

Compound hazards: An examination of how hurricane protective actions could increase transmission risk of COVID-19

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ARTICLE INFO

Keywords:

Multi-hazard preparedness

Location intelligence

COVID-19

ABSTRACT

Hurricane season brings new and complex challenges as we continue to battle the COVID-19 pandemic. In May 2020, the National Oceanic and Atmospheric Administration has predicted nearly twice the normal number of tropical storms and hurricanes this season, while projections of COVID-19 models continue to rise in the United States as the Atlantic hurricane season progresses. Our research examines the critical intersection of hurricane response and public health in Harris County, Texas. We examine a hypothetical case of the 2017 Hurricane Harvey occurring amid the current pandemic. This research uses point of interest visitations as location intelligence data provided by SafeGraph together with Social Vulnerability Index and historical flood data to examine the critical intersection of natural hazard planning and response and the COVID-19 pandemic to assess the risks of a compound hazard situation. COVID-19 transmission hotspots and businesses in a community due to storm preparation activity were identified. The main drivers of transmission risk arise from overall pandemic exposure and increased interpersonal contact during hurricane preparation. Residents of health-risk areas will need to make logistical arrangements to visit alternative medical facilities for treatments related to either COVID-19 or physical impacts, such as injuries, due to the hurricane risks. Points of interest needed for disaster preparation are more likely to be situated in high-risk areas, therefore making cross-community spread more likely. Moreover, greater susceptibility could arise from social vulnerability (socioeconomic status and demographic factors) and disrupted access to healthcare facilities. Results from this study can be used to identify high-risk areas for COVID-19 transmission for prioritization in planning for temporary healthcare centers and other essential services in low-risk areas. Understanding the interplay between disaster preparation and the restrictive environment laid out by the pandemic is critical for community leaders and public health officials for ensuring the population has sufficient access to essential infrastructure services. The findings from this study can help guide the direction of disaster planning and pandemic response strategies and policies.

1. Introduction

1.1. Background

While restrictions due to COVID-19 continue to loosen in states across the United States for fully-vaccinated adults, the risks of the disease still remain at large. As of July 2021, COVID-19 has taken more than 600,000 lives in the US alone whereas cases have surpassed 30 million [1]. The risk of infection and death is greatest for the elderly and immunocompromised [2] and for those unvaccinated. 99.2% of U.S.

COVID-19 deaths in June 2021 have been attributed to unvaccinated people [3]. As of mid-July 2021, nearly 60% of the US population was vaccinated [4], but this number varies significantly by location. Many low-vaccinated populations include Louisiana, Alabama, and Texas, all of which have been impacted by intense hurricanes in the recent past. The state of Texas falls behind the national vaccination rate by about a quarter [4]. A literature review reveals that mostly indoor settings are associated with transmission clusters of COVID-19 [5]. The concurrence of a natural disaster with relaxed non-pharmaceutical interventions (NPIs) and increased visits of people can create more uncertainty in

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<https://doi.org/10.1016/j.ijdr.2021.102560>

Received 24 November 2020; Received in revised form 23 July 2021; Accepted 3 September 2021

Available online 16 September 2021

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infection and fatality predictions [6] and potentially increase the spread of COVID-19 in communities. In a pandemic situation, COVID-19 hotspots could be potential 'super-spreader' point of interests (POIs) [7], because visits to hotspots can greatly increase the risk of contact and transmission of disease. Understanding visitation patterns to urban hotspots is thus critical for developing and monitoring not only the pandemic situation [8,9] but for natural hazard planning as well as another Atlantic Hurricane season arrives.

Meanwhile, natural disasters are increasing in frequency and severity [10]. The National Oceanic and Atmospheric Administration (NOAA) predicts between 3 and 5 major hurricanes this Atlantic Hurricane Season which could bring wind speeds of 111 miles per hour or higher. In addition to economic and human tolls, events like heat waves, drought, hurricanes, wildfire, and flooding disrupt the food-water-energy-health nexus, which can cause cascades of crisis, such as geopolitical struggles over scarcity and forced migration [11]. During Hurricane Harvey, access to critical facilities, such as healthcare centers, were severely disrupted due to unprecedented flooding [12]. Large evacuations are likely to quicken the coronavirus' spread, as it will be hard for people to maintain recommended physical distancing. A study has estimated that such an evacuation for a hurricane could lead to 6000 to 60,000 new coronavirus cases in Southeast Florida [13].

The occurrence of two or more hazardous events is not exactly a new phenomenon [6,14,15], have summarized several examples of multi-hazard events that have occurred worldwide in the last three decades involving the spread of infectious diseases. Most notably is the cholera outbreak in Haiti following a fatal and disruptive earthquake in 2010. The daily new infected rate shows an apparent increase following the Zagreb earthquake on 22 March 2020 within the COVID-19 incubation time range. Due to the moderate size of the event and relatively localized damage zone, the Croatian government managed to institute partial lockdown measures whereby the natural human behavior of congregating in numbers and comforting each other in the aftermath of such an event was disrupted. Silva and Paul [16] published a combined index to highlight regions with high risk to COVID-19 cases and seismic activity to highlight areas at risk for COVID-19 outbreaks due to earthquakes.

1.2. Protective actions for hurricanes

Transmission from increased contact in the preparative and protective actions for disaster events should be a concern for city officials and emergency planners. In preparing for a hurricane event, citizen preparedness strategies play a major role in reducing the effects of hazards that cannot be mitigated [17–19] as such strategies seek to improve the ability of individuals and communities to respond in the event of a natural hazard [17,20]. Most of us might prepare for a hurricane by obtaining necessary resources to shelter in place (e.g. water, non-perishable food, toiletries, batteries). It is logical to assume that when individuals go out to purchase such items, there will be increased interpersonal contact at certain businesses. Especially, given the short forewarning period associated with Hurricanes, preparedness behaviors usually lead to a sudden surge of visits to grocery stores, gas stations, and other POIs. So many people in one place heighten transmission risks of COVID-19. We looked at hurricane preparation for Harvey within Harris County to indicate potential transmission hotspots.

1.3. Social vulnerability as a disaster risk multiplier

Another aspect of our assessment is evaluating risk concerning social vulnerability and disrupted access to healthcare. People who are most vulnerable in hurricanes, socially and economically, are also vulnerable medically [21]. Nursing home residents normally face increased risks during hurricane season; many low-lying facilities have evacuation agreements with facilities on higher ground. However, according to the Florida Health Care Association, for example, evacuation approaches

will need to be adjusted, especially if positive cases of COVID-19 are present [21]. Additionally, those already suffering from COVID-19 and those who might contract the virus due to actions described above may require healthcare services. This includes diagnostic testing, at-home treatment, and/or treatment at a hospital. Individuals with social vulnerability are more likely to lack easy access to such health services, due to insurance issues, language challenges, and many other factors. Also, flooding causes road closures and further hinders one's ability to access important healthcare facilities. In this component, we look at how a hurricane might create barriers to healthcare access during a pandemic, especially for vulnerable populations.

1.4. Disaster response in the context of COVID-19

There is some indication of how organizations would respond to a compound hazard event through the experience with Hurricane Laura, a Category 4 hurricane that made landfall between Texas and Louisiana on August 26th, 2020. FEMA, The American Red Cross, and local organizations prepared for the compound hazard situation by preparing hotels and dormitories with sufficient social distancing measures among evacuees. Measures such as health screening and temperature checks to get into shelters have been put into place. In the case of suspect cases of COVID-19 and other virus risk factors, organizations have made alternative accommodation [22]. Other protective actions such as stockpiling face coverings and disinfectants for shelter cleaning were taken [22], while hospitals in evacuation areas transferred their most critically ill and COVID-19 patients in advance to new, safer locations. This protocol is typical in 'traditional' storm preparation, where hospitals aim to reduce the capacity of their facilities to ensure sufficient food, medical supplies for incoming patients from the storm [22].

One could argue that approaches to mitigating COVID-19 risks share some commonalities with natural hazard mitigation. For example, enacting social distancing protocols to reduce COVID-19 exposure could be considered analogous to land-use planning to reduce exposure to natural hazards [6]. COVID-19 health and service policies aimed to protect vulnerable groups including the elderly, those with ill health and comorbidities, the homeless, and people from vulnerable socioeconomic groups are crudely analogous to defining and enforcing seismic building codes and strengthening earthquake-vulnerable buildings, to reduce life safety risks [23,24] via [6]. However, in some areas, activities during a natural hazard scenario such as a hurricane may conflict or counter recommended protocol for controlling the spread of infectious disease and vice-versa: preparation and evacuation. When preparing for a hurricane event, households taking preparative actions to stockpile necessary items in case of service disruptions could increase community exposure to and transmission of COVID-19. Furthermore, during and after the hurricane, disruptions to roads due to flooding and damages can prevent people from seeking healthcare services [12] for both COVID-19 symptoms and hurricane-related injuries. It is anticipated that the evacuation of households to nearby areas can potentially place non-hurricane impacted areas at a greater risk of cross-county spread of COVID-19, meaning that those counties need to take necessary actions to curb the spread. Given the novelty of this compound hazard, an understanding of how preparative and protective actions and evacuation during a hurricane event may help trigger or stop the transmission of a viral outbreak is critical.

1.5. Research gaps

How COVID-19 interacts with other systems, namely other natural hazards is still not fully known. So far, researchers have proposed policies and approaches to manage disasters during the COVID-19 pandemic [6,14,15,25–27]. Quigley et al. [6], has offered a high-level quantitative and qualitative assessment of the likelihood of natural hazards coinciding with and influencing epidemiological characteristics of COVID-19 pandemic by using natural hazard curves for seasonal

hazards plotted against COVID-19 time-series forecasts. Their epidemic phenomenological model with a concurrent disaster event predicts a greater infection rate following events during the pre-infection rate peak period compared with post-peak events. However, Quigley et al. [6], does not assess how human behaviors and patterns during disaster phases interplay with the spread of an infectious disease.

Several Existing studies have focused on seismic activity [15,28]. Earthquakes have sudden onsets or shocks [16] and lack phases for people to prepare in advance, hurricanes bring new and untold challenges as we continue to battle the COVID-19 pandemic. Tripathy, Bhatia, Mohanty, Karmakar, and Ghosh [29] developed a framework that aims to assist stakeholders in managing compound hazard and 'conflicting objectives in disaster management planning in the context of flood hazards and COVID-19 in India [13] have released a non-peer-reviewed study that supports the notion that hurricane evacuation could trigger the number of COVID-19 cases in both evacuated and destination areas. Moreover, "these compound risks will exacerbate and be exacerbated by the unfolding economic crisis and long-standing socioeconomic and racial disparities" [30]. Government agencies and other emergency response stakeholders would need to restructure and introduce new approaches for mitigating both COVID-19 risks and protocols with disaster response and recovery operations while taking into consideration the diverse needs and characteristics of the populations at risk [26]. Disasters disproportionately harm certain populations; it is far more difficult to recover from physical harm and/or financial damage when one's initial position is unsatisfactory/unstable. A study of hurricane risk on the U.S. Gulf Coast during 1950–2005 found that "white, young adult and nonpoor populations have shifted over time away from zones with a higher risk of wind damage, while more vulnerable population groups—the elderly, African Americans, and poor—have moved in the opposite direction" [31]. Furthermore, a damage assessment of 1500 single-family homes after Hurricane Ike revealed statistically significant relationships between hurricane damage and ethnicity and socioeconomic status, with compound effects for poor people of color [32]. COVID-19, too, has disproportionately affected poor, highly segregated Black communities in Chicago, likely due to entrenched patterns of inequality and exclusion [33]. Hence, a study of the overlapping hurricane and COVID-19 hazards should also consider compounding aspects of social vulnerability.

2. Research scope

The framework ties together three different datasets that model population movement patterns, COVID-19 case counts, and social vulnerability to examine the associated risks of a compound hazard event. The research delves into the intersection of planning and response for natural hazards and a pandemic situation. This paper presents a novel approach to quantifying multi-hazard risk with digital trace data. The objectives of the new multi-hazard risk quantification approach are twofold. First, this work seeks to analyze and quantify the compound risks of COVID-19 and Hurricanes. Secondly, this work outlines a modifiable framework for future hazard and risk modeling approaches that can be enhanced using digital trace data. Human movement and behavioral patterns related to hurricane preparation actions and disease transmission risk is modeled by POI visitation data [34]. The Social Vulnerability Index [35] is used to identify social disparities in compound-hazard risks, while historical flood data during for Harris County, Texas during Hurricane Harvey in 2017 [12] is used to map physical risks due to hurricane induced-damages. The framework supplemented by the three datasets will be used to understand the potential COVID-19 transmission risks posed by protective actions for a hurricane event (e.g., preparedness and purchasing of preparatory goods). COVID-19 case count data in Harris County through July 2020 is interpolated with population mobility and flooding impact data from August through September 2017 to model a hypothetical Hurricane Harvey-Pandemic scenario. The framework designed and implemented

in this study can be used to help stakeholders in disaster planning and management as well as urban resilience modeling anticipate potential compound risk outcomes as they relate to COVID-19 and future disease outbreaks.

Using the POI visitation data as an indicator of transmission spread risk during different stages of a disaster, the following research questions are addressed:

1. Which geographic areas present the most significant risks to a community spread due to disaster preparation?
2. What are the POIs that present the most significant risks to a community spread due to disaster preparation?
3. What are the sources of risks and vulnerability if a hurricane like Harvey were to happen during a pandemic situation in Houston, Texas?

The framework provides a potential solution for stakeholders needing to make critical decisions about prioritization planning for evacuation, emergency and risk communication, and safe locations for temporary critical infrastructure services, such as healthcare centers and shelters. When applied, the framework can facilitate information that can be used by stakeholders to ensure the provision of essential services in low compound risk areas. The methodological approach and development of the conceptual framework are detailed in the following sections.

3. Methodology

3.1. Case study: Hurricane Harvey

As of July 2021, Texas had recorded more than 3 million confirmed cases since the start of the pandemic in March 2020 [4] while Harris County continues to lead the state in confirmed COVID-19 cases surpassing 400,000 and total deaths nearing 7000 (HCPH, 2020). As of July 18th, 2021, about 53% of the eligible population of Harris County was vaccinated (HCPH) 2021) Hurricane Harvey is well-documented and valuable data is available regarding people's movements before, during, and after the events in question. It is prudent to examine hurricane preparation, evacuation, and recovery procedures as seen in 2017 Texas to inform about the possible spread of COVID-19 if a similar hurricane occurs in the region during the pandemic. The study therefore follows the timeline of Hurricane Harvey in Harris County, Texas, which made landfall in the area on August 26th, 2017. Population movements measured by the POI dataset provided by SafeGraph are analyzed from August 1st through September 15th, 2017 in order to capture movement trends before, during, and after the disaster impact. This timeline will allow for the identification of trends related to the preparation, impact, and recovery stages of disaster management. Harris County is a highly populated county encompassing the city of Houston, with a southeast portion bordering the Gulf of Mexico. By combining the COVID-19 model with data from the Hurricane time period, we can identify the hurricane protective actions that have the potential to exacerbate transmission throughout a community. Our analysis can help stakeholders anticipate possible compound hazard outcomes and inform emergency management strategies to better address the unique challenges presented by a multi-hazard situation.

3.2. Conceptual framework

Network analysis is used to identify high-risk areas with location data from SafeGraph and a combination of Pearson-chi square tests and logistic regression are used to assess the association between different hazards, COVID-19 risk-factors and transmission risk as well as social disparities in compound risk. A framework is developed to conceptualize three primary risk phenomena during Hurricane Harvey in the context of a pandemic (Fig. 1). The proposed methodology can be applied to

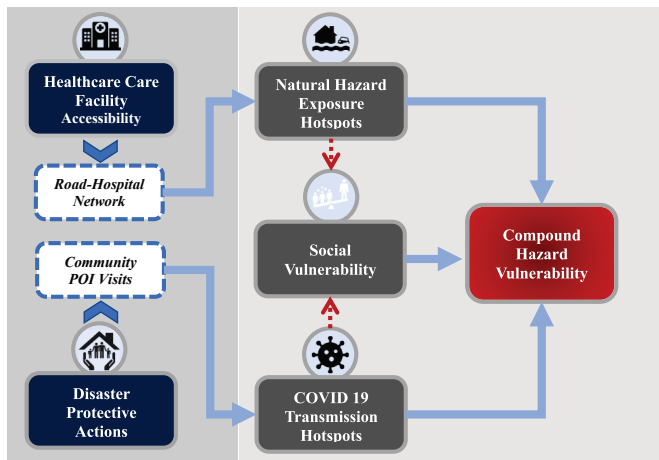


Fig. 1. The Compound Hazard Risk Framework; Transmission hotspots are indicated by POI visits for storm preparation, social vulnerability indicated by the Social Vulnerability Index [35], and hazard risk measured by historical data aggregate together to form the Compound Hazard Vulnerability of a community.

natural hazard events in other parts of the US as well as other regions of the world, contingent upon the availability of data. The Compound Hazard Risk Framework (Fig. 1) conceptualizes the pathways of the Compound Hazard Vulnerability depicted in the red box of the figure. There are three primary risk phenomena that are being modeled as risk factors of Compound Hazard Vulnerability represented by the boxes shaded in grey: Natural Hazard Vulnerability, Social Vulnerability, and COVID-19 Transmission Vulnerability. The underlying principle of the connectivity between these pathways is based on the premise of the presence of a strong association between urban mobility and infectious disease spread [36].

Each of the Compound Hazard Risk components is measured by a different set of indicators by means of publicly available data or digital trace data. Disruptions to Road-Hospital networks is used as indicator of healthcare facility accessibility, and consequently, probable natural hazard vulnerability hotspots for future hurricane situations. POI visitation trends measured by population movement data is used as an indicator of COVID-19 transmission risk hotspots, where higher concentrations of POI visits to particular store types and geographic locations are proposed as transmission hotspots. Concurrently, community POI visits are indicative of population and location specific protective actions taken by individuals or households in face of the hurricane event. The following sections discuss the datasets used to measure the various components outlined in the Compound Hazard Risk Framework in further detail (Fig. 1).

3.3. Data

3.3.1. Points of interests (POIs)

During the COVID-19 pandemic, location data has helped researchers study stay-at-home orders and pandemic hotspots. Population visits to POIs were studied as an indicator of infectious disease spread risk [7,9]. Extant works using POI visit data to identify patterns of urban mobility and movement patterns reveal important characteristics of urban dynamics as well as collective human behavior and social interactions [37]. A comprehensive human mobility dataset of POI visitation patterns from SafeGraph is used to model COVID-19 transmission risk. SafeGraph is location data platform company that uses machine learning based methods to trace digital borders around retail spaces and other places in the US and Canada of interest, and records the number of people that visit in specified time intervals (i.e., daily or weekly visitation counts) [34]. According to Safegraph, a point of interest is “a place you spend time or money”. POIs are used more generally in maps or

geo-datasets to represent a particular feature, as opposed to linear features like roads or areas of land-use. Some examples of POIs can range from postal offices, grocery stores, specialty stores, and tourist attractions.

In relation to the Compound Hazard Risk Framework, it is proposed that POI data can help indicate general behavioral trends and priorities of people as they relate to movement and protective actions during disasters. SafeGraph collected and anonymized POI visit data from various sources (e.g., third-party data partners such as mobile application developers). The POI data includes important base information of a POI, such as location name, address, latitude, longitude, brand, and business category. The data reveal trends in visits to POIs, including total visits over a given period, the number of visits each day, and the overall visitors to POIs from different geographic areas called Census Block Groups (CBGs). CBGs are the smallest geographic unit used by the United States Census Bureau, and each CBG is identifiable by a unique 12-digit code. For the Hurricane Harvey case-study, POI visit data was collected from August to September 2017.

3.3.2. Social vulnerability index (SVI)

Socially vulnerable populations are at heightened risk during public health emergencies because of factors like socioeconomic status, household composition, minority status, housing type, and transportation. The resilience of communities is highly associated with the socioeconomic and demographic factors [38]. In conjunction with the SafeGraph data, the Social Vulnerability Index (SVI), developed and made publicly available by the CDC, is used to capture the social vulnerability context of the potential POI/COVID hotspot areas and to identify populations at risk. The index uses 15 U.S. census variables aimed at measuring a community’s need for “support before, during, or after disasters. Vulnerability involves socioeconomic and demographic factors that affect community resilience (Juntunen, 2005). Including the SVI dataset helps to identify socially vulnerable populations and understand how and where socially vulnerable communities may be affected in order to allocate resources more effectively during the disaster cycle [38]. Hazards and vulnerability literature reveals that people living in a disaster-stricken area are not affected equally [38]. Population characteristics “are an important indicator of everything from evacuation compliance during an event to successful long-term recovery after one” with the socially vulnerable “more likely to die in a disaster event and less likely to recover after one” (Juntunen 2005). The most vulnerable people are likely those whose needs are not sufficiently considered in the planning of local response and relief organizations [38].

According to the SVI, social vulnerability refers to the potential negative effects on communities caused by external stresses on human health. Such stresses include natural or human-caused disasters or disease outbreaks. Reducing social vulnerability can decrease both human suffering and economic loss. The SVI themes and social factors measured are the following [35]:

- Socioeconomic status (below poverty, unemployed, income, no high school diploma)
- Household composition & disability (aged 65 or older, aged 17 or younger, older than age 5 with a disability, single-parent households)
- Minority status & language (minority, speak English “less than well”)
- Housing type & transportation (multi-unit structures, mobile homes, crowding, no vehicle, group quarters).

Knowing the location of socially vulnerable communities, planners can more effectively target and support community-based efforts to mitigate and prepare for disaster events. Responders can plan more efficient evacuation of those people who might need transportation or special assistance, such as those without vehicles, the elderly, or residents who do not speak English well. Local governments can identify

neighborhoods that may need additional human services support in the recovery phase or as a mitigating measure to prevent the need for the costs associated with post-response support.

3.3.3. Transmission risk: COVID-19 cases per 100,000

To examine pandemic transmission risks in a community, daily COVID-19 case counts are used. Harris County Public Health and City of Houston publishes confirmed case counts daily by zip code [39]. Using the existing number of cases up to July 28, 2020, per zip code, we calculated the total number of cases per 100,000 people according to each zip code per the 2010 Census population data. The rate was converted to the census tract scale to maintain consistency of the scale of our analysis (Fig. 2). We use a rate as opposed to the number of cases alone as a rate takes into consideration the population from which the cases come from and it is also easier to compare geographic areas that may have different population sizes.

3.3.4. Natural hazard vulnerability: disrupted access to hospital

Data regarding the flooding scenario in Harris County during Hurricane Harvey was collected from Ref. [12]. In their study, a percolation analysis is used to determine the percentage of nodes in the Harris County road network that lost road access to critical health facilities in all census tracts in Harris County due to flooding during Hurricane Harvey. For example, if there are 100 nodes (intersections) in the road network, the percolation analysis might show that in a flood scenario, 40 would be disconnected to the hospital either directly or indirectly due to flooding; the index would be 0.6 for that scenario in the respective census tract. The percentage of nodes with disrupted access to critical healthcare facilities is thus the indicator we use to measure the natural hazard exposure and risk of census tracts during Hurricane Harvey. A visualization of this data has been reproduced from Dong et al. in Fig. 3.

3.4. Analysis

In the previous section, the data sources and their application in the Compound Hazard Risk index were detailed. We considered four types of risks to map the compound risks: COVID-19 exposure, transmission risks from preparedness actions, social vulnerability and natural hazard vulnerability and risk (illustrated in Table 1). In this section, the analytical approach using these data is described. A summary of the key statistical approaches is provided in Fig. 4.

3.4.1. Identifying high-risk POIs

We identified high-risk POIs to epidemic transmission due to preparation actions for Hurricane Harvey based on examining the number of visits to POIs. We included POI data of August, and September 2017.

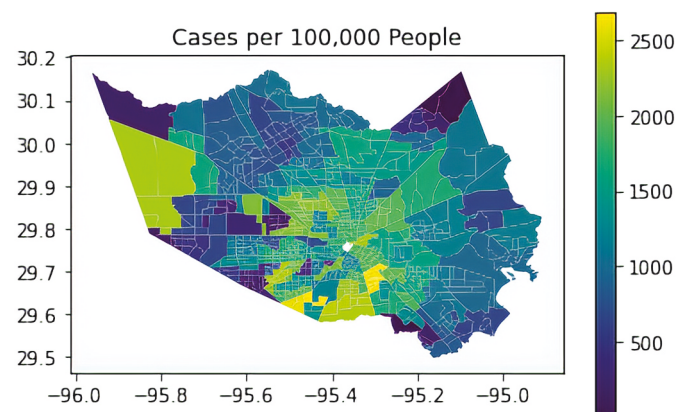


Fig. 2. COVID-19 Cases per 100,000 according to Harris County census-tracts and total cases as of July 28th, 2020. X and Y axes are longitudes and latitudes respectively.

Two weeks prior to Harvey, there were no indications of an impending Hurricane, and hence, the POI visits could be considered as a normal state in this period. Therefore, we used the POI visits two weeks before the hurricane to construct a baseline. We used POI data one week before Harvey (i.e., August 18–25, 2017) as the period that the population prepared for Harvey. Furthermore, we extended the POI data to September 15, 2017 to include the recovery period after Harvey. To remove the noise in the data, instead of looking into visits to individual POIs, we grouped POIs by Top Category as provided by the North American Industry Classification System [40] to examine daily visits to each category throughout the three months. Then, we used a rolling seven-day mean to account for increased visits during weekends and determined average visits and standard deviation for the number of visits to POIs of each category during the baseline (August 1–August 17, 2017). We compared the number of visits to POI of each category in the week of hurricane preparation (i.e., August 18–25, 2017) with the number of visits during the baseline.

A POI category was deemed significant to hurricane preparation and with high transmission risk if there were more visits than normal and the visits increased sharply during the preparation period (there was an upsurge rather than gradual climb in percentage). POI categories with significant visit spikes during the hurricane preparation period, therefore, were identified, if they had one or more days of visitation with Z-scores higher than 3 (99% confidence level) and if there was a high rate of change in visitation (Z-score jumps 1.645 or more from one day to the next). Also, we compared visits to POI categories in the three months in 2018 and 2019 to account for the non-Harvey-related variation. We ignored POI categories with comparable trends observed in 2018 and 2019 as we considered the variation as seasonal influence rather than hurricane related. Furthermore, categories with daily visits less than 25 were removed from the results. Finally, after the removal, the rest categories with significant visit spikes were identified with high transmission risk and were used to evaluate compound risk presented in subsection 3.4.2.

3.4.2. Mapping hazard exposure and compound risks

We considered two risk factors for COVID-19 exposure: general exposure and COVID-19 cases. To evaluate general exposure, we mapped an origin-destination network in Harris County, in which CBGs are origin nodes and POIs are destination nodes and the number of visitors as edge weights. We checked the weighted node degree centrality of CBGs (the sum of the edge weights for edges linked to that CBG). Then we grouped CBGs in the same census tracts to get the degree centrality of census tracts as the indicator of general exposure because a census tract with higher weighted degree centrality tends to have more visitors to POIs. To evaluate the risks from COVID-19 Cases, we determined which census tracts lay within each zip code, and we used data from Harris County/Houston Public Health COVID-19 dashboard to quantify their respective COVID-19 cases as of July 23, 2020.

Two risk factors for transmission risks for preparedness actions were considered: presence of high-risk POIs and preparation period visits. To measure the risk factor of presence of high-risk POIs, we also used weighted node degree centrality of census tracts as an indicator of transmission from preparedness action. Here, we only performed network analysis using high-risk POIs (as filtered based on the procedure explained in section 3.1). This means that the CBG-POI movement network here only included POI nodes with high transmission risks, and grouped CBGs to census tracts to check number of visitors to high-risk POIs. To measure the risk factor of preparation period visits, we checked census tract visitors during August 18–25, 2017 (specifically, Z-scores of each zip code's visitors during this period) as the second gauge of transmission from preparedness action. As stated previously, to assess health vulnerability, we used data regarding disrupted access to hospitals during Hurricane Harvey, as provided by Dong et al. [12]. Additionally, we used the Social Vulnerability Index's total score for each census tract to measure the risk factor of social vulnerability.

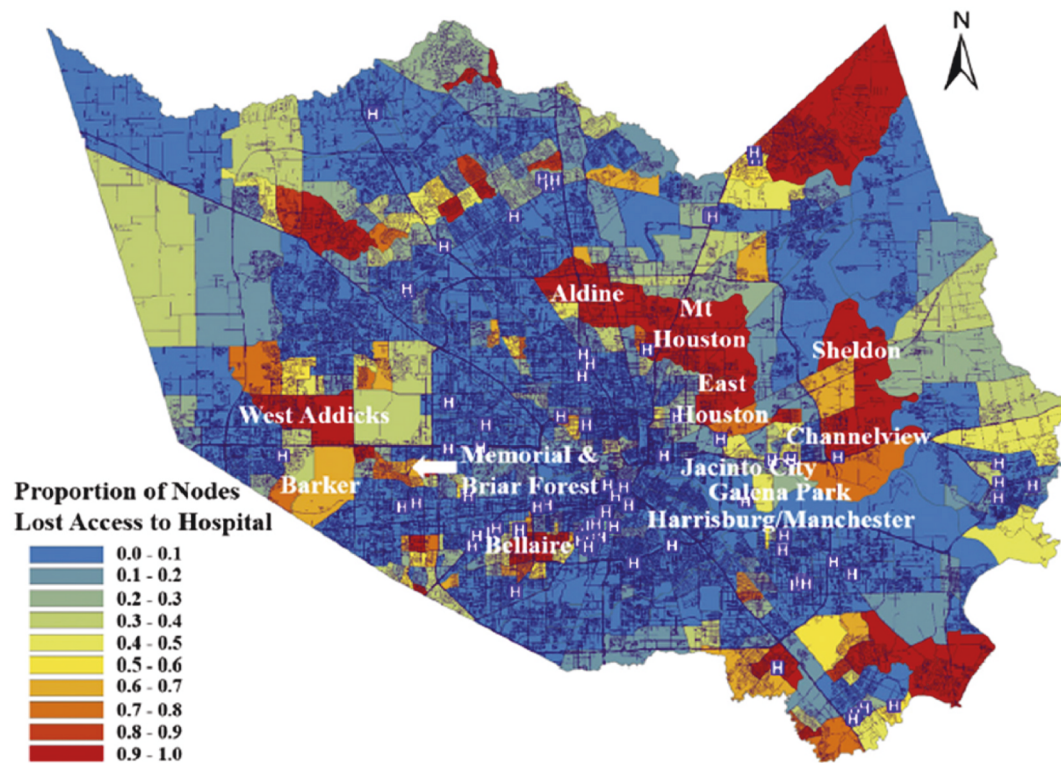


Fig. 3. Disrupted access to healthcare facilities in Harris County under Harvey flooding scenario [12].

Table 1

Risk breakdown with factors and methods of assessment - summarizes the risk components, factors, and data sources used to measure the four types of Risk. Collectively, these four risk components comprise the Compound Hazard Risk of census tracts within Harris County.

Type of Risk	Risk Factors	Description	Data/Source of Analysis
COVID-19 Exposure	General Exposure	High and geographically diverse visitation	Weighted node degree centrality in network analysis, using all POIs
	COVID-19 Cases	Confirmed COVID-19 cases per 100,000 people	Harris County/Houston COVID-19 Cases Dashboard and 2010 Census data
Transmission Risk from Protective Actions	Presence of High-Risk POIs	Increased visits to grocery stores, gas stations, etc.	Weighted node degree centrality in network analysis, using only at high-risk POIs (as found in 3.1)
	Preparation Period Visits	Higher visitation before/during Harvey	Census tract visitation Z-score, averaged Aug 18th-25th, 2017
Social Vulnerability	Social Vulnerability	Community ability to prevent human suffering and financial loss	The overall ranking of the Social Vulnerability Index from CDC
Natural Hazard Vulnerability	Disrupted Access to Healthcare and critical infrastructure facilities	Loss of access to healthcare facilities due to flooding on roads	Percent of nodes disconnected from hospitals (directly and indirectly)

For each risk factor, a census-tract is given a score between 1 and 3, measured by its relative percentile range to other census-tracts in Harris County, where higher scores represent higher risk census tracts. Compound risk is measured by taking the average of all three risk factor scores. A risk type is high if both factors are 3; medium if the factors are 2 and 3 or both 2; low if the factors are 1 and 2 or both 1.

3.4.3. Compound hazard risk disparity analysis methods

Pearson chi-square tests were used to determine statistically significant differences among census-tract areas concerning their SVI ranking and other compound hazard risk factors. This analysis is done to evaluate whether socially vulnerable populations are at greater risk of a compound hazard event and whether or not compound hazards are experienced the same way in low SVI areas and high SVI areas. It is anticipated that census-tracts with higher social vulnerability rankings would be more likely to fall into areas of high compound hazard risk compared to census tracts of low social vulnerability. Chi-square tests are performed by testing whether or not there are statistically significant differences in the compound hazard risk factors described in the Com-

pound Hazard Risk framework (Fig. 1) across three segment groups: low, medium, and high SVI census tracts. The null hypothesis for this test is that there is no relationship between SVI ranking and compound hazard factors. The alternative hypothesis is that there is a relationship between SVI ranking and compound hazard factors, signifying a potential role of social disparities in the heightened exposure to compound hazard risks. The critical value for the chi-square statistic is determined by a level of significance where $\alpha = 0.05$.

Logistic Regression was used to evaluate the sources of risks and vulnerability if a hurricane like Harvey were to happen during a pandemic situation. Logistic regression further allows us to control for the various interactions among the compound hazard risk factors and allows for the measurement of both the magnitude and direction of the relationship among the compound hazard risk factors. The logistic regression models used are summarized below, where the independent variable Y is Preparation Transmission Risk and dependent variables X_1 , X_2 , X_3 are Natural Hazard Vulnerability, COVID-19 Exposure Risk, and SVI ranking respectively. A statistically significant association between the independent and dependent variable is determined at a sig-

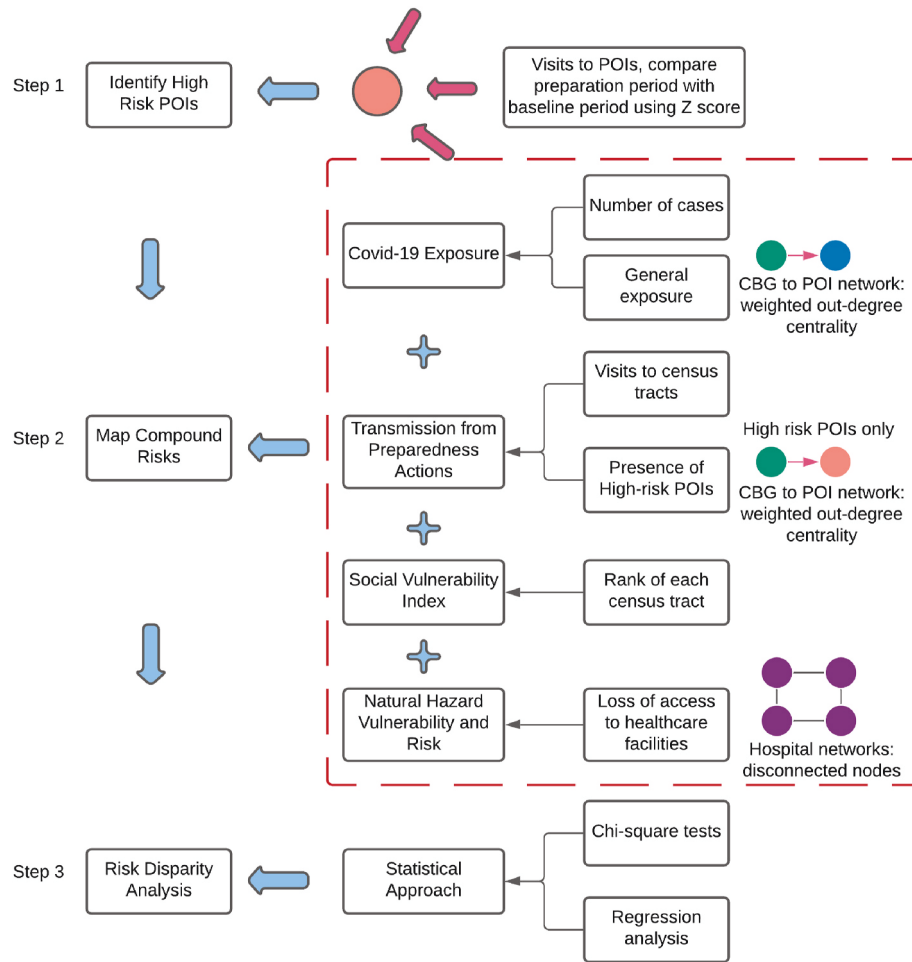


Fig. 4. Methodological approach.

nificance level of $\alpha = 0.05$.

assessed and filtered to narrow down to POI's that pose the most sig-

$$\ln\left(\frac{P(Y_{n1,2,3} = 1)}{P(X_n = x)}\right) \sim \text{Natural Hazard Risk}_1 + \text{COVID-19 Exposure Risk}_2 + \text{SVI Rank}_3$$

The purpose of using the above outlined statistical approaches is to draw statistical insights regarding compound hazard hotspots identified in the mapping process. All statistical computations and models have been performed in R [41].”

4. Results

The results from this analysis provide information about the movement of people ahead of a hurricane event and how these patterns can potentially evolve into COVID-19 transmission hotspots and increase their vulnerability due to the impact of a hurricane event.

4.1. At-risk POIs during disaster preparation

Identifying locations and places within a community where people congregate in large numbers can indicate potential transmission hotspots. In this segment of the analysis, 142 POIs from SafeGraph were

nificant risks to a COVID-19 community spread as a result of disaster preparation behavior. The Z-score, mean, standard deviation, total count of increased visits from the baseline measurement, and the percent increase for the selected POIs are presented in Table 2.

Out of 142 total POI categories, 12 observed significantly higher than normal visits in the week leading up to the hurricane landfall between August 18th and August 25th, 2017 (Table 2). A full list of the business categories used by SafeGraph can be found in the Appendix section. SafeGraph Places uses the North American Industry Classification System (NAICS) (NAICS, 2020) categorization taxonomy developed by the US Census Bureau that consists of a numeric NAICS code up to 6 digits in length. It is reasonable to deem Colleges, Universities, and Professional Schools as a non-hurricane related POI because the percent increase in visitation is an outlier. Although a similar trend is observed in 2018, no such trend is present in 2019; this may be due to the academic year beginning later. The POIs appear to mirror the consumer level and industrial level demand for basic human necessities and resources, which are primarily food, water, energy, and shelter. A description of the establishments and businesses included in the POI categories is shown in

Table 2

Percent change in visits to POI categories significant to hurricane preparedness; August 18 to August 25th, 2017 from baseline years 2018, 2019.

Category	Z- Score	Mean	SD	Increased Visit	Percent Increase (%)
Colleges, Universities, and Professional Schools	16.04	2486.98	173.94	5277.00	112.18
Building Equipment Contractors	11.25	99.44	3.01	133.29	34.04
Grocery Stores	10.33	13769.65	366.53	17556.14	27.50
Building Material and Supplies Dealers	6.87	5594.99	121.45	6429.57	14.92
Gasoline Stations	6.06	17452.46	477.66	20347.14	16.59
Bakeries and Tortilla Manufacturing	6.05	682.34	9.92	742.29	8.79
Insurance Carriers	5.47	27.18	1.04	32.86	20.87
Offices of Real Estate Agents and Brokers	4.69	49.13	2.35	60.14	22.40
Chemical and Allied Products Merchant Wholesalers	4.67	26.52	1.54	33.71	27.12
General Merchandise Stores, including Warehouse Clubs and Supercenters	4.42	15444.83	507.04	17685.43	14.51
Beer, Wine, and Liquor Stores	4.05	1330.57	35.47	1474.29	10.80
Lumber and Other Construction Materials Merchant Wholesalers	3.75	175.31	6.44	199.43	13.76

Table 3A. POIs within the significant categories are deemed high-risk locations for COVID-19 transmission in a hurricane scenario; more people will interact nearby within these businesses as the community prepares for hurricane landfall. From the POIs identified in the above table, it is clear that not all of the categories are places that the average household will visit for preparation purposes. Wholesalers and contractors are more likely to attract industrial workers and stakeholders. This signifies the importance of industry protocols and regulations that protect workers in warehouses and on construction sites. Implications of these results are explored further in the Discussion section. The POIs identified as having increased visitation not only signify the businesses and industries important for disaster preparation but also businesses and industries that have heightened susceptibility to disease spread. This information can serve to alert businesses in these industries to increase

the protection and safety measures and protocols of its workers and customers while ensuring customers access to products and items they need for storm preparation.

The graphs in Fig. 5 show the visitation to grocery stores over time, with vertical lines marking the recognition of Hurricane Harvey (Aug 18th), its landfall (Aug 25th), and its departure (Sep 1st), respectively. Fig. 5a shows the visits in 2017 (red line) compared to 2018 (blue) and 2019 (green), normalized by Z-score, and we can assume that the spike in 2017 is not indicative of an annual pattern (e.g. back-to-school activities). In Fig. 5b, the blue line shows raw data of visits by day, and the red shows a seven-day rolling mean of visits by day. The grey shaded area marks a normal range (i.e., Z score less than 3) of visits for the rolling mean. In this chart, we observe that visits to this category of POIs reached unusually high levels during the preparedness stage of

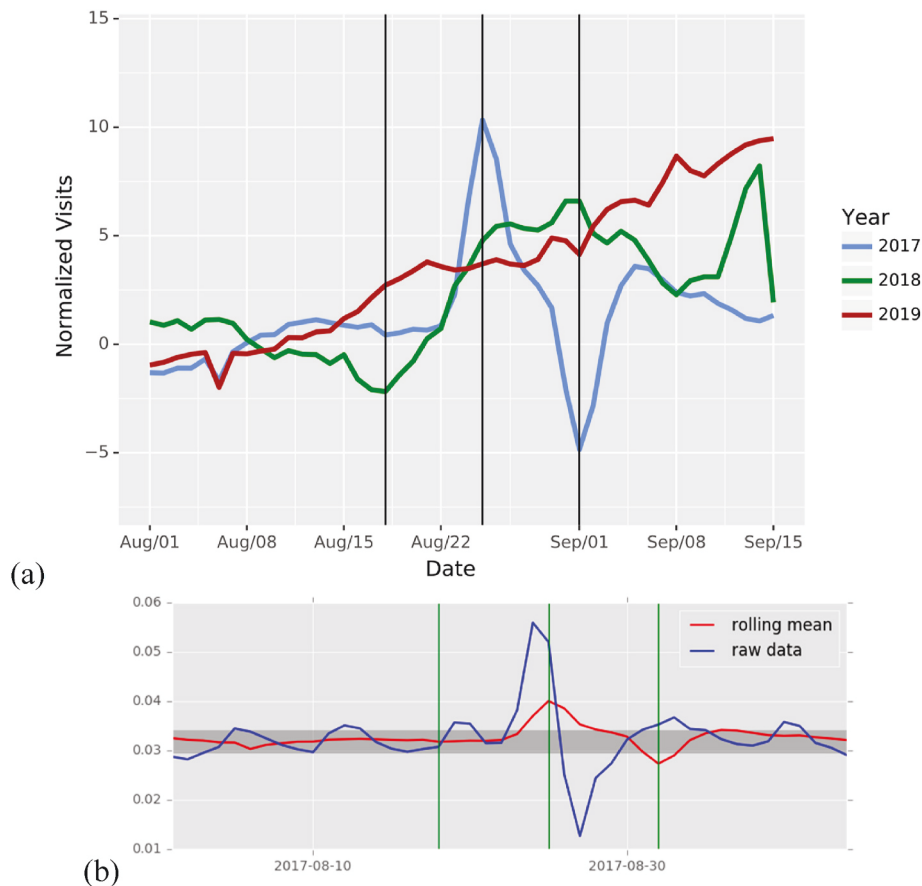


Fig. 5. Visitation to grocery stores during study period; Vertical lines in the graphs represent the hurricane preparation, impact, and 1 week recovery periods. (a): Grocery store visitation in Harris County from August to September, during Harvey (2017) and 2 years post-Harvey (2018–2019), (b): The raw data of visits by day versus the seven-day rolling mean visits by day to Grocery Store POIs in Harris County, 2017 (Harvey).

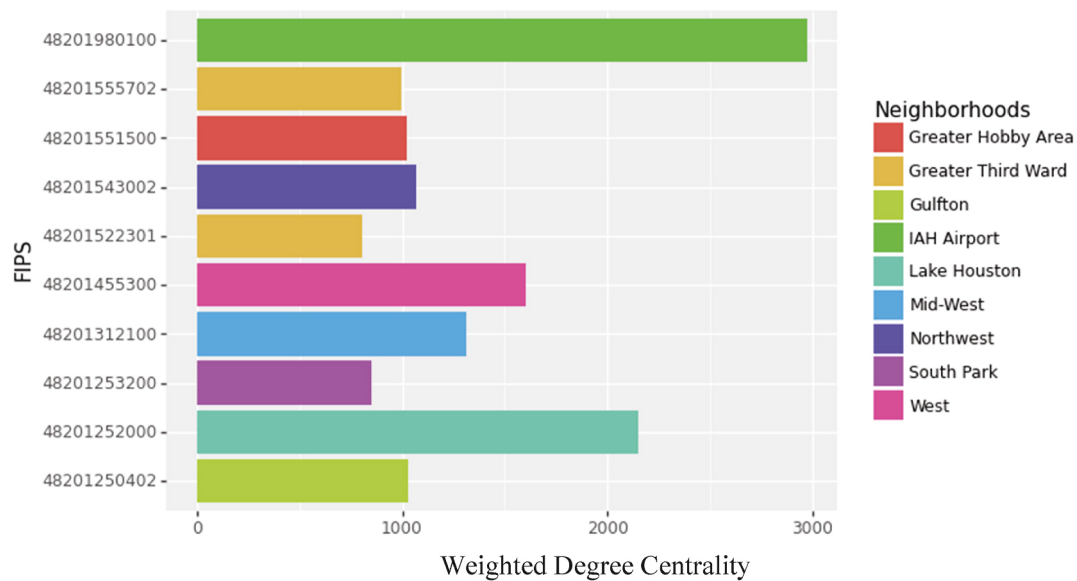


Fig. 6. The most connected and visited census tracts (FIPS) and their associated Super-neighborhood measured by POI categories experiencing abnormal increases in POI visits.

Hurricane Harvey.

4.2. At-risk compound hazard zones

Identifying areas within a community where people congregate in large numbers can indicate potential transmission hotspots. In this segment of the analysis, census tracts areas in Harris County SafeGraph were assessed to determine hot spot areas associated with disaster preparation behavior. This was used to determine which geographic areas present more risks to COVID-19 community spread due to disaster preparation. A total of 782 census tracts exist in Harris County, Texas. Visitors to high-risk POIs were most likely to originate from the census tracts and associated neighborhoods listed in Fig. 6. In Fig. 6, FIPS on the y axis is the census tract number and their associated Super Neighborhood is represented by the color code found in the legend. The x-axis measures the total weighted degree centrality of connected census tracts. The weighted degree centrality represents the total number of POI visits interacted with a census tract. Therefore, higher weighted degree centrality of a census tract would have more risks to community spread. The super neighborhoods, IAH Airport and Lake Houston, were found to contain the two most connected census tracts in Harris County during the preparation period for Harvey. The higher connectivity of people to high-risk POIs can indicate greater exposure and faster spread of the SARS-CoV-2 virus. These areas would therefore require prioritized attention and increased safety measures for COVID-19 intervention.

These census tracts were used to determine high-risk areas to COVID-19 hotspots and Compounded Hazard hotspots as a result of a multi-hazard scenario. Table 4 summarizes the descriptive statistics of the individual risk factors contributing to COVID-19 transmission as a result of preparative actions for Hurricane Harvey, exposure to existing COVID-19 cases, areas that experienced disrupted access to healthcare facilities due to Harvey, and the census-tract SVI. On average, the 782 census tracts in Harris County were found to be at medium-level risk for all risk

Table 4
Descriptive Statistics; n = 782.

Risk Factor	M	SD	Risk Category
Preparation Transmission Risk	1.669	0.612	Low
COVID-19 Exposure	2.071	0.471	Medium
Natural Hazard Vulnerability	2.279	0.643	Medium
SVI	2.844	0.875	Medium

factor categories except for “preparation risks.” Moreover, we can see the overlapping of different risk types in Fig. 7, where pink shows high exposure, black shows high health vulnerability, and white shows high preparation activity. State, local, and tribal agencies are most knowledgeable about the people in their communities. The social vulnerability index is designed to aid them in their efforts to ensure the safety and well-being of their residents. The components of the SVI can assist state and local personnel concerned with all phases of the disaster cycle. Knowing the location of socially vulnerable communities, planners can more effectively target and support community-based efforts to mitigate and prepare for disaster events. Responders can plan more efficient evacuation of those people who might need transportation or special assistance, such as those without vehicles, the elderly, or residents who do not speak English well. Local governments can identify neighborhoods that may need additional human services support in the recovery phase or as a mitigating measure to prevent the need for the costs associated with post-response support.

South Houston areas show more overlap of risk categories indicating greater compound risk. Census tracts located in the Northwestern region of Harris County appear to have higher preparation risk as a result of higher concentrations of POI visits. Areas shaded in white on the map in Fig. 7 visualize census tract areas receiving the highest number of visits within the preparation period for Harvey. Many of these areas appear to be isolated from other high-risk categories, i.e., low exposure and health risk indicating the potential of viral outbreaks in new areas. Health risk areas are concentrated primarily in the downtown Houston area, where the Texas Medical Center (TMC) is located. The implication of health risk areas is relevant to the aftermath of the hurricane. Healthcare accessibilities appear to be generally isolated as a risk measure. However, areas of high compound risk including healthcare accessibility risk would result in unfavorable outcomes in the aftermath of a disaster. In these areas, healthcare centers need to take care of existing COVID-19 cases while anticipating more cases due to high preparation exposure risk in the area. Healthcare centers in these areas are further challenged by the probability of being disrupted during the hurricane. While healthcare centers in these areas will need to take measures to protect existing patients, in certain situations, patients may need to be transported to medical facilities away from hurricane affected areas. Similarly, residents of health-risk areas will need to make logistical arrangements to visit alternative medical facilities for treatments related to either COVID or physical impacts, such as injuries, due to the

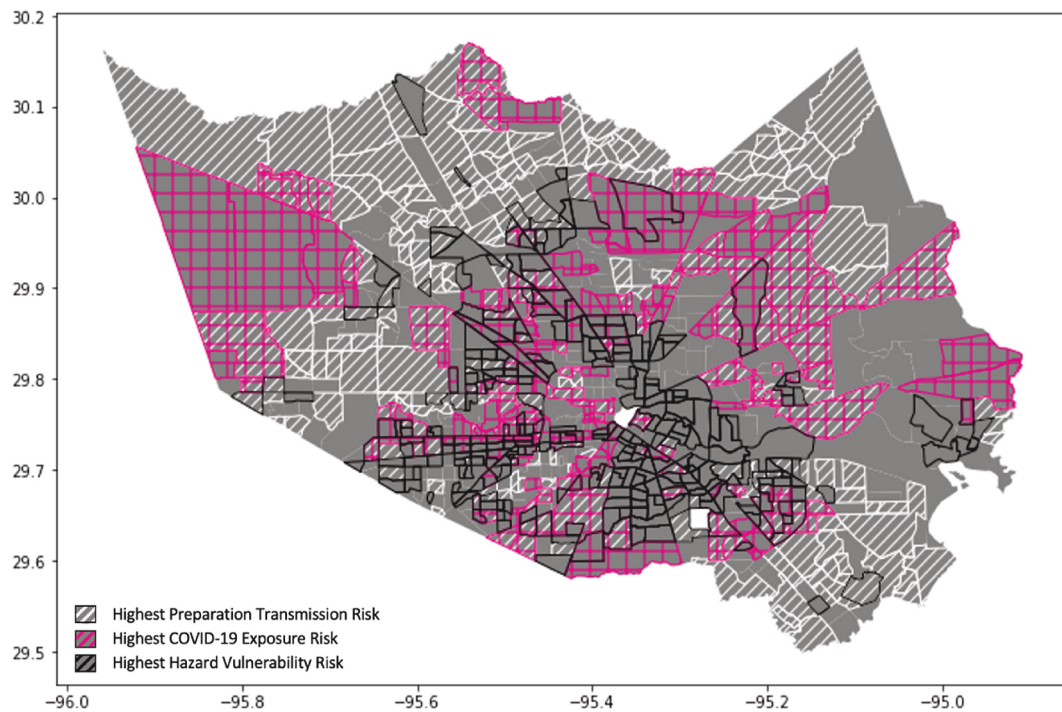


Fig. 7. Compound Hazard Risk Areas by Census Tract boundaries in Harris County. Shaded areas represent the three compound hazard risk components: Preparation Transmission Risk, COVID-19 Exposure, and Natural Hazard Vulnerability.

Table 5

Comparison of compound hazard risk by census-tract SVI rank.

SVI Rank	Risk Level	Total Count (%)			
		COVID-19 Exposure	Natural Hazard Vulnerability	Preparation Transmission Risk	Compound Hazard
High N = 302	High	15 (.05)	138 (.46)	17 (.06)	42 (.14)
	Medium	209 (.69)	76 (.25)	133 (.44)	181 (.59)
	Low	78 (.26)	88 (.29)	152 (.50)	79 (.26)
Medium N = 184	High	16 (.09)	85 (.46)	23 (.13)	27 (.03)
	Medium	128 (.70)	38 (.21)	111 (.60)	104 (.43)
	Low	40 (.22)	61 (.33)	50 (.27)	53 (.52)
Low N = 296	High	19 (.06)	107 (.36)	66 (.22)	11 (.14)
	Medium	188 (.64)	77 (.26)	153 (.52)	129 (.56)
	Low	89 (.30)	112 (.38)	77 (.26)	156 (.28)
Total = 782					

hurricane.

4.3. Factors of Preparation Transmission Risk

The sources of risks and vulnerability in communities if a hurricane like Harvey were to happen during a pandemic situation were explored by comparing the total number of risk areas within census-tract areas of different SVI levels.

Table 5 displays the contingency across the different levels of the three risk components and the aggregated compound hazard risk with respect to the three levels of SVI (low, medium, high) for census tracts in Harris County to draw a correlation between the compounded hazard risk categories and the census tract's social vulnerability status. Each census tract Using Pearson's chi-squared tests, it was determined that the risk of COVID-19 transmission during hurricane preparation is significantly different concerning a census tract's SVI rank ($X^2 (4, N = 782) = 66.54, p < .001$). Differences among SVI ranks according to Natural Hazard Vulnerability ($X^2 (4, N = 782) = 8.98, p = .062$) and

COVID-19 Exposure Risk ($X^2 (4, N = 782) = 6.47, p = .167$) were found to be statistically insignificant. There is evidence of a significant relationship between compound hazard risk and SVI: $X^2 (4, N = 782) = 183.48, p < .001$. The statistical analysis implies that less socially vulnerable communities (i.e., low SVI) are more likely to be transmission hotspots and are more vulnerable to compound hazard risks. However, this finding is also telling of the need for socially vulnerable communities to visit high-risk areas to prepare for disasters. POIs needed for disaster preparation are more likely to be situated in high-risk areas, therefore making cross-community spread more likely. Regression was used to evaluate the sources of risks and vulnerability if a hurricane like Harvey were to happen during a pandemic situation (Table 6).

b represents unstandardized regression weights. sr^2 represents the semi-partial correlation squared. LL and UL indicate the lower and upper limits of a confidence interval, respectively. ‘.’ indicates an interaction term. * indicates $p < .05$. ** indicates $p < .01$.

Before Harvey landfall, the mobility patterns of people show a greater concentration of visits to high-risk POIs in census-tracts (b =

Table 6

Regression results to measure the association of Preparation Transmission Risk (dependent variable) and SVI rank, COVID-19 Exposure Risk, and Natural Hazard Vulnerability (independent variables).

Predictor	b	b 95% CI [LL, UL]	sr ²	sr ² 95% CI [LL, UL]	Fit
(Intercept)	2.25**	[1.78, 2.73]			R ² = .169**95% CI [.12,.21]
Natural Hazard Vulnerability	−0.18**	[−0.30, −0.07]	.01	[−.00, .02]	
COVID-19 Exposure Risk	0.27*	[0.05, 0.48]	.01	[−.00, .02]	
SVI Rank	−0.38**	[−0.60, −0.16]	.01	[−.00, .03]	
Natural Hazard Vulnerability: SVI	0.05	[−0.00, 0.10]	.00	[−.00, .01]	
COVID-19 Exposure Risk: SVI	0.03	[−0.07, 0.13]	.00	[−.00, .00]	

0.27, $p < .05$) with lower SVI scores ($b = -0.38$, $p < .01$). There is a statistically significant indication that the census-tract areas visited during this time frame of preparation are less likely to be in areas that have previously faced major flooding and disruption of access to critical healthcare facilities ($b = -0.18$, $p < .01$). When assessing the association of SVI with hazard risk and exposure risk, its association with preparation visits are insignificant.

5. Discussion

The analysis of POI visitation patterns in the week leading up to the landfall of Hurricane Harvey was used to assess a hypothetical case of a hurricane-pandemic scenario. The movement of people to certain POIs prior to hurricane landfall during a pandemic can provide decision makers with two primary pieces of information. First, for mitigating risks due to a hurricane, the POI data and network analysis can indicate which industries and businesses are targeted for hurricane protective actions. Secondly, from a pandemic perspective, the data and analysis can highlight which areas in a community need to be prioritized in terms of ensuring safe distancing practices and protective measures against COVID-19 spread.

It is clear that certain establishments tied to specific industries critical for human-wellbeing and survival (construction, food, water, energy services) are visited at a statistically higher rate than normal day-to-day rates. Furthermore, certain areas measured at the census-tract are at greater risk to compound hazard impacts. Both findings indicate that protective actions for a hurricane event do have the potential to increase

the risk of transmission of disease within a community. Preparation as a protective action influences people to concentrate in specific areas, which can indicate increased exposure to the virus. The results of the analysis in this paper can be used to inform and provide directions to public health officials on sufficient measures and protocols to be taken to mitigate the spread of infectious disease while people prepare for impending natural hazards. For example, temporary stay-at-home orders can be put into place to allow for safe preparation measures. POIs relevant to disaster preparation were identified classified and ranked according to COVID-19 transmissibility risk. Census-tracts in Harris County were ranked according to highest POI visits and percent changes. Furthermore, the identification of compound hazard-risk areas hotspots can help stakeholders plan for temporary healthcare centers and other essential services in low-risk areas.

5.1. Identifying Compound Hazard Risk Zones in communities to control viral outbreaks during natural hazards

An important component of this research was to determine the geographic areas and POIs present the most significant risks to a community spread due to disaster preparation. The regression and chi-square tests were able to identify general trends and associations between the individual compound risk factors. However, they may overlook census tracts with high compounded risk. These census tracts would be important for planners to prioritize in disaster and COVID-19 risk-reduction planning. The Compounded Hazard Risk map in Fig. 8 is a high-level representation of the hazard category risks combined.

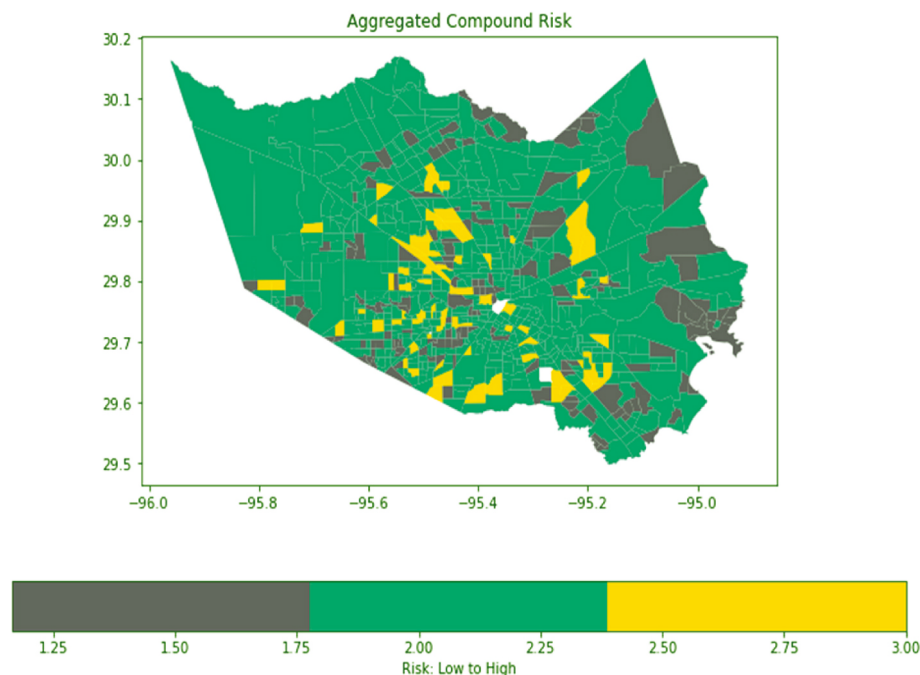


Fig. 8. Compound Hazard Risk Zones; Census Tracts in Harris County: A mapping of compound risk is shown where low-risk census tracts are shown in purple, medium risk in teal, and high risk in yellow. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Emergency planners and interested stakeholders can utilize this map tool to identify and prioritize areas for different purposes related to natural hazard mitigation (hurricanes and flooding) and COVID-19 response. Purple areas shown in the map could be suitable for evacuation sites within Harris County where temporary shelter, medical, and other critical infrastructure services could be provided to the most vulnerable members of the community. It would be critical for planners to set up stringent measures to prevent outbreaks of COVID-19 cases to these low Compound risk areas. High-risk areas on the map would alert emergency planners to prioritize their evacuation and COVID-19 response in these areas. Responders can plan more efficient evacuation of those people who might need transportation or special assistance, such as those without vehicles, the elderly, or residents who do not speak English well. Local governments can identify neighborhoods that may need additional human services support in the recovery phase or as a mitigating measure to prevent the need for the costs associated with post-response support. Census tracts in North-Central Harris County were located in the towns of Spring and Klein. A complete list of the census tracts and their associated neighborhood name along with their Compound Hazard Risk score is provided in the Appendix section, Table 2A.

5.2. Identifying at-risk POIs in communities

The at-risk POIs show us not only the types of businesses and industries most visited and therefore at-risk for being a transmission hotspot, but also the types of businesses that are critical for disaster preparedness from a household perspective and industrial scale outlook. Enforcement of protective measures (social distancing, building capacity, mask-wearing, limited hours and store closures for extra cleaning) would be highly advisable for POI businesses receiving high traffic to implement to control the spread of infectious disease. It would be beneficial for businesses and local governments to collaborate on ensuring protective measures are in place for customers and employees while also ensuring equitable access to critical supplies that households purchase in preparation for a natural hazard.

5.3. Construction industry POIs

One industry that was shown to have a major role in both the pandemic and hurricane is the construction industry, indicated by increased visits to Building Equipment Contractors, Lumber and Other Construction Materials Merchant Wholesalers, Building Material and Supplies Dealers, and Chemical and Allied Materials Wholesalers. The construction industry is highly susceptible to acute and long-term impacts caused by hurricanes and other natural hazards. Hurricanes in particular pose acute threats to construction sites, with their incomplete structures; expensive machinery and equipment; materials and finishes that are easily damaged by water; flood-prone excavations; and building materials such as lumber, sheathing, and piping that can quickly become projectiles in high winds [42].

For the construction industry, preparing for a storm includes protecting supplies and materials, covering building openings, removing debris, removing or securing equipment, lowering cranes, documenting the conditions at the site, and coordinating job site security [43]. These protective actions may also entail stockpiling or prepositioning materials and supplies that might become temporarily inaccessible or unavailable in the storm aftermath. Stockpiling supplies in preparation for disaster response is a regular practice in many critical infrastructure service industries, especially relief organizations [44]. Hurricane Harvey set record levels of physical damages to residential housing and commercial buildings and major disruptions to the supply chain of materials and equipment to contractors were similarly experienced. The prices of materials, especially plastic, due to the closure of natural gas facilities were significantly disrupted. Other direct construction-related expenditures related to the procurement of building and flood repair

supplies[45], driving up the demand and costs for plywood, drywall, and steel building supplies substantially [45]. PVC pipe and fittings are always one of the hardest commodities to get after a major storm (Mader and Spaulding 2017). The damages and disruptions experienced indicate the importance for companies to preposition supplies in preparation for disaster response.

Before Harvey made landfall, consumers within a 250-mile radius of Houston's 77001 zip code-focused their purchases on oil and gas industry needs, such as machining, pressure vessels, and contract manufacturing. In the aftermath, buyers predictably searched for materials related to building supplies [45,46]. Workers and stakeholders in the construction field likely made increased visits to Building Material and Supplies Dealers and Lumber and Other Construction Materials Merchant Wholesalers to secure supplies needed for both preparation and in anticipation of repairs and rebuilding in the storm's aftermath in case supplies became inaccessible due to infrastructure disruptions. Interior product categories (i.e., plumbing, HVAC, flooring, cabinetry) can also be supplied from Chemical and Allied Products Merchant Wholesalers. Harris County houses several chemical and allied products merchant wholesalers including Brenntag, CLP Chemicals, and the Plaza Group. Increased visits by contractors and clients could have been made to secure supplies and stocks of materials in preparation for the storm impact and potential disruptions that would inhibit access to the supplies in the aftermath of the storm.

Overall, developers, general contractors, and the broader construction industry must be proactive to ensure their hurricane procedures are in place and ready to implement should a storm threaten the region. Surges in visits to these businesses might also signify various players of the supply chain of the construction industry, suppliers, distributors, and dealers, to be prepared to move substantial stocks into the area for the rebuilding effort.

5.4. Real-estate and insurance brokerages POIs

Real estate agents and insurance carriers have overlapping or supporting roles in the context of natural hazards. Increased visits to these two POIs can be tied to the heightened concern of property owners or buyers over the potential hazards and risks exposures to their home or property. Another consideration is to understand what types of hazard insurance they may be eligible for to mitigate and/or transfer those risks. For property owners, mitigating the risk would involve steps to make their property less vulnerable to hurricane losses, such as strengthening their home against wind damage and raising its height to make it less susceptible to flooding [47]. Transferring the risk implies buying insurance or using some other means to move part or all of their losses to someone else. Insurance can be an efficient means of transferring many risks [47]. Property owners and residents of hazard-prone areas may need guidance to navigate the complexities and varying costs of insurance, thus resulting in increased visits to such offices in preparation for Harvey.

For real estate agents, it is important to understand the economic impact of natural hazards, and how they affect real estate markets. A real estate agent can potentially guide clients to homes with lower hazard risks [48]. Some real estate agents work alongside insurance brokers to understand the changing costs of natural disaster insurance for floods and hurricanes every year.

Food, Water, and Energy POIs.

In times of natural disaster, "buying frenzies" in preparation for the upcoming event are normal occurrences [49]. For example, a week before hurricane Irma's landfall compared to the same period a year earlier, spending at gas stations rose 63.2%, at grocery stores 41%, and overall retail spending rose by 20% in six major metro areas across Florida [50]. Shopping for the essentials like food, water, and batteries and stocking up on gasoline is essential for household hurricane preparation. In a study by Kemp et al. [51]; the authors relate consumption as a coping mechanism of negative emotions experienced due to the

“collective stress” induced by an impending natural disaster. In addition to the essential items like bottled water, batteries, and flashlights, people also purchased “hedonic products” or “junk food items” such as cookies, chips, and alcohol [51,52]. The products people purchase to prepare for a stressful event such as a hurricane are controlled by “emotion-regulation consumption” which assumes that comfort foods or items can induce positive emotions that reduce negative emotions brought on by the hurricane [51]. With increased visits to bakeries and tortilla manufacturing businesses, it is also likely that such businesses increased the supply of their products for their consumers. During Hurricane Florence, solid preparation plans by milling and baking companies in the Carolinas helped prevent significant disruptions in service before and after Hurricane Florence hit the region in 2018. In preparation of Hurricane Florence, Flowers Foods said it worked around the clock to meet the needs of customers and consumers, baking products as long as it was safe for employees to do so [53].

5.5. Sources of risk and vulnerability

In general, POI visits in Harris County were concentrated in census tract areas with low SVI, high COVID-19 exposure and high Hazard risk. This finding is supported by the concept of COVID-19 transmission hotspots. People are more likely to visit areas with high COVID-19 exposure risk, thus increasing the likelihood of cases and a potential spread to other locations. In a study by Ref. [54] poorer zip code areas in Chicago were found to have fewer and smaller retail outlets overall than nonpoor areas including fewer supermarkets, banks, and large drug-stores. High-poverty neighborhoods have lower overall retail employment density, controlling for population density and distance to the Central Business District, along with other economic and demographic factors [55]. This could give context as to why low SVI ranking areas receive higher visits and thus transmission risk and why these areas have pre-existing exposure risks.

However, these areas with high exposure and transmission risk were less likely to be in areas that were historically impacted by flooding due to Hurricane Harvey. The transmission of COVID-19 during the preparation and evacuation phases of disaster response could potentially cause concern for the recovery and post-recovery stages of a disaster. With an incubation period between 2 and 14 days, an individual can be contagious while not exhibiting symptoms (fever, cough, sore throat, breathlessness, and fatigue), although the current consensus is most cases are spread by symptomatic individuals [56,57]. Furthermore [5], suggest that mostly indoor settings are associated with transmission clusters. Because the incubation period can last up to two weeks and infected individuals are most infectious on the fifth day [58], spikes in cases could occur during times in which infrastructure systems are most vulnerable to outages or inaccessible due to flooding and other damages caused by a storm. Our results did not indicate that in the context of Harvey and the COVID-19 cases in Harris County and surrounding areas, disruptions to healthcare access are correlated to high-risk pandemic areas. This is a significant finding and the context is location-specific. However, outcomes of high-risk areas would most likely change based on different geographical locations. Therefore, compound risk areas will be unique to the community. Other communities can benefit from this research by implementing the methodology and approach discussed in this paper to help in identifying high-risk businesses and areas of a community for COVID-19 transmission in general and concerning natural hazards and other events that require mass gatherings of people and mass evacuations to nearby areas. Furthermore, the methodology and approach of this research can be applied for similar scenarios and different infectious diseases, such as influenza (flu). As we enter into flu season overlapped with COVID-19, we will again enter into uncharted territories. One big concern is coinfection—people getting COVID-19 and flu at once [59].

Transmission risks within the identified high-risk POIs or businesses can be mitigated by mask-wearing and social distancing, but the overall

risk remains higher than normal in the event of extreme weather. Census-tracts in Harris County were ranked in the same process according to their increase in POI visits during hurricane preparation. Moreover, the exposure of census-tracts was quantified, and the vulnerability of Harris County residents was taken into account - including access to healthcare facilities. In this way, we assessed the compound risk of a hurricane-pandemic event. Emergency management, health departments, and local organizations must consider the probable exacerbation of COVID-19 transmission due to extreme weather conditions. Our research findings can inform such actions. We recommend that high-risk areas for COVID-19 transmission as identified through the above analysis are prioritized in planning public health response. Temporary shelters and healthcare centers can be placed in lower-risk areas, and neighboring counties can be alerted of increased influx of evacuees.

5.6. Future work: COVID-19 transmission related to evacuation patterns and behavior

Experts and stakeholders involved with disaster risk have two primary concerns with the compound hurricane-pandemic situation. First, there is speculation over the risk of COVID-19 outbreaks at shelters and hospitals. Secondly, there is concern regarding how evacuation can serve as a vector of disease to new locations where infrastructure services might already be overburdened, or, to areas with low case and infection rates. Low-risk areas might not have the facilities or capacity to handle potential outbreaks triggered by evacuation from other cities. The degree to which areas are prepared to host, isolate, and meet the needs of evacuees while also minimizing virus exposure through public health directives such as social distancing and mask-wearing will be a key determinant of the evacuation impact on COVID-19 case numbers [13]. Preparedness within destination counties is particularly important because, as this analysis shows, destination counties will bear the brunt of the excess COVID-19 cases that result from an evacuation event [13]. Therefore, counties must be notified of the potential arrival of evacuees for sheltering purposes for counties to allocate the financial and human resources needed to ensure the safety of both their residents and the evacuees they are sheltering [13]. One factor not addressed by the presented framework and analysis is the effect of POI category on the time total time spent at the respective POI. It is possible that the type of POI influences the type of interpersonal contact that occurs within or at the premises of a POI, and as a result, affects the risk of COVID-19 transmission. As of now, Safegraph does not record the total time spent at POIs. Furthermore, the analysis performed did not assess the potential contributing factors leading to the higher connectivity of certain census-tracts or super neighborhoods over others. Additional analysis can be performed in future studies to understand the factors contributing to the disparity in the connectivity of census-tracts, and as a result, enhanced decision-making abilities.

We identified thirty-two counties in Texas as “evacuation destinations” of the total 254 counties in the state of Texas during Hurricane Harvey. Figure A1 of the Appendix displays each origin to the destination edge as blue to red for August 2017. The destination nodes vary in the darkness of red depending on the weighted in-degree (number of visits) from Harris County. As such, we may infer that red counties are evacuation destinations for Harris County residents and are thus at higher risk for contracting COVID-19 from evacuees. Furthermore, the counties that are darker blue may be at risk for viral transmission as a consequence of recovery and rebuilding efforts. A list of counties and their qualitative transmission risk score is provided in Table 1A of the Appendix.

6. Concluding remarks

It was determined through this research that hurricane protective actions will likely increase the community spread of COVID-19 in Harris

County, Texas. The major transmission risks arise from increased contact at high-risk POIs related to hurricane preparation, movement of potential COVID-19 carriers to vulnerable areas within Harris County, and disruption of healthcare services due to flooding. However, it is not only policy that steers the outcome of disaster; individuals' decisions to evacuate or shelter in place (and their manner of doing so) govern much of the response process. The next step in this research is to model the potential spread of COVID-19 in a variety of hurricane events, taking into consideration individual behavior via agent-based modeling. In this way, a variety of disaster scenarios can be simulated, and the most-likely outcomes can be anticipated.

The research presented has two novel scientific contributions. First, the research examines the protective actions of people during a hurricane event within the context of a pandemic. Research surrounding human behaviors in disaster commonly focus on evacuation of people as opposed to the household other protective actions people take to prepare for incoming storms. Protective actions for natural hazards commonly entail the purchasing and securing goods and services deemed as necessities by households and other entities in case certain infrastructure system services are disrupted during and following a disaster. The pandemic due to COVID 19 has changed the way households can shop for access such necessities for a natural hazard. Supermarkets across the country have placed purchase restrictions on key items due to frenzy buying behaviors of households in the height of stay-at-home orders and lockdowns for curbing the spread of the virus. An issue of product availability and accessibility for in-need households could potentially arise. Furthermore, the risk of contacting the infectious disease may discourage households from going to POIs to purchase essential goods for protective measures. Inaccessibility to key POIs prior to the landfall of a hurricane therefore increase a household's vulnerability to disruptions in infrastructure services during and in the aftermath of a disaster. Understanding the interplay of disaster preparation

and the restrictive environment laid out by the pandemic is critical for community leaders and public health officials for ensuring the population has sufficient access to essential infrastructure services.

The second novel contribution of this research is the use of POI visitations as location intelligence data for examining community vulnerability to compound hazards. Our research uses POI visit data provided by SafeGraph together with SVI and historical flood data to examine the critical intersection of natural hazard planning and response and the COVID-19 pandemic to assess the risks of a compounded hazard situation. More notably, COVID-19 transmission hot-spots and businesses in a community due to storm preparation activity were identified, providing stakeholders with critical knowledge for informing both disaster planning and pandemic response strategy and policies.

Declaration of competing interest

The authors declare that there are no known conflicts of interest associated with his publication.

Acknowledgement

This material is based in part upon work supported by the National Science Foundation CAREER Award under grant number 1846069, the National Science Foundation under Grant Number SES-2026814 (RAPID), and Urban Water Innovation Network (UWIN) Undergraduate Research Program for funding this research. We would also like to acknowledge SafeGraph for providing the data used in this study. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation, UWIN, or SafeGraph.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ijdr.2021.102560>.

Appendix

Full List of POI categories used by SafeGraph data, Harris County 2017.

Medical Services (11).

Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly;

General Medical and Surgical Hospitals;

Home Health Care Services;

Medical and Diagnostic Laboratories;

Outpatient Care Centers;

Psychiatric and Substance Abuse Hospitals;

Nursing Care Facilities (Skilled Nursing Facilities);

Offices of Dentists;

Offices of Other Health Practitioners;

Offices of Physicians;

Other Ambulatory Health Care Services.

Utility and Transportation (7).

Electric Power Generation;

Transmission and Distribution;

Gasoline Stations;

Cable and Other Subscription Programming;

Waste Treatment and Disposal;

Wired and Wireless Telecommunications Carriers;

Rail Transportation;

Interurban and Rural Bus Transportation.

Other Essential Workers (7).

Grocery Stores;

General Merchandise Stores, Including Warehouse Clubs and Supercenters;

Health and Personal Care Stores;
 Postal Service;
 Depository Credit Intermediation;
 Justice, Public Order, and Safety Activities;
 Child Day Care Services.
 Traveling and Transportation (8).
 Travel Arrangement and Reservation Services.
 Traveler Accommodation.
 Support Activities for Road Transportation, (Towing Companies).
 RV (Recreational Vehicle) Parks and Recreational Camps.
 Specialized Freight Trucking, (Moving Companies).
 Freight Transportation Arrangement.
 Other Support Activities for Transportation.
 Other Transit and Ground Passenger Transportation (Health Transportation).
 Finances and Government (13).
 National Security and International Affairs.
 Securities and Commodity Contracts Intermediation and Brokerage.
 Other Financial Investment Activities.
 Accounting, Tax Preparation, Bookkeeping, and Payroll Services, (Taxes).
 Activities Related to Credit Intermediation, (Loans).
 Agencies, Brokerages, and Other Insurance Related Activities, (Insurance Providers).
 Nondepository Credit Intermediation, (Pawn).
 Grantmaking and Giving Services, (Habitat for Humanity).
 Investigation and Security Services.
 Insurance Carriers.
 Executive, Legislative, and Other General Government Support,*
 Administration of Economic Programs,*
 Administration of Human Resource Programs,*
 *POIs are closed to the public.
 Stores and Dealers (21).
 Other Miscellaneous Store Retailers.
 Warehousing and Storage.
 Beer, Wine, and Liquor Stores.
 Clothing Stores.
 Used Merchandise Stores.
 Sporting Goods, Hobby, and Musical Instrument Stores.
 Specialty Food Stores.
 Shoe Stores.
 Department Stores.
 Office Supplies, Stationery, and Gift Stores.
 Electronics and Appliance Stores.
 Home Furnishings Stores.
 Furniture Stores.
 Jewelry, Luggage, and Leather Goods Stores.
 Lawn and Garden Equipment and Supplies Stores.
 Automotive Parts, Accessories, and Tire Stores.
 Book Stores and News Dealers.
 Building Material and Supplies Dealers.
 Other Motor Vehicle Dealers.
 Automobile Dealers.
 Direct Selling Establishments.
 Services (22).
 Restaurants and Other Eating Places.
 Drinking Places (Alcoholic Beverages).
 Personal Care Services, (Hair Salons).
 Other Personal Services.
 Business Support Services.
 Employment Services.
 Other Information Services.
 Other Professional, Scientific, and Technical Services, (Photography and Vet Hospitals).
 Other Support Services.
 Drycleaning and Laundry Services.
 Couriers and Express Delivery Services.
 Data Processing, Hosting, and Related Services.
 Death Care Services.
 Individual and Family Services (YMCA).

Advertising, Public Relations, and Related Services.
 Personal and Household Goods Repair and Maintenance.
 Electronic and Precision Equipment Repair and Maintenance.
 Automotive Repair and Maintenance.
 Services to Buildings and Dwellings.
 Printing and Related Support Activities.
 Management of Companies and Enterprises.
 Florists.
 Contractors and Construction (6).
 Building Equipment Contractors.
 Building Finishing Contractors.
 Foundation, Structure, and Building Exterior Contractors.
 Residential Building Construction.
 Offices of Real Estate Agents and Brokers.
 Lessors of Real Estate.
 Education (7).
 Colleges, Universities, and Professional Schools.
 Elementary and Secondary Schools.
 Educational Support Services.
 Technical and Trade Schools.
 Junior Colleges.
 Other Schools and Instruction.
 Business Schools and Computer and Management Training.
 Entertainment (8).
 Other Amusement and Recreation Industries.
 Promoters of Performing Arts, Sports, and Similar Events.
 Museums, Historical Sites, and Similar Institutions.
 Amusement Parks and Arcades.
 Motion Picture and Video Industries.
 Gambling Industries.
 Independent Artists, Writers, and Performers.
 Spectator Sports.
 Religious Establishments (1).
 Religious Organizations.
 Rental (4).
 General Rental Centers.
 Automotive Equipment Rental and Leasing.
 Commercial and Industrial Machinery and Equipment Rental and Leasing.
 Consumer Goods Rental.
 Wholesalers (13).
 Chemical and Allied Products Merchant Wholesalers.
 Household Appliances and Electrical and Electronic Goods Merchant Wholesalers.
 Apparel, Piece Goods, and Notions Merchant Wholesalers.
 Miscellaneous Nondurable Goods Merchant Wholesalers.
 Metal and Mineral (except Petroleum) Merchant Wholesalers.
 Miscellaneous Durable Goods Merchant Wholesalers.
 Motor Vehicle and Motor Vehicle Parts and Supplies Merchant Wholesalers.
 Lumber and Other Construction Materials Merchant Wholesalers.
 Machinery, Equipment, and Supplies Merchant Wholesalers.
 Hardware, and Plumbing and Heating Equipment and Supplies Merchant Wholesalers.
 Petroleum and Petroleum Products Merchant Wholesalers.
 Drugs and Druggists Sundries Merchant Wholesalers.
 Grocery and Related Product Merchant Wholesalers.
 Professional.

Table 1A
 Total out-degrees (OD) from Harris County to Texas
 Counties in August 2017.

County	Visits from Harris County
Austin	–15
Bastrop	–25
Bexar	–286
Bowie	–5
Burleson	–5
Burnet	–10

(continued on next page)

Table 1A (continued)

County	Visits from Harris County
Caldwell	−206
Collin	−6
Colorado	−14
Comal	−133
Denton	−10
De Witt	−5
Freestone	−1
Grayson	−5
Grimes	−11
Guadalupe	−15
Hays	−63
Kerr	−5
La Salle	−5
Lee	−34
Llano	−14
Lubbock	−31
Madison	−71
Milam	−5
Nacogdoches	−25
Navarro	−5
Nueces	−17
Robertson	−9
Rusk	−5
Washington	−89
Wharton	−20
Williamson	−21

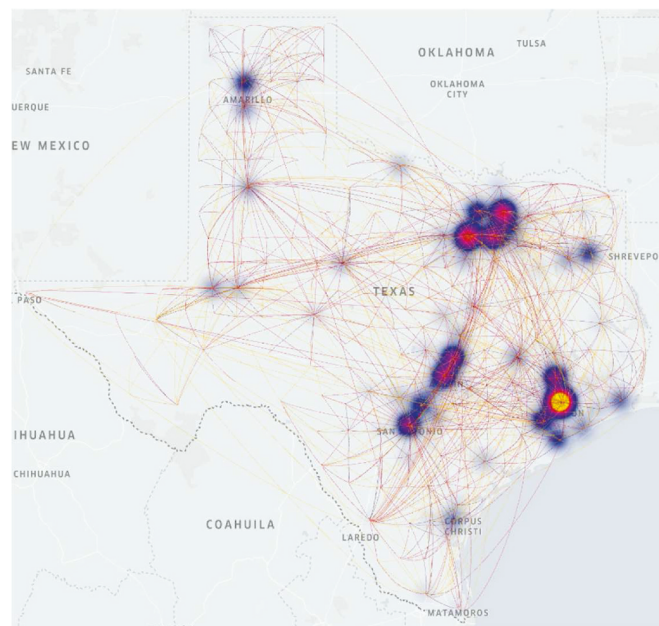


Fig. A1. The origin-destination network of cross county movements originating from Harris County, September 2017 between August 2017. The node sizes show the degree of nodes. The difference of the weighted in-degree centrality of each destination node of August to September is used to measure the transmission risks due to cross county movements during and after Hurricane Harvey (e.g., evacuation).

Table 3A

Establishments and industry services defined by the POI categories

POI Type	POI Category	Description
Shelter, Construction	Building Equipment Contractors	Installing or servicing equipment that forms part of a building mechanical system (e.g., electricity, water, heating, and cooling). The work performed may include new work, additions, alterations, maintenance, and repairs. Contractors installing specialized building equipment, such as elevators, escalators, service station equipment, and central vacuum cleaning systems are also included.
	Lumber and Other Construction Materials Merchant Wholesalers	Establishments primarily engaged in the merchant wholesale distribution of lumber, plywood, millwork, and wood panels; brick, stone, and related construction materials; roofing, siding, and insulation materials; and other construction materials, including manufactured homes (i.e., mobile homes) and/or prefabricated buildings.
	Building Material and Supplies Dealers	Retail of new building materials and supplies.
	Insurance Carriers	

(continued on next page)

Table 3A (continued)

POI Type	POI Category	Description
Water, Energy, Food	Offices of Real Estate Agents and Brokers	Establishments that are primarily engaged in initially underwriting and assuming the risk of annuities and insurance policies and establishments that are primarily engaged in assuming all or part of the risk associated with an existing insurance policy.
	Chemical and Allied Products Merchant Wholesalers	Establishments primarily engaged in acting as agents and/or brokers in one or more of the following: (1) selling real estate for others; (2) buying real estate for others; and (3) renting real estate for others.
	Gasoline Stations	Establishments primarily engaged in the merchant wholesale distribution of chemicals; plastics materials and basic forms and shapes; and allied products.
	Bakeries and Tortilla Manufacturing	Sale of gasoline and lubricating oils. These establishments frequently sell other merchandise, such as tires, batteries, and other automobile parts, or perform minor repair work.
	General Merchandise Stores, including Warehouse Clubs and Supercenters	Manufacturing of fresh and frozen bread and other bakery products. It falls under the broader category of Industries in the Food Manufacturing subsector transform livestock and agricultural products into products for intermediate or final consumption.
	Beer, Wine, and Liquor Stores	Establishments primarily engaged in retailing new goods in general merchandise stores (except department stores). These establishments retail a general line of new merchandise, such as apparel, automotive parts, dry goods, hardware, groceries, housewares, and home furnishings, with no one merchandise line predominating. Warehouse clubs, superstores, or supercenters are included in this industry.
		Establishments primarily engaged in retailing packaged alcoholic beverages, such as ale, beer, wine, and liquor.

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