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ORIGINAL PAPER

Can visits to certain businesses help predict evacuation decisions in real time?

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Abstract
This study aims to help understand and predict evacuation behavior by examining the relationship between evacuation decisions and visits to certain businesses using smartphone location and point of interest (POI) data collected across three hurricanes—Dorian (2019), Ida (2021), and Ian (2022)—for residents in voluntary and mandatory evacuation zones. Results from these data suggest residents visit POIs as part of preparatory activities before a hurricane impacts land. Statistical tests suggest that POI visits can be used as precursor signals for predicting evacuations in real time. Specifically, people are more likely to evacuate if they visit a gas station and are more likely to stay if they visit a grocery store, hardware store, pet store, or a pharmacy prior to landfall. Additionally, they are even less likely to leave if they visit multiple places of interest. These results provide a foundation for using smartphone location data in real time to improve predictions of behavior as a hurricane approaches.

Keywords Evacuation · Hurricane · Smartphone · Decision-making · Points of interest

1 Introduction

A great deal of research has been undertaken to attempt to predict people's behavior more accurately during a hurricane, in particular, if they will evacuate, and if so, when and to where. That work includes development of theoretical frameworks to explain behavior, such as the protective action decision model and the warning response process (Lindell and Perry 2012; Mileti and Sorensen 1990); identification of variables that help explain different behaviors (Huang et al. 2016; DeYoung et al. 2016); and development of quantitative

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models to predict behavior (Anyidoho et al. 2022; Xu et al. 2016). Despite decades of research and many advances, efforts to manage hurricane evacuations in practice would benefit from additional improvement in the predictive power of such models. As discussed in Anyidoho et al. (2022), with current state-of-the-art models, for future hurricanes we can estimate: (1) total evacuation rate within 10 percentage points, sometimes much less, (2) evacuation rate for each county within 10–15 percentage points, and (3) departure curves within plus or minus several hours.

The new availability of smartphone location data offers a new way to potentially improve evacuation prediction, since it could be collected in real time as a hurricane approach and therefore can reflect the particularities of the specific hurricane. Most previous research has relied on surveys, focus groups, and interviews, all traditional data collection methods that require time to implement. Smartphone location data could potentially provide signals of a person's intended evacuation behavior in real time as a hurricane approaches. Movements made in the days between hurricane formation and landfall—in particular, visits to certain types of businesses—may provide clues as to whether a person in an area threatened by a hurricane is preparing to evacuate or preparing to shelter in place. As a first step towards developing this advance, Li et al. (2022) studied the relationship between visits to four points of interest- grocery stores, gas stations, pharmacies and home improvement stores (hardware), and hurricane. However, their study relies on data from only Harris County during hurricane Harvey (2017).

As a next step towards advancing this potential, we utilized smartphone location data and points of interest data from multiple hurricanes—Dorian (2019), Ida (2021) and Ian (2022) with focus on five types of businesses of interest —gas stations, groceries, hardware stores, pet stores, and pharmacies. Specifically, to identify and understand their relationship to evacuation patterns, we develop and investigate two research questions (RQs):

RQ1 Does the frequency of visits to gas stations, groceries, hardware stores, pet stores, or pharmacies change as a hurricane approaches?

RQ2 Can visits to gas stations, groceries, hardware stores, pet stores, and/or pharmacies help predict evacuation, and if so, how and under what circumstances?

To address RQ1, we compare the frequency of visits to the businesses during normal times (N), during the period just before hurricane impact when people are preparing to leave or stay (P), and during the impact period (I) when hazardous conditions exist. For RQ2, we conduct *t*-tests to compare the probability of evacuation for those who visited one of the business types and the probability of evacuation for those who did not.

We discuss the literature on population evacuation behavior decisions in Sect. 2 and the smartphone location data in Sect. 3. The methodology and results are presented in Sects. 4 and 5 respectively. The study concludes with discussion of results implications and recommendations for future work.

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2 Background

2.1 Population hurricane evacuation behavior

Research on hurricane evacuation decision-making spans multiple methodological approaches and research questions (Baker 1991, Dash and Gladwin 2007, Murray-Tuite and Wolshon 2013, Sorensen 2000, Bowser and Cutter 2015, Huang et al. 2016, and Thompson et al. 2017). Theoretical models inform behavioral research on warnings, evacuations, and disaster response, in part by anticipating influences on and cues used by people in their evacuation decision-making. These models include the protective action decision model (PADM) and the warning response process (Lindell and Perry 2012; Mileti and Sorensen 1990). Key predictor variables that have emerged in decades of evacuation research include socio-demographics (DeYoung et al. 2016; Huang et al. 2016; Thiede and Brown 2013; Elder et al. 2007)—including having children (Tierney et al. 2001) or pets (Whitehead et al. 2000), hazard characteristics (Hasan et al. 2013; Xu et al. 2016), transportation and infrastructure variables (Murray-Tuite et al. 2013, Wolshon 2009, Yazici et al. 2008), risk communication (Cahyanto et al. 2016; Dash and Gladwin 2007; Huang et al. 2016), social networks (Collins et al. 2018), exposure to warning messages (Sorensen and Sorensen 2007), and housing type (Kusenbach and Christmann 2013).

Additionally, quantitative models have been developed to help predict evacuation behavior and decisions via two approaches- two-step approach, one-step approach. In the two-step approach, one first computes the total number of evacuees with a static model, then distributes their departures over time (Murray-Tuite and Wolshon 2013). Such static models are typically logit or probit regressions (e.gWhitehead et al. 2000; Xu et al. 2016), although other types exist, such as neural networks (Wilmot and Mei 2004). In the one-step approach, a single dynamic model simultaneously determines the number of evacuees and their departure times, i.e., probability an individual evacuates in time interval *t* (e.g., Serulle and Cirillo 2017; Anyidoho et al. 2022).

These studies despite their massive contribution to evacuation study over the years, have relied on traditional data types, such as surveys and interviews. First, these traditional data types require laborious efforts to collect usable data. Additionally, small sample sizes and low response rates limit their representativeness, relying on sampling rather than large-scale data. When relying on traditional data types, predictions are necessarily based on data collected during previous events. However, each hurricane has its own unique context (e.g., it occurred during the COVID pandemic or right after another damaging hurricane) and it is very difficult to include enough variables to capture all those factors that may be important.

The limitations of traditional data types could be overcome with the increasing availability and popularity of location-based data in the forms of call detail records (CDRs), Twitter, and smartphones—in disaster-related applications (Yu et al. 2018). CDRs have been used to examine population movements after the Haiti (2010), New Zealand (2011), and Nepal (2015) earthquakes (Bengtsson et al. 2011; Wilson et al. 2016). For every mobile phone text or call, the CDR contains the time and location of the nearest cell tower. The frequency and accuracy of location data points can vary widely. The accuracy of the location data points from Twitter also varies and typically are not as frequent as those in smartphone location data. Nevertheless, Twitter data is relatively easily available. Wang and colleagues (Wang and Taylor 2014, 2016) used Twitter data from Hurricane Sandy and other events to analyze changes in distributions of trip distances during disasters. Chae et al. (2014) and Chae et al. (2015) analyzed

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geotagged Twitter data from Hurricane Sandy, the Moore tornado, and the Boston bombing. They discovered, for example, that many individuals in Manhattan went to a supermarket right after an official evacuation order was issued for Sandy. Han et al. (2019) and Martín et al. (2017) used geotagged Twitter data to describe the evacuation in Hurricane Matthew (2016)—number of evacuees, their origins, and destinations. Jiang et al. (2021) used long-term human mobility data retrieved from Twitter to develop gravity models to predict evacuation flows in Hurricane Matthew (2016). Likewise, Hong and Frias-Martinez (2020) analyzed geotagged Twitter data from Hurricane Irma and developed machine learning models to predict evacuation flows. Recent studies by Li et al. (2022) and Roy et al. (2021) also utilized twitter data from Hurricane Irma to study evacuation behavior. Li et al. (2022) built a text classifier distinguishing positive evacuation tweets from negative and irrelevant ones through active learning with additional demographic analysis and content clustering to investigate factors influencing evacuation decisions, while Roy et al. (2021) on the other hand developed an input output hidden Markov model (IO-HMM) to infer evacuation decisions from user tweets. Finally, using Facebook user data, a study by Fraser et al. (2022) studies the intersection of roles of evacuation orders, policy tools, bonding, bridging, and linking social capital, and social vulnerability.

Fewer studies have used smartphone location data. Song and colleagues in three different studies used GPS records of 1 + million people over a year to analyze human mobility after the Tōhoku earthquake (2011) (Song et al. 2017, 2014, 2013). They identified important places for each individual (e.g., home, work), and demonstrated the change in time spent in each place type from before to after the event. They also developed a Hidden Markov Model to predict an individual's trajectory during a period of time based on their trajectory during the previous period; and predicted possible evacuation from the area using a Markov decision process to predict the evacuation route. Yabe et al. (2019) used pre-disaster web search behavior to predict evacuation for a 2018 flood in Japan and employed smartphone location data to validate that model. Darzi et al. (2021) employed data from mobile phone location-based services to examine how people evacuated during Hurricane Irma. Deng et al. (2021) merged detailed human mobility data with socio-demographic factors to uncover disparities in evacuation behavior related to race and socioeconomic status during disasters. In a recent study like the one here, Li et al. (2022) utilized large-scale high-resolution smartphone location data to assess hurricane preparedness by observing fluctuations in point of interest (POI) visits leading up to Hurricane Harvey in 2017. New metrics were developed to quantify the extent, timing, and spatial variations of preparedness, focusing on visits to grocery stores, pharmacies, gas stations, and home improvement stores. However, limitations include potential biases due to reliance on smartphone data, which may exclude certain demographic groups, with the study focusing on data from only a single county (Harris County) under Hurricane Mathew (2017). The study described in this paper seeks to address this gap by exploring the relationship between preparedness and visits to five businesses of interest by analyzing data across multiple hurricanes, thus multiple geographies and broader hurricane conditions are captured.

3 Data

3.1 Hurricanes

This study focuses on three hurricanes—Dorian (2019), Ida (2021) and Ian (2022). They cover multiple geographic areas and represent various storm intensities, timings, and characteristics (Table 1, Fig. 1). Hurricane Ida (2021) and Hurricane Ian (2022)

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Table 1 Summary of data by hurricane

Attribute	Dorian	Ida	Ian
U.S. landfall location	Cape Hatteras, NC	Port Fourchon, LA	Cayo Costa Island, FL
Maximum category	Cat. 5	Cat. 4	Cat. 5
Category at landfall	Cat. 1	Cat. 4	Cat. 4
Damage in U.S	$1.6 billion	$75 billion	$112.9 billion

Dorian: NCEI (2020) for damage and fatalities, Ida: Beven et al. (2021), Ian: Bucci et al. (2023)

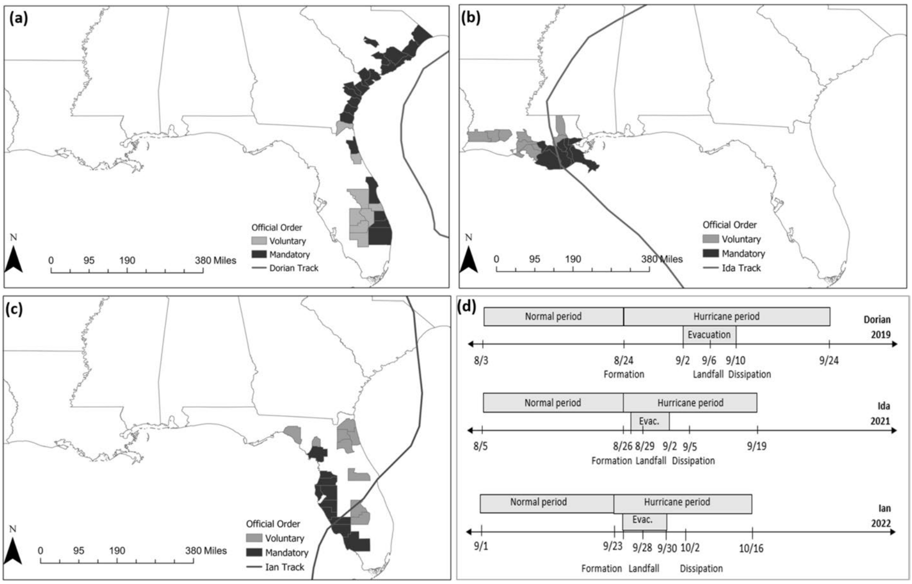

Fig. 1 Hurricane tracks and counties/parishes included in the study area by order type (voluntary or mandatory) for **a** Dorian, **b** Ida, **c** Ian and **d** hurricane timelines

made landfall in the Gulf of Mexico, whereas Hurricane Dorian (2019) affected the Atlantic coast (Fig. 1). Hurricane Dorian initially struck the Bahamas, then followed the coast from Florida to North Carolina; while Ida happened rapidly and struck the coast of Louisiana while causing substantial impacts (Table 1).

For each hurricane, we divide the timeline into normal (N), preparation (P), and impact (I) time periods (Fig. 1d, Table 2). The *normal* period, meant to capture the behavior during times when no hurricane threat exists, is defined to be the period 3 weeks prior to formation. The *preparation* period, intended to be the period during which the population is aware of a hurricane threat and is preparing to either evacuate or stay, is defined to be after formation till the 2 days prior to landfall. The *impact* period, when the hurricane hazards are occurring in the study area, is defined to be from 2 days prior to landfall to a day after landfall.

Table 2 Summary of timelines and point of interest data

Quantity	Dorian	Dorian-FL	Dorian-GA	Dorian-SC	Ida	Ian	Total
Date of max. threat	06 Sep	03 Sep	04 Sep	05 Sep	29 Aug	28 Sep	n/a
Normal period (N)	03 Aug- 24 Aug	03 Aug- 24 Aug	03 Aug- 24 Aug	03 Aug- 24 Aug	05 Aug- 26 Aug	01 Sep- 23 Sep	n/a
Preparation period (P)	28 Aug-03 Sep	28 Aug-01 Sep	31 Aug-03 Sep	30 Aug-03 Sep	26 Aug-28 Aug	25 Sep -27 Sep	n/a
Impact period (I)	03 Sep-06 Sep	01 Sep-04 Sep	03 Sep-05 Sep	03 Sep-06 Sep	28 Aug-30 Aug	27 Sep-30 Sep	n/a
Num devices	25,133	7947	3542	13,644	7917	4451	37,501
Num devices in mandatory	23,534	6348	3542	13,644	4383	4082	31,999
Num devices in voluntary	1599	1599	0	0	3534	369	5,502
Num devices visiting at least 1 business	19,374	5916	2628	10,830	5071	2829	27,274
Num evacuees	6009	960	1388	3661	2113	2523	10,645
Num non-evacuees	19,124	6987	2154	9983	5804	1928	26,856
Num evacuees in mandatory	5807	758	1388	3661	2312	1325	9,444
Num non-evacuees in mandatory	17,727	5590	2154	9983	1770	3058	22,555
Num evacuees in voluntary	202	202	0	0	211	788	1,201
Num non-evacuees in voluntary	1397	1397	0	0	158	2746	4,301
Num gas stations	46	18	13	15	13	18	77
Num grocery stores	52	17	15	20	14	16	82
Num hardware stores	124	40	36	48	36	37	197
Num pet stores	41	13	13	15	12	19	72
Num pharmacies	17	8	4	5	5	6	28
Num devices visiting gas stations	2888	658	472	1758	1947	405	5,240
Num devices visiting grocery stores	3178	968	397	1813	769	683	4,630
Num devices visiting hardware stores	9727	3082	1233	5412	1310	909	11,946
Num devices visiting pet stores	2952	971	403	1578	755	699	4,406
Num devices visiting pharmacies	629	237	123	269	290	133	1,052
Total num visits to gas stations	10,856	2417	1884	6555	5299	1164	17,319
Total num visits to grocery stores	10,148	3028	1158	5962	1723	1725	13,596

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Table 2 (continued)

Quantity	Dorian	Dorian-FL	Dorian-GA	Dorian-SC	Ida	Ian	Total
Total num visits to hardware stores	35,628	10,556	4293	20,779	3703	2887	42,218
Total num visits to pet stores	8719	2733	1089	4897	1703	1685	12,107
Total num visits to pharmacies	1958	716	374	868	653	325	2,936

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3.2 Smartphone location data

The data were obtained from the Spectus Data Cleanroom platform for 3 hurricanes—Dorian, Ida and Ian. The mobility data are de-identified and privacy enhanced. Locations were passively collected though the mobile apps based on an opt-in framework. For each device (i.e., smartphone), we have location data on average about 128 times per day or once every 11 min. iOS (iPhone) collects data when the device detects movement, so the sampling is more frequent in the daytime. Android collects data via a time-based sampling methodology. While one could argue the possibility of bias in results due to different data collection approaches, we would like to point out that each device is processed independently, which eliminates such possibilities. Each, observation consists of a unique, anonymized, and encrypted identification number, time stamp, latitude, and longitude. To preserve the device owners' privacy, home areas are upleveled to the census block group level, sensitive points of interest such as military bases, sexual reproductive health centers, places of worship, and elementary schools, are removed from the dataset, and device IDs are changed randomly every few months, limiting the time over which a particular phone's movement can be tracked.

3.3 Points of interest data

In addition to the privacy-enhanced location data, the Spectus platform also provides data on *stops*, *points of interest (POI)*, and *visits*, all of which are derived from the smartphone location data. A *stop* identifies a single stay of a device in a precise location (i.e., a point in space where a device spends some time). Stops are determined by means of a stop-detection algorithm which detects the sequence of points that constitute a single stay of a user, and then aggregates them into a single entity with latitude, longitude, and duration of stay.

The *point of interest* table includes a row for each business in a geographic region and columns to characterize the category to which it belongs, its brand name, its geographic location (longitude and latitude, zip code, and county codes), and its hours of operation. The brand names are specific companies within the broader categories. For instance, Shoprite and Walgreens are brand names within the grocery and pharmacy categories, respectively. We also assumed supermarkets such as Walmart and Costco are categorized as grocery to simplify our analysis.

The *visit* table contains data about which place of interest (POI) a user visits, and when the visit is made. A visit is an event occurring when at least one detected stop made by a device overlaps with a POI and meets certain criteria. In other words, a visit is generated when a device stops and dwells within the boundaries of a POI for a specified period of time. Each row of the visit table is a visit made by a device, marked by a device identifier and a place identifier (typically stores, restaurants, gas stations, etc.) within the POI's hours of operation. Additionally, the opening and closing dates of the POI are considered to ensure that visits are only computed when a POI is in active business or location.

For this analysis, we focused on five types of businesses that we hypothesize are related to preparations people might make as a hurricane approach and as identified in the study by Li et al. (2022): gas stations, grocery stores, pet stores, hardware stores (hardware and home goods stores), and pharmacies. Table 2 summarizes the number of each type of POI located within the study area for each hurricane. Table 2 also indicates how many visits are made to each POI type in each hurricane. In total, the dataset includes 17,319, 13,596, 42,218, 12,107 and 2936 visits to gas stations, grocery stores, hardware stores, pet stores and pharmacies, respectively, for the entire study period from the start of normal period to hurricane dissipation for all three hurricanes combined. An individual may make multiple trips to a place of interest over the duration of the hurricane period.

4 Methodology

4.1 Evacuee identification

We apply the method described in Anyidoho et al. (2023) to identify evacuees using anonymized smartphone location data sampled from areas in Fig. 1. In this application, we sample devices from areas for which either mandatory or voluntary orders were issued. A total of 37,501 devices were sampled, out of which 25,133, 7917, 4451 are from Dorian, Ida and Ian respectively. Location-based data described in Sect. 3.2, is obtained for each device over the normal period (3 weeks to formation) and hurricane period (Fig. 1d). Normal period (Fig. 1d) data is used to infer the home location of each individual. The approach herein relies on first identifying census tracts in which the aggregate behavior differs substantially from normal behavior, providing evidence of evacuation, and then identifying evacuees within those tracts. Evacuating census tracts are those for which the peak rate observed during the hurricane period is at least 15% higher than the peak travel rate in the normal period. Within those tracts, a device is denoted as an evacuee if it is at least a mile from home on the peak evacuation date (date of maximum travel rate for associated census tract) of the corresponding census tract. The dataset includes a total of 9444 evacuees and 22,555 non-evacuees in mandatory order zones, and 1201 evacuees and 4301 non-evacuees in voluntary order zones (Table 2). The evacuation rate in mandatory zones is 30% compared to 22% in voluntary zones. The study in Anyidoho et al. (2023) compares evacuation rates and departure curves from three hurricanes (Florence, Michael, and Dorian) computed from survey data and the smartphone location method applied here. Results suggest a good comparison between the two data types. Their study also suggests, the data is representative of the population within which the sample was drawn.

5 Results

5.1 Frequency of POI visits during hurricanes (RQ1)

To determine if the frequency of business visits (i.e., number of visits per day) changes during the hurricane preparation period and/or during the hurricane impact period relative to normal times, we extract data on visits for the five business types over the entire duration, from the start of the normal period to hurricane dissipation (Fig. 1d). In Fig. 2, we compute the aggregate frequency of visits per day across all five businesses for each hurricane. Dorian affected different geographic zones at different times, so we considered the effect on each state separately (Dorian-Florida, Dorian-Georgia, Dorian-South Carolina). The dots on each line plot represent frequencies for weekends.

Figure 2, which shows the normal variability in POI visit frequency, indicates that weekly peaks tend to occur on Saturdays. Relative to the normal period across all hurricanes, visits increase during the preparation period (P) followed by a significant drop to almost zero during the hurricane impact period (I). The peak is more pronounced for Ida

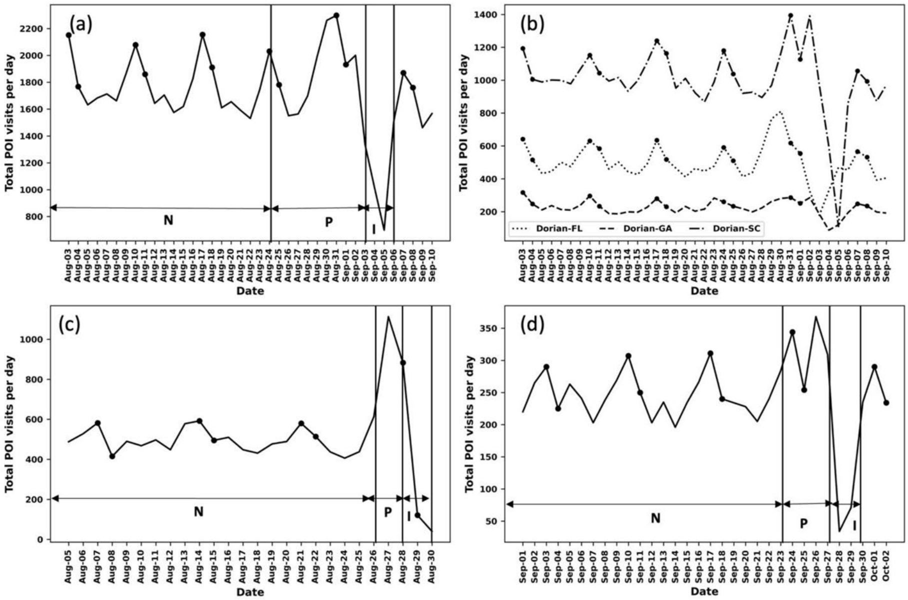

Fig. 2 Total number of all POI visits together for **a** Dorian, **b** Dorian by state, **c** Ida, and **d** Ian

during the preparation period, likely because this period aligns with a weekend. The impact period minima in Fig. 2b show how the impact of Dorian occurs first in Florida (Sept. 3), then in Georgia (Sept. 4), and then in South Carolina (Sept. 5), as expected.

To further understand how these frequencies vary, we compute the frequency of visits separately for each business type (Fig. 3a-f). Across all businesses, hardware stores record the highest frequencies except for Hurricane Ida, where visits to gas stations are most frequent especially during the hurricane period. Visits to hardware stores are likely highest due to the fact that there are more hardware stores than other types because that category includes home goods stores.

In terms of frequency variation across days of the week, visits generally tend to peak during the weekends for grocery stores, hardware stores, and pet stores, but not as much for gas stations and pharmacies (Fig. 3a-f). In general, visits to gas stations and pharmacies do not vary as much from across days of the week as grocery, hardware, and pet stores do. Generally, for each business type, frequencies tend to increase during the preparation period (P) and decline significantly during the impact period (I). The differences between these three phases (N, P, I) are more pronounced for hardware stores across each hurricane. In Hurricane Ida, however the differences are largest for gas stations.

5.2 Relationship between POI visits and evacuation (RQ2)

The second research question asks whether visits to the five business types can help predict evacuation decisions. We extract data describing business visits within the hurricane period (Fig. 1d) for both evacuees and non-evacuees. For each business type, a *t*-test (carried out in python) was conducted to compare the probability of evacuation between two groups: (1) people who visited a business from a specified time, t_0, to the time of maximum

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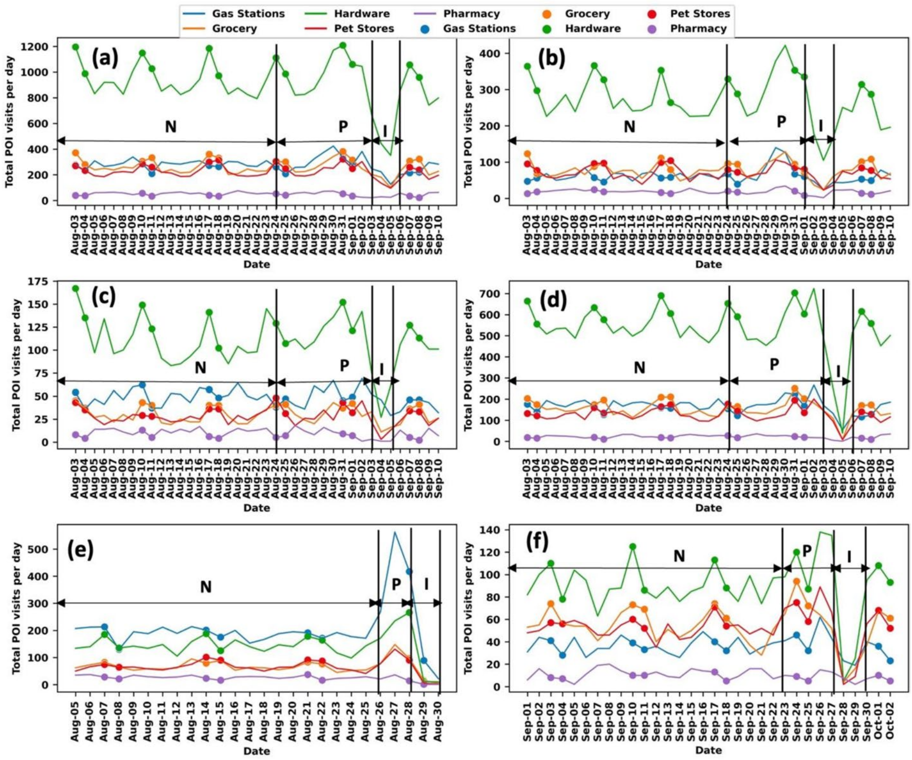

Fig. 3 Total number of visits per business **a** Dorian, **b** Dorian-FL, **c** Dorian-GA, **d** Dorian-SC, **e** da, and **f** Ian

threat, t_{max}, and (2) people who did not visit a business during that time period. For evacuees, the time of maximum threat, t_{max}, is the departure time; for non-evacuees in Hurricane Ida and Hurricane Ian, it is the time of landfall; for non-evacuees in Hurricane Dorian (which never made landfall), it is the time the hurricane passed the state and is defined separately for Florida, Georgia, and South Carolina. The tests were conducted for multiple values of $t_0 - t_{max}$ (24, 28, 72, 96, > 96 h). In addition, similar tests were conducted to determine if people who had visited two types of businesses were even less likely to evacuate than people who had not. The tests were conducted separately for each hurricane and results are presented in Tables 3 and 4, for a visit to one type of business and combinations of POIs, respectively.

Results indicate that a visit to a gas station is associated with a higher probability of evacuation, with results significant for Dorian and Ida but not for Ian. For example, in Hurricane Dorian, one is approximately twice as likely to evacuate if they visit a gas station 24 h prior to the time of maximum threat, though this difference decreases as the $t_0 - t_{max}$ period increases. A person who visits a hardware store, pet store, or grocery store is less likely to evacuate than one who does not. A visit to a pharmacy is not a statistically significant for any hurricane or time period $t_0 - t_{max}$, possibly at least in part because there are relatively few visits to pharmacies in the dataset, compared to the other business types (Table 2). The difference between probabilities for hardware stores are the most statistically

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Table 3 Hypothesis testing results for one POI visit

POI	Time t_0-t_{max}	Dorian			Ida			Ian		
	(hrs)	P(evac|POI)	P(evac|no POI)	pvalue[a]	P(evac|POI)	P(evac|no POI)	pvalue[a]	P(evac|POI)	P(evac|no POI)	pvalue[a]
Gas Stations	24	0.425	0.247	0.000*	0.226	0.156	0.003*	0.643	0.573	0.457
	48	0.331	0.243	0.000*	0.173	0.147	0.081	0.544	0.538	0.914
	72	0.301	0.241	0.000*	0.188	0.164	0.076	0.559	0.545	0.774
	96	0.279	0.239	0.002*	0.217	0.194	0.112	0.525	0.550	0.558
	> 96	0.267	0.241	0.023*	0.295	0.267	0.068	0.556	0.565	0.796
Grocery	24	0.191	0.260	0.038*	0.110	0.169	0.183	0.425	0.579	0.053*
	48	0.199	0.249	0.017*	0.091	0.155	0.016*	0.436	0.543	0.043*
	72	0.200	0.247	0.004*	0.116	0.172	0.019*	0.522	0.547	0.552
	96	0.198	0.244	0.001*	0.151	0.201	0.043*	0.524	0.551	0.412
	> 96	0.214	0.245	0.006*	0.260	0.273	0.600	0.548	0.566	0.547
Hardware	24	0.188	0.264	0.000*	0.078	0.176	0.000*	0.400	0.587	0.001*
	48	0.189	0.256	0.000*	0.086	0.159	0.000*	0.422	0.550	0.000*
	72	0.196	0.254	0.000*	0.115	0.175	0.001*	0.448	0.556	0.000*
	96	0.197	0.251	0.000*	0.141	0.205	0.001*	0.478	0.558	0.004*
	> 96	0.203	0.254	0.000*	0.227	0.278	0.011*	0.501	0.574	0.003*
Pet Stores	24	0.158	0.261	0.002*	0.085	0.169	0.087	0.472	0.578	0.124
	48	0.178	0.251	0.000*	0.147	0.152	0.872	0.496	0.541	0.329
	72	0.175	0.248	0.000*	0.158	0.169	0.654	0.474	0.550	0.040*
	96	0.179	0.245	0.000*	0.209	0.198	0.667	0.480	0.555	0.021*
	> 96	0.201	0.246	0.000*	0.316	0.270	0.088	0.483	0.572	0.002*
Pharmacy	24	0.250	0.257	0.947	0.154	0.167	0.902	0.714	0.573	0.452
	48	0.340	0.247	0.139	0.093	0.152	0.281	0.600	0.538	0.578
	72	0.258	0.244	0.760	0.148	0.169	0.656	0.667	0.544	0.203
	96	0.214	0.241	0.440	0.145	0.199	0.291	0.629	0.549	0.344
	> 96	0.268	0.243	0.399	0.221	0.273	0.334	0.633	0.564	0.334

[a]The symbol * and gray shading denotes significant levels at 0.05

significant (p-value ≤ 0.05) across all three hurricanes and times. This could be in part because there are more hardware stores in the dataset than other businesses. Pet stores are significant for Dorian and Ian but not Ida. Gas stations are significant for Dorian and Ida 24 h prior to maximum threat. Hurricane Dorian likely has the most statistically significant results at least in part because it has the most observations (Table 2).

Comparing across alternative values of t_0 suggests that in general, across business types and hurricanes, the effect of business visits on the probability of evacuation decreases as the time window increases, perhaps because the larger time window dilutes the influence of the hurricane threat. This is true especially for visits to gas stations. The difference in probability of evacuation for those who went to a gas station in the period $t_0 - t_{max}$ and those who did not, when $t_0 = 24h$ is 0.18, 0.07, and 0.07 for Dorian, Ida, and Ian, respectively. For $t_0 > 24$ h, it is an average of 0.05, 0.03, and 0.00 for Dorian, Ida, and Ian, respectively. There is not, however, a clear relationship between the time t_0 and the p-value associated with the t-tests. It may be that while the smaller time window is associated with a stronger business visit effect, it also leads to fewer visits and potentially therefore, more difficulty finding evidence of statistical significance.

Since a visit to a hardware store, pet store, or grocery store in the period before maximum threat was associated with a decreased likelihood of evacuating, we also examined if visiting two or three of those types of stores is associated with an even smaller likelihood of evacuating (Table 4). Note that only POI combinations with observations are presented in Table 4. Since the numbers of people who went to two or three of these types of stores decrease with the time window $t_0 - t_{max}$, the results were not statistically significant for the shorter times (24 and 48 h). Nevertheless, the results suggest that visiting two or three of these businesses (hardware, pet store, and grocery store) is associated with an even smaller probability that the person will evacuate. For example, while the probability of evacuating is 0.05 lower for a person who went to a grocery store within 72 h of the maximum threat than one who did not (0.20 vs. 0.25), and 0.06 lower for a person who went to a hardware store than one who did not (0.20 vs. 0.25), it is 0.14 lower for a person who went to both a grocery store and a hardware store (0.11 vs. 0.25, or less than half as likely).

To investigate the effect of the official order type, we repeated the exercise separately for people in areas receiving voluntary evacuation orders and in areas receiving mandatory evacuation orders. However, the results from the two areas align with what is reported in Table 3, and thus per our analysis the order type does not affect the probability of evacuation across visitors and non-visitors to these places of interest.

6 Discussion

6.1 Implications for research

This study supports exploration of an emerging area of research for evacuation prediction. Specifically, we explore the relationship between visits to places of interest and evacuation decisions. With the current results being encouraging, this serves as a foundation for a new avenue of future research using real-time population movement data to enhance hurricane evacuation management, and development of evacuation demand models in particular. Anyidoho et al. (2022) compared five evacuation demand models, with model predictors related to individual socio-demographic attributes, hurricane and forecast attributes, official actions, and housing types. In addition to these features, future research can use

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Table 4 Hypothesis testing results for multiple POI visits

	Time t_0-t_{max} (hrs)	Dorian			Ida			Ian		
		$P(evac \mid POI)$	$P(evac \mid no\ POI)$	pvalue[a]	$P(evac \mid POI)$	$P(evac \mid no\ POI)$	pvalue[a]	$P(evac \mid POI)$	$P(evac \mid no\ POI)$	pvalue[a]
Hardware, grocery	24	0.000	0.257	0.188	0.000	0.167	0.317	0.000	0.575	0.245
	48	0.135	0.248	0.113	0.000	0.152	0.081	0.000	0.540	0.008*
	72	0.112	0.245	0.002*	0.094	0.169	0.256	0.250	0.547	0.017*
	96	0.121	0.242	0.000*	0.094	0.199	0.137	0.370	0.551	0.061
	> 96	0.144	0.245	0.000*	0.194	0.273	0.291	0.415	0.566	0.051*
Hardware, pet stores	24	0.444	0.257	0.198	0.000	0.167	0.273	0.000	0.575	0.245
	48	0.190	0.248	0.391	0.125	0.152	0.715	0.364	0.539	0.244
	72	0.176	0.245	0.096	0.128	0.169	0.497	0.368	0.546	0.120
	96	0.162	0.242	0.012	0.171	0.198	0.657	0.379	0.551	0.064
	> 96	0.175	0.244	0.005*	0.227	0.273	0.499	0.455	0.566	0.138
Pet stores, grocery	24	0.000	0.257	0.188	0.000	0.167	0.655	0.500	0.574	0.832
	48	0.211	0.248	0.709	0.000	0.152	0.300	0.667	0.538	0.655
	72	0.149	0.245	0.127	0.100	0.169	0.561	0.556	0.545	0.950
	96	0.129	0.242	0.027*	0.100	0.198	0.435	0.560	0.549	0.915
	> 96	0.127	0.244	0.002*	0.100	0.273	0.220	0.512	0.565	0.496
Pet stores, hardware, grocery	24	0.000	0.257	0.556	NaN	0.167	NaN	NaN	0.574	NaN
	48	0.000	0.248	0.417	0.000	0.152	0.672	NaN	0.538	NaN
	72	0.111	0.245	0.351	0.000	0.169	0.652	NaN	0.545	NaN
	96	0.071	0.241	0.138	0.000	0.198	0.619	0.500	0.549	0.888
	> 96	0.088	0.243	0.035*	0.000	0.273	0.541	0.500	0.565	0.749

[a]The symbol * and gray shading denotes significant levels at 0.05

business visits as additional features. In one-step models such as traditional logistic regression, these features can be coded as binary which indicates whether a person visits the business or not prior to landfall. However, for the two-step approaches such as the dynamic discrete choice model (Anyidoho et al. 2022), business visits can be integrated as a binary dynamic attribute, where in each decision step, the individual either makes a visit to the business or not.

Future research might also consider a similar analysis but including additional data from new hurricanes and from people in areas that do not receive a voluntary or mandatory official evacuation order. Since the results herein indicate differences in probabilities become more significant as we move closer to landfall, future research integrating these features into predictive models may focus on visits that are closer to maximum threat time which is forecast by the National Hurricane Center. Additional future social science focused research could investigate why people decide to make these visits when evacuating and not, and what, if anything, would be helpful in either changing the mind of non-evacuees or helping them to evacuate during these visits.

6.2 Practical implications

While this study serves as a first step in developing the idea of leveraging point of interest data in hurricane evacuations, the current results are promising enough for practical applications. Emergency managers rely on estimates of how many people are likely to evacuate from where, and at what time to help them make decisions such as issuing official evacuation orders, messaging to the public, opening shelters, staging materials, and staff, and implementing traffic plans. With results indicating evacuees are more likely to visit gas stations, the number of visits to a gas station for a future hurricane can serve as an estimate of the aggregate evacuation demand and can be compared with what existing approaches such as the traditional participation rate suggests. The smartphone location data can be tracked in real time, which can help determine who evacuates in real time as the hurricane approaches. Also, the expected number of visits to hardware, pet, grocery stores and pharmacies help store owners to supply sufficient materials/resources to meet the demands of the community during emergency periods. Finally, emergency managers can liaise with store operators to communicate with the public with regards to preparedness, evacuation orders, evacuation routes, and shelters. The messaging could be targeted and specific to the type of business– for example, pet stores might provide information supplies that are useful for pet evacuation and sheltering.

In the most practical scenario, the availability of smartphone data for future hurricanes means we can estimate evacuation demand in real time. As a hurricane approaches the coast, we can track the number of people that make visits to these businesses. For instance, if we know those estimates every 24 h, we can use these to forecast demand for the next 24–48 h. Ultimately, integrating these visit signals into the DDC model has the potential to greatly improve predictions and the practical utility of evacuation demand models.

7 Conclusions and future work

In this study, we leverage smartphone location data to improve understanding of evacuation behavior in hurricanes. Specifically, we curated data across three diverse hurricanes, and explored the possible relationship between visits to places of interest and hurricane evacuations. The first research question compares the frequency of visits to businesses in the hurricane preparation and impact periods relative to the normal period. Results generally suggest people tend to visit businesses more often during the hurricane preparation period, and that the frequency of visits decreases significantly as the hurricane impacts land.

The second research question examines whether business visits can be used to predict evacuation behavior. Results from the *t*-test of difference in proportions suggest if a person visits a gas station, they are more likely to evacuate, but if they make a visit to a hardware store, pet store, grocery store or pharmacy, then they are less likely to evacuate. The likelihood of evacuating further decreases if a person visits two or three of the following: hardware stores, pet stores, and pharmacies. Business visits thus can be helpful in predicting evacuation. There are some important potential policy implications and interventions for these findings. For example, emergency management could use these data to engage in targeted messaging about the hurricane at these key business types leading up to the event.

The study, however, has some limitations. First, the analysis does not include devices in geographic areas not under voluntary or mandatory orders. Since evacuation orders are mostly issued to coastal counties, the behavior of inland residents is therefore not captured. Second, our analysis captures behavior from three hurricanes, and while a good deal of variability is present, future research should include data from additional hurricanes. Third, while the analysis establishes possible relationship between visits to places of interest and evacuation behavior, further statistical analysis such as a multivariate approach could strengthen these findings. Finally, future research should investigate integrating business visits as additional signals/features in evacuation demand models.

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Declarations

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References

Anyidoho PK, Davidson RA, Rambha T, Nozick LK (2022) Prediction of population behavior in hurricane evacuations. Transp Res Part Policy Pract 159:200–221. https://doi.org/10.1016/j.tra.2022.03.001

Anyidoho, P. K., Ju, X., Davidson, R. A., Nozick, L. K. (2023) A machine learning approach for predicting hurricane evacuee destination location using smartphone location data. *Computational Urban Science*, in press.

Baker EJ (1991) Hurricane evacuation behavior. Int J Mass Emerg Dis 9(2):287–310

Bengtsson L, Lu X, Thorson A, Garfield R, Von Schreeb J (2011) Improved response to disasters and outbreaks by tracking population movements with mobile phone network data: a post-earthquake geospatial study in Haiti. PLoS Med 8(8):e1001083

Beven II JL, Berg R, Hagen A (2021) Hurricane Ida. National Hurricane Center. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL092021_Ida.

Bowser GC, Cutter SL (2015) Stay or go? examining decision making and behavior in Hurricane evacuations. Environ Sci Policy Sustain Dev 57(6):28–41. https://doi.org/10.1080/00139157.2015.1089145

Bucci, L., Alaka, L., Hagen, A., Delgado, S., and Beven, J. Hurricane Ian (2023) National Hurricane Center. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL092022_Ian.

Cahyanto I, Pennington-Gray L, Thapa B, Srinivasan S, Villegas J, Matyas C, Kiousis S (2016) Predicting information seeking regarding hurricane evacuation in the destination. Tour Manag 52:264–275

National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2020). https://www.ncdc.noaa.gov/billions/.

Chae J, Thom D, Jang Y, Kim S, Ertl T, Ebert DS (2014) Public behavior response analysis in disaster events utilizing visual analytics of microblog data. Comput Graph 38:51–60

Chae, J., Cui, Y., Jang, Y., Wang, G., Malik, A., and Ebert, D. S. (2015, May). Trajectory-based Visual Analytics for Anomalous Human Movement Analysis using Social Media. In EuroVA@EuroVis (pp. 43–47).

Collins J, Ersing R, Polen A, Saunders M, Senkbeil J (2018) The effects of social connections on evacuation decision making during Hurricane Irma. WCAS 10(3):459–469

Darzi, A., Frias-Martinez, V., Ghader, S., Younes, H. & Zhang, L. Constructing evacuation evolution patterns and decisions using mobile device location data: A case study of hurricane irma. Preprint at http://arXiv.org/2102.12600 (2021).

Dash N, Gladwin H (2007) Evacuation decision making and behavioral responses: individual and individual. Nat Hazard Rev 8:69–77

Deng H et al (2021) High-resolution human mobility data reveal race and wealth disparities in disaster evacuation patterns. Humanit Soc Sci Commun 8:1–8

DeYoung S, Wachtendorf T, Davidson R, Xu K, Nozick L, Farmer A, Zelewicz L (2016) A mixed method study of hurricane evacuation: demographic predictors for stated compliance to voluntary and mandatory orders. Environ Hazards 15(2):95–112

Elder K, Xirasagar S, Miller N, Bowen SA, Glover S, Piper C (2007) African Americans' decisions not to evacuate New Orleans before Hurricane Katrina: a qualitative study. Am J Public Health 97(Supplement_1):S124–S129. https://doi.org/10.2105/AJPH.2006.100867

Fraser T (2022) Fleeing the unsustainable city: soft policy and the dual effect of social capital in hurricane evacuation. Sustain Sci 17(5):1995–2011

Han SY, Tsou MH, Knaap E, Rey S, Cao G (2019) How do cities flow in an emergency? tracing human mobility patterns during a natural disaster with big data and geospatial data science. Urban Sci 3(2):51

Hasan S, Mesa-Arango R, Ukkusuri S (2013) A random-parameter hazard-based model to understand household evacuation timing behavior. Transp Res C: Emerg Technol 27:108–116

Hong L, Frias-Martinez V (2020) Modeling and predicting evacuation flows during hurricane Irma. EPJ Data Sci 9:29. https://doi.org/10.1140/epjds/s13688-020-00247-6

Huang SK, Lindell MK, Prater CS (2016) Who leaves and who stays? a review and statistical meta-analysis of hurricane evacuation studies. Environ Behav 48(8):991–1029

Jiang Y, Li Z, Cutter S (2021) Social distance integrated gravity model for evacuation destination choice. Int J Digital Earth 14(8):1004–1018. https://doi.org/10.1080/17538947.2021.1915396

Kusenbach M, Christmann G (2013) Understanding hurricane vulnerability: lessons from mobile home communities. In: Kapucu N, Hawkins CV, Rivera FI (eds) Disaster Resiliency. Routledge, New York City, NY, pp 83–105

Li, X., Hasan, S., & Culotta, A. (2022, May). Identifying Hurricane Evacuation Intent on Twitter. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 16, pp. 618–627).

Li B, Mostafavi A (2022) Location intelligence reveals the extent, timing, and spatial variation of hurricane preparedness. Sci Rep 12(1):16121

Lindell MK, Perry RW (2012) The protective action decision model: Theoretical modifications and additional evidence. Risk Analysis: an International Journal 32(4):616–632

Martín Y, Li Z, Cutter SL (2017) Leveraging Twitter to gauge evacuation compliance: spatiotemporal analysis of Hurricane Matthew. PLoS ONE 12(7):e0181701

Mileti, D. S. and Sorensen, J. H. (1990). Communication of Emergency Public Warnings: A Social Science Perspective and State-of-the-ART Assessment (Report No. ORNL-6609). Oak Ridge, Tennessee, United States: Oak Ridge National Laboratory.

Murray-Tuite P, Wolshon B (2013) Evacuation transportation modeling: an overview of research, development, and practice. Transp Res Part C 27:25–45. https://doi.org/10.1016/j.trc.2012.11.005

Roy KC, Hasan S (2021) Modeling the dynamics of hurricane evacuation decisions from twitter data: an input output hidden Markov modeling approach. Transp Res Part C Emerg Technol 123:102976

Serulle NU, Cirillo C (2017) The optimal time to evacuate: a behavioral dynamic model on Louisiana resident data. Transp Res Part B 106:447–463. https://doi.org/10.1016/j.trb.2017.06.004

Song X, Shibasaki R, Yuan NJ, Xie X, Li T, Adachi R (2017) DeepMob: learning deep knowledge of human emergency behavior and mobility from big and heterogeneous data. ACM Trans Inf Syst (TOIS) 35(4):41

Song X, Zhang Q, Sekimoto Y, Horanont T, Ueyama S, Shibasaki R (2013) Modeling and probabilistic reasoning of population evacuation during large-scale disaster. In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 1231–1239). ACM.

Song, X., Zhang, Q., Sekimoto, Y., and Shibasaki, R. (2014). Prediction of human emergency behavior and their mobility following large-scale disaster. In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 5–14). ACM.

Sorensen JH, Sorensen BV (2007) Community processes: Warning and evacuation. In: Rodríguez H, Quarantelli EL, Dynes RR (eds) Handbook of Disaster Research. Springer New York, New York, NY, pp 183–199. https://doi.org/10.1007/978-0-387-32353-4_11

Thiede BC, Brown DL (2013) Hurricane Katrina: who stayed and why? Popul Res Policy Rev 32(6):803–824

Thompson RR, Garfin DR, Silver RC (2017) Evacuation from natural disasters: a systematic review of the literature. Risk Anal 37(4):812–839. https://doi.org/10.1111/risa.12654

Tierney KJ, Lindell MK, Perry RW (2001) Facing the unexpected: Disaster preparedness and response in the United States. Joseph Henry Press, Washington, D.C, Transportation Research Board

Wang Q, Taylor JE (2014) Quantifying human mobility perturbation and resilience in Hurricane Sandy. PLoS ONE 9(11):e112608

Wang Q, Taylor JE (2016) Patterns and limitations of urban human mobility resilience under the influence of multiple types of natural disaster. PLoS ONE 11(1):e0147299

Whitehead JC, Edwards B, Van Willigen M, Maiolo JR, Wilson K, Smith KT (2000) Heading for higher ground: factors affecting real and hypothetical hurricane evacuation behavior. Environ Hazards 2(4):133–142

Wilmot CG, Mei B (2004) Comparison of alternative trip generation models for hurricane evacuation. Nat Hazard Rev 5(4):170–178. https://doi.org/10.1061/(ASCE)1527-6988(2004)5:4(170)

Wilson R, Zu Erbach-Schoenberg E, Albert M, Power D, Tudge S, Gonzalez M, Pitonakova L (2016) Rapid and near real-time assessments of population displacement using mobile phone data following disasters: the 2015 Nepal Earthquake. PLoS Currents. https://doi.org/10.1371/currents.dis.d073fbece328e4c39087bc086d694b5c

Wolshon, P. B. (2009). Transportation's role in emergency evacuation and reentry (Vol. 392). Transportation Research Board.

Xu K, Davidson RA, Nozick LK, Wachtendorf T, DeYoung SE (2016) Hurricane evacuation demand models with a focus on use for prediction in future events. Transp Res Part A 87:90–101

Yabe T, Sekimoto Y, Tsubouchi K, Ikemoto S (2019) Cross-comparative analysis of evacuation behavior after earthquakes using mobile phone data. PLoS ONE 14(2):e0211375

Yazici MA, Ozbay K (2008) Evacuation modelling in the United States: does the demand model choice matter? Transp Rev 28(6):757–779

Yu M, Yang C, Li Y (2018) Big data in natural disaster management: a review. Geosciences 8(5):165