeling. Moreover, different factors such as time and place of evacuation order, population under evacuation order, location of the evacuees, evacuation start time, and traffic congestion are critical to predict evacuation traffic demand in future hurricanes. Since MVDS detectors are widely deployed in major highways of Florida, we perform an empirical analysis to understand the impact of these spatiotemporal factors on evacuation traffic patterns. Thus, this study has made several contributions for evacuation traffic analysis and modeling using large-scale traffic detector data:

- It identifies a new data source to understand evacuation traffic in real time.
- It develops a data pipeline incorporating extensive data assessment approaches to examine the quality of the network wide traffic detectors' data including imputation techniques for evacuation traffic analysis and modeling.
- It analyzes large-scale traffic detector data during Hurricane Irma's evacuation, providing insights on network wide spatiotemporal patterns of evacuation

traffic. The data and insights obtained will help emergency agencies better understand the extent and spatiotemporal distribution of evacuation traffic.

- It assesses the influence of different spatiotemporal features on changes in evacuation traffic patterns.

The findings of this study have potential implications to deal with the challenges in large-scale network level evacuation traffic management.

II. DATA DESCRIPTION

Hurricane Irma made its landfall at Florida Keys on September 10, 2017 at category 4 intensity; then it passed over several regions of Florida between September 10, 2017 and September 12, 2017. Prior to the landfall, the authorities started ordering mass evacuation from September 6, 2017 for different evacuation zones based on the location and projection of hurricane path. A massive demand surge was seen on the highways after these evacuation orders were issued. To understand major evacuation routes, we observed previous evacuations patterns, which show that a large portion of residents living in Florida evacuates to Georgia or adjacent States. Thus, two major highways I-75, I95 and other two highways I-4 and Florida Turnpike connecting them were expected to serve a substantial amount of evacuation traffic during Hurricane Irma.

To analyze evacuation traffic patterns, we have collected traffic data for the northbound direction of I-95, I-75, Florida Turnpike, and eastbound direction of I-4 (Fig. 1). We have collected data form Regional Integrated Transportation Information System (RITIS) from September 4, 2017 to September 9, 2017. RITIS gathers data from Microwave Vehicle Detection System (MVDS) detectors deployed by the Florida DOT, giving real-time information on traffic speed, volume, and occupancy at a very high resolution (20 to 30s frequency). For analysis purpose, we aggregate the data over 5 min interval.

Figure. 1. Distributions of the 1426 detectors in the study network

In general, MVDS detectors have a minimum 200-feet range and the capability to detect 8 lanes of traffic. These detectors cover multidirectional traffic and most of the entry and exit ramps; the distance between two consecutive detectors varies between 0.5 and 1.5 miles. We extract information from 1426 detectors without any entry or exit ramp detectors (Fig. 1).

III. DATA PRE-PROCESSING

The raw data collected from traffic detectors are subjected to errors. Several factors such as detector's malfunctioning, false encoding during storing the data into the server, overlapping of multiple entries, duplicate entries, bad weather conditions etc. can cause errors. Moreover, during congested stop and go traffic conditions, sometimes microwave radar detectors fail to detect vehicles, hence provide misleading information. Therefore, before proceeding to any data analysis, we need an extensive data cleaning and quality checking. Fig. 2 shows the framework for the data processing steps.

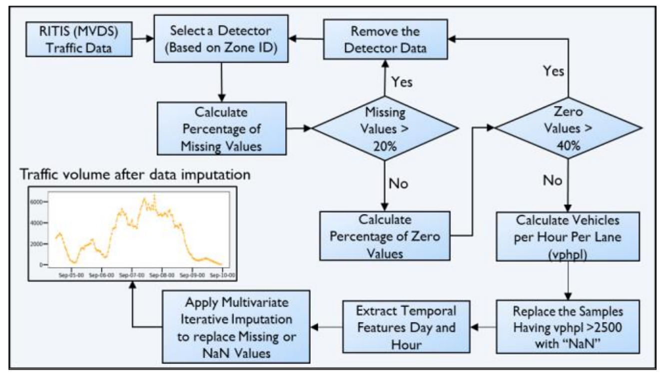


Figure 2. Framework for data processing

To check the quality of the data, we followed several steps starting with checking the percentage of missing data for different detectors. We consider the detectors having a higher percentage of missing values as unreliable ones. Moreover, data imputation is not feasible for the detectors with too many missing values as it will produce unrealistic data distribution. Considering this issue, we retain the detectors having missing values less than 20% of total data samples. Moreover, we find a few detectors with higher percentage of zero entries. Considering the regular traffic pattern on freeways, we expect near zero or minimal traffic flow during nighttime, especially from 10 pm to 5 am, which means about 25% of the total entries per day per detector could be zero. However, during evacuation, mostly from September 06 – September 08, 2017, we may not see this trend, there will be a large number of vehicles throughout the day regardless of the time. Additionally, since Hurricane Irma made its landfall on September 10, we expect minimal traffic on September 9, 2017. Thus, it is likely that 30-40% data for each detector might have zero entries. However, we observe that some detectors have between 40% and 100% zero values, which indicates anomaly in vehicle detection. Therefore, we remove the detectors with more than 40% zero entries.

We also consider the lane capacity of the highways. In regular periods under free flow condition, the capacity of a highway segment varies from 2,000 to 2,400 *vehicle per hour per lane* (vphpl) depending on the prevailing traffic speed. However, during evacuation there could be a significant reduction in traffic speed. We analyzed the traffic speed for I-75 during Hurricane Irma's evacuation and found average traffic speed varying from 50 mph to 65 mph. Thus, overall capacity of the highways (2,000 vphpl) should be less than theoretical values. However, we cannot directly estimate actual highway capacity, it depends on many factors such as incidents, traffic crashes, lane closures etc. which can substantially reduce capacity. On the other hand, emergency shoulders use (ESU) during evacuation can increase overall capacity. During Hurricane Irma's evacuation ESUs were used from September 7- September 9, 2017 to help evacuating traffic along I-75. Such ESUs increase the overall throughput of the roadways by 25% [21]. Thus, we consider the maximum possible capacity of the highway as 2500 vphpl. For each detector data sample, we divide the total traffic volume per hour by the number of lanes to obtain vehicles per hour per lane (vphpl), these values should remain close to the maximum capacity (2500 vphpl).

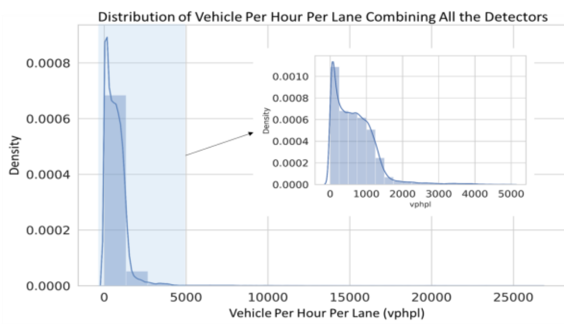


Figure. 3. Distribution of data samples based on vehicles per hour per lane

Fig. 3 shows the distribution of vphpl values combining all the detectors' data. Almost all the data samples except a few, have vphpl less than 2500. A few data samples show unrealistic values, nearly 25,000 vphpl. We check all the detectors individually and find that, for most of the detectors, less than 5% of data samples show higher values of vphpl compared to per lanes capacity. For each detector, the erroneous volume (corresponding to vphpl > 2500) is replaced with "NaN" values.

Later, we use a technique known as multivariate iterative imputation adapting Bayesian ridge regression as estimator to impute the missing or "NaN" values. To fit the estimator, we use time of the day (hour), day of the week (day), and volume with missing values as inputs. For each imputation the algorithm takes a sample from gaussian posterior of the fitted estimator. We use Python scikit learn [22] library to implement the algorithm. The details about the data imputation algorithm are provided in reference [23].

IV. Data Exploration

In this section, we determine the size of the population under mandatory evacuation orders for different evacuation zones to understand the impact of evacuation order on traffic demand. Previous studies found that households are more likely to evacuate under a mandatory evacuation order; hence the spatiotemporal traffic patterns are likely to depend on the timing of evacuation declaration and type of evacuation order.

A. *Spatiotemporal Pattern of Population Under Evacuation*

We collect the time and location of evacuation orders issued for different areas for Hurricane Irma from the Florida Division of Emergency Management**.** However, the declaration dates of evacuation order for all the zones are not available in a single source, thereby, in a few cases, we collect the declaration date by manually checking the emergency management agency's social media posts (e.g., Twitter, Facebook) of the respective county and contemporary news article available online. Fig. 4 shows the mandatory evacuation zones with declaration time. We observe that most of the evacuation zones are by the coast; smaller zones in the central part of Florida mainly represent mobile homes or low-lying areas vulnerable to inland flooding.

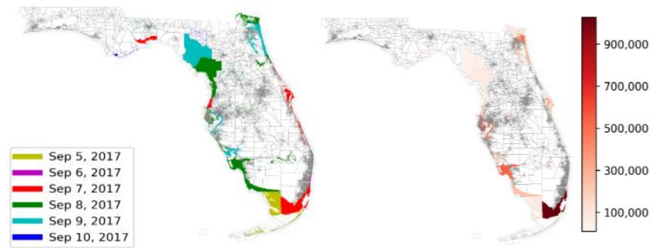


Figure 4. (a) Zone wise mandatory evacuation orders with corresponding declaration dates (b) Population of mandatory evacuation zones

Florida Keys and other low-lying zones such as Everglades were issued mandatory order in early September 5, 2017. Evacuation zones in the east coast, such as Miami-Dade, Daytona were issued evacuation order on September 7, 2017 (Hurricane Irma was supposed to hit the east coast of Florida until Sep. 7, 2017). After September 7, 2017, as the projected path shifted from the east coast to the west coast, evacuation zones of Naples, Cape Corals, Tampa, Levy, Jacksonville, were ordered mandatory evacuation on September 7, 2017 and onward (see Fig. 4(a)). We have collected population data for the mandatory evacuation zones to understand how many people were under mandatory evacuation order. Since, population data is not available for the evacuation zones, we collect block group level population data from 2017 5-year American Community Survey and sum the population that falls within an evacuation zone to retrieve the population for the zone. The light grey boundaries of Fig. 4(a) and 4(b) represent the block group boundary within Florida. Spatially most people under mandatory evacuation are from Miami, Fort Meyer, and Tampa area during Hurricane Irma (see Fig. 4(b)); the highest number of people were under a mandatory evacuation order on Sept. 8, 2017 (about 3,420,271 people), followed by Sept. 9, 2017 (about 2,629,161 people).

B. *Spatiotemporal Patterns of Evacuation Traffic*

In a normal operating condition, traffic state shows predictable patterns such as heavy traffic demand during peak hours (e.g., 4pm to 8pm) and comparatively lighter traffic demand during off peak hours (e.g., 8pm to 12 am). However, during an emergency event such as hurricane evacuation, overall traffic condition has to bear severe disruption due to a drastic increase in traffic demand [24]. To compare the evacuation traffic volume with non-evacuation period traffic volume, we have collected traffic data from May 1 to August 31, 2017. For each detector, we calculate the average hourly traffic volume for different time periods (1 to 24 hr.) and days (weekdays and weekends). Finally, we calculate the difference between hourly traffic volume during evacuation period and non-evacuation period. Fig. 5 shows the difference between evacuation traffic and regular traffic for I-75 and I-95. From the figure, we find that during Hurricane Irma's evacuation from September 6 to September 8, 2017, overall traffic flow is higher all the time regardless of whether it is a peak hour or not; there is a significant amount of traffic congestion on the major interstates even after peak hours (4pm - 8pm).

We also explore the spatial patterns of evacuation traffic to understand the impact of mandatory evacuation orders on traffic demand variations (Fig. 6). During Hurricane Irma, mandatory evacuation order was placed at different evacuation zones of Florida from September 5, 2017 to onwards depending on the predicted time and intensity of hurricane landfall. Initially the projected path showed south east coastal region of Florida (Miami, West Palm, Fort Lauderdale etc.) as the most critical zones: these areas were supposed to take major impact from Hurricane Irma. From September 5 - September 7, 2017 nearly 3.5 million people were under mandatory evacuation from these regions including some major cities such as Miami, West Palm Beach, Fort Lauderdale etc. and other low-lying areas such as Florida Keys, Everglades. Thus, from September 6, 2017 to September 7, 2017, we observe a drastic increase in traffic demand on I75 and I95, two major highways connecting south east and south west regions with the rest of Florida and the neighboring states such as Georgia and Alabama. However, since after September 7, 2017 Irma's projected path shifted from the east coast to the west coast, many cities such as Naples, Cape Corals, Tampa, Levy, Jacksonville became the most vulnerable area. Nearly 6 million people were under mandatory evacuation from these regions. The added traffic from these population caused a severe congestion on downstream of I75 and I95. To serve this increased demand, emergency shoulder use (ESU) was activated in I-75 on September 7, 2017 from Ocala towards Georgia. On Sept 9, 2017 before the hurricane landfall day we observe a large volume of traffic at downstream of I-75 and I-95 (Fig. 6), while in the upstream zones traffic volumes were nearly zero. Traffic volumes started to decrease after 1pm on September 9.

One of the major challenges in evacuation traffic management is to deal with such unexpected events, especially when there is severe traffic congestion at the last moment close to hurricane landfall. To make thing worst, all the shelters may be full. Another important issue with evacuation management is late response of the evacuees to evacuation orders. Most of the cases people wait for the last moment before taking evacuation decisions, thus causing severe traffic congestion at the eleventh hours. To deal with such unexpected events, evacuation plans should learn from the experiences of previous hurricanes and prepare accordingly.

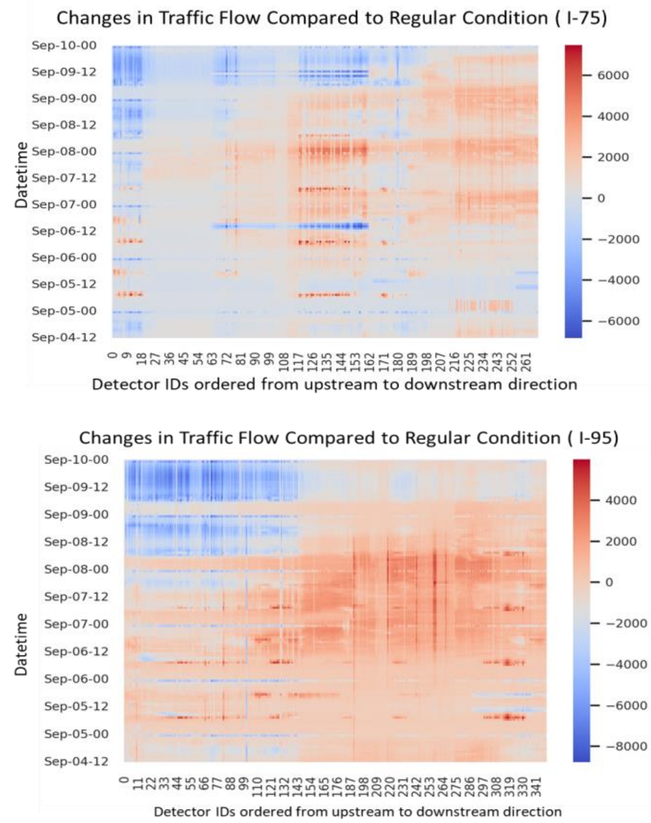


Figure 5. Spatiotemporal traffic flow distribution, here we plot the traffic detectors based on (latitudes, longitudes)/unique zone ids

V. Empirical Analysis

In this section, we demonstrate the application of such network-wide traffic data by estimating the influence of different spatiotemporal factors on variations of evacuation traffic patterns.

A. Linear Regression

We implement a simple linear regression model to estimate the influences of different factors on spatiotemporal variations

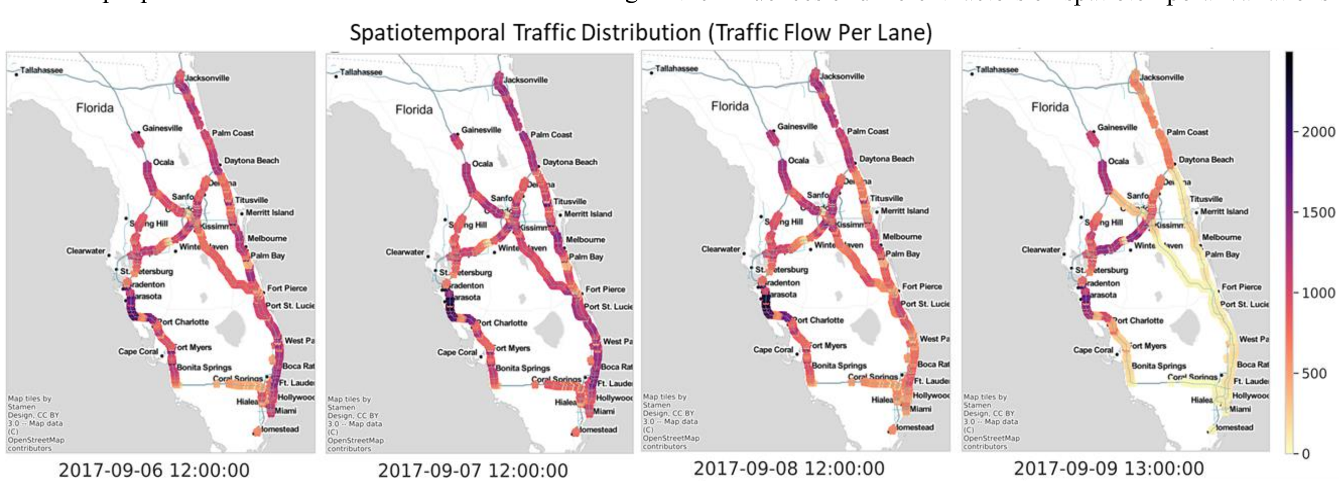


Figure 6. Spatial traffic flow pattern during hurricane Irma's evacuation period over different days (Sep. 06- Sep. 09, 2017)

of evacuation traffic flow. We consider several exogenous variables such as whether the detector located in an evacuation zone or not, distance of the detector from nearest evacuation zone, county wise population with respect to detector location and time period of the day (i.e., Late Night, Early Morning, Morning, Noon, Evening, Night), hour left before hurricane landfall and cumulative total of population under mandatory evacuation from September 5 to onwards aggregated over one-hour period. We also use average traffic volume for each of the detectors over different hour (1 -24 hr.) and different days (weekdays and weekends) to capture the usual traffic demand for different locations over the transportation network, it will capture the importance of different detectors (or location) based on its position inside the network. Table 1 reports all the significant variables based on t-stat. The variables are significant at 95% confidence interval (P-value < 0.05).

TABLE I. Estimates from linear regression model.

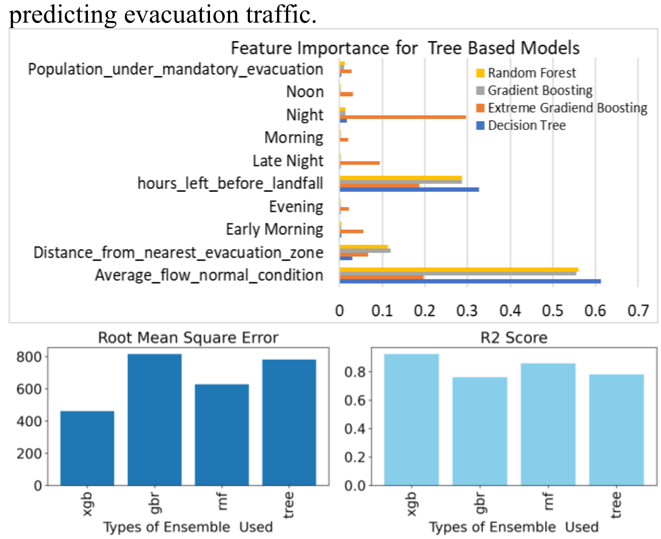
Variables	Estimates	t-stat	P-value
Constant	311.97	23.79	<0.001
Average flow in non-evacuation condition	0.59	263.64	<0.001
Distance from the nearest evacuation zone	-4.90	-17.90	<0.001
Population (in 10,000) under mandatory evacuation (shifted by 18 hr)	0.24	11.39	<0.001
Hours before landfall	7.37	80.40	<0.001
Early Morning	292.75	22.93	<0.001
Morning	302.09	22.22	<0.001
Noon	338.64	25.42	<0.001
Evening	167.07	11.69	<0.001
Night	-116.21	-9.41	<0.001
Late Night (reference)	-	-	-

In the table, the variable *"Average flow in non-evacuation condition"* indicates the average hourly traffic volume (i.e., 1 to 24 hr.) for different locations on the network and different days of the week (i.e., Mon., Tues. etc.) over a period of May 1 to August 31, 2017. From the model estimates, we find that the coefficient corresponding to this variable is positive, which means that during evacuation period traffic flow will be higher at the locations with high traffic volume in non-evacuation periods. The reason is that roadway segments with high capacity accommodates more traffic hence overall traffic flow will be higher regardless of evacuation or non-evacuation period. Additionally, some of the roadways connect highly populated major cities (i.e., Miami, Tampa, Orlando etc.), consequently they serve heavy traffic demand during non-evacuation period. Likewise, they have to accommodate large volume of traffic during evacuation period due to mass evacuation from these populated cities.

The coefficient corresponding to the variable *"distance from the nearest evacuation zone"* is negative, indicating that if a detector is located far away from evacuation zone it will be less impacted by evacuation traffic. We observe that the central part of the interstate network (I-4) is far away from evacuation zones, they are less impacted from evacuation traffic. In case of the variable "*population under mandatory evacuation*" we consider the time lag between declaration of evacuation order and the time when people start to evacuate. To capture this time lag we continuously shift the cumulative population by one *(t+1)* hour interval and estimate the coefficient of that variable by running the model. We do not see any significant value of associated coefficient (estimated value remains negative) till 17 hr., however after that time period which means from 18 hour to onwards, we observe that the coefficient associated with the variable total population under mandatory order is positive; moreover, it gradually increases with the increase in lag time (from 18 to onwards). It means that after the declaration of evacuation order it takes approximately 18 hr. for the people to start evacuating, thereby increase total traffic on the roadway. We also find that, the coefficient associated with variable "hours before hurricane landfall" is positive, which means that closer to landfall time the chances of evacuation is lower, as a result total traffic flow during this time period will also remain low. From the spatiotemporal analysis, we observe similar patterns. In the first three days of evacuation period, traffic is significantly higher, whereas close to landfall time traffic flow is lower except some downstream location of the network. Moreover, from the estimated results we find that people are less likely to evacuate during nighttime.

B. *Tree Based Model to Estimate the Feature Importance*

We further analyze the importance of these features running tree-based models such as decision tree, random forest, gradient boosting and extreme gradient boosting regression models. Fig. 7 (a) demonstrates the importance of all the significant features running different models. From the figure we find that two features: average traffic volume for a given detector under regular condition and hours left before hurricane landfall are the two most important variables when predicting evacuation traffic.



xgb = extreme gradient boosting; gbr = gradient boosting; rnf = random forest; tree = decision Tree

Fig 7**.** Illustrates (a) features importance (b) Root Mean Square Error (RMSE) and (c) R^2 Score for the tree-based models

We also check the performance of the models for evacuation traffic prediction considering two performance measures: root mean square error (RMSE) and R^2 score. As shown in figure 7(b) and (c)., extreme gradient boosting algorithm performed best (RMSE = 450) compared to other three models. Although we do not consider any information on individual evacuation decision, the model performed reasonably well indicating the importance of these features in developing evacuation traffic prediction model.

VI. Conclusions and Discussion

In this paper, we present an extensive analysis to understand the coverage and quality of MVDS detectors' data (i.e., traffic volume) for evacuation traffic analysis and modeling for hurricane Irma. We have made some reasonable assumptions in this study to clean the data. Traffic agencies can make different assumptions about the threshold values. However, we believe that these assumptions will not significantly impact the amount of data to be available for understanding hurricane evacuation patterns.

We conduct spatiotemporal data analysis to understand the changes in evacuation traffic pattern during Hurricane Irma. The analysis reveals that although evacuation order was placed early (September 6,2017), still a significant traffic congestion occurred at the downstream of I-75 and I-95 just before the landfall day. This happened because of the changes in hurricane path from the east coast to the west coast, forcing more people from south Florida and Jacksonville to evacuate at the last moment. The empirical analysis further reveals that there is at least about an 18-hr. time lag between the time of evacuation order and the time when people started to evacuate. Moreover, the location of the detectors with respect to evacuation zone, time left before hurricane landfall and time period of the days influence the variations of evacuation traffic. Such findings have potential implications in large network-scale evacuation traffic modeling.

Evacuation traffic management is a complex process that requires rapid responses from emergency management agencies to address unexpected events. Hence, it is important that transportation agencies utilize available real-time data sources to understand the responses from evacuees as evacuation unfolds over time. This study serves this purpose by identifying a new data source, providing valuable insights on the quality of the data, and their capacity to model spatiotemporal correlation among traffic state to predict network level evacuation traffic demand at different zones.

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