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RELIABILITY OF MOBILE LOCATION DATA AND THE INFLUENCE OF SOCIAL DEMOGRAPHICS ON EVACUATION TRAFFIC

WILLIAM SEITES-RUNDLETT[1], ROSS B. COROTIS[2] AND CRISTINA TORRES-MACHI[3]

[1]University of Colorado
UCB 428, Boulder, CO 80309
William.seitesrundlett@colorado.edu

[2]University of Colorado
UCB 428, Boulder, CO 80309
Corotis@Colorado.edu

[3]University of Colorado
UCB 428, Boulder, CO 80309
Cristina.torresmachi@colorado.edu

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Abstract. Hurricane evacuations are difficult to reconstruct when endeavoring to explore and analyze the movements of evacuees, making it difficult to validate model predictions with actual evacuation traffic. Mobile location data offers an opportunity to reconstruct evacuation traffic and associate mobile evacuees with place-based social demographics such as income, race/ethnicity, and family size. These data offer a unique insight into the evacuation travel behavior of different social groups but is imprecise in several aspects. The objective of this study is twofold: to analyze the reliability of mobile location data to capture evacuation traffic and to explore the influence of social demographic variables on travel behavior. Specifically, the study analyzes the timing of evacuation during Hurricane Michael, which affected Florida, USA, in 2018. The limitations of mobile location data are reviewed through a sensitivity analysis comparing mobile location data with actual traffic counts. Results comparing travel behavior between demographic groups show that the high-income group tend to increase trips, while low-income and Black groups show a tendency to decrease trips. This presentation contributes to evacuation modeling theory by exploring the social influences of evacuation and evacuation modeling practice and demonstrating the applicability and limitations of imprecise information of mobile location data to reconstruct evacuation behavior.

1 INTRODUCTION

Evacuation is one of the most effective means of reducing mortality and morbidity associated with natural disasters [1]. Evacuation has particular importance for events with forewarning, such as the tropical storms and hurricanes which threaten the southern and eastern coastlines of the United States. These destructive events can disrupt livelihoods, environmental health, infrastructure systems, and community health. Among weather-related disasters, hurricanes are a leading cause of economic damage in the continental United States and globally [2]. Growth in coastal population and wealth have led to increasing hurricane-related damage along the U.S. coastline, with Florida being one of the states more severely affected by hurricanes [2].

In response to the devastating hurricane seasons in 2004 and 2005, Florida developed one of the most comprehensive evacuation plans in the country, including a comprehensive behavioral response survey [3]. However, gleaning evacuation behavior from the results of statewide behavioral surveys did not prevent the traffic management problems derived from hurricane evacuations. During hurricane Irma in 2017, about 6 million residents in Florida were evacuated from coastal areas, creating the largest mass evacuation in U.S. history [4] and terrible traffic jams and fuel shortages. These evacuation experiences, however, have also presented an opportunity for improving evacuations through the use of tools and data focused on analyzing social impacts on evacuation. An objective of this study is to use mobile location data to review the social factors influencing evacuation and determine how well they are captured in prominent composite indices measuring Social Vulnerability, Social Capital, and Resilience currently used in disaster planning efforts.

2 BACKGROUND

Modeling evacuations should reflect the fact that each event is unique, reflecting the physical and social constructs of the community, as well as the characteristics of the hazard event. Recent research has identified the need to incorporate and validate more social and human-centric indicators into evacuation models [5]. This has spurred an emerging field of research into evacuations using mobile location data and evaluating behavior at the individual level [6,7]. However, there appears to be a lack of research using such location data to analyze potential influences of social demographics on evacuation behavior. An important attribute of these location data is the ability to connect the mobile device user to their home location and census-based social demographics.

The questions of who evacuates and what factors influence this decision are frequently investigated, mostly in the social sciences. Among the many factors affecting an evacuate/stay decision, previous studies [8,9,10,11] have identified that the strongest predictors of evacuation participation are: (1) receiving evacuation notice, (2) housing type and duration of residence, and (3) geographic location. These factors are considered in aggregate models of evacuation participation, such as the one proposed by Lindell and Prater [12] to predict evacuation rates as a function of residents' risk areas and the Saffir–Simpson hurricane category of an approaching storm. This aggregate model, however, neglects the influence of social ties in evacuation participation. Empirical evidence [13,14,15] has shown that aspects related to social capital influence the decision of whether to evacuate. A recent study developed by Sadri et al. [16] developed interviews to understand evacuation behavior during Hurricane Sandy and found that social network ties, their strength, and type of information warning received affects the decision to evacuate. A serious limitation of most existing studies is that they rely on survey data, limiting the sample size, representativeness, and capacity for extrapolation of the analysis.

Few studies have explicitly examined the interplay between social capital and social vulnerability, particularly in relation to evacuation behavior. However, empirical evidence suggests that each plays a role in shaping the likelihood and timing of evacuation. In comparing experiences from two New Orleans neighborhoods during Hurricane Katrina, Elliot et al. [13] found that Lower Ninth Ward residents tended to belong to social networks that were homogeneous in terms of disadvantage relative to those in the more affluent Lakeview community. Collective lack of access to resources within the Lower Ninth Ward population limited residents' ability to quickly leverage social capital to access materials (e.g., personal vehicles) they lacked, highlighting the structural dimensions of social vulnerability. Yet while there were substantial disparities between the two populations, the data nonetheless suggested that social connections yielded pre-storm assistance that supported evacuation within both groups. Other studies have similarly explored how particular dimensions of social capital and social vulnerability influence evacuation decision-making [14,15,17,18] and post-disaster recovery [7,19,20]; however, there remains a need for more robust integration of and theoretical engagement with these concepts.

Although both social capital and social vulnerability influence evacuation options, community-level factors set the broader context in which important decisions are made. It is thus vital to evaluate these settings in relation to individual behavior. Klinenberg's "social autopsy" of the 1995 Chicago heat found that community environments that either encouraged or constrained low-income seniors' ability to participate in social life—areas of high versus low social capital—directly influenced whether these individuals left their overheated apartments for safer environs or remained in conditions that ultimately contributed to their mortality [21]. Similarly, Gehlot et al. [22] found that as the size of an individual's social network increases, the probability to travel long trips (more than 3 hours) during Hurricane Harvey evacuation also increases. It is thus critical to understand how community-level indicators of social vulnerability and social capital reflect the infrastructure of support for evacuation behavior. This paper evaluates the reliability of mobile location data by comparing them to actual traffic count data and explores the potential of these data to analyze potential influences of social demographics on evacuation behavior. The literature review will also highlight limitations of prevailing data collection methods and compare these limitations to recognized shortcomings of using mobile location data. Another motivation of this research is to contribute to evacuation modeling practice by considering the accuracy and representativeness of these data compared to prevailing evacuation research methods and demonstrating the applicability of using these data to analyze traffic counts during an evacuation.

3 METHODS

First, the 33 traffic sites that are in the Apalachee region were identified in FDOT data. Then, 2018 average annual daily traffic (AADT) data were obtained from 32 of the traffic sites (one was new in 2020). These 32 traffic sites and their associated AADT and vehicle classification history were used to calibrate the mobile location data in accordance with the data provider guidance, such as the calibration checklist proposed by Yang et al. [23]. Once this was calibration completed, several analyses were performed to determine the sensitivity of the mobile location data to choices made in the analysis. These choices correspond to settings the user must define when extracting data from the mobile location platform. In each of these analyses, calibrated mobile location data are compared to actual traffic data to determine trends in accuracy of the mobile location data and determine the optimal settings for this analysis. The data were compared using traffic counts. The results obtained from this analysis are further used to derive guidance for future users of this platform.

Once the mobile location data set was finalized, the next step focused on analyzing traffic counts and their distribution over the 48-hour time period of the evacuation. First, traffic count data, both mobile location data and FDOT data, were aggregated into 6-hour bins. Mobile location data do not necessarily provide an estimate for every given hour over the analysis period, given data privacy and security concerns, and the number of missing counts increases as overall traffic volumes decrease at a location. Aggregating traffic counts to 6-hour intervals addresses this issue by reducing the need to deal with many missing counts. Furthermore, the hourly estimates for a given site were checked to ensure they agreed in summation with predicted total daily traffic counts in the mobile location data. The initial sensitivity analyses focused on comparing daily counts, and hourly counts were only collected from the final mobile location data set.

Traffic counts were further segregated directionally (i.e., east-west, north-south), creating 16 paired counts of traffic during the evacuation period, one from mobile location data and one from FDOT. A second set of 16 paired counts was then created for the normal traffic period, occurring one week before the evacuation period. These two sets of 16 paired counts were used to perform paired t-tests (two-tailed) comparing mobile location data and observed traffic data for the normal period and the evacuation period.

Paired t-tests were used to study paired data sets collected under homogenous conditions. In this analysis, the homogenous conditions of each data pair are the identical time period, direction, and traffic site for each collected pair of data. The difference for each pair corresponds to the analysis of interest, such as normal vs. evacuation period, different social demographics, and comparing mobile location data to observed traffic data. The parameter of interest is the difference in trip counts over 6-hour windows of time. Note that although mobile location data is collected from mobile devices, the unit of measurement is still traffic counts identical to those produced by observing traffic. Mobile location data traffic counts are the result of aggregating data obtained from all the devices in the sample.

4 RESULTS AND DISCUSSION

This section discusses the results of the sensitivity analysis of mobile location data and the reliability of these estimated when compared to actual traffic counts. A more detailed analysis will appear in a journal paper that will be prepared once all the data are thoroughly analyzed.

First, the number of calibration zones was adjusted to see if there is a point at which more calibration zones do not change the output. We found that the output always changed, and more calibration zones improved the results. Therefore, all 32 calibration zones were used to generate the mobile location data set.

Next, the dates of analysis were examined. Since data from single days were needed to compare traffic counts to actual traffic data [23], various lengths of analysis were examined (i.e., one day, three-day, five-day and seven-day analysis). The number of days was capped at a seven-day window, (e.g., October 3 to October 10) to capture traffic data for specific days in a week. Any longer of an analysis window (e.g., October 1 to October 14), would begin to average duplicative days (e.g., average Monday traffic) losing single day estimates. The seven-day window provided the most accurate output, as the individual estimates differed depending on the length of the analysis window.

Additional sensitivity analysis explored different options related to when the date of interest was located within the seven-day window. To quantify this, the difference between the mobile location data and the traffic count data was evaluated for different scenarios. The most accurate output was identified when the dates of interest were at the end of the seven-day window. Figure 1 shows how the absolute error (i.e., measured as the difference between mobile location and FDOT observed counts) generally decreases as the date of analysis is moved later in a 7-day window. Therefore, mobile location data between October 3 and 9, 2018 were used to analyze the evacuation travel behavior, and the dates September 26 to October 2, 2018 (one week prior to the evacuation) were used to analyze normal travel behavior. The combination of these two periods of analysis constitutes the final mobile location data set.

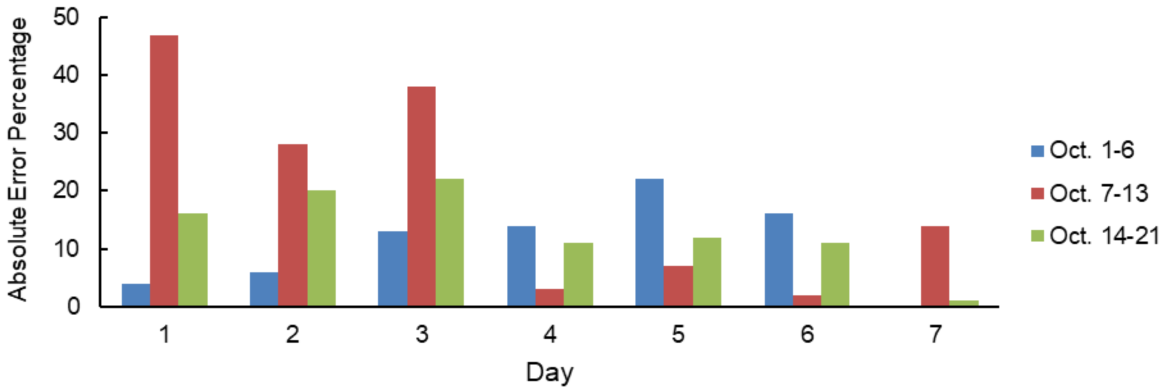

Figure 1. Effect of Location of Date of Analysis

The sensitivity analysis highlighted several points of consideration when using mobile location data that are of value for future users. The most important recommendation is to consider the location of temporary traffic patterns within these data. Temporary traffic patterns refer to any traffic event that would cause a change in traffic patterns compared to normal conditions, such as a hurricane or a large special event causing normal traffic to change route, destination, or trip purpose. Given that the translation of mobile location data to traffic is based on machine learning algorithms that learn from patterns, analyses over a time period that only captures temporary traffic or begins with temporary traffic can impact the accuracy of estimated trip counts. Therefore, the analysis of special events that may cause changes in normal traffic patterns require a detailed analysis on the optimal length of the time period to analyze and the location of the special event within this period. In the case study under analysis, the optimal settings resulted to be a one-week analysis period and locating the special event (i.e., hurricane) at the end of this time window. Lastly, these data have shown improvement over time, and there is increased confidence in the accuracy of these data in analysis of future events (see Table 1 below).

Table 1: Mobile Location Data Accuracy Over Time

Year	2016	2017	2018	2020
Error %:	458%	1025%	5%	32%

Note: Traffic was evaluated during the time periods surrounding hurricane events affecting the Apalachee region. 2016 saw Hurricane Hermine, 2017 Hurricane Irma, 2018 Hurricane Michael, and 2020 Hurricane Sally. There were no Hurricanes to affect the area in 2019, despite one weak tropical storm (Nestor) that affected the area.

Another interesting feature of mobile location data is that it enables the socio-demographic characterization of travellers and can therefore be used to explore whether the socio-demographic characteristics of travellers may impact their travel behaviour during evacuation. Our study has discovered that the influence of social vulnerability and social capital is not fully considered in current evacuation plans. In an exploratory study, authors analysed the social vulnerability of different counties in Florida (measured in terms of the social vulnerability index, SoVI, developed by Cutter et al. [24] and compared it to the expected evacuation rates obtained from Florida evacuation plans [25]. Figure 2 shows that there are no significant differences in the expected evacuation rates of counties having different social vulnerability. The proposers have performed additional analyses exploring alternative indices measuring social vulnerability and resilience, including Baseline Resilience Index for Communities [26,27]; and the CDC Social vulnerability Index (SVI) [28]. This suggests that current evacuation plans do not reflect the empirically proven influence of social capital and social vulnerability on the decision of whether to evacuate and certainly do not include the comprehensive issues needed for adequate evacuation planning.

One of the unsolved issues with mobile location data is the penetration rate, and whether it varies among different socioeconomic groups, thus distorting what otherwise would be an unbiased sample. Table 2 shows the penetration rates for StreetLight [29], computed for 2020 in Florida, compared to census data. Since StreetLight provides data at the census block level, the socioeconomic information is extremely valuable, Table 2 indicates good agreement between the two sources, but the variation in penetration rates mandates further study, especially for evacuation situations.

Additional analyses performed by the authors have discovered significant discrepancies in the actual evacuation behaviour that appear to be highly correlated to community social characteristics. As an example of these results, Figure 3 shows a heat map of actual trip destinations during Irma for evacuees departing from counties differing in their social vulnerability (measured in terms of SoVI [24]. These results suggest social characteristics influence evacuation decisions. Figure 3 shows that evacuees from high-vulnerability counties (i.e., Franklin County, delineated with a thick black line in Figure 3a) tend to seek shelter in the same county; whereas evacuees from low-vulnerability counties (i.e., Leon County, delineated with a thick black line in Figure 3b) tend to evacuate to further destinations and are more likely to leave the county. These results reveal that social characteristics (i.e., social vulnerability) influence the decision of where to evacuate. These promising results need to be further analysed to derive theoretically grounded evidence on how social vulnerability and social capital influence the decisions evacuees take before and during an evacuation.

Table 2: StreetLight Data Device Penetration Rate Bias 2020

	StreetLight Data Sample	Florida Census Data
Percentage of Population		
Black or African American	13.3%	15.8%
White	77.8%	75.2%
Asian	2.6%	2.4%
Hispanic	20.5%	22.4%
Older than 70	13.8%	13.9%
Average age	42.6	42.5
Average income	$66,797	$64,386

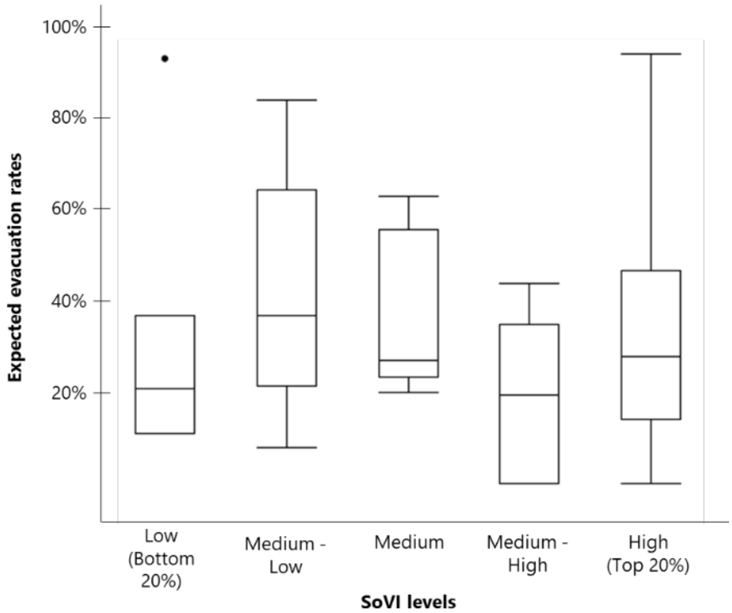

Figure 2: Evacuation rates in current evacuation plans for communities having different levels of social vulnerability

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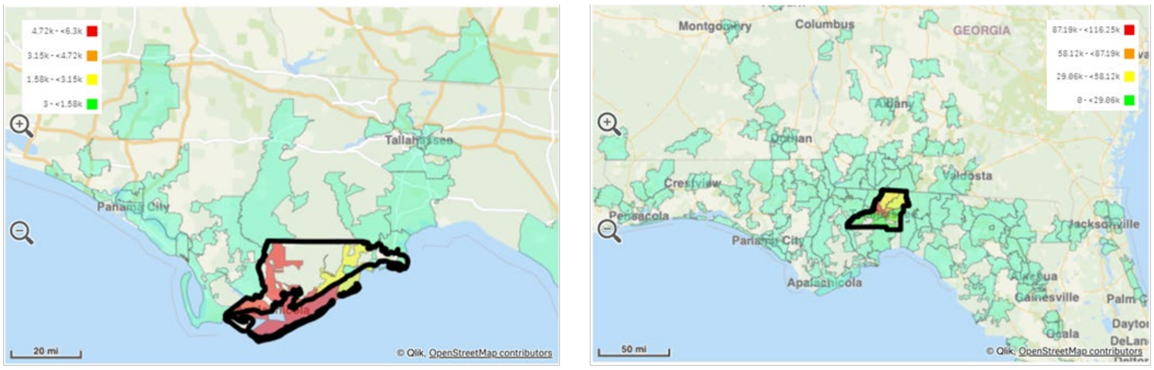

a) Destinations of evacuees from Franklin county (high vulnerable county in terms of SoVI)

b) Destinations of evacuees from Leon county (low vulnerable county in terms of SoVI)

NOTE: The thick black line denotes the area where trips are originated. Destinations are colored on a red to green scale depending on the number of trips attracted. Red areas attract the higher number of trips, whereas green areas attract less trips.

Figure 3: Heat map of actual trip destinations during Irma

5 CONCLUSIONS

Modern data techniques such as the use of mobile location data offer great promise to better understand evacuation behavior related to natural hazards. These new sources provide valuable information that is often lacking due to the emergency situations associated with evacuation. These data have limitations, however, and it is critical to understand their sensitivity and reliability before attempting to incorporate them into evacuation models. Evacuation behavior is a function not only of the physical attributes of a community and the characteristics of the hazard event, however. Therefore, data such as location tracking can provide important information when it can be linked to social and demographic characteristics on the census scale. This is currently possible with commercial mobile location data, but there are distinct shortcomings related to the preservation of privacy information for individual users. Such restriction also makes it more difficult to validate the representativeness of samples from location data. This study is the importance of including such social and demographic data in predicting evacuation characteristics.

The techniques used in this study were validated through one large natural hazard event; a hurricane in Florida, USA, for which the Florida Department of Transportation also collected on-route data. But the concepts need further evaluation through additional actual events.

A review of social vulnerability studies indicates a sensitivity to both social vulnerability and social capital. These factors deserve more detailed study, particularly for their effects during evacuation periods. Such studies should include all aspects associated with evacuation, and not just participation rate.

New techniques and approaches, such as the incorporation of mobile location data, can lead to better understanding of natural hazard response choices such as whether, when and where to evacuate.

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