Understanding Evacuation Behavioral Patterns Using Anonymized Device Data and High Resolution Parcel Level Data: Application to Hurricanes Irma and Matthew

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ABSTRACT
Hurricanes can have devastating impacts on coastal populations in the US and across the world. To mitigate the potential impacts of hurricanes, emergency personnel need to prepare detailed evacuation plans to ensure the population has adequate time to evacuate in the event of a hurricane. The traditional approach to collecting evacuation behavior information involved conducting surveys, which are time-consuming, costly, and increasingly suffer from lowering response rates. In this study, we document a novel approach that relies on mobile location data and high-resolution parcel data to analyze evacuation decision processes such as decision to evacuate (Yes/No), and evacuation destination type (family/friends, hotel/motel, public shelter and out-of-state). The mobile location data were used to analyze the evacuation travel patterns across two major hurricanes in Florida 2016 and 2017. The location data was augmented with high-resolution land use data sourced from Florida Department of Revenue to determine the land-use patterns to understand the home and destination characteristics of the devices. Using processed device data, we estimate evacuation participation rate and evacuation destination type (or refuge) rates by multiple variables including evacuation zone type, residential land use type, median income, and rural/urban location. Further, we employ a linear regression model system to model participation rate (per thousand) and a multinomial logit fractional split model to understand evacuation destination choice behavior. The results from the estimated models indicate that evacuation zone type, hurricane characteristics, zonal level demographic characteristics, and land use characteristics are key determinants of county-zone level participation rate and refuge rate.

Keywords: Hurricane Evacuation; Device Data; Land Use; Participation Rate; Refuge Rate; Linear Regression

1 INTRODUCTION

Coastal regions in the US contribute nearly $6.6 trillion in GDP and accommodate for 51.7 million jobs (NOAA 2021). In Florida, coastline gross state product (GSP) is about two and a half times of its inland GSP highlighting the importance of the coastline to the state economy and its residents (Florida Oceans and Coastal Resources Council 2021). Unfortunately, coastal regions are subjected to massive and catastrophic losses due to hurricanes. Florida has faced multiple major hurricanes such as Irma, Matthew, Michael, Ian, Helene and Milton between 2016 and 2024 that have adversely affected Florida's coastline economy and the communities. Hurricane Irma made landfall near southwest Florida on September 10, 2017, as a category-3 storm with a peak wind gust of 142mph (NOAA n.d.). This major hurricane, ranked as the fifth costliest hurricane in US history, resulted in 7 direct and 80 indirect fatalities and caused economic damage of approximately $50 billion (NOAA 2018). In October 2016, hurricane Matthew did not make landfall in Florida but caused high surges and strong winds as it passed close to the Florida coastline. This hurricane caused 5 deaths in Florida and left 1 million Floridians without power (Complete 2020). Hurricane Ian, in September 2022, caused 150 deaths and damages costing $112 billion in the US, mainly in Florida (NBC6 2023). The recent hurricanes in 2024, Helene and Milton, have also caused widespread damages across the state and elsewhere. With changing climate, the frequency and magnitude of hurricanes are expected to worsen. Hence, emergency management agencies develop elaborate plans to ameliorate the impacts of hurricanes on human life and property. A significant mechanism to avoid catastrophic losses due to a hurricane requires an effective evacuation plan and its execution.

A successful evacuation planning exercise requires incorporating behavioral responses of residents to evacuation guidelines. Traditionally, behavioral studies are conducted by surveying residents affected by hurricanes to understand their decision process. The surveys elicit information on residents' decisions starting with the decision to evacuate (yes/no). For residents that decide to evacuate dimensions of interest include time of evacuation, evacuation destination type (such as hotel/shelter) and travel mode of evacuation. For residents not evacuating, dimensions of interest include reasons for not evacuating and decision in the future for a similar hurricane. While surveys conducted allow us to compile very useful information, they have some limitations. Eliciting survey responses from affected residents is not always easy. Even those respondents who provide their responses might not recall their actions precisely. Thus, there has been consideration for employing emerging data sources to understand behavioral responses to hurricanes.

Emerging data sources such as smartphone location-based services (LBS), geotagged social media data in conjunction with high resolution parcel level land-use data offer an automated mechanism to investigate population responses to hurricanes. LBS data provides high resolution spatio-temporal information for smartphone devices that can be appropriately processed to determine home location, work location, activity purpose and duration, and travel route (for example, see Wakamiya et al. 2011; Cheng et al. 2011; Frias-Martinez et al. 2012; Laman et al. 2019). Given the wide prevalence of smartphones and availability of LBS data products, data processed from these sources are slowly being applied for transportation applications including hurricane evacuation behavior (see Wang and Taylor 2014; Roy and Hasan 2019; Darzi et al. 2021 for details). However, LBS data-based approach may not incorporate resident specific information such as sociodemographic and important evacuation decisions which can be captured by survey-based approach (Younes et al. 2021). Thus, evacuation studies using survey data can offer deeper understanding decision making process (Swanson and Guikema 2023). Therefore, LBS data complemented by survey data can offer both accuracy in evacuation rates at different geography levels and comprehensive understanding of evacuation behavior.

The value of the LBS data can be further enhanced using high resolution parcel level data. Specifically, the parcel level data provides land use and built environment information that can be employed to identify work and home, land use patterns, and destination location type (such as if the location is hotel/shelter). The proposed research contributes to literature on understanding hurricane behavioral response by employing LBS data and parcel level data. The research will examine evacuation behavior patterns for two hurricanes Irma and Matthew in Florida. For these two hurricanes, we estimate evacuation participation rate, and evacuation destination type (or refuge) rates. The inferred evacuation characteristics are employed to develop statistical models that identify different contributors to evacuation decisions. In developing these models, we consider multiple factors including evacuation zone type, hurricane characteristics (distance from hurricane path and intensity), socio-demographic characteristics (population, employment, median income, etc.) and land use characteristics of the zones. The results offer insights on the factors influencing evacuation decision processes and are useful for emergency management agencies to incorporate within future planning. The research exercise clearly demonstrates the value of LBS data and parcel level land use data for examining evacuation response behavior.

2 LITERATURE REVIEW

2.1 Earlier Studies

In this study, we undertake a review of research relevant to our study goals. The studies summarized in this section can be broadly categorized into two broad groups: (a) studies identifying evacuation behavioral patterns using traditional survey-based data, and (b) studies employing LBS data and geotagged social media data for analyzing transportation decisions with a focus on evacuation analysis.

The first group of studies rely on traditional survey-based data to estimate evacuation behavioral rates and study the impact of different independent variables on evacuation patterns. Baker (1990) investigated evacuation destination choice behavior and found that most of the evacuees travel out of county and low-income households move to shelter. Fu and Wilmot (2004) used survey-based data to develop a sequential logit model where they explored the influence of speed of the hurricane, distance from the hurricane, time of day, evacuation order and type of origin on evacuation behavior. Lindell et al. (2005) investigated evacuation participation decision and time of evacuation using mail survey data and concluded geographic characteristics are the major determinants for evacuation. Lindell and Prater (2007) conducted statistical meta-analysis on previous evacuation studies based on multiple hurricanes and found significant impact of type of residence, hurricane risk area, type of warning, and social cues such as business closing and peers evacuating on participation decision. Hasan et al. (2011) developed a mixed logit model analyzing evacuation decision using survey data and concluded that origin type, household demographics and distance from hurricane track significantly influence the decision process. Mesa-Arango et al. (2013) modelled evacuation destination type using nested logit model and identified household demographics, geographic location of households, preparation time, evacuation notice and hurricane distance as the important factors. Yang et al. (2019) investigated impact of hurricane evacuation planning approaches on participation rate and found that adaptive and repeated plans work best regarding increased participation. Arabi et al. (2023) identified critical links in evacuation network based on social, economic and environmental vulnerabilities.

The second group of studies employ location-based services data for understanding transportation decisions. Multiple studies in transportation employed LBS data for understanding (a) mobility patterns and activity intensity (Hasan and Ukkusuri 2014; Laman et al. 2019; Wei and Mukherjee 2023), (b) land use and point of interest patterns (Frias-Martinez et al. 2012; Hu et al. 2015), and (c) LBS data accuracy (Cao et al. 2015). More recently, LBS data from smartphones or social media (such as Twitter) have been employed specifically for evacuation analysis. Martín et al. (2017) employed geotagged twitter data to understand evacuation preparation and plan of the residents and identified the percentage of evacuees during hurricane Matthew. Kumar and Ukkusuri (2018) employed geotagged twitter data to understand evacuation pattern during hurricane Sandy and found that evacuees from coastal areas travel more before typhoon events. Yin et al. (2019) developed an offline knowledge database regarding evacuee's real time location, hourly distribution using LBS data to improve the online computation time for planning optimal evacuation strategy. Chen et al. (2020) studied human mobility patterns before, during and after hurricane events by employing flow clustering method and concluded that urban flows reduce significantly during typhoons and substantially recover after the event. A study most relevant to our research effort was recently developed using LBS data for Hurricane Irma (Darzi et al. 2021). Using smartphone data and passive machine learning algorithms, evacuation decision processes were examined. The authors employed a one-mile threshold criteria for determining evacuation decision and destination. The LBS generated patterns were augmented with evacuation zone, sociodemographic variables and individual mobility patterns to understand evacuation behavior. The study developed a logistic regression models of evacuation decision at the individual level to evaluate the influence of individual trip frequency and spatial coverage on evacuation decisions. The study found that people who travel more during pre-disaster condition are more likely to evacuate their homes. Roy and Hasan (2021) employed hidden Markov model to understand evacuation participation behavior using twitter data and found landfall characteristics, distance of the hurricane, home activity type, and evacuation similarity score as significant factors. Brower et al. (2023) developed a random forest model of evacuation rate using LBS data during hurricane Laura and concluded that weather conditions, geographic features and COVID-19 cases are important factors affecting evacuation rate. Jiang et al. (2023) proposed a Meta-knowledge-Memorizable Spatio-Temporal Network (MemeSTN) to predict human mobility during a disaster using social media data. Wei and Mukherjee (2023) examined income segregation towards mobility patterns during natural disasters and found that mobility patterns are different across economic groups. Rashid et al. (2025) employed Facebook population data to study evacuation patterns in response to hurricane Ian in Pinellas and Lee counties. They identified census tracts with high share of mobile homes and seniors (age >65) and home built prior to 2000 as factors increasing evacuation while a higher share of homeowners and Hispanic population contributes to lower evacuation rates.

2.2 Contribution of the Current Study

While earlier studies adopted both survey-based approach and location-based services data to estimate evacuation participation and destination choice behaviors, this study aims to further improve our understanding of evacuation behavior. In our study, we hypothesize that hurricane evacuation behavior (defined as evacuation decision and evacuation destination) can be associated with a wide range of factors (including evacuation zone type, hurricane characteristics, demographic characteristics, and land use). We evaluate the specific impacts of these variables on the evacuation behavior using unique LBS data and high-resolution parcel level data. The study also investigates whether we can generalize the insights on evacuation behavior across hurricanes (using variables such as distance to the hurricane path).

With these aforementioned objectives, the current study makes a twofold contribution in evacuation behavioral research. The ***first contribution*** of the study arises from evacuation data enhancement by identifying evacuation patterns across the state of Florida for two hurricane events including Irma and Matthew. In our study, we collect location data of the devices residing in regions affected by the two hurricanes. In our analysis, we processed 680,032 and 77,764 anonymized cellphone devices before, during and after hurricane Irma and Matthew, respectively. Using these data, we estimate evacuation participation rate, and evacuation destination type (or refuge) rates. Employing parcel-level data we determine the land-use patterns to understand the home and destination characteristics of the devices. The characteristics of interest at the home location include share of single-family and multi-family units, and median income characteristics. At the destination level, identifying the presence of hotels/shelters is useful for identifying destination type.

While the LBS data and parcel data provide an understanding of behavioral response to hurricanes, it is important to recognize that the behavior estimates are specific to the hurricane. The behavioral rates cannot be directly applied to any future hurricane because hurricane characteristics such as path, intensity and size are likely to be different. However, it is plausible that there might be some common behavioral patterns observed from evacuation data for different hurricanes. Hence, in our study, we attempt to parameterize the hurricane evacuation behavior using data from the two hurricanes. For this purpose, the inferred evacuation characteristics are employed to develop statistical models that identify different contributors to evacuation decisions. The ***second contribution*** of the current study is to identify the key determinants of evacuation participation rate and destination type at an aggregate level of county-evacuation risk zone. In Florida, each coastal county is classified into 6 risk zones A, B, C, D, E and inland/no zone – with "A" being the most at-risk classification and "inland/no zone" is the least at-risk classification. In this study, we include 243 affected county-zone pairs for hurricane Irma and 107 affected county-zone pairs for hurricane Matthew. We aggregate the device data to generate evacuation numbers and destination type at the county-zone spatial resolution. These dependent variables are further augmented with a host of independent variables including zone type, hurricane characteristics, zonal level demographic characteristics (such as median income, population, employment, and vehicle ownership), and land use characteristics (such as proportion of residential land use types i.e., single family residential, multifamily residential, and vacant residential land use). Using the prepared evacuation data, we employ a linear regression model to analyze county-zone level participation rate (per thousand) and a multinomial logit (MNL) fractional split model to understand evacuation destination choice behavior.

3 DATA PREPARATION

In this section, we present the data preparation steps we followed for processing LBS data, parcel level land use data, destination type (refuge rate), and provide a summary of dependent and independent variables.

3.1 LBS Data Collection and Processing

The data preparation steps for processing Location-based services (LBS) data are quite involved. Hence, in the interest of space, an overview of the LBS data preparation is presented in the paper with more details included in supplementary materials. LBS data is collected by applications running on anonymized mobile devices and provide individual breadcrumb like information about the location of a device at specific times. Data is collected at irregular intervals and data collection frequency varies from device to device based upon use patterns. Several features of the data that are utilized in this study include:

- Locational coordinates at GPS level precision, typically less than 50 feet.
- Timestamp that the location was recorded.
- Unique device identifier, which can be used to track the movements of a device over a period of days, weeks, and months.

3.1.1 Hurricane Data Collection

In our analysis we focused on data collected immediately before, during, and after a hurricane made landfall in the state of Florida. While several major hurricanes impacted the state between 2016 and 2022 including Matthew, Irma, Michael and Ian, our analysis is focused on two hurricanes: Irma and Matthew. Therefore, we mainly analyze LBS data from the geographic areas that were impacted by these two hurricanes. Figure 1 illustrates the geographic regions analyzed for the two hurricanes. As illustrated in the figures, Hurricane Irma was a large hurricane that impacted the entire state, and Hurricane Matthew primarily impacted the eastern coast of the state (and technically never actually made landfall). The reader would note that to minimize the computation complexity in processing the data, each observation was tagged to a hexagon (or hex-bin) using the H3 Python library (shown in Figure 1). The chosen resolution was such that individual hex-bins had edge length of 0.1 miles and total area of about 26 acres. It was determined that this resolution was ideal because it was small enough to capture device location without noise due to GPS or other errors but also not too small to overwhelm computing resources (more details are included in supplementary material).

In addition to limiting the geographic extent of data analyzed, the data was parsed according to date with the day of landfall serving as the key date for each hurricane. Three time periods totaling approximately two months were defined around the day of landfall:

- The landfall period was defined as the five-day period ending on the day of landfall and beginning four days earlier.
- The steady-state period was defined as the four-week period ending the day prior to the landfall period.
- The re-normalization period was defined as the three-week period beginning the day after landfall.

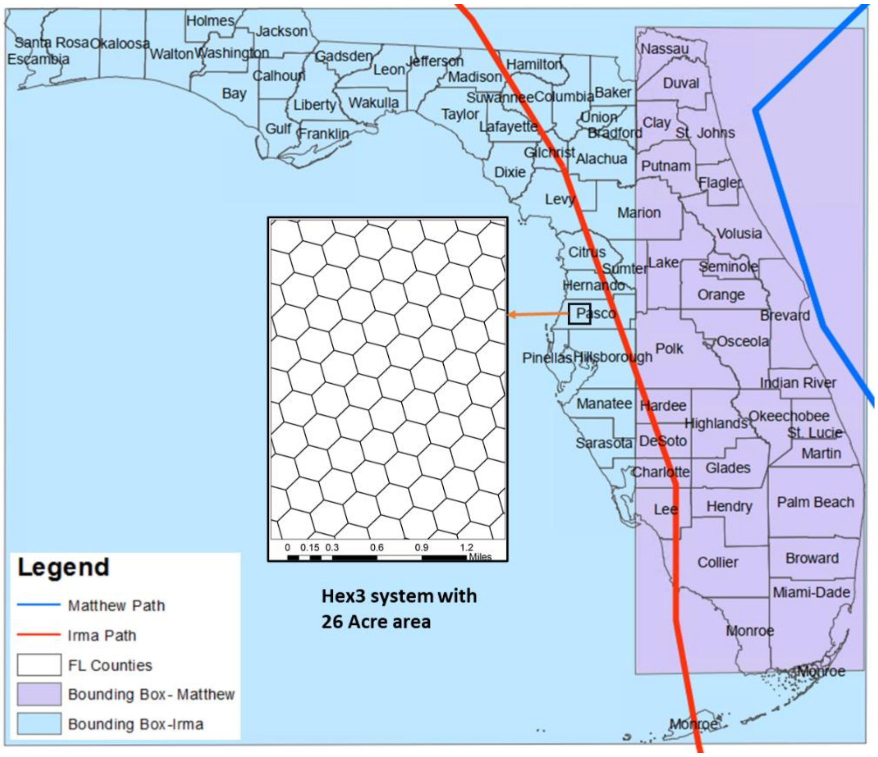


FIGURE 1 Bounding box for the two hurricanes

3.1.2 Algorithms

The data obtained was analyzed using several metrics to ensure the data depicts the population behavior in a meaningful way (see description of this process and visual representations in supplemental material). A variety of literature exists with roadmaps to processing raw mobile location data into trips and determining key attributes like home locations. However, new algorithms were needed here for analyzing key behavioral metrics related to hurricane evacuations. Figure 2 shows the overall process of data analysis and development. Each step is further described below.

First, all raw data points showing up in the study area are selected and processed. In addition, all data points outside the study area are processed for any device that shows up in the study area at any point during the period of analysis. Clustering and filtering processes are used to translate the raw LBS records into activities.

As described earlier, the LBS data for each hurricane event was divided into three analysis periods: the steady-state period (before the hurricane threatens the coast), the landfall period (immediately preceding and including the day of landfall), and the re-normalization period (following landfall). Only devices that have data in all three periods are retained for further analysis. This allows us to study the behavior of devices across different phases of a hurricane event.

The next step of the analysis infers the home location for all remaining devices. This is done through analysis of the steady-state period data alone since many people evacuate during the hurricane. Note that this process also distinguishes residents of the study area from non-residents since we analyze all data from any device that appears within the study area. Once the home location is identified, evacuations are inferred as follows:

- First, the highest duration location for each day in the landfall and re-normalization periods is identified. We applied duration thresholds (minimum of six or eight or 10 hours were tested and settled on six hours) for a location to qualify as a viable candidate.
- Next, we find the first instance where this highest duration location is different from the device's home location. This location is then labeled as a candidate evacuation day.
- The candidate location is only accepted if the device does not return home before the end of the candidate evacuation day and the evacuation location does not neighbor the home location.
- The last departure time from the home was identified, which represents the candidate start time for evacuation.
- Once the day of evacuation is inferred, the refuge location is determined by finding the location where the device spends the most amount of time while evacuated (until the device returns home).
- For within-state evacuees, three refuge types were considered: friends/family, hotel/motel and public shelters. From parcel level land use data, we found these locations are the potential destinations for the evacuees. For out of state evacuees, we did not classify their destinations further as they are outside of the study region. It might be possible to consider other spatial alternatives (such as counties or cities). However, this can increase the number of alternatives substantially and alter the focus of the analysis.
- The type of refuge (public shelter, hotel, or friends/family) was determined by checking whether the evacuation location or neighboring locations had a public shelter or hotel. If either was present, the type of refuge was labeled accordingly as either public shelter or hotel. Otherwise, the type of refuge was labeled as friends/family.

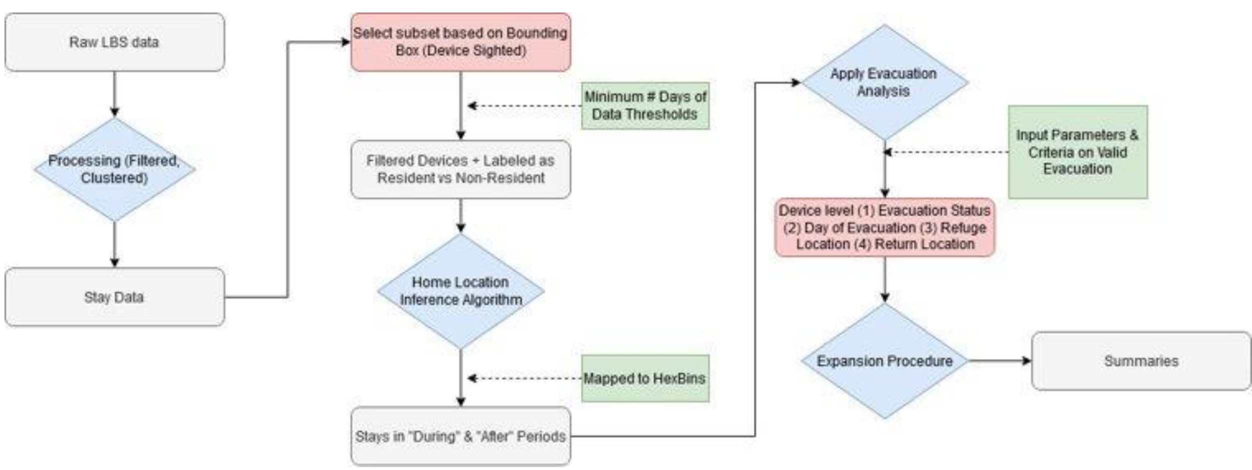


FIGURE 2 Data processing flow chart (Source: Florida SRESP 2021)

Evacuations that were identified where the device returns home before the day of landfall were considered to be invalid and were treated as non-evacuee devices. Furthermore, we found that the conditions needed to be relaxed somewhat on the day of landfall to allow for a second wave of evacuations that tends to occur at the last minute.

To test the validity of our algorithms, we applied them to a set of data that was absent a hurricane. In this case, we expect the algorithm to infer very few evacuees since we do not expect evacuations to occur. Even then, however, we expect the algorithm to have trouble distinguishing between a true evacuee and a person that traveled (either for work or leisure). Applying our algorithms to the non-evacuation period resulted in a false positive rate of about 10 percent. This level of evacuation was considered to be acceptable given the number of people that travel for work or tourism during a given two-month period.

3.1.3 Population Expansion and Validation

Expanding the sample data is a critical step in this type of analysis in order that the data be truly representative of the population. Failure to expand the data could lead to biased estimates of key metrics with certain geographic areas being over-represented in the sample due to higher sample penetration rates in those areas. In order to expand the data, American Community Survey (ACS) estimates were used at the Census tract level based upon a device's imputed home location. This approach ensured that residents within the study area were expanded appropriately. However, non-residents (living outside the study area) needed special consideration because only a fraction of non-resident devices show up in the study area during the two-month sampling time frame. To deal with this issue, non-resident devices were expanded by using the average of the expansion weights of resident devices.

Finally, to ensure that the results were reliable, a validation check has been considered. In this check, we examined overall levels of evacuation for the two hurricanes. In total, Hurricane Irma saw about 6.1 million, and Hurricane Matthew 2.2 million evacuees. These estimates are consistent with the speed, intensity, and duration of each hurricane. Matthew, though a major hurricane mainly stayed off the Florida coast and did not make landfall in Florida. Irma shows higher evacuation rates due to the buildup. While third party estimates of the numbers of people that evacuated for Hurricanes Matthew were not available, new releases for Hurricane Irma report that about 6.8 million evacuated during that hurricane (WFSU News 2022). These estimates are very much in line with the 6.1 million estimated in this study.

As noted above, estimates of the actual number that evacuated during Hurricane Matthew were not available, news releases of the number of people ordered to evacuate for the hurricane was over 1.5 million (The New York Times 2016). While this figure is slightly lower than our estimates of the total evacuated, our estimate is roughly in line with the outside sources.

3.1.4 Evacuation Zones

According to the Florida Division of Emergency Management, Florida evacuation zones primarily include zone A (the highest risk zone), B, C, D, E, and inland/no zone (the least risk zone). The distribution of the evacuation zones is presented in Figure 3.

3.2 Land Use Data Processing

In this current research, we identify land use distribution at the hex level and estimate the area of residential land use types such as vacant residential, single family residential, and multi-family residential units. The Florida Department of Revenue (DOR) parcel data shape file is intersected with the hex layer to generate Hex level land use information in ArcGIS. A sample of hex level land use distribution for a selected area is presented in Figure 4. From the area of different land uses, we retain residential land uses and estimate their proportion to estimate behavioral rates by land use types at the aggregate resolution.

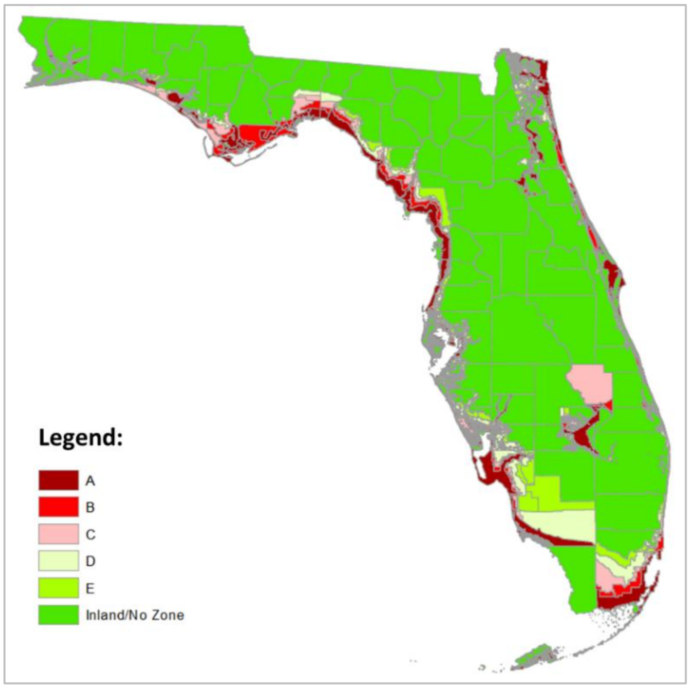


FIGURE 3 Evacuation zones in Florida

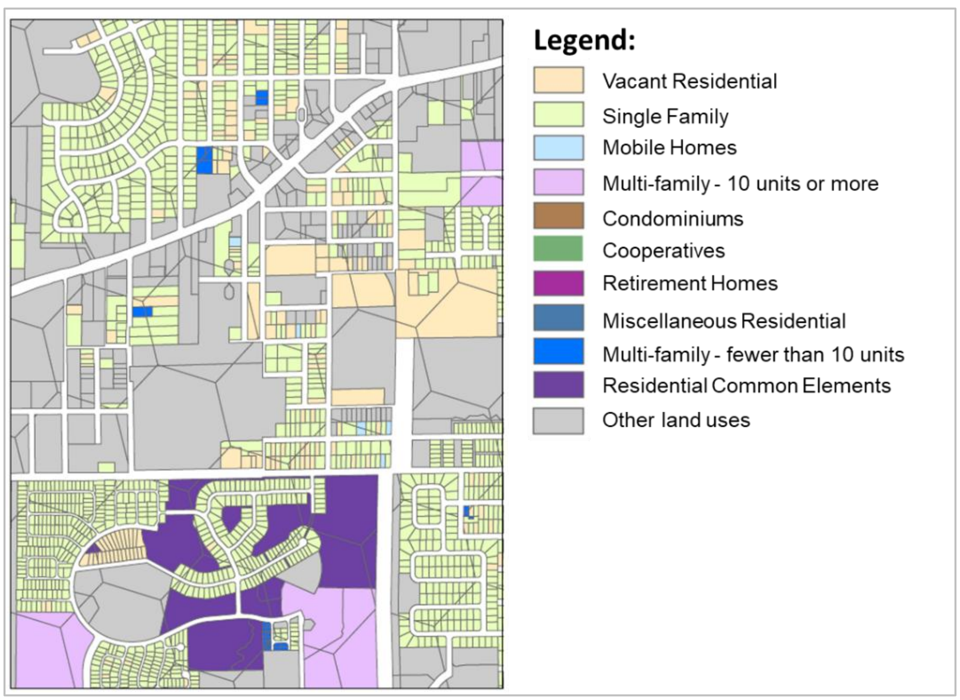
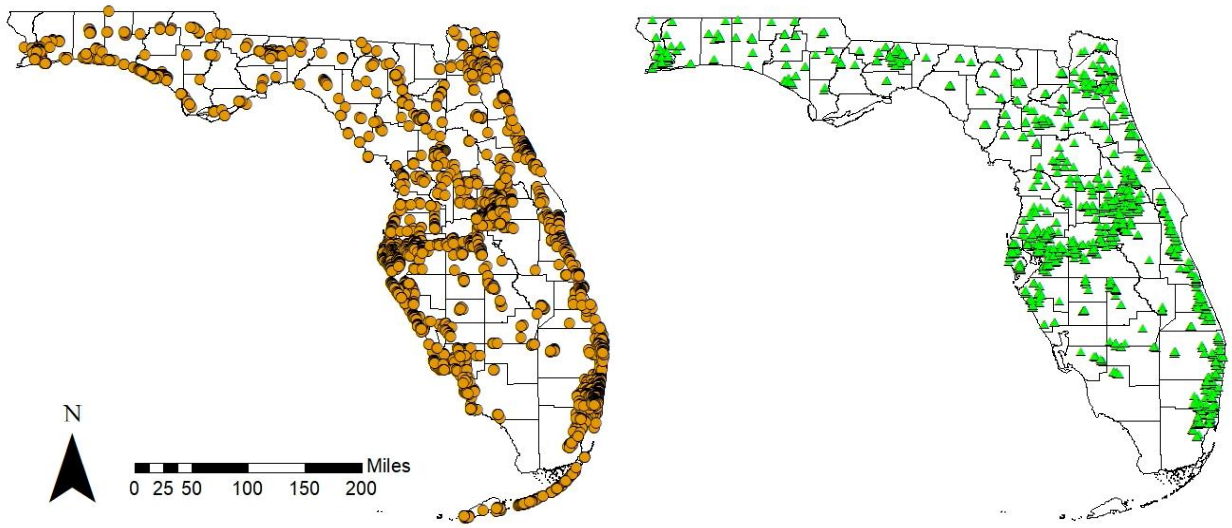


FIGURE 4 Sample of hex level land use distribution

In addition to land use type proportion estimation, we also employ parcel level land use data to identify hotel/motel locations in Florida. We separate all hotel/motel parcels from entire statewide parcel data and centroid of the parcels indicates hotel/motel locations in Florida. We also collect public shelter locations from Florida Division of Emergency Management. We consider both hotel/motel, and public shelter as potential evacuation destination alternatives (see Figure 5).



(a) Hotels/Motels (b) Public Shelters

FIGURE 5 Hotel/Motel and public shelter location in Florida

3.3 Identification of Evacuation Destination

We consider four evacuation destination alternatives for each device including friends/family, hotel/motel, public shelter, and out of state. In the proposed method, we allocate the device (with its population weight) among the alternatives based on the land use pattern of the evacuation destination hex. The algorithm we follow to assign devices is illustrated in Figure 6. First, we identify whether the evacuation hex is within Florida or out of state. If evacuation destination is outside Florida, we allocate the device to out of state alternative. If evacuation destination is within Florida, we identify whether the evacuation hex has any hotel/motel, public shelter, or both. If evacuation hex does not have any hotel/motel or shelter, we assign the device to friends/family. If evacuation hex has only one of hotel/motel or shelter, we assign the device to the category present. If evacuation hex has both, we distribute the device population weight equally among hotel/motel and shelter. The simple approach was deemed adequate in our analysis because there were only a very small number of hexagons with such conflicts (less than 0.2% of the hexs considered in our analysis).

3.4 Dependent Variables

The second objective of the research effort is to process the data generated to obtain insights on evacuation planning for future hurricanes. For this purpose, we model evacuation participation rate (per thousand) and destination type for hurricane Irma and hurricane Matthew. In preparation of the estimation sample, we consider county-zone pairs in the bounding area selected for the two hurricane events. Given the difference in Hurricane size and intensity, the county-zone pairs vary by hurricane. While we consider all 243 county-zone pairs in Florida for hurricane Irma, 107 county-zone pairs are considered for hurricane Matthew. The distribution of participation rate per thousand and destination types are presented in Figure 7a and Figure 7b.

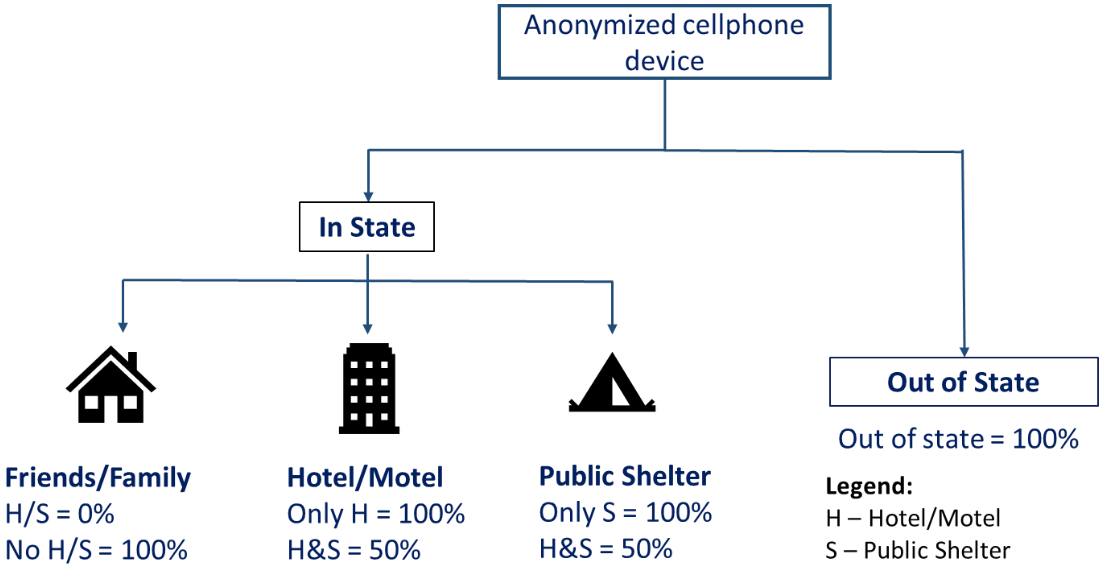


FIGURE 6 Destination type identification method

3.5 Independent Variables

The dependent variables, participation rate and destination type are augmented with a host of independent variables including zone type, hurricane characteristics, zonal level demographic characteristics (such as median income, population, employment, and vehicle ownership), and land use characteristics (such as proportion of residential land use types i.e., single family residential, multifamily residential, and vacant residential). Hurricane characteristics are sourced from the National Hurricane Center (NHC). Zonal level demographic characteristics are sourced from American Community Survey (ACS) and land use characteristics are processed from parcel level data provided by Florida Department of Revenue. Summary statistics for independent variables are provided in Table 1.

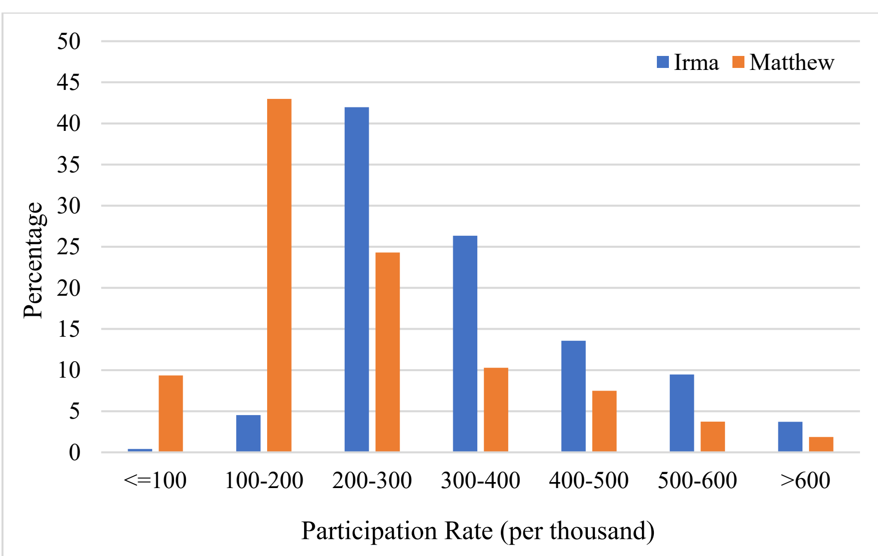


FIGURE 7a Distribution of participation rate (per thousand)

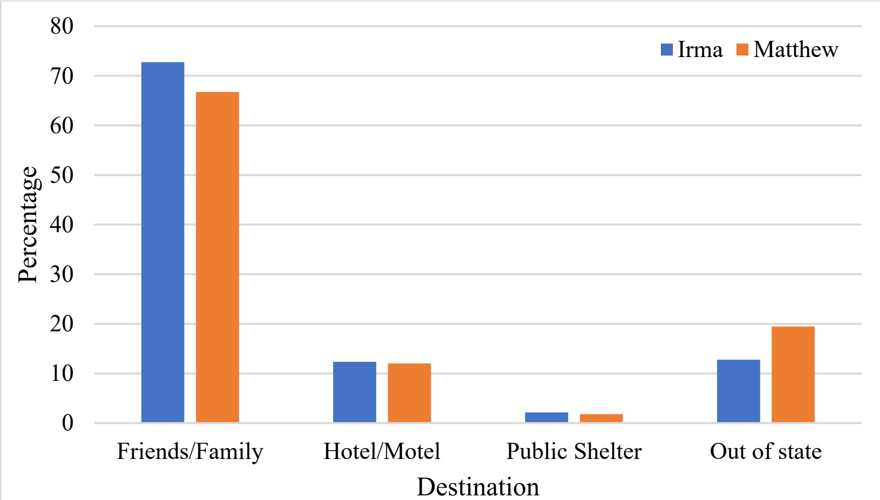


FIGURE 7b Distribution of destination types

TABLE 1 Descriptive Analysis of the Independent Variables

Categorical Variable					
Variables	**Description**	**Hurricane Irma**		**Hurricane Matthew**	
		Frequency	**Percentage**	**Frequency**	**Percentage**
Zone Type Variables					
Zone A		40.00	16.46	19.00	17.76
Zone B		36.00	14.81	13.00	12.15
Zone C		37.00	15.23	19.00	17.76
Zone D		35.00	14.40	15.00	14.02
Zone E		29.00	11.93	11.00	10.28
Inland/No Zone		66.00	27.16	30.00	28.04
Continuous Variable					
Variables	**Description**	**Hurricane Irma**		**Hurricane Matthew**	
		Mean	**Min/Max**	**Mean**	**Min/Max**
Hurricane Characteristics					
Distance path	Distance between county-zone and hurricane path (mile)	64.05	0.82/198.29	66.05	11.40/204.45
Intensity	Wind speed at nearest hurricane path (mph)	68.91	40.00/115.00	113.36	110.00/115.00
Zonal Level Demographic Characteristics					
Population	Population in thousand	83.77	0.02/1622.61	140.21	0.10/1622.61
Employment rate	Employment/Population	0.43	0.22/0.63	0.68	0.00/0.86
Income	Income in thousand	54.15	28.55/125.66	57.85	28.55/125.66
Vehicle ownership level					
veh0	Percentage of HH with 0 vehicle	2.53	0.00/9.67	2.73	0.00/9.00
veh1	Percentage of HH with 1 vehicle	22.80	7.49/41.12	23.43	8.33/41.12
veh2	Percentage of HH with 2 vehicles	45.24	28.63/68.85	45.06	28.63/67.05
veh3	Percentage of HH with 3 or more vehicles	29.39	10.67/50.44	28.70	10.67/44.68

Vacant Residential	Fraction of Vacant Residential among all residential land use types	0.34	0.01/1.00	0.34	0.01/1.00
Single Family	Fraction of Single Family	0.32	0.00/0.91	0.30	0.00/0.91
Mobile Homes	Fraction of Mobile Homes	0.11	0.00/0.52	0.07	0.00/0.34
MF>=10 units	Fraction of Multi-family - 10 units or more	0.01	0.00/0.10	0.01	0.00/0.10
Condominiums	Fraction of Condominiums	0.16	0.00/0.96	0.21	0.00/0.96
Cooperatives	Fraction of Cooperatives	0.01	0.00/0.31	0.01	0.00/0.25
Retirement Homes	Fraction of Retirement Homes	0.00	0.00/0.10	0.00	0.00/0.10
Miscellaneous	Fraction of Miscellaneous Residential	0.01	0.00/0.14	0.01	0.00/0.14
MF<10 units	Fraction of Multi-family - fewer than 10 units	0.01	0.00/0.10	0.01	0.00/0.10
Residential Common	Fraction of Residential Common Elements	0.03	0.00/0.30	0.03	0.00/0.23

4 ANALYSIS AND RESULTS

In this section, we present the results of the analysis we performed in this study. First, we present a descriptive analysis of behavioral rates including evacuation participation rate and refuge rate. Then, we present results of a linear regression model of evacuation participation and a multinomial logit fractional split model of destination type (refuge rate).

4.1 Descriptive Analysis

4.1.1 Participation Rate

The analysis result indicates that overall participation rates in the bounding box are 29.30% and 15.70% for Irma and Matthew, respectively. In Figure 8a through Figure 8d, we present evacuation participation rates by different variable combinations. First, we examine participation rates in rural and urban areas and present the result in Figure 8a. The figure shows that residents from urban regions evacuated more in both hurricane events compared to residents from rural areas.

Second, we examine participation rate by evacuation risk zones and present the result in Figure 8b. The figure clearly illustrates that participation rate is higher for high-risk zones compared to participation rate for low-risk zones. Third, we present participation rate by residential land use types in Figure 8c. The figure indicates that participation rate is the highest for mobile homes for both hurricanes. Finally, we investigate evacuation participation rate by zonal level median income. The result is presented in Figure 8d, and we do not observe any specific pattern of participation rate in for hurricane Irma. But for hurricane Matthew, it is evident that people from high-income areas evacuated more than people from low-income and medium income areas.

4.1.2 Refuge Rate

In this study, we estimate the share of different destination types chosen by the evacuees. In the analysis, we consider four destination alternatives including friends/family, hotel/motel, public shelter and out of state. Overall shares of the alternatives are presented in Figure 9a. Figure 9a indicates that friends/family has the largest share while public shelter has the smallest share. Further, we investigate refuge rate in relation to other variables including evacuation zone, land use type and median income. A subset of these results is presented in Figures 9b through 9c. In Figure 9b, we present refuge rates by evacuation risk zone for both hurricanes, and we observe that friends/family is the most prominent destination choice across all zone types. It is also evident that evacuees from low-risk zones choose friends/family most compared to evacuees from high risk-zones i.e., zone A and B. Besides, evacuees from zone A move to hotel/motel more compared to evacuees from all other zones. Evacuation zone A usually is located right next to the coast and corresponds to high value real-estate. Thus, these residents are typically high-income households. Hence, it is not surprising that these residents are more likely to evacuate to hotel/motel. In Figure 9c, we present refuge rate by residential land use types. From the figure, we find that evacuees living in mobile homes choose friends/family the most among all evacuees. Finally, refuge rate by zonal level median income presented in Figure 9d indicates that evacuees from low-income areas choose friends/family the most among all evacuees. On the other hand, evacuees from high-income areas choose hotel/motel the most among all evacuees (as pointed out earlier).

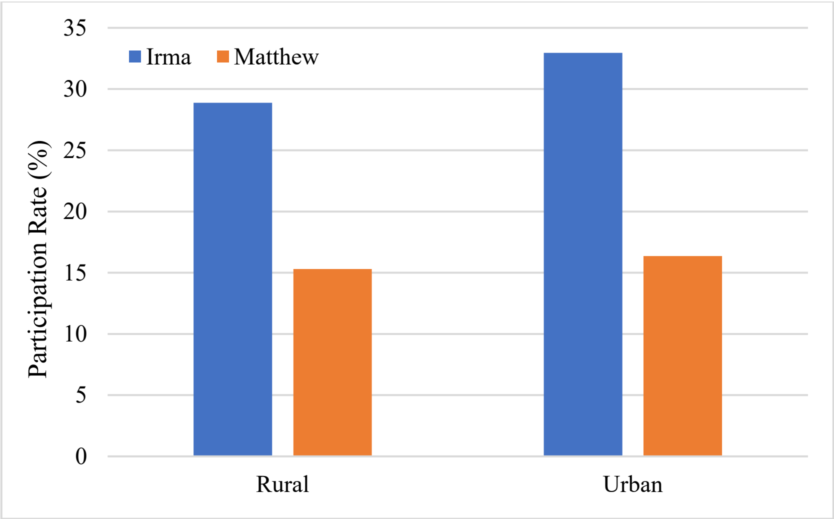


FIGURE 8a Participation rate for rural and urban areas

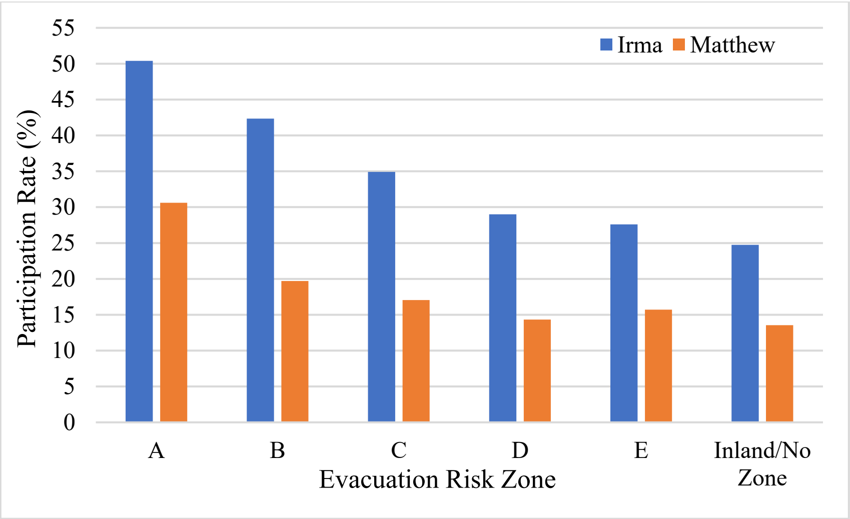


FIGURE 8b Participation rate by evacuation risk zone

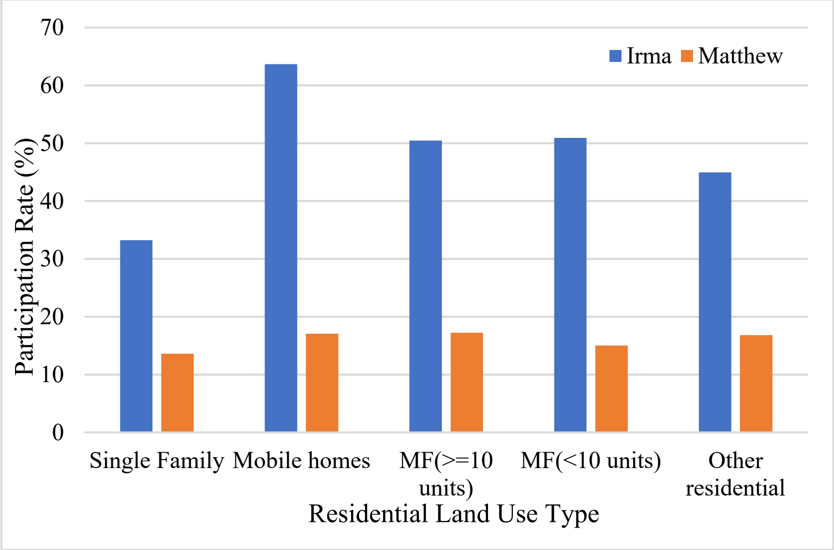


FIGURE 8c Participation rate by land use types

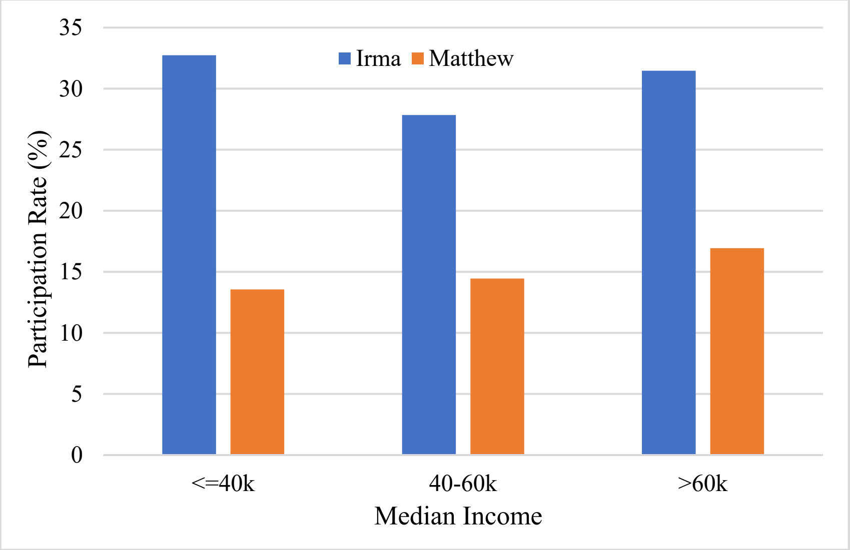


FIGURE 8d Participation rate by median income

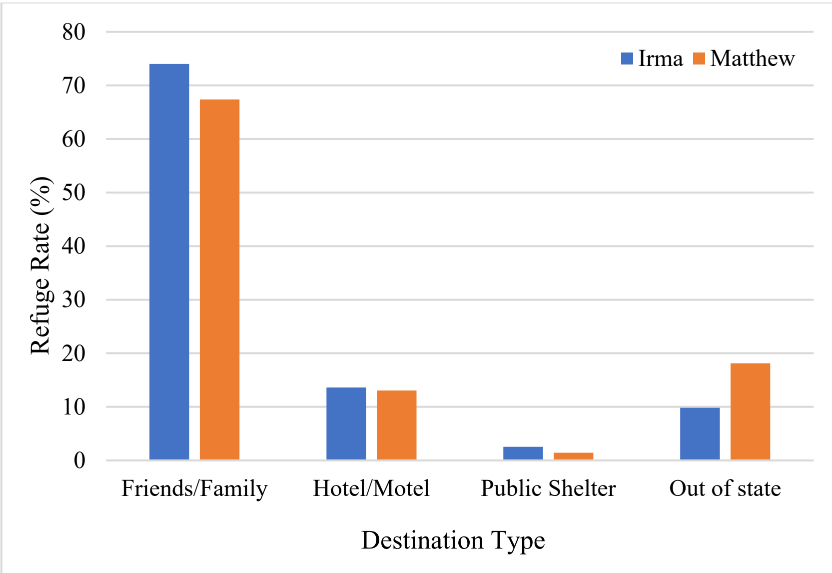


FIGURE 9a Refuge rate by destination type

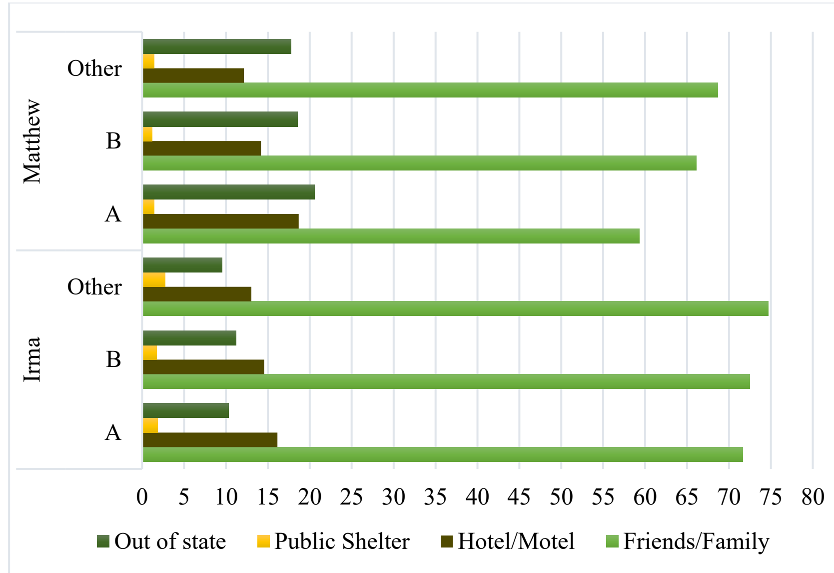


FIGURE 9b Refuge rate by evacuation risk zone

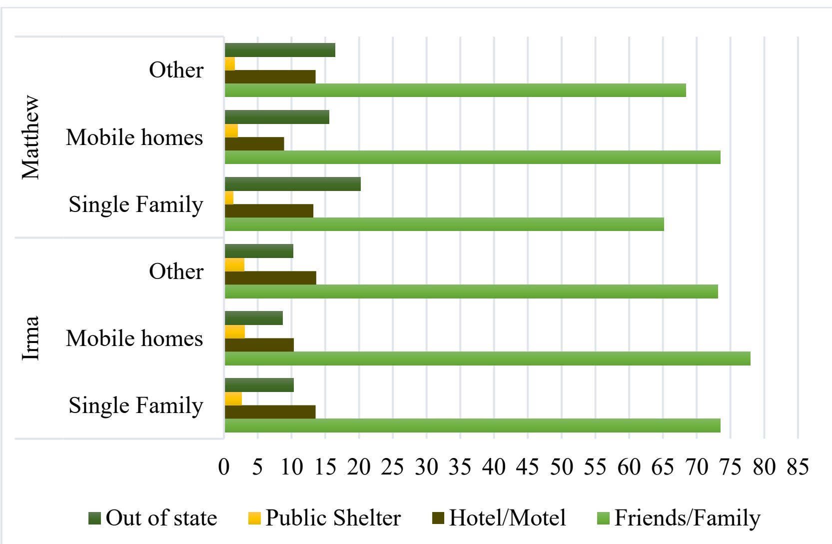


FIGURE 9c Refuge rate by land use type

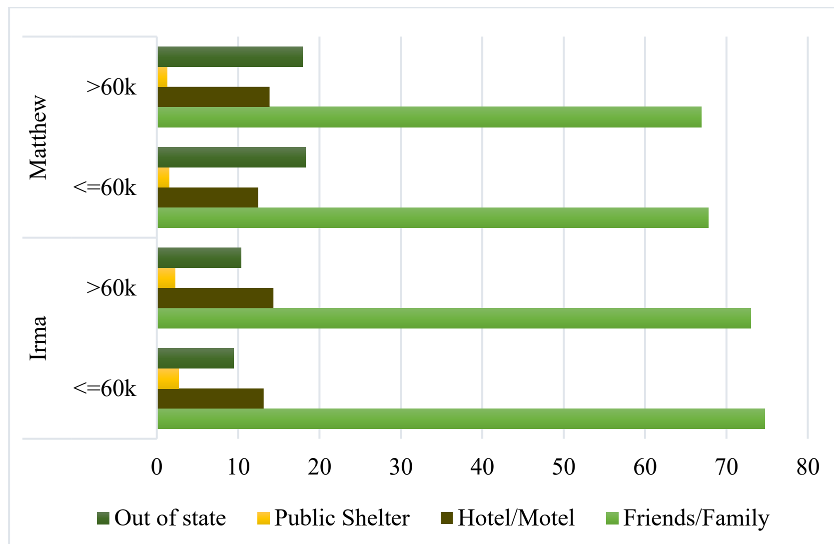


FIGURE 9d Refuge rate by median income

4.2 Participation Rate Model

In this section, we discuss the results from linear regression model of participation rate (per thousand). The parameter estimates from linear regression model for hurricane Irma and hurricane Matthew are presented in Table 2 (please see Rahman et al. 2019; Bhowmik et al. 2021 for mathematical details of the linear regression model). Positive (negative) value of a parameter indicates that an increase of the variable increases (deceases) participation rate.

4.2.1 Evacuation Risk Zone

The parameter estimates indicate that participation rate is correlated with evacuation zone type. The result is consistent across hurricane Irma and Matthew and suggests that participation rate is significantly higher in Zone A and Zone B compared to other risk zones. The result is very intuitive because people from high-risk zones are more likely to evacuate compared to low-risk zones.

4.2.2 Hurricane Characteristics

From the results, it is evident that participation rate is dependent on hurricane characteristics. The result shows that distance between a zone and hurricane path is an important factor influencing participation rate in that zone. The result indicates that participation rate decreases with increased distance of the hurricane path. Intensity of the hurricane is also found to be significant for Irma, and the result indicates that a higher intensity of the hurricane increases participation rate. The result illustrates evacuation behavior responsiveness to hurricane characteristics.

4.2.3 Zonal Level Demographic Characteristics

Zonal level demographic characteristics are also found to be significantly associated with participation rate. County-zone level population is found significant for both hurricanes and parameter estimates indicate that participation rate is lower in densely populated areas. We found that median income has a significant positive association with evacuation rate for hurricane Matthew. We found vehicle ownership of more than 2 vehicles reduces participation rate for hurricane Irma. This is contrary to what we expected and warrants further investigation.

4.2.4 Land Use characteristics

The parameter estimates indicate that county-zone level land use characteristics influence participation rate. For hurricane Irma, it is observed that increased percentage of single-family residential units and condominiums is associated with decreased participation rate. On the other hand, participation rate increases with increased percentage of cooperatives and retirement homes. The result might be indicative of state/institutional mandates for evacuation in senior living facilities. For hurricane Matthew, as expected, an increased proportion of mobile homes and multifamily residential homes (fewer than 10 units) increases participation rate at the county-zone level.

TABLE 2 Parameter Estimates for Participation Rate Model

Variables	Hurricane Irma		Hurricane Matthew	
	Estimates	**t stat**	**Estimates**	**t stat**
Constant	491.643	5.527	101.593	1.820
Evacuation Risk Zone				
Evacuation Zone Type (Base: other zones)				
Zone A	132.342	7.650	87.017	2.944
Zone B	86.420	4.856	56.827	1.700
Hurricane Characteristics				
Distance from hurricane path	-0.795	-4.950	-1.127	-4.348
Intensity (mph)	1.237	2.797	--	--
Zonal Level Demographic Characteristics				
Population	-0.102	-3.052	-0.058	-1.452
Median Income	--	--	2.713	3.499
Vehicle Ownership (base: <= 1 vehicle)				
% of HH with 2+ vehicles	-2.350	-2.387	--	--
Land Use Characteristics				
Single Family	-96.563	-2.513	--	--
Mobile Homes	--	--	236.109	1.720
Condominiums	-48.832	-1.767	--	--
Cooperatives	975.495	4.102	--	--
Retirement Homes	1236.180	2.667	--	--
MF<10 units	--	--	793.982	1.590
Goodness of Fit				
Adjusted R^2	0.530		0.306	

4.3 Evacuation Destination Choice Model

In this section, we discuss the results from a multinomial logit fractional split model of refuge rate (evacuation destination type). The parameter estimates from refuge rate model for hurricane Irma and hurricane Matthew are presented in Table 3 (please see Lee et al. 2018; Rahman et al. 2020 for mathematical details of the MNL fractional split model). Positive (negative) value of a parameter corresponding to an alternative indicates that an increase of that variable increases (decreases) the likelihood of a higher share for that alternative.

4.3.1 Evacuation Risk Zone

The parameter estimates indicate that evacuation zone type is associated with refuge rate. It is evident from the results that during hurricane Irma, evacuees from “Zone A” are more likely to select hotel/motel and are less inclined to travel to a public shelter compared to evacuees from other zones. For hurricane Matthew, evacuees from “Zone A” are likely to select hotel/motel and travel out of state alternatives compared to evacuees from other zones. The results are intuitive. Evacuation zone A locations are the most proximal to the coast and represent high priced real estate. Residents from these locations are likely to be high-income households and are likely to evacuate to hotel/motels.

4.3.2 Hurricane Characteristics

For both hurricane Irma and Matthew, hurricane characteristics are found to be important in predicting evacuation destination type. Interestingly, our findings for two hurricane events are different. For hurricane Irma, with increasing distance from hurricane path, evacuees choose hotel /motel and are less inclined to select public shelter. For hurricane Matthew, evacuees are less likely to move to hotel/motel with increasing distance. The variation in results across the two hurricanes could be attributed to the wobble in hurricane Irma path after landfall. The eventual hurricane Irma path was significantly different from the forecasted path affecting evacuation decision processes across the state. We also found the effect of intensity significant and the result for hurricane Irma indicates that with increased intensity, hotel/motel and public shelter are chosen more by evacuees. For hurricane Matthew, as the intensity of the hurricane near the corresponding county-zone increases, hotel/motels are more likely to be chosen while public shelters are less likely to be chosen.

4.3.3 Zonal Level Demographic Characteristics

The results for hurricane Irma show that an increased county-zone level population decreases the share of hotel/motel and out of state evacuation. The result also indicates that evacuees from high employment county-zone combination are likely to prefer the hotel/motel alternative. Increased affordability associated with higher employment rates are likely to contribute to increased share of hotel/motel evacuation destination adoption in high employment county-zones. Median income is also found to affect refuge rate indicating that evacuees from high income county-zones are more likely to travel out of state compared to evacuees from low-income county-zones. For hurricane Matthew, only median income is found to be significant, and it is observed that evacuees from high income county-zones are more likely to travel out of state.

TABLE 3 Parameter Estimates for Refuge Rate Model (Base: Friends/Family)

Variable	**Hurricane Irma**			**Hurricane Matthew**		
	Hotel/ Motel	**Public Shelter**	**Out of state**	**Hotel/ Motel**	**Public Shelter**	**Out of state**
Constant	-4.1987 (-15.239)*	-3.5342 (-8.690)	-2.3505 (-11.318)	-18.1897 (-4.287)	14.9766 (1.147)	-2.0623 (-6.077)
Evacuation Risk Zone						
Evacuation Zone Type (Base: other zones)						
Zone A	0.1576 (1.476)	-0.4816 (-2.604)	-- (--)	0.7582 (3.258)	-- (--)	0.3920 (1.500)
Hurricane Characteristics						
Distance from hurricane path	0.006 (6.097)	-0.0099 (-4.854)	-- (--)	-0.0113 (-4.527)	-- (--)	-- (--)
Intensity (mph)	0.0145 (4.249)	0.0081 (1.634)	-- (--)	0.1499 (3.991)	-0.1647 (-1.435)	-- (--)

Zonal level demographic characteristics						
Population	-0.0004 (-2.067)	-- (--)	-0.0009 (-3.746)	-- (--)	-- (--)	-- (--)
Employment rate	2.3096 (3.263)	-- (--)	-- (--)	-- (--)	-- (--)	-- (--)
Median income	-- (--)	-- (--)	0.0123 (3.054)	-- (--)	-- (--)	0.0129 (2.483)
Goodness of Fit						
ρ_o^2	0.407			0.356		

* Values indicate parameter estimate and t statistics in parenthesis

5 CONCLUSION

Earlier studies predominantly adopted survey-based approaches for understanding evacuation behavior and destination choices. In recent years, the emergence of smartphone location-based services (LBS) data in conjunction with high resolution parcel level land-use data offer an automated mechanism to investigate population responses to hurricanes. The current study is focused on estimating evacuation behavioral rates using LBS data and identifying the key factors influencing evacuation behavior. The current study makes a twofold contribution in evacuation behavioral research. The first contribution of the study arises from evacuation data enhancement by identifying evacuation patterns across the state of Florida for two hurricane events including Irma and Matthew. For these two hurricanes, we collect location data of anonymized cellphone devices residing in the affected regions before, during and after hurricanes. Using these data, we estimate evacuation participation rate and evacuation destination (or refuge) rates. Further, employing parcel-level data we determine the land-use patterns to understand the home and destination characteristics of the devices. The characteristics of interest at the home location include share of single-family and multi-family units, and median income characteristics. At the destination level, we identify the presence of hotels/shelters that is useful for identifying destination type.

While the LBS data and parcel data provide an understanding of behavioral response to hurricanes, it is important to recognize that the behavior estimates are specific to the hurricane. The behavioral rates cannot be directly applied to any future hurricane because hurricane characteristics such as path, intensity and size are likely to be different. Hence, in our study, we attempt to parameterize the hurricane evacuation behavior using data from the two hurricanes. For this purpose, the inferred evacuation characteristics are employed to develop statistical models that identify different contributors to evacuation decisions. We identify the key determinants of evacuation participation rate and destination type at an aggregate level of county-evacuation risk zone. Using the prepared evacuation data, we employ linear regression model to study county-zone level participation rate (per thousand) and multinomial logit fractional split model to understand evacuation destination choice behavior. The results from the estimated models indicate that evacuation zone type, hurricane characteristics, zonal level demographic characteristics, and land use characteristics are key determinants of county-zone level participation rate and share of the evacuation destination types.

The model results can be employed to make important management and policy decisions. For example, the model can be used to identify zones with high evacuation rates. In addition, it can be used to identify the zones with high demand for public shelters in a hurricane event. Thus, it can allow agencies to prepare adequate transportation infrastructure (such as buses) and shelter facilities (such as beds and other essential supplies) based on the intensity of the hurricane. The evacuation demand can also serve as a useful input for evacuation route analysis for transportation agencies monitoring evacuation flow patterns.

To be sure, the current study is not without limitations. We could complement our study by considering additional behavioral patterns such as travel distance, and time of evacuation. Moreover, complementing the LBS data by additional resident survey data could potentially reveal the effect of individual socio-demographics, preferences and circumstances on evacuation decisions. Furthermore, it is possible evacuation rate and refuge rate may have common unobserved factors influencing them. Therefore, a joint econometric model system might enhance model accuracy.

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Competing Interests
The authors have no competing interests to disclose.

Author Contributions
The authors confirm contribution to the paper as follows: study conception and design: Naveen Eluru, Krishnan Viswanathan, Jason Lemp, Sudipta Dey Tirtha, Pragun Vinayak; data collection: Sudipta Dey Tirtha, Pragun Vinayak, Dewan Ashraful Parvez, Michalis Xyntarakis, Jason Lemp, Naveen Eluru, Andrew Sussman, Elizabeth Payne, Roberto Miquel; model estimation: Sudipta Dey Tirtha, Dewan Ashraful Parvez, Naveen Eluru; analysis and interpretation of results: Sudipta Dey Tirtha, Dewan Ashraful Parvez, Naveen Eluru; draft manuscript preparation: Sudipta Dey Tirtha, Dewan Ashraful Parvez, Naveen Eluru, Jason Lemp. All authors reviewed the results and approved the final version of the manuscript.

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