Emergency Management and Underserved Communities: Using Big Data to Improve Emergency Management Preparedness, Response and Resilience

Zachery Key, Andrea Parrish, Conner Snavely, and Majid Shafiee-Jood, Ph.D.

Abstract— **In anticipation of high impact weather events such as hurricanes, wildfires, and flash floods, public officials need to make life saving and time sensitive decisions under uncertainty. For example, when a hurricane is forming in the Atlantic, public officials need to decide whether and when to issue an evacuation order. However, there is always a large risk in issuing an order early because of the uncertain nature of weather forecasting. Besides the preparation costs, the public could lose trust in officials and forecast information. Previous studies have identified a number of sociodemographic factors contributing to individuals' likelihood to evacuate. These research efforts have proven that the probability of evacuation shares a strong positive correlation with both economic and physical mobility, meaning older populations, low-income populations or those with larger families are less likely to evacuate. While these efforts have provided policy makers with valuable insight to provide for these low evacuation populations, there has been very little analysis of the impact of evacuation orders on constituents' evacuation mobility patterns. To bridge the gap in literature, we investigate the relationship between evacuation policy and observed evacuation patterns during Hurricane Florence (2018). Specifically, we evaluate the evacuation index at the census block group level of communities in Virginia encountering a false positive compared to those in South Carolina experiencing a true positive. By overlaying evacuation order data with cellular mobility data and forecast information from the National Hurricane Center, we aim to capture interactions between policy measures and socioeconomic factors to assess their relationship with evacuation behavior.**

I. Introduction

Current Hurricane evacuation techniques rely on a complex sequence of events that begin with an extreme weather forecast issued to the state governments by federal agencies (e.g., National Weather Service, National Hurricane Center) and culminate in state or local governments issuing an evacuation order. Because modeling the uncertainty of a hurricane strike is an inverse function of time, governing bodies must decide early on whether to risk the lofty expenditures of a false alarm or wait and risk endangering lives. The decision to evacuate is not an easy one: the cost of premature evacuations in the US totals more than $10 billion dollars per year and repeat offenses can cost local governments their credibility [1]. Although most individuals report evacuation preparation times of less than 6 hours, many are hesitant to leave unless they have personally witnessed the evacuation order or have a high level of confidence in the authority of the messenger [2]. Furthermore, the government must be cautious of the order in which it issues evacuation mandates to avoid overwhelming inland transportation routes [3]. Despite the advances in forecasting technology, emergency evacuation orders are only acted on by fewer than 10% of the endangered population [4]. Prior research has proven that there is a significant difference in the demographic makeup of the populations that evacuate and those who shelter in place. Health concerns, family size, pets, play into the decision on whether to seek shelter locally or to evacuate [5].

Historical efforts to quantify public evacuation patterns have utilized an assortment of datasets ranging from traffic counters to community survey responses. While these data sources provide a decent low-resolution approximation of human behavior, they are limited in their scope and can only account for a small subset of the total population. Fortunately, recent advances in technology have provided us with a much higher resolution, detailed source of data via cell phones' location services. By collecting this location data through third party applications, private agencies can access a wealth of information about communities' mobility patterns and generate models and predict future trends.

The major goal of this research is to understand the effect of an evacuation order on the public's decision to evacuate prior to a hurricane strike. Specifically, in this research, we 1) evaluate whether those outside of an evacuation zone exhibit different evacuation levels than those within evacuation zones under mandatory evacuation, and 2) determine the differential response of distinct communities to evacuation orders based on demographic characteristics (e.g., as income, education, age).

This research was partially sponsored by the Environmental Resilience Institute at the University of Virginia.

Z. Key is with the Department of Engineering Systems and Environment at the University of Virginia, Charlottesville, VA (email: ztk2qv@virginia.edu).

A. Parrish is with the Department of Engineering Systems and Environment at the University of Virginia, Charlottesville, VA (email: alp5pt@virginia.edu).

C. Snavely is with the Department of Engineering Systems and Environment at the University of Virginia, Charlottesville, VA (email: cs3fd@virginia.edu).

M. Shafiee-Jood is with the Department of Engineering Systems and Environment at the University of Virginia, Charlottesville, VA (email: ms2dm@virginia.edu).

II. Related Work

Emergency managers have a significant role in planning out evacuation procedures and these procedures must be reviewed frequently to ensure that when a hurricane occurs then the impacted communities will be prepared. Researchers have completed numerous studies examining evacuation patterns to give recommendations on how to improve these procedures. In summer of 2020, a case study was conducted by a team at Old Dominion University (ODU) [6] to determine connections between the current emergency operation plans for the Hampton Roads area and the perceived evacuation behaviors of those who lived in the area. Through the study's interviews with emergency managers, it was determined that there was a disconnect between the emergency managers and the communities they served as they had a uniform policy they used for everyone, rather than policies for different social groups. So, the study recommended that the emergency managers increase their engagement with the surrounding community in order to gain a better understanding of their potential needs and create specialized plans for different social groups in the area. Another ODU study [5] completed in November of 2020 examined how the COVID-19 pandemic would impact evacuation behaviors should a natural disaster hit VA. The study surveyed 2000 households in the Hampton Roads area, asking how their current evacuation plans would change if an evacuation was necessary during the pandemic. The team of researchers found that the perceived risks of an exposure would alter behaviors, stating that they "anticipate a sizable increase in the number of households remaining in the region … households that would have otherwise either evacuated or sheltered in a public shelter" [5].

Due to cell phone-based mobility data in recent years, there has been a renewed interest in this topic. Researchers have used this mobility data to create plots and maps depicting where people are traveling from during an evacuation and where they are traveling to. A team of researchers from the University of South Carolina and the University of Central Florida conducted a study that used geotagged tweets and a survey questionnaire to analyze evacuation patterns for hurricanes Matthew and Irma [7]. The same group in 2017 conducted a case study just on the impacts of geotagged tweets for evacuation compliance during Hurricane Matthew [8]. They used thousands of geotagged tweets, only using those that had the following keywords: “matthew”, “hurricane”, “evac”, and “storm,” that were written between October 2nd and October 11th, 2016. In their analysis, the team noticed that there was usually a peak in evacuation-related tweets for each state the day its mandatory evacuation order was made, and by the time of the hurricane’s landfall, the number of tweets had decreased considerably. Also, most of the evacuation-related tweets came from those on the coastline, and most evacuees would stay within the same state or travel to the bordering states [8].

Other studies have collected GPS location data from cell phones to look at mobility patterns for areas recovering from a natural disaster. In 2021, a team of researchers from Purdue University and University of California Berkeley conducted an analysis of recent studies that used mobile phone location data to study natural disasters and epidemics, focusing on what had been done and what future challenges could arise [9]. A year earlier, the same researchers partnered with several universities in Japan and looked at recovery patterns and population displacement rates for areas that experienced hurricanes, earthquakes, and tsunamis and how the patterns and demographics of these areas differed [10]. The study analyzed location data from millions of cell phones in Japan, Puerto Rico, and the United States and created maps depicting the displacement rates for each area at several time periods after the disaster occurred (day of landfall, 10 days after, a month after). They found that the differences in displacement rates between right when the disaster hit and months after could be explained by a handful of demographic factors. These are the area’s median income level, population, housing damage rates, and its distance to nearby cities, proportional to the size of these nearby cities. [10].

The ODU studies demonstrate the ways researchers have attempted to improve evacuation guidelines using mostly surveys and interviews; however, these methods have limitations as what people say might not match their actions. The studies using mobility data and Twitter have been able to track people’s locations during an evacuation in order to access evacuation order compliance. However, these studies look at tweets from local users to focus on how social media can be useful during a natural disaster. The usage of quantitative data on communities' mobility patterns at the census block group (CBG) level will provide a higher resolution of data for a better analysis to study evacuation behaviors and patterns. Furthermore, by looking at previous hurricane evacuations in VA and SC, this research will help emergency managers improve their evacuation plans through a better understanding of their communities and help predict future evacuation behaviors.

III. Methodology

A. Datasets

Our analysis relies primarily on three different datasets: evacuation orders, mobility data, and census data (see Table I for more details). To the best of our knowledge, no such public database of historical evacuation orders exists in the United States. Specifically, the announcement time of evacuation orders, effective time, and targeted areas were of interest for this dataset. In VA and SC, evacuation orders are issued at the state-level on a zone basis, and official Twitter accounts were used to collect evacuation order data. In NC, evacuation orders are issued at the county-level. When official Twitter or Facebook accounts were nonexistent or inactive in 2018, official government websites were used. Due to the disparate nature of North Carolina’s evacuation processes during Hurricane Florence in 2018, the scope of the analysis in this paper is limited to VA and SC.

To capture a high level of detail in evacuation patterns, we partnered with Spectus, a Data Cleanroom that unlocks the full potential of geospatial analytics at scale and provides users with clarity and a holistic view of consumer behavior to make informed decisions. Through Spectus' Social Impact program, we received evacuation index data at the CBG level. These data for VA and SC were calculated over a three-month period centered around the landfall of Hurricane Florence (September 2018). Evacuation index is defined as the proportion of mobile devices who do not dwell in their home county during a "clock day" (00:00 - 23:59) and are subsequently seen in a different county that day. That device will be considered as an evacuee until it is seen again in the home county. While mobile device observations are county level, Spectus's aggregation was given to us at CBG level. Evacuation index at CBG level allows us to gain an understanding of an entire community's mobility patterns without needing to look at individual records. Spectus data is collected from location-based smartphone app users who opted in to anonymized data sharing through a GDPR and CCPA compliant process. To further protect users' privacy, the data we received from Spectus is anonymized and aggregated, we are required to strictly follow a data use agreement.

Census data were obtained from the American Community Survey, which contains many demographic variables for each CBGs in VA and SC. Together, the above three data sources were merged for analysis. Evacuation zone data were also obtained from official government websites and organizations to aid in identifying CBGs under mandatory evacuation. Because CBGs may not fully lie in an evacuation zone, for this analysis, a CBG was coded as being under mandatory evacuation if at least 50% of the land area resided in an evacuation zone.

For the scope of this paper, the demographic variables considered were median income, renter occupied units, median age, and education level of CBGs. Further, several other variables were created to show the percentages in a CBGs of some of these variables. For example, the absolute count of rental occupied units fails to provide a relative standard as it does not account for the total number of housing units in the block group. See Table I below for an overview of these variables.

TABLE I. DATA SOURCES AND ATTRIBUTES

Data Source	**Variables Present**	**Variables Created**
Spectus (mobility data)	Evacuation Index	Percentage of Renter Occupied Units Percentage of Residents without a High School Degree Percentage of Residents with a College Degree
Evacuation Orders Dataset (CBGs under mandatory evacuation order)	Evacuation Order	
American Community Survey (demographic data)	Median Income Median Age Renter Occupied Units Number of Residents without a High School Degree Number of Residents with a College Degree	

B. *Statistical Testing*

To understand whether those outside of an evacuation zone exhibit different evacuation levels than those within evacuation zones under mandatory evacuation, we conduct independent sample t-tests on CBGs in VA and SC. The tests were conducted for each state, comparing the average evacuation indexes for CBGs under evacuation orders and outside of the evacuation orders to determine any difference. Further, to understand the effectiveness of evacuation orders, paired t-tests on evacuation index were conducted solely on CBGs under mandatory evacuation. The samples were compared for three days prior to and after the mandatory order.

It is also of interest to determine the differential response of distinct communities to evacuation orders based on demographic characteristics such as income, education, race, and age, among other census data available. The dataset was filtered to only include CBGs under mandatory evacuation. Many variables in the dataset are continuous, without distinct categories for analysis, so intuitive cutoffs were established to carry out parametric ANOVA and non-parametric Kruskal-Wallis statistical tests. Particular attention was paid to ensure that there was an adequate sample size of CBGs within each category. For each metric of interest, an ANOVA test was performed to discern if the mean evacuation index was different among the aforementioned categories. When parametric assumptions were not met, the equivalent non-parametric Kruskal-Wallis test for differences in medians was performed.

C. *Linear Models*

While statistical analysis on individual variables to determine differential response to evacuation orders is insightful, performing many tests leads to the problem of multiplicity nor does it account for confounding variables [11]. As such, several linear regression models were created using demographic variables: full main effects model, stepwise main effects model, full main effects plus interaction model, and stepwise main effects plus interaction model. Moreover, many of these models were iterated upon with transformed variables. After the creation of the first four models (on full data), several metrics were compared. These included adjusted r-squared, AIC, BIC, and MSE. Next, diagnostic plots were examined to ensure assumptions for linear regression models were met, and potential influential outliers were removed.

IV. RESULTS

A. *Decision Making Process*

The decision-making process that emergency managers use for hurricane evacuation orders is complex with numerous steps which must be completed in the constantly changing environment of hurricane trajectories. The evacuation orders decisions are made partially is based on the current path of the hurricane, its projected track and severity, and time to landfall. However, the path of a hurricane changes constantly and once an evacuation order is instituted, it is difficult to rescind without harming public trust. Therefore, there are some instances where there is a premature evacuation for a hurricane that never reaches the areas to which it was forecasted. These premature evacuations can cost billions of dollars and can damage the public's trust in emergency managers. Hurricane Florence in VA is an example of a premature evacuation or false alarm. The evacuation order for VA’s Zone A, located on the eastern coast, was announced on September 10th, 2018, and effective the following morning. On September 11th, the National Hurricane Center projected that Hurricane Florence would make landfall in VA in five days, as seen in Fig. 1. However, the hurricane quickly changed direction after the order was put into effect. By the end of the day on September 13th, most of VA was no longer under a hurricane watch and only a few areas along the coastline of southeastern VA had a tropical storm warning. Additionally, Hurricane Florence’s projected path (Fig. 2) showed Florence completely bypassing coastal VA. and on September 14th, Governor Northam lifted the evacuation order for Zone A.

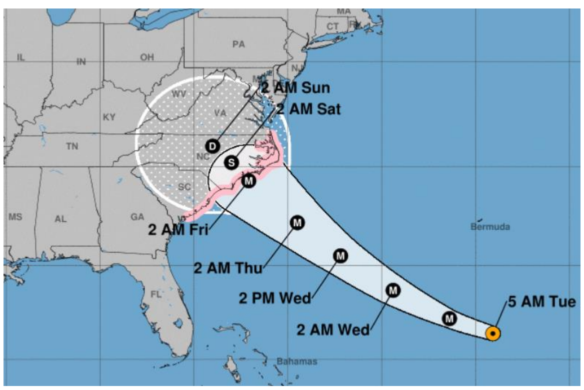

Figure 1. National Hurricane Center (NHC) Graphics Archive on September 11th at 5:00AM AST

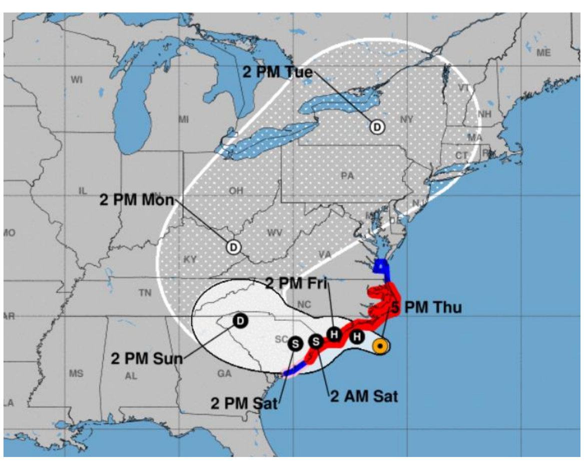

Figure 2. National Hurricane Center (NHC) Graphics Archive on September 13th at 5:00PM AST

B. *Statistical Analysis for Evacuation Index*

In the first statistical test, we conducted an independent samples t-test comparing the means of the evacuation index of all CBGs in SC and VA during a 3-day window centered around the evacuation order. When we separate out the populations by state (Fig. 3), we find that VA has a significant difference between populations under evacuation orders (N=146, μ=.1) and populations not under evacuation orders (N=4049, μ=.22) while SC displays the opposite behavior with a significantly higher evacuation index (N=390, μ=.37) where an evacuation order was issued vs without an order (N=1794, μ=.22). The results of this statistical test suggest that the mean evacuation index was lower around the time of the hurricane in CBGs under mandatory evacuation in comparison to other CBGs in the state of Virginia. Next, we performed a paired t-test to compare the mean evacuation index of CBGs under a mandatory evacuation order, averaged for 3 days before the evacuation order and 3 days after the evacuation order. As we can see in Fig. 4, there is a significant difference in the SC evacuation rate before (N=390, μ=0.07) vs. after (N=390, μ=0.28) the evacuation order as well as a smaller, but still significant difference in the VA evacuation index before (N=145, μ=.07) vs. after the evacuation order (N=145, μ=.14)*. This finding suggests that even though the evacuation index in VA’s CBG’s was lower than the rest of the state during the evacuation around hurricane Florence, there was still a non-negligible increase in evacuation index after the evacuation order was given. Note that there is one less CBG in the paired t-test than the independent samples t-test: this is the result of that CBG missing data after the evacuation order but not before.

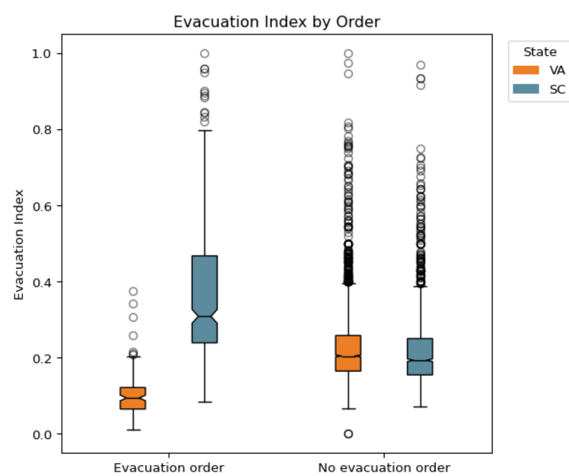

Figure 3. The variation in evacuation index in CBGs with and without evacuation order.

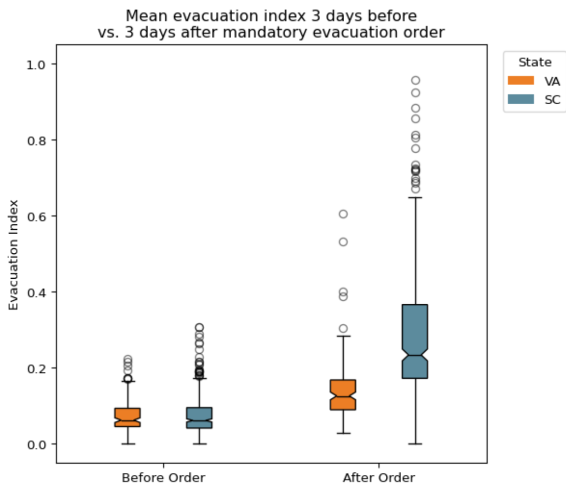

Figure 4. The impact of evacuation orders on evacuation index in CBGs under evacuation order.

C. *Statistical Demographic Analysis and Linear Model*

To understand how various demographic variables affect evacuation index, statistical testing and the construction of several linear regression models was completed. For statistical inference, it is integral that model assumptions are met, and the best model is analyzed. The optimum model was a stepwise main effects plus interaction model with four influential outlier data points removed based on diagnostic plotting. This model performs best on all metrics except BIC. In Table II below, one can see the various performance metrics of each model. Additionally, there were no major issues with diagnostic plots. For the residual vs. fitted plot, there was an absence of patterns, mostly constant variance, and a symmetric display around zero. For the Q-Q plot for normality of residuals, it was mostly Gaussian except for the upper tail. A box-cox transformation was done on the response variable, but it reduced the overall performance of the model significantly. After the outliers were removed, the residuals vs. leverage plot showed no large residuals for data points with high leverage. Many of the variables of interest were significant at the 0.05 level in this model. Fig. 5 illustrates the main effects results of the linear regression model. There were several interaction coefficients which will be briefly discussed later.

TABLE II. PERFORMANCE METRICS FOR THE LINEAR MODELS TESTED

Model	**AIC**	**BIC**	**Adjusted r-squared**	**MSE**
Main effects	-408.92	-345.79	0.27	0.024
Stepwise main effects	-413.00	-362.50	0.27	0.024
Main effects plus interaction	-429.59	-38.19	0.39	0.017
Stepwise main effects plus interaction	-504.72	-336.38	0.42	0.018
Stepwise transformed variables main effects plus interaction	-508.80	-344.67	0.43	0.018
Stepwise main effects plus interaction without outliers	-512.78	-290.05	0.44	0.017
Stepwise transformed variables main effects plus interaction without outliers	-523.99	-334.88	0.45	0.017
Stepwise transformed variables main effects plus interaction without outliers plus box-cox transformation	139.99	329.10	0.40	0.065

* Selected model

```
Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)              -1.658e+00  6.948e-01  -2.386 0.017450 *
Black_percent             1.829e+00  7.099e-01   2.577 0.010290 *
Asian_percent             9.576e-01  1.116e+00   0.858 0.391092
Hispanic_percent         -1.272e+00  5.910e-01  -2.153 0.031863 *
White_percent             2.256e+00  7.436e-01   3.034 0.002549 **
Median_House_Value       -5.872e-08  7.836e-08  -0.749 0.454007
renter_percentage         9.197e-01  2.605e-01   3.530 0.000458 ***
Median_Age                3.421e-02  1.389e-02   2.463 0.014151 *
health_insurance_percent  8.564e-01  9.024e-01   0.949 0.343158
Median_Income             9.761e-06  6.038e-06   1.617 0.106645
poverty_percent          -2.199e-01  1.050e+00  -0.209 0.834235
no_hs_percent             6.600e+00  1.864e+00   3.542 0.000439 ***
college_percent          -4.455e+00  1.150e+00  -3.875 0.000123 ***
public_income_percent    -5.256e+00  2.214e+00  -2.374 0.018033 *
```

Figure 5. Coefficients from Multiple Linear Regression

Renter Occupied Units

Percentage of Renter Occupied Units was broken down into three groups: Low [0% - 25%), Middle [25% - 50%), and High [50+%). Both ANOVA and Kruskal-Wallis tests were statistically significant, and the Tukey procedure showed that the High rental percentage group had a significantly higher mean evacuation index (0.323) than the Middle group (0.255). In the linear model, the percentage of renter occupied units was statistically significant with a positive coefficient, indicating that evacuation index increases with an increased percentage in renter occupied households.

Age

Median Age was broken into three groups: Young [0 – 35), Middle [35 – 55), and Old [55+). Both tests were statistically significant, and the Tukey Method showed that older residents tend to evacuate more. Median age is also significant in the linear model with a positive coefficient, which shows that CBGs with older residents tend to evacuate more than those with younger residents.

Education

Percentage of Residents without a High School Degree was broken down into three groups: Low [0% - 5%), Medium [5% - 10%), and High [10+%). Only the ANOVA test was significant, and the Tukey procedure revealed that the High group had a significantly lower evacuation index than the Low group, suggesting that less high school educated census blocks tend to evacuate fewer. The Percentage of Residents with a College Degree broken into three groups: Low [0% - 15%), Medium [15% - 30%), and High [30+%). Both statistical tests were significant, and the Tukey procedure showed that the High group had a significantly higher evacuation index (0.330) than the Low group (0.272). The linear model revealed that the percentage of residents without a high school degree is significant, as well as the percentage of residents with a college degree. Positive and negative coefficients, respectively, illustrate that less educated block groups tend to evacuate more often.

Income

Median household income was broken down into three groups: Low [$0 - $50,000), Middle [$50,000 - $100,000), and High [$100,000+). Parametric and non-parametric tests were statistically significant, and a post-hoc Tukey Method revealed that the Low-income group had a significantly higher mean evacuation index (0.32) than the other groups. However, median income was not a significant predictor of evacuation index in the model. This phenomenon may be due to confounding variables. The interaction between median income and the percentage of residents with a college degree was significant, though, with a coefficient of 1.27e-05. This implies that as more residents have a college degree, higher income leads to further evacuation.

V. Conclusion

By integrating census data, mobility data and evacuation orders, we can partially attribute higher evacuation response rates to demographic factors at the CBGs level. We expand upon the findings from the literature to show that median age, number of rental occupied units, high school and college education rates also have a significant impact on evacuation behavior. Furthermore, we observe a significant difference between evacuation behaviors in VA (False Positive) and SC (True Positive) for Hurricane Florence in 2018, providing evidence that the two states observed very different evacuation patterns despite their similar evacuation timeline. To validate our results, we took the difference in evacuation index before and after receiving a mandatory order in VA and found that there was not a significant difference in evacuation index around the time the order was issued.

Despite significant improvements in weather forecasting and modeling technologies, we must accept the great uncertainty and unpredictability of natural forces to change course on a dime. In this research, we have investigated the impact of various demographic factors on evacuation index to understand which communities are most at risk during an evacuation emergency. We have also found significant differences in the response rate between localities in the path of the hurricane (SC) and outside the path of the hurricane (VA) even though the evacuation orders were issued at approximately the same time. Future research efforts looking to explore this disconnect may benefit from evaluating the relationship between emergency managers and their constituencies in order to improve trust and adherence to evacuation policy.

Acknowledgment

We thank the Virginia Department of Emergency Management (VDEM) and the Commonwealth Center for Advanced Logistics Systems (CCALS) for supporting our research. We also thank Mr. Bruce Sterling (VDEM), Mr. Stewart Baker (VDEM), Mr. Mark Manasco (CCALS), and Mr. Tom Polmateer (UVA and CCALS) for their guidance and support.

References

[1] E. Regnier, “Public evacuation decisions and hurricane track uncertainty,” *Management Science*, vol. 54, no. 1, Jan., pp. 16-28, 2008.

[2] M. K. Lindell, J. H. Sorensen, E. J. Baker, and W. P. Lehman, "Community response to hurricane threat: Estimates of household evacuation preparation time distributions," *Transportation Research Part D: Transport and Environment*, vol. 85, Aug., 2020.

[3] H. Nakanishi, S. Wise, Y. Suenaga, and E. Manley, “Simulating emergencies with transport outcomes Sim (SETOSim): Application of an agent-based decision support tool to community evacuation planning,” *International Journal of Disaster Risk Reduction*, vol. 49, Oct., 2020.

[4] H. Deng, D. P. Aldrich, M. M. Danziger, J. Gao, N. E. Phillips, S. P. Cornelius, and Q. R. Wang, “High-resolution human mobility data reveal race and wealth disparities in disaster evacuation patterns,” *Nature News*, vol. 8, no. 144, Jun., 2021.

[5] J. G. Behr, R. Diaz, W. Yusuf, B. Giles, K. Lawsure, and G. McLeod, “COVID-19 evacuation and sheltering risk perception study,” Institute for Coastal Adaptation & Resilience, Old Dominion University, Norfolk, VA, USA, 2020.

[6] M. B. Smith, “Social vulnerability and hurricane evacuation behavior in Hampton Roads, VA: Emergency management stakeholders’ perceptions of low-to-moderate income households in a social construction paradigm,” Ph.D. dissertation, School of Public Service, Old Dominion Univ., Norfolk, VA, USA, 2020.

[7] Y. Martín, S. Cutter, and Z. Li, “Bridging Twitter and Survey Data for Evacuation Assessment of Hurricane Matthew and Hurricane Irma,” *Natural Hazards Review*, vol. 21, no. 2, May 2020.

[8] Y. Martín, Z. Li, and S. Cutter, “Leveraging Twitter to gauge evacuation compliance: Spatiotemporal analysis of Hurricane Matthew,” *PLoS ONE*, vol. 12, no. 7, Jul. 2017.

[9] T. Yabe, N. K. W. Jones, P. S. C. Rao, M. C. Gonzalez, and S. V. Ukkusuri, “Mobile phone location data for disasters: A review from natural hazards and epidemics,” *Computers, Environments, and Urban Systems*, vol. 94, Jun. 2022.

[10] T. Yabe, K. Tsubouchi, N. Fujiwara, Y. Sekimoto, and S. V. Ukkusuri, “Understanding post-disaster population recovery patterns,” *J. R. Soc. Interface*, vol. 17, no. 163, Feb., 2020.

[11] J. Quinn, S. Baee, and L. E. Barnes. SYS 4021. Class Lecture, Topic: “Multiple linear regression basics.” School of Engineering and Applied Science, Univ. of Virginia, Charlottesville, VA, 2021.